WETLAND LANDSCAPE DYNAMICS AND ITS SOCIO-ECOLOGICAL IMPLICATIONS

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by
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University of Missouri – Kansas City, 2021

ABSTRACT

The dynamics on the earth landscape impact both the biotic and abiotic components. One of the abiotic components of the landscape are wetlands, whose terrestrial part is also serving as a habitat for many biotic components. Many species cannot survive without wetlands, which have benefits that serve ecological values for both plants and animals. Wetlands have been loosely defined as a transitional habitat between aquatic systems and highlands; they may be a part of coasts, estuaries, floodplains, or watersheds of surface waters. As a relatively fragile part of the Earth ecosystem, wetlands are often regarded as a socio-ecological system (SES). Wetland SES functions and services include habitats for fish, wildlife, and plants, natural water quality improvement and biochemical cycling, atmospheric maintenance, hydrologic cycling, food storage, shoreline erosion protection, education research, and aesthetics. As such, it is critical to fully understand wetlands' responses to the surrounding landscape changes in relation to the change impact on wetlands' SES benefits. However, the research issue was less addressed by previous studies, especially in identifying resultant terrestrial habitat loss and fragmented edges mostly caused by urban development. This landscape change process was found to be one of the primary drivers of species endangerment and extinction.

The social and natural components of wetlands that were affected by fragmentation in terrestrial habitats are the major focus of this study. The study selected ten wetlands situated in the three major watersheds in the Kansas City area. The physical boundaries and changes of these study wetlands were adequately captured using remote sensing and GIS techniques. The study is divided into four parts. The first part employed an object-based image analysis (OBIA) approach for image classification performed in ENVI software. This approach involves segmentation and grouping imagery into objects to preserve the spatial, spectral, and temporal scale. Two classification algorithms support vector machine (SVM) and K-Nearest Neighbor (K-NN) were used. The second part involved deriving secondary terrain attributes using the compound topographic index (CTI) and the stream power index (SPI) generated from the United States Geological Survey (USGS) digital elevation model (DEM). The third part involved metric calculations, which were implemented based on the spatial patterning of the structure of landscape heterogeneity in relation to some aspect of ecological function. The fourth part is the wetland landscape dynamic (WELD) modeling performed to estimate the changes impacted on ecological services indicators between 1992 and 2017, as it relates to wetland terrestrial habitat. In addition, demographic data were used to analyze the socio-spatial interaction of terrestrial habitat surrounding wetlands.

The result of the study at the landscape level (watershed) revealed a general swell in the wetland coverage of the three major watersheds in the Kansas City area. At the patch level (wetland), the study showed modified wetland terrestrial areas, with more impacts on the smaller wetlands. The resulting indices for terrain analysis showed an increase in potential wetness for nine out of ten wetlands studied and relatively no change for the stream power. American Community Survey (ACS 2010) and major connecting roads data were used in socio-spatial interaction. The result for ACS revealed an increase in the total sum population per 100 people (sum_POP100), followed by the sum of households per 100 people

(sum_HU100), the least increase revealed by census block count. The major connecting roads interaction revealed 84 locally connected roads intersecting the terrestrial portion of nine out of the ten wetlands. This may imply a limited impact on the terrestrial wetland habitats for amphibians and reptiles since they are all local roads. Overall analysis for the socio-spatial interaction showed smaller wetlands had greater changes within the 25-year study period.

APPROVAL PAGE

The faculty below, appointed by the Dean of the School of Graduate Studies, have examined a dissertation titled “Wetland Landscape Dynamics and Its Socio-Ecological Implications”, presented by Olusola O. Festus, candidate for the Doctor of Philosophy degree, and hereby certify that in their opinion, it is worthy of acceptance.

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DEDICATION

This research is dedicated to God, and to the loving memory of my late father, Festus Folorunsho Yakubu. It would have been a great privilege for you to witness this moment. I can still remember the question you asked me when I had issues at the university for my B.Sc., “Sola, do you still want to go to school?” Right now, I have gone past where you wanted me to go, I will forever remember your struggle for us to be a better person. Thank you for laying a very good foundation.

CHAPTER 1

INTRODUCTION

Background

Many species cannot survive without wetlands, which have benefits that serve ecological values for both plants and animals. Arnold & Van der Valk (2012) described wetlands as a habitat with around 6 percent of the Earth's surface but supporting one-fifth of the global biodiversity. It provides suitable habitat for a wide array of flora and fauna and serves as the last refuge for many threatened species. Kumar et al. (2009) suggested that at least 20 percent of the threatened bird species might inhabit various wetlands in Asia. These have further buttressed the roles played by wetlands in maintaining the population of wild flora and fauna making it a very vital issue in wildlife and conservation (Zhao et al. 2005). The ecological benefits of wetlands include a reduction in soil erosion, shoreline protection, flood attenuation, drought control, groundwater recharge, retention of nutrients and pollutants cleaning of water, modification of microclimates, and carbon sequestration (Prasad et al. 2002; Sheoran & Sheoran, 2006). Brander & Schuyt (204) valued these benefits accruing from wetlands economically with a global economic assessment of 63 million hectares of wetlands valued at $3.4 billion per year. The study revealed the highest benefits coming from Asia with an estimated economic value of $1.8 billion per year. Most of the identified wetland benefits are valuable economically, socially, and environmentally to the ecosystem. Wetlands are important is due to their socio-economic and environmental values that cover more than 12.8 million km^2 of the earth, worth approximately US$ 70 billion per year (Brander & Schuyt, 2004).

With all the benefits mentioned and the value estimated, the continuous decline in area, extent, and quality of wetland habitat may lead to a severe threat to species such as amphibians and reptiles. The large anthropogenic impact on biodiversity due to urban development has led to several habitat loss and subsequent fragmentation in urban growth (Groom et al. 2006; Collinge, 1996). Examples of such impacted species are the Missouri Cavesnail and Missouri Saddled Darter, with the former requiring further research as regards species population size and distribution trends, according to the International Union for Conservation of Nature and Natural Resources (IUCN red list 2011). Newbold et al. (2015) identified habitat loss and fragmentation as the primary driver of species extinctions. Habitat loss or fragmentation due to urban development is only one of many anthropogenic impacts on biodiversity (Tilman & Lehman, 2001), which has been described as one of the principal causes of species endangerment in the United States (Dobson et al. 1997; Vitousek et al. 1997). Changing ecosystem functions such as wetland habitat is observed to have drastically led to the loss of species (Estes & Duggins, 1995). This may otherwise result in the invasion of new species (Vitousek et al. 1997). The continuous species loss due to fragmentation following disturbances may have important implications for ecosystem functioning and may negatively affect the flow of ecosystem services (Estes & Duggins, 1995). This may affect the valuation and diversity of the composition of species, structural, and functional biotic elements of the ecosystem, which include wetland habitats. Girvetz et al. (2008) in a study in California compared the relative impact of different types of land use disturbances such as roads and agriculture to analyze the changes in landscape structure for early warning habitat degradation. Most of the research in these direction have been more subtle with the advent of very high resolution (VHR) imagery that may provide a new technique for gathering information about biodiversity and its heterogeneous habitat. VHR has been used in several efforts for watershed and wetland research. The issue of grain sizes and spatial extent that has been a major issue in the study of an urban heterogeneous landscape are well considered in this study. Nagendra (2001) described some of the major ways in which habitat mapping has been previously studied to include the mapping of one or a few dominant species in the upper canopy or by establishing links with their broader biophysical characteristics. Lucas et al. (2011) described the mapping of less complex habitat mosaics as being relatively straightforward, but they describe the problems with the landscape increasing as a result of heterogeneity in habitat (Varela et al. 2008; Lucas et al. 2011).

Considering all these, it is important to understand the environmental drivers of habitats to give more credence to the levels of species richness and their associated socio-ecological benefits. For example, the landscape barriers of many species to access terrestrial wetland habitats that can be identified by remote sensing data have encouraged the study of monitoring species loss and habitat fragmentation. However, no single environmental parameter drives the pattern of species distribution and richness (Nagendra, 2001). To investigate the interactions between social structures and ecological factors, the concept of social-ecological systems (SES) will be valuable. The SES are linked systems of people and nature, emphasizing that humans must be seen as a part of, not apart from, nature (Berkes & Folke, 1998). For adequate assessment of these interactions, Holling (2001) proposed a method for setting up an interdisciplinary research framework, which must be developed from a theoretical analysis of how research is conducted. In addition, the issue of scales and models, which are very necessary to study the dynamics of interrelated wetland and social-ecological systems, are considered. To model these scenarios effectively, remote sensing can assist conservation biologists to better understand wetland dynamics and interactions. The accuracy of this process is important most especially in relation to wetland extraction and classification, which is a very critical step in the analysis of long time series of wetland landscapes (Dronova et al. 2012). The study presented in this dissertation considers the implications of wetland habitat change effect on species with estimation and assessment using land cover maps. The importance of this study stems from the urgent need to curb the loss of biodiversity most especially in the wetland habitat area, resulting mostly from human activities. The application of remote sensing for biodiversity might require two general approaches: direct and indirect remote sensing approaches (Wang et al. 2010). The former deals with individual organisms, species assemblages, or ecological communities from airborne or satellite sensors, while the latter deals with reliance on environmental parameters as proxies. The approach adopted for this study tilted more towards the indirect remote sensing methodology. To address some of the issues identified in this study, developing innovative approaches to automate image classification, which may include image extraction and object-oriented techniques may be required (Bock et al. 2005; Förster & Kleinschmit, 2008; Comber et al. 2010; Haest et al. 2017; Lucas et al. 2011; Kosmidou et al. 2014). In addition to the classification method used, the integration of extracted wetland habitat with topographic indices provided useful information about landscape structure. Furthermore, a geospatial model was built to assess the impact of natural and human activities on ecological service indicators on wetland habitat.

Research Questions

For these issues identified to be successful study research questions will be needed. The research questions considered relevant for this study include:

- What classification algorithm better reveals wetland landscape patterns in the study area using the object-based image analysis (OBIA) approach?
- What are the impacts of the changing wetland landscape patterns on species habitat in the study area?
- How does the changing wetland landscape pattern affect socio-spatial interactions among the ecological component?
- How and what activities, both natural and human, have created a unique disturbance (act quickly and with great effect) regime on wetland landscape dynamics in the study area?

The answers to the above questions are captured in the entire body of this study, which includes the main procedures of identifying the research objectives, analyzing high-resolution imageries, and calculating and quantifying landscape and topographic indices. In addition, a terrestrial wetland habitat for reptiles and amphibians assessed using geospatial modeling.

Research Objectives

The research goal for this study is to assess wetland dynamics and its associated benefits. To address this goal, this study integrates terrain and landscape metrics into an object-based image analysis for assessing associated change benefits derived from wetlands, with the specific objectives as below:

- Apply different image classification algorithms on a high-resolution image to reveal the variation in identified patterns for the same wetland landscapes.
- Statistically assess wetland change detected on land-use/cover change in the classified image.
- Calculate landscape structure of wetland terrestrial habitat vulnerability using indices from terrain analysis.

- Quantify landscape structure and pattern of change at patch level (wetland) and landscape-level (watershed), and their impact on fragmentation and habitat loss.
- Model wetland vulnerability using the SES framework to assess changes on terrestrial wetland habitat as a result of human and natural activities on ecosystem services.

Study Area

The three major watersheds in the Kansas City metropolitan area and ten of its major wetlands were included in this study. The Kansas City metropolitan area is located along the eastern boundary of Kansas and the western boundary of Missouri in the central United States (Mid-America Regional Council). The general topography of the area is characterized by rolling hills with open plains (Ji et al. 2006). The predominant land-cover types are grasslands, forests, and croplands (MARC). Figure 1 shows the three major watersheds in the Kansas City area, which include the Blue River, Little Blue River, and Shoal Creek-Missouri River watersheds. Ten major wetland areas in the three major watersheds were also included (Figure 1). These wetlands are Missouri River, Lake Tapawingo, Blue Springs Reservoir, East Lake Wood, West Lake Wood, Lake Jacomo, Prairie Lee Lake, Longview Lake, Heritage Park Lake, and Loch Lloyd Lake.

In recent decades, population growth, increased economic activities, and the continued expansion of urbanized areas in the watersheds and wetland areas have affected the natural environment of the area (Ji et al. 2006; Weilert et al. 2018; Zubair et al. 2017; Zubair et al. 2019). This continued depletion of the natural area provided a basis for investigating the terrestrial wetland landscape of the study area. While the landscape dynamics and trends of the area have been well studied (e.g. Ji et al. 2015; Weilert et al. 2018; Zubair et al. 2017), not so much has been done in identifying and quantifying the landscape structure of the terrestrial habitat surrounding the urban wetland landscape. In addition, the economic activities in these have increased resulting in urbanization (Zubair et al. 2017), impacting the wetland terrestrial edge as the city expands. Therefore, this study seeks to investigate the landscape structure and assess the socio-ecological benefits impact on wetlands and the terrestrial habitat.

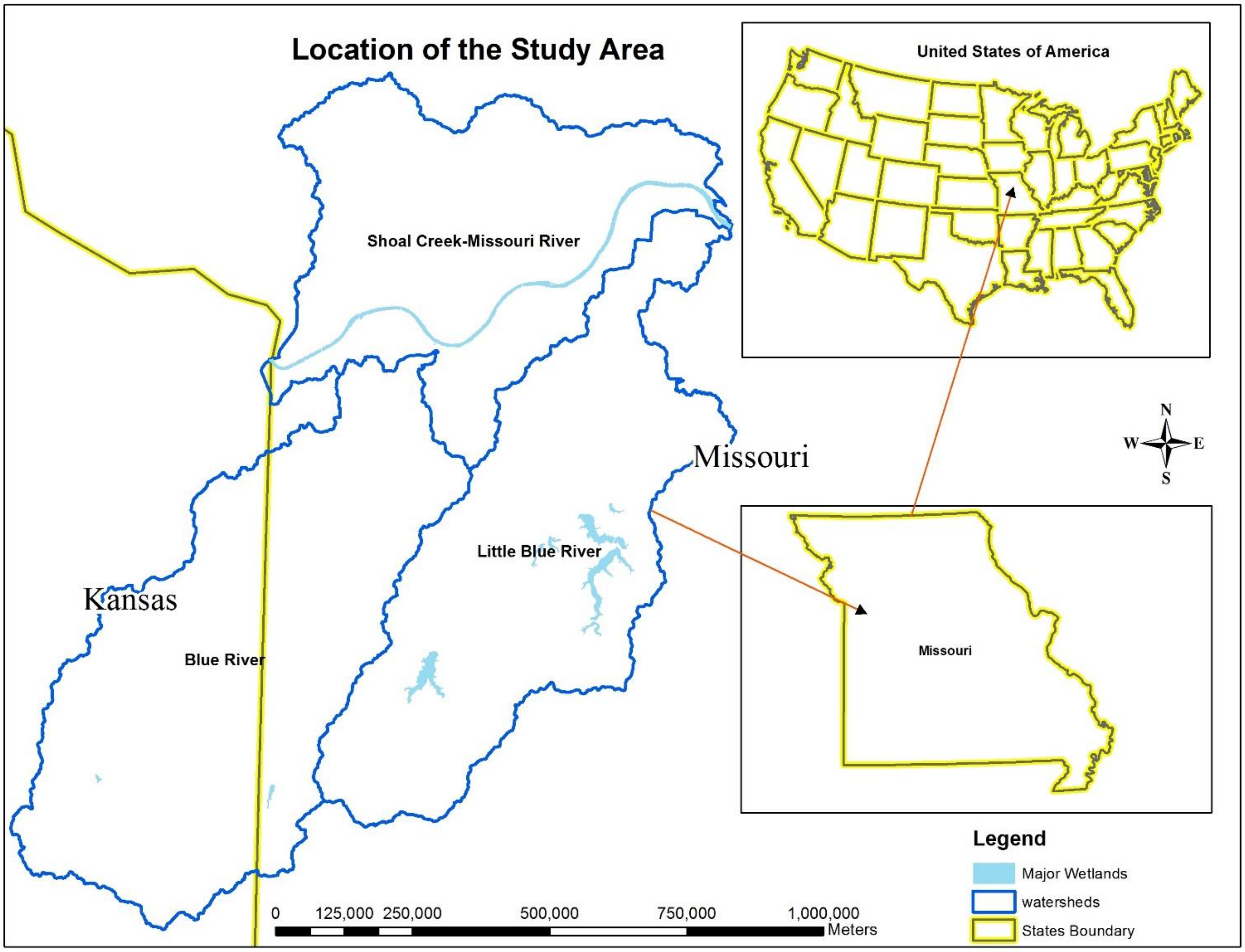


Figure 1: Study area: the major wetlands and watersheds.

CHAPTER 2

LITERATURE REVIEW

Wetlands

Approximately 6% of the earth's surface is loosely considered as wetlands (Barros et al. 2014). Brander & Schuyt (2004) suggested that 87 million hectares, which is about 54% of original wetlands (Tiner 1984) in the United States, been converted, mainly for agricultural purposes. Similarly, Pullan (1988) revealed that about 70% of the Algarve region been converted for agriculture and industrial development in Portugal. Similarly, in the Philippines, 300,000 hectares which are about 67% of the country's mangrove resources were lost between 1920 and 1980 (Zamora, 1984) mainly due to urban development. Mitsch & Gosselink (2000) described wetlands as the transition between terrestrial and aquatic ecosystems where the water table is near the surface or shallow water surface covering the land. They identify wetlands as a functioning part of the landscape with or without humans. Wetlands are a very productive and fragile part of the ecosystems. Mitsch & Gosselink (2000), the wetland landscape is a multifunctional part of the ecosystem, and this has performed many processes simultaneously.

A wetland is often portrayed as "the kidney of the Earth" mainly functioning as storage for floodwater and waste collection points from natural and human sources (William et al. 2015). According to the United States Environmental Protection Agency (EPA), wetlands support a variety of fish and wildlife species and contribute to the aesthetic and environmental quality of the United States (EPA's 2008 Report on the Environment). The EPA further classified wetlands as a swamp, shrub swamp, marsh, wet meadow, bog/fan, and vernal pool. In addition, the EPA has described the functions and values of wetlands to include high productivity, habitat diversity, flood control, groundwater recharged, filtration and nutrients, recreation, agricultural uses, fisheries, rare and endangered species. Mitsch & Gosselink (2000) also consider wetland as serving as groundwater recharging areas and contaminant filters.

In addition, wetlands have demonstrated a net carbon sink and are not radioactive sources of climate change, due to the contribution to carbon sequestration and methane emissions (Mitsch et al. 2013). Significantly, wetlands may incorporate other water bodies such as riparian and adjacent coastal zones, and marine water deeper than six meters at low tide. They help to buffer coastal areas against storm and wave damage and stabilize shorelines (Stedman & Dahl, 2008). The EPA report of environment shows that "the total wetland acreage has declined since the 1950s". The EPA (2008) report also showed that "from the 1950s to 1970s, an average of 456,000 acres" were lost per year. In addition, the period "from 1998 to 2004 saw an increase in the total wetland area, at a rate of 32,000 acres per year, while the most recent study period (2004-2009) experienced losses of 13,800 acres per year". In summary, the report showed varied gains and losses of wetland types between the years identified. The report points to urban development, rural development, silviculture, and conservation practices to be the major contributors to wetland losses.

Urban Wetlands Landscape Dynamics

Wetlands, either natural or man-made that are situated in urban areas, are generally referred to as "urban wetlands" because most of these water bodies are closely associated with residential and business facilities. Several types of research have also shown that urban wetlands could play active roles in ecology and human life in urban areas. Even though researchers have found many wetlands in the metropolis, towns, and cities, the study of wetland effects on socio-ecological systems has been limited. The dynamism in urban wetlands have resulted in various changes and modifications, and most times total disappearance of the water bodies. Hall et al. (1998) described how scarcity in urban land could drive the destruction of small wetlands due to their proximity to the developed areas. Increased urbanization leading to more land consumption in the Kansas City area has been identified and characterized using multi-stage satellite images and landscape metrics (Ji et al. 2006; Zubair et al. 2017). The study described how urbanization has increased significantly in the past three decades in the Kansas City area, showing an increase in built-up areas at the expense of the non-forest land and the spread of urban development away from the urban core.

Wetlands Socio-ecological Benefits

Wetlands formerly considered useless and disease-ridden have been found to provide many benefits to society and serve many ecological functions. Constanza et al. (1997) identified several socio-ecological benefits provided by wetlands, some of which include providing a habitat for plants and animals, biochemical cycling, hydrologic cycling, shoreline erosion protection, recreation, education, research, and aesthetics. A wetland's primary productivity is very high, making it suitable for organisms as a base for the food web. These activities provide nutrient-enriched particles called detritus, which are broken down and made available for use by several species of animals. Other larger predictor animals like amphibians, reptiles, fish, and birds may feed on these lower species.

Overall, just as wetland provides food for animals, it also provides habitats as a shelter for migrating and breeding animals. Many of these animals need wetlands for part or all of their life cycles (e.g., frogs, salamanders, snakes, turtles, herpetofauna, etc.). Most of these species of animals migrate from uplands to wetland areas for breeding and egg deposition in winter and early spring. They leave the wetland area back to the upland area to continue their adult life. For this reason, the survival of these species of animals depends largely on the availability of wetlands and migration to the uplands.

Wetlands also perform the ecological function of regulating mineralization in the habitats. Some important minerals such as nitrogen and sulfur transformed into gaseous forms and made available to plants through nitrogen-fixing bacteria in the soil. Furthermore, minerals that do not have a gaseous form such as phosphorous can transform into organic form through vascular plants in wetlands. Also, carbon which provides atmospheric functions is stored in wetlands within the plant biomass and prevents its release into the atmosphere as carbon dioxide which can increase the available greenhouse gases. However, some of these stored gases could be released during degradation, clearing of lands, landfilling, etc.

Most of the wetlands store the water at the surface, and some as underground water for various usages. Wetlands play major roles in the hydrological cycle and are important water storage meant for evapotranspiration (precipitation and evaporation). The hydrological cycle helps to maintain the ecosystem, aid biological transportation by vegetation, and fill up depressional wetlands needed for nesting by wildlife. According to the U.S. Fish and Wildlife Service estimated that “up to 43% of the federally threatened and endangered species rely directly or indirectly on wetlands for their survival”.

On the other hand, while wetlands may serve as a good spot for breeding it is also very important in influencing the quality flow of water. Water is filtrated, inorganic nutrients retained, organic waste processed, suspended segments reduced, and water quality improved for drinking. In addition, filtration by wetland helps to control environmental problems such as algal blooms and dead zones that may directly or indirectly result in excess nutrients loading. The excess minerals and decomposed organic pollutants trapped as suspended sediments.

Groundwater maintenance and replenishment are mostly by streamflow, which may help to provide water for drinking. The topography of the area might be potential flood zones. Wetlands are low land areas, surrounding uplands discharge water into it. This water is stored, controlled, and slowly released as surface water, rain, snowmelt, groundwater, and floodwater. The intercepted floodwater and other surface water are important for economic purposes, saving the cost of providing expensive dredging and levees for wetland preservation and restoration. Also, the insurance cost that may result in flood damage to houses and crops in agriculture zones are saved by the wetland habitats.

Wetlands have created a lot of benefits and opportunities for recreational, educational, and research purposes, these are in the form of hunting, fishing, bird watching, or photographing wildlife. The benefits derived from wetlands are huge most especially from nature-based tourism. The scenery provided by the most protected wetlands serves as an opportunity for tourist and artist to derive their contents. Wetlands provide the basis for most studies in the institutions, and these have increased research in environmental education. The socio-ecological and socio-economic benefits of wetlands can be well captured in different courses, so making them excellent research sites to learn more about vegetation structure, landscape ecology, habitat and biodiversity, plant successions, plants, and animal interactions, etc.

Landscape Ecology

Landscape ecology has been described as a study that examines the pattern and interaction between ecosystems within a region of interest, and the way the interactions affect ecological processes, most importantly the unique effects of spatial heterogeneity on the interaction (Clark, 2010). Recently, the availability of more reliable geospatial techniques that involves the integration of GIS and remote sensing has provided a platform for quantitative assessment of landscape ecology (McGarigal & Marks, 1995; Turner et al. 2001; McGarigal, 2000). Some of the terminology and concepts in landscape ecology used in this study are well examined and represented. There are many terms and metrics proposed by researchers (e.g. Forman & Godron, 1981; McGarigal & Marks, 1995) used to characterize landscapes, but a few will be described in this section of the study. Starting with the patch that can be described as habitat differing from its surroundings, and often the smallest ecologically distinct landscape feature (Clark, 2010). The matrix, on the other hand, is said to be an extensive and connected landscape element type with a dominant role in landscape functioning (Forman & Godron, 1986). An example of this matrix is an area of farming activities where pesticides used on the farm tend to flow to the nearest wetland patch. Another important term here is the "corridor" described as a narrow patch that may act as links or barriers in a landscape (Haddad et al. 2003). In addition, corridors have been found to be an important landscape structure influencing the dispersal of plants and animals in the landscape (Haddad et al. 2003).

Importance of Scale in Landscape Ecology

The issue of spatial scale (grain and extent) is one of the most discussed and important considerations in landscape ecology (Kotliar & Wiens, 1990; Forman, 1995). The importance attached to scale cannot be underestimated when using remote sensing datasets in land cover mapping and their correlation analysis (McDermid et al. 2005). However, this term 'scale' has been plagued by imprecise and inconsistent usage, Wiens & Milne (1989) suggested a definition that includes grain as the minimum resolution of the data while the extent depicts the spatial size of the study area. Grain and spatial extent are inversely correlated, scarifying fine grain for a large extent have been performed in several studies. For more understanding and clarity, the grain and spatial extent in an ecosystem study need to be separated. While grain refers to the spatial domain of study, the spatial extent is the organization at the population-level or ecosystem-level. The studies carried out at the population-level examine the interactions among individuals, while the studies at the ecosystem-level examine the interactions and processes among biotic and abiotic components of the ecosystem.

This study is carried out at the ecosystem-level using temporal images. The type of image used, sources, and quality dataset selection for habitat mapping is very critical to achieve good results (Devillers et al. 2007). For this study, the spatial scale used was determined by the distribution and heterogeneity of the species and habitats being monitored, factors impacting species distribution, and availability of ancillary datasets required for proper interpretation of remote sensing datasets (Nagendra, 2001). Relatively in an ecosystem-level study, the size of the pixel should be matched to the observed object so that it is one-quarter to one-third of the size of the smallest of habitat or species assemblage (Nagendra, 2001). A similar suggestion was proposed by O'Neill et al. (1997). They suggested that "in general, the grain should be 2 to 5 times smaller than the smallest feature of interest and the calculation unit should be 2 to 5 times larger than the largest feature of interest". This has thrown up various research and discussions about the ecological scale and the need to match spatial scale to the object being observed (e.g. habitat or species of focal interest). Some of these images are too expensive to be acquired at the desired scale for the research study and may not be readily available for research purposes, such as very high resolution (VHR) data from the QuickBird, SPOT, IKONOS, GeoEye, and WorldView-2 sensors. The cost limitation associated with VHR data has its own consequence on scaling, though more preference is given to VHR (Nagendra & Rocchini, 2008) for ecological study at a local scale. The availability of

United States Geological Survey (USGS) Landsat data which is free of charge has provided an opportunity to map habitats at a relatively finer scale.

Furthermore, on the scale, Delcourt et al. (1982) argued that an ecological phenomenon tends to have characteristic spatial and temporal scales or spatiotemporal domains. Similarly, Levin (1992) advised that there is no single natural scale at which ecological phenomena should be studied. He suggested that systems generally show characteristic variability on a range of spatial, temporal, and organizational scales. Levins & Culver (1971) proposed the importance of spatial patterns in structuring ecological communities and maintaining the coexistence of competitors. A study by O'Neill et al. (1997) suggested that developing the principles of landscape ecology by an individual investigator on a relatively small spatial scale may suffice. However, for the purpose of monitoring status and assessing changes across the continent, there is a need to consider the regional scale.

In conclusion, to the use of scale at both fine and coarse levels in the ecological study, it is best to consider the scale at which an organism perceives its environment. Some studies demonstrated the benefits of very high-resolution (VHR) imageries for mapping successional fine-scale habitats such as bogs (Bock et al. 2005). However, in most cases, the choice and availability of remote sensing datasets will determine the amount of information that is available to be mapped (Devillers et al. 2007). Overall, the unit area or extent of analysis should reveal the sensitivity of the indices to the scale of calculation, at which it is been computed (O'Neill et al. 1997).

Landscape Ecological Modeling and Framework for Socio-Ecological Systems (SES)

Landscape ecological modeling provides the template for a better understanding of the interactions between biophysical and social drivers of land-use and the changing ecological systems. Landscape ecological modeling has been widely accepted due to the recent advancement in landscape ecology and availability of spatial data that are integrated into GIS technology. This integration has provided researchers with the opportunity to model and evaluate, monitor, and assess wildlife habitats using the combination of remote sensing satellite imagery and GIS spatial datasets (e.g., Forman & Godron, 1981). Several models have been used to quantify landscape patterns and structure for the management of wildlife populations and conservation planning in the past (U.S. Fish and Wildlife Service 1980, 1981). Understanding the spatial structure and landscape patterns have been found to be an important aspect of landscape modeling and evaluation using GIS technology (Donovan et al. 1995; Rickers et al. 1995; Robinson et al. 1995). Some of the spatial datasets used for landscape modeling may be demographic data on human settlements, road data, or impervious data to assess and evaluate wildlife habitat (Barve et al. 2005).

Many models and frameworks have been employed in socio-ecological studies (e.g. Collins et al. 2011; Smith et al. 2009). Collins et al. (2011) in their research proposed a framework that integrates the internal and interactive dynamics of social and natural systems. The study suggested the process of the press–pulse dynamics (PPD) for ecosystem services. “Press” described as an extensive, pervasive, and subtle change while “pulses” are infrequent cumulative observed changes. Four components used in the framework to model the drivers of ecosystem services. The model encapsulates the critical linkage between social and biophysical domains to serve as the foundation for long-term study across scale, the focus was not on wetland landscape dynamics. Smith et al. (2009) in a similar study proposed the hierarchical-response framework (HRF) which leverages ecological mechanisms of change to provide a theoretical basis for testing hypotheses. The study suggested two disturbance regimes; natural disturbance and global change that drive the ecosystem responses. This study is a very good complement to other frameworks that focus on dynamic regimes and ecological thresholds, but it does not focus on wetland landscape dynamics. Other related frameworks like that of Shaver et al. (2000) in a study that describes challenges and provided the conceptual framework for interpreting experimental results. The study looks at predicting the effects of warming on the ecosystem. This study is important and looks at the direct and indirect effects of warming, response to warming, and interactions with other drivers of global change on the ecosystem. The study focused more on temperature and predicting warming response and not on the wetland landscape dynamic ecosystem. Similarly, Briske et al. (2006) proposed a unified framework for threshold assessment to link ecological theory and process with management knowledge and application. The study is vital to a conservation management application and defined operational thresholds based on probabilistic interpretation. However, the study does not look at the dynamics occurring at wetland levels specifically, but the threshold proposed can be adopted for wetland conservation.

Considering all these studies mentioned above, the adoption of the wetland landscape model for SES would further complement existing frameworks and models. The proposed framework for wetland landscape dynamic (WELD) modeling emphasizes more on the approaches needed to understand the dynamics and processes of wetland landscape SES. This aimed at further bridging the enormous gap in interdisciplinary science. Different researchers may interpret Socio-ecological changes and processes differently, but the most effect imping on biophysical and social components that result in landscape modifications. Table 1 shows the relationship between key threatening processes associated with landscape modification and biological attributes of species, which ameliorate extinction processes (Fischer and Lindermayer, 2007)

Table 1: Landscape Modification and Threat to Biological Attributes of Species

Threatening process	Ameliorating biological attribute	Explanation
Habitat loss and habitat degradation	Low habitat specialization	Specialized species are more likely to lose their habitats as a result of degradation landscape change.
	Disturbance tolerance	Disturbance-tolerant species are more likely to find suitable habitat in modified landscapes.
	Ability to live in the matrix (degree of landscape connectivity) Specie	Species can live in the matrix experience no habitat loss as a result of landscape modification
Habitat isolation and sub-division	Ability to move through the matrix.	Species that can move through the matrix are less likely to suffer the negative consequences of habitat isolation.
	Dispersal ability	Strong dispersers may be more likely to maintain viable metapopulations
Disrupted species interactions	Limited dependence on particular prey or mutualist species	Species that can switch prey or mutualists are more likely to withstand landscape change
	Competitive ability	Species that are strong competitors are less likely to be outcompeted by species whose habitat expands as a result of landscape change
Disrupted biology	Low biological and behavioral complexity	Species with a complex biology (e.g. social or breeding systems) are complexity more likely to have their biological processes disrupted as a result of landscape change than species with simpler biological systems
Stochastic events	Population density	High density populations contain many individuals even in a small area, and hence are more resilient to stochastic threats

Adopted from Fischer and Lindermayer, 2007

Landscape Metrics

The term 'landscape metrics' refers exclusively to indices developed for categorical maps. The focus is on grain size and the spatial extent to categorize the geometric and spatial properties of a pattern represented on a map at a single scale. McGarigal (1995) points out that it is important to note that while metrics at higher levels are derived from patch-level attributes, not all metrics are defined at all levels and that most of these metrics are correlated. McGarigal (1995) defined landscape metrics at three levels: patch-level metrics (individual patches and spatial characterization of patches), class-level metrics (integration using averaging overall the patches of a given type), and landscape-level metrics (integration overall patch types and classes over the full extent of the data). In addition to the three levels of landscape metrics, he further categories metrics into two major components, those that quantify composition (proportional abundance, richness, evenness, and diversity) and those that quantify configuration (patch size distribution and density, patch shape complexity, core area, isolation/proximity, contrast, dispersion, contagion and interspersion, subdivision, connectivity).

Furthermore, the composition is the relative proportion of habitat types in the landscape, regardless of spatial distribution (habitat area), while configuration (spatial pattern of patches) refers to almost limitless aspects of landscape heterogeneity, especially the physical and spatial distribution of landscape elements (Clark, 2010). Landscape ecologists have shown more interest in how the spatial distribution of elements affects ecological processes. To measure the ecological processes and spatial interaction the patch area (PA) is a very important factor, especially for organisms that use a specific patch type as habitat. PA measures the amount of edge (ecotone) between a focal patch type and the surrounding matrix. Ecotone represents the transition zone of influence on ecological processes. Both composition and configuration described above affect the dynamics of any habitat, in terms of altered area (composition) and spatial pattern. Landscape metrics are effective quantifications of landscape patterns and ecological processes, but users must be careful about how the results of the analysis are interpreted (McGarigal, 2000). The researcher or investigator must take some measures before the quantification of the landscape. The investigator or user must define the grain size and spatial extent of the patches before computing any of the metrics. The bias involving edge or perimeter can be introduced into computation depending on the format used either raster or vector. The raster data format will have an upward bias for edge lengths, because of the stair-step outline, and the magnitude of this bias will vary with the grain or resolution of the image used. It is important to specify additional input parameters such as edge effect distance, edge contrast weights, and search distance. The measured pattern of the landscape must be seen as corresponding to a pattern that is functionally meaningful for organisms or species under consideration for the analysis to be useful. It is important to understand each landscape metrics before selection for use in interpretation.

This study considered landscape metrics as measuring landscape patterns with reference to a particular ecological process. McGarigal (1995) referred to this as functional metrics. They explicitly measure landscape pattern that makes it functionally relevant to the organism or process in the study area. On the other hand, structural metrics refer to the analysis that measures the physical composition or configuration of the patch mosaic without explicit reference to an ecological process.

Digital Terrain Analysis

Modeling the digital elevation model (DEM) for landscape provides a quantitative detailed, objective, repeatable process to accurately model real landscape processes. The integration of DEM with Geographic Information System (GIS) and Remote Sensing (RS) technology allows for accurate characterization of large areas. Digital terrain analysis integration into the GIS model enables researchers to geospatially describes landscapes in a hydrological, biological, or geomorphological context in several applications (Wilson & Gallant, 2000). Terrain analysis applied to areas that may be essential for restoring and protecting water. Essential in this sense can be loosely defined as an area of the landscape that accumulates overland flow and is hydrologically connected to surface waters, either by an overland flow path or by sub-surface drainage. According to a study by Galzki et al. (2008), the areas as described have a higher likelihood of conveying contaminants to surface waters than other portions of the landscape. These areas are mostly found in a depression or riparian area and can be a major contributor to the contaminants in the water. These could be in the form of sediments, nutrients, and pesticides, to nearby surface waters.

Advantages of using terrain models:

1. Repeatable results (non-subjective)
2. Numerical results (Spatial)
3. Analysis and interpreting topographically related features
4. Consistent with the level of details needed for conservation plans

Terrain attributes are primary and secondary attributes data. Primary attributes data may include aspect, slope, catchment areas, profile curvature; all can be calculated directly from the elevation data. While the secondary attributes are the combination of the primary attributes data (see Figure 2), these include derivative calculations such as compound topographic index (CTI) that is also referred to as the steady state of wetness index or wetness index (Wilson & Gallant, 2000). In addition to this is the stream power index (SPI) which is the potential erosive power of overland flow (see Figure 3), with isolated areas where water or ponds are collected in a landscape (Wilson & Gallant, 2000).

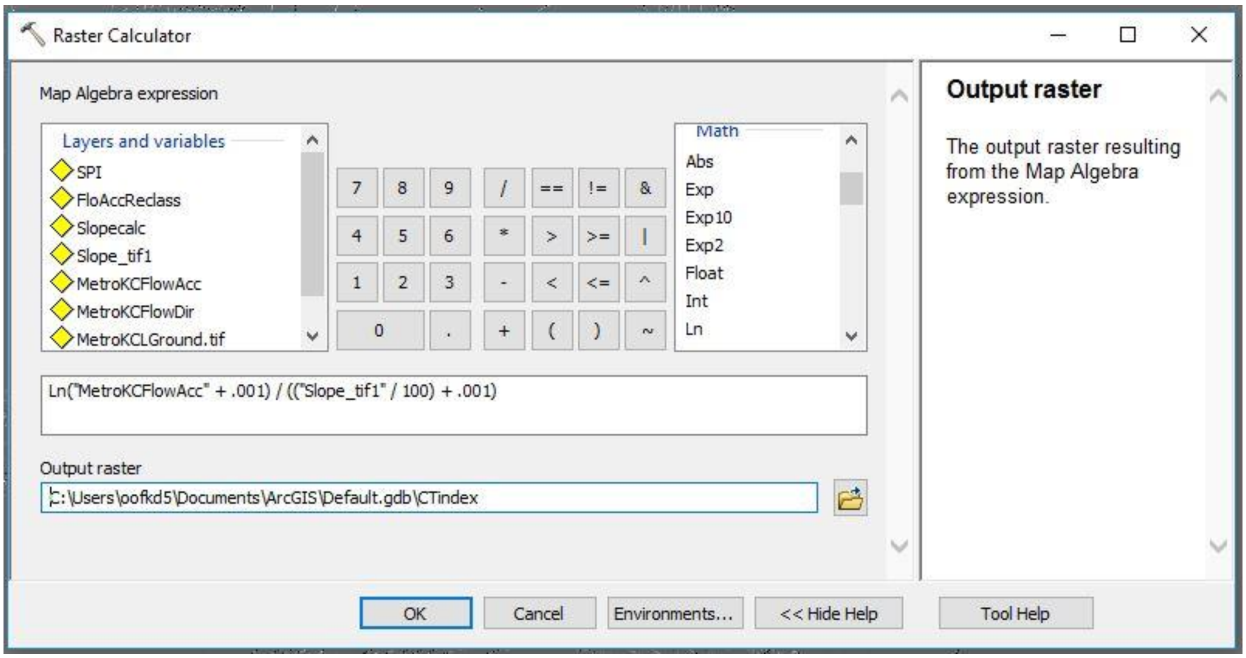


Figure 2: Compound topographic index (CTI) in raster calculator.

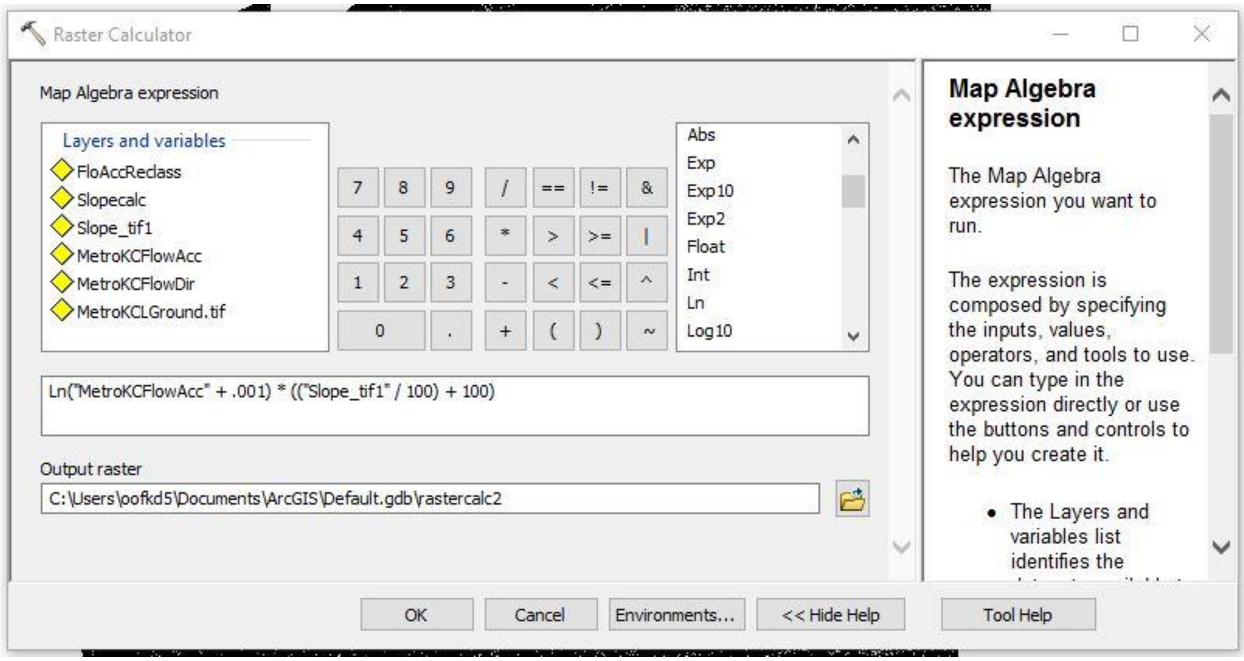


Figure 3: Stream power index (SPI) in raster calculator.

Land Cover Classification Algorithms

Image classification is one of the most effective processes employed for the production of land use and land cover maps in remote sensing. The results of image classifications are the basis for many calculations and quantifications. Image classification described as the process of categorizing all pixels in an image such as raw remotely sensed satellite data to obtain a given set of labels or land cover themes (Lillesand & Keifer, 1994). The major steps in the remote sensing classification process may include the determination of a suitable classification system, selection of training samples, image preprocessing, and feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment (Jensen, 2015). Several studies have used various classification approaches that have been developed and widely used to produce land cover maps (e.g. Aplin & Atkinson, 2004). Whatever the approach used, they are associated with two broad types of classification procedures: supervised classification and unsupervised classification. For this study emerging methods of image classification referred to as object-based image analysis (OBIA) is applied. This is performed with object extraction using the example-based process for OBIA (segmentation) and further classified using two different machine-learning algorithms: Support Vector Machine (SVM) and K-Nearest Neighbor (K-NN) classification algorithm.

OBIA (segmentation): Image segmentation is not a new idea for the image classification process in remote sensing. It has its roots in industrial image processing, but it was not used extensively in geospatial applications throughout the 1980s and 1990s (Blaschke, 2003). This process requires meaningful object identification and attributes labeling. The attributes considered for segmentation include spatial attributes, spectral attributes, texture attributes, color space, and band ratio attributes. Training data output from this process is used to assign objects of unknown to identify to one or more known features using supervised classification. Using the OBIA techniques can help to improve image shadow regions using the rule-based approaches or spectral unmixing that can eventually improve image accuracy (Sawaya et al. 2003; Förster & Kleinschmit, 2008; Haest et al. 2017; Mücher & Kooistra, 2011).

***Support Vector Machine (SVM)*:** The proficiency of this classification method was put forward by Vapnik and colleagues in the 1990s. SVM has been known to be effective for face and object recognition in a photo before its adoption for use in remote sensing (Pal & Mather, 2005; Hermes et al. 2000). The SVM considers the critical elements of the training set and uses the pairwise classification strategy for multiclass classification. The SVM classification output is the decision values of each pixel for each class, used for probability estimates. This process allows an optional threshold to report pixels with all probability values less than the threshold as unclassified. SVM tries to identify the hyperplane, the central distance between the closest points of each of the two classes, which is referred to as support vectors (Pal & Mather, 2005).

A trade-off between training errors and forcing rigid margins is set to allow control of pixel information as a penalty parameter. SVM assumes that, if two classes separated by a line drawn in the feature space, to separate these two classes, the space between the two classes identifying a central hyperplane should be maximized (Pal & Mather, 2005).

***K-Nearest Neighbor (K-NN)*:** This is one of the simplest and most used instance-based learning algorithms. The 'k' in KNN is a parameter that refers to the number of nearest neighbors to include in the majority of the voting process. This classification algorithm assumes that all instances are points in some n-dimensional space and defines neighbors in terms of distance (usually Euclidean in R-space). K-NN has been known to have a few remarks that have increased its usage in the research community for land use land cover classification. K-NN works well on many practical problems and is fairly noise tolerant (depending on the value of K). When K increases, it makes K-NN less sensitive to noise but if K decreases it will allow capturing the finer structure of space. It all depends on the study and the data, but it is better to make K not too large or too small. Though the K-NN classifier is one of the simplest and most widely used nonparametric classifications, it has been successfully used for hyperspectral image classification (Huang et al. 2016)

Accuracy Assessment Issue in Modeling

Accuracy assessment in remote sensing is the comparison of classification with ground truth data to evaluate how well the classification represents the real world. This can be referred to as the degree to which the derived image classification agrees with reality or conforms to the ‘truth’ (Campell, 1996; Smits et al. 1999). However, after the classified image, ground truth can be collected in the field to validate the results, though this can be very expensive and time-consuming. Ground truth data can also be performed by interpreting high-resolution imagery

(Google Earth), existing classified imagery, or GIS data layers. The most common way to carry out accuracy assessment on a classified map is to create a set of random points from the ground truth data and compare that to the classified data in a confusion matrix. For this study, an accuracy assessment was conducted on all four classified images, for each of the two algorithms used. The confusion matrix was constructed, and it consists of overall accuracy, overall kappa coefficient, ground truth wetland producer's accuracy, and user's accuracy, commission, and omission. The overall accuracy is calculated by summing the number of correctly classified values dividing by the total number of values.

Previous Studies related to Wetland Dynamics, and Socio-Ecological Systems

Several studies have used different methodologies and techniques to better understand the dynamics of wetlands. Researching urban wetland landscape dynamics is far from being straightforward, due to its heterogeneous nature. Mapping a heterogeneous landscape is more relatively challenging (e.g. Lengyel et al. 2008). This is no exception to this study. The wetland landscape dynamic of the Kansas City area has been well studied. But not much has been done on wetland terrestrial habitat change and how it affects the function and values of socio-ecological benefits derived from it. Ji (2016) in his study of an urban wetland landscape in the Kansas City area, referred to urban wetland as "urban wet-landscape". Wetland in this study was described as a sensitive indicator in detecting the coupling effect of two major driving forces of the urban landscape: human impact and climate change. The study employs the rule-based classification algorithm at a fine-scale, which was able to detect hidden wetlands that could not be detected using the traditional image classification. While this study successfully verified that the urban wet-landscape was an effective indicator of the two major urban change drivers, it did not address the socio-ecological benefits of urban wetlands. A similar study by

Ji et al. (2005) in the Kansas City metropolitan area characterized the urban sprawl using remote sensing methods and landscape metrics. The study suggested that the effect of landscape response to urbanization could better reveal within larger spatial units (Metropolitan area, habitat, or county) as compared to a finer scale unit like a city. The result of the study is very important and a pointer to the scale factor, but it did not dwell specifically on wetland terrestrial habitat and its socio-ecological components. Zubair et al. (2017) studied wetland changes in the three watersheds in the Kansas City area between 1992 and 2010, which revealed wetland increase in two watersheds historically and loss to urban expansion in one. This study did not look at the effect of these changes observed on wetland socio-ecological benefits.

Away from the Kansas City area, many other researchers have demonstrated how different forces can drive wetland landscape dynamics. In this light, Baker et al. (2007) investigated the changes observed in the wetland ecosystem in the Gallatin Valley of southwest Montana, using stochastic gradient boosting (SGB) for classification and change vector analysis (CVA) to identify predicted area of change. This technique was able to achieve high accuracy of 81-86% but changes to wetland socio-ecological benefits were not investigated. Mitsch et al. (2000) in a study carried out to value wetlands using the location in the landscape. The study suggested that a range of 3–7% of temperate-zone watersheds should be in wetlands to provide adequate flood control and water quality values for the landscape. The research concluded that consideration must be given to what constitutes the basis for valuation, it is the adjacent biological population, wetland ecosystem, or the entire biosphere where the wetland is located. The study provided important answers to some wetland questions but less related to socio-ecological benefits change of wetlands terrestrial habitat. A couple of other studies have actually work on investigating the general changes of wetland landscape using VHR, diverse classification techniques, and other auxiliary data. Most of these studies did not lay much emphasis on the implication of changes on wetland terrestrial habitat and how it affects the associated socio-ecological benefits (e.g. Burgin et al. 2016; Dronova et al. 2012; Ji et al. 2006 & 2015; Lawrence et al. 2014; Szantoi, 2015; Wu et al. 2016; Weilert et al. 2018; Zubair et al. 2017 & 2019). Therefore, considering all the aforementioned studies, their suggestions, and area of concentration, this study will seek to further improve on the techniques used, and create a better understanding of the associated socio-ecological benefit of wetland relatively researched in the past. To achieve this purpose high-resolution imagery at a fine-scale was employed for data extraction and classification. In addition, archival digital elevation model data was used for the assessment of landscape structure. Landscape metrics change detection statistics and ecosystem service modeling were applied to understand the perspective for policy and decision-makers, urban planners, and conservationists.

CHAPTER 3

METHODOLOGY

To better address the goal and objectives set for this study and give an adequate and quantitative answer to the major research questions, the study has adopted a salient research technique and framework. The methodology used in this study is divided into four parts (see Figure 5). The first part employed an object-based image analysis (OBIA) approach for image classification. Two classification algorithms, Support Vector Machine (SVM) and K-Nearest Neighbor (K-NN), were used. Both methods involved feature extraction using an example-based method for segmentation and merging. Furthermore, change detection statistics (CDS) was performed on the classified images resulting from the application of both algorithms. This was done to understand the class change among the LULC in different classes. CDS was used specifically for the calculation of wetland coverage change at the watershed level in this study. The second part involved deriving secondary terrain attributes using compound topographic index (CTI) and stream power index (SPI) from the United States Geological Survey (USGS) digital elevation model (DEM). These indices were used for wetness and stream power quantification around the terrestrial wetlands. Furthermore, in this part, a 30-meter inward buffer was performed on the extracted wetlands to serve as estimated core areas. These then clipped to derive secondary terrain attributes (CTI and SPI) at 340-meter buffers, which served as the terrestrial wetland habitat area (see Figure 5 & 6). The third part involved metric calculations, which were implemented based on the spatial patterning of the structure of landscape heterogeneity in relation to some aspect of ecological function (e.g. direct or indirect role). The major metrics employed for analysis were related to the edge, diversity, shape, and size of wetland patches (see Table 1). Fourthly is the wetland landscape dynamic (WELD) modeling performed to estimate the changes impacted on ecological services indicators between 1992 and 2017, as it relates to wetland terrestrial habitat (see Figure 7 & 8).

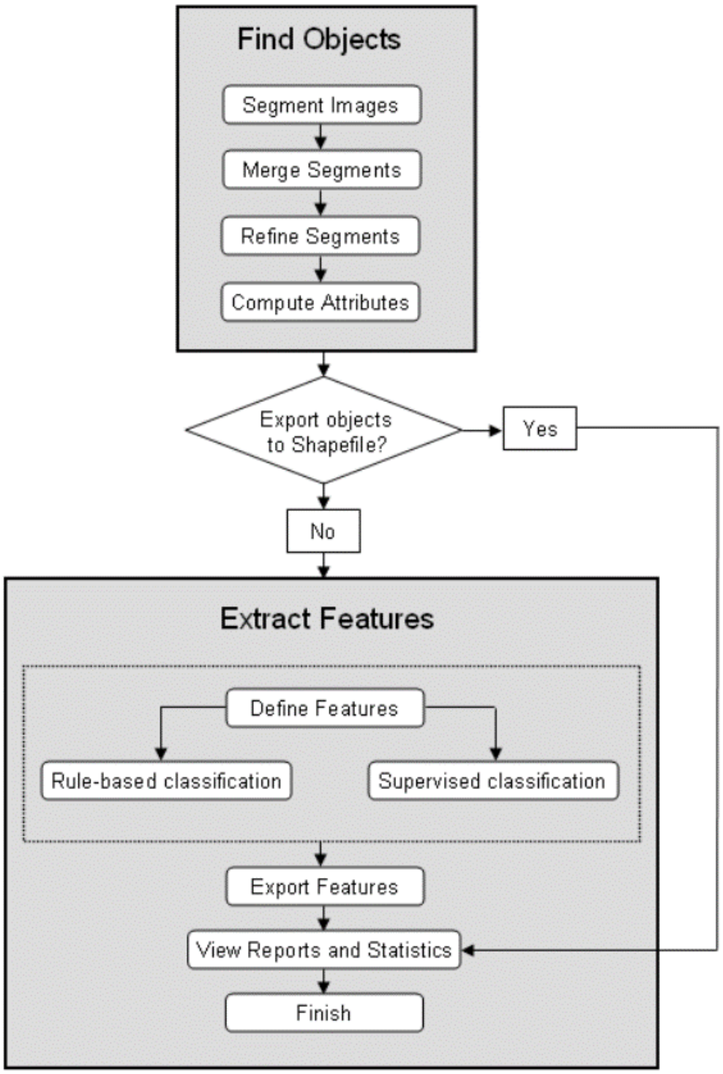


Figure 4: Feature extraction for object-based supervised classification

Source: Adopted from ENVI software feature extraction workflow Manual

Flow Chart of the Major Tasks Performed in this Study

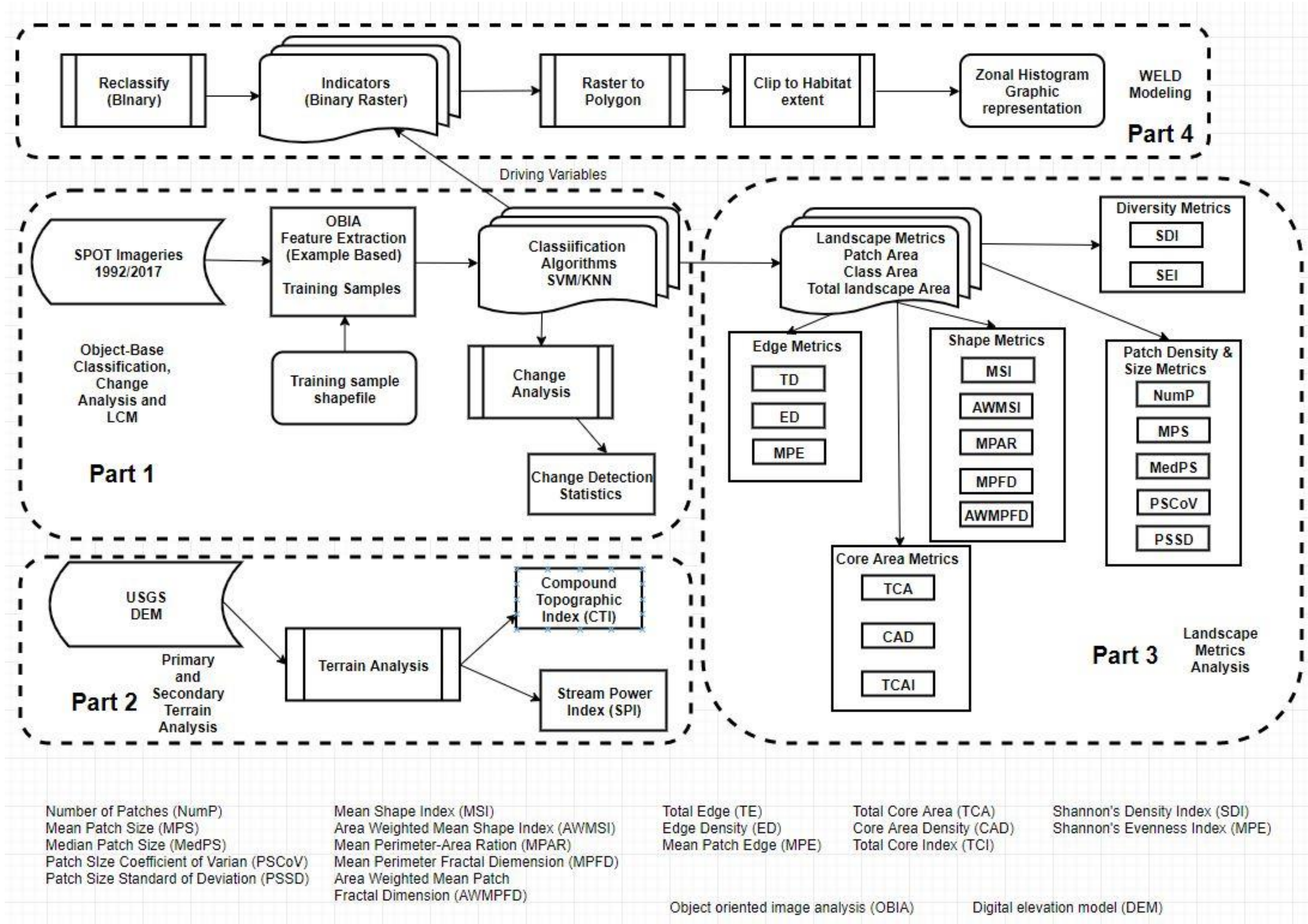


Figure 5: Major tasks in this study

Image Classification Techniques

The data for this study were carefully sourced, cleaned, and validated. For the first part of this study, object-based feature extraction and the two algorithmic supervised image classification were performed. These research objectives require identifying and detecting the predicted spatial wetland landscape pattern, with a focus on interpreting the wetland landscape change using multiple algorithmic classification techniques. The two algorithms were compared to achieve a better result for the image classification, which avoids possible misinterpretations that could have resulted from using different multispectral images (Lu & Weng, 2007). To address this need for research, spectral analysis was performed in ENVI before the image extraction and classification. SPOT 2 sensors with the data collected in three relatively broad multispectral bands and one panchromatic band were compared to SPOT 7 that contains four similar bands (Table 2). In this study, the two images were compared using the spectral signature to distinguish the types of ground cover or objects performed in ENVI software. The processing level 1A, which means correction by normalizing the charge-coupled device (CCD) response to compensate radiometric variations due to detector sensitivity has been applied, was applied to SPOT 2 image 1992. On the other hand, the 2017 SPOT 7 image was pre-processed on the 2A level, meaning scenes have been rectified to match a standard map projection (UTM WGS 84) without using ground control points. Level 2A is the entry-level map product for the SPOT image. This means no geometric correction was needed for SPOT 7 and the systematic distortion effects and transformations have been compensated by projecting the image in a standard map projection UTM WGS 84.

The OBIA techniques was applied, which involved image segmentation and merging processes which were performed on two archived SPOT imageries. Both SPOT 2 (29 January

1992; 20 m x 20 m resolution) and SPOT 7 (22 October 2017; 6 m x 6 m resolution) were classified using K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM) algorithms, respectively. Both datasets were resampled to a uniform pixel size with a representative minimum mapping unit (6 m x 6 m) adopted. Jensen (2015) reiterated that this does not present much impact on the results, because the resampled data can never be greater than the instantaneous field of view (IFOV). He mentioned that additional information should not be expected from the resampled image. In addition, object-based classification may be a good alternative to traditional pixel-based methods. This is to overcome the high-resolution problem and the "salt and pepper effect". Salt-and-pepper noise is a form of noise caused by close neighbors which often have different classes, despite being similar. The object-based segmentation was used to reduce this effect by grouping pixels, characterizing, and organizing it into objects, and treat each object as a minimum classification unit (Yu et al. 2006).

Table 2: Characteristics of SPOT imagery included in the study.

Sensor	Date	Spectral mode	No. of bands	Processing level	Spatial Resolution	Source
SPOT 2	29-Jan-92	XS	3	1A	20 meters	SPOT Image Corporation
SPOT 7	09-Sep-17	PMS	4	2A	6 meters	EADS

The images were selected with the consideration of their availability and the type of classification methods used to ensure that they will not affect the accuracy of the result. In addition, the classification method adopted for segmentation and merging were focused more on the spatial, spectral, and textual information of the images. Segmentation is the process of partitioning an image into objects by grouping neighboring pixels with common values (L3 Harris Geospatial documentation center). Merging, on the other hand, combines the adjacent segments with similar spectral attributes textural information together based on image resolution (L3 Harris Geospatial documentation center). This process is example-based, which is also referred to as supervised classification. It is used to obtain training data as objects and then assigns them to one or more known features. Archived SPOT images with a temporal resolution of 25 years between the two images were classified (see Figure 6). Overall, a segmentation process using feature extraction, and machine learning techniques were sequentially applied in the classification process. For most of the analysis in the study, the SVM classification result was used because it provided higher accuracy than the other methods.

Adopted Classification Scheme

This study adopted a classification scheme that grouped the different classes on the images into four categories of land cover (Table 3). This was done mostly because of the issue of spectral signature similarity experienced during the process of image segmentation when generating the training sites. The four categories as shown in Table 3 include Impervious Surfaces (IS), which represent urbanized areas; Forestland (FL), which covers all areas with a collection of trees. Further, all areas with brush, crops and non-forest vegetation/grassland were classified as Farmland/grassland (FGL) and Open water bodies were classified as Wetlands (WL). The output was a classified raster grid, which was then converted to vector polygons to perform landscape metrics calculation on them. Patch Analyst 5, an extension of ArcGIS 10.6 software, was used for the landscape metrics calculations.

Table 3: The land-cover classification scheme.

Class name	Class Description
Wetlands (WL)	Rivers, lakes, ponds, riparian area, vegetated depressions
Farmland/Grassland (FGL)	Cultivated land, grasslands, golf courses, lawns
Impervious surfaces (IS)	Built-up areas (buildings, roads, paved walk-ways, etc.)
Forestland (FL)	Trees and shrubs

Accuracy Assessment

ENVI software confusion matrix was used to calculate the accuracy of the Object-Oriented Classification, with emphasis on wetland classification. 50 regions of interest (ROI) polygons for each class were selected and referenced using Google Earth archival imageries and other classified maps of the Kansas City area. The report of the calculation pairs ROIs with the classes of classified images to show what percentage of the ROI pixels were or were not contained in a resulting class. The overall accuracy was calculated by summing the number of correctly classified values and dividing by the total number of values. Table 4 shows the accuracy assessment reports with a higher overall accuracy percentage for SVM classification for both SPOT 1992 and 2017 images and the overall accuracy for K-NN SPOT 1992 and 2017. SVM–based classification for SPOT 2017 revealed 89.14% accuracy while the K-NN-based classification on the same image resulted in a 79.54% total accuracy. The SVM-based classification for SPOT 1992 resulted in 63.84% while the K-NN approach for the same year generated an overall accuracy of 61.42%. Overall, little disparity was revealed for both algorithms when results for each year were compared. However, the SVM accuracy results were better when compared to that of K-NN (Table 4). Despite that two different classification algorithms were used on the same image, their accuracy reports revealed a consistent trend.

Similar trends in landscape patterns were obvious using the two classification algorithms (see Table 4).

Table 4: Accuracy assessment with emphasis on wetland accuracy from both classifications.

Confusion Matrix: Accuracy of Object-Oriented Classification Results								
SPOT Image	**Supervised Classification Method**	**Overall Accuracy (%)**	**Overall Kappa Coefficient**	**Ground Truth Wetland (%)**	**Prod. Acc. (%)**	**User Acc. (%)**	**Commission (%)**	**Omission (%)**
1992	SVM	63.84	0.48	96.75	96.75	92.25	7.75	3.25
	K-NN	61.42	0.45	96.75	96.75	93.20	6.80	3.25
2017	SVM	89.14	0.80	95.86	97.29	94.91	6.26	4.14
	K-NN	79.54	0.65	97.29	95.86	93.74	5.09	2.71

Urban Wetland Terrestrial Habitat Buffer

To understand the landscape structure surrounding the terrestrial wetland habitat necessary for the urban wetland ecosystem, a buffer of 340-meters from the core area was adapted for the study (Murcia, 1995; Semlitsch & Bodie, 2003). To achieve this, a 30-meters inward buffer was performed on the extracted wetland files, which serves as the aquatic buffer zone from the core wetland. Another 260-meters outward buffer was created from the extracted wetland files, which served as the core habitat area. The aquatic buffer is also a part of the core habitat area; an additional 50-m buffer recommended by Murcia (1995) to protect the core habitat from edge effects was used (see Figure 6). This implementation is similar to a study by the Environmental Law Institute (2008), in which the area served as the terrestrial wetland area sufficient for the movement of wetland wildlife (e.g., Amphibians and Reptiles) through the landscape (see Table 5).

Table 5: Mean minimum and maximum core terrestrial habitat for amphibians and reptiles.

Group	Mean minimum (m)	Mean maximum (m)
	Amphibians	
Frogs	205	368
Salamanders	117	218
	Reptiles	
Snakes	168	304
Turtles	123	287

Adapted from Semlitsch & Bodie (2003) study on criteria for buffer zones around wetlands and riparian habitats for Amphibians and Reptiles.

For this study, the buffered terrestrial wetland area files were clipped to derive secondary terrain attributes, CTI and SPI. The clipped portion was reclassified into wetness and non-wetness areas for CTI, and stream power and non-stream power areas for SPI using the reclassify tool in the ArcGIS. This was done for the ten major wetlands in the study area. The percentage of vulnerability is the potential area of gully erosion for CTI and the potential area of increased stream power for SPI. These were calculated using the pixels spilling into the different segments of the reclassified and clipped terrestrial wetland habitats. Following this process, the study estimated the percentage vulnerability for both years studied and the results compared (see Equation 3 & 4).

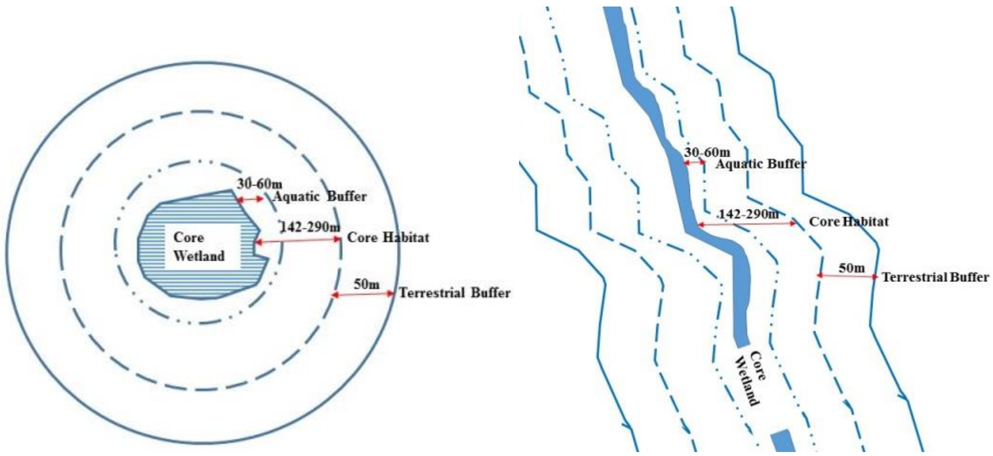
The change in vulnerability estimate for CTI

$$\%\Delta vE = \frac{x_1}{(\chi_0 + x_1)} * 100 \tag{1}$$

The change in vulnerability estimate for SPI

$$\%\Delta vE = \frac{y_1}{(y_0 + y_1)} * 100 \tag{2}$$

$\%\Delta vE$—percentage change in vulnerability estimate
χ_1—wetness area for CTI
y_1—stream power area for SPI
χ_0—non-wetness area for CTI
y_0—non-stream power area for SPI



(a) (b)

Figure 6: Buffered protection zones: wetlands (a) and streams (b).

Source: Adapted for this study based on Semlitsch & Bodie (2003), with an additional 50-m buffer to protect core habitat from edge effects recommended by Murcia (1995).

Quantification of Landscape Structure

Landscape metrics quantification was performed at two major levels and was loosely grouped according to the heterogeneity and spatial patterns of urban wetlands in the study area. These two levels are landscape level (three major watersheds), and patch level (individual wetland core area). Spatial statistics in Patch Analyst 5, an extension to the ArcGIS for spatial analysis of landscape patches and modeling, was used for the analysis. The default map unit for area is in meters (m) and later stated in hectares (ha), which is an option, provided by the Patch Analyst tool. The choice of these metrics (see Table 6) is because most other landscape metric results are correlated and statistically redundant. As such, they may quantify a similar or identical aspect of landscape pattern (McGarigal, 2000; Turner et al. 2001). However, some metrics may be empirically redundant not because they measure the same aspect of the landscape pattern, but they are alternative ways of representing similar information for the landscape under investigation (McGarigal, 2000).

The metrics used in this study took into consideration the scale of change patterns of the variables under study. This was done with specific consideration to the spatial pattern of the entire landscape and the patch types, bearing in mind the heterogeneity of the terrestrial wetland area. The major components (extent, subdivision, geometry, isolation, and connectedness) of habitat landscape composition and configuration were also considered when interpreting the landscape structure of our study area. For the three major watersheds, “landscape-centric” metrics were considered for measurement at this level; these are metrics that summarized patches using the mean and the area-weighted mean (McGarigal, 2000). Also, for the individual patches such as wetlands, “patch-centric” quantifications were performed which measured or described the spatial context of an isolated patch (McGarigal, 2000). Landscape metrics quantification was performed on the derived watershed polygons for the three major watersheds. This study followed the recommendation of Semlitsch & Bodie (2003) to preserve terrestrial wetland habitats such as amphibians and reptiles. Table 6 depicts the metrics used in this study, including acronyms, descriptions, and justification.

Table 6: Landscape metrics selected for this study.

Acronym	Name (units)	Description	Justification
TCAI	Total Core Area Index (ha)	Total core area index is a measure of the amount of core area in the patch or landscape	Fragmentation
SI	Shape index (ha)	normalized ratio of patch perimeter to area	Fragmentation
CA	Core Area (ha)	The total size of disjunct core patches (hectares).	Fragmentation
ED	Edge Density (m/ha)	Amount of edge relative to the landscape area	Fragmentation
TE	Total edge (m)	Perimeter of patches	Fragmentation
MPE	Mean Patch Edge (m/patch)	Average amount of edge per patch	Fragmentation
MPS	Mean Patch Size (ha)	Mean Patch Size of Patches (Class or Landscape Level)	Fragmentation
MSI	Mean Shape Index (ha)	sum of each patch's perimeter divided by the square root of patch area (in hectares)	Fragmentation
AWMSI	Area Weighted Mean Shape Index (ha)	AWMSI equals the sum of each patch's perimeter, divided by the square root of patch area (in hectares)	Fragmentation
MPFD	Mean Patch Fractal Dimension (ha)	Measure shape Complexity	Fragmentation
SDI	Shannon's Diversity Index (ha)	Measure of relative patch diversity	Diversity
SEI	Shannon's Evenness Index (ha)	Measure of patch distribution and abundance	Diversity

Adapted from McGarigal, K. (1995)

Wetland Landscape Modeling (WELD) for Socio Ecological Systems (SES)

Developing a robust geospatial decision model for SES requires examining previous decision-making tools used for monitoring or assessing ecosystem services (e.g. Brown & Vivas, 2005; Leitão & Santos, 2019; Larson et al. 2003). Several geospatial decision models have used the advantage of small-scale habitat variables to quantify field data (e.g. Seto & Kaufmann, 2003). Most of these models focus more on using known indexes to assess wetland conditions and quantification of baseline information between wildlife and habitat management. For this study, a couple of indexes and ecosystem service indicators were considered for the geospatial modeling of wetland terrestrial habitat in the study area, as shown in Table 7.

For this study, the ten major wetlands in three major watersheds in the Kansas City area were selected for the WELD modeling. The assessment was performed to see the impact of both natural and human variables, on wetland socio-ecological services, as regards benefits to amphibians and reptile's terrestrial habitat. In total, four species habitats were assessed, two Amphibians; Frogs and Salamanders, two Reptiles; Snakes, and Turtles. These species were chosen because they are semiaquatic and have close dependence on the terrestrial habitat surrounding wetland. In addition, these species spend most part of their critical life cycle, which spans from few days during breeding on the wetland to several weeks on terrestrial habitat (Semlitsch & Bodie, 2003). This part of the habitat needed protection and seems to have been underappreciated by conservation planners. These have been estimated to be a few meters away from the core wetland area (Brosofske et al. 1997; Burbrink et al. 1998). The buffer area protecting the core habitat from edge effects has been recommended to be about

290 meters (Semlitsch & Bodie, 2003), with an additional 50-m buffer recommended by Murcia (1995) (see Table 5 above).

The WELD modeler focused on assessing changes in the major functions of a terrestrial wetland landscape in relation to the socio-ecological aspect. A GIS-based decision support system was developed to integrate classified images and the DEM binary files into a model builder. Model builder in ArcGIS 10.6 was used to examine the change in the terrestrial wetland habitat for forestland, farmland/grassland, impervious surface, CTI, and SPI (see Figure 7). These are binary files and collectively referred to as ecosystem service indicators (ESI) in this study. Ecosystem services (ES) described as the benefits provided by Nature and could have a direct impact on wildlife. ESI in this study was calculated to estimate the species vulnerability with proximity to the wetland core. The binary files were then clipped to the extracted and buffered terrestrial wetland files for the two different years under study. These were performed for the maximum core terrestrial habitat occupied by the species under consideration. The zonal histogram tool in ArcGIS 10.6 was used to investigate the frequency distribution of pixels in the binary files (ESI) to the core area of the wetlands for both years under study. The result is a graphical representation and a bar graph is output for comparison of the changes between 1992 and 2017. In addition to this, an estimated percentage of vulnerability between 1992 and 2017 for each species habitat ESI was calculated from the core terrestrial wetland habitat. The differences in the area covered were quantified and compared side-by-side for impacted ESI (see Equation 5).

Table 7: Ecosystem Service Indicators, Metrics and Geospatial data

Indicators	Metrics	Geospatial Data Used
	Ecosystem Hydrological Vulnerability	
Stream Power Surface runoff	Stream power index (SPI), number of contributing cells to the energy of water flow	USGS DEM
Wetness Water retention and accumulation potential	Compound Topographical Index (CTI), wetness index indicating surface water collection	USGS DEM
	Social-ecological Vulnerability	
Farmland/Grassland Proximity to agricultural land	Proximity to agricultural lands (Farmland/Grassland)	Classified SPOT image grassland/farmland
Forestland Proximity to forestland	Proximity of species to standing forest trees	Classified SPOT image forestland
Impervious Surfaces Proximity to human settlements and distribution	Proximity to built-up areas (Impervious surfaces: roads and housing)	Classified SPOT image impervious surfaces

Percentage area covered ecosystem services indicator (ESI)

$$\%\Delta \mathrm{ESI} = \frac{s_1}{(s_0+s_1)} * 100 \quad (5)$$

$\%\Delta$ESI—percentage change in vulnerability estimate for ESI
s_1—estimated ESI area for Species Habitat
s_0—estimated non ESI area for Species Habitat

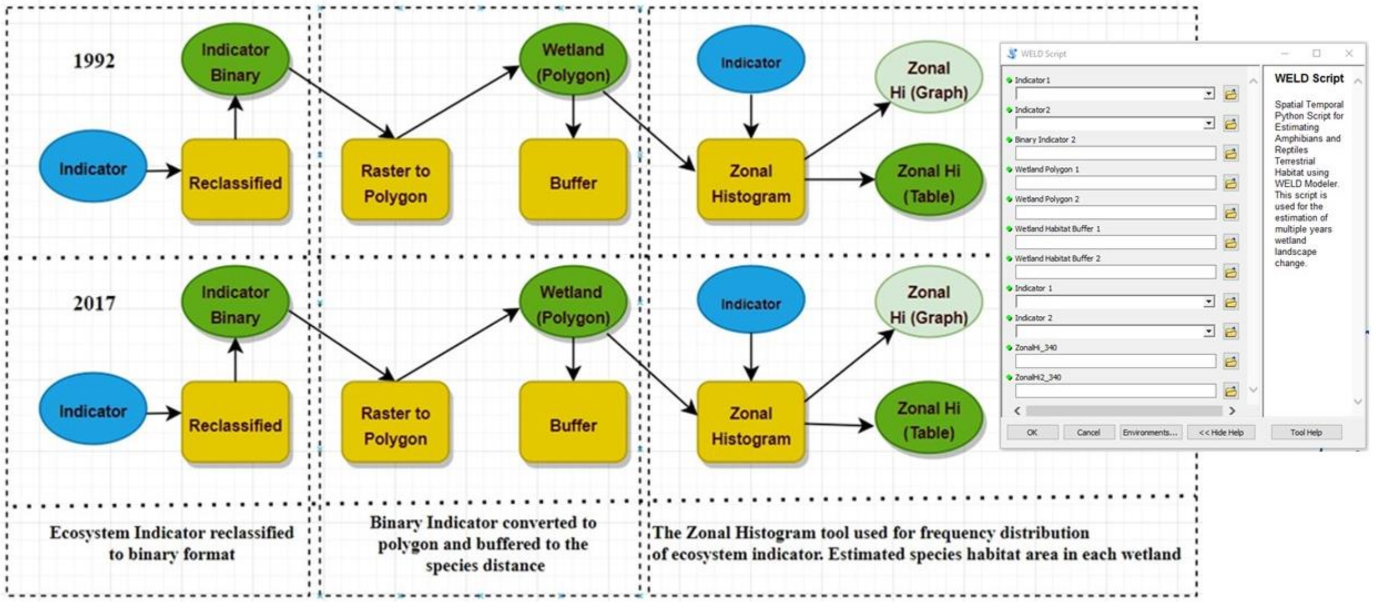


Figure 7: Model Builder and Script for Estimating Amphibians and Reptiles Terrestrial Habitat in WELD Modeler

WELD Framework

The framework provides a platform to understand the relationship between social and biophysical components in WELD, and how the benefits provided by the ESI have been affected. Figure 8 depicts two different dimensions, with the left hand showing the changes in the human dimension in the society while the right hand is the ecological research domain. Together the two templates were driven by human and natural factors as the benefits provided by ES have been influenced by these impacts.

In general, wetland ecological drivers are the main determinant of habitat loss and degradation and can be grouped into; infrastructure development, land conversion, water withdrawal, eutrophication, and pollution, overharvesting and over exploration, and introduction of invasive species (Galatowitsch, 2016). For this study, the complexity of these multiple drivers results in grouping them into human and natural factors. The drivers play a major role in the social and biophysical components of ecosystem services. The social template deals with policies, legal regulations, and social networks which help to structure the dynamics of human behaviors and possible outcomes. The biophysical template, on the other hand, plays a major role in monitoring the biotic structure and ecosystem functioning. However, the ability of the wetland ecosystem to deliver services can be assessed by a variety of qualitative and quantitative methods. Assessing wetland ecosystem services is very vital and they are mostly disturbed by both human and natural factors. The quality and quality of wetland services and terrestrial habitat are essential for humans and wildlife, but they have been altered by these factors.

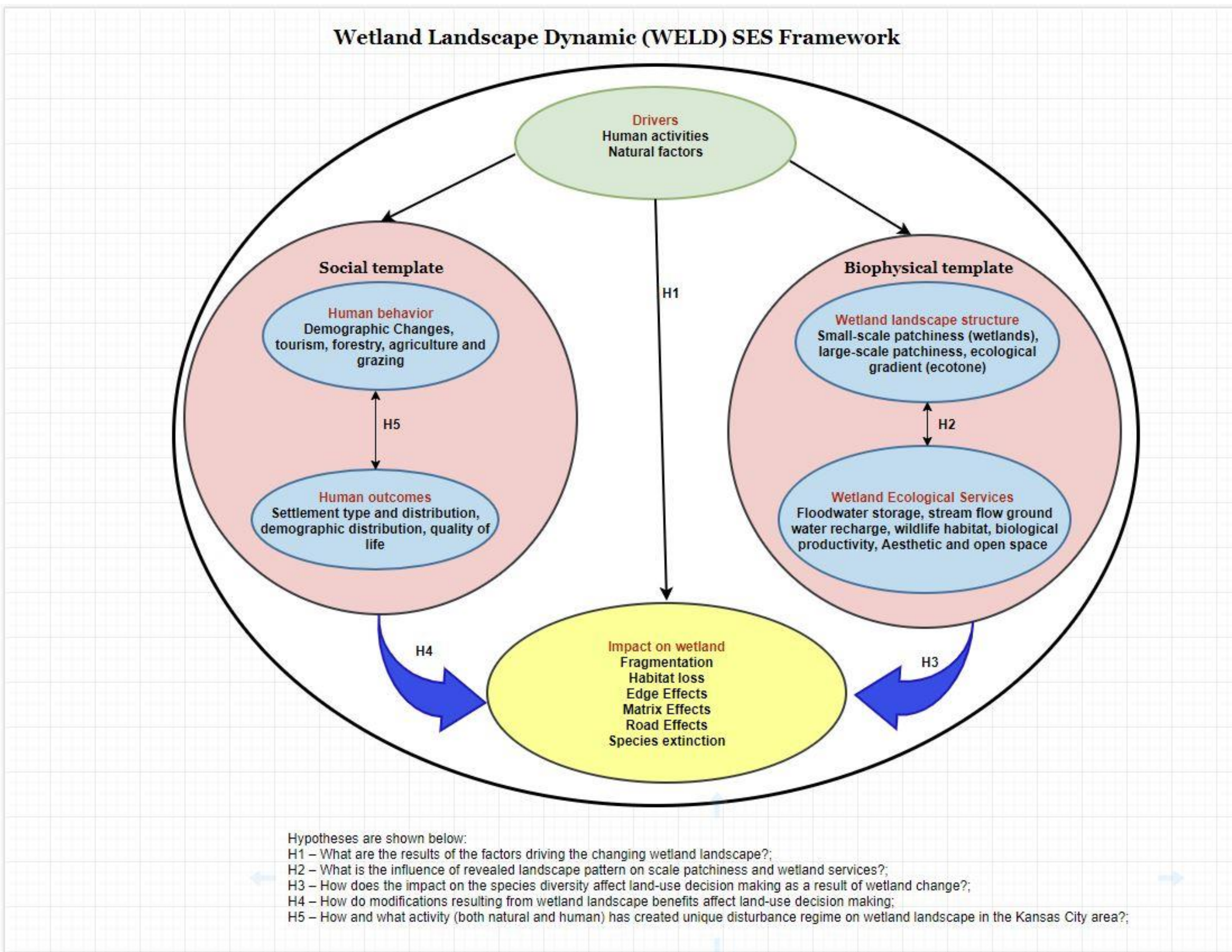


Figure 8: WELD framework for SES.

CHAPTER 4

RESULTS

This chapter presents the results and interpretation of all the analyses performed in this study. The analysis based on the methodology as depicted in Figure 5, including the results from the four different parts of the study. The general interpretation of results was broken down into two, landscape-level analysis and wetland-level analysis. This quantification was due to the level of heterogeneity in the study area. The landscape-level analysis included the classification algorithms used, change detection statistics (CDS), landscape metrics, and wetland landscape dynamic modeling. The two classification methods employed to achieve better image classification with a higher accuracy value. The CDS was performed to get a clearer view of the overall change in wetland coverage in the three major watersheds. The landscape metric quantification was performed for the three major watersheds. The other part of the analysis was at the wetland level that describes the patches. Furthermore, the assessment of the terrestrial wetland habitat using the ecosystem service indicators (ESI) was performed at this level to build a geospatial model. On the other hand, calculating and deriving secondary terrain attributes and integration with extracted wetland files were performed at the wetland level. Also, the quantification of patch metrics was performed to assess the ten major wetlands in the three major watersheds in the study area. In addition, included in the two-level of analysis was a socio-spatial analysis, assessed to see the impact on wildlife terrestrial wetland habitat using the census track data and proximity to the roads.

Landscape-Level Analysis

Object-Based Image Classification and Change Detection Statistics (CDS)

Firstly, the study revealed a similar trend for class change for the two algorithms used, with SVM having a better accuracy assessment report compared to K-NN. The CDS was performed with the two algorithms and the change detection revealed K-NN with a value of 21% and SVM with a value of 18%. This indicates that the total percentage change in pixels from other classes to wetland increased for K-NN by 21% but not as much for SVM at 18%. The two algorithms were compared to achieve a better result for the image classification, which avoids the possible misinterpretations that could have resulted from using different multispectral images (Peña-Barragán et al. 2011). Regardless of the class change in the CDS, results from using both algorithms revealed a swell in the wetland coverage for the study area. Zubair et al. (2017) observed swell in two major watersheds out of three in the Kansas City area in the past decade in a study. In addition, this result is similar to a study by Ji et al. (2015) which showed that larger wetlands accumulated more precipitation, while the smaller wetlands were prone to human impacts. Similarly, Zubair et al. (2017) in their study of urban wetland modeling in the study area observed that wetlands increased in two of the major watersheds historically but reduced as a result of urban expansion in one. These results generally support the findings that wetlands swelled in the study area within the study period, and this can be associated with the effects of human and natural factors as suggested by previous studies, such as reference (Ji et al. 2015).

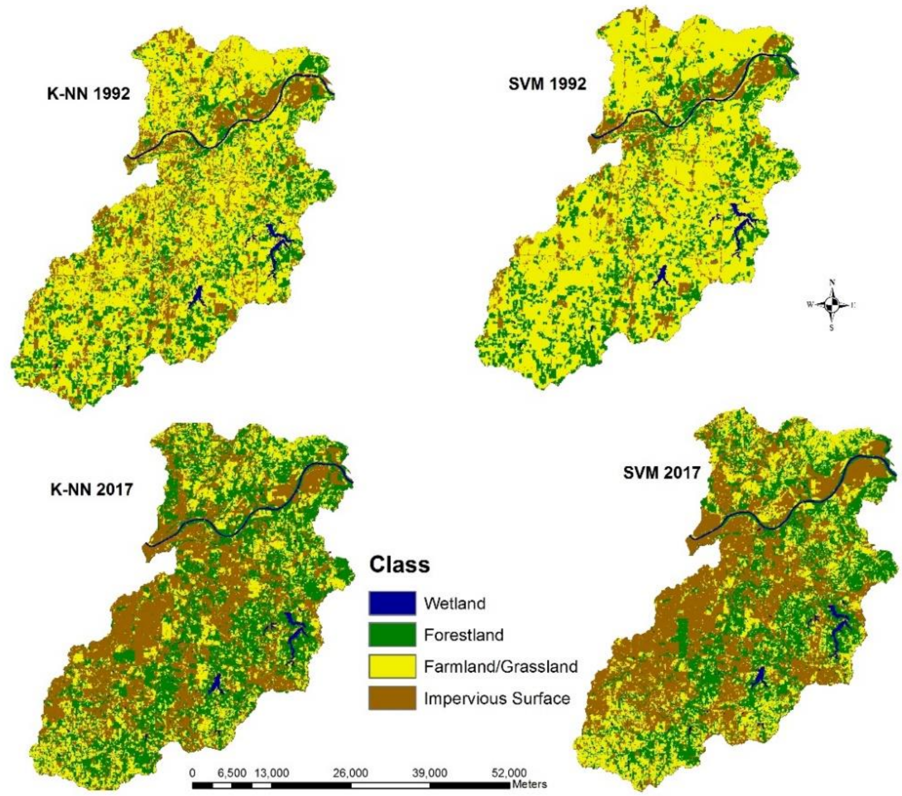


Figure 9: Classified satellite images for the two detection years, using both K-NN and SVM.

At the landscape level, the CDS was used to measure the changes between a pair of images that present the initial state (SPOT 1992) and the final state (SPOT 2017). This was performed for three watersheds to quantify the total wetlands coverage between 1992 and 2017 in the study area. The CDS results will guide the interpretation of the metrics and terrain analysis, as it provides prior knowledge of the general wetland level. The CDS as summarized in Tables 4 for SVM algorithms classification reveals an increase in wetland coverage from 1992 to 2017. The result showed an increase of 21% class change from the initial state (1992) to the final state (2017) for the three watersheds. The CDS in Table 5 for K-NN algorithms revealed an 18% class change. This result is similar to the change observed for SVM algorithm classification for the three watersheds between 1992 and 2017.

Table 8: SVM Change Detection Statistics (Initial State SVM 1992, Final State SVM 2017).

		Initial State		
		Wetland (%)	Row Total (%)	Class Total (%)
Final State	Wetland	82.18	99.91	100.00
	Class Total	100.00	100.00	100.00
	Class Changes	17.82		
	Image Difference	9.17		

Table 9: K-NN Change Detection Statistics (Initial State K-NN 1992, Final State K-NN 2017).

		Initial State		
		Wetland (%)	Row Total (%)	Class Total (%)
Final State	Wetland	79.00	99.81	100.00
	Class Total	100.00	100.00	100.00
	Class Changes	21.00		
	Image Difference	8.08		

Landscape-level Metric Calculation

The result of the metrics calculation examined at the landscape level for watersheds is shown in Figure 10. For the landscape metric calculation, at the watershed level, the three major watersheds in the Kansas City area were quantified. Indices used were Shannon's Diversity Index (SDI), Shannon's Evenness Index (SEI), Area Weighted Mean Shape Index (AWMSI), Mean Shape Index (MSI), Mean Patch Fractal Dimension (MPFD), edge density (ED), and Mean Patch Size (MPS). The identified diversity indices used are SDI and SEI, which measure at the landscape level. For the shape metrics MSI, we used MPFD, ED, and AWMSI to quantify the shape complexity of the watershed at the landscape level. Further, MPS was used to quantify the size irregularities between the study periods. The result of the metric calculations reveals SEI with little or no change for wetland distribution in the three watersheds for the study periods. It shows an equal trend in wetland proportions, 0.81 ha for 1992, and 0.82 ha for 2017. SDI, on the other hand, reveals a small increase in the distribution of wetlands from 0.89 ha for 1992 to 1.14 ha for 2017. This indicates a slight dynamic in the diversity of wetland patches for the watersheds in 2017. The result for MSI reveals 1.58 ha for 1992 and 1.55 ha for 2017. This quantification reveals little or no change for shape irregularities or complexity between 1992 and 2017 at the watershed level. However, both MPFD and AWMSI indexes for shape metrics reveal a slight change in shape complexity between 1992 and 2017. MPFD has a slight change from 1.35 ha for 1992 to 1.40 ha for 2017, and AWMSI slightly increased in shape irregularity from 19.91 ha for 1992 to 21.58 ha for 2017. Further quantification reveals an increased ED from 64.85 m/ha for 1992 to 135.28 m/ha for 2017. This indicates an increase in edge density (ED) in 2017 relative to the landscape area in 1992. ED was calculated using the amount of edge present in 1992 as compared to the amount present in 2017 for watershed at the landscape level. On the other hand, the MPS shows a reduction in the size of the watersheds for 2017 compared to the increase in 1992.

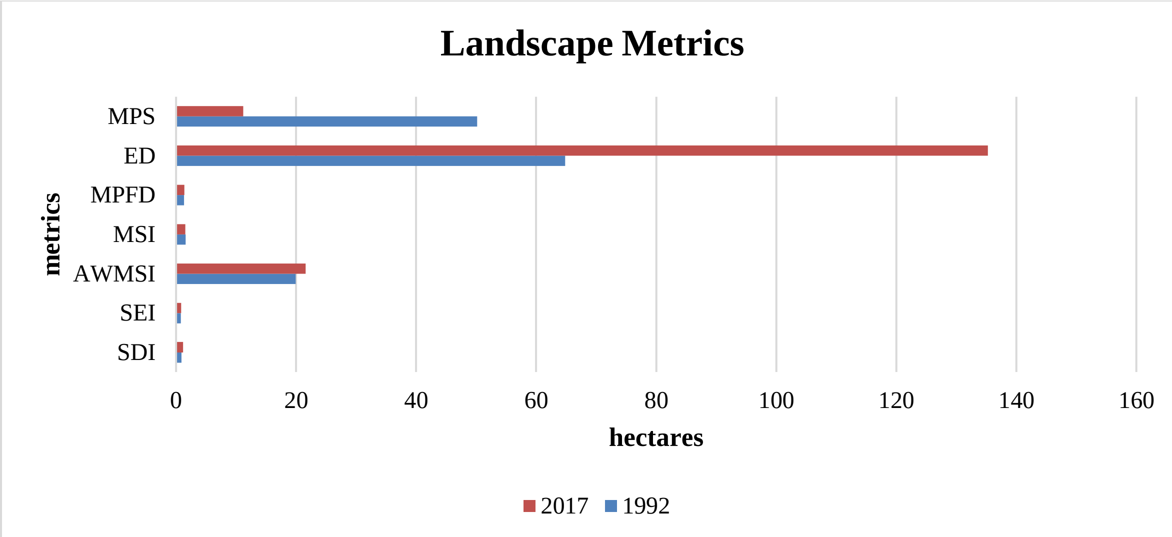
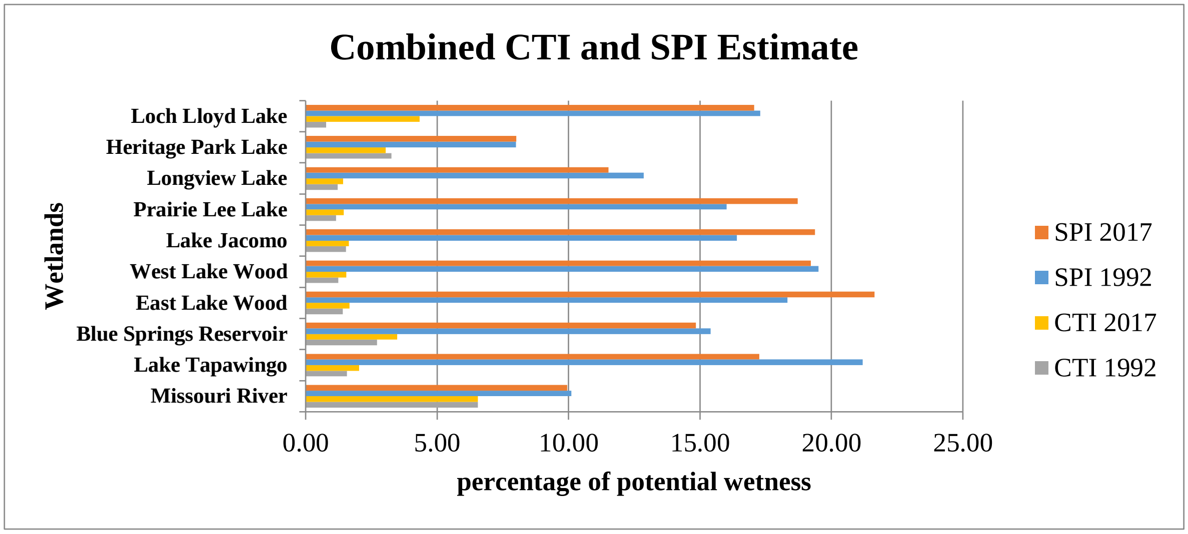


Figure 10: Landscape level metrics at the watersheds scale.

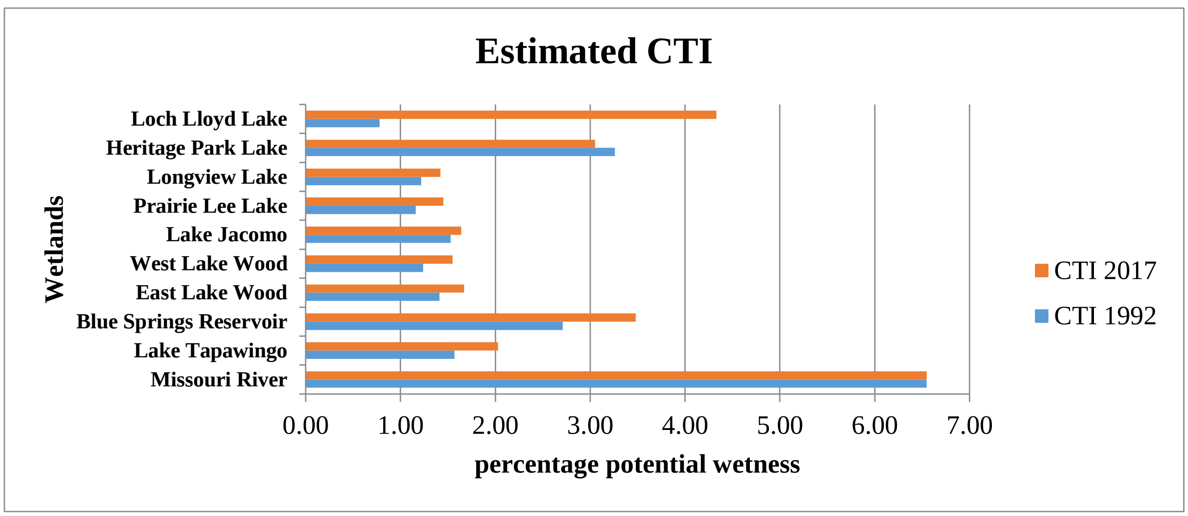
Wetland-Level Analysis

Terrain Calculation

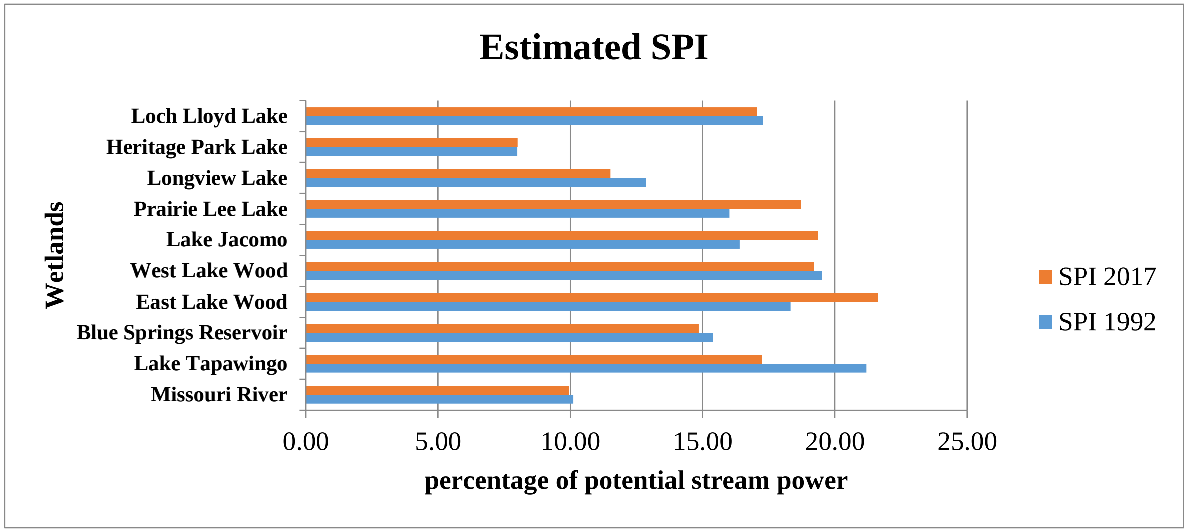
The analysis at this level deals with individual wetland patches; ten major wetlands were calculated in the study area using digital terrain analysis. The terrain analysis involves integrating extracted wetland files, buffered at a distance of 340-meters from the core area with secondary terrain attributes. The results are summarized in Figure 11 (a, b, and c). All the major wetlands except the Heritage Park Lake showed a slight reduction in the core area for 2017. Similarly, nine out of the ten major wetlands examined for wetness vulnerability using the CTI reveal potential wetness in wetlands within the study area in 2017 (see Appendix A). The only wetland that did not show a slight wetness potential is Heritage Park Lake, with – 0.16%. On the other hand, the SPI calculated revealed a relatively little or no change in stream power, except for three averagely small wetlands. The three wetlands slightly increased with a net change of 3.31% for East Lake Wood, 2.97% for Lake Jacomo, and 2.71% for Prairie Lee Lake in 2017 (see Appendix B).


Combined CTI and SPI Estimate
Wetlands
Loch Lloyd Lake
Heritage Park Lake
Longview Lake
Prairie Lee Lake
Lake Jacomo
West Lake Wood
East Lake Wood
Blue Springs Reservoir
Lake Tapawingo
Missouri River
0.00
5.00
10.00
15.00
20.00
25.00
percentage of potential wetness
SPI 2017
SPI 1992
CTI 2017
CTI 1992

(a)


Estimated CTI
Wetlands
Loch Lloyd Lake
Heritage Park Lake
Longview Lake
Prairie Lee Lake
Lake Jacomo
West Lake Wood
East Lake Wood
Blue Springs Reservoir
Lake Tapawingo
Missouri River
0.00
1.00
2.00
3.00
4.00
5.00
6.00
7.00
percentage potential wetness
CTI 2017
CTI 1992

(b)

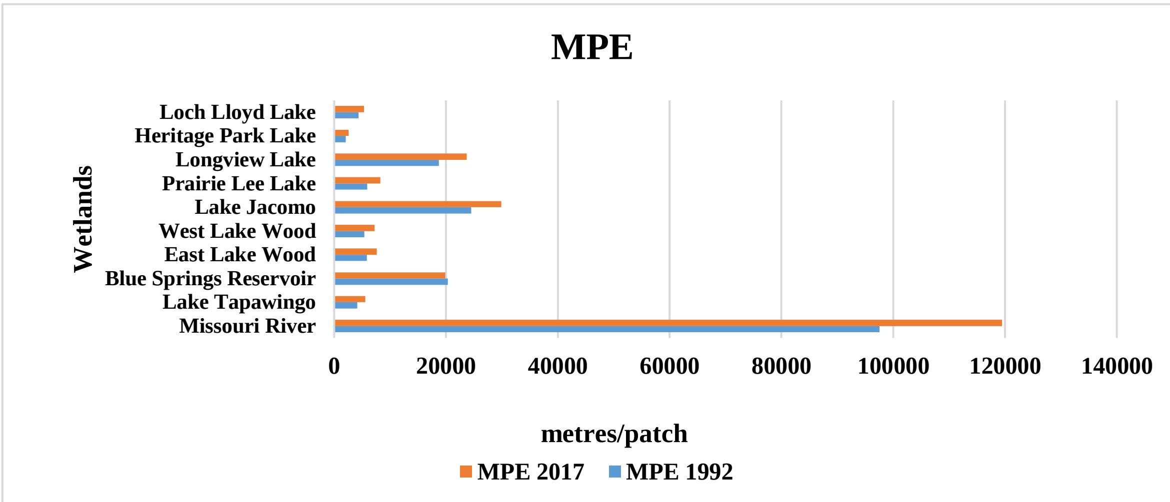


(c)

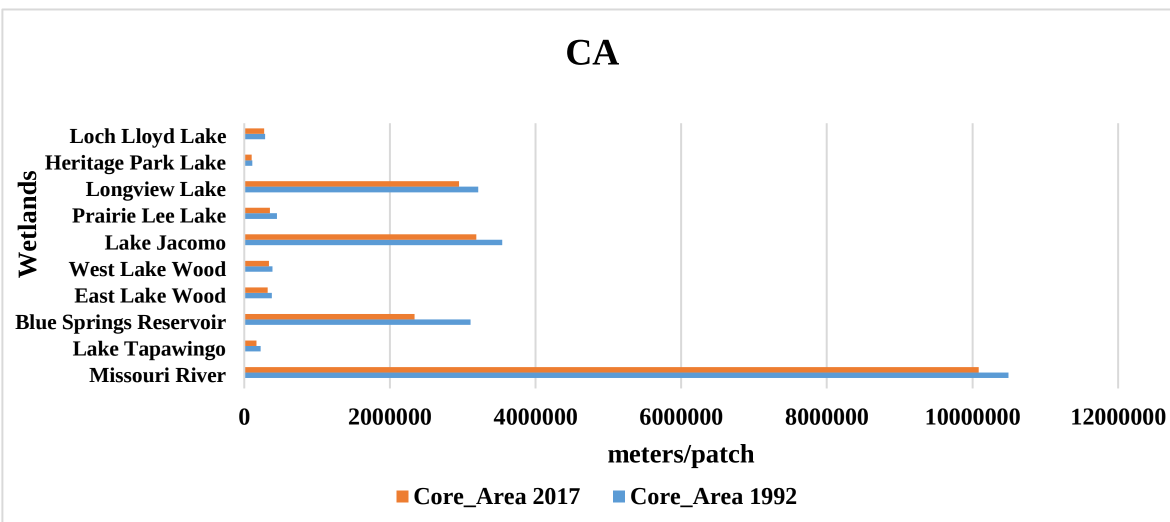
Figure 11: (a–c) SPI, and CTI for each wetland.

Patch level metric calculation

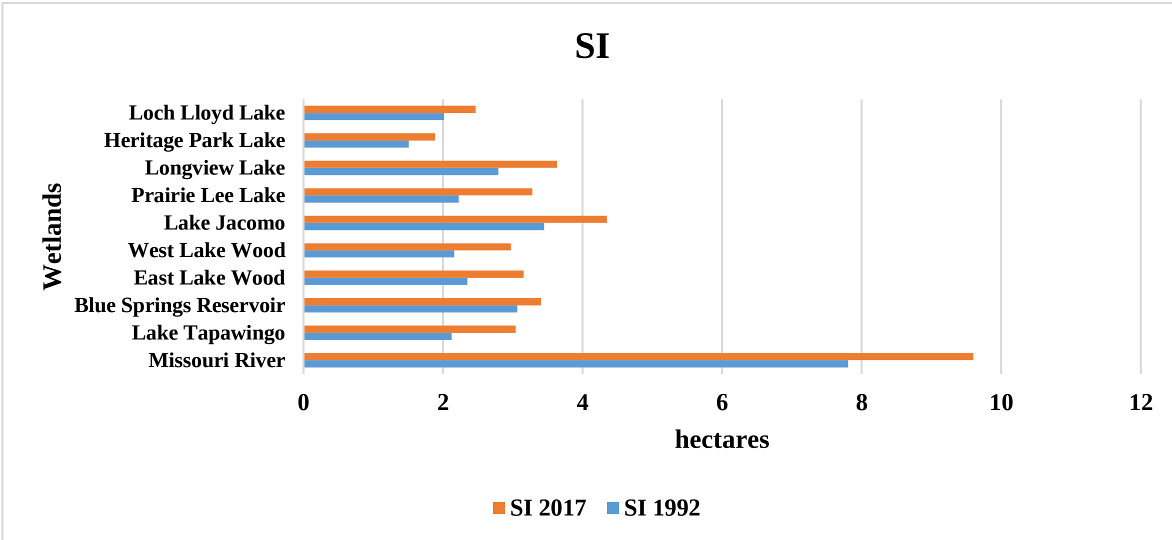
Similar to the terrain analysis, the patch metrics were calculated for the ten major wetlands in the study area. Patch-centric metrics were used to quantify the patch in terms of shapes and sizes. Indices used include MPE, CA, MSI, SI, and TE. As summarized in Figure 12 (a, b, c, d, e), CA reveals a general decrease for all ten wetlands for 2017. Heritage Park Lake and Loch Lloyd Lake revealed the least decrease in terms of core area change for 2017. Heritage Park Lake showed 10.86 ha for 1992 and 10.31 ha for 2017, with a net loss of 0.56 ha between 1992 and 2017. Similarly, the Loch Lloyd Lake showed 28.72 ha for 1992 and 27.12 ha for 2017, with a net loss of 1.60 ha. Blue Springs Reservoir revealed the most decreased core area change for 2017 with 310.79 ha for 1992 and 233.90 ha for 2017, a net loss of 76.89 ha. On the other hand, the SI and MSI indices used to quantify the wetland shape revealed increased shape complexity and irregularities for all the ten wetlands in 2017. This was not the case for the TE and MPE used to quantify the wetland edge. While nine of the ten wetlands show an increase in the edge difference, Blue Springs Reservoir did not increase the edge difference for 2017, as compared to 1992.



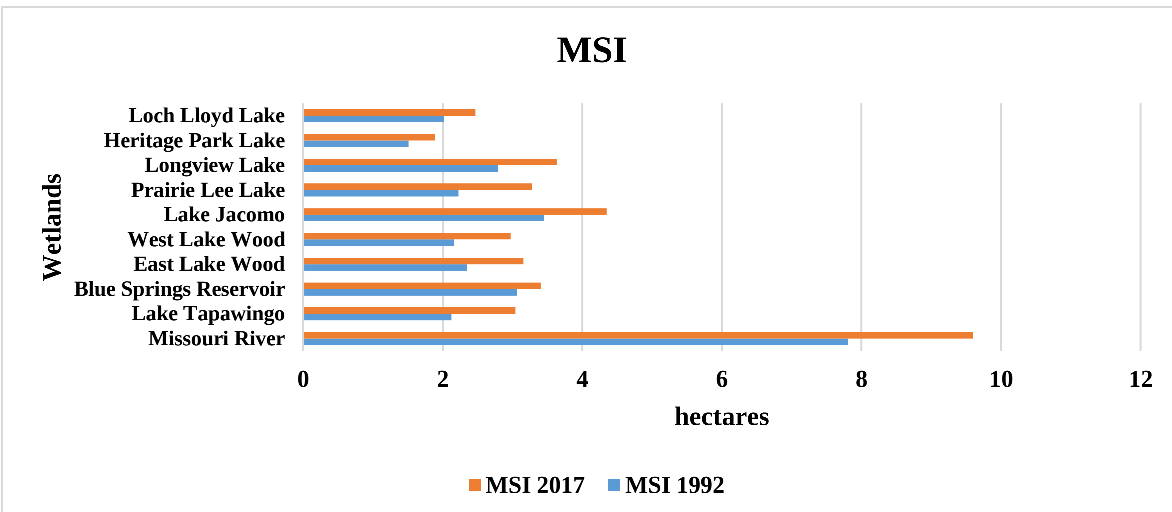
(a)



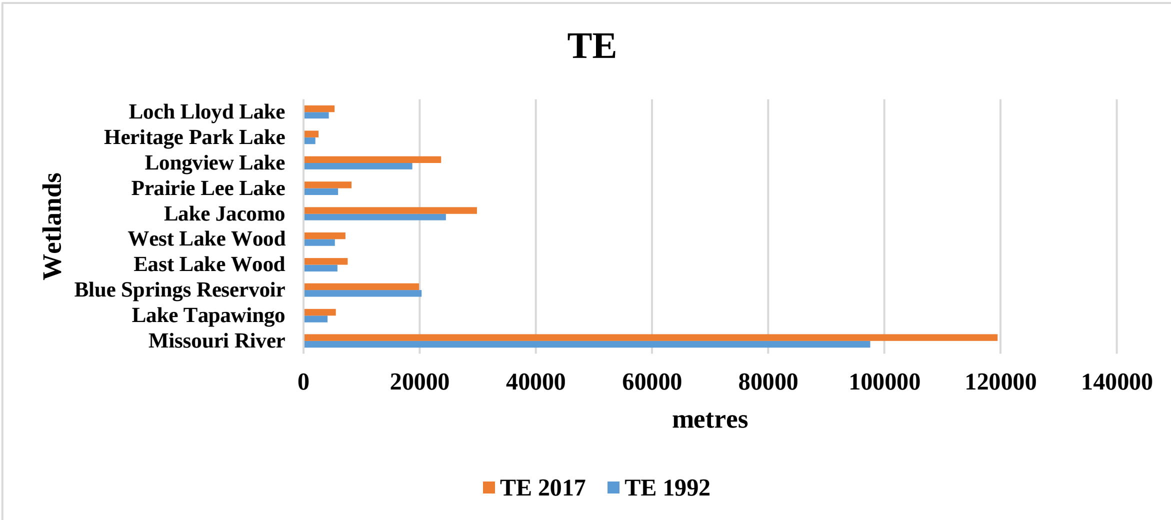
(b)


SI
Wetlands
Loch Lloyd Lake
Heritage Park Lake
Longview Lake
Prairie Lee Lake
Lake Jacomo
West Lake Wood
East Lake Wood
Blue Springs Reservoir
Lake Tapawingo
Missouri River
0
2
4
6
8
10
12
hectares
SI 2017
SI 1992

(c)


MSI
Wetlands
Loch Lloyd Lake
Heritage Park Lake
Longview Lake
Prairie Lee Lake
Lake Jacomo
West Lake Wood
East Lake Wood
Blue Springs Reservoir
Lake Tapawingo
Missouri River
0
2
4
6
8
10
12
hectares
MSI 2017
MSI 1992

(d)



(e)

Figure 12: (a–e) Patch-level metric analysis at the wetland scale.

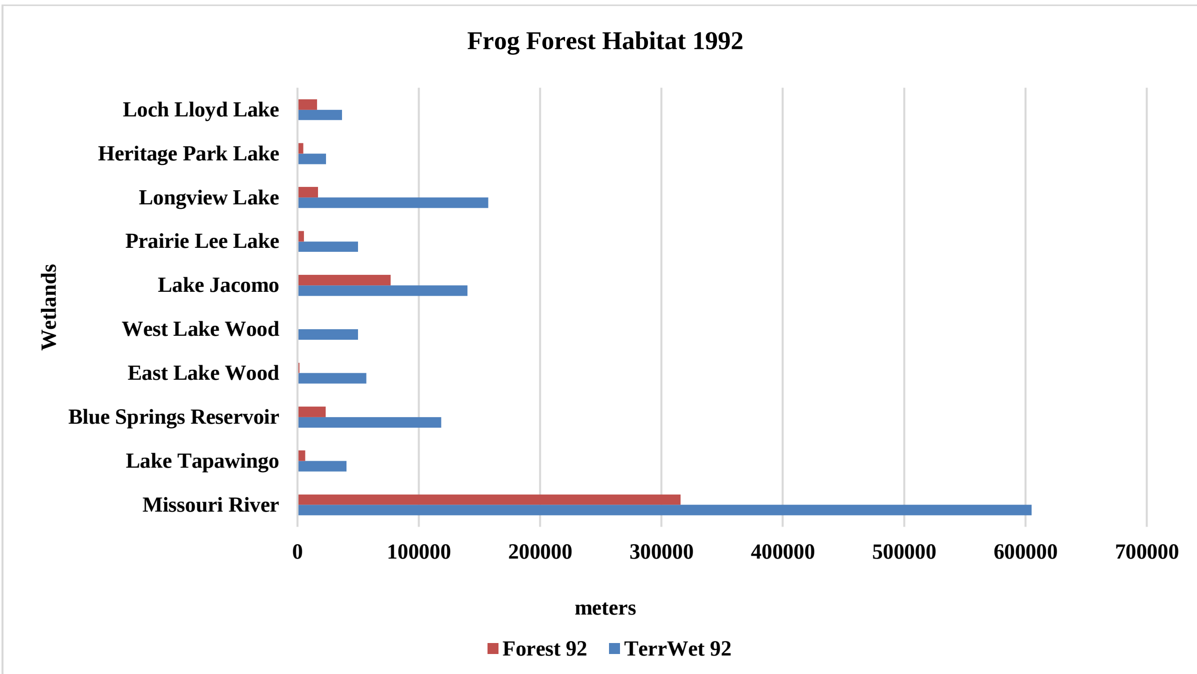
WELD Modeling, estimation for Amphibians and Reptiles Terrestrial habitat

The WELD modeler is built using the ecosystem service indicators (ESI). These are selected ecosystem services (ES) that could influence benefits to humans and biodiversity directly or indirectly (see Table 7 & 8 above). ES are the benefits provided by nature that helps to maintain the conditions of life on Earth. ES in the model is quantified with consideration to the impact of human and natural drivers influencing terrestrial wetland habitat (see Figure 8 above).

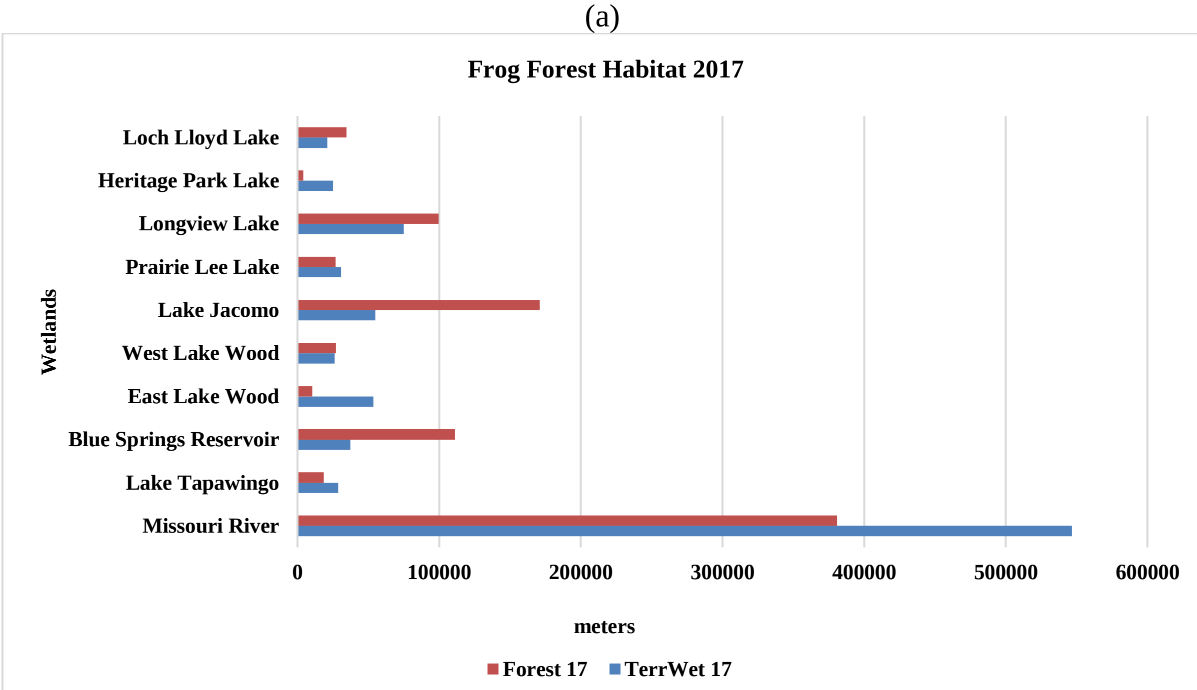
In this study, the habitat of seven terrestrial wetland species of amphibians and reptiles were examined using the WELD model. For example, the first species ES benefits examined is Frog with all the ESI quantified and estimated. This was followed by the six other species within the terrestrial wetland areas. All the species examined, occupy the same terrestrial wetland habitats with different buffered distances in the study area. The terrestrial wetland (terrwet) graphical pattern of individual species for the temporal periods (1992 and 2017) are shown in Figure 13-32 (a-c). These include forestland, farmland/grassland (fam/gra), impervious surfaces, CTI, and SPI for all species habitat under study.

FROGS

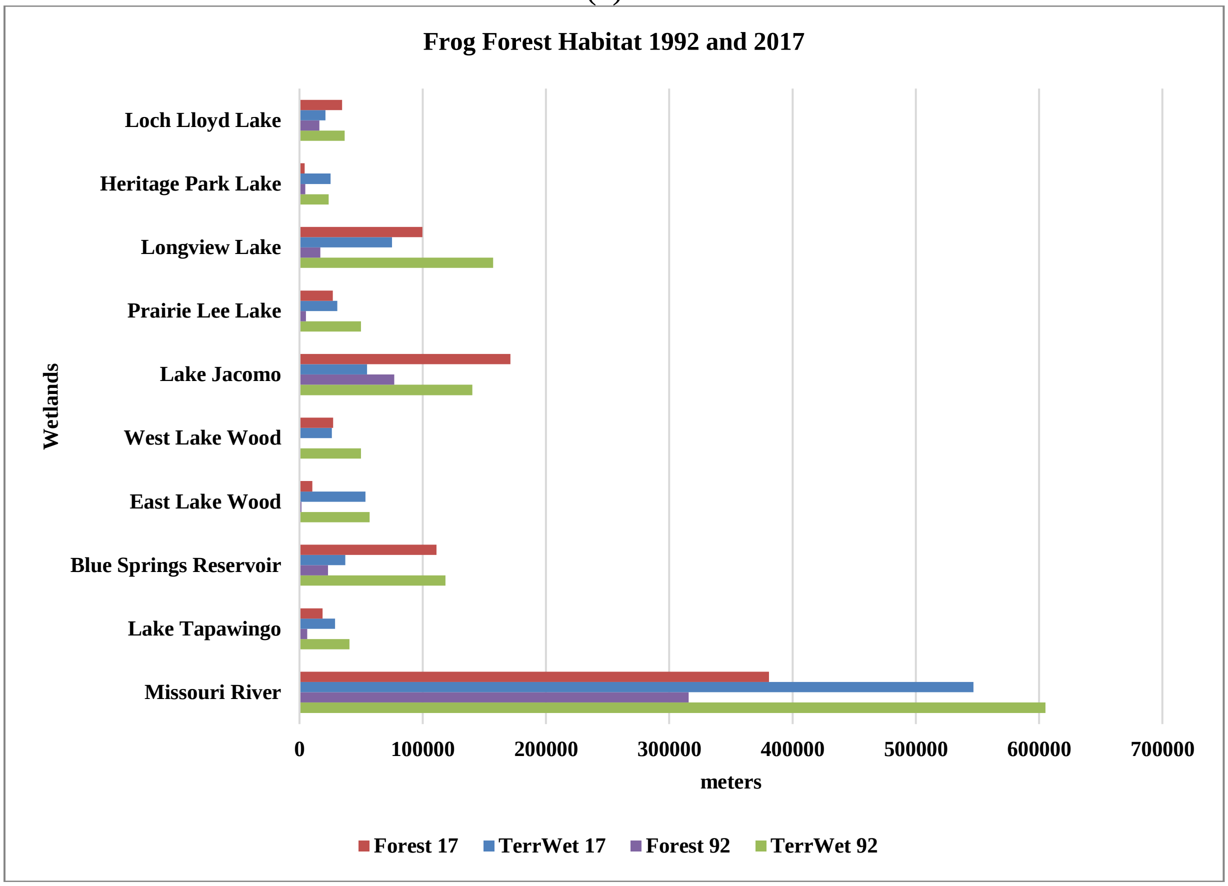
Estimated Forest Habitat for Frogs



(a)



(b)

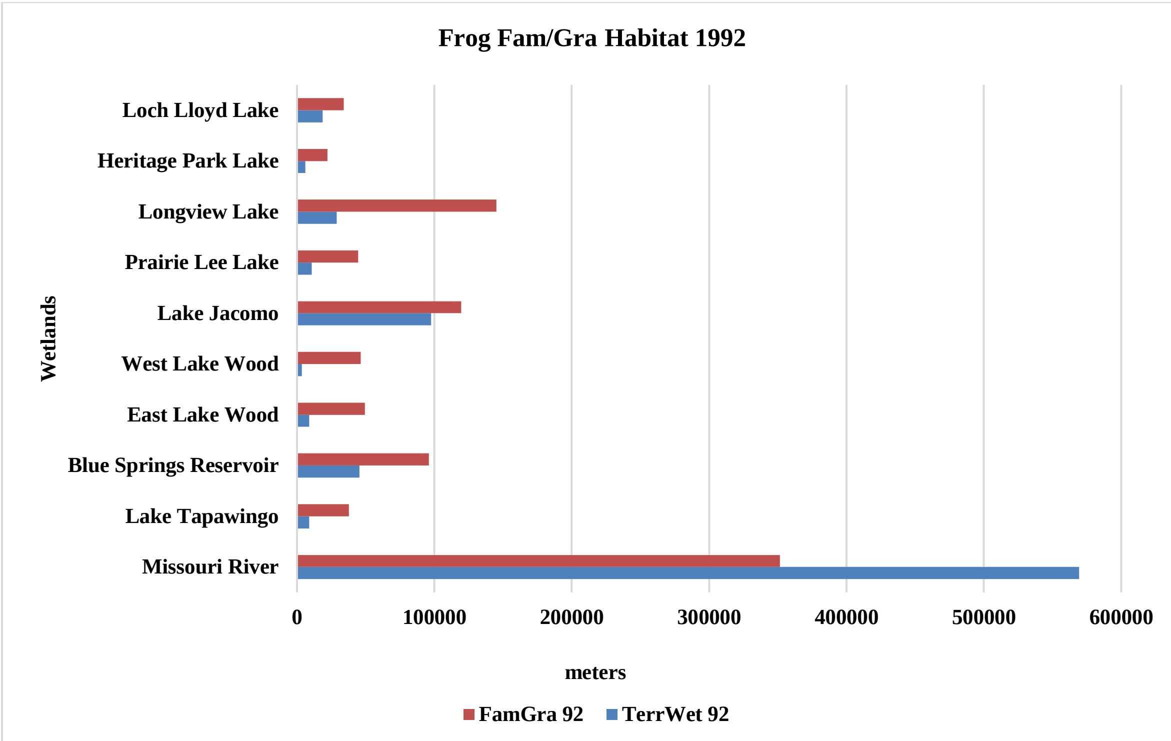


(c)

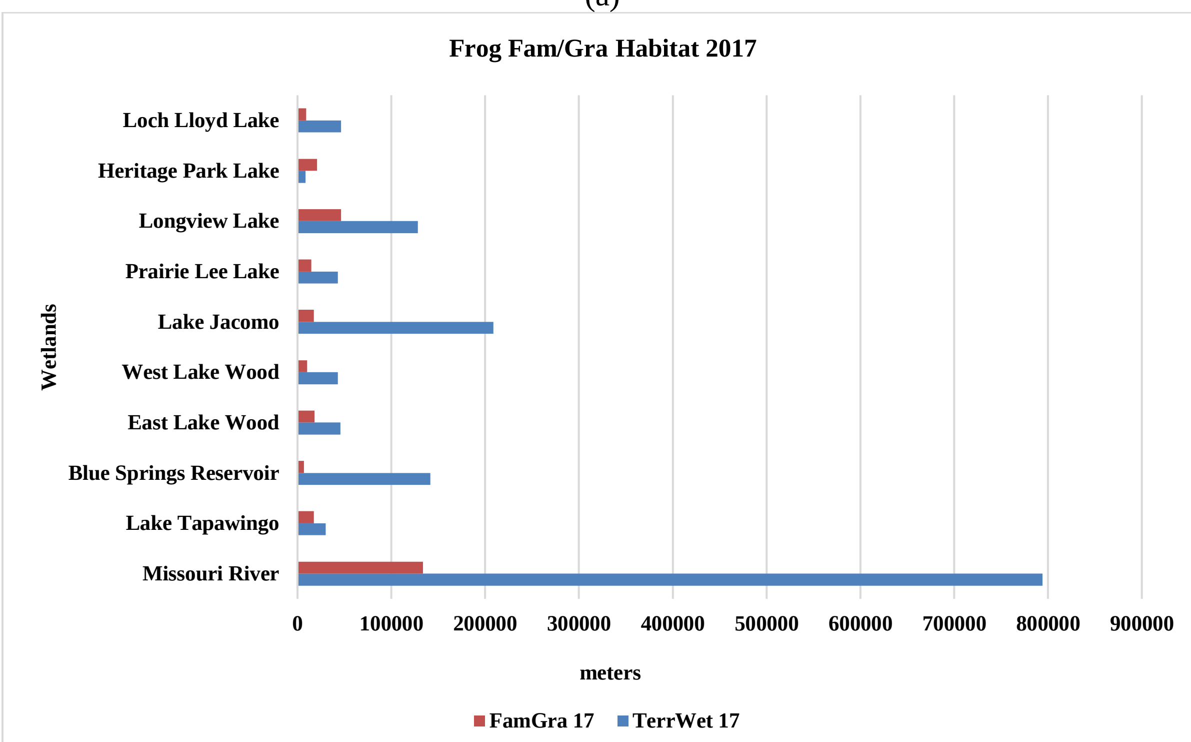
Figure 13: (a-c) Estimated Frog Forest Habitat.

The Frog terrestrial habitat within the recommended mean maximum core area of 368 m showed increasing forest habitat for 1992 as compared with 2017. Most of the larger wetlands revealed a huge increase in forest terrestrial habitat in 2017 while the smaller wetlands showed a slight increase for smaller wetlands (see Figure 13: (a-c)).

Estimated Farmland/Grassland Habitat for Frogs



(a)



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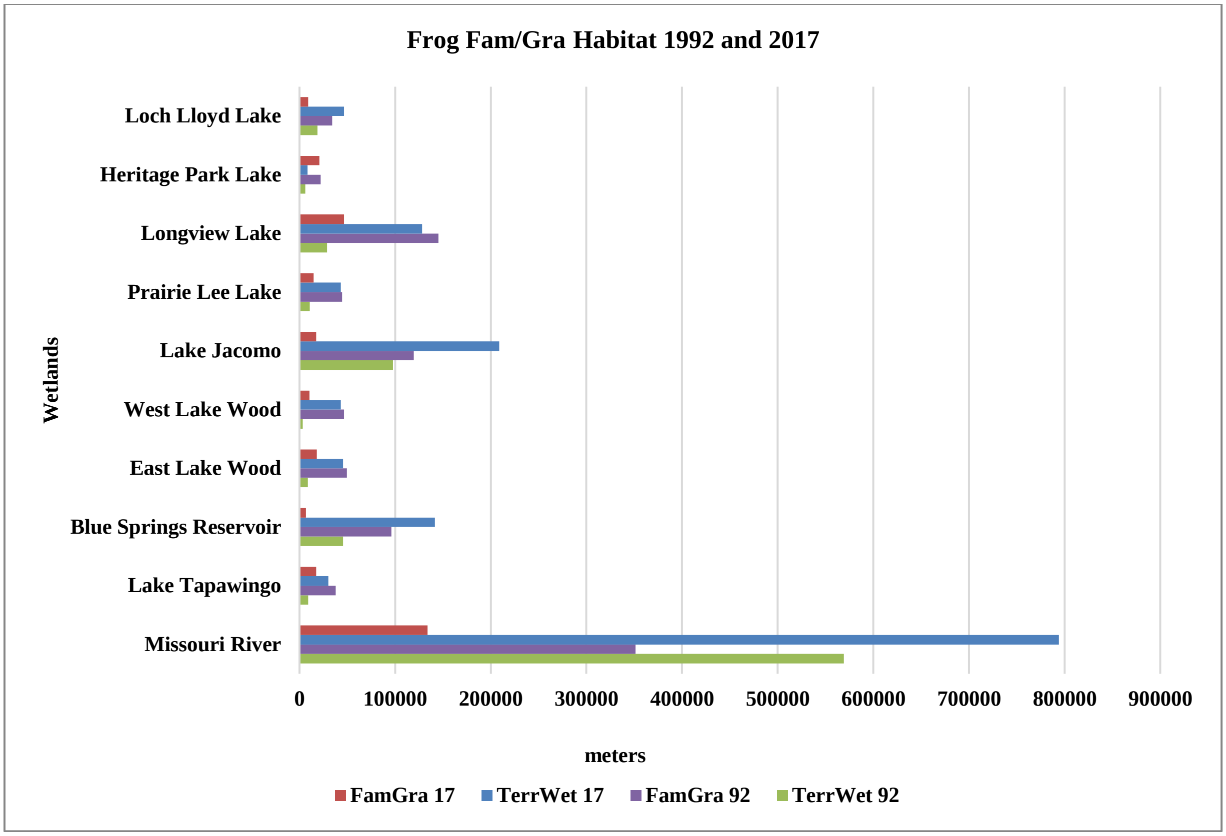
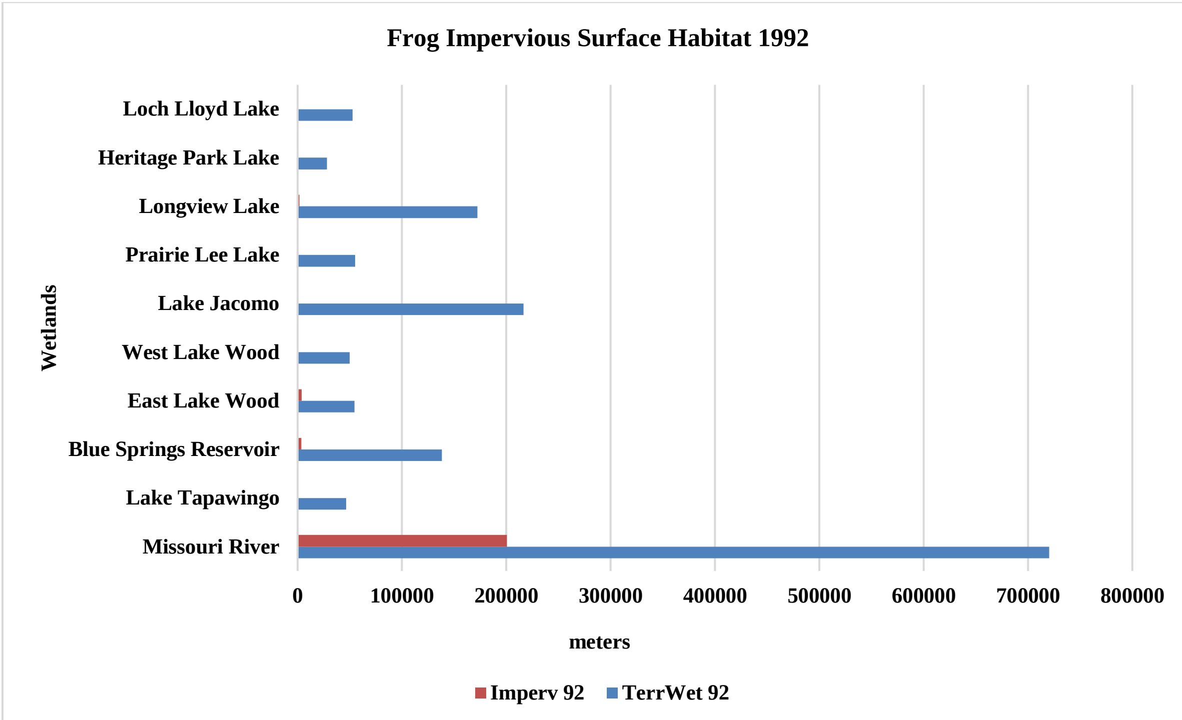


(c)

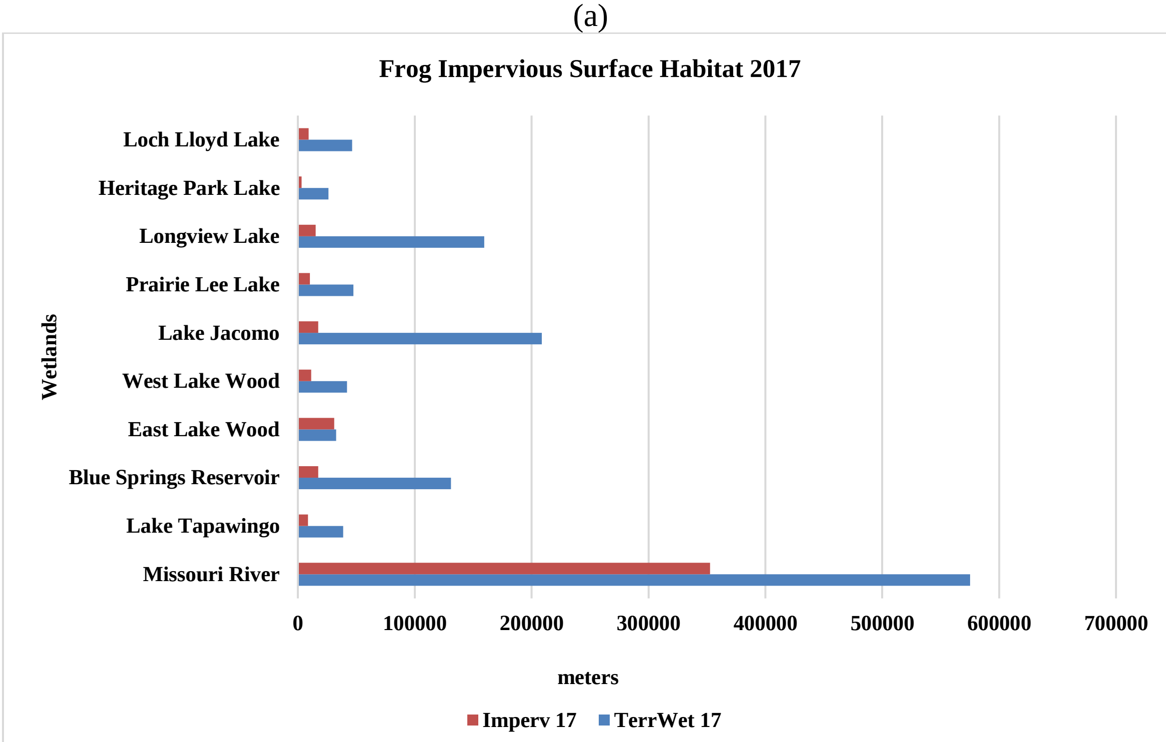
Figure 14: (a-c) Estimated Frog Farmland/Grassland Habitat.

The Frog terrestrial habitat within the recommended mean maximum core area of 368 m showed an increase in farmland/grassland for 1992 as compared to 2017. Increasing farmland/grassland was revealed for all wetlands except the Heritage Park Lake which showed no change between the study periods (see Figure 14: (a-c)).

Estimated Impervious Surface Habitat for Frogs



(a)



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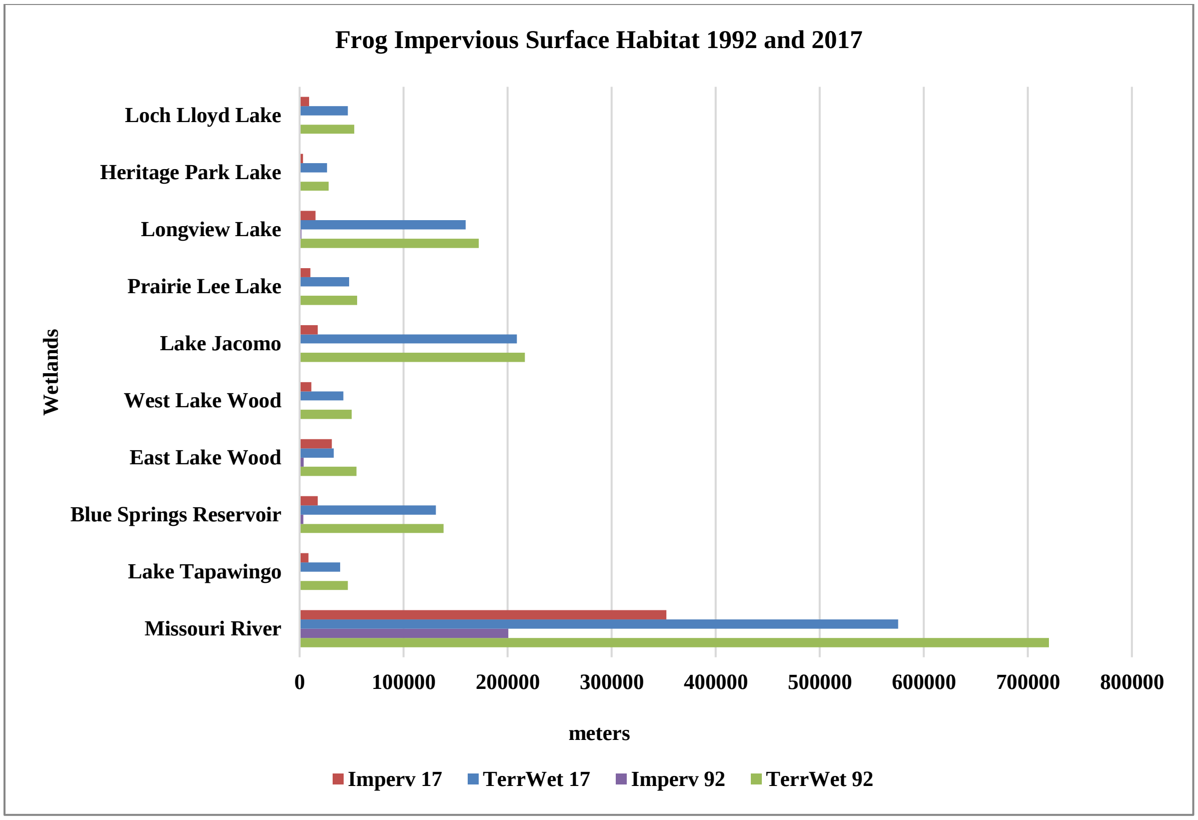
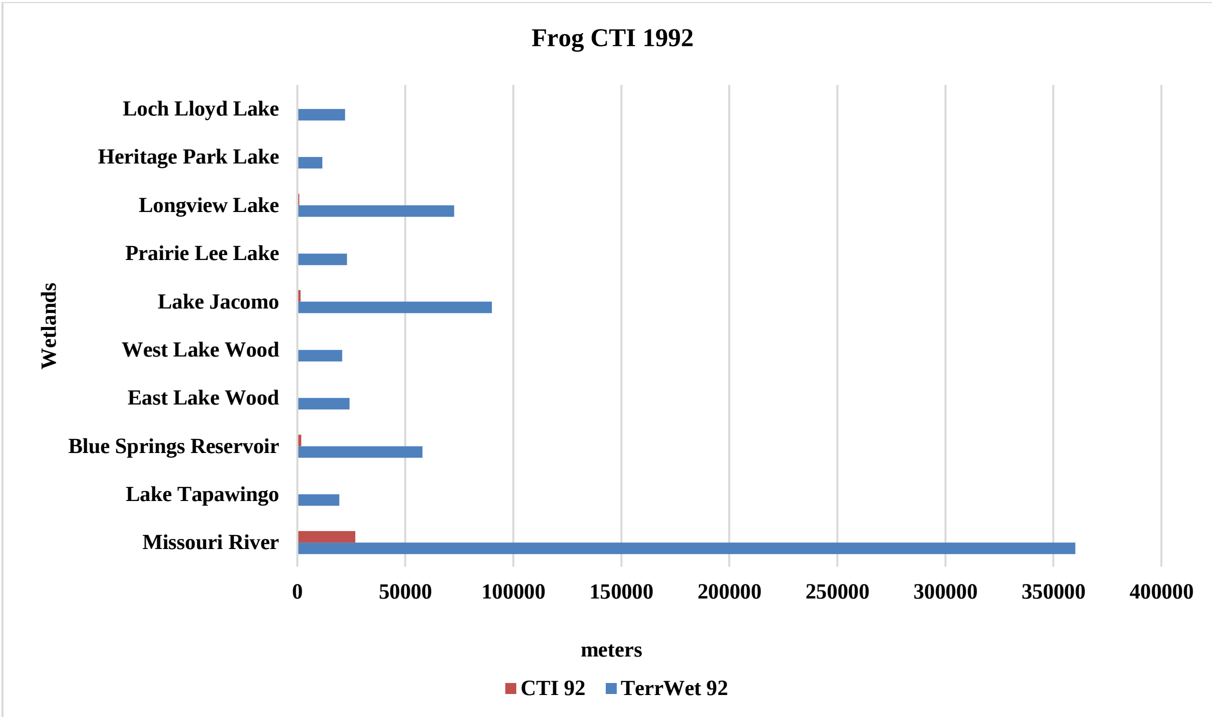


(c)

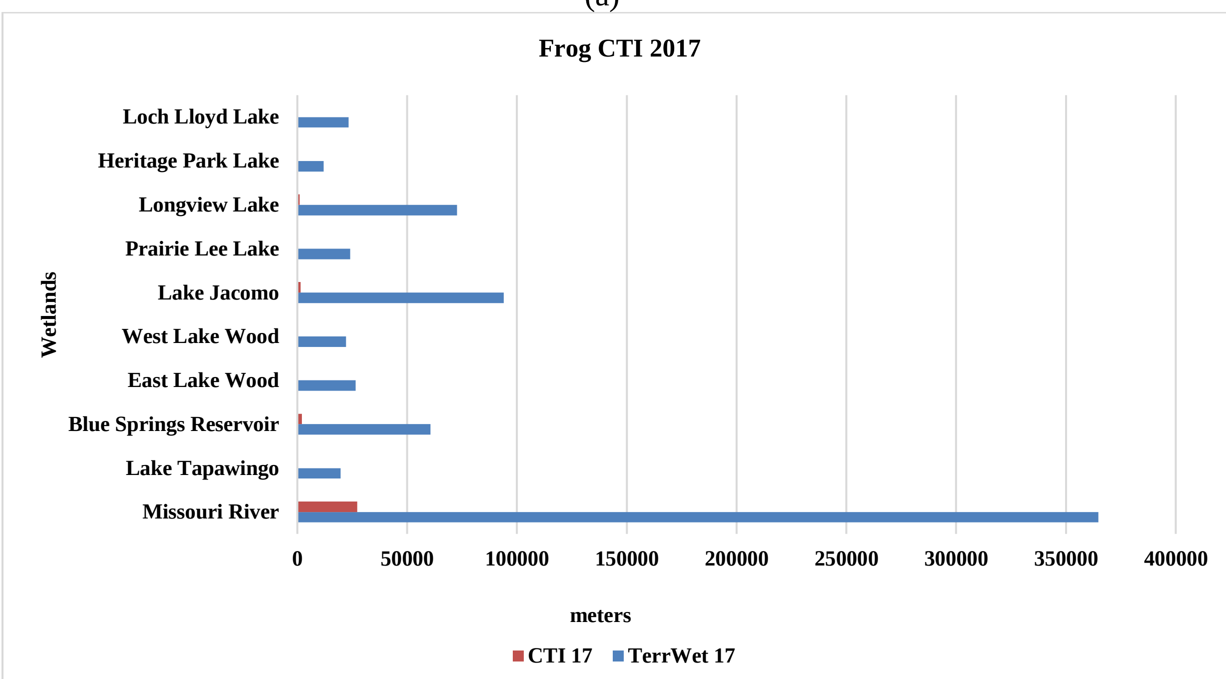
Figure 15: (a-c) Estimated Frog Impervious Surface Habitat.

The Frog terrestrial habitat within the recommended mean maximum core area of 368 m showed an increase for all impervious surfaces in 2017 as compared with 1992. The largest change of 145,156 m was revealed for the Missouri river in 2017 (see Figure 15: (a-c)).

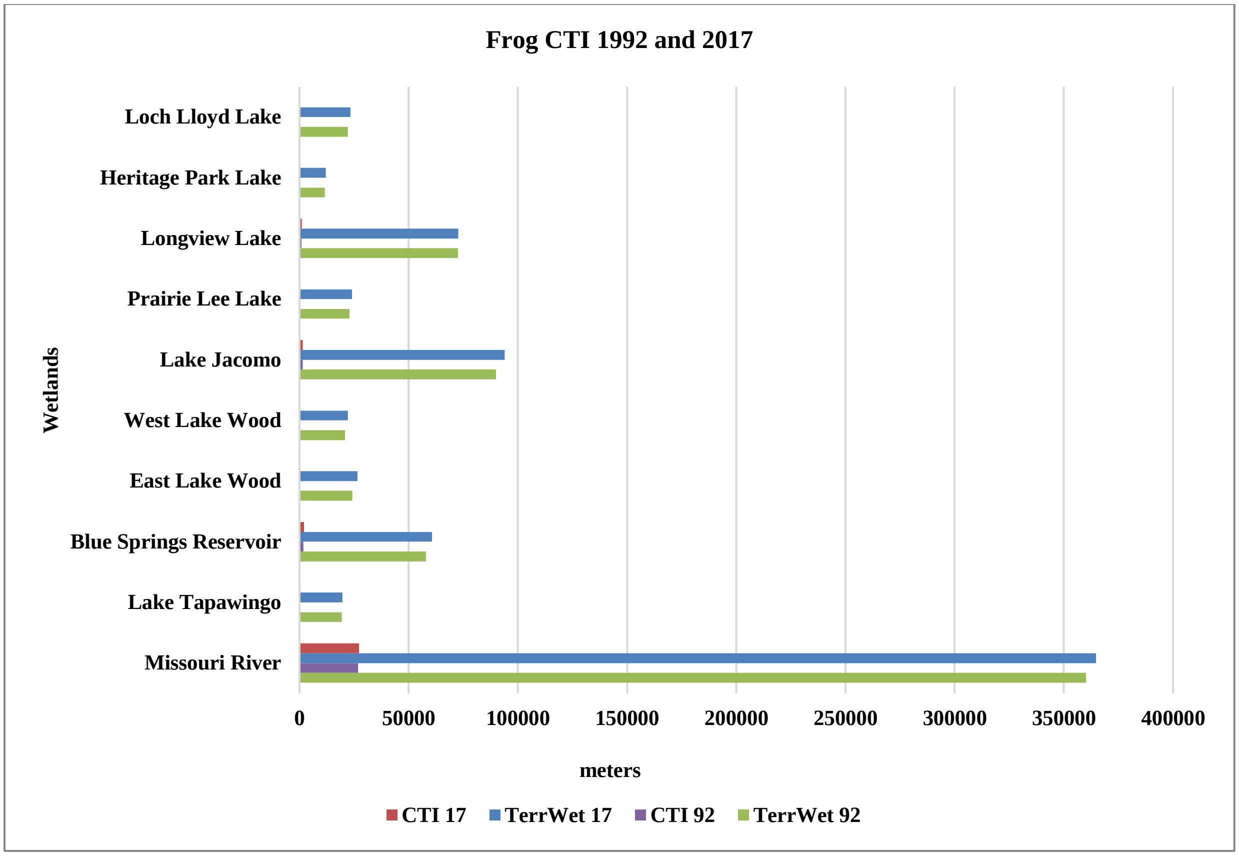
Estimated CTI for Frog Terrestrial Habitat



(a)



(b)

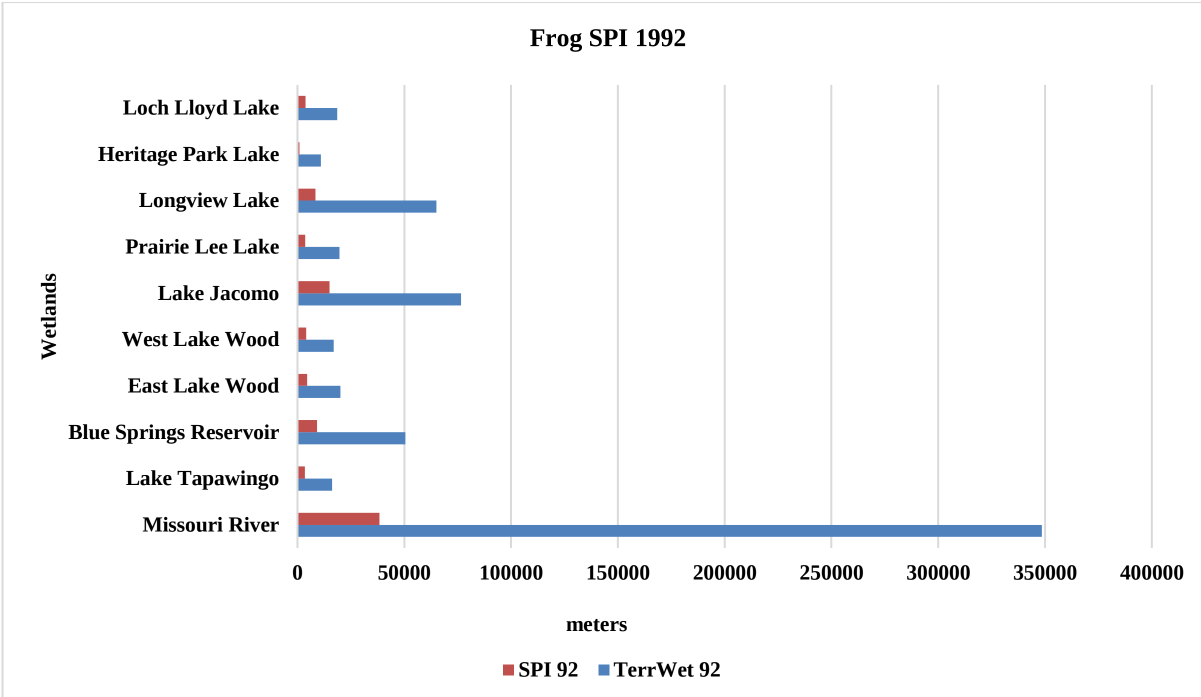


(c)

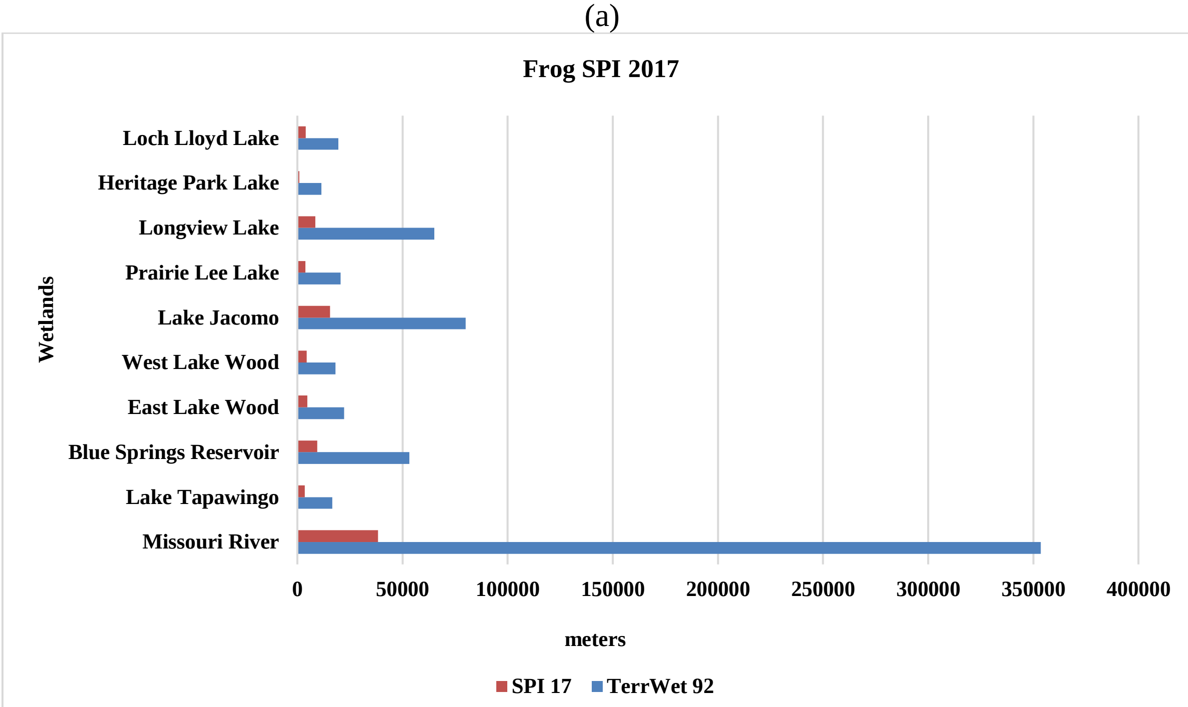
Figure 16: (a-c) Estimated CTI for Frog Habitat.

The Frog terrestrial habitat within the recommended mean maximum core area of 368 m showed a relatively slight CTI change in favor of 1992 as compared with 2017 (see Figure 16: (a-c)).

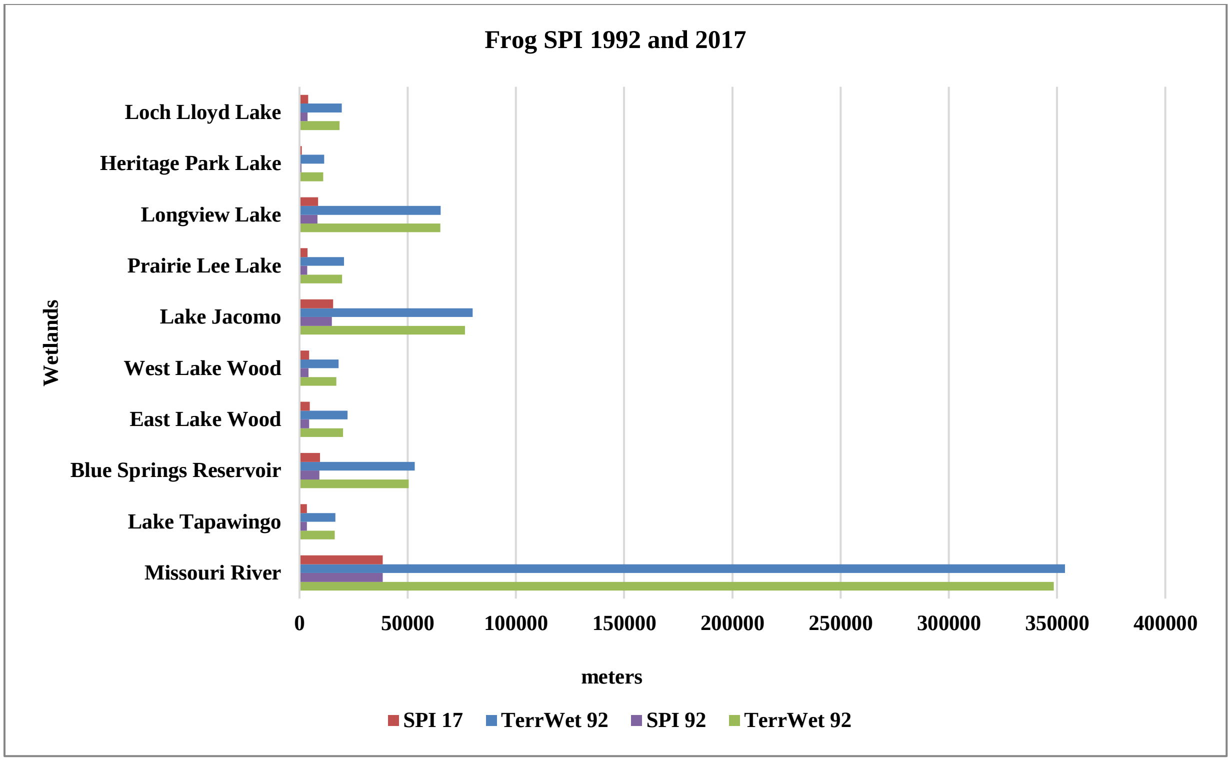
Estimated SPI for Frog Terrestrial Habitat



(a)



(b)



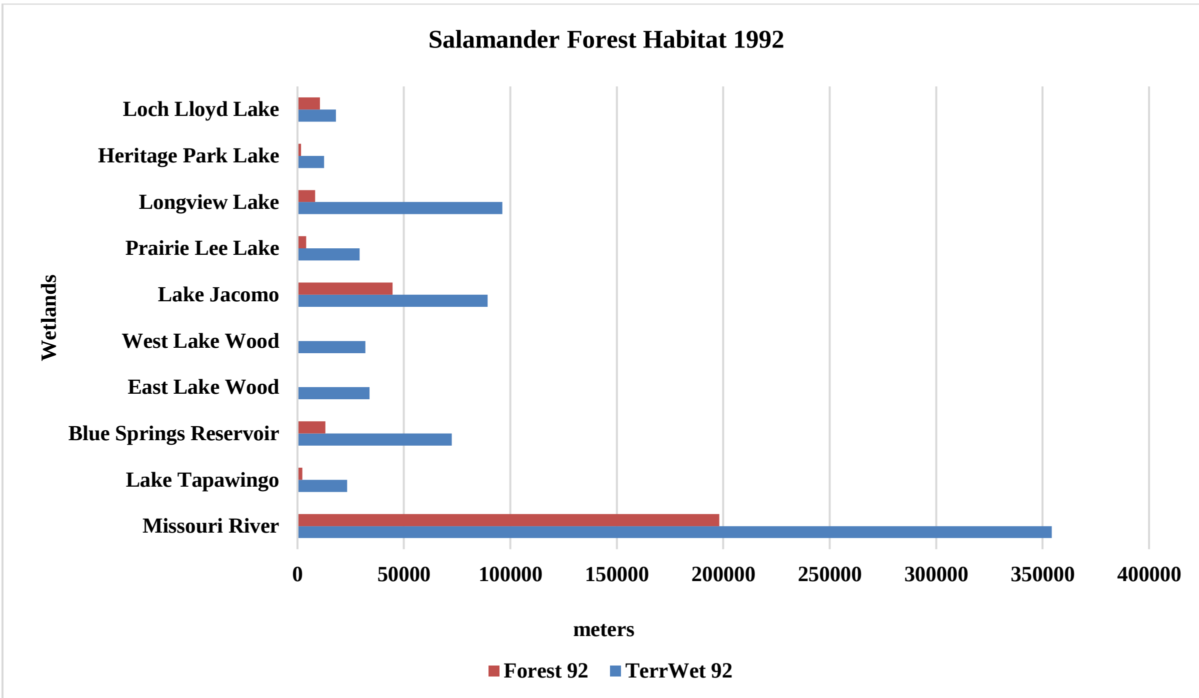
(c)

Figure 17: (a-c) Estimated SPI for Frog Habitat.

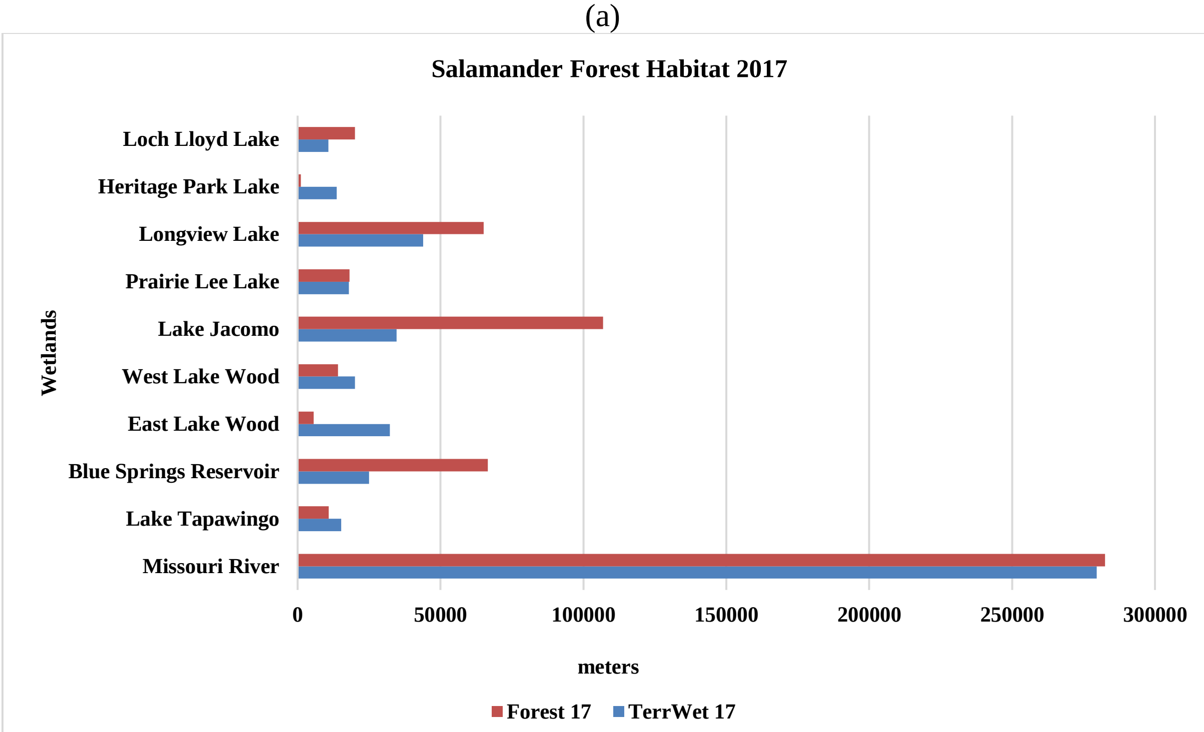
The Frog terrestrial habitat within the recommended mean maximum core area of 368 m showed a relatively slight SPI change in favor of 2017 as compared with 1992 (see Figure 17: (a-c)).

SALAMANDERS

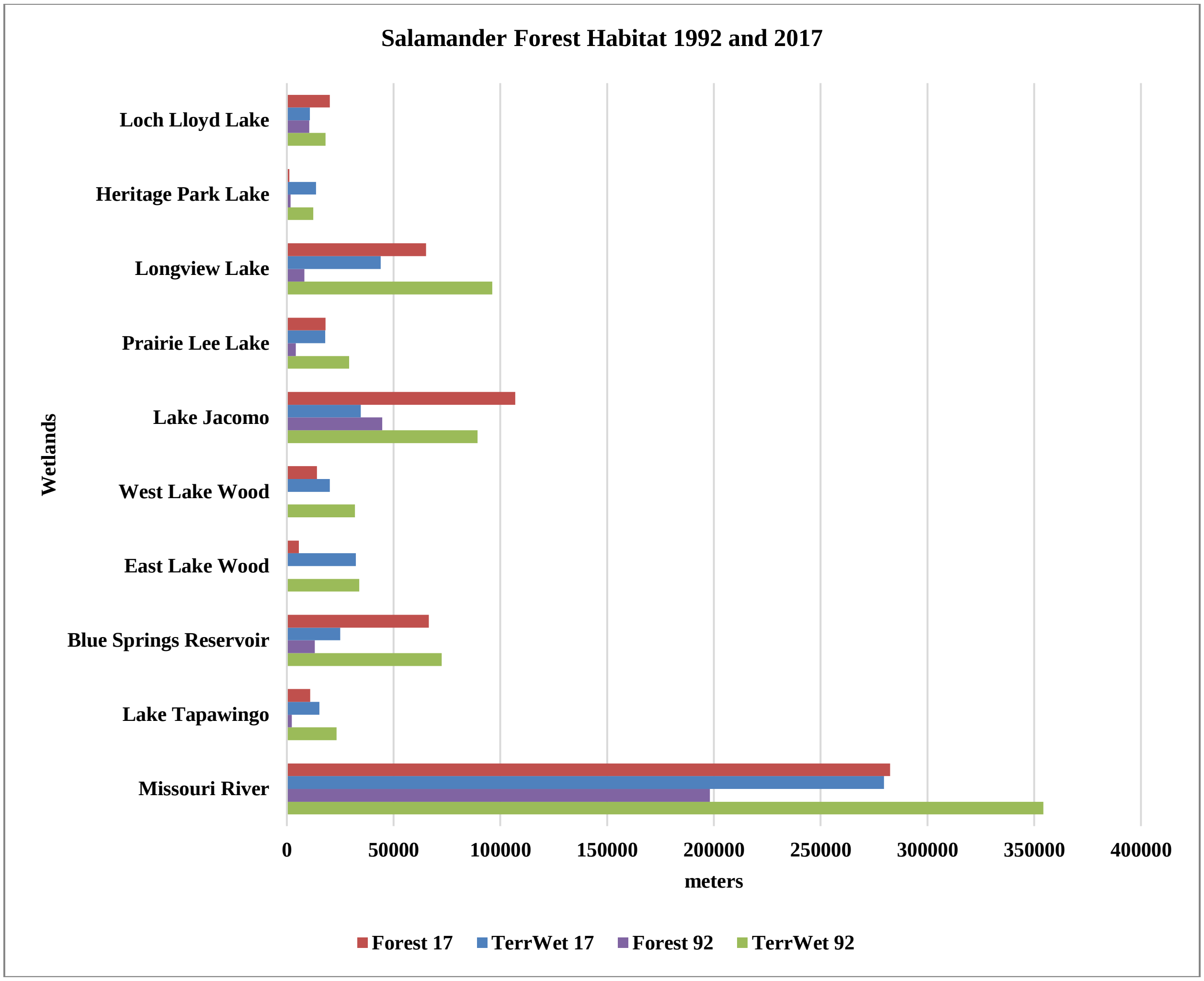
Estimated Forest Habitat for Salamanders



(a)



(b)

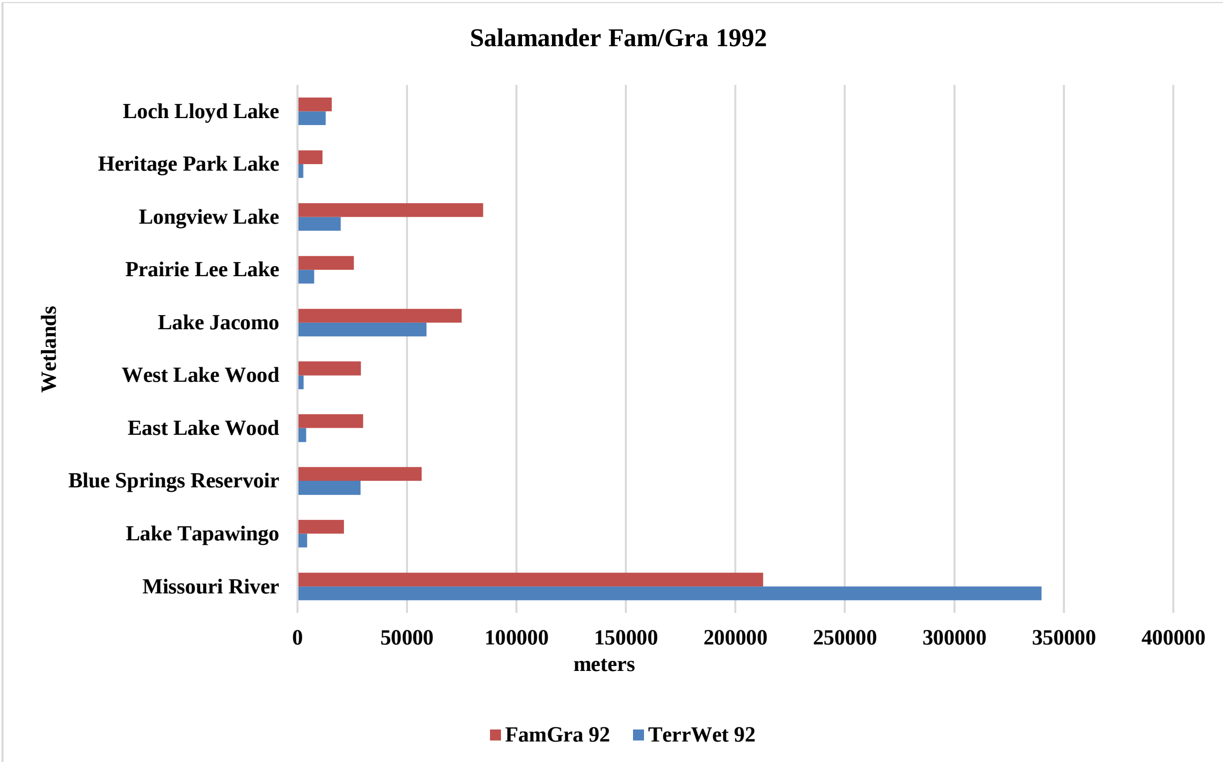


(c)

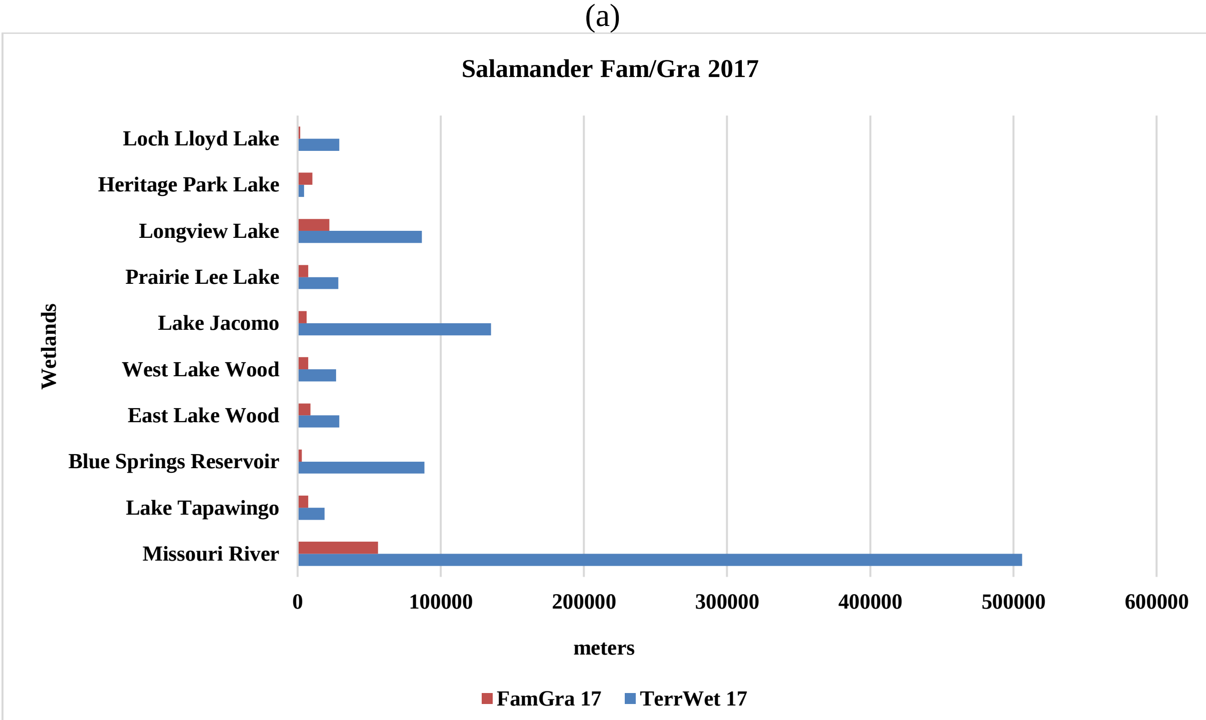
Figure 18: (a-c) Estimated Salamander Forest Habitat

The Salamander terrestrial habitat within the recommended mean maximum core area of 218 m showed increasing forest habitat for 2017 as compared with 1992. Most of the wetlands revealed increasing forest terrestrial habitat in 2017 except for Heritage Park Lake (see Figure 18: (a-c)).

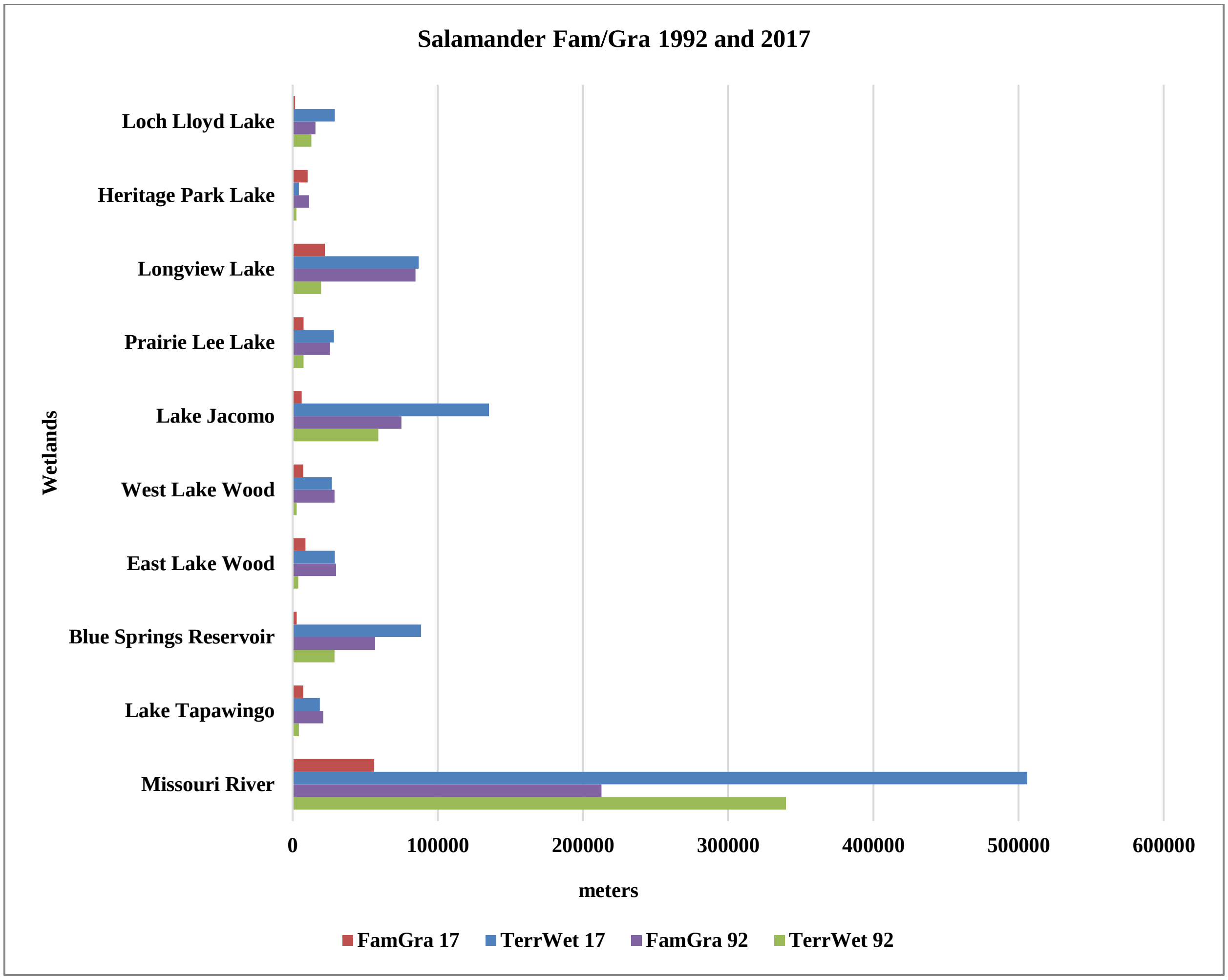
Estimated Farmland/Grassland Habitat for Salamanders



(a)



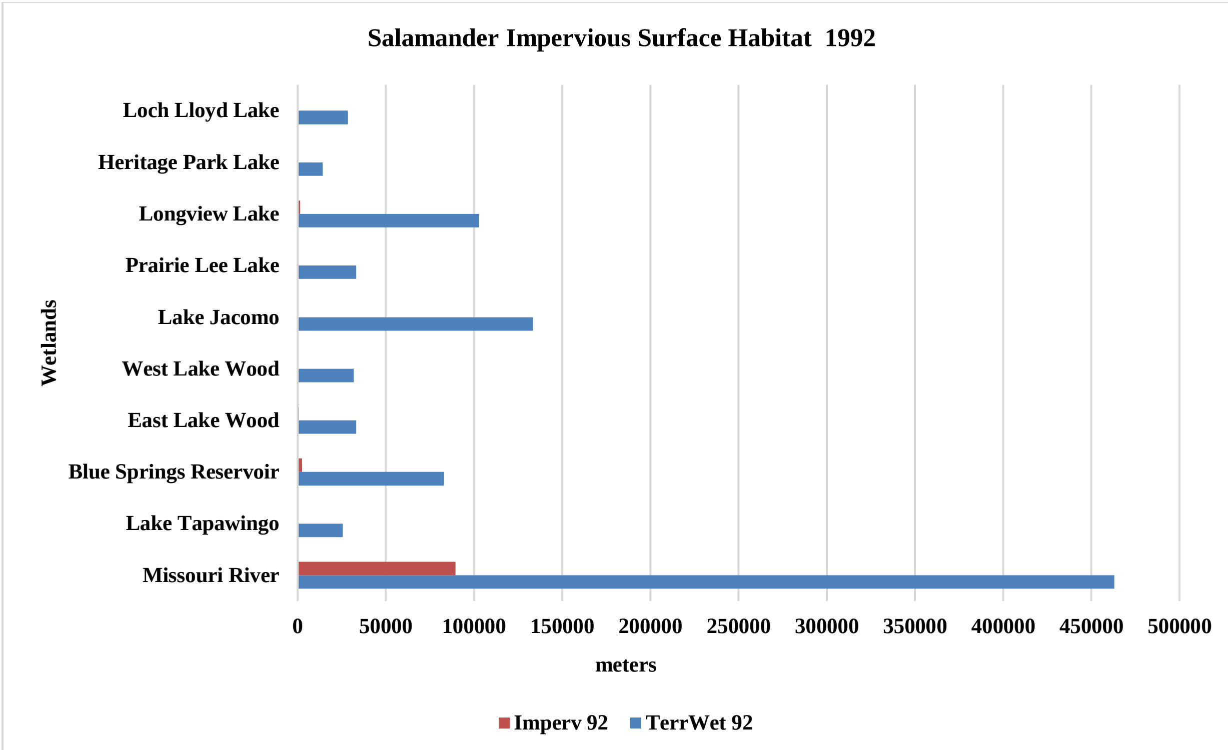
(b)



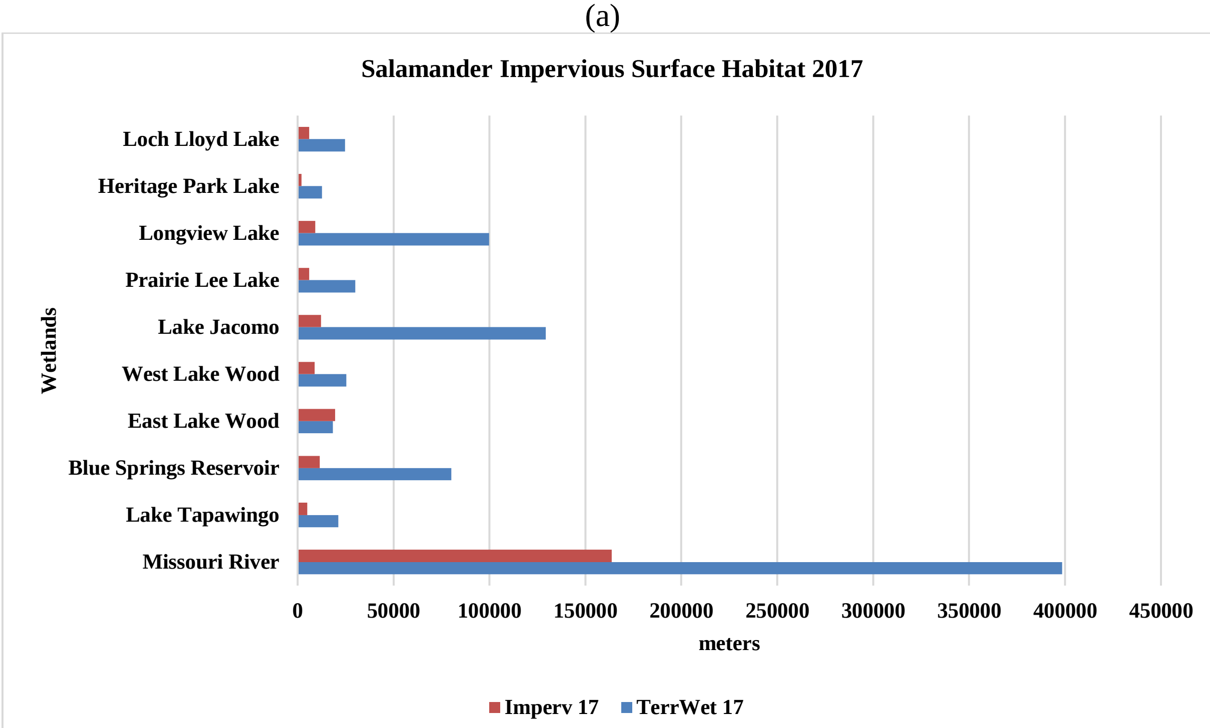
(c)

Figure 19: (a-c) Estimated Salamander Farmland/Grassland Habitat.
The Salamander terrestrial habitat within the recommended mean maximum core area of 218 m showed an increase in farmland/grassland for 1992 as compared to 2017. Increasing farmland/grassland was revealed for all wetlands except the Heritage Park Lake which showed no change between the study periods (see Figure 14: (a-c)).

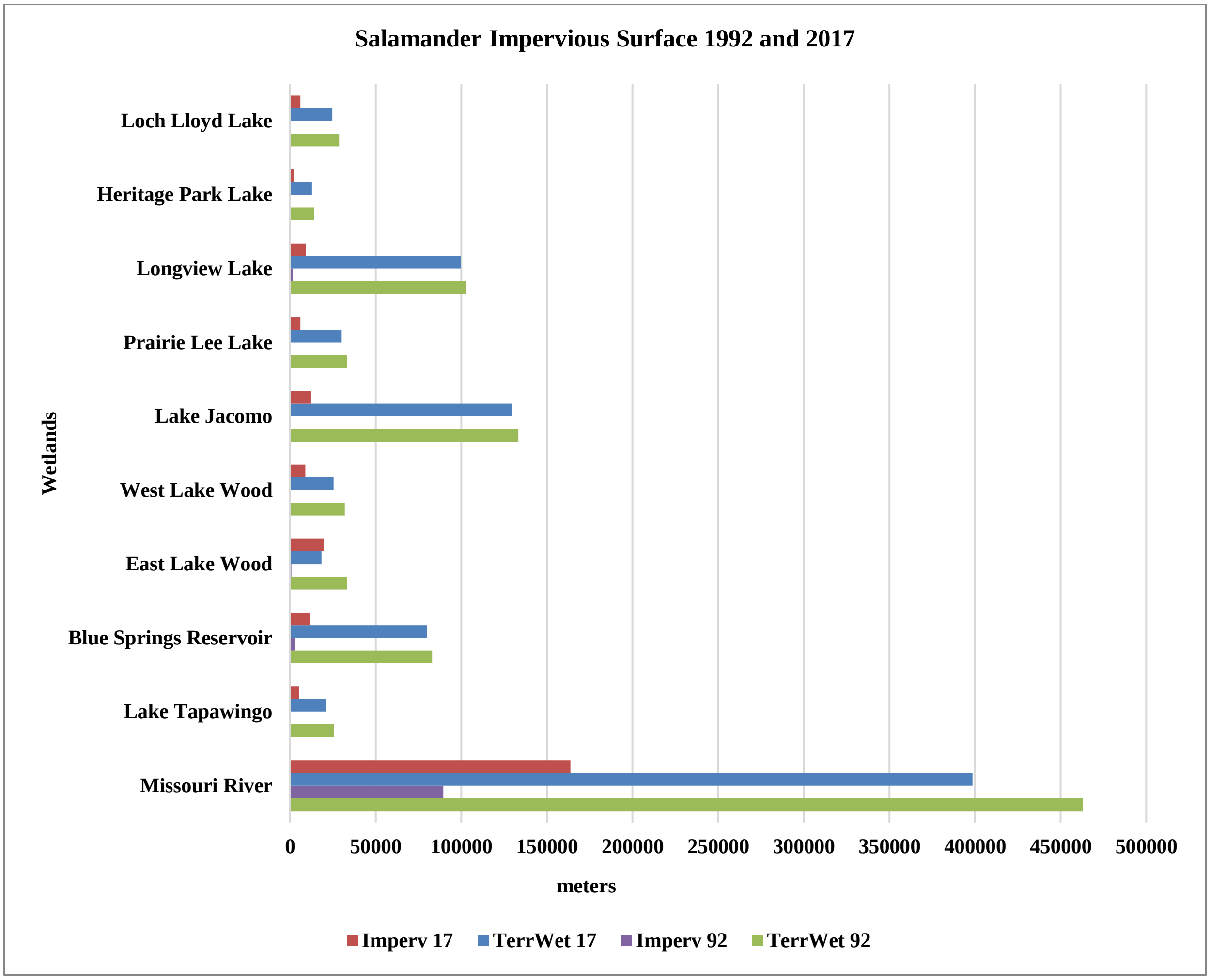
Estimated Impervious Surface Habitat for Salamanders



(a)



(b)

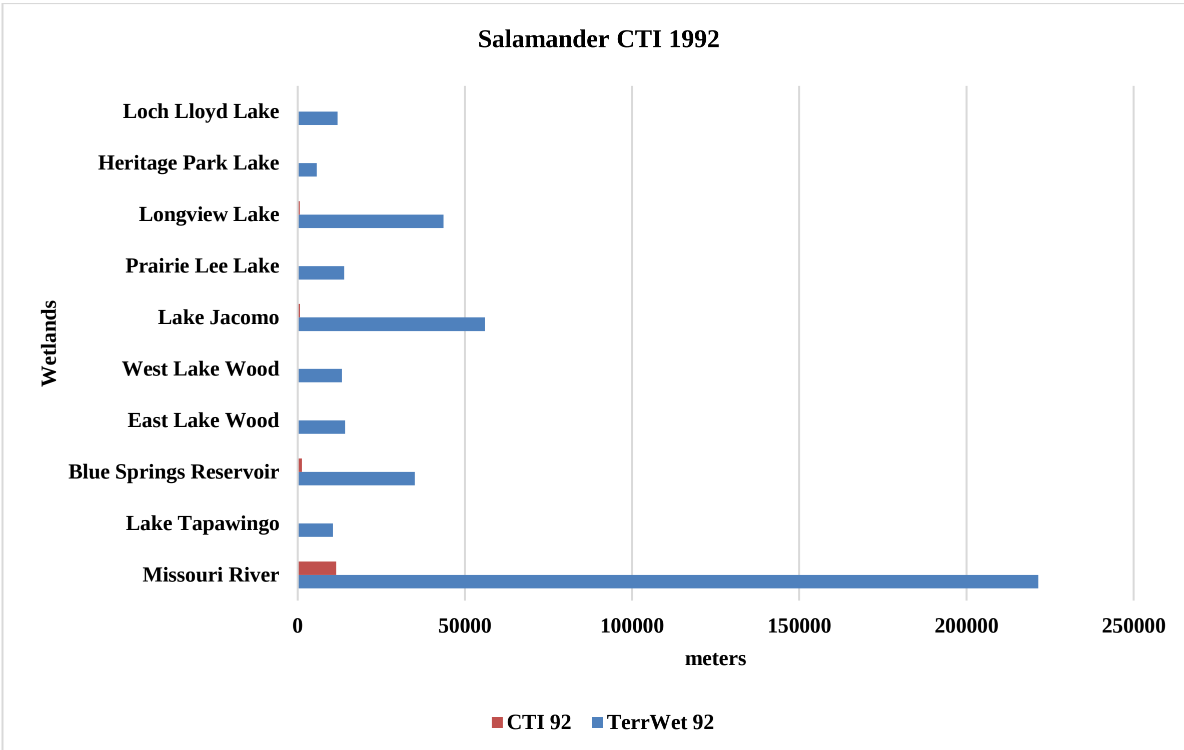


(c)

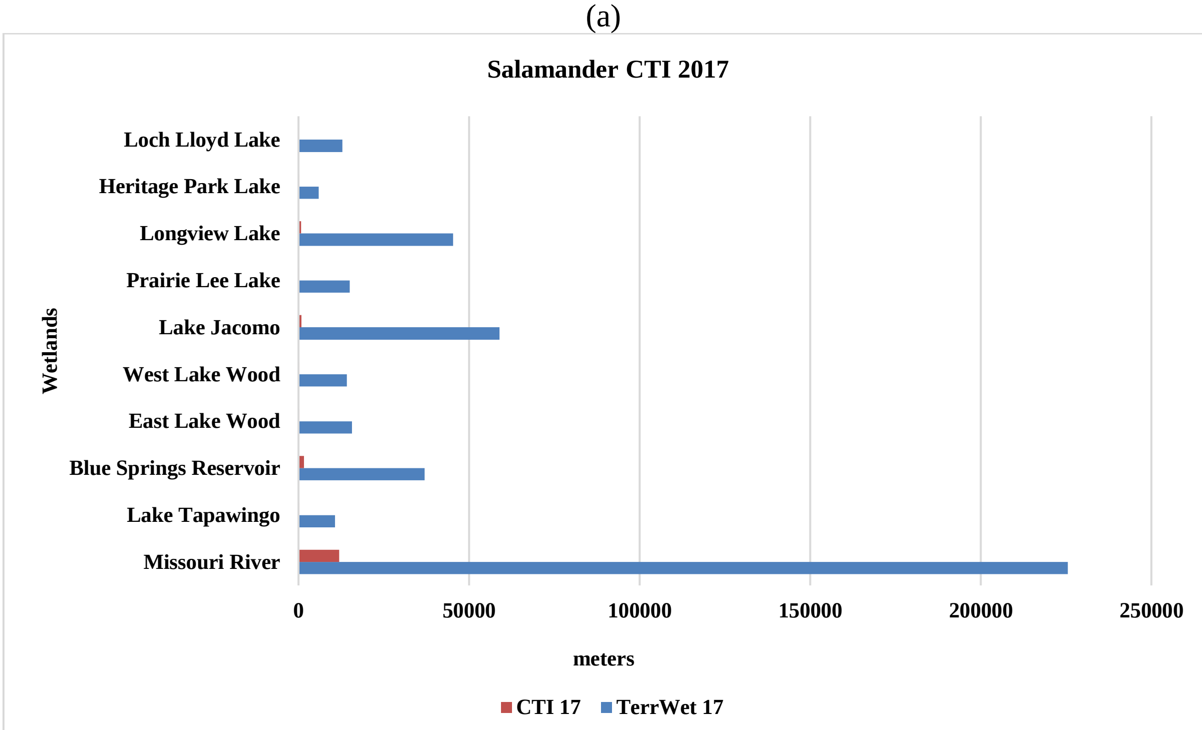
Figure 20: (a-c) Estimated Salamander impervious surface habitat.

The Salamander terrestrial habitat within the recommended mean maximum core area of 218 m showed an increase impervious surfaces for all wetland in 2017 as compared with 1992 (see Figure 20: (a-c)).

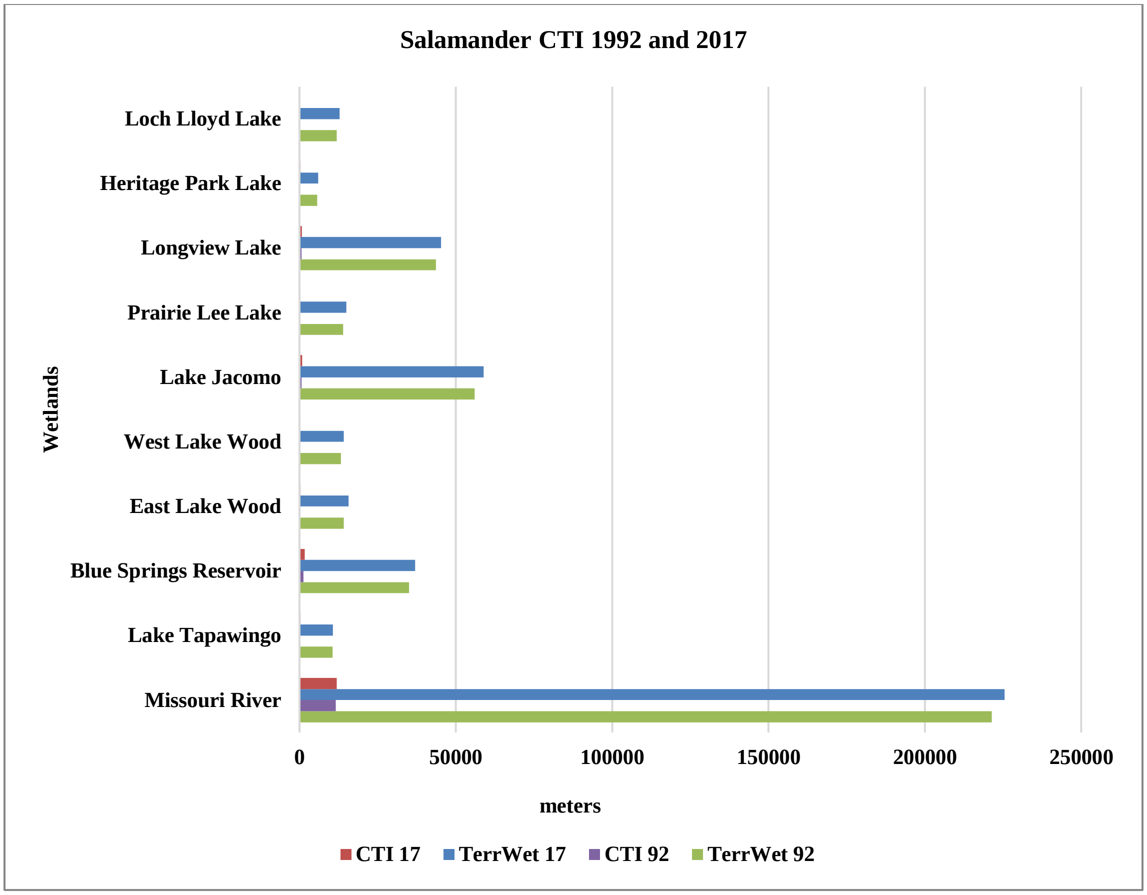
Estimated CTI for Salamander Terrestrial Habitat



(a)



(b)

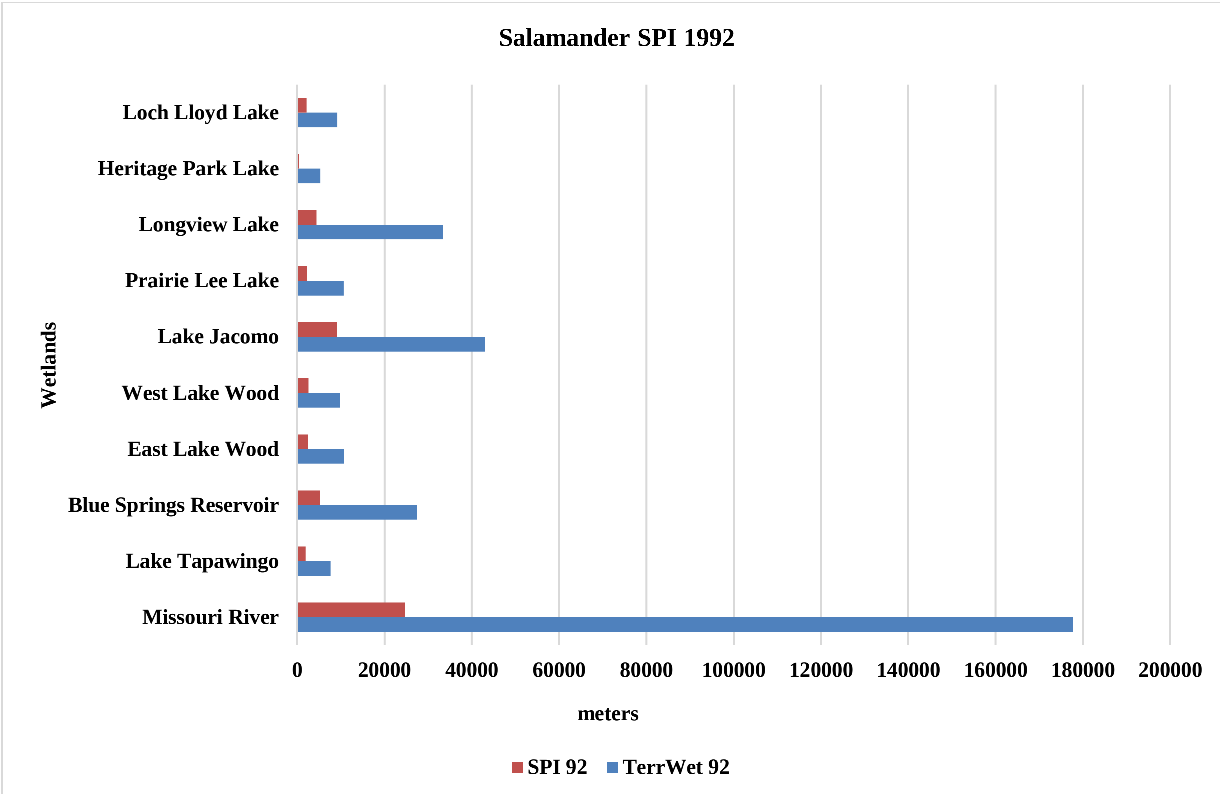


(c)

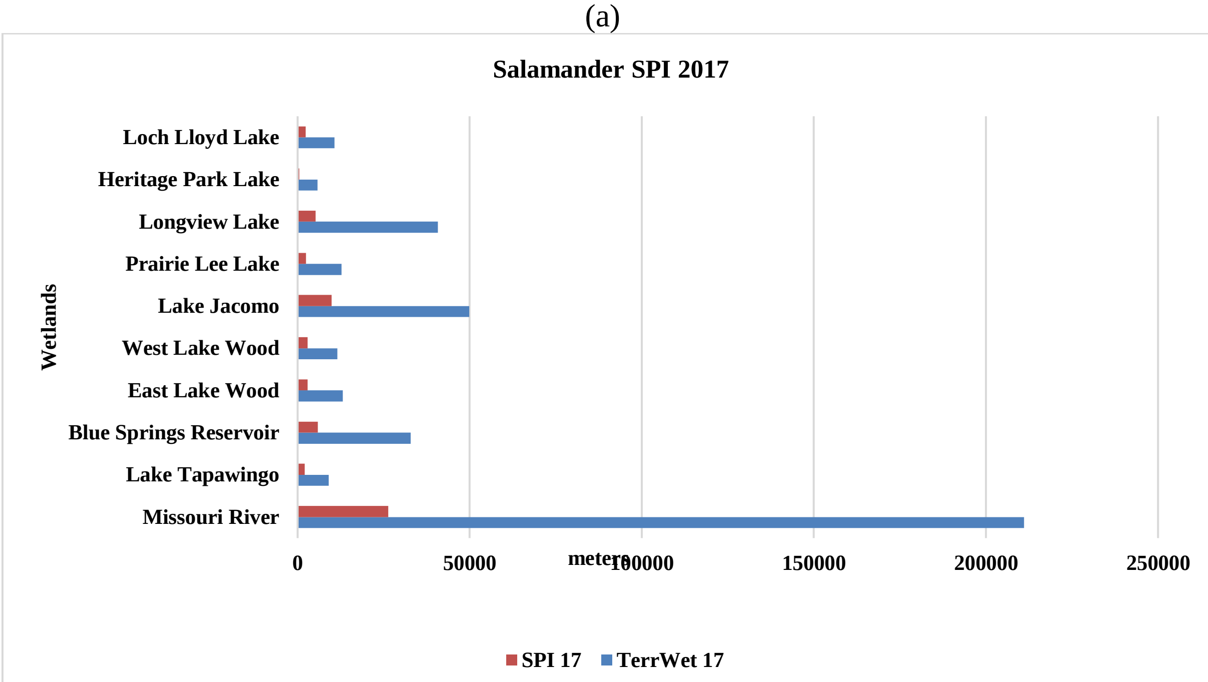
Figure 21: (a-c) Estimated CTI for Salamander Habitat.

The Salamander terrestrial habitat within the recommended mean maximum core area of 218 m showed a relatively slight CTI change in favor of 1992 as compared with 2017 (see Figure 21: (a-c)).

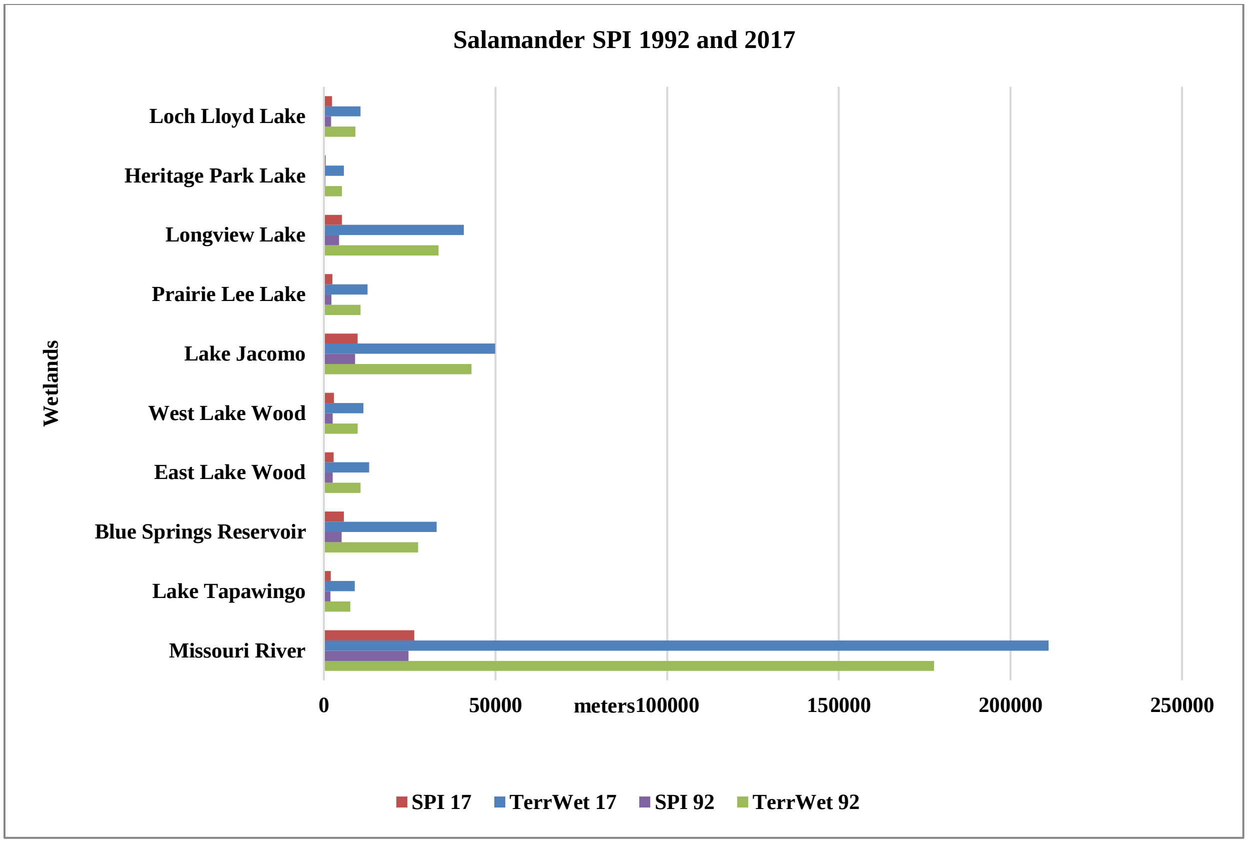
Estimated SPI for Salamander Terrestrial Habitat



(a)



(b)



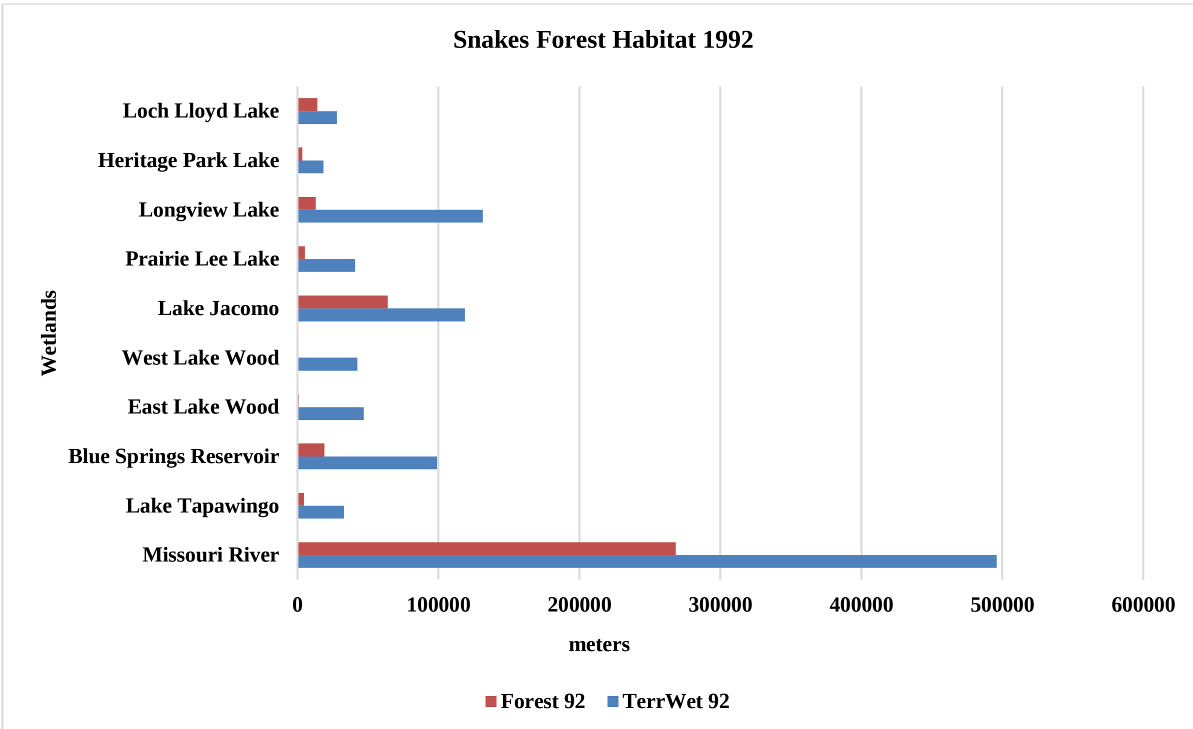
(c)

Figure 22: (a-c) Estimated SPI for Salamander Habitat.

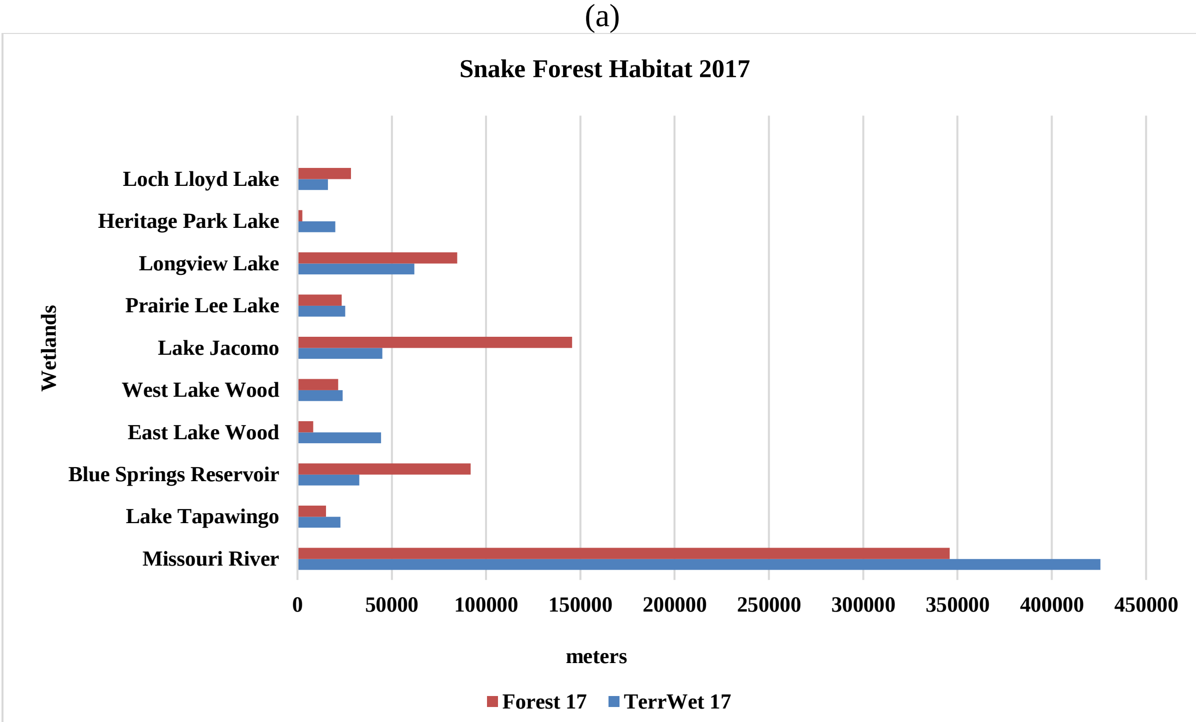
The Salamander terrestrial habitat within the recommended mean maximum core area of 218 m showed a relatively slight SPI change in favor of 2017 as compared with 1992 (see Figure 22: (a-c)).

SNAKES

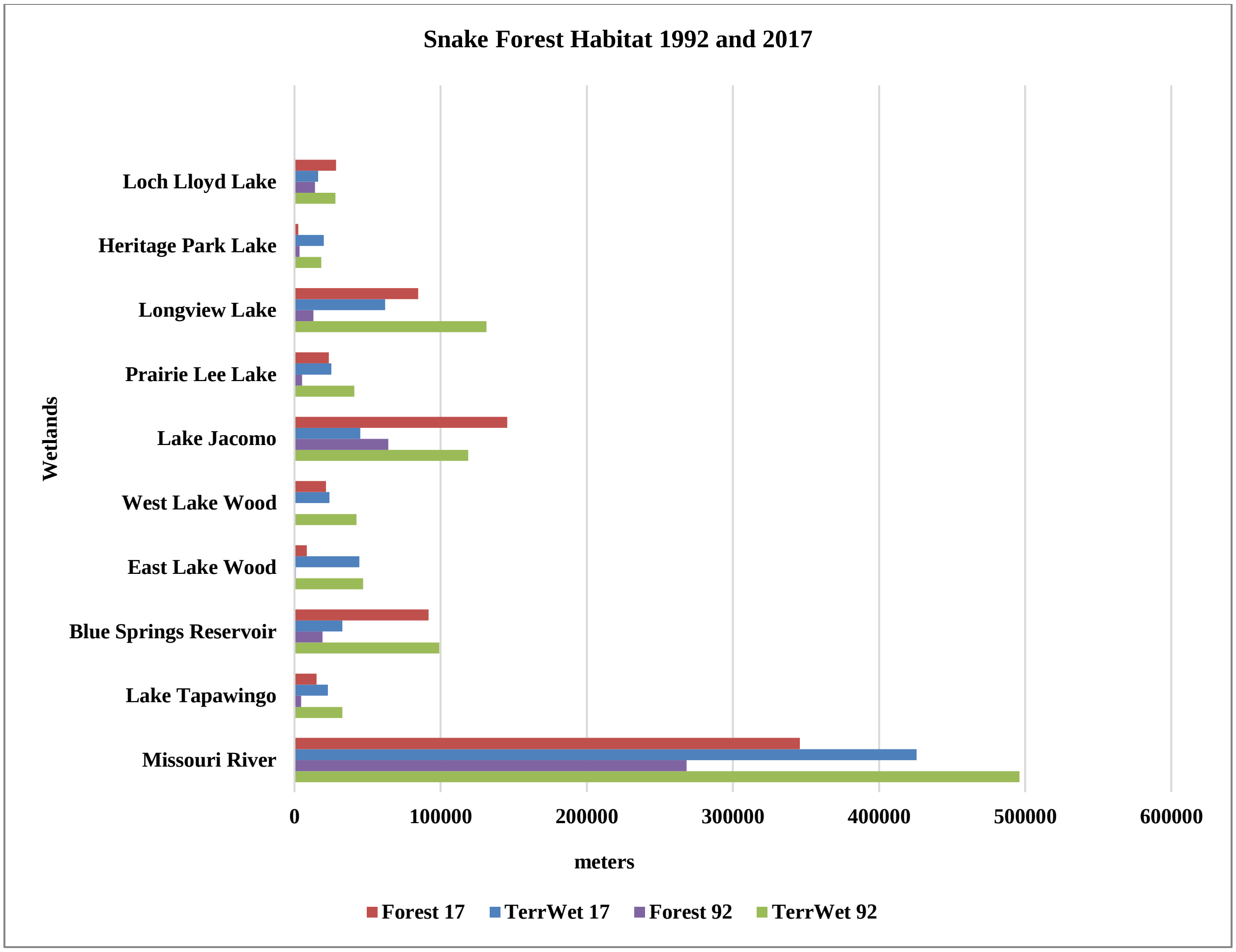
Estimated Forest Habitat for Snakes



(a)



(b)

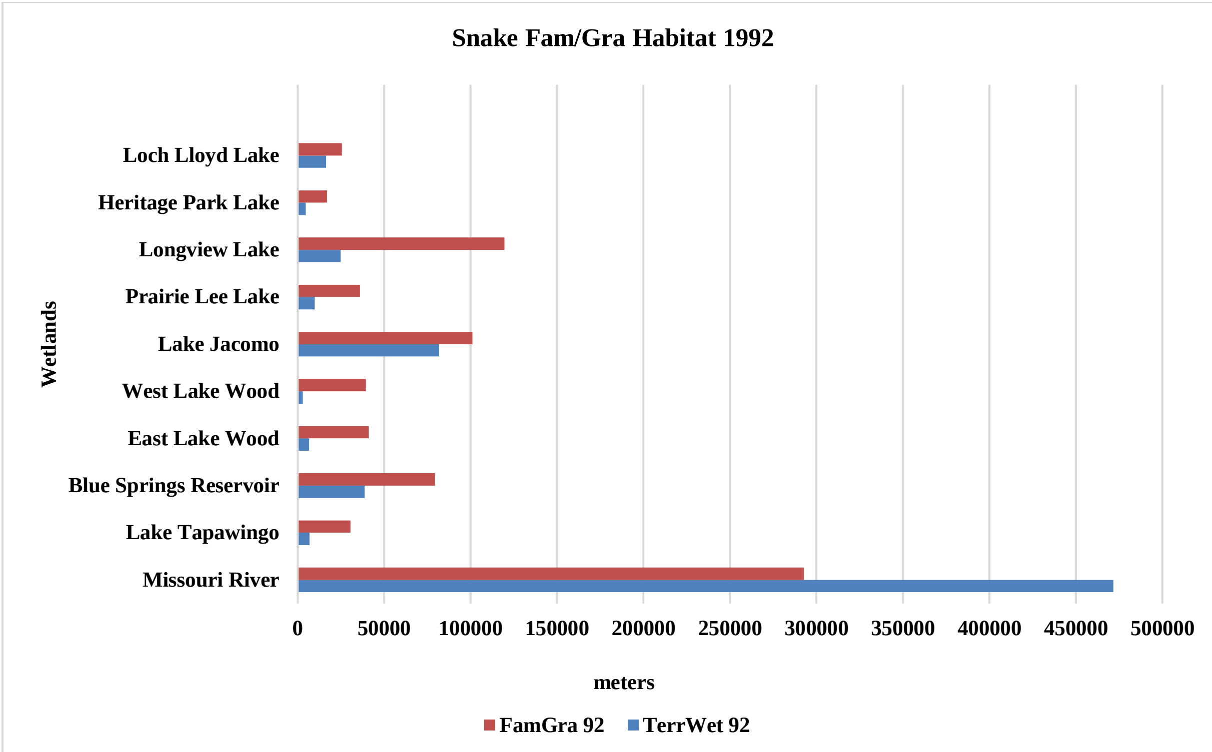


(c)

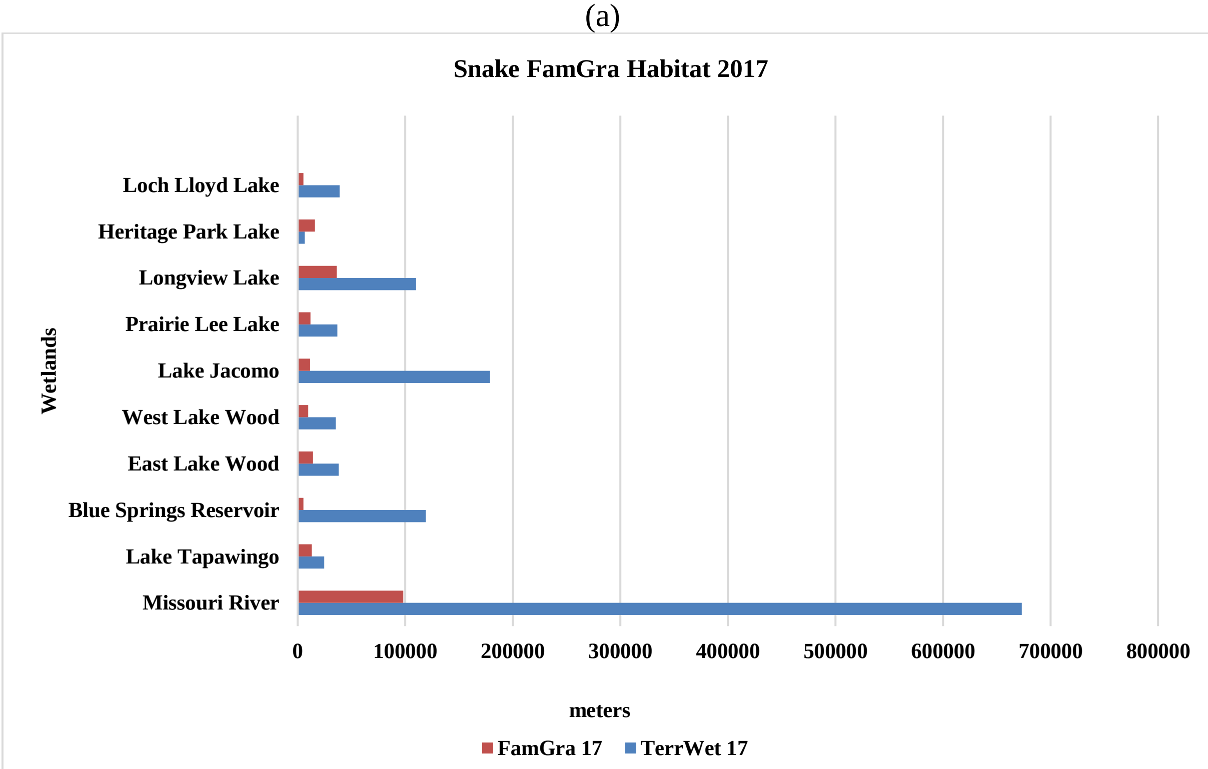
Figure 23: (a-c) Estimated Snake Forest Habitat.

The Snake terrestrial habitat within the recommended mean maximum core area of 304 m showed increasing forest habitat for 2017 as compared with 1992. Most of the wetlands revealed increasing forest terrestrial habitat in 2017 except for Heritage Park Lake (see Figure 23: (a-c)).

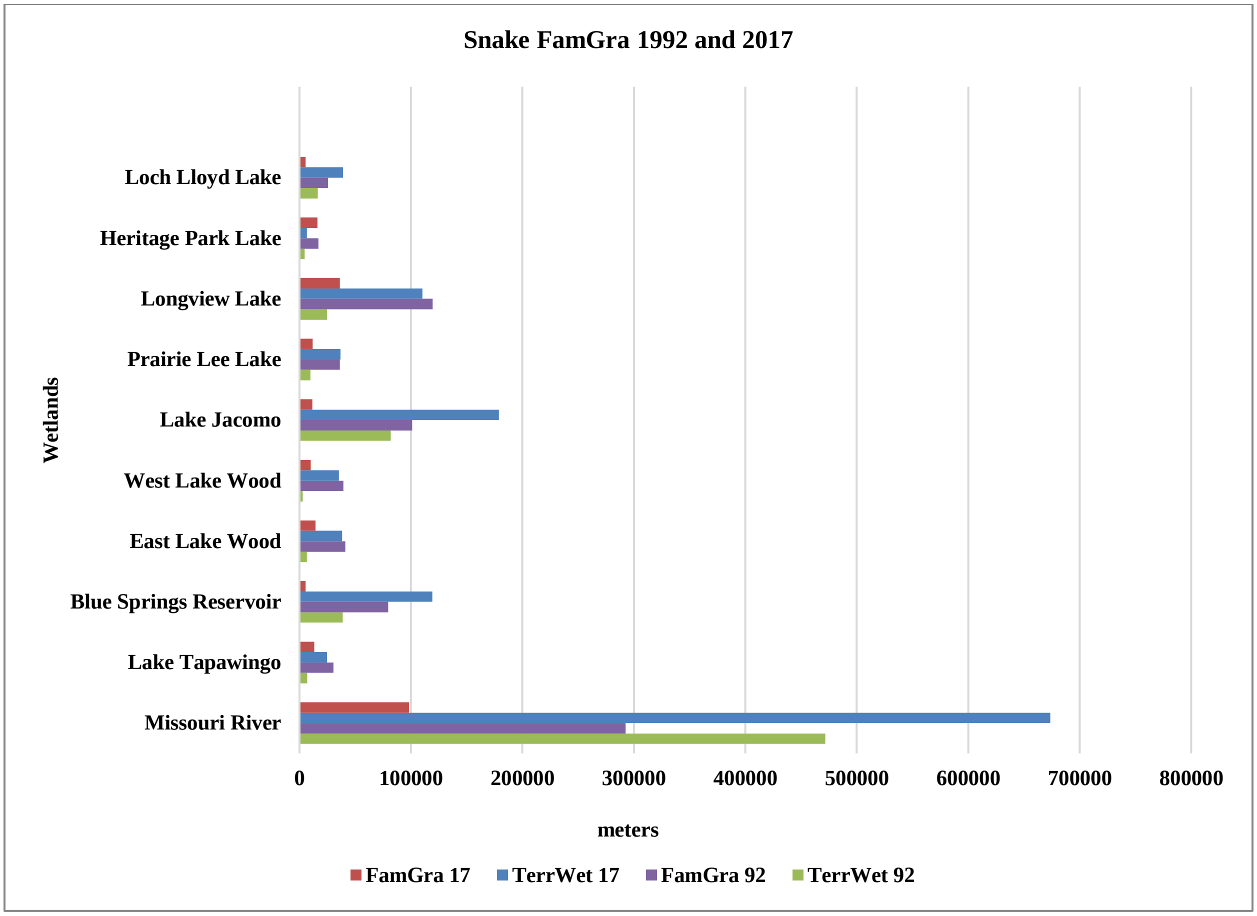
Estimated Farmland/Grassland Habitat for Snakes



(a)



(b)

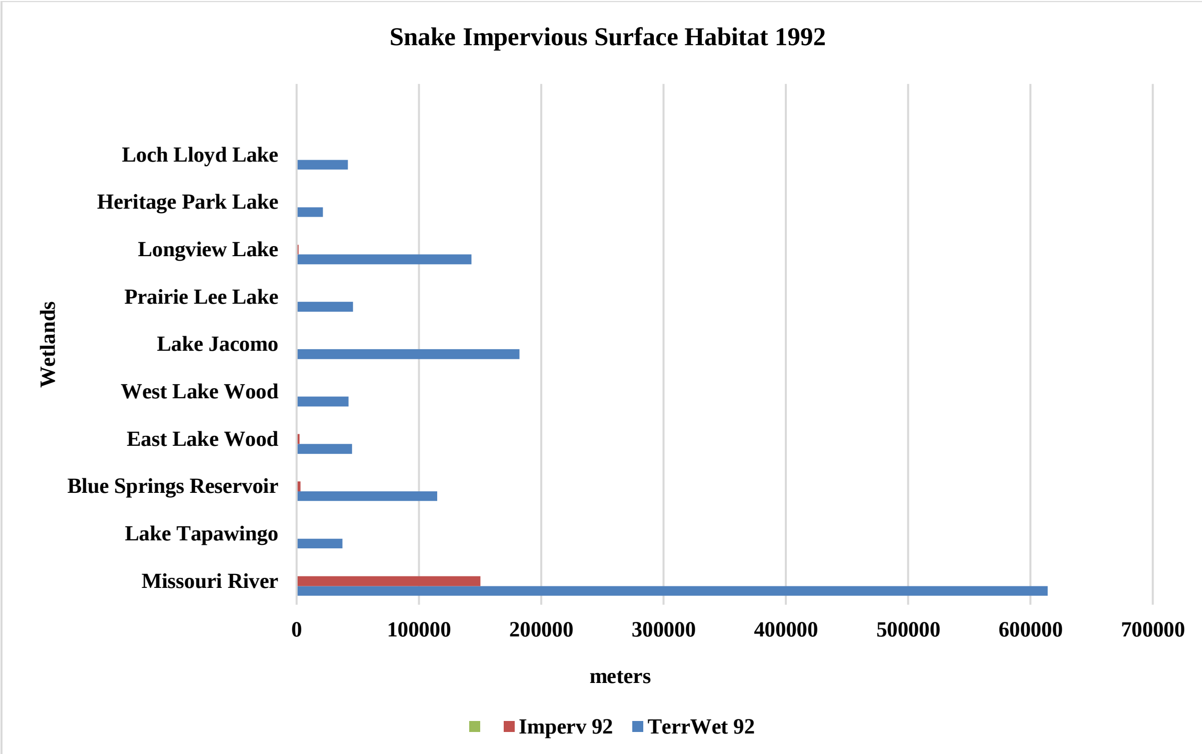


(c)

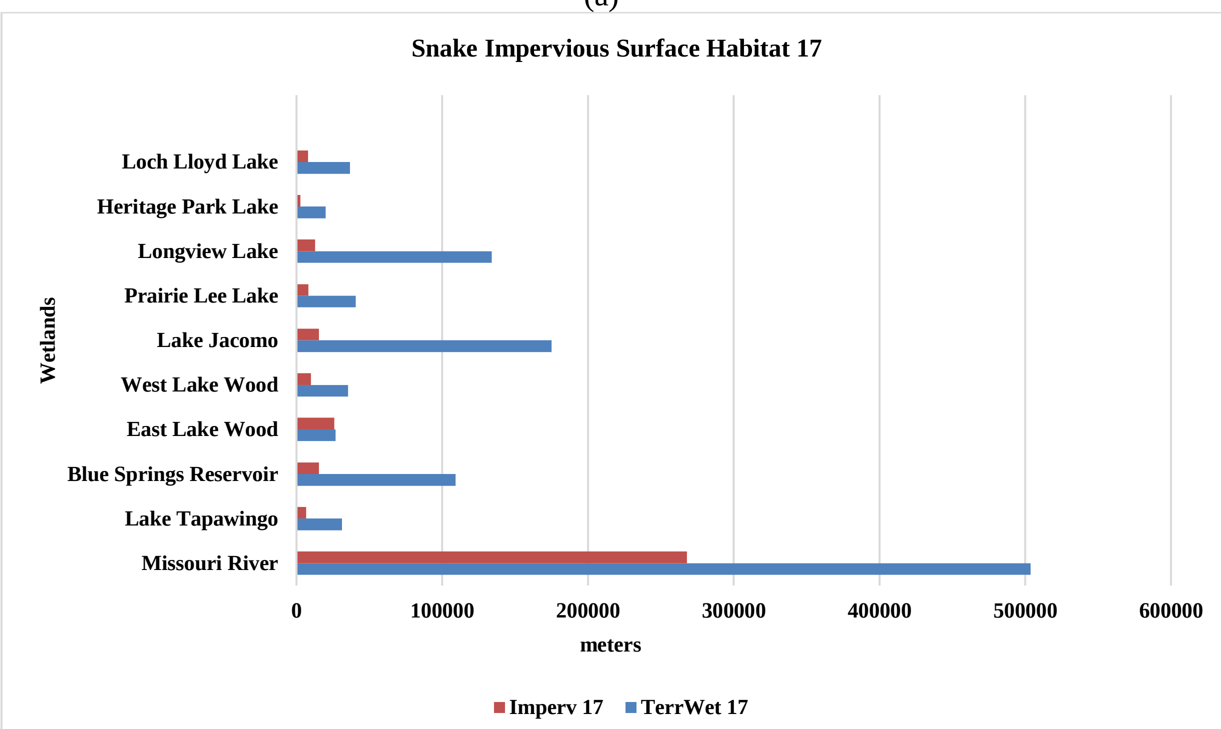
Figure 24: (a-c) Estimated Snake Farmland/Grassland Habitat.

The Snake terrestrial habitat within the recommended mean maximum core area of 304 m showed an increase in farmland/grassland for 1992 as compared to 2017. Increasing farmland/grassland was revealed for all wetlands except the Heritage Park Lake which showed no change between the study periods (see Figure 24: (a-c)).

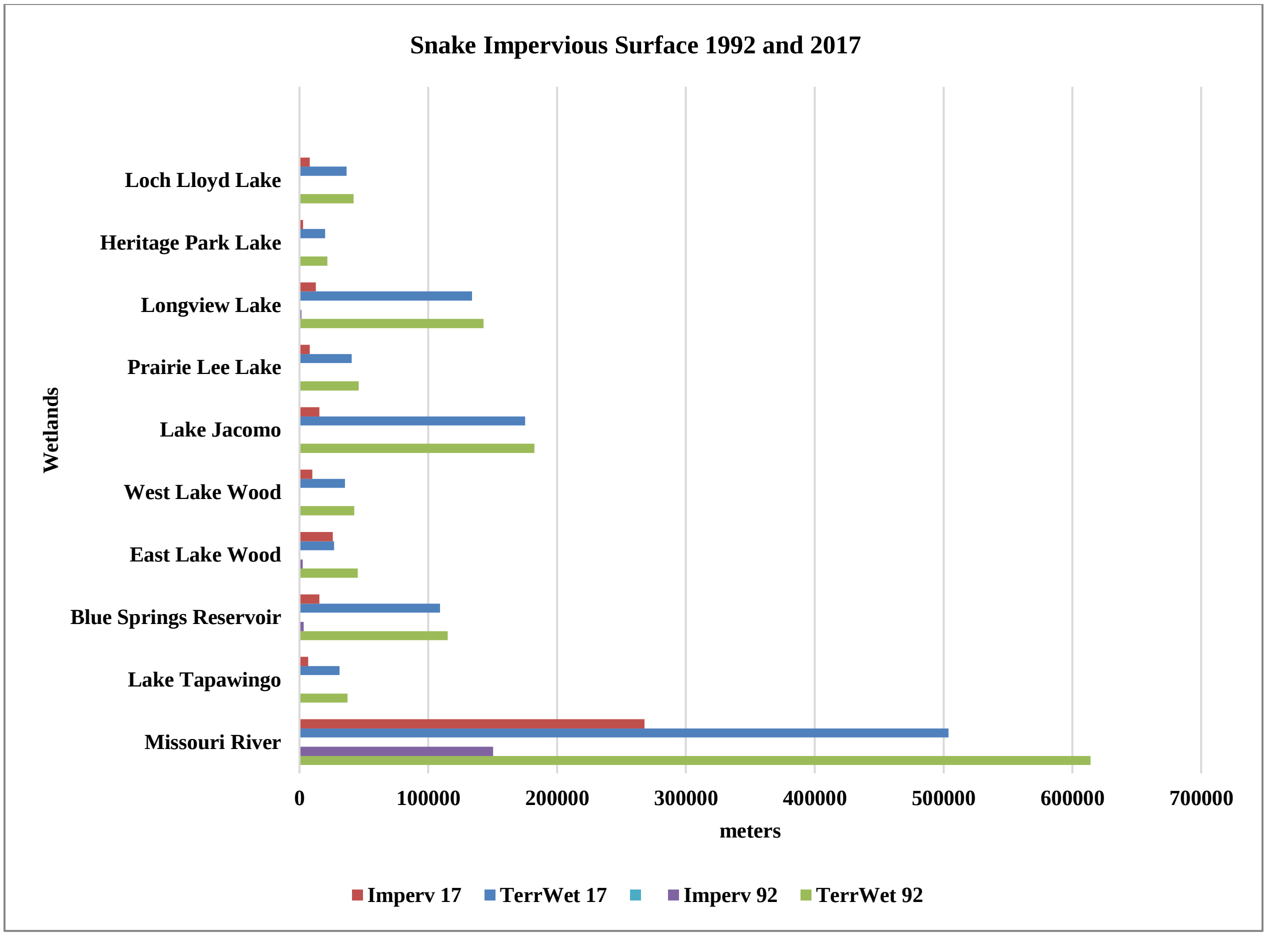
Estimated Impervious Surface Habitat for Snakes



(a)



(b)

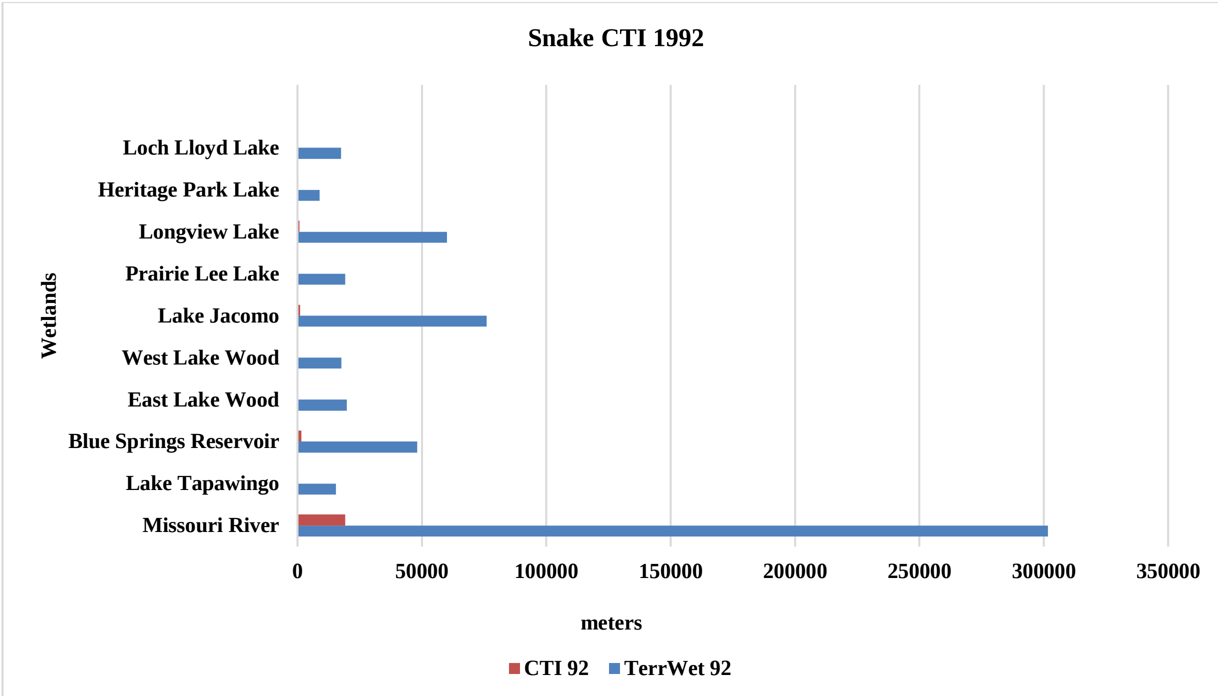


(c)

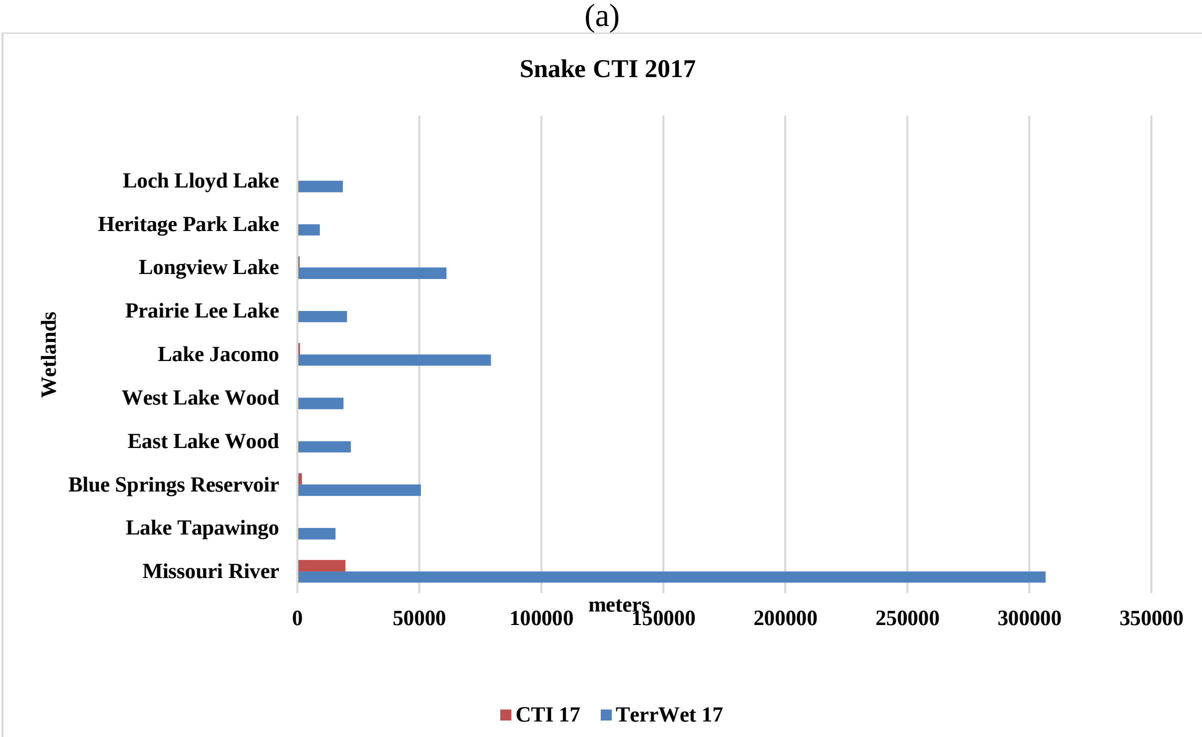
Figure 25: (a-c) Estimated Snake Impervious Surface Habitat.

The Snake terrestrial habitat within the recommended mean maximum core area of 304 m showed an increase impervious surfaces for all wetland in 2017 as compared with 1992 (see Figure 25: (a-c)).

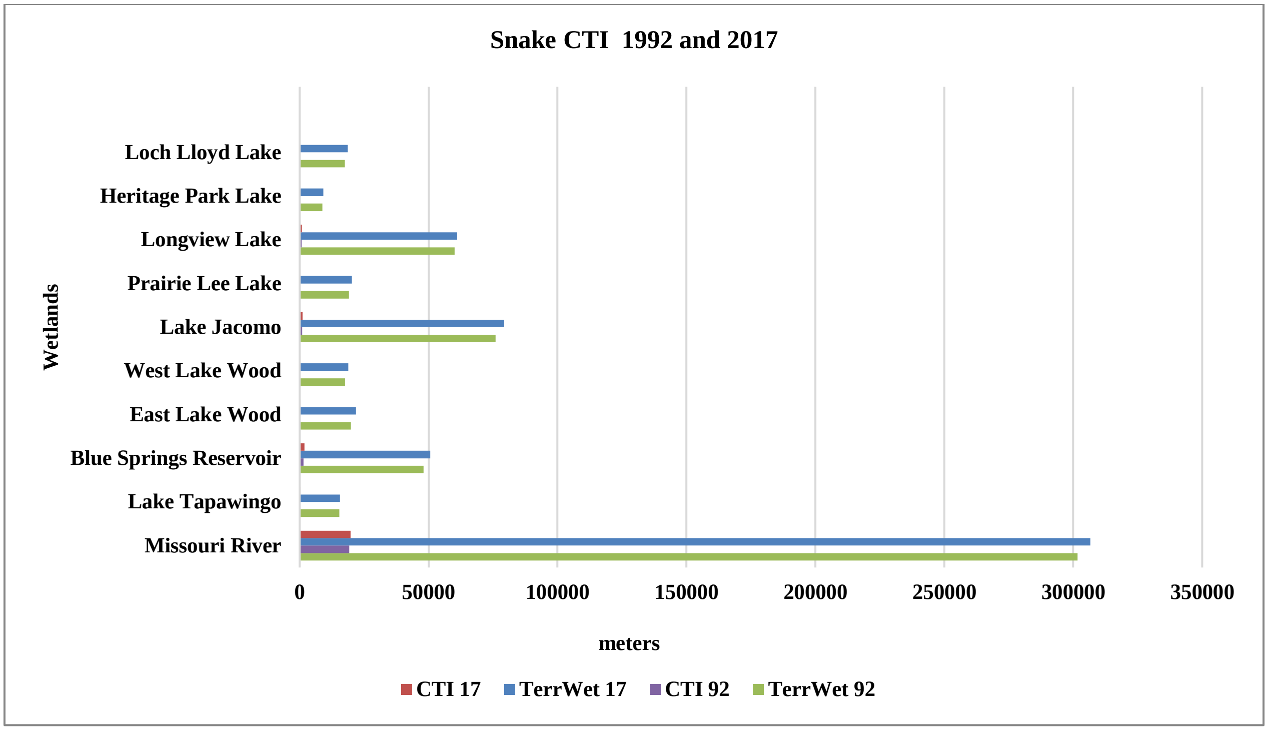
Estimated CTI for Snake Terrestrial Habitat



(a)



(b)

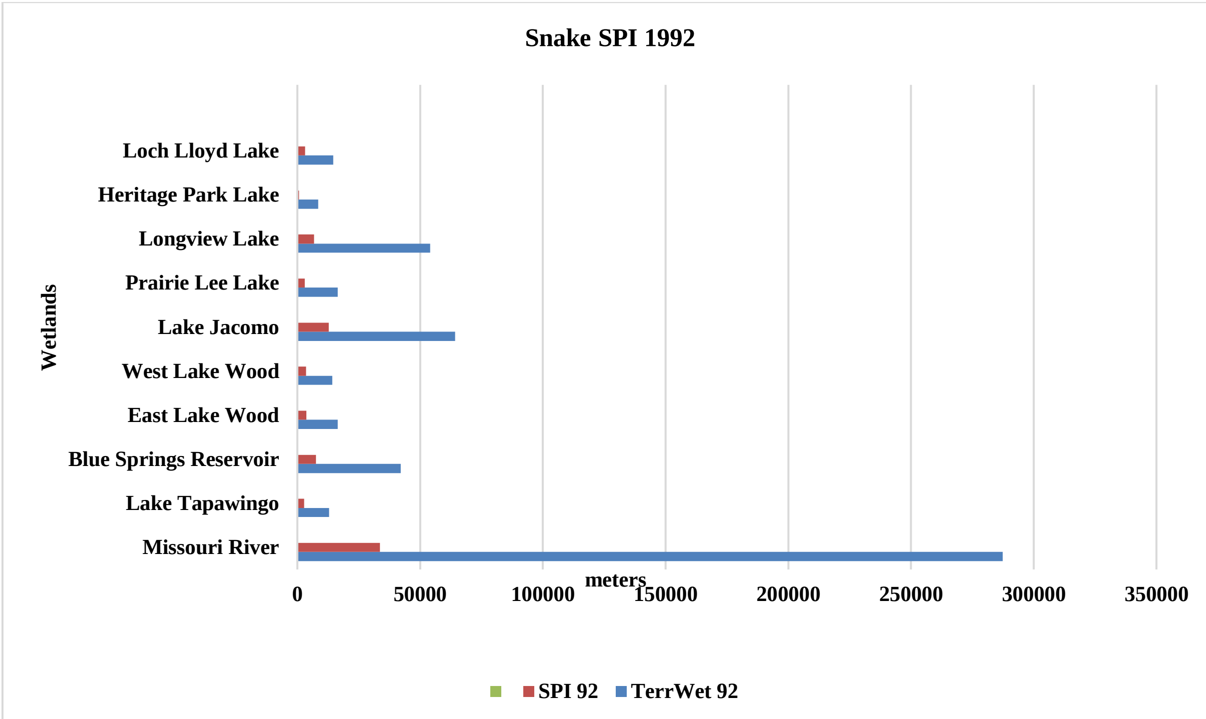


(c)

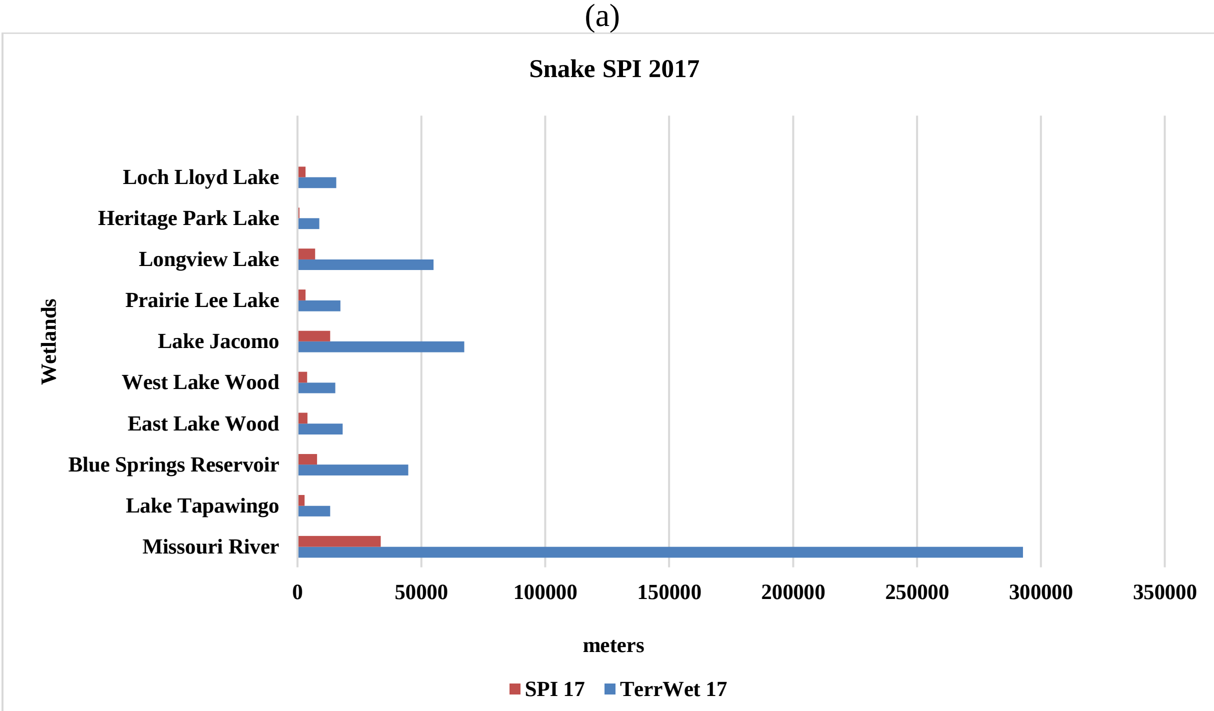
Figure 26: (a-c) Estimated CTI for Snakes Habitat.

The Snake terrestrial habitat within the recommended mean maximum core area of 304 m showed a relatively slight CTI change in favor of 1992 as compared with 2017 (see Figure 26: (a-c)).

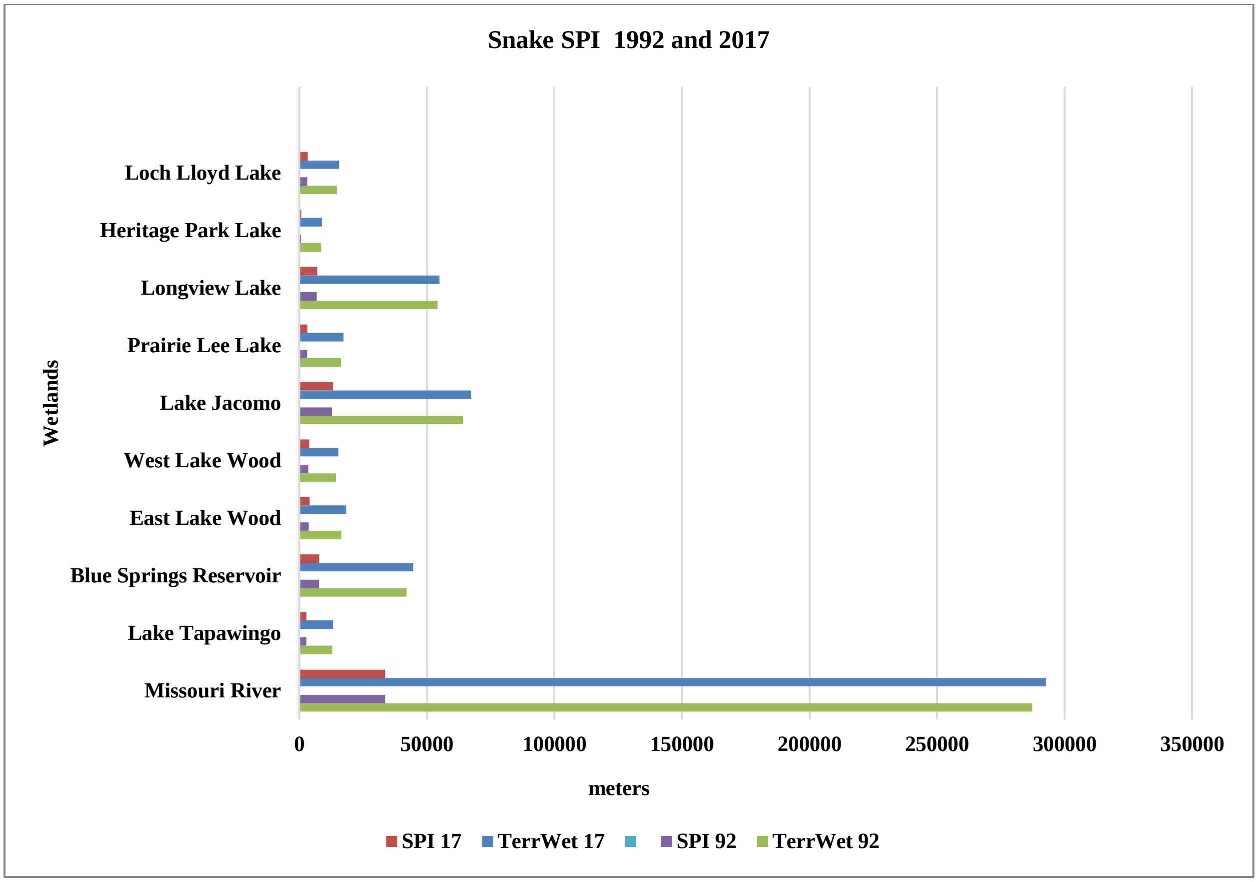
Estimated SPI for Snake Terrestrial Habitat



(a)



(b)



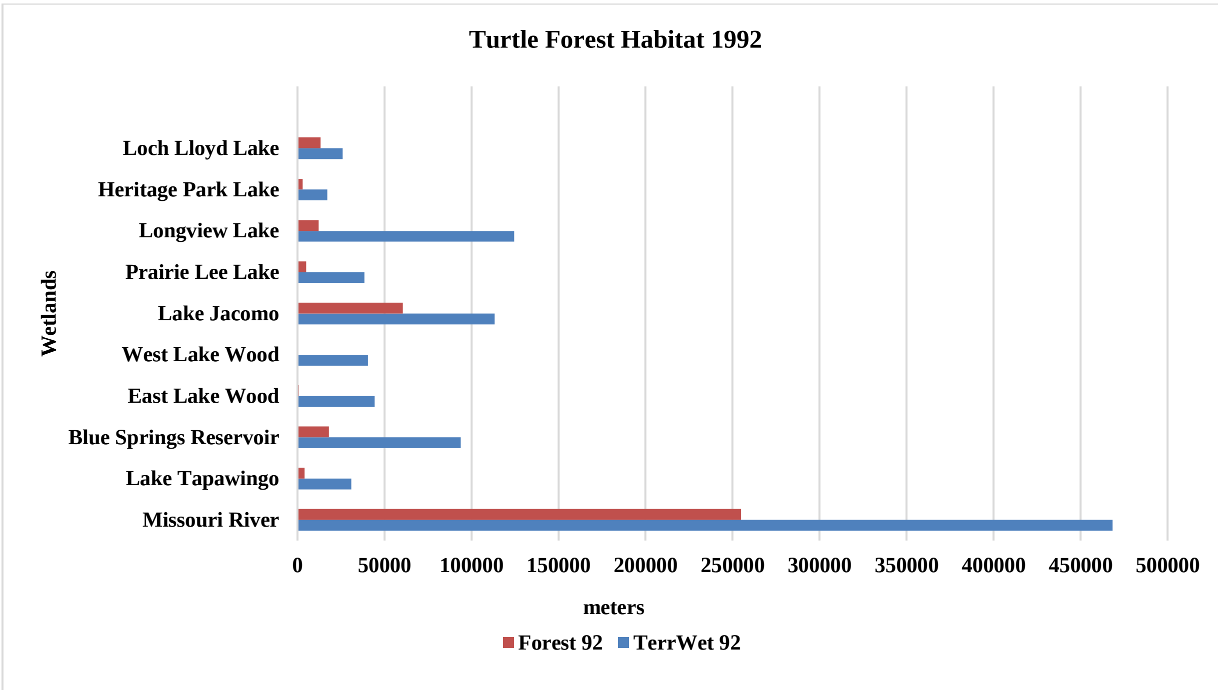
(c)

Figure 27: (a-c) Estimated SPI for Snake Habitat.

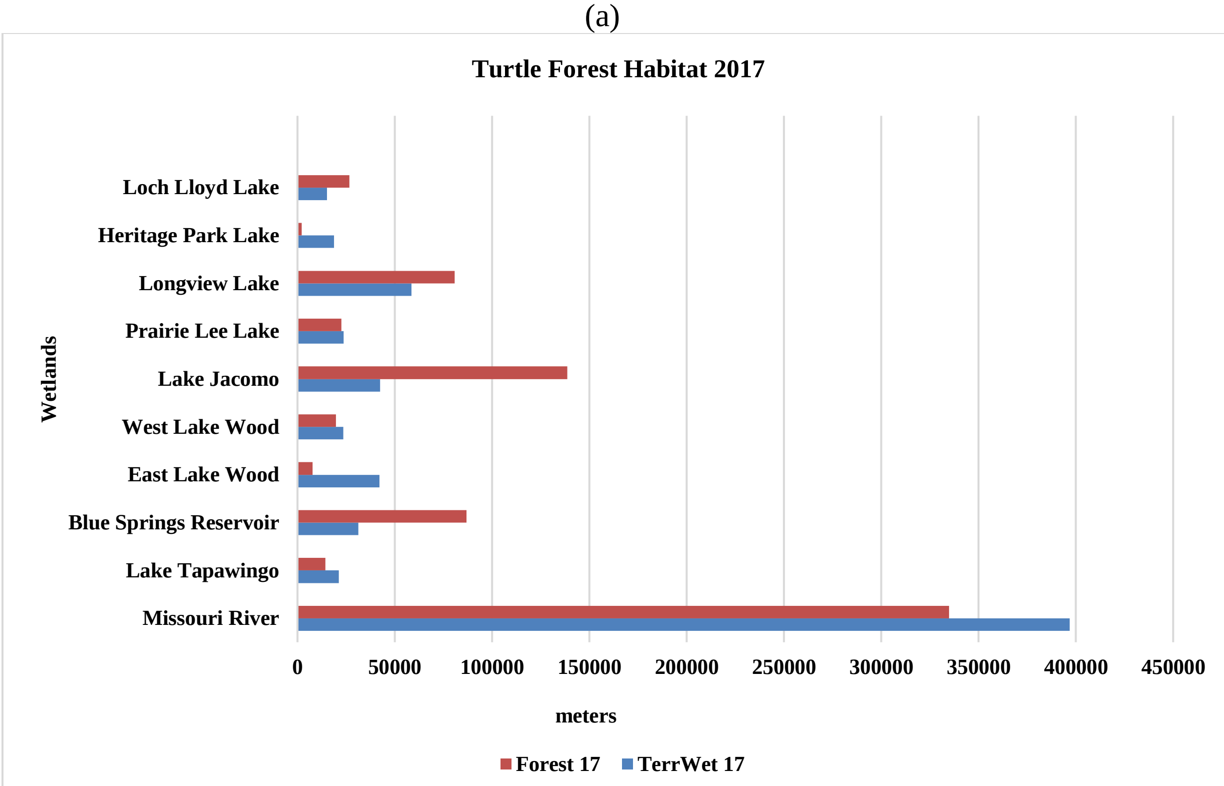
The Snake terrestrial habitat within the recommended mean maximum core area of 304 m showed a relatively slight SPI change in favor of 2017 as compared with 1992 (see Figure 27: (a-c)).

TURTLES

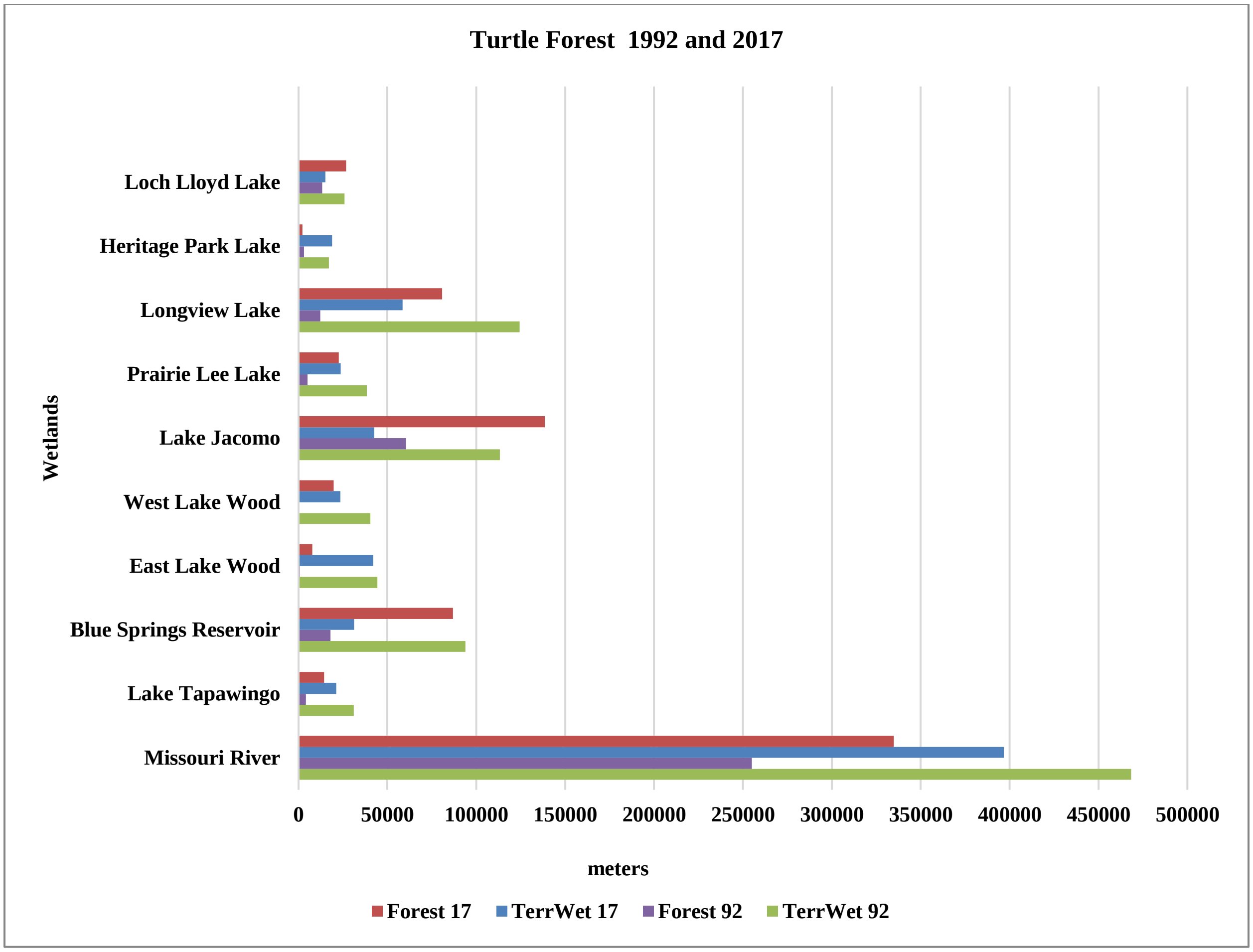
Estimated Forest Habitat for Turtles



(a)



(b)

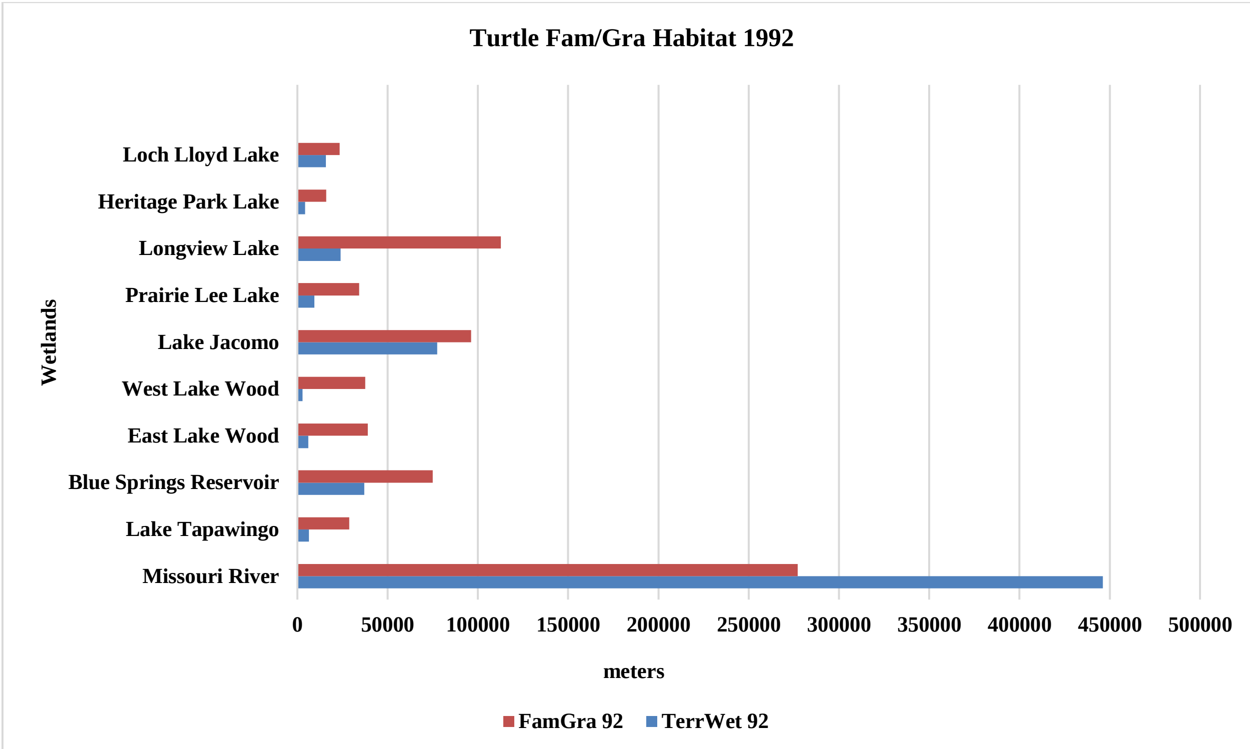


(c)

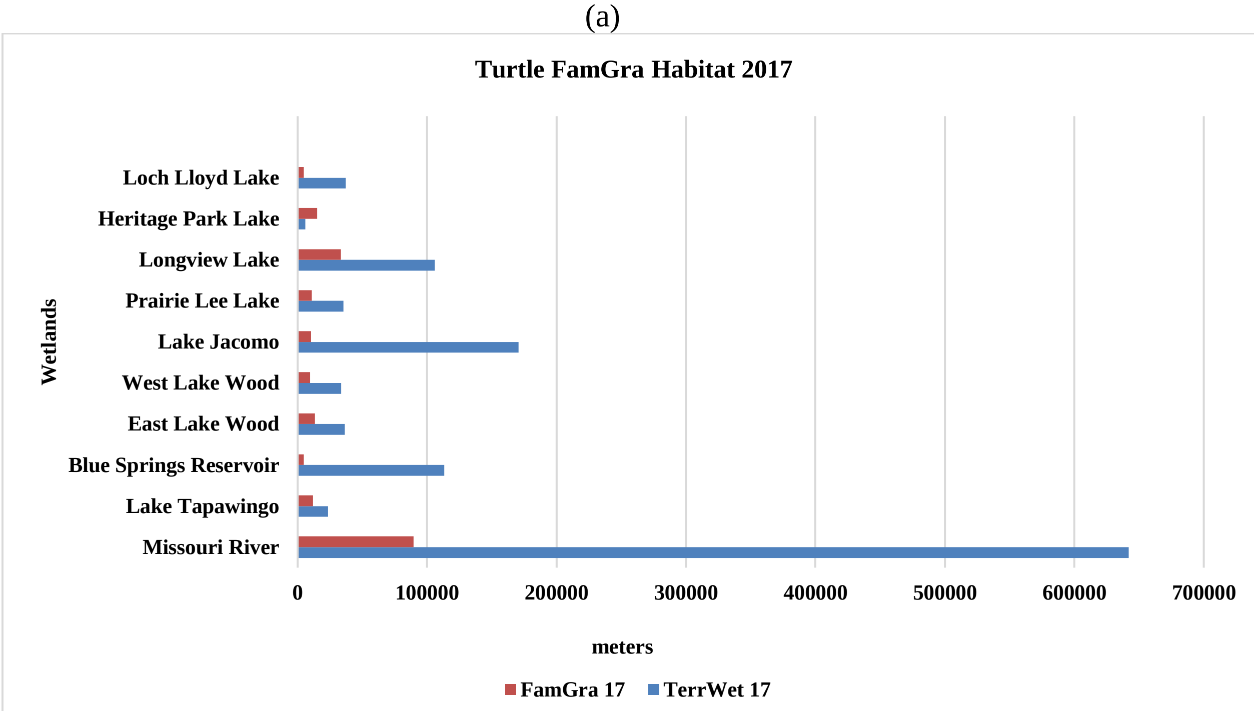
Figure 28: (a-c) Estimated Turtle Forest Habitat.

The Turtle terrestrial habitat within the recommended mean maximum core area of 287 m showed increasing forest habitat for 2017 as compared with 1992. Most of the wetlands revealed increasing forest terrestrial habitat in 2017 except for Heritage Park Lake (see Figure 28: (a-c)).

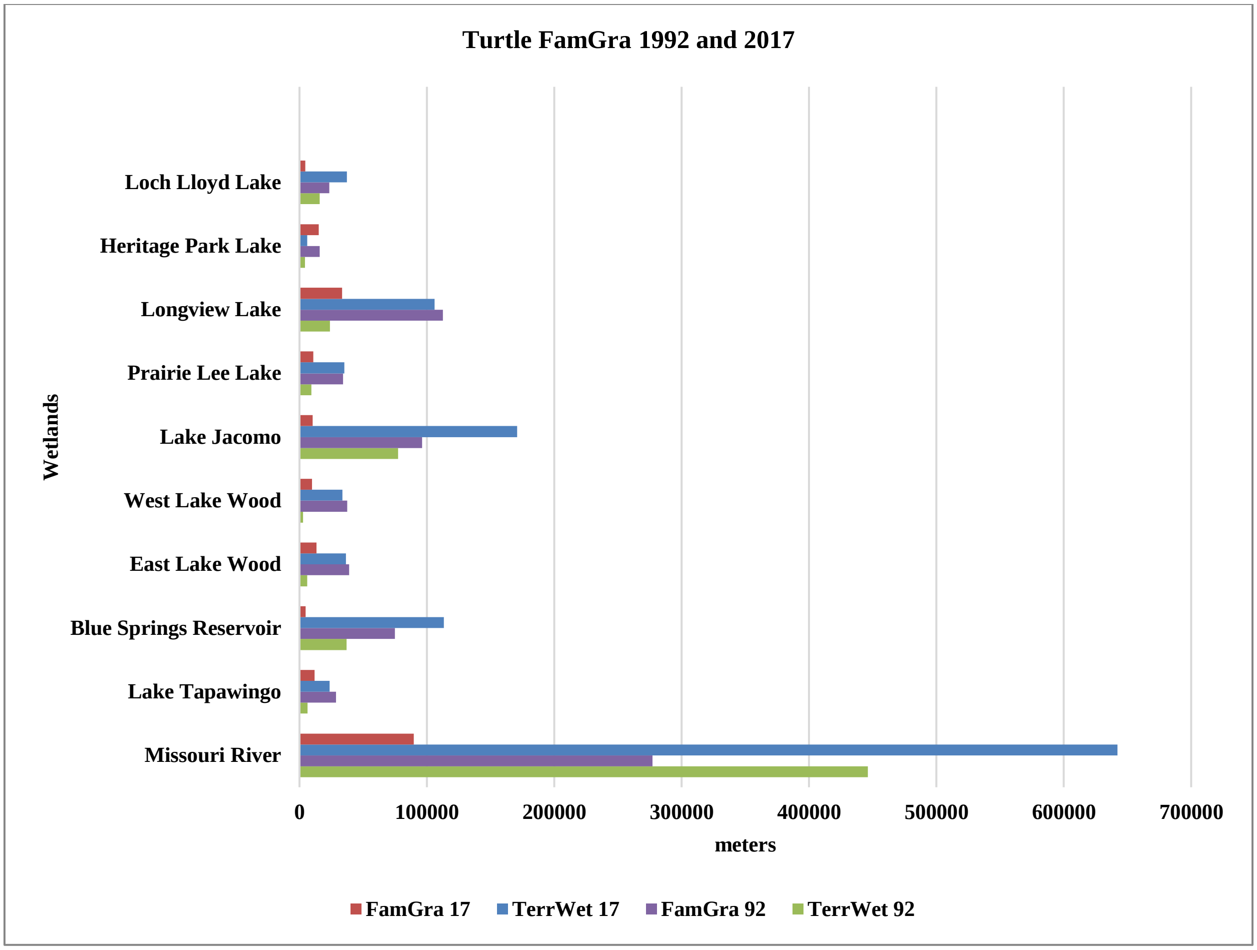
Estimated Forest Habitat for Turtles



(a)



(b)

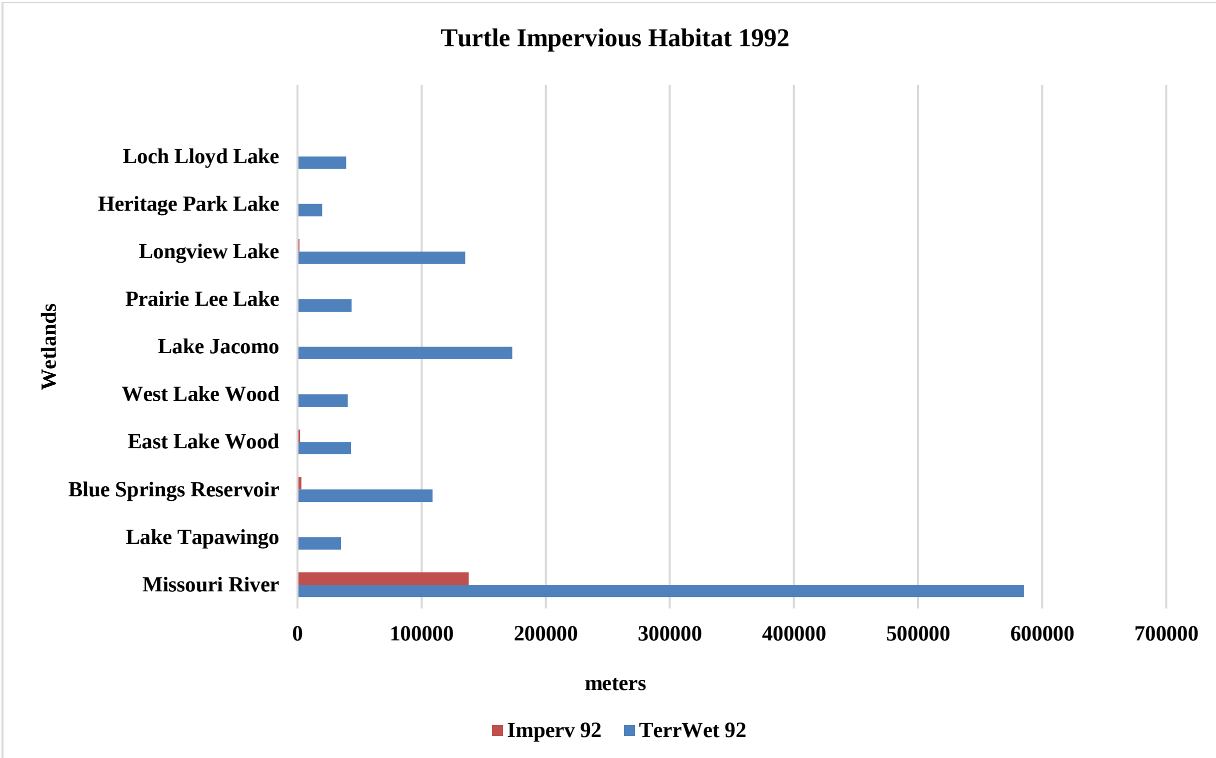


(c)

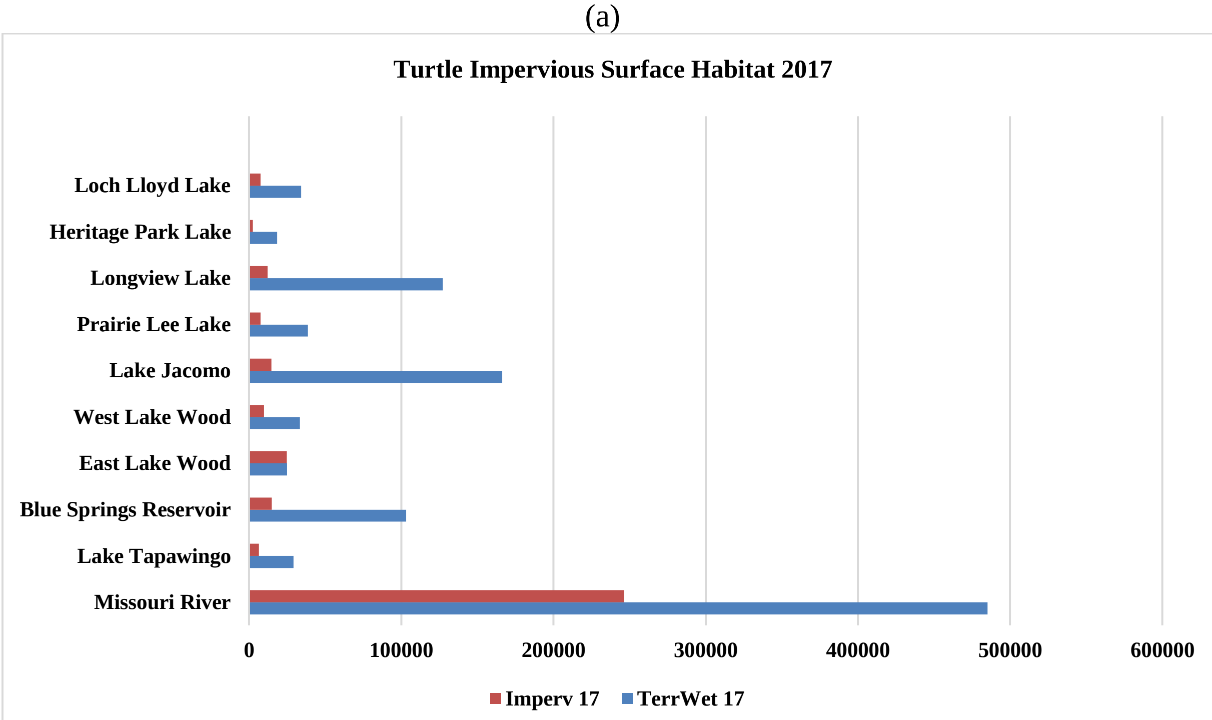
Figure 29: (a-c) Estimated Turtle Farmland/Grassland Habitat.

The Turtle terrestrial habitat within the recommended mean maximum core area of 287 m showed an increase in farmland/grassland for 1992 as compared to 2017. Increasing farmland/grassland was revealed for all wetlands except the Heritage Park Lake which showed no change between the study periods (see Figure 29: (a-c)).

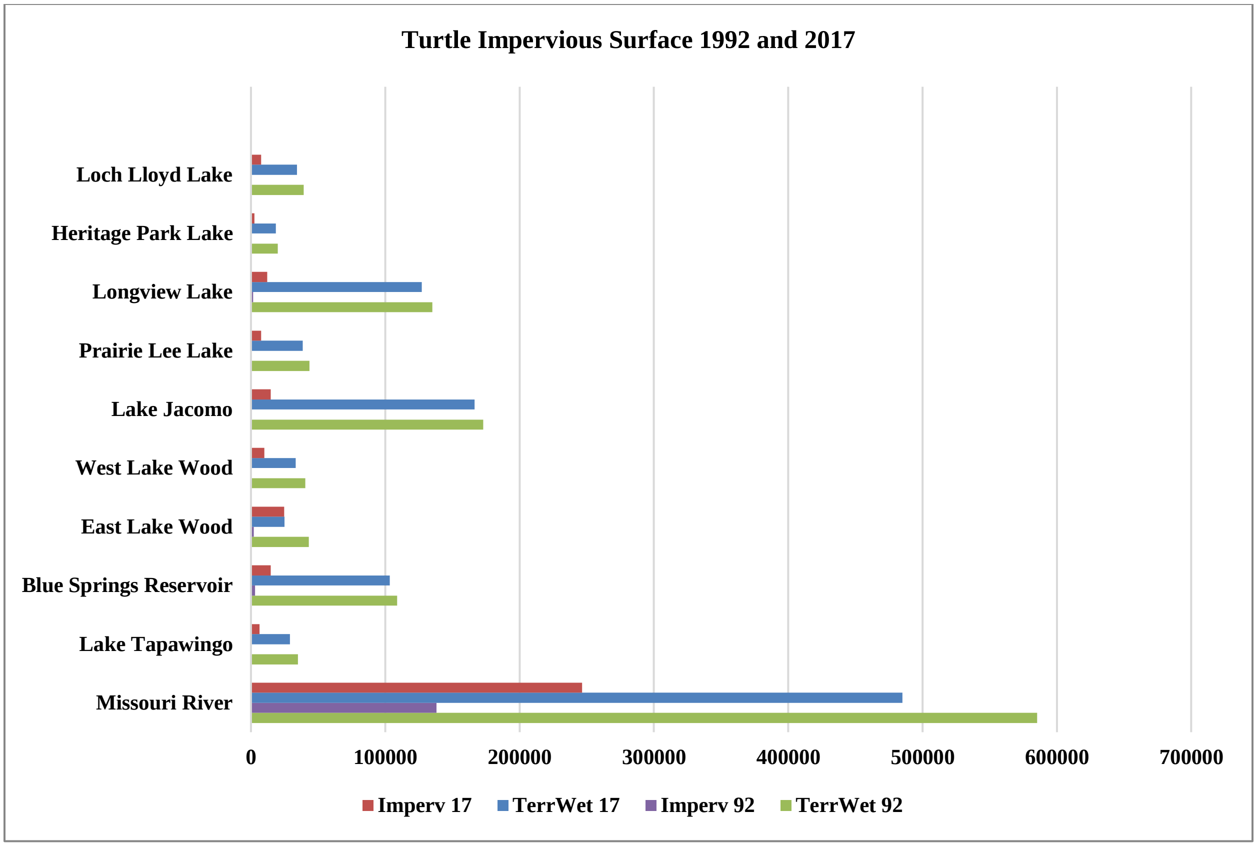
Estimated Impervious Surface Habitat for Turtles



(a)



(b)

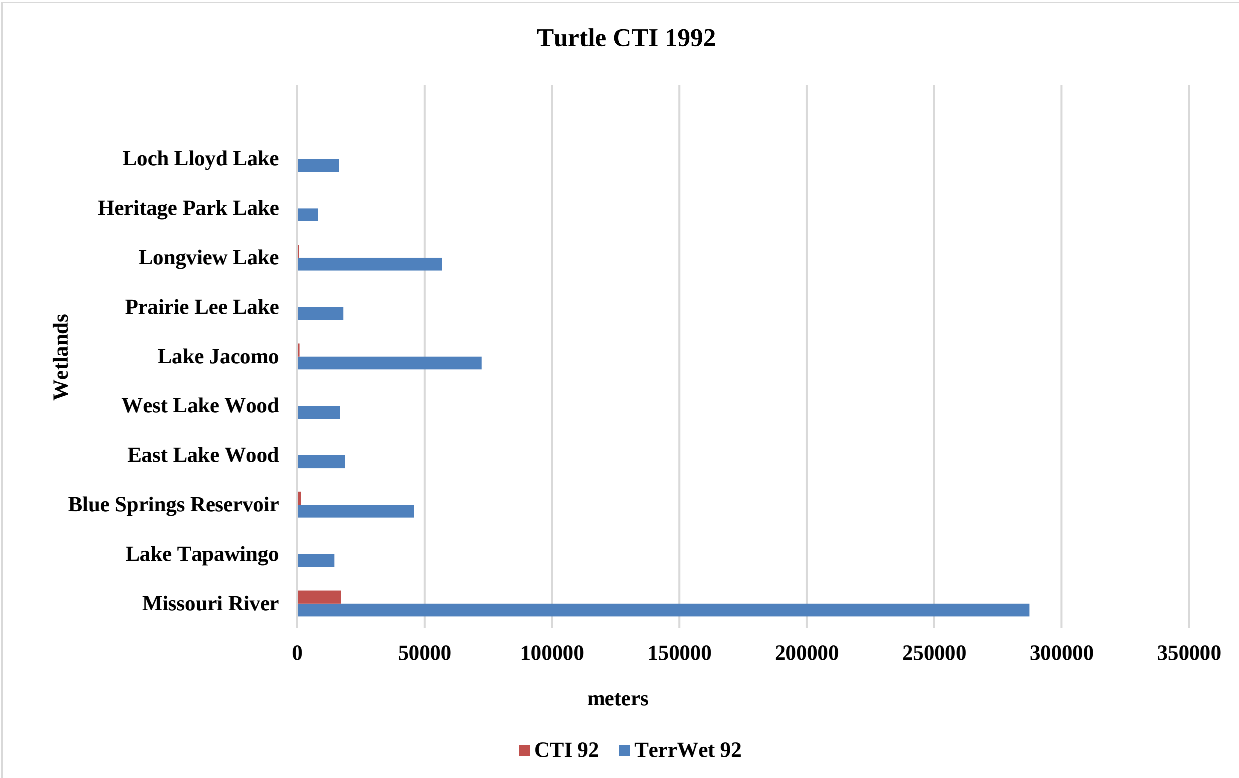


(c)

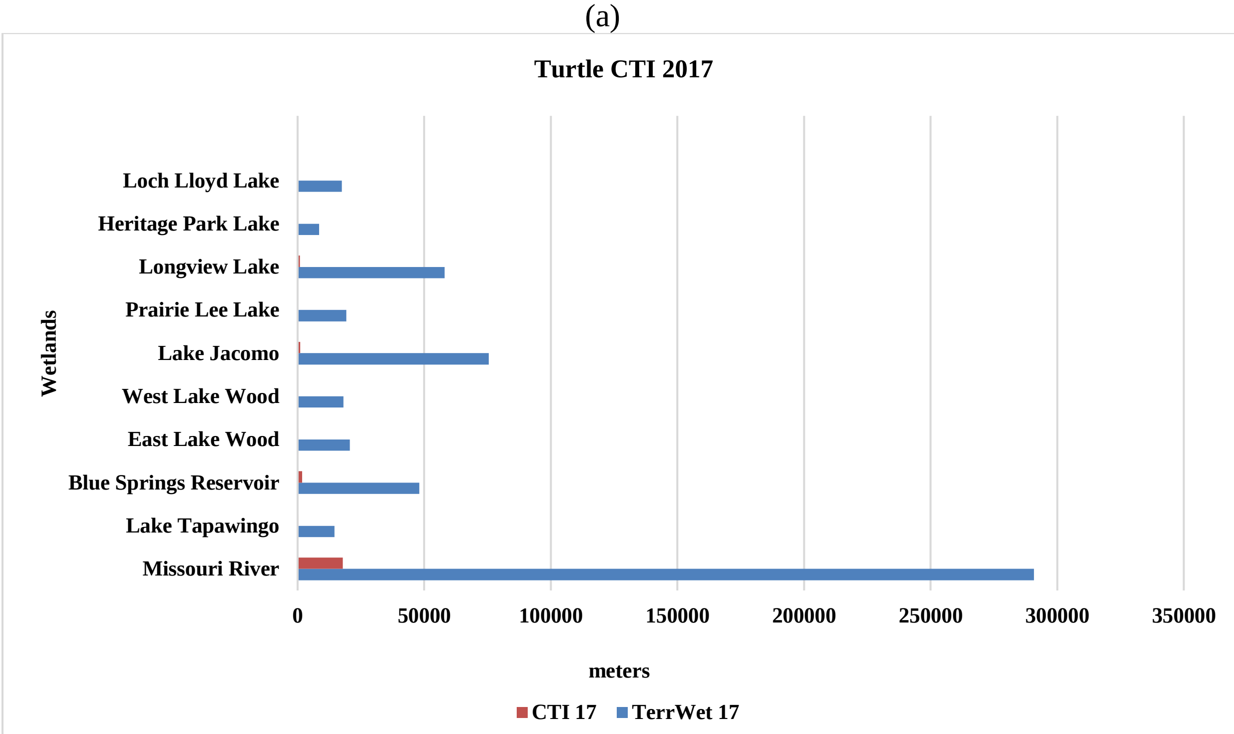
Figure 30: (a-c) Estimated Turtle Impervious Surface Habitat.

The Turtle terrestrial habitat within the recommended mean maximum core area of 287 m showed an increase impervious surfaces for all wetland in 2017 as compared with 1992 (see Figure 30: (a-c)).

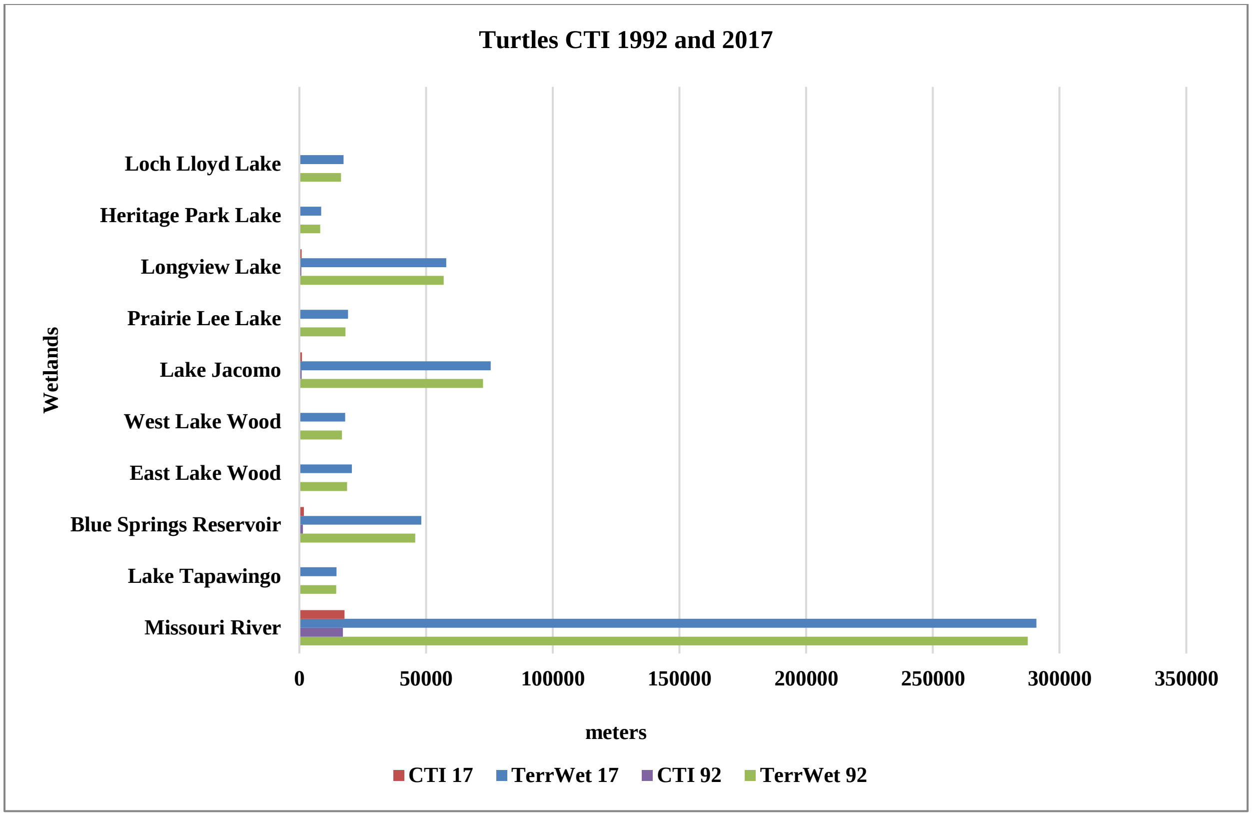
Estimated CTI for Turtle Terrestrial Habitat



(a)



(b)

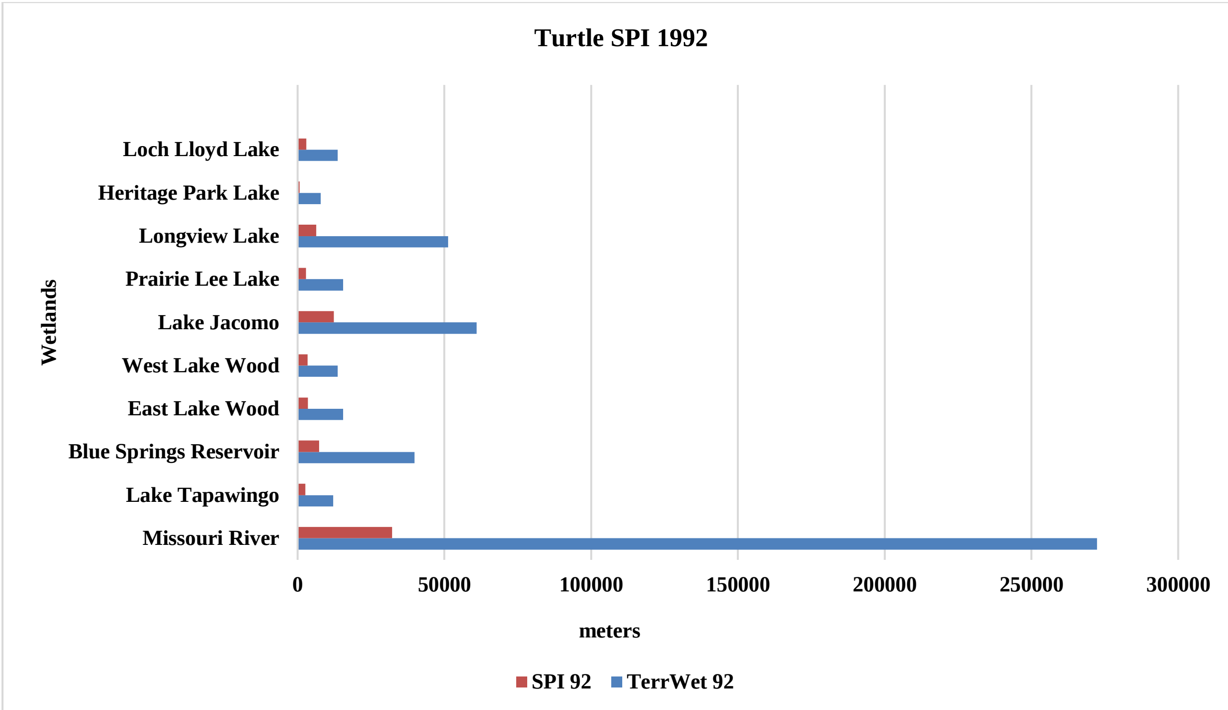


(c)

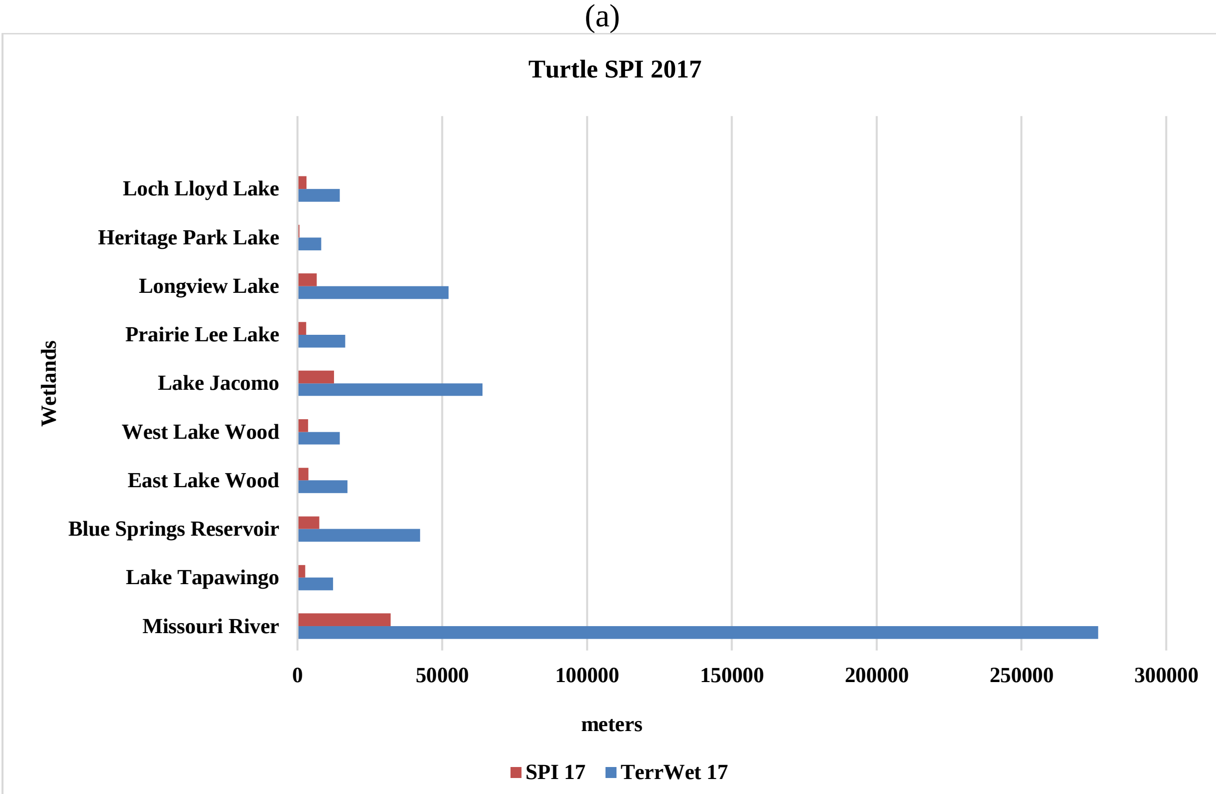
Figure 31: (a-c) Estimated CTI for Turtle Habitat.

The Turtle terrestrial habitat within the recommended mean maximum core area of 287 m showed a relatively slight CTI change in favor of 1992 as compared with 2017 (see Figure 31: (a-c)).

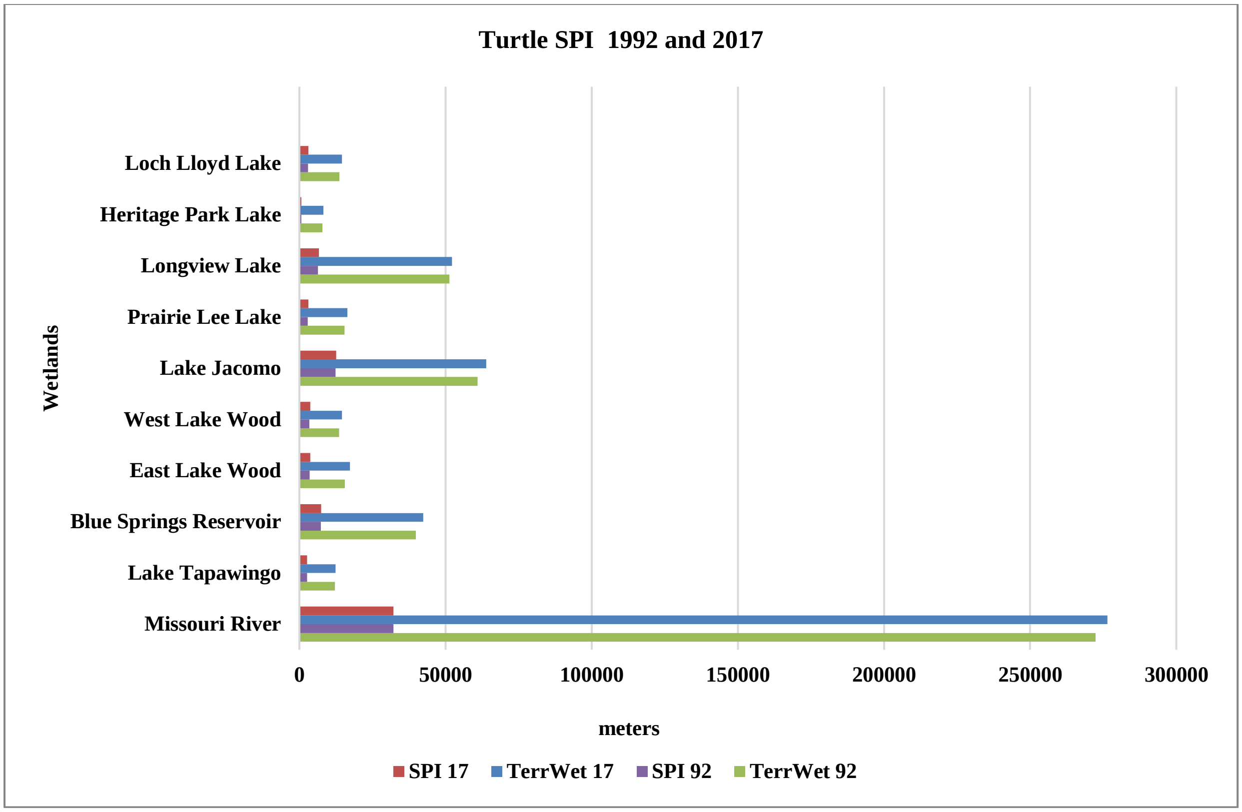
Estimated SPI for Turtle Terrestrial Habitat



(a)



(b)



(c)

Figure 32: (a-c) Estimated SPI for Turtle Habitat.

The Turtle terrestrial habitat within the recommended mean maximum core area of 287 m showed a relatively slight SPI change in favor of 2017 as compared with 1992 (see Figure 32: (a-c)).

Estimated Species Habitat Change Summary

To estimate the percentage area covered by the ecosystem service indicators (ESI) as shown in Table 10, Equation 5 in the methodology under the WELD modeling section was applied. The estimated ESI area for species habitat is divided by the total area occupied (estimated ESI area for Species Habitat and estimated non ESI area for Species Habitat), multiplying by 100. The percentage estimated habitat area changes between 1992 and 2017 are shown in Fig. 33.

Table 10: Estimated Species Habitat Change in 1992

Indicators	**Frogs**	**Salamanders**	**Snakes**	**Turtles**	% Change 1992
Forestland	36.50	27.04	27.13	27.15	**28.47**
Fam/Gra	54.26	53.75	54.07	54.04	**54.04**
Impervious	12.09	9.10	10.96	10.64	**10.68**
CTI	4.70	3.53	4.01	3.76	**3.91**
SPI	12.38	13.37	12.71	12.85	**12.83**

Table 11: Estimated Species Habitat Change in 2017

Indicators	**Frogs**	**Salamanders**	**Snakes**	**Turtles**	% Change 2017
Forestland	49.46	54.32	51.47	52.05	**51.90**
Fam/Gra	19.76	12.04	14.95	14.45	**14.95**
Impervious	19.76	22.47	25.08	24.62	**23.70**
CTI	4.50	3.72	4.08	3.97	**4.03**
SPI	12.35	13.11	12.63	12.72	**12.70**

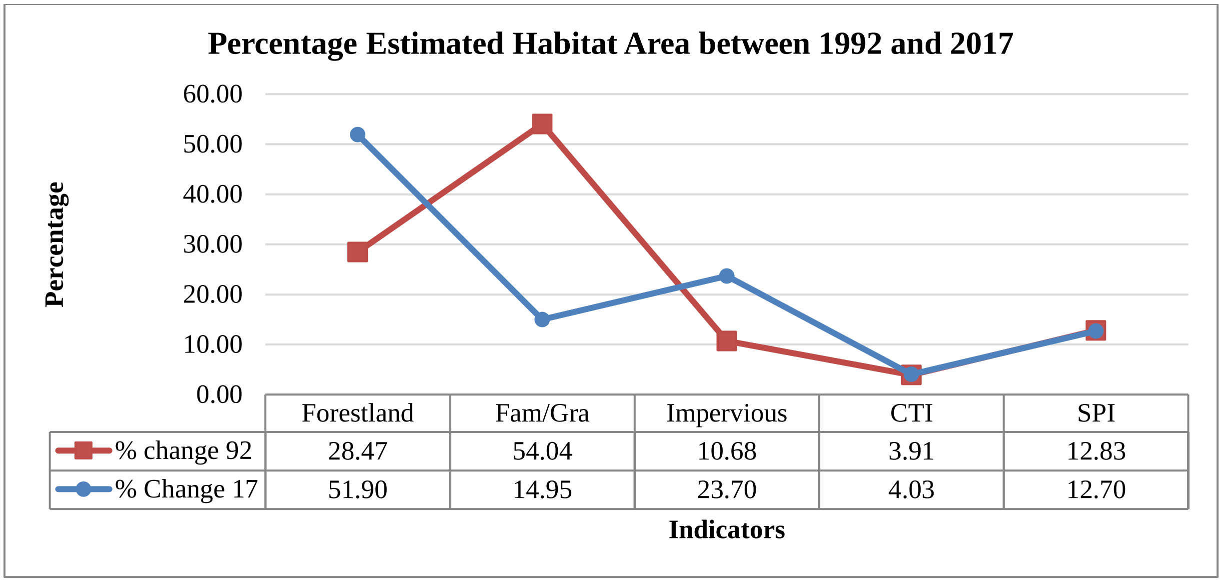


Figure 33: Percentage estimated habitat area for ESI between 1992 and 2017

Tables 10 & 11 reveal the general trend of changes between 1992 and 2017. The forestland, impervious surfaces, and wetness observed to increase in 2017. This is not the same for farmland/grassland and stream energy in 2017, revealing a decrease.

Socio-Spatial Interactions Within the Terrestrial Wetland Habitat

The major parts of the wetland landscape dynamics in this study are social and biophysical components. The interaction between these components and the terrestrial wetland habitat were quantified using the American Community Survey (ACS) 2010 census blocks data, and the intersection with the local connected roads (ESRI Roads and Highways). The estimation was performed using the zonal histogram tool in ArcGIS 10.6 showed in Fig. 34 and 35. The factors considered for measurement in ACS 2010 are the total census block count, the sum of households per 100 people (sum_HU100), and the total sum population per 100 people (sum_POP100), respectively. These factors were analyzed using the zonal histogram, as shown in Fig. 34. Observed from the analysis, is the increase in the total sum population per 100 people for all areas in the wetlands under consideration. This increase was far more than the other two factors (block counts and households). The increase in the total population per 100 people was followed by the total sum of households in the terrestrial wetlands area for the year 2017. The least increased among these factors is the total census block counts examined in the terrestrial wetlands area for the year 2017. For overall analysis, the smaller wetlands showed greater changes within the 25-year study period. Some of the small wetlands include the East and West Lake Wood, Prairie Lee Lake, Lake Tapawingo which are relatively small but experienced increase significant changes. The large wetlands are the Blue Springs Reservoir, Longview Lake, and Lake Jacomo which are relatively large with minimal changes. Secondly, further analysis revealed that 84 locally connected roads intersect with the terrestrial portion of nine out of the ten wetlands. The only wetland without local connecting roads encroaching into its terrestrial portion is Loch Lloyd Lake, see Fig. 36 (a & b).

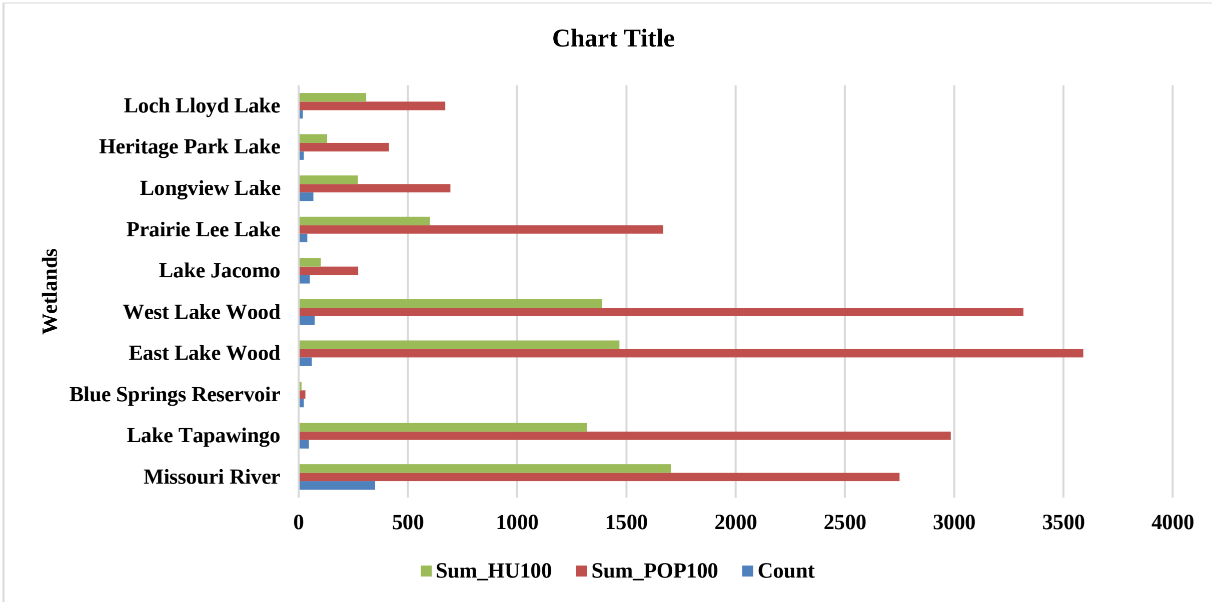


Figure 34: Estimated Census block count, Sum_HU100, and Sum_POP100 in Terrestrial Wetland Habitat area in the year 2017

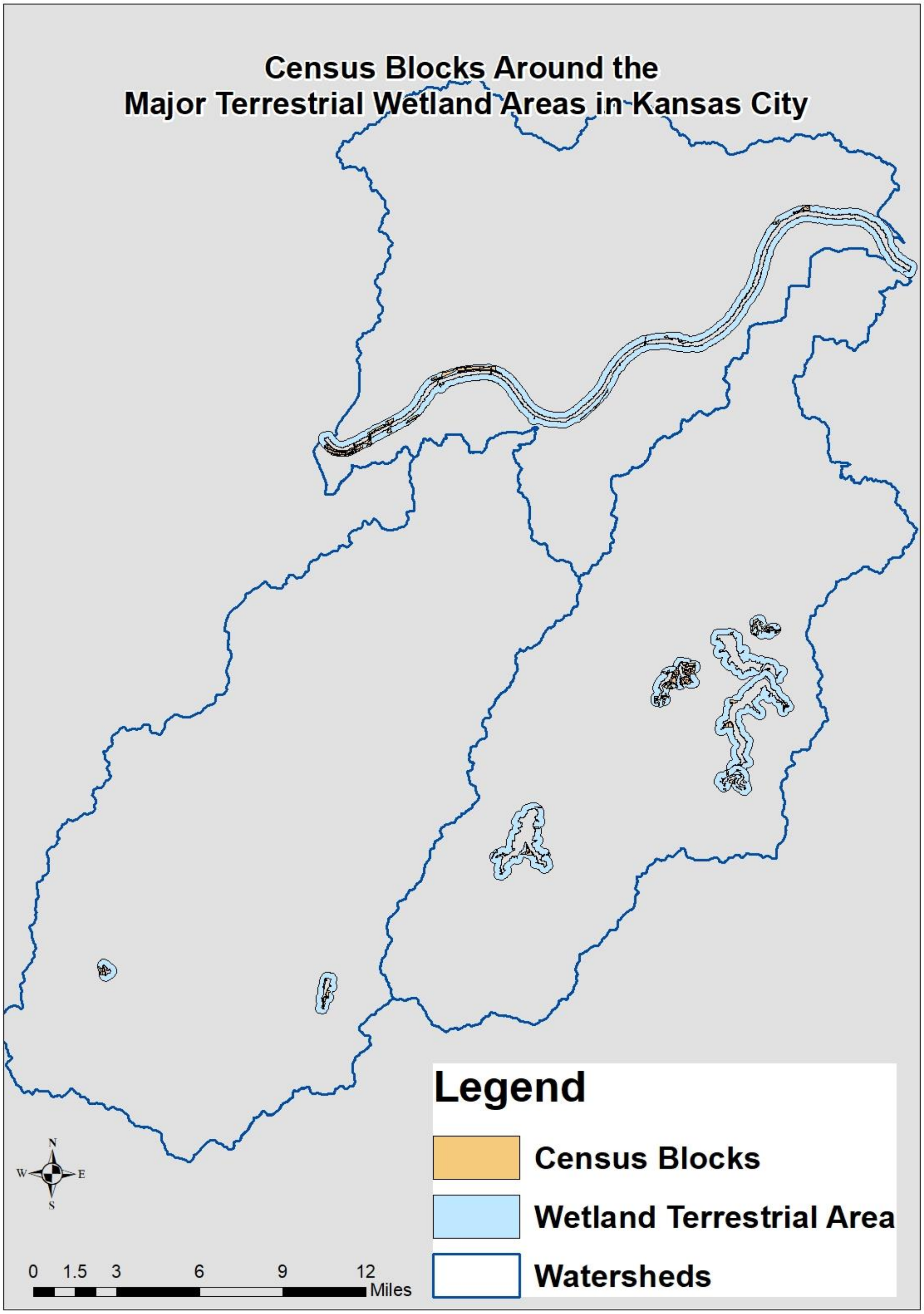
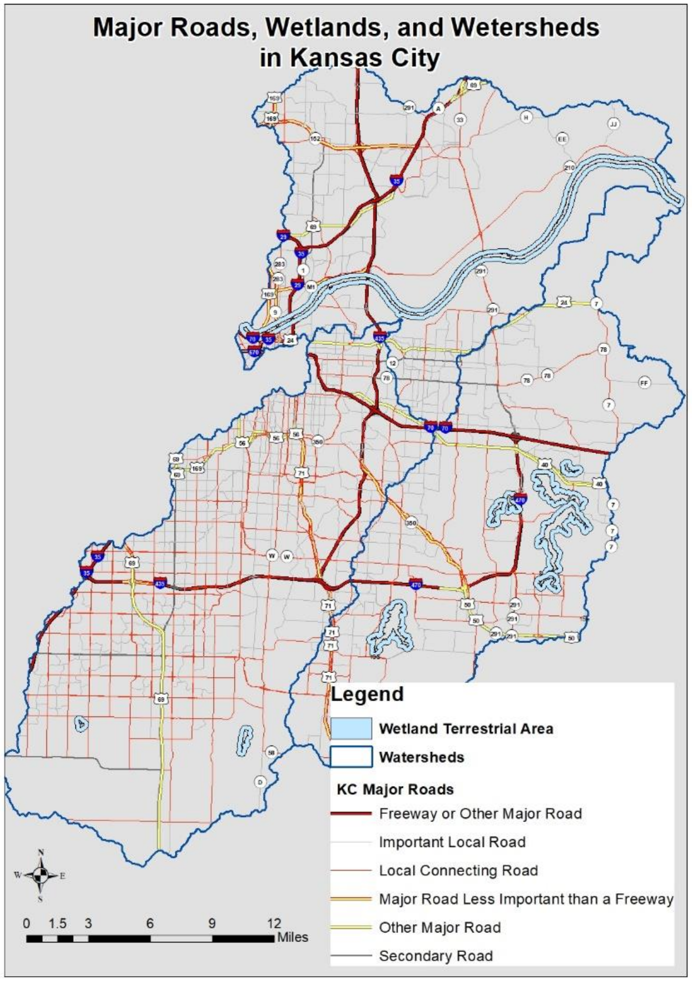
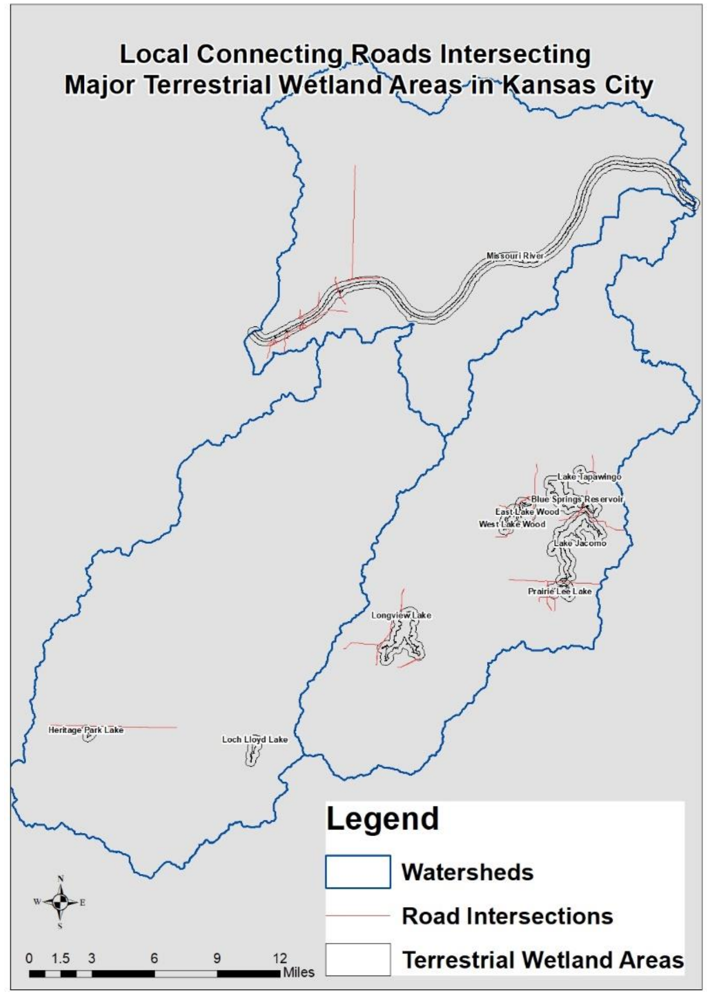


Figure 35: Estimated Census block in the terrestrial wetland habitat area in the year 2017.



(a)



(b)

Figure 36: Maps a & b shows the local connecting roads intersecting with the wetland terrestrial area

CHAPTER 5

DISCUSSION AND CONCLUSION

Discussion

The discussion generally encapsulates all assessments of wetland dynamics between 1992 and 2017 in the study area, at both watershed and patch levels. The analysis was used to examine the edge effect, as it affects the terrestrial wetland habitats. To achieve the goal and objectives set for this research, satellite remote sensing, elevation data, and other ancillary datasets were considered to evaluate the socio-ecological system of terrestrial wetlands. The study started with OBIA and change detection analysis performed, the result showed SVM with better accuracy, and such adopted for the most part of the study. In addition, the change detection analysis revealed a swell in wetland coverage for the study area between 1992 and 2017. It then moved to terrain analysis, where the landscape calculated using secondary terrain indices at the wetland level. Furthermore, different relevant metrics were used for both landscape and patch quantification to assess the impact of edge on terrestrial wetland habitat. Finally, a geospatial model (WELD) used to assess the general condition of the ecosystem services considered as an indicator to measure wetland terrestrial species habitat. In addition, socio-spatial interactions within the terrestrial wetland habitat were examine using the ACS 2010 datasets and local connected roads in Kansas City. All the steps, analysis, and interpretation of results are discussed in this section to further throw more light on observations.

Image Classification and Change Detection Analysis

Firstly, the study revealed a similar trend for class change for the two algorithms used, with SVM having a better accuracy assessment report compared to K-NN. The change detection statistics (CDS) was performed showed the K-NN method revealed a change of 21% while the SVM revealed 18%, respectively. This indicates that the total percentage change in pixels from other classes to wetland increased for K-NN by 21% but not as much for SVM at 18%. The two algorithms were compared to achieve a better result for the image classification, which avoids the possible misinterpretations that could have resulted from using different multispectral images (Lu & Weng, 2007). Regardless of the class change in the CDS, results from using both algorithms revealed a swell in the wetland coverage for the study area. This swell may be a result of increased precipitation in the past decade (Zubair et al. 2017), and improved streamside ordinance protection for wetlands (e.g. Weilert, 2018) in the study area. In addition, this result is like a study by Ji et al. (2015) which showed that larger wetlands accumulated more precipitation, while the smaller wetlands were prone to human impacts. Similarly, Zubair et al. (2017) in their study of urban wetland modeling in the study area observed that wetlands increased in two of the major watersheds historically but reduced because of urban expansion in one. These results from this study generally support the findings that wetlands swelled in the area within the study period, and this can be associated with the effects of human and natural factors as suggested by previous studies, such as Ji et al. (2006).

Terrain Analysis

Secondly, the resulting indices for terrain analysis showed an increase in potential wetness for nine out of ten wetlands studied. This may indicate the level of activities around these wetlands. This may be associated with the size of the wetland core area. Heritage Park Lake is one of the smallest of the ten major wetlands, and the effect of natural and human activities may have more influence on this wetland. This is like the study by Tomaselli et al. (2012) where the small landscape that could harbor biodiversity was highly fragmented in small patches. On the other hand, wetlands with a slight increase for compound topographic index (CTI) can be an indirect influence on soil moisture and provide information about the soil condition near the wetland. O'Neill et al. (1997) in a similar study revealed how the topsoil is lost through erosion because of fragmentation due to distance between patches. This can also be an indirect indication of changes in the type of vegetation surrounding the terrestrial wetland areas over the years. Furthermore, Weilert et al. (2018) when studying the effects of a streamside ordinance protecting the riparian vegetation within the ordinance area, found that the streamside ordinance can effectively reduce human impacts within the protected area. Most vegetated areas are close to the wetlands, and the availability of moisture in a protected wetland can improve the growth rate of trees and reduce erosive power. The condition of the wetland terrestrial soil and vegetation can impact biodiversity, especially for reptiles and amphibians. The slight stream power increase for the averagely small wetlands can result in the vulnerability of the terrestrial wetlands. These impacts may indirectly increase the erosive potential for the terrestrial wetland and expose the locations to severe gullies (Li et al. 2014). In addition, the results of the topographic indices can be used to assess the vulnerability of the terrestrial wetland habitat condition available for biodiversity sustainability, as shown in the studies conducted by Murcia (1995), and Semlitsch & Bodie (2003).

Landscape Analysis

Thirdly, the landscape structure was also quantified at the patch and landscape level. It is important to interpret each metric in a manner appropriate to its scale (Ji et al. 2006; Turner et al. 1989; O'Neill et al. 1997). At the patch levels, which describe wetlands in this study, the indices used for the metric quantification are MPE, CA, MSI, SI, and TE (see Table 6 for full description). In this study, decreases in the core area for all the ten wetlands were revealed for the studied period between 1992 and 2017. According to McGarigal (2017), all other things held constant, increasing shape complexity decreases the core area, and increasing patch area increases the core area. This decreased in the core area implies that wetlands during the period of study may have an increased patch area. The complexities and irregularities in the core area may be a result of human activities (e.g., agriculture, etc.) around most of the terrestrial wetland areas (Zubair et al. 2017; Weilert et al. 2018). The revealing effect of MSI and SI on shape increased for 2017. This implies a decrease in the core area. In addition, the increased edge effect revealed by the TE and MPE may also result in a decreased core area. The edge effect differs among organisms at different ecological habitats (Hansen et al. 1992). This implies that an increase in edge effects may impact the wildlife and biodiversity around the terrestrial wetland areas, particularly the amphibians and reptiles. Also, core areas are a much better predictor of habitat quality than patch areas (Temple 1986). Some human-induced activities can result in habitat loss and may have a considerable impact on the terrestrial habitat. These effects are bound to affect most species with low mobility, a narrow feeding niche, and low reproduction (Öckinger et al. 2010) around the terrestrial habitat. These effects can be very useful to assess when monitoring the landscape structure surrounding wetland and riparian habitats. They provided a good link between LULC and ecological modeling for predictions or informed management.

Fourthly, at the landscape level quantification, the diversity indices used SDI and SEI revealed little or no proportional diversity within the study period. Similarly, the shape indices MSI, MPFD, and AWMSI revealed slight shape complexity at the watershed level. An increase in edge density (ED) in 2017 relative to the landscape area in 1992 was exhibited. This increased edge effect may reflect a reduced core area resulting from more activities around the watershed in 2017 compared to 1992. This indicates that some parts of the wetland landscape areas might have been converted to other usages as a result of urbanization, similar to a study conducted by Liu et al. (2014). Generally, the landscape level quantification revealed changes in ED and a slight increase in shape complexities and irregularities. This might have resulted from human activities in the form of urbanization or agriculture impacting the area during the period of study. This is similar to another study by Zubair et al. (2019) revealing the depletion of wetland landscape at the sub-watershed level in this area due to agriculture activities. This shows that the response of species richness for agriculturally induced fragmented wetlands for wildlife such as amphibians and reptiles can be monitored, even at a very large-scale map (small area), similar to the study by Kolozsvary & Swihart (1999).

WELD Modeling Analysis (socio-ecological implications)

The final part of the discussion is the wetland landscape dynamic modeling (WELD modeling). The WELD model was developed to take full advantage of the SES framework. The interactions between the social and natural components of the ecosystem were considered to assess the impact of the changed ESI on the wetland terrestrial habitat. For this study, the general interpretation of the model results was based on the trends revealed by the habitat change for all species habitats considered. The terrestrial wetland area is interpreted collectively based on ESI impacted by human and natural factors. The interpretation started with the forestland analysis for the percentage area covered. The forestland showed a relative increase in favor of 2017 compared to 1992 with forestland area cover of 28.47% in 1992 to 51.90% in 2017. This implies that the rate at which trees were cut down between these periods reduced. This may be because of forestland protection provided for most of the terrestrial areas around the wetlands as reveal by Weilert et al. (2018). The study assessed the impact of the streamside ordinance in a protected area. The study acknowledged the loss of trees in recent times in the non-ordinance area, but the rate of loss was reduced in areas with ordinance compared to non-ordinance implemented areas. This will be beneficial to some species that depend on these trees for dispersal as part of their short life cycle. Continuous exploitation of these resources by human activities may reduce the reproductive potential and leads to the extinction of most of these species. The forestland is closely associated with the farmland/grassland. The farmland/grassland (fam/Gra) showed a reduction in 2017 compared to 1992, 54.04% in 1992 to 14.95% in 2017. This is maybe associated with increasing human activities at the edge of the wetlands. A study by Zubair et al. (2019) is in tandem with previous research, (e.g., Ji et al. 2005) on urban sprawl in the study area. They observed the depletion of agricultural and grassland in all six sub-watersheds mostly due to human activities. These studies attributed most of these losses of prairies and agricultural land to urban expansion and development of human activities. However, for the impervious surface, there was a general increase in 2017 compared to 1992 for the terrestrial wetland areas. There was an increase from 10.68% in 1992 to 23.70% in 2017. The increase in the impervious surface can be associated with built-up and the construction of roads in this area. This previously corroborated in several studies performed for this area (e.g. Zubair et al. 2017; Ji et al. 2005). This may be an indicator of the increase in human activities due to urban expansion and increase agricultural practices. The effect of the increasing impervious surfaces may directly or indirectly affect the terrain surface of these areas.

Similar to the individual wetlands, the general trend for terrain indices, CTI for 2017 revealed an increase compared to that of 1992. The potential wetness (CTI) for the wetland terrestrial habitats increased from 3.91% in 1992 to 4.03% in 2017. This attributed to the impact on other ESI earlier discussed, the conversion of the farmland or agricultural land to other uses for human development. In addition, the increase in impervious surfaces, such as paved roads, and construction of buildings, can reduce the rate of water percolation. This may indicate potential flooding for some of the wetland terrestrial habitats. Similarly, a reduction in the energy of the surface water flow (SPI) is observed, 12.83 in 1992 to 12.70 in 2017. However, this reduction is minimal and the effect on wetland terrestrial habitat might not be much. Considering the general topography of the area characterized by rolling hills with open plains (Ji et al. 2005), a lift shift in topography can increase the potential for flooding in this area. Past studies have shown the swell of the wetlands and the total watersheds in these areas (e.g., Zubair et al. 2017 and Ji et al. 2015). The study observed that most of the smaller wetlands experienced more impact by human activities compared to larger wetlands (Festus et al. 2020). Overall, most EPA reports point to urban development, rural development, silviculture, and conservation practices to be the major contributors to the losses of wetland acreage. This is like the landscape observation for this study (see Appendix A and Appendix B). Overall, the WELD model has been able to show the impact on ESI as it affects the terrestrial wetland habitat for the species. Some of these are due to human activities; the natural and anthropogenic disturbances at abrupt boundaries may affect soil moisture variation on small agricultural watersheds at the surface (e.g. Hawley et al. 1983).

Benefits of WELD modeler tool:

- It allows the use of assessable environmental geospatial data to assess the changed wetland terrestrial habitat made available for wetland management.
- It allows rapid integration of topographic indices, LULC classification, and other spatial data for assessing wetland landscape structure.

- It allows the indirect assessment of the SES indicators that could result in fragmentation and habitat loss needed for planning and decision-making.
- To evaluate anthropogenic and natural events that may impact the benefits of terrestrial wetland habitat.
- Assess wetland coverage change using estimated vulnerability index from the topography.
- Provide the baseline for monitoring and assessing wetland change that could help in restoration and planning at local scales.

Limitations of WELD model

- Difficulty in acquiring a very high-resolution image for temporal change analysis.
- Limitation of available DEM in terms of resolution and the unavailability of Light Detection and Ranging (LiDAR) coverage for most areas.
- The need to carefully consider the indexes and the image classification for the landscape quantification and calculation.
- Lack of demographic data at the scale of study to be integrated into the model.

Conclusions

In the last 25 years, several remote sensing-based methods have been employed to address issues bordering watersheds and wetlands. The techniques used during this period were mostly pixel-based or knowledge-based classification. The results of these previous studies contributed immensely to the body of knowledge. However, to further improve on these studies an object-based approach integrating machine learning was considered for this study. These techniques were able to preserve the spatial, spectral, and temporal characteristics during image classification. At the watershed level, a swell in watersheds between the 25-year study period was observed using the object-oriented classification algorithm approach. Also observed during the classification were the increasing forestland and built-up areas, which may be an indication of developmental activities around most of the watershed and wetlands within the period of study.

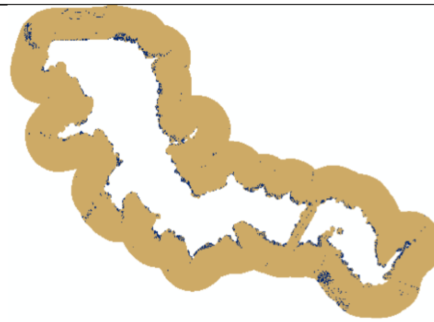
In addition, the landscape patterns were quantified, and changes observed. These changes impacted more on smaller wetlands than larger wetlands, resulting to edge effect, size, and shape complexity for most of the wetlands. The analysis at fine-scale with the integration of object-based machine learning classification approach provided more information to detect an impact on smaller wetlands, which would have been difficult with the traditional classification techniques, using coarse grain sizes. The ability to detect these changes for smaller wetlands will avail natural resource managers the opportunity to put restoration plans in place for the smaller wetlands quickly. This is because landscape changes observed at that level may be faster to manage than the larger wetland levels.

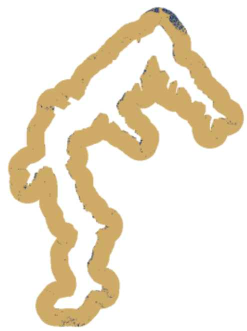
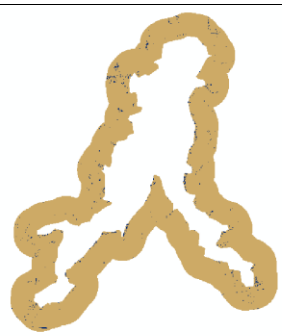
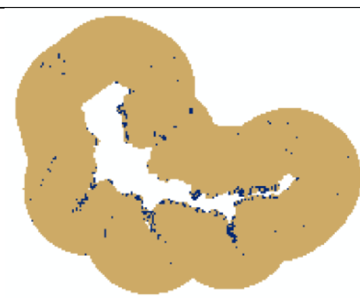
Furthermore, the impacts on wetlands in terms of potential wetness (CTI) and stream power energy (SPI) were observed. The reducing stream power energy in this area might be an indication of the increasing wetness among many other factors in the study area. These indices were integrated to build a geospatial model (WELD), which could be a useful tool for monitoring the migratory pattern of species in the terrestrial habitat, most especially the amphibians and reptiles. On the other hand, the socio-spatial interaction analysis showed an increase in the total sum population per 100 people, an increase in the total sum of households, and little or no change in census blocks. This may be the result of developmental activities in areas close to the wetlands during the study period. The development in terms of built-up and road construction might impact semiaquatic species that depend on these areas for survival. Most times the migratory pattern of these species required movement across the roads. In addition to the socio-spatial interaction, the impacts of roads on the proximity to the habitats were investigated. The study observed 84 locally connected roads intersecting with the terrestrial portion of nine out of the ten wetlands. Though these roads may be regarded as local roads with little or no impact on the terrestrial wetlands. More impact on species can be caused by the major roads which can dictate the migratory pattern of the species crossing the roads. The intersection with local roads may indicate less impact on most species during migratory movement, amphibians and reptiles are slow-moving animals and will not survive busy roads.

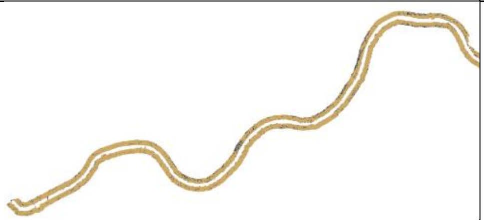
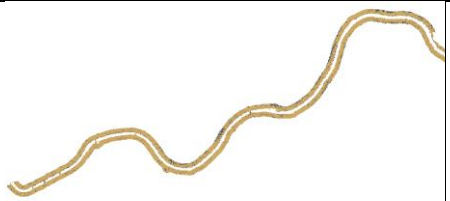
Summarily, this study proposed a more efficient technique for classifying images at a fine scale using OBIA segmentation and machine learning algorithms. In addition, the usefulness of quantifying terrestrial wetland habitat using landscape metrics and terrain analysis were observed, showing more impact on smaller wetlands. The proposed geospatial model (WELD) can be a very good tool in the hands of conservationists and wetland managers. This tool will be useful for monitoring the impact on ecosystem services and tracking the movement of species that depends on the terrestrial portion of the wetlands for survival.

APPENDIXES

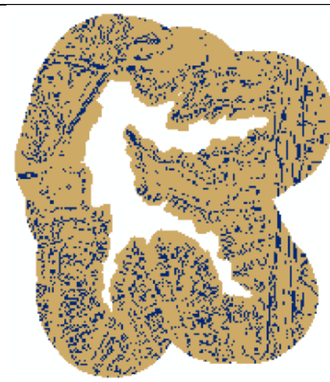
A. ***Estimated CTI at 340-meter from the wetland core area***

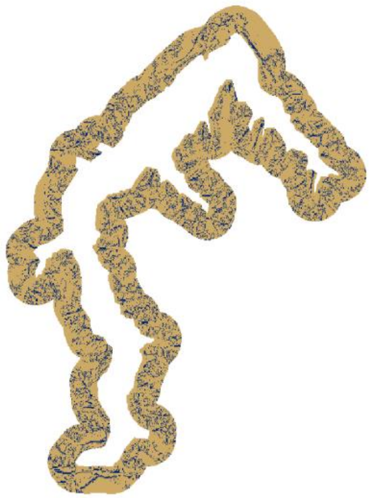
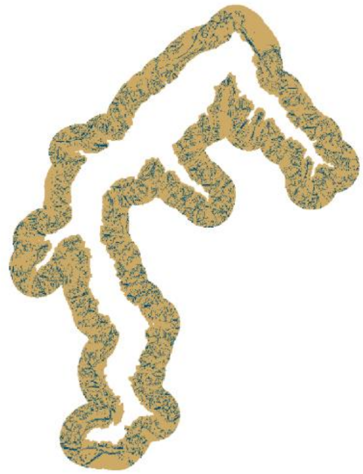
Compound Topographical Index Estimate		
1992	**2017**	**Wetland Impact**
		**Blue Springs Reservoir** Estimated CTI 1992 = 2.71% 2017 = 3.48%
		**East Lake Wood** Estimated CTI 1992 = 1.41% 2017 = 1.67%
		**Heritage Park Lake** Estimated CTI 1992 = 3.26% 2017 = 3.10%

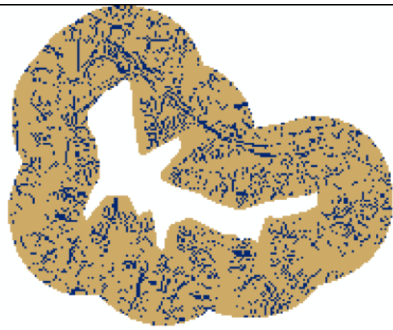
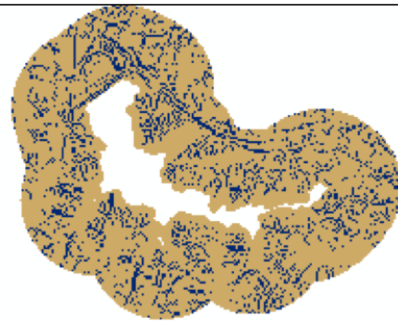
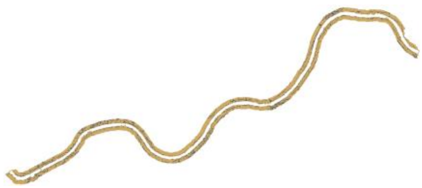
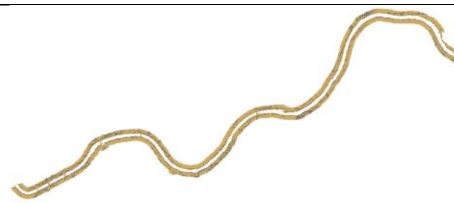
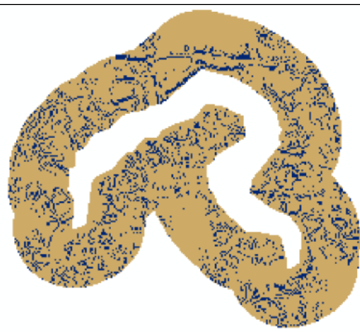
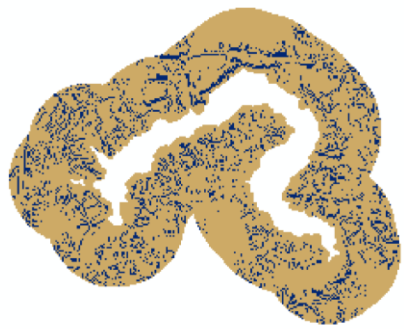
Compound Topographical Index Estimate		
1992	**2017**	**Wetland Impact**
		**Lake Jacomo** Estimated CTI 1992 = 1.53% 2017 = 1.64%
		**Loch Lloyd Lake** Estimated CTI 1992 = 0.78% 2017 = 4.33%
		**Longview Lake** Estimated CTI 1992 = 1.22% 2017 = 1.42%
		**Lake Tapawingo** Estimated CTI 1992 = 1.57% 2017 = 2.03%

Compound Topographical Index Estimate		
1992	**2017**	**Wetland Impact**
		**Missouri River** Estimated CTI 1992 = 6.55% 2017 = 6.55%
		**Prairie Lee Lake** Estimated CTI 1992 = 1.16% 2017 = 1.45%
		**West Lake Wood** Estimated CTI 1992 = 1.24% 2017 = 1.55%

B. ***Estimated SPI at 340-meter from the wetland core area***

Stream Power Index Estimate		
1992	**2017**	**Wetland Impact**
		**Blue Springs Reservoir** Estimated SPI 1992 = 15.40% 2017 = 14.85%
		**East Lake Wood** Estimated SPI 1992 = 18.33% 2017 = 21.64%
		**Heritage Park Lake** Estimated SPI 1992 = 8.00% 2017 = 8.01%

Stream Power Index Estimate		
1992	**2017**	**Wetland Impact**
		**Lake Jacomo** Estimated SPI 1992 = 16.40% 2017 = 19.37%
		**Loch Lloyd Lake** Estimated SPI 1992 = 17.29% 2017 = 17.06%
		**Longview Lake** Estimated SPI 1992 = 12.86% 2017 = 11.52%

Stream Power Index Estimate		
1992	**2017**	**Wetland Impact**
		**Lake Tapawingo** Estimated SPI 1992 = 21.19% 2017 = 17.25%
		**Missouri River** Estimated SPI 1992 = 10.11% 2017 = 9.95%
		**Prairie Lee Lake** Estimated SPI 1992 = 16.01% 2017 = 18.72
		**West Lake Wood** Estimated SPI 1992 = 19.51% 2017 = 19.22%

REFERENCES

Aplin, P., & Atkinson, P. M. (2004). Predicting missing field boundaries to increase per-field classification accuracy. *Photogrammetric Engineering & Remote Sensing, 70*(1), 141-149.

Arnold G. van der Valk. (2012). *The biology of freshwater wetlands:* Vol. 2nd ed. OUP Oxford.

Assessment, M. E. (2005). *Ecosystems and human well-being* (Vol. 5, p. 563). United States of America: Island press. Available from Internet: http://www.bioquest.org/wp-content/blogs.dir/files/2009/06/ecosystems-and-health.pdf

Baker, C., Lawrence, R. L., Montagne, C., & Patten, D. (2007). Change detection of wetland ecosystems using Landsat imagery and change vector analysis. *Wetlands, 27*(3), 610.

Barros, D. F., & Albernaz, A. L. M. (2014). Possible impacts of climate change on wetlands and its biota in the Brazilian Amazon. *Brazilian Journal of Biology, 74*(4), 810-820.

Barve N., Kiran M. C., Vanaraj G., Aravind N. A., Rao D., Shaanker R. Uma, Ganeshaiah K. N., & Poulsen J. G. (2005). Measuring and mapping threats to a wildlife sanctuary in Southern India. *Conservation Biology, 19*(1), 122–130.

Berkes, F., Folke, C., & Colding, J. (Eds.). (2000). *Linking social and ecological systems: Management practices and social mechanisms for building resilience.* Cambridge University Press.

Blaschke, T. (2003). *Object-based contextual image classification built on image segmentation. In IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data, 2003* (pp. 113-119). IEEE. Available from Internet: https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=1295182

Bock, M., Xofis, P., Mitchley, J., Rossner, G., & Wissen, M. (2005). Object-oriented methods for habitat mapping at multiple scales: Case studies from Northern Germany and Wye Downs, UK. *Journal for Nature Conservation, 13*(2-3), 75-89.

Bodie, J. R. (2001). Stream and riparian management for freshwater turtles. *Journal of Environmental Management*, *62*(4), 443-455.

Brander, L., & Schuyt, K. (2004). *The economic values of the world's wetlands*. Available from Internet: http://lukebrander.com/wp-content/uploads/2012/06/Schuyt-and-Brander-2004-The-economic-values-of-the-worlds-wetlands.pdf

Briske, D. D., Fuhlendorf, S. D., & Smeins, F. E. (2006). A unified framework for assessment and application of ecological thresholds. *Rangeland Ecology & Management, 59*(3), 225-236.

Brosofske, K. D., Chen, J., Naiman, R. J., & Franklin, J. F. (1997). Harvesting effects on microclimatic gradients from small streams to uplands in western Washington. *Ecological Applications, 7*(4), 1188-1200.

Brown, M. T., & Vivas, M. B. (2005). Landscape development intensity index. *Environmental monitoring and assessment, 101*(1-3), 289-309.

Burbrink, F. T., Phillips, C. A., & Heske, E. J. (1998). A riparian zone in southern Illinois as a potential dispersal corridor for reptiles and amphibians. *Biological Conservation, 86*(2), 107-115.

Burgin, S., Franklin, M. J., & Hull, L. (2016). Wetland loss in the transition to urbanization: A case study from Western Sydney, Australia. *Wetlands, 36*(6), 985-994.

Clark, W. (2010) Principles of landscape ecology. *Nature Education Knowledge 3*(10),34

Collinge, S. K. (1996). Ecological consequences of habitat fragmentation: Implications for landscape architecture and planning. *Landscape and Urban Planning, 36*(1), 59-77.

Collins, S. L., Carpenter, S. R., Swinton, S. M., Orenstein, D. E., Childers, D. L., Gragson, T. L., ... & Knapp, A. K. (2011). An integrated conceptual framework for long-term social–ecological research. *Frontiers in Ecology and the Environment, 9*(6), 351-357.

Comber, A., Medcalf, K., Lucas, R., Bunting, P., Brown, A., Clewley, D., ... & Keyworth, S. (2010). Managing uncertainty when aggregating from pixels to objects: Habitats, context-sensitive mapping and possibility theory. *International Journal of Remote Sensing, 31*(4), 1061-1068.

Costanza, R., d'Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R. V., Paruelo, J., Raskin, R. G., Sutton, P., & van den Belt, M. (1997). The value of the world's ecosystem services and natural capital. *Nature, 387*(6630), 253–26

Delcourt, H. R., Delcourt, P. A., & Webb III, T. (1982). Dynamic plant ecology: the spectrum of vegetational change in space and time. *Quaternary Science Reviews, 1*(3), 153-175.

Devillers, R., Bédard, Y., Jeansoulin, R., & Moulin, B. (2007). Towards spatial data quality information analysis tools for experts assessing the fitness for use of spatial data. *International Journal of Geographical Information Science, 21*(3), 261-282.

Dobson, A. P., Rodriguez, J. P., Roberts, W. M., & Wilcove, D. S. (1997). Geographic distribution of endangered species in the United States. *Science, 275*(5299), 550-553.

Donovan, T. M., Lamberson, R. H., Kimber, A., Thompson III, F. R., & Faaborg, J. (1995). Modeling the effects of habitat fragmentation on source and sink demography of Neotropical migrant birds. *Conservation Biology, 9*(6), 1396-1407.

Dronova, I., Gong, P., Clinton, N. E., Wang, L., Fu, W., Qi, S., & Liu, Y. (2012). Landscape analysis of wetland plant functional types: The effects of image segmentation scale, vegetation classes and classification methods. *Remote Sensing of Environment, 127*, 357-369.

Environmental Protection Agency (EPA), U. (2008). *EPA'S 2008 report on the environment.* Available from Internet: https://cfpub.epa.gov/roe/documents/EPAROE_FINAL_2008.PDF

Estes, J. A., & Duggins, D. O. (1995). Sea otters and kelp forests in Alaska: generality and variation in a community ecological paradigm. *Ecological Monographs*, *65*(1), 75-100.

ENVI EX. (2009). *ENVI EX user's guide*. Available from Internet: https://www.l3harrisgeospatial.com/portals/0/pdfs/enviex/envi_ex_user_guide.pdf

Festus, O. O., Ji, W., & Zubair, O. A. (2020). Characterizing the landscape structure of urban wetlands using terrain and landscape indices. *Land, 9*(1), 29.

Fischer, J., & Lindenmayer, D. B. (2007). Landscape modification and habitat fragmentation: A synthesis. *Global Ecology and Biogeography*, *16*(3), 265-280.

Forman, R. T. T. (1995). *Land mosaics: The ecology of landscapes and regions.* Cambridge University Press.

Forman, R. T. T., and M. Godron. 1986. *Landscape Ecology*. New York, John Wiley & Sons.

Forman, R. T., & Godron, M. (1981). Patches and structural components for a landscape ecology. *BioScience*, *31*(10), 733-740.

Förster, M., & Kleinschmit, B. (2008). *Object-based classification of QuickBird data using ancillary information for the detection of forest types and NATURA 2000 habitats. In Object-based image analysis* (pp. 275-290). Springer.

Galatowitsch, S. M. (2018). Natural and anthropogenic drivers of wetland change. In Finlayson C., Milton G., Prentice R., Davidson N. (Eds.), *The wetland book II: Distribution, description, and conservation* (Vol. 1, pp. 359-367). Springer Nature. https://doi.org/10.1007/978-94-007-4001-3_217

Galzki, J., Mulla, D., Joel, N., & Wing, S. (2008). *Targeting best management practices (BMPs) to critical portions of the landscape: Using selected terrain analysis attributes to identify high-contributing areas relative to nonpoint source pollution.* Minnesota Department of Agriculture, 31.

Girvetz, E. H., Thorne, J. H., Berry, A. M., & Jaeger, J. A. (2008). Integration of landscape fragmentation analysis into regional planning: A statewide multi-scale case study from California, USA. *Landscape and Urban Planning*, *86*(3-4), 205-218.

Groom, M. J., Meffe, G. K., Carroll, C. R., & Andelman, S. J. (2006). *Principles of conservation biology*. Sunderland: Sinauer Associates.

Haddad, N. M., Bowne, D. R., Cunningham, A., Danielson, B. J., Levey, D. J., Sargent, S., & Spira, T. (2003). Corridor use by diverse taxa. *Ecology*, *84*(3), 609-615.

Haest, B., Borre, J. V., Spanhove, T., Thoonen, G., Delalieux, S., Kooistra, L., Mücher, C. A., Paelinckx, D., Scheunders, P., & Kempeneers, P. (2017). Habitat mapping and quality assessment of NATURA 2000 heathland using airborne imaging spectroscopy. *Remote Sensing*, *9*(3), 266.

Hall, B. D., Rosenberg, D. M., & Wiens, A. P. (1998). Methyl mercury in aquatic insects from an experimental reservoir. *Canadian Journal of Fisheries and Aquatic Sciences, 55*(9), 2036-2047.

Hansen A.J., Risser P.G., di Castri F. (1992). Epilogue: Biodiversity and ecological flows across ecotones. In Hansen A.J., & di Castri F. (Eds.), *Landscape boundaries. Ecological studies (analysis and synthesis)* (Vol 92, pp. 423-438). Springer. https://doi.org/10.1007/978-1-4612-2804-2_22

Hawley, M. E., Jackson, T. J., & McCuen, R. H. (1983). Surface soil moisture variation on small agricultural watersheds. *Journal of Hydrology, 62*(1-4), 179-200.

Hermes, T., Miene, A., & Kreyenhop, P. (2000). *On textures: A sketch of a texture-based image segmentation approach. In classification and information processing at the turn of the millennium (pp. 210-218).* Springer.

Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. *Ecosystems, 4*(5), 390-405.

Huang, K., Li, S., Kang, X., & Fang, L. (2016). Spectral–spatial hyperspectral image classification based on KNN. *Sensing and Imaging, 17*(1), 1.

Jensen, J. R. (1996). *Introductory digital image processing: A remote sensing perspective* (No. Ed. 2). Prentice-Hall Inc.

Ji, W. (2016). *Remotely-sensed urban wet-landscapes: An indicator of coupled effects of human impact and climate change.* Available from Internet: https://kuscholarworks.ku.edu/bitstream/handle/1808/23346/gis_day2016_ji.pdf?sequence=1

Ji, W., Ma, J., Twibell, R. W., & Underhill, K. (2006). Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics. *Computers, Environment and Urban Systems, 30*(6), 861-879.

Ji, W., Xu, X., & Murambadoro, D. (2015). Understanding urban wetland dynamics: Cross-scale detection and analysis of remote sensing. *International Journal of Remote Sensing, 36*(7), 1763-1788.

Kolozsvary, M. B., & Swihart, R. K. (1999). Habitat fragmentation and the distribution of amphibians: patch and landscape correlates in farmland. *Canadian Journal of Zoology, 77*(8), 1288-1299.

Kosmidou, V., Petrou, Z., Bunce, R. G., Mücher, C. A., Jongman, R. H., Bogers, M. M., ... & Manakos, I. (2014*)*. Harmonization of the land cover classification system (LCCS) with the general habitat categories (GHC) classification system. *Ecological Indicators, 36*, 290-300.

Kotliar, N. B., & Wiens, J. A. (1990). Multiple scales of patchiness and patch structure: A hierarchical framework for the study of heterogeneity. *Oikos 59* (2), 253-260.

Kumar, S., Simonson, S. E., & Stohlgren, T. J. (2009). Effects of spatial heterogeneity on butterfly species richness in Rocky Mountain National Park, CO, USA. *Biodiversity and Conservation, 18*(3), 739-763.

L3 Harris Geospatial documentation center. Available on Internet: https://www.harrisgeospatial.com/docs/using_envi_Home.html

Larson, M. A., Dijak, W. D., Frank III, R., & Millspaugh, J. J. (2003). *Landscape-level habitat suitability models for twelve species in southern Missouri. Gen. Tech. Rep. NC-233.*

US Department of Agriculture, Forest Service, North Central Research Station. Available on internet: fs.usda.gov/treesearch/pubs/11865

Lawrence, R., Bunn, A., Powell, S., & Zambon, M. (2004). Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. *Remote Sensing of Environment*, *90*(3), 331-336.

Leitão, P. J., & Santos, M. J. (2019). Improving models of species ecological niches: A remote sensing overview. *Frontiers in Ecology and Evolution,* 7, 9.

Lengyel, S., Déri, E., Varga, Z., Horváth, R., Tóthmérész, B., Henry, P. Y., ... & Christia, C. (2008). Habitat monitoring in Europe: A description of current practices. *Biodiversity and Conservation, 17*(14), 3327-3339.

Levin, S. A. (1992). The problem of pattern and scale in ecology: The Robert H. MacArthur award lecture. *Ecology, 73*(6), 1943-1967.

Levins, R., & Culver, D. (1971). Regional coexistence of species and competition between rare species. *Proceedings of the National Academy of Sciences, 68*(6), 1246-1248.

Li, F., Wang, R., Hu, D., Ye, Y., Yang, W., & Liu, H. (2014). Measurement methods and applications for beneficial and detrimental effects of ecological services. *Ecological Indicators, 47*, 102-111.

Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). *Remote sensing and image interpretation*. John Wiley & Sons.

Liu, G., Zhang, L., Zhang, Q., Musyimi, Z., & Jiang, Q. (2014). Spatio–temporal dynamics of wetland landscape patterns based on remote sensing in Yellow River Delta, China. *Wetlands, 34*(4), 787-801.

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, *28*(5), 823-870.

Lucas, R., Medcalf, K., Brown, A., Bunting, P., Breyer, J., Clewley, D., Keyworth, S., & Blackmore, P. (2011). Updating the Phase 1 habitat map of Wales, UK, using satellite sensor data. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(1), 81–102.

MARC (Mid-America Regional Council). *Census Data for the MARC Region* (2010). Available from Internet: https://www.marc.org/Data-Economy/Maps-and-GIS/Census-Data

McDermid, G. (2005). *Remote sensing for large-area, multi-jurisdictional habitat mapping.* (Unpublished doctoral thesis). University of Waterloo. Available from Internet: https://uwspace.uwaterloo.ca/bitstream/handle/10012/977/gjmcderm2005.pdf?sequence=1

McGarigal, K. (1995). *FRAGSTATS: spatial pattern analysis program for quantifying landscape structure (Vol. 351)*. US Department of Agriculture, Forest Service, Pacific Northwest Research Station. Available from internet: https://play.google.com/books/reader?id=FsI_GzPd5UUC&hl=en&pg=GBS.PA4

McGarigal, K. (2000). *Introduction to Landscape ecology. Duke University*. Available from Internet: http://www. umass. edu/landeco/about/landeco. pdf.

McGarigal, K. (2017). *Landscape metrics for categorical map patterns*. Lecture Notes. Available from Internet: http://www.umass.edu/landeco/teaching/landscape_ecology/schedule/chapter9_metrics. pdf (accessed on 3 July 2018).

McGarigal, K., & Marks, B. J. (1995). *Spatial pattern analysis program for quantifying landscape structure. Gen. Tech. Rep. PNW-GTR-351*. US Department of Agriculture, Forest Service, Pacific Northwest Research Station, 1-122.

Mitsch, W. J., & Gosselink, J. G. (2000). The value of wetlands: importance of scale and landscape setting. *Ecological Economics, 35*(1), 25-33.

Mitsch, W. J., Bernal, B., & Hernandez, M. E. (2015). Ecosystem services of wetlands. *International Journal of Biodiversity Science, Ecosystem Services & Management, 11*(1), 1–4.

Mitsch, W. J., Bernal, B., Nahlik, A. M., Mander, Ü., Zhang, L., Anderson, C. J., ... & Brix, H. (2013). Wetlands, carbon, and climate change. *Landscape Ecology, 28*(4), 583-597.

Mücher, C. A., Kooistra, L., & Hantson, W. (2011). *Relationship between remote sensing classification success and site complexity*. Abstract from 7th EARSEL Workshop of the Special Interest Group in Imaging Spectroscopy, Edinburgh, Scotland.

Murcia, C. (1995). Edge effects in fragmented forests: Implications for conservation. *Trends in Ecology & Evolution, 10*(2), 58-62.

Nagendra, H. (2001). Using remote sensing to assess biodiversity. *International Journal of Remote Sensing*, *22*(12), 2377-2400.

Nagendra, H., & Rocchini, D. (2008). High resolution satellite imagery for tropical biodiversity studies: The devil is in the detail. *Biodiversity and Conservation, 17*(14), 3431-3442.

Newbold, T., Hudson, L. N., Hill, S. L., Contu, S., Lysenko, I., Senior, R. A., ... & Day, J. (2015). Global effects of land use on local terrestrial biodiversity. *Nature, 520*(7545), 45-50.

Öckinger, E., Schweiger, O., Crist, T. O., Debinski, D. M., Krauss, J., Kuussaari, M., ... & Bommarco, R. (2010). Life-history traits predict species responses to habitat area and isolation: a cross-continental synthesis. *Ecology Letters, 13*(8), 969-979.

O'Neill, R. V., Hunsaker, C. T., Jones, K. B., Riitters, K. H., Wickham, J. D., Schwartz, P. M., ... & Baillargeon, W. S. (1997). Monitoring environmental quality at the landscape scale: using landscape indicators to assess biotic diversity, watershed integrity, and landscape stability. *BioScience, 47*(8), 513-519.

Pal, M., & Mather, P. M. (2005). Support vector machines for classification in remote sensing. *International Journal of Remote Sensing, 26*(5), 1007-1011.

Peña-Barragán, J. M., Ngugi, M. K., Plant, R. E., & Six, J. (2011). Object-based crop identification using multiple vegetation indices, textural features and crop phenology. *Remote Sensing of Environment, 115*(6), 1301-1316.

Prasad, S. N., Ramachandra, T. V., Ahalya, N., Sengupta, T., Kumar, A., Tiwari, A. K., ... & Vijayan, L. (2002). Conservation of wetlands of India-a review. *Tropical Ecology, 43*(1), 173-186.

Pullan, R. A. (1988). *A survey of the past and present wetlands of the Western Algarve, Portugal. Department of Geography, University of Liverpool, UK. Liverpool Papers in Geography, 2*, 99.

Rickers, J. R., Queen, L. P., & Arthaud, G. J. (1995). A proximity-based approach to assessing habitat. *Landscape Ecology, 10*(5), 309-321.

Robinson, S. K., Thompson, F. R., Donovan, T. M., Whitehead, D. R., & Faaborg, J. (1995). Regional forest fragmentation and the nesting success of migratory birds. *Science, 267*(5206), 1987-1990.

Sawaya, K. E., Olmanson, L. G., Heinert, N. J., Brezonik, P. L., & Bauer, M. E. (2003). Extending satellite remote sensing to local scales: land and water resource monitoring using high-resolution imagery. *Remote Sensing of Environment, 88*(1-2), 144-156.

Semlitsch, R. D., & Bodie, J. R. (2003). Biological criteria for buffer zones around wetlands and riparian habitats for amphibians and reptiles. *Conservation Biology, 17*(5), 1219-1228.

Seto, K. C., & Kaufmann, R. K. (2003). Modeling the drivers of urban land use change in the Pearl River Delta, China: integrating remote sensing with socioeconomic data. *Land Economics*, *79*(1), 106-121.

Shaver, G. R., Canadell, J., Chapin, F. S., Gurevitch, J., Harte, J., Henry, G., ... & Rustad, L. (2000). Global warming and terrestrial ecosystems: A conceptual framework for analysis: Ecosystem responses to global warming will be complex and varied. Ecosystem warming experiments hold great potential for providing insights on ways terrestrial ecosystems will respond to upcoming decades of climate change. Documentation of initial conditions provides the context for understanding and predicting ecosystem responses. *Bioscience, 50*(10), 871-882.

Sheoran, A. S., & Sheoran, V. (2006). Heavy metal removal mechanism of acid mine drainage in wetlands: A critical review. *Minerals Engineering*, *19*(2), 105-116.

Smith, M. D., Knapp, A. K., & Collins, S. L. (2009). A framework for assessing ecosystem dynamics in response to chronic resource alterations induced by global change. *Ecology, 90*(12), 3279-3289.

Smits, P. C., Dellepiane, S. G., & Schowengerdt, R. A. (1999). Quality assessment of image classification algorithms for land-cover mapping: A review and a proposal for a cost-based approach. *International Journal of Remote Sensing, 20*(8), 1461-1486.

Stedman, S.-M., & Dahl, T. E. (2008). *Status and trends of wetlands in the coastal watersheds of the eastern United States, 1998 to 2004* (electronic resource) / Susan-Marie Stedman and Thomas E. Dahl. Silver Spring, MD.: *Washington, DC: National Oceanic and Atmospheric Administration, National Marine Fisheries Service; U.S. Dept. of the Interior, U.S.* Fish and Wildlife Service, 2008.

Szantoi, Z., Escobedo, F. J., Abd-Elrahman, A., Pearlstine, L., Dewitt, B., & Smith, S. (2015). Classifying spatially heterogeneous wetland communities using machine learning algorithms and spectral and textural features. *Environmental Monitoring and Assessment, 187*(5), 262.

Temple, S. A. (1986). *Predicting impacts of habitat fragmentation on forest birds: A comparison of two models.* Pages 301-304 In J. Verner, M. L. Morrison, and C. J. Ralph, Eds. Wildlife 2000: *Modeling habitat relationships of terrestrial vertebrates* (pp. 301-304). Univ. of Wisconsin Press.

Tilman, D., & Lehman, C. (2001). Human-caused environmental change: impacts on plant diversity and evolution. *Proceedings of the National Academy of Sciences, 98*(10), 5433-5440.

Timm, D. (2016). *Identifying critical source areas for best management practice targeting in impaired Zumbro River watersheds using digital terrain analysis* (Unpublished bachelor's thesis). University of Minnesota. Available from Internet: https://conservancy.umn.edu/handle/11299/185105

Tiner, R. W. (1984). *Wetlands of the United States:* Current status and recent trends. National Wetlands Inventory, Fish and Wildlife Service, US Department of the Interior. Available from Internet: https://play.google.com/store/books/details?id=P2x6Hbsm0-QC&rdid=book-P2x6Hbsm0-QC&rdot=1

Tomaselli, V., Tenerelli, P., & Sciandrello, S. (2012). Mapping and quantifying habitat fragmentation in small coastal areas: A case study of three protected wetlands in Apulia (Italy). *Environmental Monitoring and Assessment*, *184*(2), 693-713.

Turner, M. G., Gardner, R. H., O'neill, R. V., & O'Neill, R. V. (2001). *Landscape ecology in theory and practice* (Vol. 401). Springer.

Turner, M. G., O'Neill, R. V., Gardner, R. H., & Milne, B. T. (1989). Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecology*, *3*(3-4), 153-162.

Vapnik, V., Guyon, I., & Hastie, T. (1995). Support vector machines. *Machine Learning*, *20*(3), 273-297.

Varela, R. D., Rego, P. R., Iglesias, S. C., & Sobrino, C. M. (2008). Automatic habitat classification methods based on satellite images: A practical assessment in the NW Iberia coastal mountains. *Environmental Monitoring and Assessment*, *144*(1), 229-250.

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science, 277*(5325), 494-499.

Wang, K., Franklin, S. E., Guo, X., & Cattet, M. (2010). Remote sensing of ecology, biodiversity and conservation: A review from the perspective of remote sensing specialists. *Sensors*, *10*(11), 9647-9667.

Wang, X., Blanchet, F. G., & Koper, N. (2014). Measuring habitat fragmentation: an evaluation of landscape pattern metrics. *Methods in Ecology and Evolution, 5*(7), 634-646.

Weilert, T., Ji, W., & Zubair, O. (2018). Assessing the impacts of streamside ordinance protection on the spatial and temporal variability in urban riparian vegetation. *ISPRS International Journal of Geo-Information, 7*(7), 282.

Wiens, J. A., & Milne, B. T. (1989). Scaling of 'landscapes' in landscape ecology, or, landscape ecology from a beetle's perspective. *Landscape Ecology, 3*(2), 87-96.

Wilson, J.P., & J.C. Gallant, (Eds.). 2000. *Terrain analysis: Principles and applications.* John Wiley & Sons.

Wu, X., Gong, W., & Xu, Y. (2016). Analysis of urban wetland changes and their driving forces based on RS and GIS: A case study in the Longfeng Wetland Natural Reserve, China. *Nature Environment and Pollution Technology, 15*(2), 377.

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., & Schirokauer, D. (2006). Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. *Photogrammetric Engineering & Remote Sensing, 72*(7), 799-811.

Zamora, P. M. (1984). *Philippine mangrove: Assessment of status, environmental problems, conservation and management strategies.* In Proceedings of the Asian Symposium on Mangrove Environment- Research and Management. (pp. 696-707).

Zhao, B., Li, B., Zhong, Y., Nakagoshi, N., & Chen, J. K. (2005). Estimation of ecological service values of wetlands in Shanghai, China. *Chinese Geographical Science, 15*(2), 151-156.

Zubair, O. A., Ji, W., & Festus, O. (2019). Urban expansion and the loss of prairie and agricultural lands: A satellite remote-sensing-based analysis at a sub-watershed scale. *Sustainability*, *11*(17), 4673.

Zubair, O., Ji, W., & Weilert, T. (2017). Modeling the impact of urban landscape change on urban wetlands using similarity weighted instance-based machine learning and Markov model. *Sustainability*, *9*(12), 2223.

VITA

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PEER REVIEWED JOURNALS

Collaborations

1. Aremu, O., Bello, E., & Aganbi, B. **Festus O. O.** (2017). Trend analysis and change point detection of rainfall across the Agro-ecological zones for sustainability development in Nigeria. Environ Risk Assess Remediat. 2017; 1 (2): 36, 46, 3-8.
2. Zubair, O. A., Ji, W., & **Festus, O. O.** (2019). Urban Expansion and the Loss of Prairie and Agricultural Lands: A Satellite Remote-Sensing-Based Analysis at a Sub-Watershed Scale. Sustainability, 11(17), 4673.

Author

1. **Festus, O. O.**, Ji, W., & Zubair, O. A. (2020). Characterizing the Landscape Structure of Urban Wetlands Using Terrain and Landscape Indices. Land, 9(1), 1-25.
2. **Festus, O. O.** (2020) Synergetic Wetland Landscape Change Assessment for Surging Water Weed: Lake Chad Region (under review).
3. **Festus, O. O.** (2002) Wetland Landscape Metric and Lidar Based Analysis to Moderate the effect of Flood Peaks Events (in progress).

CONFERENCE PRESENTATIONS

Paper Presentation

- Characterizing the landscape structure of urban wetlands using terrain and landscape Indices. Association of American Geographers (AAG), DC USA.

1. The Scenarios of Wetland Landscape Dynamics Identified with different Image Classification Algorithms. Association of American Geographers (AAG), Boston USA.
2. Spatial Characterization of infectious diseases risk areas: A case study of Meningitis outbreak in Northwestern Nigeria. Association of American Geographers (AAG), New Orleans USA.
3. LIDAR Remote Sensing: Assessing the Impact of Urban Wetland Dynamics as Indicator of Landscape and Climate Chan. Association of American Geographers (AAG), New Orleans USA.
4. Building geodatabases (Polio Eradication) African User Conference, Cape Town, South Africa, Polio Presentation.

5. Identifying emergency routes for safe evacuation of COVID-19 cases among the internally displaced people in northeastern Nigeria.

Poster:

1. Spatial distribution and rating of Hotels around Murtala International Airport Ikeja, Lagos**,** Nigeria American Association of Photogrammetry and Remote Sensing, Baltimore (ASPRS), Maryland USA