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Comparing Methods for Estimating Habitat Suitability

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Abstract: Habitat suitability (HS) describes the ability of the habitat to support living organisms. There are several approaches to estimate habitat suitability. These approaches are specific to a species or habitat or estimate general HS broadly across multiple species or habitats. The objectives of the study were to compare the approaches for estimating HS and to provide guidelines for choosing an appropriate HS method for conservation. Three HS estimation methods were used. Method 1 scores the suitability based on the naturality of the habitat. Method 2 uses the average of HS values found in the literature. Method 3 uses the species richness as an indicator for HS. The methods were applied to a case study in the Choctawhatchee River Watershed. GIS applications were used to model the suitability of the watershed. The advantages and disadvantages of the HS methods were then summarized. The multiple HS maps created using the three methods display the suitability of the watershed. The highest suitability occurred in the southern parts of the region. Finally, a decision support tool was developed to help determine which approach to select based on the available data and research goals.

Keywords: conservation; ecology; GIS; habitat suitability; indicators; land use/cover; spatial data; watershed

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1. Introduction

Habitat suitability (HS) describes a habitat's ability to support a particular fish or wildlife species [1,2]. HS relates to environmental variables such as vegetation to the probability of a species' occurrence [3,4]. A simple way to describe HS is to determine how natural a habitat is [5]. The more a habitat resembles its natural state, the more suitable it is for the species to live in it. It is important to study HS as it is used to characterize how ideal a habitat is. Anthropogenic pressures on biodiversity such as urban growth and agriculture are key factors that cause HS decline [6,7]. Efforts to limit anthropogenic impacts on species and habitats can be strengthened by using tools for biodiversity monitoring. These include the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, the ecological niche model (ENM), and the habitat suitability index model (HSIM) [8,9].

Understanding of the interactions between species and their environment is needed to determine the optimum habitat conditions. Indicators are powerful tools to represent the complex interactions between multiple components of the environment in simple terms [10]. Living and nonliving components such as plant/organism growth or climate are important in categorizing suitability [11]. Resources that a species needs to survive are often used as indicators. Parameters such as vegetation density, the abundance of water, and sediment characteristics also serve as indicators [12,13]. Other parameters such as road density [14] and the shell dissolution of mollusks [15] can be used as indicators in HS. Sometimes, the presence of a species can also be used as an indicator. For example, the presence of bird species has been used as indicators of habitat structural components and complexity [16].

Since HS is a measure of species–habitat interactions, mapping HS is useful in conservation efforts. The consistent estimation of HS is necessary to create reliable maps [17].

In the past, approaches for estimating HS were either species-focused or habitat-focused. HS is calculated based on the needs of individual species or species group in the species-focused approach [3]. The habitat-focused approach considers the presence of habitat components that may either be biotic or abiotic [18,19]. The different approaches are chosen based on the research goals [20,21].

A habitat-focused approach is common for estimating suitability [22]. With the habitat-focused approach, the HS index is calculated by dividing the current habitat conditions by the optimum habitat conditions. This results in a value between 0 and 1. When a simulation modeling framework is used, the index is the ratio of a model's output compared to an established standard of comparison or an optimum habitat condition. The comparison standard is either (1) an assigned numerical value that corresponds with the qualitative rankings (excellent = 4, average = 2, etc.); (2) a maximum regional value for models that use defined units (productivity, population density, etc.); or (3) the maximum rank for models that classify habitats hierarchically [1]. The denominators in all of these methods are related to the optimum habitat conditions. Factors affecting the optimum habitat conditions can be biotic (i.e., vegetation density and predation [2,23,24]) or abiotic (i.e., topography, water availability, soil characteristics, and temperature for soil systems and sediment concentration, and dissolved oxygen for aquatic environments [12,25–28]). The habitat is completely unsuitable when HS is characterized with a value of 0, while a value of 1 represents the optimum conditions [29].

A species-focused approach is used when the goal is to conserve a certain species. An example is the evaluation of habitat suitability based on the ability of each landscape to provide the needs of song birds [19]. Alternatively, a habitat-focused approach is taken to conserve a specific land use or land cover. For instance, water parameters such as water presence frequency and water depth re used to estimate HS for the wetlands. Description of lad use/land cover can be obtained in [30]. However, these approaches are very specific. It is important to compare the results of different methods in any region.

Objective

The objective of this paper was to compare three methods for estimating the habitat suitability and to develop a way to choose a method for estimating HS based on the available data and research goals.

These methods were then applied in a case study in the Choctawhatchee River Watershed. The study watershed is a biodiversity hotspot that houses more species of trees than any other forests in temperate North America [31].

2. Study Region, Materials, and Methods

2.1. Study Region

Figure 1 shows a map of the study region created using ArcMap® 10.4.1. The Choctawhatchee River and Bay Watershed is an important location in the Southeast of the United States. It is a biodiversity hotspot containing an abundance of native plant and wildlife species as well as being a critical habitat for gulf sturgeon and Choctawhatchee beach mice. Over 60% of the watershed is in Alabama, where there is a significant agriculture component [32].

As of 2019, the land use in Choctawhatchee River Watershed is provided in Figure 1 [33]. The region has high species richness when compared to the rest of the United States [34].

2.2. Methodology

ArcMap 10.4.1 was used to analyze the datasets. Python programming was also used. The libraries used were the Geospatial Data Abstraction Library (GDAL) 3.2.0 developed by the Open Source Geospatial Foundation in Chicago, IL, USA; NumPy 1.19.2 created by

Travis Oliphant in Provo, UT, USA; and Pandas 1.2.1 created by Wes McKinney in New York City, NY, USA. Three methods of modeling HS were used. Spatial data were obtained for LULC, species richness, and region extents. Table 1 lists the data and their sources.

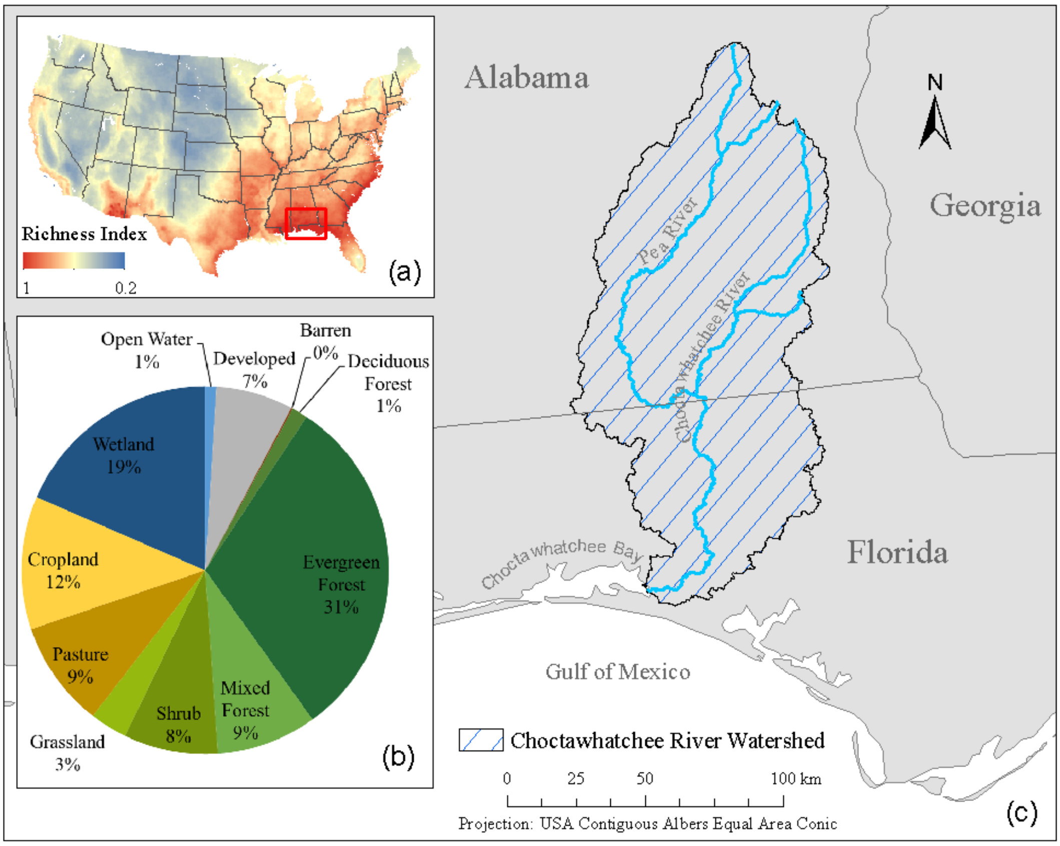

Figure 1. Location of the Choctawhatchee River Watershed. (**a**) The species richness index of the United States is shown as are where the watershed is in the United States, higher richness index values are shown as red and lower values in blue. (**b**) A pie chart of the proportion of each LULC. (**c**) The full extent of the watershed and the locations of the Choctawhatchee and Pea Rivers.

Table 1. The details of the spatial data used in the study.

Data	Year	Source	Reference
National Land Cover Dataset (NLCD)	2019	USGS	[33]
Species Richness	2018	Florida International University	[34]
Choctawhatchee River Watershed Extents	2016	USGS	[35]
Southeast Plains Ecoregion extents	2017	EPA	[36]
Eastern Temperate Forest Ecoregion Extents	2018	EPA	[37]

Method 1—Binary Method: Step 1: Download the Multi-Resolution Land Characteristics Consortium (MRLC) LULC data [38]; the land use/land cover data from the National Land Cover Dataset (NLCD) for the year 2019 and its legend were obtained [33]. Step 2: Classify the natural and unnatural groups and assign index; agriculture and developed land use classes were deemed unnatural, and the land cover classes open water, wetland, grassland, shrubland, and forests were considered as natural. Step 3: Obtain the binary

HS index; Unnatural LULC classes were assigned an HS index value of 0 and natural LULC classes were given an HS index value of 1. Step 4: Create an index map (natural and unnatural) where the LULC values were replaced with the corresponding HS index values (0/1) to create an index map. The analysis involved using the following software: ArcMap 10.4.1 (Clip tool from Raster Processing toolbox) and Python codes (Geospatial Data Abstraction Library with Jupyter notebook).

Method 2—Literature Review: Step 1 was the same as in method 2. Step 2: A document search was performed using Google Scholar (e.g., habitat suitability), which gave 500,000 plus results, and a more focused search using words in quotes, additional words (e.g., "habitat suitability", "InVEST"), and selected time-period (2010–2020) was carried out. Priority was given to articles based on the following three criteria: (1) the full articles were accessible; (2) the articles used a similar definition for habitat suitability; and (3) the articles provided the numerical habitat suitability values for LULCs comparable to those found in the study region. A total of 21 articles were retrieved. In Scholar search, InVEST, as an additional search term, was used in the search to narrow down the results in a systematic way. Step 3: Obtaining HS index (between 0 and 1). The results of the search were summarized in a table and graphs provided in the Results section. Habitat suitability values were organized by the specific LULC. The LULC were further grouped into broad classifications according to the LULC descriptions provided by the MRLC [39], for example, rivers, lakes, reservoirs, and glaciers were grouped as simply "water", while open forests, orchards, and native forests were grouped as simply "forest". When multiple values for a group were obtained from the literature, the average values for suitability were calculated and used to create the table. The box plot was created using Python. The HS vales were placed into single column arrays for each LULC group. A box plot was then created for each LULC group and displayed in the same figure. Step 4: Create an index map (natural and unnatural). The LULC values between 0 and 1 were replaced with corresponding HS index values (0/1) to create an index map. The analysis was carried out using the software described in Method 1. A table (Table 2) lists the references for each land use/cover type along with the number of data points obtained for them. The LULC values in the map clipped to the watershed's extents were replaced with the mean values obtained in the literature review.

Method 3—Species Richness Method: Step 1: Bring the datasets to uniform scales and obtain the species richness data [34]. National Land Cover Data (NLCD) land use/land cover map's resolution (30 m $\times$ 30 m) were rescaled to species richness maps with a 10 km $\times$ 10 km resolution. ArcMap 10.4.1 software with the Resample tool using the MAJORITY technique was used [40]. Step 2: Average the richness/land use. The major LULC from ~111 pixels (30 m) now represent the LULC for the 10 km map. The richness and LULC data were merged into one raster file by using the Combine ArcMap Spatial Analysist tool to observe both the number of species and LULC for each pixel. Step 3: Clip the watershed area. Shapefiles for the Choctawhatchee watershed (HUC 031402) and the Southeast Plains and Eastern Temperate Forest ecoregions were obtained [35–37]. The combined richness raster was clipped to the extent of each shapefile. Step 4: Estimate the average richness value. The average species richness for each LULC was then calculated for each region as well as the entire contiguous United States. Habitat suitability indices were normalized using the species richness results by dividing the species richness of each LULC by the highest species richness value for each region. If a 10 km grid cell for a forest within the Southeast Plains has a richness value of 300 and the highest richness value in that region is 600, the HS index would be 0.5 (300 divided by 600). Step 5: Mapping HS. The LULC values in the original 30 m map were replaced with the corresponding habitat suitability index values.

A table (Table 3) listing the total species richness, standard deviation, and count of grid cells was created by importing the attribute tables of the species richness raster images clipped to the extents of the Choctawhatchee River Watershed, Southeast Plains Ecoregion, Eastern Temperate Forest Ecoregion, and the contiguous United States.

3. Results

3.1. Method 1—Binary Method

A hypothesis map was created using the binary method where it was assumed that developed lands such as urban and agriculture have a suitability index score of 0, and every other landscape was assumed to have an index score of 1. The number of grid cells with a value of 0 were counted and compared to the number of grid cells that had a value of 1. Approximately 27.33% of the watershed had low suitability. The areas with low suitability appeared near the middle and northern parts of the watershed. Most grid cells with zero suitability occurred on the Alabama side of the watershed. Figure 2 displays the resulting HS index map of the watershed.

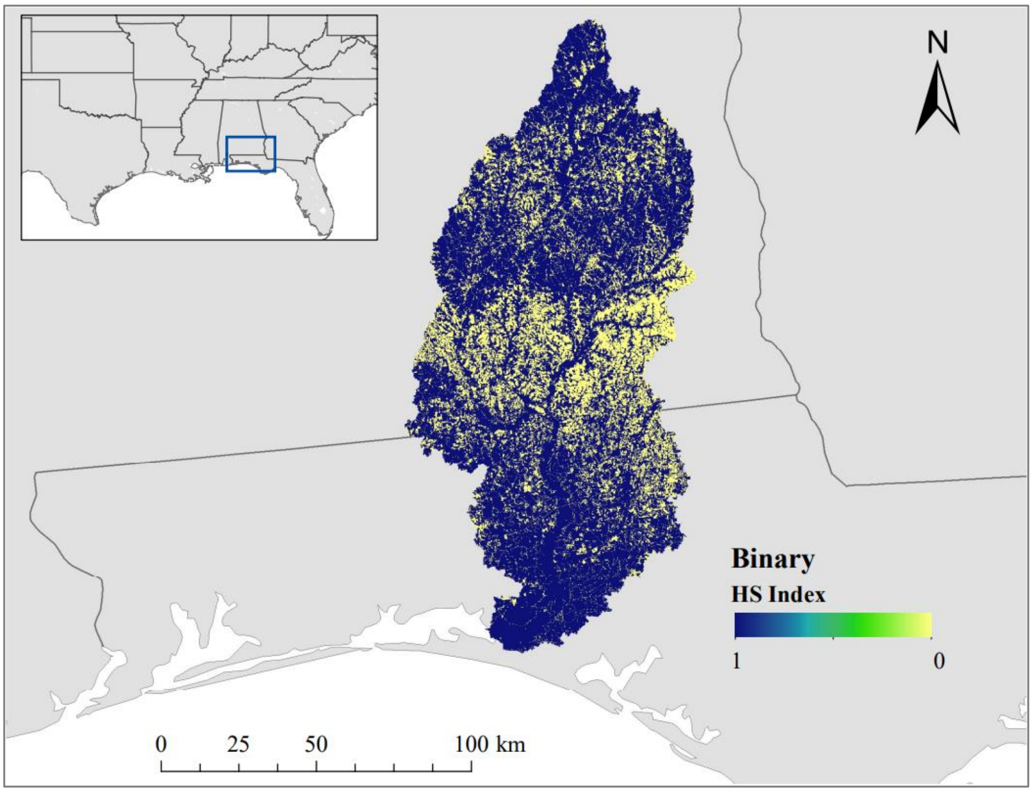

Figure 2. The habitat suitability map of the Choctawhatchee Watershed using the binary method (Method 1).

3.2. Method 2—Literature Review Method

A total of 21 studies were analyzed. Of the 21, 15 studies originated in China [9,41–54], two studies were from Ethiopia [29,55], and only one study each originated in India [56], Indonesia [57], Spain [58], and the United States [19]. A total of 36 values were used to calculate the average suitability for water, 17 were used for bare lands, 30 were used for grasslands, ten were used for shrub lands, 36 values were used for forests, 18 were used for wetlands, 24 were used for agricultural, and 15 were used for developed lands. The habitat with the highest mean value was forest land. Next was shrubland, followed by water and wetlands that had nearly the same average suitability. Developed lands predictably had the lowest mean suitability.

Table 2 breaks down the broad land use/cover classes into specific types and lists the references that site each LULC. The number of values obtained for each LULC type is listed, along with the average suitability. Different LULC within the same class sometimes had very different suitability values. For instance, raw land and beaches were both considered bare land, but had an HS of 0.05 and 0.9, respectively. The overall average HS for each broad LULC class is also listed.

Table 2. The average habitat suitability for each land use/cover type obtained from the literature review.

LULC Class	Types	References	Data Points	Average HS
Water	Water	[19,29,41,42,51,53–56]	10	0.75
	Rivers	[9,44,46–48]	6	0.88
	Lakes	[9,44–47,50,54]	6	0.98
	Pond	[9]	1	0.9
	Reservoirs	[44,45,47,50,58]	6	0.83
	Shallows	[44]	1	0.6
	Streams	[58]	4	0.73
	Channels	[45]	1	1
	Canals	[50]	1	0
		Overall		0.807
Bare Land	Bare Land	[19,29,50,56]	4	0.125
	Dry Land	[43,44,47]	7	0.243
	Desert	[49]	1	0.1
	Raw	[54]	2	0.05
	Unused Land	[41,48]	2	0.255
	Beach	[9]	1	0.9
		Overall		0.224
Grassland	Grass	[9,19,42–45,47–49,51,53–55,58]	29	0.727
	Meadow	[41]	1	1
		Overall		0.736
Shrub Land	Shrub	[9,29,43–45,50,51,54,58]	9	0.84
	Bush	[48]	1	0.8
		Overall		0.837
Forest	Forest	[9,19,29,41–43,45,47,49,51–53,57,58]	25	0.931
	Woodland	[9,29,44,47,50]	8	0.844
	Orchard	[43,52]	2	0.25
	Forestry	[48]	1	0.9
		Overall		0.873
Wetland	Wetland	[9,19,45,49,51,54,56]	9	0.844
	Marsh	[43,46,47]	5	0.74
	Mudflat	[46]	1	0.8
	Bottom Land	[44]	1	0.6
	Mangrove	[57]	1	0.8
	Swampy Bush	[57]	1	1
		Overall		0.806
Agriculture	Agricultural land	[19,41,58]	6	0.375
	Farmland	[42,53,55,57]	5	0.4
	Cropland	[29,45,48,54]	4	0.363
	Pasture	[29]	1	0.5
	Irrigable Land	[43,54]	2	0.35
	Paddy Field	[9,43,44,47,50]	6	0.267
		Overall		0.354

Table 2. *Cont.*

LULC Class	Types	References	Data Points	Average HS
Developed Land	Built-up Land	[29,42,53]	3	0
	Urban	[19,41,48,58]	5	0.03
	Suburban	[54]	1	0
	Construction	[54]	1	0
	Rural Residence	[53]	1	0
	Roads	[46,54]	2	0
	Infrastructure	[54]	1	0
	Transportation	[54]	1	0
		Overall		0.01

The landscapes with the largest range of suitability values were water habitats, which had values ranging from 0 to 1. This was followed by forest habitats with values ranging from 0.1 to 1. The land use with the lowest variability was developed land, which ranged from 0 to 0.15, with most studies reporting the suitability to be 0. The median and average values were similar for grasslands, shrub lands, wetlands, and developed lands. Median and average values for the remaining landscapes were not as close with averages falling well below the median value, except for bare lands, where the average was higher than the median. This is displayed in the box plots of Figure 3. The bold line represents the median, the diamond marker represents the mean, and the circles represent the outliers.

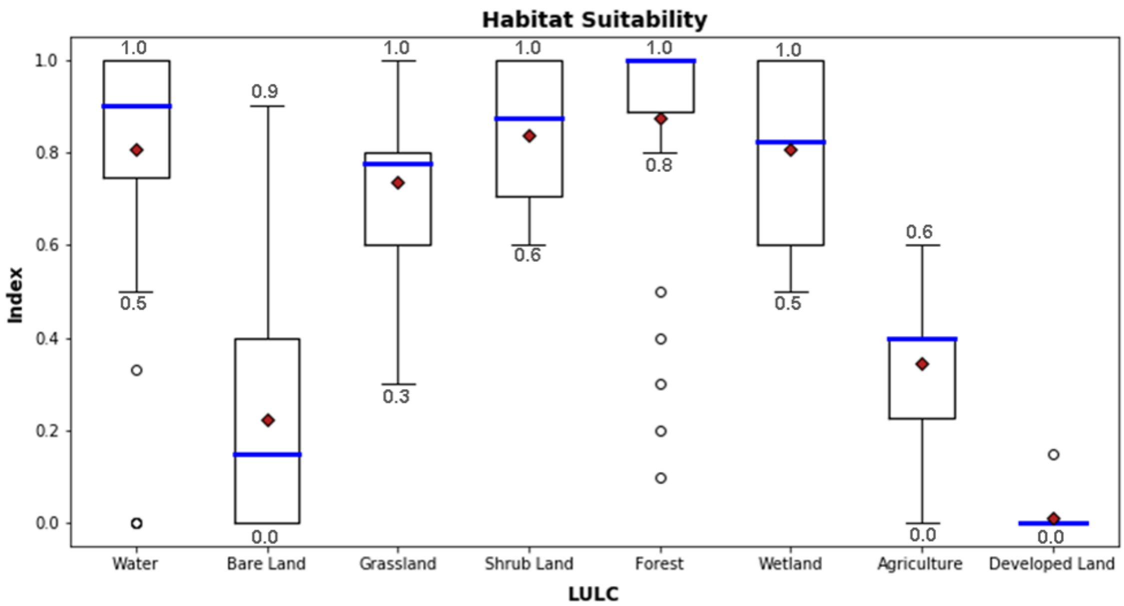

Figure 3. The suitability box plots for each LULC class. The whiskers indicate 1.5 times the interquartile range values. The bold line represents the median and the diamond shaped markers represent the mean. The circles are the outliers.

Figure 4 displays a HS map of the watershed based on the average values derived from the literature. The Alabama side of the watershed in the North generally had a lower HS when compared to the Florida side in the South. Urban areas had the lowest HS at 0.012. Urban land uses made up 6.80% of the watershed. Bare land had the second lowest HS at 0.224 and made up 0.12% of the watershed. The habitat with the third lowest HS was agriculture, having a HS near the median at 0.354. Agriculture made up 21.26% of the watershed. Overall, about 28% of the watershed had a relatively low HS.

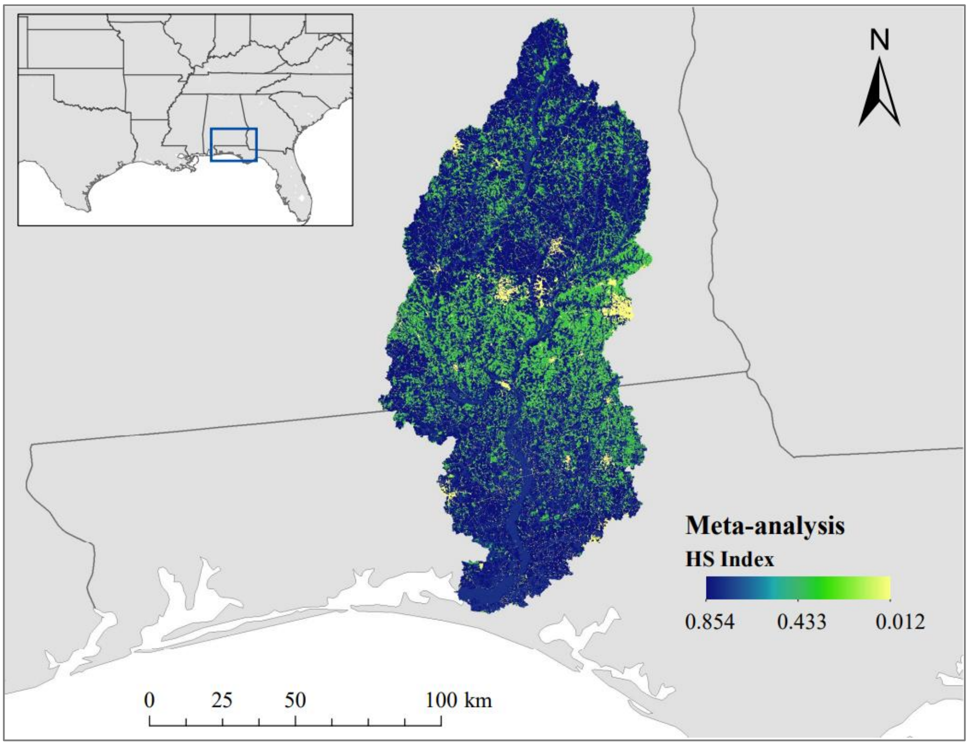

Figure 4. The habitat suitability map of the Choctawhatchee Watershed created using the results of the literature review.

3.3. Method 3—Species Richness Method

The area of interest was the Choctawhatchee River and Bay Watershed located in the Southeast United States. The watershed was within the boundaries of the Southeastern Plains ecoregion, which was in the Eastern Temperate Forest ecoregion that encompassed most of the Eastern United States. A visual representation of these regions is shown in Figure 5.

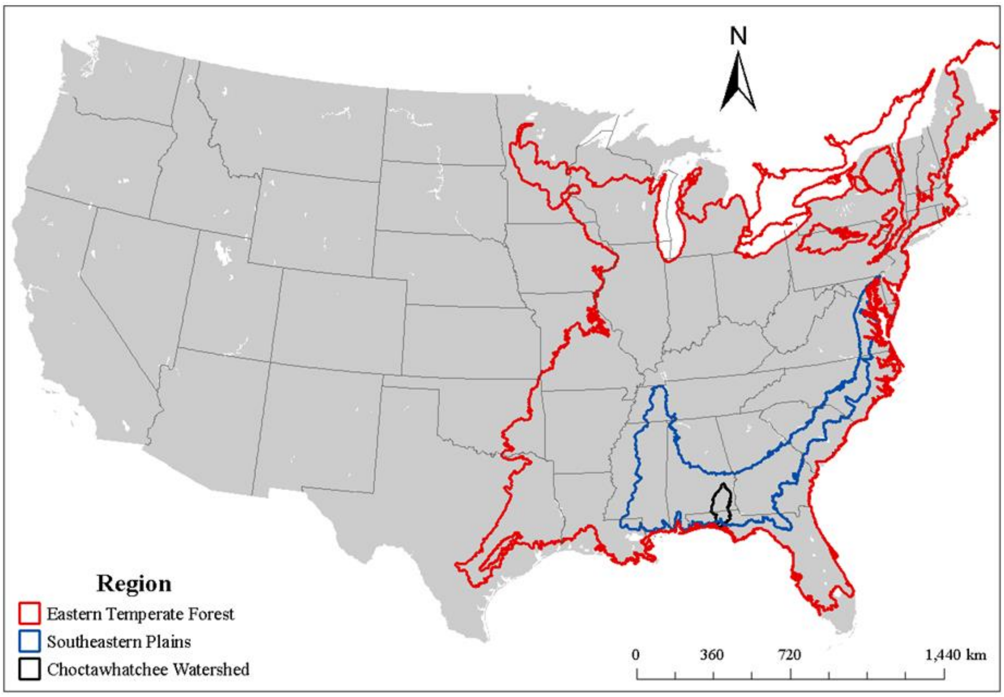

Figure 5. A location map with boundaries of the Choctawhatchee River Watershed, Southeastern Plains Ecoregion, and Eastern Temperate Forest Ecoregion overlaid in the United States.

Table 3 lists the average total richness and standard deviation values for each LULC. The number of pixels is also listed. Each pixel represents 100 square kilometers. The watershed had higher values than the averages at broader levels. Since the LULC raster was resampled from 30 m to 10,000 m, there were no pixels where high intensity developed land, barren land, or herbaceous wetland were the majority LULC. The values for these LULCs were estimated based on the most similar region (Southeast Plains). The trends also did not match across levels. Richness was high in the medium intensity developed land within the watershed, but richness generally decreased as the intensity (amount of impervious surface) increased. Broad generalizations might not be accurate when assessing a watershed. A visual representation of Table 3 can be seen in Figure S3 in the Supplementary Materials.

Table 3. The average and standard deviation of the species richness for each land use/cover type.

	Contiguous USA			Eastern Temperate Forest			Southeastern Plains			Choctawhatchee River Watershed		
LULC	**Mean**	**Std**	**Pixels**	**Mean**	**Std**	**Pixels**	**Mean**	**Std**	**Pixels**	**Mean**	**Std**	**Pixels**
Open Water	316.84	52.56	2246	345.1	40.324	1105	383.96	25.846	94	417.56	19.90	9
Developed, Open Space	335.01	46.072	2427	353.91	34.221	1671	390.16	28.627	247	414.72	18.34	19
Developed, Low Intensity	333.75	40.63	1126	348.23	31.222	753	381.41	23.211	79	415.75	14.66	4
Developed, Medium Intensity	331.57	41.125	402	349.55	34.137	212	377.25	22.493	24	432	0	1
Developed, High Intensity	339.32	40.082	95	350.31	33.576	52	384.75	22.833	8	ND	ND	ND
Barren Land	262.92	37.884	768	355.89	36.131	53	391.5	26.588	10	ND	ND	ND
Deciduous Forest	329.65	30.388	9441	340.77	24.622	6931	373.61	20.356	389	404.31	7.11	16
Evergreen Forest	311.82	54.033	10,764	384.92	34.983	2999	401.53	26.248	1069	424.55	18.76	126
Mixed Forest	328.44	40.853	1976	345.5	35.622	1358	385.3	22.14	247	403.06	3.84	16
Shrub Land	274.71	40.996	17,894	375.09	37.557	244	404.89	28.416	76	428.77	22.30	13
Grassland	251.83	38.533	10,275	368.41	44.047	146	399.43	31.225	40	450.33	3.21	3
Pasture	331.45	40.55	4099	346.19	28.541	2682	389.56	25.549	192	408.1	6.97	21
Cropland	279.5	50.227	13,052	327.76	32.584	4941	392.03	22.139	393	425.3	9.71	20
Woody Wetlands	352.32	54.173	2463	377.99	43.896	1707	397.48	24.934	441	431.61	17.34	33
Herbaceous Wetland	305.69	49.801	429	333.04	50.352	135	402.2	29.072	5	ND	ND	ND

Figure 6 shows the resulting maps. The lowest index value when using the average species index for the Southeast Plains ecoregion was close to 1, meaning that there was very little variability in the values. The variability increased as the sample size used to calculate the average increased. The lowest HS values occurred the most in the northern parts of the watershed in the Southeastern Plains and Eastern Temperate Forest maps. The map derived from using the entire contiguous United States did not seem to have a pattern aside from the highest suitability occurring in wetlands along the streams of the watershed.

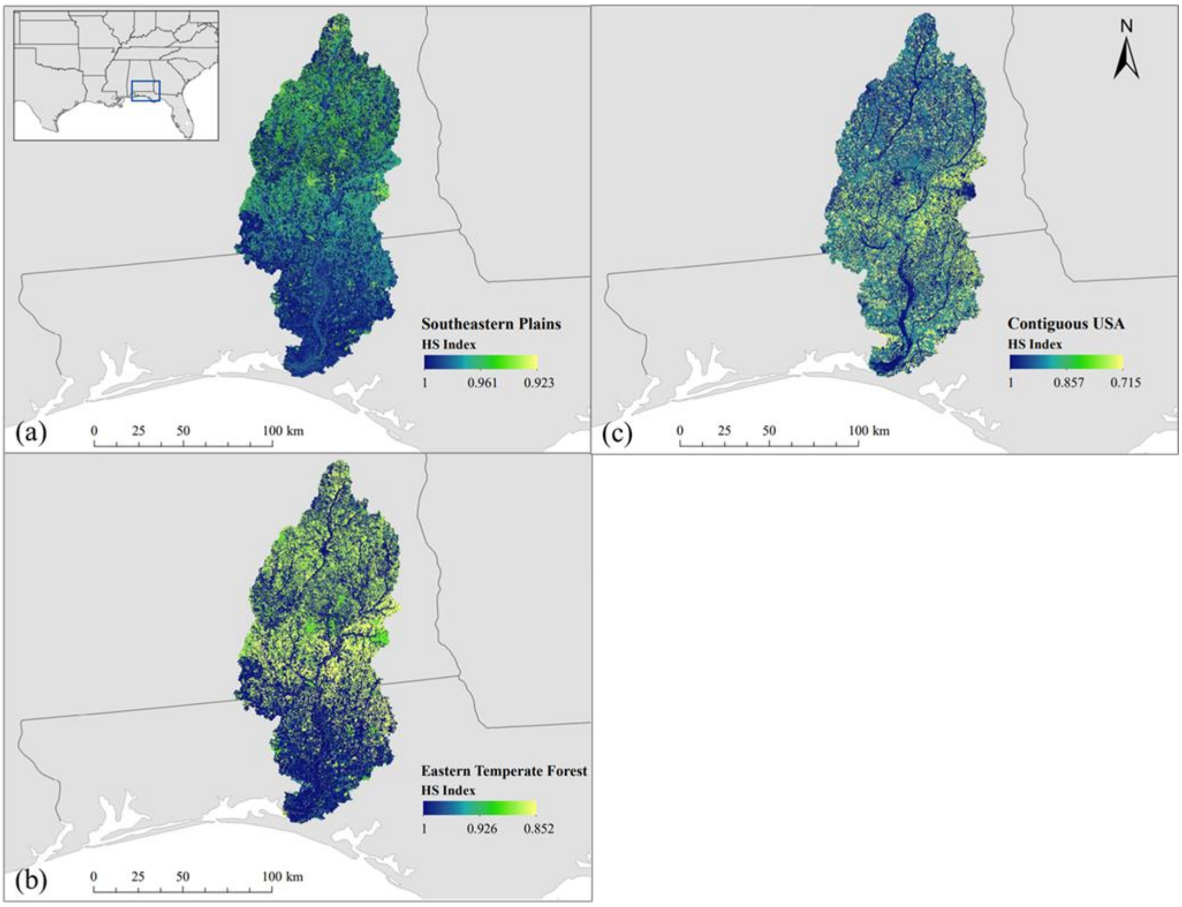

Figure 6. The habitat suitability maps of the Choctawhatchee Watershed based on species richness derived from averaging the values within regions of varying sizes. Maps created using the average values from grid cells in the (**a**) Southeastern Plains ecoregion; (**b**) Eastern Temperate Forest ecoregion; (**c**) contiguous USA.

3.4. Comparison of the Methods

The average HS values of each LULC is shown in Figure 7. The landscapes with consistently high HS values, regardless of method, are open water, forests, and wetlands. The most apparent differences in HS were seen with agriculture and urbanization. These two land uses were low when using the binary and literature review methods. However, HS was high for these land uses when using the species richness data.

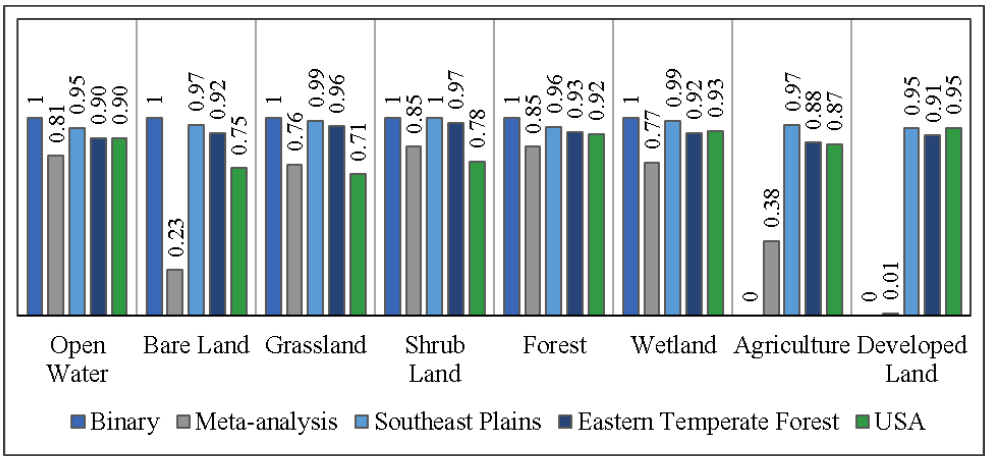

Figure 7. The habitat suitability index for the various land use/cover obtained.

The binary method is the simplest method. It only requires a list of the habitats present in a region and an understanding of which ones are natural or unnatural. The literature review method requires more research than the other methods. This method is also heavily reliant on values from previous works. The obtained values are assumed to be correct. The species richness methods require species count data. The completeness of the data has a large impact on the outcome, so the values will be inaccurate if many species are not accounted for.

3.5. Choosing a Method

Assessing what data are available is vital when deciding on a method. The natural/unnatural binary method is used when minimum data are available. If the habitats are known, it is possible to determine whether the habitat is natural or unnatural. A list of habitats is derived from the literature or datasets. Mapping HS requires spatial data. Research goals may require the HS values to be more exact. Using 0 and 1 for unnatural and natural, respectively, would be too broad. Expressing variation between the HS of different habitats requires expert knowledge of the target region. The literature review method is used when there is no access to expert knowledge. A literature review is used to synthesize the results of multiple studies [59]. Existing literature is needed to perform a literature review and gathering results from similar studies is preferred [60]. HS indicators such as species richness are used in a data driven approach. Using an indicator requires available data for the study region or a similar region. Indicators that are used for this are biophysical, socio-economic, or management attributes [61]. The characteristics of each landscape were studied to determine an indicator that could be used to model the suitability across all landscapes, which included the biotic and abiotic components of deciduous forests [62], evergreen forests [63], mixed forests [64,65], wetlands [66,67], shrub lands [68], grasslands [69,70], and bare lands [71,72]. Species richness was used as an indicator to estimate the overall health of any habitat and to identify priority conservation areas [73–75].

Figure 8 summarizes when to use each method and lists the information required to perform them. The figure indicates the specificity and complexity of the methods in relation to each other. The binary method is the simplest and least specific of the methods. Next is the literature review method, followed by the species richness method, the most complex and specific method of the three.

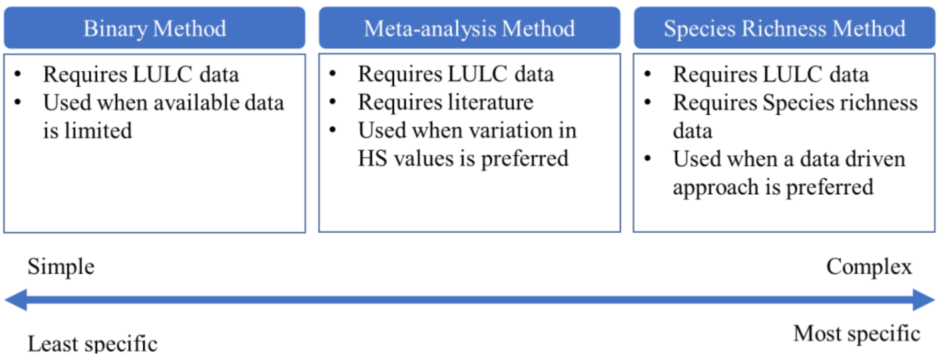

Figure 8. A comparison of the three methods. Method selection depends on the available data, complexity level, and research goals.

4. Discussion

The results revealed that there were significant differences in the habitat suitability scores when using the different methods. However, the Florida side of the watershed consistently had a higher average suitability than the Alabama side.

4.1. Assumptions and Limitations in the Case Study

The three methods to estimate habitat suitability are the natural/unnatural binary method, a literature review of published works, and the indicator method using species richness. The binary method is the simplest method since calculations are not required. This method requires the knowledge of the landscapes present in the area of interest. Some land covers such as forests and wetlands could be managed and therefore considered unnatural. It was assumed that the only unnatural LULC were urban areas, cropland, and pastures. The literature review resulted in a map that was similar to the binary map. The key difference was the absence of 0 or 1 values in the map based on the literature review. Bare land also had an index value that was less than agriculture. There was also some variability between the index values of the urban and agricultural lands instead of both being assumed to be equally unsuitable. Generally, the areas that had the lowest suitability were nearly the same.

The map of species richness (Figure 1a) showed that the index values were all close to one. This is likely due to the region being a biodiversity hotspot [31,76]. During the development of the three maps using the species richness data in conjunction with LULC, the species richness values were higher in the Choctawhatchee River Watershed than in the rest of the United States due to (1) the watershed being more diverse than average or (2) there was a smaller sample size, which resulted in higher average values. Furthermore, there were not enough data points within the Choctawhatchee River Watershed to calculate the average species richness for every LULC. Using the average richness values resulted in maps dissimilar to each other, aside from the values having low variability compared to the results of the literature review. These maps also did not resemble the hypothesis binary map. Developed land was among the land uses with the highest suitability when using the average based on the contiguous United States. However, developed land is usually thought to be 0 or very close to it [29,41,42,46,48,53,54,58]. This could either mean that the species richness is a more accurate indicator of HS than averaging the results from past studies, or that the species richness was not adequate on its own to estimate HS. It could also mean that the species richness dataset is too limited.

A study in another region would use the species richness data available in that region. If no data are available, the values from a nearby region are useable. A literature review can also be used to estimate the values. The number of species in an area could also be counted manually when working in a small area. It is also possible to use the presence of one species as an indicator of the species richness of another species based on how important the indicator species is to the diversity of a habitat [77–79].

4.2. Advantages and Limitations of the Methods Used

The advantage of the binary method (Method 1) is that it can be applied in the absence of data or expert knowledge. Its limitation is that it is broad and does not account for the differences between LULCs. Agriculture (both cropland and pastures) and all other different types of developed lands are assumed to have the same suitability. It is possible that agricultural lands are more suitable than developed lands because they are not entirely unnatural. Open space also may be more suitable than high intensity developed lands.

The advantage of obtaining HS values from literature (Method 2) is that this method does not require expert knowledge. The more variable values are more descriptive than the simple binary method. The assumption is that the values used in the literature are accurate. However, the accuracy of the values changes when using an average of the values. This method is limited by the publications available, which requires other scientists and researchers to have conducted studies beforehand. These HS values come from the literature originating in various regions due to the lack of studies conducted in the Choctawhatchee River Watershed. This may be a potential advantage as HS can be estimated in a region where no previous studies are available. Studies based on regions that are unlike the area of interest cause this method to have the same disadvantage as the binary method (i.e., LULCs are given the same suitability values despite being different). This is because the values for all types of similar habitats are used to calculate an average. Every type of developed land, agricultural land, forest, and wetland is assumed to have the same suitability, which may not be accurate. There are also habitats that have a wide range of values. Both beaches and deserts are bare land. Beaches have high HS and deserts have low HS. In this case, using the average may not be adequate to account for the range in values.

Furthermore, the HS values were the average value from 23 articles. The limitation of this method is that the average value is subjective to the literature used.

The species richness method (Method 3) presents a way to estimate the general habitat suitability, whereas other methods estimate the suitability for a single species, a species group, or a specific habitat. This method does not require knowledge of the individual species, the present, or optimum habitat conditions. The binary method where natural is suitable, and unnatural is not suitable, is currently how HS is modeled in cases where there is no specific habitat data or when the goal is to estimate HS in general [5].

The main disadvantage is that the results of these methods are sensitive to the amount of data that is present. There is currently a lack of wildlife population data in most locations. The database used in this study only presented the species richness for the vertebrates (mammals, birds, reptiles, amphibians, and fish) and trees. The available data did not cover all macro-organisms. There was no species richness data for invertebrates such as arthropods and mollusks, non-tree plant species such as grasses and shrubs, or fungi. The total population of each species group was also unavailable. The details found in Table S3 in the Supplementary Materials cannot be utilized given the obtainable data.

The resolution of the spatial data also influences the accuracy. Accuracy decreases as the grid cell size increases because it becomes harder to account for the evenness of a species. For instance, a grid cell can represent a hectare. Most of the species might live in a section that is a tenth of a hectare. However, all of the species were counted to obtain a total value for the entire hectare. Smaller grid cell sizes allowed for more precise species mapping.

Using species richness by itself is not adequate when estimating the habitat suitability.

When looking at suitability maps made from individual species group richness (Figure 9), tree richness had the highest range of index values. Despite the index values, the range of bird species was the highest, with the lowest being three species and the highest being 249 species. The distribution of values in the total richness index map (Figure 1a) was most influenced by the number of trees and birds. This means that areas in the Southeast United States and along the coasts had the highest biodiversity. The distribution of species did not seem to be driven by general land use types, but rather a combination of climate, terrain, and other factors.

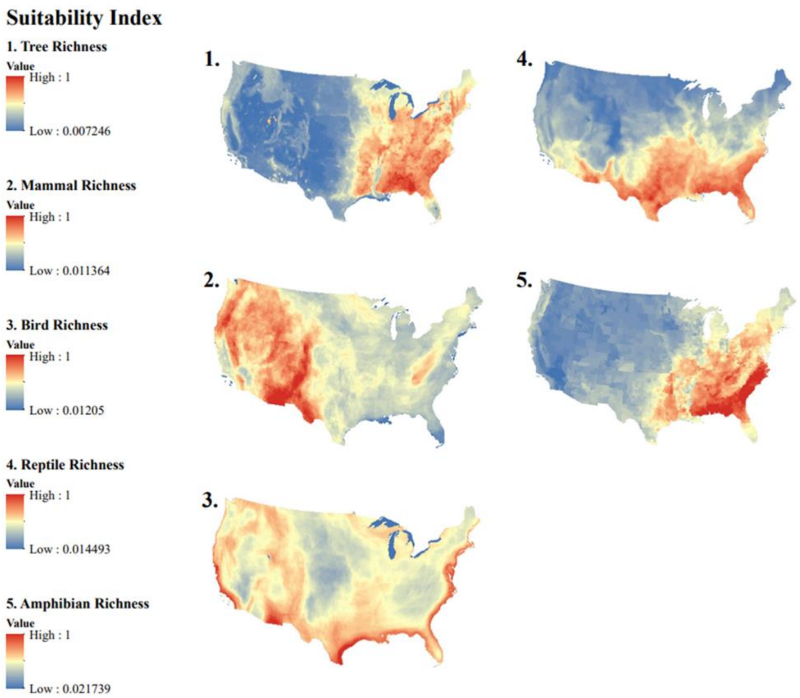

Figure 9. The national HS maps based on 1. tree richness, 2. mammal richness, 3. bird richness, 4. reptile richness, and 5. amphibian richness. Higher species richness values are shown as red and lower values in blue.

The advantage of relating the species richness to specific land uses is that it gives an extra dimension to maps in comparison to the existing methods that estimate HS using LULC alone. This method also grants the ability to determine the typical suitability of a habitat based on data. As new data become available, HS can be adjusted to reflect the changes in biodiversity [80–82]. Being based on observable data can be an advantage and a disadvantage for the method.

The HS estimation methods are based entirely on the number of species, assuming that the species are distributed independently of spatial evenness. Doing so increased the possibility of the inaccuracy in the results. In addition, functional species such as predators, raptors, or primary productivity as indicators of HS could be used as relevant factors for the study. Validating theoretical concepts is a challenge because there are not observations to validate the model [83,84]. These apply to HS, also a theoretical concept.

4.3. Implications for Conservation

The spatial representation of HS is a good tool for supplementing conservation strategies. Biodiversity maps are used to protect biodiversity in many conservation programs [85]. Studies have shown a link between habitat suitability and wildlife population viability for a variety of species [86–89]. The binary method of estimating HS may not be a good tool for biodiversity conservation as it is not a function of biodiversity or habitat conditions directly, but it does show where human land uses occur [5]. The results of the literature review provide a good idea of which habitats are the most suitable. The most suitable habitats can then be studied to determine the species viability [90]. The HS maps where suitability is an index of species richness are direct estimations of biodiversity. These maps can be used to rank habitats in an area to determine which habitats are the most viable and which habitats potentially need conservation attention.

HS are linked both directly and indirectly to almost all the 17 Sustainability Development Goals (SDGs). For example, HS is important for water and land resource conservation, which are related to SDG-14 (life below water) and SDG-15 (life on land). HS is indirectly related to SDG-6 (clean water and sanitation) because it is an integral part of water integrity, which is influenced by the physical characteristics of the waterbodies (physical integrity) and impacts the life below water (biological integrity) [91,92].

5. Conclusions

The objective was to compare the three approaches for estimating habitat suitability, summarize the advantages and disadvantages of these methods, and provide guidelines for selecting a HS method for conservation. The study focuses on the Choctawhatchee River Watershed (in Alabama and Florida, USA). The three habitat suitability estimation methods were as follows. Method 1 provides a suitability score based on the naturality of the habitat. Method 2 uses the average values from the literature with similar definitions for habitat suitability. Method 3 uses species richness. HS estimation is approachable from the perspective of a single species or species group, from a habitat-focused standpoint, or with the goal of estimating the suitability for wildlife in general. These approaches can be too specific or too broad. Estimating HS using species richness data is more specific than the existing binary method while being broad enough to use when modeling large multi-habitat areas such as a watershed. If complete species richness data are available, this method is advantageous. Using a more complete dataset may reveal that natural habitats are more suitable than developed lands. It is therefore important to gather more data before using species richness as an indicator.

In choosing a method, approaches can be chosen after determining what types of data are feasibly obtainable and based on the research goals. Things to consider are the specificity of the method, the accuracy of the data, and the assumptions made. Different methods change how conservation strategies are chosen. Broad methods assist in identifying how natural each habitat is. Specific methods assist in identifying the species or resource distribution in each habitat [74]. It is important to consider conservation goals when choosing a method. Using a method that includes one or multiple HS indicators such as species diversity, the presence of invasive species, and/or water quality makes it easier to decide on which conservation measures to take [75,93].

Steps should be taken in the future to improve HS mapping. This includes using models and techniques such as machine learning to predict species richness based on inventory data for terrestrial species [94,95] and aquatic species [96]. Modeling the change in HS in real-time is also a possibility [97]. These methods are currently not being used to produce maps for habitat conservation or the general public. Using functional species or primary productivity as indicators of HS could be used as relevant factors for study in the future. Habitat suitability modeling will become accessible and more evidence-based when accurate and complete species maps become obtainable. This will make it possible to consistently identify habitats to apply conservation actions. Currently, it is best to have expert knowledge of the region to estimate the suitability of the habitats or use the literature review carried out in this study. If this is not an option, using the natural/unnatural approach is the next best method.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land11101754/s1, Figure S1: Venn diagram comparing deciduous forest, evergreen forest, and wetland habitats; Figure S2: Venn diagram comparing shrub land, grassland, and bare land habitats. [1] Steppe grasslands have very fertile soils. [2] Savannah grasslands have sandy/stony soil; Figure S3: Average terrestrial species richness for each LULC class.; Figure S4: Venn diagram that compares the Brillouin, Shannon–Wiener, and Hurlbert biodiversity index equations.; Table S1: Potential habitat conditions and components: A—all; B—bare land; D—deciduous forests; E—evergreen forests; G—grassland; S—shrub lands; W—wetlands; Table S2: Optimum habitat conditions; Table S3: Biodiversity Index Equations.

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