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LAND SUITABILITY ANALYSIS FOR WINDFARM DEVELOPMENT IN TEXAS

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By

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ABSTRACT

Due to the negative impact on the environment of conventional electric power generation methods, especially coal and oil-fired generating plants, wind power as an alternative for sustainable energy has received more attention in recent years. The purpose of this project was to apply Geographic Information System (GIS), integrated with Multi Criteria Decision Making (MCDM), for identifying suitable areas for wind turbine applications in Texas. Factors taken into consideration included socioeconomic criteria such as distance to highways, proximity to airports and urban areas, localized environmental criteria such as terrain slope and distance to rivers, affected waterbodies, and wildlife management areas. Also included is the most critical criterion, the wind power density defined by the National Renewable Energy Laboratory that integrated the abundance and quality of wind, the complexity of the terrain, and the geographical variability of the resources. GIS analysis models were built by applying different map overlay techniques, including Weighted Sum, Weighted Overlay and Fuzzy Overlay. For Weighted Sum and Weighted Overlay, each input factor was classified and weighted through an Analytical Hierarchy Process (AHP). The weights for each criterion were assigned using a pair-wise comparison, where the Wind Class received the greatest weight of 0.377

followed by slope with 0.2509. As to Fuzzy Overlay, different methods, including Large, Small, MSLarge, and MSSmall, were used to assign fuzzy membership on each participating criterion, followed by using the overlay methods of SUM, PRODUCT, AND, and OR. Each model output was rescaled to having a range of 1 to 5, where 5 represents a location that is highly suitable for windmill development. Each GIS model output was validated by existing wind turbine locations. The suitability index value for each existing wind turbine location was identified for each model output. The Fuzzy Overlay Three model resulted in the highest mean index value of 3.86, followed by the Weighted Overlay of 3.77, and the Weighted Sum of 3.71. It was found that the model outputs were statistically different in terms of accuracy. A general trend was observed that the western and northwestern portions of Texas are the most feasible areas for wind turbine installation.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLE

INTRODUCTION

Energy supply is one of the most urgent challenges in the 21st century that human beings are facing (Zhang 2015). Due to excessive carbon emissions from conventional fossil fuel power generating plants, wind energy has developed rapidly in the last decade. Wind energy is a source of renewable energy that can be utilized if the land is suitable. The demand for renewable energy has increased and has triggered development in many countries (Zhang 2015). 2017 marked the third largest gain in wind power capacity within a year. Within one year, 60GW of wind power was added worldwide. In 2018, the total generated electricity reached 26,700 TWh worldwide, with the leading source being coal fired generation a 10,146 TWh (38%), followed by natural gas with 6,141 TWh (23%). Wind energy accounts for 5%, part of the 26% of total electricity, generated by renewable sources.

Windfarms are areas where many large wind turbines have been grouped together to harvest the power of wind. These windfarms may consist of hundreds of wind turbines spreading out over hundreds of miles if the land is suitable. Studies have shown that Geographic Information Systems (GIS) are a versatile and powerful tool in performing a wind suitability analysis. However, selecting sites for wind turbine positions is a complex process involving technical, physical, socioeconomic, environmental, and political requirements (Bennui *et al.* 2007). Thus, the demand for decision support tools for such projects is critical and typically involves GIS integrated with Multi Criteria Decision Making (MCDM) and Analytical Hierarchy Process (AHP).

Generally, MCDM in a GIS environment is used to combine various layers of spatial data in a form of criteria while AHP has been developed to assign weight to each criterion within GIS. The criteria, or in other words factors, include socioeconomic criteria such as distance to highways, airports and urban areas, environmental criteria such as slope and distance to rivers, waterbodies, and wildlife management areas, as well as the most critical criterion, the wind power density.

The purpose of this study was to apply GIS, integrated with MCDM for identifying suitable areas for wind turbine applications in Texas. Each factor was classified and weighted through an Analytical Hierarchy Process (AHP). Developing a land use suitability assessment has become more available for land managers in the last decades due to advancements in GIS. Performing a suitability analysis using GIS with spatial data from public domain reduces time and cost in the decision making process. However, to make effective use of any GIS, it is important to understand the potential inaccuracy that is associated with any spatial information. Errors can be resulted from different sources such as user error, data error and processing error. Data error can be reduced by acquiring accurate spatial data from reliable sources. Providing reliable results through models built to conduct a suitability analysis can be challenging. This study involved building models by applying different map overlay techniques including Weighted Overlay, Weighted Sum, and Fuzzy Overlay. It is crucial to have alternative models so that model outcomes can be compared for accuracy where different overlay methods are applied. The results from each overlay technique were validated with existing wind turbine locations from the U.S Wind Turbine Database. The model validation assessed the reliability of the model outcome that eventually will help land managers to make informed decisions.

OBJECTIVES

This focus of this study was to find the best possible locations for windfarm development in the state of Texas. The software package that was used was ArcGIS Desktop 10.7.1 Advanced Edition, with the Spatial Analyst extension. By enabling the aforementioned extension, various geoprocessing tools was accessed including Weighted Overlay, Weighted Sum, Fuzzy Membership, and Fuzzy Overlay. The objectives of this study are listed below:

1. Build a geodatabase including multiple factors considered for windfarm development in Texas.
2. Build models, each with multiple criteria including distance to rivers, highways, airports, waterbodies, urban areas, wildlife management areas, wind energy potential, and slope for finding suitable locations for windfarms.
3. Run the models and compare the outputs from each model for suitable locations.
4. Validate each model output by using existing wind turbine locations.

LITERATURE REVIEW

Wind Energy

Wind energy has been used by man for centuries. Vertical-axis windmills were used primarily for grain grinding in Persia in the tenth century and in China in the thirteenth century (Nelson 2009). The very first wind turbine designs were relatively simple, as the wind velocity increased the turbine rotated at a proportional rate (Carlin *et al.* 2001). These simple turbines were primarily used to pump water, cut lumber, and for numberless other tasks (Carlin *et al.* 2001). In human history, civilizations used wind as a major source of energy for transportation (sailboats), grinding grain, and pumping water (Nelson 2009). Although, wind as a renewable energy source has been utilized for different purposes, the main long-term use of wind has been for pumping water (Nelson 2009, Gipe 2004). Around the twelfth century, horizontal-axis windmills were introduced that was based on the principles of aerodynamic lift instead of drag (Carlin *et al.* 2001). The main difference between vertical and horizontal-axis wind turbines lies within the rotational speed. The former was designed to have a constant rotational speed while the horizontal-axis turbine was allowed to run at varying speeds. This was proved to be more efficient of extracting significantly greater energy from the wind (Carlin *et al.* 2001). This development made the settlement on America's Great Plains viable for European migrants to build windmills across the land (Nelson 2009, Gipe 2004). Countries in the nineteenth century began building windfarms where tens of thousands of windmills were manufactured (Nelson 2009). These areas where many windmills were grouped together to harvest the power of the wind, are commonly called windfarms. In the early twentieth century when electricity became more available to households, manufacturers built stand-alone windmills to create electricity (Nelson 2009). After the two World Wars, countries, especially in Europe showed that large scale wind turbine applications to generate electricity could work (Kaldellis and Zafirakis 2011). While Europe during 80s and 90s continued building windfarms to supply electricity for the increasing demand, the first use in United States was in California, where over 16,000 machines were installed between 1981 and 1990 (Kaldellis and Zafirakis 2011).

Wind power has been receiving considerable attention in the 21st century, as it contributes no pollution to the environment that can contribute to climate change, ground-level pollution or public health problems (Musial and Ram 2010). Energy companies continue to install wind turbines to supply electricity for the increasing demand. In 2018, the total generated electricity reached 26,672 TWh, where 1,217 TWh was generated solely by wind energy.

This number is significant and accounts for near 6% of the global electricity demand (WWEA 2018).

Suitability Analysis

Land Suitability Analysis (LSA) is a tool that has been used to identify the most suitable locations or lands for specific land uses (Collins *et al.* 2001, Jafari and Zaredar 2010). Land suitability analysis can be used for different purposes including ecological analysis, suitability of land for agricultural activities, landscape evaluation, environmental impact assessment, regional planning and selecting the best site for the public and private sector facilities (Malczewski 2004). Suitability assessment is the core of land-use planning that generally requires scientific approach and appropriate techniques to allow the decision makers for an efficient, long term utilization of land resources (Bagheri *et al*. 2012). The complexity of land suitability analysis depends on various factors such as the defined use of the land, consideration of different requirements or criteria (Duc 2006). Figure 1 shows the general process of land suitability analysis based on Bagheri *et al.* 2012.

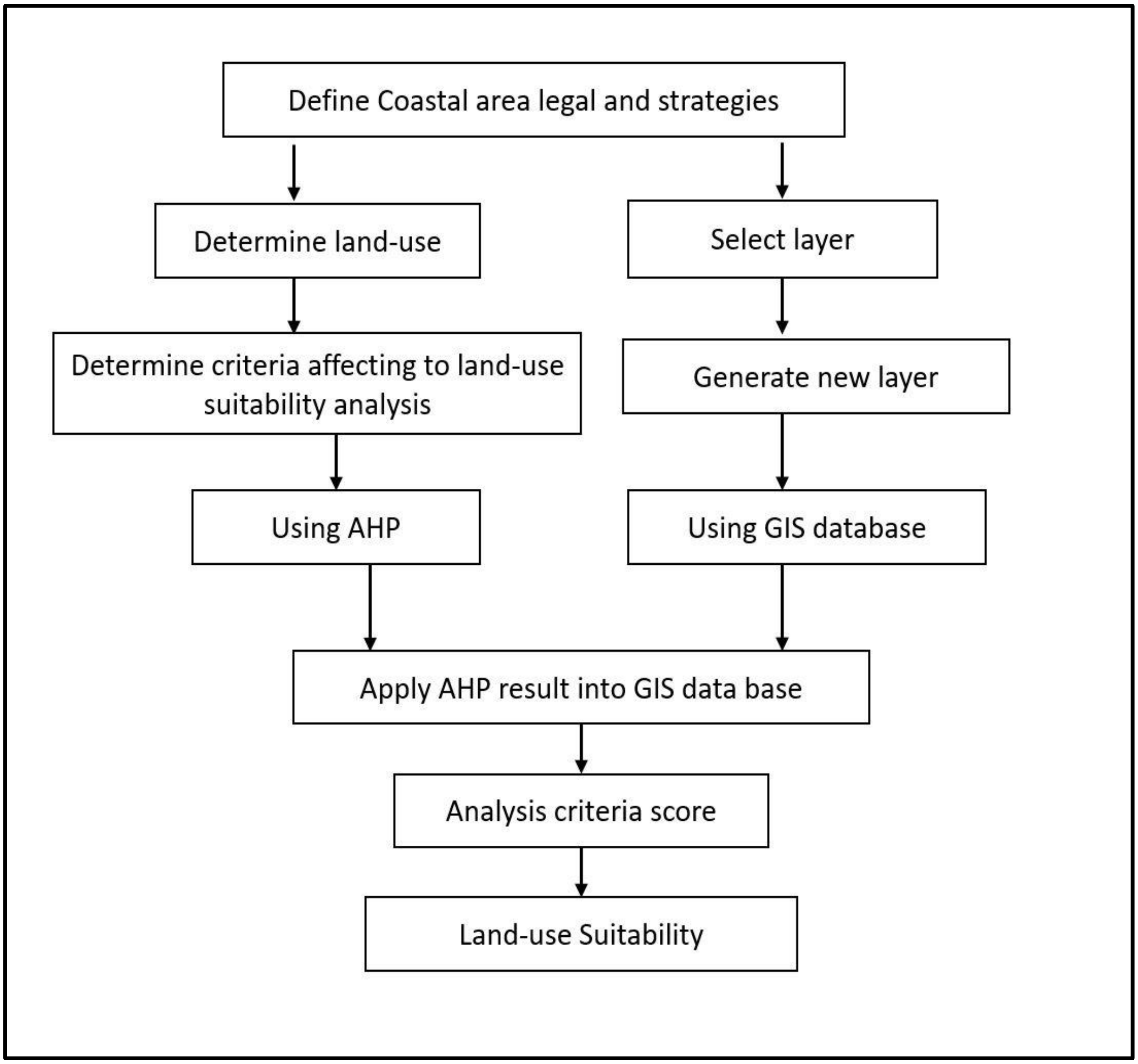

Figure 1. General process of land-use suitability analysis (Bagheri *et al.* 2012).

Map-based approaches can be traced back to the late 19th and early 20th century where simple hand-drawn overlay techniques were used by American landscape architects (Malczewski 2004). In 1950, the Town and Country Planning Textbook was published that included an article by Jacqueline Tyrwhitt that dealt with overlay techniques (Collins *et al.* 2001). The evolution of land suitability analysis continued with Tyrwhitt who specifically dealt with overlay techniques and proposed an example of four maps (relief, hydrology, rock types and soil drainage) that each was drawn on a transparent sheet using the same scale with a common control features (Collins *et al.* 2001). Combining four maps into one that shows land characteristics was a widely accepted overlay technique that was incorporated into planning in Great Britain and North America after the Second World War (Collins *et al.* 2001, Malczewski 2004). During the late 60s and 70s the application of suitability analysis became more popular as more diverse disciplines were involved and also the growth of computing technologies that helped to increase the amount of mapped data (Collins *et al.* 2001). One of the most significant improvements in computer-based application took place at Harvard University. Howard Fisher in 1963, developed a program called SYMAP (Synagraphic Mapping System) that was able to overprint multiple results to create suitable gray scales. The program was widely used at the Laboratory for Computer Graphics at the Harvard University (Collins *et al.* 2001). Progress in computer science immensely contributed to the formal development of GIS (Joerin *et al*. 2001).

After the development of GIS, it rapidly became an important tool for monitoring land change on both small and large scale (Bagheri *et al*. 2012). As of today, modern computers and advanced GIS software make land suitability analysis even more feasible and commonly used for land use planning. However, in almost every situation, assigning relative weight for each defined criterion is particularly difficult, especially when it comes making a decision for a proposed land-use, based only the suitability map (Duc 2006). Thus, adopting Analytical Hierarchy Process (AHP) for such analysis to help decision makers and environmental managers is indispensable.

Multi-Criteria Decision Making (MCDM)

Decision making problems are important in all aspect of life. Multi-Criteria Decision Making (MCDM) or also known as Multi-Criteria Decision Analysis (MCDA) became widely used in the last decades. The technique Multi-Criteria Decision Making (MCDM) is a branch of decision making which basically deals with the process of making decisions in the presence of multiple objectives (Pohekar and Ramachandran 2003). MCDM is the major class of operation research model that is divided into multi-objective decision making (MODM) and multi-attribute decision making (MADM), where each of the two subclasses have multiple methods including priority based, outranking, distance based and mixed methods (Pohekar and Ramachandran 2003). Often used MCDM methods are Multi-Attribute Utility Theory (MAUT), Analytic Hierarchy Process (AHP), Fuzzy Set Theory, Case-based Reasoning (CBR), Data Envelopment Analysis (DEA), Simple Multi-Attribute Rating Technique, PROMETHEE, and ELECTRE, etc. (Velasquez and Hester 2013, Sagbansua and Balo 2017). These approaches were developed to provide solutions for problems occurring in conflict of multi-objectives (Sagbansua and Balo 2017). Fuzzy set theory for instance, in a GIS environment where uncertainty appears in spatial analysis, is known to be more than useful in land-use plan and land suitability analysis (Murgante and Casas 2004). This is called fuzzy logic, a form of multi-valued logic which was derived from fuzzy set theory. It is an approach that transforms a spatial entity to a common suitability scale based on the possibility of being in a membership [1] or not [0] (Abbaspour *et al.* 2011). Lack of information, uncertainty, and complexity are the essential factors that led the adoption of fuzziness in many fields. In recent decades, multi-criteria analysis has been applied to a variety of areas by decision makers that include but not limited to water and agriculture management, evaluation of technology investment, integrated manufacturing systems, and energy planning (Pohekar and Ramachandran 2003).

Analytical Hierarchy Process (AHP)

Analytical Hierarchy Process (AHP) was developed by Thomas L. Saaty (Saaty 2008). The principle of this process is to break down a complex problem into a hierarchy with goal (objective) at the top of the hierarchy followed by criteria and sub-criteria at sub-level and decision alternatives at the bottom of the hierarchy (Pohekar and Ramachandran 2003, Bagdanaviciute and Valiunas 2012). The method is considered one of the most popular MCDM methods (Messaoudi *et al.* 2019). As any method, AHP has its advantages and disadvantages. Advantages begin with the ease of use, followed by its major characteristic, the pair-wised comparison (Bagdanaviciute and Valiunas 2012). Pair-wise comparison allows decision makers to assign weights and compare alternatives with respect to the various criteria (Velasquez and Hester 2013, Al-shabeeb 2016). AHP requires data to successfully perform a pair-wise comparison, although it is not as data intensive as the similar popularity of Multi-Attribute Utility Theory (MAUT). Additionally, AHP is scalable and due to its hierarchical structure, it can effortlessly adjust in size to suit different decision problems (Velasquez and Hester 2013). The fundamental scale was created by Thomas L. Saaty (Table 1), that consists of numbers that indicate the relative preferences between two elements. The scale ranges from 1 to 9 where the value of 1 indicates equal importance, 3 moderately more, 5 strongly more, 7 very strongly and 9 is extremely more importance (Saaty 2008 and Bagheri *et al.* 2012). The values 2, 4, 6 and 8 between the odd numbers are allotted to indicate compromise values of importance (Pohekar and Ramachandran 2003, Messaoudi *et al.* 2019)). The method involves calculation and aggregation of the eigenvector until the complex final vector of weight coefficients for alternatives is obtained. Although the simplicity and the ease of use account for advantages, there are some disadvantages of this MCDM method. Since AHP is a pair-wise comparison, it can experience inconsistencies in judgement and ranking the criteria. The inconsistency value should be lower than 0.10. If the value is higher than that, it requires re-evaluation for pair-wise comparisons (Lee 2010). The method has also been exposed to problems with interdependence between criteria and alternatives (Velasquez and Hester 2013).

Table 1. The fundamental scale for pairwise comparison for the analytical hierarchy process (AHP) developed by Thomas L. Saaty (2008).

Intensity of Importance	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgement slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
Reciprocals of above	if activity *i* has one of the above non-zero numbers assigned to it when compared with activity *j*, then j has the reciprocal value when compared with *i*	A reasonable assumption
1.1-1.9	If the activities are very close	May be difficult to assign the best value but when compared with other contrasting activities the size of the small numbers would not be too noticeable, yet they can still indicate the relative importance of the activities

METHODOLOGY

Study Area

The study area covered the entire state of Texas (Figure 2). Texas is the second largest state with roughly 268,600 square miles and joined the United States in 1845 as the 28th state. Texas has diverse climate types that range from arid and semi-arid in the west to humid and subtropical in the east. For the western part of the state, the average annual precipitation ranges from 8” (203 mm) to 20” (508 mm) where the climate exhibits arid or semi-arid conditions. The climate in the eastern part of the state is humid subtropical that results from higher annual average precipitation around 60” (1,524 mm). Generally, there are seven different wind classes (Figure 3), each determined by the wind speed or wind power density. Wind Class I is generally not suitable for utility scale wind turbine application, nor is wind Class II. The first wind class that provides enough wind speed for wind turbines is Class III. Wind speed in Texas varies across the state from the lowest wind Class I at the eastern part, while stronger wind Class VI can be found in the western part of the state. In terms of elevation, the lowest elevation in Texas is 0 ft (0m) along the coast of Gulf of Mexico and the highest at the Guadalupe Peak at 8,751 ft (2,667 m). The state is ranked as the 17th highest state in The United States in elevation with a mean elevation of 1,706 ft (520 m). Due to rapid wind energy development, Texas is the leading state in the country in terms of installed wind capacity (Parker 2008). As of 2019, the total installed wind capacity in Texas has reached 27,036 MW followed by Iowa with 8,957 MW.

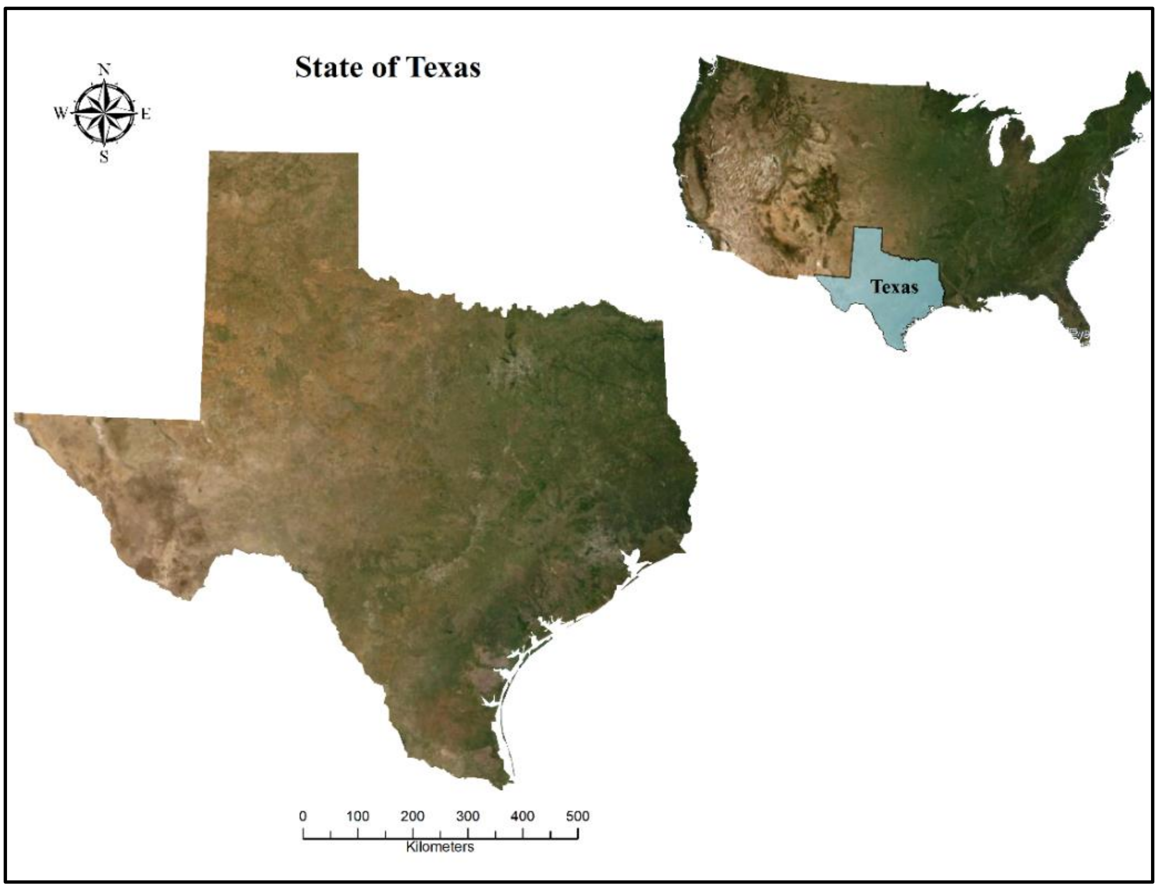

Figure 2. Location map of the study area – Texas.

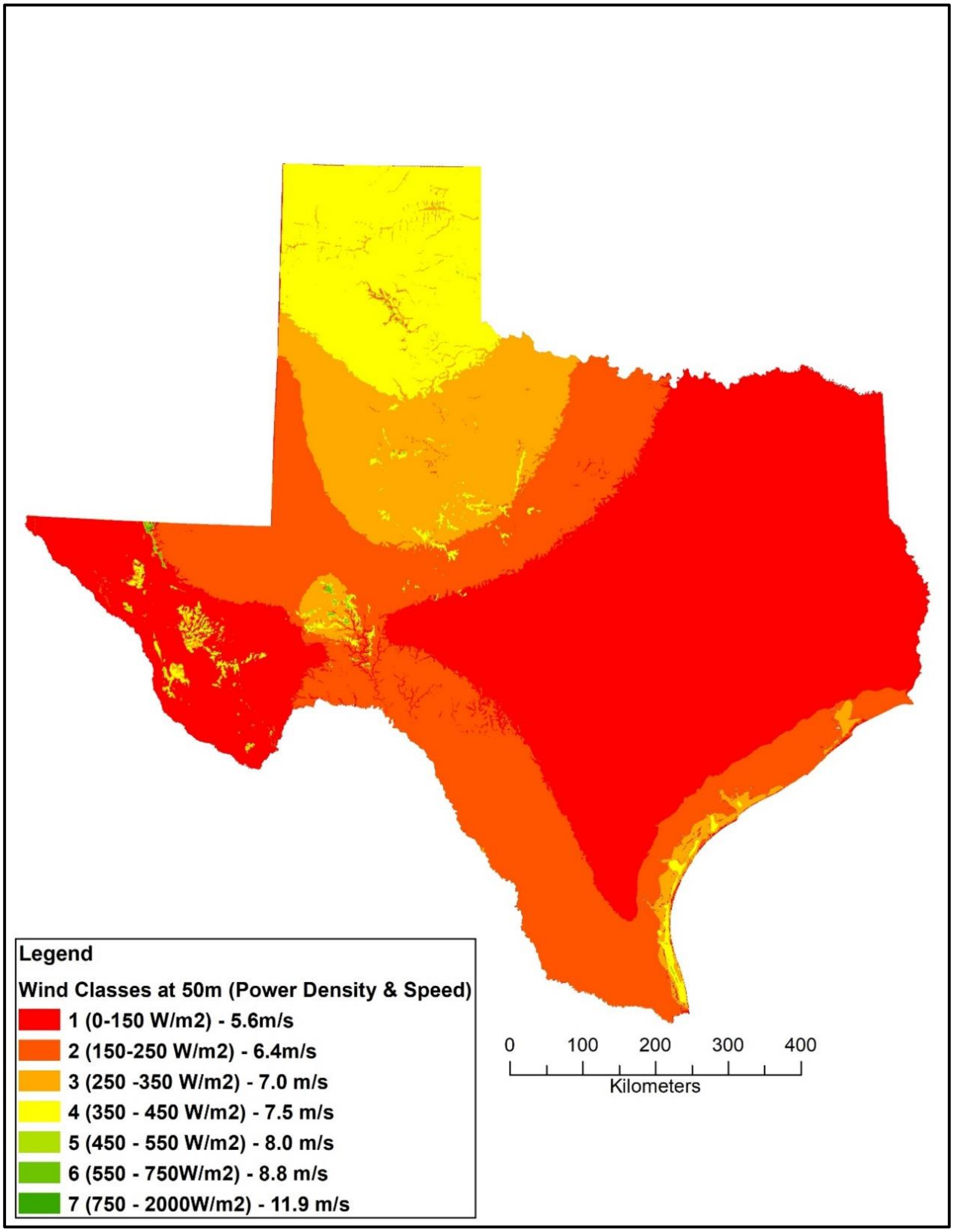

Figure 3. Wind class map of Texas based on National Renewable Energy Laboratory.

Data Acquisition

The analysis consists of eight different datasets where each one of them represents a criterion in considering windfarm development (Table 2). These datasets were obtained from multiple data sources.

Table 2. Source of the eight GIS datasets used for suitability model development.

GIS Data	Criterion	Data Source
Layer 1	Urban	Texas Department of Transportation (TxDOT)
Layer 2	Wildlife	Texas Parks & Wildlife (TPWD)
Layer 3	Airport	Texas Natural Resources Information System (TNRIS)
Layer 4	Highway	
Layer 5	River	
Layer 6	Waterbody	
Layer 7	Wind	National Renewable Energy Laboratory (NREL)
Layer 8	Slope	Derived from digital elevation model

The first six datasets (Figure 4) including urban area, wildlife management area, airport, highway, river, and waterbody were used to measure the distance from each object of interest. The urban area dataset was obtained from the Texas Department of Transportation (TxDOT) and must take it into consideration the noise pollution generated by the wind turbines. The Texas Parks & Wildlife (TPWD) website was visited for downloading the wildlife management area dataset. Airport, highway, river, and waterbody datasets were obtained from the Texas Natural Resources Information System (TNRIS). Each dataset was taken into consideration for different reasons. The airport dataset is a crucial criterion that was used to calculate the distance from each existing airport. As a location is farther away from the airports the land becomes more suitable due to safety reasons and also the fact that wind turbines can interfere with signals of aviation radars (Azizi *et al.* 2014). However, on the other hand, highways were taken into consideration as the high transportation costs for wind turbine establishment increases significantly when it is farther away from existing highways (Azizi *et al.* 2014). As the distance increasing from the roads, the land became less and less suitable. River, waterbody, and wildlife management area datasets were used as the object of interest to calculate the distance that later in the analysis was used to create exclusion zone, primarily to minimize environmental impact as well as the risk of collision with birds that could have a negative effect on the population. Wind energy potential dataset was obtained from the National Renewable Energy Laboratory (NREL), which contains the different wind classes and potential energy. There are seven wind power classes based on the mean measured speed. Wind class one ranges from 0 to 5.6 m/s (12.5 mph), wind class two is from 5.6 m/s to 6.4 m/s (14.3 mph), the third wind class is from 6.4 m/s to 7.0 m/s (15.7 mph), wind class four is from 7.0 m/s to 7.5 m/s (16.8 mph), five is from 7.5 m/s to 8.0 m/s (17.9 mph), wind power class six is from 8.0 m/s to

8.8 m/s (19.7), and the wind class seven is from 8.8 m/s to 11.9 m/s (26.6 mph). This dataset is one of the most important criteria in this study, thus the most recently available dataset was acquired to provide an updated information regarding wind speed. The digital elevation model (DEM) was obtained from the Texas Natural Resources Information System (TNRIS) using the National Elevation Dataset of 2013. The elevation surface was then used to derive slope. Slope is also a critical factor that was taken into consideration when it comes to building windfarms. Besides the accessibility issues, abrupt changes in slope can cause turbulence that may affect the wind turbines. Therefore, lands with lower slope is more preferable when it comes to large scale wind turbine application.

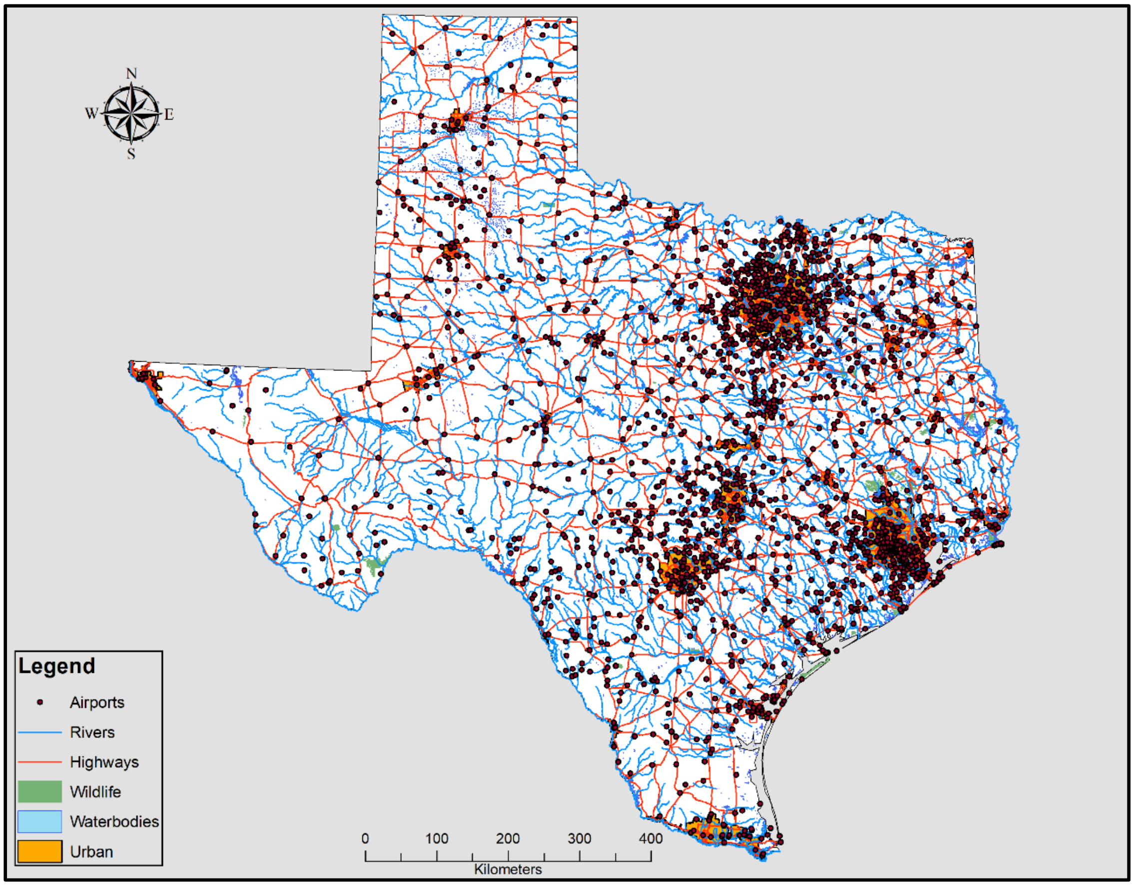

Figure 4. Map of the five criteria, airport, river, highway, wildlife, waterbody, and urban for distance measurement from each object of interest.

Data Preparation

The data preparation was done in ArcCatalog and ArcMap 10.7.1 using several tools in ArcToolbox with enabled extensions of 3D Analyst and Spatial Analyst. Each of the obtained datasets was projected from the default coordinate system to NAD 1983 Texas Statewide Mapping System (Meters) using the Project tool in ArcToolbox. The possibility of encountering problems due to inconsistent coordinate system during the analysis was reduced when all participating datasets were referenced to the same coordinate system. Each GIS dataset was then imported into a file geodatabase to maintain a clean, organized layer for the suitability models. The suitability models were raster based overlay analysis that requires each layer to be a raster dataset. Most of the criteria or layers were originally obtained as a vector dataset (Table 3) that was converted to raster using different tools. Urban areas, wildlife management areas, airports, highways, rivers, waterbodies, and wind classes were originally in a vector format. These dataset besides the wind classes were then used to calculate each cells distance to the closest source or the boundary of Texas using the Euclidian Distance tool. The processing extent was set to the state of Texas boundary shapefile. Each dataset was then set to have the same output cell size, which was 150 by 150 meter (492.13 by 492.13 feet) indicating a general level of detail for the entire state of Texas. The purpose of using this resolution for the raster analysis was to optimize the suitability on a statewide scale. Wind classes vector dataset was handled differently. The Feature to Raster tool was used (Table 3) to convert the dataset to raster. The field used to assign values to the output raster dataset was the wind classes in the attribute table and the output cell size was 150 by 150 meter as well.

Table 3. Data type and the process for each of the eight criteria for suitability model development.

GIS Data	Description	Default Data Type	Tool used to convert to Raster
Layer 1	Urban	Vector	Euclidian Distance
Layer 2	Wildlife		
Layer 3	Airport		
Layer 4	Highway		
Layer 5	River		
Layer 6	Waterbody		
Layer 7	Wind		Feature to Raster
Layer 8	Slope	Raster	None

The slope raster surface was derived from a Digital Elevation Model (DEM) which was obtained from TNRIS. The cell size of the original DEM raster dataset was 60 by 60 meter (196.85 feet) and it was resampled to cell size of 150 by 150 meter (492.13 feet) to match with the rest of the participating raster datasets representing different criteria. The output measurement for the slope was set to percent.

Weighting

The weighting scores for each criterion was attained through Analytical Hierarchy Process (AHP), by performing a pair-wise comparison. The scores were defined by the intensity of importance developed by Thomas L. Saaty (Saaty 2008). Table 4 shows the pair-wise comparison matrix where each criterion in the rows was compared to each criterion in the column. The score was equal to 1 when criteria in row have equal importance with criteria in column. A score was assigned 3 when criteria in row have moderate, 5 when strong, 7 when very strong and 9 when extreme importance compared to criteria in column. Intermediate values 2, 4, 6, and 8 was used when compromise is needed.

Reciprocal values were assigned if a criterion in row had one of the numbers assigned to it when compared with a criterion in column, then criteria in the column will have the reciprocal value when compared with criterion in the row (Messaoudi *et al.* 2019). Figure 5 shows the distribution of the relative weights for each criterion. Wind class criteria received the greatest weight with a 0.3770 as its importance exceeded all other factors which takes up 38%. The greatest value 8 (Very strong importance) was given to the wind speed when compared to waterbodies and rivers. The second greatest weight was assigned to the slope layer with a calculated 0.2509 that takes up 25% of the overall weights. This is due to the fact that slope plays an important role in wind farm development. Slope affects the wind velocity, can cause accessibility issues when it comes to wind turbine establishment or maintenance, and can cause turbulence that has a negative effect on the turbines. Comparison of highways to other criteria resulted a 0.0672 calculated weigh, which is equal to 7% of the total weights. Urban areas and airports received the same weight, as both criteria are equally important in this study. Both criteria were assigned with a 0.1014 weight, which is the third greatest weights in the matrix. This weight takes up 10% of the overall weights. Comparing wildlife management areas to rivers and waterbodies resulted in a greater importance over those criteria. The goal was to lower the risk of collision with birds that could reduce the population by assigning greater values to result a slightly higher weight. The calculated weights for the wildlife management area factor was 0.0443 which is equal to 4% of the total weights. Rivers and waterbodies were determined to be equally important considering wind farm development. Both criteria have received the lowest weights in the matrix with a 0.0288 value. This number is equal to 3% of the total weights. Summing the weights together resulted precisely 1.000 (100%), which means during a series of calculation there was not a single decimal dropped by rounding error.

Table 4. Process of weighting and scores assignment to each criterion for suitability model development.

Decision Parameters (Criterion)	1. Urban	2. Airport	3. Highway	4. Waterbody	5. River	6. Wildlife	7. Slope	8. Wind	Weight Score
1. Urban	1	1	2	4	4	3	1/4	1/5	**0.1014**
2. Airport	1	1	2	4	4	3	1/4	1/5	**0.1014**
3. Highway	1/2	1/2	1	3	3	2	1/5	1/6	**0.0672**
4. Waterbody	1/4	1/4	1/3	1	1	1/2	1/7	1/8	**0.0288**
5. River	1/4	1/4	1/3	1	1	1/2	1/7	1/8	**0.0288**
6. Wildlife	1/3	1/3	1/2	2	2	1	1/6	1/7	**0.0443**
7. Slope	4	4	5	7	7	6	1	1/3	**0.2509**
8. Wind	5	5	6	8	8	7	3	1	**0.3770**
Total									**1.0000**

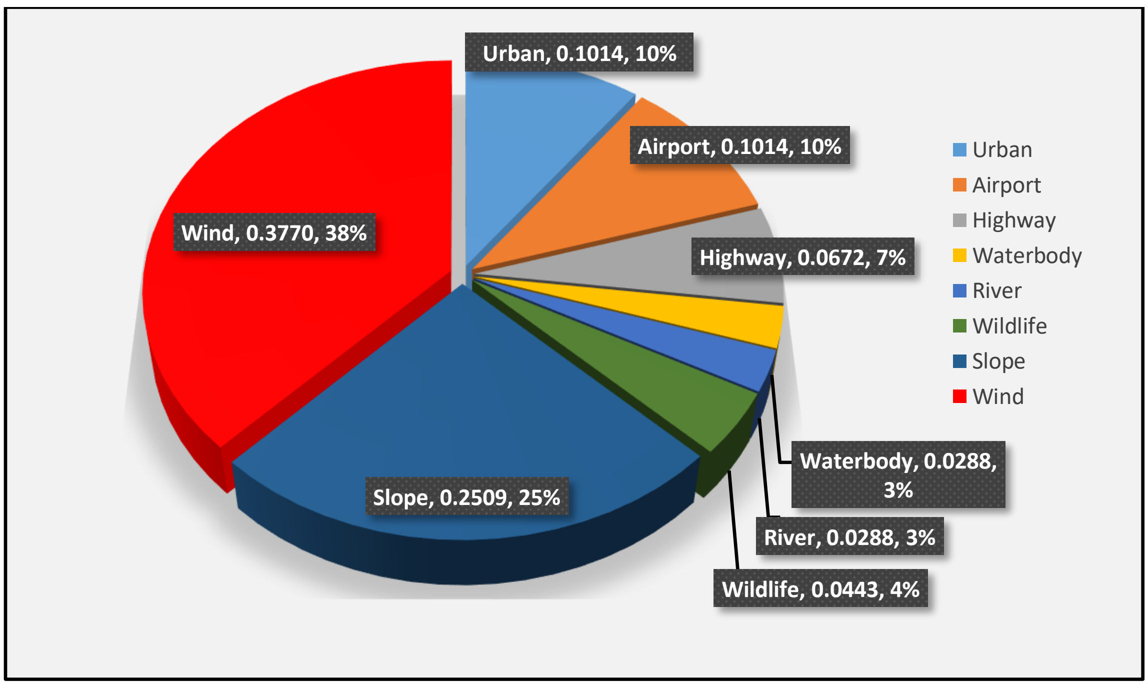

Figure 5. Weight assigned to each criterion for suitability model development derived from analytical hierarchy process (AHP).

The development of the comparison matrix (Table 4) was followed by assessing the Consistency Ratio (CR). AHP strongly depends on the consistency ratio and it should be less than 0.1. Thus, CR was calculated to check whether the weights are experiencing inconsistency (Saaty 1987). If the CR value is greater than 0.1, the final weights cannot be established and must be reassigned (Saaty 1987, Boroushaki and Malczewski 2007).

The equation for the consistency ratio (CR) is defined as follows:

$CR = \frac{\mathrm{CI}}{RI}$, where CI is the consistency index which is calculated by the equation of: $CI = \frac{\gamma_{max} - \mathrm{n}}{\mathrm{n} - 1}$, and RI is a random consistency index value and it was created by Saaty. γ_{max} is the maximum eigenvalue of the matrix and the n is the number of elements. Table 5 shows a summary of each calculated value from the equation above. The study conducted by Saaty and Tran (2007) includes the complete calculation of CR and the random index which was demonstrated in a form of a table. In Table 6, the random index value was determined to be 1.40 based on the number of criteria, which has a total of eight. Lambda max was calculated to be 8.32, by averaging the ratio values of total score divided by the weight for each criterion. This was followed by the calculation of consistency index which resulted a 0.046. Given the CI and RI, the calculated consistency ratio was 0.0329 which is less than 0.1. The pair-wise comparison matrix was not experiencing inconsistency throughout the weighing process; thus, reevaluation of the weights was not necessary.

Table 5. The calculation of consistency ration (CR) based on consistency index (CI) and random index (RI) for the participating criteria for suitability model development ratio.

Decision Parameter (Criterion)	Total Score	Weight	Total Score/ Weight
1. Urban	0.839	0.1014	8.271
2. Airport	0.839	0.1014	8.271
3. Highway	0.543	0.0672	8.082
4. Waterbody	0.236	0.0288	8.184
5. River	0.236	0.0288	8.184
6. Wildlife	0.357	0.0443	8.043
7. Slope	2.194	0.2509	8.745
8. Wind Class	3.319	0.3770	8.802
Lambda max:		8.3229	
Consistency Index (CI):		0.0461	
Random Index (RI):		1.4000	
Consistency Ratio (CR):		0.0329	

Table 6. Random index (RI) values by total number of criteria used for suitability model development based on Saaty and Tran 2007.

Order	1	2	3	4	5	6	7	**8**	9	10
RI	0.00	0.00	0.52	0.89	1.11	1.25	1.35	**1.40**	1.45	1.49
First Order Differences		0.00	0.52	0.37	0.22	0.14	0.10	**0.05**	0.05	0.04

Classification

Classification is an important part of a raster based land suitability analysis. Each layer was reclassified through the Reclassify tool in ArcToolbox. As suggested in the study conducted by Bagheri *et al.* (2012), Al-Shalabi *et al.* (2006), and Bennui *et al.* (2007)**,** criteria must be on a standardized scale in order to apply them in an overlay analysis. The scale ranges from 0 to 5, where 0 is the exclusion zone which was done by applying buffer zone around the features before the reclassification process. Score 1 represents Not Suitable (S1) areas, score 2 is Marginally Suitable (S2), score 3 is Somewhat Suitable (S3), score 4 is Moderately Suitable (S4), and score 5 is Highly Suitable (S5). Each class was reclassified based on its importance and also proximity to the source. Source defines the location of the object of interest for instance airports, rivers, highways, urban areas, waterbodies, and wildlife management areas. Table 7 shows that a 2.5km buffer zone was applied for the urban area features representing the exclusion zone. Due to high noise level that these wind turbines generate and controversy about the aesthetics, it is a common practice to install them in rural areas. As the distance increases from a feature, it becomes more suitable. Table 8 demonstrates the applied buffer zone for the airport locations in Texas, as well as the different categories based on the distance. Table 9 shows the correspondent categories with the associated distance values for the highway criterion. This layer was reclassified the other way around. Considering economics and transportation cost, it is crucial to have a highway or road nearby a wind farm. Thus, the closer the wind turbines to the highway, the more suitable the land is. Table 10 and 11 shows the different categories for rivers and water bodies, respectively. Both layers were classified the same way, considering environmental factors such as preserving the natural habitats for various species. Wildlife management areas received a 2.5 km buffer zone that serves as the exclusion zone (Table 12). These areas consist higher diversity when it comes to species, thus increasing the exclusion zone is logical. Table 13 Shows the classification for the slope criterion. As the highway feature class, slope was classified based on the same logic. The less percentage the slope is, the more favorable the land becomes. Slope is an important factor regarding wind turbines, as it can affect the wind direction and velocity. Wind speed or wind power density was the last criterion reclassified. The original seven wind classes from the National Renewable Energy Laboratory were reclassified into only five categories. Extremely high wind speed (Class 6 and 7) received score five, Class 5 received score 4, and Class 4 and 3 were assigned to have a score of 3. The last two original wind classes were not reclassified (Table 14).

Table 7. Suitability classification on urban area data for model development.

Urban			
Category	Distance (km)	Score	Class
1	0.0 - 2.5	0	Exclusion Zone
2	2.5 - 3.5	1	Not Suitable (S1)
3	3.5 - 4.5	2	Marginally Suitable (S2)
4	4.5 - 5.5	3	Somewhat Suitable (S3)
5	5.5 - 6.5	4	Moderately Suitable (S4)
6	> 6.5	5	Highly Suitable (S5)

Table 8. Suitability classification on airport data for model development.

Airport			
Category	Distance (km)	Score	Class
1	0.0 - 3.0	0	Exclusion Zone
2	3.0 - 6.0	1	Not Suitable (S1)
3	6.0 - 9.0	2	Marginally Suitable (S2)
4	9.0 - 12.0	3	Somewhat Suitable (S3)
5	12.0 - 15.0	4	Moderately Suitable (S4)
6	> 15.0	5	Highly Suitable (S5)

Table 9. Suitability classification on highway data for model development.

Highway			
Category	Distance (km)	Score	Class
1	1.0 - 2.0	5	Highly Suitable (S5)
2	2.0 - 3.0	4	Moderately Suitable (S4)
3	3.0 - 4.0	3	Somewhat Suitable (S3)
4	4.0 - 5.0	2	Marginally Suitable (S2)
5	5.0 - 6.0	1	Not Suitable (S1)
6	> 6.0	0	Exclusion Zone

Table 10. Suitability classification on river data for model development.

River			
Category	Distance (km)	Score	Class
1	0.0 - 0.4	0	Exclusion Zone
2	0.4 - 0.8	1	Not Suitable (S1)
3	0.8 - 1.2	2	Marginally Suitable (S2)
4	1.2 - 1.6	3	Somewhat Suitable (S3)
5	1.6 - 2.0	4	Moderately Suitable (S4)
6	> 2.0	5	Highly Suitable (S5)

Table 11. Suitability classification on waterbody data for model development.

Waterbody			
Category	Distance (km)	Score	Class
1	0.0 - 0.4	0	Exclusion Zone
2	0.4 - 0.8	1	Not Suitable (S1)
3	0.8 - 1.2	2	Marginally Suitable (S2)
4	1.2 - 1.6	3	Somewhat Suitable (S3)
5	1.6 - 2.0	4	Moderately Suitable (S4)
6	> 2.0	5	Highly Suitable (S5)

Table 12. Suitability classification on wildlife management area data for model development.

Wildlife			
Category	Distance (km)	Score	Class
1	0.0 - 2.5	0	Exclusion Zone
2	2.5 - 3.5	1	Not Suitable (S1)
3	3.5 - 4.5	2	Marginally Suitable (S2)
4	4.5 - 5.5	3	Somewhat Suitable (S3)
5	5.5 - 6.5	4	Moderately Suitable (S4)
6	> 6.5	5	Highly Suitable (S5)

Table 13. Suitability classification on slope data for model development.

Slope			
Category	%	Score	Class
1	> 15	0	Exclusion Zone
2	15 - 9	1	Not Suitable (S1)
3	9 - 7.5	2	Marginally Suitable (S2)
4	7.5 - 5.0	3	Somewhat Suitable (S3)
5	5.0 - 2.5	4	Moderately Suitable (S4)
6	< 2.5	5	Highly Suitable (S5)

Table 14. Suitability classification on wind data for model development.

Wind			
Category	Power (W/m^2)	Score	Class
1	0 - 250	1	Not Suitable (S1)
2	250 - 350	2	Marginally Suitable (S2)
3	350 - 450	3	Somewhat Suitable (S3)
4	450 - 550	4	Moderately Suitable (S4)
5	> 550	5	Highly Suitable (S5)

Suitability Models

Weighted Overlay

The Weighted Overlay model used six datasets, urban, airport, highway, river, waterbody, and wildlife to calculate the distance from the object of interest. Each dataset served as input for the Euclidean Distance tool that describes each cell's relationship to a source that identifies the location of the object of interest. The processing extent in the tool was limited to the state of Texas (Figure 6), thus only calculating the distance within the state boundaries to the nearest feature. The output was a raster dataset (Figure 7) with a cell size of 150 by 150 meter that served as the input for the Reclassify tool. This tool had eight input datasets including the aforementioned six datasets, plus slope and wind. Figure 8 and 9 show the reclassified images derived from Table 7 to 13. This step is crucial in order to create a common scale that serves as the new classes for the Weighted Overlay tool. The scale range was set to one to five where one is the least preferable value and 5 is the most suitable value. Once the new classes were established, the eight raster datasets with common measurement scale were used as the inputs for the Weighted Overlay tool. Weights derived from AHP were assigned to each criterion for this model. The advantage of this tool is the user can define the scaling range with or without the input raster been reclassified already or not. For this Weighted Overlay tool, the evaluation scale may range from 1 to 5 or 1 to 10, or even a custom scale defined by the user, for instance 1 to 7. This option provides a wide range of evolution based on a proposed scenario. For this study, the final suitability raster dataset consisted five index values, where the lowest cell value represented the least suitable areas and the highest cell value the most suitable locations for windfarm development in Texas. This Weighted Overlay process was summarized in Figure 10.

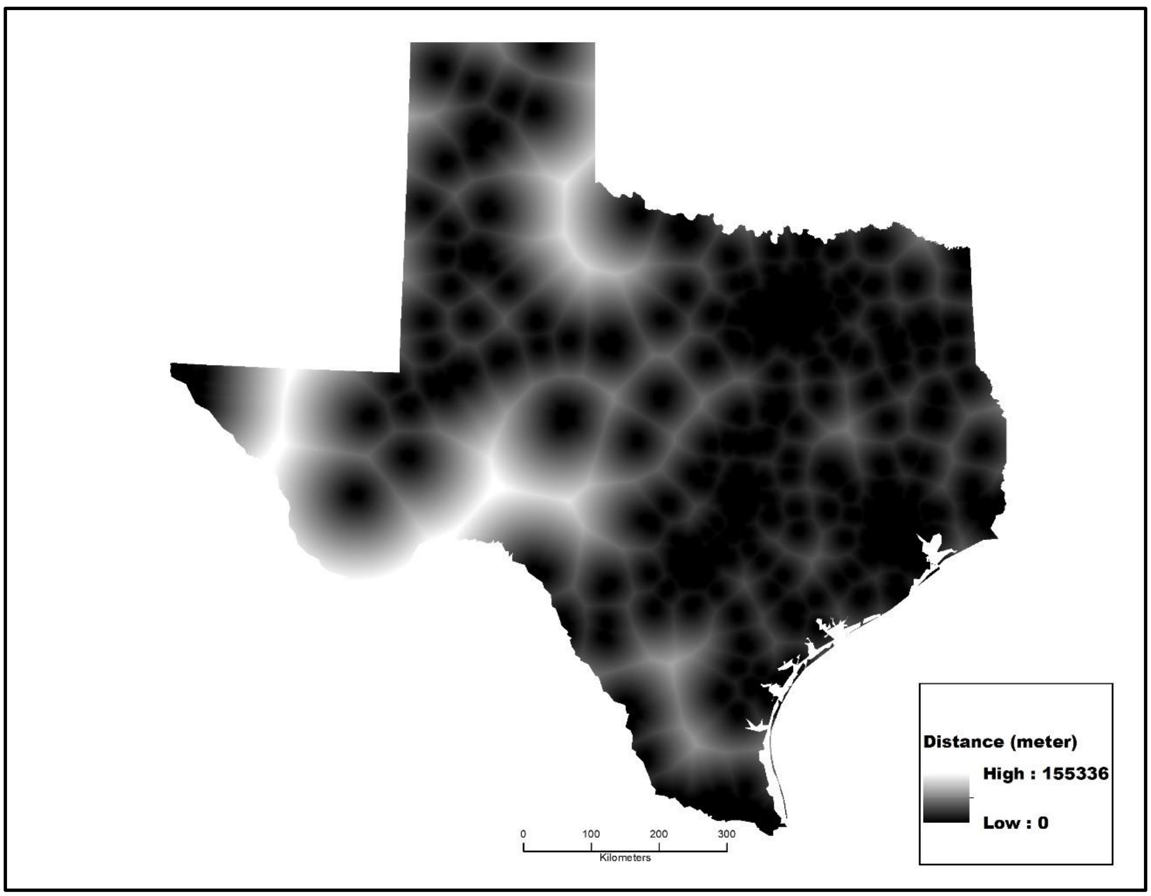

Figure 6. Map showing Euclidean distance from urban areas.

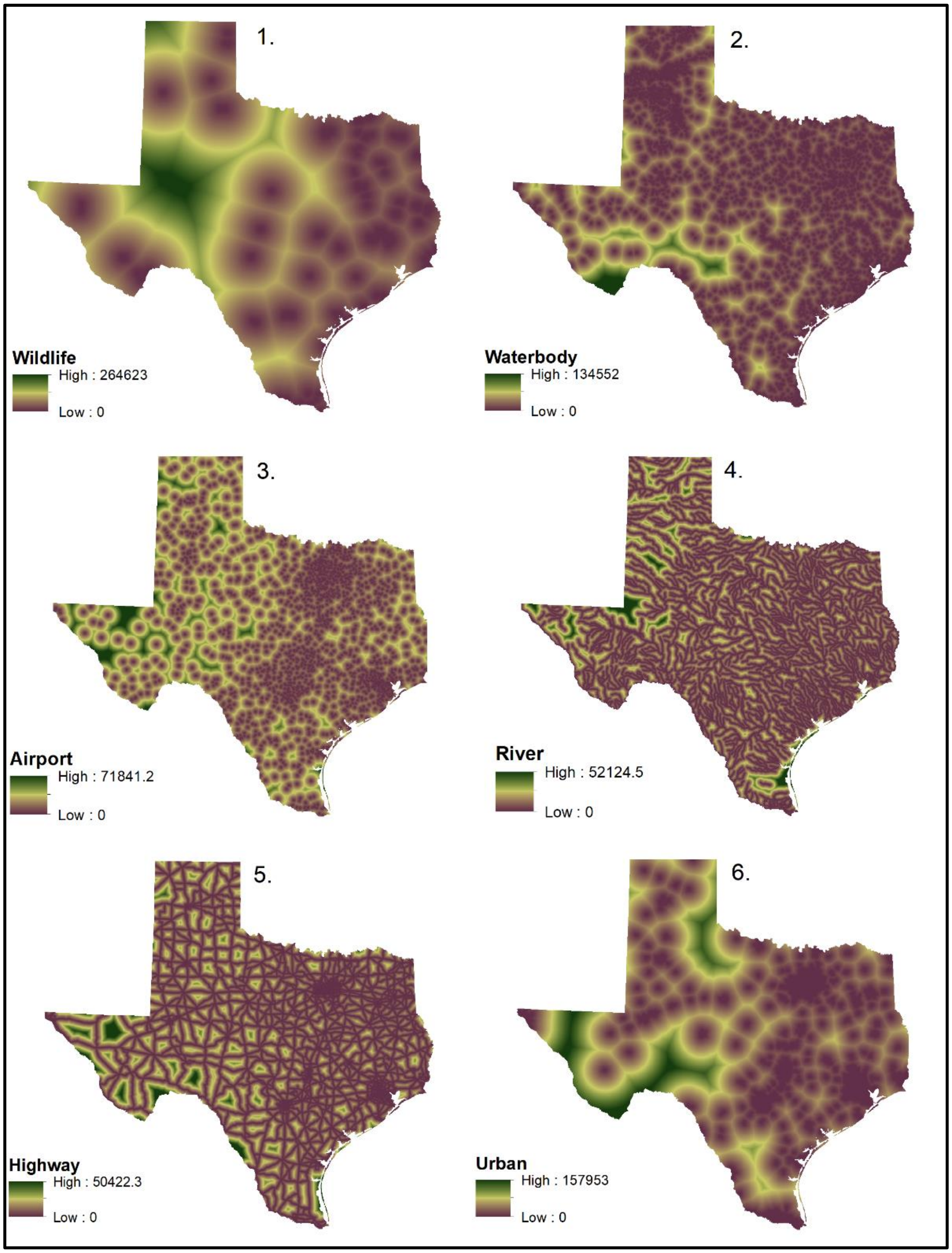

Figure 7. Maps showing Euclidean distance from each feature type: 1. Wildlife, 2. Waterbody, 3. Airport, 4. River, 5. Highway, and 6. Urban.

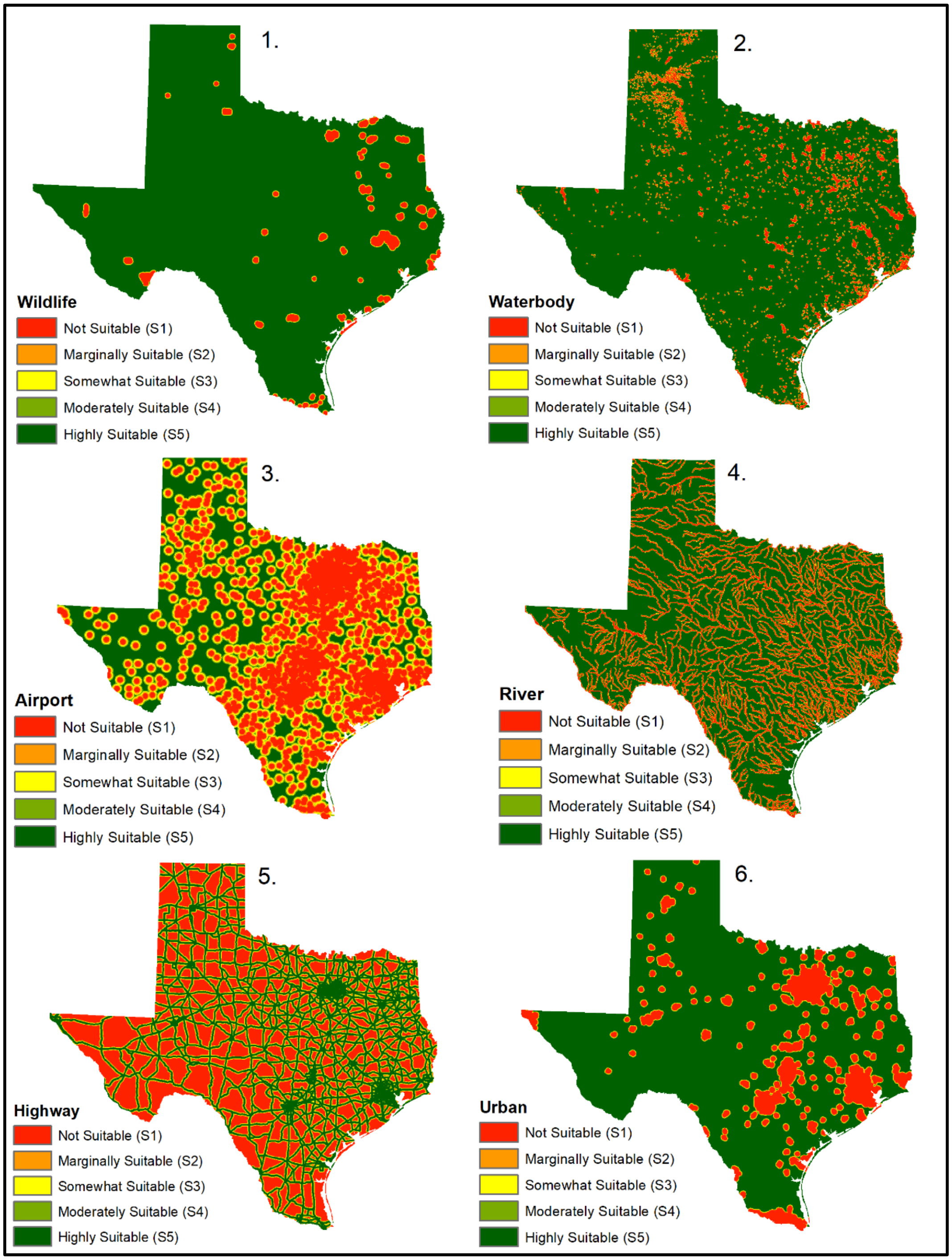

Figure 8. Suitability classification maps derived from Euclidean distance based on each feature type: 1. Wildlife, 2. Waterbody, 3. Airport, 4. River, 5. Highway, and 6. Urban.

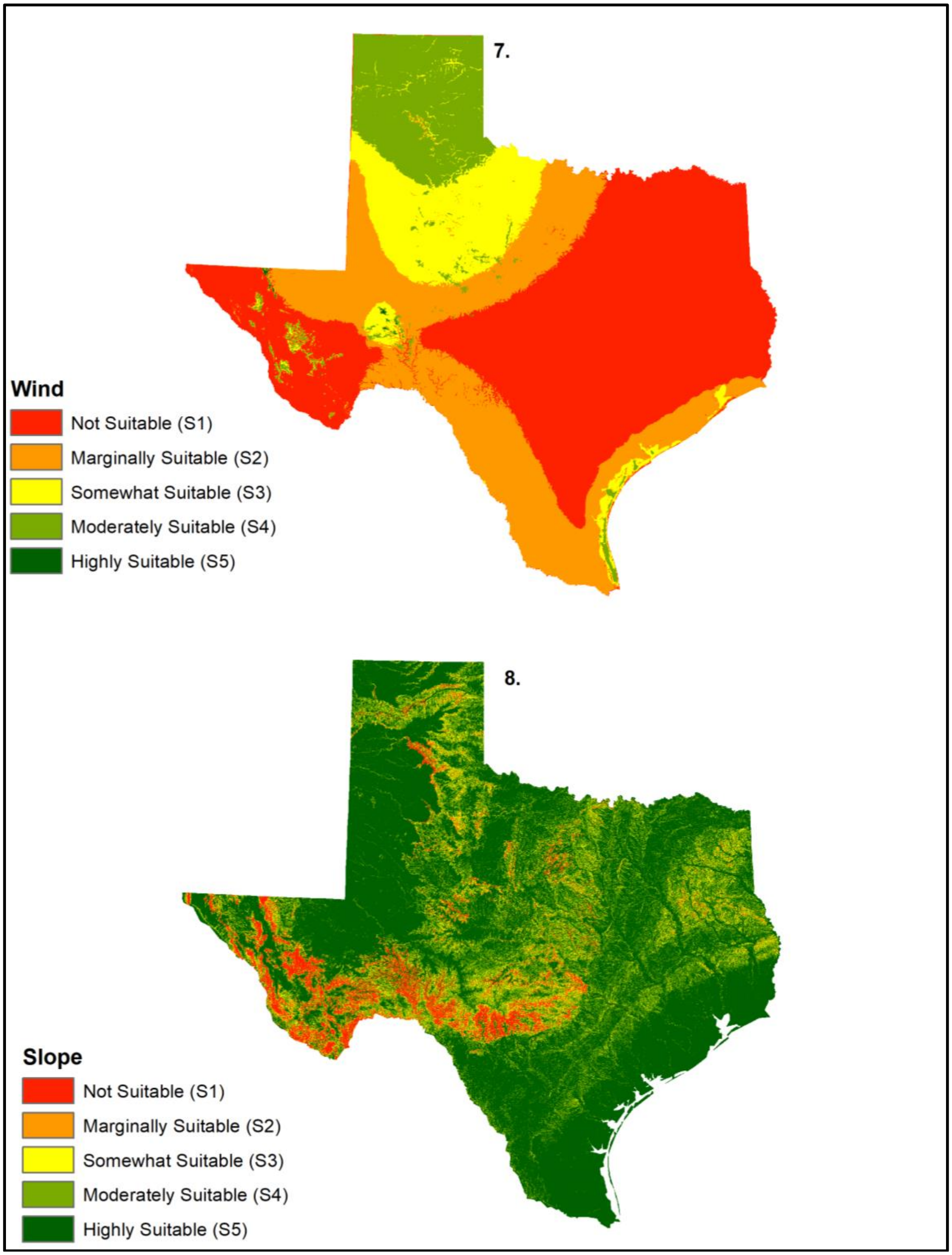

Figure 9. Suitability classification map for the criteria of Wind and Slope.

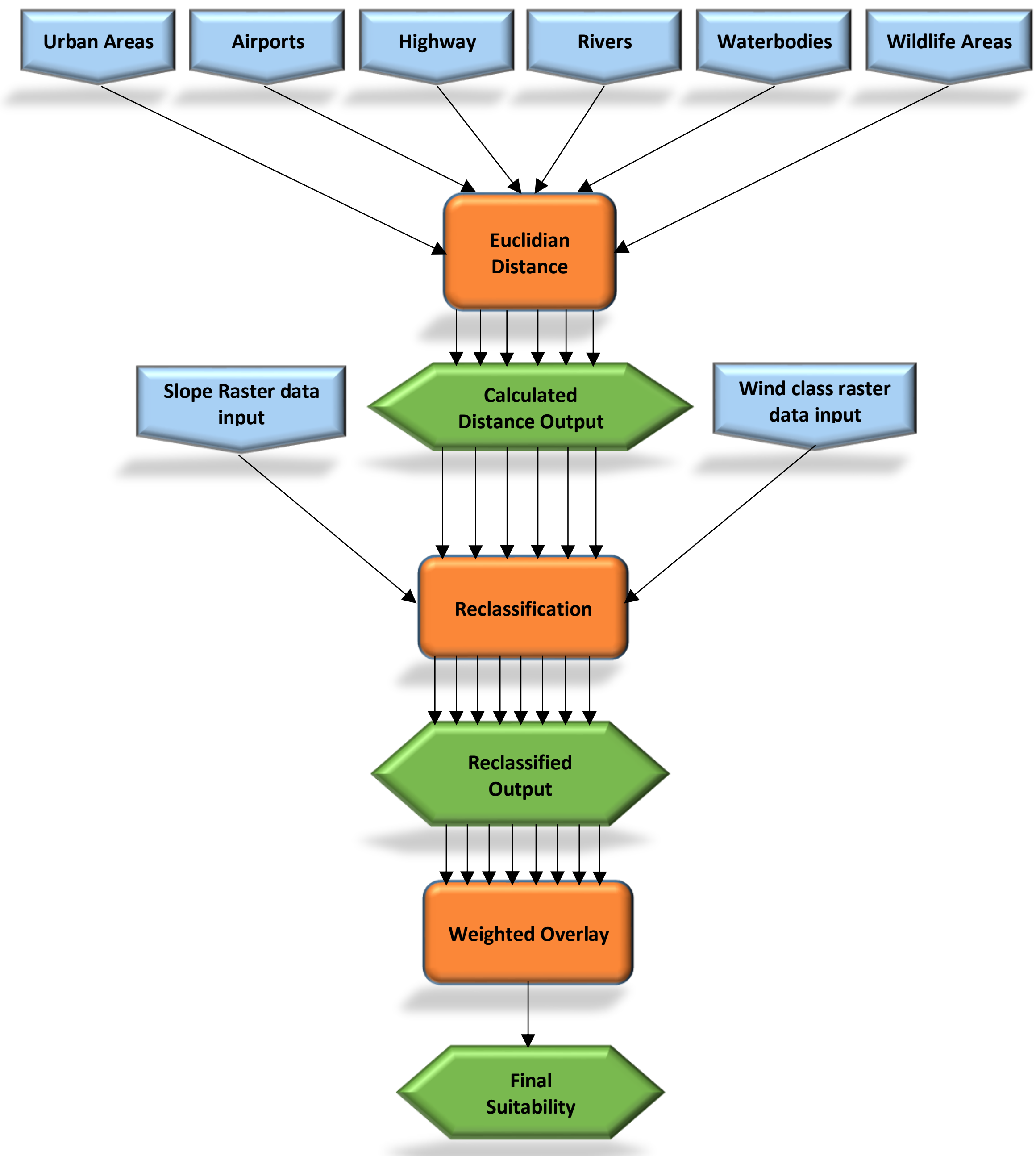

Figure 10. Flow chart of the Weighted Overlay model.

Weighted Sum

The Weighted Sum model (Figure 11) was constructed the same way as the Weighted Overlay in terms of the inputs and process steps involved. However, unlike Weighted Overlay, the Weighted Sum simply adds the pixel values from all of the input raster without any rescaling. First, the six vector datasets were used as input to calculate the distance from the object of interest and converted to raster. Every single input was set to have the same parameters such as output cell size and processing extent as the Weighted Overlay model. The output from the Euclidean Distance tool resulted 6 raster datasets (Figure 7), each representing range of distance to its closest features within the processing extent. Then each output raster dataset was used to reclassify to create a common scale ranging from one to five, where one represents the least favorable and five is most preferable. The same classification was applied based on the Table 7 to 13. These reclassified raster datasets served as the inputs for the Weighted Sum model, which weighs each input raster based on the same Analytical Hierarchy Process (AHP). This Weighted Sum tool executed a pixel by pixel map algebra by summing the weighted pixel values together. The output suitability map was reclassified to maintain the five suitability categories for windfarm development.

Data classification methods are playing a significant role on the output suitability map. Each methods are based on different approach in terms of classifying numerical fields for graduated symbology which is considered to be the core of a suitability map. Manual interval, defined interval, equal interval, quantile, natural breaks (Jenks), geometrical interval, and standard deviations are the available classification methods in ArcGIS. To match the five suitability class resulted by the Weighted Overlay, natural breaks (Jenks) was used to reclassify the output suitability map generated by Weighted Sum. This classification method is based on natural groupings inherent in the data. Thus, breaks are selected to differentiate between values where large changes in value occur. The natural breaks method seeks to reduce the variance within classes and maximize the variance between classes. Each output from the suitability models were based on this classification method to eliminate inconsistencies between the suitability maps.

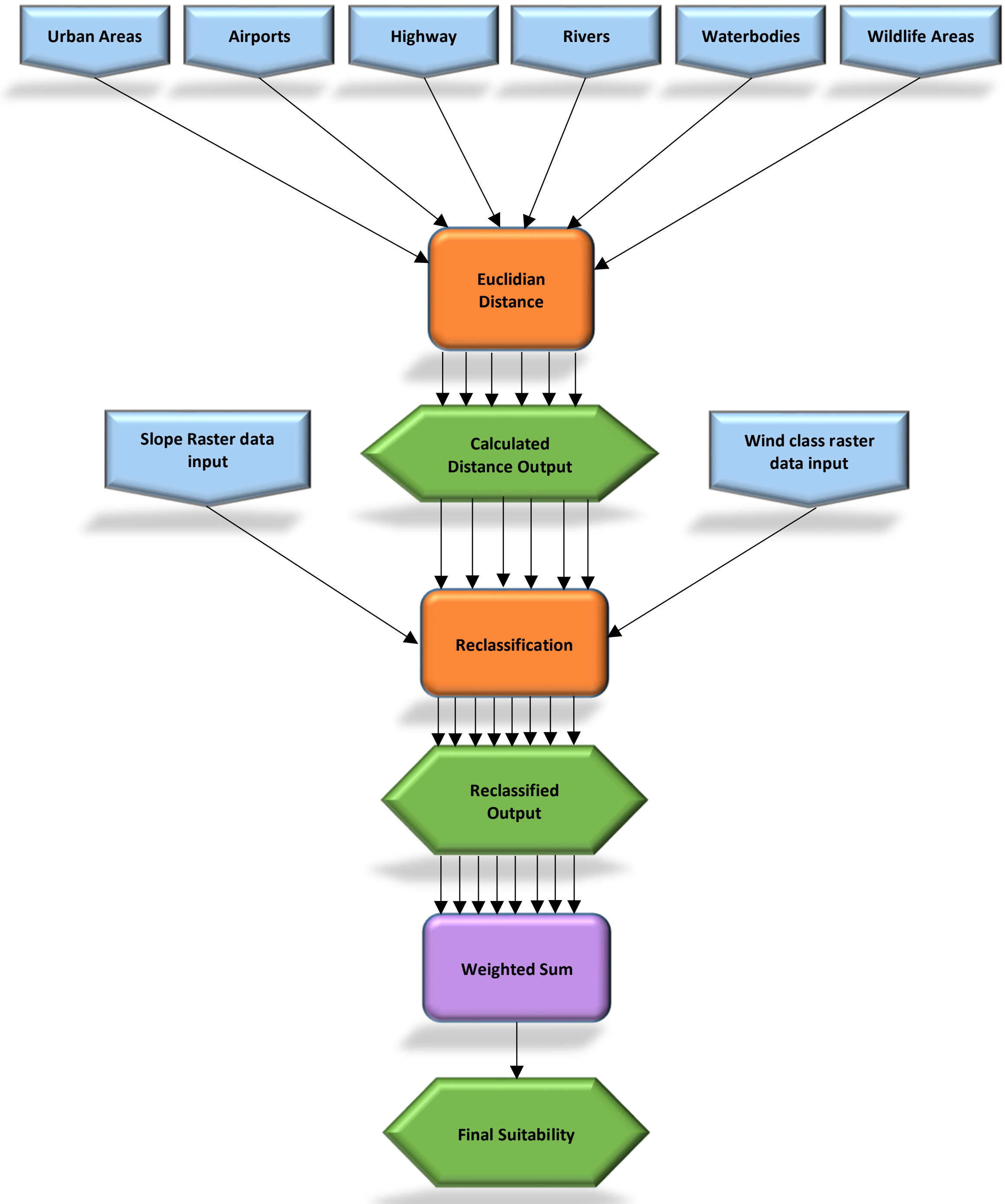

Figure 11. Flow chart of the Weighted Sum model.

Fuzzy Overlay

The third model was the Fuzzy Overlay (Figure 12). The data preparation of the six vector criteria was the same as the Weighted Overlay and Weighted Sum models. Euclidian distance tool was used to calculate each layer's cell values representing the distance to the nearest feature of a certain type. However, this model did not require classification on the distance raster datasets. Instead, each pixel is assigned a fuzzy membership value through fuzzy logic based on the possibility of a pattern or phenomenon belonging to multiple sets in a multicriteria overlay analysis. Thus, Fuzzy Membership tool replaced the Reclassify tool. This tool converted the input raster into a 0 to 1 scale, indicating the strength of the membership in a set (Figures 13 and 14). Value 0 indicates that the member is not part of the fuzzy set, and value 1 indicates full membership in the fuzzy set. The membership types were manipulated in different ways to observe different outcomes from the analysis. Each output raster from the Fuzzy Membership process was then used to serve as the input for the Fuzzy Overlay tool. This tool combines multiple fuzzy membership raster data together based on the selected overlay type, determined by the user. The available fuzzy types are And, Or, Product, Sum, and Gamma.

The first fuzzy model (Method One) was based on a forward approach, which means where the distance was increasing in some layer, the cell values become more favorable. Six datasets including river, airport, urban, wildlife, and wind were set to Large membership type as shown in Table 15. Highway and slope on the other hand, were assigned with a Small membership type. This was crucial because the aforementioned layers must be classified the other way around as the lower distance is more favorable in highways as well as lower slope percentage. The midpoints were set to the layer's maximum distance divided by two. This means, when the set midpoint was reached, a 0.5 membership value was assigned. The spread was set to default value of five. The overlay analysis was divided into three part. The first part was concerned about five datasets (urban, wildlife, waterbody, river, and airport). These layers were calculated using the SUM function in the Fuzzy Overlay tool. This is an increasive function as the combination of the inputs was more important than each of them alone. This was followed by another Fuzzy Overlay process on the two-dataset assigned with small fuzzy membership, highway and slope. The PRODUCT function was used as it is a decreasive function. Finally, a third Fuzzy Overlay was applied to the precious two outputs and the last criterion, wind. The SUM function was used preferring higher cell values to emphasize the importance of the wind. The output suitability map was then reclassified as fuzzy overlay converts the inputs into a 0 to 1. Thus, natural breaks (Jenks) classification was used to reclassify the output into five categories to match the output of the Weighted Overlay and Weighted Sum, where value one represents Not Suitable (S1) and five is Highly Suitable (S5).

Table 15. Parameters of the fuzzification process for Method One of the Fuzzy Overlay.

Fuzzy Membership			
Criteria	**Membership type**	**Midpoint**	**Spread**
Urban (m)	Large	77668.0	5
Wildlife (m)	Large	131008.5	5
Airport (m)	Large	34412.7	5
Highway (m)	Small	24993.0	5
River (m)	Large	25877.2	5
Waterbody (m)	Large	67125.0	5
Wind	Large	3.5	5
Slope (%)	Small	107.2	5

The second method of Fuzzy Overlay (Method Two) introduced a reverse approach. Table 16 shows the input values for fuzzification. The six datasets that were used to assign Large membership type in the Method One, now received a Small membership. Highway and slope criteria received a Large membership. Each layer used the same midpoint values as in the previous method. The maximum distance values were divided by two, in order to calculate the midpoint. The spread parameter was set to value two, which represents the shape and the transition zone of a fuzzy membership. The lower the spread value, the slower the transition will be from 0 to 1. This overlay analysis was also divided into three parts. The first part was concerned about the first six datasets assigned with the same membership type. Urban, wildlife, waterbody, wind, river, and airport were added to the Fuzzy Overlay by using AND function to calculate the minimum values of the input memberships. This was supported by the input values as they were utilizing Small membership types. The second part dealt with the two datasets using Large membership types, highway, and slope. The OR function was used in order to receive the maximum value from both inputs. Finally, the SUM function was used on the last Fuzzy Overlay having two inputs from the first two parts.

Table 16. Parameters of the fuzzification process for Method Two of the Fuzzy Overlay.

Fuzzy Membership			
Criteria	**Membership type**	**Midpoint**	**Spread**
Urban (m)	Small	77668.0	2
Wildlife (m)	Small	131008.5	2
Airport (m)	Small	34412.7	2
Highway (m)	Large	24993.0	2
River (m)	Small	25877.2	2
Waterbody (m)	Small	67125.0	2
Wind	Small	3.5	2
Slope (%)	Large	107.2	2

The third fuzzy model (Method Three) was based on the same approach as Method One. However, instead of using Small and Large membership types, each layer was assigned with MSLarge or MSSmall depending whether large or small pixel values were preferable. Table 17 shows the parameter values of the third approach. Where higher pixel values were favorable, MSLarge membership type was assigned. Mean multiplier and standard deviation multiplier were set to one. This was the default value. As the previous approaches, this one was divided into three parts as well. The first was focusing on assigning MSLarge membership type for the six datasets where larger values were favorable. SUM function was used in the Fuzzy Overlay process because the combination of all layers was more important than each of them alone. Highway and slope were assigned with MSSmall membership type as smaller the pixel values, more preferable the location is. These two criteria were input to a second Fuzzy Overlay process by using the PRODUCT function. Finally, a third Fuzzy Overlay process was applied to the outputs from the first two parts using the SUM function, to emphasize the increasive approach for this analysis. The output suitability map was then reclassified based on natural breaks (Jenks) from one to five.

Table 17. Parameters of the fuzzification process for Method Three of the Fuzzy Overlay.

Fuzzy Membership			
Criteria	**Membership type**	**Mean multiplier**	**Standard deviation multiplier**
Urban	MSLarge	1	1
Wildlife	MSLarge	1	1
Airport	MSLarge	1	1
Highway	MSSmall	1	1
River	MSLarge	1	1
Waterbody	MSLarge	1	1
Wind	MSLarge	1	1
Slope	MSSmall	1	1

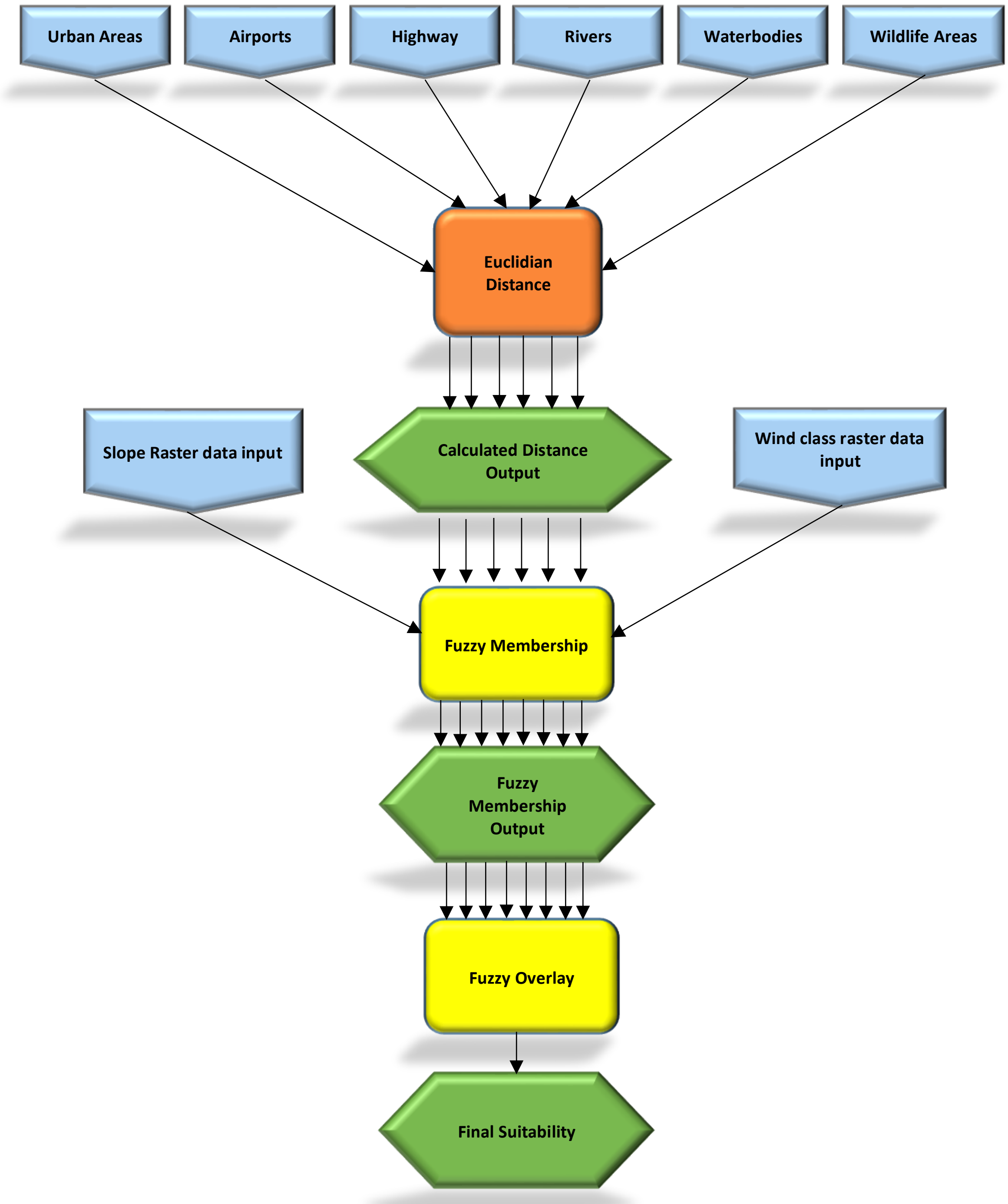

Figure 12. Flowchart of the Fuzzy Overlay model.

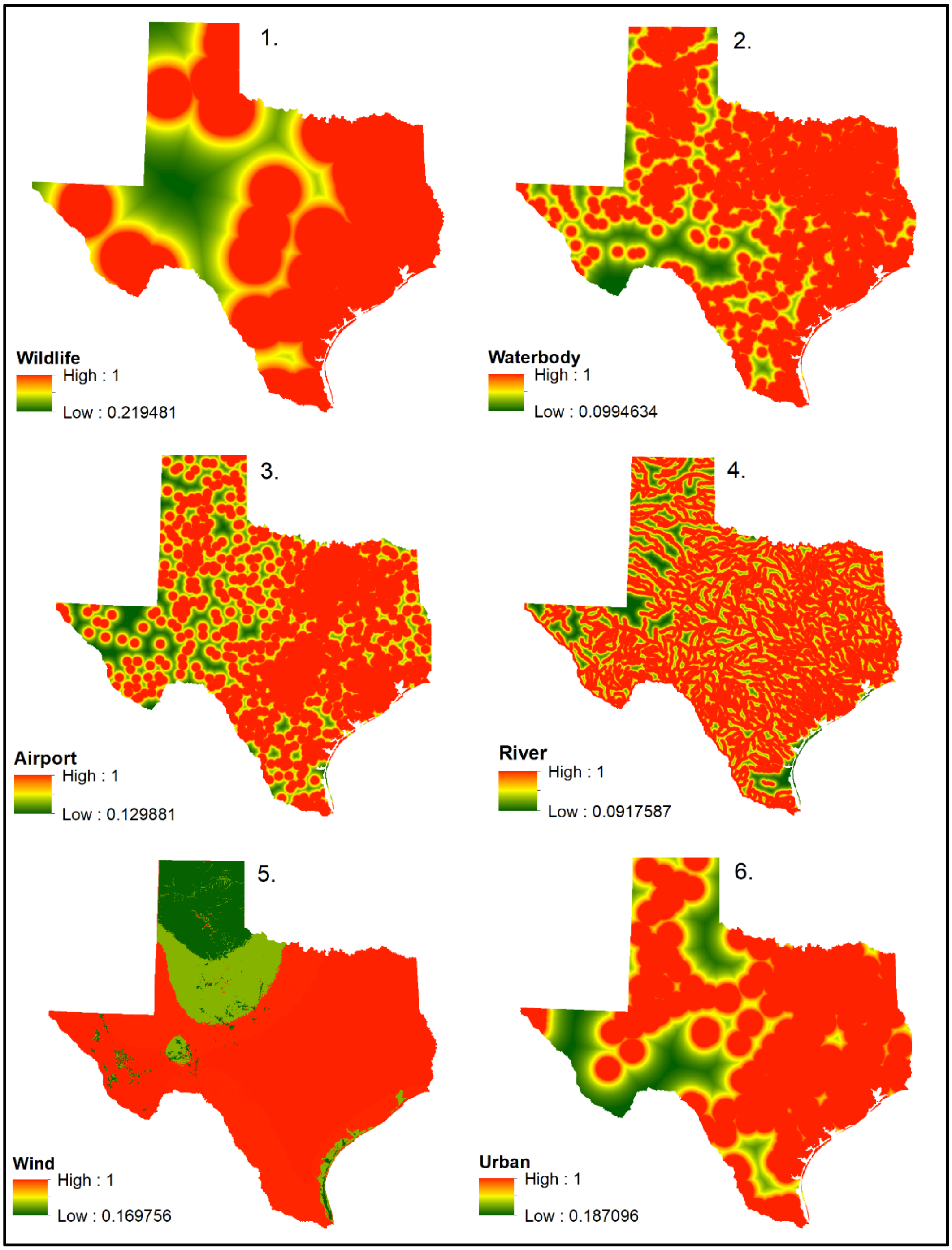

Figure 13. Maps of assigned fuzzy membership using Small membership type for each feature type: 1. Wildlife, 2. Waterbody, 3. Airport, 4. River, 5. Wind, and 6. Urban.

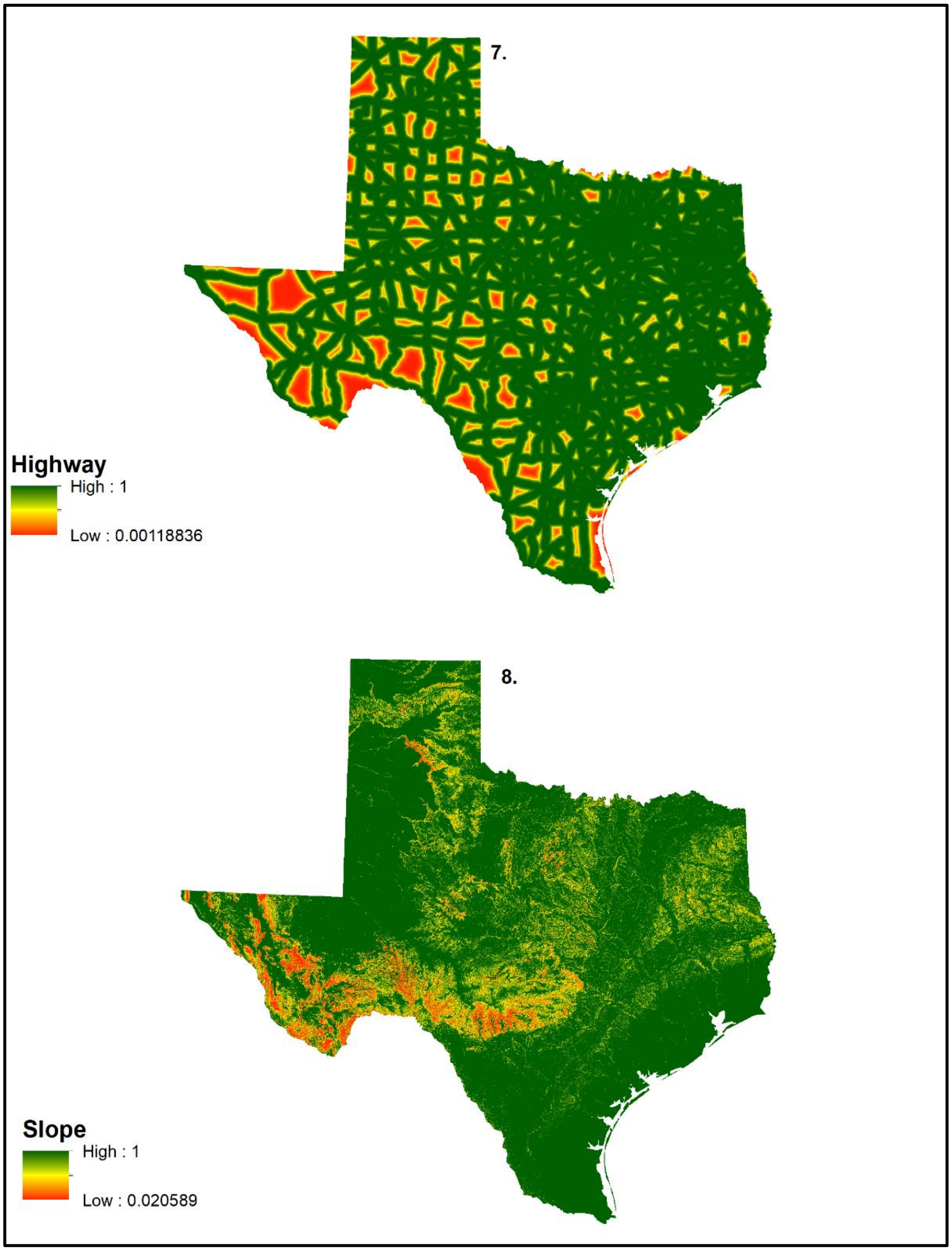

Figure 14. Maps of assigned fuzzy membership using Large membership type for the criteria of Highway and Slope.

Accuracy Assessment

The validation was done by using a point shapefile obtained from the U.S Wind Turbine Database, which shows the existing wind turbine locations across the United States. The point features were clipped to the state of Texas that resulted in a total of 15,230 existing wind turbine locations (Figure 15). This step was followed by overlaying each raster suitability map with the validation dataset. The output rater dataset consisted different index values that ranged from 1 to 5. If existing windmill locations show high index values on the suitability map, the analysis is considered accurate. The closer the windmill locations to a high index value pixel, the more accurate the analysis outcome. Each point feature was then populated with the correspondent index value based on the actual location of the existing wind turbine. Extract Multi Values to Points is the tool used to extract the index values from the raster suitability maps overlaid with the validation dataset. The values derived from the tool were exported into Microsoft Excel, where further statistical analysis was conducted. Summary statistics of suitability index from the five overlay model outputs were compared against each other. When an existing wind turbine location received a high index value such as 5 or 4, it indicates that the suitability model output is successful. Since each overlay output was classified to five categories, the number of existing wind turbines fell into each category was tallied. A two-way table, suitability category by overlay model, of the count values was built. This count dataset was further normalized by the land area of each suitability category to depict the number of existing wind turbines per unit area, where a higher value indicates a more successful model output.

In order to assess if there is a significant difference between the five overlay methods, a Chi-square test was conducted on existing wind turbine counts. The following equation was used for the test:

$$x^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\left[\frac{\left(o_{ij} - e_{ij}\right)^2}{e_{ij}}\right]$$

o_{ij} represents the observed count of the i^{th} model and j^{th} suitability class; e_{ij} is expected count of the i^{th} model and j^{th} suitability class. The level of significance (alpha value) was set for 0.05. The degree of freedom (*df*) was calculated by the following equation: $df = (r-1)(k-1)$ where *r* is the number of rows and *k* is the number of columns. Degree of freedom was calculated to be 16.

- The null hypothesis was H_0: There is no association between the method and the suitability class.
- The alternative hypothesis was H_a: There is a significant association between the method and suitability class.

If the p-value was less than 0.05, then the null hypothesis was rejected.

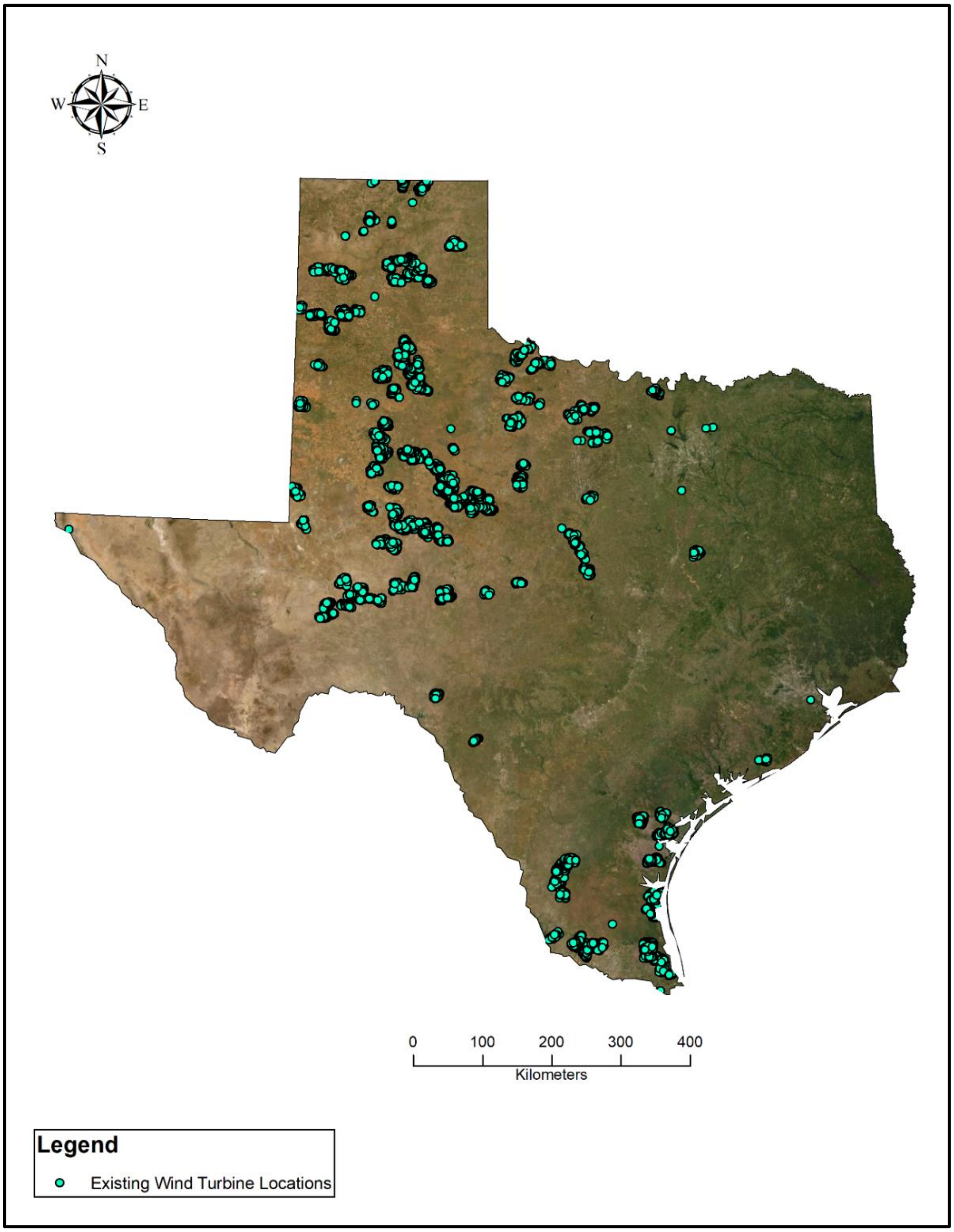

Figure 15. Existing wind turbine locations in Texas.

RESULTS AND DISCUSSION

Weighted Overlay

Figure 16 shows the suitability map of the weighted overlay analysis overlaid with the existing wind turbine locations. The best locations for large scale wind turbine application is in the northern part of Texas. Rolling plains and the high plains possess the greatest amount of S4 and S5 areas that represent moderate and high suitability. Some areas along the coastline shows possible locations for successful wind turbine application due to sufficient windspeed. The analysis also resulted unsuitable areas across east Texas and some part of the western region as well. This is due to the weight distribution of the criteria where wind is the most critical factor that received the greatest weight. The most dominant wind class in the eastern region is wind class one, which is generally unsuitable for windmills. Figure 17 shows the land area for each suitability class in Texas. This Weighted Overlay method resulted in 44,706 km^2 (17,261 mi^2) of highly suitable (S5) area that equals to 6.6% of the entire state. The next suitability class is the moderately suitable (S4), one below the highest suitability class which resulted in126,203 km^2 (48,727.3 mi^2). This takes up 18.6% land of Texas. It was found that as suitability decreases, the land area of the class increases due to the model input criteria, in particular the wind factor. The somewhat suitable (S3) class resulted in 180,858 km^2 (69,829.6 mi^2) that equals to 26.7% land of Texas. After merging S3, S4, and S5 classes (Figure 18), it was found that 351,767 km^2 (135,818 mi^2) of land is suitable, which equals to 52% of Texas. In other words, about half of the entire state is indeed suitable for wind farm development. A marginally suitable (S2) location is generally not preferable when it comes to wind farm development. However, it might be a viable option in some remote areas where adequate wind velocity can be found. This class resulted in 205,948 km^2 (79,517 mi^2) that equals to .45% of the total area. Areas with colored red in Figure 16 represent locations that are not suitable (S1) for wind turbine application. This is primarily caused by the lack of sufficient wind and some areas across east Texas. These not suitable areas were found to be 118,690 km^2 (45,826 mi^2) that covers east, west, and some part of south Texas. This number takes up 17.55% land of the entire state. Combining the not suitable (S1) and marginally suitable (S2) classes (Figure 17), as these classes are generally not preferable for wind farm development, resulted in 324,638 km^2 of land area that accounts for 48% of the entire state. The suitability map using the Weighted Overlay analysis showed that more than 50% of the entire state is either somewhat (S3), moderately (S4), or highly (S5) suitable for wind turbine application and precisely 48% of the state are not suitable for a proposed wind farm development.

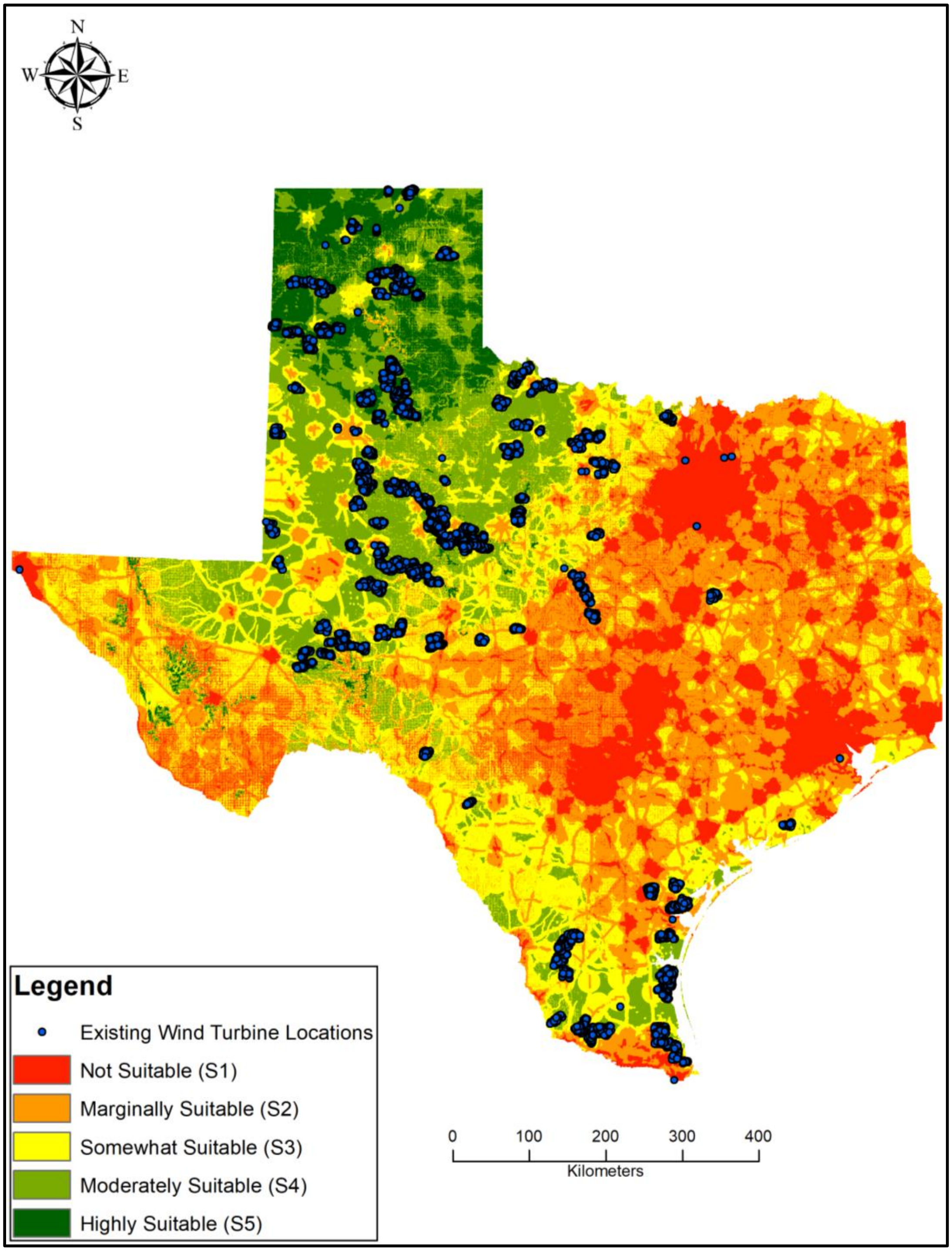

Figure 16. Suitability map for windfarm development based on the Weighted Overlay model output.

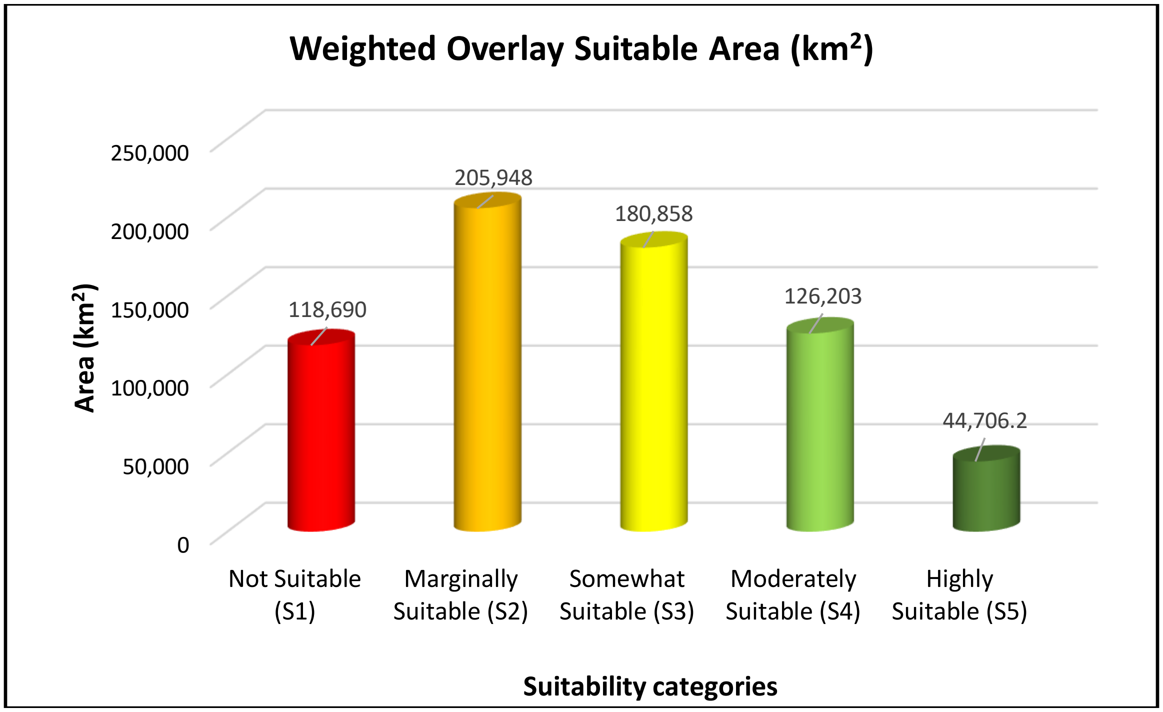

Figure 17. Land area distribution by suitability class resulted from the Weighted Overlay model.

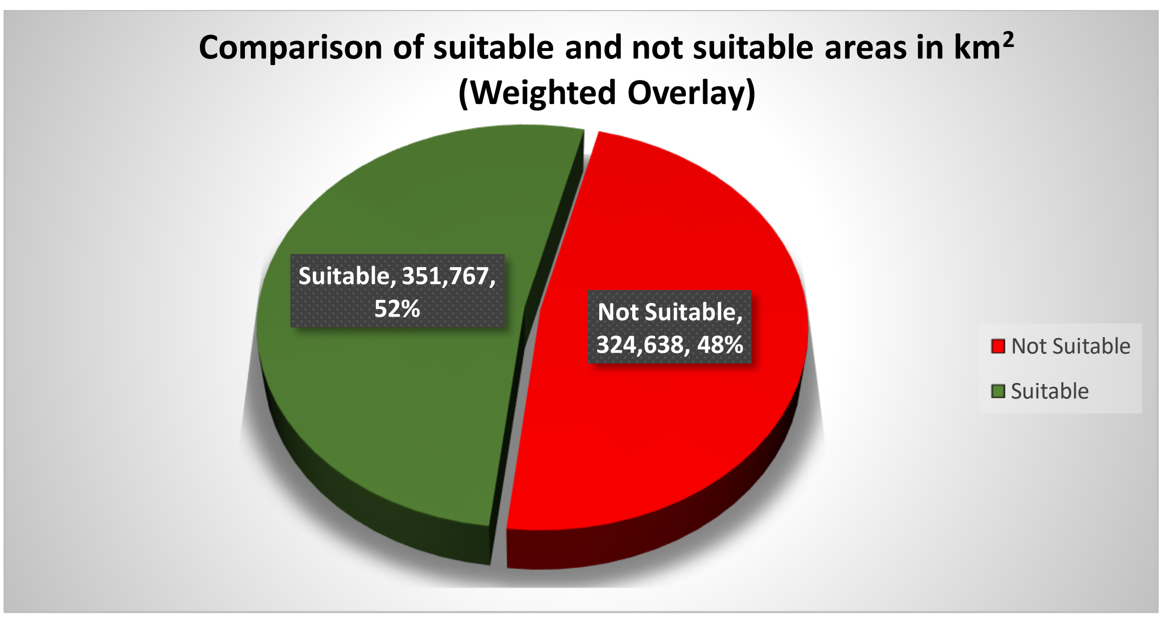

Figure 18. Land area comparison between suitable and not suitable for windfarm development based on the Weighted Overlay model output.

Weighted Sum

The output suitability map resulted from the Weighted Sum model is shown in Figure 19. The map shows that most suitable region in Texas was found in the north. High plains and rolling plans are the best locations for wind farm development, as these regions have a higher elevation providing higher windspeed. Some areas in Trans-Pecos ecoregion were also found suitable, showing higher pixel values in the raster model output. South Texas Plains and Gulf Prairies and Marshes provide large area of suitability class S3 and S4, representing somewhat and moderately suitable locations. The coastline provides adequate wind velocity to be harvested by wind turbines, that was found suitable in the model output as well. Figure 20 demonstrates the area for each suitable class. Starting with highest possible category, it resulted in 37,920.2 km^2 (14,641.1 mi^2) land of highly suitable (S5) areas that is responsible for 5.6% land of Texas. These small areas were found to meet all criteria, including wind speed as the most important requirements for a successful wind farm development. The moderately suitable (S4) class resulted in a much larger area with 146,958 km^2 (56,740.8 mi^2) that takes up 21.7% land of the state. The greatest area was found to be covered by the somewhat suitable (S3) class represented by pixel value 3. This was equal to 202,127 km^2 (78,041.7 mi^2) of land and is responsible for 29.83% land of Texas. This class covers 1/3rd of the state. Combining S3, S4, and S5 classes (Figure 21), as each class provides suitable locations for wind farm development, resulted in 387,005 km2 (149,423.5 mi^2). Thus, 57.12% of the total area of Texas is suitable based on the Weighted Sum model output. The marginally suitable (S2) class resulted in 143,859 km^2 (55,544.3 mi^2) of land, which takes up 21.23% of Texas. These areas are usually found in east Texas, and also some part of western Texas, mainly due to the lack of windspeed and urbanization in the eastern region. The not suitable (S1) areas equal to 146,679 km2 (56,633.1 mi2) which was found primarily across east Texas and some western regions as well. It takes up 21.65% of the total area. Furthermore, merging S1 and S2 suitability classes (Figure 20) of the Weighted Sum model output resulted in 290,538 km^2 (112,177.3 mi^2) that equals to 42.88% of the entire state. Generally, the first two lowest classes are not suitable for large scale wind turbine application as none or only a few criteria were found met in the analysis. Ultimately, based on this Weighted Sum analysis, more than half of the entire state was found somewhat (S3), moderately (S4), or highly (S5) suitable and less than 45% area was found to be not suitable for successful wind farm development (Figure 21).

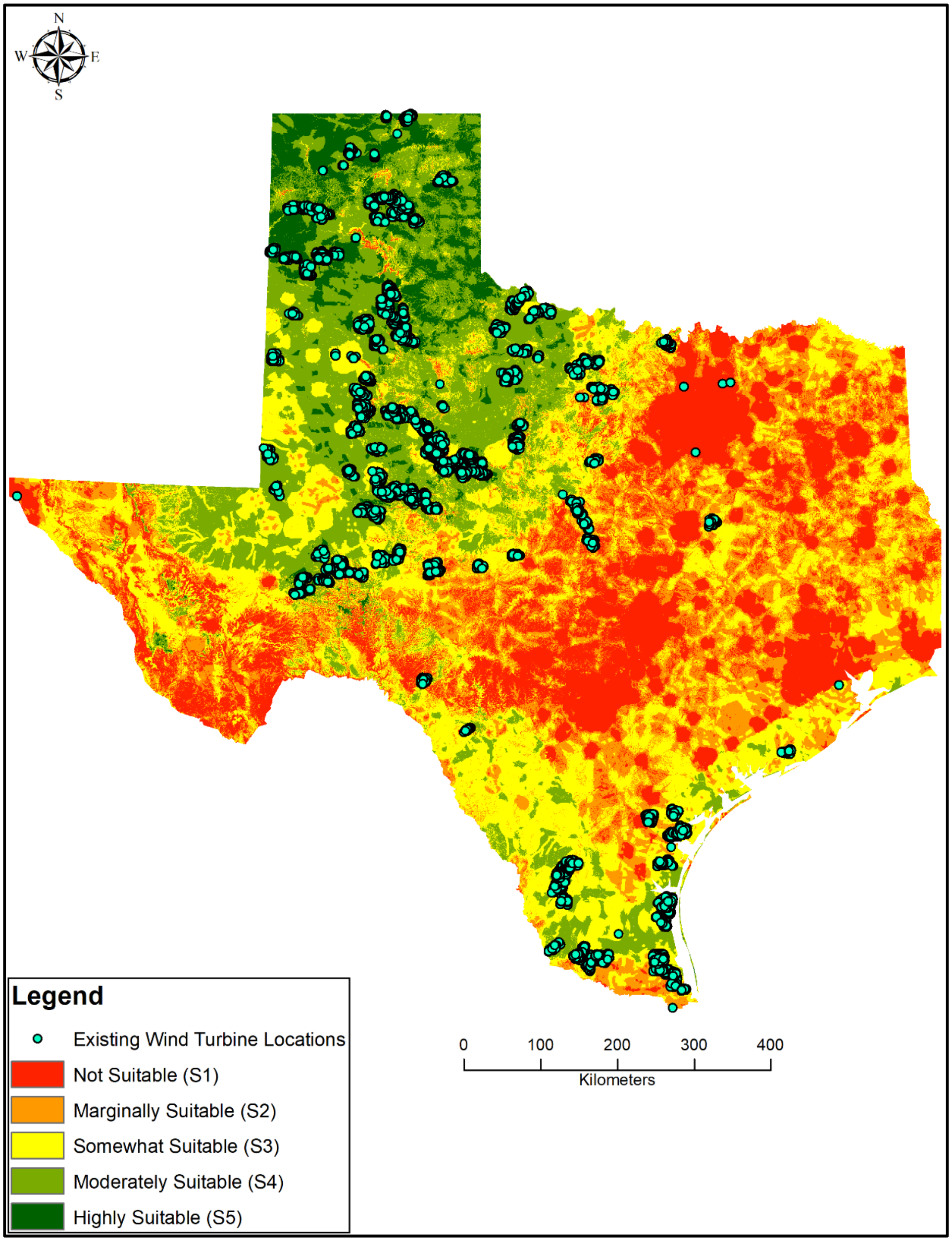

Figure 19. Suitability map for windfarm development based on the Weighted Sum model output.

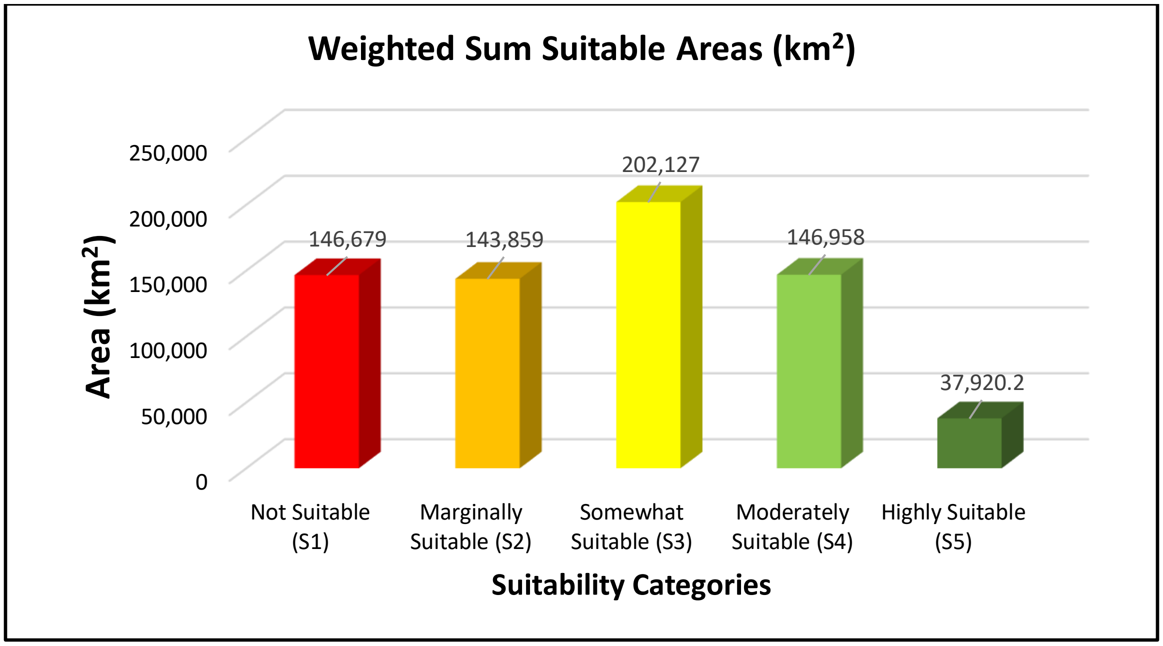

Figure 20. Land area distribution by suitability class resulted from the Weighted Sum model.

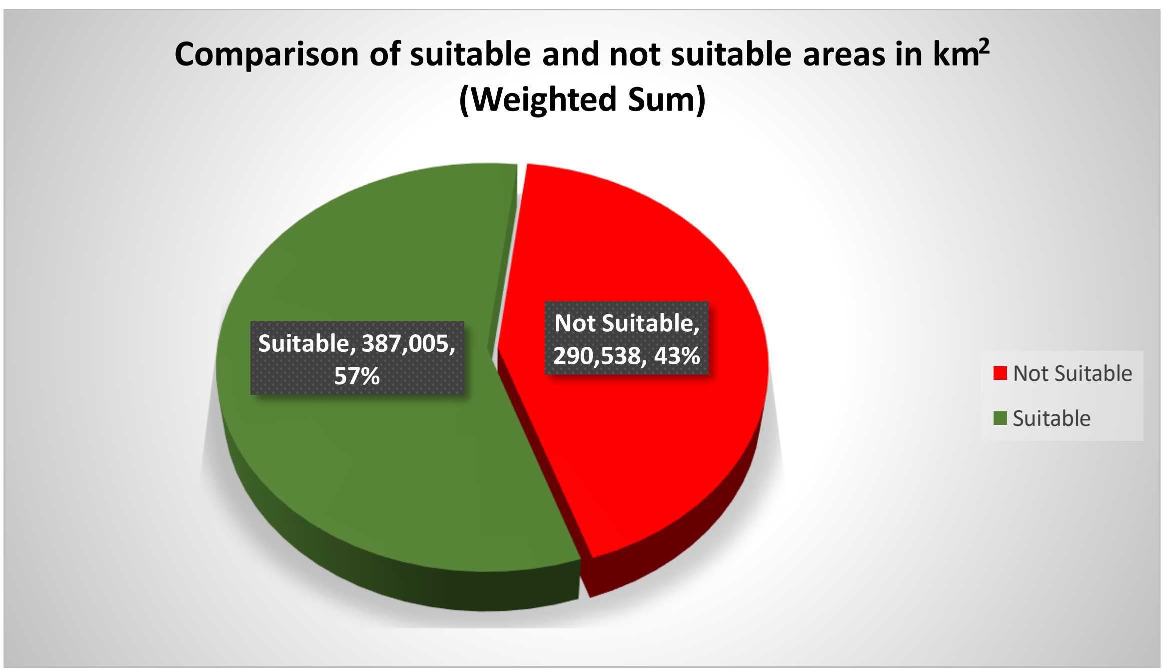

Figure 21. Land area comparison between suitable and not suitable for windfarm development based on the Weighted Sum model output.

Fuzzy Overlay

Model One

Figure 22 shows the suitability map resulted from the Fuzzy Overlay – Method One. This method consisted of six datasets (urban, wildlife, waterbody, river, airport, and wind) that were used to assign Large membership type and two datasets (slope and highway) with Small membership type as the greater or smaller pixel values were more favorable, respectively. Similar spatial pattern was found in this model output as in the Weighted Overlay and Weighted Sum. The Fuzzy Overlay analysis was done by manipulating the membership type based on favorable pixel values, because the weights and classification in fuzziness were not assigned by the user. Figure 23 demonstrates the area for each suitability class resulted from this Fuzzy Overlay analysis. The highest suitability class (S5) was responsible of 60,570 km^2 (23,386 mi^2) of land. These are the most suitable locations and were found in the high and rolling plains of Texas. The area takes up 11% of the total aera of Texas. Moderately suitable (S4) locations were found in the same regions and it accounts for 94,607 km^2 (36,528 mi^2) that equals to 17.7% of the entire state. Somewhat suitable (S3) class accounts for 67,565 km^2 (26,087 mi^2) and generally it can be found in the Edwards Plateau and south Texas plains. Some areas with pixel value three can also be found along the coastline, due to adequate wind velocity. Summing the suitable locations (Figure 24) resulted in 222,742 km^2 (86,001 mi^2) of land which only accounts for 42% of the entire area of Texas. The marginally suitable (S2) locations resulted in an area of 71,494 km^2 (27.603 mi^2) that equals to only 13.4% of the entire state. This category is considered to be marginal for wind farm development. The least favorable locations (S1) resulted in a much larger area, 240,926 km^2 (93,022 mi^2) that is 45% land of the entire Texas. Combining the two unsuitable categories (Figure 24), it returned a 312,420 km^2 (120,625 mi^2) which equals to 58.38% land of Texas. In Figure 22, there are areas colored white that represent the actual features of each criterion that were not included in the analysis, as wind farm development cannot be done on those locations. They were assigned with a pixel value of no data during the process. The total area of Texas was acquired by using the state boundaries that equals to 677,543 km^2 (261,601 mi^2). Thus, the area of no data was calculated to be 142,381 km^2 (54,974 mi^2) by subtracting the sum of the suitability categories from the total area of Texas.

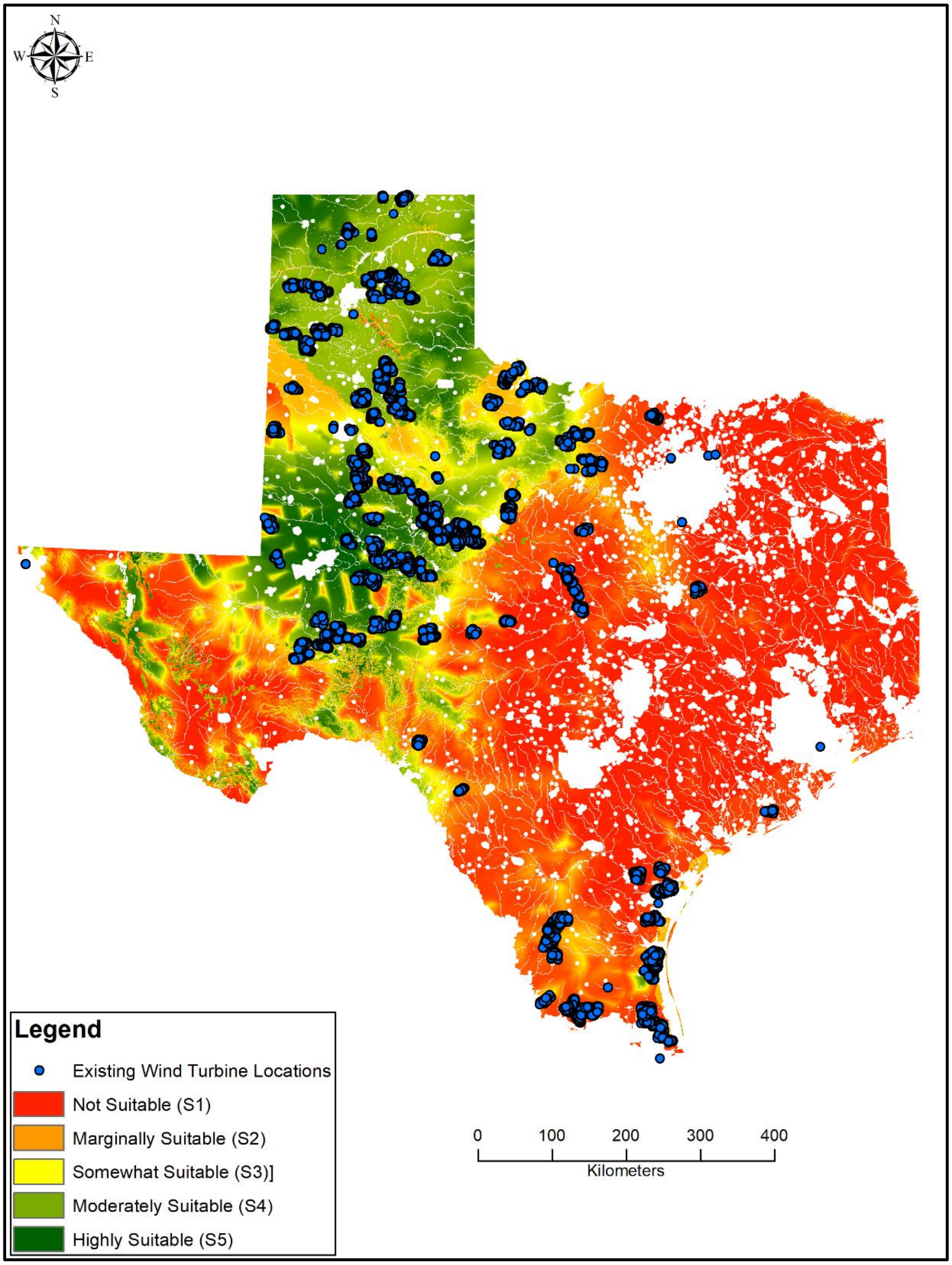

Figure 22. Suitability map for windfarm development based on the Model One of Fuzzy Overlay output.

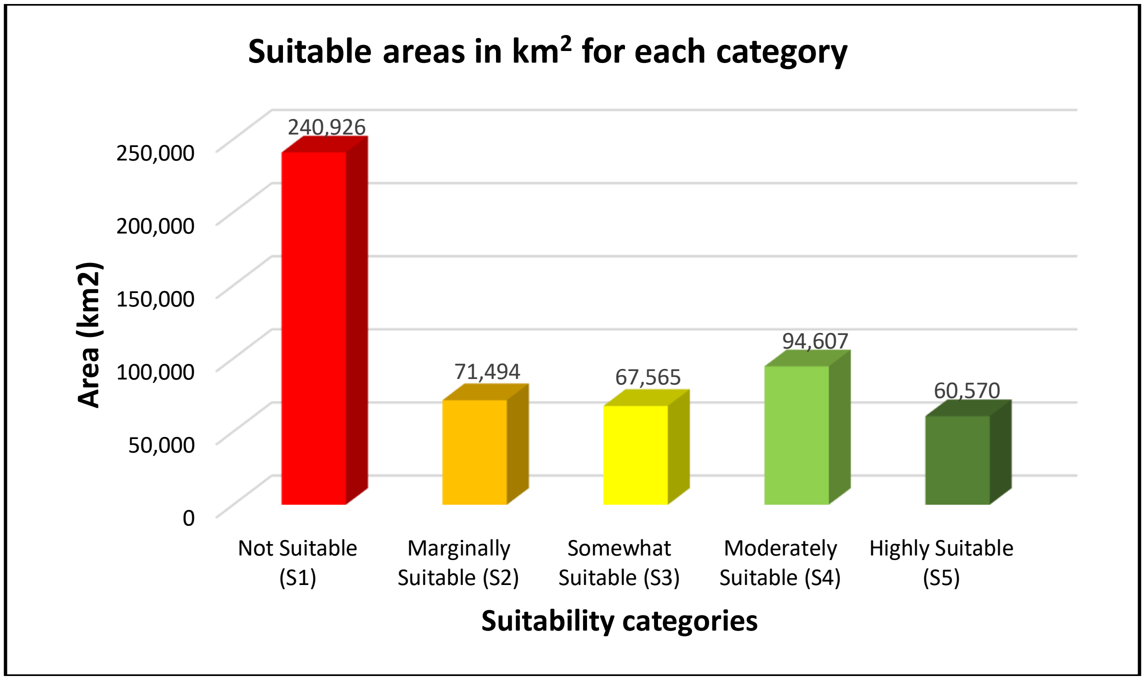

Figure 23. Land area distribution by suitability class resulted from the Model One of Fuzzy Overlay.

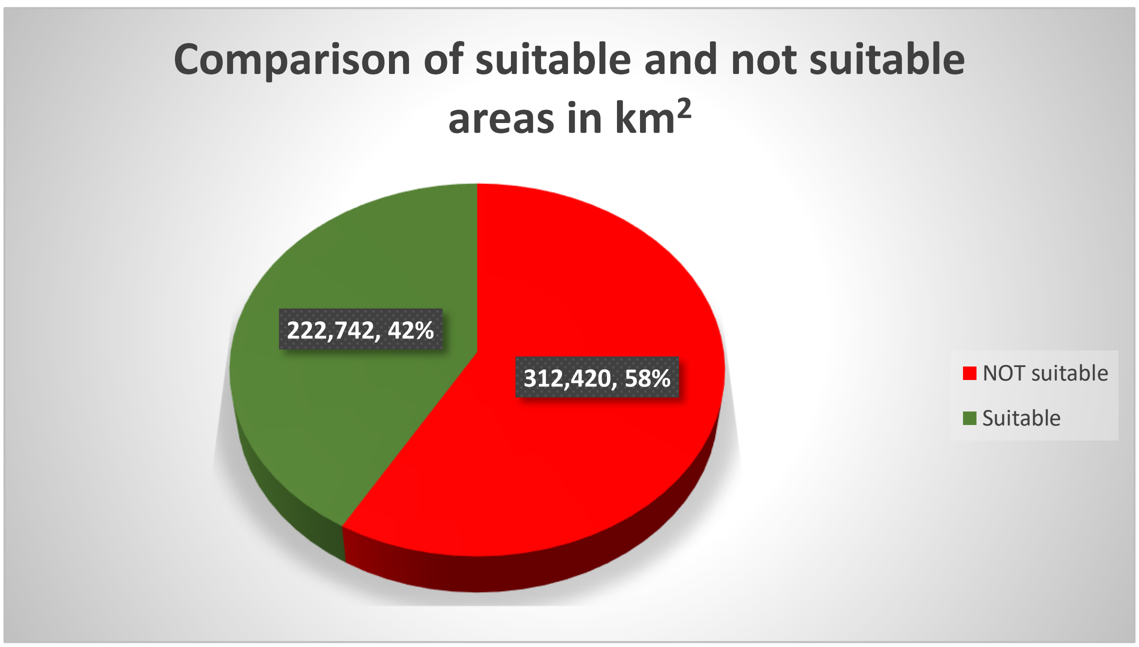

Figure 24. Land area comparison between suitable and not suitable for windfarm development based on the Model One of Fuzzy Overlay.

Model Two

Figure 25 shows the suitability map resulted from the second method of Fuzzy Overlay, Model Two. This method was based on a reverse approach for fuzzification. The highest suitability class in this analysis was found in the high plains and Edwards Plateau. The highest suitability (S5) class resulted in a relatively small area, 60,834 km^2 (23,488 mi^2) that equals 10% of the entire state (Figure 26). However, the moderately suitable (S4) class resulted in a much greater area across Texas. It is responsible for 140,265 km^2 (54,156 mi^2) area that takes up 23% of the state. These areas were found in the rolling plain and the high plains as well as in the Edwards Plateau. Somewhat suitable (S3) class takes up 111,021 km^2 (42,865 mi^2) of Texas. Merging S3, S4, and S5 classes into one category (Figure 27), it resulted in 312,120 km^2 (120,510 mi^2) which is 51% of the entire state. Marginally suitable (S2) locations were found in the southern and the eastern part of Texas around areas. Marginally suitable (S2) locations equal to 142,519 km^2 (55,026 mi^2) and it takes up 23.3% of the entire state. Lastly, the largest area was received by the least favorable locations which is represented by pixel value one. Not suitable (S1) areas were found to show similar pattern to the previous model outputs. East and some southern part of Texas possess these not suitable locations mainly due to heavy urbanization and the lack of windspeed. Pixel value one resulted in 155,894 km^2 (60,191 mi^2) that equals to 25.5% of the total area where wind farm development is not suitable.

Summing the two least suitable classed resulted in 298,413 km^2 (115,217 mi^2), which equals to 48.9% of the state. In this Fuzzy Overlay process, areas of highway was assigned no data, which applied Large type for fuzzy membership. It accounts for a total of 67,009 km^2 (25,873 mi^2).

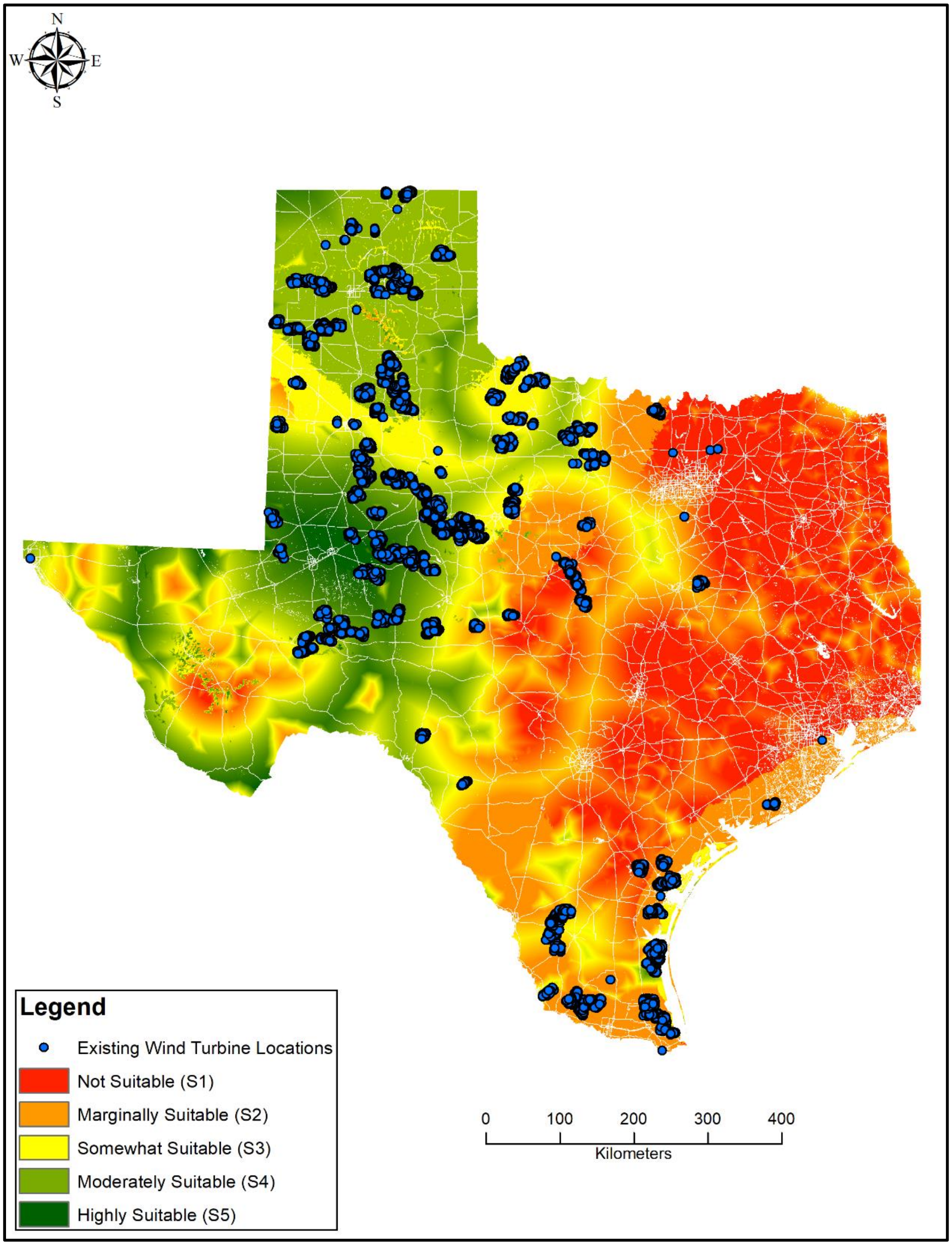

Figure 25. Suitability map for windfarm development based on the Model Two of Fuzzy Overlay output.

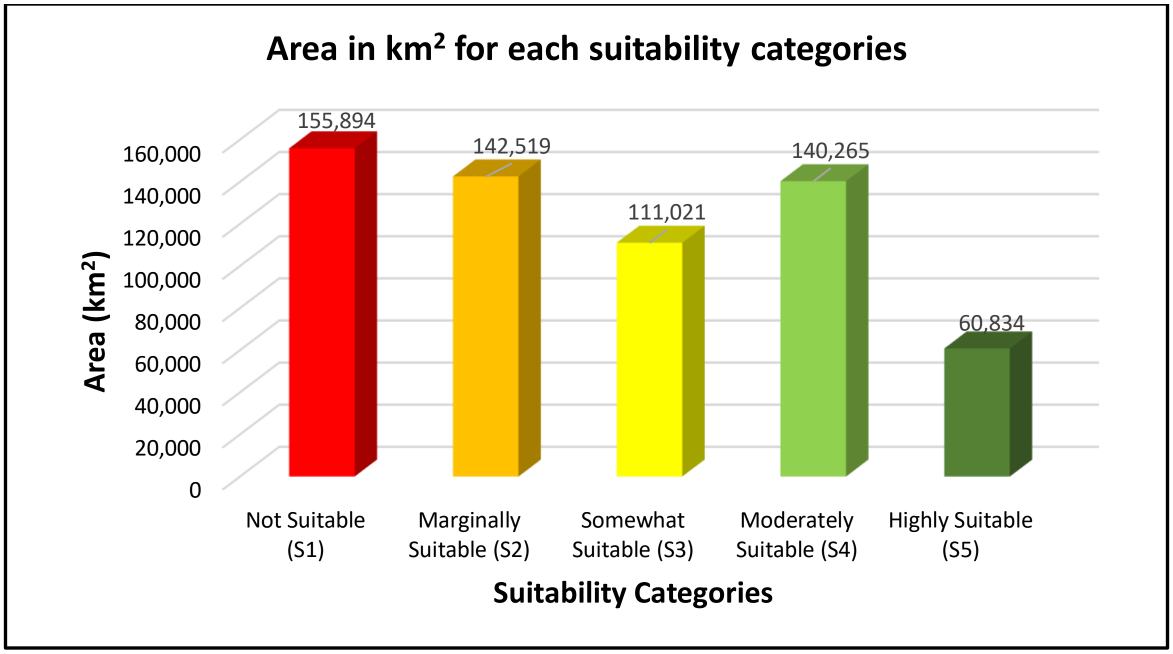

Figure 26. Land area distribution by suitability class resulted from the Model Two of Fuzzy Overlay.

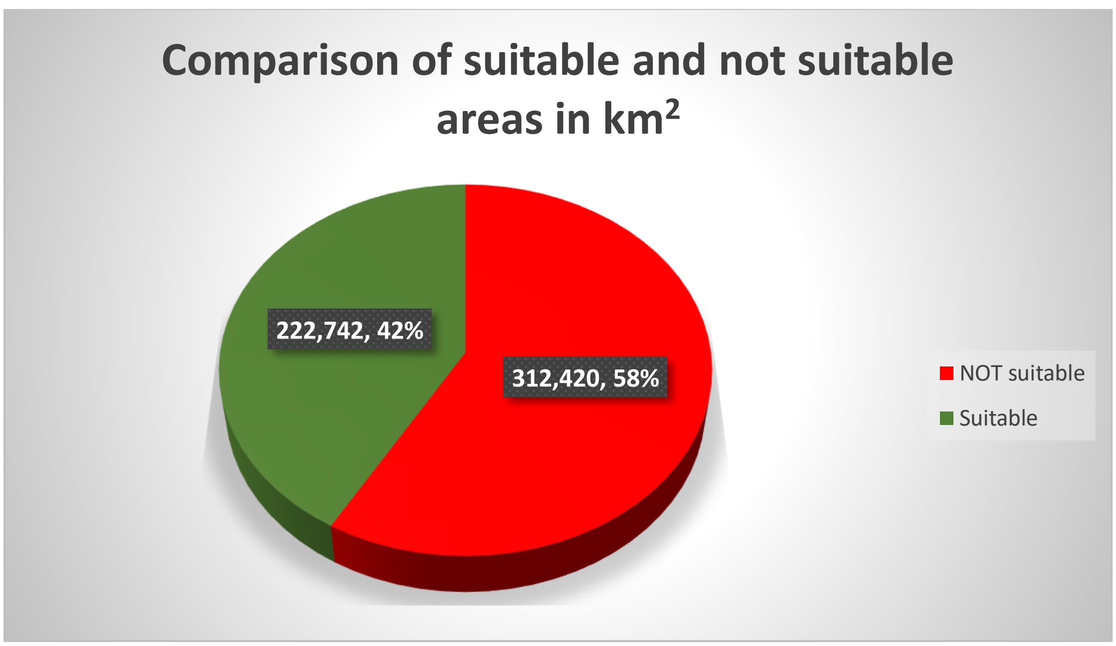

Figure 27. Land area comparison between suitable and not suitable for windfarm development based on the Model Two of Fuzzy Overlay.

Model Three

The last suitability map resulted from the third Fuzzy Overlay method, Model Three, which was based a specified mean and standard deviation. This model consisted of six datasets (urban, wildlife, waterbody, river, airport, and wind) where the MSLarge membership type was assigned, as well as two datasets (slope and highway) where the MSSmall membership type was assigned. A similar spatial pattern was observed when compared to the previous model outcomes (Figure 28). Figure 29 shows the distribution of area between the suitability classes in Texas. This analysis resulted in an area of 78,192 km^2 (30,190 mi^2) for the highly suitable (S5) class. It accounts for 11.5% land of Texas and is the smallest among the five suitability classes in terms of land area. Rolling plains and the high plains possess these high suitability areas due to less urbanization and increasing wind velocity. Moderately suitable (S4) areas were equal to 151,539 km^2 (58,509 mi^2). This takes up 22.4% land of the state providing twice the size of S5. The somewhat suitable (S3) class resulted in 127,141 km^2 (49,089 mi^2) area, generally located in central and southern part of the state. This was equal to 18.8% land of Texas. Merging S3, S4, and S5 suitability classes into one, it resulted in a total of 53% (Figure 30) with 358,872 km^2 (137,789 mi^2). Marginally suitable (S2) areas resulted in 22% coverage in Texas, that equals to 149,290 km^2 (59,938 mi^2). The location of this class was found to spread across in east Texas, due to high urbanization and lack of wind velocity. The not suitable (S1) class resulted in the largest total area of 171,391 km^2 (66,174 mi^2), which takes up 25.3% of the entire state. Combining the marginally (S2) and not suitable (S1) locations, it has an area of 320,681 km^2 (123,815 mi^2), which takes up 47% land of Texas. The distribution between suitable and not suitable classes was found to be similar to the previous model outcomes.

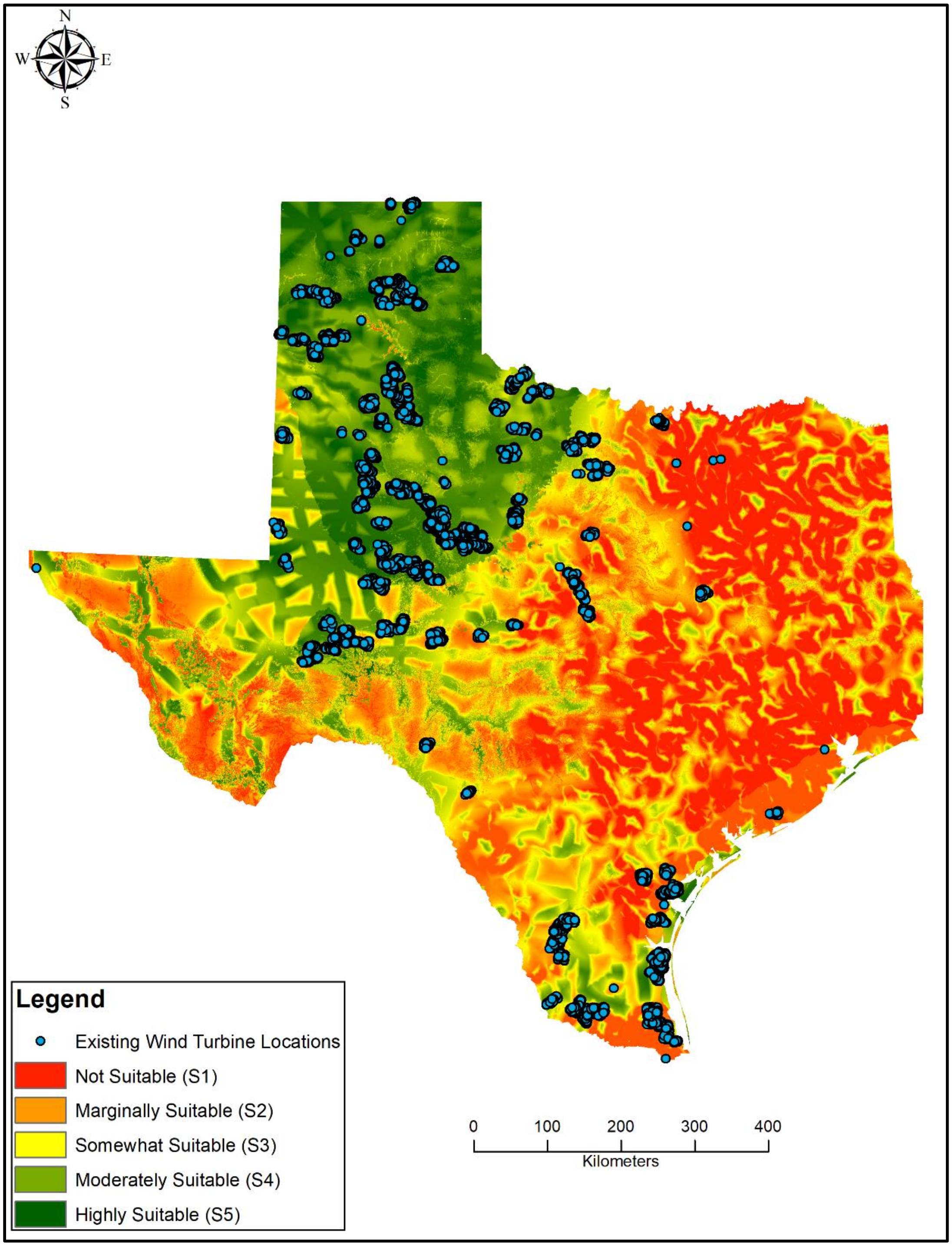

Figure 28. Suitability map for windfarm development based on the Model Three of Fuzzy Overlay output.

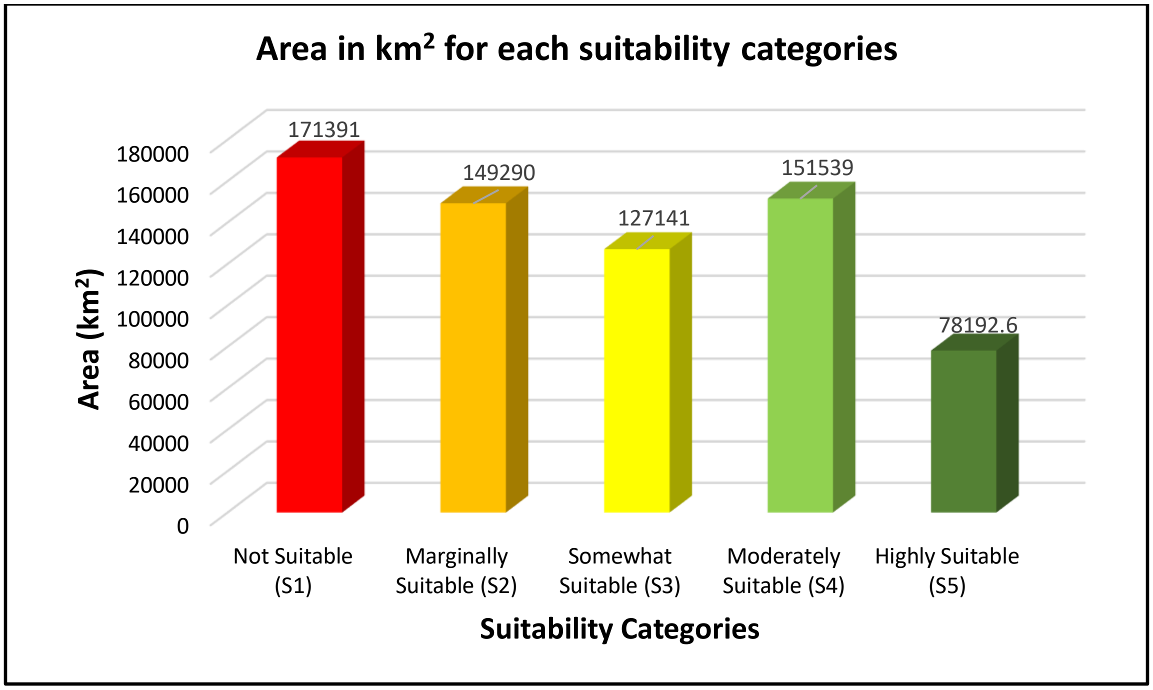

Figure 29. Land area distribution by suitability class resulted from the Model Three of Fuzzy Overlay.

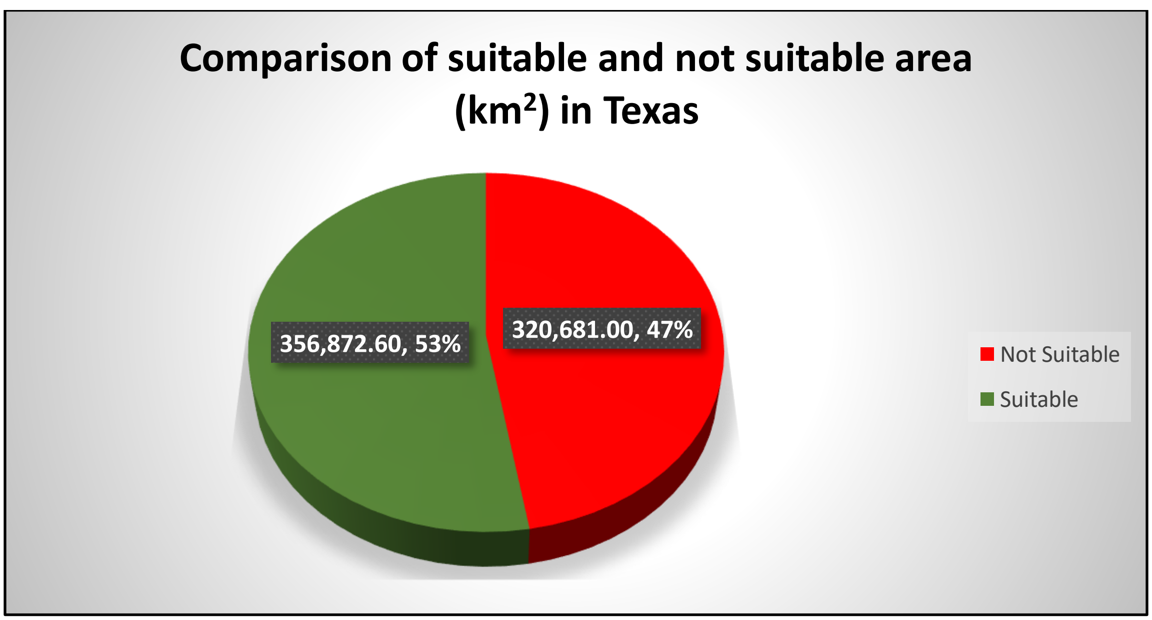

Figure 30. Land area comparison between suitable and not suitable for windfarm development based on the Model Three of Fuzzy Overlay.

Comparison of Overlay Models

Figure 31 shows the land area comparison of different suitability classes between the overlay models. The lowest area was found in the highly suitable class (S5) across the five model outputs. This is primarily due to the input criteria and the landscape of Texas, where urbanization and low wind velocity is found in the eastern part and steep slope terrains occur in the western region. The greatest area in the highly suitable class was achieved by the third Fuzzy Overlay model with 78,189 km^2 (30,189 mi^2) land featuring MSSmall and MSLarge membership types. Method One and Method Two of the Fuzzy Overlay models resulted similar high suitability (S5) areas, followed by Weighted Overlay and Weighted Sum. For the moderately suitable class (S4), Method Three of the Fuzzy Overlay had the greatest area of 151,539 km^2 (58,509 mi^2), followed by the Weighted Sum with 146,958 km^2 (56,740 mi^2). Method One of Fuzzy Overlay, which was based on a forward approach utilizing either Small or Large membership types, resulted in the lowest area in the moderately suitable (S4) class. This value, 94,607 km^2 (36,527 mi^2) is 37% lower than the largest area of this suitability class. A general trend was observed across the five overlay models, where the land area decreases when the suitability increases. The first forward approach of fuzzy overlay (Method One) resulted in the lowest area in the somewhat suitable (S3) class with 67,565 km^2 (26,086 mi^2) of land. This is a

66% reduction compared to the Weighted Sum model, which was equal to 202,127 km^2 (78,041 mi^2). Weighted Overlay generated similar values when compared to Weighted Sum. A total of 180,858 km^2 (69,829 mi^2) was classified as somewhat suitable (S3) and it is the second largest class of the Weighted Overlay model output. For the marginally suitable (S2) class, the Weighted Overlay model resulted in a total of 205,948 km^2 (79,516 mi^2), which is much higher than any other models. The models of Weighted Sum, Fuzzy Overlay Two and Three resulted in similar areas of the S2 class, which is generally not suitable for large scale wind turbine application. However, it can exist in some rural areas where wind speed is adequate. The lowest area, 71,494 km^2 (27,603 mi^2) classified by Method One of Fuzzy Overlay is much lower than other model outputs, precisely a 50% reduction when compared to the Fuzzy Overlay Two with 142,519 km^2 (55,026 mi^2). As Fuzzy Overlay One resulted in the least amount of area across almost every suitability class, it was expected to observe a peak in the not suitable class (S1). The total of 240,926 km2 (93,022 mi2) in the S1 class demonstrated a 40% increase compared to the second largest area resulted from Fuzzy Overlay Three. Weighted Sum, Fuzzy Overlay Two and Three resulted in similar areas for this not suitable class. The lowest not suitable area was received by Weighted Overlay with 118,690 km^2 (45,826 mi^2).

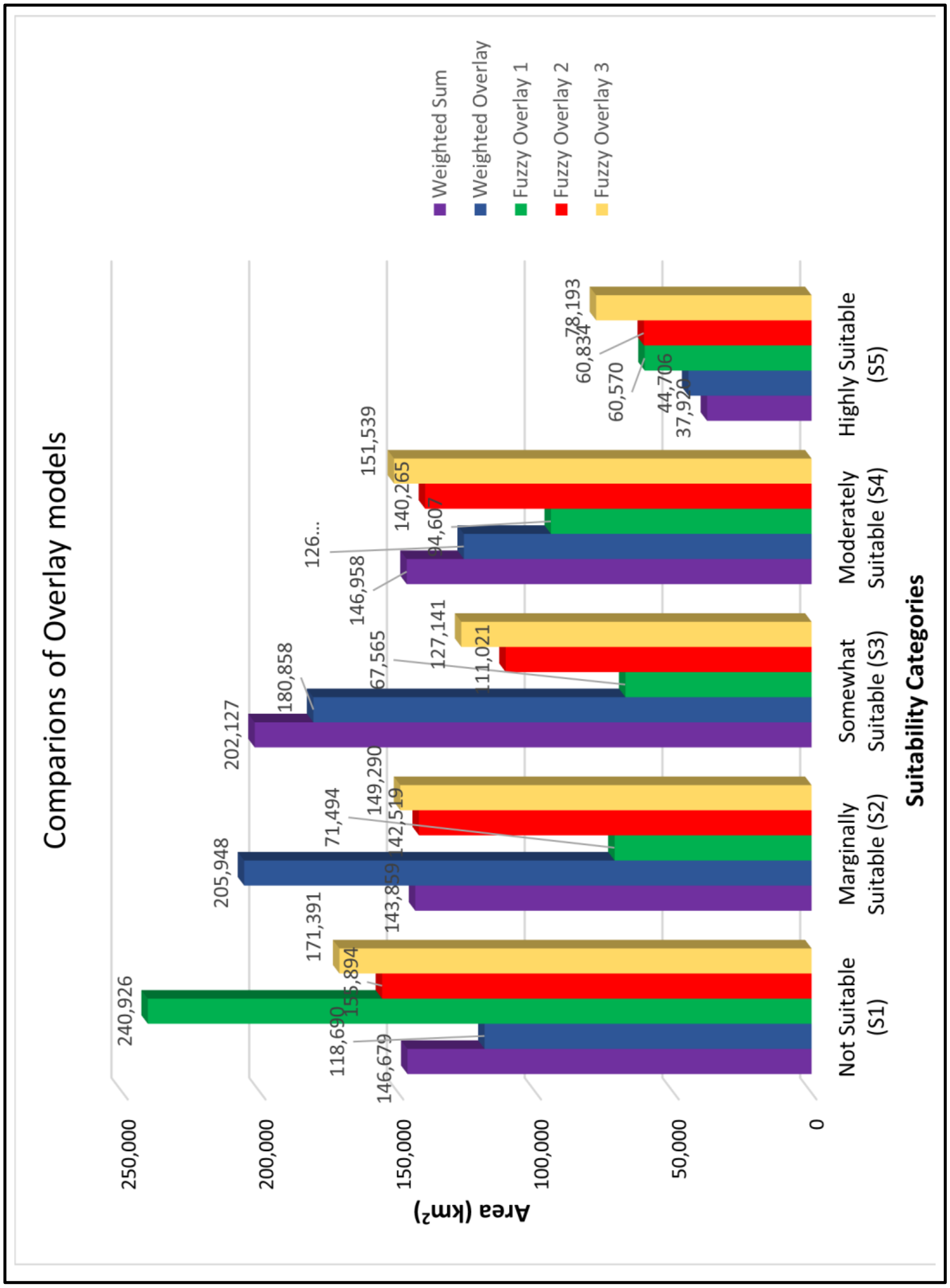

Figure 31. Land area distribution across five suitability classes by each overlay model output.

Validation with Existing Wind Turbines

Each suitability map was overlaid with the validation dataset to derive the cell value of each existing wind turbine locations. A model output is considered more accurate when more exiting wind turbines land on a higher suitability class such as moderately suitable (S4) or highly suitable (S5). Figure 32 shows the frequency distribution of wind turbines in each suitability class across different model outputs. Excluding Fuzzy Overlay One, a general trend was observed where the number of existing wind turbines increased when the land class is more suitable until the highly suitable class (S5). The greatest numbers of existing wind turbines were found to be in the moderately suitable (S4) class, indicating that all models performed well in suitability analysis. In this S4 class, the Weighted Sum model received the greatest number of 7,559 turbines, followed by Fuzzy Overlay Two (6,943) and Weighted Overlay (5,751). The total number of wind turbines from the validation dataset is 15,230, thus 49% of them were found in the moderately suitable (S4) class based on the Weighted Sum. On the other hand, Fuzzy Overlay One resulted in only 5,499 existing wind turbines in the S4 class. This is reflects the fact that a much larger total area was classified as not suitable by the Fuzzy Overlay One model. The highly suitable (S5) class did not receive the largest numbers of existing wind turbines as would be expected. The Fuzzy Overlay Three model resulted in the greatest number of wind turbines (4,667) in this highly suitable (S5) class. In comparison, the Weighted Sum model observed a 66% reduction from the moderately suitable (S4) class to the highly suitable (S5) class, whereas the Fuzzy Overlay Two class observed 56%. On average, the reduction from S4 to S5 is 49.5%. For the somewhat suitable (S3) class, the Weighted Sum and Weighted Overlay resulted in very similar, almost identical numbers of existing wind turbines with 3,746 and 3,833, respectively. It is reasonable since they were based on the same classification and weighting. The same was found among the Fuzzy Overlay models. Fuzzy Overlay One and Two resulted in 2,421 and 2,250 wind turbines, respectively, indicating a 7% difference. The Fuzzy Overlay Three model resulted in the least amount of wind turbines in the somewhat suitable (S3) class, only 1,718. For the marginally suitable (S2) class, the overserved number of existing wind turbines are lower, ranging from 999 to 2,107. The greatest number was found in the Fuzzy Overlay Two model, which is much larger than other overlay models in this suitability class. Fuzzy Overlay Three resulted in the second largest with a total of 1,507 wind turbines, which is 28% less than Fuzzy Overlay Two in this class. Weighted Sum, Weighted Overlay, and Fuzzy Overlay One resulted in very similar numbers. The last category, the not suitable (S1) class received low numbers varying from 190 to 2,158. The Fuzzy Overlay One resulted in an unexpected number that is much higher than other models. This echoed what was found in Figure 31, where the Fuzzy Overlay One model resulted in a much larger total area in the S1 class than others. When the land area increases, the possibility of a location be in that area increases. The 2,158 wind turbines of Fuzzy Overlay One is 3.15 times greater than that of Fuzzy Overlay Three, the second largest in this S1 class with 684 wind turbines. This was followed by the Weighted Sum model, which observed exactly 400 turbines. Lastly, Weighted Overlay and Fuzzy Overlay Two resulted in very similar numbers, 190 and 232, respectively. Worth to mention is that the Fuzzy Overlay One and Two have areas assigned with NO DATA in the modeling process. That lead to areas on the final output that were not classified into any suitability for windfarm development. When validating the model outputs with existing wind turbine locations, some of them happened to be in these areas as shown in Figure 32. The Fuzzy Overlay One model contributed 645 wind turbines into this No Data category, while Fuzzy Overlay Two contributed 657. It is about 4% of all the exiting wind turbines that were excluded in the analysis.

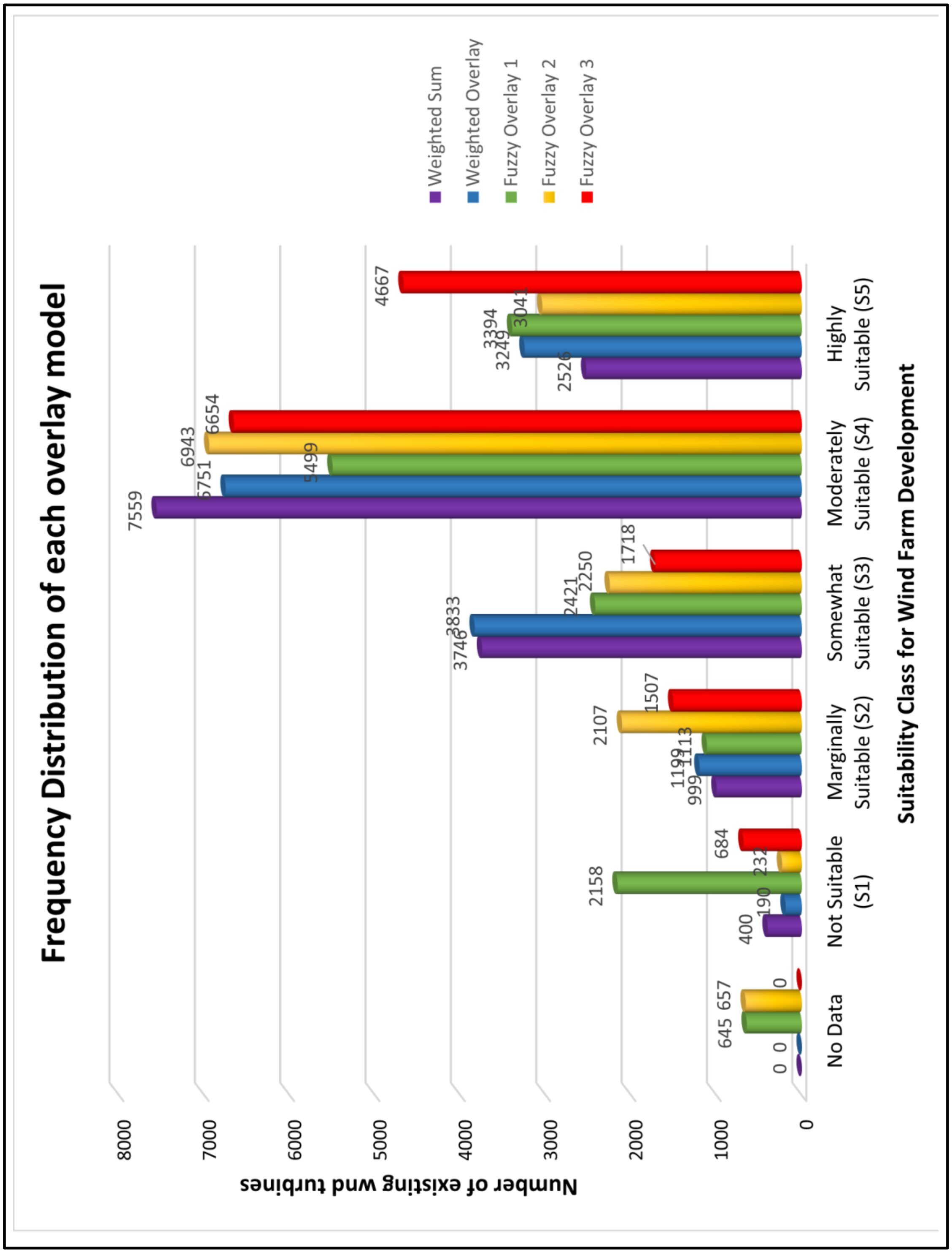

Figure 32. Number of existing windmills in each suitability class by different overlay model.

Statistical Analysis

When the total numbers of existing wind turbines within each suitability class was normalized by the land area of that class, it gives a picture that better represents how the models performed (Figure 33). A higher number of wind turbines per area unit indicates a more suitable area for windfarm development. The pattern in Figure 33 confirmed that all models did well as higher values were found in the more suitable classes. Linear increase was observed in most models among the suitability classes. The highly suitable (S5) class resulted in an average of 6.1 wind turbines per unit area, where the highest value of 7.27 wind turbines per 100 km^2 was observed from the Weighted Overlay model output. This was followed by Weighted Sum, producing 6.6 wind turbines per 100 km^2. For the three Fuzzy Overlay methods, Model Three outperformed the other fuzzy models, resulting in almost precisely 6.0 wind turbines per unit area. Fuzzy Overlay Two generated 5.6, and Fuzzy Overlay One generated 5.0 wind turbines per 100 km^2. The average number of wind turbines per area unit for the moderately suitable (S4) class was 5.13. The greatest number was achieved by Fuzzy Overlay One with 5.81. Weighted Overlay, Weighted Sum and Fuzzy Overlay Two did not show much differences in terms of number of wind turbines per unit area, with 5.31, 5.14 and 4.95 wind turbines per 100 km^2 received by the three models, respectively. The least amount of wind turbines was generated by the Fuzzy Overlay Three model. The difference among the five models for the somewhat suitable (S3) class was more dramatic. The average for this S3 class was 2.19 windmills per 100km^2. The greatest value was achieved by the Fuzzy Overlay One model with 3.58. Weighted Overlay and Fuzzy Overlay Two generated 2.12 and 2.03 per 100km^2, respectively, outperforming the Weighted Sum and Fuzzy Overlay Three models. In this class, Fuzzy Overlay Three had the least amount of wind turbines per area unit with 1.35 per 100km^2. Fuzzy Overlay One remained the highest for number of wind turbines per unit area in all suitability classes, except the highly suitable (S5). Its high numbers in the less suitable classes is an indication of low accuracy.

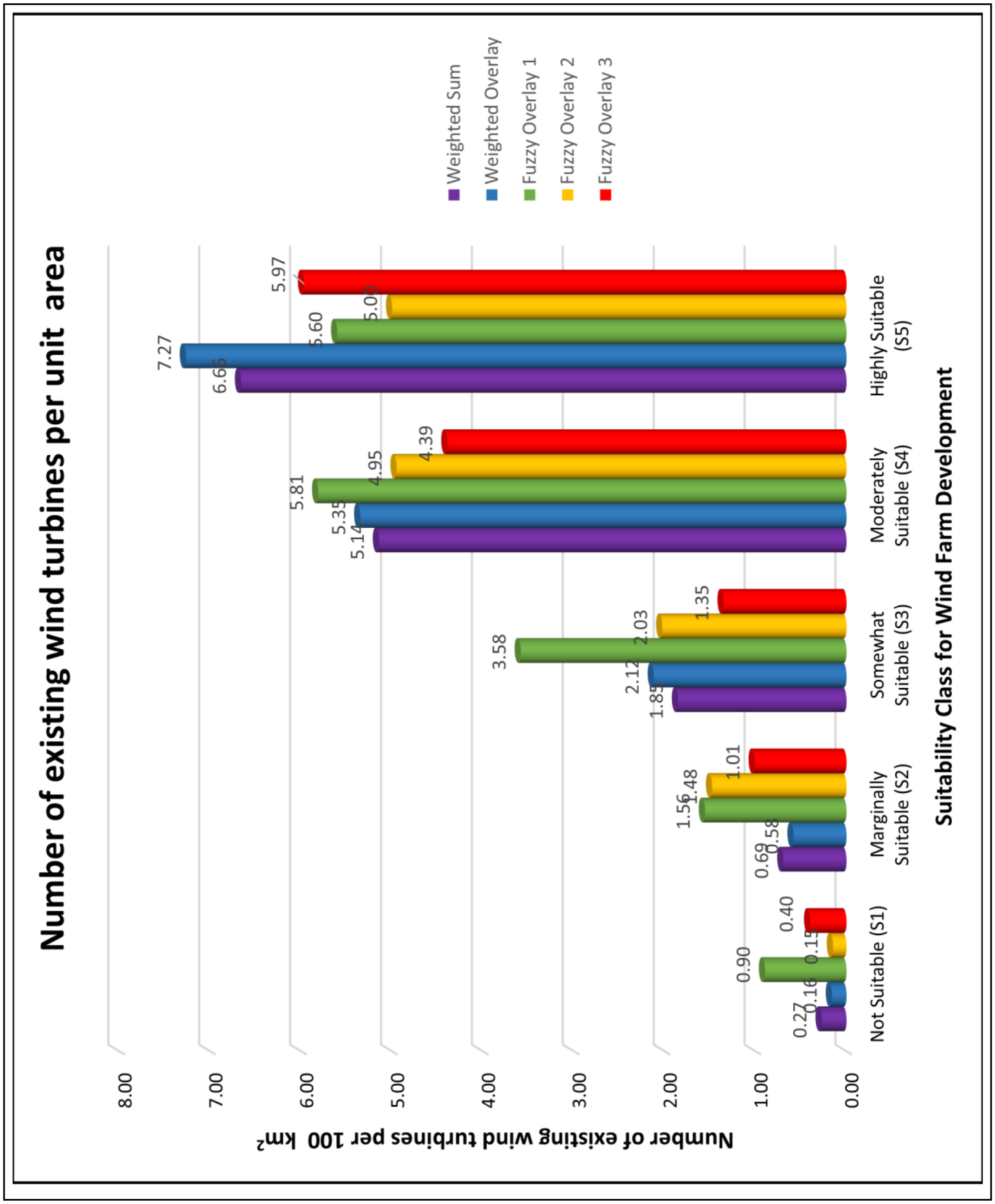

Figure 33. Number of existing wind turbines per unit area in different suitability class by overlay models.

Table 18 furthered the analysis by calculating the average of pixel values where the existing wind turbine are located for each overlay model. A higher average value indicated a more accurate model output since a windmill is expected to be built on a more suitable location with a higher index value. The highest mean pixel value was found to be from the Fuzzy Overlay Three model, which as 3.86. This is due to its highest total number of existing wind turbines located in the highly suitable (S5) areas (Figure 32), although its number per unit area is less than those of Weighted Sum and Weighted Overlay (Figure 33). The mean pixel value of Weighted Sum's 3.71 and Weighted Overlay's 3.77 reconfirmed their good performance in finding suitable locations for windfarm development. The least accurate was found to be Fuzzy Overlay One, which has the lowest mean pixel of 3.32. Its high numbers of wind turbines found in the less suitable classes (Figures 32 and 33) contributed to the results

Table 18. Average pixel values of existing wind turbines for each suitability model.

Suitability Models	Weighted Sum	Weighted Overlay	Fuzzy Overlay 1	Fuzzy Overlay 2	Fuzzy Overlay 3
Average pixel value	3.71	3.77	3.32	3.56	3.86

In order to test if there is association between the overserved numbers of existing windmills along the five suitability classes in relation to the five overlay models, the observed and expected count values were organized in Tables 19 and 20, respectively. Expected values were derived by the observed values by the following method. The subtotal of each column was multiplied by the subtotal of the rows divided by the total number which was 74,840. A chi square test was conducted. Using the software R, the p-value was calculated to be 2.2×10^{-16}, which is much less than the alpha level that was set to 0.05. The null hypothesis (H_o) was rejected and the alternative hypothesis (H_a) was accepted, indicating that there is association between the overlay method and the distribution of each suitability class count. It suggests that the models generated different suitability outcomes significantly. Based on the average pixel values in Table 18, it is concluded that Fuzzy Overlay Three is the most accurate model, while Fuzzy Overlay One is the least.

Table 19. Number of existing windmills observed in each suitability class by different model outcomes.

OBSERVED						
	Weighted Sum	Weighted Overlay	Fuzzy Overlay 1	Fuzzy Overlay 2	Fuzzy Overlay 3	SUM
1. Not Suitable	400	190	2158	232	684	3664
2. Less Suitable	999	1199	1113	2107	1507	6925
3. Suitable	3746	3833	2421	2250	1718	13968
4. Moderate Suitable	7559	6751	5499	6943	6654	33406
5. High Suitable	2526	3249	3394	3041	4667	16877
SUM	15230	15222	14585	14573	15230	74840

Table 20. Numbering of existing windmills expected in each suitability class by different model outcomes.

EXPECTED						
	Weighted Sum	Weighted Overlay	Fuzzy Overlay 1	Fuzzy Overlay 2	Fuzzy Overlay 3	SUM
1. Not Suitable	745.63	745.24	714.05	713.46	745.63	3664.00
2. Less Suitable	1409.24	1408.50	1349.56	1348.45	1409.24	6925.00
3. Suitable	2842.50	2841.01	2722.12	2719.88	2842.50	13968.00
4. Moderate Suitable	6798.15	6794.58	6510.24	6504.89	6798.15	33406.00
5. High Suitable	3434.48	3432.68	3289.03	3286.32	3434.48	16877.00
SUM	15230.00	15222.00	14585.00	14573.00	15230.00	74840.00

CONCLUSION

The northern region of Texas was found to be the most suitable locations for wind farm development because it provides sufficient wind speed that can be harvested by the turbines. Although in remote areas, they met most of input criterion requirement. This conclusion was based on the output suitability maps and validated on each overlay model output with existing wind turbine locations. Although not the best based on the classification scheme, the moderately suitable (S4) class observed the highest numbers of existing wind turbines. On the other hand, not suitable locations are mainly found in the eastern and southern parts of Texas, except some small areas where the criteria were met. In fact, some existing wind turbines are indeed located in these areas as found on the model output maps. All of the five suitability analysis models revealed the same spatial pattern on windfarm development suitability across the state of Texas.

There are many factors that affect the outcome of a land suitability analysis. For this study, the commonly referred criteria including urban, wildlife, airport, highway, river, waterbody, slope, and the most critical factor, wind were used in finding the best locations for wind turbines. There is limitation in a GIS based analysis when data sources rely solely on those available in public domain.

The most critical criterion, the wind dataset used for this study was recorded in 2015 by the National Renewable Energy Laboratory and it measured at 50-meter height above ground. If long-term observed wind data were available, the model outcomes would be more reliable when predicting into the future. Another important factor that could affect the output suitability map is the classification methods. For this study, natural breaks (Jenks) was used to reclassify the index values into the final five classed of suitability for four of the five models. However, using a different classification method, such as standard deviation or geometrical interval, the distribution of suitability classes for each model could be different.

The use of existing wind turbine data for accuracy assessment was based on the assumption that each wind turbine was built on a more suitable location. It does not tell how much electricity actually generated at each wind turbine. To further assess the accuracy, power generated at each turbine should be monitored and incorporated in the assessment in order to increase the reliability of each model output.

Although the five models resulted in similar outputs where more existing wind turbines were found in more suitable areas, there is difference on their accuracy performance that is verified by the chi-square test. Fuzzy Overlay Three model is the most accurate as it had most existing windmills in higher suitability class locations. The total number of wind turbines in the validation dataset is 15,230 and 74.3% of them are located within either moderately suitable (S4) or highly suitable (S5) locations based on the Fuzzy Overlay Three model output. This high accuracy is also supported by the highest index value of 3.86 from its model output, when validated with existing wind turbine locations.

It is clear that Texas is very capable of providing lands for successful windfarm development. The state is currently ranked as having the highest number of installed wind turbines. This study provides a roadmap for finding the next suitable locations for installing wind turbines. However, when it comes down to deciding on a location, the land ownership should be taken into consideration.

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