A GROUP-BASED SPATIAL DECISION SUPPORT SYSTEM FOR WIND FARM SITE SELECTION IN NORTHWEST OHIO

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ABSTRACT

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This paper presents a spatial decision support system (SDSS) framework for evaluating the suitability for wind farm siting in Northwest Ohio. It is intended for regional planning but also for promoting group decision making that considers different participants in the development of decision alternatives. The framework integrates environmental and economic criteria and builds a hierarchy for wind farm siting using weighted linear combination (WLC) techniques and GIS functionality. The SDSS allows multiple participants to develop an understanding of the spatial data and to assign importance values to each factor. The WLC technique is used to combine the assigned values with map layers, which are standardized using fuzzy set theory, to produce individual suitability maps. The maps created by personal preferences from the participants are aggregated for producing a group solution using the Borda method. Sensitivity analysis is performed on the group solution to examine how small changes in the factor weights affect the calculated suitability scores. The results from the sensitivity analysis suggest that the economic objective is more sensitive than the environmental objective while population density and land use were the most sensitive factors.

This is dedicated my brother Carl, my mother Mary, and my father Carl. Thank you for all the love, support, and especially the humor not only throughout this project, but throughout my life.

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Introduction

A growing number of regional problems driven by social, cultural, and environmental forces require assistance of spatial decision support systems (SDSS) for enhancing variety of management solutions (Bone and Dragićević, 2009; Barkan et al., 2006; Jankowski et al., 2006; Nyerges et al., 2006; Jankowski, 2000; Jankowski et al., 1996). There are many examples where SDSS are used to resolve issues of locally unwanted land uses that involve "not in my back yard" (NIMBY) controversies including the siting of municipal solid waste facilities (Chiueh et al., 2008; Kontos et al., 2003), construction of road infrastructures in a metropolitan area (Bana and Carlos, 2001), nuclear waste disposal (Evans et al., 2004), urban regeneration projects (Horita, 2000), stream restoration (Corsair et al., 2009), and watershed management (Ramanathan et al., 2004; Bender and Simonovic, 2000). However, the need of SDSS tools is much greater when problems emerge from developing industries such as renewable energy where planners are unable to identify important elements and establish relevant theories for the problems they are trying to solve.

Planning of new wind energy farm sites is one of the problems that requires combination of diverse planner backgrounds for resolving conflicting interests and views for achieving a single decision goal acceptable to multiple planners (Simão et al., 2009; Gamboa and Munda, 2007; Kaldellis, 2005). Although the United States has been steadily ramping-up the amount of wind energy production (Swofford and Slattery, 2010; Bolinger and Wiser, 2009), wind farm development is often confronted with strong opposition throughout the country. For example, in Nantucket Sound, Massachusetts, a proposed offshore wind farm that would provide three-fourths of the electrical needs for the region is strongly opposed by residents along the shoreline who fear that the turbines would obstruct the view from their property and decrease property values (Kempton et al., 2005). The proposal is still entangled in debate and no turbines have been installed. The turbines constructed in the San Gorgonio Pass, California, faced intense public resistance when they were proposed for development and are still blamed for their affects on the desert landscape (Pasqualetti, 2001). Wind turbines in Altamont Pass, California are criticized for the number of avian deaths caused by the turbines and for the open space development (Rodman and Meentemeyer, 2006).

Evaluating suitable locations for wind energy is a difficult undertaking as different planners and decision-makers value interests and priorities differently. For instance, variations among decision-makers opinions exist in the choice of important criteria and their relative importance for solving the problem. Different decision-makers will likely place different values on the criteria and use information in different ways (Dye and Shaw, 2007). Some examples of conflicting criteria involved in the selection of wind farm locations include: landscape aesthetics (Swofford and Slattery, 2010; Wolsink, 2007; Jobert et al., 2007; Ek, 2005; Warren et al., 2005; Begoña and Hanley, 2002), turbine noise (Aydin et al., 2010; Wolsink, 2007; Devine-Wright, 2005) avian deaths (Aydin et al., 2010; Farfán et al., 2009), and shadow flicker (Harding et al., 2008; Baban and Parry, 2001). While there are clear challenges with the choice and relative importance of conflicting criteria, improvements of SDSS frameworks that can support conflict resolution and promote consensus among planners are necessary for the decision making process.

SDSS are explicitly designed to help decision makers solve complex problems by coupling analytical multiple criteria evaluation (MCE) models and Geographic Information Systems (GIS). MCE models provide a system for choosing and rating decision criteria, and for developing and evaluating decision alternatives. A GIS is commonly defined as a set of tools for the input, storage, manipulation and analysis, and output of spatial data. Such frameworks have been used in several studies to analyze site suitability for wind turbines (Baban and Parry, 2001; Rodman and Meentemeyer, 2006; Tegou et al., 2010; Aydin et al., 2010; Janke, 2010). Some of these frameworks have used the MCE approach of weighted linear combination (WLC) to develop suitability scores over the study area. With WLC, the decision maker assigns relative importance values to each criterion in the analysis. These values are multiplied by standardized map layers representing the suitability of the criteria at that location. A total score is calculated by summing these products over each location (Malczewski, 1999).

Fuzzy set theory (Zadeh, 1965; 1978) is often used for criteria standardization before it is combined with WLC methods (Gorsevski et al., 2006; Gorsevski and Jankowski, 2010; Comber et al., 2010). Standardization is the process of rescaling original data values from different criterion map layers to comparable units. The standardization of raster GIS-based criteria assigns a value between zero and one to each grid cell using a fuzzy membership function. Fuzzy set standardization not only aims to transform different decision criteria into comparable units, but it is also used to manage decisional uncertainty inherent in spatial decision making (Malczewski, 1999). The planning of new wind farm sites requires the consideration of criteria that involve a high degree of uncertainty and imprecision. Also, value judgments from decision makers on the relative importance of the criteria will involve high levels of uncertainty and ambiguity. Fuzzy set theory coupled with WLC approaches can help support the decision process of wind farm site selection.

Although the existing SDSS frameworks have incorporated fuzzy standardization techniques and WLC methods to analyze site suitability for wind farms, very few methods have used multiple participants in the decision process. Such methods are aimed to address the need that different participants will likely perceive the importance of the criteria differently and produce unique decision alternatives. As citizen (stakeholder) participation in environmental decision making increases, the number and variety of unique alternatives will also increase. Environmental decisions are often influenced by a wide range of stakeholder agendas, making it more difficult to achieve acceptance for a final solution (Shmoldt and Peterson, 2001). A model that promotes collaboration among participants can be used to build consensus and derive a solution with minimal conflict that maybe more equitable with lasting outcomes.

Collaborative spatial decision support system (CSDSS) is one of the SDSS frameworks that implements interactive group-based modeling using multi-criteria decision making methods and GIS (Armstrong and Densham, 1995). CSDSS addresses the need for group participation in spatial decision making. Such modules have been used in problems that require collaborative decision making techniques such as wetland planning and management (Goosen et al., 2007), restoration management (Jankowski, 2000), water resource administration (Nyerges et al., 2006), transportation improvement projects (Nyerges et al., 1997), habitat restoration (Jankowski and Nyerges, 2001b), urban green space development (Balram and Dragićević, 2005) and natural resource allocation (Dragićević and Balram, 2004). Simão et al. (2009) used a CSDSS to analyze site suitability for wind farms in the United Kingdom. Their framework supports asynchronous collaboration among multiple participants via the internet. Several decision factors are grouped into larger criteria sets, and participants use a rating technique to assign importance values to these sets. The results from all participants can be seen in an argumentation map and dialog among participants is promoted through a discussion board. However, the contribution of this work is aimed in the support of participant learning during the planning process through distributed collaboration among participants.

The presented approach builds upon previous SDSS framework ideas and presents a hierarchical structure of group decision making process that considers different hierarchy levels including a clear goal, constraints, objectives or criteria and factors. The proposed SDSS framework for wind farm site suitability analysis is intended for regional planning in Northwest Ohio but also for promoting a group decision making that considers different participants in the development of decision alternatives. The framework integrates environmental and economic criteria and builds the hierarchy for wind energy farm siting using WLC techniques and GIS functionality. Continuous spatial layers related to wind farm siting, which have been standardized using fuzzy set theory, are included as decision factors in the analysis. The SDSS allows multiple participants to examine and develop an in-depth understanding of the spatial data and assign importance values to each factor. The WLC technique is used to combine the assigned values with the standardized map layers to produce individual suitability maps. The maps created by personal interpretation and preferences of each participant are later aggregated for producing a group solution using the Borda method. The results of this methodology are illustrated through an experimental decision scenario discussed in Chapter 1. Chapter 2 describes the SDSS tool used in the experiment. Chapters 3 and 4 contain the results and discussion.

1. Wind Farm Site Suitability Decision Scenario

This section provides an overview of the case study of wind farm site suitability analysis in Northwest Ohio. The research, which is a prototype of a collaborative spatial decision problem, served as a context for the implementation of the SDSS analysis. Multiple participants with different judgments on the importance of decision criteria for wind farm siting were tasked to evaluate suitable locations for wind farm development. The following describes the case study design; including the study area, materials, and composition of the study group.

1.1 Study Area

The study area is a 27-county region in Northwest Ohio (Figure 1) with relatively high winds throughout the year. A wind resource assessment conducted at 50 m heights by the National Renewable Energy Laboratory (NREL) suggests that the region has sufficient annual wind speeds to support large scale wind farms (NREL, 2004). The glaciated topography of this region has few natural obstacles to wind movement in the area (Elliot et al., 1987). Prevailing northerly and westerly winds are the most dominant across the region. The coastal areas of Lake Erie are associated with the strongest winds in the area and within Ohio with annual average speeds of 7.0 to 7.5 m/s while the rest of the area has annual average wind speeds of 5.6 to 6.4 m/s.

The extensive wetlands in the region provide vital habitats for many birds and other plant and animal species. Bird habitats and migratory bird routes are of special concern in the area. There are sixteen locations in the region identified as Important Bird Areas by the Ohio Audubon Society (2009). The endangered Indiana Bat *(Myotis sodalis)* is found in every county in the study area (U.S. Fish and Wildlife Service, 2009).

The demand for energy in the area comes from the estimated 1.8 million people, or about 16.4 % of the state population (U.S. Census Bureau, 2009) The industrial sector accounts for more than one-third of electrical consumption in the state while the residential sector accounts for nearly one-fourth of electricity used, with nearly one-fifth of households relying on electricity for home heating (USEIA, 2010). Ohio's alternative energy portfolio mandates that by 2025, at least 25 percent of all electricity sold in the state must come from alternative energy sources and one half of this electricity must be produced in the state (USEIA, 2010). In the study area, the city of Bowling Green has a total of four 85 m tall utility-scale wind turbines which generate 7.2 MW of power. In addition, the Ohio Power Siting Board, the agency that administers permits for wind farm development, has approved six new wind farm projects in the study area which will support a total of 501 turbines with approximately 900 MW capacity (OBSP, 2011). The potential for more wind energy in the state is also promising; according to a study conducted by the NREL, Ohio has adequate wind resources to potentially install 55 GW of onshore wind power (NREL, 2010). Offshore wind energy is also viable because a total of four counties have shoreline on Lake Erie within the study area. The first offshore wind farm to be installed in the Great Lakes is set to begin construction in Lake Erie, near Cleveland, Ohio, in 2012 (Gallucci, 2011).

1.2. Wind farm site selection factors

Site selection of a wind farm requires consideration of multiple criteria and evaluation steps to identify the best possible location and to minimize or eliminate obstacles to wind power development (e.g., visual intrusion, shadow flicker, turbine noise). Figure 2 shows the hierarchical structure of the decision process. It contains four levels; a goal, constraints, objectives or criteria and factors. The first level represents the ultimate goal of the suitability analysis. The second level represents constraints which limit the possible areas that can be considered in the suitability analysis. The third level represents the multi objective nature of the decision process. The first objective involves satisfying criteria that pertains to, and protects, the environment and the second objective considers economic factors related to wind farm siting. Each objective requires a number of factors which are represented in the last level in the figure. A detailed description of these factors is given below.

1.2.1 Environmental factors

Wind speed

Wind speed is a crucial factor in determining the best location for new wind farms. Energy output of wind turbines increase as wind speeds increase until nominal wind speed is reached, which is the speed that maximizes the energy production. Therefore, areas classified with higher wind speeds are more suitable than areas classified with lower speeds.

The wind data set that measures annual average wind speed at a 50 m height and produces wind speed maps at 200 m horizontal resolution was acquired by TrueWind Solutions and validated by the NREL (NREL, 2009). The data is partitioned in four categories of annual average wind speeds classified by the NREL from poor (1) to good (4). The description of the categories indicate that areas designated as Class 3 or higher are suitable for utility-scale wind development. Class 2 speeds can be considered suitable, especially in rural areas where the topography is flat and there are no obstacles. Areas designated as Class 1 are not considered suitable, but the degree of certainty of which the wind power class can be specified depends on factors such as the complexity of the terrain and the variability associated with wind resources (NREL, 2004). Also, data collected at different heights other than 50 m may classify some areas designated as Class 1 into higher wind speed classes. In this project, the data was imported into a

GIS, converted to a raster format, and resampled to 30 x 30 m cell size. Figure 3(a) shows the standardized wind speed data layer which used membership values assigned to each wind class shown in Table 1.

Distance to Important Bird Areas

An environmental impact assessment for new wind farms mandates the inclusion of potential threat to local wildlife. The importance of bird assessment is intended to minimize collisions and mortality by birds and bats with operating wind turbines. The threat that wind farms pose to the health and safety of bird populations is an issue routinely brought up in the planning phase of wind farms. A major concern is avian collisions with the turbines near bird habitats and migratory routes and the change of air pressure around the wind turbines that is fatal especially for bats. Studies have shown that other man-made features such as power lines, skyscrapers and automobiles kill far more birds than do turbines (Devereux et al., 2008; Sovacool, 2009; Farfan et al., 2009). Nevertheless, the potential threat to birds is an issue that we have decided to address in this study example.

The Ohio Audubon Society has identified a total of 16 locations in the study area as Important Bird Areas (IBA). An IBA is defined as an essential habitat that one or more avian species use during their nesting season, the winter, and/or while they are migrating (Ohio Audubon Society, 2009). A digital map published by the Ohio Audubon Society in 2006 (1:2,000,000) that depicts all the IBAs located in the state was imported into GIS and the boundaries of each IBA in the study area were digitized to a new data layer. The distances from IBAs were calculated using Euclidean distance functions that measure the straight-line distance from each cell to an IBA. Table 1 shows that a linear increasing fuzzy function was used to standardize the distances. The first control point (a = 5,000 m) indicates the least suitable distance and the second control point (b = 30,000 m) and beyond indicates the most suitable distances for siting new wind farms (Fig. 3(b)).

Land Use

Although individual wind turbines have a relatively small footprint on the land, a concern surrounding wind farms is the impact on land related to the construction and operation of the turbines. A study published by the NREL (Denholm et al., 2009) examined the amount of land impacted by utility-scale wind farms on different types of land uses. The study showed that wind farms located on the same land use are often associated with the same layout configurations, and the layout of the turbines correlates with how much land is permanently impacted. The study suggested that wind farms located on cropland, pasture, and shrub impact less amount of land than grassland and forestland. For instance, installation patterns such as parallel string configuration is often used in grassland and that is not the case in forested areas where clearing for access roads, turbine pads, and set back areas around each turbine is required (Denholm et al., 2009).

The US EPA's Multi-Resolution Land Characteristics Consortium (MRLC) developed land cover data primarily from Landsat TM imagery acquired in 2001 based on Anderson's classification system (Anderson et al., 1976). This data was imported into GIS and the classes representing different levels of land use suitability were extracted into new data layers. Classes representing cropland, pasture, shrub land, or barren land are considered the most suitable land cover. Grassland and forested land represent moderately suitable land cover. Classes such as developed areas, open water, and wetlands are considered constraints in this analysis and represent the least suitable land cover (Fig. 3(c)). Table 1 shows the membership values assigned to each of the land use categories used here.

1.2.2. Economic Factors

Proximity to Major Transportation

The proximity to major transportation infrastructure is essential step in the planning process because transportation of oversized turbines can be complex and costly. For instance, tower sections for the common 80 m turbine can weigh more than 70 tons, be 36 m long, have a diameter of 4.5 m, and have blades that can range between 33 to 44 meters in length (AWEA, 2009). Often, these components must be transported as single pieces, thus requiring large equipment for shipment. Small residential roads cannot easily support the size and weight of such components and may have inadequate turning radii for bringing the turbine components to the site. Railroads is another transportation alternative but often roads are still required to carry the turbines from the railroads to the project site. The distance from the potential wind farm site to major roads or railroads should be minimized to lower costs by making the transportation of wind turbines as efficient as possible.

The road transportation dataset used in this study was produced by the USGS (1999) and considers interstates, and US or state routes while the railroad data was produced by the National Atlas of the United States (2005) (1:2,000,000). The major road and the railroad layers were combined to create a major transportation layer. The distances from major transportation were calculated using a Euclidean Distance algorithm and then the distances were standardized using a two point linear decreasing function (a = 1,000 m, b = 10,000 m). Distances less than 1,000 m were assigned a membership value of 1 (the most suitable) and distances greater than 10,000 m are assigned a membership value of 0 (the least suitable). Figure 4(a) shows the standardized data layer.

Proximity to Transmission Lines

The proximity to high-voltage transmission lines is important consideration for wind farm development for minimizing the cost of delivered electricity to the consumer. At present, wind power developers have used regions with high wind resources that are close to adequate transmission line capacity and where transmission costs are low to develop. Siting a wind farm where transmission lines are lacking will require new transmission lines to be installed, which will increase the costs associated with wind farm development.

Existing transmission line data was digitized from a map produced by TrueWind Solutions and published by the NREL in 2004 (1:2,000,000). The data depicts the locations of existing transmission lines in the study area that can potentially be used to manage the energy created by a wind farm. The minimum capacity of the transmission lines found in the study area is 100 kV and the maximum is 735 kV. The data was generalized to a single layer. A distance function was also used to calculate distances from transmission lines. This was standardized using a linear decreasing function with two control points (a = 1,000 m, b = 20,000 m). Distances less than 1,000 m are given a membership of 1 and distances greater than 20,000 m are assigned a membership of 0 (Fig. 4(b)).

Soils

Different types of soils can affect the installation costs of a wind farm. If a potential wind farm location does not contain soil that can adequately support large structures like wind turbines, costly measures will be needed in order to do so. This can include the removal and replacement of poor soil and the installation of deep foundation supports onto underlying bedrock (Fitzpatrick, 2010). Soils that are characterized by high contents of gravel and sand can better support large structures than silt and clay soils. Soils containing high organic matter are the least suitable for large structures (Terzaghi et al., 1996).

The SSURGO (Soil Survey Geographic database) data produced and distributed by the Natural Resources Conservation Service (NRCS) and National Cartography and Geospatial Center (NCGC) was used in this analysis (USDA, 1994). It depicts multicounty-level soil compositions across the country. The attribute information contains classifications that coincide with the Unified Soil Classification System, a system used in engineering and geology to describe texture and grain size (ASTM, 1985). Using this classification system, the data can be categorized into one of five groups based on composition; gravel, sand, silt and clay with a liquid limit less than 50 percent, silt and clay with a liquid limit greater than 50 percent, and highly organic soils. Liquid limit refers to the water content at which soil changes from a plastic to a liquid behavior. The membership values assigned to each type is presented in Table 1. The higher the membership value, the more suitable that soil type is for a wind farm. The standardized data layer is shown in Figure 4 (c).

Population Density

Areas of higher population density require more energy than areas of lower densities. It becomes an important economic factor, therefore, to locate a wind farm near areas with high population densities so the energy produced from the farm can quickly be transferred to areas that have the highest energy demand. Energy produced from wind farms located near high population densities will have a shorter distance to travel and will depend on fewer transmission lines to transfer the energy, thus reducing the cost of supplying the energy to consumers. Population data was acquired from the National Atlas of the United States dataset. It depicts cities in the United States as vector point data with associated population figures from the 2000 US Census. A kernel density function with a bandwidth of 20 km was used to calculate the density of population around each output raster cell. The population attribute was used to assign a greater influence to the cities that had a higher population. A linear decreasing function was applied to the kernel density output using two control points (a = 200, b = 20). Densities greater than 200/km^2 are given a membership of 1 and densities lower than 20/km^2 are given a membership of 0. Figure 4(d) shows the standardized data layer.

1.3 Study Group

The study group comprised of 30 undergraduate and graduate students participants from Bowling Green State University. A one-hour facilitated presentation was given prior to using the SDSS prototype that included a background on the decision problem and current wind energy issues and operation in Northwest Ohio; a summary of each decision factor, why it was included in the decision process, and how the values were standardized; and instructions on how to use the decision tool. Participants were encouraged to ask questions at any time during the presentation and while they were using the model. Each participant was assigned a computer to complete the exercise independently. Roughly one hour was allotted to complete the task. The participants could run the model as many times as desired until they were satisfied with a result. They were instructed to select one output and submit it as their final decision alternative.

2. Spatial Decision Support Tool

The SDSS prototype used in this research was developed within ESRI's ArcMap (9.3) user interface using custom Visual Basic for Applications (VBA) code. The intention of the prototype was to provide an easy-to-use interface of which even non-experienced GIS users could examine spatial data and convey their judgments on what aspects they think are important to wind farm siting in Northwest Ohio. A description of the user interface is given, as well as an explanation of how the model calculates suitability scores based off users values. The Borda method, which is the technique used to develop weights based on the ranking of the factors is presented also. Sensitivity analysis, which examines how small changes in factor weights affect the results, is discussed as well.

2.1 User Interface

The user interface comprises of a set of steps and inputs that are organized by the presented hierarchy levels to build up the SDSS model (Fig. 5). The individual decision process starts with the examination of spatial data related to wind farm siting in Northwest Ohio. The main purpose of this step is to acquaint the participants with the farm siting problem and to develop an in-depth understanding of factors and constrains that should be taken in consideration when developing a wind farm. Users select radio buttons that activate and expand corresponding data frames in the table of contents to explore the data. These data frames contain layers related to each decision factor that users can turn on and off (Fig. 5(a)). In the second step, users choose which, if any, constraints to include in the analysis (Fig. 5(b)). If a constraint is included, then the pixels classified as that constraint will be excluded from the analysis. Following the selection of constraints, the participants are prompted to select their preference for inclusion of environmental factors and to assign importance values based on a personal interest and understanding of the decision problem. This is done using slider bars, with values ranging from 0 to 100, with an associated text field that displays the exact value of the slider bar. A value of 0 means the factor is not important, and a value of 100 indicates the factor is very important. Also included on this window is a button that opens a help file containing brief descriptions and justification on why each environmental factor is included in the analysis. Buttons linked to each factor that activate the corresponding data frame in the table of contents are also built-in to this window (Fig. 5(c)). The next step is the selection and assignment of importance values to the economic factors that is accomplished by slider bars. This window also contains a button that opens a help file containing brief descriptions on the importance of the economic factors in the analysis. Each window in the SDSS model includes a "Back" button that allows the users to return to the previous window at any time and change the values. In the last step of the decision process, users indicate which set of criteria they think is more important to the overall decision. A slider bar is displayed with the text "Environmental Criteria" on one end and "Economic Criteria" on the other. The initial value of the slider bar is set to 50, which indicates equal importance for both criteria. The closer the slider bar is to 100 in either direction indicates higher level of importance for that set of criteria over the other (Fig. 5(e)). Clicking "Submit" on this window initiates the calculation of suitability scores.

2.2 Calculation of Suitability Scores

The WLC method is used to calculate the suitability score for each location (30 m cell) in the study area. The scores of the environmental and economic criteria are calculated independently, using equation 1:

$$V_i = \sum_{j=1}^{n} w_j v_{ij} \tag{1}$$

where V_i is the suitability index for cell i, w_j is the relative importance weight of criterion j, v_{ij} is the assigned value of cell i under criterion j, and n is the total number of criteria. The outputs from the SDSS include three data layers that are created and displayed in ArcMap: an environmental layer solution showing the suitability considering only the environmental factors, an economic layer solution showing the suitability considering only the economic factors, and a combined suitability layer that aggregated the two. A green-to-red color legend is automatically applied to each layer, with the green areas representing low suitability scores and red representing high suitability scores. For obtaining the group solution a text file is created by each participant that includes the values assigned to each factor and the values assigned to each set of criteria.

2.3 Borda Count

A Borda count method is used in this analysis to determine the collective rank, and relative importance of each decision factor based on values assigned by the participants. The values are used to determine the rank of each decision factor for each participant. For example, if a participant assigns a higher value to wind speed than to land use, then wind speed is assigned a higher rank on that participant's ballot, regardless of the difference in values between the two. The Borda count is a positional voting system devised by the 18th century French mathematician, Jean Charles Borda (Munda, 2008). The Borda method assigns points to each factor corresponding to the position in which it is ranked by each participant. For a set of *n* decision criteria, *n-1* points are given to the most preferred factor, *n-2* points are given for the second most preferred, down to zero points for the least preferred factor. The individual preferences of the participants can be aggregated into a group preference by summing the total number of points for each factor. The factor with the highest total Borda score is considered to be the most important. The importance of Borda's aggregation is that prevents a contentious participants who rank some factors very high and some very low from dominance and promotes a consensual solution. The Borda method has been applied to evaluate decision alternatives in similar multi-criteria analysis involving multiple participants in the fields of habitat restoration (Jankowski, 2000), strategic forestry planning (Hiltunen, et al., 2008), ecological risk management (Fanghua and Guanchun, 2010), and natural hazard decision making (Chen, et al., 2001).

In this study, the Borda scores for the environmental factors are calculated independently from the economic factors. Therefore, environmental factors are ranked from 2 to 0, and economic factors are ranked from 3 to 0. The scores are standardized by dividing a factor's Borda score by the total Borda score for that set of criteria. The result can be used as the relative importance weight for that factor.

2.4 Sensitivity Analysis

Uncertainty is often involved in multi-criteria decision making due to many different reasons such as the inability for decision-makers to provide precise judgments relative to the importance of decision factors. The uncertainty can also be attributed to limited or imprecise information about the decision problem and to inconsistency involved in the decision-makers preferences (Malczewski, 1999). Sensitivity analysis is often used to deal with this uncertainty and to assess the reliability of the method involved in identification of the highly suitable areas. A small perturbation in the decision weights may have a significant impact on the solution. Thus, the sensitivity analysis is conducted on the solutions where the decision weights are systematically varied to investigate the relative impacts of the weights on the suitable areas. A range of weight deviations is applied to each factor weight and altered by a small increment throughout this range. All other factor weights are adjusted proportionately to satisfy the requirement that the weights sum to 1.0. The total number of simulation runs required for a decision participant is calculated using equation 2:

$$Runs = \sum_{i}^{m} r_i \tag{2}$$

where m is the set of criteria, and r_i is the number of increments within the feasible weight range for criterion i (Chen et al., 2009). For example, in this paper a ±10 % weight range with 1 % increment was applied to seven decision factors and two objectives.

3. Results

Fig. 6 shows the results from the study group who evaluated the factors and the objectives. The factors for the environmental objective are wind speed (WS), important bird areas (IBA) and land use (LU) while the factors for the economic objective are proximity to major transportation (PTp), proximity to transmission lines (PTm), soils (S) and population density (PD). Fig. 6 (a) shows that participants considered wind speed as the most important environmental factor, followed by land use and distance to IBA which contains two very opposite views from the rest of the group (two outliers). On the other hand Fig. 6 (b) shows that proximity to transmission and proximity to transportation are the two highest-valued economic factors, with proximity to transmission valued slightly higher than proximity to transportation followed by population density and soil. Fig. 6 (c) shows that the participants considered the economic objective as more important than the environmental objective.

Fig.7 shows group solution for wind farm site suitability generated by the Borda method. Fig. 7 (a) is the solution obtained from the environmental factors, (b) is the solution obtained from the economic factors, and (c) is the weighted aggregation of the environmental and economic objectives. The aggregation output shown in (c) used a weight of 0.47 for the environmental criteria and 0.53 for the economic criteria. The weights used here represent the average values assigned by the participants to each objective. The Borda weights that were used in the calculations are shown in Table 2. The most suitable locations for a wind farm in Fig. 7 (a) are non-urban areas located far from IBAs and where wind speed is 5.6 m/sec or greater. The most suitable locations in Fig. 7 (b) are urban areas with high population densities and areas closer to existing transmission lines and transportation routes. The legends in the figure represent a measure of wind farm suitability where possibility is expressed on a scale range between 0 and

1. In the figure, the percentage of area is categorized by suitability in terms of fuzzy membership values. For example, the percentage of area with high suitability scores between 0.8 and 1 is shown in the pie charts where solution obtained from (a) classifies 29.4 % and (b) classifies 1.5 %. It is interesting to note that the environmental factors in this case study are associated with much higher suitability than the economic factors but this is flexible and can change as new factors or criteria are added or modified.

The aggregated decision map in Fig. 7 (c) shows that 2.4 % of the total area has high suitability scores between 0.8 and 1.0 for wind farm siting but this decision map also classifies 78.3 % of the total area with suitability scores between 0.6 and 0.8. Most of the areas having high suitability scores are located near high population densities; however, there are some in areas with low population densities. These areas are characterized by close proximity to both transportation and transmission lines, and where wind speed is at least 5.6 m/s. It is interesting to note that the suitability calculated for the existing wind farm in the city of Bowling Green is between 0.6 and 0.8. The suitability calculated for the areas that have been approved for wind farms by the OPSB (2011) range between 0.4 and 1.0, with 1.6 % of the approved areas having suitability between 0.8 and 1.0; 83.3 % between 0.6 and 0.8; and 15.1 % between 0.4 and 0.6.

Fig. 8 shows the results from the sensitivity analysis for the most suitable areas with scores ranging between 0.8 and 1.0 for the environmental and the economic factors as well as the objectives. Fig. 8 (a) shows that environmental objective is the most sensitive by changing the weight of the land use factor. When land use weight is decreased by 10 % a total of 1.5 % of the area is classified as highly suitable while when the weight is increased by 10 % a total of 3.2 % becomes classified as highly suitable. The least sensitive environmental factor is the wind speed. Fig. 8 (b) shows that the high suitability areas are the most affected by population density weights. For example the figure shows that high suitability areas increase 11 % when the population density weight is decreased by 10 % and high suitability areas decrease to less than 1 % when the weight is increased by 10 %. However the decrease in population density weight is more sensitivity than the increase in population density weight. At this point it is unclear the real cause for this sensitivity but it may be driven by the density function and the bandwidth used for the creation of the population density layer or other scale related issues from the layers used in the analysis. The least sensitive economic factor is the proximity to transportation.

Fig. 8 (c) shows that the percentage of area of high suitability increases when the environmental weight increases or when the economic weight is decreases. This percentage of high suitability decreases when the environmental weight decreases or when the economic weight increases. However, these results are mostly driven by the fact that environmental factors have much higher suitability than the economic factors as shown in Fig. 7 (a) and (b). Applying more restrictive standardization control points to the factors or adding other factors will yield different outcomes from Fig. 8 (c).

The spatial change in areas of high suitability (0.8 to 1.0) from Fig. 8 is shown in Fig. 9. The change of high suitability areas is represented as the difference between simulation maps from the sensitivity analysis. The "no change" areas in the legend are the locations which were suitable and did not change throughout the simulation and the "change" areas are the locations that have changed throughout the simulation at least one or more times. Much of the change in highly suitable areas occur in or near the same locations for each factor, with the notable exception of population density (Fig. 9 (g)), which shows the greatest amount of change among any of the factors. Also it is interesting to note that the changes in the figure appear to be located mostly at the fuzzy boundaries which transition from full membership to non-membership.

4. Discussion

The sensitivity analysis suggests that the suitability scores are most affected by the changes in the weights of some factors. For example, for the environmental criteria the most sensitive factor is the land use that affects a total of 1.8 % of the high suitability area while the influence of change from wind speed and important bird areas is less than 0.8 %. For the economic criteria the most sensitive factors is the population density and the least sensitive is the soils factor. The population density affects a total of 8.4 % of the high suitability area while the soils factor affects a total of 1.8 %. For instance, in the standardized population density layer a significant portion of the study area is classified with low suitability scores. The majority of the study area is rural; therefore, the suitability in regards to population density is poor. Decreasing the influence of population density on the overall solution will allow the areas having low suitability to have a higher overall suitability score. Additionally, if the weight of the population density layer is increased, areas with low population densities will have low overall suitability scores even if they are characterized by high suitability in other layers. The percentage of area classified as having high suitability increases when the weights of transportation or transmission lines increase, and it decreases when the weights of soil or population density increase.

Thus, factors with high scores and weights can compensate for low scores from other factors but when scores are low while the weights are high factors can only weakly compensate for the poor scores from other factors. Malczewski (1999) notes that factors associated with high importance weights are the most likely candidates for sensitivity analysis. Since the weights of such factors are high, even slight changes can result in large changes in the output. This concept is important because manipulating a large number of factors for sensitivity analysis results in a large number of iterations, and the results may be difficult to interpret. Recognizing which factors are most prone to sensitivity analysis can save time during the decision process.

The confidence of the decision maps with high suitability areas can be examined spatially using the sensitivity results. For instance, Fig. 9 depicts the changes associated with the manipulation of the factor weights. When deciding on locations for a wind farm, decision makers should be cautious of the areas that are prone to rapid changes influenced by weights such as from poorly ranked factors. In multi-criteria decision making, it must be understood that uncertainty is inherent in the assignment of importance weights by the participants. Therefore, one cannot be completely certain in the weights used to calculate suitability. Identifying locations or alternatives that are susceptible to slight changes is important in the decision making process to ensure that the best possible solution is implemented.

5. Conclusion

This study presents an application of a GIS-based multi-criteria evaluation approach that uses opinions from multiple participants for assessing wind farm site suitability in Northwest Ohio. The group-based SDSS was developed and implemented with a total of 30 student participants who used the system to assign importance and attribute weights to environmental and economic decision factors. The selection of participants was exploratory for highlighting the strength of this technique but there are many different participant models that can be implemented such as representation of major interest positions (citizen advisory), a random pool of citizens (citizen juries), on the basis of being affected by the decision (citizen initiatives) and on showing interest in the problem (Dutch study group). The assigned factor weights by individual participants used the Borda method for ranking and for generating group weights which were used for consequent WLC aggregation and generation of wind farm suitability scenario.

The sensitivity methods used in this study are a small fraction of the possible sensitivity analysis techniques that can be applied to the results, each of which could possibly produce different outcomes. In the SDSS prototype the participants assigned importance values to decision factors using slider bars but other more simplified tools can be also implemented. For example, participants could use a ranking user interface that may be more consistent with the participants inputs and reasoning. For instance, ranking modules for assigning weights have been implemented for direct pairwise comparison between alternatives (Jankowski et al., 1996; Reza, 2005) or for conversion of fuzzy linguistic terms (i.e., low, medium, high) for providing a precise numerical judgment with respect to the alternatives (Boroushaki and Malczewksi, 2010).

In summary, the intention of this research is to show the strengths of a group-based SDSS for wind farm site suitability. The example was demonstrated through a case study for regional planning in Northwest Ohio but the methodology provides other flexibilities such as the use of specific criteria for different study areas, employment of different criteria weighting techniques and aggregation methods, and implementation in a variety of settings. Whereas this study required participants to be present at the same location and at the same time, implementing SDSSs over the internet can eliminate these restrictions and promote collaboration among participants all over the world. Although methods and techniques used in this research can be changed and improved upon, the presented approach is a valuable tool for simplifying and enhancing decision-making process of complex spatial multi-criteria problems.

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APPENDIX A: FIGURES

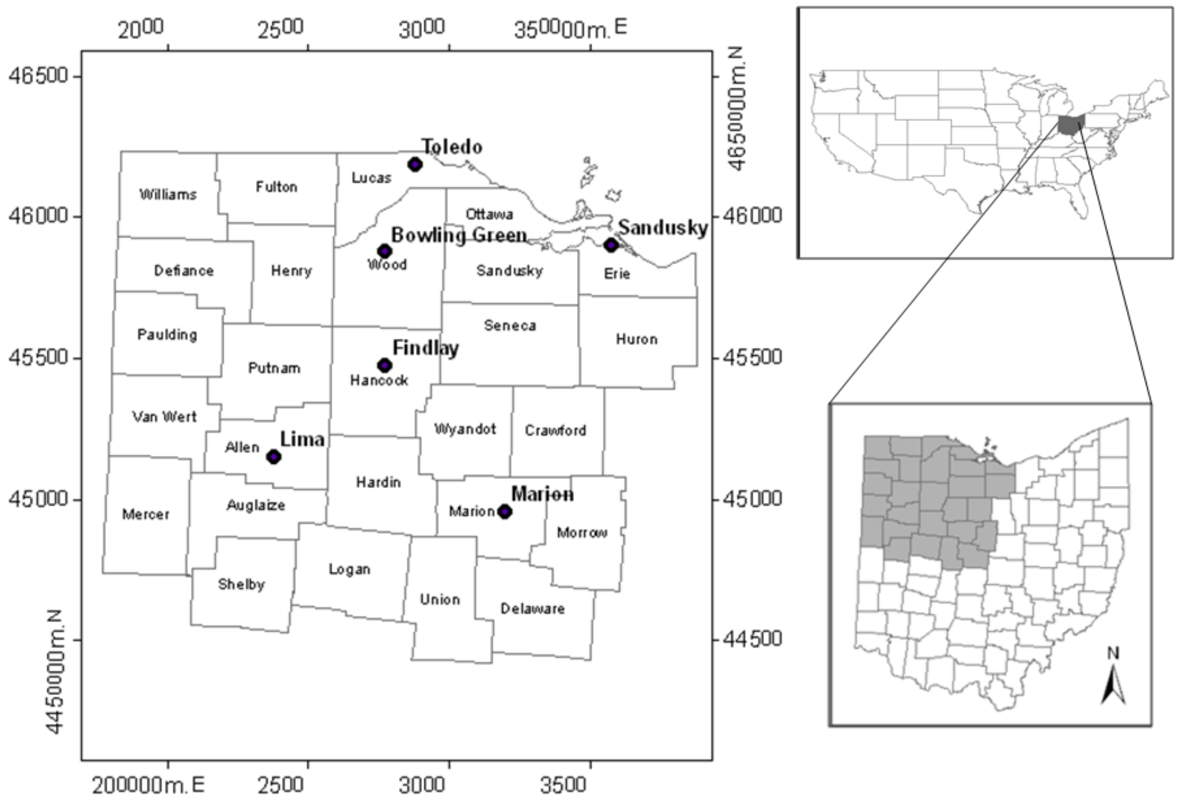

Fig. 1. Location of the study area.

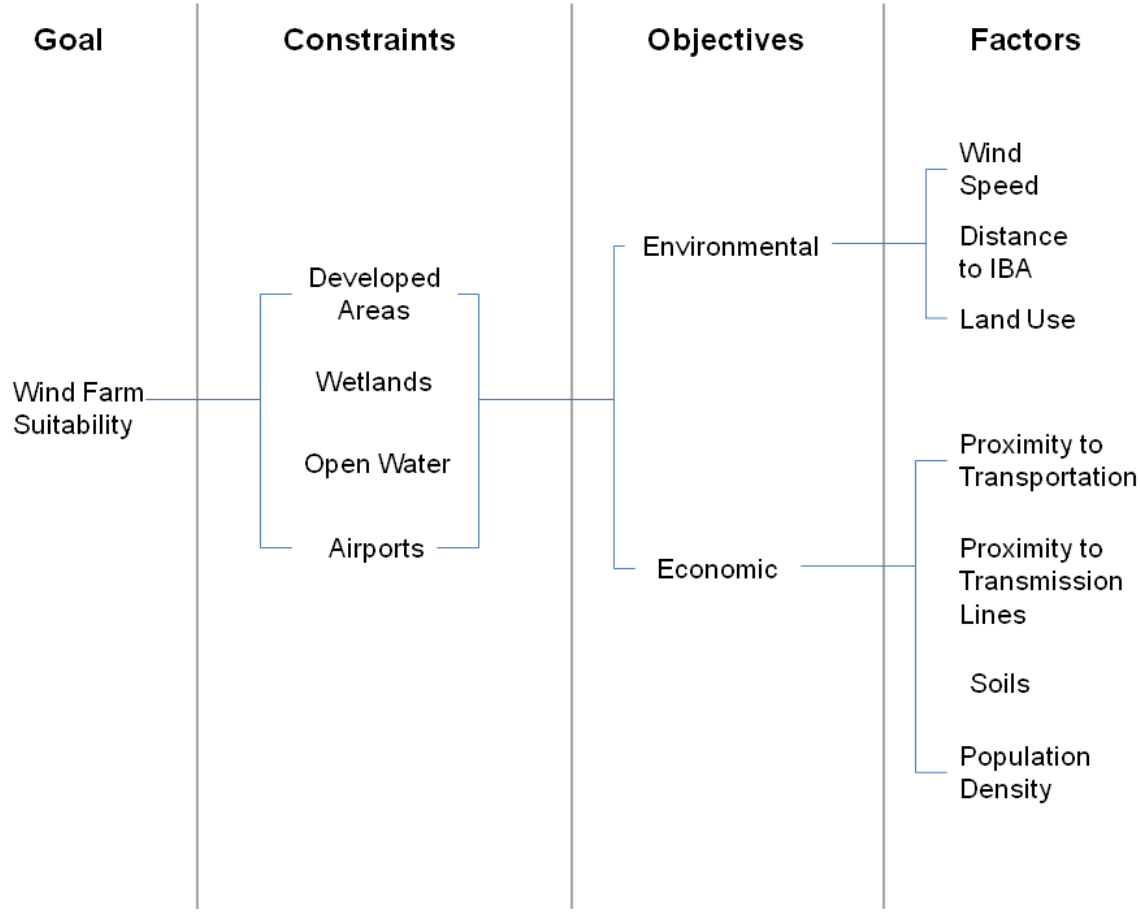

Fig. 2. Decision process hierarchy.

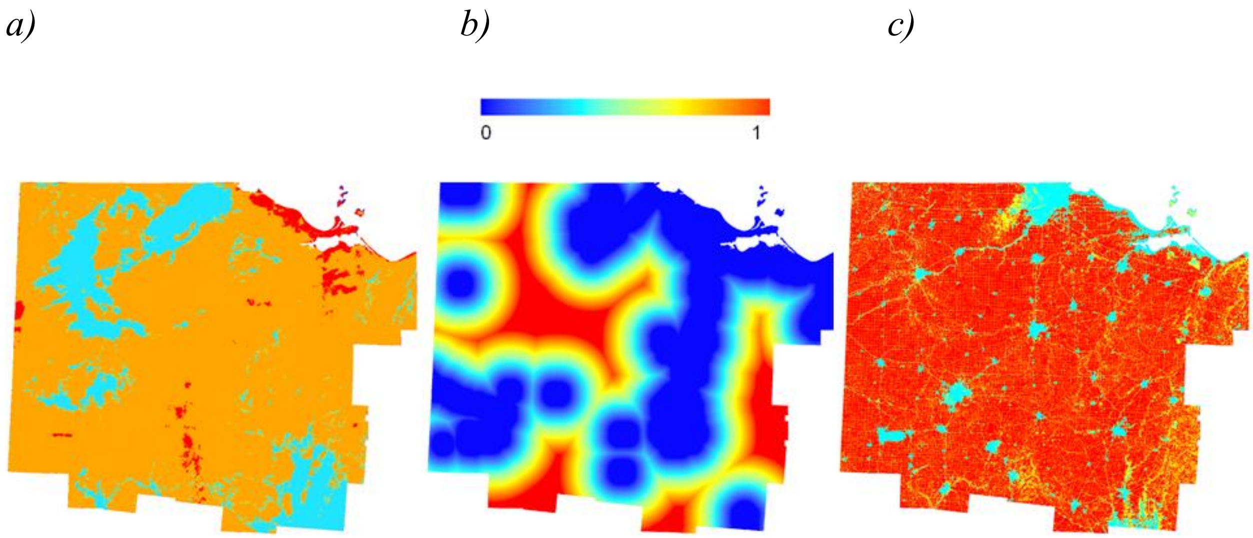

Fig. 3. Standardized environmental factors a) wind speed; b) distance to important bird areas; and c) land use.

a) *b)* *c)*

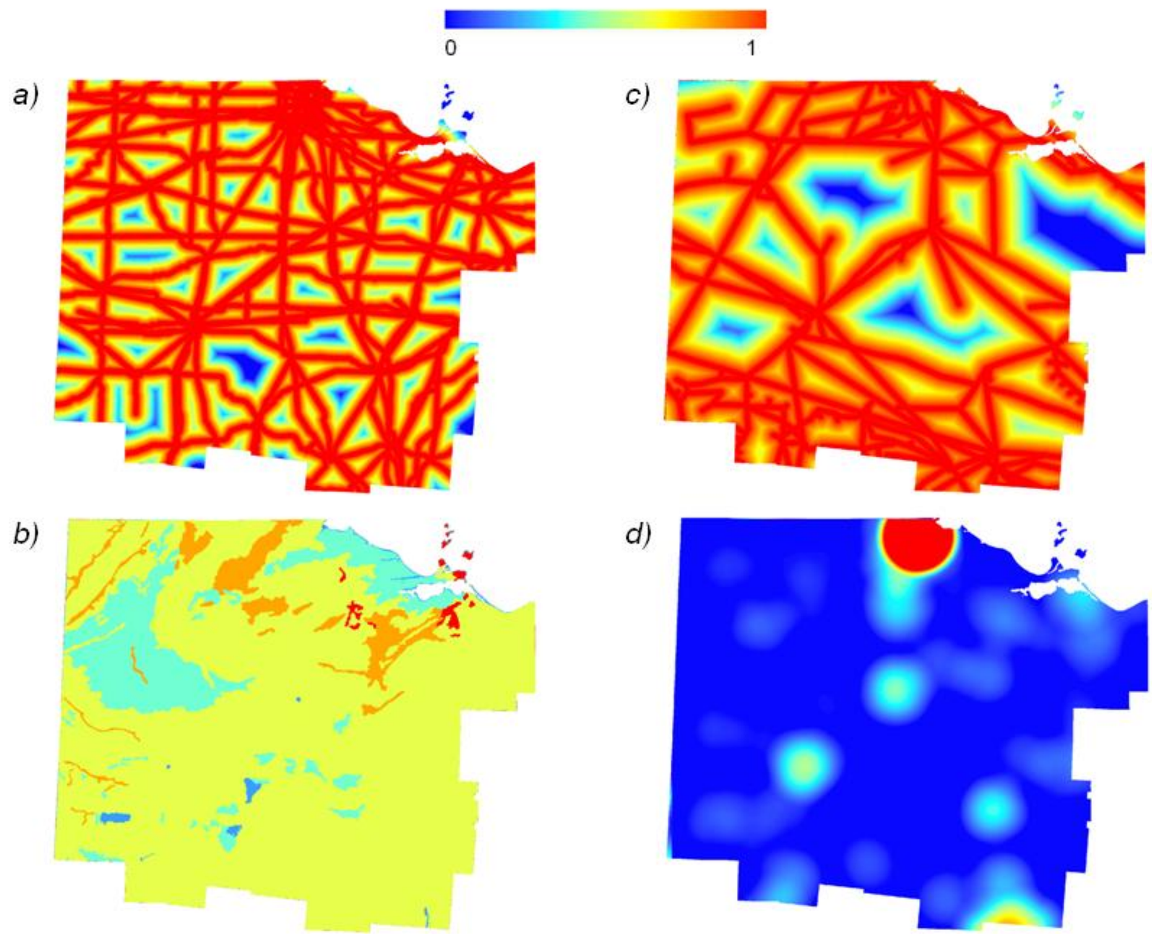

Fig. 4. Standardized economic factors a) proximity to transportation; b) proximity to transmission lines; c) soil; d) population density.

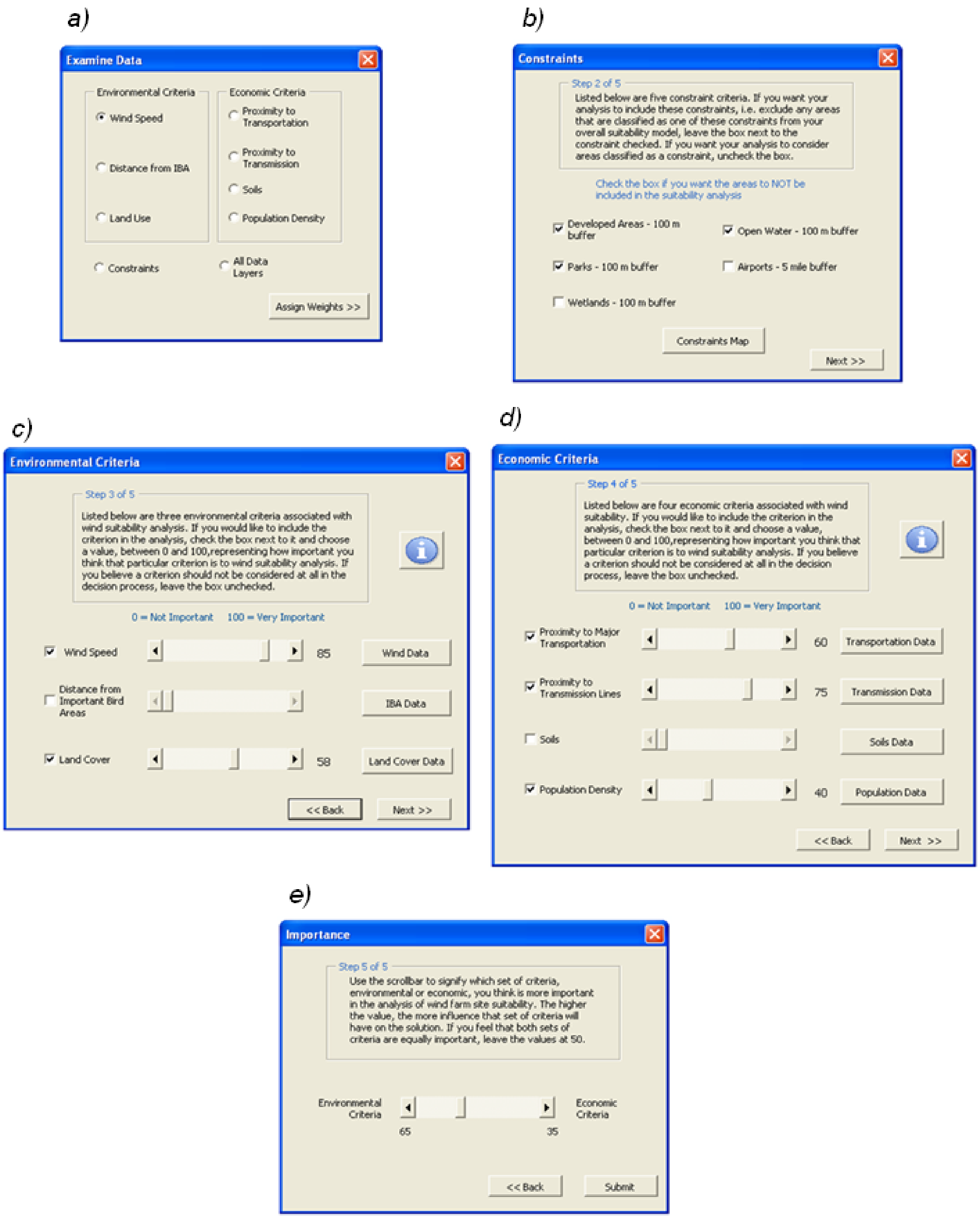

Fig. 5. Sequential steps of the SDSS model.

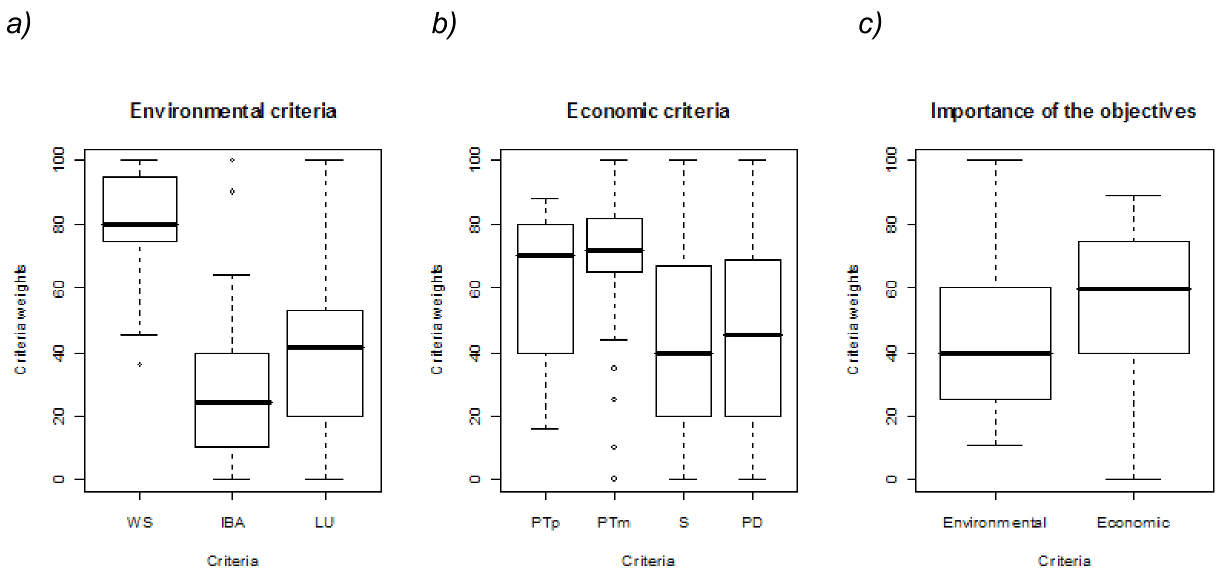

Fig. 6. Distribution of importance values assigned by the participants for the environmental factors (a), the economic factors (b) and for the objectives (c).

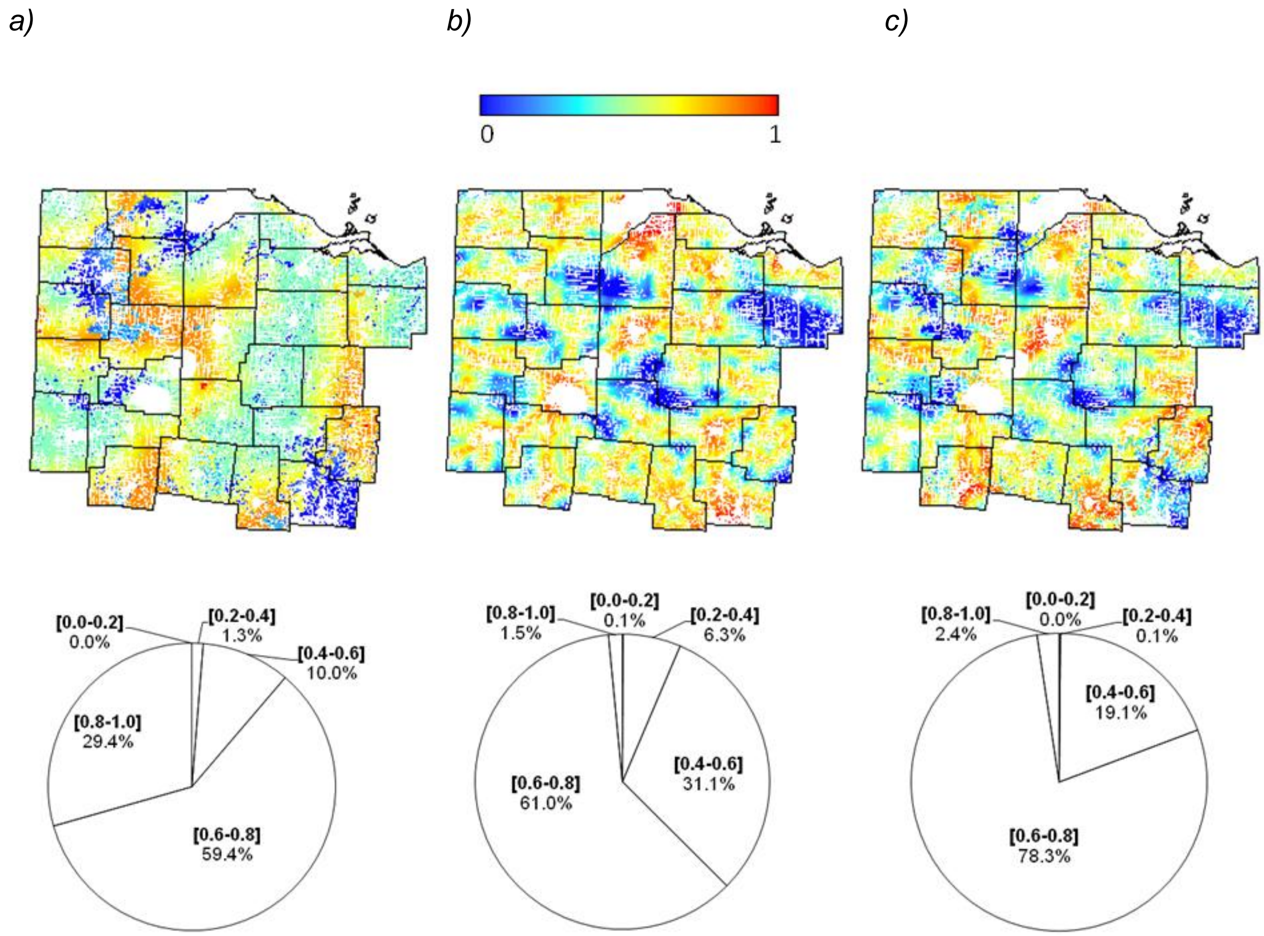

Fig. 7. Results using weights calculated from the Borda method. Alternative (a) is the suitability of the environmental factors, (b) is the suitability of the economic factors, and (c) is the weighted aggregation of (a) and (b).

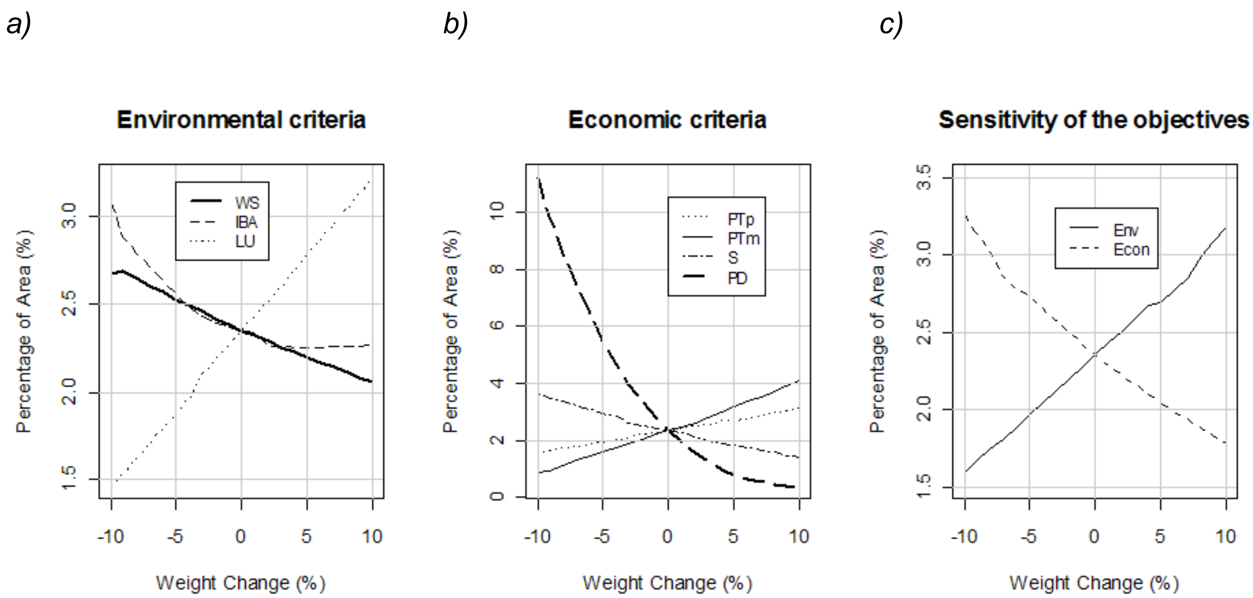

Fig. 8. Sensitivity analysis applied to the area classified with high suitability (0.8 – 1) for (a) the environmental factors, (b) the economic factors, and (c) the objectives.

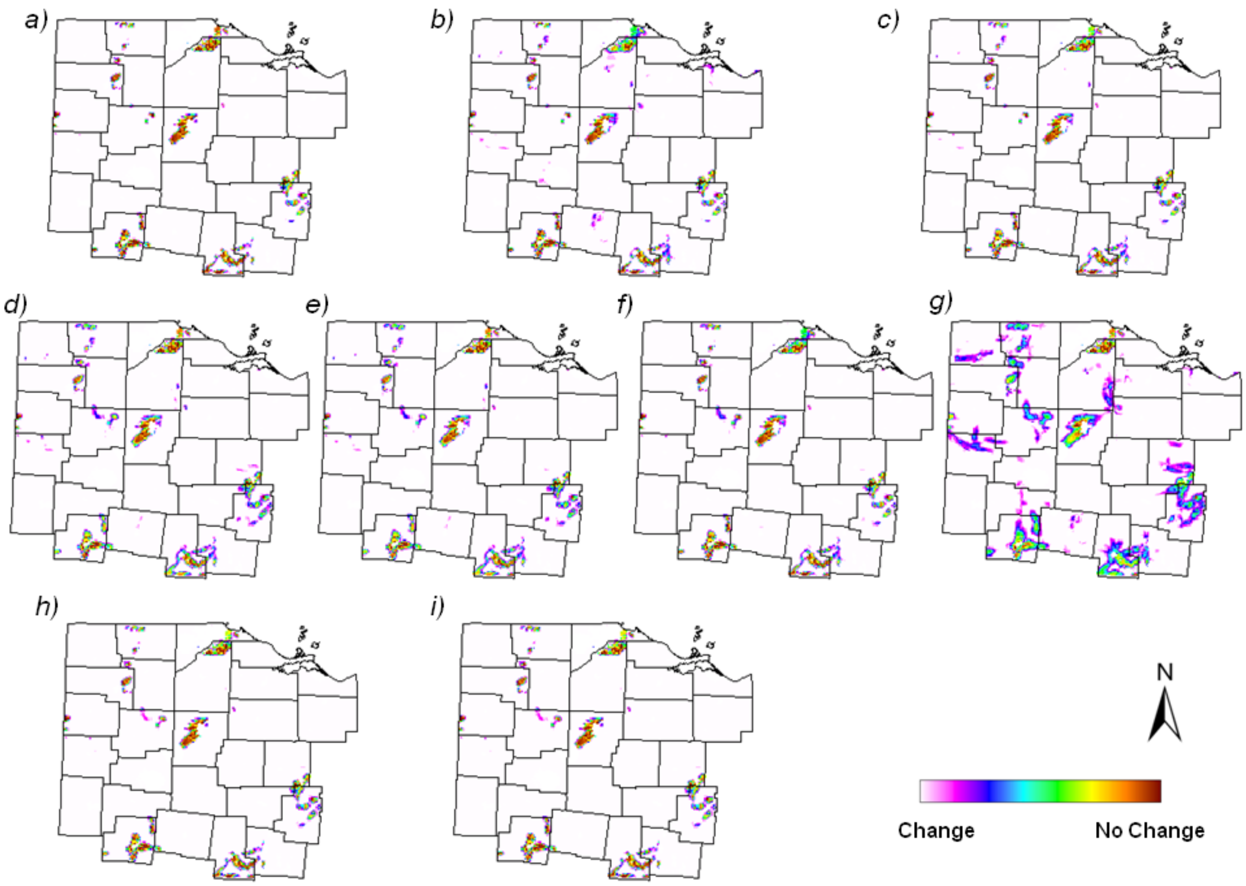

Fig. 9. Relative change in areas of high suitability associated with the sensitivity analysis for, (a) wind speed, (b) IBA, (c) land use, (d) proximity to transportation, (e) proximity to transmission, (f) soil, (g) population density, (h) the environmental objective and (i) the economic objective.

APPENDIX B: TABLES

Table 1
Fuzzy set memberships and membership functions with control points used for wind farm site suitability

Project Objectives and Criteria	Control Point a	Control Point b	Fuzzy Function/ Membership
Environmental Factors			
Wind Speed (m/sec)			
0.0 – 5.6 (Class 1)			0.3
5.6 – 6.4 (Class 2)			0.8
6.4 – 7.0 (Class 3)			1.0
7.0 – 7.5 (Class 4)			1.0
Distance from Important Bird Area (m)	5000	30000	Linear - Increasing
Landuse (no units)			
Shrub, Barren, Pasture, Cropland			1.0
Grassland, Forest			0.667
Developed Areas, Water, Wetlands			0.333
Economic Factors			
Proximity to Major Transportation (m)	1000	10000	Linear - Decreasing
Proximity to Transmission Lines (m)	1000	20000	Linear - Decreasing
Soil (no units)			
Gravel			1.0
Sand			0.8
Silt and Clay, LL < 50			0.6
Silt and Clay, LL > 50			0.4
Highly Organic			0.2
Population Density	20	200	Linear - Increasing

Table 2
Borda scores and normalized weights. Rankings shown in parenthesis

Objective Aggregation Weight	Factor	Borda Score (v_i)	Normalized Borda Weights
Environmental env= 0.47	WS	52	$\boldsymbol{W_1}$ **=** 0.55 (1)
	IBA	18	$\boldsymbol{W_2}$ **=** 0.19 (3)
	LU	24	$\boldsymbol{W_3}$ **=** 0.26 (2)
Economic econ = 0.53	PTp	55	$\boldsymbol{W_4}$ **=** 0.29 (2)
	PTm	66	$\boldsymbol{W_5}$ **=** 0.35 (1)
	S	33	$\boldsymbol{W_6}$ **=** 0.17 (4)
	PD	36	$\boldsymbol{W_7}$ **=** 0.19 (3)

APPENDIX C: CONSENT LETTER

BGSU®
BOWLING GREEN STATE UNIVERSITY
Department of Geology

My name is Steven Cathcart and I am a graduate student in the Geology Department at Bowling Green State University. My thesis advisor is Dr. Gorsevksi from the School of Earth, Environments and Society here at BGSU. I am conducting thesis research that involves gathering the opinions of people on what factors they feel are important to consider when choosing an optimal location for a wind farm in Northwest Ohio. This research involves using a Geographic Information Systems (GIS) model to gather those opinions. Because you are enrolled in a GIS course here at BGSU, you are being asked to participate in this research.

The development of wind energy is an important spatial land-use issue that is relevant to this area. Like many land-use issues, finding the best location to install a wind farm requires the participation of many individuals in order to achieve the best solution possible. Different participants involved in the decision-making process will likely have different opinions on where the best location for a new wind farm is. This research aims to demonstrate how different opinions from multiple participants can be used to develop alternatives that best represent a group solution. You are being asked to use a GIS model as a method to express your opinions on how important different factors related to wind farm siting are to the overall decision scenario. It is important to note that there are no direct benefits to you for participating in this research (i.e. monetary compensation, extra credit, etc.).

In this experiment, you will be using a tool within GIS to assign "importance values" to seven different factors related to wind farm siting. The value assigned to a factor represents how important you feel that factor is to finding a suitable location for a wind farm. The values you assign to each factor will be used to compute a "suitability map" in GIS. This map will show how suitable different areas are in Northwest Ohio for a wind farm. I will be using the values that you chose, along with your classmates, to determine the importance of each factor based off of all participants. Your participation in this research solely involves the assignment of values to these factors. You are allotted one-hour to complete this exercise.

Your participation is completely voluntary. You are free to withdraw at any time. You may decide to skip questions (or not do a particular task) or discontinue participation at any time without penalty. Deciding to participate or not **will not** affect your grade in this class or you relationship with your professor or with BGSU.

The data you create by using this GIS tool will be stored on a password-protected external hard drive. One step in the exercise requires you to provide your initials. **This is for naming the maps you create only**. Your initials will not be used or shared in any portion of this research. No other individuals will see the outputs you create or see what values you personally assign to the factors.

There are no risks involved in completing this exercise.

If you would like to contact me with any questions about your involvement in this research, my email address is stevecc@bgsu.edu and telephone number is 440-570-6636. My advisor can be reached at peterg@bgsu.edu or at 419-372-7201. You may also contact the Chair, Human Subjects Review Board at 419-372-7716 or hsrb@bgsu.edu, if you have any questions about your rights as a participant in this research. Thank you for your time.

*** Note: Your submission of your results indicates that you are consenting to participate in this research.**