Energy Policy 55 (2013) 374–385

Contents lists available at SciVerse ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

A group-based spatial decision support system for wind farm site selection in Northwest Ohio

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HIGHLIGHTS

- ► We present a prototype tool that we developed for wind farm site selection.
- ► Multiple participants rank the factors for promoting group-based decision making.
- ► The factors are aggregated by WLC technique to generate maps from participants.
- ► Group-based solution uses Borda method to aggregate the maps from participants.
- ► Sensitivity analysis is performed on the group solution to examine solution affects.

ARTICLE INFO

Article history:
Received 25 August 2011
Accepted 4 December 2012
Available online 5 January 2013

Keywords:
Spatial decision support system
Wind farm siting
Borda method

ABSTRACT

The purpose of this paper is to demonstrate the benefits of applying a spatial decision support system (SDSS) framework for evaluating the suitability for wind farm siting in Northwest Ohio. The multiple criteria evaluation (MCE) prototype system is intended for regional planning but also for promoting group decision making that could involve participants with different interests 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 the multiple participants to interact and develop an understanding of the spatial data for assigning 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 are intended to aid understanding of compromised solutions through changes in the input data from the participant's perspective.

1. Introduction

A growing number of regional problems driven by social, cultural, economic and environmental forces require assistance of spatial decision support systems (SDSS) for enhancing a variety of management solutions (Gorsevski and Jankowski, 2010; Bone and Dragićević, 2009; Goosen et al. 2007; Barkan et al., 2006; Jankowski et al., 2006; Nyerges et al., 2006; Jankowski, 2000). Specifically, SDSS are explicitly designed to help planners to solve complex problems by coupling analytical multiple criteria evaluation (MCE) models used for selecting and rating decision criteria and alternatives in combination with geographic information systems (GIS) (Malczewski, 2006, 1999). Such frameworks have been used to resolve complex issues such as siting of municipal solid waste facilities (Gorsevski et al., 2012; Donevska et al., 2012; Wiedemann and Femers, 1993), watershed management (Jankowski et al., 2006; Ramanathan et al., 2004), and land suitability analysis (Boroushaki and Malczewski, 2010a, 2010b, 2010c; Balram and Dragićević, 2005).

A number of SDSS methods and techniques have been also proposed to analyze site suitability for wind farm siting (Aydin et al., 2010; Janke, 2010; Rodman and Meentemeyer, 2006; Baban

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http://dx.doi.org/10.1016/j.enpol.2012.12.013

and Parry, 2001). Some of the methods emphasize the role of conflicting objectives such as landscape esthetics (Swofford and Slattery, 2010; Warren et al., 2005), turbine noise (Aydin et al., 2010; Devine-Wright, 2005) avian deaths (Aydin et al., 2010; Farfán et al., 2009), and shadow flicker (Harding et al., 2008; Baban and Parry, 2001). However, complex spatial problems such as wind farm suitability not only face multiple conflicting objectives but also require public–private collaborations for formulating and implementing public policies and decision-making capabilities (Nyerges and Jankowski, 2010; Jankowski, 2000; Jankowski and Nyerges, 2001a, 2001b). Other shortcomings with current SDSS include complex methodological computer applications that are mostly designed for GIS uses, lack of support of multi-user interface, and restricted access for general public participation.

Within this context, the specific processes and key players for a local level policy-making vary by location but interest groups who are directly affected by a decision and its planning consequences are often the primary candidates as stakeholders and participants in public land planning. It is argued that solving public–private problems introduces unreasonable conflicting views, such as public demand for strict environmental regulations, and on the other hand, private interests that may be alleged to be solely aimed at financial prosperity and economic greed. Thus, such antagonistic views involved in the decision process often cannot be structured adequately, quantified and modeled, which halts the planning process. In the literature, those problems are referred as "ill-defined" or "wicked" decision problems, which result in unfeasible solutions that are driven by differences in values, motives, and/or locational perspectives (Jankowski and Nyerges, 2001a, 2001b; Malczewski, 1999).

The way to overcome this weakness is through the development of new tools that allow for synergetic work that integrates computer technologies to facilitate decision-making processes through group collaboration and a flexible problem-solving environment. The empowerment of stakeholders to access those tools allows for the problem to be explored and understood at individual and group levels as well as to understand potential trade-offs between conflicting objectives (Wolsink, 2010, 2007; Devine-Wright, 2009, 2005; Toke et al., 2008; Gomboa and Munda, 2007; Kingston, 2007; Warren et al., 2005). It is expected that the main benefit of such collaborative GIS tools would provide interactive mapping and spatial analysis capabilities for enhancing group decision making in a bottom-up fashion involving all the participants from the very beginning of the planning process. In addition, the planning process is expected to evolve continuously through discussions among the participants and implementations of (1) committed effort on the part of the participants to collectively frame and address tasks that require exploration of spatial attributes and alternatives and visualization of geographical data; (2) a systematic group communication setting for participants to be fully aware of each other and collaboratively act on common goals; and (3) through provided mechanisms for exploring alternatives and building consensus from group preferences.

Some of the new approaches are implemented in a web-based environment that can support an unlimited number of users who are free to participate at their own convenient time and location (i.e., asynchronous distributed interaction model) (Berry et al., 2011; Bishop and Stock, 2010; Boroushaki and Malczewski, 2010a, 2010b, 2010c; Simão et al., 2009; Malczewski, 2006). However, any successful implementation of tools for group decision-making requires a structured theoretical framework that considers issues such as knowledge of involvement and how decisions are being made, values and expectations, including ethical concerns (i.e., justice, equity, and trust), data and information about the problem, understanding of socio-political influence, and data processing and communication tools (Nyerges and Jankowski, 2010; Gross, 2007; Kingston, 2007; Gomboa and Munda, 2007; Carver et al., 2001; Wiedemann and Femers, 1993; Arnstein, 1969).

The main goal of this paper is to present a prototype tool that we developed and demonstrate its potential for use in the context of a group-based SDSS for wind farm site selection in Northwest Ohio. Although many group-based SDSS have been developed for various spatial decision problems in environmental and economic domains (Gorsevski and Jankowski, 2010; Boroushaki and Malczewski, 2010a, 2010b; Tang and Waters, 2005; Balram and Dragićević, 2005), there are only a few SDSS which have been developed for applications related to wind farm siting (Berry et al., 2011; Bishop and Stock, 2010; Simão et al., 2009). Thus the contribution of the proposed approach is intended to demonstrate a proof-of-concept of prototype software that we presently maintain under development and which we present here, intended for a traditional 'face-to-face' and multi-user interaction. Although our short-term goal is to develop a web-based approach, the underlined principles of the group-based and participatory planning process are similar and designed to involve expert and non-expert participants in the decision-making process. However, at this early stage of this project we demonstrate the methodological steps involved in the process through non-expert views, using a study group constituted by both graduate and undergraduate students. To set the context for the envisioned implementation of this flexible methodology, the prototype system is illustrated through an experimental decision scenario. This scenario demonstrates the potential of the proposed tool for assisting decision or policy-makers; the decision tool is discussed in Sections 2 and 3 describe the SDSS tool used in the experiment. Section 4 contains the results and discussion. The conclusion offers discussion ideas for future directions for collaborative SDSS tools for wind farm siting.

2. 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 following describes the case study design; including the study area, materials, and composition of the study group.

2.1. Study area

The study area is a 27-county region in Northwest Ohio (Fig. 1) with relatively high winds throughout the year. A wind resource assessment conducted at 50 m heights 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. 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 7.0–7.5 m/s while the rest of the area has annual average wind speeds of 5.6–6.4 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 16 locations in the region identified as important bird areas (IBA) including the endangered Indiana Bat (*Myotis sodalis*) (OAS, 2009; USFWS, 2009). The demand for energy in the area comes from the estimated 1.8 million people and mostly by the industrial sector (USEIA, 2010). Ohio's alternative energy portfolio mandates that by 2025, at least 25% of all electricity sold in the state must come from alternative sources and one-half of this electricity must be produced in the state (USEIA, 2010).

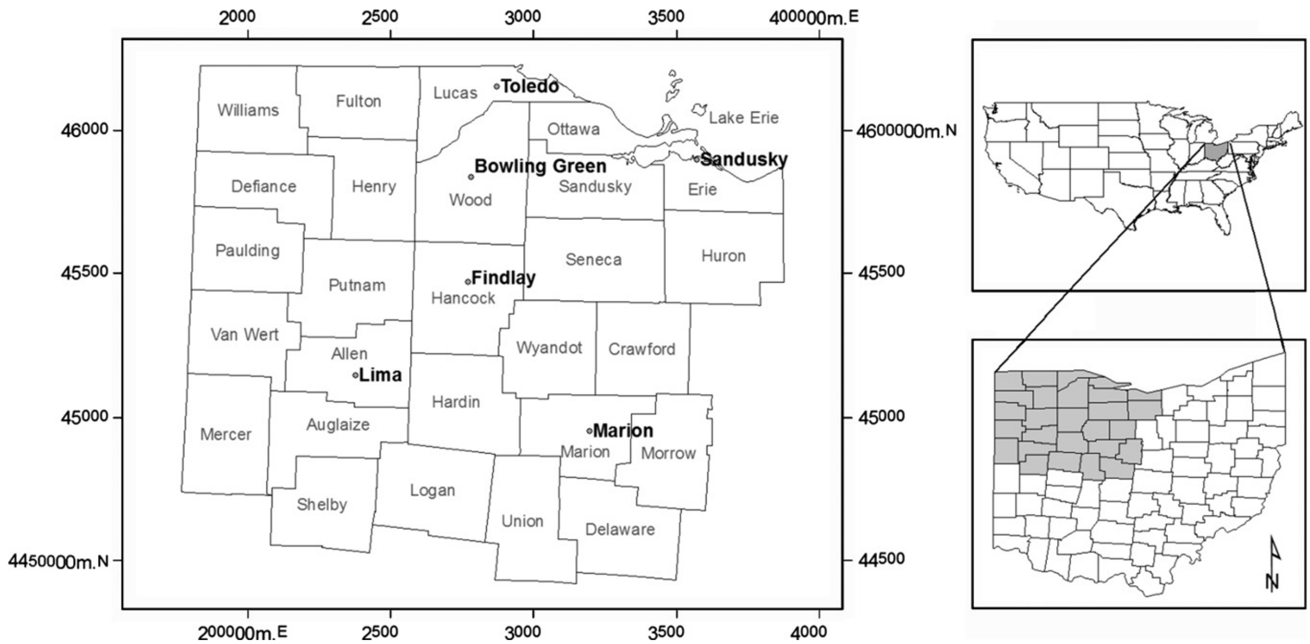

Fig. 1. Location of the study area.

In the study area, the city of Bowling Green has a total of four 85 m tall large-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 (OPSB, 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. 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.

2.2. *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). Fig. 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.

2.2.1. *Environmental factors*

2.2.1.1. 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. The data is partitioned in four categories of annual average wind speeds classified by the NREL ranging from poor (1) to good (4). The description of the categories indicates that areas designated as Class 3 or higher are suitable for large scale wind development. Class 2 speeds can be considered suitable, especially in rural areas where the topography is flat and there are no obstacles while Class 1 is not considered suitable. In this project, the data was imported into a GIS, converted to a raster format, and resampled to 30×30 m cell size. Fig. 3(a) shows the standardized wind speed data layer which used membership values assigned to each wind class shown in Table 1.

2.2.1.2. 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 a wind turbine 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 (Sovacool, 2009; Farfán et al., 2009). Nevertheless, the potential threat to birds is an issue that we have decided to address in this study example.

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 (OAS, 2009). A digital map published by the OAS (2009) 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

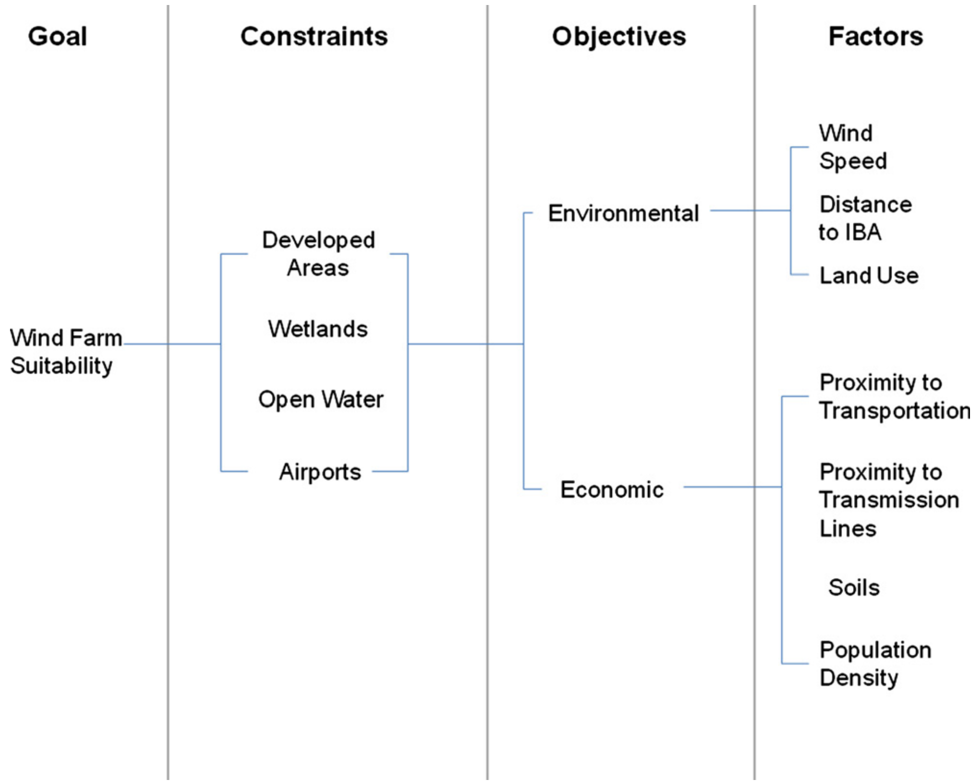

Fig. 2. Decision process hierarchy.

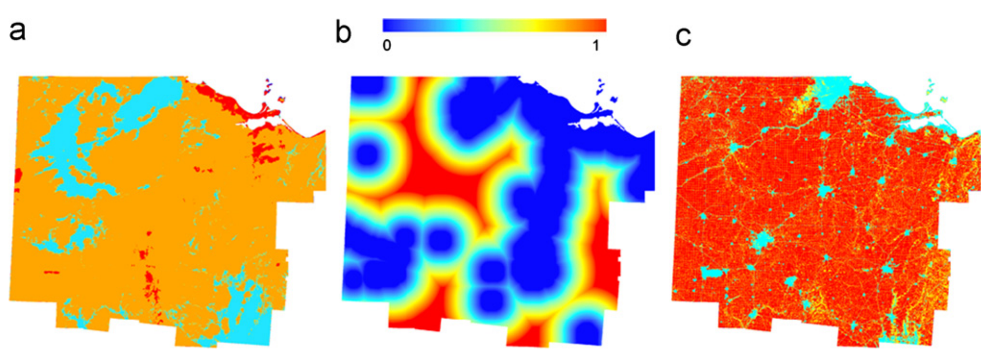

Fig. 3. Standardized environmental factors (a) wind speed, (b) distance to important bird areas, and (c) land use.

from each cell to an IBA. Table 1 shows that a linear increasing fuzzy function was used to standardize the distances (Gorsevski et al., 2012, 2010, 2006). The first control point (a=5000 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)).

2.2.1.3. 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 large-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 configurations are often used in grassland which is not the case in forested areas where clearing for access roads, turbine pads, and set back areas around each turbine is required.

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 low intensity residential areas are considered as the least suitable areas while developed areas, open water, and wetlands are considered constraints in this analysis (Fig. 3(c)). Table 1 shows the membership values assigned to each of the land use categories used here.

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/s)			
0.0–5.6 (Class 1)			0.3
5.6–6.4 (Class 2)			0.8
6.4–7.0 (Class 3)			1
7.0–7.5 (Class 4)			1
Distance from important bird area (m)	5000	30,000	Linear—increasing
Landuse (no units)			
Shrub, barren, pasture, cropland			1
Grassland, forest			0.667
Low intensity residential areas			0.333
Economic factors			
Proximity to major transportation (m)	1000	10,000	Linear—decreasing
Proximity to transmission lines (m)	1000	20,000	Linear—decreasing
Soil (no units)			
Gravel			1
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

2.2.2. Economic criteria

2.2.2.1. 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. Often, 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 transportation dataset used in this study was produced by the USGS and considers interstates, and US or state routes and the railroad data. 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=1000 m, b=10,000 m). Distances less than 1000 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). Fig. 4(a) shows the standardized data layer.

2.2.2.2. 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

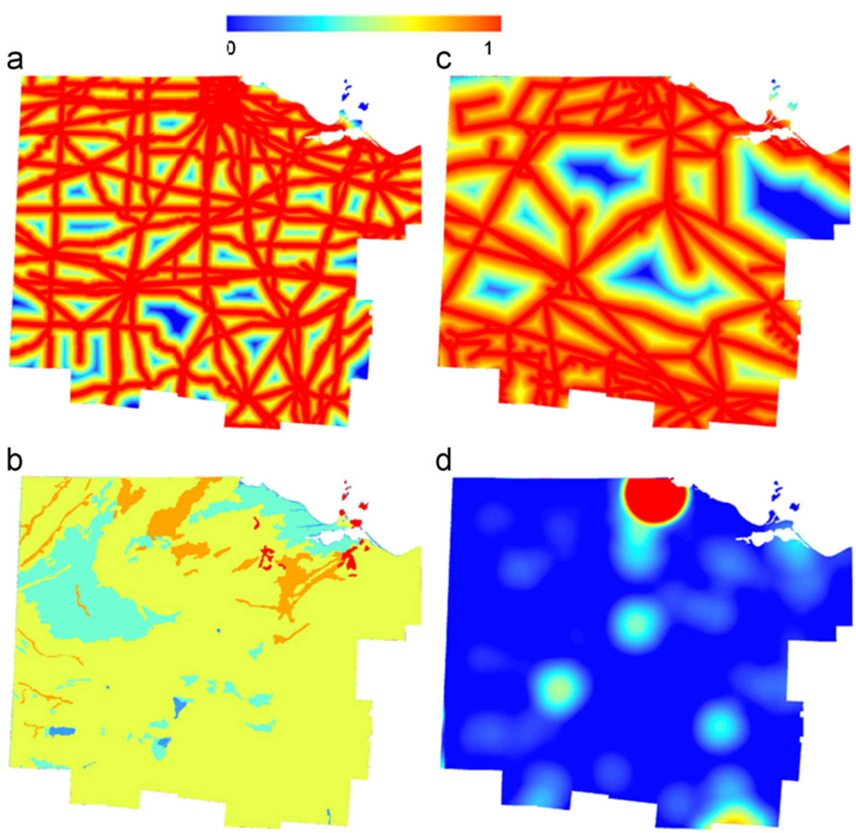

Fig. 4. Standardized economic factors (a) proximity to transportation, (b) proximity to transmission lines, (c) soil, and (d) population density.

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. 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 ($a = 1000$ m, $b = 20{,}000$ m). Distances less than 1000 m are given a membership of 1 and distances greater than 20,000 m are assigned a membership of 0 (Fig. 4(b)).

2.2.2.3. Soils. Different types of soils can affect the installation costs of a wind farm when a potential location does not contain soil that can adequately support large structures like wind turbines. This can include the removal and replacement of poor soil and the installation of deep foundation supports onto underlying bedrock. 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 Soil Survey Geographic database (SSURGO) was used in this analysis (USDA-NRCS, 1994). 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%, silt and clay with a liquid limit greater than 50%, 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 Fig. 4(c).

2.2.2.4. 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. Here, the density estimation was calculated by a kernel density function with a bandwidth of 20 km around each output raster cell (US Census Bureau, 2010). 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. Fig. 4(d) shows the standardized data layer.

2.3. 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 and interact 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 1 h 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.

3. Spatial decision support tool

The SDSS prototype used in this research was developed within ESRI's ArcMap (9.3) user interface system 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. A description of the user interface, the Borda ranking method and the sensitivity analysis is discussed below.

3.1. User interface

The user interface comprises of a set of steps and inputs that are organized by different hierarchy levels to build up the SDSS model (Fig. 5). The individual decision process starts with the examination of spatial data. 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 considered in the wind farm development (Fig. 5(a) and (b)). Following the selection of constraints, the participants are prompted to select their preference for inclusion of environmental and economic factors and to assign importance values based on a personal interest and understanding of the decision problem. A low value is assigned for not important factors and a high value for very important factors. Help files containing brief descriptions and justification on different factors are also included in each step (Fig. 5(c) and (d)). 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. The last step assigns the importance of the "Environmental Criteria" and the "Economic Criteria" and calculates the suitability scores (Fig. 5(e)).

3.2. 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 the following equation:

$$V_i = \sum_{j=1}^{n} w_j v_{ij} \quad (1)$$

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 from the environmental factors, an economic layer solution showing the suitability from the economic factors, and a combined suitability layer that aggregated the two. A blue-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

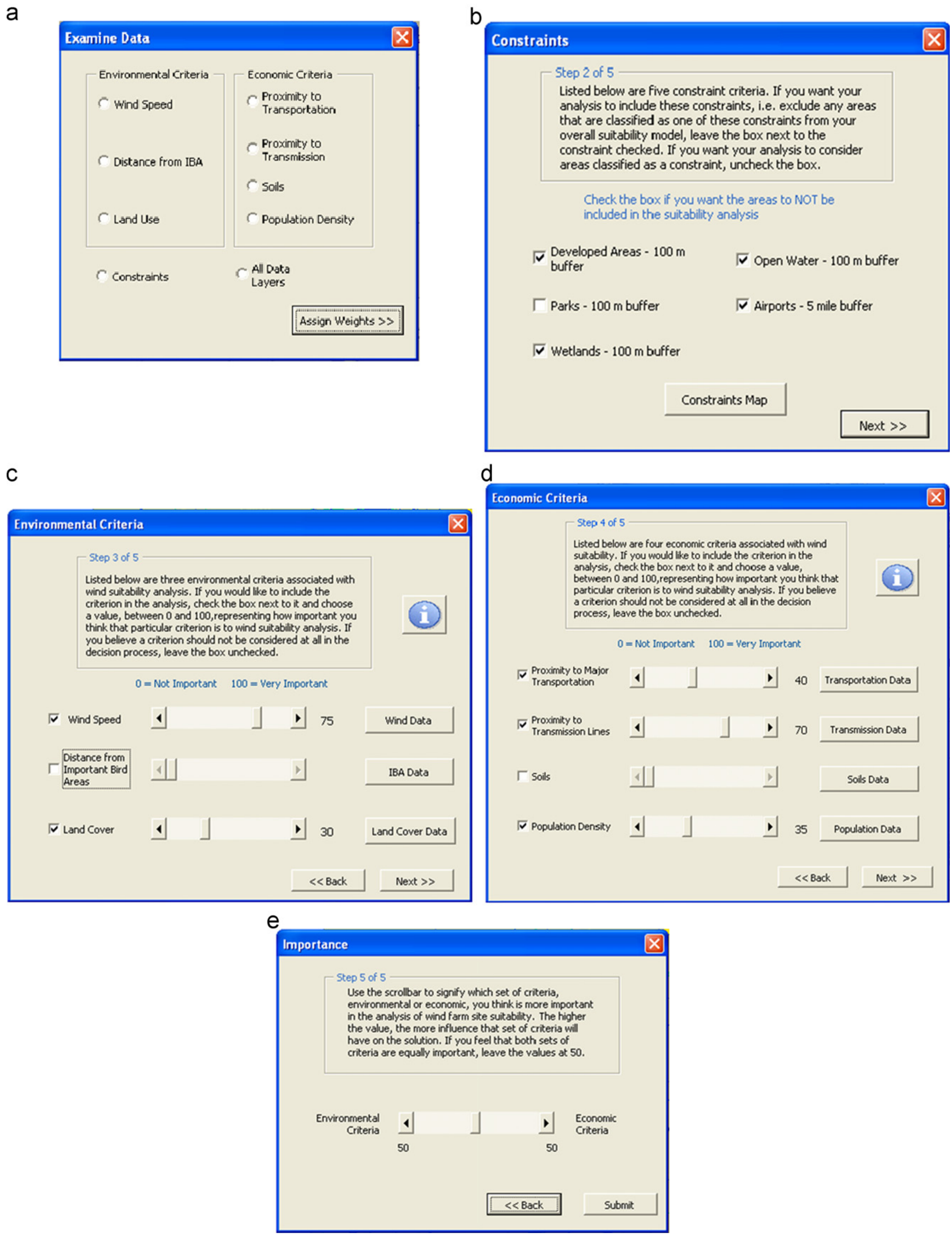

Fig. 5. Sequential steps of the SDSS model.

obtaining the group solution a text file is sent to a server by each participant that includes assigned values to factors and criteria.

3.3. 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. 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.

3.4. 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 are 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 is calculated using the following equation:

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

where m is the set of criteria, and r_i is the number of increments within the weight range for criterion i (Chen et al., 2010). For example, in this paper a $\pm$10% weight range with 1% increment was applied to seven decision factors and two objectives.

4. Results and discussion

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. However, this is based on an experimental scenario and for collaborative processes the composition of the group is one of the most important aspects that is used to maintain and balance different interests.

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 Fig. 7(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/s or greater. The most suitable locations in

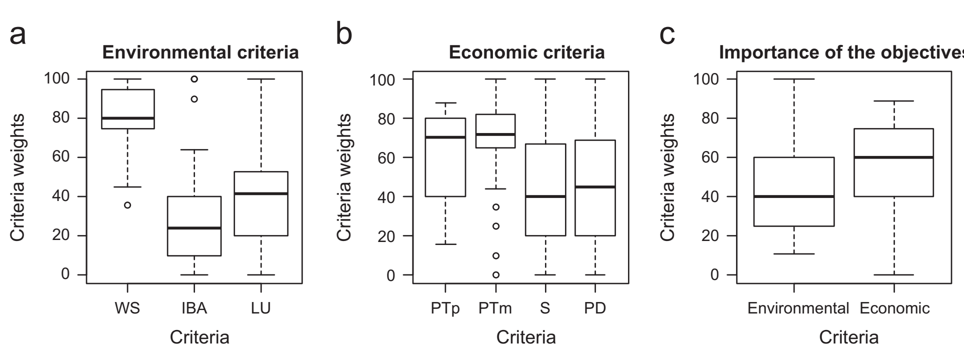

Fig. 6. Distribution of importance values assigned by the participants for the environmental factors (a), the economic factors (b), and for the objectives (c).

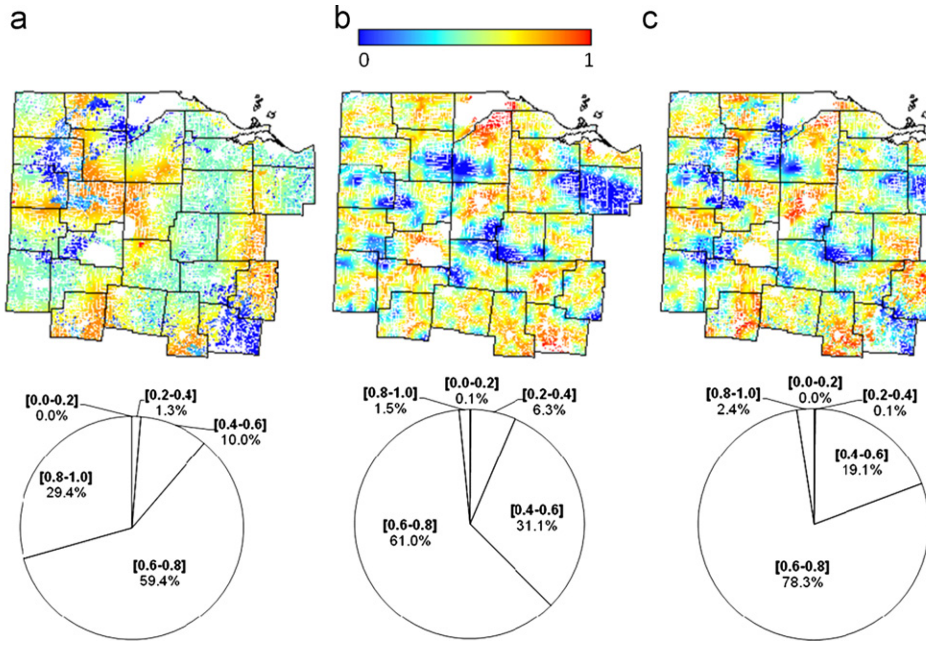

Fig. 7. Results using weights calculated from the Borda method. Alternative (a) is the suitability of the environmental factors, (b) is the suitability of the economic factors, and (c) is the weighted aggregation of (a) and (b).

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)
		$\sum_{j=1}^{n} envv_1 = 94$	$\sum = 1.000$
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)
		$\sum_{j=1}^{n} envv_1 = 190$	$\sum = 1.000$

Fig. 7 (b) are close to 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 or if different participants are considered in the process.

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 sensitive 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. However, these results are mostly driven by the fact that environmental factors have much higher suitability than the economic factors as shown in Fig. 8(a) and (b). Applying more restrictive standardization control points to the economic factors or adding other factors will yield different outcomes from Fig. 8(c).

The spatial change in areas of high suitability (0.8–1.0) from Fig. 8 is shown in Fig. 9. The change of high suitability areas is represented as the difference between simulation maps from the

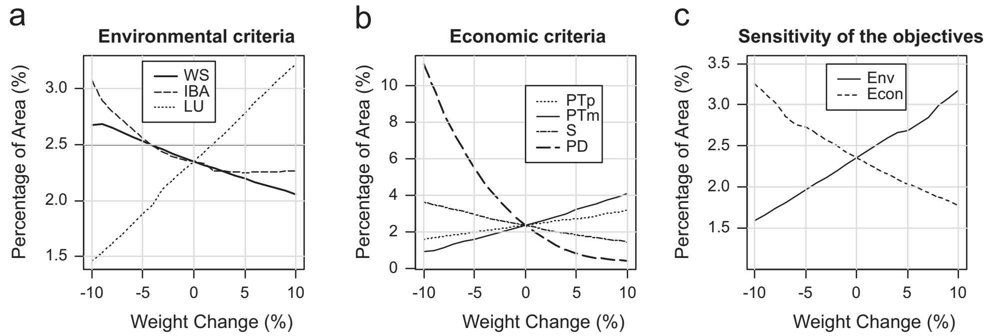

Fig. 8. Sensitivity analysis applied to the area classified with high suitability (0.8–1) for (a) the environmental factors, (b) the economic factors, and (c) the objectives.

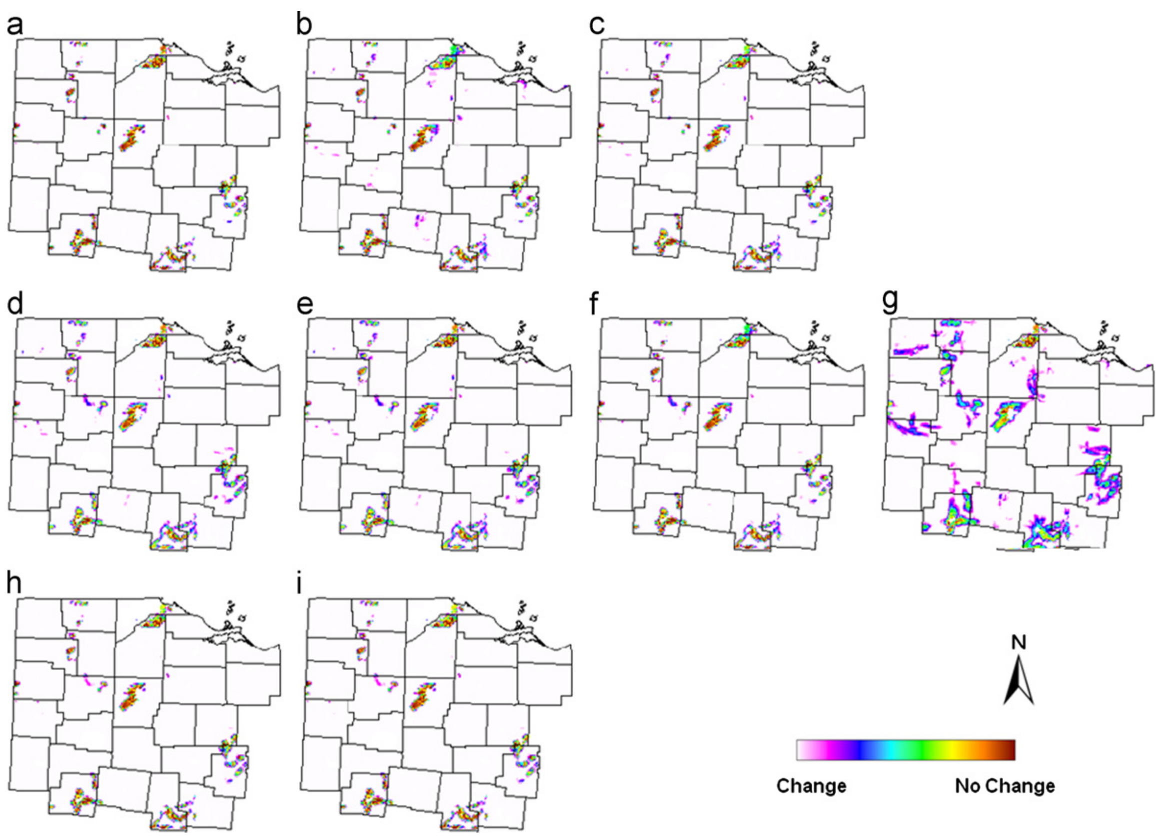

Fig. 9. Relative change in areas of high suitability associated with the sensitivity analysis for (a) wind speed, (b) IBA, (c) land use, (d) proximity to transportation, (e) proximity to transmission, (f) soil, (g) population density, (h) the environmental objective, and (i) the economic objective.

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 occurs 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.

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 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 Malczewski, 2010a).

In summary, the intention of this research is to show the strengths of this group-based SDSS tool 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 that enables group communication for enhancing decision-making process of complex spatial multi-criteria problems.

Acknowledgments

This investigation was supported partly by Bowling Green State University's Graduate Assistant Competitive Stipend Pool, which supported Steven C. Cathcart master's thesis work, and partly by the US Department of Energy, Coastal Ohio Wind Award Number DE-FG36-06GO86096. Also, the authors would like to thank the three anonymous reviewers, who provided helpful suggestions and excellent additions to the manuscript.

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