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Lieske, Scott; Hamerlinck, J D

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Integrating Planning Support Systems and Multicriteria Evaluation for Energy Facility Site Suitability Evaluation

Scott N. Lieske and Jeffrey D. Hamerlinck

Abstract: *Suitability modeling seeks to identify the continuum of best or worst sites for a facility, development, activity, or particular use based on site characteristics and preference assessments. The purpose of this paper is to assess the quality of a planning support system-based suitability model through presentation of an energy infrastructure development case study. The presentation of the case includes the suitability model and a second, complementary approach, the Kepner-Tregoe problem-solving and decision-analysis framework. The suitability model is presented within the context of the methods, assumptions, and best practices of multicriteria evaluation and weighted linear combination modeling. The primary finding of this research is the CommunityViz planning support system suitability model is a valid tool for spatial multicriteria evaluation and demonstrably effective at producing trusted outcomes. The contributions of this paper are an evaluation of the scientific rigor of the CommunityViz suitability model as well as discussion of planning support system–based interactive and iterative model development within a multicriteria evaluation process.*

INTRODUCTION

The core of suitability modeling is the analysis and interpretation of data to produce information useful to decision makers and stakeholders in a decision process (Malczewski 2004). Suitability modeling may consider a number of geographic conditions, including location, development actions, and environmental elements (Collins et al. 2001), as well as legal requirements and social factors reflecting the values and interests of decision makers, individuals, or other stakeholders. While the use of the word suitability often refers specifically to the idea of site selection and development, the analytical concepts are more general (Hopkins 1977) and applications more wide ranging.

Discussing spatial expert systems, Malczewski (1999) notes a number of decision-making obstacles relevant to suitability modeling: spatial decision problems are not well understood; knowledge of spatial processes and decisions includes causal, common sense, and meta-knowledge but differs from person to person; people will approach and solve spatial problems differently; and communication barriers may exist between experts and people who operationalize decision support. Some of these obstacles can be overcome using an information-structuring process such as multicriteria evaluation (MCE). Geographic information systems (GIS)–based spatial decisions support systems (SDSS) (Densham 1991) also are useful to apply to siting problems to bridge the gap between decision makers and complex quantitative analytic models (Maniezzo et al. 1998). With long-standing motivation for research on SDSS stemming from the recognition that some spatial decision problems are characterized by many of the previously mentioned problems, MCE has come to be recognized as an inherent part of SDSS (Jankowski et al. 2008).

Developed as a subset of SDSS, planning support systems (PSS) are a special type of planning information technology consisting of geospatial application software and information frameworks designed to support planning processes (Klosterman 1997, Geertman and Stillwell 2003). PSS extend GIS capabilities in analysis and problem solving, and add design, decision-making and communication capabilities (Nedovic-Budic 2000). Unlike complex land-use or resource modeling software, PSS often take the form of a toolbox from which decision makers can draw for assistance in decision management, modeling, analysis and design, communication, visualization, and information dissemination (Klosterman 1997, Batty 2003).

The purpose of this paper is to assess the quality of a PSS-based suitability model. While the utility of PSS is broadly supported in the literature, implementation of PSS technologies has been slow and often unsuccessful (Geertman 2013, Te Brömmelstroet 2012). Vonk et al. (2006) mentioned a number of bottlenecks to PSS usage, including lack of experience, lack of awareness, and problems or uncertainties with instrument quality. Following Vonk and Geertman (2008), we assess the quality of the CommunityViz® suitability model with: (1) a literature-based overview of MCE, weighted linear combination modeling, the Kepner-Tregoe (K-T) decision-analysis framework, CommunityViz and the CommunityViz suitability model, and uncertainty evaluation in MCE; (2) a stepwise presentation of PSS and K-T methods; and (3) a comparison of outputs between the PSS and K-T decision-making frameworks. Methods and outputs are presented using a case example of an energy facility siting decision situation in the U.S. West.

BACKGROUND

Multicriteria Evaluation

MCE is defined by Voogd (1983) as a flexible framework for appraisal of a set of decision options using a number of criteria. MCE techniques are able to accommodate the political, social, and values dimensions of a decision process or problem-solving situation. In discussing the theory underpinning MCE, Voogd (1983) argues that classification theory, not decision theory, provides the basis for MCE work. MCE assists with inventory, classification, and arrangement of the information needed to make choices. This added structure can produce a deeper knowledge of the decision situation, which would not have been obvious, given its complex nature. A key caveat, however, is that while MCE provides a structure for solving a problem, it does not provide the solution per se (Voogd 1983).

There are a number of benefits to using MCE. MCE is seen as a transparent and systematic approach that increases objectivity and yields reproducible results (Janssen 2001). As detailed in Kiker et al. (2005), the use of MCE to structure a problem improves on heuristic approaches to reducing complexity in problem solving. MCE processes are a means of getting greater insight into value judgments, incorporating differing views in an analytical framework, providing a tangible means of demonstrating openness in decision making, and reducing information incorporated in decision situations. Incorporating social and political concerns in an evaluation structure can generate circumstances that lead to acceptance, adoption, and implementation of resulting decisions. Integrating preferences with geographic data yields results that are feasible and accurate as well as acceptable to decision makers (Jankowski and Richard 1994) and the public (Lieske et al. 2009). MCE is a means to both justify and account for policy decisions (Voogd 1983). MCE facilitates the documentation of decision processes and enables decision-maker learning (Hajkowicz 2007). MCE may, through evaluation of alternatives, facilitate compromise (Malczewski 1996). Another benefit of MCE is bringing scientific information to situations or people who might not otherwise have it. Most important, MCE processes are a way to arrive ". . . at substantially better considered decisions" (Voogd 1983, p. 33).

There also are potential disadvantages of MCE. MCE may lead to premature or over disclosure of information or intentions; MCE may be seen as too complex and/or technocratic. MCE may be seen as providing a false sense of accuracy, be subject to manipulation (Janssen 2001), and, like any research, MCE may be used as ". . . a 'scientific sauce' over a decision already made" (Voogd 1983, p. 34).

GIS-based MCEs are distinctive because results depend on the patterns of spatial data-based evaluation criteria and how spatial data and preferences are combined (Malczewski 2011). Voogd (1983) defines an evaluation criterion as "a measurable aspect of judgment by which a dimension of the decision options under consideration can be characterized" (p. 55). Evaluation criteria used in GIS-based MCE are based on spatial relationship tests, including simple location factors such as proximity, conditional location factors, overlap, conditional overlap, Boolean tests, complex factors, or numerical or lexical data attributes. With complex factors, evaluation criteria are determined using a separate model (Walker and Daniels 2011). Baban and Flannagan (1998) also mention consideration of criteria that are not site-specific such as impacts on human health and the environment.

Evaluation criteria may be differentiated between benefit criteria and cost criteria and further differentiated between requirements and preferences. With benefit criteria, higher data values are correlated with better performance. With cost criteria, lower data values are correlated with better performance (Nyerges and Jankowski 2010). Requirements are evaluation criteria in a decision situation that are absolute and not subject to preferences or tradeoffs. While MCE most often is focused on preferences, identification of requirements, especially in spatial modeling, is extremely useful for it can speed up processing by a priori elimination of unsuitable decision options.

The MCE literature provides a number of recommendations for establishing a set of evaluation criteria. The set of criteria should cover all aspects of the decision problem. Criteria should be able to be included in an analysis in a meaningful way. Criteria should be comprehensive, measurable, and nonredundant (Malczewski 2000). The definition and measure of criteria should be in accord with their intended use (Voogd 1983) and the overall set of evaluation criteria should be minimized (Malczewski 1999). Per Voogd (1983), limiting the number of criteria minimizes uncertainty.

Voogd (1983) offers several recommendations for addressing uncertainty in MCE: comparison of initial with final evaluation criteria, sensitivity analysis, and comparison of multiple MCE methods. Comparison of the initial list of evaluation criteria with the final list of evaluation criteria allows assessment of whether all pertinent criteria have been considered (Voogd 1983). Comparison of multiple methods helps minimize what Jiang and Eastman (2000) call decision risk, the probability that a decision will be made incorrectly. Sensitivity analysis is an exploratory process that allows one to gain a deeper understanding of a problem structure through evaluation of how changes in inputs (evaluation criteria and weights) affect changes in outputs. The purpose of MCE sensitivity analysis is to facilitate uncertainty evaluation and assess the spatial impact of differing weights (Jankowski et al. 2008). If small changes in evaluation criteria or weights result in no changes in the preferred decision option, one may have more confidence in output rankings (Nyerges and Jankowski 2010). If small changes in inputs result in changes in outputs, it may be necessary to reevaluate the structure of the model. Sensitivity analysis also helps to indicate which criteria have more and which criteria have less influence on model outcomes. Sensitivity analysis can reduce complexity by enabling the identification of criteria that do and do not influence decision-option ranking. Criteria with minimal influence on outcomes may be removed (Nyerges and Jankowski 2010). In general, there are two types of sensitivity analysis, one-at-a-time (OAT) factor analysis and global sensitivity analysis, with OAT being more common and easy to implement (Ligmann-Zielinska and Jankowski 2014). Sensitivity analysis couches MCE outputs by making clear outputs depend on the technique employed, the criteria chosen, criteria scores, and data quality, as well as weights (Voogd 1983). Outputs, therefore, are conditional.

WEIGHTED LINEAR COMBINATION

One of the more widely used MCE methods is weighted linear combination (WLC) modeling. With WLC, evaluation criteria are standardized to a common numeric range, weighted, and combined to create a composite score for each decision option. Weights indicating relative importance are assigned to each evaluation criteria. The larger the weight, the more important a criterion is. For each decision option, a score for each criterion is calculated by multiplying the weight by the standardized value of that criterion. Scores are summed for all criteria to generate an overall suitability score for each decision option. The result is a continuous measure of suitability. Results generally are not compared with a separate benchmark or empirical standard (Hopkins 1977). WLC is one of the most straightforward and often-used GIS-based MCE methods (Malczewski 2011); WLC is easy to implement within GIS, is easy to understand, and is intuitively appealing to decision makers (Nyerges and Jankowski 2010, Malczewski 2004, Voogd 1983). It also has been described as methodologically sound and transparent (Janssen 2001). WLC-based results derived from GIS often are presented visually, using maps where scores are displayed with a graduated color ramp. Importantly, WLC and similar techniques provide reasonable problem solutions (Janssen 2001).

Primary assumptions of WLC modeling are the linearity and independence of evaluation criteria. The linearity assumption means a change in desirability of an attribute is constant for any change in the level of an attribute. For example, the change from zero to one acres of buildable land has the same impact on the model as the change from 999 to 1,000 acres of buildable land. The independence assumption means there are limited to no interaction effects among evaluation criteria. Results may be incorrect if interaction among attributes has not been taken into account (Malczewski 2000) through multiple counting of like or near-identical criteria. The independence assumption is conceptually similar to the assumption of no perfect correlation among independent variables in ordinary least squares regression analysis. With MCE, if there is a high measure of correlation between two criteria, one may be excluded from the set of evaluation criteria (Malczewski 1999). However, correlated criteria may be both incorporated in an analysis if they are likely to receive different weightings (Voogd 1983).

Table 1. Steps in weighted linear combination modeling (modified from Malczewski 1999, p. 199)

1. State the decision.
2. Define the set of evaluation criteria and the set of decision options.
3. Standardize each criterion map layer.
4. Define the criterion weights.
5. Construct the weighted standardized map layers.
6. Generate the overall score for each alternative.

Table 1 lists key steps in WLC modeling. In the first step, it is necessary for decision makers and stakeholders, in the language of Drobne and Lisec (2009), to recognize and agree on the problem to be addressed. WLC step two is actually three tasks, establishing the evaluation criteria, establishing the set of decision options, and calculating raw suitability scores. In a GIS-based suitability model evaluation, criteria typically are spatial layers and decision options are areal units. WLC step three is criterion standardization where raw suitability values are transformed to comparable units (Malczewski 1999). Many criteria, for example distance to infrastructure and slope, use different measurement scales. Raw suitability scores more often than not require transformation to a common scale suitable for direct comparison. There are two scale transformation techniques, linear and nonlinear standardization. Nonlinear standardization is the common approach used in suitability modeling (Walker and Daniels 2011). With nonlinear standardization, criteria are standardized to a consistent range, often zero to one or zero to 100. Nonlinear standardization makes weights more easily understandable and removes potential problems with differences stemming from a lack of knowledge or confusion over units of measure (Hopkins 1977). When raw data values include both negative and positive numbers, nonlinear standardization should be used (Nyerges and Jankowski 2010). Disadvantages of nonlinear standardization include the loss of clear meaning of well-understood measurement scales (Malczewski 1996) and that model outputs do not relate to the raw scores in a linear fashion (Nyerges and Jankowski 2010). While there is some obfuscation associated with the loss of well-understood measurement scales, the issue of model outputs not relating to raw scores in a linear fashion does not ordinarily appear to be a problem. The latter issue especially is more than compensated for by the easier interpretation of evaluation criteria including relaxed requirements for knowledge of the units of the evaluation criteria. It also is noted that scores standardized with a nonlinear transformation will not necessarily be normally distributed. Negatively skewed standardized criteria will impact an analysis as though they are given a high weight, while positively skewed standardized criteria will impact an analysis as though they are given a low weight.

WLC step four is assigning weights. Preferences may be captured in MCE numerically, using ordinal expressions (e.g., low, medium, high), or as Boolean values. In MCE, quantitative values are referred to as weights while ordinal and other expressions of value are referred to as priorities (Voogd 1983). Weights and priorities improve an analysis by enabling a better understanding of tradeoffs among evaluation criteria as well as the consequences of different preferences (Hajkowicz 2007). A common option for incorporating weights in a WLC model is a numeric point scale where respondents indicate a number for each evaluation criterion on a one to X or zero to X scale. Osgood et al. (1957) found a seven-point number scale augmented with semantically differentiated (opposite) labels allowed respondents to adequately express their preferences. Voogd (1983) presents the results of an empirical comparison of several methods of measuring preferences that indicates a seven-point scale is one of two methods that perform better, take less time, and are less difficult than other methods. WLC steps five and six, constructing weighted standardized map layers and generating scores for each decision option, may be automated with GIS-based weighted overlay technologies, including purpose-built PSS.

KEPNER-TREGOE DECISION ANALYSIS

The Kepner-Tregoe decision model is part of a broader organizational management framework first conceptualized at the RAND Corporation in the 1950s by Drs. Charles Kepner and Benjamin Tregoe. Grounded in the rational theory of organizational behavior (Dawson 1996), the K-T framework was formalized in the 1960s and made widely available through a popular business literature monograph (Kepner and Tregoe 1965). Decision analysis is one of four analytic processes that make up the K-T framework, the others being Problem Analysis, Potential Problem (or Opportunity) Analysis, and Situation Appraisal (Kepner and Tregoe 1997). The framework has been extensively applied in a diversity of business-management applications when issues are complex and when a number of solution options exist (Kepner and Tregoe 1997, Finlow-Bates et al. 2000), in environmental management and remediation (Linkov et al. 2004, Kiker et al. 2005), and physical infrastructure development (Thorpe and Kumar 2002). Watson (1987) points out that much of the success of the framework is because of its approach in structuring individual and organizational thought processes in a highly systematic manner.

Table 2. Kepner-Tregoe decision analysis steps (Source: Kepner and Tregoe 1997, pp. 85-86)

1. State the decision.
2. Develop objectives.
3. Classify objectives into MUSTs and WANTs.
4. Weigh the WANTs.
5. Generate alternatives.
6. Screen alternatives through the MUSTs.
7. Compare alternatives against the WANTs.
8. Identify adverse consequences.
9. Make the best-balanced choice.

Table 2 outlines the nine steps of a traditional K-T decision-analysis process. The first step in the K-T process is identical to the first step in WLC modeling: to recognize and agree on the problem to be addressed. K-T step two involves developing objectives that are identical to evaluation criteria in MCE. In K-T step three, objectives are categorized as requirements ("musts") and operational objectives ("wants"). In step four, wants are ranked and assigned relative weights. In step five, alternatives are generated that in step six are screened against the musts. In step seven, alternatives are compared against the wants by assigning relative scores for each alternative on an objective-by-objective basis and calculating weighted scores for each of the alternatives to identify the top-scoring choices. Step eight involves identifying adverse consequences for each top alternative and evaluating risk probability (high, medium, low) and severity (high, medium, low), before making a final, single choice between top alternatives (step nine).

The K-T framework shares many characteristics with WLC modeling. K-T modeling has predominately been operationalized in business applications using common spreadsheet technology. While K-T does not enable the direct incorporation of spatial data, the framework may represent spatial concerns in the abstract, for example, by considering travel time between locations.

COMMUNITYVIZ®

The CommunityViz suitability model is a spatial MCE framework built on a WLC model. Developed by the Orton Family Foundation (Rutland, Vermont), CommunityViz is a modular system built on the ArcGIS platform (ESRI Inc., Redlands, California). It consists of two integrated extensions to ArcGIS: Scenario 360 and Scenario 3D. The Scenario 360 module of CommunityViz extends the quantitative capabilities of ArcGIS by allowing formula-based spreadsheet-like calculations to be performed on geographic data. Formula-based GIS data attributes allow on-the-fly adjustment of geographic and numeric inputs as well as automated recalculation of maps and quantitative output in a process referred to as "dynamic analysis" (Walker and Daniels 2011, pp. 32-35). Scenario 3D allows for three-dimensional display of the built environment and landscape with real-time movement and object manipulation in a semi photo-realistic setting. CommunityViz is a promising tool for suitability modeling and spatial MCE generally because of the ability of the software to link weights with geographic data and automatically update the model when there are changes in either weights or geographic data inputs.

Sitting within the Scenario 360 module, the CommunityViz suitability model generates two kinds of evaluation criteria scores, raw and standardized. A raw evaluation criterion score is a direct query based on spatial relationships or attribute values. CommunityViz uses a formula-based dynamic attribute to calculate raw scores. Raw scores may be specified as a benefit or cost by indicating whether lower or higher suitability scores result from the calculation of a suitability criterion value.

As shown in Figure 1, evaluation criterion weighting is incorporated in CommunityViz with easily changeable "assumptions" (Walker and Daniels 2011, p. 34) linked to dynamic attributes via a slider-bar interface. Weight sliders provide a graphical display of values as well as an easy means of adjusting weights. On changing a weight or attribute value, the CommunityViz suitability model will recalculate the suitability analysis based on the new input(s) then graphically display the new results in maps and charts. Weighted assumptions in the CommunityViz model often are set up using a numeric point scale. Given the ability to rapidly recalculate a model, a numeric point scale that includes a zero

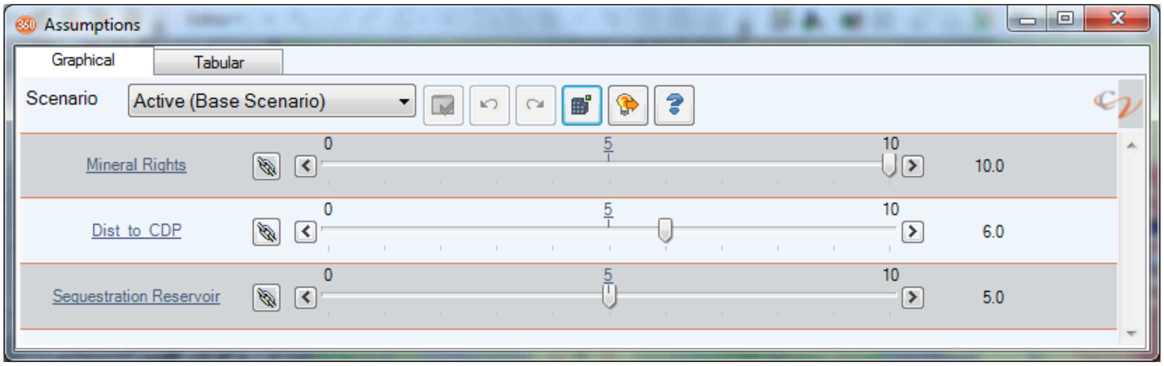

Figure 1. Representative CommunityViz weight sliders on an 11-point scale

value allows one to easily temporarily or permanently remove a criterion from the analysis.

This technology invites interactive experimentation, supports discussion of the relative importance of each criterion, provides an approach for working through the difficulty of conflicting preferences, supports sensitivity analysis, and enables PSS-based suitability analysis to be used as a thinking tool in site selection.

SUITABILITY MODEL CASE EXAMPLE

The High Plains Gasification-Advanced Technology Center (HPG-ATC) was envisioned as a $120 million synthesis gas research and development facility in the state of Wyoming. Goals of the facility were to advance both the technical understanding of the conversion of feedstocks (e.g., coal) by gasification into synthetic gas (or syngas) for use in power generation, subsequent downstream conversion of syngas into liquid fuels and chemicals, and to increase in-state utilization of Wyoming minerals. As a research and development facility, the HPG-ATC was planned to be approximately 1/100th the size of a comparable commercial facility. Major components identified as part of the facility were feedstock storage, rainwater retention, feedstock processing, industrial gas processing, a gasifier, gas flare, byproducts handling, a control center, and electrical, maintenance, and educational facilities.

In February of 2008, the University of Wyoming (UW) entered into a partnership with a U.S.-based energy company to design, construct, and operate the HPG-ATC. The project utilized a Front End Engineering Design (FEED) approach for determining the technical requirements and estimated costs of the facility (Plummer 2007). The FEED process addresses all aspects of facility construction, from process design, equipment and material selection, to plant layout, health, safety and environment (HSE) planning, and civil, mechanical and electrical engineering (Baron 2010). The purpose of the FEED process is to develop the necessary strategic information for developers to address risk and commit resources to maximize the potential for a successful project. A completed FEED process serves as the basis for the start of facility construction (CII 2012). For the HPG-ATC, the development of a project FEED plan involved completing a number of preliminary or pre-FEED steps. These included analysis of facility requirements in tradeoff studies, determination of facility capabilities and configurations, total construction costs estimations, permitting process initiation, and site selection. The site-selection process is the focus here.

SITE-SELECTION PROCESS

The purpose of the site-selection process was to identify the most preferred land parcel or set of contiguous parcels for HPG-ATC construction and operation based on criteria mutually agreed on by UW and the industry partner. This multi-scale internal evaluation process involved three distinct yet overlapping analyses: (1) a PSS-based statewide suitability assessment, (2) an evaluation of site proposals offered by local government and economic development entities through a public request for proposals (RFPs) process, and (3) parallel evaluation of the final six decision options using both PSS at the parcel level and K-T methods. The major activities, workflow, and approximate timeline of the suitability analysis are presented in Figure 2. The overall site-selection process was structured around the steps of the K-T decision analysis process, presented in Table 2.

A generalization of the evaluation criteria used in the HPG-ATC site assessment is presented in the RFP (UW 2008). The site was to be at least 35 acres in size, level ground with minimal vegetation, at or above 4,000-feet elevation. The elevation requirement came from the U.S. Energy Policy Act of 2005. The act specified a national research and development focus on high-elevation integrated gasification combined cycle plants that would be carbon-capture and sequestration-capable, driven in part to tackle technology shortcomings in gasification of high-moisture coals such as those abundant in the state of Wyoming (CRN 2009). Other influences on criteria development were HSE, greenfield status, suitable power, transportation infrastructure, distance to commercial air service, availability of natural gas fuel,

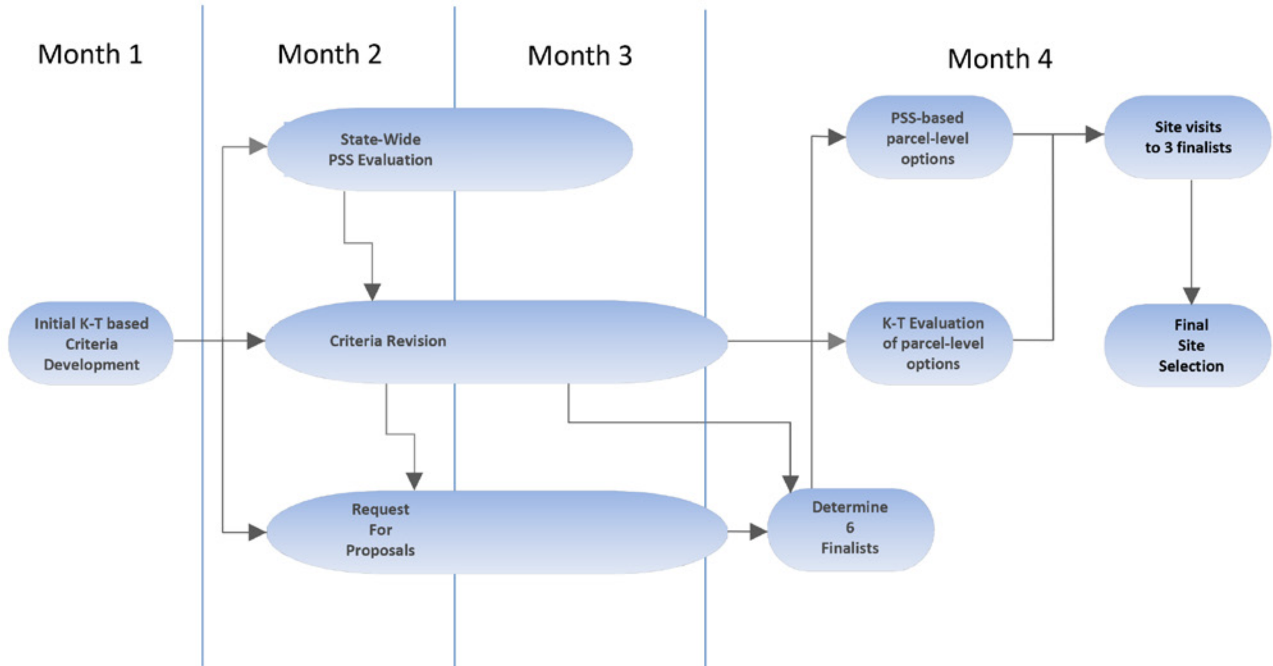

Figure 2. Major activities and timeline of the site-selection process

public utility water and sewer, the quality and locations of wells and aquifers, landfill requirements, and distance to laboratory facilities. Anthropological, archaeological, historical, and cultural resources, as well as compatibility with natural areas, parks, and monuments, were also of concern. Proximity criteria included distance to wetlands, threatened and endangered species, species of critical concern, and wildlife migration corridors. Criteria were generated based on the amenities of nearby communities, including the availability of emergency medical services, groceries, health care, housing, and restaurants. Criteria also were developed based on legal encumbrances, including zoning, air quality, and noise restrictions. Other infrastructure criteria included roads, flood management, and telecommunications availability (UW 2008).

K-T CRITERIA DEVELOPMENT

The evolution of thought surrounding evaluation criteria and weights occurred in a series of meetings of the site-selection team between November of 2008 and February of 2009. The process was similar to that described by Erdoğan (2009) where the knowledge of an interdisciplinary group of experts is modeled and refined over the course of the modeling process.. Originally (month one), 75 evaluation criteria were identified. During month two, the number of evaluation criteria had expanded to 97. At the same time, it was becoming clear that discussions of the statewide suitability model were causing experts to begin to think more spatially. For example, the month-one criteria specified proximity to CO_2 sink. The month-two criteria refined proximity to CO_2 sink as a cost criterion. Wetlands changed from a proximity-based criterion to a Boolean criterion for the team decided distance to wetland was not of concern as long as the facility was outside of the wetland. The month three criteria were annotated with a Boolean value indicating the availability of GIS data. This version of the criteria also indicated thresholds for a number of criteria, for example, distance no greater than 20 miles. Weighting the wants (K-T step four) proceeded from the evolution of K-T criteria over the course of the decision process. During month three, weights were specified as one (low), two (medium), or three (high) importance. By month four, there was a substantial paring down of the number of criteria driven by data availability and the articulated need to consider independence given obvious redundancy in the original 75 criteria.

Assignment of criteria attribute values initially were categorical, based on specific conditions, and were transformed to numerical values. For example, site conditions where the site is level were given a value of nine where they meet specifications, three where they require work, or one where they require substantial construction or improvement. Final scores were calculated by multiplying the criterion attribute values by the weight. As part of the process, different components of the team determined weights separately. UW and the industry partner scorecards differed slightly in what they considered to be low-impact, medium-impact, and high-impact criteria. Weights were reconciled during the middle of month four. K-T criteria were contracted to 47 early in month four then further reduced to 31 by the middle of month four. The final list of criteria included weights and explanations of the attribute value designation for each criterion. Following K-T step seven, alternatives were compared with the wants by calculating weighted scores for each of the alternatives.

STATEWIDE SUITABILITY

As the RFP was being circulated for responses and the set of evaluation criteria were evolving, the CommunityViz suitability model was used to develop a suitability map to guide the selection team on suitable locations for the HPG-ATC across the state of Wyoming. The steps used in this statewide model follow Malczewski's (1999) steps for WLC modeling summarized in Table 1.

The base layer used in the statewide model was a dataset of public land-survey system (PLSS) sections. Standard sections are one square mile in size. The raw data contain nearly 99,000 records. To speed up processing, this layer was made smaller by removing unsuitable data records where (a) elevations are < 4,000 feet, (b) most public lands, and (c) big-game migration corridors. The resulting data layer contained 55,892 records. Removing clearly unsuitable decision options at the beginning of a GIS-based suitability analysis minimized the processing time required for subsequent calculations.

WLC steps five and six, which result in a suitability score for each decision option, are operationalized in CommunityViz with two dynamic attributes, raw suitability score and suitability. Both scores are calculated for each decision option (in this case, areal unit). The raw suitability score is determined by first calculating proportional weights (criterion weight divided by the sum of suitability weights) then multiplying the proportional weight by the standardized score for each evaluation criterion. Using CommunityViz, evaluation criteria were weighted using an 11-point scale where values range from 0 to 10 in increments of 0.1. Raw suitability scores are standardized with the suitability dynamic attribute using nonlinear standardization formulas for benefit criteria (Equation 1) and cost criteria (Equation 2):

$$x'_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{1}$$

$$x'_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \tag{2}$$

(Nyerges and Jankowski 2010, Malczewski 1999)

The result is a suitability score assigned to each decision option. There are advantages and disadvantages to the use of a final suitability score to implement nonlinear standardization of raw suitability score results. The primary advantage of standardized suitability scores is being able to directly compare alternative combinations of evaluation criteria and weights on a standardized suitability output scale. A drawback to this standardization is that while key ordinal results do not change, the standardized scores suggest a larger range of variation between the sites than do the raw scores. While the consequences of this transformation are beneficial for the direct comparison of differing evaluation criteria and weights, the consequences of the transformation are more ambiguous for the presentation of suitability results. For maximum clarity, one may present both the raw and standardized scores when evaluating specific choice possibilities.

To summarize, CommunityViz creates a raw score (direct measurement), a standardized score (nonlinear standardization of the raw scores), a raw suitability score, and a suitability score (the raw suitability scores transformed via nonlinear standardization). The majority of the evaluation criteria used in the spatial models were a subset of the criteria employed in the K-T analysis. Criteria were included in the spatial model where spatial data of sufficient quality were available or could be developed within the scope of the project.

PARCEL-LEVEL SUITABILITY

The statewide PSS analysis was used in conjunction with the K-T analysis to develop and assess evaluation criteria, including, as shown in Figure 2, the site-selection criteria put forward in the RFP. The RFP process was the means of generating site-specific decision options. The RFP resulted in 15 responses, each indicating specific parcels for potential construction of the HPG-ATC.

Following K-T step six, decision options that did not meet a must were dropped from consideration. Of the 15 responses to the RFP, six met the musts and subsequently were evaluated as choice possibilities, using both the PSS and K-T frameworks. The PSS-based parcel-level evaluation was a modification of the statewide model that assessed suitability for the final six decision options. The parcel-level analysis offered direct comparison between PSS and K-T outputs. In addition to testing multiple methods, the rationale for developing a parcel-level PSS-based model stemmed in part from the observation that MCE results are not necessarily consistent across spatial scales (Malczewski 2000). Weights incorporated in the parcel-level PSS analysis were based on the designations of criteria as low impact, medium impact, or high impact from K-T step four.

The final evaluation criteria incorporated in the K-T analysis, the PSS-based statewide HPG-ATC suitability model, and parcel-level site selection are presented in Table 3. There were a total of 36 evaluation criteria incorporated in the three analyses. Thirty-one evaluation criteria were used in the K-T analysis. Fifteen evaluation criteria were incorporated in the statewide suitability model and the parcel-level model, 12 of which were present in both models. The site-selection team worked to make criteria as consistent as possible across the three analyses. Differences between the criteria incorporated in the K-T analysis and the two PSS models were because of limitations in the availability and quality of spatial data. Differences in criteria between the statewide suitability model and the parcel-level site selection model were the result of the inappropriateness of some evaluation criterion being included in a meaningful way at multiple spatial scales. For example, spatial data on soils were incorporated within the parcel-level model but not in the statewide model. The high degree of spatial heterogeneity in the soils data within the areal

Table 3. Evaluation criteria used in the K-T, PSS statewide site suitability model, and PSS parcel-level site selection mode

Criterion Name	Criterion Type	K-T	Statewide Site Suitability	Parcel-level Site Selection
Highway	Proximity Benefit	✓	✓	✓
Power	Proximity Benefit	✓	✓	✓
Fuel	Proximity Benefit	✓	✓	✓
Transportation	Proximity Benefit	✓	✓	✓
Landfill	Proximity Benefit	✓	✓	✓
Seismic	Complex	✓	✓	✓
CO2	Proximity Benefit	✓	✓	✓
Air Quality	Proximity Cost	✓	✓	✓
Public Receptor	Proximity Cost	✓	✓	✓
Municipality	Proximity Benefit		✓	✓
Hospital	Proximity Benefit		✓	✓
Fire Department	Proximity Benefit		✓	✓
Rail	Proximity Benefit		✓	
Analytical and Lab Statewide	Proximity Benefit		✓	
Analytical and Lab Local	Proximity Benefit	✓	✓	
Air Quality	Boolean	✓		✓
Soil	Complex	✓		✓
Surface Water	Proximity Cost	✓		✓
Land Use	Attribute	✓		
Greenfield	Attribute	✓		
Water quality	Attribute	✓		
Grey Water	Attribute	✓		
Sanitary	Attribute	✓		
Site Condition	Attribute	✓		
Public Support	Attribute	✓		
Fire Hydrants	Attribute	✓		
Neighboring Site Information	Attribute	✓		
Chemical Supply	Attribute	✓		
Slag	Attribute	✓		
Local Climate	Attribute	✓		
Local Support	Attribute	✓		
Labor	Attribute	✓		
Syngas	Attribute	✓		
Laydown	Boolean	✓		
Food and Shelter	Proximity Benefit	✓		
Emergency Services	Proximity Benefit	✓		

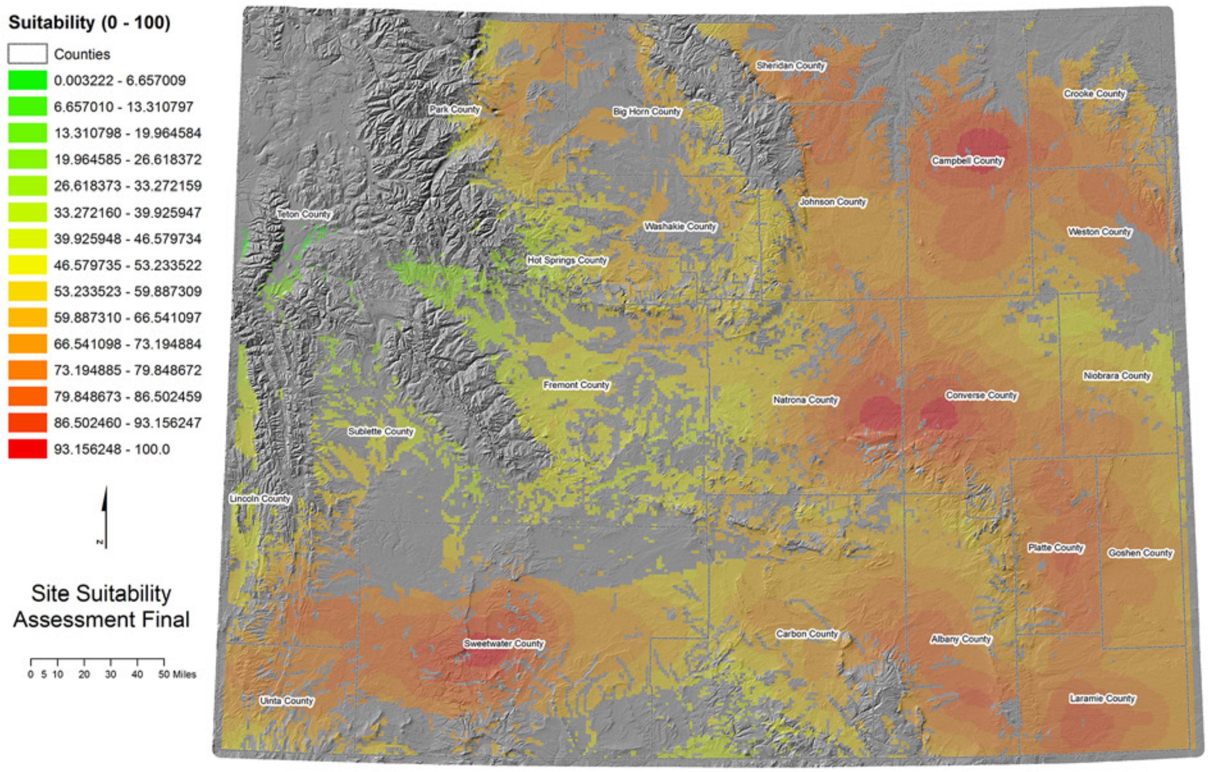

Figure 3. Statewide suitability standardized scores

units of the statewide model (approximately one square mile in size) made consideration of soil characteristics problematic at the statewide scale. Specific weights for the evaluation criteria are not shown because of the confidentiality constraints associated with a nondisclosure agreement governing the facility development partnership.

RESULTS

Results of the statewide suitability model are presented in Figure 3. Areas presented as gray hillshade are outside the study area based on elevation, public lands, and/or the presence of migration corridors as described previously. Suitability results are presented with a green to red color ramp where dark green areas identify the least suitable lands and dark red areas identify the most suitable lands. Figure 3 allowed the site-selection team members to see a clear visual representation of the implications of their collective preferences.

Figure 4 presents the results of the PSS-based site-selection analysis (raw suitability score, upper panel) and the K-T–based results (lower panel). Although the K-T analysis incorporated 31 evaluation criteria and the PSS site-selection analysis only 15, the processes led to similar outcomes. Site E located in Laramie County and site C located in Campbell County were the top two sites in both the PSS parcel-level model and the K-T analysis. Sites A, B, and F (all located in Albany County) and site D (located in Goshen County) were ranked differently by the K-T and PSS analyses. Top-rated appraisal scores that are reasonably close to one another (e.g., less than 15 percent difference) should invite additional scrutiny such as verifying evaluation criteria have been assessed properly and that no relevant evaluation criteria have been excluded.

In this case, multiple methods were demonstrated to yield similar site-selection outcomes. The number of final evaluation criteria in all the analyses (presented in Table 3) was considerably less than the number of initial set of 75 criteria considered in the K-T analysis. The difference between initial and final criteria was because of the elimination of redundant criteria and criteria eliminated because of poor quality or unavailable data. The final set of evaluation criteria were viewed as both comprehensive and nonredundant by the site-selection team.

One-at-a-time (OAT) sensitivity analysis was performed during site-selection team interactive discussions by reducing the weight of individual criterion to zero and observing the effect on suitability outputs. The OAT approach to sensitivity analysis is easily implemented using CommunityViz because of on-the-fly input adjustment and automated recalculation of maps and quantitative output. By applying sensitivity analysis to the statewide model, each of the 15 evaluation criteria incorporated in the PSS model may be mapped, analyzed, and evaluated separately. One is able to see the contribution of the individual components to

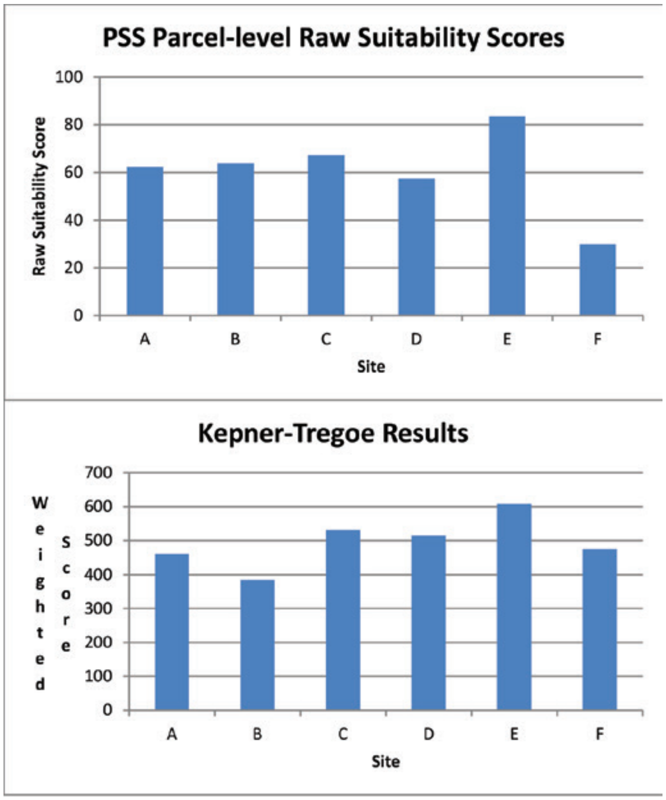

Figure 4. PSS-generated raw suitability and Kepner-Tregoe scores

the overall analysis, inspect the components and formulas created by CommunityViz, and make changes if needed to improve accuracy or performance. Sensitivity analysis allowed the team members to investigate the drivers of their suitability assessment, primarily negatively skewed attributes of spatial data that tended to overwhelm weights in determining suitability model outputs. Finding similar results from different methods, well-developed understanding of the evaluation criteria, consideration of multiple input alternatives, and rapid assessment of the resulting impacts on the outputs of these alternatives helped the team become very confident in the process and the modeling efforts helped inform the best possible choices.

DISCUSSION AND CONCLUSION

This assessment of the CommunityViz suitability model covered methodological foundations, a stepwise walk-through of methods, and a comparative analysis augmented by consideration of uncertainty and assessment of best practices. The primary findings of this research are that the CommunityViz suitability model closely follows the methods of multicriteria evaluation and weighted linear combination modeling, is a beneficial thinking and spatial decision support tool for facility site selection, and, therefore, is more broadly a valid tool for spatial multicriteria evaluation. Congruence with MCE and WLC methods serves to validate the CommunityViz suitability modeling framework. Comparison of PSS results with K-T results, especially as the models were built with differing criteria (see Table 3) both served to validate PSS outputs and assisted in reducing decision risk.

With the HPG-ATC facility siting, the CommunityViz suitability model was demonstrably effective at producing trusted outcomes. As the CommunityViz suitability model and the K-T decision analysis framework both lack a built-in quantitative assessment of uncertainty, the site-selection team followed Voogd's (1983) recommendations for addressing uncertainty in MCE: comparison of initial with final evaluation criteria, sensitivity analysis, and comparison of multiple MCE methods. The addition of the K-T framework to the CommunityViz analysis addressed method uncertainty through separate verification of outputs. The collaborative internal decision nature of the HPG-ATC site-selection process assisted with mitigating problems associated with the interdependence of evaluation criteria and developing weights that accurately reflected requirements and preferences. The evolution of evaluation criteria as part of an interactive and iterative model development process over several months, coupled with the sensitivity analysis of the final model enabled by the dynamic analysis capabilities of CommunityViz, resulted in a transparent process and built confidence among the team members. These observations are congruent with Kleinmuntz (2007), who notes that considering the effects of uncertainty helps build confidence in a model. This occurs, in part, because outputs may be viewed more broadly than a single modeling process resulting in a specific result, but as a framework where varied inputs may consistently produce similar results. Sensitivity analysis and the exploration of alternative inputs deemphasizes the outputs of any specific combination of inputs but bolsters the decision process when there is consistency of outputs.

Determining the set of evaluation criteria serves as a basis for MCE best practices, including quality documentation, easy repetition, objectivity, and transparency (Janssen 2001). Additional best practices suggested by this research include removing clearly unsuitable decision options at the beginning of an analysis, which minimizes the processing time required for subsequent calculations. Enabling faster processing can be important when challenging the processing capability of a computer in an analysis with a larger number of decision options and when waiting on the results of a dynamic update in a meeting setting.

This assessment shows the CommunityViz suitability model meets the requirements for planning methods proposed by Voogd (1983), including increasing insight to a decision situation, the ability to quickly handle changing inputs, transparency, and making values incorporated in a decision process explicit. A potential drawback to the use of PSS for MCE is that it is a tool rather than a problem-driven approach. Voogd (1983) recommends drivers of an MCE process should be the characteristics of the problem and not the characteristics of the problem-solving technique. This is an inherent challenge for planning support systems. Consideration of the flexibility of PSS for adapting MCE modeling to specific decision situations may be part of the answer but this remains an area for future research. It also is noted that while the PSS modeling process was transparent to the site-selection team, nonexpert and/

or third-party audiences would likely require considerable effort to ensure the workings of the model were clearly understood.

Final selection of the HPG-ATC site, site E from Table 4, was based on criteria guided by the PSS and K-T frameworks but ultimately went beyond these methods. After using the PSS and K-T process to identify the top three ranked proposals, visits were made by the team to each potential site. Final selection occurred after these visits based in part on information acquired during the visits and not exclusively based on criteria included in the models. The final decision on site selection was outside the bounds of MCE. At the same time, the final decision incorporated options and choices from the common and understood MCE framework. The process corroborates Voogd's (1983) argument that MCE is a tool for classifying the information needed for choice and providing a structure for solving a problem rather than a decision-making tool that provides a "correct" solution.

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About the Authors

Dr. Scott N. Lieske is a research fellow at the Sustainability Research Centre within the Faculty of Arts and Business at the University of the Sunshine Coast, Australia. His research interests center around the use of geographic information science and spatial tools to support place-based decision making.

Corresponding Address:
Sustainability Research Centre - ML28
University of the Sunshine Coast
Locked Bag 4, Maroochydore DC
Queensland, Australia 4558
Telephone: 61 7 5456 5812
Fax: 61 7 5430 2887
E-mail: slieske@usc.edu.au

Dr. Jeffrey D. Hamerlinck is the Director of the Wyoming Geographic Information Science Center and Senior Research Scientist in the Department of Geography at the University of Wyoming, Laramie. His research interests are in the area of geographic information science with an emphasis on spatial data infrastructures, decision support, and geographic visualization, as well as planning and resource management, including planning support systems, land use, landscape ecological planning, and regional planning.

Wyoming Geographic Information Science Center
Department 4008
1000 E. University Avenue
University of Wyoming
Laramie, Wyoming 82071
Telephone: (307) 766-2736
Fax: (307) 766-2744
E-mail: jeff.hamerlinck@uwyo.edu

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