Hacettepe Journal of Mathematics and Statistics
Volume 45 (4) (2016), 1245 – 1273

Spatial decision making under determinism vs. uncertainty: A comparative multi-level approach to preference mapping

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Abstract

The aim of this study is to highlight the importance of uncertainty assessments in GIS-based multi-attribute land-use decision making. To this end, and based on the basic premise that *uncertainty makes a difference,* it makes use of an existing deterministic goal-driven and hierarchical GIS-based land-use conflict model known as LUCIS (Land-Use Conflict Identification Strategy), the aim of which is to create a land-use conflict map between agricultural, urban and ecologically sensitive land-use preferences for future planning scenarios. Being confined to its agricultural preference (overall goal) mapping, the newly developed uncertainty models and maps are compared with their corresponding deterministic models and maps at each level of the LUCIS hierarchy. The comparative models are applied to the case of Hillsborough County in Florida, which is characterized by a high level of conflict between the three land uses. Different levels of differences in terms of pattern/shape/form and the degree of agricultural land-use suitability are identified and assessed at all levels of the hierarchy.

Keywords: Multi-attribute decision making (MADM/MCDM), Land-Use Conflict Identification Strategy (LUCIS), determinism, uncertainty, probability, fuzzy logic.

2000 AMS Classification: 62C99

Received : 05.08.2014 *Accepted* : 22.06.2015 *Doi* : 10.15672/HJMS.20157712084

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1. Introduction

The limitations associated with the classical Boolean logic representation of spatial data in standard geographic information systems (GIS) [41; 6; 1], which is "crisp, deterministic, and precise in nature" [1:143], has resulted in the integration of multi-attribute decision making (MADM) techniques (referred to in general as multi-criteria decision making – MCDM – in MADM literature) with GIS [29]. This approach facilitates a wide range of analytical procedures [7], and has gained increasing interest among modelers over the last two decades, based on its ability to assess uncertainty in spatial MCDM process.

GIS-based or spatial MADM is based on the discrete representation of spatial data, generally in the form of a hierarchical structure [28]. Unlike the multi-objective process of MCDM [28; 15], as in all multi-attribute decision making approaches this process involves the definition of objectives, the choice of criteria for measuring these objectives and their standardization, the criteria weighting that reflects the decision-makers' preferences, and an aggregation of the weighted standardized criterion values, allowing the alternatives to be ranked, after which the best alternative will be selected [29; 30; 27].

1.1. Uncertainty analysis in land-use planning and environmental management in spatial MCDM literature, and context of the current study. The uncertainties in the decision-making process related to planning or environment-related problems, including land-use suitability, are distinguishable in three dimensions, that is, (1) location, (2) level, and (3) nature of the uncertainty [30]. In their review of some basic works (see [45; 36; 46]) Mosadeghi et al. [30] suggest a linkage between uncertainty analysis in MCDM and the dimensions of uncertainty with respect to uncertainty in environmental decision making (Figure 1). As can be seen in the figure, uncertainties that are stochastic in nature are found in the context and model structure, and are related to the decision makers' preferences and knowledge of the MCDM process, while epistemic uncertainties are found in the context, modeling technique and input, and are related to model uncertainty. By definition, stochastic uncertainty, which is inherent in the context of natural, behavioral, social, economic, and cultural systems, is random in nature and cannot be eliminated [18; 30]. On the other hand, epistemic uncertainties are a result of imperfect or incomplete knowledge, and can be reduced through empirical efforts and high-quality data, monitoring and longer time series [18; 30; 32].

The following list explains the sources of uncertainty found in modeling that may be dealt with in an uncertainty analysis in which stochastic uncertainties are excluded. Uncertainty in the final result may originate from any of these stages [41], or may be found in one or more of the different stages of the spatial (GIS-based) MCDM process that may propagate in the final result [32]. As is common in many works [41; 18; 12; 11; 13; 40; 30; 32; 27], these stages of the modeling process, which are characterized by assessable (i.e., epistemic) uncertainty, can be listed as in the following with reference to the locational dimension presented in Figure 1.

1. Selecting a particular/appropriate model (model structure);
2. Setting or defining the problems, goals and/or objectives (model structure);
3. Identifying appropriate attribute/criteria and/or parameters (model structure);
4. Obtaining high-quality data with minimal measurement and data processing (context and input) or algorithm (model technique) errors;
5. Decision making to obtain standardized criterion maps (context and model technique);
6. Decision making for assigning of weights (model structure); and
7. Interpretation of the final results (context and model technique).

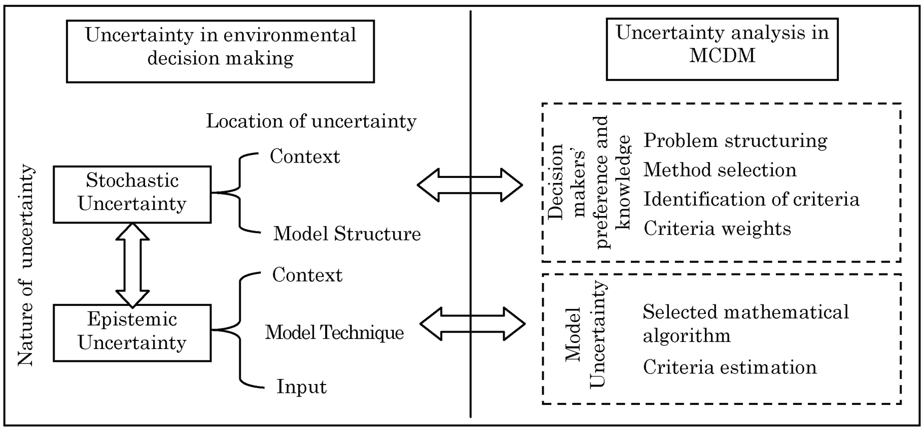


Figure 1. Linkage between uncertainty terminology in environmental decision-making science and MCDM
Source: [30:1104]

Although the number of studies that focus on uncertainty assessments in MCDM are increasing in number, they are still considered insufficient by many scholars who concentrate on the requirement for the proper expression of uncertainty in GIS-based works (see e.g., [14; 35; 40]). The shortfall, specifically, is in the quantification of uncertainty in decision making and policy assessment concerning land-use planning [32] and for environmental processes [18].

The level of resolution to the problem of uncertainty in the above listed stages of the modeling process in land-use or environmental decision making differs in existing literature. That is, while in some studies uncertainty is dealt with to a greater extent in terms of both the number of works and the variety of techniques used, others are subject to less attention by the modelers. For example, although the number of works that consider uncertainty in relation to the selection of the model, goal/objectives, criteria/parameters (stages 1 to 3) above is very limited [29; 11], those that are related to stage 4 on data quality and processing is relatively high (see e.g., [2; 26; 39]). That said, it is also known that in MCDM methods, the input data is generally assumed to be error free (see e.g., [41]), precise and accurate [29]. The majority of spatial MCDM literature focuses on stages 5 and 6 [16], and to a much lesser degree, on stage 7, which deal with decision making in terms of criteria standardization and weight assignment, and results interpretation, respectively. In literature, different MCDM techniques for dealing with uncertainty, especially in stages 5 and 6, have been developed since the first introduction of this decision-making process into the fields of economics and finance in the 1960s [30]. These multi-attribute (multi-criteria) evaluation methods include the weighted linear combination (WLC), and as an extension to its limitations, the ordered weighted averaging (OWA), as well as other additive techniques, such as multi-attribute value/utility theory (MAVT/MAUT) and analytic hierarchy process (AHP). Some WLC-variant decision rules are also included, such as ideal point methods (e.g., Technique for Order Preference by Similarity to Ideal Solution-TOPSIS) and concordance methods (e.g., Elimination et Choice Translating Reality-ELECTRE, Preference Ranking Organization Method for Enrichment Evaluations-PROMETHEE), and also some other methods that utilize theories of Fuzzy sets, Random sets and Game [28; 41; 29; 16; 30].

Literature contains a number of works that discuss the similarities and differences between uncertainty analysis (UA) and sensitivity analysis (SA); and based on these, it can be stated that while some authors claim there is no distinct difference between the two concepts and that they may be used interchangeably [35; 16; 30; 31], others consider them to be separate (see e.g., [28; 27;], but still emphasize the need of their integrated use. As Ligmann-Zielinska and Jankowski [27] point out, UA is used to quantify the variability of outcomes in a multi-criteria evaluation, given the model input uncertainty, whereas SA is used to identify which criteria or criteria weights are most responsible for this variability.

In spatial MCDM, works on land-use suitability or environmental management uncertainty are dealt with using different methods, based on different theoretical backgrounds, assumptions and different levels/types of data requirement. With reference to some basic works [25; 8; 28; 41; 29; 35; 16; 11; 30; 31] a summary table charting these uncertainty/sensitivity analysis methods, in addition to those that are deterministic, is presented, with respect to their modeling type/underlying theory, typology, uncertainty handling, method of criterion map combination, level of objectiveness and ease of communication to the decision makers (Table 1).

The purpose of an uncertainty analysis in decision making is to determine the risk in choosing a particular alternative [11]. Based on the above-listed basic works, it can be stated that in turning the uncertainty into 'risk', in addition to either data-driven traditional *(a priori)* probabilistic (e.g., logistic regression and Monte Carlo simulation), data and knowledge-driven conditional *(a posteriori)* probabilistic (e.g., Bayesian network) and their extensions (e.g., Dempster-Shafer Belief functions) or artificial intelligence (e.g., neural network and fuzzy sets) methods, there are many other approaches, including analytical error propagation, one-at-a-time (OAT), indicator-based (distance-based) analysis, variance-based analysis, methods using random sets theory and game theory (Table 1).

In spatial MCDM literature, which deals mainly with subjects of land-use suitability in land-use planning and environmental management, uncertainty is handled mainly within the 5^{th} and 6^{th} stages of the modeling process described earlier.

In environmental GIS-based MCDM studies, Falk et al. [18] assess the uncertainty estimates of the outcomes of a deterministic environmental model (Revised Universal Soil Equation-RUSLE), along with its input parameters; while Store and Kangas [41] integrate expert knowledge with a spatial multi-criteria evaluation to model GIS habitat suitability. As a resolution to the classical Boolean representation of GIS in uncertainty modeling, and to make empirical data cost savings, Store and Kangas [41] utilize expert knowledge that is based on the theoretical background of MAUT in habitat suitability. For cost saving purposes, Castrignanò et al. [10] opted for multivariate geostatistics in GIS, utilizing ancillary less-expensive information to improve the estimate uncertainty of a soil quality index. Facing the same GIS representation problem, Avdagic et al. [6] and Reshmidevi et al. [37] developed a methodology to integrate a Mamdani-type fuzzy inference rule base in GIS in land valorization for land-use planning and land suitability for particular crops, respectively. In addition, Reshmidevi et al. [37] used the local knowledge of farmers and experts, and compared two different aggregation methods: WLC and Yager's aggregation. Based on the same GIS limitation, but criticizing the integration of Mamdani-type fuzzy logic in GIS, Adhikari and Li [1] utilize a Sugeno-type fuzzy inference. Similar to Falk et al. [18], who utilized Bayesian melding in a cell-based GIS environment, O'Brien et al. [35] developed a tool called CaNaSTA (Crop Niche Selection in Tropical Agriculture) to define site suitability for particular crops and forages using sparse and uncertain data based on Bayesian modeling. In their tool, called the Catchment Evaluation Decision Support System (CEDSS), which enables the explicit

Table 1. Deterministic vs. uncertainty or sensitivity analysis methods in multi-attribute modeling that utilize GIS and other spatial analysis software in land-use suitability or environmental management

Deterministic / Uncertainty or Sensitivity analysis methods[1]	Modeling type / "Underlying theory"	Typology	Uncertainty handling	Method of criterion map combination	Objectiveness / Communication
Boolean logic (operations)	Deterministic "Determinism" Traditional set theory	The most traditional	No uncertainty assumed Probability is either 0 or 1 Set membership value is either 0 or 1	No weighting (simple overlay of 0-1 maps)	Easy communication to decision makers
Binary evidence -extension to Boolean logic				WLC	
Index overlay -extension to binary evidence				WLC/OWA/MAVT/ AHP/ideal point methods/ concordance methods	
Logistic regression	Data-driven probabilistic "Probability theory"	Traditional probability (*a priori*)	Uncertainty due to limitation in knowledge (epistemic) or randomness in occurrence of an event (stochastic) Based on probability density, probability distribution Probability is between 0 and 1	Methods listed in the leftmost column used for combining the criterion maps. However, in case they are used for criterion map estimation then Probabilistic additive weighting/OWA/ MAUT/ AHP/ideal point methods/ concordance methods is/are used (In addition, MAUT is also used in standardizing criterion maps)	Being data-driven and a priori, more objective Relatively complicated
Generalized Linear and Generalized Additive Models -extension of logistic regression					
Monte Carlo Simulation					
Bayesian network	Both data-driven and knowledge-driven probabilistic "Bayesian theory"	Conditional (Bayesian) probability (*a posteriori*)	Based on *a priori* probability and knowledge-base a posteriori probability is obtained with the principle of excluded middle		Being knowledge-driven, and to a certain extent, being a posteriori, more subjective Complicated
Dempster-Shafer Belief functions	Knowledge-driven probabilistic "Dempster-Shafer Belief theory"	Extension of Bayesian probability	Makes a distinction between probability and ignorance removing the assumption of excluded middle		
Classification and regression trees -based on decision trees	Data-driven for robust results but allow knowledge-driven assessment for deterministic or probabilistic rule base	Artificial intelligence[2]	Tolerant of imprecision, ambiguity, vagueness, uncertainty		Not necessarily more accurate but "more informed" decisions "Black box" to the decision makers
Neural network					
Cellular automata					
Fuzzy logic (operations)	Fuzzy sets theory "Possibility theory"		Uncertainty due to imprecision of knowledge or the ambiguity of an event, i.e., to which degree an event occurs Set membership value is between 0 and 1	Fuzzy additive weighting/ Fuzzy MIN/Fuzzy MAX/OWA/AHP/ ideal point methods/ concordance methods is/are used	

[1] Other basic uncertainty or sensitivity analysis methods not detailed here are analytical error propagation, one-at-a-time (OAT), indicator-based (distance-based) analysis, variance-based analysis, methods using random sets theory and game theory.

[2] Evolutionary (genetic) algorithms is a multi-objective decision making (MODM) method that utilizes artificial intelligence, and so is not included in the table.

Source: Compiled from the explanations found in [25; 8; 28; 41; 29; 35; 16; 11; 30; 31]

visual exploration of uncertainties in decision making resulting from both weights and attribute (criterion) values in GIS-based catchment management, Chen et al. [11] utilize an indicator (distance)-based method facilitated by an OAT approach. On the other hand, Ligmann-Zielinska and Jankowski [27] use a Monte Carlo simulation in addition to a variance-based analysis in an uncertainty analysis in their UA-SA integrated methodology aimed at defining habitat suitability for a wetland plant.

More transparent graphical display facilities of GIS, such as the work by Chen et al. [11], have taken a novel approach, visualizing the uncertainties in criterion weighting based especially on the AHP method, and thus its pairwise comparisons. In this respect, to evaluate epistemic uncertainties in coastal land-use planning decisions Mosadeghi et al. [31] examine the sensitivity of AHP weighting decisions to input uncertainties, and to this end, combine the conventional UA with the visualization capability of GIS and the Monte Carlo simulation algorithm. Similarly, Chen et al. [12] developed a GIS-based AHP-SA tool that utilizes the OAT method to assess the behavior and limitations of a GIS-based irrigated cropping land-use suitability model. The tool provides access to an interactive range of user-defined simulations to evaluate the dependency of the model output on the weights of the input parameters, identifying the criteria that are sensitive to weight changes. In further developing their work (AHP-SA), Chen et al. [13] developed the AHP-SA2 to increase the tool's efficiency, while also improving its flexibility and enhancing its visualization capability to analyze the weight sensitivity resulting from both direct and indirect weight changes using the OAT technique. Likewise, based on the subjectivity limitation of AHP, Ahmad et al. [3] developed a new technique called the "Objective Spatial Analytic Hierarchy Process (OSAHP)", combining AHP with regression modeling to identify potential agroforestry areas using GIS. With the aim of sustainable development and consensus building, and considering the uncertainties in the land-use planning process, Soltani et al. [40] utilize a GIS-based urban land-use model combined with UA. In their GIS-based MCDM they used AHP, sensitivity analysis, Monte Carlo simulation and probability classification methods, and made use of the visual spatial representation of the results for different stages of the decision-making process under different conditions.

As in the above-mentioned literature, this study deals mainly with the uncertainty in the 5^{th} and 6^{th} stages (decision making on criteria standardization and weight assignment) of the spatial MCDM modeling process listed earlier, and with the 7^{th} stage to the extent of discussing the possibility of different results based on different interpretations of the results of the modeling.

In doing this, rather than carrying out classical sensitivity analysis procedures on criterion values and weights, the intention is to examine the differences between the results of a deterministic approach and an uncertainty approach using standardized criterion maps at lower levels of a hierarchical GIS-based multi-criteria model, and those of weighted and aggregated maps at higher levels. By assessing the differences at each level (multi levels) in the two modeling approaches, and between their equivalent overall goal (preference) maps, this study aims to show that *uncertainty makes a difference* in the ranking and the spatial pattern of the alternatives in land-use decision making, and presents empirical proof of the importance of uncertainty assessment in spatial multi-criteria modeling.

In this respect, the study does not deal with the question of uncertainty in terms of the potentially subjective decisions given by the decision makers, in this case, the two modelers. In other words, the study does not make a sensitivity analysis of the criterion values and weighting of the two models, but rather shows that the deterministic results should not be seen as the only solution set with a particular ranking and spatial pattern of alternatives in land-use suitability, and reveals that they are subject to change under different conditions of decision making, which is characterized by uncertainty.

As mentioned earlier, although there is an increasing number of works on uncertainty assessment, related especially to the 5^{th} and 6^{th} stages of spatial multi-criteria modeling, there has to date been no one-to-one comparison of the deterministic and uncertainty maps at each level of an MCDM land-use suitability model in a GIS environment.

With this study, two main types of uncertainty method, being probability and fuzzy set theories, in addition to MAUT (Table 1), were used to obtain standardized criterion maps at the lowest levels of the hierarchical structure of the existing deterministic model. Then, a weighting process was carried out, which included trade-offs at levels under the goal level and entropy at the goal level compared to existing model's AHP at all levels of hierarchy with two exceptions (i.e., for one lower level sub-objective and for goals). After weighting, each criterion map at the lower levels was aggregated at the higher levels to obtain the preference (overall goal) map for a particular land-use type via either modeling approach (deterministic vs. uncertainty). In these stages, each map pair from either of the modeling approaches at each level of the hierarchy was compared for the case study area, being Hillsborough County in the state of Florida.

The deterministic model used in this study is the Land-Use Conflict Identification Strategy (LUCIS), the structure of which is described in brief in the following section.

1.2. Deterministic spatial multi-attribute land-use modeling: Land-Use Conflict Identification Strategy (LUCIS). The Land-Use Conflict Identification Strategy (LUCIS) is a deterministic MADM process and "a goal-driven GIS model that produces a spatial representation of probable patterns of future land use" [9:9]. In order to assess the conflicts between the three main land-use types (agricultural, urban, and ecologically sensitive) and possible future land-use patterns, models are established to obtain preference maps related to each of these land uses (Figure 2). Even though the complete LUCIS deals with conflict identification based on three different land uses, and in total involves a 6^{th} level at the top of the hierarchical structure, the scope of this study is limited up to 5^{th} level, and to the agricultural land use (Figure 2). In this respect, the uncertainty maps obtained in this study, like their corresponding deterministic equivalents from existing models, consist of the overall goal map, referred to as the preference map hereafter, at the top of the hierarchical structure, followed by maps charting the goals, objectives, sub-objectives and lower level sub-objectives at the lower levels.

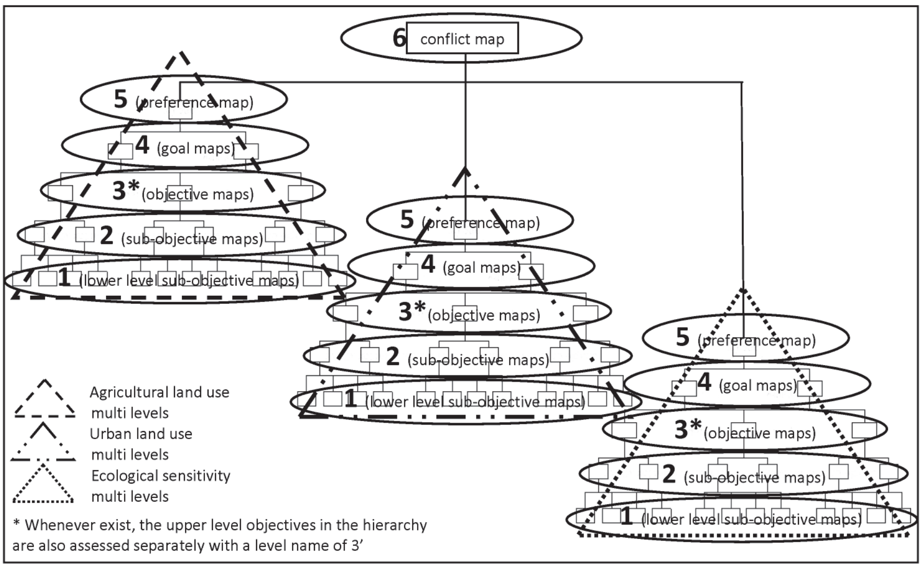


Figure 2. Symbolic representation of multi-level LUCIS hierarchies (study covers the levels concerning agricultural land use on the left, the preference map being at the top)
Source: Adapted from [9:231,233,236]

The related numbering, naming and a short description of the LUCIS hierarchical levels for the agricultural land-use preference map seen on the left part of Figure 2 is

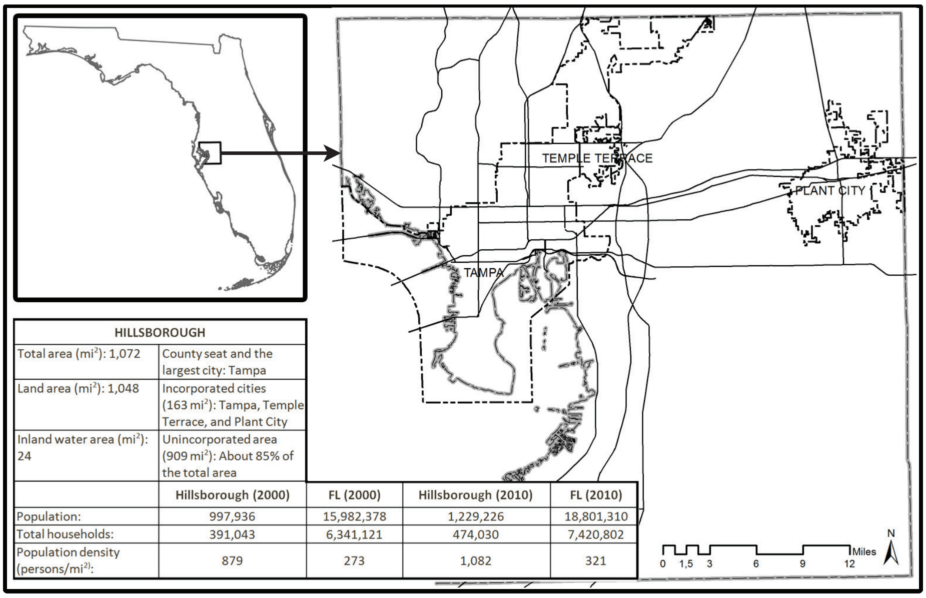
Table 2. Numbering, naming, and a short description of the LUCIS hierarchical levels for the agricultural land-use preference map

Level 4 Goal maps	Level 3' Upper level objective maps*	Level 3 Objective maps	Level 2 Sub-objective maps	Level 1 Lower level sub-objective maps
Row crops land suitability (1)	-	Physical suitability (11)	Soils suitability (111)	a:Grass; b:Strawberries; c:Corn; d:Sugarcane; e:Cabbage; f:Peppers; g:Soybeans; h:Snapbeans; i:Watermelons; j:Peanuts; k:Cucumbers
			Land-use suitability (112)	-
		Proximity suitability (12)	Local markets proximity (122)	a:City population; b:Row crops distance
			Major roads proximity (123)	-
		Land value suitability (13)	-	-
Livestock suitability (2)	High-intensity livestock suitability (2A)	Physical suitability (21)	Land-use suitability (211)	-
			Distance to open water resources (212)	-
			Aquifer recharge suitability (213)	-
			Soils suitability (214)	-
			Distance to existing urban areas (215)	-
		Proximity suitability (22)	Local markets proximity (221)	-
			Major roads proximity (223)	-
		Land value suitability (25)	-	-
	Low-intensity livestock suitability (2B)	Physical suitability (23)	Land-use suitability (231)	-
			Distance to open water resources (232)	-
			Aquifer recharge suitability (233)	-
			Soils suitability (234)	-
		Proximity suitability (24)	Local markets proximity (241)	-
			Major roads proximity (243)	-
		Land value suitability (26)	-	-
Specialty farming suitability (3)	-	Physical suitability (31)	Land-use suitability (311)	-
			Distance to open water resources (312)	-
			Aquifer recharge suitability (313)	-
			Soils suitability (314)	-
		Proximity suitability (32)	Proximity to processing plants (321)	-
			Major roads proximity (323)	-
		Land value suitability (33)	-	-
Nursery suitability (4)	-	Physical suitability (41)	Land-use suitability (411)	-
			Parcel size suitability (412)	-
		Proximity suitability (42)	Local markets proximity (421)	-
			Major roads proximity (423)	-
		Land value suitability (43)	-	-
Timber suitability (5)	-	Physical suitability (51)	Land-use suitability (511)	-
			Aquifer recharge suitability (513)	-
			Soils suitability (514)	-
			Parcel size suitability (515)	-
		Proximity suitability (52)	Local markets proximity (521)	-
			Major roads proximity (522)	-
		Land value suitability (53)	-	-

presented in Table 2, in which all of the goals and objectives at all levels are phrased in such a way that they are tried to be maximized in the decision-making process. As is clearly apparent in Table 2, the LUCIS agricultural land-use hierarchical levels, each of which is in fact a GIS map layer, follow a naming convention that is composed of an alphanumeric code for each different level. For example, Level 4: Goal map 1, Level 3: Objective 11, Level 2: Sub-objective 111 and Level 1: Lower Level Sub-objective criterion maps under sub-objective 111 are named respectively with codes ag1; ag1o11; ag1o11o111; and criterion maps under sub-objective ag1o11so111, which are named with a letter a–k to ensure ease in following, and since the maps at these levels are only a few in number.

2. Study area and data

Hillsborough County is located on the west coast of central Florida (Figure 3). It has total of surface area of 1,072 square miles (1,048 sq mi of land and 24 sq mi of inland water). Tampa is the County seat and the largest city in Hillsborough, in which there are two more municipal cities: Temple Terrace and Plant City [23]. It is a rapidly urbanizing county [44] with a population increase of 23.2 percent (from 997,936 to 1,229,226) and a population density increase from 879 to 1082 persons/sq mi between 2000 and 2010 [43]. The rapid and continuous urban development, which has been mainly in the form new suburban construction, especially into the more rural, unincorporated part of the county [23], has caused both the environmental degradation of natural resources, such as soil erosion and compaction, deforestation and disturbance to aquifers [44], and a decrease in valuable agricultural lands, which makes up one of the most important production capacities in the state total [38].



HILLSBOROUGH	
Total area (mi^2): 1,072	County seat and the largest city: Tampa
Land area (mi^2): 1,048	Incorporated cities (163 mi^2): Tampa, Temple Terrace, and Plant City
Inland water area (mi^2): 24	Unincorporated area (909 mi^2): About 85% of the total area

	Hillsborough (2000)	FL (2000)	Hillsborough (2010)	FL (2010)
Population:	997,936	15,982,378	1,229,226	18,801,310
Total households:	391,043	6,341,121	474,030	7,420,802
Population density (persons/mi^2):	879	273	1,082	321

Figure 3. The study area, Hillsborough County in the state of Florida Source: Map data compiled from [19]; Tabular data compiled from [23;43]

The strong competition with an essentially high level of decision-making uncertainty among the urban, agricultural and natural land uses in Hillsborough County was the main reason for the selection of this area for a study of the impact of uncertainty on a deterministic multi-criteria land-use modeling, aiming to identify land-use conflicts (LUCIS) among the three land uses.

Aside from the annual agricultural sales of Hillsborough County, obtained from Census of Agriculture data, and the 'Critical Lands and Waters Identification Project (CLIP): Version 2.0 data [21], all other data used in the study at both the county and state level were obtained from the 'Florida Geographic Data Library' (FGDL) website [19], as the source of the most recent available data at the time of writing.

In this study, all the models for the deterministic approach were built and run using ArcGIS® software. The same software was used also for the uncertainty approach, although for some models, additional software was needed, such as, spreadsheet environment (MS Excel®) and spatial data analysis (CrimeStat®).

3. Methodology and application

In this section, the methodology and its applications to the study area will be explained in three subsequent stages. The first stage includes the development of uncertainty models for LUCIS and the comparisons with their deterministic equivalents in terms of the standardization of criterion maps (each different GIS layer) at the different hierarchical levels (levels 1, 2 and 3) prior to any weighting being applied. The second stage involves a comparison of the decision rules of the two different approaches (deterministic vs. uncertainty) for combining the criterion maps under each relevant level of hierarchy (levels 1, 2, 3, 3' and 4). In the final stage, a comparison is made for the preference maps of the two modeling approaches (level 5). The results of the two modelings of these three stages, considering all hierarchical levels of LUCIS (up to the 5^{th}), are explained in Section 4.

3.1. Comparison of newly developed uncertainty models and their existing deterministic equivalents in criteria standardization (levels 1, 2 and 3). The criteria standardization in uncertainty modeling was carried out using seven different groups of methods, each applied to a different group of maps prior to any weighting (i.e., the maps have no other sub-level maps) (Table 2). The seven groups of methods are listed in Table 3 according to the groups of criterion maps (GIS layers) to which they were applied, which are referred using their alphanumeric names described earlier.

In general, the GIS-based uncertainty models in criteria standardization were developed with reference to the characteristics of the decision variable: whenever they are numeric, the uncertainty is assumed to be a result of limited information related to the decision-making process in a particular spatial system and dealt with traditional probability [25; 4; 28] (Table 1), contrary to the unit probability of an alternative in the deterministic DM process [20; 22]. However, if the variables are categorical, and imply that the uncertainty is a result of the imprecision or ambiguity of the information or, in other words, if the variables are linguistic or fuzzy, the fuzzy set membership methods [28] are used to obtain the criterion maps. Both of these two types of maps are then compared with those obtained from the deterministic variables with binary, discrete or continuous values at each level of the hierarchy.

In the former type of variables, probabilistic maps are obtained with discrete, continuous or mixed variable values, and the transformation processes are based on probability density or cumulative probability density functions, in which most of the maps can be considered to be data-driven, based on objective probabilistic methods (Table 1) using relative frequency (or area) distributions. The only exceptions to this are the two lower level sub-objectives handled by MAUT, in which the derivation of utility functions includes the assessment of the decision maker's expected utility. The remaining assessments of uncertainty involve the use of fuzzy logic (Table 1) by means of linguistic variables.

In Table 4 below the detailed methodology applied to the seven different groups of criterion maps are explained in terms of both the deterministic and uncertainty approaches.

3.2. Comparison of decision rules in criteria aggregation and weighting in the deterministic and uncertainty models (levels 1, 2, 3, 3' and 4). In the deterministic modeling, the decision rule for combining the criterion maps at each weighting

Table 3. Seven groups of uncertainty methods for criteria standardization, and the criterion maps (GIS layers) to which they were applied

Methods	Uncertainty method type	Hierarchical level	Criterion map name	Objective (in terms of minimization or maximization)
Method 1	Expected utilities based on frequencies multiplied by a particular value (yield)	Level 1	Lower Level Sub-objective under Sub-objective ag1o11so111	- row crops-physical-soils
Method 2	Utility functions and utility function multiplied by a particular value (probability of standard deviation of the prediction)	Level 1	Lower Level Sub-objective under Sub-objective ag1o12so122	- row crops-proximity-local markets
Method 3	Fuzzy set membership (and fuzzy overlay) based on expert knowledge and spatial MCDM literature	Level 2	Sub-objective ag1o11so112 Sub-objective ag4o41so411 Sub-objective ag5o51so511 Sub-objective ag2o21so213 Sub-objective ag2o23so233 Sub-objective ag3o31so313 Sub-objective ag5o51so513 Sub-objective ag2o21so214 Sub-objective ag2o23so234 Sub-objective ag3o31so314 Sub-objective ag5o51so514 Sub-objective ag4o41so412 Sub-objective ag5o51so515	- row crops-physical-land-use - nursery-physical-land-use - timber-physical-land-use - livestock-high-intensity livestock physical- aquifer recharge - livestock-low-intensity livestock physical-aquifer recharge - specialty farming-physical-aquifer recharge - timber-physical-aquifer recharge - livestock-high-intensity livestock physical-soils - livestock-low-intensity livestock physical-soils - specialty farming-physical-soils - timber-physical-soils - nursery-physical-parcel size - timber-physical-parcel size
Method 4	Fuzzy set membership based on the mean and standard deviations of already grouped data with respect to their fuzzy membership values, based on expert knowledge and spatial MCDM literature	Level 2	Sub-objective ag1o12so123 Sub-objective ag4o42so421 Sub-objective ag5o52so521 Sub-objective ag4o42so423 Sub-objective ag5o52so522	- row crops-proximity-roads - nursery-proximity-local markets - timber-proximity-local markets - nursery-proximity-roads - timber-proximity-roads
Method 5	Functional transformation of probabilities based on areas	Level 2	Sub-objective ag2o21so211 Sub-objective ag2o23so231 Sub-objective ag3o31so311	-livestock-high-intensity livestock physical-land-use -livestock-low-intensity livestock physical-land-use -specialty farming-physical-land-use
Method 6	Fuzzy set membership based on the mean and standard deviations of already grouped data with respect to their functional transformation of probabilities, based on areas	Level 2	Sub-objective ag2o21so212 Sub-objective ag2o23so232 Sub-objective ag3o31so312 Sub-objective ag2o21so215 Sub-objective ag2o22so221 Sub-objective ag2o24so241 Sub-objective ag3o32so321 Sub-objective ag2o22so223 Sub-objective ag2o24so243 Sub-objective ag3o32so323	-livestock-high-intensity livestock physical-open water -livestock-low-intensity livestock physical-open water -specialty farming-physical-open water -livestock-high-intensity livestock physical-existing urban -livestock-high-intensity livestock proximity-local markets -livestock-low-intensity livestock proximity-local markets -specialty farming-proximity-processing plants -livestock-high-intensity livestock proximity-roads -livestock-low-intensity livestock proximity-roads -specialty farming-proximity-roads
Method 7	Fuzzy set membership based on enumeration derived from spatial k-means clustering and non-spatial mean and standard deviations	Level 3	Objective ag1o13 Objective ag2o25 Objective ag2o26 Objective ag3o33 Objective ag4o43 Objective ag5o53	-row crops-land value -livestock-high-intensity livestock-land value -livestock-low-intensity livestock-land value -specialty farming-land value -nursery-land value -timber-land value

Table 4. Detailed deterministic and uncertainty methodology applied to the seven different groups of criterion maps

	Level	Map name	Aim	Deterministic models	Uncertainty models
Method 1	Level 1 maps	(a-k: different types of crops) under so111	maximize soil suitability for each crop type	Score assignment by linearly increasing values between 1and 9 to either individual or classified increasing crop yield amounts	Expected utility estimation for each row crop type by the number of pixels (i.e., area) of each row crop type, multiplied by the yield value of that crop, and divided by the total of these products (spreadsheet used for floating point rasters, conditional map algebra operation in GIS used for value assignment)
Method 2	Level 1 maps	(a:city population; b:row crops distance) under so122	maximize proximity to local markets for row crops (cities' population and row crop areas)	- Results from a deterministic interpolation method (inverse distance weighting – IDW) on the cities of the county with non-zero population were used for reclassifying the raster - An Euclidian distance map of row crop areas used for reclassification based upon the mean and 1/4 standard deviation distances found in the zonal statistics table for row crop areas [9]	- Cities' populations (including neighbor counties) interpolation by a geostatistical process of kriging that provided a prediction and its variance raster. Prediction surface is used with an estimated utility function by using indifference method for standardization. This 0-1 range prediction map was multiplied by the probability of square root of the variance raster to give higher weights to the values having less errors and vice versa.[1] - Row crops distance standardized utility scores was estimated by application of a utility function to the raw scores obtained by Euclidian distances.[1]
Method 3	Level 2 maps	so112, so411, so511	maximize agricultural land-use suitability in terms of land cover, soils and parcels	Expert knowledge and spatial MCDM literature used in assigning the deterministic values of either 1 and 9 or all or some of the values between 1 and 9. The higher and the highest suitability (9) values were given to the existing and higher potential areas or to the lower criticality areas for the respective five agricultural goals, while the lower and the lowest (1) suitability values were given to areas that have a reverse impact on suitability	Conversion of deterministic assignments (1-9) into linguistic rankings (1-very low and 9-very high) to use fuzzy large or small transformation in GIS to obtain different levels of standardized suitability scores between 0 and 1.[2] Contrary to final combination method max cell statistics operation in the deterministic approach, of land cover and soils map for so112 map a fuzzy OR overlay was used here, however, similar to deterministic approach a focal statistics was used for so213, so233, so313 and so513 maps.
		so412, so515	minimize and maximize parcel size for nursery and timber respectively		
		so214, so234, so314, so514	maximize drainage capacity of soils		
		so213, so233, so313, so513	maximize disturbance to aquifers		
Method 4	Level 2 maps	so123, so423, so522	maximize proximity to roads for row crops, nursery and timber	First, Euclidian distance raster maps were created from major roads and from local market objects that were considered to be the median center of vacant lands for nursery (so421) and lumber yd/mill for timber (so521). Then, a reclassification was made [9] based upon the mean and 1/4 standard deviation distances found in the zonal statistics for the selection of a set of objects related to each of the respective sub-objectives: row crop areas for so123, plant nursery for so421 and so423, and timber for so521 and so522.	Uncertainty models for these criterion maps were derived from fuzzy set memberships large transformation function in GIS by grouping of previous land-use sub-objective maps (so112, so411 and so511).[3]
		so421, so521	maximize proximity to local markets for nursery and timber		
Method 5	Level 2 maps	so211, so231	maximize land-use suitability for high- and low-intensity livestock	Expert knowledge and MCDM literature used in assigning the deterministic suitability scores from 1 to 9 to the selected and rasterized objects on the related fields out of the parcel data	Based on computation of probabilities and the functional transformation of the probabilities for the areas found to have been given a suitability score greater than 1 in the respective deterministic models. [4]
		so311	maximize land-use suitability for specialty farming		

Table 4. (cont.)

Method 6	Level 2 maps	so212, so232, so312	maximize distance to open water areas for high-intensity livestock; and wetlands and open water areas for low-intensity livestock and specialty farming	- The same methodology used in the method 4 above based on the Euclidian distance raster maps obtained by selected objects that the distance is either aimed to be maximized or minimized. - The distance maps for the major roads were the same as prepared for so123, so423 and so522. - For the zonal statistics table a set of selections of the objects, which had a suitability score of 9 from so211 for so212, so215, so221 and so223; from so231 for so232 and so243; from so311 for so312; a selection of miscellaneous agriculture or pasture parcels for so241; and a selection of orchard/citrus for so321 and so323 were used. - Linearly increasing or decreasing suitability scores between 1 and 9 was determined by whether the goal is the maximization or minimization of distances from the respective sources	The same Euclidian distance maps were used as a base in the corresponding models with a similar way of uncertainty assessment as in method 4 above. However, there were differences in terms of - number of mean-standard deviation pairs of zonal statistic raster maps - number of groups of selections from raster maps - the way that linguistic hedges were ordered (interfering in this case) - the way that constant rasters were created The models ended with either fuzzy small (for so212, so232, so312, so215) or large (for so221, so241, so321, so223, so243, so323) transformation functions with the default mid-point and spread values. (5)
		so215	maximize distance to existing urban areas for high-intensity livestock		
		so221, so241 so321	maximize proximity to packing plants and food processing parcels for high- and low-intensity livestock and specialty farming, in addition to four main restaurants in the county for high-intensity livestock		
		so223, so243, so323	maximize proximity to roads for high- and low-intensity livestock and specialty farming		
Method 7	Level 3 maps	o13, o25, o26, o33, o43, o53	maximize land value suitability for row crops, high- and low-intensity livestock, specialty farming, nursery, timber	Just values (market value) per acre for a set of selected parcels, which were greater and equal to 1 acre, for o13, o25, o26, o33 and o53 and 0.2 acre for o43 to exclude the sliver areas, included 'crops' and 'pasture'; 'dairies/feedlots', 'packing plants', 'poultry/bees/fish'; 'pasture', 'vacant acreage', 'miscellaneous agriculture'; 'orchard/citrus'; timber'; and 'plant nursery', respectively. Then, the mean and standard deviation of the just value/acre was used to update the vector data and then to reclassify its (1-9 value) raster form later [9]. Score (1) was given to parcels with 'header' and 'note' information as their land-use description.	The uncertainty in obtaining the utilities for suitability of the land values was handled by fuzzy set membership functions based on both alternatives' (i.e., parcels') spatial and non-spatial aspects. (6)

(1) See Appendix 1 for details of uncertainty method 2
(2) See Appendix 2 for details of uncertainty method 3
(3) See Appendix 3 for details of uncertainty method 4
(4) See Appendix 4 for details of uncertainty method 5
(5) See Appendix 5 for details of uncertainty method 6
(6) See Appendix 6 for details of uncertainty method 7

level (1, 2, 3, 3' and 4) is the weighted summation of the standardized map scores using Equation 3.1.

$$A_i = \sum_j w_j x_{ij} \tag{3.1}$$

In this equation, x_{ij} is the score of the i^{th} alternative with respect to the j^{th} attribute (criterion), and the weight w_j is a normalized weight, so that $\sum_j w_j = 1$ [28].

Similar to this, in the uncertainty approach the weighted summation turned out to be of the linear utility function [33], where the scores are replaced by utilities [28] (Equation 3.2).

$$U_i = \sum_j w_j u_{ij} \tag{3.2}$$

In the deterministic models, the combining methods also involved some other operations, including conditional map algebra or cell statistics, whereby the related land-use layers or urban land-use layers were used as constraint maps. In these operations, the existence of urban uses were given the minimum suitability at the final level (for the result of level 3 for goals 1, 3, 4, 5 and level 3' for goal 2), or the agriculture-related land uses were given maximum suitability or maximum cell statistic at each level at which they were utilized (at level 2 for goal 1, for the result of level 2 and level 3' for goal 2, for the result of level 2 for goal 3). In the uncertainty approach, the only additional method used after weighting was a transformation using Equation A.1.2 in Appendix 1 to obtain the final so111 map. In this approach, the constraint mapping for existing urban and suburban land uses was made only once on the final preference map.

In the deterministic modeling, all of the priority weights were obtained from the AHP method carried out with the community and experts of a similar county, with only two exceptions. These included the use of information obtained from the annual agricultural sales of Hillsborough County in determining the weights for each row crop type at level 1 to obtain the so111 at level 2, and the weights for five different goals at level 4 to obtain the preference map at level 5.

After the row crops weighting at level 1, the objectives weighting at level 3 under goal 1, and after goals weighting at level 4, the deterministic approach used Equation 3.3 to transform the suitability scores to a range of 1 to 9. The comparison of the final preference map with the one obtained from the uncertainty approach was made on the final untransformed map.

$$(X'_{ij}) = \frac{(X_{ij} - X_{j\,\mathrm{old}}^{\mathrm{min}})(X_{j\,\mathrm{new}}^{\mathrm{max}} - X_{j\,\mathrm{new}}^{\mathrm{min}})}{(X_{j\,\mathrm{old}}^{\mathrm{max}} - X_{j\,\mathrm{old}}^{\mathrm{min}})} + 1 \tag{3.3}$$

In Equation 3.3, X'_{ij} is the transformed standardized score for the i^{th} alternative of the j^{th} attribute (criterion), X_{ij} is the raw standardized score, and $X_{j\,\mathrm{old}}^{\mathrm{min}}$ and $X_{j\,\mathrm{new}}^{\mathrm{min}}$ and $X_{j\,\mathrm{old}}^{\mathrm{max}}$ and $X_{j\,\mathrm{new}}^{\mathrm{max}}$ are the minimum and maximum scores for the j^{th} attribute before and after transformation, respectively.

In the uncertainty approach, to assess the decision maker's (here, the modeler) preference uncertainty on the priority weights at levels 1, 2, 3 and 3' for all goals, with the aim of maximizing agricultural suitability, a direct weighting estimation method – a trade-off – was utilized with consistency checks [33].

For the weighting of the goals themselves (at level 4), a mixed methodology was used to assign weights based on their size in terms of acreage, just (market) value and annual sales. This raised a question of how to weight these weights for different criteria. For this purpose, and to assess the uncertainty in this process, the concept of entropy was utilized by applying a series of formulations to the decision matrix (see [24:52-56]), consisting of goals versus their weightings, based on the three different data sets.

3.3. Comparing the final stages in the two modelings to obtain the agricultural preference maps, and the comparison of these two maps (level 5). The deterministic and uncertainty approaches resulted in their own agricultural preference maps after a weighted sum operation (Equations 3.1 and 3.2) on the goal maps. These maps were finalized by merging them with the constraint map data relating to existing urban-suburban land uses, which were assigned values of 1 and 0 – the minimum standardized scores – in the deterministic and uncertainty models, respectively. However, the comparison of preference maps also involved the exclusion of these areas from their final forms, since they covered the areas that were given and were not a result of the either of the modelings.

4. Results and discussion

In the following sections the results obtained from the deterministic and uncertainty modeling approaches are presented in the order in which they were compared in terms of their methodology and application, as explained in Section 3.

4.1. Comparison of results of the criteria standardization obtained from the two modeling approaches (levels 1, 2 and 3).

Method 1: The results of the maximization of soil suitability for each crop type from the deterministic and uncertainty approaches were found to be different in terms of the level of suitability assigned to areas of similar shapes, in that the latter approach (in this case, the probabilistic one) considered not only yield values, but also their occurrences in space. Since the frequencies have a much greater influence in the multiplication than yield values, the larger areas assumed higher utilities for soil suitability, even though they had lower yield values. When considering long-term land-use planning, this result can be seen as a positive impact on the preservation of large row crop areas, despite their low yields.

Method 2: The uncertainty method (in this case, the probabilistic one) adopted in these two level-1 criterion maps, required subjective evaluations of the decision makers (here, the modeler) by means of utility functions that result from the indifference technique (see Appendix 1). This and the other differences in data processing (such as kriging and additional processes on its results as opposed to IDW in the deterministic approach) yielded highly different results in terms of patterns and the levels of suitability for the cities' population map. In contrast, the deterministic model's linear value assignment for the Euclidian distance map and the non-linear utility function's utility assignment in the uncertainty approach produced rather similar results in terms of the relative placement of higher values to alternatives closer to row crop areas (for an illustrative comparison of the results of the two approaches having different and similar patterns and/or suitability scores, refer to Figure 4 in Section 4.2).

Method 3: The resultant maps from the two approaches were found to be similar in terms of patterns, although the levels of suitability that they reflected were found to be different to the extent that their raw data value ranges were either different (as in so213, so233, so313 and so513) or as a natural result of nonlinear fuzzy membership functions (as in so112, so214, so234, so314, so514 and so412) (see Appendix 2). The remaining group of sub-objective criterion maps (so411, so511 and so515) displayed similarities both in terms of their patterns, and in their level of suitability, as an essential result of two discrete groupings of the same selections from the raw data.

Method 4: The resultant maps from the two approaches were found to be different, which resulted from the uncertainty approach's assessment of major roads or local markets proximities, based on the two-group categorization of the study area (see Appendix 3). In addition to the variations between different levels for the land-use suitability groups, the results showed also internal variations within each group. For each related distance map, the uncertainty approach provided different series of suitability levels for each different parcel of the highly suitable land uses, and for the areas having lower land-use suitability based on a constant mean and standard deviation. On the other hand, the deterministic criterion maps were distinguished by small quarter standard deviation increments around the most suitable area distance buffer, as defined by the mean zonal distance of the existing/ most suitable land for each respective agricultural goal, i.e., goal 1 (row crops), goal 4 (nursery) and goal 5 (timber).

Method 5: When the results of the two approaches were compared, a more significant variety was observed on the 0-1 uncertainty maps than on the 1-9 deterministic maps. The probabilities computed in the former maps allowed the assignment of utilities for land-use suitability with respect to their occurrences in space for the three different agricultural activities (high- and low-intensity livestock, and specialty farming) that were evaluated (see Appendix 4). The transformation of smaller probabilities to higher utilities for high-intensity livestock (so211) and specialty farming (so311), and of higher probabilities to higher utilities for low-intensity livestock (so231), were based on the increasing and decreasing revenues per unit area for the respective agricultural activities.

Method 6: The evaluations of the results of the two approaches were found to be quite similar to those made in the Section Method 4, although differences existed in the higher level of variety in the uncertainty maps. This was due to the grouping of the respective land-use maps into three rather than two, in which the study area was divided into areas of high-, moderate- and low-level land-use potential. Another difference was found in the interfering fuzzy ranking in models so212, so232 and so312, which were set in such a way that the nearer and then the nearest areas to the water resources were left to be given the least suitable ranking in each of the three groups of land-use potentials, i.e., high- and low-intensity livestock and specialty farming (see Appendix 5). Finally, in contrast to the only proximity maximization problems handled in the Method 4 models, both approaches dealt with both the aims of maximization of proximity and distance (i.e., minimization of proximity) on the Euclidian distance maps.

Method 7: In comparing the results from the two approaches, although at first look, the non-spatial component of the resultant corresponding objective criterion maps from the uncertainty approach seems to resemble the deterministic maps, the final uncertainty maps were found to have different patterns and levels of suitability. This was due to a variety of factors, including (1) the existence of their spatial components, (2) the overall fuzzy hedge ordering in each of the components after the enumeration process carried out for both types, and (3) the respective fuzzy set membership values (see Appendix 6).

4.2. Comparison of results for criteria aggregation after weighting from the two modeling approaches (levels 1, 2, 3, 3' and 4). The results of the two approaches after any weighting process at levels of 1, 2, 3, 3' and 4 turned out to be different from each other, to the extent that their component maps are different. The level of differences with respect to the same alternatives (pixels) between the two groups of results at the same level can be categorized into four groups, such that they have either:

1. very different patterns/shapes/forms and different levels of suitability;
2. partially different patterns/shapes/forms and different levels of suitability;
3. similar patterns/shapes/forms and different levels of suitability; or
4. similar patterns/shapes/forms and similar levels of suitability.

Each of the above-listed groups of aggregated weighted map result differences are illustrated by some of the level 2 and level 3 results in Figure 4's 1a-4a (deterministic) vs. 1b-4b (uncertainty) sections.

4.3. Comparison and interpretation of agricultural preference maps from the two modeling approaches (level 5). For a comparison of the preference maps (overall goal) obtained from the two modeling approaches at level 5 of the hierarchical structure of LUCIS, the z-scores of each pair of maps (including and excluding the existing urban-suburban areas) and the z-score differences were computed. The maps, their distributions and the summary statistics of these comparisons are shown in Figure 5.

When the first case was evaluated in terms of its z-scores, the deterministic result was found to vary between -1.153 and 1.783, and the uncertainty between -1.157 and 1.978 (Figure 5). However, when the given urban-suburban areas were excluded from

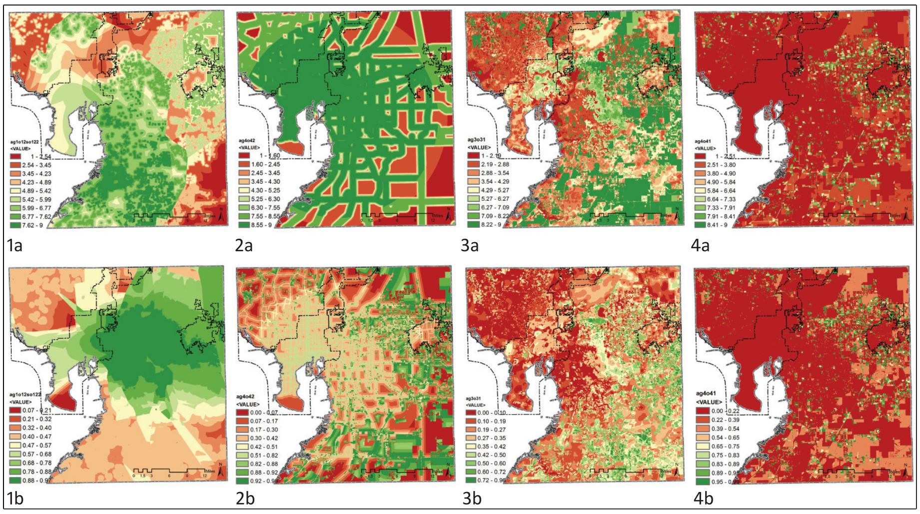


Figure 4. Deterministic (1a, 2a, 3a, 4a) and uncertainty (1b, 2b, 3b, 4b) aggregated maps for sub-objective 122 (1a and 1b), objective 42 (2a and 2b), objective 31 (3a and 3b), and objective 41 (4a and 4b)

the analysis, which composed the modes (i.e., the most repeated land-use type) for both distributions (see the 1^{st} and 3^{rd} graph in the 2^{nd} row of Figure 5), the minimum values of the maps increased to -0.825 and -0.946, respectively. In the second case, the graph of the deterministic result revealed a bi-modal distribution, with one near to its mean (0.742), and the other towards the end of its lower tail (at about 1.53). Accordingly, it suggested a data spread that cannot be attributed to a normal distribution (see the 2^{nd} graph in the 2^{nd} row of Figure 5); however, looking at the graph of the uncertainty result (see the 4^{th} graph in the 2^{nd} row of Figure 5), it is seen that it was more or less normally distributed about its own mean (0.744). The main difference between the two results was observed in the uncertainty result filling the gap between the two modes of the deterministic approach. This comparison can be illustrated by overlaying the two graphs after converting them to the same scale, after which the difference can be seen in the light grey tone frequency distribution in the 2^{nd} graph on the bottom row of Figure 5. It can also be seen in this graph that following the exclusion of unsuitable areas from the analysis, a substantial part of all alternatives (pixels) in both results is observed on the positive side of the z-score distribution.

The z-score difference maps for the two cases (i.e., including and excluding urban and sub-urban areas) was found to vary between a minimum of -1.629 and a maximum of 1.263, suggesting a non-statistically significant difference between the two results in a one-to-one comparison of each pixel (alternative) at a 95 percent confidence interval (see the summary statistics in the 3^{rd} and 4^{th} rows of Figure 5). Moreover, in the second case, when the given urban-suburban areas were excluded, as would be expected, the distribution of the difference map was found to be approximating a normal distribution around a mean value, which was very close to zero (-0.0088) (see the 1^{st} graph and the summary statistics on the bottom row of Figure 5). Accordingly, based on the comparison of agricultural preference maps in terms of their z-score pixel values, it can be stated that the newly developed uncertainty models did not result in a significant difference over the existing deterministic models of LUCIS.

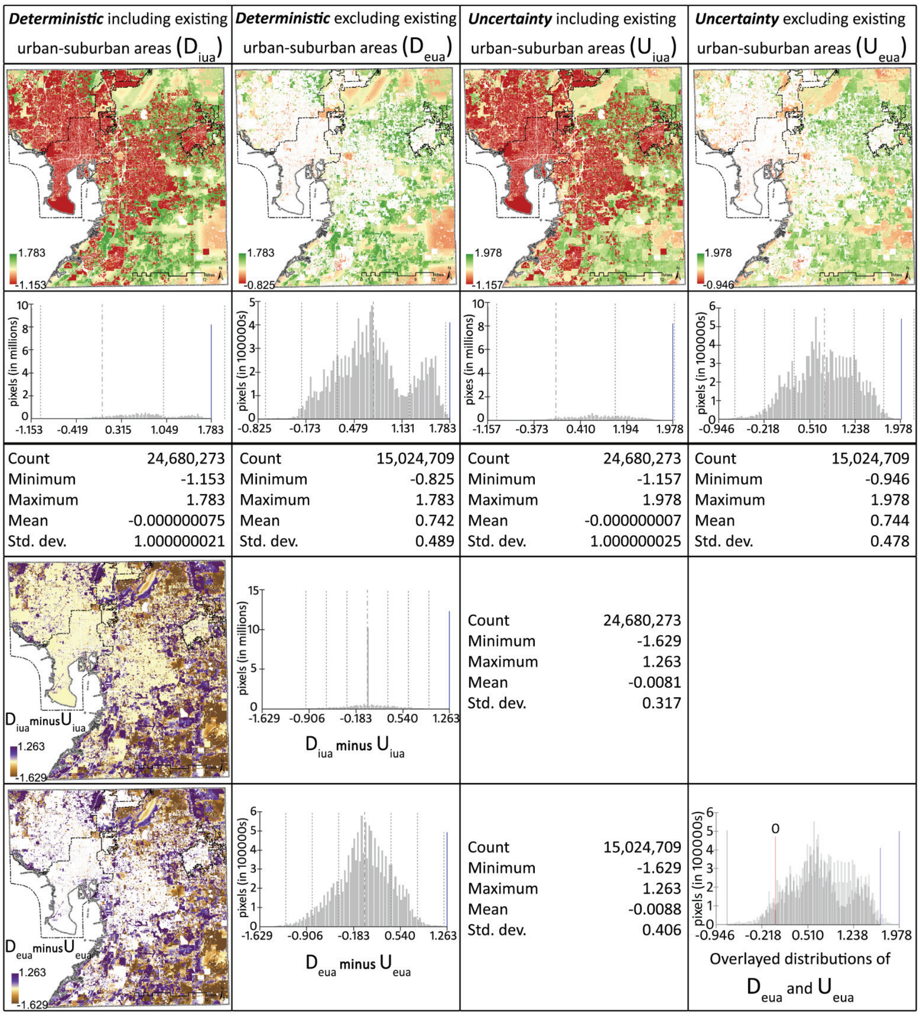


Figure 5. Z-score agricultural preference maps of deterministic and uncertainty approaches and their z-score difference maps, including and excluding the existing urban-suburban areas, distributions and summary statistics of maps

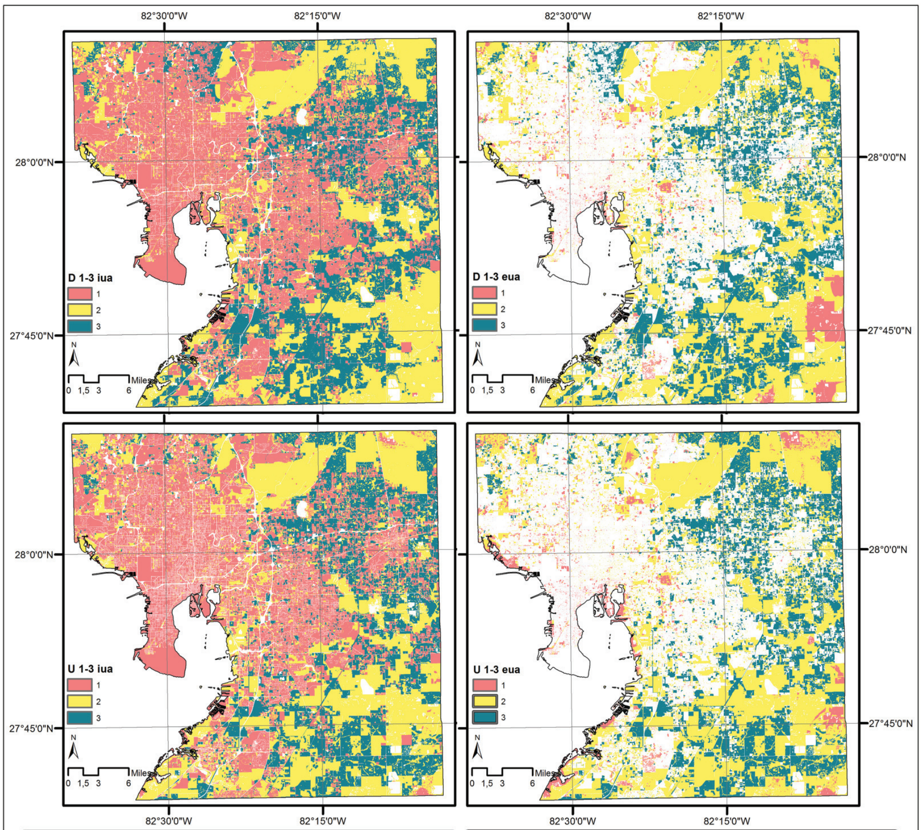
On the other hand, as stated earlier, by means of three different land-use preference maps (agricultural, urban and ecologically sensitive), the ultimate aim in LUCIS modeling is to achieve a land-use conflict map (Figure 2), and based on this, to develop possible future land-use scenarios. The first step in the conflict analysis requires the three preference maps to be collapsed into three classes, in which each map is differentiated by low, moderate and high levels of preferences [9]. Therefore, to be evaluated as a base map in the conflict analysis, the two agricultural preference maps from deterministic and uncertainty modeling were also compared after being collapsed into three equal interval rank groups, labeled 1 for low, 2 for moderate and 3 for high preferences, i.e., their agricultural land-use suitability. The results of these analyses for both cases, i.e., including and excluding the given urban-suburban areas, are shown in Figure 6.

In the first case, as expected, the total number of alternatives (pixels) on the two preference maps was found to have a correspondence level as high as 83.72 percent, about 40 percent of which was a result of the same given urban-suburban areas having the same preference level of 1 (see the table on the left in Figure 6). Accordingly, the Cohen's Kappa, which is a measure of agreement between the two ordered preference groups [34] of the two maps, was found to be 0.75 (Figure 6). Since the used data was the population itself, its significance was not assessed. Nevertheless, the results for the second case suggested a higher level of difference between the two maps. When the existing urban-suburban areas were excluded, the total difference in one level of preference from 1 to 2 or 2 to 1, and from 2 to 3 or 3 to 2, increased by almost two times, i.e., from 16.28 percent to 32.04 percent (see the two tables in Figure 6). In addition, although negligible, the difference in two levels of preference from 1 to 3 or 3 to 1 increased to 0.18 percent from 0.00058 percent, which was the result of only one category of the collapsed map having a value of 1 in the deterministic and 3 in the uncertainty components. That is, in the second case, the collapsed map had a newly emerged category for two levels of preference difference with a value of 3 from the deterministic component and 1 from the uncertainty map. As a result of the second case analysis, as expected, the Cohen's Kappa value decreased to 0.39 (Figure 6), which suggested only a moderate level of agreement between the two ordered preference groups of the two maps rather than a strong one [34].

5. Conclusion

Recognizing the need for studies relating to the proper expression of uncertainty in GIS-based multi-criteria in land-use planning, this study has concentrated on epistemic uncertainties, concerning particularly the last three stages of the spatial multi-criteria modeling process commonly defined in spatial MCDM literature, being decision making on criteria standardization, criteria weighting and the interpretation of the final results. In general, the uncertainty associated with criteria standardization and weighting processes is assessed by way of classical error propagation or sensitivity analyses, which measure the impact of the errors found in, or perturbations made to the criterion values and their weights on the outputs in terms of the suitability ranking of alternatives. Instead of utilizing these indirect methods of uncertainty assessment at the final output level in decision making [28], this study set out with the main premise that *uncertainty makes a difference* in terms of both the pattern and level of suitability of the alternatives at each hierarchical level of multi-criteria land-use planning. In doing this, no consideration was given to how "objective" or "sensitive" the decisions were, and by whom they were taken in the decision-making process, whether individual modelers, a group of experts with different backgrounds – such as planners [42] –, community participants [9; 17] and/or politicians.

To this end, the study tried to show the importance of determining the risk in choosing a particular alternative [11] in land-use planning, and for this purpose it made use of LUCIS (Land-Use Conflict Identification Strategy), which is a deterministic GIS-based multi-criteria decision process, and compared it with a newly developed equivalent uncertainty modeling at each level of the hierarchical structure. Although the ultimate aim of LUCIS is to represent the probable patterns of future land use based on a conflict map obtained from the overlaying of low, moderate and high levels of preferences or suitability



Determinstic 1-2-3 map including existing urban-suburban areas ($D_{1\text{-}3\ iua}$)	
Count	24,680,273
Mean	1.852
Std. dev.	0.795

Deterministic 1-2-3 map excluding existing urban-suburban areas ($D_{1\text{-}3\ eua}$)	
Count	15,024,709
Mean	2.256
Std. dev.	0.582

Uncertainty 1-2-3 map including existing urban-suburban areas ($U_{1\text{-}3\ iua}$)	
Count	24,680,273
Mean	1.816
Std. dev.	0.778

Uncertainty 1-2-3 map excluding existing urban-suburban areas ($U_{1\text{-}3\ eua}$)	
Count	15,024,709
Mean	2.258
Std. dev.	0.574

	$U_{1\text{-}3\ iua}$ (1)	$U_{1\text{-}3\ iua}$ (2)	$U_{1\text{-}3\ iua}$ (3)	**Total**
$D_{1\text{-}3\ iua}$ (1)	9844203 39.89%	47095 0.19%	142 0.00058%	**9891440** **40.08%**
$D_{1\text{-}3\ iua}$ (2)	299110 1.21%	6729315 27.27%	1522482 6.17%	**8550907** **34.65%**
$D_{1\text{-}3\ iua}$ (3)	0 0.00%	2150388 8.71%	4087538 16.56%	**6237926** **25.27%**
Total	**10143313** **41.10%**	**8926798** **36.17%**	**5610162** **22.73%**	**24680273** **100.00%**

Cohen's Kappa = 0.75

	$U_{1\text{-}3\ eua}$ (1)	$U_{1\text{-}3\ eua}$ (2)	$U_{1\text{-}3\ eua}$ (3)	**Total**
$D_{1\text{-}3\ eua}$ (1)	556759 3.71%	528431 3.52%	25158 0.17%	**1110348** **7.39%**
$D_{1\text{-}3\ eua}$ (2)	479183 3.19%	6604299 43.96%	1869867 12.45%	**8953349** **59.59%**
$D_{1\text{-}3\ eua}$ (3)	887 0.01%	1935323 12.88%	3024802 20.13%	**4961012** **33.02%**
Total	**1036829** **6.90%**	**9068053** **60.35%**	**4919827** **32.74%**	**15024709** **100.00%**

Cohen's Kappa = 0.39

Figure 6. Agricultural preference maps and distributions of three-class equal interval z-score agricultural preference maps, including and excluding the existing urban and suburban areas, their cross-tabulations and Cohen's Kappa values

for the three land uses (agricultural, urban, and ecologically sensitive) at the 6^{th} level of the hierarchy, the scope of this study was limited to the agricultural preference (overall goal) map at the 5^{th} level, starting from the maps in the 1^{st} level, corresponding to lower level sub-objectives.

The two modeling approaches were applied to the case of Hillsborough County in the state of Florida, which is characterized by heavy urbanization and an urban footprint [44] that continues to expand into the valuable natural and agricultural areas. The comparison of the methodologies and results of the two modeling were made in three stages of the analysis: (1) in criteria standardization, prior to the application of any weighting at levels 1, 2 and 3; (2) in criteria weighting and aggregation at levels 1, 2, 3, 3' and 4; and (3) in obtaining the preference maps and the interpretation of these maps at level 5.

The first stage at which uncertainty is assessed by means of probability, fuzzy sets and multi-attribute utility theories under seven different groupings of the unweighted criterion maps of the model revealed:

- different suitability levels and more variability in the alternatives for similar physical boundaries (method 1 and method 5, respectively);
- different suitability levels with similar patterns (part of method 3);
- different suitability levels with different patterns (part of method 2, method 4, method 7) with more variability (method 6); and
- similar suitability levels with similar patterns (part of method 2, part of method 3).

Similarly, the comparisons of the maps at the aggregation levels after the weighting which were handled by Analytic Hierarchy Process in the deterministic modeling and using the trade-off method, except for the weights of goal maps in the uncertainty modeling, were found to have differentiating levels of differences in terms of pattern/shape/form and the degree of land-use suitability.

In the final stage of the analysis, which addresses directly the agricultural land-use preferences in the decision-making process, a moderate level of difference was identified between the two approaches when the given urban-suburban areas are excluded from the analysis and when the agricultural preference map is collapsed into three different levels of preference (low, moderate and high), which is a critical, and in fact an uncertain, process in defining and interpreting the results of modeling. This process needs special attention when the preference maps results are not utilized on the basis of individual alternatives (pixels), but rather on the basis of data that is collapsed into only a few broad categories. The main difference in these broad categories was reflected in the change between the moderate and high levels of suitability between the two approaches in about 13 percent of the alternatives in either direction, that is from moderate to high and vice versa, and their locations in the southeast and north east parts of the county. The use of different algorithms for modeling uncertainty in decision making in the standardization of criteria values and criteria weighting would have given rise to a different set of solutions in terms of the ranking and spatial pattern of agricultural land-use suitability. This study has aimed to show this possibility, and to clarify that the unique solution set obtained through a deterministic approach should not be considered as the only one, and also that uncertainty assessments are an indispensable part of land-use planning, since they make a difference. This point should be considered when engaged in informed decision and policy making to allocate limited land resources to their most appropriate land uses in future, being aware of the limitations and assumptions of the utilized modeling.

Acknowledgement

This study was carried by Aygün Erdoğan (PhD) between Feb 1, 2012 and Feb 1, 2013 while she was a visiting research scholar in the Dept. of Urban and Regional Planning, College of Design, Construction and Planning, University of Florida. The authors owe great thanks to Bill O'Dell, the Director of the Schimberg Center for Housing Studies in the University of Florida, for providing the office space, hardware and software that allowed them to carry out the study. Appreciation also goes to the two researchers from the Center, Abdulnaser Arafat (PhD) and Liz Thompson, for their valuable comments on the study and for their help in evaluating some of the data, and also to the anonymous reviewers for their constructive comments and suggestions.

Appendices

A.1. Details of uncertainty method 2. The probability raster of the standard deviation of prediction for "cities' population" was obtained by applying a probability distribution (exponential) function observed for its distribution given in Equation A.1.1.

$$\text{(A.1.1)} \quad f(x;\lambda) = \lambda e^{-\lambda x}$$

In this equation, the value of λ, which is a scale parameter, is estimated by calculating the observed mean nearest neighbor distance of the used cities' distribution. The final criterion map was obtained by applying a cumulative exponential distribution with the formula given in Equation A.1.2 on the multiplied raster.

$$\text{(A.1.2)} \quad f(x;\lambda) = 1 - e^{-\lambda x}$$

The value of λ, which is now a rate parameter and is the reciprocal of the scale parameter, found by dividing 1 by a denominator that was assumed to be the mean of the distribution of the weighted cities' population map obtained by Equation A.1.1.

Figure A.1.1 below shows the estimated utility function obtained in the spreadsheet environment applied on the "row crops" Euclidian distance raster.

Outcome	Utility (Probability)
24213	0
15000	0.0625
10000	0.125
7000	0.25
5000	0.5
2500	0.75
500	0.875
0	1

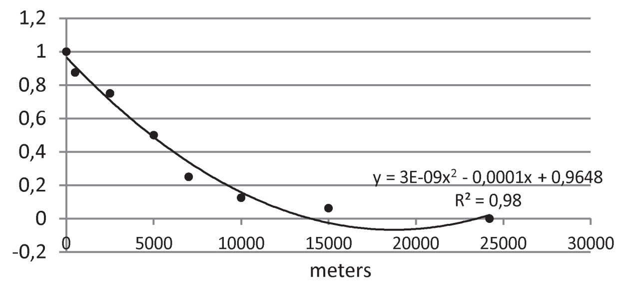


Figure A.1.1. Utility scores and curve estimated through the indifference technique for distance to row crop areas to obtain the row crops distance criterion map

A.2. Details of uncertainty method 3. Fuzzy large or small transformation functions with their default mid-point and spread values were used, whereby the larger and smaller input values are more likely to be a member of the set, respectively [5]. The only two exceptions to the use of mid-point default values were the use of the mean of the distribution of the raster values as for so213, so233, so313 and so513, and the mean of parcels having a size of equal or greater than 10 acres for so412. After the rasterization of this map, the values for Nodata (null) pixels were computed using a conditional map algebra, assigning them a value through the multiplication of the number of cells by 100 to find their area in square meters, which was then converted to acres. Similarly, in the model for the timber parcel size sub-objective (so515), a conditional map algebra was run so that the null pixels had a value of 1 in contrast to other selected and rasterized pixel values of 9 before the fuzzy membership operation. Moreover, in the aquifer recharge models, a conditional map algebra was run in which the null values (originally water surfaces) were set to a membership value of 0. A final additional operation in the row crops land-use model (so112) was a fuzzy OR overlay on the fuzzy membership maps.

A.3. Details of uncertainty method 4. The models followed the course of actions below.

1. Two zonal statistics raster maps were obtained for the regions having a fuzzy set membership value of $0.5 < x \leq 1$ (higher level of suitability from so112, so411 and so511): one for the mean, and the one for the standard deviation, based on the five respective Euclidian distance maps obtained for the deterministic approach.
2. To assign the utilities of distances to major roads and/or local markets for the three goals' land-use values with a suitability level of $0.5 < x \leq 1$, two conditional map algebra were operated respectively on each of these statistical raster maps described above, and on the respective Euclidian distance maps. As a result, two new raster maps were obtained showing the rankings seen in Table A.3.1.

Table A.3.1. Ranks assigned to conditional rasters

Conditional Raster 1	
Euclidian distances having a value lower than mean – 3 standard deviations	8
Euclidian distances having a value lower than mean – 2 standard deviations	7
Euclidian distances having a value lower than mean – 1 standard deviation	6
Euclidian distances having a value lower than mean	5
Otherwise	4
Conditional Raster 2	
Euclidian distances having a value higher than mean + 3 standard deviations	1
Euclidian distances having a value higher than mean + 2 standard deviations	2
Euclidian distances having a value higher than mean + 1 standard deviation	3
Otherwise	4

3. For the areas with a value of 4 in the 2^{nd} conditional raster, the values of the 1^{st} conditional raster were computed (otherwise the values of the 1^{st} were taken) on a new raster that combined the two. The assignments in the first and second conditional raster maps and the combined raster are illustrated on a normal curve in Figure A.3.1.
4. In a similar way, the regions with a fuzzy set membership value of $0 \leq x \leq 0.5$ (lower level of suitability from so112, so411 and so511) were reclassified with the same range of 1-8 by means of the constant rasters. These rasters were created using the mean values of the mean and standard deviation zonal statistics maps of the complementary areas (i.e., where $0.5 < x \leq 1$).

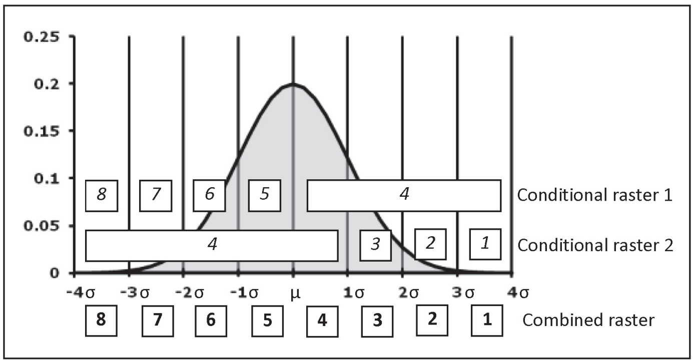


Figure A.3.1. The rank assignments for row crops, nursery and timber land-use suitability levels of $0.5 < x \leq 1$ with respect to their mean and standard deviations found from their distances to major roads and/or local markets

5. The final ranking of the utilities for suitability, which gave higher priority to the more suitable areas, were used in a fuzzy set membership operation after the reclassification of the combined conditional maps for higher-to-lower suitability rank groups, one after the other. That is, from 1-7 to 8-15 (for so123, so423 and so522) or from 1-8 to 9-16 (for so421 and so521), and merging the two resultant combined rasters. This was achieved through a maximum cell statistic operation to obtain raster maps having values of 1-15 or 1-16 in different rankings for the distances. Finally, the resultant maps for the five sub-objectives were obtained through a fuzzy large transformation function with default mid-point and spread values.

A.4. Details of uncertainty method 5. In the uncertainty models, the objects with suitability scores greater than 1 in the deterministic models were selected. Since the high-intensity livestock (so211) and specialty farming (so311) activities were carried out mainly on smaller farmland areas and low-intensity livestock (so231) on larger farmland areas, their probabilities were computed from the area of each selected object divided by the total area of all the selected objects. For the former two sub-objectives (so211 and so311), the probability values with a value of 0 at a 1/1,000,000 precision level were assumed to be slivers, and were thus excluded from any further analysis. This was to prevent them from having higher utilities for suitability based on the subsequent transformation of their probabilities. The probabilities were then recalculated in the same way, with the results processed on a spreadsheet, after which a transformation function of a logarithm of base 0.000001 was carried out, resulting in a maximum utility of 1 for the smallest probabilities for so211 and so311. The results of these functional transformations were merged with the original vector data in the model, and raster maps were created based on these utilities by way of a polygon-to-raster operation, followed by the assignment of 0 to any pixels having null values by a map algebra operation. In the model for low-intensity livestock land use (so231), after obtaining a raster map of the computed probabilities in the first step, the cumulative exponential distribution function given in Equation A.1.2 was applied. The value of the rate parameter of λ was found by dividing 1 by the mean of the probability distribution, which was assumed to be the scale parameter. The model for so231 was then finalized by the assignment of 0 to any pixels having null values.

A.5. Details of uncertainty method 6. Although the uncertainty models utilized the same Euclidian distance maps as a base in the corresponding deterministic models, their results were different due to the uncertainties in these models, which were assessed in a similar way to that explained in Method 4. The difference here was the evaluation of three rather than two mean-standard deviation pairs of zonal statistic raster maps (total of 6 rasters) by means of the three different selections. These were based on the pixels from the resultant land-use suitability maps from so211, so231 and so311 for sub-objective groups of (1) so212, so215, so221 and so223 related to high-intensity livestock activities; (2) so232, so241 and so243 related to low-intensity livestock activities; and (3) so312, so321 and so323 related to specialty farming, respectively. In addition, instead of two groups, the selection of three groups from the raster maps here included the selection of alternatives (x) having utility levels based on the functional transformations of the probabilities found for the respective land-use parcels, which were $0.5 < x \leq 1$; $0 < x \leq 0.5$ and x=0. Another difference was found in the interfering linguistic hedges (as in so212, so232 and so312) for these groups of probabilities (an example is given in Figure A.5.1), rather than their one-after-the-other ordering (as in so215, so221, so241, so321, so223, so243 and so323). Moreover, the constant rasters were created using the mean values of the mean and standard deviation zonal statistics maps of the complementary land-use probability groups having a value of $0 < x \leq 0.5$ for models so212, so312, so215, so221, so321, so223, so323, and by the one having a value of $0.5 < x \leq 1$ for models so232, so241 and so243. Finally, the models ended with a fuzzy small (for so212, so232, so312, so215) or large (for so221, so241, so321, so223, so243, so323) transformation function with default mid-point and spread values.

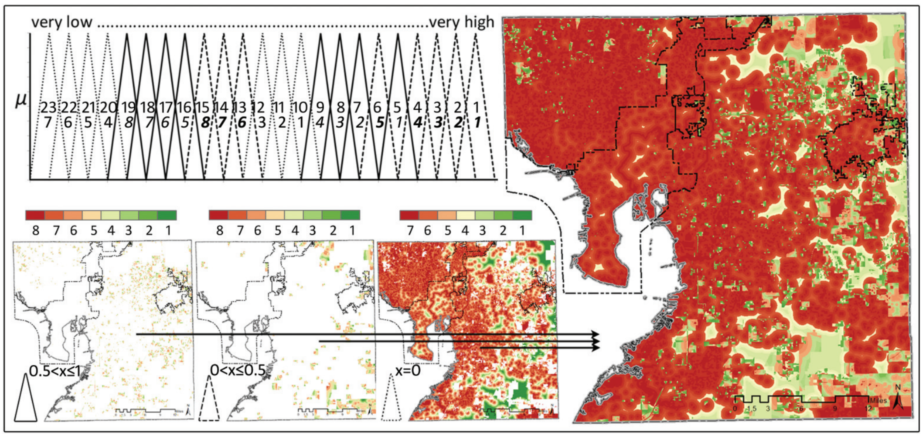


Figure A.5.1. Simplified fuzzy representations and combined rasters, and the resultant fuzzy ranked sub-objective 212 criterion map

A.6. Details of uncertainty method 7. In order to handle any uncertainties in the fuzzy set membership functions based on both the spatial and non-spatial aspects of the alternatives, i.e., parcels, the uncertainty models involved the following steps:

1. To obtain the spatial component of the model, the parcel objects having the land uses that were selected in the deterministic model were selected based on the same sliver assumption criteria for each respective objective.
2. The X-Y coordinates of the selected data centroids were computed in the GIS, and the data was inputted into the spatial data analysis software in order to run a K-means clustering routine, for which the separation parameter was set as 5. Since the main clustering regions were observed to be 3 for objectives 13, 26, 33 and 43, and 2 for objectives 25 and 53, the K-location values were set as 3 and 2 for the respective objectives.
3. The first and second standard deviation ellipses of the computed three or two respective K-means clusters were visualized in the GIS, and their parameters were used to compute the third standard deviation ellipses through a table to ellipse operation.
4. The model continued with dissolving, erasing and merging operations (and geometry repairment operations when needed to remove slivers etc.) to obtain combined concentrated zones of three standard deviation ellipses with no self-intersecting areas. Subsequently, these areas were rasterized and reclassified with respect to their standard deviation ellipse numbers and as Nodata around the third ellipses to be combined with the non-spatial component of the model.
5. As for the non-spatial component, the parcel objects having descriptions other than 'header' and 'note' were selected, and a raster layer was obtained from these objects based on just value per acre field. This raster was reclassified with the listed ranks below for the 3 K-means cluster objectives of 13, 26, 33 and 43, and without rank 4 for the 2 K-means cluster objectives of 25 and 53.
   - 0 and mean ($\overline{x}$) as rank 1;
   - ($\overline{x}$) and ($\overline{x}$)+ one standard deviation (s) as rank 2;
   - $(\overline{x}) + (s)$ and $(\overline{x}) + 2(s)$ as rank 3;
   - $(\overline{x}) + 2(s)$ and a value that is more than the largest just value/acre value in the data set as rank 4;
   - Nodata as Nodata
6. Two separate map algebra tools were used in an enumeration process of the two classified standard deviation raster maps, with one based on the spatial (cluster location) properties of the selected parcels, and the other on the just value/acre values of all the parcels with respect to the mean and the standard deviation statistics of the selected parcels. The enumeration processes involved the multiplication of the first component by 10, then adding the second component to the result. These processes, their respective maps, the assignment of ranking to the enumeration results and the combined enumeration map through a mean cell statistic (max or min operations would also have given the same result) operation can be seen in Figure A.6.1 with the example for objective 13. While all other 3 K-means cluster objectives (o26, o33, o43) utilized a similar 4x4 enumeration and a 10-level ranking, 2 K-means cluster objectives (o25 and o53) used a 3x3 enumeration tables removing the 4^{th} column and 4^{th} row from the 4x4 one, and a 6-level ranking, which replaced 7 with 6 in the 4x4 table (Figure A.6.1).
7. Before carrying out the final fuzzy membership operation to obtain the final objective criterion maps, the parcel objects having descriptions of 'header' and 'note' were selected and assigned a value of 11 for objectives 13, 26, 33 and 43, and a value of 7 for objectives 25 and 53, and then merged with the final raster map obtained in the previous step already having a 1-10 or 1-6 ranking, respectively.

		Spatial			
		1	2	3	4
Non-spatial	1	11	12	13	14
	2	21	22	23	24
	3	31	32	33	34
	4	41	42	43	44

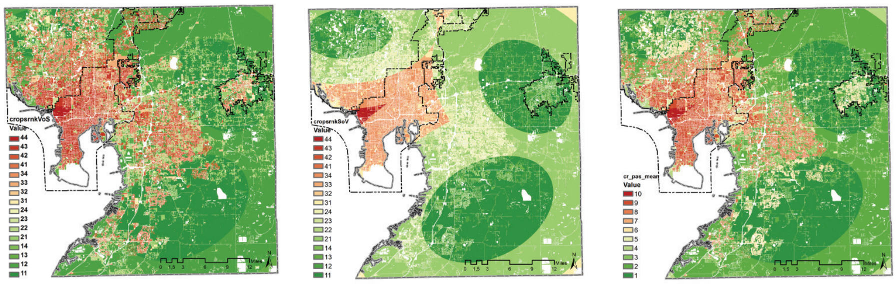
a.

		Non-spatial			
		1	2	3	4
Spatial	1	11	12	13	14
	2	21	22	23	24
	3	31	32	33	34
	4	41	42	43	44

b.

		Fuzzy set membership ranking			
		1	2	3	4
Fuzzy set membership ranking	1	1	2	4	6
	2	2	3	5	8
	3	4	5	7	9
	4	6	8	9	10

c.



d. Nonspatial values over spatial values e. Spatial values over nonspatial values f. Combined values

Figure A.6.1. The enumeration processes (a and b), rank assignment to the enumeration results (c) and the respective maps (d for a and e for b), including their combined cell statistic resultant map (f) for a further fuzzy set membership operation in the model for objective 13

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