

**Expanding and comparing GIS-based  
multi-criteria decision making methods: A soft  
computing logic for agricultural land suitability  
evaluation**

**by**

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B.Sc., University of San Francisco, 2013

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Master of Science

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## **Abstract**

The Logic Scoring of Preference (LSP) method is a multi-criteria evaluation (MCE) method that expands the commonly used multi-criteria decision making approaches. The LSP method is used to determine various evaluation objectives; it is based on soft computing logic and provides enhanced human decision-making. As a result, the LSP method is flexible and has the ability to incorporate a larger amount of evaluation criteria. The main objective of this research is to integrate the LSP method with geographic information systems (GIS) for agricultural land suitability evaluation. In addition, the LSP method has been compared with commonly used MCE methods within the GIS framework. Geospatial datasets for Boulder County, Colorado, USA were utilized for this study to determine various scenarios for agricultural land suitability evaluation. The obtained results indicate that the LSP method can be used as a useful tool to assist land use planning and the decision making process.

**Keywords:** Logic Scoring of Preference method; Soft Computing; Multi-criteria Evaluation; Geographic Information System; Agricultural Land Suitability Analysis

## Dedication

*To my loved ones and those who came before me. You  
are always in my heart with love and gratitude.*

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# Table of Contents

Approval.....	ii
Abstract.....	iii
Dedication.....	iv
Acknowledgements.....	v
Table of Contents.....	vi
List of Tables.....	viii
List of Figures.....	ix
List of Acronyms.....	xi
<b>Chapter 1. Introduction .....</b>	<b>1</b>
1.1. Context of Study.....	1
1.2. Theoretical Background.....	1
1.2.1. Overview of MCE Methods.....	2
1.2.2. MCE Method Comparisons and Sensitivity Analysis.....	6
1.2.3. MCE for Agricultural Land Suitability Analysis .....	7
1.3. Research Problem and Objectives.....	8
1.4. Study Area and Datasets.....	10
1.5. Thesis Structure .....	13
1.6. References.....	14
<b>Chapter 2. The Logic Scoring of Preference method for agricultural land capability and suitability * .....</b>	<b>20</b>
2.1. Abstract.....	20
2.2. Introduction.....	21
2.3. Theoretical Background.....	22
2.4. Methods .....	25
2.4.1. Study Area.....	25
2.4.2. Data Sets.....	26
2.4.3. Logic of Scoring Preference Method.....	27
2.4.3.1 LSP Attribute Tree .....	28
2.4.3.2 Attribute Criteria .....	29
2.4.3.3 Definition of Attribute Criteria.....	30
2.4.3.4 LSP Aggregation Structure .....	35
2.5. Results .....	39
2.5.1. LSP Structure and Output Map for Agricultural Land Capability ...	40
2.5.2. LSP Structure Output Map for Agricultural Land Suitability .....	43
2.6. Discussion and Conclusions.....	51
2.7. Acknowledgements .....	52
2.8. References.....	53
<b>Chapter 3. Comparison of GIS-based multi-criteria evaluation methods and the logic scoring of preference methods using receiver operating characteristic metrics * .....</b>	<b>60</b>
3.1. Abstract.....	60

3.2.	Introduction.....	61
3.3.	Theoretical Background.....	63
3.3.1.	Analytical Hierarchy Process .....	63
3.3.2.	Ordered Weighted Averaging .....	64
3.3.3.	Combination of AHP and OWA.....	65
3.3.4.	Logic Scoring of Preference.....	65
3.4.	Methods for Comparison of GIS-based MCE .....	67
3.4.1.	Study Area, datasets and context .....	67
3.4.2.	MCE methods comparisons.....	68
3.4.3.	Metrics for comparison of the suitability maps .....	70
3.5.	Case Studies.....	72
3.5.1.	Urban Land Suitability.....	72
3.5.1.1	AHP.....	73
3.5.1.2	OWA.....	76
3.5.1.3	AHP-OWA.....	78
3.5.1.4	LSP .....	79
3.5.2.	Agricultural Land Suitability .....	81
3.5.2.1	AHP.....	84
3.5.2.2	OWA.....	84
3.5.2.3	AHP-OWA.....	86
3.5.2.4	LSP .....	86
3.6.	Comparison Results .....	89
3.6.1.	Urban Land Suitability.....	89
3.6.2.	Agricultural Land Suitability .....	92
3.7.	Discussions and Conclusions .....	94
3.8.	Acknowledgements .....	96
3.9.	References.....	96
<b>Chapter 4.</b>	<b>Conclusions.....</b>	<b>101</b>
4.1.	Thesis Conclusions .....	101
4.2.	Future Research.....	103
4.3.	Thesis Contributions.....	105
4.4.	References.....	106

## List of Tables

Table 2.1	The attribute trees of (1) land capability, and (2) land suitability for agriculture .....	29
Table 2.2	Table 2: The distribution of levels for agricultural capability and suitability scores for the USDA generated land capability and respectively obtained LSP maps for agricultural land capability and suitability for all four scenarios.....	50
Table 2.3	Table 3: The distribution of overall levels for agricultural suitability in respect to initial land use map categories and Scenario 1. ....	51
Table 3.1	AHP preference scale for pairwise comparison derived from Saaty (1980) and Akinci et al. (2013). ....	64
Table 3.2	The pairwise comparison matrix for urban land suitability evaluation.....	75
Table 3.3	Criteria weights and their corresponding ordered weights to represent tradeoff and risk in urban and agricultural land suitability evaluations.....	77
Table 3.4	Criteria weights and their corresponding ordered weights to represent tradeoff and risk in urban and agricultural land suitability evaluations.....	85
Table 3.5	Fundamental MCE property comparison results and Area under the Curve values obtained for (A) urban land suitability and (B) agricultural land suitability. ....	91



## List of Figures

Figure 1.1	Study area: The eastern portion of Boulder County, Colorado, USA. ....	12
Figure 2.1.	Study area: Boulder County, Colorado, USA.....	26
Figure 2.2.	Suitability functions characterizing agricultural land capability and suitability. ....	32
Figure 2.3	LSP Aggregators representing <i>replaceability</i> , <i>neutrality</i> , and <i>simultaneity</i> . ....	37
Figure 2.4	Example of aggregating two input criteria within the Idrisi GIS software environment. ....	40
Figure 2.5	The LSP aggregation structure for agricultural land capability using nine input criteria and nine aggregators. ....	41
Figure 2.6	Land capability maps (A) obtained using GIS-based LSP method and (B) generated by United States Department of Agriculture (USDA) data.....	42
Figure 2.7	The LSP aggregation structure for agricultural land suitability using twenty-five input criteria and twenty-seven aggregators....	44
Figure 2.8	The obtained LSP map with agricultural land suitability values representing scenario 1.....	45
Figure 2.9	Agricultural land suitability LSP output maps emphasizing (A) land management criteria as scenario 2; (B) accessibility to physical land characteristics as scenario 3; and (C) agricultural economic criteria as scenario 4. ....	49
Figure 3.1	The study area in Boulder County, Colorado, USA.....	68
Figure 3.2	Suitability functions characterizing urban land suitability evaluation criteria. ....	74
Figure 3.3	The urban land suitability map obtained with the AHP-based MCE method. ....	76
Figure 3.4	The urban land suitability map obtained with the OWA-based MCE method. ....	78
Figure 3.5	The urban land suitability map obtained with the AHP-OWA-based MCE method. ....	79
Figure 3.6	The LSP attribute tree for urban land suitability. ....	79
Figure 3.7	The LSP aggregation structure for urban land suitability created with 15 evaluation criteria.....	80
Figure 3.8	The urban land suitability map obtained with the LSP-based MCE method. ....	81
Figure 3.9	Suitability functions characterizing agricultural land suitability evaluation criteria. ....	83

Figure 3.10	The agricultural land suitability map obtained with the OWA-based MCE method. ....	86
Figure 3.11	The LSP attribute tree for agricultural land suitability. ....	87
Figure 3.12	The LSP aggregation structure for agricultural land suitability created with 31 evaluation criteria. ....	88
Figure 3.13	The agricultural land suitability map obtained with the LSP-based MCE method. ....	89
Figure 3.14	The suitability output maps generated by the GIS-based (A) AHP, (B) OWA, (C) AHP-OWA, and (D) LSP methods. ....	90
Figure 3.15	Receiver operating characteristic curves (ROC) for (A) urban land suitability and (B) agricultural land suitability. Each curve is constructed using three thresholds. ....	92
Figure 3.16	The suitability output maps generated by the GIS-based (A) OWA and (B) LSP methods using 31 criteria. ....	93

## List of Acronyms

AHP	Analytical Hierarchy Process
AHP-OWA	Combination of AHP and OWA methods
AUC	Area Under the Curve metric
GIS	Geographic Information Systems
LSP	Logic Scoring of Preference method
MCE	Multi-criteria evaluation
OWA	Ordered Weighted Averaging
ROC	Receiver operating characteristic
USDA	United States Department of Agriculture
WLC	Weighted Linear Combination

# **Chapter 1.**

## **Introduction**

### **1.1. Context of Study**

With global population increasing, especially in urban settings, there is an increased demand for food to sustain growth (Godfray et al., 2010). To meet these demands, increases in available housing and agricultural production must be achieved. As a result, residential development has expanded into agricultural lands and available lands, converting them to urban land use. With decreases of agricultural land on a global scale, available land for increasing agricultural production is reduced, forcing the intensification of agricultural processes on less land (Ramankutty et al., 2006). Intensification of agricultural production has led to environmental degradation and intrusion upon grasslands and forests to accommodate increasing demands (Lambin and Meyfroidt, 2010). In order to effectively address urban population growth and subsequent food demand, spatial decision-making tools are needed to evaluate the suitability of available land. Spatial decision-making tools can provide insight to suitability across a landscape derived by using the actual data, criterion outcomes and preferences of various stakeholders and decision. As a result, multi-criteria evaluation (MCE) methods can evaluate decision-making alternatives for future land-use planning (Malczewski and Rinner, 2015).

### **1.2. Theoretical Background**

Spatial decision making problems rely on a multitude of criteria, sometimes conflicting, to generate decision alternatives. Decision alternatives must represent a range of factors that influence suitability and reflect the perspectives of various stakeholders. Decision

problems such as agricultural land suitability require socio-economic, environmental, and physical land factors to effectively evaluate the available land in question (Fischer et al., 2005). Moreover, stakeholder preferences influence which factors are the most important and must be satisfied when determining how suitable land is for future agricultural production. In order to effectively incorporate these factors and perspectives for evaluating agricultural land suitability, spatial optimization methods such as multi-criteria evaluation (MCE) can be used.

### **1.2.1. Overview of MCE Methods**

MCE is a well-known method for spatial decision making used in the evaluation of land-suitability and the assistance of land-use planning (Voogd, 1983; Carver, 1991; Thill, 1999). MCE is comprised of four main components: input criteria and attributes, weights of relative importance, an aggregation structure, and a suitability output map (Jankowski, 1995). MCE models are able to produce a suitability score based on the input criteria and their attribute values (Malczewski, 2006b; Malczewski and Rinner, 2015). Input criteria are important factors that are derived from stakeholder and decision maker preferences and can be characterized by their corresponding attributes. Attributes are standardized on a continuous scale (0-1, 1-100 or 0-255), to remove variance among units and data types (Hopkins, 1977; Voogd, 1982). Standardization methods that are frequently applied include: linear methods, nonlinear methods, fuzzy logic and reasoning (Voogd, 1983; Jankowski et al., 1997; Jiang and Eastman, 2000). Weights of relative importance are applied to reflect stakeholder and decision maker preferences. Input criteria are aggregated together until a final suitability output map is obtained.

The linking of geographic information systems (GIS) and MCE allows the methods to utilize common databases to store, manage, and manipulate data (Jankowski, 1995; Ceballos-Silva and Lopez Blanco, 2003). Moreover, the expanded data capabilities of GIS supports the evaluation of decision problems on larger spatial scales and with a larger amount of input criteria. Spatial applications coupling GIS and MCE methods include, to name a few: urban land use (Wu 1998), environmental planning and management (Store and Kangas, 2001), natural resources planning (Kangas et al. 2000), geology (de Araújo and Macedo, 2002), landslides (Lai et al., 2013), marine protection (Wood and Dragičević,

2006), and climate change (Yan et al., 2013). In addition, GIS-MCE methods have been applied to agricultural land suitability applications, such as agricultural catchment systems (Hill et al., 2005), changes in crops over time (Ceballos-Silva and Lopez-Blanco, 2003), and irrigated agriculture (Tiwari et al., 1999), to develop realistic suitability methods for spatial models and spatial decision-making processes.

Various MCE methods are used to evaluate land use suitability including: simple additive scoring (SAS) (Massam, 1988; Heywood et al., 1995), multiattribute value technique (MAVT) (Pereira and Duckstein, 1993; Keeney, 1996), multiattribute utility technique (MAUT) (Janssen and Rietveld, 1990; Keeney and Raiffa, 1993), analytic hierarchy process (AHP) (Banai, 1993; Jankowski, 1995), ordered weighted average (OWA) (Yager, 1988; Jiang and Eastman, 2000; Malczewski et al., 2003; Malczewski, 2006a), and outranking methods (Kangas et al., 2001; Joerin et al., 2001). MCE methods attempt to determine realistic results through their variations in aggregation structures and weighting schemes.

The SAS method is used to provide relative importance to suitability criteria scores based on a simple weighted average where suitability criteria scores are multiplied by the weights and added together to provide an overall suitability score. Applications involve the incorporation of criteria combined with equal weights and linear weighted aggregation in a planning environment (Massam, 1988), and the incorporation of urban criteria for the comparison of modeling environments integrating GIS data and calculating appropriate suitability maps (Heywood et al., 1995). Issues have been found in the uncertainty of criteria priority in linear weighted aggregation models.

MAVT determines value functions to calculate the degree to which a decision objective is achieved. This is done through single-attribute value functions which represent the performance of alternative attribute values. Weights are used as scaling constants to provide a representation of tradeoffs between suitability attributes. MAVT utilizes fixed-ness to rank multiple attributes in a GIS environment. In addition, MAVT has been applied in habitat evaluation to compare suitability maps with observed data and to closely represent expert knowledge. Changes in data aggregation have been found to result in

new solutions, which represented various alternatives for the decision maker (Pereira and Duckstein 1993).

Similar to MAVT, MAUT is applied with a large variety of attributes; however, MAUT calculates risks and uncertainties in determining alternatives for its overall decision making output. Risk is calculated using single-attribute utility functions and translates suitability values into utility units, representing the worst or best alternatives for the decision making problem. In this way, MAUT differs from MAVT as utility units determine the best and worst alternatives rather than providing values that represent the degree to which an objective is achieved. MAUT and GIS have been linked to determine political alternatives that are possible in agricultural land policy and planning (Janssen and Rietveld 1990), to categorize objectives to determine resident housing and noise distribution in urban settings (Keeney and Raiffa, 1993), and calculate habitat suitability (Store and Kangas, 2001).

AHP differs from the previous methods by utilizing a hierarchy containing the decision goal, alternatives to reach it, and the suitability attributes needed to represent the alternatives (Saaty, 1980). Overall suitability is determined through an aggregation tree, which computes an additive weighting function with normalized weights derived from pairwise comparisons at each level of the hierarchy structure. When linked with GIS, AHP has been used to determine agricultural land suitability alternatives, deriving hierarchy and weights from expert knowledge and physical characteristics (Akinci et al., 2013). Hill et al. (2005) developed a multi-criteria decision analysis tool to incorporate the AHP method and spatially analyze agricultural catchment systems, and Reshmidevi et al. (2009) utilized a GIS-based fuzzy rule-based inference system and the AHP method to evaluate land suitability in agricultural watersheds. Additional applications combined MCE to evaluate agricultural resources (Hayashi 2000) and evaluate aquaculture (Hossain et al., 2007).

The OWA method is an MCE method that extends Boolean and Weighted Linear Combination (WLC) (Jiang and Eastman, 2000). OWA is developed through the use of specific decision-relevant suitability attributes, which are ranked, preferred criteria values and weights. OWA operators are used to combine attributes and reflect input preferences. Operators provide mean-type aggregation such as maximum, mean, median, and

minimum to parameterize the attributes. Specifying different weights will result in different operators and a newly calculated suitability score (Yager, 1988). OWA has been applied with fuzzy quantifiers to evaluate arable land and irrigated agriculture (Mokarram and Aminzadeh, 2010) and fuzzy membership functions to evaluate short rotation coppices (Corona et al., 2008). Other OWA applications include the evaluation of watershed rehabilitation (Malczewski et al., 2003), comparing AHP, OWA, weighted linear combination methods to evaluate industrial allocations and the use of fuzzy set membership (Jiang and Eastman, 2000), and urban land suitability (Malczewski, 2006a).

Combinations of multi-criteria evaluation methods have been integrated in order to combine weighting calculations and decision operators. The AHP-OWA method combines the criterion weight calculations of AHP with the OWA operators and fuzzy quantifiers of OWA (Yager and Kelman, 1999; Boroushaki and Malczewski, 2008). Such applications have been incorporated into agricultural land use suitability studies, such as evaluating the expansion of irrigated agriculture (Chen et al., 2010a; Chen and Paydar, 2012) and landfill suitability analysis (Gorsevski et al., 2012).

Outranking methods utilize strictly relative criteria to calculate a range between indifference and strong preference for a specific alternative. Each alternative is compared with other alternatives to determine the preferences of individual attributes. These are averaged to promote the relation between each alternative, and inputs can be mandatory or optional based on the specific outranking method. These methods have been limited in their application for land suitability (Pereira and Duckstein, 1993; Jankowski, 1995). Applying additional functions allows for the incorporation of more criteria, provide more alternatives, and enhance the ranking scheme (Joerin et al., 2001).

MCE methods have been used to represent human decision-making logic through their ability to evaluate choice alternatives based on a variety of input criteria. Based on the properties of the MCE methods presented, not all MCE methods are able to address a full spectrum of human decision-making logic. Many methods utilize fixed logic to determine decision alternatives for planners and stakeholders that can be intuitively understood (Hayashi, 2000; Malczewski, 2006b; Dujmović et al. 2009); thus, a new method is needed to comprehensively model human decision-making logic.



### **1.2.2. MCE Method Comparisons and Sensitivity Analysis**

The use of many different MCE methods brings to attention the question of which method to use and how methods can be compared. A majority of MCE method comparisons include AHP, weighted summation methods, multiattribute techniques, and outranking methods (Zanakis et al., 1998; Hajkovicz and Higgens, 2008). These comparisons primarily focused on how a user could use MCE methods for analysis. Further research has compared the theoretical properties of commonly used MCE methods (Dujmović et al., 2009; Dujmović and de Tré, 2011) and compared ideal point, Boolean, Weighted Linear Combination (WLC), AHP, and OWA methods based on their suitability outputs for evaluating real world case studies (Hall et al., 1992; Jiang and Eastman, 2000; Feizizadeh and Blaschke, 2012; Jankowski et al., 2014). In addition, the sensitivity of the suitability output maps has been used as a metric for testing weighting schemes (Chen et al., 2010b) and comparing various MCE studies (Delgado and Sendra, 2004).

Sensitivity analysis (SA) measures how changes in input parameters influence the output of a model (Ligmann-Zielinska and Jankowski, 2008), which can be used to validate, calibrate, and test robustness of a model (Chen et al., 2010b). When applied to GIS-based MCE applications, comparisons have focused primarily on aspatial SA procedures, such as the effects of choice alternatives, attributes and weights of relative importance on suitability outputs (Delgado and Sendra, 2004). However, recent research has studied the spatial aspects of SA. Spatial aspects include the proximity and topological relations of suitability location and how location influences spatial weights (Ligmann-Zielinska and Jankowski, 2008). Spatial MCE-SA applications have been applied for MCE and weighting method comparison (Feick and Hall, 2004), the development of empirical MCE-SA tools (Chen et al., 2010), applying proximity-adjusted preferences for MCE analysis (Ligmann-Zielinska and Jankowski, 2010), and coupling uncertainty and sensitivity analyses to compare land suitability output maps (Ligmann-Zielinska and Jankowski, 2014). Despite the application of various spatial SA studies with MCE methods, there are only a limited number of studies that compare GIS-based MCE methods utilizing SA.

Based on the available studies outlined above, MCE method comparisons are limited in three ways: 1) the methods by which MCE methods are compared have

oversimplified the suitability results, 2) most of the studies do not provide any statistical metric for comparing suitability output maps, and 3) the studies did not incorporate a large amount of criteria to create the MCE methods. As a result, MCE comparisons are limited in their ability to analyze complex decision-making, generating errors and relying on fixed logic (Dujmović et al. 2009; Dujmović and de Tré, 2011). Consequentially, comparison studies without any statistical comparison metric are limited in their ability to compare MCE methods beyond theoretical and case study applications.

### **1.2.3. MCE for Agricultural Land Suitability Analysis**

Agricultural land use suitability can be characterized by a variety of input criteria. These input criteria are typically generalized. Many studies include between 5 and 10 input criteria, including combinations of physical and chemical characteristics pertaining to specific crop production and general agricultural land suitability (Akinci et al., 2013). In addition, studies have focused primarily on physical land characteristics (Bandyopadhyay et al., 2009; Chen et al., 2010a), accessibility (Mendas and Delali, 2012), remote sensing-derived (Ceballos-Silva and Lopez-Blanco, 2003), farming potential (Hossain and Das, 2010), environmental-economic criteria (Tiwari et al., 1999; Kalogirou, 2002), and agricultural system characteristics (Berger, 2006). Based on the choice of input criteria used to characterize agricultural land suitability, suitability outputs can vary greatly. Another shortcoming of these studies is that they fail to incorporate other socio-economic or environmental categories that help to fully characterize the decision problem. As a result, studies that use a small amount of input criteria can cause errors by oversimplifying their results and their applicability in land-use planning.

MCE methods generally used in the evaluation of agricultural land suitability and MCE method comparison are limited in their use of input criteria, their expression of suitability results and the way MCE methods are compared. As many studies utilize a small amount of input criteria, they are not able to fully characterize a decision problem, limiting their results and their use in land-use planning. Moreover, the MCE methods used for agricultural land suitability evaluation are unable to represent a full range of human decision-making logic due to the aggregation of input criteria and fixed logic, which result in errors in suitability output maps (Dujmović and de Tré, 2011). As a result of these

issues, MCE methods with flexible aggregation structures are capable of incorporating a large number of input criteria for evaluation without losing input criteria significance. The Logic Scoring of Preference (LSP) method can address these issues. Through the use of a flexible aggregation structure and a full range of logic aggregators, the LSP method can address the shortcomings of commonly used MCE methods applied in an agricultural land suitability context. However, in order to demonstrate the evaluation capabilities of the LSP method, it is important to compare it with commonly used MCE methods. Through the use of fundamental MCE properties, the receiver operating characteristic and the incorporation of a large amount of input criteria, comparing the LSP method with commonly used MCE methods will provide further insight into how the LSP method can address the shortcomings of previous MCE applications for agricultural land suitability evaluation.

### **1.3. Research Problem and Objectives**

As global populations increase, so does the demand for agricultural land. Much land has been developed for urban land use or other land uses. Securing agricultural land is important to satisfy both food demand and food security while maintaining economic profitability (Ramankutty et al., 2002; Kalogirou, 2002). With the expansion of urban landscapes and the increased need to satisfy urban food demands, it is important to utilize MCE methods and analytical tools to evaluate the suitability of available land for future agricultural production and assist in land-use planning processes.

MCE methods are capable of evaluating the suitability of various land use applications. When linked to GIS, MCE methods are able to incorporate a variety of socio-economic and environmental evaluation criteria to determine land use alternatives. Commonly used MCE methods provide simplistic and easy-to-interpret results (Malczewski, 2006b); however, these methods are limited by their ability to model a full range of observed human decision-making logic (Dujmović et al., 2009). In order for MCE methods to fully address a range of human reasoning, they should have the following fundamental MCE properties: the ability to combine any number of attributes ranging from objective and subjective inputs, combine absolute criteria and relative criteria which reflect attribute values that are known unknown, respectively, and be able to provide flexibility in

adjusting the relative importance of attributes in order to be closer to real human reasoning. The logic scoring of preference (LSP) method (Dujmović, 1979; Dujmović, 2007) is able to meet all of these fundamental properties and extend commonly used MCE methods. The LSP method can model simultaneity and replaceability requirements, modeling mandatory, sufficient, optional, and desired requirements, and the ability to express suitability as an aggregate of overall usefulness (Dujmović et al., 2009).

The Logic Scoring of Preference (LSP) method is a soft computing method used to evaluate choice alternatives by representing a range of human decision-making logic. LSP is unique in its capability to use a range of simultaneity (andness) and replaceability (orness) when aggregating inputs (Dujmović et al., 2009). Simultaneity and replaceability represent various logic conditions to determine whether inputs must all be satisfied for evaluation or whether input satisfaction can replace the need for the satisfaction of other inputs, respectively (Dujmović, 2007). MCE methods such as ordered weighted averaging (OWA) apply similar aggregation operators (OWA operators) to aggregate inputs; however, OWA does not evaluate mandatory or optional requirements (Dujmović and de Tré, 2011). Furthermore, the LSP method improves MCE methods by including a large number of inputs that can be incorporated into a flexible, stepwise aggregation structure that operates with the continuous logic of simultaneity and replaceability to better represent a full range of human decision-making logic. As a result, the LSP method provides a potentially improved approach for combining a large amount of inputs for the evaluation of agricultural and urban land suitability.

This research is based on the use of the LSP method due to its ability to address the identified limitations of existing MCE methods and attempt to find solutions to the following research questions. The LSP method is first incorporated into a case study to evaluate agricultural land capability and agricultural land suitability, and then is compared to the commonly used GIS-based MCE methods to determine the strength of soft computing methods.

1. *Can the LSP method be used within the GIS to expand the commonly used MCE approaches and to improve agricultural land suitability analysis?*
2. *How do the LSP-based results compare to the results from commonly used GIS-based MCE methods?*

In order to address these research questions, the main goals of the thesis are to develop and implement the LSP method for evaluating agricultural land capability and suitability. The LSP method was linked with a GIS utilizing real geospatial datasets to develop each model and compare its results with commonly used MCE methods. The following objectives are the main focus of the thesis:

1. *To integrate the LSP method into a GIS framework to evaluate agricultural land capability and suitability with the use of geospatial datasets.*
2. *To compare and contrast the GIS-based LSP, AHP, OWA, and AHP-OWA methods for land suitability evaluation.*

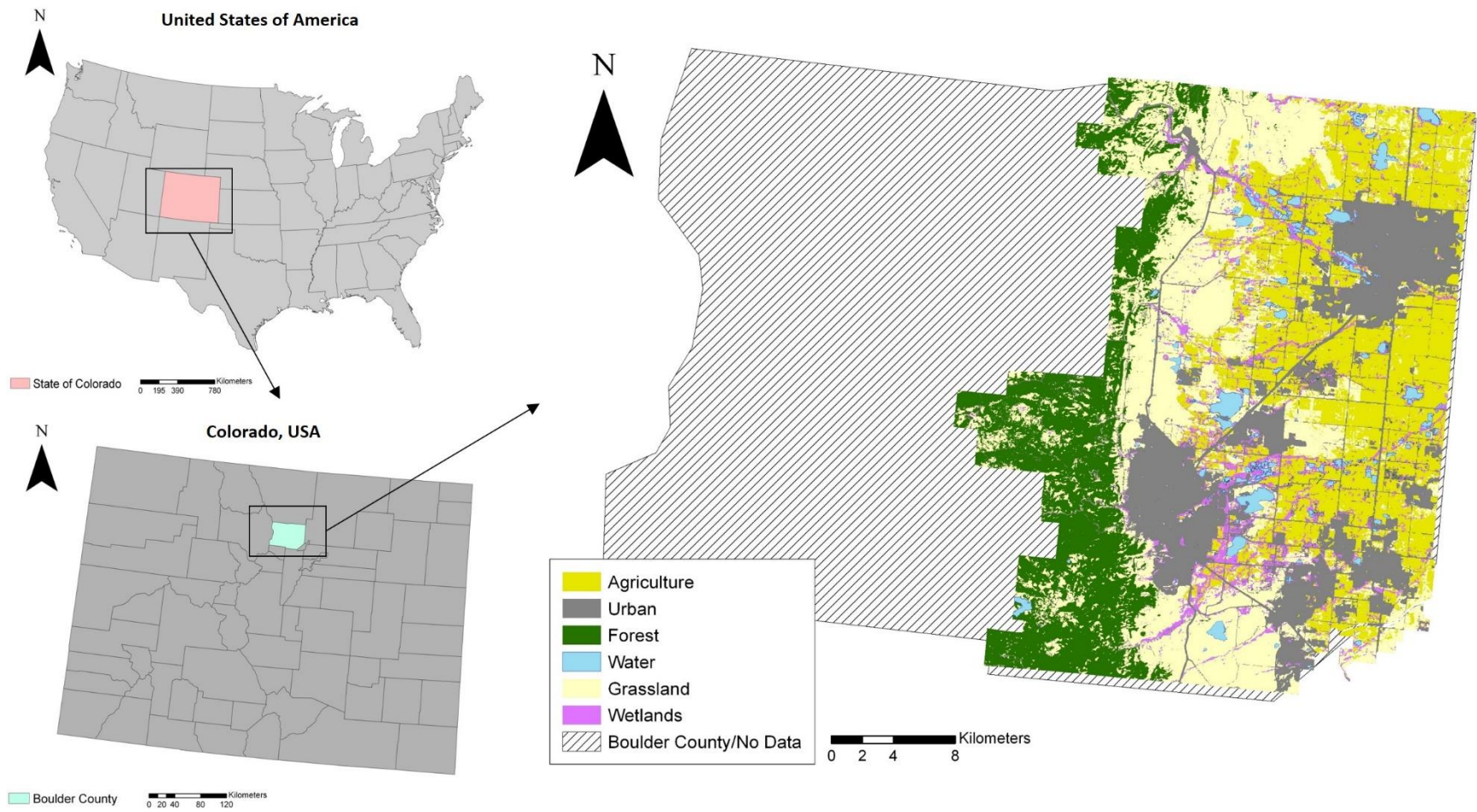
## **1.4. Study Area and Datasets**

Geospatial data from Boulder County, Colorado, USA (Figure 1.1) were used. GIS datasets covering the entire study area were used in development of the LSP method and its resulting suitability output maps in raster format.

Boulder County, Colorado, USA was chosen for this study because it has demonstrated increased agricultural and urban development on a regional scale (Boulder County Department of Land Use, 1999; Andrews et al., 2011). Unlike previous studies that focus on the conversion of agricultural land use to urban land use, in this study area there is a potential for land conversion to agricultural land use. In previous years, the region has designated open space that provides available land for agricultural production and to improve access of farmers to highly productive land. Moreover increased access for farmers helps to meet local, statewide, and nationwide demand for the Boulder County's agricultural products and limits urban development to current urban zoning (Andrews et al., 2011; USDA, 2014a). Despite the high demand for agricultural production, the study area is characterized by a semi-arid climate that can experience very hot temperatures and seasonal droughts that can reduce agricultural productivity and reduce economic gains (Soil Conservation Service, 1975). In this study, only the eastern half of the study area was used because the western half of the study area is steep mountainous terrain that is not useful for agricultural production. Overall, Boulder County, Colorado, USA is an important study area because it displays opposite dynamics to previous studies, produces

agricultural crops that are used at state and national scales and applies land-use planning to encourage both agricultural and urban development.

In order to model the suitability of the study area, a variety of datasets were used at a 50 m spatial resolution. To determine land capability, soil data was derived from national and regional soil surveys (NRCS, 2009) and digital elevation models (Geospatial Data Gateway, 2014). When determining land suitability, datasets comprising climatic, economic, accessibility, and management perspectives were needed. Climatic and accessibility datasets were derived from the national data tools (Geospatial Data Gateway, 2014) and national weather datasets (NOAA, 2014). The remaining datasets were derived from regional datasets (USDA, 2014a) and national agricultural datasets (Han et al., 2012; USDA, 2014b).



**Figure 1.1 Study area: The eastern portion of Boulder County, Colorado, USA.**

## 1.5. Thesis Structure

The thesis is divided into four chapters, beginning with the introduction. Chapter 2 is focused on the development and implementation of the GIS-based LSP method for evaluating agricultural land capability and agricultural land suitability for future agricultural production. The LSP method was integrated within a GIS framework utilizing geospatial datasets from Boulder County, Colorado, USA at a spatial resolution of 50 meters. Agricultural land capability and suitability was evaluated using evaluation criteria and logic conditions developed in the LSP aggregation structures. The LSP aggregation structures were comprised of elementary criteria, which were categorized based on usefulness and standardized using suitability functions. Mandatory and optional logic conditions were assigned based on their ability to satisfy decision maker requirements. The suitability output maps were generated with suitability values ranging from 0 (unacceptable) to 1 (excellent) and compared with a land capability map derived from United States Department of Agriculture (USDA) datasets used in the study. Four scenarios were designed with a larger amount of evaluation criteria and various decision-making perspectives in order to present possible decision-making alternatives for agricultural land suitability analysis. Four different weight schemes were used to represent different decision-making alternatives. The main goal was to propose an extended MCE method for evaluating agricultural land capability and suitability to improve land use decision-making processes.

In Chapter 3, the main goal was to compare commonly utilized MCE methods with the LSP-based MCE. For the purpose of comparison, urban land suitability and agricultural land suitability case studies were designed and implemented using datasets from Boulder County, Colorado, USA. LSP and commonly used MCE methods were developed using evaluation criteria specific to each case study, method-specific aggregation structures, and method-specific weighting schemes. The LSP aggregation structures were derived from the agricultural land suitability aggregation structures in Chapter 2. Suitability output maps generated by LSP and MCE methods were compared using the receiver operating characteristic as a statistical and graphical metric for determining the strongest evaluation method. In order to implement the LSP method and compare the commonly used MCE methods, the Idrisi GIS software (Eastman, 2012) was used. Chapter 4 concludes the



thesis by addressing the overall results and contribution of this research. Furthermore, the chapter explains research limitations and the areas of potential research for future studies.

## 1.6. References

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## Chapter 2.

# The Logic Scoring of Preference method for agricultural land capability and suitability \*

### 2.1. Abstract

Urban and industrial growth, increases in global population and climate change are impacting the environment and directly contributing to the reduction in valuable agricultural lands. The land reduction severely impacts agricultural production and global food security. To effectively address this issue, spatial analytical and optimization methods such as multi-criteria evaluation (MCE) are needed to evaluate the capability and suitability of available lands for current and future food production. The main objective of this study was to propose and implement the GIS-based Logic Scoring of Preference (LSP) method as an improved method of multicriteria decision making for evaluating areas suitable for agriculture. The LSP method allows for the stepwise aggregation of a large number of inputs to represent a full range of human decision logic without losing weighted significance of the inputs. Geospatial datasets from Boulder County, Colorado, USA have been used to demonstrate the use of the LSP method for agricultural land capability and land suitability assessment. The LSP method uses a large number of inputs and suitability functions integrated into the development of LSP aggregation structures to represent a range of human decision-making logic and to evaluate decision-making objectives. Results indicate that the LSP method produces realistic agricultural land capability and suitability maps, and thus represents an improved method that can be integrated in regional land-use planning.

\* The version of this chapter will be submitted to the journal *Computers and Electronics in Agriculture*, coauthored with Drs. Suzana Dragičević, Jozo Dujmović, and Margaret Schmidt.

## 2.2. Introduction

The reduction of valuable agricultural land as a consequence of the constant process of urban and industrial growth has a direct impact on the ability of land to produce food for growing populations (Chen, 2007, Godfray et al., 2010). As a result, agricultural production must be moved to other available land or to land currently used for other purposes to meet global food demand (Ramankutty et al., 2006; Lambin and Meyfroidt, 2010). Additionally, climate change may exacerbate a shortage of productive agricultural land due to changes in temperature, precipitation, and growing seasons (Gregory et al., 2005; Godfray et al., 2010) and regional sensitivity to climate change may increase (Ramankutty et al., 2002; Parry et al., 2004). Moreover, climate change may also increase the frequency of risks such as drought, flooding, soil degradation, and regional shifts in cash crop production. Effects from physical changes in the climate may drastically alter economic markets, trade, and socioeconomic development (Gregory et al., 2005; Fischer et al., 2005; Schmidhuber and Tubiello, 2007). Thus, urbanization and climate change have the potential to cause severe impacts on current and future global food security.

To effectively address the demand for agricultural production and regional food security, it is important to find adequate spatial analytical and optimization methods proficient in assessing the capability and suitability of available lands for current and future food production. Land capability is defined as the inherent ability of the land to produce common crops (FAO, 1976). Land suitability is defined as the fitness of a given type of land for a defined use (USDA, 1961; FAO, 1976). Specifically, land capability focuses on how the inherent, natural capabilities of the land can be used for a general use, while agricultural land suitability indicates how well land can be adapted to suit specific agricultural uses taking social and economic factors into consideration (FAO, 1976). Since evaluating land suitability is a complex task, multi-criteria evaluation (MCE) methods are one of the spatial analytical methods that can assist in the land-use planning process and incorporate inherent properties and socio-economic factors from stakeholder perspectives into land suitability evaluation. As a result, MCE methods have become an important part of evaluating available land for agricultural production. Multi-criteria evaluation methods have been used to determine agricultural suitability (Ceballos-Silva and Lopez-Blanco, 2003; Hossain et al., 2007; Akinci et al., 2013), but none have addressed both land



capability and agricultural land suitability. These studies used a limited number of criteria and operated from structures lacking in flexibility. Larger amounts of socio-economic and environmental criteria are needed to evaluate land capability and agricultural land suitability problems, and previous MCE models have not been able to capture the complexities of such problems. In order to address these issues, the main objective of this study is to extend the standard GIS-based MCE method by proposing the evaluation of agricultural land capability and suitability using suitability maps based on the Logic Scoring of Preference (LSP) method which incorporates a large amount of criteria into a flexible, adaptive structure.

### **2.3. Theoretical Background**

There is a need for further enhancement and development of procedures by which to define and determine criteria needed to evaluate land suitability. Many studies have focused on physical and chemical characteristics of the soil while some have included environmental or economic criteria. For example, Bandyopadhyay et al. (2009) utilized general parameters of land use/land cover, soil type, organic matter, soil depth, and slope to evaluate agricultural land. Additionally, Wang (1994) applied internal and external soil characteristics such as temperature, moisture, aeration, natural fertility, depth, texture, salinity, slope, flooding, and accessibility to assess agricultural land suitability. Hydraulic conductivity of soil, slope, soil texture, depth to water-table, and electrical conductivity of groundwater was used by Chen et al. (2010b).

In some cases, accessibility and the abundance of labor were used in determining whether regions could be cultivated, while maintaining the importance of physical and chemical characteristics of the soil (Mendas and Delali, 2012). Another application of soil criteria can be found through crop comparisons, which utilize similar criteria for both crops and crop-specific criteria to determine suitability. Ceballos-Silva and Lopez-Blanco (2003) compared suitable areas for maize and potato crops using comparable criteria (minimum temperature, soil depth, soil texture class, slope, altitude, and maximum temperature) and crop-specific criteria (P/E index, pH of the soil, and precipitation).

Suitability studies utilize a multitude of criteria and weights derived from expert knowledge in a spatial context and using geospatial datasets (Store and Kangas, 2001; Kalogirou, 2002; Malczewski, 2006b; Yu et al., 2011). The output of a GIS-based MCE method is suitability map that can be used for planning purposes and to facilitate decision-making processes (Malczewski, 2004, Malczewski and Rinner, 2015). Suitability maps as standard spatial planning and decision tools are a recent addition to GIS software (Stauder, 2014). MCE has also been used for the development of spatial decision support systems to assist decision makers in addressing complex spatial problems (Jankowski et al., 1997). Furthermore, MCE also provides a tool for analyzing the trade-offs between alternatives with various environmental and socio-economic impacts for a given problem (Carver, 1991). MCE models produce a suitability score through the utilization of input attributes. Attributes are evaluated through the application of such methods as fuzzy logic, analytical hierarchy process (AHP), and weighted linear combination (WLC). Typically these methods calculate a suitability index or suitability map with values ranging from 0 to 1, where 0 is not suitable (unacceptable) and 1 is the highest suitability (Hopkins, 1977; Voogd, 1982; Jiang and Eastman, 2000). Furthermore, weights are applied to express importance of components in the process of aggregation of inputs. The result of evaluation is always a single overall suitability output (Jiang and Eastman, 2000).

Different MCE methods include various techniques to evaluate land suitability and support land-use planning: simple additive scoring (SAS) (Massam, 1988; Heywood et al., 1995), multiattribute value technique (MAVT) (Pereira and Duckstein, 1993; Keeney, 1996), multiattribute utility technique (MAUT) (Janssen and Rietveld, 1990; Keeney and Raiffa, 1993), analytic hierarchy process (AHP) (Banai, 1993; Jankowski, 1995), ordered weighted average (OWA) (Yager, 1988; Jiang and Eastman, 2000; Malczewski et al., 2003; Malczewski, 2006a), and outranking methods (Kangas et al., 2001; Joerin et al., 2001).

MCE methods have been integrated with GIS for variety of spatial applications spanning from waste management (Carver, 1991), location-based services (Rinner and Raubal, 2004), recreation and tourism (Feick and Hall, 2004), geology (de Araújo and Macedo, 2002), marine protection (Wood and Dragičević, 2006), management of route selection for the design and implementation of water supply lines (Jankowski and Richard,

1994), and improvement of ecological forest planning (Kangas et al. 2000). Many studies have developed GIS-MCE methods to address suitability analyses for agricultural land-use (Wang, 1994). For example, the AHP method was incorporated for agricultural catchment systems analysis in Australia (Hill et al. 2005) and to assess agricultural land use in the production of aquaculture Hossain et al. (2007). The GIS-based fuzzy rule-based inference system and the AHP method were used to evaluate land suitability in agricultural watersheds (Reshmidevi et al. 2009) and in mountainous regions (Akinci et al. 2013). MCE was used to develop an environmental impact assessments tool to locate optimal agricultural land use areas (Matthews et al., 1999), to evaluate agricultural land use scenarios when in conflict with natural park management (Kächele and Dabbert, 2002), and to improve irrigation of agricultural lands (Morari et al. 2004). To determine agricultural land allocation, Janssen and Rietveld (1990) utilized MAUT and a combination of policy and conflict criteria. The combination of SAS, MAUT, and AHP methods were used to analyze and evaluate agricultural resources (Hayashi 2000). Chen et al. (2010a) combined OWA and AHP methods with fuzzy linguistics to evaluate the removal and expansion of irrigated agricultural land use. The remote sensing approach for land cover and crop changes over time has been incorporated for creation of suitability maps (Ceballos-Silva and Lopez-Blanco, 2003; Bandyopahyay et al., 2009), and farming potential (Hossain and Das, 2010). Other studies have focused on the utilization of environmental-economic decision-making and expert systems in determining agricultural land suitability (Tiwari et al., 1999; Kalogirou, 2002) or as a decision support tool for growing particular agricultural crops (Elsheikha et al 2013; Mendas and Delali, 2012).

The application of existing GIS-based MCE methods in the evaluation of agricultural land suitability have rarely been able to incorporate larger amounts of criteria (greater than 10 criteria) and address a wider range of human decision-making logic (Dujmović et al., 2009). The Logic Scoring of Preference (LSP) method (Dujmović, 1979; Dujmović and Larsen, 2004) has been developed to provide the necessary components to fully address these shortcomings. Through the use of the soft computing logic operation of hard and soft partial conjunction/disjunction as well as conjunctive and disjunctive partial absorption, human reasoning has been represented more closely (Dujmović and De Tré, 2011). The LSP method was initially used for applications in the field of computer science. Recent applications of this methodology are in spatial management (Dujmović

and Scheer, 2010; Dujmović and De Tré, 2011), and with a pilot application in geography (Hatch et al., 2014).

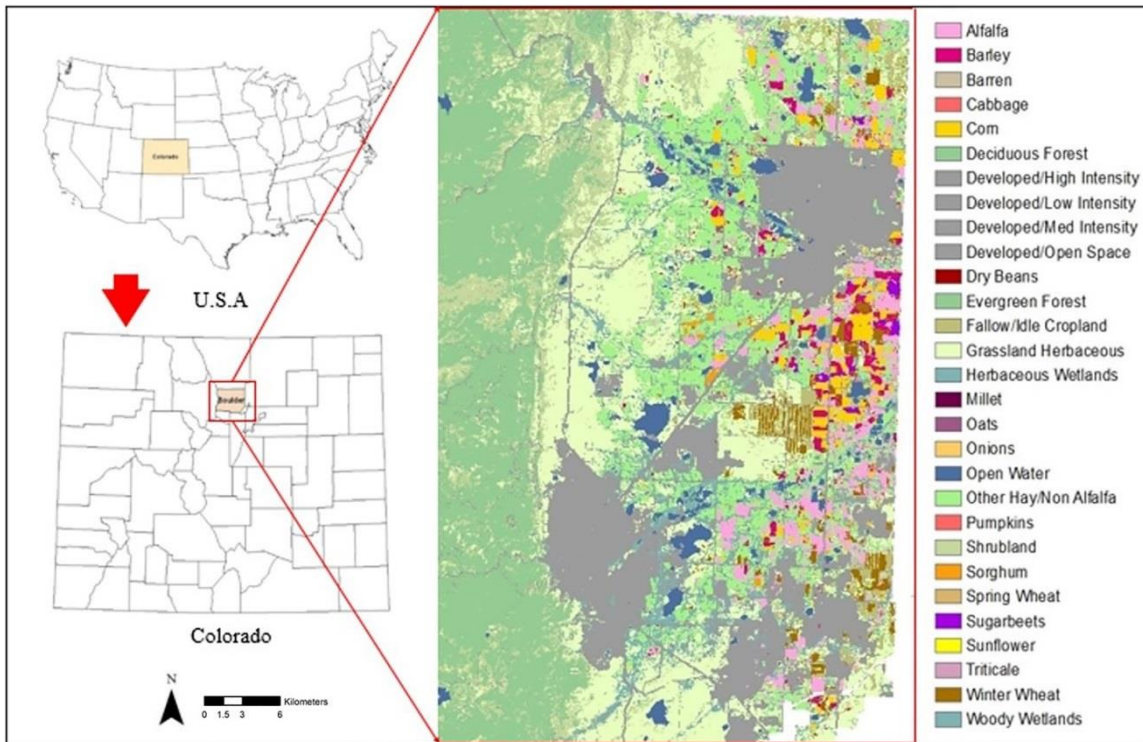
Therefore the main objective of the study was to implement and test the GIS-based LSP method to assess agricultural land capability and suitability. The method was applied to the case study from Boulder County, Colorado, USA. The LSP method was selected because it extends previous MCE methods and that have not yet been applied for agricultural land capability or suitability analysis. This study is unique as it aims to assess areas of suitable agricultural land through the use of social, economic, and physical attributes with the LSP method.

## **2.4. Methods**

### **2.4.1. Study Area**

Boulder County, Colorado, USA (Figure 2.1) was chosen as the study area because of its national importance to agricultural production and sustainable land-use planning. Boulder County has strategically used land-use planning to minimize urban development and increase agricultural production by expanding open spaces to buffer urban regions and provide access for additional agricultural development. Furthermore, open space policies have provided farmers and land owners the opportunity to lease land for additional cultivation, while limiting urban growth and promoting local production.

Boulder County is characterized as a semi-arid region, with low annual precipitation, low humidity, mild winters, and seasonal droughts (Soil Conservation Service, 1975). According to the United States National Oceanic and Atmospheric Administration (NOAA), the average annual precipitation ranges from 1,016 mm in the west to 254 mm in the east, while the average monthly temperature is 10.3° Celsius (NOAA, 2014). Additionally, mild winters in the high plains contribute to growing seasons ranging from 140-148 days per year (Soil Conservation Service, 1975) which make it suitable for cultivation of several agricultural crops. The use of irrigation and abundant groundwater provides improved growing conditions for otherwise dry soils. More sustainable practices are used in non-irrigated soils. Summer fallow and crop rotation



**Figure 2.1. Study area: Boulder County, Colorado, USA.**

practices regenerate soil nutrients and moisture for winter wheat production, while generating reduced crop yields. The majority of agricultural production includes livestock, hay, forage, and grain products (Soil Conservation Service, 1975; Andrews et al., 2011). Based on these facts this County has been chosen for agricultural land capability and suitability evaluation as it can inform current and future land-use planning in the region.

#### **2.4.2. Data Sets**

In this study the soil data were used from the United States Department of Agriculture (USDA) Web Soil Survey tool (NRCS, 2009). The tool provides land classifications and soil characteristics gathered in national and regional soil surveys. Climatic and accessibility data were obtained from the USDA Natural Resources Conservation Service Geospatial Data Gateway (Geospatial Data Gateway, 2014) tool and NOAA (NOAA, 2014) providing spatial and numerical datasets for the study area. The datasets were raster GIS data layers at 50 m spatial resolution. Additional datasets for land use were created by Boulder County Department of Geographic Information Systems (Boulder County Maps &

Data, 2014) and numerical economic datasets were derived from the 2012 USDA Census of Agriculture (USDA, 2014a). Topographical data were obtained from the National Elevation Datasets (Geospatial Data Gateway, 2014) and were used to derive the Digital Elevation Model (DEM), aspect, and slope. Agricultural land use data were obtained from the USDA CropScape tool (Han et al., 2012; USDA, 2014b), which provides raster GIS data layers of agricultural land use. The datasets were standardized for 50 m spatial resolution in this study.

### **2.4.3. Logic of Scoring Preference Method**

The Logic Scoring of Preference (LSP) method is an MCE method that was introduced in the early 1970s, and descriptions of the method can be found in papers devoted to evaluation of computer systems (Dujmović 1987, 1996, Su et al., 1987, Dujmović and Nagashima 2006). The mathematical infrastructure of the LSP method is based on soft computing concepts of generalized conjunction/disjunction (Dujmović 1979, 2007). The use of LSP method for computing suitability in suitability maps was first proposed in Dujmović et al. (2008). The basic concepts were subsequently refined, expanded, and applied for various suitability maps (Dujmović et al. 2009, 2010a, 2010b, 2011, De Tré et al. 2009, 2010, 2011, and Hatch et al., 2014).

LSP suitability maps are defined as maps that in each point  $(X, Y)$  of a selected region show the suitability of that point for a specific use. Therefore, in each point  $(X, Y)$  we have an array of  $n$  attributes  $(a_1(X, Y), a_2(X, Y), \dots, a_n(X, Y))$  that are used as inputs of an LSP criterion for computation of suitability  $S(X, Y) = g(a_1(X, Y), a_2(X, Y), \dots, a_n(X, Y))$ . An LSP suitability map is a graphic representation of the suitability distribution  $S(X, Y)$  within a given region. The LSP suitability map can be presented as a standalone map or a transparent overlay.

The main advantage of the LSP method is the consistency with observable properties of human evaluation reasoning where aggregation of criteria is nonlinear and based on soft computing models of simultaneity and substitutability. Another advantage of the LSP method is its capability to include a large amount of inputs while maintaining the importance of each input throughout the multicriteria evaluation. Some MCE models

rely on weighted additive aggregators to aggregate input attributes. In these cases, weights are normalized and summed to a total value of 1. In other words, each weight is a composite value of the total weight found in the model. As the number of input attributes increases, the significance of each input attribute decreases. Furthermore, these models rely upon fixed aggregators such as arithmetic mean and geometric mean. In terms of human decision making, these aggregators are not flexible in aggregating mandatory and optional input attributes and supporting soft and hard partial conjunction/disjunction. As a result, these models do not reflect the observed properties of human reasoning.

Despite the LSP method's ability to model the case study, the LSP method has not been used to evaluate agricultural land capability and suitability. Other MCE methods such as AHP have been used in agricultural land suitability analyses, but the methods were unable to include more than 10 inputs while maintaining the importance of those inputs throughout their aggregation structures (Dujmović et al. 2009; Dujmović and De Tré, 2011). Moreover, agricultural land suitability analyses primarily focused on soil characteristics of the study area. In this study, the LSP method utilizes geospatial datasets containing social, economic, and environmental data to evaluate land capability or suitability for agriculture. In addition, the LSP method is used in this study because of its ability to manage any number of inputs while maintaining structural flexibility.

The LSP method consists of three main steps: (1) the development of an attribute tree, (2) the definition of elementary attribute criteria, and (3) the development of the logic aggregation structure. Each of the steps is now introduced in the context of the analysis of agricultural land capability and suitability.

#### **2.4.3.1 LSP Attribute Tree**

The LSP attribute tree is a decomposition structure that generates all attributes that characterize the evaluated object. Two independent attribute trees (for land capability and for agricultural suitability) are shown in Table 2.1. At each level the decomposition process consists of defining components of the analyzed compound item. For example, the suitability for agriculture is decomposed into climate, economics, accessibility, management, and soil. In the next step this process continues; e.g. the climate is decomposed into precipitation, temperature, the frost free days, drought, and flood.

**Table 2.1 The attribute trees for (1) land capability, and (2) land suitability for agriculture**

<ul style="list-style-type: none"> <li>1. Capability for Agriculture               <ul style="list-style-type: none"> <li>1.1 Terrain                   <ul style="list-style-type: none"> <li>1.1.1 Slope (+)</li> <li>1.1.2 Elevation (-)</li> <li>1.1.3 Aspect (-)</li> </ul> </li> <li>1.2 Fertility                   <ul style="list-style-type: none"> <li>1.2.1 Soil Texture (+)</li> <li>1.2.2 Organic Matter (+)</li> </ul> </li> <li>1.3 Depth                   <ul style="list-style-type: none"> <li>1.3.1 Depth to Restrictive Layer (+)</li> <li>1.3.2 Available Water (+)</li> </ul> </li> <li>1.4 Density                   <ul style="list-style-type: none"> <li>1.4.1 Drainage Class (+)</li> <li>1.4.2 Bulk Density (+)</li> </ul> </li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>2. Suitability for Agriculture               <ul style="list-style-type: none"> <li>2.1 Climate                   <ul style="list-style-type: none"> <li>2.1.1 Precipitation (+)</li> <li>2.1.2 Temperature (+)</li> <li>2.1.3 Frost Free Days (+)</li> <li>2.1.4 Water Retention (-)</li> <li>2.1.5 Flood (-)</li> </ul> </li> <li>2.2 Economics                   <ul style="list-style-type: none"> <li>2.2.1 Cash Crops Demand (+)</li> <li>2.2.2 Economic Hazards (+)</li> </ul> </li> <li>2.3 Accessibility                   <ul style="list-style-type: none"> <li>2.3.1 Location of Highly Capable Soils (+)</li> <li>2.3.2 Distance to Water for Irrigation (-)</li> <li>2.3.3 Distance to Open Space (-)</li> <li>2.3.4 Distance of Major Roads (+)</li> <li>2.3.5 Distance to Local Roads (+)</li> </ul> </li> <li>2.4 Management                   <ul style="list-style-type: none"> <li>2.4.1 Crop Type (+)</li> <li>2.4.2 Farm Product Consumption (+)</li> <li>2.4.3 Designated Open Space/Land Use (+)</li> <li>2.4.4 Zoning (+)</li> </ul> </li> <li>2.5 Land Capability                   <ul style="list-style-type: none"> <li>2.5.1 Slope (+)</li> <li>2.5.2 Elevation (-)</li> <li>2.5.3 Aspect (-)</li> <li>2.5.4 Soil Texture (+)</li> <li>2.5.5 Organic Matter (+)</li> <li>2.5.6 Depth to Restrictive Layer (+)</li> <li>2.5.7 Available Water (+)</li> <li>2.5.8 Drainage Class (+)</li> <li>2.5.9 Bulk Density (+)</li> </ul> </li> </ul> </li> </ul>
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### **2.4.3.2 Attribute Criteria**

The decomposition process terminates when we reach components that cannot be further decomposed. For example, in the soil evaluation group we take into account the elevation. Obviously the elevation can be easily measured, and it cannot be further decomposed into



simpler components. So, the elevation is one of the leaves of the decomposition tree. All such leaves are called the attributes and they are inputs for the LSP elementary attribute criterion. The attributes are independently evaluated in subsequent evaluation steps.

After deriving the attributes it is useful to analyze whether an attribute is mandatory or optional but not mandatory. For example, both the slope and the elevation of terrain are mandatory requirements because if the slope or the elevation are too high, then such terrain is not suitable for agriculture, and the overall suitability must be zero. This example also shows why additive evaluation models, such as simple additive scoring or the original OWA aggregator (Yager, 1988), cannot be used in evaluation because they cannot model mandatory requirements. In order to model mandatory requirements we need mathematical models that have multiplicative and not additive properties. Obviously, not all attributes are mandatory. For example, if from time to time the terrain might be flooded, that does not mean the agricultural use is not possible. Therefore, it would be wrong to combine attributes using strictly multiplicative aggregators (e.g. like the geometric mean) where all inputs are mandatory. Therefore, we need more flexible aggregation procedures. In Table 2.1 the symbol (+) denotes mandatory attributes and (-) denotes nonmandatory attributes.

#### **2.4.3.3 Definition of Attribute Criteria**

Each input attribute is separately evaluated using an elementary attribute criterion. The elementary attribute criteria represent stakeholder requirements that are to be satisfied by the input attributes. Let us use the case of precipitation (the first attribute in the climate group) to illustrate the definition of an elementary attribute criterion. Suppose that we intend to grow plants that are completely satisfied (denoted either 100% or 1) with the precipitation  $p \geq 35$  cm/year. Consequently, if  $p < 35$  cm/year then the degree of satisfaction with precipitation is less than the maximum value 1. Since the zero precipitation must yield zero satisfaction, in the range  $0 \leq p \leq 35$  cm/year the simplest way to define the degree of satisfaction  $x$  is the linear function  $x = p/35$ . Therefore, the simplest elementary attribute criterion for any value of precipitation can be defined as  $x = \max(0, \min(1, p/35))$ ,  $x \in [0,1]$ . This criterion function can be graphically presented as the first graph shown in Fig. 2. Of course, if we have more precise information about requirements, we can use more precise nonlinear criteria.

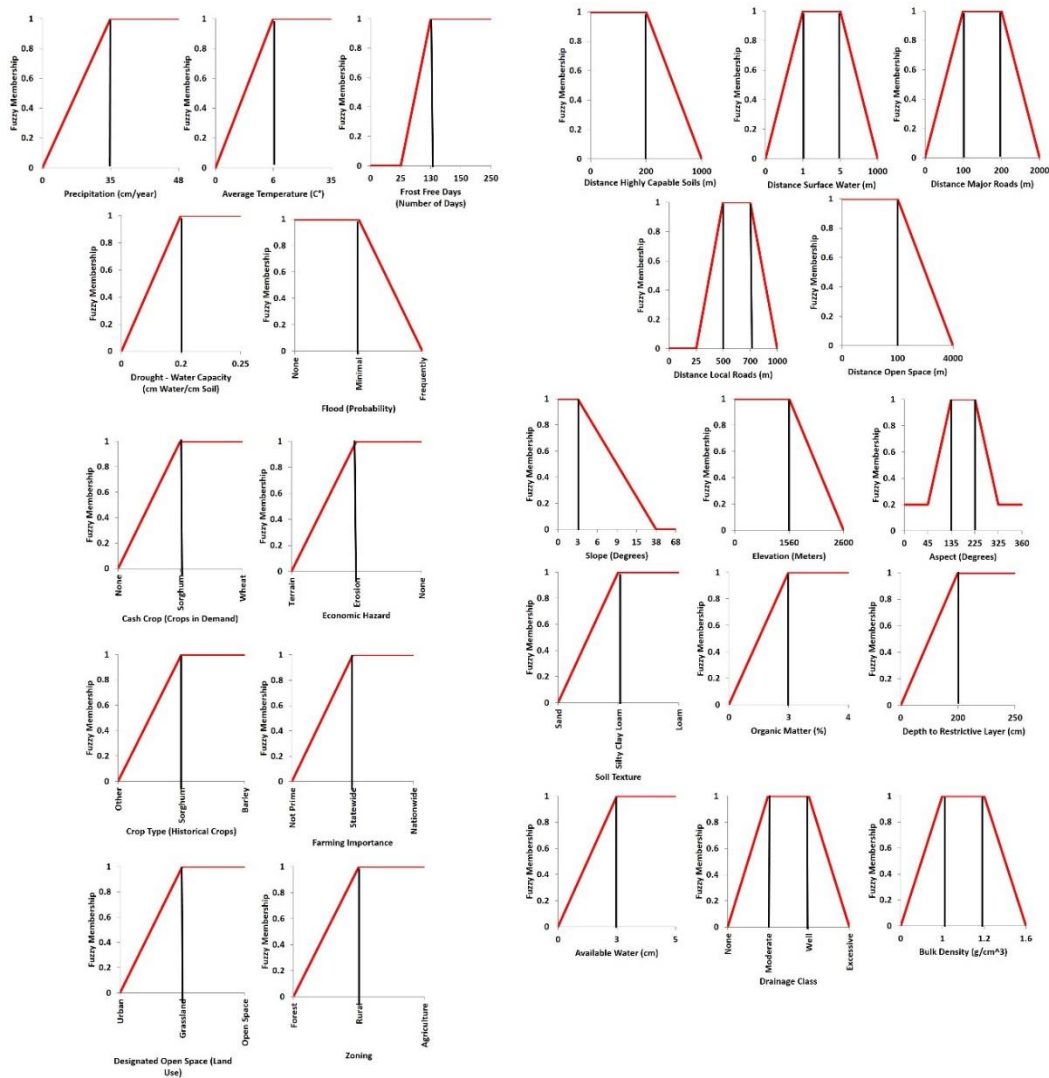
It is important to note that  $x$  can be interpreted in four alternative ways. The first way is to interpret  $x$  as a suitability score, i.e. an unspecified quantitative indicator of the satisfaction of stakeholder's requirements (suitability or preference degree). The second approach, native for the LSP method, is the logic interpretation where  $x$  is interpreted as a degree of truth of the assertion that the precipitation  $p$  completely satisfies all requirements. The third approach is to interpret  $x$  as a degree of membership of the given precipitation in the fuzzy set of ideally satisfied precipitation requirements. Finally, if we define  $x$  as a percentage,  $x = 100 \max(0, \min(1, p/35))$  [%], then  $x$  can be interpreted simply as a percentage of satisfied requirements. The logic and the fuzzy interpretation are equivalent.

The complete list of suitability functions representing attributes which characterize the attribute criteria used in determining agricultural land capability and suitability are presented in Figure 2.2. We use a symbolic notation of elementary attribute criteria and not actual graphs; that is the reason, why the x-axis scales are not linear. However, all straight lines denote the use of simple linear interpolation between the selected breakpoints.

Most inputs are mandatory (+), with the exception of the terrain category where we use one optional (-) input. For each input we show a suitability function, where 0 does not belong to a particular set while 1 represents full suitability or full membership in a set of completely satisfied requirements. The choices of attribute criteria for both agricultural land capability and suitability were determined via suitability functions that are derived based on expert knowledge acquired from discussions with soil professionals and review of the literature (Tiwari et al., 1999; Ceballos-Silva and Lopez-Blanco, 2003; Yu et al., 2011; Akinci et al., 2013; USDA, 2014a). When using the LSP method it is important to carefully select inputs, attribute criteria, and suitability functions because they have a significant influence on the output. Moreover, the initial attribute criteria and suitability functions can be refined depending on the selection of evaluation and obtaining more stakeholder requirements specific to the evaluation.

Attribute criteria used in this study to evaluate agricultural *land capability* include: slope, elevation, aspect, soil textural class, organic matter, depth to restrictive layer,

available water, drainage class, and bulk density. They are divided to form four categories: *terrain, texture and fertility, depth and water, and density and drainage*. When determining agricultural *land suitability*, attribute criteria were divided into five categories: *climate, economics, accessibility, management, and land capability*. These five categories are selected to represent social, economic, and environmental factors necessary for evaluating agricultural land suitability.



**Figure 2.2. Suitability functions characterizing agricultural land capability and suitability.**

The detailed descriptions of chosen attribute criteria (Figure 2.2) influencing agricultural land capability and suitability are as follows:

*Terrain Attributes:* The three attribute criteria include: slope (%), elevation (m), and aspect (degrees). The study area presents a wide variety of slope ranging from 1% to 68%. Almost 80% of the land in the study area has a slope below 7%, which makes a good part of the region very suitable for agricultural production. It was assumed that land with slopes ranging between 0 and 3 degrees would be the most capable (Soil Conservation Service, 1975; Chen et al., 2010b). Aspect influences the degree of sunlight exposure, and thus southern and western aspects were assumed to be most capable for agriculture (NRCS, 1999; Akinci et al., 2013). Finally, elevation varies between 2,611 and 1,491 meters across the study area, and the growing season varies from 90-148 days per year. Longer growing seasons correspond to lower elevations, such that elevation below 1,560 meters was assumed to be the most capable land for agricultural production (Ceballos-Silva and Lopez-Blanco, 2003; Akinci et al., 2013).

*Fertility Attributes:* Soil attributes included soil textural class and percent organic matter. Soil texture provides a measure of the proportions of sand, silt, and clay particles in the soil (NRCS, 1999). The soil textural class influences a soil's ability to drain water, be aerated, hold on to moisture, grow crops, and react to changes in climate (Soil Conservation Service, 1975). The soil textural class assumed to be most capable for agriculture is loam, which contains a mix of sand, silt, and clay particles (Soil Conservation Service, 1975; Hall and Wang, 1992; Ceballos-Silva and Lopez-Blanco, 2003). In the study area, loam and silty clay loam represent about 71% of the land. Soil organic matter is a major source of plant-available nutrients. These nutrients are derived from the decomposition of plant material. Soils containing large quantities of organic matter found on flat or minimally sloping areas are typical locations for agricultural production (Natural Resources Conservation Service, 1999; Mzuku et al, 2005; Bandyopadhyay et al., 2009). Due to the semi-arid climate in the study region, soil organic matter concentrations are relatively low. We assumed that land with surface soil organic matter between 3 and 4 percent was the most capable for agriculture (Mzuku et al., 2005).

*Depth Attributes:* For the purpose of this study, depth to restrictive layer is used as an indicator for soil depth. By definition soil depth provides the depth to which plant roots can access water and nutrients within the soil. Deep soils are characteristically stable and are subject to improved soil development over time (Fu et al., 2011). It was assumed that a depth of 200 cm or more is characteristic of capable land (Soil Conservation Service, 1975; Ceballos-Silva and

Lopez-Blanco, 2003; Bandyopadhyay et al., 2009). More than 75% of the study area contains soil with a depth greater than 200 cm. The available water-holding capacity was used as an indicator of water availability. Available water-holding capacity is the amount of water that can be held in the soil and is readily available for use by crops and is quantified as the water that is held between field capacity and the wilting point (Soil Conservation Service, 1975). In the study area, available water ranges between 0 and 5 centimeters of water. Soil with available water ranging between 3 and 5 centimeters was assumed to be the most capable as it provides enough water for the soils to provide moisture in semi-arid conditions (Soil Conservation Service, 1975; Mzuku et al., 2005).

*Density Attributes:* Due to the use of irrigation in the study area, it is important to characterize soil drainage in the region. Soils containing mostly sand particles drain well, while soils containing mostly clay particles will drain poorly. In general, soils with a mix of particle sizes are moderately well drained. The majority of the study area contains soils which drain well, and it was assumed that moderate and well drained soils were the most capable for agricultural production (Soil Conservation Service, 1975; Reshmidevi et al., 2009; NRCS, 2009). Bulk density is an indicator of the compactness of the soil, measured as a ratio of the weight of the soil (grams) per total soil volume (cubic centimeters). The denser the soil, the less capable the land is because bulk density affects root growth. The range of bulk density in the study area is between 0 and 1.63 g/cm<sup>3</sup>. Based on expert knowledge, it was determined that a moderate bulk density is the best for agriculturally capable land; the assumed range for the best bulk density was between 1.0 and 1.2 g/cm<sup>3</sup> (NRCS, 2009).

*Climate:* Attribute criteria used to represent the climate include: precipitation, temperature, seasonality, flood, and drought. The study area has a semi-arid climate, with overall low precipitation, high temperatures, and mild winters. Seasonal drought and occasional flooding are characteristic as dry conditions may limit agricultural production. The use of irrigation is necessary to maintain productivity. Seasonality was assumed to be the most important attribute criteria to influence the production of agriculture (Soil Conservation Service, 1975). The importance of climate is reflected in the final aggregation of the LSP structure.

*Economics:* The attribute criteria representing economics include: cash crop demand and economic hazards. Cash crops provide the highest economic return in the marketplace and influence crop types and crop production (Parton et al., 2003). In the study area, wheat and other grains are the most profitable crops as they are well adapted to the climate and are used for feeding livestock. The economic viability of growing crops which are not adapted to the climate

may be restricted by environmental hazards of the region (Soil Conservation Service, 1975). Environmental hazards pertaining to shallow soil, water interference, weather damage, and erosion can all negatively impact crop yields, reducing the economic returns for that growing season. For the study, having no environmental hazards and erosion hazards were determined as the least likely to reduce crop yields. Additional irrigation and management of these crops may also increase financial expenses needed to maintain high crop yields. Base on the literature it was assumed that cash crops such as wheat were the most important attribute criteria (USDA, 2014a).

*Accessibility:* Distance to major roads, distance to local roads, distance to surface water, location of highly capable soils, and distance to open space represent the attribute criteria describing the accessibility of agricultural land. Accessibility is an important aspect of evaluating agricultural land suitability because it provides an indication for farmer access to highly capable soils and infrastructure while facilitating the transportation of equipment, produce, resources, and agricultural technology and to urban markets for selling the produce (Berger, 2001). The study area contains an abundance of surface water and highly capable soils, supplying sufficient resources for irrigation and cultivation. As a result, highly capable soils were considered as one of the most important accessibility criteria (Soil Conservation Service, 1975; Andrews et al., 2011).




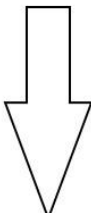
*Management:* Management attribute criteria include activities related to the crop type, farming importance, designated open space, and zoning. The agricultural zoning directly influences increased agricultural production for the county and the state (Andrews et al., 2011). In addition, specific regions in the study area are designated as having local or statewide importance. In order to support local and statewide agricultural production, recent management regulations have designated specific areas of open space for future agricultural cultivation that expands current agricultural zoning in the region (Soil Conservation Service, 1975; Mzuku et al., 2005). Thus, the zoning was considered as one of the most important attribute criterion.

#### **2.4.3.4 LSP Aggregation Structure**

After applying elementary criteria to  $n$  input attributes we generate  $n$  *attribute* suitability degrees (interpreted as degrees of truth or fuzzy membership). The next step is to aggregate these  $n$  attribute suitability degrees to generate a single overall degree of suitability that reflects the overall quality of the evaluated object. Consequently, the next step of the LSP method is to develop an aggregation structure that aggregates attribute suitability degrees, taking into account

specific stakeholder's goals and requirements. Those requirements affect the selection of logic aggregation operators, and the relative importance of individual attributes and their groups.

The process of aggregation follows the attribute tree (Figure 2.2) going step by step from leaves towards the root. Suppose for simplicity that we have to aggregate only two inputs, like soil texture and organic matter that are used for evaluation of fertility. There are nine basic categories of LSP logic aggregators of two inputs: (1) pure conjunction [C], (2) hard partial conjunction [HPC], (3) soft partial conjunction [SPC], (4) neutrality (or the arithmetic mean, [A]), (5) soft partial disjunction [SPD], (6) hard partial disjunction [HPD], (7) pure disjunction [D], (8) conjunctive partial absorption [CPA], and (9) disjunctive partial absorption [DPA]. The user must select one of these aggregators, where the first seven aggregators are basic, and the last two are compound. The basic aggregators are models of simultaneity and replaceability shown in Figure 2.3 (for details see Dujmović (2007)). In the case of soil textural class and organic matter we need a model of simultaneity because for good fertility it is best to have simultaneously both suitable soil textural class and suitability amount of organic matter. Simultaneity models shown in Figure 2.3 can be hard or soft. The property of hard models is that inputs are mandatory, i.e. if one of the inputs is zero the output will be zero regardless of the values of other inputs. In the case of soft simultaneity, the inputs are not mandatory; if one of the inputs is zero, the output suitability will be penalized (reduced) but it will not necessarily be zero. In the case of fertility we cannot accept a less suitable soil textural class or zero organic matter and consequently we need a hard simultaneity. According to Figure 2.3, there are six aggregators that model hard simultaneity (C+, CA, C+-, C+ C++, C) going from the weakest (C+-) to the strongest (C). We selected C+ to model a strong effect of simultaneity.

	Aggregator	Exponent r		
 Replaceability	<b>D</b>	$+\infty$	} Partial disjunction	
	<b>D++</b>	20.63		
	<b>D+</b>	9.521		
	<b>D+-</b>	5.802		
	<b>DA</b>	3.929		
	<b>D-+</b>	2.792		
	<b>D-</b>	2.018		
 Neutrality	<b>A</b>	1		
 Simultaneity	<b>C--</b>	0.619	} Nonmandatory requirements (soft partial conjunction)	
	<b>C-</b>	0.261		
	<b>C+</b>	-0.148		
	 Simultaneity	<b>CA</b>	-0.72	} Mandatory requirements (hard partial conjunction)
		<b>C+-</b>	-1.655	
		<b>C+</b>	-3.51	
		<b>C++</b>	-9.06	
	<b>C</b>	$-\infty$		

**Figure 2.3 LSP Aggregators representing *replaceability*, *neutrality*, and *simultaneity*.**

In the general case of  $n$  inputs the basic aggregators shown in Figure 2.3 are called the *generalized conjunction disjunction* (GCD) function and implemented using the weighted power mean (WPM):

$$GCD(X_1, \dots, X_n) = (W_1 X_1^r + \dots + W_n X_n^r)^{1/r} \quad (1)$$

Here  $GCD(X_1, \dots, X_n)$  denotes the output suitability for the input suitability degrees  $X_1, \dots, X_n$ . Normalized weights  $W_1, \dots, W_n$ ,  $0 < W_i < 1$ ,  $i = 1, \dots, n$ ,  $\sum_{i=1}^n W_i = 1$  represent the relative importance of inputs  $X_1, \dots, X_n$ . The parameter  $r$  is used for adjusting the degrees of *simultaneity* and *replaceability* for all of the inputs. For example, let's use the aggregation of distance to surface water and distance to important soils in the accessibility category. The surface water input is  $X_1$  with a weight of 0.70; distance to important soils is  $X_2$  with a weight of 0.30. The



LSP aggregator used is C-+, which corresponds to an  $r$  value of -0.148. When applied to the GCD function, the corresponding GCD aggregator is as follows:

$$GCD(X_1, X_2) = (0.70X_1^{-0.148} + 0.30X_2^{-0.148})^{-1/0.148}$$

All of the inputs are aggregated in a similar fashion throughout the aggregation structure until a single output value is determined.

The conjunctive partial absorption (CPA) function is used to combine mandatory and optional inputs. Dujmović (1979) introduced the CPA function and further elaborated in Dujmović et al. (2009). The suitability output is calculated when mandatory requirements,  $X$ , and optional requirements,  $Y$ , are aggregated as follows:

$$S(X, Y) = [(1 - W_1)[W_2X^{r_1} + (1 - W_2)Y^{r_1}]^{\frac{r_2}{r_1}} + W_1X^{r_2}]^{1/r_2} \quad (2)$$

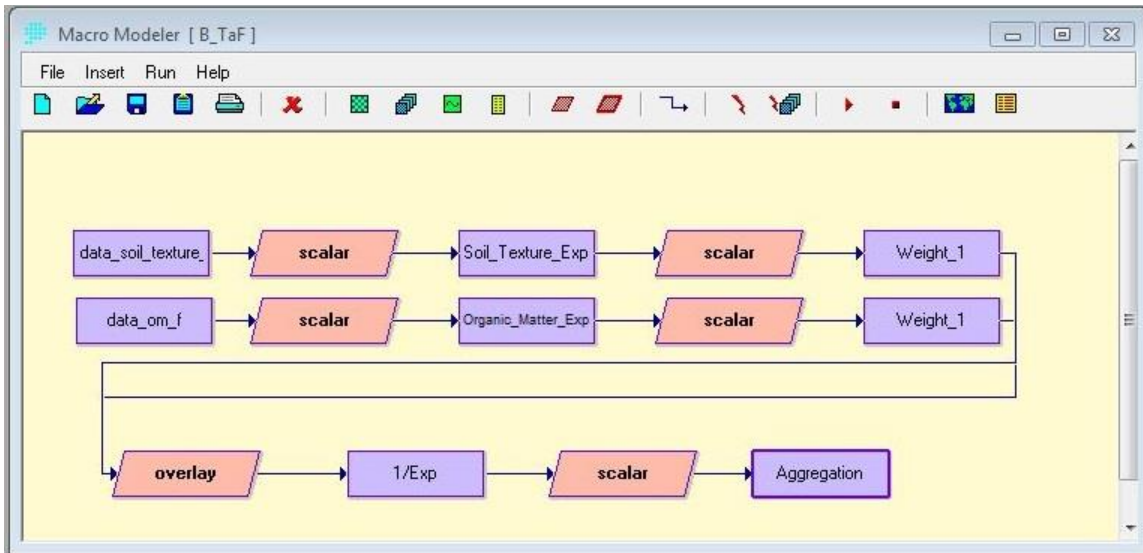
The next step in the aggregation tree is combining mandatory and optional inputs. The mandatory input is represented by the output from Equation 2, and the optional input is the distance to open space attribute criterion. When applied in the CPA function, the weight applied to the mandatory input is  $W_2$  while the weight for the optional input is  $W_1$ . The output suitability map from Equation 2 is given the weight of 0.80, and the distance to open space input is given the weight of 0.20. Equation 2 utilizes two aggregators, explaining the need for both  $r_1$  and  $r_2$ . The LSP aggregators are neutral A and CA, corresponding to values of 1 and -0.72, respectively. When applied to the CPA function, the equation is as follows:

$$S(X, Y) = [(1 - 0.20)[(0.80)X^1 + (1 - 0.80)Y^1]^{-0.72/1} + (0.20)X^{-0.72}]^{1/-0.72}$$

Overall, each LSP structure in the study applied a combination of the GCD and CPA functions to mathematically represent the aggregation of mandatory and optional inputs. The importance of each attribute criterion in the LSP structure is represented by the assigned weights applied during aggregation; higher levels of influence correspond with higher weight values. Importance was derived from previous studies (Dujmović et al., 2008; Dujmović and Scheer, 2010, Dujmović and De Tre, 2011; Hatch et al., 2014), policy initiatives (Andrews et al., 2011; Graff et al., 2013), and the desired levels of influence for inputs and outputs at each aggregation in the LSP aggregation structure.

## 2.5. Results

The processing of geospatial data and implementation of the LSP method has been achieved by using both Esri ArcGIS and Idrisi GIS software. An example of the Idrisi GIS software environment can be seen in Figure 2.4. LSP aggregation structures were designed to follow aggregation schemes, ranging from soft partial conjunction to hard partial conjunction, as well as the partial conjunctive absorption. Typically, simultaneity or andness increases from the leaves of the aggregation structure towards the root, where hard partial conjunction aggregators are used. The leaves of the aggregation structure are considered to be simple and the least complex, meaning that neutrality and soft partial conjunction aggregators are used. As simultaneity or andness increases, so too does the complexity. This type of aggregation structure is called the conjunctive canonical aggregation structure (Dujmović and de Tré, 2011). Fuzzy functions were implemented within raster GIS environment using map algebra tools in Idrisi GIS to generate capability and suitability maps. The equal interval classification method was used to group the categories for the obtained capability/suitability scores for all generated maps to form the following range: excellent [1.00-0.86], very good (0.86-0.71], good (0.71-0.57], average (0.57-0.43], poor (0.43-0.28], very poor (0.28-0.14], and unacceptable (0.14-0.00]. Excellent capability/suitability represents the satisfaction of the inputs given the attribute tree and aggregation structure parameters, as well as specified logic conditions. The resulting aggregation structures and obtained LSP maps for agricultural land capability and suitability are presented below.



**Figure 2.4** Example of aggregating two input criteria within the Idrisi GIS software environment.

### 2.5.1. LSP Structure and Output Map for Agricultural Land Capability

The LSP structure for agricultural land capability (Figure 2.5) contains four categories: terrain, texture and fertility, depth and water, and density and drainage. They rely on the neutrality (A), soft partial conjunction (C-), and hard partial conjunction (C-+, CA and C+) aggregators. Both the weighted power mean (Equation 1) and the conjunctive partial absorption (Equation 2) were used to combine mandatory or optional only inputs and mandatory and optional input combinations, respectively. The obtained LSP output map for agricultural land capability is presented in Figure 2.6 A, while Figure 2.6 B presents the soil capability map generated by the United States Department of Agriculture (USDA). Table 2.2 summarizes the amounts of land under each of the categories for the LSP output map and the USDA map. The LSP scores indicate that excellent agricultural land capability can be found in 28.0% (27,467 ha) of the study area, while unacceptable land capability comprises 40.1% (39,385 ha) of the study area. The remaining area contains 6.5% (6,364 ha) very good capability, 6.9% (6,741 ha) good capability, 4.7% (4,597 ha) average capability, 4.3% (4,178 ha) poor capability, and 9.5% (9,284 ha) very poor capability land. In order to compare the LSP output map obtained for agricultural land capability (Figure 2.6 A) with the map derived by similar USDA data (Figure 2.6 B), the quantity and allocation disagreement statistics (Pontius and Gilmore, 2011) have been used. When compared, the two agricultural land capability maps resulted in a quantity disagreement of 12.5% and an allocation disagreement of 12.0% for a total disagreement of 24.5%. Overall the two maps have a strong agreement of 75.5%.

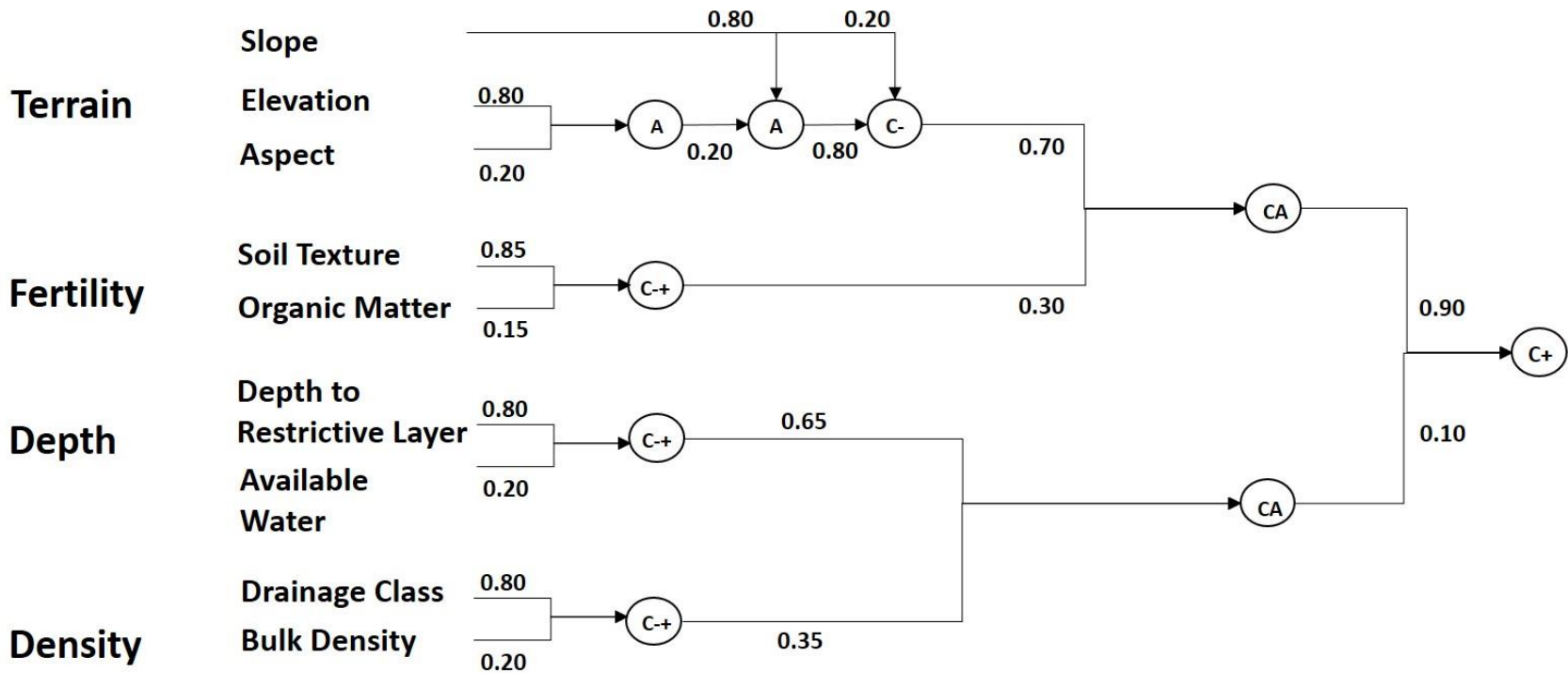
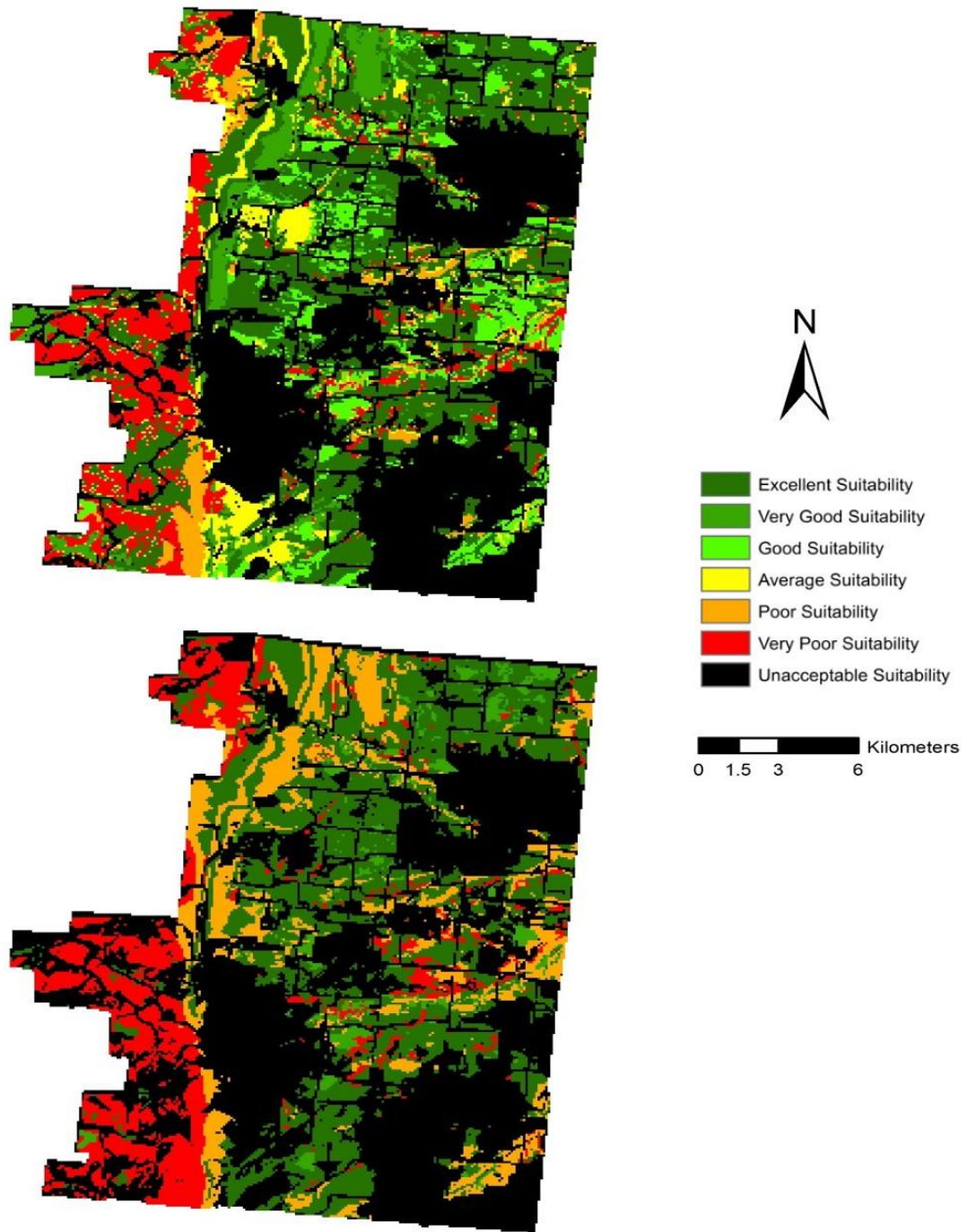


Figure 2.5 The LSP aggregation structure for agricultural land capability using nine input criteria and nine aggregators.



**Figure 2.6** Land capability maps (A) obtained using GIS-based LSP method and (B) generated by United States Department of Agriculture (USDA) data.

### 2.5.2. LSP Structure Output Map for Agricultural Land Suitability

Four scenarios of agricultural land suitability have been designed to present possible and different decision-making alternatives. The LSP structure for agricultural land suitability was designed to combine the criteria for land capability combined with *climate, economics, accessibility, management, and land capability*. Each group of inputs represents criteria important in the production and development of agriculture in the study area. Scenario 1 was designed to focus on the importance on inherent natural soil capabilities, three other scenarios were created to provide outputs concentrated on land management (Scenario 2), accessibility to physical characteristics of the land (Scenario 3), and agricultural economics (Scenario 4), respectively.

For Scenario 1 the agricultural land aggregation structure (Figure 2.7) were designed considering the importance of soil capability that has been assigned higher weights. The obtained suitability map was presented in Figure 2.8. Based on the obtained suitability values (Table 2.2), excellent suitability land are within 4.6% (4,486 ha) of the study area, 17.6% (17,245 ha) is in very good suitability, 17.5% (17,217 ha) good suitability, 8.9% (8,757 ha) average suitability, 10.3% (10,090 ha) poor suitability, 1.6% (1,613 ha) very poor suitability, and unacceptable suitability 39.5% (38,808 ha) respectively. For the other three scenarios different LSP structure for agricultural land suitability has been developed to reflect various decision-making perspectives emphasizing different criteria and weights schema, respectively. Figures 2.9 A, 2.9 B and 2.9 C present respectively LSP structures and output maps for Scenario 2, 3, and 4.

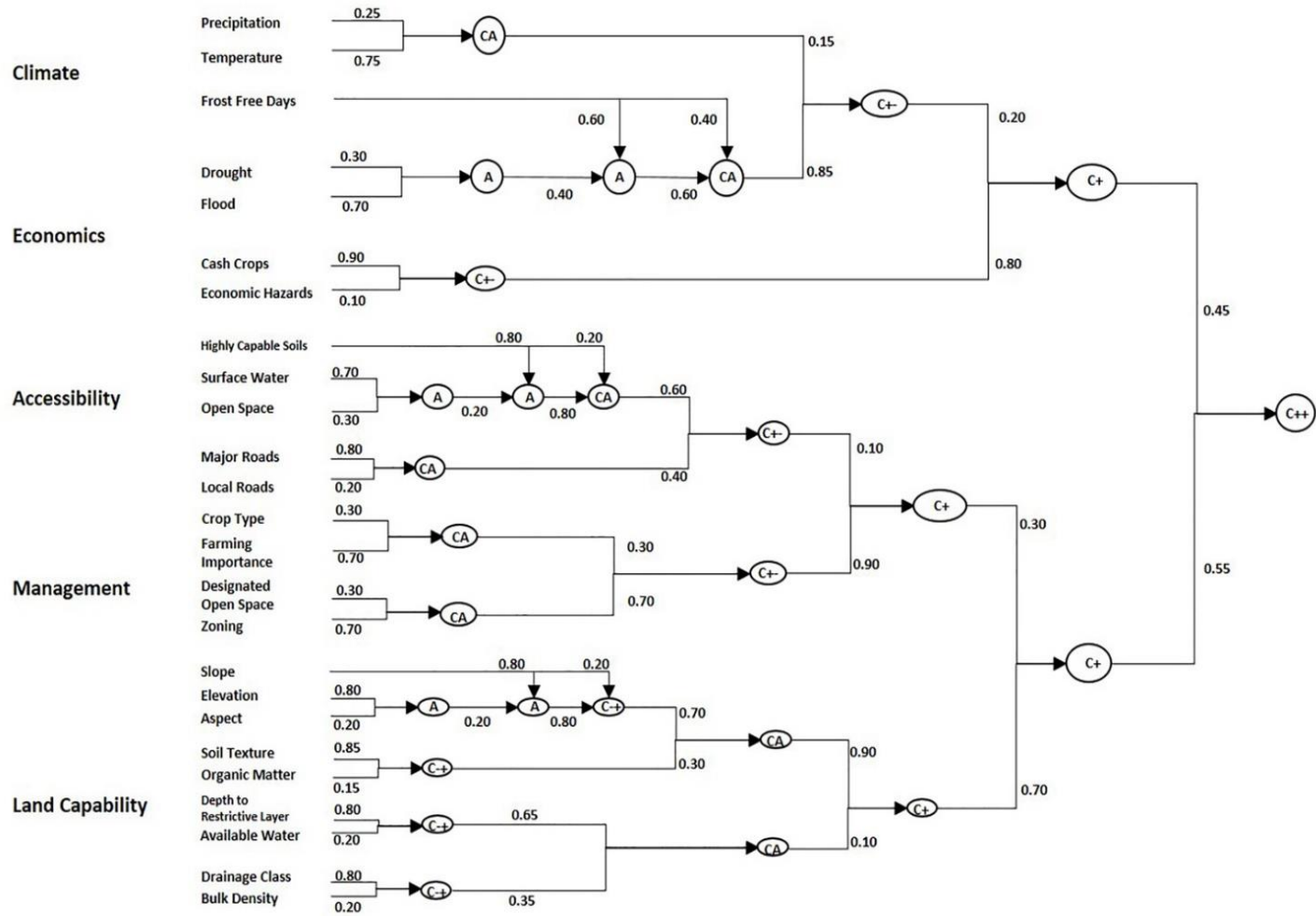
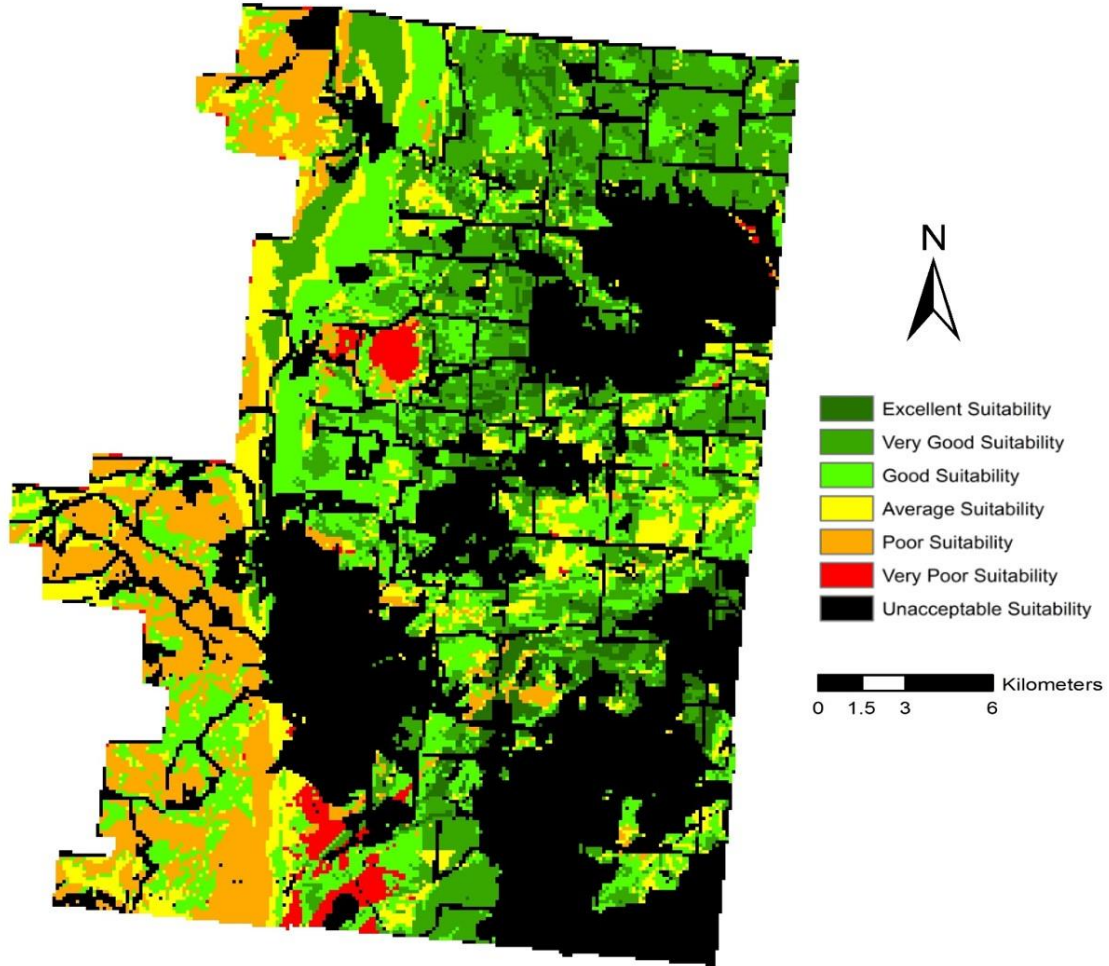


Figure 2.7 The LSP aggregation structure for agricultural land suitability using twenty-five input criteria and twenty-seven aggregators.





**Figure 2.8** The obtained LSP map with agricultural land suitability values representing scenario 1.

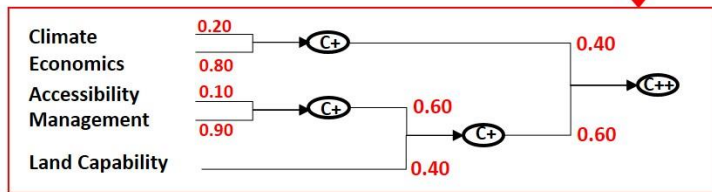
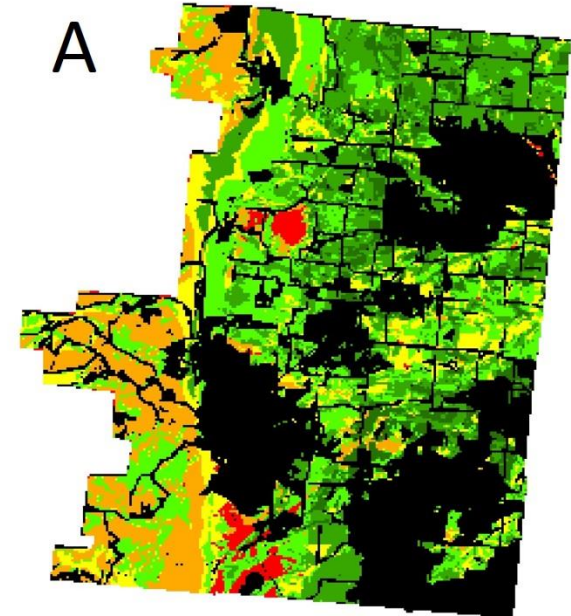
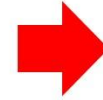
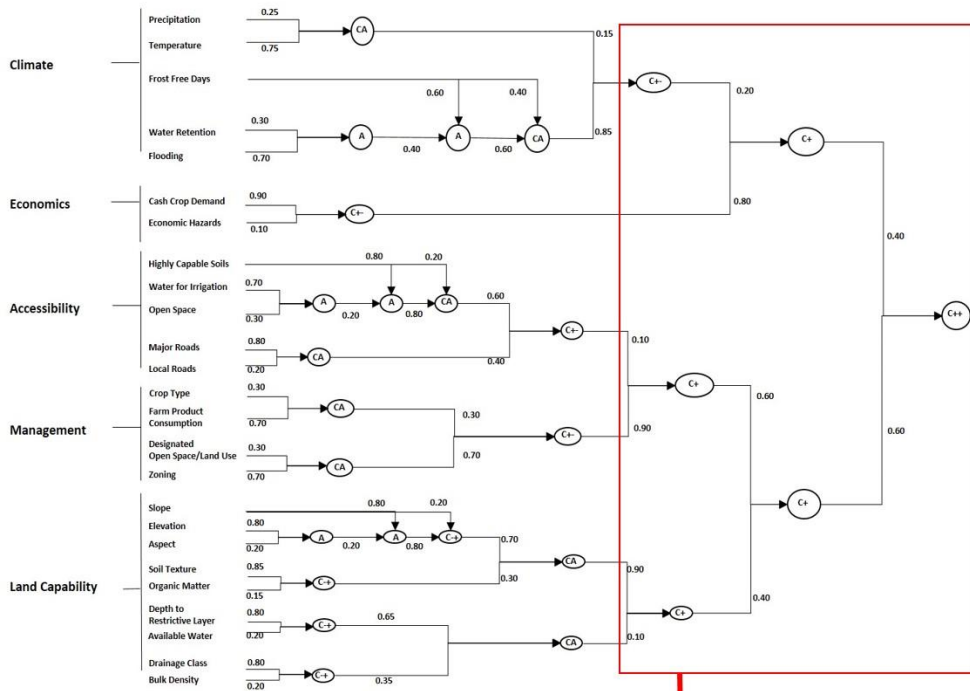
The LSP structure and suitability map for Scenario 2 is focused on attribute criteria representing land management in order to determine agricultural land suitability (Figure 2.9 A). Management attribute criteria encompass local policies and zoning in determining suitable areas for agricultural production. Regions corresponding to agricultural zoning and legislation were determined as excellent suitability. Next, the LSP structure and the output map for Scenario 3 placed relative importance upon accessibility to physical characteristics of the land (Figure 2.9 B).

Accessibility represented the spatial location for agricultural production in terms of access to roads and natural resources, such as surface water for irrigation. Easier accessibility was assumed to provide excellent suitability for agricultural production. Finally, the LSP structure for Scenario 4 emphasized agricultural economic attribute criteria in determining agricultural land



suitability (Figure 2.9 C). Economic attribute criteria represented regions of profitable crops and regions with minimal economic hazard. As a result, the obtained suitability map indicated that regions of highly profitable crops were assumed to be the most suitable areas for agricultural production as they provide economic viability for future production in the study area.

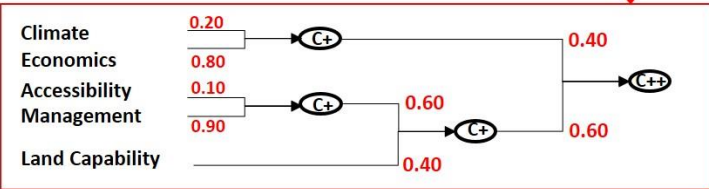
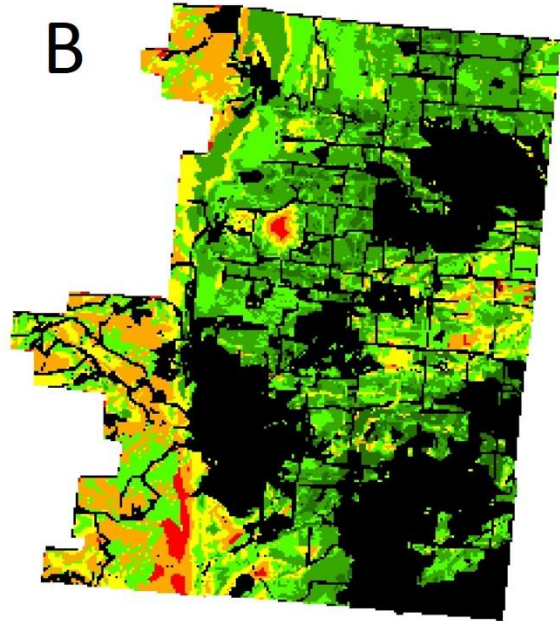
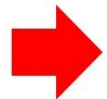
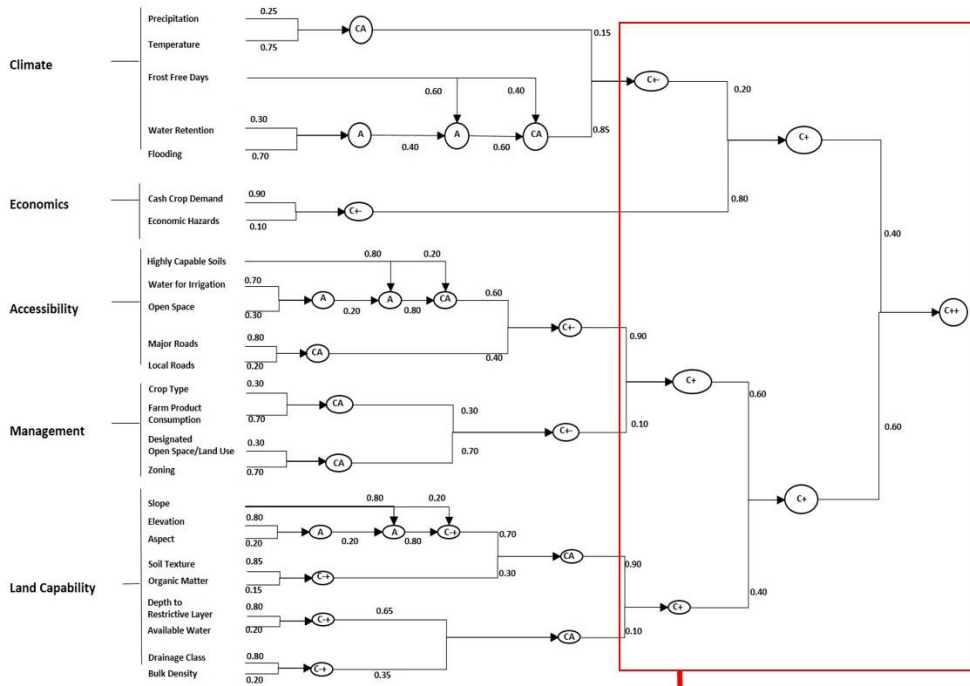
The additional three scenarios differed in categorical distribution from the LSP structure for agricultural land suitability presented as Scenario 1 in Figure 2.8. Scenario 2 (Figure 2.9 A) mostly consisted of very good suitability (17.3%) and good suitability (17.5%) land when representing management perspectives. Scenario 3 (Figure 2.9 B) was comprised mostly of very good (20.3%) and good (17.2%) suitability land while representing accessibility perspectives. Scenario 4 (Figure 2.9 C) represented economic perspectives while the study was comprised mostly of very good (14.4%), good (17.3%) and average suitability (14.3%) land. Table 2.2 presents the summary of overall distributions of obtained values for various levels of capability and suitability scores (excellent, very good, good, average, poor, very poor, and unacceptable) in percentage and hectares of land for all of the LSP maps generated in this study. Table 2.3 presents the summary distribution of overall levels for agricultural suitability in respect to initial land use categories used as inputs for the GIS-based LSP analysis and calculated for Scenario 1.



- Excellent Suitability
- Very Good Suitability
- Good Suitability
- Average Suitability

- Poor Suitability
- Very Poor Suitability
- Unacceptable Suitability





- Excellent Suitability
- Very Good Suitability
- Good Suitability
- Average Suitability

- Poor Suitability
- Very Poor Suitability
- Unacceptable Suitability



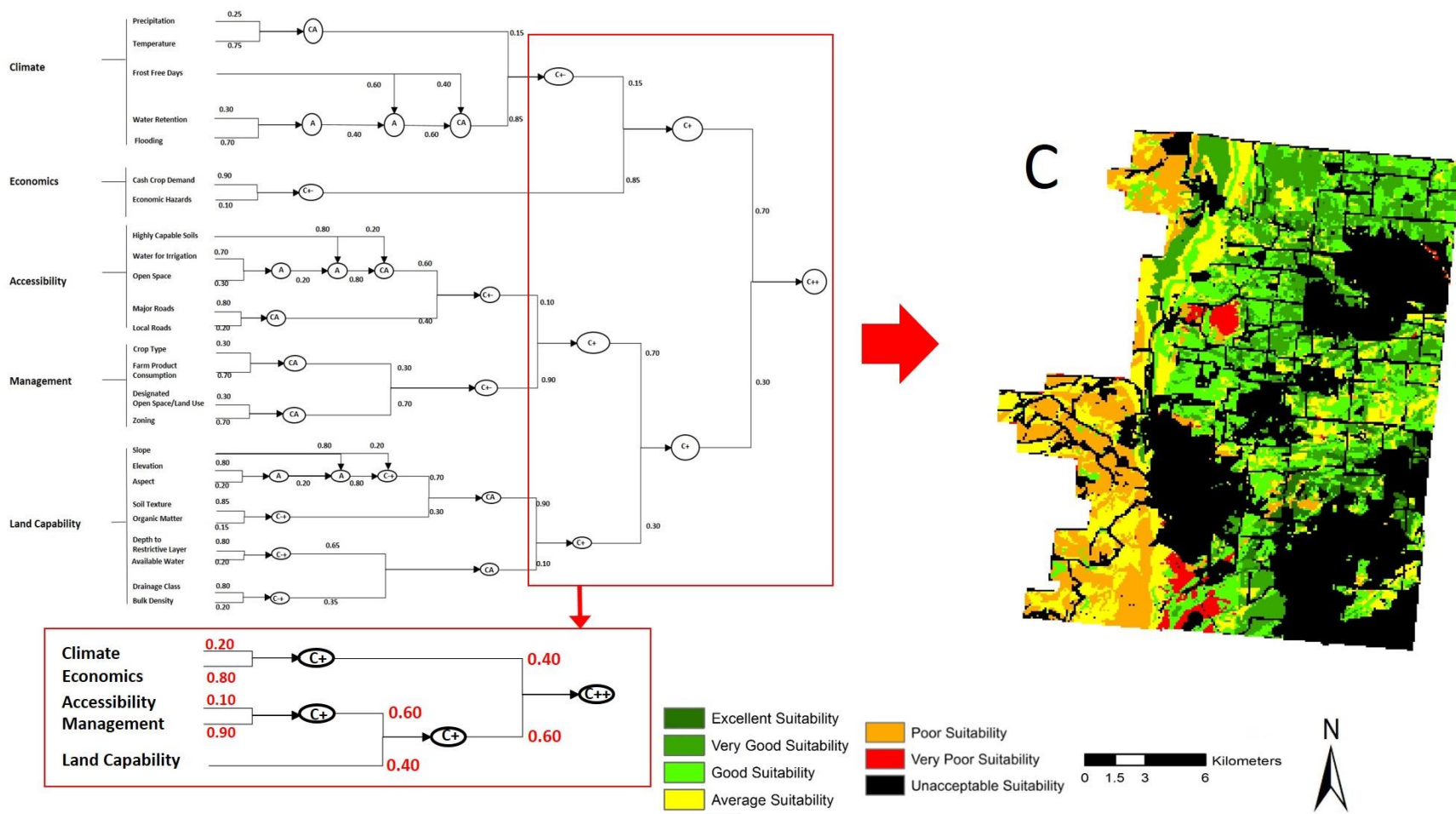


Figure 2.9 Agricultural land suitability LSP output maps emphasizing (A) land management criteria as scenario 2; (B) accessibility to physical land characteristics as scenario 3; and (C) agricultural economic criteria as scenario 4.

**Table 2.2 Table 2: The distribution of levels for agricultural capability and suitability scores for the USDA generated land capability and respectively obtained LSP maps for agricultural land capability and suitability for all four scenarios.**

Capability/Suitability Levels	USDA Land Capability		LSP Land Capability		LSP Agricultural Land Suitability Scenario 1	
	%	ha	%	ha	%	Ha
Excellent	27.3	26,764	28.0	27,467	4.6	4,486
Very Good	2.8	2,746	6.5	6,364	17.6	17,245
Good	0	0	6.9	6,741	17.5	17,217
Average	0	0	4.7	4,597	8.9	8,757
Poor	10.9	10,725	4.3	4,178	10.3	10,090
Very Poor	11.5	11,264	9.5	9,284	1.6	1,613
Unacceptable	47.5	46,653	40.1	39,385	39.5	38,808

Capability/Suitability Levels	LSP Agricultural Land Suitability Scenario 2		LSP Agricultural Land Suitability Scenario 3		LSP Agricultural Land Suitability Scenario 4	
	%	ha	%	Ha	%	Ha
Excellent	5.2	5,086	4.7	4,606	2.5	2,466
Very Good	17.3	17,002	20.3	19,889	14.4	14,129
Good	17.5	17,190	17.2	16,862	17.3	16,955
Average	8.6	8,399	8.8	8,640	14.3	14,052
Poor	10.3	10,143	8.5	8,348	10.3	10,137
Very Poor	1.6	1,589	1.0	1,013	1.7	1,670
Unacceptable	39.5	38,808	39.5	38,808	39.5	38,808

**Table 2.3      Table 3: The distribution of overall levels for agricultural suitability in respect to initial land use map categories and Scenario 1.**

Land Use Class	Excellent	Very Good	Good	Average	Poor	Very Poor	Unacceptable
Agriculture	2.8%	7.5%	4.4%	2.2%	0.3%	0.0%	7.9%
Grassland/Shrubland	0.8%	5.9%	6.9%	3.2%	3.2%	1.2%	7.0%
Forest	0.1%	0.6%	2.8%	2.1%	5.7%	0.1%	2.6%
Wetlands	0.4%	1.3%	1.2%	0.5%	0.4%	0.1%	2.4%
Water	0.2%	0.7%	0.9%	0.2%	0.1%	0.0%	0.8%
Urban	0.3%	1.6%	1.3%	0.7%	0.6%	0.2%	18.8%
Total	4.6%	17.6%	17.5%	8.9%	10.3%	1.6%	39.5%

## 2.6. Discussion and Conclusions

This study successfully implemented a GIS-based LSP method as an advanced and more precise MCE approach to evaluate agricultural land capability and land suitability. The case study was used to derive several different LSP aggregation structures and maps based on significant criteria encompassing physical land (land capability), climatic, economic, accessibility, and land management characteristics. The LSP input attributes were evaluated using suitability functions. The highest values of capability and suitability scores as presented in the output maps were mostly obtained for areas of highly capable soils and close accessibility to urban infrastructure. Moreover, comparison of the LSP agricultural land capability map with the USDA soil capability map indicated small disagreements, demonstrating the effectiveness of the GIS-based LSP method. In the eastern region of the study area the large portion of the agricultural land has the highest capability scores confirming that current agricultural land was developed on highly capable land. The utilization of four additional agricultural land suitability scenarios provided a good indication of how suitability output maps vary as a result of different decision-making perspectives. Scenario 2 favoring management criteria, indicates that areas of excellent suitability are concentrated around open space and close to agricultural zoning areas. Scenario 3 presented

the largest amount of excellent and very good suitability lands. Scenario 4 displayed similar results to Scenario 2, but overall results in a reduced amount of excellent suitability lands. When comparing all scenarios, Scenario 3 (focused on the accessibility to physical land characteristics) indicates that most of the land in the study area is in the first three categories of excellent, very good, and good suitability. Scenario 4 (focused primarily on agricultural economic criteria), indicates the smallest amount of excellent suitability land for agricultural production.

The LSP-MCE method proposed in this study was able to demonstrate the capabilities of the method for land suitability evaluation; however, the LSP-MCE method has limitations. The development and design of the LSP-MCE method may be too complex for some users to understand. Specifically, when applying the logic aggregators, it may become difficult to determine the range of human decision-making logic that is needed and selecting the proper logic aggregators to reflect the range of logic. Moreover, the LSP-MCE method was only able to combine two input criteria at a time due to the combination capabilities within the Idrisi software. This limits the combining capabilities of the method, as previous literature presents combinations of three or more input criteria (Dujmović, 2007; Dujmović and Scheer, 2010; Dujmović et al., 2010). Future research should focus on using real stakeholders to help determine the parameters of the study in order to improve the selection of the logic aggregators. Moreover, future research should look at using different modeling software to allow for the combination of three or more input criteria using the same logic aggregator. This should improve the LSP-MCE method and will provide enhanced suitability results.

Overall, the LSP method was capable of encompassing a much larger number of input criteria than the commonly used GIS-based MCE approaches and was used to evaluate overall agricultural land capability and suitability using real datasets. The proposed GIS-based LSP method is an improved MCE approach that represents an excellent tool for discussion and deliberation among stakeholders, decision makers, land-use planners and other experts.

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## **Chapter 3.**

# **Comparison of GIS-based multi-criteria evaluation methods and the logic scoring of preference methods using receiver operating characteristic metrics \***

### **3.1. Abstract**

Multi-criteria evaluation (MCE) methods can be useful tools to evaluate the land suitability for agricultural or urban use and assist effective management of available land. When using these methods, it is assumed that they address observable human decision-making logic; however, many common GIS-based MCE methods do not represent human reasoning at a full spectrum. Some improved methods are needed to address some of the drawbacks of commonly used GIS-based MCE. The main objectives of this study are to: (1) propose and implement a soft computing-based Logic Scoring of Preference (LSP) approach as an improved GIS-based MCE method to evaluate agricultural and urban land suitability and (2) to compare the LSP method with other commonly used GIS-based MCE methods. The study compared the LSP approach with the analytical hierarchy process (AHP), ordered weighted averaging (OWA), and a combination of AHP and OWA methods (AHP-OWA) for the cases of urban and agricultural land suitability evaluation. Receiver operating characteristic (ROC) statistics are used as comparison metrics. Results indicate that soft computing methods were the strongest among GIS-based MCE methods for both land use applications.

\*A version of this chapter will be submitted for publication in *Geographical Analysis* and is coauthored with Dr. Suzana Dragičević.

## 3.2. Introduction

Multi-criteria evaluation (MCE) is a well-known method for spatial decision making in the field of geography (Voogd, 1983, Carver, 1991, Jankowski, 1995, Thill, 1999). MCE is comprised of a multitude of evaluation criteria, and a preference weighting scheme to evaluate decision-making alternatives. The coupling of MCE with geographic information systems (GIS) has improved spatial decision-making processes when dealing with semi structured decision problems that are typical for land suitability evaluations. GIS has the capabilities to analysis, process, display, and manage spatial data that can be integrated with decision maker preferences to determine evaluation alternatives (Ceballos-Silva and Lopez-Blanco, 2003; Boroushaki and Malczewski, 2008). GIS-based MCE spatial applications have been extensively used but are focused primarily on urban land use (Wu 1998), environmental planning and management (Store and Kangas, 2001), agriculture (Ceballos-Silva and Lopez-Blanco, 2003), and land suitability (Malczewski et al., 2003).

Many GIS-based MCE methods have been applied to geographic contexts to optimize decision-making processes for land suitability (Store and Kangas, 2001; Kalogirou, 2002; Malczewski, 2006b; Yu et al., 2011). The most commonly used MCE methods are simple additive weighting (Malczewski, 1999), multiattribute value and utility techniques (Keeney, 1996; Keeney and Raiffa, 1993), the analytical hierarchy process (AHP) (Saaty, 1980), ordered weighted averaging (OWA) (Yager, 1988), and outranking methods (Kangas et al., 2001). Specifically, MCE methods such as AHP, OWA, and methods constructed with fuzzy sets or quantifiers are developed for the GIS-based Idrisi software (Jiang and Eastman, 2000) to optimize evaluation alternatives. AHP (Saaty, 1980) has been a widely utilized MCE method because of its pairwise comparison matrix providing objective weight calculations. Criticisms have suggested that the theoretical functions and lack of flexibility from its hierarchy aggregation structure limit the ability to realistically evaluate geographic decision problems (Malczewski, 2004; Dujmović et al., 2009). To improve upon the limitations of AHP, OWA has gained popularity for its ability to describe a number of decision-making strategies, tradeoffs and risk through the utilization of OWA operators (Yager 1988, Jiang and Eastman, 2000). Additionally, OWA operators provide flexibility and address a range of human decision-making logic. Issues arise when evaluation criteria are not described based on their satisfaction in evaluation and its inability to address a full spectrum of human decision-making logic (Dujmović et al., 2009). The application of the OWA has also



prompted research combining AHP and OWA methods as an enhanced method. The method is comprised of pairwise comparisons and OWA operators, allowing for objective weight calculation and additional flexibility to determine alternatives (Yager and Kelman, 1999).

Despite the effort to optimize GIS-based AHP and OWA methods, there is a lack of information in the literature on comparisons between these methods. Many studies have focused primarily on AHP, weighted summation methods, multiattribute techniques, and outranking methods to compare the applicability and ease of use for decision makers as well as the accuracy of their results with previous land use problems (Karni et al., 1990; Zanakis et al., 1998; Hajkowicz and Higgins, 2008; Yalcin, 2008). As a result, decision-making alternatives were oversimplified for planners and stakeholders to intuitively understand (Hayashi, 2000; Malczewski, 2006b; Dujmović et al. 2009).

Comparisons involving both AHP and OWA originate from the comparison of Boolean and Weighted Linear Combination (WLC) by Hall and Wang (1992) and were later extended to include AHP and OWA to address land suitability problems and display differences in suitability scores between methods (Jiang and Eastman, 2000). Dujmović et al. (2009) and Dujmović and de Tré (2011) compared the theoretical properties of MCE methods including AHP and OWA and their ability to evaluate land use suitability maps. Feizizadeh and Blaschke (2012) compared known landslides with landslide susceptibility output maps derived from AHP, OWA, and WLC methods. Finally, the ideal point method, WLC, and OWA methods were compared using ancillary multiple criteria to determine the most effective OWA method (Jankowski et al., 2014). Although these studies used MCE methods to compare and evaluate land-use change that has occurred over time, the comparisons do not provide any statistical metrics by which to compare the resulting suitability output maps, and have thus, limited their comparisons.

MCE methods are simplified through the use of a small number of evaluation criteria and making the models user friendly for stakeholders and decision makers. These simplifications have reduced the capability of these methods to express complex decision-making, which these methods were designed to model. As a result, the models do not provide enough complexity to completely address observable human decision-making logic (Dujmović et al. 2009). This can be attributed to reliance on simple additive models, which restricted theoretical and operational validation of MCE methods (Malczewski, 2006). Other complications included the use of fixed logic, situating decision-making logic between conjunction (andness) and disjunction (orness)

(Dujmović and de Tré, 2011). Through the use of partial conjunction/disjunction, partial absorption, and a range of logic conditions, the Logic Scoring of Preference (LSP) method provides the necessary components to effectively represent observed human reasoning and address previous MCE method limitations. Previous comparisons including those suggesting the use of LSP method did not provide statistical evidence to validate the LSP method as the best method to use for land suitability evaluation. Therefore the main objectives of this study are to: (1) present the GIS-based LSP method for agricultural and urban land suitability evaluations, and (2) compare the LSP-based MCE approach with other commonly use GIS-based MCE methods.

### **3.3. Theoretical Background**

Four GIS-based MCE methods are used for comparison in this study: 1) analytical hierarchy process (AHP), 2) ordered weighted averaging (OWA), 3) a combination of AHP and OWA methods (AHP-OWA), and 4) logic scoring of preference (LSP) methods. The characteristics of each method are explained in the following sections.

#### **3.3.1. Analytical Hierarchy Process**

AHP is an effective MCE method used in land suitability analysis (Akinci et al., 2013; Hill et al., 2005) and weight calculation (Saaty, 1980). Reasoning for its use is derived from the ability to simplify complex decision-making problems by identifying and weighting evaluation criteria, while testing for consistency of evaluation criteria weights (Hossain et al., 2007).

AHP utilizes pairwise comparisons to objectively calculate elementary criteria weights through the use of a pairwise matrix (Borouhaki and Malczewski, 2008). Sets of evaluation criteria are compared and assigned preference values (Table 1) to derive their specific relative importance (Saaty, 1980). In order to maintain objectivity, a consistency ratio is calculated to identify judgement consistency. Consistency ratios ranging between 0 and 0.10 are considered acceptable for evaluation. If the range of consistency is not met, the decision maker must adjust values in the pairwise matrix until consistency is met.

**Table 3.1 AHP preference scale for pairwise comparison derived from Saaty (1980) and Akinci et al. (2013).**

Intensity of Importance	Definition	Explanation
1	Equal importance	Equal contribution
3	Somewhat more important	One slightly more in favor over another
5	Moderate importance	One favored strongly over the other
7	Strong importance	One favored very strongly over another
9	Absolute importance	One favored over another is of highest possible order of affirmation
2,4,6,8	Intermediate values	Compromise needed

Once evaluation criteria are weighted, normalized, and ranked, additive weighting functions are applied at each level of the hierarchy to calculate an aggregated suitability score (Jankowski, 1995). Issues with AHP arise due to the meaning of method assumptions and priorities, its inability of pairwise comparisons to handle the ambiguity of value conversions (Malczewski, 2006b; Feizizadeh and Blaschke, 2012), and its lack of flexibility to represent a range of human decision-making logic (Dujmović et al., 2009; Dujmović and de Tré, 2011).

### 3.3.2. Ordered Weighted Averaging

OWA is a class of operators used to describe a range of decision-making solutions through the utilization of criteria and ordered weights in a decision-strategy space (Yager 1988). The application of OWA operators has been used as an extension of Boolean and weighted linear combination (WLC) methods to generate strategy alternatives for evaluating land suitability (Jiang and Eastman, 2000; Malczewski et al. 2003). Criteria weights are calculated and assigned to indicate relative importance of a specific criterion in the evaluation criteria set. Ordered weights are applied to evaluation criteria and their associated weights within the decision strategy space to determine decision-making strategies (Malczewski, 2006a) (Table 2). Moreover, the application of ordered weights incorporates a range of tradeoff and risk associated with how well higher suitability values compensate for lower suitability values and how much the final solution will be affected by specific evaluation criteria (Jiang and Eastman, 2000; Feizizadeh and Blaschke, 2012).

OWA operators parameterize the attributes and reflect decision maker preferences through the use of mean-type aggregation. Specifying different combinations of ordered weights produces a range of different OWA operators. Variance in OWA operators generates various

decision-making alternatives addressing a range of human decision-making logic. Issues arise due to the inability of describing the desired satisfaction for elementary criteria and fully representing observable human decision-making logic (Dujmović and de Tré, 2011). To account for these issues, studies have improved the capabilities of OWA by utilizing fuzzy linguistic quantifiers (Yager, 1996; Malczewski, 2006a) and incorporating AHP for weight calculations (Boroushaki and Malczewski, 2008).

### **3.3.3. Combination of AHP and OWA**

The coupling of AHP and OWA methods (AHP-OWA) combines the hierarchy structure and pairwise comparisons of AHP with the operators and ordered weights of OWA to determine decision-making strategies (Yager and Kelman, 1999; Boroushaki and Malczewski, 2008) and evaluate land suitability (Gorsevski et al., 2012; Chen and Paydar, 2010). The AHP hierarchy structure and pairwise comparisons provide a structured model to objectively determine the relative importance of evaluation criteria and organize the decision problem. OWA operators apply aggregations at each level of the AHP hierarchy using the OWA combination function until a final aggregated suitability output is obtained (Boroushaki and Malczewski, 2008). Within the OWA decision strategy space, ordered weights provide an indication of the tradeoff and risk associated with the evaluation criteria. As a combined method, AHP-OWA provides enhance capabilities for evaluating suitability while maintaining objective weight calculation and providing flexibility in the determination of decision-making strategies.

### **3.3.4. Logic Scoring of Preference**

The Logic Scoring of Preference (LSP) method is a soft computing method for evaluation of criteria and their attributes using logic operators observed in human reasoning (Dujmović et al., 2009). LSP was designed for applications in computer science, but has been recently coupled with GIS to evaluate land use suitability for urban points of interest (Dujmović and Scheer, 2010), residential home location (Dujmović and de Tré, 2011), and urban residential land use (Hatch et al., 2014).

The LSP method is comprised of three main components: an attribute tree, elementary criteria, and LSP aggregation structure. The attribute tree is created by the hierarchical

decomposition of suitability attributes, which are decomposed into categories based on their usefulness (Dujmović et al. 2010). This process continues until suitability attributes are simple and can no longer be decomposed (Dujmović 2007).

Mandatory (+) and optional (-) logic conditions are applied to suitability attributes to represent their satisfaction and a range of simultaneity (andness) and replaceability (orness). Mandatory suitability attributes must be satisfied to determine the evaluation as useful, while optional suitability attributes do not need to be satisfied to complete the evaluation. Optional suitability attributes are satisfied if mandatory suitability attributes are satisfied first; however, if optional suitability attributes are satisfied without the satisfaction of mandatory suitability attributes, then the evaluation is deemed unusable. Once logic conditions are applied, weights of relative importance are determined in order to reflect decision maker preferences in the evaluation.

Elementary criteria represent the individual requirements of each attribute (Dujmović and Scheer, 2010) and are standardized using suitability functions. The application of suitability functions determines the level of satisfaction for specific attributes. Satisfaction is determined on a scale from 0 to 1. A value of 0 represents unacceptable satisfaction, and a value of 1 represents complete or perfect satisfaction. Values ranging between 0 and 1 represent partial satisfaction (Dujmović et al., 2010).

Elementary criteria are combined by LSP aggregators until a final suitability output map is generated. LSP aggregators comprise the LSP aggregation structure, which follows the hierarchical structure of the attribute tree (Dujmović et al., 2010; Dujmović and de Tré, 2011). Moreover, LSP aggregators represent a range of logic conditions observed in human decision-making logic through the use of a general conjunction/disjunction (GCD) function (Dujmović 2008), the conjunctive partial absorption (CPA) function, and the disjunctive partial absorption (DPA) function (Dujmović 1979). A range of simultaneity (andness) and replaceability (orness) is utilized from the selection of aggregators to model hard and soft partial conjunction/disjunction (Dujmović et al., 2010). Hard and soft partial conjunction/disjunction aggregators are applied to mandatory elementary criteria, and the CPA function is used when combining mandatory and optional elementary criteria (Dujmović et al., 2010; Dujmović and de Tré, 2011). The suitability is calculated when a mandatory input, X, and an optional input, Y, are aggregated together:

$$S(X, Y) = \{(1 - W_1)[W_2 X^{r_1} + (1 - W_2) Y^{r_1}]^{\frac{r_2}{r_1}} + W_1 X^{r_2}\}^{\frac{1}{r_2}} \quad (1)$$

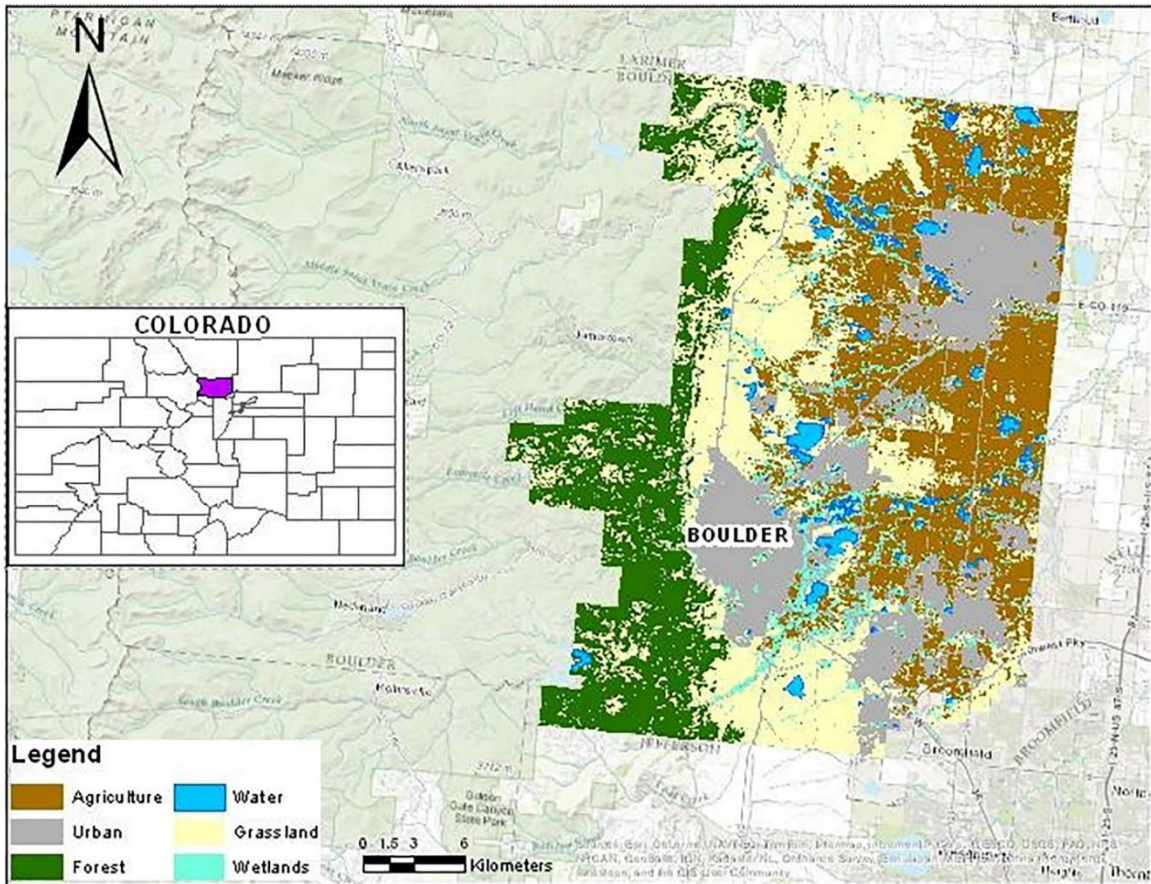
$$\forall X > 0, \quad S(X, 0) > 0, \quad S(0, Y) = 0$$

where  $S(X, Y)$  denotes the output suitability for the combination of mandatory and optional suitability inputs. The weighting parameters,  $W_1$  and  $W_2$ , are normalized weights that represent the relative importance of each input, and the parameters,  $r_1$  and  $r_2$ , represent the logic aggregators. The application of aggregators representing a range of simultaneity and replaceability provides a continuous, step-wise logic, which is useful in providing flexibility and incorporating a large number of elementary criteria without losing significance (Hatch et al., 2014). These capabilities make the LSP method more effective than other MCE methods and thus, LSP should be utilized as an extension of previous MCE methods.

### 3.4. Methods for Comparison of GIS-based MCE

#### 3.4.1. Study Area, datasets and context

The study was developed using data from Boulder County, Colorado, USA (Figure 3.1). The study area is experiencing increases in its urban population, converting agricultural land use for urbanization. Consequentially, as the demand for food increases as population increases, it is important to allocate available land for agricultural production. Moreover, an opposite process exists and this is the conversion of available land to agricultural land use by designating open space for agricultural production and reducing urbanization. As agricultural land in the study area provides agricultural products at local, statewide, and nationwide scales (Andrews et al., 2011; USDA, 2014), Boulder County, Colorado, USA is an important study area. In order to satisfy increasing urban and agricultural demands, MCE methods can be used to address the socio-economic and environmental factors which influence agricultural and urban land suitability.



**Figure 3.1 The study area in Boulder County, Colorado, USA.**

Spatial and numerical datasets used for the study were comprised of socio-economic and environmental data. Most of the data pertaining to soil, agricultural land use, accessibility, and topographical data were obtained through the United States Department of Agriculture's (USDA) various web-based tools and databases (Geospatial Data Gateway, 2014; NRCS, 2014; USDA, 2014b). Land use and climate data were obtained from the Boulder County Department of Geographic Information Systems and the National Oceanic and Atmospheric Administration (NOAA), respectively (Boulder County Maps & Data, 2014; NOAA, 2014). Additional data was obtained from the 2012 USDA Census of Agriculture (USDA, 2014a) and the United States Census Bureau (US Census Bureau, 2014).

### **3.4.2. MCE methods comparisons**

The LSP, AHP, OWA, and AHP-OWA were used in both case studies to evaluate land suitability. For evaluation consistency, each method utilized the same parameterization: 1) evaluation criteria

and their corresponding suitability functions, 2) relative importance of all evaluation criteria, and 3) compared using fundamental properties of MCE methods.

There are ten fundamental properties of human evaluation logic that MCE methods should address according to Dujmović et al. (2009):

1. Ability to combine any number of attributes
2. Ability to combine objective and subjective inputs
3. Ability to combine absolute and relative criteria
4. Flexible adjustment of relative importance of attributes
5. Modelling of simultaneity requirements (soft and hard)
6. Modelling of replaceability requirements (soft and hard)
7. Modelling of balanced simultaneity/replaceability
8. Modelling of mandatory and optional requirements
9. Modelling of sufficient and optional requirements
10. Ability to express suitability as an aggregate of usefulness and inexpensiveness

In this study fundamental properties 1-5 and 8 were used for comparisons, as the evaluation criteria used in the study are characterized with a high degree of simultaneity and that most of the remaining properties only characterize the LSP method. Furthermore, the study does not take into account the use of sufficient requirements as evaluation criteria must be satisfied and cannot be evaluated on the basis of sufficiency. As a whole, these properties provide an indication of strengths and limitations of MCE methods.

MCE methods were compared using fundamental MCE properties throughout model development. The properties chosen for comparison reflected the structure and flexibility of each method and how their modeling capabilities were affected. The decision maker can determine whether or not each method addressed the fundamental properties through the development and implementation of the MCE methods.



### 3.4.3. Metrics for comparison of the suitability maps

Suitability output maps generated by the MCE methods were compared using fundamental properties of MCE as outlined in Dujmović et al. (2009), the receiver operating characteristic's area under the curve (AUC) metric, and the shape of the resulting ROC curves. Methods that addressed the most fundamental properties, the highest obtained AUC values and the best fitting ROC curves were determined the strongest MCE method.

The ROC method was often used for statistical characteristics in the validation and comparison of land suitability maps and use of a single Boolean variable (candidate region) describing the presence and absence of a given classification (Schneider and Pontius, 2001). The candidate region represents a specific region of the study area where high suitability values are expected. For example, the candidate region represents a portion of the study area where agricultural development is expected to take place. Higher accuracy is attributed to the proportion of higher ranking index values (suitability scores) observed in the candidate region where presence is displayed and the proportion of lower ranking index values that are observed where absence is displayed (Pontius and Parmentier, 2014).

Thresholds are applied to the range of index values to determine presence and absence of the candidate region. Index values higher than a given threshold indicate presence and values below the threshold indicate absence. A contingency table is then generated to summarize the total presence and total absence in the candidate region associated with each threshold (Pontius and Si, 2014).

A ROC curve is designed to represent the relationship between the proportion of presence and proportion of absence in the candidate region. This ROC curve plots the rate of true positives and false positives obtained from the application of thresholds to the range of index values. (Pontius and Parmentier, 2014). Thresholds are plotted between the points (0, 0) and (1, 0) to display where point (0, 0), represents the highest threshold where no high-ranking index values are above the threshold, and point (0, 1) represent the lowest threshold where no low-ranking values are below the threshold.

ROC describes accuracy using two metrics: the area under the curve (AUC) metric and the shape of the ROC curve. The AUC metric is a comparison value that summarizes the

relationship between the candidate region and the applied thresholds (Overmars et al., 2007; Pontius and Parmentier, 2014). AUC is represented on a scale between 0 and 1, where a value of 1 is perfect accuracy and an AUC value of 0 is unacceptable.

When determining the accuracy of land suitability maps using the shape of the ROC curve, one can gain a better understanding of the relationship between the index values and the candidate region (Pontius and Parmentier, 2014). Thresholds displaying a vertical trend in close proximity to the Y-axis represents a high proportion of high ranking index values are observed as presence in the candidate region ( $\text{Hits} / (\text{Hits} + \text{Misses})$ ) and provides higher accuracy. Similarly, thresholds displaying a horizontal trend located in close proximity to the upper boundary of the graph indicates a high proportion of low ranking values observed as absence in the candidate region ( $\text{False Alarms} / (\text{False Alarms} + \text{Correct Rejections})$ ); this, too, provides higher accuracy.

In this study, the ROC module in the Idrisi software was used to compare suitability output maps generated from the MCE methods. The MCE methods were compared using three thresholds and a case study-specific candidate region. For urban land suitability, the candidate region corresponded to areas of potential urban development as specified in the Boulder County Comprehensive Plan (Boulder County Land Use Department, 1999). Similarly, the agricultural land suitability candidate region corresponded to regions of current agricultural zoning and designated open space under the Boulder County Comprehensive Plan.

Suitability output maps, the case study-specific candidate regions, and the three thresholds were implemented within the ROC module to generate contingency tables outlining presence (true positives) and absence (false positives) within the candidate region and the corresponding AUC value. ROC curves were constructed using the three thresholds and the resulting true positives and false positives associated with each threshold. ROC curves constructed for each MCE method were plotted together to show differences between each method for the give case studies. The strongest MCE method for each case study was determined by: 1) the highest AUC value and 2) ROC curves displaying the strongest shape.

## **3.5. Case Studies**

The GIS-based Idrisi software was used to implement various MCE methods and generate their respective suitability output maps. The suitability output maps were generated as raster maps and utilized GIS-based datasets that were utilized at a spatial resolution of 50 m. Suitability scores were standardized on a scale from 0 to 1, with 0 as unacceptable and 1 as excellent, and then classified into seven suitability levels using the equal interval classification method: excellent [1.00-0.86], very good (0.86-0.71], good (0.71-0.57], average (0.57-0.43], poor (0.43-0.28], very poor (0.28-0.14], and unacceptable (0.14-0.00]. The six of the fundamental MCE properties were used to compare suitability output maps and the construction of each MCE method in order to determine the method that met the most properties. Moreover, resulting suitability output maps were statistically compared using the ROC method.

### **3.5.1. Urban Land Suitability**

The urban land suitability case study was developed in order to evaluate available land for future residential development using a large amount of evaluation criteria. Urban land suitability studies have previously utilized MCE methods such as AHP (Wu, 1998), OWA (Malczewski, 2006), AHP-OWA (Borouhaki and Malczewski, 2008), and LSP (Dujmović and de Tré, 2011; Hatch et al., 2014) for evaluation; however, many of the studies relied on a small amount of evaluation criteria, which reduces the ability to incorporate enough evaluation criteria to fully represent observed human decision-making logic. The LSP method has utilized a larger amount of evaluation criteria in a previous study (Hatch et al., 2014), but did not compare LSP to commonly used MCE methods. In this study, the MCE methods integrated a larger amount of evaluation criteria than in previous studies to determine the strongest method for urban land suitability evaluation.

To characterize urban land suitability in Boulder County, Colorado, USA, 15 evaluation criteria were used to describe terrain, amenities, population, and accessibility perspectives: slope, elevation, aspect, distance to surface water, distance to parks and open space, distance to residential housing, distance to agriculture, price of housing, household income, renting, vacancy, distance to major roads, distance to employment, population density, distance to existing urban land use. Suitability functions were developed to standardize evaluation criteria on a scale from 0 to 1 (Figure 3.2). Evaluation criteria were integrated in method-specific aggregation structures

where weights calculated by method-specific weighting schemes reflect the relative importance of each criterion.

### **3.5.1.1 AHP**

AHP is comprised of a pairwise comparison matrix used to generate criterion weights (Table 3.1). Evaluation criteria were incorporated into the pairwise comparison matrix and assigned values from the preference scale suggested in Saaty (1980) (Table 3.2). The preference scale includes values ranging from 1 to 9, representing equal importance to absolute importance, respectively. Values were derived from the literature and were assigned in the pairwise comparison matrix. Once values were assigned, column values were divided by the sum of each column. Row elements are summed and divided by the number of values per row (Akinici et al., 2013).

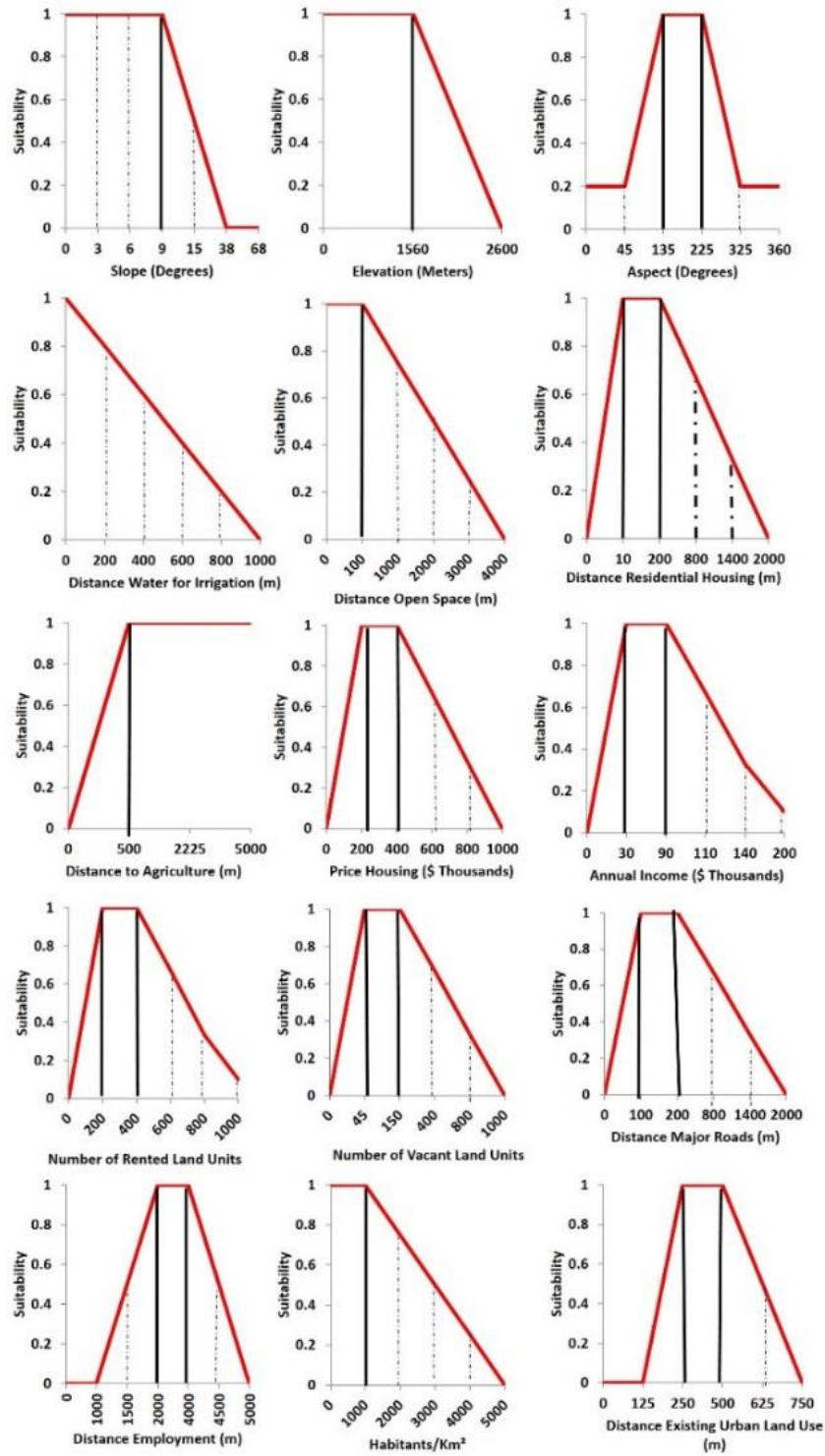


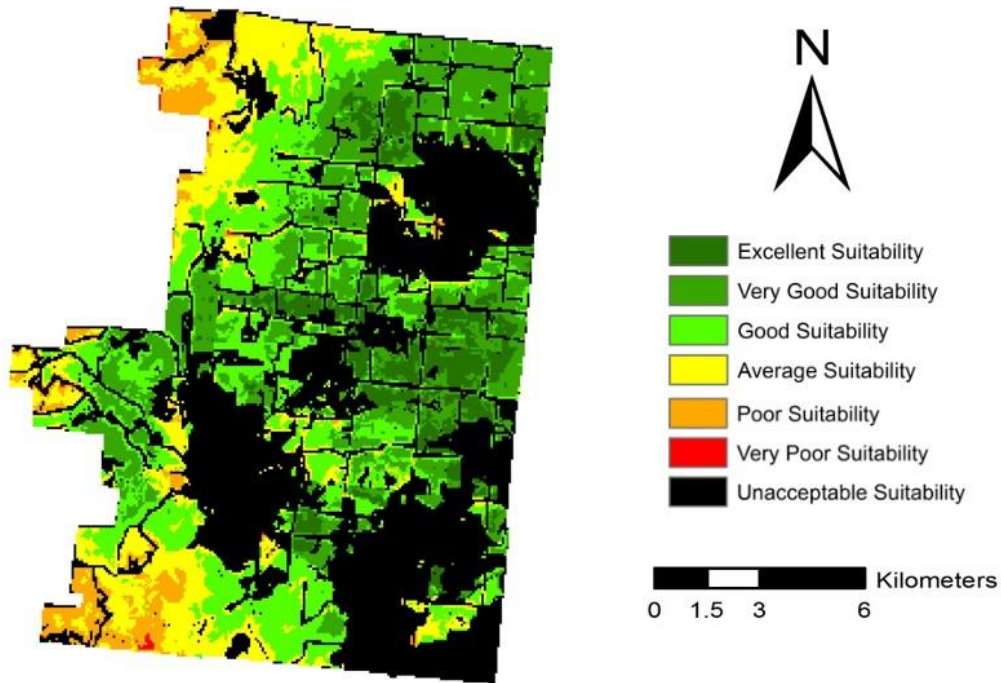
Figure 3.2 Suitability functions characterizing urban land suitability evaluation criteria.

**Table 3.2 The pairwise comparison matrix for urban land suitability evaluation.**

	HI	MR	RH	Employ	PH	EULU	Ag	Slope	Elevation	PD	P & OS	SW	Vacancy	Aspect	Renting	Weights
Household Income	1	3	3	3	5	5	5	5	7	7	7	7	9	9	9	0.2166
Major Roads	1/3	1	3	3	5	5	5	5	5	7	7	7	9	9	9	0.1823
Residential Housing	1/3	1/3	1	1	3	3	5	5	5	5	7	7	9	9	9	0.1262
Employment	1/3	1/3	1	1	3	3	5	5	5	5	5	7	9	9	9	0.1238
Price of Housing	1/5	1/5	1/3	1/3	1	1	1	3	3	5	5	5	7	7	7	0.0664
Existing Urban Land Use	1/5	1/5	1/3	1/3	1	1	1	3	3	3	5	5	5	7	7	0.0622
Agriculture	1/5	1/5	1/5	1/5	1	1	1	1	3	3	5	5	5	7	7	0.0542
Slope	1/5	1/5	1/5	1/5	1/3	1/3	1	1	3	3	5	5	5	7	7	0.0490
Elevation	1/7	1/5	1/5	1/5	1/3	1/3	1/3	1/3	1	1	1	3	5	5	5	0.0287
Population Density	1/7	1/7	1/5	1/5	1/5	1/3	1/3	1/3	1	1	1	1	3	3	5	0.0228
Parks and Open Space	1/7	1/7	1/7	1/5	1/5	1/5	1/5	1/5	1	1	1	1	3	3	3	0.0199
Surface Water	1/7	1/7	1/7	1/7	1/5	1/5	1/5	1/5	1/3	1	1	1	1	3	3	0.0168
Vacancy	1/9	1/9	1/9	1/9	1/7	1/5	1/5	1/5	1/5	1/3	1/3	1	1	1	3	0.0122
Aspect	1/9	1/9	1/9	1/9	1/7	1/7	1/7	1/7	1/5	1/3	1/3	1/3	1	1	1	0.0098
Renting	1/9	1/9	1/9	1/9	1/7	1/7	1/7	1/7	1/5	1/5	1/3	1/3	1/3	1	1	0.0091

Consistency Ratio = 0.07

Calculated values represented normalized weights and sum to a total of 1. Obtained weights were ranked and applied at each level of the hierarchy structure, and evaluation criteria were aggregated using additive weighting functions to generate a suitability output map (Figure 3.3).



**Figure 3.3** The urban land suitability map obtained with the AHP-based MCE method.

### **3.5.1.2 OWA**

OWA utilized a combination of criteria and ordered weights to develop a suitability output. Evaluation criterion weights were applied to the 15 evaluation criteria based on decision maker perspectives and relative importance similar to those used for AHP (Table 3.3).

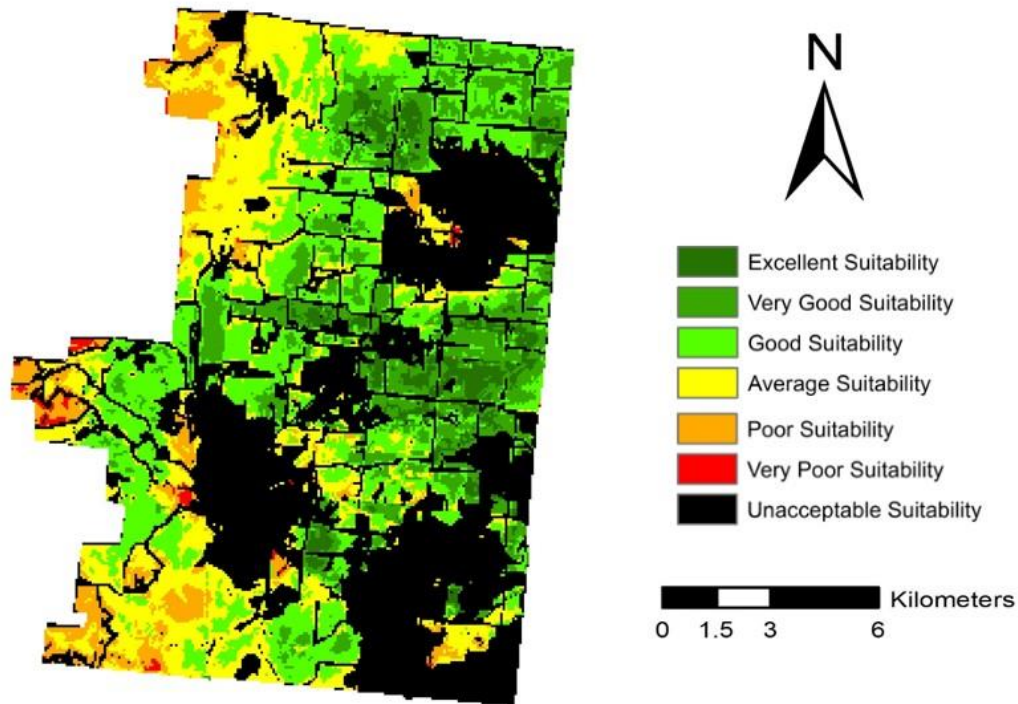
**Table 3.3 Criteria weights and their corresponding ordered weights to represent tradeoff and risk in urban and agricultural land suitability evaluations.**

Urban Land Suitability		
Criteria	Criteria Weights	Ordered Weights
Household Income	0.2166	0.0727
Major Roads	0.1823	0.0712
Residential Housing	0.1262	0.0704
Employment	0.1238	0.0697
Price of Housing	0.0664	0.0689
Existing Urban Land Use	0.0622	0.0681
Agriculture	0.0542	0.0673
Slope	0.0490	0.0666
Elevation	0.0287	0.0658
Population Density	0.0228	0.0651
Parks and Open Space	0.0199	0.0643
Surface Water	0.0168	0.0636
Vacancy	0.0122	0.0628
Aspect	0.0098	0.0621
Renting	0.0091	0.0613

Household income was determined as the most important evaluation criteria based on the fact that housing in the study area is expensive and requires a high household income to live within the region. Ordered weights represented tradeoff and risk between evaluation criteria based on how many evaluation criteria need to be satisfied and the distribution of the weights. In the study, most of the evaluation criteria had to be satisfied for evaluation and a modest amount of tradeoff was desired. As a result, the calculated weights corresponded to aggregators reflecting a high degree of simultaneity (andness) (Malczewski, 2006a), which resulted in ordered weights closer towards a high degree of simultaneity and provided a relatively average amount of tradeoff (Jiang and Eastman, 2000). Moreover, ordered weights were distributed so that lower ordered weights received lower values and higher ordered weights received higher values. Additionally, the summation of the ordered weights equaled 1. The OWA aggregators determined by the ordered



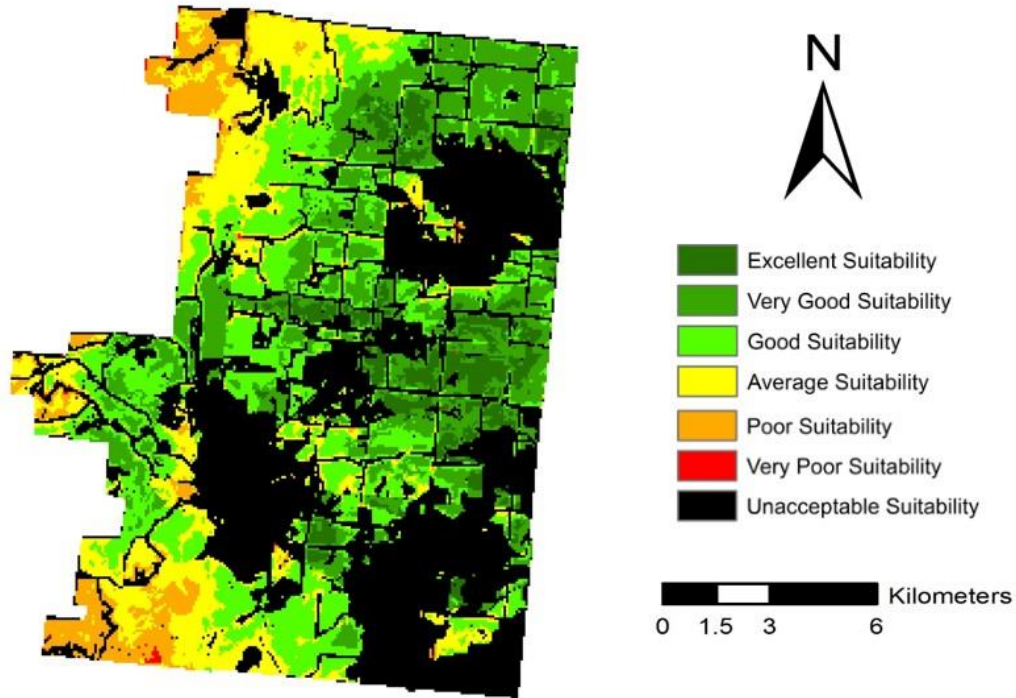
weights aggregated evaluation criteria together until a suitability output map was generated (Figure 3.4).



**Figure 3.4** The urban land suitability map obtained with the OWA-based MCE method.

### **3.5.1.3 AHP-OWA**

Third, the AHP-OWA method was designed to implement components of both AHP and OWA used in the study. The AHP pairwise comparison matrix and its calculated weights were coupled with the ordered weights and OWA operators of OWA to produce a suitability output map. Based on the previous methods, AHP-OWA was comprised of criteria weights and ordered weights reflecting a high degree of andness and a large amount of tradeoff. Resulting OWA operators aggregated evaluation criteria until a suitability output map representing the decision making alternative was generated (Figure 3.5).



**Figure 3.5** The urban land suitability map obtained with the AHP-OWA-based MCE method.

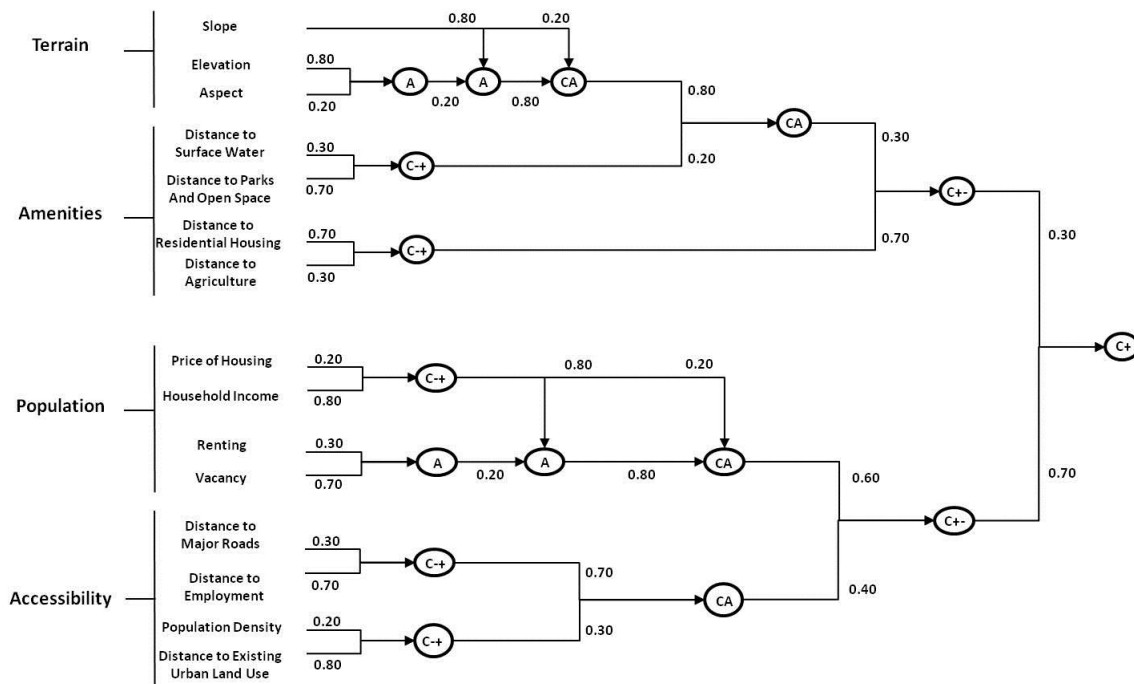
### 3.5.1.4 LSP

When the evaluation criteria were incorporated into LSP, they were organized using an attribute tree (Figure 3.6) and determined as either mandatory or optional and categorized based

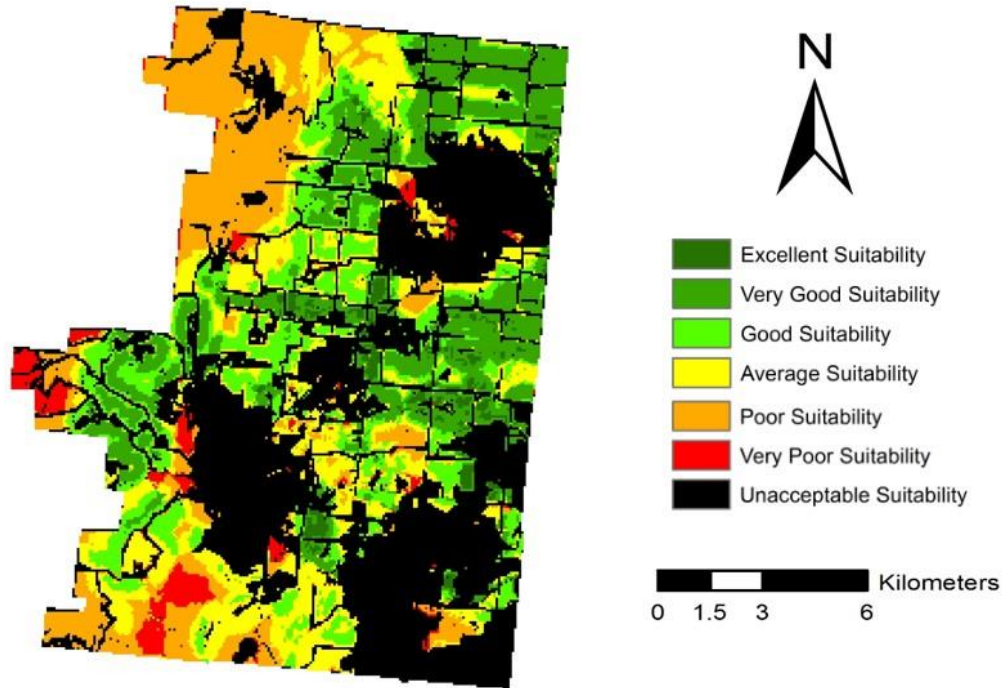
1. Suitability for Urban Land	
1.1 Terrain	
1.1.1	Slope (+)
1.1.2	Elevation (-)
1.1.3	Aspect (-)
1.2 Amenities	
1.2.1	Distance to Surface Water (+)
1.2.2	Distance to Parks and Open Space (+)
1.2.3	Distance to Residential Housing (+)
1.2.4	Distance to Agriculture (+)
1.3 Population	
1.3.1	Price of Housing (+)
1.3.2	Household Income (+)
1.3.3	Renting (-)
1.3.4	Vacancy (-)
1.4 Accessibility	
1.4.1	Distance to Major Roads (+)
1.4.2	Distance to Employment (+)
1.4.3	Population Density (+)
1.4.4	Distance to Existing Urban Land Use (+)

**Figure 3.6** The LSP attribute tree for urban land suitability.

on the perspectives they reflect. A range of LSP aggregators were assigned to combine evaluation criteria in each category. LSP aggregators were determined based on previous literature to display a range of decision making logic and constitute the LSP aggregation structure (Figure 3.7). LSP aggregators ranged from neutral to hard partial conjunction (A, C-+, CA, C+-, C+) as most of the evaluation criteria were mandatory. Weights of relative importance were applied to represent relative importance determined by expert knowledge and previous studies. Evaluation criteria were aggregated through continuous and step-wise logic until one final suitability output map was generated and presented in Figure 3.8.



**Figure 3.7** The LSP aggregation structure for urban land suitability created with 15 evaluation criteria.



**Figure 3.8** The urban land suitability map obtained with the LSP-based MCE method.

### 3.5.2. Agricultural Land Suitability

The agricultural land suitability case study was developed to evaluate the suitability of available land for future agricultural production. Previous studies have utilized AHP, OWA, and AHP-OWA methods with a small amount of evaluation criteria focusing primarily on physical soil properties (Ceballos-Silva and Lopez-Blanco, 2003; Malczewski et al., 2003; Hill et al., 2005; Chen et al., 2010; Akinci et al., 2013) and economic criteria (Tiwari et al., 1999); however, no studies have used the LSP method. The utilization of a small amount of evaluation criteria reduces the ability to incorporate additional socio-economic and environmental criteria and improve evaluation complexity. Moreover, the LSP method is designed to evaluate complex suitability problems with the number of evaluation criteria ranging to 100 or more (Dujmović and de Tré 2011). In this case study, a larger amount of evaluation criteria are applied to each MCE method to represent a larger range of observed human decision-making logic and determine the strongest MCE method.

A total of 31 evaluation criteria were used to evaluate agricultural land suitability in Boulder County, Colorado, USA (Figure 3.1). The evaluation criteria represented climate, economic, proximity, management, and land capability perspectives: slope, elevation, aspect, soil textural

class, organic matter, depth to restrictive layer, available water, drainage class, bulk density, precipitation, temperature, frost free days, water retention, flooding, location of highly capable soils, distance to water for irrigation, distance to open space, distance to major roads, distance to local roads, distance to urban areas, distance to markets, designated open space, zoning, crop type, food product consumption, vacant land, cash crops, annual income, price of land, economic hazards, land renting. Similar to the urban land suitability case study, suitability functions were developed to standardize the evaluation criteria on a scale from 0 to 1 (Figure 3.9) and integrated into method-specific weighting schemes and aggregation structures. Weighting schemes and aggregation structures were expanded to incorporate a larger amount of evaluation criteria than the urban land suitability application.

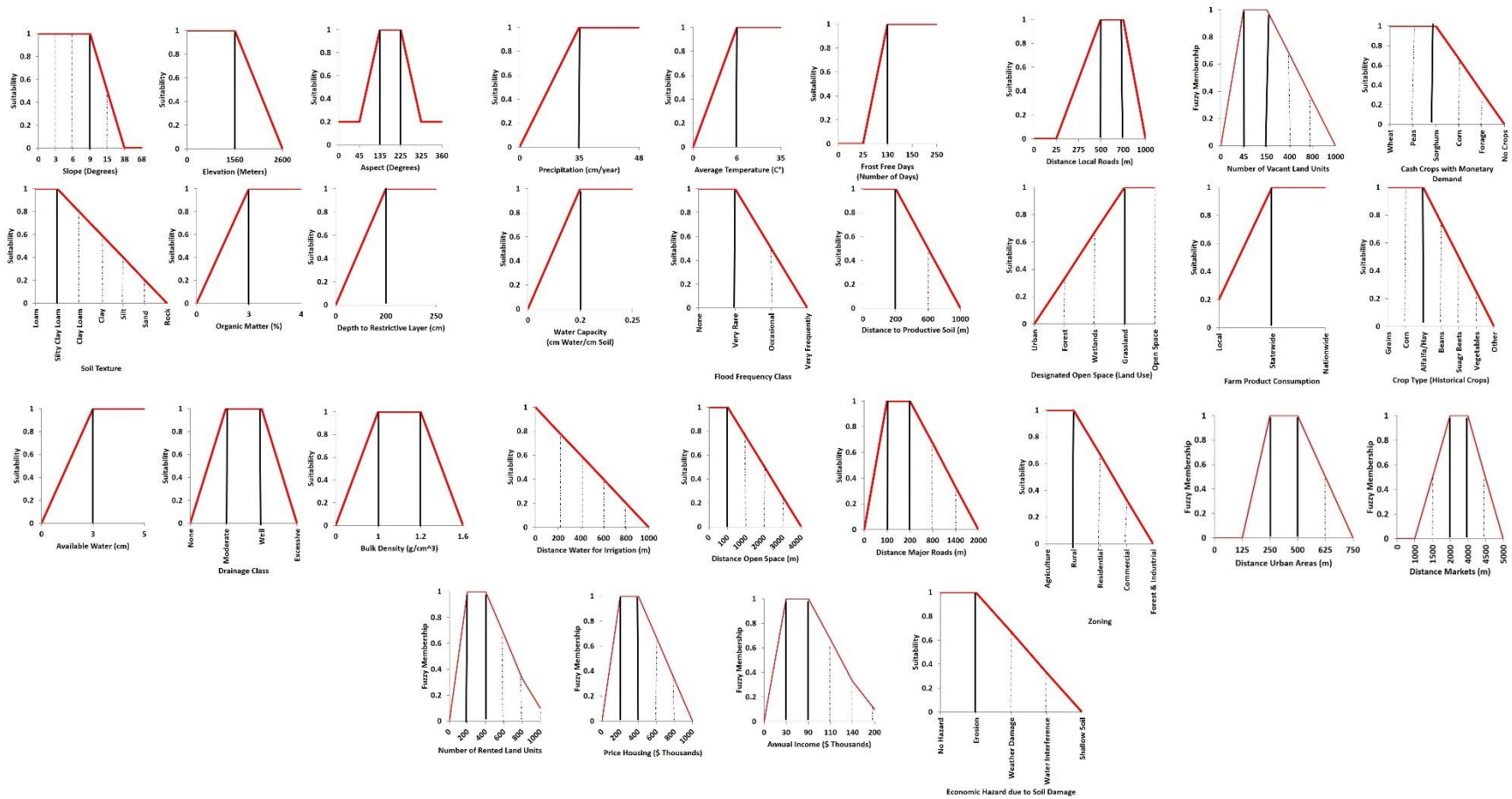


Figure 3.9 Suitability functions characterizing agricultural land suitability evaluation criteria.

### **3.5.2.1 AHP**

The construction of AHP for agricultural land suitability was designed with the same logic as the urban land suitability case study, except with the use of 31 evaluation criteria. However, currently available software for AHP was limited to only 15 evaluation criteria as the number of required pairwise comparisons was too large. As a result, AHP was unable to include the 31 evaluation criteria needed to evaluate agricultural land suitability.

### **3.5.2.2 OWA**

OWA was constructed using similar logic as the urban land suitability case study. For the evaluation of agricultural land suitability, OWA used 31 evaluation criteria comprised of criteria and ordered weights. Criteria weights were calculated using the literature. Despite the small weights assigned as criterion weights, the study required that the majority of evaluation criteria had to be satisfied for evaluation and provide a moderate amount of tradeoff. The ordered weights were distributed similarly to the urban land suitability case study where low ordered weights were assigned low values, higher ordered weights were assigned high values, and the summation of the ordered weights equaled to 1. Likewise, the OWA aggregators aggregated the evaluation criteria until a single suitability output map was generated and presented in Figure 3.10.

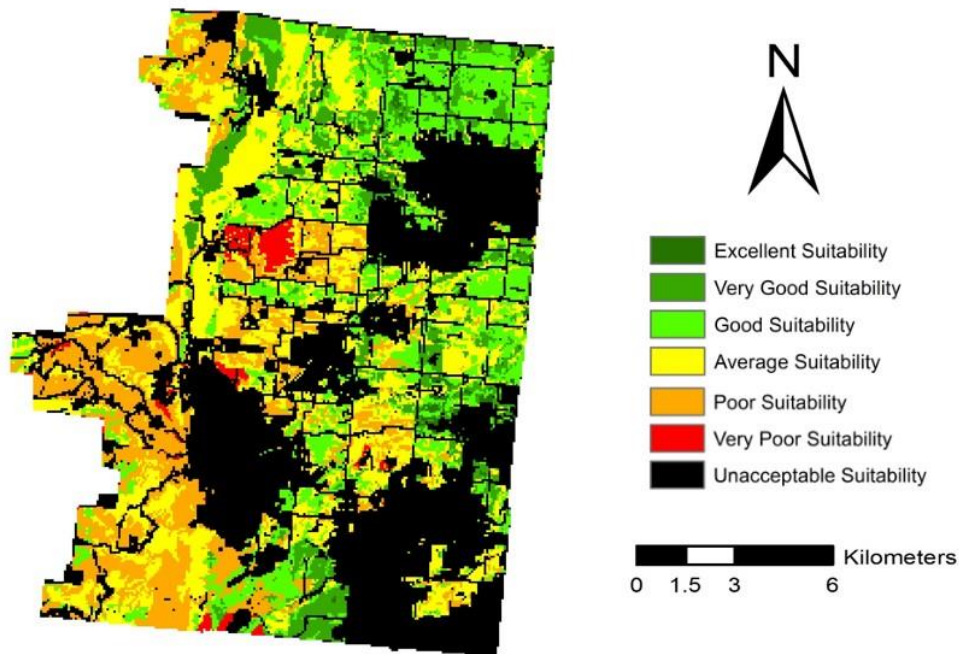
**Table 3.4 Criteria weights and their corresponding ordered weights to represent tradeoff and risk in urban and agricultural land suitability evaluations.**

Agricultural Land Suitability		
Criteria	Criteria Weights	Ordered Weights
Cash Crops Demand	0.1485	0.0502
Zoning	0.1061	0.0491
Crop Type	0.1002	0.0479
Slope	0.0998	0.0468
Temperature	0.0901	0.0456
Annual Income	0.0636	0.0443
Designated Open Space/Land Use	0.0572	0.0432
Price of Land	0.0566	0.0420
Soil Texture	0.0416	0.0409
Markets	0.0350	0.0396
Urban Areas	0.0287	0.0386
Farm Product Consumption	0.0268	0.0373
Frost Free Days	0.0194	0.0362
Elevation	0.0183	0.0350
Precipitation	0.0159	0.0339
Major Roads	0.0153	0.0326
Water Retention	0.0111	0.0316
Depth to Restrictive Layer	0.0094	0.0303
Land Renting	0.0085	0.0292
Organic Matter	0.0073	0.0280
Vacant Land	0.0067	0.0269
Highly Capable Soils	0.0061	0.0257
Economic Hazards	0.0057	0.0246
Drainage Class	0.0051	0.0233
Flood	0.0048	0.0222
Local Roads	0.0038	0.0210
Aspect	0.0028	0.0199
Available Water	0.0024	0.0187
Bulk Density	0.0013	0.0176
Water for Irrigation	0.0012	0.0117
Open Space	0.0008	0.0062



### 3.5.2.3 AHP-OWA

AHP-OWA was designed to combine AHP and OWA methods to evaluate agricultural land suitability using 31 evaluation criteria. As a consequence of structural limitations within AHP when incorporating a large amount of evaluation criteria, AHP-OWA could not evaluate agricultural land suitability.



**Figure 3.10** The agricultural land suitability map obtained with the OWA-based MCE method.

### 3.5.2.4 LSP

LSP was developed using an expanded attribute tree comprised of 31 evaluation criteria (Figure 3.11). Each evaluation criterion was denoted as mandatory or optional and categorized by which perspectives they reflect. Similar to the urban land suitability case study, LSP utilized a range of LSP aggregators to combine evaluation criteria, represent human decision-making logic, and comprise the LSP aggregation structure (Figure 3.12).

Weights of relative importance were applied using expert knowledge and available literature on these agricultural studies. Evaluation criteria were aggregated until one suitability output map was generated (Figure 3.13).

1.	Suitability for Agricultural Land
1.1	Land Capability
1.1.1	Slope (+)
1.1.2	Elevation (-)
1.1.3	Aspect (-)
1.1.4	Soil Texture (+)
1.1.5	Organic Matter (+)
1.1.6	Depth to Restrictive Layer (+)
1.1.7	Available Water (+)
1.1.8	Drainage Class (+)
1.1.9	Bulk Density (+)
1.2	Climate
1.2.1	Precipitation (+)
1.2.2	Temperature (+)
1.2.3	Frost Free Days (+)
1.2.4	Water Retention (-)
1.2.5	Flood (-)
1.3	Accessibility
1.3.1	Location of Highly Capable Soils (+)
1.3.2	Distance to Water for Irrigation (-)
1.3.3	Distance to Open Space (-)
1.3.4	Distance to Major Roads (+)
1.3.5	Distance to Local Roads (+)
1.3.6	Distance to Urban Areas (+)
1.3.7	Distance to Markets (+)
1.4	Management
1.4.1	Designated Open Space/Land Use (+)
1.4.2	Zoning (+)
1.4.3	Crop Type (+)
1.4.4	Farm Product Consumption (-)
1.4.5	Vacant Land (-)
1.5	Economics
1.5.1	Cash Crops Demand (+)
1.5.2	Annual Income (+)
1.5.3	Price of Land (+)
1.5.4	Economic Hazards (-)
1.5.5	Land Renting (-)

**Figure 3.11 The LSP attribute tree for agricultural land suitability.**

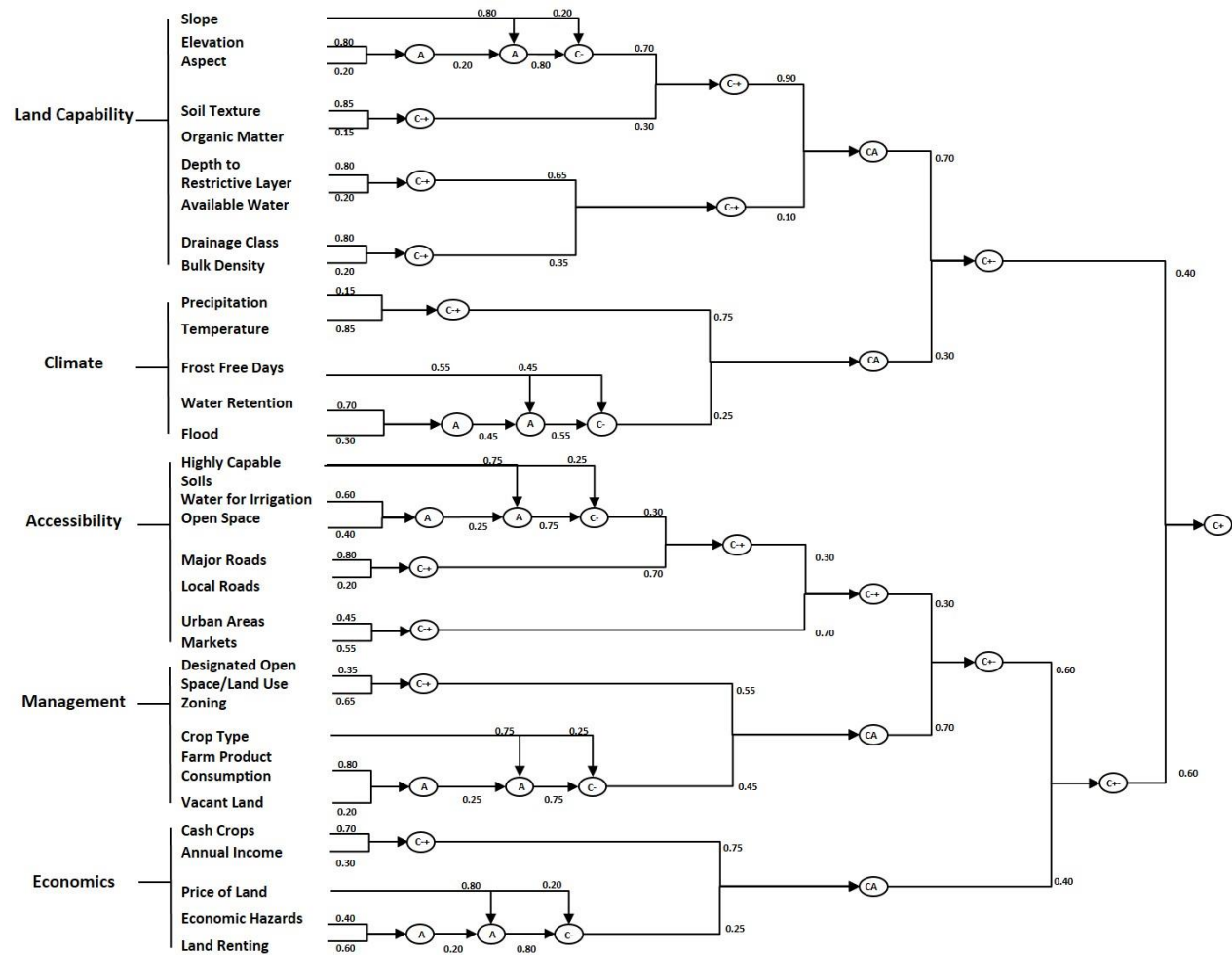
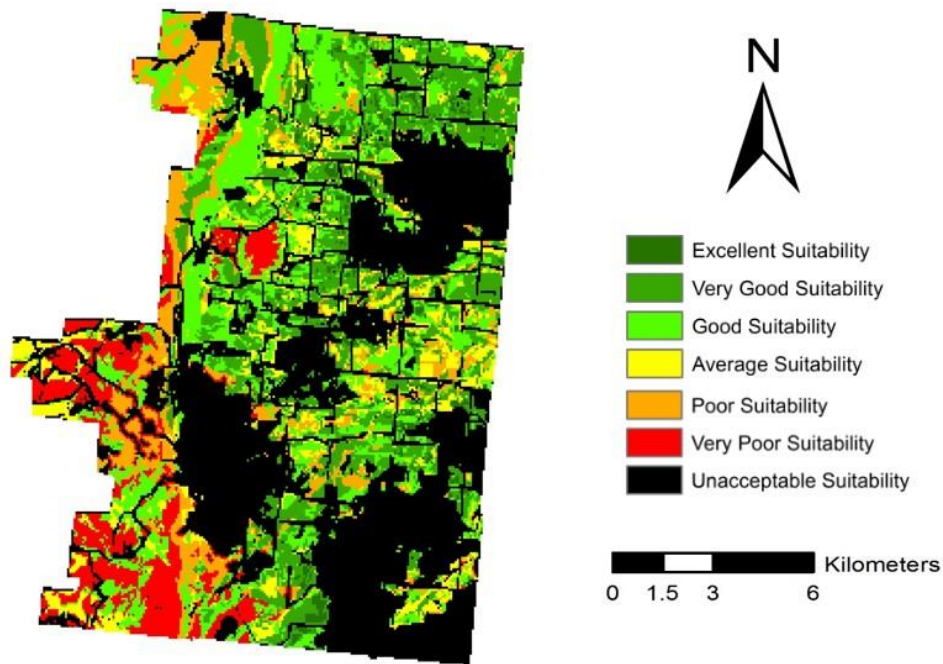


Figure 3.12 The LSP aggregation structure for agricultural land suitability created with 31 evaluation criteria.



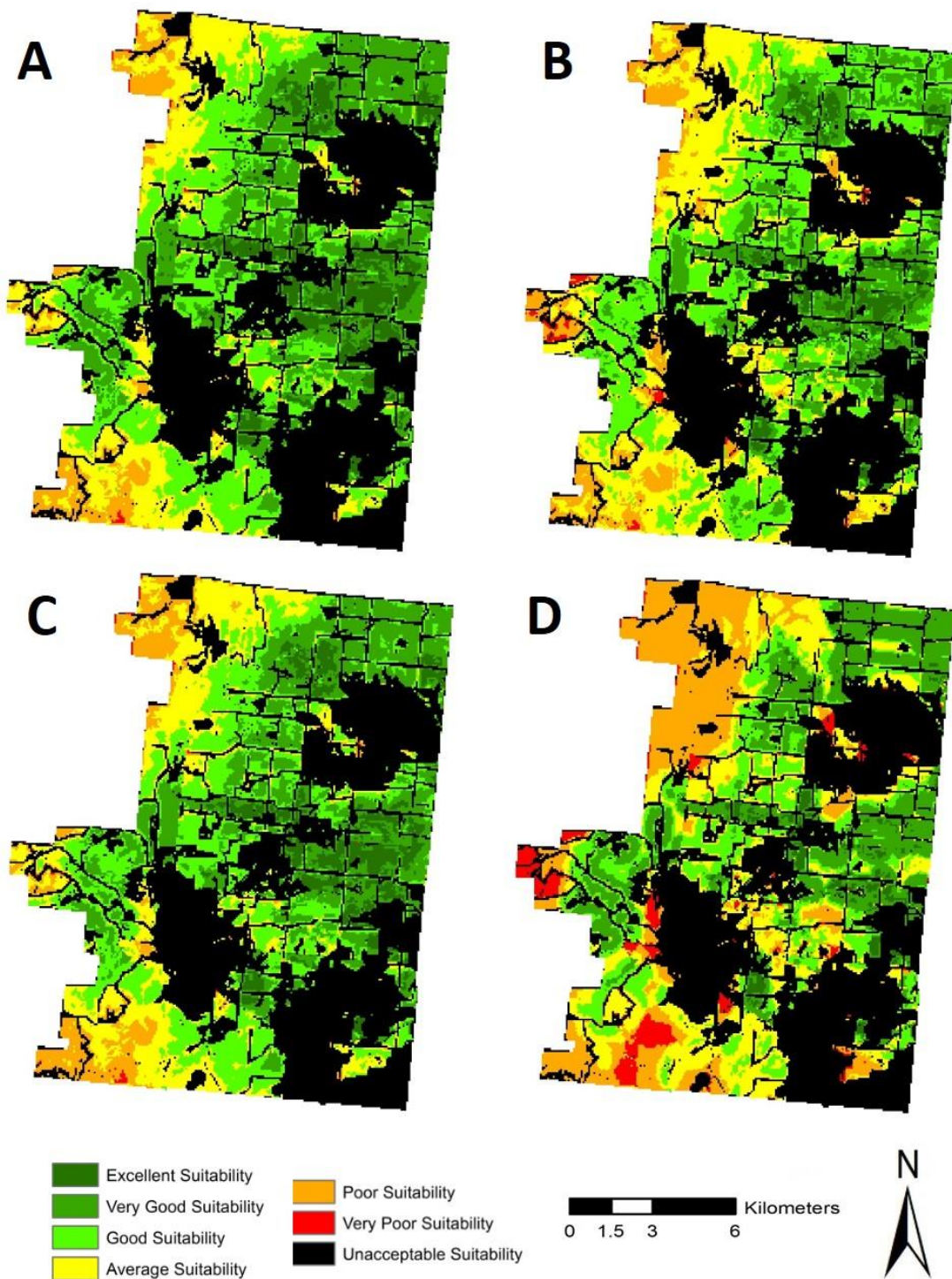
**Figure 3.13** The agricultural land suitability map obtained with the LSP-based MCE method.

## 3.6. Comparison Results

### 3.6.1. Urban Land Suitability

The urban land suitability case study was constructed using 15 evaluation criteria and method-specific aggregation structures and method-specific weighting schemes. Each MCE method was designed using the same 15 evaluation criteria to maintain evaluation consistency and allow for the comparison of the methods. All four of the MCE methods were able to evaluate urban land suitability without any limitations. The resulting suitability output maps are presented in Figure 3.14 so the visual comparison can be performed. Visual comparison has indicated that excellent suitability is found in areas adjacent to urban land use, categorized as unacceptable suitability, which follows the growth strategies outlined in the Boulder County Comprehensive Plan (Boulder County Land Use Department, 1999). Moreover, the LSP method provides more refined and complex results.





**Figure 3.14** The suitability output maps generated by the GIS-based (A) AHP, (B) OWA, (C) AHP-OWA, and (D) LSP methods.

Table 3.4 A presents results of the comparison of MCE methods for urban land suitability using the six fundamental MCE properties and AUC values. The results suggest that LSP was able to address all 6 fundamental properties, while OWA and AHP-OWA addressed five of six properties, and AHP only addressed four of six properties. OWA, AHP-OWA, and AHP methods were unable to model mandatory and optional requirements. Both AHP and AHP-OWA was also unable to provide flexible adjustment of relative importance of weights. Furthermore values of AUC indicated that each of the methods produced an AUC value above 0.850, with LSP generating the highest value at 0.961. AHP-OWA generated the second highest AUC value of 0.885. OWA and AHP generated the lowest AUC values of 0.878 and 0.857, respectively. The LSP method generated an AUC value that was 10.4% higher than AHP, 8.3% higher than OWA, and 7.6% higher than AHP-OWA.

**Table 3.5 Fundamental MCE property comparison results and Area under the Curve values obtained for (A) urban land suitability and (B) agricultural land suitability.**

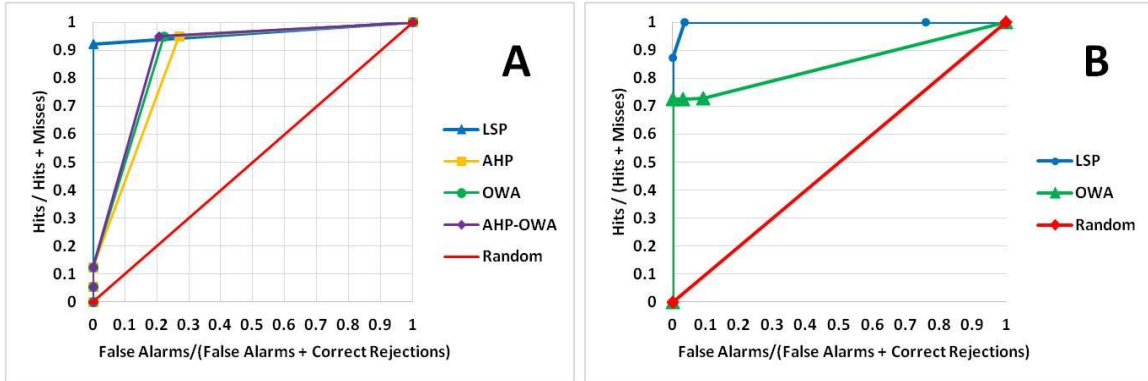
<b>A</b>							
MCE Methods	Combining Number of Attributes	Combine Objective and Subjective Inputs	Combine Absolute and Relative Criteria	Flexible Adjustment of Relative Importance	Modelling of Simultaneity Requirements	Modelling Mandatory, Desired, and Optional Requirements	AUC Value
AHP	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>		<input checked="" type="checkbox"/>		0.857
OWA	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>		0.878
AHP-OWA	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>		0.885
LSP	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	0.961

<b>B</b>							
MCE Methods	Combining Number of Attributes	Combine Objective and Subjective Inputs	Combine Absolute and Relative Criteria	Flexible Adjustment of Relative Importance	Modelling of Simultaneity Requirements	Modelling Mandatory, Desired, and Optional Requirements	AUC Value
AHP		<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>				--
OWA	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>		0.849
AHP-OWA		<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>				--
LSP	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	0.998

Figure 3.15 displays the ROC curves of each MCE method. According to the LSP ROC curve, 91% of the candidate region observed presence at high ranking index values, represented by a vertical trend along the Y-axis. Likewise, a high proportion of absence was observed at low ranking index values, indicated by the horizontal trend near the upper

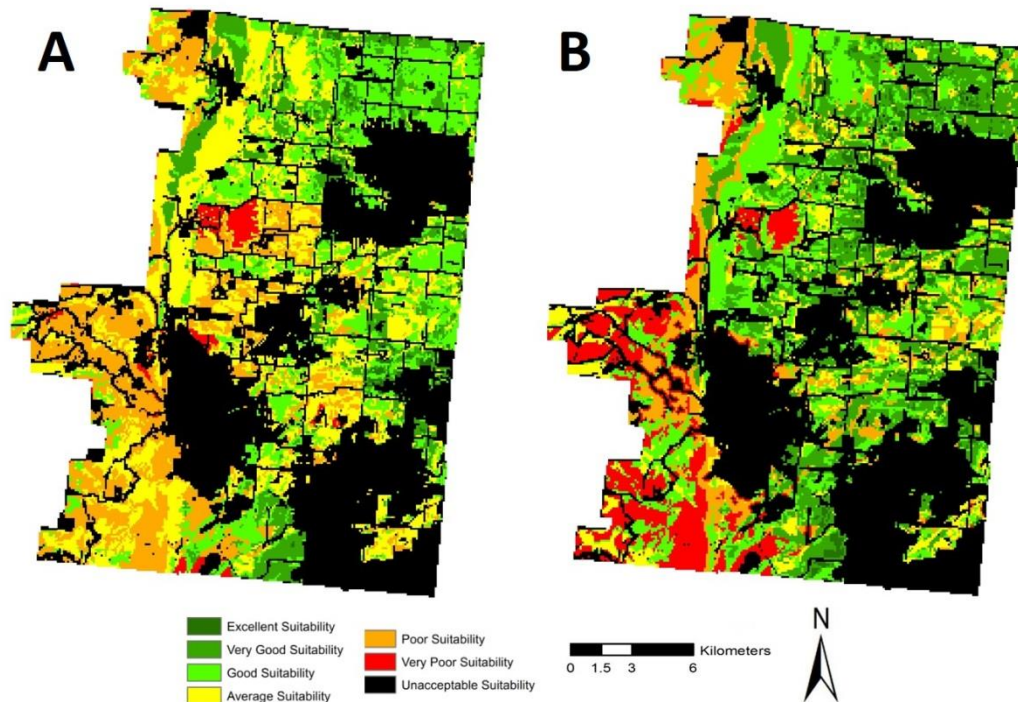
boundary of the graph. The remaining MCE method evaluated only 12% of the candidate region observed presence at high ranking index values as a larger proportion of absence was observed at higher thresholds.



**Figure 3.15 Receiver operating characteristic curves (ROC) for (A) urban land suitability and (B) agricultural land suitability. Each curve is constructed using three thresholds.**

### 3.6.2. Agricultural Land Suitability

The MCE methods used for the agricultural land suitability case study were constructed from 31 evaluation criteria, MCE method-specific aggregation structures, and method-specific weighting schemes. Due to a large number of inputs, the AHP and AHP-OWA methods were not able to evaluate agricultural land suitability. The Decision Wizard module in the GIS-based Idrisi software could only incorporate a maximum of 15 evaluation criteria for AHP-based evaluations, which limited AHP and AHP-OWA when 31 evaluation criteria were used. Figure 16 presents the agricultural land suitability maps generated by OWA (Fig. 3.16 A) and LSP (Fig. 3.16 B) methods for visual comparison. Upon visual comparison, excellent suitability is found in areas adjacent to urban land use, categorized as unacceptable suitability, in the eastern portion of the study area. These results indicate improved access for farmers to urban markets and follows agricultural zoning used for current agricultural production. Both OWA and LSP provide refined complex results, with LSP generating more excellent and very good suitability as well as more very poor suitability.



**Figure 3.16** The suitability output maps generated by the GIS-based (A) OWA and (B) LSP methods using 31 criteria.

The limitations of the MCE methods were indicated in Table 3.4 B, where LSP and OWA were the only methods capable of producing suitability output maps. Moreover, LSP was able to address all six fundamental properties, while OWA was limited by its inability to model mandatory and optional requirements. Both AHP and AHP-OWA methods were able to combine various inputs and criteria, but were unable to incorporate a larger number of evaluation criteria as explained above.

In Table 3.4 B, the results indicate that the AUC value for both methods was above 0.80. Specifically, the LSP method produced an AUC value of 0.998, 14.9% higher than OWA produced at 0.849. According to the ROC curves in Figure 15 B, the LSP ROC curve determined that 88% of the candidate region observed presence at high ranking index values and a high proportion of absence was observed at low ranking index values. In Figure 15 A, the OWA ROC curve determined 72% of the candidate region observed presence at high ranking index values, but a larger proportion of absence at higher thresholds than LSP.



### **3.7. Discussions and Conclusions**

Across both case studies, the LSP method was determined the strongest MCE method, demonstrated by addressing all six fundamental MCE properties, the highest AUC values, and the best fitting ROC curves. The strength of AHP, OWA, and AHP-OWA methods across both case studies could not be determined as only OWA was capable of evaluating both case studies. OWA was limited across both case studies by its inability to denote evaluation criteria as mandatory or optional, but it provided strong capabilities in modeling simultaneity requirements.

The obtained AUC values for the urban land suitability case study indicates that each of the four MCE methods are capable of evaluation. With the differences in AUC values ranging from 7.6 - 10.4%, the LSP method demonstrated better values and measures than the other MCE methods. As indicated by the results, AHP-OWA was 2.1% stronger than OWA and 2.8% stronger than AHP, but OWA was only 0.7% stronger than AHP. The differences between each method indicate that methods using a larger range of human decision-making logic produced slightly better results.

As indicated in the results for agricultural land suitability, LSP and OWA calculated AUC values above 0.800, indicating their strength in agricultural land suitability evaluation. In contrast, the LSP method was 14.9% stronger than the OWA method according to the AUC value. Differences between the two methods occurred where low ranking values were present at higher thresholds. The LSP method generated very few low ranking index values at higher thresholds, while OWA displayed many low ranking index values at higher thresholds. Although LSP calculated a much higher AUC value than OWA, this study only provides a relative indication to the strength of OWA as AHP and AHP-OWA could not evaluate the large number of evaluation criteria. The inability of AHP and AHP-OWA to evaluate a large amount of criteria is a strong technical limitation within the Idrisi software when implementing the MCE methods for land suitability analysis.

Overall, the resulting comparison of six fundamental MCE properties, obtained AUC values and ROC curves determined that the LSP method was the strongest of the

four MCE methods to evaluate both agricultural and urban land suitability. As this study is one of the first studies to statistically compare LSP, AHP-OWA, OWA, and AHP, future research should improve the comparisons twofold: 1) increasing the number of fundamental MCE properties and improving the ability to compare and represent all ten fundamental MCE properties in a comparison, and 2) using the total operating characteristic (TOC) rather than ROC to statistically compare suitability output maps. TOC provides more information regarding thresholds and allows the user to express the results beyond the shape of the ROC curve and its corresponding AUC value (Pontius and Si, 2014). Furthermore, future research should focus on comparing the LSP method to additional MCE methods and land suitability applications.

Despite the LSP method's strength in the study, there are potential limitations with its use. The LSP method is very complex in its design and may be too difficult for some users to determine the appropriate parameters and logic aggregators needed to evaluate various case studies. Further, the use of the Idrisi software limits the combination of only two evaluation criteria at a time, where previous studies (Dujmović, 2007; Dujmović and Scheer, 2010; Dujmović et al., 2010) combine more than two evaluation criteria with the same logic aggregator.

The main objectives of this study were to propose the GIS-based LSP method as an improved MCE method for the evaluation of land suitability and to compare the LSP method with three other commonly utilized GIS-based MCE methods. Each of the four GIS-based MCE methods were designed using socio-economic and environmental criteria to evaluate land suitability case studies. The urban land suitability case study utilized 15 evaluation criteria, and the agricultural land suitability case study utilized 31 evaluation criteria. Both case studies were constructed using method-specific aggregation structures and weighting schemes. GIS-based MCE methods and their obtained suitability output maps were compared using six fundamental MCE properties, AUC values, and ROC curves.

The GIS-based LSP method can potentially be used for various decision-making processes to address food security and urban development. Furthermore, the MCE

method comparisons support the basis for utilizing LSP over commonly used MCE methods as an excellent tool for land-use planning. Overall, the LSP method was the strongest MCE method for evaluating urban and agricultural land suitability utilizing a large range of evaluation criteria and human decision-making logic.

### **3.8. Acknowledgements**

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## **Chapter 4. Conclusions**

### **4.1. Thesis Conclusions**

The focus of this thesis research was to develop a multicriteria evaluation approach to evaluate agricultural land capability and land suitability particularly through the implementation of the LSP method based on soft computing. Moreover, various GIS-based MCE methods including LSP were compared using the receiver operating characteristic's (ROC) area under the curve (AUC) metric, the shape of the resulting ROC curve, and land use suitability case studies. The overall results obtained from this research concluded that the implementation of the LSP method provided realistic results for evaluating agricultural land capability and suitability, while indicating how differences in stakeholder perspectives could influence suitability results.

The first component of this thesis was extending commonly used MCE methods with the LSP method. The LSP method was proposed as an extension because of its ability to provide a flexible aggregation structure, incorporate a large amount of evaluation criteria, and fully represent human reasoning. Agricultural land capability and land suitability were calculated using the GIS-based LSP method and datasets from Boulder County, Colorado, USA. Agricultural land capability was evaluated using the GIS-based LSP method. Evaluation criteria describing the physical land characteristics of the study area were used to model land capability. The evaluation of agricultural land suitability displayed the LSP method's ability to incorporate a large amount of input criteria and represent a variety of land-use perspectives (Chapter 2). Resulting suitability maps were developed in the GIS-based Idrisi software as raster maps. Evaluation criteria were standardized using fuzzy-based suitability functions, and their suitability values were scaled from 0 to 1 where 0 was unacceptable and 1 was excellent.

The standardized evaluation criteria were grouped categorically based on the usefulness of the criteria and aggregated using LSP aggregators until suitability output maps were calculated. Different aggregation structures were designed to provide four



scenarios that are used for evaluating agricultural land suitability. The aggregation structure designed for agricultural land capability produced a suitability output map for comparison with the USDA land capability map derived from similar data. Four scenarios were designed using climatic, economic, accessibility, management, and land capability perspectives. Evaluation criteria were implemented into four expanded aggregation structures with scenario-specific weights of relative importance to reflect different perspectives. Scenario 1 utilized weights that emphasized the land capability evaluation criteria as the most important determining suitability. Scenarios 2, 3, and 4 utilized weights reflecting land management, accessibility, and economic perspectives, respectively.

Agricultural land capability results determined that most of the study area was comprised of excellent and very good capability. Moreover, results were comparable to the USDA land capability map with a 75.5% agreement. Agricultural land suitability results varied between each of the four scenarios. Scenarios 1 and 2 determined that very good and good suitability comprised most of the study area; while Scenarios 3 and 4 determined that good and very good suitability and good and average suitability comprised most of the study area, respectively. Furthermore, areas of excellent and very good suitability corresponded to current agricultural, grassland/shrubland, and urban land uses. The findings described above suggested that the LSP method is an improved and extended MCE method that has many advantages over other commonly used GIS-based MCE methods.

In order to compare GIS-based MCE modeling capabilities (Chapter 3), the LSP – MCE method was compared to multicriteria evaluation methods based on AHP, OWA, and AHP-OWA methods for urban and agricultural land suitability using datasets from Boulder County, Colorado, USA and were statistically compared with the receiver operating characteristic. Each method was implemented in the Idrisi-GIS software as raster maps. Method-specific aggregation structures and weighting schemes were used to evaluate the criteria. Resulting suitability output maps were compared using the AUC value and the shape of the ROC curve derived from the receiver operating characteristic and its Boolean variable where higher AUC values and well-fitting ROC curves determined the strongest method. In addition, the MCE methods were compared in their ability to

satisfy fundamental MCE properties outlined in Dujmović et al. (2009). The results indicate that the LSP obtained the highest values and the best-fitting ROC curves for both land suitability case studies. Moreover, the LSP method was the only GIS-based MCE method to address each of the fundamental MCE properties for both land use suitability case studies. Based on the obtained results, the LSP method was determined as the strongest GIS-based MCE method for evaluating agricultural and urban land suitability and was suggested for future land suitability evaluations.

## **4.2. Future Research**

Despite the improvements and obtained results stemming from this research, there are several disadvantages when using the GIS-based LSP method for land use suitability evaluation. The GIS-based LSP method is a subjective method that relies on expert knowledge and stakeholder perspectives to effectively choose, design, and categorize evaluation criteria, construct LSP aggregation structures, determine logic aggregators, and determine weights of relative importance. As a result, suitability outputs can vary, making it difficult to determine which decision-making alternative should be used for land suitability analysis. In this study, two aggregation structures and five weighting schemas were developed, displaying a limited number of possible attribute trees. In order to extend this research, the GIS-based LSP approaches can benefit from allowing stakeholders to directly design evaluation criteria and help to develop attribute trees and weighting frameworks. In addition, these attribute trees and weighting frameworks can benefit from detailed sensitivity analysis of the LSP method.

The development of the GIS-based LSP approaches can benefit from sensitivity analysis as it allows for the testing and optimization of model parameters. It has proven to be a successful method for optimizing parameters in previous LSP studies (Su et al., 1987; Dujmović and Larsen, 2004; Dujmović, 2007) and displaying how sensitive regions are to small changes in model parameters (Feick and Hall, 2004; Chen et al., 2010; Ligmann-Zielinska and Jankowski, 2008; Ligmann-Zielinska and Jankowski, 2014). Utilizing the frameworks and procedures outlined in Ligmann-Zielinska and Jankowski (2008) and

Ligmann-Zielinska and Jankowski (2014) can provide a foundation for further sensitivity analysis of the LSP method and will provide insight of sensitivity in model parameterization and changes in suitability results.

The use of ROC statistics for the GIS-based MCE method comparison can be improved to provide more information in regards to interpreting the ROC curve. Additional information will improve how decision makers present ROC results and can reduce reliance on the AUC value. The interpretation recommendations and the total operating characteristic (TOC) method outlined in Pontius and Parmentier (2014) and Pontius and Si (2014), respectively, allow for the decision maker to better represent the ROC curve, calculate the AUC value, and display any additional information that may be useful for comparison.

Furthermore, the GIS-based MCE method comparison can benefit from sensitivity analysis and increasing the number of land use suitability case studies. Sensitivity analysis can be used as an additional comparison metric through analyzing the sensitivity of each GIS-based MCE method in terms of model parameters, how suitability results change across the study area, and how suitability results compare across case studies. In addition, sensitivity analysis can help display the sensitivity of ROC results in response to changes in candidate regions and model parameters. Although GIS-based MCE methods were evaluated with the same evaluation criteria and similar weighting frameworks for each different case study, the method comparison can benefit from incorporating multiple frameworks. Moreover, an increase in the number of land suitability case studies will help determine the strength of GIS-based MCE methods across many disciplines and can provide a basis for suggesting which method should be used for future land use suitability evaluations. The GIS-based LSP method has proven to be useful in the evaluation of agricultural land capability and suitability and urban land suitability. Thus, the GIS-based LSP method can enhance other MCE land use suitability case studies such as agricultural product warehouse location (Garcia et al., 2014), flood management (Masuya, 2014), and environmental restoration (Rahman et al., 2014).

### **4.3. Thesis Contributions**

The research conducted in this thesis is the first study to evaluate agricultural land capability and suitability using the GIS-based LSP method. The study was unique by evaluating agricultural land capability and by incorporating a large amount of socio-economic and environmental evaluation criteria to assess agricultural land suitability. The proposed GIS-based LSP method extends previous MCE methods by addressing a full range of human decision-making logic and statistically comparing the GIS-based LSP method with commonly used GIS-based MCE methods. Through the integration of the LSP method, this research contributes to the use of soft computing methods in the evaluation of agriculture production, urban development, and multicriteria evaluation. The LSP method was effective in addressing the limitations in expressing human decision-making logic and reduces evaluation errors in land suitability analysis. This thesis implements the LSP method into GIS to evaluate land use and compare results with other MCE methods utilizing a large amount of evaluation criteria at a regional scale.

This thesis is the first to use the LSP method for evaluating agricultural land capability, the first to use the LSP method to evaluate agricultural land suitability, and the first to compare the LSP method with other MCE methods in the evaluation of agricultural and urban land suitability. The methods utilized in this research contribute to the scientific fields of GIS, geography, and land use science. Specifically, the methods and their associated results contribute to the improvement of GIS-based MCE methods used in the research of agricultural land capability and suitability.

In conclusion, the research presented in this thesis proposed and implemented the GIS-based LSP method as an extension of previous GIS-based MCE methods for evaluating agricultural land capability and suitability and for comparison with commonly used GIS-based MCE methods. Overall, the research presented in this study provides only a limited number of possibilities for the LSP method, but also indicates future research opportunities in the fields of GIS, multicriteria evaluation and spatial decision making.

## 4.4. References

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