IMPLEMENTATION OF GIS-AHP-OWA FOR LAND SUITABILITY ASSESSMENT IN INFRASTRUCTURE INVESTMENT PROJECTS: A CASE STUDY IN YUCATÁN, MEXICO

Tatiana Merino-Benítez[1]
Posgrado en Ciencias de la Sostenibilidad
Laboratorio Nacional de Ciencias de la Sostenibilidad, Instituto de Ecología,
Universidad Nacional Autónoma de México,
Mexico City, Mexico
tatianam@iecologia.unam.mx

Víctor Hernández
Laboratorio Nacional de Ciencias de la Sostenibilidad, Instituto de Ecología,
Universidad Nacional Autónoma de México,
Mexico City, Mexico
victor.hernandez@iecologia.unam.mx

Luis Antonio Bojórquez-Tapia[2]
Laboratorio Nacional de Ciencias de la Sostenibilidad, Instituto de Ecología,
Universidad Nacional Autónoma de México,
Mexico City, Mexico
luis@multicriteria.org

ABSTRACT

This article presents an approach to land suitability assessment (LSA) that accounts for the opposing interests and viewpoints of multiple stakeholders. LSA is a widely used geospatial technique for locating optimal sites for infrastructure investment. The approach described in this paper uses the Analytic Hierarchy Process (AHP) to elicit relative importance weights of a set of geographical attributes, the evaluation of the state of each attribute in spatial units using value functions on a geographic information system (GIS), and the implementation of the Ordered Weighted Average (OWA) as an aggregation operator. The approach is illustrated through the location of potential sites

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[2] Corresponding author.

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for swine plant investments, taking into consideration environmental conflicts in Yucatán, Mexico. This approach provides a systematic and transparent procedure for analyzing infrastructure projects' land suitability and developing investment recommendations that promote sustainable development.

Keywords: land suitability scenarios; risk attitudes; environmental conflicts; sustainable development

1. Introduction

Land suitability assessment (LSA) refers to the geospatial analysis of land's appropriateness for a specific use (Dengiz, 2013; Rabia & Terribile, 2013). In essence, LSA involves the incorporation of multicriteria decision analysis in a geographic information system (GIS-MCDA) to find optimal locations for infrastructure investment projects (Mazahreh et al., 2019; Latinopoulos & Kechagia, 2015; Joerin et al., 2001). Operationally, LSA entails the elicitation of relative importance weights of a set of geographical attributes, the evaluation of the state of each attribute in spatial units (pixels or polygons), and the implementation of an aggregation operator also known as aggregation function (Jin et al., 2021; Khalid & Awais, 2015), such as the Weighted Linear Combination (WLC) (Bojórquez-Tapia et al., 2003; Malczewski et al., 1997). The importance weights are obtained through MCDA, in which Saaty's (1980) Analytic Hierarchy Process (AHP) has been widely applied (Jafari & Zaredar, 2010). The evaluation of the state of the attributes is carried out through value functions (Bausch et al., 2014; Beinat, 1997). Therefore, LSA gives rise to geographic patterns that correspond to both stakeholders' preferences and geographic characteristics.

Although the LSA tacitly implies consensus building among different stakeholders with a plurality of interests and viewpoints (Bojórquez-Tapia et al., 2001), finding optimal locations for infrastructure investment projects is often far from simple (Weber et al., 2016; LaGro, 2008). These projects often generate environmental conflicts that may prevent their implementation whenever sustainable development is undermined (Bojórquez-Tapia et al., 1994). Environmental conflicts are defined as the reduction caused by an investment project to the capacity of the territory or natural resources to meet the demands of human activities (Crowfoot & Wondolleck, 1990). Settling these conflicts, then, involves finding the optimal location for infrastructure and, simultaneously, minimizing the risk of environmental impacts across a region.

According to Malczewski (2006), LSA approaches can be generalized within the framework of Ordered Weighted Average (OWA). OWA is an aggregation operator that allows the preferences and opposing views of stakeholders on a specific input to be efficiently modeled (Jin et al., 2021; Yager, 2017; Fernández et al., 2014). In essence, this operator provides land suitability scenarios by fuzzy quantifiers between a continuum of intersection (MIN or AND) and union (MAX or OR) (Malczewski, 2006, 2004; Jiang & Eastman, 2000). OWA scenarios are intended to address different levels of risk-taking (i.e., risk-seeker or optimistic, risk-neutral, and risk-averse or pessimistic) and provide a better understanding of land patterns that emerge from the LSA decision-making process

(Ferretti & Pomarico, 2013). In this article, we present a GIS-MCDA-OWA implementation to locate optimal investment sites considering the restrictions imposed by environmental law. We illustrate the approach through the location of potential sites for swine plant investments in Yucatán, Mexico. This article expands upon the work presented at the 2022 International Symposium on the Analytic Hierarchy Process (Merino-Benítez et al., 2022).

2. Literature review

LSA involves alternative plans, evaluation criteria, and stakeholders (Malczewski et al., 1997). This assessment has been implemented through GIS-MCDA to classify alternative land use patterns so that stakeholders may achieve consensus (Pedroza et al. 2020; Khalid & Awis, 2015; Cook, 2006). The AHP, a MCDA method, has been widely used to determine stakeholders' priorities over the attributes of a territory (Pilevar et al., 2020; Vasu et al., 2018; Zhang et al., 2015; Jafari & Zaredar, 2010; Eastman et al., 1993). Although LSA typically involves operations that follow compensatory combination rules (Latinopoulos & Kechagia, 2015; Chen et al., 2011), such as the AHP and the WLC, Pereira and Duckstein (1993) expanded the scope to include non-compensatory and partially-compensatory ones. These operations can be generalized through OWA, as it can be used to generate a wide range of alternative land suitability maps for different degrees of compensation regarding stakeholders' attitudes towards risk (Al-Yahyai et al., 2012; Malczewski, 2006).

The field of LSA has witnessed extensive implementation of GIS-AHP-OWA approaches. These approaches have been utilized for evaluating land suitability scenarios across various domains. For instance, Al-Yahyai et al. (2012) used GIS-AHP-OWA for evaluating land suitability scenarios for wind farms in Oman, while Ferretti and Pomarico (2013) employed them for assessing ecological connectivity in Italy. Similarly, Zabihi et al. (2019) and Mokarram and Mirsoleimani (2018) used these approaches for evaluating land suitability scenarios for citrus cultivation in Iran, and Luan et al. (2021) and Chen et al. (2011) used them for urban and industrial development scenarios in China. In contrast, other LSA approaches have used GIS remote sensing (Vasu et al., 2018; AbdelRahman et al., 2016; Halder, 2013; Bandyopadhyay & Jayaraman, 2009; Quan et al., 2007), parametric methods (El Baroudy, 2016; Rabia & Terribile, 2013), decision trees (Bydekerke et al., 1998), logic networks (Stoms et al., 2002), fuzzy sets (Karasan, 2019; Zhang et al., 2015), and compromise programming (Thinh et al., 2004). In the *International Journal of the Analytical Hierarchy Process*, the location of optimal infrastructure investment sites has been developed using GIS-AHP (Shrestha et al., 2022; Otay & Kahraman, 2018; Minhas, 2015; Lami et al., 2011; Girard et al., 2012). However, none of these approaches involved the OWA operator.

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3. Methods

3.1 Study area

Yucatán, a state located in Mexico, as illustrated in Figure 1, encompasses a total area of 40,000 km^2. This region is characterized by its high environmental sensitivity, owing to its extensive forest cover (which constitutes 50% of the total area) and bodies of water (including 5% of the total area as wetlands, serving as the primary source of groundwater recharge). However, according to Céspedes-Flores and Moreno-Sánchez (2010), approximately 230 km^2 of forest cover are lost annually, leading to deterioration in environmental services and an increase in vulnerability to climate change-related threats. The primary reasons behind this transformation of natural ecosystems in Yucatán can be mostly attributed to the expansion of agriculture, the swine industry, and urban sprawl (Ellis et al., 2017). Notably, the swine industry in Yucatán accounts for 9% of the national pork production (OECD, 2019) and is projected to increase at a rate of 4.5% per year (Calderón et al., 2021). Consequently, as Yucatán is one of the primary national pork producers, stakeholders are confronted with investment challenges associated with environmental conflicts, such as groundwater contamination, air pollution, and soil degradation (Méndez-Novelo et al., 2009; Ducker et al., 2003).

Figure 1 Yucatán, Mexico

3.2 Land suitability assessment

The development of the LSA encompassed a participatory framework that included workshops, ensuring that the suitability maps resulted from a process of translating the expertise and preferences of specialists. The organizational aspects of these workshops were aligned with the established formalized procedures in Mexico for LSA. Under the guidance of the environmental authorities, the workshop activities were designed to shape a salient, legitimate, and credible analytical framework, a foundation conducive to consensus-building, as highlighted by Pedroza et. al (2020). In essence, the state environmental authorities officially convened the workshops to generate the

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corresponding suitability maps for both swine and poultry plant investment (SPI) and environmental protection (EP).

Forty people attended the SPI workshop and 53 people participated in the EP workshop. The participants included specialists from (1) governmental entities at the state, federal, and municipal level, (2) businesses, industries, consulting firms, and professional organizations, (3) cooperatives, social enterprises, and civil society organizations, (4) academic and research institutions, and (5) concerned citizens. Each workshop was organized into four sessions, each lasting three hours. During the workshops, the AHP (Saaty, 1980) was implemented through the freeware *Super Decisions* (CDF, 2023). Both the pairwise comparisons of decision criteria and the determination of value functions for geographical attributes were achieved through consensus. The pairwise comparison process was not considered complete unless the consistency index (CI) fell below 0.1.

The geospatial analysis (see Figure 2) implemented the WLC in QGIS to obtain the land suitability maps for SPI and EP, formally (Bojórquez-Tapia et al., 2003; Malczewski et al., 1997):

$$S_j^k = \sum_j^J w_{ij}\, x_{ij}^k \prod_j^J r_{ij} \tag{1}$$

where S_j^k is the land suitability, w_{ij} is the importance weight obtained from the AHP, x_{ij}^k is the normalized value of the geographic attributes, r_{ij} is the restriction, and i, j, and k are indices for attribute, activity, and pixel, respectively.

The process of normalizing the values of the geographical attributes involved the transformation of the state of spatial units into numerical values using discrete and continuous value functions (Figure 2), in which the minimum score, 0, denoted the worst condition, while the maximum score, 1, denoted the best one. Accordingly, normalization involved a raster cartographic database with a universe or set of pixels, $X = \{x^1, x^2, \ldots, x^k\}$; $k = 1,2, \ldots, K$. Each pixel, x^k, was associated with thematic layers that described the set of geographic attributes, I, with respect to the set of activities, J, and a set of restrictions, R, which denoted that the activity could not be carried out. Consequently, pixels, $x_{ij}^k = \{x_{1j}^k, x_{2j}^k, \ldots, x_{ij}^k\}$, that corresponded to each attribute, $i = 1,2, \ldots, I$, of an activity, $j = 1,2, \ldots, J$, and restriction, $r = \{1,0\}\ \forall r_{ij} \in R$, were normalized, $x_{ij}^k = [0,1]\ \forall x_{ij}^k \in X$.

Next, the OWA operator (Malczewski, 2006) was implemented to obtain six land suitability scenarios according to opposing attitudes towards risk (Figure 2). This implementation required the development of a program in Python-QGIS (available upon request) that involved: (a) the normalized values of the attributes, x_{ij}^k, arranged as $z_{1j}^k \geq z_{2j}^k \geq \cdots \geq z_{Ij}^k$; (b) the importance weights , w_{ij}, reordered as $u_{ij} = u_{1j}, u_{1j}, \ldots u_{Ij}$, according with x_{ij}^k; and (c) a fuzzy set, $Q = \{at\ least\ one, half, all\}$, related to a linguistic quantifier, $Q(p) = p^{\alpha}$, $\alpha > 0$. Accordingly, land suitability, $S_j^{k\alpha}$, was determined by:

$$S_j^{k\alpha} = \sum_{i}^{I}\left(\left(\sum_{k=1}^{j} u_{ij}\right)^{\alpha} - \left(\sum_{k=1}^{j-1} u_{ij}\right)^{\alpha}\right) z_{ij}^{k} \qquad (2)$$

Then, the OWA operator was implemented for the following land suitability scenarios:
If $\alpha = 2 \because Q = all$, then $Q(p)$ corresponds to a risk-averse attitude.
If $\alpha = 1 \because Q = half$, then $Q(p)$ corresponds to a risk-neutral attitude (WLC results).
If $\alpha = 0.5 \because Q = at\ least\ one$, then $Q(p)$ corresponds to a risk-seeker attitude.

Finally, an *if…and if…then…* rule-based model, prediction of a sample from a set of conditional statements, (Kuhn & Johnson, 2016) was implemented to find the optimal locations for swine plants (Figure 2).

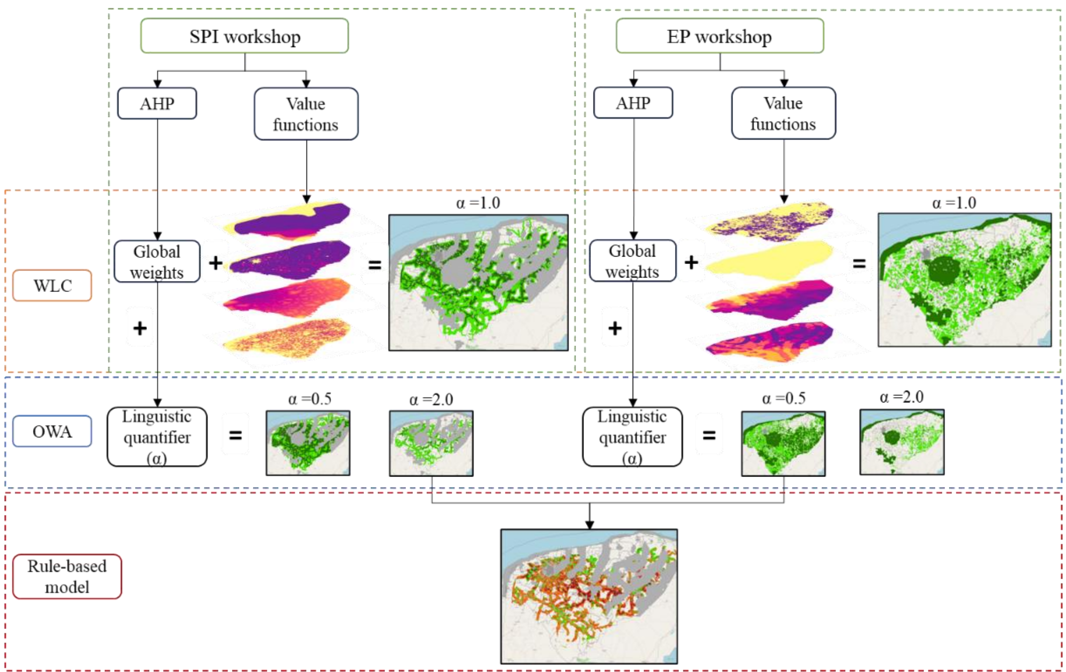

Figure 2 Implementation of GIS-AHP-OWA for LSA

4. Results

4.1 Analytic Hierarchy Process

The SPI model was developed as a four-level hierarchy (Figure 3; Tables 1-6). Level 1 includes the goal of identifying the sites that minimize the risk and socio-environmental impacts of SPI; level 2 includes three criteria for geographic attributes (Biophysical, Labor availability, and Infrastructure); level 3 includes the sub-criteria for Biophysical

(Forest cover and Water extraction cost), Labor availability (Rural zones, Urban zones, and Urban-rural zones), and Infrastructure (Electrical grid, Port, Roads, and Slaughterhouses); and level 4 includes two sub-criteria for Roads (Dirt roads and Highways). The results of the AHP model (Table 7) showed that the most important geographic attributes for SPI were Highways (0.265), Water extraction cost (0.232), Electrical grid (0.161), and Dirt roads (0.066).

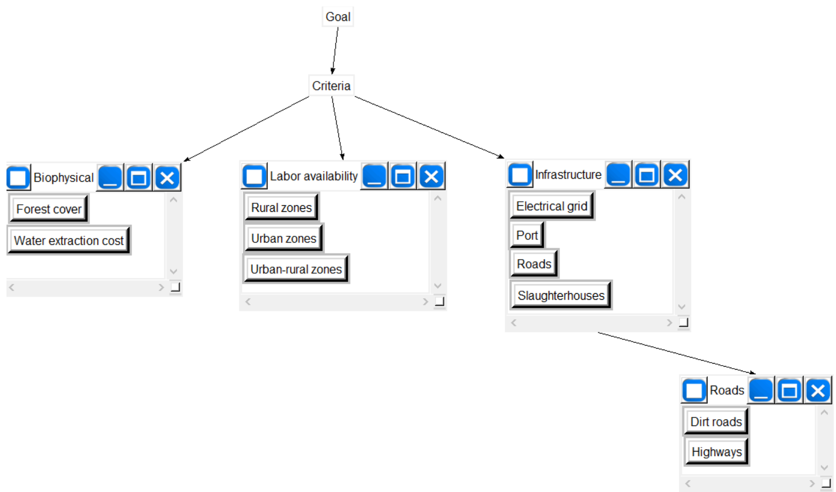

Figure 3 AHP model for SPI in *Super Decisions*

Table 1
Criteria of SPI model

Criterion	Sub-criterion	Definition
Biophysical	Forest cover	Current vegetation type
	Water extraction cost	Depth or distance (m) at which the aquifer is located
Infrastructure	Electrical grid	Distance (km) to the primary power grids of the Mexican Federal Electricity Commission (CFE)
	Slaughterhouses	Distance (km) to swine and poultry slaughterhouses and processing plants
	Port	Distance (km) to the food production plants located at Yucatán's main port
	Roads	Distance to highways and dirt roads
	Dirt roads	Distance (km) to secondary roads
	Highways	Distance (km) to primary two-lane paved highways
Labor availability	Rural zones	Distance (km) to rural settlements with less than 2,500 inhabitants

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Criterion	**Sub-criterion**	**Definition**
	Urban zones	Distance (km) to urban settlements with more than 15,000 inhabitants
	Urban-rural zones	Distance (km) to rural-urban settlements with more than 2,500 and less than 15,000 inhabitants

Table 2
Pairwise comparison matrix of SPI model with respect to criteria (CI = 0.08)

	Labor availability	Infrastructure
Biophysical	4	1/3
Labor availability		1/5

Table 3
Pairwise comparison matrix of SPI model with respect to infrastructure (CI = 0.07)

	Port	Slaughterhouses	Electrical grid
Roads	5	4	3
Port		1/3	1/3
Slaughterhouses			1/3

Table 4
Pairwise comparison matrix of SPI model with respect to roads (CI = 0.00)

	Highways
Dirt roads	1/4

Table 5
Pairwise comparisons matrix of SPI model with respect to biophysical (CI = 0.00)

	Water extraction cost
Forest cover	1/5

Table 6
Pairwise comparisons matrix of SPI model with respect to labor availability (CI = 0.02)

	Urban-rural zones	Urban zones
Rural zones	1/2	3
Urban-rural zones		4

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Table 7
Relative importance weights of SPI model (ocal weights are in parenthesis)

Criterion	**Sub-criterion**	**Global weight**
Biophysical (0.278)	Forest cover (0.166)	0.046
	Water extraction cost (0.833)	0.232
Infrastructure (0.626)	Electrical grid (0.256)	0.161
	Slaughterhouses (0.139)	0.087
	Port (0.074)	0.047
	Roads (0.528)	
	Dirt roads (0.200)	0.066
	Highways (0.800)	0.265
Labor availability (0.094)	Rural zones (0.319)	0.030
	Urban zones (0.121)	0.012
	Urban-rural zones (0.558)	0.053

The EP model was developed as a five-level hierarchy (Figure 4; Tables 8-20). Level 1 includes the goal of identifying the sites that maximize the conservation and sustainable use of biophysical and biocultural attributes of the territory; level 2 includes two criteria for geographic attributes (Environmental services and Functionality); level 3 includes the sub-criteria for Environmental services (Cultural, Provision, Regulation, and Support) and Functionality (Ecosystem fragility, Karst fragility and Water vulnerability); level 4 includes the sub-criteria for Cultural (Administrative and Biophysical and social), Provision (Forest cover, Bodies of water and Wild crops), Regulation (Carbon capture, Forest cover, and Melliferous species), Support (Aerial biomass, Forest cover, Forest richness, and Recharge zones), Ecosystem fragility (Bird conservation sites, Ecological integrity, and Natural and RAMSAR), Karst fragility (Doline density and Natural wells), and Water vulnerability (Intrinsic vulnerability, Recharge zones, Natural wells, and Wetlands); and level 5 includes the sub-criteria for Administrative (Biocultural, Commons, Conservation, Management, and Payment) and Biophysical and social (Archaeological zones, Indigenous population, and Grottoes). The results of the AHP model (Table 21) show that the most important geographic attributes for EP are Ecological integrity (0.136), Forest cover (0.112) and Recharge zones (0.087).

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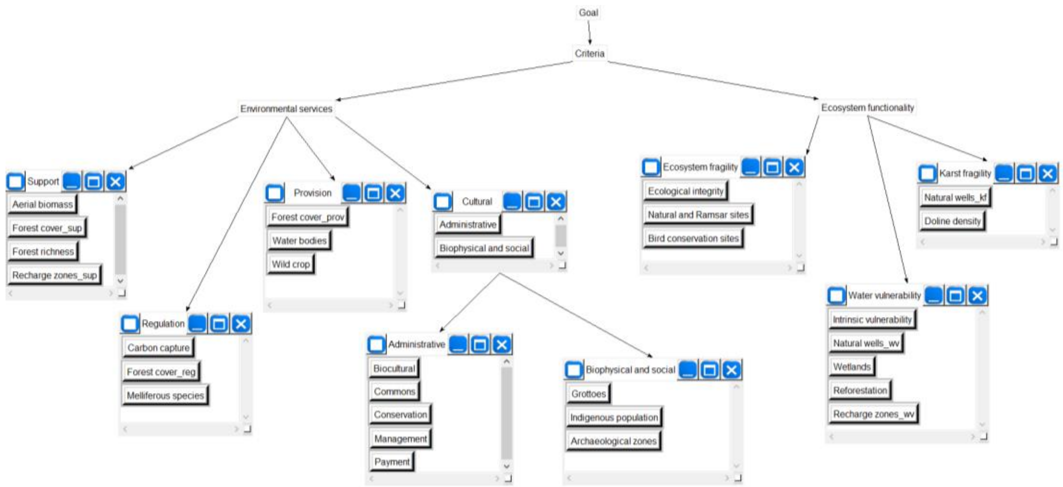

Figure 4 AHP model for EP in *Super Decisions*

Table 8
Criteria of EP model

Criterion	**Sub-criterion**	**Definition**
Environmental services	Cultural	Non-material values or benefits obtained from nature
	Administrative	Administrative and management attributes
	Biocultural	Presence of protected natural areas with a biocultural approach
	Commons	Presence of communal ejido areas
	Conservation	Presence of areas voluntarily destined for conservation
	Management	Presence of environmental management units
	Payment	Presence of environmental payment for ecosystem services projects
	Biophysical and social	Biophysical and social attributes related to cultural ecosystem services
	Archaeological zones	Presence of locations with remains of ancient civilizations or cultures
	Grottoes	Presence of cavities that form naturally in the ground or rock due to erosion
	Indigenous population	Percentage of municipal Mayan speakers
	Provision	Products obtained from nature for consumption or use, either directly or after processing
	Forest cover	Vegetation as a provision of food, genetic resources, and medicinal plants,

Criterion	Sub-criterion	Definition
		raw materials, and renewable fuels
	Bodies of water	Presence of bodies of water that provide water for human consumption and agricultural use
	Wild crops	Frequency of genetic resources for agriculture and biotechnology
	Regulation	Ecological processes that enhance or make human life possible,
	Carbon capture	Carbon capture as an indicator of climate regulation
	Forest cover	Type of coverage as an indicator of soil fertility maintenance, erosion control, disease control, and reduction of natural disasters
	Melliferous species	Aggregated distribution of honeybee species as an indicator of pollination
	Support	Ecological processes necessary for the other three types of ecosystem services
	Aerial biomass	Tree vegetative biomass as an indicator of primary productivity
	Forest cover	Forest cover type as an indicator of primary productivity
	Forest richness	Number of forest species as an indicator of primary productivity
	Recharge zones	Aquifer recharge zones as an indicator of the water cycle
Functionality	Ecosystem fragility	Conservation status and health of ecosystems and their resilience capacity
	Bird conservation sites	Presence of areas destined for the preservation of birds
	Ecological integrity	Ecological Integrity Index for top predators
	Natural and RAMSAR	Presence of protected natural areas and RAMSAR sites
	Karst fragility	Soil vulnerability to be affected by human activities or their effects
	Doline density	Number of sinkholes per hectare
	Natural wells	Presence of natural wells
	Water vulnerability	Vulnerability of the aquifer to external factors
	Intrinsic vulnerability	Inherent vulnerability to contamination of the karst aquifer
	Recharge zones	Presence of aquifer recharge zones
	Reforestation	Potential areas to be reforested or restored

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Criterion	**Sub-criterion**	**Definition**
	Natural wells	Presence of cenotes, sinkholes, poljes, and uvalas
	Wetlands	Presence of bodies of water that exclude natural wells and artificial ponds

Table 9
Pairwise comparison matrix of EP model with respect to criteria (CI = 0.00)

	Environmental services
Functionality	1

Table 10
Pairwise comparison matrix of EP model with respect to environmental services (CI = 0.03)

	Regulation	Provision	Cultural
Support	1	3	5
Regulation		2	5
Provision			4

Table 11
Pairwise comparison matrix of EP model with respect to support (CI = 0.09)

	Forest cover	Forest richness	Recharge zones
Aerial biomass	1/3	1/3	1/4
Forest cover		4	1/2
Recharge zones			1/3

Table 12
Pairwise comparison matrix of EP model with respect to regulation (CI = 0.08)

	Forest cover	Melliferous species
Carbon capture	1/3	4
Forest cover		5

Table 13
Pairwise comparison matrix of EP model with respect to provision (CI = 0.00)

	Bodies of water	Wild crops
Forest cover	3	3
Bodies of water		1

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Table 14
Pairwise comparison matrix of EP model with respect to cultural (CI = 0.00)

	Biophysical and social
Administrative	1/3

Table 15
Pairwise comparison matrix of EP model with respect to biophysical and social (CI = 0.00)

	Indigenous population	Archaeological zones
Grottoes	1	1
Indigenous population		1

Table 16
Pairwise comparison matrix of EP model with respect to administrative (CI = 0.09)

	Biocultural	Payment	Management	Commons
Conservation	1	4	1	1
Biocultural		2	3	2
Payment			2	1/2
Management				1

Table 17
Pairwise comparison matrix of EP model with respect to functionality (CI = 0.00)

	Water vulnerability	Karst vulnerability
Ecosystem fragility	1	2
Water vulnerability		2

Table 18
Pairwise comparison matrix of EP model with respect to ecosystem fragility (CI = 0.08)

	Natural and RAMSAR	Ecological integrity
Bird conservation sites	1/3	1/5
Natural and RAMSAR		1/4

Table 19
Pairwise comparison matrix of EP model with respect to water vulnerability (CI = 0.04)

	Wetlands	Reforestation	Intrinsic vulnerability	Recharge zones
Natural wells	1	3	1/5	1/3
Wetlands		3	1/3	1/3
Reforestation			1/5	1/3
Intrinsic vulnerability				1

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Table 20
Pairwise comparison matrix of EP model with respect to *Karst fragility* (CI = 0.00)

	Doline density
Natural wells	1/3

Table 21
Relative importance weights of EP model (local weights are in parenthesis)

Criterion	**Sub-criterion**	**Global weight**
Environmental services (0.50)	Cultural (0.063)	
	Administrative (0.251)	
	Biocultural (0.260)	0.002
	Commons (0.183)	0.001
	Conservation (0.260)	0.002
	Management (0.235)	0.001
	Payment (0.131)	0.001
	Biophysical and social (0.748)	
	Archaeological zones (0.333)	0.008
	Grottoes (0.333)	0.008
	Indigenous population (0.333)	0.008
	Provision (0.184)	
	Forest cover (0.594)	0.055
	Bodies of water (0.204)	0.018
	Wild crops (0.201)	0.018
	Regulation (0.355)	
	Carbon capture (0.280)	0.050
	Forest cover (0.625)	0.112
	Melliferous species (0.093)	0.016
	Support (0.395)	
	Aerial biomass (0.083)	0.016
	Forest cover (0.328)	0.065
	Forest richness (0.148)	0.030
	Recharge zones (0.439)	0.087
Functionality (0.50)	Ecosystem fragility (0.405)	
	Bird conservation sites (0.102)	0.021
	Ecological integrity (0.673)	0.136
	Natural and RAMSAR sites (0.224)	0.046
	Karst fragility (0.198)	
	Doline density (0.745)	0.074
	Natural wells (0.254)	0.025

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Criterion	Sub-criterion	Global weight
	Water vulnerability (0.396)	
	Intrinsic vulnerability (0.380)	0.075
	Recharge zones (0.309)	0.061
	Reforestation (0.063)	0.013
	Natural wells (0.118)	0.024
	Wetlands (0.128)	0.025

4.2 Geographic information system

The geospatial analysis with the participants of the SPI workshop resulted in 10 value functions (Figure 5) as follows: two discrete (Forest cover and Water extraction cost), and eight continuous (Electrical grid, Slaughterhouses, Port, Dirt roads, Highways, Rural zones, Urban zones, Urban-rural zones).

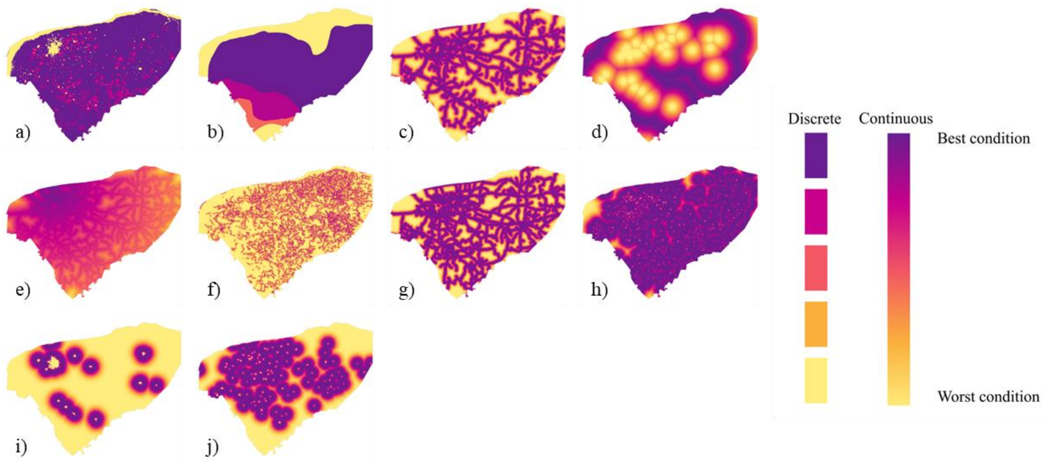

Figure 5 SPI value functions

a) Forest cover, b) Water extraction cost, c) Electrical grid, d) Slaughterhouses, e) Port, f) Dirt roads, g) Highways, h) Rural zones, i) Urban zones, j) Urban-rural zones

The geospatial analysis with the participants of the EP workshop resulted in 28 value functions (Figure 6) as follows: 22 discrete (Biocultural, Commons, Conservation, Management, Payment, Archaeological zones, Grottoes, Indigenous population, Forest cover (Provision), Bodies of water, Wild crops, Forest cover (Regulation), Forest cover (Support), Recharge zones (Support), Bird conservation sites, Natural and RAMSAR, Natural wells (Karst fragility), Intrinsic vulnerability, Recharge zones (Water vulnerability), Reforestation, Natural wells (Water vulnerability), and Wetlands), and six continuous (Carbon capture, Melliferous species, Aerial biomass, Forest richness, Ecological integrity, and Doline density).

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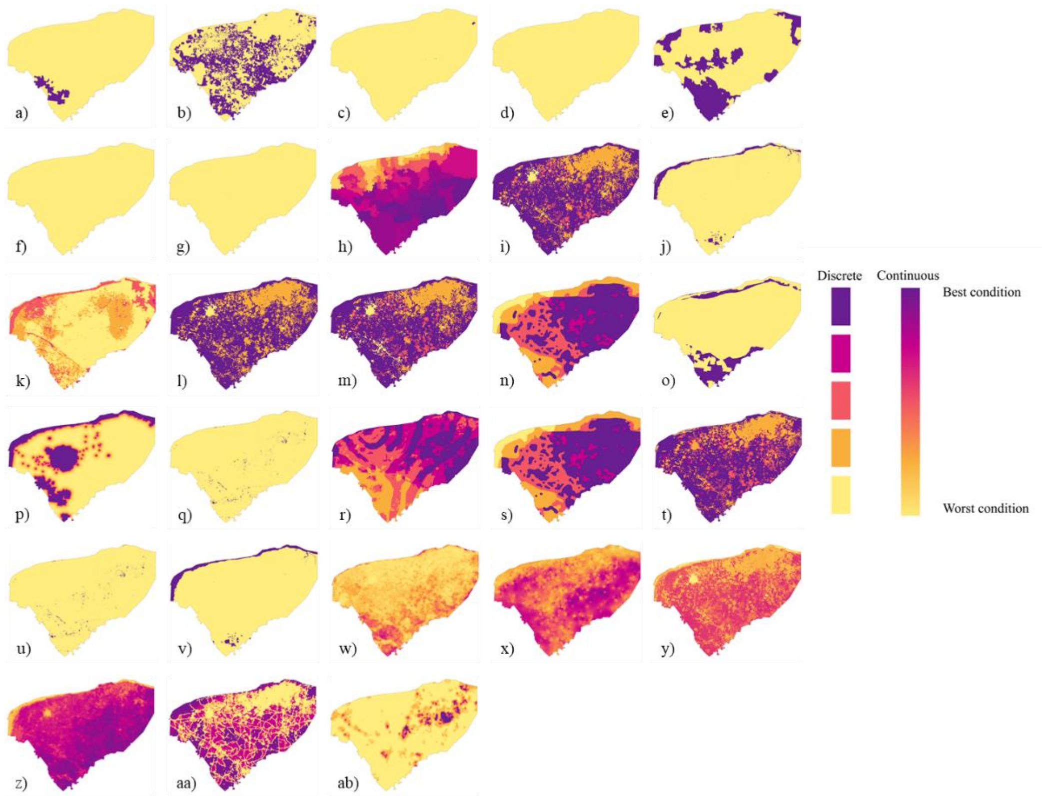

Figure 6 EP value functions
a) Biocultural, b) Commons, c) Conservation, d) Management, e) Payment, f) Archaeological zones, g) Grottoes, h) Indigenous population, i) Forest cover (Provision), j) Bodies of water, k) Wild crops, l) Forest cover (Regulation), m) Forest cover (Support), n) Recharge zones (Support), o) Bird conservation sites, p) Natural and RAMSAR, q) Natural wells (Karst fragility), r) Intrinsic vulnerability, s) Recharge zones (Water vulnerability), t) Reforestation, u) Natural wells (Water vulnerability), v) Wetlands, w) Carbon capture, x) Melliferous species, y) Aerial biomass, z) Forest richness, aa) Ecological integrity, ab) Doline density

The land suitability maps depicted the locations suitable for both SPI and EP (Figure 7). The most suitable sites for SPI were found near roads and cities, while those for EP were dispersed across the state, except for agricultural lands primarily concentrated in the northern areas.

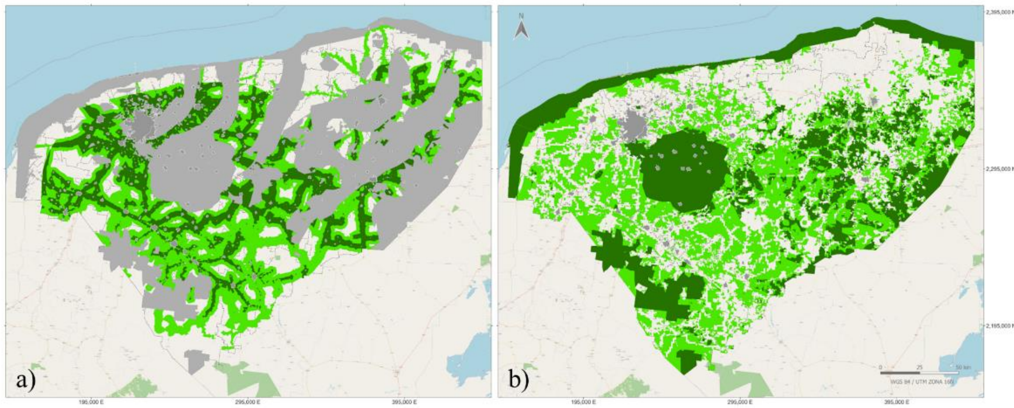

Figure 7 WLC results for a) SPI and b) EP
Land suitability: very high (dark green), high (light green), restricted (gray), null (white)

4.3 Ordered Weighted Average

The application of the OWA operator enabled the calculation of land suitability scores for each spatial unit (pixel). Following Equation 2, for instance, in a given pixel k, the OWA operator entailed the reordering of criteria weights, w_{ij}, into u_{ij}, based on the normalized values of the attributes, x_{ij}^k, reordered as z_{ij}^k (Table 22). Next, the OWA operator involved changing the linguistic quantifier, α, to consider the risk-taking attitudes (Figure 8, Table 23).

An example is necessary to illustrate the application of the OWA operator. In line with Malczewski's (2006) reformulation, Table 22 highlights the distinction between importance weights and order weights. The former were assigned to evaluation criteria to indicate their relative importance; consequently, all pixels on the i-th criterion map were assigned an identical weight of w_{ij}. Conversely, order weights were linked to criterion values on a location-specific basis. They were assigned to the attribute value of the k-th location in descending order, regardless of the source criterion map. For its part, the three distinct land suitability patterns presented in Figure 8, both for SPI and EP, were associated with a specific linguistic quantifier, α, which indicate risk attitudes (Table 23). Accordingly, the fuzzy quantifier '*all'* signified a risk-averse attitude or a worst-case scenario, where each location was assigned the lowest criterion value (MIN operator). In contrast, the fuzzy quantifier '*at least one'* embodied a risk-seeking attitude or a best-case scenario, assigning the highest criterion value to each location (MAX operator). Finally, the fuzzy quantifier '*half'* corresponded to a risk-neutral attitude, aligning with the results of the WLC method.

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Table 22
OWA operator values for SPI in pixel k

Criterion	$\boldsymbol{w_{ij}}$	$\boldsymbol{x_{ij}^k}$	$\boldsymbol{z_{ij}^k}$	$\boldsymbol{u_{ij}}$
Forest cover	0.046	1.000	1.000	0.232
Water extraction cost	0.232	1.000	1.000	0.053
Electrical grid	0.161	0.593	1.000	0.046
Slaughterhouses	0.087	0.980	0.980	0.087
Port	0.047	0.604	0.924	0.030
Dirt roads	0.066	0.056	0.604	0.047
Highways	0.265	0.535	0.593	0.161
Rural zones	0.030	0.924	0.535	0.265
Urban zones	0.012	0.000	0.056	0.066
Urban-rural zones	0.053	1.000	0.000	0.012

Table 23
Land suitability score of SPI in pixel k

Quantifier	**Operator**	**Risk-taking attitude**	$\boldsymbol{\alpha}$	$\boldsymbol{S_j^{k\alpha}}$
At least one	MAX	Seeker	0.5	0.832
Half	WLC	Neutral	1.0	0.713
All	MIN	Averse	2.0	0.565

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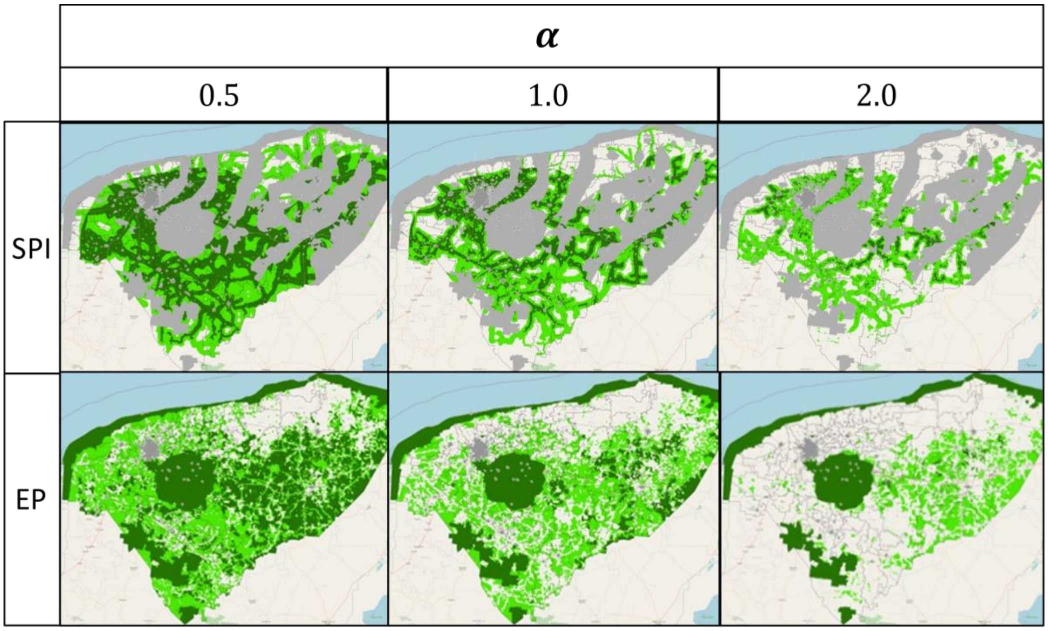

Figure 8 OWA scenarios: seeker ($\alpha = 0.5$), neutral ($\alpha = 1$), and averse ($\alpha = 2$)
Land suitability: very high (dark green), high (light green), restricted (gray), and null (white)

4.4 Rule-based model

The implementation of the rule-based model used GIS to locate the intersection in pixel x_{ij}^k of categories high and very high between the map layers of risk-seeker attitude for environmental protection and risk-averse attitude for swine plant investment $\alpha(SP) = 2 \wedge \alpha(EP) = 0.5$ (Table 24; Figure 9).

Table 24
Rule-based model for investment risk: low (L), high (H), very high (VH)

If suitability for SP is	*and if* suitability for EP is	*then* investment risk is	Area (km^2)
Less than H	Less than H	Does not apply	-
H	Less than H	L	2,394
H	H	VH	4,164
H	VH	VH	1,580
VH	Less than H	L	488
VH	H	H	638
VH	VH	VH	235

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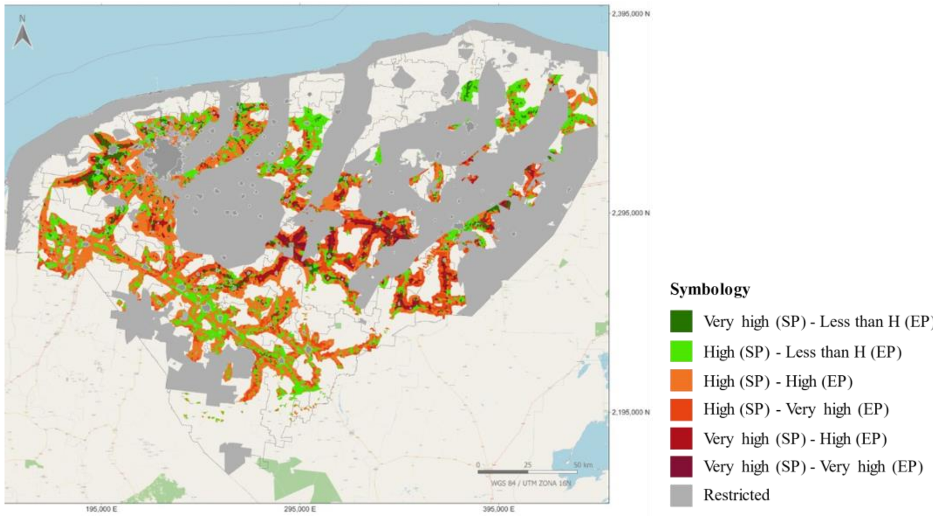

Figure 9 Results of rule-based model

The rule-based model results showed, on the one hand, the environmental conflict area (6,617 km^2) between SPI and EP. The results indicated, on the other hand, that land suitability for SPI was optimal in 488 km^2 and high in 2,394 km^2, which did not overlap with zones of high or very high land suitability for EP. These areas accounted for 2,882 km^2 (7% of the study area) of low investment risk.

5. Discussion

We have demonstrated the application of GIS-AHP-OWA in mitigating the risks posed by infrastructure investment projects to regional sustainable development. In doing so, we have validated the observations made by Malcksewsky (2006) regarding the importance of generating customized land-use suitability maps that are tailored to stakeholders' risk attitudes. Our study also confirms the effectiveness of OWA as a multi-objective combinatorial optimization operator, as pointed out by Fernández et al. (2014). In our case, the integration of OWA with AHP was particularly useful in exploring land use patterns that align with the opposing goals established for SPI and EP models. The former minimized the socio-environmental impacts and investment risks, while the latter maximized the conservation and sustainable use of the territory. By combining OWA with the AHP, we were able to conduct a more nuanced and comprehensive assessment of land use patterns in the context of LSA.

The participatory workshops successfully served as a designated "safe space" of participation, fostering an environment where individuals felt uninhibited in expressing their perspectives. This approach effectively prevented the dominance of any single viewpoint and facilitated the extraction, discussion, and communication of knowledge, as emphasized by Pedroza et al. (2020). We concur with Moreno-Jimenez and Vargas (2018) that measurement-based approaches in the workshops aid in conflict resolution. In our case, the comparison of relative suitability scores between SPI and EP enabled us to identify locations that minimized environmental conflict. Consequently, our approach facilitated an objective treatment of subjective preferences, values, and interests of the stakeholders, a concern emphasized by Keeney (1992). For example, the AHP pairwise comparison process facilitated the evaluation of both geographic attributes and stakeholders' preferences from a cognitive point of view. Thus, with the AHP we were able to consider all relevant elements for conflict resolution in LSA. In contrast to Khalid and Awais (2015), who proposed three methods to attain a "perfect" consensus, our study yielded results that align with Bojórquez-Tapia et al.'s (2016) proposal for addressing contentious projects, namely Rawlsian's "overlapping consensus." This consensus approach allows for stakeholders with divergent worldviews to support an outcome for different reasons, leading to a resolution that is more robust and sustainable. Our study identified over 1,400 plants that could be sited in regions with low investment risk and minimal environmental conflicts, considering that a swine plant occupies around 2 km^2. The fact that stakeholders with divergent worldviews could support this outcome for different reasons indicates that overlapping consensus was achieved. Consequently, a comprehensive and faithful portrayal emerged, encompassing the ongoing and forthcoming infrastructure development as well as conservation endeavors within the Yucatán region.

The implementation of GIS-MCDA-OWA was not without its limitations. One of the primary operational limitations was its time-consuming nature. The calculations required were not only linked to Python-QGIS but also took up to four hours per scenario. Therefore, the approach could not be used during participatory workshops where real-time decision-making was required. This limitation highlights the need for faster, more efficient methods to explore land suitability scenarios for infrastructure projects. Another limitation of the approach was its inability to pinpoint the exact locations to construct SPI projects. While it helped to identify the most appropriate areas to consider in an infrastructure investment planning process, a more comprehensive analysis would be required to determine potential infrastructure investment sites. This limitation underscores the need for complementary methods that can provide more detailed information on specific locations for infrastructure projects. Despite these limitations, the implementation of GIS-MCDA-OWA effectively facilitated discussions among the specialists and improved estimations of SPI suitability in Yucatán. The approach can be used to identify suitable locations for various types of infrastructure projects and can be an essential tool for policymakers and infrastructure planners.

6. Conclusion

This article demonstrated a successful implementation of GIS-MCDA-OWA for land suitability assessment, using the example of infrastructure investment projects of swine plants in Yucatán, Mexico. The approach was discussed in the context of environmental conflicts, highlighting the importance of sustainable development. Through this approach, systematic and transparent procedures were provided for documenting and assessing land suitability, leading to consensual investment recommendations about infrastructure projects. This approach has the potential to enhance the objectivity of how land suitability assessments can incorporate and analyze the diverse preferences, values and interests of multiple stakeholders. Furthermore, it has the potential to generate geographic representations that can serve as decision tools in spatial planning processes. Overall, this implementation provides a valuable contribution to the fields of LSA and conflict resolution, offering a robust and comprehensive approach to decision-making for infrastructure development.

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