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Multicriteria Evaluation in Real Estate Land-use Suitability Analysis:

The case of Volos, Greece

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Abstract

The integration of Geographic Information Systems (GIS) into real estate analysis has long been considered an interesting interdisciplinary pursuit, but has yet to become mainstream. Despite the increasing academic focus over the last twenty years, this endeavour has mostly been approached from the scientific side of Geography. Inversely, such focus from the real estate sector remains marginal. Notably, there is an expanding theoretical and empirical basis supporting the importance of further exploring the GIS and Real Estate integration potential. Besides, the real estate sector is being increasingly scrutinised regarding the transparency and validity of decision-making practises. GIS-based analysis can help meet such requirements.

The present research looked into the role of GIS in real estate analysis. The aim was to apply multicriteria evaluation techniques for real estate land-use suitability analysis in the Greek coastal city of Volos. The multicriteria evaluation of land-use suitability was examined based on selected spatial criteria related to real estate values in the study area, using the non-fuzzy and fuzzy method of the Analytical Hierarchy Process (AHP). The analysis focused on the Commercial, Office and Residential land-uses.

Research findings showed that fuzzy AHP should always be considered in terms of providing more accurate spatial weights compared to the non-fuzzy AHP, but whether the one will be selected over the other is dependent on context and the resources needed. The AHP analysis provided clear classification of suitability for the land-uses examined. Validity of the AHP output was assessed by using correlation analysis. The research also focused on the spatial criteria weight extraction methods, which are not often detailed in relevant studies. Based on the findings, attention is needed when using pairwise comparison matrices (PCMs) for weighting spatial criteria, if the participants have no prior experience with such processes. Also, fuzzification of PCMs should not overextend unless necessary. Linked to the above, live interviews conducted provided consistent PCMs. Acknowledging integration challenges like time and data constraints, this research confirmed the potential for GIS-based multicriteria evaluation to improve real estate decision-making.

Keywords: *Geography, GIS, Real Estate, Multicriteria Evaluation, Fuzzy, AHP*

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Abbreviations

AHP	Analytic Hierarchy Process
CR	Consistency Ratio
DSS	Decision Support Systems
FAHP	Fuzzy AHP
F/AHP	Traditional and Fuzzy AHP
GIS	Geographic Information Systems
LUs	Land Uses
MCDA	Multicriteria Decision Analysis
MCDM	Multicriteria Decision Making
MCE	Multicriteria Evaluation
PCM	Pairwise Comparison Matrix
TFN	Triangular Fuzzy Number
WLC	Weighted Linear Combination

Glossary of terms

AHP	Decision-making process where the goal is broken down to set objectives, that have to be served by a combination of criteria. The criteria are weighted using pairwise comparison matrices. The AHP quantifies opinions and preferences
Boolean Logic	Binary logic of either False (0) or True (1) states, applied via Boolean operators of “Or”, “And” and “Not”
Consistency Ratio	Ratio measuring the consistency of an examined PCM against the average consistency of a large number of PCMs of the same order (size) containing random numbers
Decision Support System	Customised frameworks aiming to support decision-making processes, and including physical and digital tools e.g. maps, tables, interactive software, process guidelines
Defuzzification	Process of converting a fuzzy set of numbers into a single precise number. The opposite process is fuzzification
Fuzzification	Process of converting crisp values to fuzzy ones, using fuzzy memberships defining the level of suitability, according to set parameters. Defuzzification regards the opposite process
Fuzzy AHP	AHP using spatial criteria weights calculated based on fuzzified pairwise comparison matrices

Fuzzy Logic	Variable logic of continuous ranges between false/rejected (0) and true/accepted (1) states, applied via fuzzy memberships
Fuzzy Memberships	Algebraic expressions of fuzziness based on some continuous form e.g. triangular, trapezoidal, sigmoidal
Fuzzy PCMs	Pairwise comparison matrices were the non-fuzzy scores have been increased (upper values) and decreased (lower value) by a certain factor e.g. ±2. Fuzzy PCMs aim to account for uncertainty in opinions and preferences
Fuzzy Spatial Distances	Euclidean distances, fuzzified by using set fuzzy memberships
MCDM/MCDA	Decision-making process for selecting the best option among a set of alternatives, by considering more than one criterion
Pairwise Comparison	Ranking process based on a stepped selection of alternatives e.g. criteria, proceeding by comparing them in pairs
PCM	Matrix with the same set of criteria in its rows and columns, to be compared in pairs. The PCM is reciprocal i.e. the elements in one half of the matrix are the inverse of those in its other half
Property Class/Type	Commercial/Retail, Offices & Residential are the types of real estate property examined and discussed in this thesis
Ratings	Criteria weighting method were a set number of points e.g. 100 have to be allocated to a set number of criteria
Real Estate	The real estate sector as separate and autonomous discipline
Real estate land-uses	Commercial, office & residential land-uses used in this study
Spatial Criteria Layers	GIS layers containing geographical data corresponding to the spatial criteria i.e. bus stops, open spaces, schools to be used in geoprocessing and spatial analysis
Spatial Criteria Weights	Numerical expression of how important each spatial criterion is in determining land-use suitability, when combined with all the other criteria. Criteria weights are expressed as percentages. All criteria weights included in the analysis sum up to 100%
Stakeholders	Any party with an interest in real estate and spatial planning decision-making e.g. public bodies, financial institutions, local communities, property sellers or buyers, realtors, NGOs
Triangular Fuzzy Number	Triangular expression of fuzziness, using a set of three values (l, m, u) i.e. the most probable value m, the lowest probable value l and the upper highest probable value u. In a fuzzy PCM the value m will be the original non-fuzzy scores and the values l and u will be set according to the extent of the fuzzification e.g. ±2 points from the middle value m.

Chapter 1 – Introduction

1.1 Overview and Motivation

Theorising and discussing on the integration of GIS[1] and Real Estate goes back to the 1990s, even though this interdisciplinary pursuit remained rather niche for many years. Despite the somehow evident dependence on location, GIS tools and spatial analysis have yet to fully enter the mainstream real estate analysis (Reed & Pettit, 2019). In this recent book, editors Reed & Pettit (2019) brought together the collective work of various professionals related to Real Estate. One very important point made through this effort was that Real Estate and GIS integration can be data-driven, supporting robust analyses. Despite Real Estate and GIS being linked to locational parameters, their synergy through an interdisciplinary approach has yet to be sufficiently explored (Reed & Pettit, 2019).

During the last decade the interest and focus on the GIS and Real Estate integration potential has increased. Besides the academic research there is strong institutional and market pressure for optimisation of real estate analysis, also as the result of various property-related systemic shocks over the past years (Renigier-Bilozor *et al.*, 2018). Land valuation using traditional methods is often over-relying on the subjectivity of real estate professionals. Therefore, it is criticised regarding the lack of standardisation and transparency, affecting both the private and the public sector, for example in terms of property value appraisal and taxation respectively (Bencure *et al.*, 2019). GIS tools can provide robust technical and theoretical support to improve real estate analyses.

There have been attempts to integrate spatial fuzzy analysis into real estate research. Fuzzy logic is based on the fuzzy set theory (Zadeh, 1965; as cited in Krecji, 2018) where notions like suitability and preference are not expressed as absolute crisp numbers but as degrees of suitability and preference, using selected fuzzy memberships. For example, when asking whether a site is suitable for a certain land-use the answer is not a simple “yes” or “no” but given as a degree of suitability e.g. 0.675 within a range of 0 (unsuitable) to 1 (absolutely suitable). Fuzzy logic is ideal in cases of subjectivity, ambiguity and imprecision pertaining to judgements and/or insufficient information.

Applying fuzzy analysis methods in real estate decision-making, Lopez *et al*. (2010) used fuzzy specification for real estate valuation. They assessed the effect of client preferences like lighting, view, area, number of rooms etc. expressed as fuzzy memberships, on the assets’ marketability. Assessing the residential real estate markets in Poland and Italy according to economic, social and spatial rankings, Renigier-Bilozor *et al*. (2018) concurred that fuzzy analysis is better fit in cases of uncertain and imperfect markets with vague real estate market data. This is directly related to the Greek real estate market and its issues with transparency, accuracy and availability of data (Dimopoulos & Moulas, 2016).

[1] In this thesis, the term refers both to the technical aspect GIS and the science behind such systems

Regarding spatial multi-criteria decision making in urban land-use planning, Mosadeghi *et al*. (2015) compared the analytical hierarchy procedure (AHP) with the Fuzzy-AHP. The two quantitative techniques were assessed in selecting different land-uses (residential, recreation, extractive industry and marine industry) in southern Queensland, Australia. They argued that for the initial stages of planning when identifying possible development options, simplified methods suffice. But when planning needs to go into the detail and examine spatial extents of development, combination of simple and fuzzy AHP methods bears more accurate results. Caprioli & Bottero (2021) noted the recent interest in GIS-supported Multicriteria Decision Analysis (MCDA) for spatial planning purposes. Caprioli & Bottero (2021) used both AHP and fuzzy AHP and argued that the FAHP method can better handle cases of decision-making involving many different stakeholders, and numerous selection criteria which can be reduced. When all criteria are relevant though, the non-fuzzy AHP method seems preferable.

Focusing on the integration of GIS-based analysis and Real Estate in Greece, the research output is still limited. In one of the earliest analyses, Athanasiou & Photis (2004) used cluster analysis to assess land value in relation to public service access. They concluded that more than 60% of city blocks in Volos have different location-based values, compared to the ones attributed to them by the state. Pagourtzi *et al*. (2005) discussed on the potential of GIS techniques, including fuzzy theory, to assess real estate valuation for decision support systems. Their conceptual analysis was focused on a series of variables dependent on distance from points/areas of interest. Tsiotas *et al*. (2017) examined the spatial patterns for hotels, restaurants, banks and gas stations in relation to the bus and road network in Volos City.

This research aimed at filling-in the knowledge gap linked to the application of GIS-based multicriteria evaluation in real estate analysis in Greece. As far as the author is aware, no previous research has been made regarding the comparative application of the non-fuzzy and fuzzy multicriteria evaluation in real estate land-use suitability analysis for the city of Volos. The analysis also delved into the practical implications of extracting spatial criteria weights by using pairwise comparison matrices. Lastly, the land-use suitability output maps were assessed on their validity via correlation analysis. Therefore, the research also contributed to the overall evaluation of the procedures pertaining to the use of multicriteria evaluation in real estate analysis.

1.2 Research Aim, Questions and Objectives

The aim of this research was to apply GIS-based multicriteria evaluation for real estate land use suitability analysis, in the Greek coastal city of Volos. To support this research aim the following research questions (RQs) and research objectives (ROs) were set.

Research Questions

RQ 1: What is the relative difference between the non-fuzzy and the fuzzy AHP output for commercial, office and residential land-uses in Volos City?

RQ 2: What is the total area per land-use suitability for commercial, office and residential land-uses in the city of Volos?

Research Objectives

RO 1: Select and weight spatial criteria to be used in non-fuzzy and fuzzy AHP real estate land-use suitability analysis in the urban area of Volos City

RO 2: Develop real estate land-use suitability zones in the urban area of Volos City, using non-fuzzy and fuzzy AHP analysis

RO 3: Compare the fuzzy and non-fuzzy AHP output, for real estate land-use suitability analysis in the study area

RO 4: Visualise the AHP real estate land-use suitability zones in grid form

RO 5: Assess the validity of the AHP land-use suitability output

1.3 Thesis Structure

Having established the rationale and the research aim behind the present thesis, Chapter 2 is dedicated to key aspects regarding the integration of GIS and Real Estate. Following up on the theoretical framework, Chapter 3 analyses the connection between GIS-based MCDM and AHP, also in relation to Real Estate. Chapter 4 details the research data, design and methods used in this research. The results of the data collected and processed are presented in Chapter 5. Discussion on the findings and processes along with future research suggestions and limitations are given in Chapter 6.

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CHAPTER 2 – GIS and Real Estate Integration

Introduction

This chapter focuses on key themes of the GIS and Real Estate integration in terms of theory and application. The literature reviewed also regards various practical implications of such a more or less evident interplay between GIS and real estate themes. Table I.1 (Appendix I) summarises some interesting case studies of GIS and RE integration in the last twenty years.

2.1 Opportunities and Challenges

Even though the connection between GIS and Real Estate may today seem evident, albeit not always straightforward, the discussion is not new. In the early '90s Thrall & Marks (1993) were underlining the strong impact of GIS in real estate discipline, gradually progressing towards a paradigm shift (Thrall, 1998). Thrall & Marks (1993) extensively analysed the need to instil spatial reasoning in Real Estate, which they found rather simplistic in terms of which spatial parameters were considered and how.

Focus on the use of GIS in Real Estate has recently started to increase. This is due to GIS being gradually recognised as useful in providing geographic reasoning and data-based spatial analysis in Real Estate. For example, Mrowczynska *et al*. (2021) noted that, due to its data collection, spatial analysis and visualisation potential, GIS can effectively be used to bring together professionals and decision-makers from different fields. This was also underlined some years earlier by Podor & Nyiri (2010), where they analysed the usefulness of GIS in combining multidisciplinary knowledge on real estate investment, development and decision-making. Additionally, due to the effects and the successive aftershocks of the global financial crisis of 2008-2010, the real estate sector has been severely scrutinised in terms of the accuracy of property valuations and price prediction, transparency, DSS and monitoring (Renigier-Bilozor *et al*., 2018).

Real Estate is inherently tied to dynamic and complex spatial issues, the solution to which can be facilitated through the use of GIS (Wofford & Thrall, 1997). Typical example of such case is the suitability analysis used for asset selection, among different options existing at various locations. Thrall (1998) supported that real estate professionals would eventually have to embrace GIS tools and acquire relevant skills. Nevertheless, GIS and Real Estate integration is still far from mature. One of the key barriers to overcome in order to reach integration is convincing real estate professionals that GIS is a practical and easy alternative to traditional and well-established practices (Wofford & Thrall, 1997).

Another important issue regards the different characteristics of real estate property assets and the varying needs of real estate stakeholders. In their analysis, Podor & Nyiri (2010) argued that the various real estate types have different spatial dependencies and sensitivities, for example *Residential* (location, building regulations, taxation, population density), *Retail* (location and transportation), and *Offices* (transportation, bus stops, parking, shopping and neighbourhood). Moreover, various Real Estate actors analyse and understand the value of land according to their own needs and agendas. Investors for example focus on yield security, market transparency, infrastructure availability and operational costs (Podor & Nyiri, 2010).

Even though GIS and Real Estate integration is openly discussed, the research focus is not balanced. Geography academics delve into real estate phenomena more easily than real estate professionals (Thrall, 1998), while the opposite is still not so common. Main reason for this imbalance is a preference of the real estate sector for technocratic output which is fast and flashy, while theorisation and explanations are underplayed as overly time-consuming and resource-demanding (Wofford & Thrall, 1997). Moreover, there is a significant risk when generalising results based on small scale observation and analysis (Wofford & Thrall, 1997), which does not help make GIS-based real estate analysis more attractive.

No doubt, academic research relating to GIS and Real Estate integration has expanded, but is still heavily geography-sided. The real estate researchers remain somehow hesitant to explore such topics, unless they produce easy-to-explain, visually pleasing and marketable output. Reed & Pettit (2019) underlined that the various practical implications and potential benefits of combining GIS and Real Estate are not always evident, requiring robust argumentation and accessible interpretation.

If successful, GIS application in Real Estate may improve transparency (accurate, spatially referenced and publicly available real estate data) and fairer taxation (state-imposed property taxes dynamically reflecting the true property values in terms of spatial equity) – gradually leading towards more efficient and stable real estate markets (Thrall, 1998; Dimopoulos & Moulas, 2016; Starcek & Subic Kovac, 2019).

2.2 Selected Cases of Integration

In a recent paper, Bencure *et al*. (2019) attempted to develop and apply an AHP-based model for mass land value appraisal in Thailand sub-urban areas. They underlined the critical importance of credible and accurate land valuations for both the real estate market (financing, development, values etc.) and the public sector (taxation, land uses, expropriations etc.). Demetriou (2018) noted that even though real estate prices are dependent on supply and demand, land has its own value which is tied to spatial parameters. Vernon-Bido *et al*. (2017) made an interesting use of GIS, trying to examine the negative effect of foreclosures on property values and the overall health of the property market. They concluded in their paper that the real estate prices are subject to price and value drop, depending on the distance from densities of foreclosed properties.

Bourassa *et al*. (2005) analysed the impact of aesthetic externalities (water view, landscape and neighbourhood) on residential properties. The effect of aesthetic externalities is stronger and more persistent in cities with varying elevations, compared to flat ones. The link between land values and locational variables is rather inelastic, whereas variables related to building values are elastic. Bourassa *et al*. (2005) argued that water-view is a cross-city value-adding parameter, while the landscape and attractive locale factors are subjective and city-dependent. Making extended use of GIS capabilities, Wallner (2012) examined the effect of waterfront, sea view and forest view on the real estate prices. On the same topic, Mittal & Byahut (2016) also included open spaces like parks and green trails in their analysis.

For the Indonesian property market, Berawi *et al*. (2010) found that the impact of railroad transit to commercial property prices in Jakarta was rather weak, compared to parameters like property size, location and layout. Proximity to railroad stations may benefit land values, but the effect is dependent on the city examined and the conditions around the railroad stations (maintenance, noise, pollution, crime etc.).

One of the first attempts to use GIS in the Greek real estate was that of Athanasiou & Photis (2004) in the Greek city of Volos. They examined the effect of distance from public services and bus stations on objective values set by the state. They observed that, in more than half of the city bocks the "*institutional"* value (assigned by the state) was higher than the *locational* one (based on distance from public services and bus stations). That said, no assessment of the correlation between institutional and locational values was presented in their study.

Combining MCDA and GIS, Caprioli & Bottero (2021) analysed the site selection process for a major healthcare project in Turin, Italy. They noted that urban planning decision processes are particularly demanding. Decision-makers and stakeholders involved have their own – often conflicting – preferences, expectations and agendas. Focusing on regional planning, Sedogo & Groten (2002) argued that use of GIS can support the improvement of local government efficiency in various aspects of planning and implementation like fairer taxation, access to infrastructure, democratic participation and sustainability policies.

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CHAPTER 3 – GIS in Multicriteria Evaluation

Introduction

This chapter explores the overall concepts of multicriteria evaluation (MCE), analysis and decision-making, also in relation to real estate and spatial planning. The traditional and the fuzzy Analytical Hierarchy Process (F/AHP), as Multicriteria Decision-making (MCDM) methods, are also discussed in the second half of the chapter.

3.1 Multicriteria Decision Analysis

Multicriteria decision making, analysis and evaluation refer to similar processes and are used interchangeably (Malczewski, 1999), with MCE being the umbrella term. Eastman (1999) explained that MCE in GIS regards land allocation, according to set objectives linked to certain attributes these lands must possess. The interaction between the analyst and decision-makers is critical in MCE criteria selection and weighting, and often takes place outside the GIS environment (Gomes & Lins, 2002).

Multicriteria Decision Analysis (MCDA) refers either to *multi-objective* analysis (MODM) i.e. mathematically define and optimise spatial alternatives in land parcels, or *multi-attribute* analysis (MADM) i.e. selection of the best alternative from a predetermined set of options (Feizizadeh *et al*., 2014; Omidipoor *et al*., 2019). Eastman *et al*. (1995) noted that MODM is infrequently used in GIS and mostly when the objectives are complimentary. Each suitability map per criterion, based on a set objective, is in turn used as a factor for a new evaluation where the objectives are weighted and combined e.g. through multiplication. In MODM the best alternative is chosen based on objectives that are given relative weights and may be incompatible. In MADM selection has to be made, among a confined set of alternatives, and according to certain characteristics that are duly weighted (Lotfi *et al*., 2009). When MODM is restricted to a definite number of possible alternatives it approximates the MADM methods (Gomes & Lins, 2002).

As noted by Arratia-Solar *et al*. (2022), Multi-criteria Decision Making (MCDM) regards the assessment of various feasible alternatives to find the best one. Therefore, MCDM does not focus on finding the optimal and final solution, but on optimising decision-making overall. MCDM is about the evaluation and selection of an action compared to alternatives, based on decision-makers' preferences, and when multiple criteria are to be satisfied (Krecji, 2018). MCDM is a non-statistical method to deal with complicated issues, combining quantitative and qualitative elements (Lotfi *et al*., 2009). Table 3.1 outlines the basic MCDM/MODM definitions, as described by Eastman *et al*. (1995)

Table 3. 1 - Basic MCDM definitions (Eastman *et al.*, 1995)

Term	Description
Decision	Choice made between alternatives (actions, locations etc.)
Criteria	Measurable basis to evaluate a decision, and can be either *Factors* (adding or detracting suitability value in an alternative) or *Constraints* (limiting an alternative). Factors usually come in continuous surface raster form and Constraints in Boolean vector form
Decision Rule	Criteria combination procedures e.g. WLC aggregation, thresholds, MCEs comparison, best lands total area etc. and can be either *Classification* (evaluate alternatives based on their individual feats e.g. flood risk) or *Selection* (based on alternative feats e.g. best site). Decision Rules depend on the *Objectives* set
Objectives	Objectives usually differ from one interest group to the next, and may be conflicting or complementary (e.g. developers vs. owners). Criteria weights will also differ according to set objectives. The solution that satisfies different objectives is called multi-objective decision-making. For an objective, several criteria have to be evaluated and satisfied. Complementary objectives can be combined in a hierarchical MCE extension i.e. assign weights to each objective and combine separate suitability maps into a new composite one
MCE	Process of applying the Decision Rule through certain steps i.e. criteria standardisation, weighting, evaluation and, optionally, following some target selection guidelines

Malczewski (2004) detailed that Decision Rules can be *multiobjective* (set of alternatives selected according to a decision model; mathematical programming-oriented; not easy to implement in GIS) or *multiattribute* (Multicriteria, AHP and WLC as main methods; data-oriented). The selection of MCDA criteria or attributes should be based on an underlying theme. The number and quality of selected criteria is critical as it defines the ranking of alternatives (Malczewski & Rinner, 2015). Bencure *et al.* (2019) argued that MCDA can provide an overall picture that is closer to real-life cases, compared to e.g. regression-based resource-demanding methods. Even though structurally less-objective than regression-based models, MCDA considers the judgement of experts focusing on spatial factors.

The integration of GIS and MCDM is a potent decision-support system (Kazemi *et al.*, 2016), which helps deal with projects where the specifications and requirements are semi- or ill-structured, data are insufficient and there are various alternatives and outcomes to examine (Vahidinia *et al.*, 2009). Typical example of a DSS tool are the suitability maps generated for each spatial criterion considered (Dell' Ovo *et al.*, 2018).

According to Malczewski (2004) land-use Suitability Analysis regards the classification of land units based on their suitability for specified uses. The area and its characteristics e.g. size, contiguity may also be defined. LSA can be based on objective *hard* information (based on facts, estimates, measurements, opinion surveys etc.) or subjective *soft* information (preferences, priorities, judgements of decision-makers and/or other interest groups – based on surveys, interviews or questionnaires), or a mix of both.

Visualisation and communication options offered through GIS are able to bring different kinds of decision-makers and other stakeholders together, significantly speeding up and optimising the processes (Caprioli & Bottero, 2021; Mrowczynska *et al*., 2021). Combining GIS and MCDM/AHP leads to DSS used e.g. for land suitability analysis and selection, for uses with specific requirements (Noorollahi *et al*., 2022). In a recent GIS and urban planning book, Butler *et al*. (2019) noted that multicriteria analysis can provide common-ground in decision-making, bringing together different stakeholders with often conflicting interests and priorities. Especially for the real estate sector, Podor & Nyiri (2010) noted the potential of GIS in combining knowledge from various disciplines and fields and integrating it into practical DSS. The combination of GIS and MCDA significantly promotes transparency and rationality in decision-making (Mosadeghi *et al*., 2015; Oppio *et al*., 2016; Dell' Ovo *et al*., 2018). Oliveira & Pinho (2010) argued that multicriteria analysis brings together GIS and communicative planning (being flexible, contextual and dependent on co-learning processes; also based on discourse for selecting the best-option).

Malczewski (2004) noted some key issues regarding the integration of GIS into MCDM: data inaccuracy, ambiguity and imprecision, methods used for criteria standardisation and their theoretical basis, and the lack of a common basis for decision rules. Such issues may lead to different results based on the available data and their quality, the standardisation processes followed and the decision rules set.

3.2 Analytical Hierarchy Process

Traditional AHP

The Analytical Hierarchy Process (AHP) is a comparatively simple and flexible type of Multi-Criteria Decision Analysis, handling both numerical and non-numerical data (Bencure *et al*., 2019; Caprioli & Bottero, 2021). As an MCDM method, AHP integrates expert opinions and numerical information through pairwise comparisons and/or other ranking methods (Foroozesh *et al*., 2022). The AHP is a common MCDM method used autonomously or as part of hybrid approaches (Arratia-Solar *et al*., 2022; Foroozesh *et al*., 2022). Moreover, AHP turns Multi-attribute decision-making into a hierarchy of attributes (Jahanshahi *et al*., 2019). AHP is flexible in its nature as the levels of the hierarchical structure and the combinations of its elements (goals, objectives, attributes and alternatives) can be set according to different needs. Malczewski & Rinner (2015, p. 27) provided some examples of different AHP configurations.

As a MCDA process, AHP can also be used for weighting criteria, which can then be paired through Weighted Linear Combination (Malczewski, 2004; Omidipoor *et al*., 2019). Eastman (1999) noted that in GIS, WLC-based suitability maps are an expression of uncertainty and are unrelated to probabilities' analysis. As a method, raster-based Weighted Linear Combination lies in the middle of vector-based Boolean *Union* and *Intersection* methods (Eastman, 1999). AHP can also be used as a consensus-building tool (Malczewski, 2004). Pairwise comparison matrices (PCMs) may be set to compare different criteria or decision alternatives (Krecji, 2018). The typical PCMs used in AHP are *multiplicative* and *reciprocal* and composed of scores from 1 to 9, according to Saaty's linguistic scale (Krecji, 2018). Multiplicative pairwise comparison matrices are deemed acceptable when Consistency Ratio (CR) is less than or equal to 0.1 or 10%. However, this often-used canon is not easily satisfied when the size of the PCM increases (Krecji, 2018). The Consistency Ratio measures the consistency of an examined pairwise comparison matrix against the average consistency of a large number of pairwise comparison matrices of the same order (size) but containing random numbers (Saaty, 1990).

Fuzzy AHP

Fuzzy AHP is an advanced MCDM technique (Krecji, 2018). Fuzzy-logic has been integrated into AHP methods to alleviate the effect of uncertainty and subjectivity in human opinions, descriptions and decisions – and to add flexibility (Vahidinia *et al*., 2009; Feizizadeh *et al*., 2014; Foroozesh *et al*., 2022). Regarding flexibility, fuzzy analysis allows the quantification of linguistic expressions and forecasting through the assessment of different scenarios (Mrowczynska *et al*., 2021). In FAHP, the expert opinions and decisions are the qualitative element and the numerical processing the quantitative one (Raad *et al*., 2022). As underlined by D' Amato *et al*. (2019) attention is needed when translating linguistic preferences into crisp numbers.

Krecji (2018) highlighted that PCMs are an important tool in MCDM processes. Crisp numbers provided by simple PCMs are not able to capture uncertainty due to human subjectivity or insufficient information, and fuzzification of PCMs should be considered. Fuzzification and defuzzification of fuzzy PCM scores are subject to different methods (Krecji, 2018). The triangular fuzzy numbers are a very common fuzzy extension used (Malczewski & Rinner, 2015; Krecji, 2018). That said, Krecji (2018) underlined the point made by Saaty (2006) that fuzzification of AHP does not lead to more valid output since the numerical scale used to expressed preferences is already fuzzy. Krecji (2018) seems to agree with Saaty (2006) in that changing the PCM scores through fuzzification without the input and consent of decision-makers goes against the initial scope of the whole process, leading to non-valid output. If the decision-makers are certain on their preferences then the PCMs should not be fuzzified.

For Real Estate needs fuzzy logic seems especially attractive (Bovkir & Aydinoglu, 2018). Suitability maps generated through the AHP are useful in many regards such as the selection of suitable land for proposed development projects, identification of discrepancies between infrastructure and land demand, the identification of future development trends – among others. Mosadeghi *et al*. (2015) compared AHP and FAHP for marine development site selection. According to their analysis for the initial stages of assessing development options (focal points) traditional AHP suffices, but when going into detailed analysis (suitable lands extent) FAHP brings better results.

Caprioli & Bottero (2021) combined GIS with MCDA for urban infrastructure site selection, and into a multicriteria spatial DSS. For the MCDM used they extracted criteria weights from AHP and FAHP. AHP seems preferable when all criteria have to be considered as important, time is limited, and data are limited or unreliable. In such cases defuzzification would lead to some criteria to zeroing out. On the other hand, FAHP is stronger when weightings are uncertain, and especially useful when non-experts are included in decision-making (Caprioli & Bottero, 2021). Caprioli & Bottero (2021) concluded that AHP and FAHP gave similar results regarding the most suitable sites. Comparing AHP with FAHP, Kepaptsoglou *et al.* (2013) found a discrepancy of ≈8% between the corresponding criteria weights. It should be noted that the AHP has been criticised regarding its theoretical basis (Malczewski, 2004). However, the use of AHP and FAHP is very common in site selection studies in a variety of fields. Table I.1 (Appendix I) summarises a number of such studies.

Fuzzification of spatial criteria

Fuzzy logic is also applied to criteria used in MCE and AHP. Standardisation and subjectivity ambiguities may be alleviated by using fuzzy logic. The selected fuzzy memberships re-express raster values according to the function selected (Eastman 1999). The process of fuzzifying the spatial criteria standardises the data, and the fuzzy layers are then ready to be combined (Eren & Katanalp, 2022; Noorollahi *et al.*, 2022). Fuzzification of spatial criteria based on fuzzy memberships should not be confused with fuzzification of pairwise comparison matrices. Fuzzified criteria may very well be used without fuzzifying the PCM scale and scores. This is also explored in the data processing section in Chapter 4.

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CHAPTER 4 – Data and Research Methodology

Introduction

Before proceeding with the presentation and interpretation of the data analysis, it is important to delve into the specifics of the methodology implemented i.e. the study area, the type and collection method of the data used and the geoprocessing processes followed.

4.1 Study area

For this purpose, the urban core in the Greek city of Volos was selected (figure 4.1). Volos is a diversified (Tsiotas *et al*. 2017) and historical coastal city in the eastern coastline of central Greece, and one of the main ports and transport hubs in the country. Volos is an interesting city-case, including extended seafronts for recreation and tourism, a major university, industrial zone, and transport hubs (port, railway, and national road). Its population is around 140.000 people in the wider municipality of Volos. Also, the nearby area of Mt. Pelion is a major tourism and recreational area, supporting alternative tourism activities throughout the year. In terms of real estate, almost 70% of building stock in Volos was built after 1970 (Elstat, 2011). Volos is a vibrant and easily accessible city, with a fairly stable commercial and real estate market. Its urban form is quite clearly defined, which helps with observations and GIS-based analysis. Additionally, there is development and urban expansion potential in the surrounding areas.

The area of focus has an approximate size of 12.26 Km^2. The research stayed within the boundaries of the urban core where the spatial criteria used have or may expand their presence in the near future. Outside this area land-uses are currently mostly agricultural, low density industrial and sub-urban residential. Commercial and Offices land-uses are sparse and exceptional. For all calculations and maps the GGRS87 (ESPG: 2100, Projection: Transverse Mercator, map units: meter) projected coordinate system was used. For all raster layers the resolution was set at 5 meters (5x5m cells). It should be noted that the 200x200m block-grid was visually overlaid in all maps, for cross-reference.

Figure 4. 1 - Study area

4.2 Research Data

All data used in this research were primary and created by the author and regard the urban core of the Greek port-city of Volos, as presented in section 4.1. In GIS, primary data regard vector and raster layers created by the analyst through digitisation and by using selected software. Sources leading to GIS-ready data to be used are often considered primary sources (Ignatius, 2021). Choices during the digitisation of the data e.g. combinations of schools, bus stops and recreational areas were based on the author's knowledge of the study area, and referenced using Google Earth and also official sources like the ministry of education, Volos City urban transportation association and the University of Volos. Accuracy of the data was assessed based on the ability to clearly geo-locate the features and cross-reference them with other sources like official websites. Property locations and their announced selling prices in the study area were gathered using online real estate platforms, from October 2022 to March 2023. Tables 4.1 and 4.2 summarise the types and nature of the data used in this research.

Data needed for this research are best understood via the research design outline (figure 4.2). Main data were the spatial criteria to be selected, digitised and have their Euclidean distances fuzzified; the criteria weights from the expert insights; and the real estate property locations and online announced prices, for assessing the AHP output validity. All spatial criteria used were digitised by the author in separate map layers, using the GGRS87 projected coordinate system. The resolution of all raster layers was set at 5 meters (5x5m cells).

Table 4. 1- Data used for geoprocessing

Data	Type	File Type	Data Type
Study area boundaries	Quantitative	Vector	Primary
Spatial criteria layers	Quantitative	Vector	Primary
Suitability layers	Quantitative	Raster	Primary
Property locations & prices	Quantitative	Vector	Primary
Spatial criteria weights	Quantitative	Excel table	Primary
AHP output layers	Quantitative	Raster, Vector	Primary

Table 4. 2 - Spatial criteria data types

#	Spatial Criterion	Data Type	Digitisation Accuracy
1	Bus Stops	Feature layer - Points	High
2	Commercial/City Centre	Feature layer - Points	High
3	Education Facilities	Feature layer - Points	High
4	Health Facilities	Feature layer - Points	Very High
5	Major Roads	Feature layer - Line	High
6	Parks and Squares	Feature layer - Polygon	High
7	Port/Seafront	Feature layer - Polygon	Very High
8	Public Services	Feature layer - Points	Very High
9	Recreation Areas	Feature layer - Points	Mid to High
10	University	Feature layer - Points	Very High

Spatial Criteria Selection and AHP

For the AHP weight extraction twelve criteria were proposed to real estate experts, based on the literature reviewed (see summary table I.2 in Appendix I), and the author's knowledge of the study area. These were then narrowed down to seven criteria per real estate property type (figure 4.3), which were then used for geoprocessing. The proposed and selected criteria are also shown in tables I.3 – I.8 (see Appendix I). Considering that the AHP aim was to classify suitability zones for the different real estate land-uses i.e. *Commercial*, *Offices* & *Residential* the AHP structure can be broken down as shown below (see also figure II.1 in Appendix II).

Level 1:	Classify RE land-use suitability	Goal
Level 2:	Real estate land-uses	Objectives, different per land-use
Level 3:	Spatial criteria	Attributes, seven criteria per land-use
Level 4:	RE land-use suitability maps	Output, map layers per method used

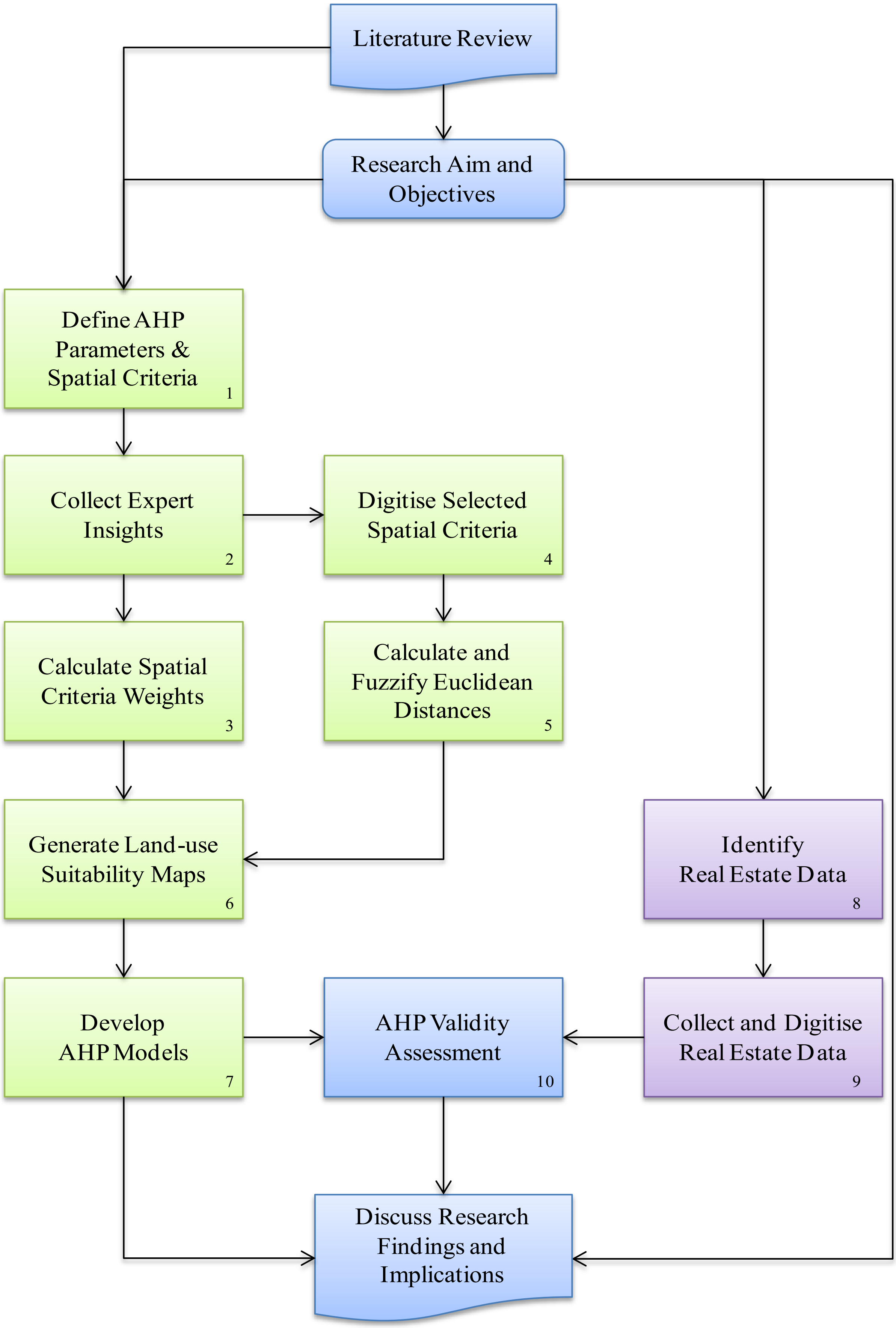


Figure 4. 2 - Research design outline

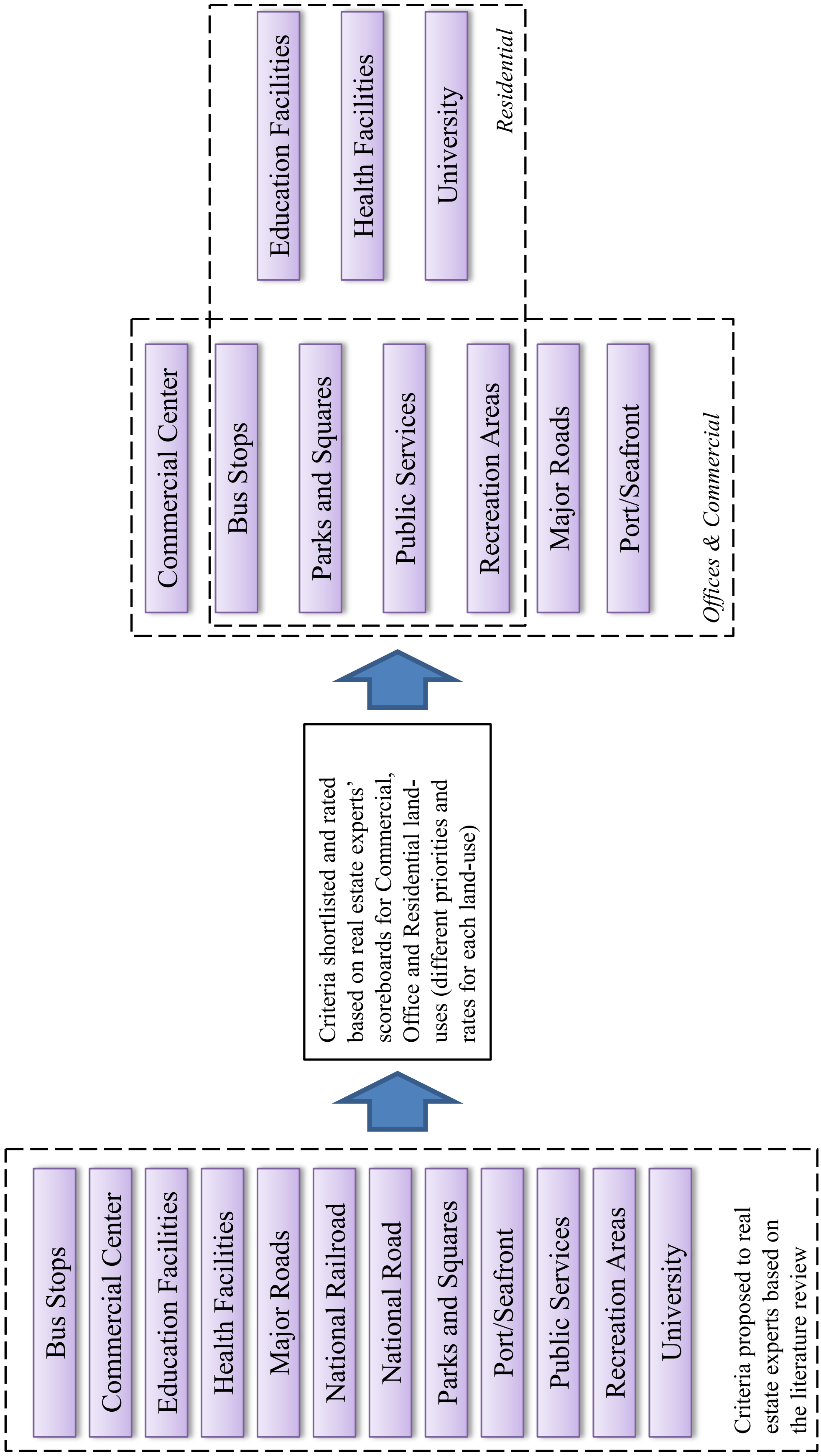


Figure 4. 3 - Spatial criteria screening

4.3 Research Design

As mentioned in chapter 1, the research aim was to apply GIS-based multicriteria evaluation for real estate land use suitability analysis, in the Greek coastal city of Volos. To support the research aim, the process outline for the research objectives was set as follows:

RO 1: Rating scoreboards and pairwise comparison matrices were used for different spatial criteria related to RE land-uses. Based on the literature review and the nature of the urban area of Volos City, twelve criteria were proposed to eleven real estate experts and then shortlisted to seven per land-use

RO 2: The criteria sorted and weighted in **RO1** were used in the non-fuzzy and fuzzy AHP analysis, focusing on commercial, office and residential land-uses

RO 3: The non-fuzzy and fuzzy spatial criteria weights and the AHP suitability rasters were compared, to assess the their differences based on utility and validity

RO 4: The urban area of Volos was divided using a 200x200m grid, and the mean AHP scores calculated in **RO3** were used in each grid-block zone

RO 5: AHP output was assessed via correlation analysis by using online announced selling prices and the mean AHP suitability scores in their grid-block

Research design defines the overall plan on how the research is to take place. For a successful research design, data types, data sources, data collection tools and data analysis approach have to be rationally set, within a realistic time-schedule and also considering budget limitations (Sekaran, 2003; Kothari, 2004). The data collection for this research can be characterised as cross-sectional since it took place at a specific time period and for a set of individuals i.e. real estate experts and land-uses, that differ in their characteristics (Sekaran, 2003; Beins & McCarthy, 2012). The research design approach was given in the flowchart in figure 4.2. For the MCE/AHP analysis twelve spatial criteria relevant to the theme of the analysis were proposed to the real estate experts for evaluation and weighting, using different methods i.e. ratings and pairwise comparison matrices (steps 1 to 3). Next, the selected spatial criteria selected were digitised and their Euclidean distance rasters were calculated and fuzzified (steps 4 and 5). Then the non-fuzzy and fuzzy land-use suitability maps were generated in step 6. It should also be noted that the fuzzy-logic was applied to steps 3 and 5. Table 4.3 summarises the basic steps of the geoprocessing sequence used in this research.

Table 4. 3 - Geoprocessing sequence used

Geoprocessing Sequence	
1	Identify spatial criteria affecting real estate land-use suitability
2	Select and weigh spatial criteria, per land-use (expert insights)
3	Create and prepare spatial map layers and datasets
4	Calculate Euclidean distance rasters for each criterion
5	Calculate fuzzy rasters based on set fuzzy memberships
6	Use weighted overlay on fuzzy layers (WLC)
7	Develop land-use suitability zones
8	Assess the AHP output validity

4.4 Primary Data Collection – Expert Insights

Process Overview

For the Analytic Hierarchy Process criteria, weight extraction was based on expert insights, which took place in two stages (step 2, figure 4.2), from June to November 2022. Real estate experts were invited via an open invitation sent to and forwarded by a local educational institute delivering real estate postgraduate programmes accredited by the Royal Institution of Chartered Surveyors (RICS). In the open invitation e-mail the potential participants were informed on the general scope of the research, type of data collected, data handling and confidentiality commitment. By directly replying to the original e-mail, those interested would confirm their participation, so they could be sent the scoreboards in Excel format. Out of thirty-nine real estate professionals contacted, thirteen confirmed their participation. The eleven Experts that eventually took part are master's degree holders, and most of them are working for more than five years in the real estate sector. Details on the two stages are shown in the table below.

Table 4. 4 - Sampling and tools used in expert interviews

Stage	Invitees	Participants	Sampling	Tools
I	39	11	Convenience	Rating and PCM scoreboards sent through e-mail
II	11	8	Judgement	PCMs filled-in during live interviews, using the seven criteria with the highest rating sum scores in Stage I

Stage I focused on rating the proposed spatial criteria affecting real estate land-use suitability in the city of Volos for each property class. Stage II was dedicated to pairwise comparison scoring of the spatial criteria selected during rating in Stage I. For both stages, pilots were run before sending them to the participants. This split in stages was done due to real estate experts being unfamiliar with PCMs, with the intention to gradually improve consistency in pairwise scorings. Even though included in stage I, PCMs did not bring consistent results. This became evident by looking into the consistency ratios in the stage I PCMs, with many of them exceeding 25%. Finally, the nature of the underlying topic i.e. what were the spatial criteria to be considered was also exploratory and not strictly delineated. Thus, the relative importance of one criterion over the other was not always easy to declare, requiring extra time and consideration. Therefore, it was deemed necessary to run live expert interviews in Stage II, dedicated to property-specific PCMs. Live interviews were conducted by using the *Google Meet* platform. Each participant was interviewed individually, to ensure their scoring would not be influenced by other experts' opinions. So, no participant had access or any idea on how others scored the criteria in their PCMs. An example of fully completed Ratings and PCM scoreboards is given in tables I.4 and I.5 in Appendix I.

The reasoning behind the selection of synchronous online expert interviews was based on the convenience of the prospective respondents, arranging the interview (scoreboard fill-in) at a time and date of their choosing. At the same time the interviewer can facilitate the process in real time and the respondents have time to go into the detail. Synchronous online interviews combine the advantages of telephone and in-person interviews (Bryman, 2012, pp. 668-669; Leavy, 2017, p. 142). The interviews were structured and based on a scoreboard on which the respondents had already been informed, following the key scientific concepts of interviewing as detailed by Kothari (2004, pp. 98-99; Sekaran, 2003, pp. 232-233). The participants were informed that no sound and/or video recording would take place, that they could withdraw at any time and with no reason, and that no sensitive personal data would be collected whatsoever. All data provided by the experts were promptly anonymised.

Stage I and II process details and sampling

In stage I, six criteria (out of twelve proposed) had to be selected and to be given points (Ratings), up to a total of 100. For stage II the PCMs per property class were revised and reformatted. The spatial criteria used here were the seven (six, +1) that got the highest total score in stage I Ratings. Participants were able to select either criterion A or B and score their comparative importance using the 1 to 9 linguistic scale (Saaty, 1980). This phase proceeded through one-to-one web-meetings at a date and time chosen by the participants. Stage II process confirmed that filling-in of the PCMs in the previous stage had not been optimal. For most of the participants the comparison mechanism had not been perfectly clear. Guided completion of the revised matrices brought significantly better and acceptable results. In the individual PCMs most consistency ratios dropped below 10% (CR<0.1), with only few of them ranging from 12% to 17% in one or two property classes. Also, the consolidated matrices Consistency Ratios remained lower than 6%. This was due to participants receiving live support and clarifications e.g. when there was some question on what the spatial criteria meant or included. To avoid influencing the participants, support requested was provided in a non-suggestive manner when they had doubts or questions regarding the criteria compared, and not for the sake of ensuring or improving consistency of the PCMs.

For this research the non-probability *Convenience* and the *Purposive* or *Judgement* sampling. *Convenience* sampling is about reaching out to subjects that are accessible to the researcher. This is the case when the researcher may access such subjects via an institution, organisation or business group (Leavy, 2017). In *Purposive* or *Judgement* sampling the researcher selects the participants considering their characteristics and the accordance with the research aim and objectives. In both methods, generalisation potential is weak (Babbie, 2012; Bryman, 2012). If no generalisation of results is required and the caveats are promptly considered, both sampling methods can be used (Babbie, 2012; Kothari, 2004). *Convenience* sampling was used in Stage I, as explained earlier. In Stage II, eight participants were invited based on their PCM consistency ratios from Stage I, along with three more that did not participate in the 1st stage but had initially expressed their interest and could still contribute.

4.5 Data Processing

4.5.1 Spatial Criteria Fuzzification

After the spatial criteria point layers were digitised, the Euclidean Distance raster layers were calculated. To standardise the different layers the following sigmoid function was used:

$$y = f(x) = 1 \big/ \left(1 + e^{(K*(\chi - \chi_0))}\right) \qquad \text{(Eq. 4.1)}$$

χ Distance from source
χ_0 Mid-point of x on the s-curve
K Slope coefficient (steepness) of the curve

This inverse form of the logistic regression function was used to express the suitability y of each raster cell in the criteria layers according to the distance χ (in meters) from the source. Slope of the curve coefficient K (unitless) and mid-points χ_0 (in meters) were set based on the author's knowledge of the study area, and the urban planning concept of the 15-minute city (see e.g. Duany & Steuteville, 2021). The premise was that spatial criteria will contribute to the suitability of real estate land-uses up to a certain walking distance threshold, after which this impact practically zeroes out. Parameters and variables for all spatial criteria s-curves are given in table I.3 (Appendix I). Examples of suitability s-curves are shown below.

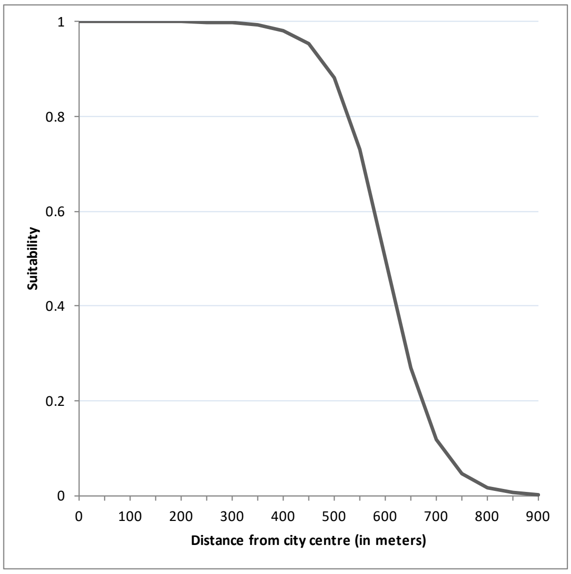


Figure 4. 4 - Suitability s-curve for distance from the city centre (Commercial)

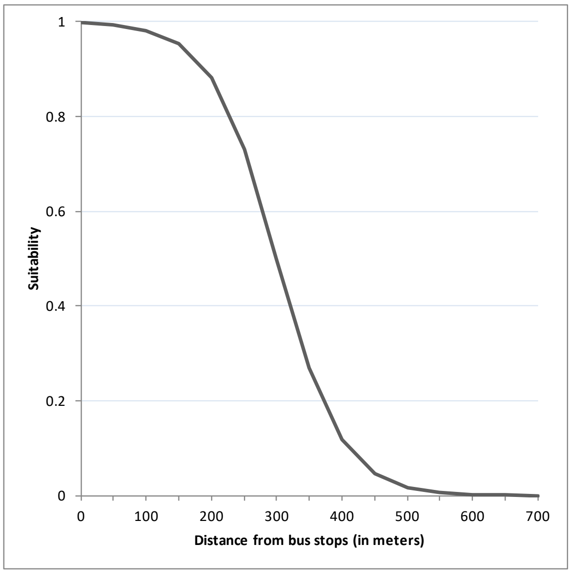


Figure 4. 5 - Suitability s-curve for distance from bus stops (Residential)

According to the literature review conducted for this research, sigmoidals are often used in the fuzzification of spatial criteria. For example, Jahanshahi *et al*. (2019) argued that sigmoid fuzzy memberships may be preferred as being more relevant to geographic phenomena. Some recent studies using such a method are those of Foroozesh *et al*. (2022), Cosimo *et al*. (2021), Pasalari *et al*. (2019), Bovkir & Aydinoglu (2018) and Gorsevski *et al*. (2012).

4.5.2 Pairwise Comparison Matrices Processing

To fuzzify the pairwise comparison matrices the scores given by the experts were increased and decreased by a factor of f = 1 to 3 (see table 4.5), even though most experts were confident on their scores. By comparing the defuzzified weights (section 5.1) the variation of f = 1 was selected for the final analysis, as more reasonable, considering the guided process of scoring during the expert interviews. As mentioned in section 3.2, fuzzification of the PCMs without input from the participants may not be optimal (Krecji, 2018). Table 4.5 shows the PCM fuzzification parameters using the triangular fuzzy number form (TFN).

Table 4. 5 - Fuzzification parameters (triangular form)

Original PCM Score (*m*)	Triangular Fuzzy PCM (*l*, *m*, *u*)
x = 1	1, 1, 1 + f
1 < x < 9	x – f, x, x + f *
x = 9	9 – f, 9, 9

* for x – f < 1 then x – f = 1 and for x + f > 9 then x + f = 9

The triangular fuzzy number form (TFN) assumes a linear gradation between the original score (value *m*) and the lower (value *l*) and upper (value *u*) values. For example, if the original PCM score given by the real estate expert was 6 then the lower and upper values were set as 5 and 7 respectively (for a fuzzification factor of f = 1). Defuzzification of the fuzzy weights (TFN form) was done using the Centre-of-Area/Gravity method, as given in Krecji (2018, p. 66) for the triangular form:

$$w_i = \frac{1}{3}(w_l + w_m + w_u) \qquad \text{(Eq. 4.2)}$$

Also expressed as the Best Non-Fuzzy Performance (Hsieh et al., 2004):

$$BNPw_i = \frac{(u_i - l_i) + (m_i - l_i)}{3} + l_i \qquad \text{(Eq. 4.3)}$$

where *u*, *m* and *l* correspond to the upper, middle and lower *w* fuzzy values. Detailed application of such a method is demonstrated in Hsieh *et al.* (2004, p. 579). Defuzzification is to combine the lower, middle and upper fuzzy scores into crisp criteria weights.

Consolidation of the PCMs

For a P_p matrix of i rows and j columns, the comparative preference of one criterion over the other is expressed as a_{ij} scores from 1 to 9 (Saaty's linguistic scale) in a PCM:

$$P_p = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1j} \\ a_{21} & 1 & \cdots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1j} \\ 1/a_{12} & 1 & \cdots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1j} & 1/a_{2j} & \cdots & 1 \end{bmatrix} \qquad \text{(Eq. 4.4)}$$

which for triangular fuzzy numbers is expressed as a fuzzy pairwise comparison matrix F_p:

$$F_P = \begin{bmatrix} 1 & (a_{12l}, a_{12m}, a_{12u}) & \cdots & (a_{1jl}, a_{1jm}, a_{1ju}) \\ (a_{21l}, a_{21m}, a_{21u}) & 1 & \cdots & (a_{2jl}, a_{2jm}, a_{2ju}) \\ \vdots & \vdots & \ddots & \vdots \\ (a_{i1l}, a_{i1m}, a_{i1u}) & (a_{i2l}, a_{i2m}, a_{i2u}) & \cdots & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & (a_{12l}, a_{12m}, a_{12u}) & \cdots & (a_{1jl}, a_{1jm}, a_{1ju}) \\ (1/a_{12u}, 1/a_{12m}, 1/a_{12l}) & 1 & \cdots & (a_{2jl}, a_{2jm}, a_{2ju}) \\ \vdots & \vdots & \ddots & \vdots \\ (1/a_{1ju}, 1/a_{1jm}, 1/a_{1jl}) & (1/a_{2ju}, 1/a_{2jm}, 1/a_{2jl}) & \cdots & 1 \end{bmatrix} \quad \text{(Eq. 4.5)}$$

and the consolidated fuzzy non-fuzzy C_p and fuzzy C_{FP} PCMs can be expressed as:

$$C_P = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1j} \\ c_{21} & 1 & \cdots & c_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ c_{i1} & c_{i2} & \cdots & 1 \end{bmatrix} \quad \text{(Eq. 4.6)}$$

$$C_{FP} = \begin{bmatrix} 1 & (c_{12l}, c_{12m}, c_{12u}) & \cdots & (c_{1jl}, c_{1jm}, c_{1ju}) \\ (c_{21l}, c_{21m}, c_{21u}) & 1 & \cdots & (c_{2jl}, c_{2jm}, c_{2ju}) \\ \vdots & \vdots & \ddots & \vdots \\ (c_{i1l}, c_{i1m}, c_{i1u}) & (c_{i2l}, c_{i2m}, c_{i2u}) & \cdots & 1 \end{bmatrix} \quad \text{(Eq. 4.7)}$$

where *u*, *m* and *l* correspond to the upper, middle and lower values. For consolidating the fuzzy and non-fuzzy PCM scores from the eight participants the geometric mean was used.

Then, the fuzzy weights of the consolidated PCM can be calculated as follows:

$$r_{1l} = \left(\prod_{1}^{n} c_{1l}\right)^{1/n} = \left(1 \times c_{12l} \times \cdots \times c_{1jl}\right)^{1/n} \quad \text{(Eq. 4.8)}$$

$$r_{2l} = \left(\prod_{1}^{n} c_{2l}\right)^{1/n} = \left(c_{21l} \times 1 \times \cdots \times c_{2jl}\right)^{1/n} \quad \text{(Eq. 4.9)}$$

...

$$r_{il} = \left(\prod_{1}^{n} c_{il}\right)^{1/n} = (c_{i1l} \times c_{i2l} \times \cdots \times 1)^{1/n} \quad \text{(Eq. 4.10)}$$

for the lower r_{il} values, and similarly for the middle r_{im} and upper r_{iu} values in each matrix row. In the non-fuzzy PCM there are only the original middle values. The calculations then continue according to the method described in Malczewski (1999, pp. 183-187).

For the triangular fuzzy PCM, the criteria weights are calculated per by using the lower, middle and upper r_i values of each matrix row:

$$w_{1l} = r_{1l} \times \left(\sum_{1}^{n} r_{1l}\right)^{-1} = r_{1l} \times (r_{1l} + r_{2l} + \cdots + r_{il})^{-1} \qquad \text{(Eq. 4.11)}$$

$$w_{2l} = r_{2l} \times \left(\sum_{1}^{n} r_{2l}\right)^{-1} = r_{2l} \times (r_{1l} + r_{2l} + \cdots + r_{il})^{-1} \qquad \text{(Eq. 4.12)}$$

...

$$w_{il} = r_{il} \times \left(\sum_{1}^{n} r_{il}\right)^{-1} = r_{il} \times (r_{il} + r_{il} + \cdots + r_{il})^{-1} \qquad \text{(Eq. 4.13)}$$

and similarly for the middle w_{il} and upper w_{iu} weight values, where *n*, *i* and j = 7 for the seven criteria examined. Lastly, the BNPs (eq. 4.3) were calculated for each criterion and for each asset class. Detailed consolidated tables are shown in figures I.7 – I.8 (Appendix I) and a calculation example for the defuzzified criteria weights is given in I.8 (Appendix I).

Fuzzification Choices

As mentioned in the literature review (section 3.2) triangular fuzzy numbers are commonly used, even though different fuzzification methods are possible i.e. trapezoidal, sigmoidal, Gaussian, polynomial. TFN was selected by the author considering the combination of two factors. First, the fact that there was no knowledge of how uncertainty fluctuated up and down from the score the participants selected. To apply more complex fuzzification methods additional input from the participants is suggested, in order for the analyst to select the most proper method. This translates to significantly increased time resources. Moreover, during the live interviews most participants expressed certainty on their scorings (see section 4.4), thus not justifying more complex fuzzification methods. Secondly, sigmoid fuzzification is simple and thus preferred (Foroozesh *et al.,* 2022).

This sigmoid function was selected as a flexible and fitting function, for the case examined. Parameters *K* and *xo* were set so as to realistically represent a graduation of suitability as distancing from criteria sources. Since no comparable studies using sigmoidal Euclidean distance fuzzification for AHP real estate land-use suitability analysis could be found, parameters were set by the author solely based on knowledge of the area and Greek reality. It should be noted that selection of fuzzification method (PCMs and Euclidean Distances) is at the analyst's discretion, according to the case examined. There is a persisting criticism about the lack of theoretical basis for such choices. This may relate to the lack of argumentation on fuzzification choices (e.g. Foroozesh *et al.* (2022); Cosimo *et al.*, 2021; Pasalari *et al.*, 2019; Bovkir & Aydinoglu, 2018; Gorsevski *et al.,* 2012). This issue is discussed throughout the thesis (e.g. see sections 3.1 and 6.3).

4.6 AHP Output Assessment

Correlation Check

For the purpose of assessing the validity of the AHP output correlation analysis was used, as an indirect but quantitative means of validity check. This was based on the assumption that if the mean AHP scores partially correlate with online announced selling prices then the AHP output maps are further supported regarding their validity. Validity check regards the assessment of the process on whether it is acceptable for the purpose it has to serve. In this case, the AHP output was to be checked on whether the GIS representation of the existing land-use suitability is of high quality, reliable and acceptable.

For the correlation assessment the Spearman's rank correlation coefficient Rho (r_s) was used:

$$r_s = 1 - \frac{(6 * \Sigma {d_i}^2)}{(n * (n^2 - 1))} \qquad \text{(Eq. 4.14)}$$

d_i Difference between the ranks of each observation pair

n Number of observations

The observations in each set of data are ranked from the highest to its lowest element. Then, the difference d_i between each pair of compared observations is calculated and squared. Calculation of r_s is then done according to Eq. 4.14. The announced selling prices used for correlation check regarded *Offices*, *Apartments*, *Detached* houses and *Retail/Commercial* properties, identified in the study area and digitised in separate map layers. These property prices and locations were sought through online real estate platforms, from October 2022 to March 2023. The majority of the properties identified were available on multiple online platforms, through which their location and attributes were cross-checked.

Consistency Ratios

As an additional tool to assess validity of the AHP, the Consistency Ratios of the participants PCM were also checked. Consistency Ratio (CR) shows how consistently the opinions or preferences are scored in the PCM. As a simplified example let us suppose that a criterion A is four times more important than a criterion B, and B three times more important than a criterion C. Then, when comparing A with C the former should be twelve times more important than the latter. If this is not the case then there is inconsistency between these pairwise comparisons. The CR expresses the level of this inconsistency within the PCM. It can be argued that a highly inconsistent PCM may be an indication that the participants are not very certain of their preferences, or that they got confused during scoring. When the number of criteria increases it is more likely to have higher CRs, since it becomes more challenging to remember and match preferences from one pairwise comparison to the next.

4.7 Urban Grid Overlay

Using a custom 200x200m grid to divide the area with was decided in order to present the AHP raster output in a grid-block form, proposed as an additional non-raster visualisation for real estate purposes. The size of the grid-blocks was subjectively decided by the author based on the overview of the urban core area, and after testing different sizes during geoprocessing. The area of focus has an approximate size of 12.26 Km^2, and was divided in 266 grid-blocks of 200x200m size and 90 grid-blocks of smaller size in the peripheral zones of the grid. The 90 grid-blocks of smaller size were created due to the overlaid 200x200m grid being clipped using the study area boundaries feature layer.

Chapter 5 – Results

Introduction

Having previously established the theoretical background and the overall research approach, this chapter is dedicated to the research output i.e. the spatial criteria weights, the maps and results of the MCE land-use suitability analysis, and the AHP validity correlation check.

5.1 Spatial Criteria Weights

The methods followed for Ratings and Pairwise Comparison Matrices of spatial criteria are those presented in Malczewski (1999, pp. 177-187). The final weights based on the non-fuzzy Ratings and PCMs (AHP), and the fuzzy AHP (FAHP) methods are shown below:

Spatial Criteria Weights								
Criteria	Commercial				Offices			
	Ratings	**AHP**	**FAHP**	**FAHP vs. AHP**	**Ratings**	**AHP**	**FAHP**	**FAHP vs. AHP**
Commercial/City Center	31.90%	32.44%	32.65%	0.65%	21.30%	16.45%	16.23%	-1.34%
Major/Commercial Roads	22.60%	17.98%	18.03%	0.28%	24.60%	22.20%	22.05%	-0.68%
Recreation Areas	9.90%	14.65%	14.82%	1.16%	6.60%	9.14%	9.28%	1.53%
Public Transportation	11.50%	16.56%	16.25%	-1.87%	18.00%	24.47%	24.33%	-0.57%
Public Services	9.90%	4.63%	4.73%	2.16%	16.40%	11.54%	11.32%	-1.91%
Parks and Squares	7.10%	7.17%	6.98%	-2.65%	6.00%	6.34%	6.56%	3.47%
Seafront View	7.10%	6.57%	6.54%	-0.46%	7.10%	9.86%	10.23%	3.75%

Criteria	Residential			
	Ratings	**AHP**	**FAHP**	**FAHP vs. AHP**
Education Facilities	22.20%	20.35%	20.45%	0.49%
Parks and Squares	21.10%	21.17%	21.77%	2.83%
Public Transportation	17.80%	22.89%	22.63%	-1.14%
Recreation Areas	13.90%	14.01%	14.26%	1.78%
Health Facilities	10.00%	11.44%	10.97%	-4.11%
University	8.30%	6.31%	6.27%	-0.63%
Public Services	6.70%	3.83%	3.65%	-4.70%

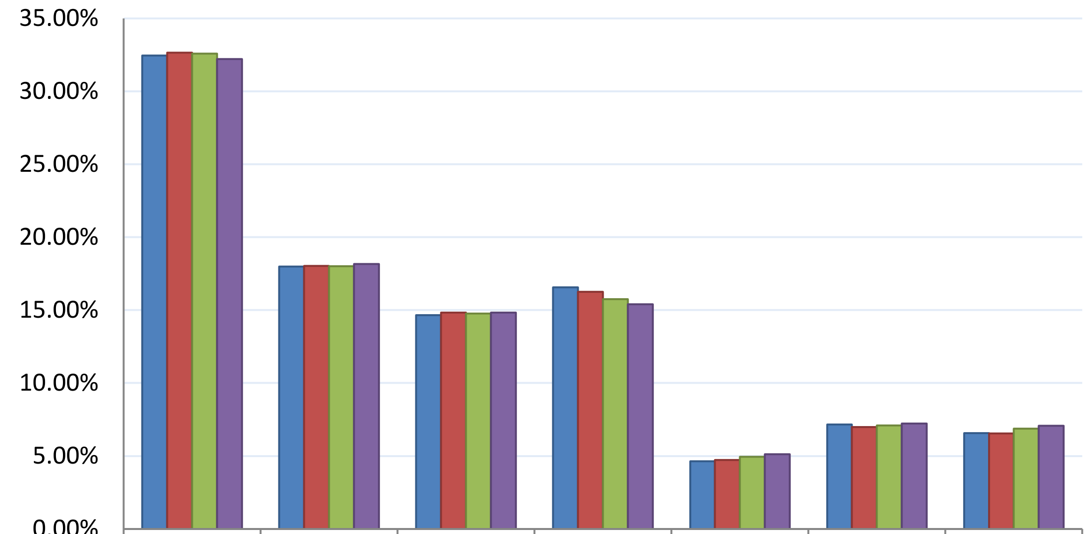
Fuzzy AHP refers to a fuzzification factor of $f = 1$ (see section 4.5.2)

Table 5. 1 – Non-fuzzy (Ratings and AHP) and fuzzy spatial criteria weights

From the AHP (non-fuzzy) weights in table 5.1 it can be observed that for *Commercial* land-uses the two most important criteria take up 50.42% of the total weight, with a strong pull around the city centre. This pattern weakens in *Office* land-uses with the first two criteria weights staying at 46.67%. In *Residential* land-uses the overall split of weights if notably more balanced. Fuzzifying the original PCMs by scores ±1 does affect these patterns. The relative difference between the non fuzzy and fuzzy AHP weights in almost all criteria and land-uses is less than 4%. Weights based on Ratings seem to mostly differ in the weights of criteria with medium importance. In *Offices* ratings there is a notable difference in the three most important criteria weights.

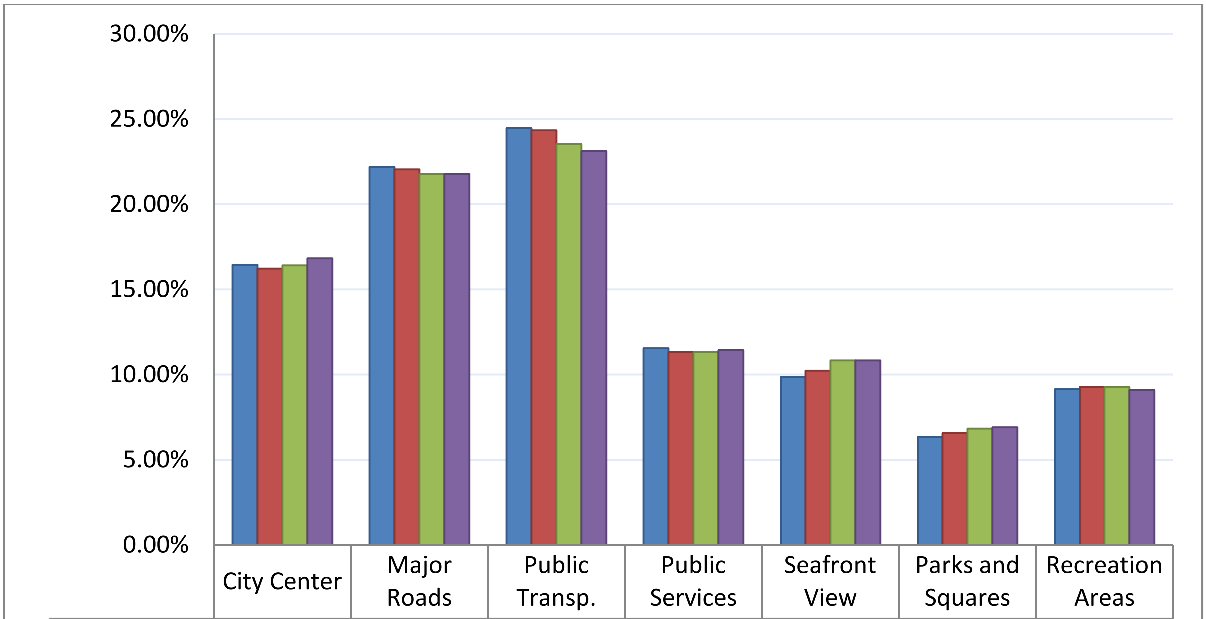
Sensitivity Analysis

To examine the fluctuation of spatial criteria weights according to the extent of the triangular fuzzification, the non-fuzzy AHP-PCM scores given by the experts were increased/decreased by ±1 to ±3 points and the respective weights were calculated (figures 5.1 to 5.3). From the graphs it can be seen that further increasing fuzzification mostly affects higher and lower values, leading to gradual decrease of the former and increase of the latter. Also, when higher values are of similar range they tend to converge (e.g. in *Residential* land-use). Sensitivity analysis showed a less than 5% difference between the fuzzy weights of ±1 and ±3, for the majority of the criteria. Of course the final defuzzified weights depend on the fuzzification extent selected. If fuzzification is deemed necessary, its extent should be done considering the certainty of answers during the expert interviews. These findings agree with the respective theoretical dimension explored in literature review (Krecji, 2018) and the arguments made by Kepaptsoglou *et al.* (2013). Considering the above, the ±1 fuzzification factor *f* was selected for developing the fuzzy AHP maps presented further in this chapter.



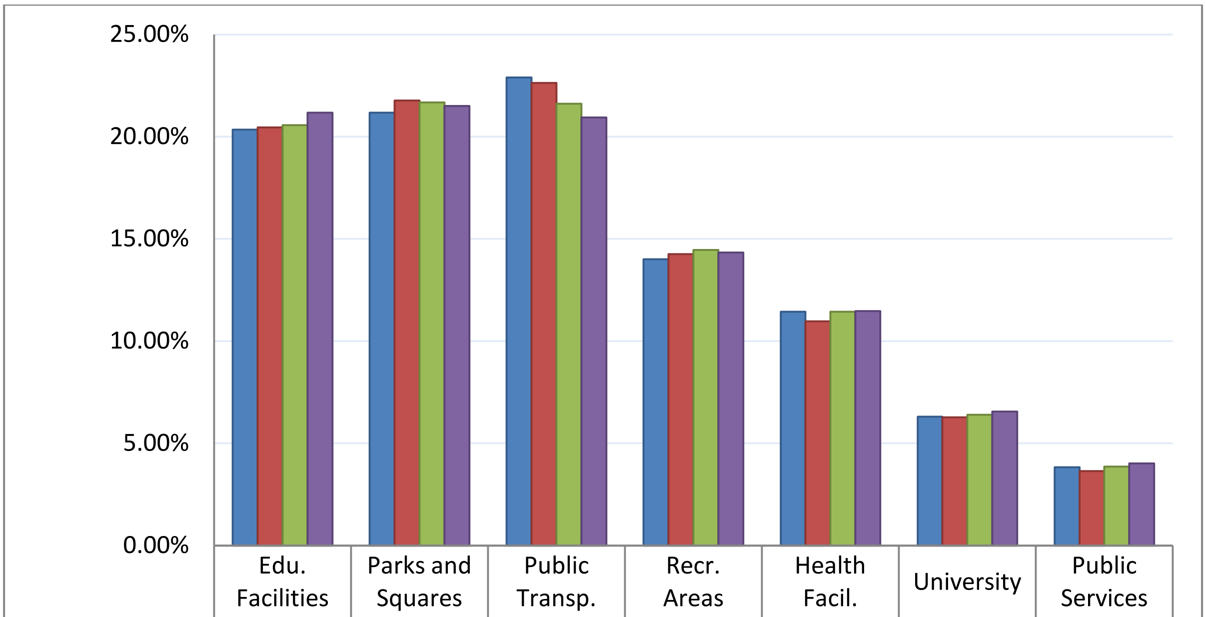
	Comm. Center	Comm. Roads	Recr. Areas	Public Transp.	Public Services	Parks and Squares	Seafront View
AHP	32.44%	17.98%	14.65%	16.56%	4.63%	7.17%	6.57%
FAHP (f = 1)	32.65%	18.03%	14.82%	16.25%	4.73%	6.98%	6.54%
FAHP (f = 2)	32.57%	18.01%	14.76%	15.75%	4.95%	7.09%	6.87%
FAHP (f = 3)	32.20%	18.15%	14.82%	15.41%	5.12%	7.22%	7.08%

Figure 5. 1 - Fuzzy and non-fuzzy AHP criteria weights for commercial LUs



	City Center	Major Roads	Public Transp.	Public Services	Seafront View	Parks and Squares	Recreation Areas
AHP	16.45%	22.20%	24.47%	11.54%	9.86%	6.34%	9.14%
FAHP (f = 1)	16.23%	22.05%	24.33%	11.32%	10.23%	6.56%	9.28%
FAHP (f = 2)	16.42%	21.78%	23.53%	11.33%	10.83%	6.84%	9.27%
FAHP (f = 3)	16.83%	21.78%	23.12%	11.44%	10.83%	6.90%	9.10%

Figure 5. 2 - Fuzzy and non-fuzzy AHP criteria weights for office LUs



	Edu. Facilities	Parks and Squares	Public Transp.	Recr. Areas	Health Facil.	University	Public Services
AHP	20.35%	21.17%	22.89%	14.01%	11.44%	6.31%	3.83%
FAHP (f = 1)	20.45%	21.77%	22.63%	14.26%	10.97%	6.27%	3.65%
FAHP (f = 2)	20.57%	21.68%	21.61%	14.46%	11.44%	6.39%	3.86%
FAHP (f = 3)	21.17%	21.50%	20.94%	14.34%	11.47%	6.56%	4.02%

Figure 5. 3 - Fuzzy and non-fuzzy AHP criteria weights for residential LUs

5.2 Land-use Suitability Maps

By closely observing the output maps shown in figures 5.4 to 5.15 there are certain patterns emerging. In the *Commercial* land-use suitability map the overall suitability coverage of the area is limited, leaving very large parts of the Volos city urban grid as unsuitable. The high and very high suitability zones seem confined close to the waterfront promenade and the close proximity of the city centre. Visual difference between the AHP and the FAHP maps cannot be distinguished as their differences are very small. The Ratings method layer shows a more favourable picture, and highlights the dependence on the main commercial roads. The respective maps are given in figures 5.4 to 5.7.

For *Office* land-uses AHP suitability remains high to very high along the axis of the Volos city centre and the port-front, up to a certain spatial extent and then drops (fig. 5.9). Large parts of the urban grid area periphery are also of very limited or no suitability. The outlying low-suitability areas in the northern part of the map are due to commercial road segments combined with open spaces in this sub-area. The AHP and FAHP maps do not differ much, while the Ratings map shows the high-suitability core extended (see figures 5.8 to 5.11).

For *Residential* land-uses AHP output is straightforward. According to the weighted sum of all spatial criteria, the zones with the highest suitability are those along the seafront next to Volos city port, peaking at the far eastern section close to the extended forest area (fig. 5.13). Suitability is also high along the major roads connecting the city centre and the mid north-eastern area. The high suitability patch near the northern border is due to extended parks, squares and open spaces, combined with recreational areas and bus stops. Most of the study area is of medium to high suitability, and the unsuitable lands are overall limited. Again, there is small difference between the AHP and FAHP output (fig. 5.13 & 5.14). Ratings map shows a more limited very high suitability area, while the mid-ranges are extended (fig. 5.12).

By using the same suitability classification ranges, the % difference between AHP and FAHP map layers was calculated and shown in table 5.2. This agrees with the visual observations and the criteria comparison in the previous section.

Table 5. 2 - Cell by cell comparison of rasterised AHP with FAHP and Ratings

Cell-by-cell % Difference*		
Land-use	**AHP vs. FAHP**	**AHP vs. Ratings**
Commercial	0.01%	5.06%
Offices	0.03%	4.30%
Residential	0.99%	16.61%

* Raster cells classified as in the AHP map ranges

All non-fuzzy and fuzzy land-suitability maps are shown in figures 5.4 to 5.15. There is no distinguishable visual difference between AHP and FAHP, so only the former was used for the final 200x200m block grid map calculations. All spatial criteria map layers are shown in the figures II.2 – II.22 (Appendix II). The detailed and comparative tables for all methods used, are given in table 5.1 (section 5.1) and tables I.6 – I.8 (Appendix I).

Using zonal statistics on the mean AHP scores for the three real estate land-uses we can get the total area in Km^2 and as % percentage of the total study area. This is shown in table 5.3.

Table 5. 3 - Area per AHP suitability and land-use

Area per AHP Suitability and Land-use (mean AHP score per grid block)						
Suitability Class	**Residential**		**Offices**		**Commercial**	
	Area (Km^2)	% Tot. Area	Area (Km^2)	% Tot. Area	Area (Km^2)	% Tot. Area
Unsuitable	0.35	2.8%	2.67	21.8%	5.31	43.3%
V. Low (0.01 - 0.20)	1.49	12.2%	4.98	40.6%	4.90	40.0%
Low (0.20 - 0.40)	2.74	22.4%	2.78	22.7%	1.15	9.4%
Medium (0.40- 0.60)	4.83	39.5%	1.01	8.3%	0.38	3.1%
High (0.60 - 0.80)	2.59	21.1%	0.62	5.0%	0.37	3.1%
V. High (0.80 - 1.00)	0.25	2.0%	0.19	1.6%	0.14	1.1%
Total	12.25	100.0%	12.25	100.0%	12.25	100.0%

Regarding residential land-uses more than 50.0% of the study area is of medium to high suitability. For office land-uses only 13.3% of the study area is of medium to high suitability, while less than 8% exceeds medium suitability. Very high suitability is limited in all three land-uses and regards less than 2.0% of the study area. Maximum AHP suitability value for residential, office and commercial land-uses is 0.87, 0.95 and 0.9 respectively. It is important to note that 43.3% of the total area examined is unsuitable for commercial land-uses.

It is also important to clarify that low or no suitability zones does not mean that commercial or office land-uses do not exist in these areas – quite the contrary. The land-suitability analysis led to the development of maps indicating were such land-uses will have the most and least favourable conditions (best sites), based on the criteria selected, the respective weights and the GIS digitisation parameters.

Note: in the following maps (figures 5.4 to 5.15), *fuzzy suitability* refers to suitability analysis based on fuzzified spatial criteria and should not be confused with the fuzzy AHP/PCMs, which is abbreviated as FAHP.

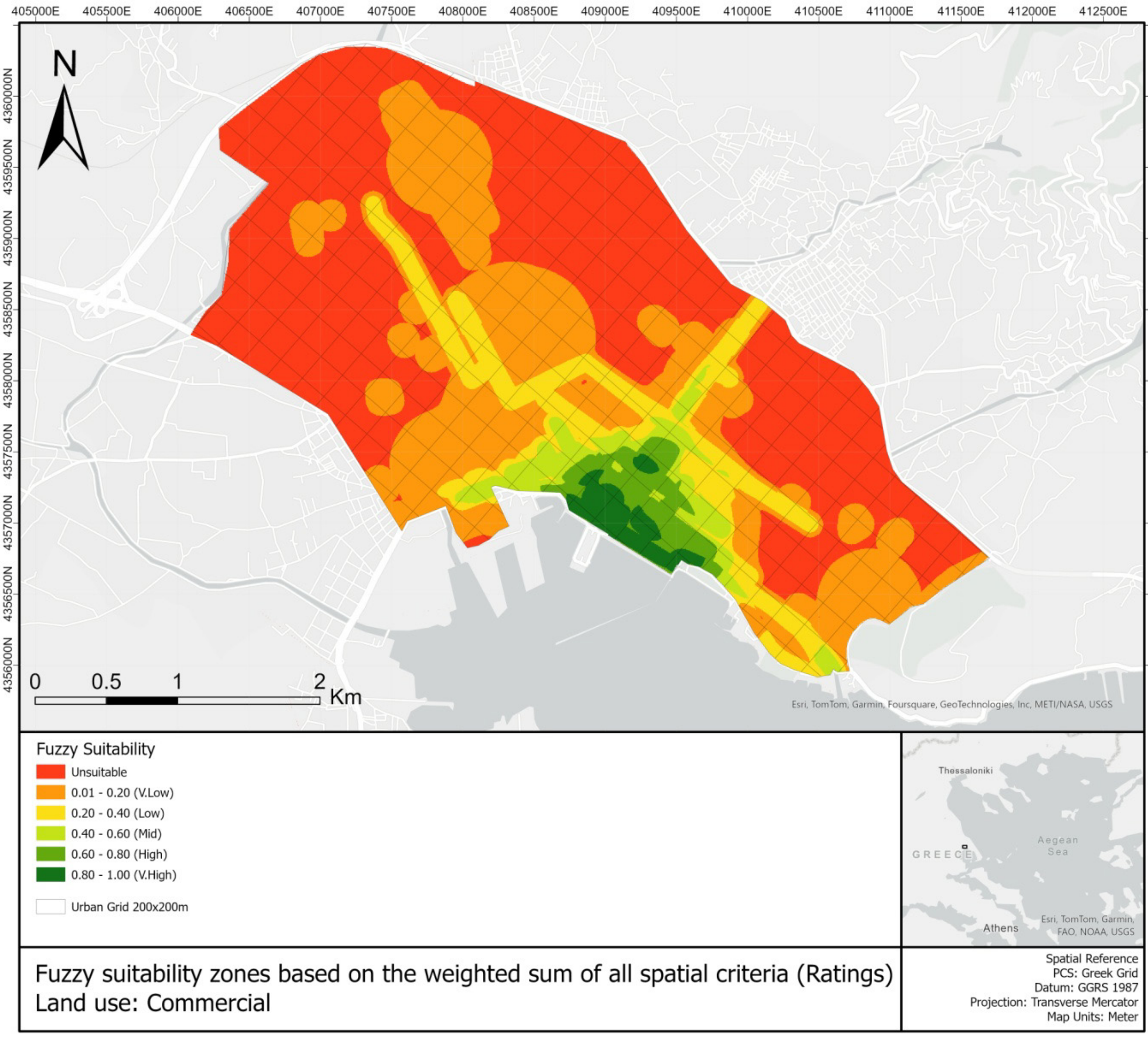


Figure 5. 4 - Fuzzy suitability zones for commercial LUs (Ratings)

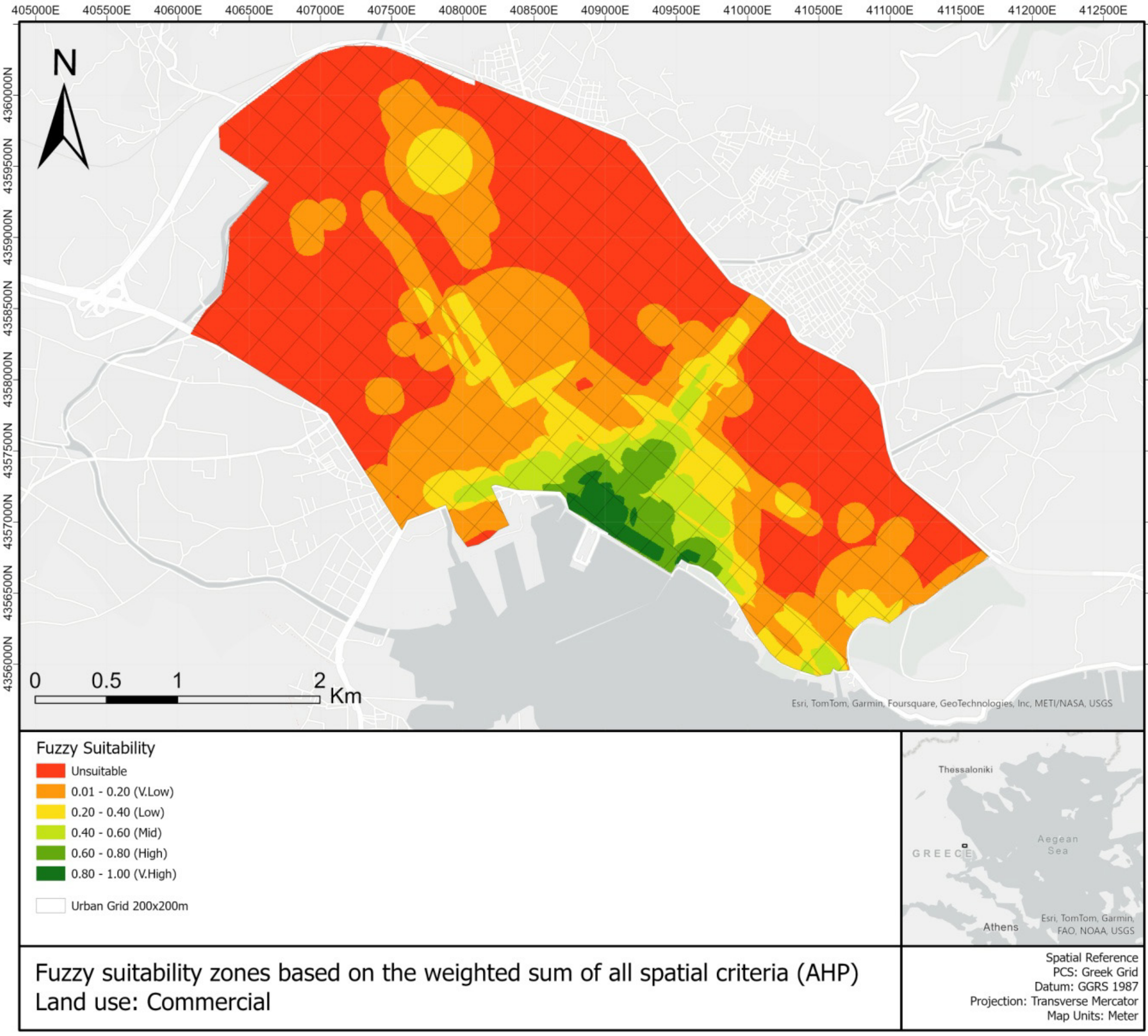


Figure 5. 5 - Fuzzy suitability zones for commercial LUs (AHP)

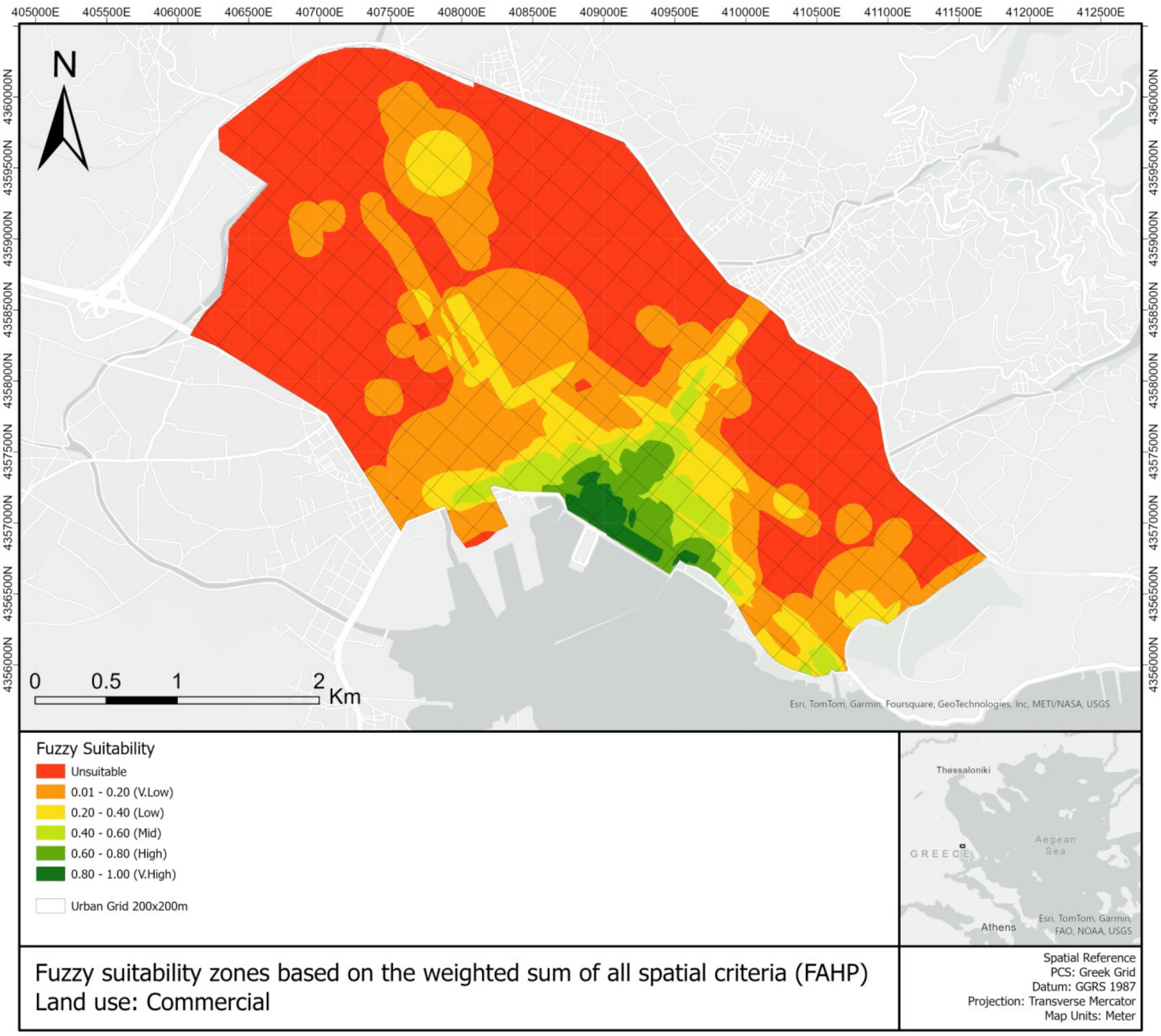


Figure 5. 6 - Fuzzy suitability zones for commercial LUs (FAHP)

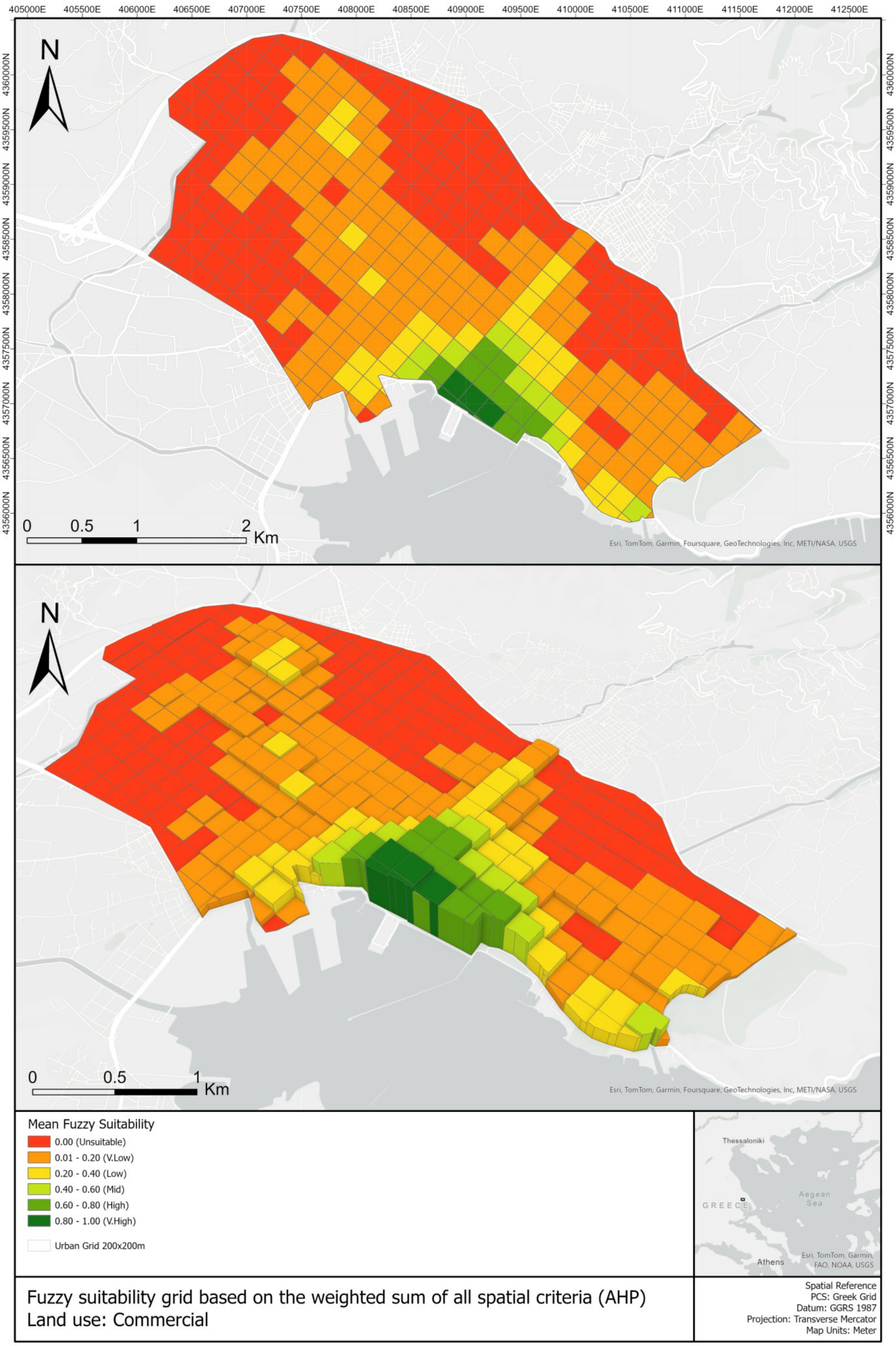


Figure 5. 7 - Fuzzy suitability grid for commercial LUs (AHP)

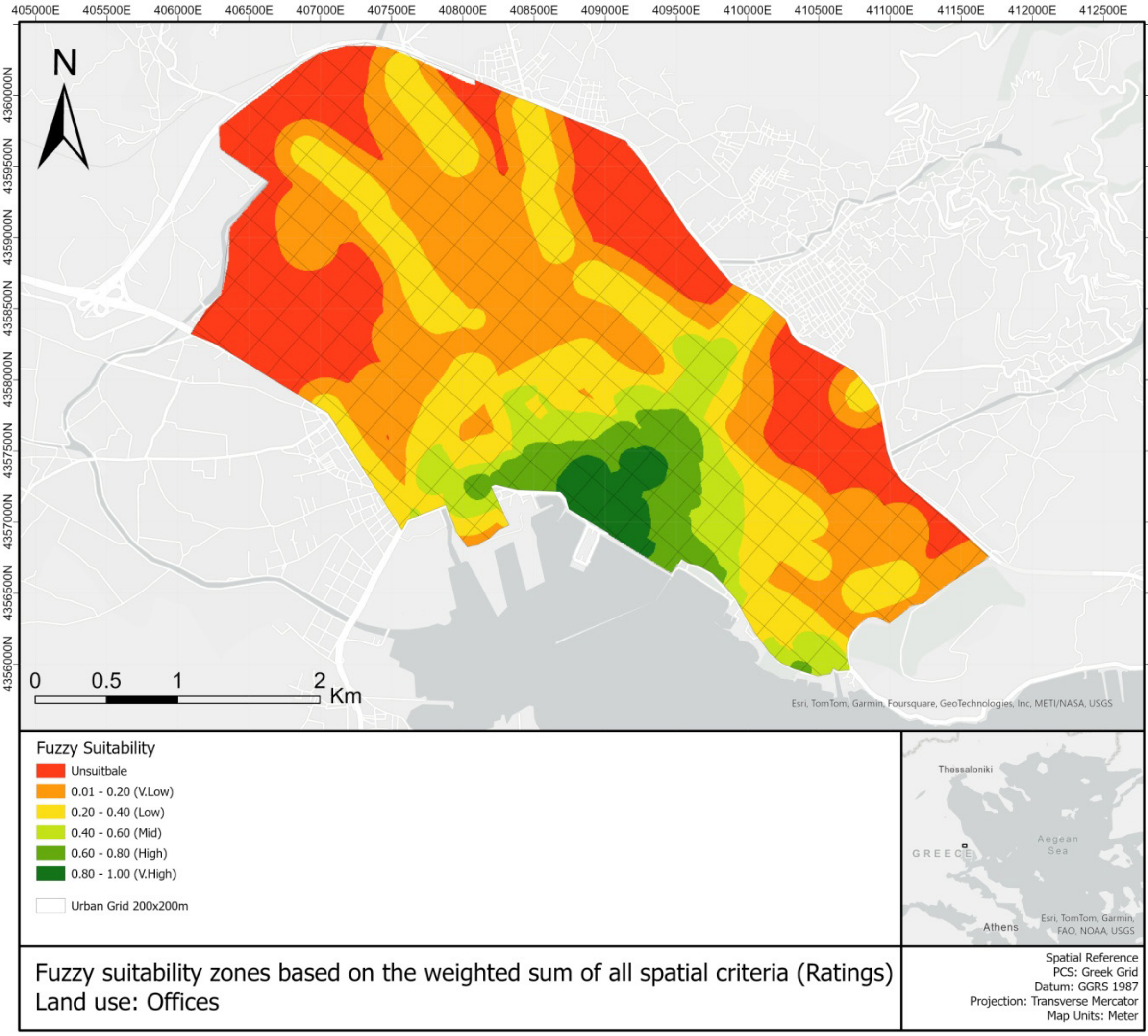


Figure 5. 8 - Fuzzy suitability zones for offices LUs (Ratings)

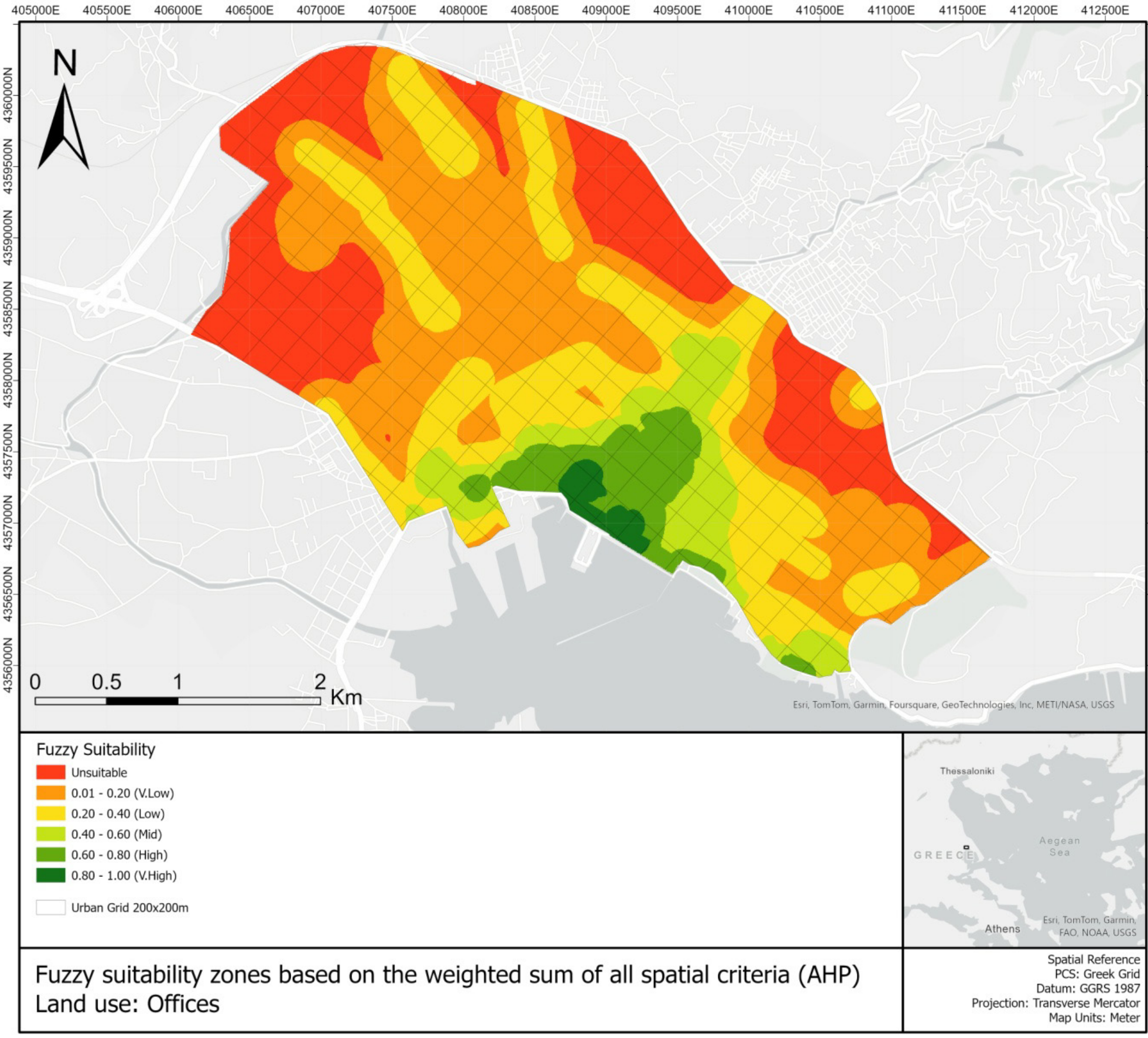


Figure 5. 9 - Fuzzy suitability zones for offices LUs (AHP)

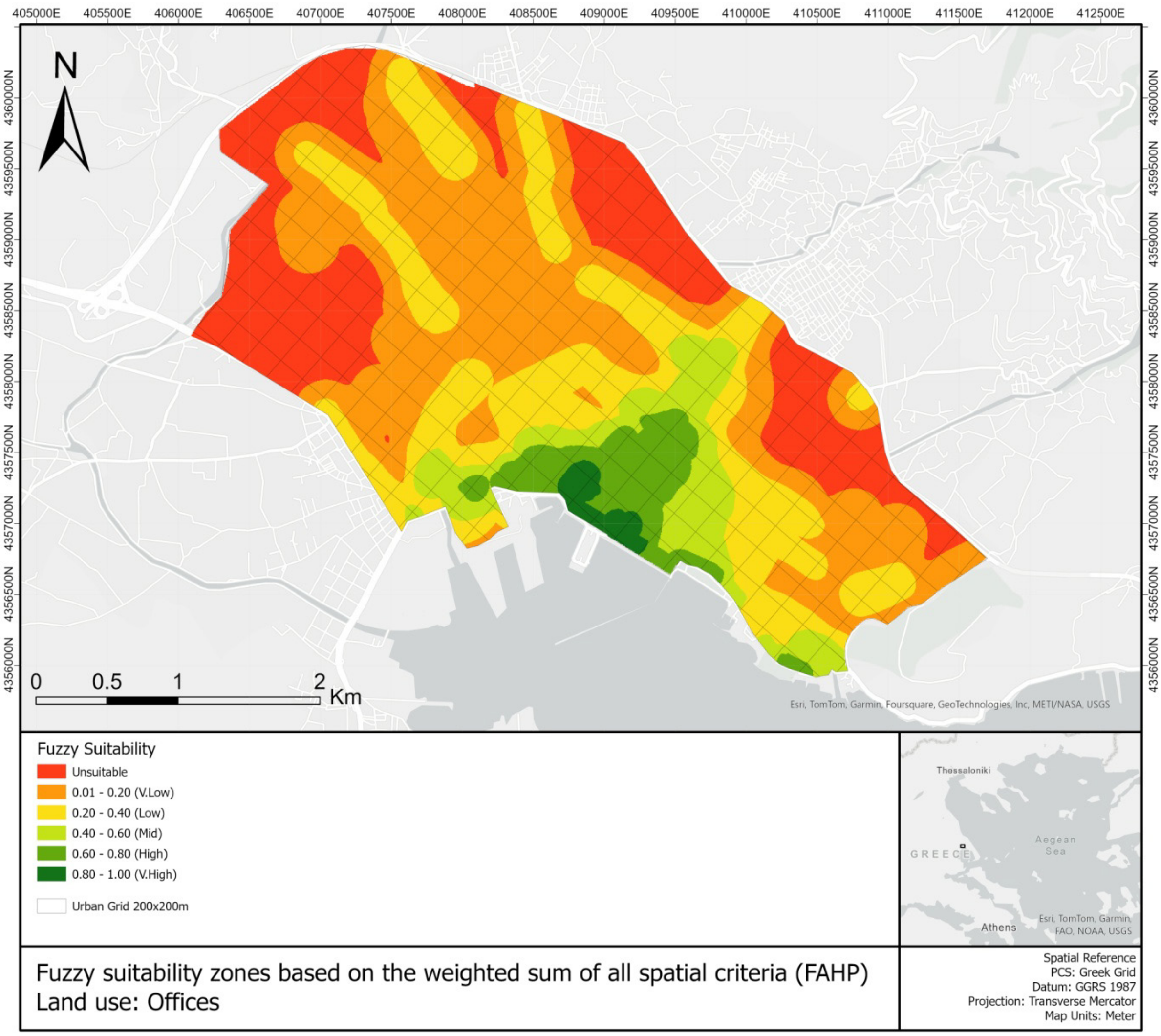


Figure 5. 10 - Fuzzy suitability zones for offices LUs (FAHP)

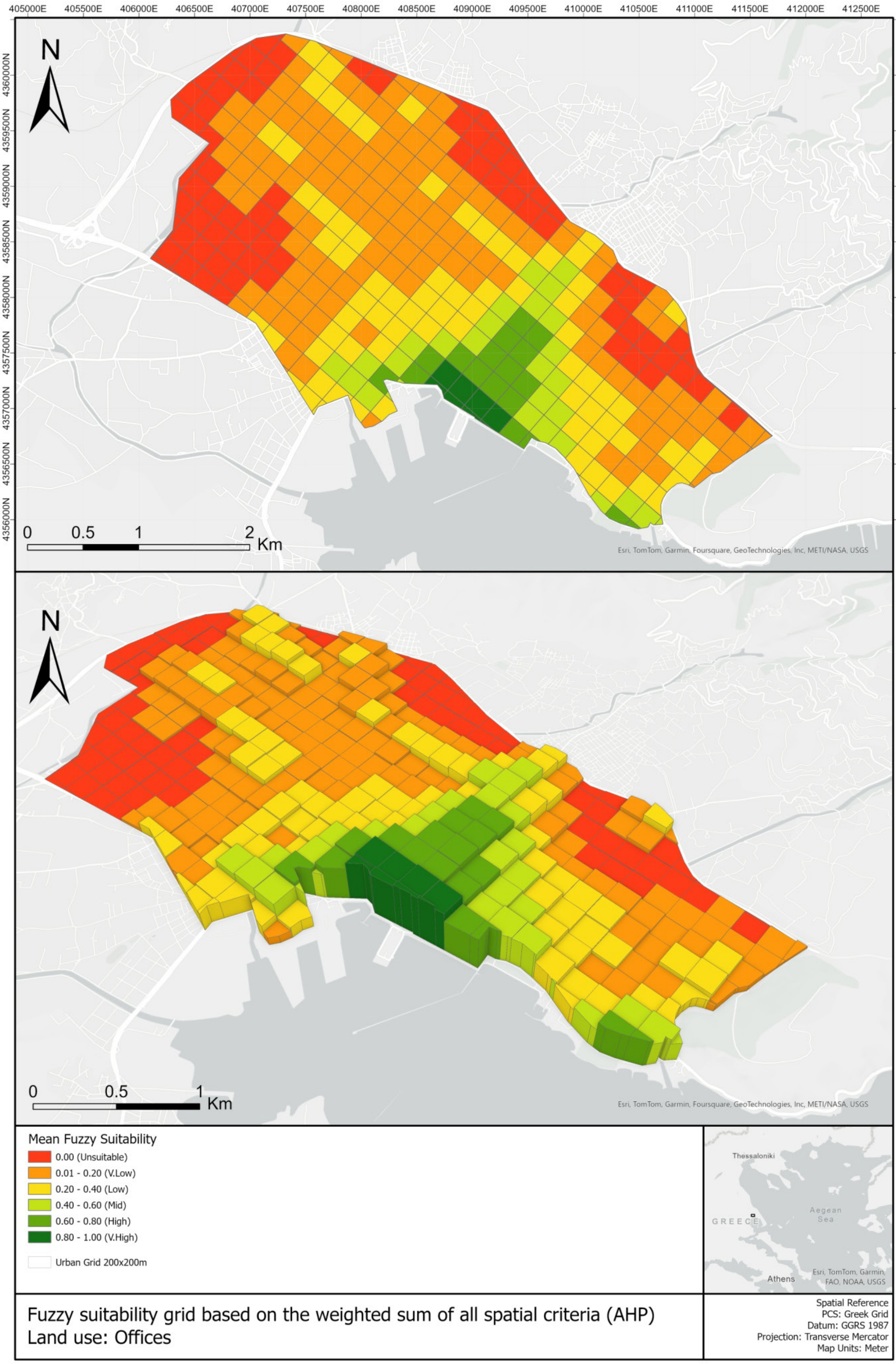


Figure 5. 11 - Fuzzy suitability grid for offices LUs (AHP)

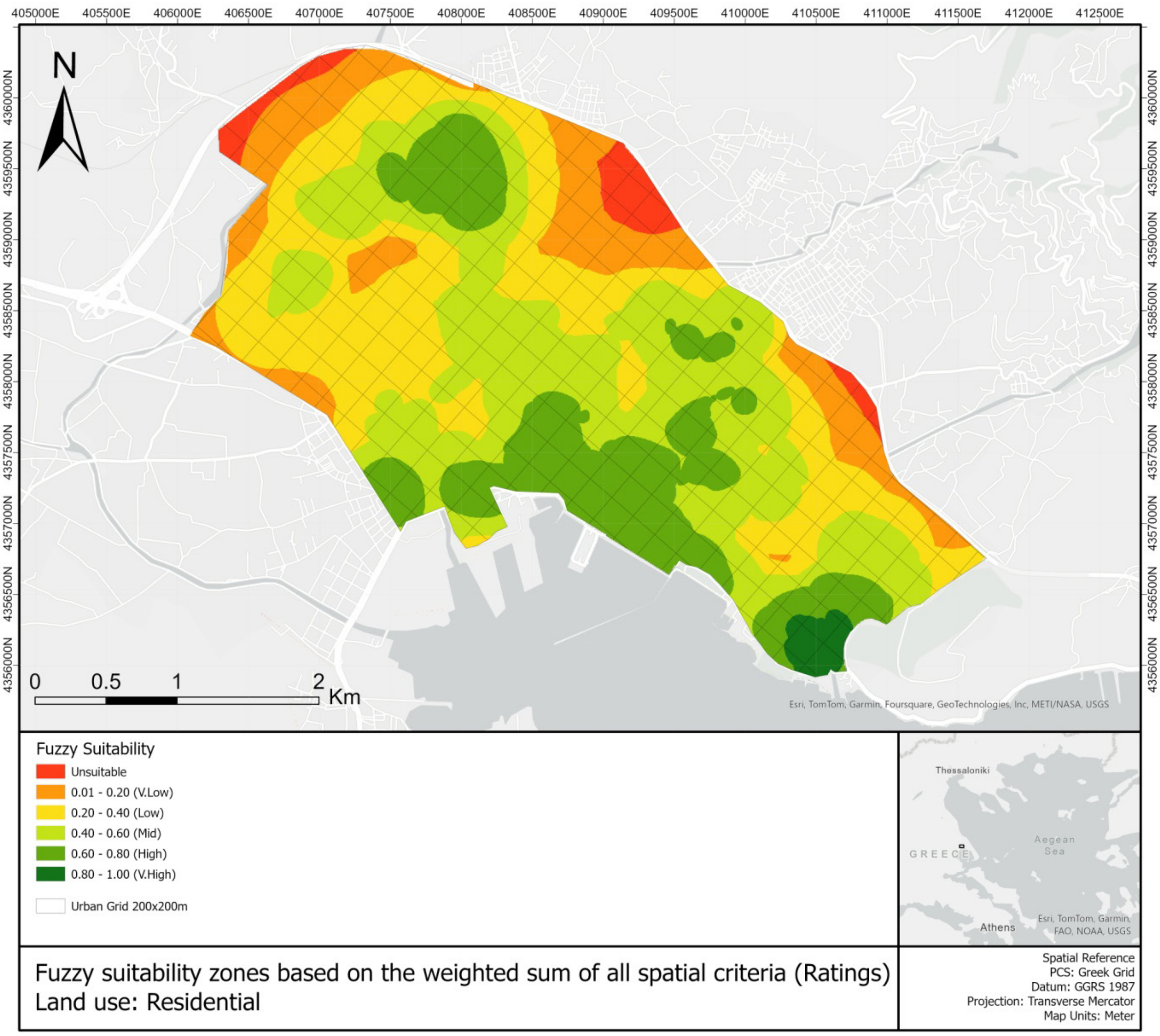


Figure 5. 12 - Fuzzy suitability zones for residential LUs (Ratings)

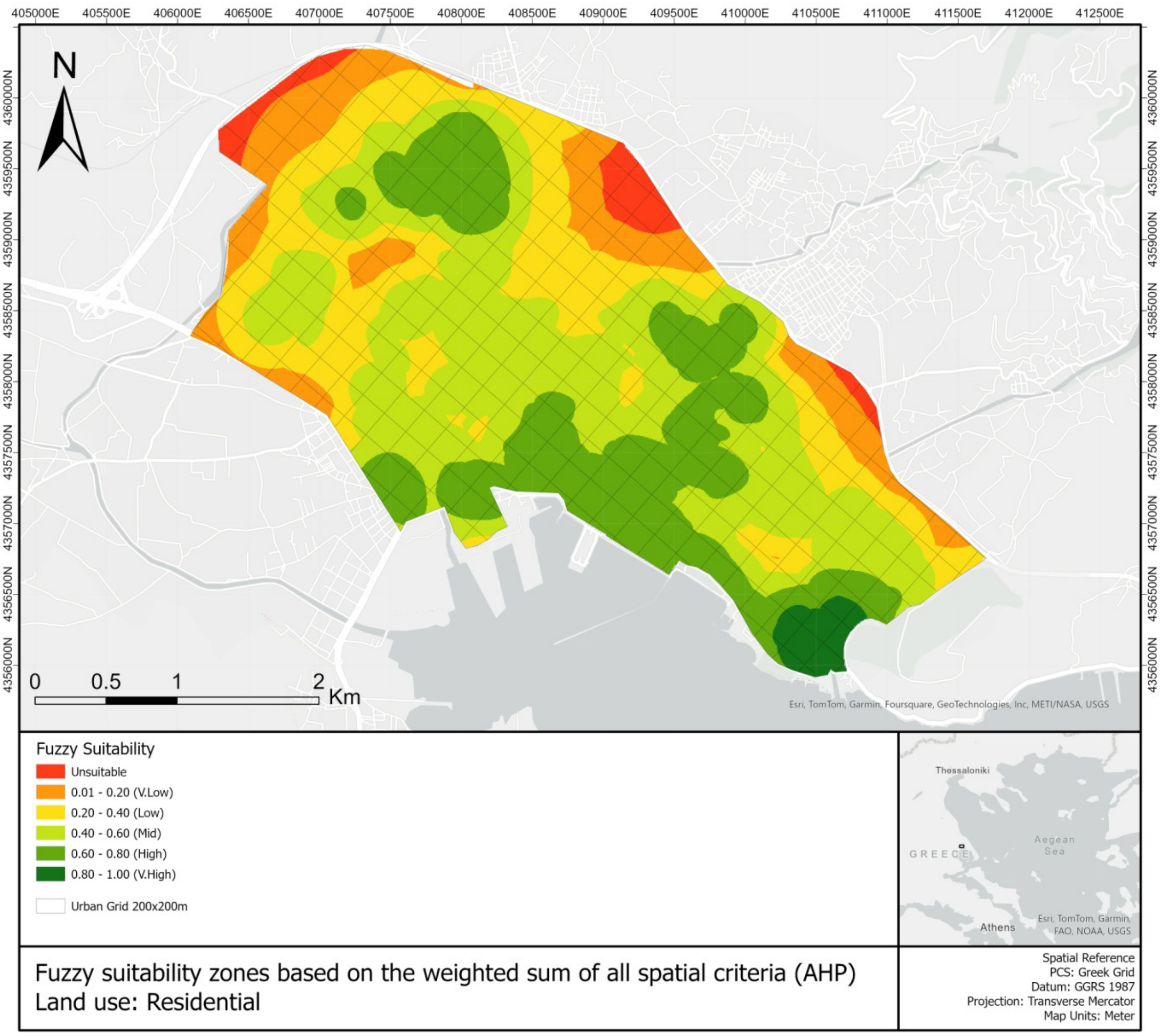


Figure 5. 43 - Fuzzy suitability zones for residential LUs (AHP)

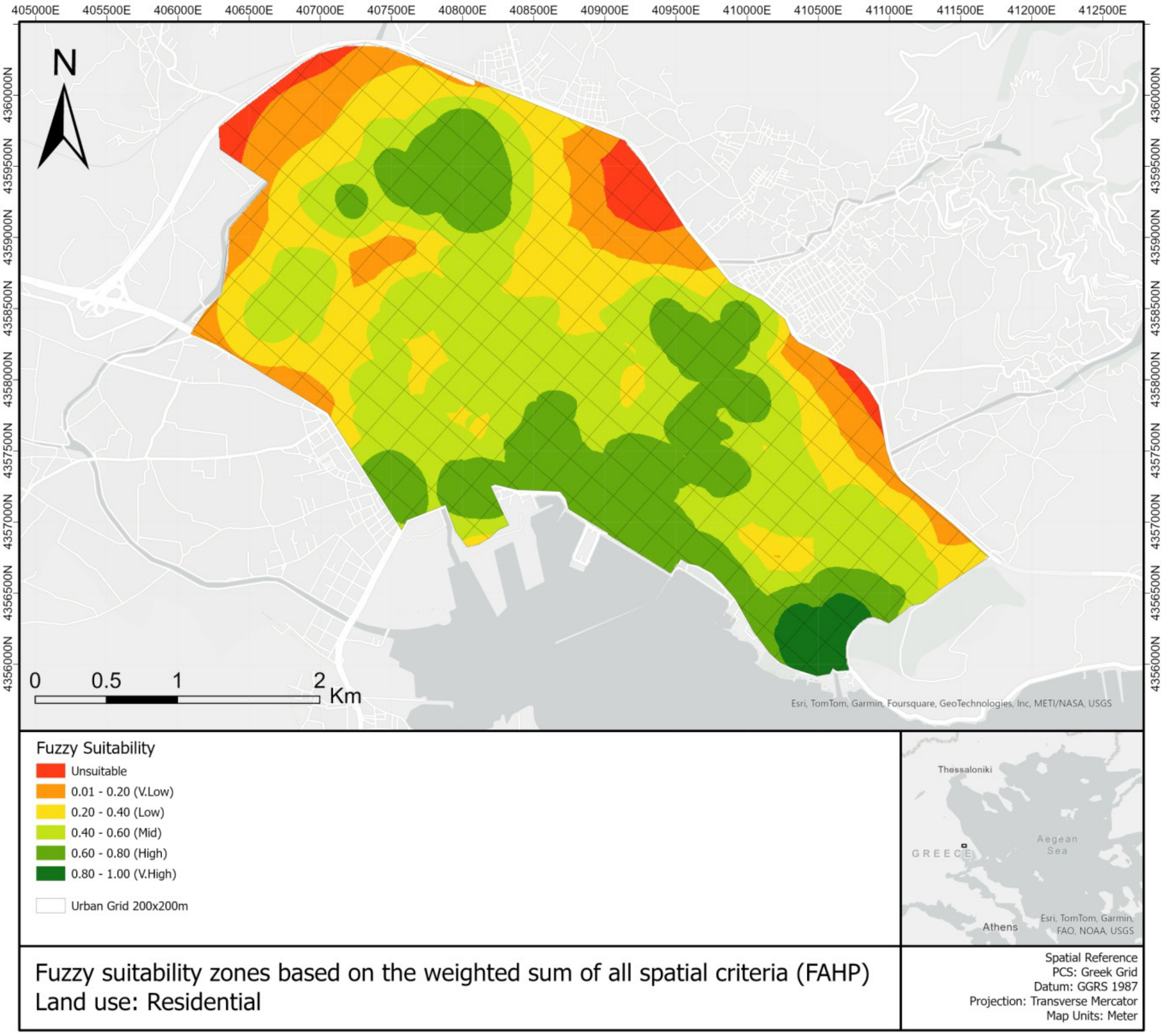


Figure 5. 14 - Fuzzy suitability zones for residential LUs (FAHP)

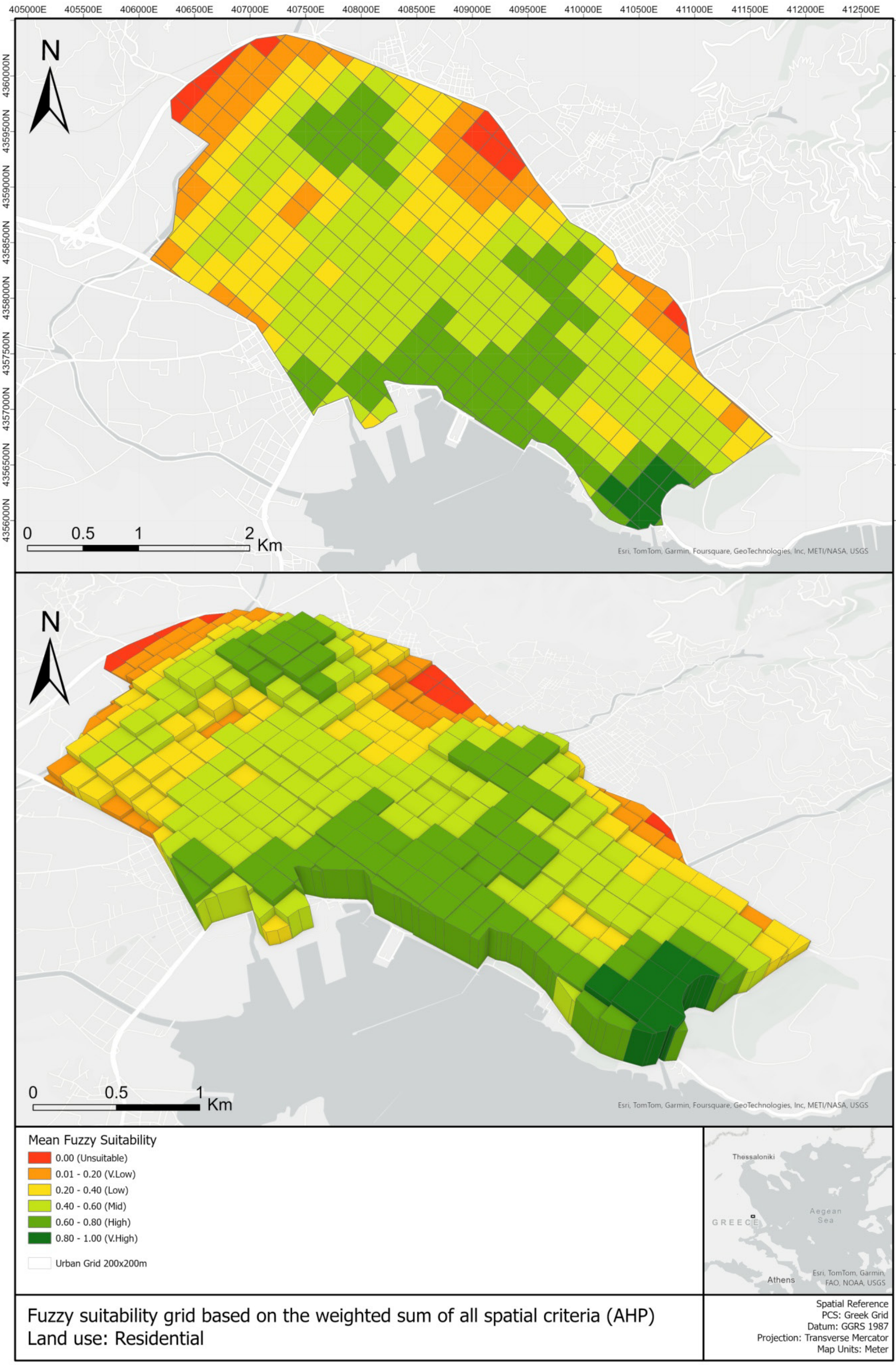


Figure 5. 15 - Fuzzy suitability grid for residential LUs (AHP)

5.3 AHP Output Validity Assessment

In order to assess the validity of the AHP output Spearman's correlation method was used, as an indirect but quantitative means of validity check. Correlation was checked between the announced selling price (in €/m^2) of real estate properties and the mean AHP score of the corresponding location. *Offices*, *Apartments*, *Detached* houses, and *Retail/Commercial* properties were identified in the study area and digitised in separate map layers. Table 5.4 shows the statistics of the property prices collected through the online real estate platforms (October 2022 to March 2023). The correlation coefficients and significance is shown in table 5.5 regarding all property types examined.

Table 5. 4 – Summary statistics for price points used

Summary Statistics for Price per Area (€/m^2)							
Property Class	**Count**	**Min**	**Max**	**Mean**	**Median**	**Std. Dev.**	**Skew.**
Retail	92	208	4938	1055	946	698	2.88
Offices	40	406	2817	1270	1137	486	1.48
Apartments	57	644	4727	1465	1388	719	2.00
Detached Houses	47	382	3000	1114	1083	521	1.86

Table 5. 5 - Correlation summary for property prices and AHP scores

Price per Area (€/m^2) and AHP Scores Correlation Summary				
		Spearman		**Strength**
Property Class	**N**	**Rho**	**Sig.**	
Retail	92	0.361	0.000	Moderate
Offices	40	0.461**	0.003	Moderate
Apartments	57	0.386**	0.003	Moderate
Detached Houses	47	0.047	0.755	N/A
**** Correlation is significant at the 0.01 level (2-tailed)**				

It can be seen that there is a moderate positive correlation between the mean AHP scores and the selling prices of all real estate property samples, except the detached houses class. This may support the argument that the announced selling prices for retail/commercial, offices and apartments moderately agree with mean AHP scores at these specific points. Being a non parametric test, robust to outliers and not assuming linearity, the Spearman's Rho coefficient is a better choice for correlation check in small datasets of real estate prices.

Chapter 6 – Discussion

6.1 Overview

For the scope of this research various theoretical and practical implications pertaining to the integration of Geographic Information Systems (GIS) and science with the discipline of real estate were examined. As analysed in the literature review this discussion is not new, but has mostly been the focus of geographers rather than real estate analysts. Notably, over the past decade there has been an increasing interest in GIS-based real estate analysis, going beyond the boundaries of GIS. That said, a paradigm shift related to GIS and Real Estate integration cannot be argued yet. The aim of this research was to apply GIS-based non-fuzzy and fuzzy multicriteria evaluation analysis to Real Estate, further supporting the GIS and Real Estate integration. For that, the Greek city of Volos has been selected as the study area.

6.2 Discussion

Since the overall aim of this research has been fulfilled, it is now useful to revisit and discuss on each of the research questions and objectives. Likewise, to discuss on some observations regarding the pairwise comparison weights extraction process and the consistency of PCMs.

RQ1: What is the relative difference between the non-fuzzy and the fuzzy AHP output for commercial, office and residential land-uses in Volos City?

As shown in sections 5.1 and 5.2 the relative difference between the non-fuzzy and fuzzy AHP output was very low. Cell-by-cell comparison of the rasterised F/AHP layers revealed a less than 1% relative difference in all real estate land-uses examined. This is reasonable considering that in almost all criteria the difference between the spatial criteria weights did not exceed 4%. Therefore, the non-fuzzy AHP layers were used for the final visualisation on a 200x200m block grid form.

RQ2: What is the total area per land-use suitability for commercial, office and residential land-uses in the city of Volos?

The detailed breakdown of the total area per land-use suitability was shown in section 5.2, but there are some interesting results to summarise. For Office land-uses only 13% of the study area is of medium to high suitability. Residential land-uses are significantly better, with more than half of the study area being of medium to high suitability. Also, 43% of the study area is unsuitable for commercial land-uses. Notably, very high suitability regarded less than 2% of the study area, for all land-uses examined. Low or no suitability does not mean that such land-uses do not exist in these zones. The AHP maps just indicate zones with more and less favourable conditions, based on the selected criteria weights and their GIS digitisation.

RO1: Select and weight spatial criteria to be used in non-fuzzy and fuzzy real estate land-use suitability analysis in the urban area of Volos City

For the first objective, focus was on selecting and weighting spatial criteria relevant to the study area of Volos City. The literature reviewed provided a number of spatial criteria, often found in real estate MCE/AHP analyses (see Table I.2 in Appendix I), from which twelve spatial criteria were proposed to real estate experts for shortlisting and weighting. This was achieved by using Ratings scoreboards sent by e-mail, and pairwise comparison matrices (PCMs) completed during live expert interviews (see section 4.4). The Ratings method provided coarser weights compared to the F/AHP approach (see section 5.1). The most important use of Ratings, in this research, was as a screening tool for shortlisting a larger pool of proposed criteria. This is especially important when there is a need to offer participants the option of selecting the most relevant criteria, while keeping the number of spatial criteria low. As the number of criteria and the PCM size increase, handling the pairwise comparisons and ensuring PCM consistency becomes challenging.

RO2: Generate real estate land-use suitability zones in the urban area of Volos City, using non-fuzzy and fuzzy AHP analysis

The second objective focused on using the selected non-fuzzy and fuzzy AHP criteria weights to generate real estate land-use suitability maps (see section 5.2). Weighted Linear Combination was also used with criteria weights from the Ratings method, for comparison reasons. From this straightforward process some interesting observations were made. Commercial and office land-uses are characterised by significantly lower suitability outside the proximity of the city centre. This may be attributed to lack of infrastructure support outside this zone. As shown in the criteria maps in Appendix II, there is an absence of points of interest in the periphery e.g. recreational activities, public services. The coastal front with its major roads has high densities of points of interest which was also reflected on the AHP maps and the increased percentage of unsuitable lands (section 5.2). For Office land-uses there are areas with low suitability in the periphery of the urban core (national road and peripheral ring) which are worth noting as these junctions can be focused in terms of urban planning and may also hold opportunities for real estate development. Residential land-uses depend on a spatial criteria mix with educational, university and health facilities being included in the calculations. Therefore, the size and dispersion of suitable lands is significantly different compared to commercial and office land-uses. Overall, the AHP-based land-use suitability analysis can be used in examining real estate investment opportunities e.g. where suitability is medium to high but expected to increase. The public sector e.g. the local planning authorities may use land suitability analysis to focus on urban sub-areas in need of infrastructure support, within the wider scope of urban planning.

RO3: Compare the fuzzy and non-fuzzy AHP output, for real estate land-use suitability analysis in the study area

For the third objective the non-fuzzy and fuzzy AHP output was compared, in terms of spatial weights and maps (see sections 5.1 and 5.2). For fuzzifying the original PCMs the triangular fuzzy number form was used, by decreasing and increasing the original scores by a factor $f = 1$, 2 and 3 (section 4.5.2). Sensitivity analysis findings showed that the small variation (< 5%) in fuzzy PCM weights moving up from $f = 1$, does not balance out the risk of overextending the fuzzification without input from the participants. So, the final maps focused only on the FAHP ($f = 1$) weights. Overall, there was no strong empirical evidence that fuzzy AHP provided better results, considering the additional time resources required. The relative difference between the non-fuzzy and fuzzy AHP rasters remained lower than 1% for all real estate land-uses. Similarly, the relative difference between most non-fuzzy and fuzzy criteria was less than 4%. Therefore, the non-fuzzy AHP mean values were used for the final grid maps. However, this is project-dependent and cannot be generalised. Concurring with the literature reviewed, the fuzzy AHP should always be considered.

RO4: Visualise the AHP real estate suitability zones in grid form

The fourth objective was achieved by using the mean non-fuzzy AHP values within each 200x200m grid-block to produce AHP maps in a grid-form, approximating city blocks. The final 2D and 3D grid maps stayed true to their non-grid counterparts (section 5.2.), providing a reliable alternative visualisation of discrete grid blocks. Grid form is more accessible to real estate professionals unfamiliar with raster maps.

RO5: Assess the validity of the AHP land-use suitability output

For the final objective correlation analysis was used, based on the assumption that if mean AHP values and online selling prices significantly correlate then the AHP maps are supported on their validity. Correlation check showed that the AHP land-use suitability values moderately correlate with property prices for apartments, retail/commercial properties and offices. For detached houses correlation analysis did not support a significant link between the AHP values and the announced selling prices. This is reasonable, since pricing in these properties does not closely link to spatial criteria distances. Indeed, homeowners opting for detached houses often seek quieter areas which usually are far from urban cores, and other criteria like proximity to natural areas and open spaces take priority over e.g. distance to public services.

Overall, the AHP output can be deemed valid. The indirect assessment provided through correlation is further enhanced, considering that real estate prices do not only depend on distances from points of interest but various additional factors like age and status of the asset and supply-demand in the real estate market. From a qualitative assessment perceptive, the Consistency Ratios of the consolidated PCMs were at 5.00%, 0.77% and 5.09% (table I.7, Appendix I) for commercial, office and residential land-uses respectively. These are significantly lower than the 10% consistency ratio threshold. PCMs are qualitative in nature (opinion-based) but combined with the high accuracy of the digitised criteria layers (table 4.2) they further support the increased validity of the AHP land-use suitability output presented in the results section of the thesis (Chapter 5).

Observations on the pairwise comparison process and PCM Consistency Ratios

In terms of extracting spatial criteria weights, using PCMs may not bring useful results without live interaction with the researcher, unless the participants are already sufficiently familiar with the process, and the underlying topic/question is not exploratory but more procedural/technical. Such observation is similar to those of La Pira *et al*. (2015), in their extensive analysis of a step-by-step optimisation of PCM process. Through a 4-step process, seventeen participants were gradually familiarised with the process of multicriteria decision making. In their study, Consistency Ratios where significantly higher than 10% in the first two phases and gradually improved toward phase 4, as participants became accustomed to how their judgments affected consistency. According to the literature reviewed for this research, the study by La Pira *et al*. (2015) is the only one presenting and analysing in detail the process and the challenges of weight extraction through pairwise comparison matrices. They concluded that the interaction between participants leads to convergence/consensus and stronger consistency in the final results. During the weight extraction process for this research no interaction between participants was sought. This would be practically challenging as all participants are established professionals and not easy to bring together at the same time and place. There was also the risk of such grouping and interaction leading to expert opinions affecting one another, reducing the exploratory reach of the process.

Regarding the reliability of PCM scores, the Consistency Ratio (CR) upper threshold of 10%, has long been used (Saaty, 1990; Malczewski & Rinner, 2015; Krecji, 2018). However, as the number of criteria exceeds seven the CR tends to increase, and repeated revisions from the participants are needed. Indeed, there seems to be some discussion on the strictness of the 10% upper threshold (Krecji, 2018), and its calculation (Franek & Kresta, 2014). Depending on the scope of the project, CRs up to 20% can be practically acceptable (Goepel, 2013). The process followed for this analysis confirms this adaptation. Participants were asked to revise their answers only when they seemed unsure, if they wanted to do so, rather than persistently being required to make changes until the CR dropped below 10%. Therefore, some CRs over 10% were kept, given that participants were satisfied with their revisions.

6.3 Research Limitations

Limitations of the research methods used regard *external validity*, *reliability* and *Replicability* (Sekaran, 2003; Kothari, 2004; Bryman, 2012). *External validity* has to do with the potential to generalise results. Focus was on a study area with specific characteristics, using cross-sectional data via non-random sampling. Moreover, comparable analyses on other Greek cities were not found. However, generalisation of the results was not an objective. *Reliability* regards the stability and consistency of the tools used for measurement. To limit biases and errors, all processes were standardised and common for all participants. *Replicability* is about the repeatability of results when identical research is done, but at different times and context. Even though each process was described in detail, it is not be possible to replicate the results since the participants and the criteria layers will differ at different spatiotemporal contexts.

Going further into the detail of the specific research limitations, it is useful to summarise the various points made throughout the thesis regarding the risk of inaccuracy. Related to the first research objective (RO1) the participants had no previous experience of the MCE process and pairwise comparison between criteria for that matter. The choice to conduct live interviews where the participants received real-time clarifications by the author, aimed at minimising this process risk. The consistency ratios of the consolidated PCMs confirmed the reliability of the PCM weights extracted, that were used to develop the AHP land-use suitability maps.

Pertaining to the second research objective (RO2) the choices regarding the fuzzification of the spatial criteria Euclidean distances and the original non-fuzzy PCMs were based on the author's discretion. The former links to the choice of sigmoidal equation and its parameters, and the latter to the selection of the triangular fuzzy number set. Minimising this risk was done by looking into the different methods used in the relevant literature reviewed, and deciding based on utility and the author's hands-on knowledge of the area (context), always considering the themes explored in the research.

6.4 Conclusions

The aim of this research was to apply GIS-based non-fuzzy and fuzzy multicriteria evaluation analysis (MCE) to real estate land-use suitability in the Greek coastal city of Volos. This was achieved by selecting and weighting seven spatial criteria, out of twelve initially proposed to real estate experts. These weighted criteria were digitised as separate layers and combined, to produce suitability maps for commercial, office and residential land-uses. For the aim of this research the land-use suitability analysis provided accurate output for the real estate classes examined. Care during weight extraction led to reliable criteria weights and suitability maps.

Comparing the rasterised non-fuzzy and fuzzy AHP layers on a cell-by-cell basis revealed a less than 1% difference in all three land-uses, using the same suitability classification. This very small difference was also evident in the criteria weight comparison, where the difference remained less than 4%, for almost all criteria and land-uses. So the non-fuzzy mean AHP values were used for the final maps on a 200x200m block grid. The AHP output provided interesting results in terms of percentage of area per land-use suitability class. Namely, 43% of the study area is unsuitable for commercial land-uses. For Office land-uses only 13% of the study area is of medium to high suitability. Residential land-uses are more favoured, with more than half of the study area being of medium to high suitability. Notably, very high suitability regarded less than 2% of the study area, for all land-uses examined.

The strength of the AHP output was assessed via correlation check between announced selling prices (€/m^2) in the study area and the mean AHP values in their position. Apartment, commercial and office property prices moderately correlated with AHP land-use suitability values. Considering that numerous factors affect real estate prices a moderate, but statistically significant, correlation is not negligible and indirectly supports the validity of the AHP maps. For detached houses no correlation between land-use suitability and market prices was found. This was attributed to the idiosyncratic nature of the detached houses property class. That being said, applying the same methods for digitising and weighting the spatial criteria indirectly supports the quantitative reliability of the AHP maps for these land-uses also.

Overall, the use of GIS-based analysis in Real Estate has evolved, but no paradigm shift can be argued yet. Along with the advantages of GIS and Real Estate integration the respective limitations and prerequisites have to be acknowledged. Apart from the persisting real estate data availability and accuracy issues, the success of GIS and Real Estate integration is also dependent on realistic expectations. The *time* factor is linked to such expectations. GIS-based analysis is not faster than rules-of-thumb used in everyday real estate practice. Collection, cross-reference, geo-processing and visualisation of data take time and are resource-intensive. What GIS-based analysis can contribute to Real Estate is a long-term framework, on which decisions will be made in a more geographically informed manner. Insisting on unrealistic expectations may lead to failure, hindering the integration of GIS and Real Estate.

Future research may focus on expanding similar spatial analysis on other Greek cities, which could provide comparable results. The methods and processes detailed in this thesis could be used also at a future time to provide an update linked to the current research. Considering the growing interest in GIS and Real Estate integration and the need for rationalising the Greek property market, relevant future research is strongly suggested.

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APPENDIX I

Auxiliary Tables

#	Authors	Year	Sector	Theme	Key Methods	Country
1	Eren & Katanalp	2022	Urban development	Bike-sharing stations	MCDM, AHP, fuzzy AHP	Turkey
2	Foroozesh et al.	2022	Real estate analysis	Urban development potential	MCDA, AHP, fuzzy AHP	Iran
3	Raad et al.	2022	Real estate development	Dryport selection	MCDA, fuzzy-logic	Iran
4	Caprioli & Bottero	2021	Urban planning	Identify suitable locations for urban infrastructure	AHP, fuzzy AHP, MCDA	Italy
5	Ding et al.	2021	Urban planning	Urban green building planning	Fuzzy-AHP	China
6	Bencure et al.	2019	Real estate valuation	Mass land value appraisal	MCDA, AHP	Thailand
7	Jahanshahi et al.	2019	Urban development	Bike-sharing stations	MCDA, fuzzy-memberships, AHP	Iran
8	Mete & Yomrlioglu	2019	Real estate valuation	Mass real estate valuation	MCDM, best-worst method	Turkey
9	Sgura Viana & Delgado	2019	Urban planning	City logistics in historic centers	MCE-GIS	Brasil
10	Dell' Ovo et al.	2018	Land-uses	Healthcare facilities site selection	MCDA-GIS, multicriteria DSS	Italy
11	Rahimi et al.	2017	Land-uses	Hospital site selection	GIS-AHP	Iran
12	Oppio et al.	2016	Land-uses	Hospital site selection	GIS-MCDA	Italy
13	La Pira et al.	2015	Transportation	AHP methods assessment	AHP, pairwise comparisons	Italy
14	Mosadeghi et al.	2015	Urban planning	Urban land-use	MCDA, AHP, fuzzy AHP	Australia
15	Jeong et al.	2013	Spatial planning	Rural spatial planning	MCE, AHP, fuzzy memberships	Spain
16	Kepaptsogou et al.	2013	Transportation	Metro stations condition	AHP, fuzzy AHP	Greece
17	Lotfi et al.	2009	Urban land use	Urban land development	MCDM	Iran
18	Vahadinia et al.	2009	Land-uses	Hospital site selection	Fuzzy AHP, MCDA-GIS	Iran
19	Kimpel et al.	2007	Urban transport	Bus stops planning	GIS, fuzzy-memberships	USA
20	Gomes & Lins	2002	MCE and GIS	GIS and MCE/MCDM integration	Theoretical analysis	Brazil

Linked to: Chapters 2 and 3 (section 3.2)

Table I. 1 - Selected cases of GIS integration with real estate and spatial planning

Table I. 2 – Commonly used spatial criteria

Spatial Criteria	Authors
Commercial/City centre	Gat, 1998; Dimopoulos & Moulas, 2017; Jahanshahi et al., 2019; Mete & Yomralioglu, 2019; Chen et al., 2020; Foroozesh et al., 2022
Cultural facilities	Podor & Nyiri, 2010; Bovkir & Aydinoglu, 2018; Mete & Yomralioglu, 2019; Foroozesh et al., 2022
Educational facilities	Pagourtzi et al., 2005; Podor & Nyiri, 2010; Jahanshahi et al., 2019; Omidipoor et al., 2019; Chen et al., 2020; Sisman & Aydinoglu, 2022
Forest	Bourassa et al., 2005; Mittal & Byahut (2016)
Health facilities	Podor & Nyiri, 2010; Yalpir, 2014; Mete & Yomralioglu, 2019; Bovkir & Aydinoglu, 2018; Sisman & Aydinoglu, 2022b; Chen et al., 2020
Hospitals	Dimopoulos & Moulas, 2017; Bovkir & Aydinoglu, 2018; Bencure et al., 2019; Foroozesh et al., 2022
Parks & squares	Pagourtzi et al., 2005; Mittal & Byahut, 2016; Dimopoulos & Moulas, 2017; Bovkir & Aydinoglu, 2018; Omidipoor et al., 2019; Mete & Yomralioglu, 2019; Chen et al., 2020; Foroozesh et al., 2022; Sisman & Aydinoglu, 2022
Major roads	Lotfi et al., 2009; Jeong et al., 2013; Yalpir, 2014; Dimopoulos & Moulas, 2017; Demetriou, 2018; Bencure et al., 2019; Mete & Yomralioglu, 2019; Chen et al., 2020; Raad et al., 2022; Sisman & Aydinoglu, 2022
Public services	Podor & Nyiri, 2010; Bovkir & Aydinoglu, 2018; Chen et al., 2020
Public transportation	Gat, 1998; Bourassa et al., 2005; Podor & Nyiri, 2010; Dimopoulos & Moulas, 2017; Bovkir & Aydinoglu, 2018; Jahanshahi et al., 2019; Mete & Yomralioglu, 2019; Omidipoor et al., 2019; Sisman & Aydinoglu, 2022; Chen et al., 2020; Balaji & Muthukannan, 2021; Foroozesh et al., 2022
Recreation facilities	Pagourtzi et al., 2005; Omidipoor et al., 2019; Chen et al., 2020; Sisman & Aydinoglu, 2022
Schools	Bourassa et al., 2005; Pagourtzi et al., 2005; Yalpir, 2014; Dimopoulos & Moulas, 2017; Bencure et al., 2019; Mete & Yomralioglu, 2019; Foroozesh et al., 2022
View	Wallner, 2012; Pagourtzi et al., 2005; Mittal & Byahut, 2016; Mete & Yomralioglu, 2019
Waterfront, seaview	Bourassa et al., 2005; Pagourtzi et al., 2005; Mittal & Byahut, 2016; Dimopoulos & Moulas, 2017; Demetriou, 2018; Bencure et al., 2019; Mete & Yomralioglu, 2019

Linked to: Chapter 4 (section 4.2)

Table I. 3 – Parameters for suitability criteria sigmoids (s-curves)

COMMERCIAL LAND-USES						
Criteria	**Distance from**	**Mid-point (Xo)**	**K**	**f(x) = 0.2**	**Tolerance (up to)**	**Comments**
Commercial/City Centre	Point	600	0.02	669.3	Medium walking distance	From the Volos City central square
Major Roads	Road axis	70	0.15	79.2	Direct access, short walking distance	Major roads with high commercial activity
Public Transportation	Points	200	0.03	246.2	Direct access or short walk	Bus stop junctions (more than two bus lines meeting)
Public Services	Points or area	400	0.02	469.3	Medium walking distance	Frequently used public services i.e. citizens' service centres, courthouses, post office
Seafront/Port view	Polygon bounds	N/A	N/A	N/A	Direct access or line-of-sight	Direct access to the waterfront promenade and unobstructed sea view
Parks and Squares	Polygon bounds	N/A	N/A	N/A	Direct access or line-of-sight	Organised open spaces, including forest zone and seafront (no undeveloped lands)
Recreation Areas/Facil.	Points or area	300	0.03	346.2	Medium walking distance	Activities junctions (cultural, sports, tourist etc.)

OFFICES						
Criteria	**Distance from**	**Mid-point (Xo)**	**K**	**f(x) = 0.2**	**Tolerance (up to)**	**Comments**
Commercial/City Centre	Polygon bounds	700	0.012	815.5	Medium to long walking distance	From the Volos City central square
Major Roads	Road axis	150	0.04	184.7	Direct access or short walking distance	National road junctions included
Public Transportation	Points	350	0.02	419.3	Direct access or short walking distance	Bus stop junctions (more than two bus lines meeting)
Public Services	Points or area	500	0.01	638.6	Medium walking distance	Frequently used public services i.e. citizens' service centres, courthouses, post office
Seafront/Port view	Polygon bounds	N/A	N/A	N/A	Direct access or line-of-sight	Direct access to the waterfront promenade and unobstructed sea view
Parks and Squares	Polygon bounds	150	0.03	196.2	Direct access or short walking distance	Organised open spaces, including forest zone and seafront (no undeveloped lands)
Recreation Areas/Facil.	Points or area	200	0.03	246.2	Direct access or short walking distance	Activities junctions (cultural, sports, tourist etc.)

RESIDENTIAL						
Criteria	**Distance from**	**Mid-point (Xo)**	**K**	**f(x) = 0.2**	**Tolerance (up to)**	**Comments**
Bus stops	Points	300	0.02	369.3	Short walking distance	All bus stops included
Education Facilities	Points	500	0.015	592.4	Medium walking distance	School combos with Gymnasium and Lyceum in same facility or in close proximity
Parks and Squares	Polygon bounds	300	0.02	369.3	Short walking distance	Organised open spaces, including forest zone and seafront (no undeveloped lands)
Health Facilities	Points	400	0.01	538.6	Medium walking distance	City hospital and private clinics
Recreation Areas/Facililities	Points or area	500	0.015	592.4	Medium walking distance	Activities junctions (cultural, sports, tourist etc.)
University	Points	600	0.01	738.6	Medium to long walking distance	Main university infrastructures i.e. lecture halls, library, public student residence halls
Public Services	Area	500	0.01	638.6	Medium walking distance	Frequently used public services i.e. citizens' service centres, courthouses, post office

Linked to: Chapter 4 (section 4.5.1)

Notes:
Mid-point x_0 values in meters;
Column “f(x) = 0.2” gives the distance (in meters) from the criterion source after which suitability *f(x)* drops below 0.2, and towards zeroing out;

Setting the sigmoid parameters x_0 and K was loosely based on the “15-minute city” urban planning concept (see e.g. Duany & Steuteville, 2021), where necessary daily activities and services can be accessed within a radius of 15-minute walking, cycling or using public transportation.

Spatial Criteria	Retail	Offices	Residential
Bus Stops	25	20	20
Commercial Center			
Education Facilities			25
Health Facilities			20
Major Roads	20	20	
National Railroad			
National Road	15		
Parks and Squares	15		10
Port Front	10	15	
Public Services		20	
Recreation Areas		15	10
University	15	10	15
Sums	**100**	**100**	**100**

Instructions
Allocate a total of **100 points** to 6 criteria. You may allocate points to different criteria per property class. Please consider these criteria in spatial terms i.e. distance from / proximity to / view on

Table I. 4 - Example of completed Ratings scoreboard

Linked to: Chapter 4 (section 4.4)

PAIRWISE COMPARISON MATRIX - OFFICES

A	B	Priority	Score
Commercial / City Centre	Major Roads	B	5
	Public Transportation*	B	3
	Public Services	A	5
	Seafront/Port View	B	5
	Parks, Squares**	A	5
	Recreational Facil.***	A	1

A	B	Priority	Score
Major Roads	Public Transportation*	B	3
	Public Services	A	6
	Seafront/Port View	A	1
	Parks, Squares**	A	7
	Recreational Facilities***	A	2

A	B	Priority	Score
Public Transportation*	Public Services	A	7
	Seafront/Port View	B	3
	Parks, Squares**	A	7
	Recreational Facil.***	A	1

A	B	Priority	Score
Public Services	Seafront/Port View	B	7
	Parks, Squares**	A	3
	Recreational Facil.***	B	5

A	B	Priority	Score
Seafront view	Parks, Squares**	A	7
	Recreational Facil.***	A	2

A	B	Priority	Score
Parks, Squares**	Recreational Facilities***	B	5

* Mainly Bus Stops (for Volos)
** Including Open Spaces of any kind
*** Areas with Bars, cafeterias, food, swimming pools, spas/saunas, tennis, playgrounds, gyms, entertainment, culture etc.

Comp. Score	Importance
1	Equal
2	Equal to moderate
3	Moderate
4	Moderate to strong
5	Strong
6	Strong to very strong
7	Very strong
8	Very to extremely strong
9	Extreme

Table I. 5 - Example of completed pairwise comparison matrix (for Offices land-use)

Note on table I.5:
For the pairwise matrices (PCMs) the real estate experts that participated in the live interviews (see Chapter 4) were asked to compare criteria A and B in pairs and selected which one they considered as more important. Then they were asked to decide on the relative important on a scale of 1 to 9 (how much more important the selected criterion was). These PCMs were then used to calculate the consolidated PCMs shown in table I.7

Retail/Commercial				
Spatial Criteria	**Rank**	**Ratio Scale**	**Orig. Wght**	**Norm. Wght**
Commercial Center	1	290	4.46	31.9%
Major Roads	2	205	3.15	22.5%
Bus Stops	3	105	1.62	11.5%
Public Services	4	90	1.38	9.9%
Recreation Areas	5	90	1.38	9.9%
Port Front	6	65	1.00	7.1%
Parks and Squares	7	65	1.00	7.1%
University	8	40	N/A	N/A
Education Facilities	9	30	N/A	N/A
National Road	10	15	N/A	N/A
Health Facilities	11	5	N/A	N/A
National Railroad	12	0	N/A	N/A

Offices				
Spatial Criteria	**Rank**	**Ratio Scale**	**Orig. Wght**	**Norm. Wght**
Major Roads	1	225	4.09	24.6%
Commercial Center	2	195	3.55	21.3%
Bus Stops	3	165	3.00	18.0%
Public Services	4	150	2.73	16.4%
Seafront/Port View	5	65	1.18	7.1%
Recreation Areas	6	60	1.09	6.6%
Parks and Squares	7	55	1.00	6.0%
Health Facilities	8	55	N/A	N/A
Education Facilities	9	15	N/A	N/A
University	10	10	N/A	N/A
National Road	11	5	N/A	N/A
National Railroad	12	0	N/A	N/A

Residential				
Spatial Criteria	**Rank**	**Ratio Scale**	**Orig. Wght**	**Norm. Wght**
Education Facilities	1	200	3.33	22.2%
Parks and Squares	2	190	3.17	21.1%
Bus Stops	3	160	2.67	17.8%
Recreation Areas	4	125	2.08	13.9%
Health Facilities	5	90	1.50	10.0%
University	6	75	1.25	8.3%
Public Services	7	60	1.00	6.7%
Major Roads	8	50	N/A	N/A
Commercial Center	9	50	N/A	N/A
Seafront View	10	0	N/A	N/A
National Road	11	0	N/A	N/A
National Railroad	12	0	N/A	N/A

Table I. 6 – Consolidated Ratings scores and criteria weights

Note:
These tables regard the consolidation of the scoreboards provided by the real estate experts during stage I, as described in Chapter 4 (section 4.5.2). The seven criteria that got the highest scores were kept and got weights. All rating scores were summed per criterion (Ratio Scale) and the normalised weights were calculated following the process described in Malczewski (1999, pp. 181-182)

Table I. 7 - Consolidated pairwise comparison matrices and criteria weights

RETAIL/COMMERCIAL - CONSOLIDATED PCM								Step I							Step II	Step III	Step IV
Spatial Criteria	Commercial/City Center	Major/Commerical Roads	Recreational Areas/Facil.	Public Transportation	Public Services	Parks & Squares	Seafront View	1	2	3	4	5	6	7	Weights	S1	S2
Commercial/City Center	1.00	3.34	2.50	2.14	5.75	3.86	3.24	0.34	0.50	0.35	0.33	0.27	0.25	0.23	0.324	2.40	7.40
Major/Commerical Roads	0.30	1.00	1.36	1.61	4.36	2.90	2.48	0.10	0.15	0.19	0.25	0.20	0.19	0.18	0.180	1.32	7.32
Recreational Areas/Facil.	0.40	0.74	1.00	0.86	3.17	3.24	2.07	0.14	0.11	0.14	0.13	0.15	0.21	0.15	0.147	1.07	7.27
Public Transportation	0.47	0.62	1.16	1.00	4.47	3.33	2.31	0.16	0.09	0.16	0.15	0.21	0.22	0.17	0.166	1.20	7.22
Public Services	0.17	0.23	0.32	0.22	1.00	0.60	0.91	0.06	0.03	0.04	0.03	0.05	0.04	0.07	0.046	0.33	7.14
Parks & Squares	0.26	0.34	0.31	0.30	1.66	1.00	1.80	0.09	0.05	0.04	0.05	0.08	0.06	0.13	0.072	0.51	7.08
Seafront View	0.31	0.40	0.48	0.43	1.09	0.56	1.00	0.11	0.06	0.07	0.07	0.05	0.04	0.07	0.066	0.47	7.18
Sums	2.91	6.67	7.13	6.57	21.49	15.49	13.81	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**		

n	7
λ	7.40
CI	0.066
RI	1.32
CR	5.00%

OFFICES - CONSOLIDATED PCM								Step I							Step II	Step III	Step IV
Spatial Criteria	Commercial/City Center	Major/Commerical Roads	Public Transportation	Public Services	Seafront/Port View	Parks & Squares	Recreational Areas/Facil.	1	2	3	4	5	6	7	Weights	S1	S2
Commercial/City Center	1.00	0.91	0.62	0.99	1.78	2.66	2.03	0.16	0.20	0.15	0.11	0.17	0.17	0.18	0.165	1.16	7.05
Major/Commerical Roads	1.10	1.00	0.89	1.96	2.58	3.39	2.72	0.18	0.22	0.22	0.22	0.25	0.22	0.25	0.222	1.57	7.06
Public Transportation	1.61	1.12	1.00	2.53	2.24	3.89	2.29	0.26	0.24	0.25	0.29	0.22	0.25	0.21	0.245	1.73	7.06
Public Services	1.01	0.51	0.40	1.00	1.11	1.85	1.06	0.16	0.11	0.10	0.11	0.11	0.12	0.10	0.115	0.82	7.06
Seafront/Port View	0.56	0.39	0.45	0.90	1.00	1.36	1.30	0.09	0.08	0.11	0.10	0.10	0.09	0.12	0.099	0.70	7.06
Parks & Squares	0.38	0.29	0.26	0.54	0.74	1.00	0.64	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.063	0.45	7.06
Recreational Areas/Facil.	0.49	0.37	0.44	0.95	0.77	1.55	1.00	0.08	0.08	0.11	0.11	0.08	0.10	0.09	0.091	0.64	7.05
Sums	6.16	4.59	4.05	8.87	10.21	15.71	11.04	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**		

n	7
λ	7.06
CI	0.010
RI	1.32
CR	0.77%

RESIDENTIAL - CONSOLIDATED PCM								Step I							Step II	Step III	Step IV
Spatial Criteria	Education Facilities	Parks & Squares	Public Transportation	Recreational Facilities	Health Facilities	University	Public Services	1	2	3	4	5	6	7	Weights	S1	S2
Education Facilities	1.00	1.46	0.98	1.78	1.99	2.60	2.86	0.22	0.30	0.23	0.22	0.19	0.16	0.11	0.203	1.49	7.32
Parks & Squares	0.68	1.00	1.09	1.96	2.15	3.68	5.46	0.15	0.21	0.25	0.24	0.21	0.22	0.21	0.212	1.56	7.37
Public Transportation	1.02	0.92	1.00	2.39	2.85	3.27	5.13	0.23	0.19	0.23	0.29	0.27	0.20	0.19	0.229	1.69	7.40
Recreational Facilities	0.56	0.51	0.42	1.00	1.87	2.57	5.24	0.12	0.11	0.10	0.12	0.18	0.16	0.20	0.140	1.03	7.39
Health Facilities	0.50	0.47	0.35	0.53	1.00	2.99	4.50	0.11	0.10	0.08	0.06	0.10	0.18	0.17	0.114	0.83	7.27
University	0.38	0.27	0.31	0.39	0.33	1.00	2.37	0.09	0.06	0.07	0.05	0.03	0.06	0.09	0.063	0.45	7.18
Public Services	0.35	0.18	0.20	0.19	0.22	0.42	1.00	0.08	0.04	0.04	0.02	0.02	0.03	0.04	0.038	0.27	7.09
Sums	4.50	4.81	4.34	8.25	10.41	16.53	26.56	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**		

n	7
λ	7.40
CI	0.067
RI	1.32
CR	5.09%

Calculation Example:

Step I (for the $I_{3,4}$): $(2.39 \div 8.25) = 0.289$

Step II (for the W_3): $(0.23 + 0.19 + 0.23 + 0.29 + 0.27 + 0.20 + 0.19) \div 7 = 0.229$

Step III (for the $S1_3$): $(1.02 * 0.203) + (0.92 * 0.212) + (1.00 * 0.229) + (2.39 * 0.14) + (2.85 * 0.114) + (3.27 * 0.063) + (5.13 * 0.038) = 1.69$

Step IV (for $S2_3$): $(1.69 \div 0.229) = 7.37$

n is the number of criteria; λ is the maximum of the $S2_i$ elements; *CI* is the consistency index calculated as $CI = (\lambda - n) \div (n - 1)$

RI is the random index based on randomly generated PCMs of the same size i.e. for *n*=7 *RI*=1.32 ; *CR* is the consistency ratio calculated as $CR = CI \div RI$

Note: Table I.7 regards the consolidation of the pairwise comparison matrices (PCMs) filled-in during live interviews based on scoreboards provided by the real estate experts during stage I, as described in Chapter 4 (sections 4.2 and 4.5.2). The seven criteria that got the highest scores (see Table I.6) were used for the PCMs. Criteria weights were calculated following the process described by Malczewski (1999, pp. 183-187). Table I.8 (next page) was formed using the non-fuzzy PCM scores (value *m*) and by decreasing (lower value *l*) and increasing (upper value *u*) by a 1 (*f=1*). For details see section 4.5.2

RETAIL/COMMERCIAL - CONSOLIDATED FUZZY PCM																															
Spatial Criteria	Commercial/City Center			Major/Commerical Roads			Recreational Areas/Facil.			Public Transportation			Public Services			Parks & Squares			Seafront View			Step I				Step II				Step III	
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u		l	m	u		l	m	u	**Centre of Area**	
Commercial/City Center	1.00	1.00	1.00	2.18	3.34	4.42	2.09	2.50	3.71	1.72	2.14	3.02	4.68	5.75	6.70	3.02	3.86	5.04	2.48	3.24	3.70	r1	2.23	2.78	3.48	w1	0.3359	0.3250	0.3186	BNP1	0.3265
Major/Commerical Roads	0.23	0.30	0.46	1.00	1.00	1.00	0.94	1.36	1.82	1.13	1.61	2.41	3.21	4.36	5.44	1.98	2.90	4.05	1.83	2.48	3.24	r2	1.16	1.54	2.03	w2	0.1745	0.1801	0.1862	BNP2	0.1803
Recreational Areas/Facil.	0.27	0.40	0.48	0.55	0.74	1.07	1.00	1.00	1.00	0.73	0.86	1.32	2.48	3.17	3.87	2.14	3.24	4.29	1.39	2.07	2.81	r3	0.97	1.27	1.64	w3	0.1460	0.1487	0.1499	BNP3	0.1482
Public Transportation	0.33	0.47	0.58	0.41	0.62	0.88	0.76	1.16	1.36	1.00	1.00	1.00	3.29	4.47	5.49	2.46	3.33	4.39	1.74	2.31	3.29	r4	1.06	1.42	1.78	w4	0.1590	0.1660	0.1626	BNP4	0.1625
Public Services	0.15	0.17	0.21	0.18	0.23	0.31	0.26	0.32	0.40	0.18	0.22	0.30	1.00	1.00	1.00	0.44	0.60	0.78	0.71	0.91	1.25	r5	0.33	0.40	0.50	w5	0.0494	0.0464	0.0459	BNP5	0.0472
Parks & Squares	0.20	0.26	0.33	0.25	0.34	0.50	0.23	0.31	0.47	0.23	0.30	0.41	1.29	1.66	2.27	1.00	1.00	1.00	1.30	1.80	2.36	r6	0.46	0.59	0.78	w6	0.0693	0.0689	0.0711	BNP6	0.0698
Seafront View	0.27	0.31	0.40	0.31	0.40	0.55	0.36	0.48	0.72	0.30	0.43	0.58	0.80	1.09	1.40	0.42	0.56	0.77	1.00	1.00	1.00	r7	0.44	0.55	0.72	w7	0.0659	0.0647	0.0657	BNP7	0.0654
Sums	2.45	2.91	3.47	4.88	6.67	8.73	5.63	7.13	9.48	5.30	6.57	9.04	16.75	21.49	26.17	11.46	15.49	20.32	10.46	13.81	17.64		6.64	8.55	10.92		**1.00**	**1.00**	**1.00**		**1.00**

OFFICES - CONSOLIDATED FUZZY PCM																															
Spatial Criteria	Commercial/City Center			Major/Commerical Roads			Public Transportation			Public Services			Seafront/Port View			Parks & Squares			Recreational Facilities			Step I				Step II				Step III	
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u		l	m	u		l	m	u	**Centre of Area**	
Commercial/City Center	1.00	1.00	1.00	0.62	0.91	1.30	0.43	0.62	0.91	0.77	0.99	1.32	1.09	1.78	2.33	1.93	2.66	3.39	1.39	2.03	2.91	r1	0.93	1.27	1.67	w1	0.1614	0.1636	0.1620	BNP1	0.1623
Major/Commerical Roads	0.77	1.10	1.61	1.00	1.00	1.00	0.67	0.89	1.36	1.33	1.96	2.76	1.82	2.58	3.40	2.21	3.39	4.49	1.71	2.72	3.51	r2	1.25	1.73	2.28	w2	0.2168	0.2226	0.2223	BNP2	0.2206
Public Transportation	1.10	1.61	2.32	0.73	1.12	1.49	1.00	1.00	1.00	1.86	2.53	3.69	1.62	2.24	3.06	2.77	3.89	4.96	1.49	2.29	3.13	r3	1.39	1.91	2.50	w3	0.2414	0.2454	0.2430	BNP3	0.2433
Public Services	0.76	1.01	1.30	0.36	0.51	0.75	0.27	0.40	0.54	1.00	1.00	1.00	0.82	1.11	1.34	1.28	1.85	2.45	0.75	1.06	1.31	r4	0.67	0.89	1.12	w4	0.1156	0.1146	0.1093	BNP4	0.1132
Seafront/Port View	0.43	0.56	0.92	0.29	0.39	0.55	0.33	0.45	0.62	0.74	0.90	1.22	1.00	1.00	1.00	1.05	1.36	1.93	0.94	1.30	2.00	r5	0.61	0.77	1.06	w5	0.1054	0.0987	0.1027	BNP5	0.1023
Parks & Squares	0.30	0.38	0.52	0.22	0.29	0.45	0.20	0.26	0.36	0.41	0.54	0.78	0.52	0.74	0.95	1.00	1.00	1.00	0.48	0.64	1.01	r6	0.39	0.50	0.68	w6	0.0674	0.0638	0.0657	BNP6	0.0656
Recreational Facilities	0.34	0.49	0.72	0.28	0.37	0.59	0.32	0.44	0.67	0.77	0.95	1.34	0.50	0.77	1.06	0.99	1.55	2.10	1.00	1.00	1.00	r7	0.53	0.71	0.98	w7	0.0920	0.0913	0.0950	BNP7	0.0928
Sums	4.70	6.16	8.38	3.52	4.59	6.12	3.22	4.05	5.46	6.88	8.87	12.11	7.37	10.21	13.14	11.22	15.71	20.33	7.75	11.04	14.87		5.76	7.76	10.28		**1.00**	**1.00**	**1.00**		**1.00**

RESIDENTIAL - CONSOLIDATED FUZZY PCM																															
Spatial Criteria	Educational Facilities			Parks & Squares			Public Transportation			Recreational Facilities			Health Facilities			University			Public Services			Step I				Step II				Step III	
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u		l	m	u		l	m	u	**Centre of Area**	
Educational Facilities	1.00	1.00	1.00	1.19	1.46	2.10	0.69	0.98	1.49	1.28	1.78	2.31	1.34	1.99	2.98	1.93	2.60	3.78	2.28	2.86	3.76	r1	1.30	1.68	2.26	w1	0.2044	0.2012	0.2079	BNP1	0.2045
Parks & Squares	0.48	0.68	0.84	1.00	1.00	1.00	0.92	1.09	1.93	1.36	1.96	2.81	1.58	2.15	2.89	2.54	3.68	4.75	4.38	5.46	6.51	r2	1.40	1.81	2.36	w2	0.2203	0.2163	0.2166	BNP2	0.2177
Public Transportation	0.67	1.02	1.45	0.52	0.92	1.09	1.00	1.00	1.00	1.59	2.39	3.24	2.03	2.85	3.85	2.50	3.27	4.12	3.99	5.13	6.13	r3	1.41	1.95	2.43	w3	0.2225	0.2333	0.2230	BNP3	0.2263
Recreational Facilities	0.43	0.56	0.78	0.36	0.51	0.73	0.31	0.42	0.63	1.00	1.00	1.00	1.41	1.87	2.77	1.89	2.57	3.66	4.17	5.24	6.28	r4	0.91	1.17	1.56	w4	0.1439	0.1402	0.1437	BNP4	0.1426
Health Facilities	0.34	0.50	0.74	0.35	0.47	0.63	0.26	0.35	0.49	0.36	0.53	0.71	1.00	1.00	1.00	1.86	2.99	4.05	3.33	4.50	5.60	r5	0.68	0.93	1.21	w5	0.1073	0.1111	0.1108	BNP5	0.1097
University	0.26	0.38	0.52	0.21	0.27	0.39	0.24	0.31	0.40	0.27	0.39	0.53	0.25	0.33	0.54	1.00	1.00	1.00	1.74	2.37	3.29	r6	0.40	0.52	0.69	w6	0.0627	0.0619	0.0636	BNP6	0.0627
Public Services	0.27	0.35	0.44	0.15	0.18	0.23	0.16	0.20	0.25	0.16	0.19	0.24	0.18	0.22	0.30	0.30	0.42	0.57	1.00	1.00	1.00	r7	0.25	0.30	0.37	w7	0.0391	0.0360	0.0344	BNP7	0.0365
Sums	3.45	4.50	5.78	3.77	4.81	6.18	3.58	4.34	6.19	6.02	8.25	10.83	7.79	10.41	14.31	12.02	16.53	21.94	20.89	26.56	32.58		6.35	8.35	10.89		**1.00**	**1.00**	**1.00**		**1.00**

Calculation Example:

Using the equations 4.2, 4.3 and 4.8 to 4.13 we calculate the weight of the *Educational Facilities* criterion (Residential land-uses) as follows:

$$r_{1l} = (1 \times 1.19 \times 0.69 \times 1.28 \times 1.34 \times 1.93 \times 2.28)^{1/7} = 1.298$$
$$r_{1m} = (1 \times 1.46 \times 0.98 \times 1.78 \times 1.99 \times 2.60 \times 2.86)^{1/7} = 1.679$$
$$r_{1u} = (1 \times 2.10 \times 1.49 \times 2.31 \times 2.98 \times 3.78 \times 3.76)^{1/7} = 2.265$$

$$w_{1l} = 1.298 \times (1 + 1.19 + 0.69 + 1.28 + 1.34 + 1.93 + 2.28)^{-1} = 0.2044$$
$$w_{1m} = 1.679 \times (1 + 1.46 + 0.98 + 1.78 + 1.99 + 2.60 + 2.86)^{-1} = 0.2012$$
$$w_{1u} = 2.265 \times (1 + 2.10 + 1.49 + 2.31 + 2.98 + 3.78 + 3.76)^{-1} = 0.2079$$

$$w_1 = \frac{1}{3}(0.2044 + 0.2012 + 0.2079) = 0.2045 \quad \text{or} \quad BNP_1 = \frac{(0.2079 - 0.2044) + (0.2012 - 0.2044)}{3} + 0.2044 = 0.2045$$

Table I. 8 - Consolidated fuzzy pairwise comparison matrices and criteria weights

APPENDIX II

AHP & Criteria Maps

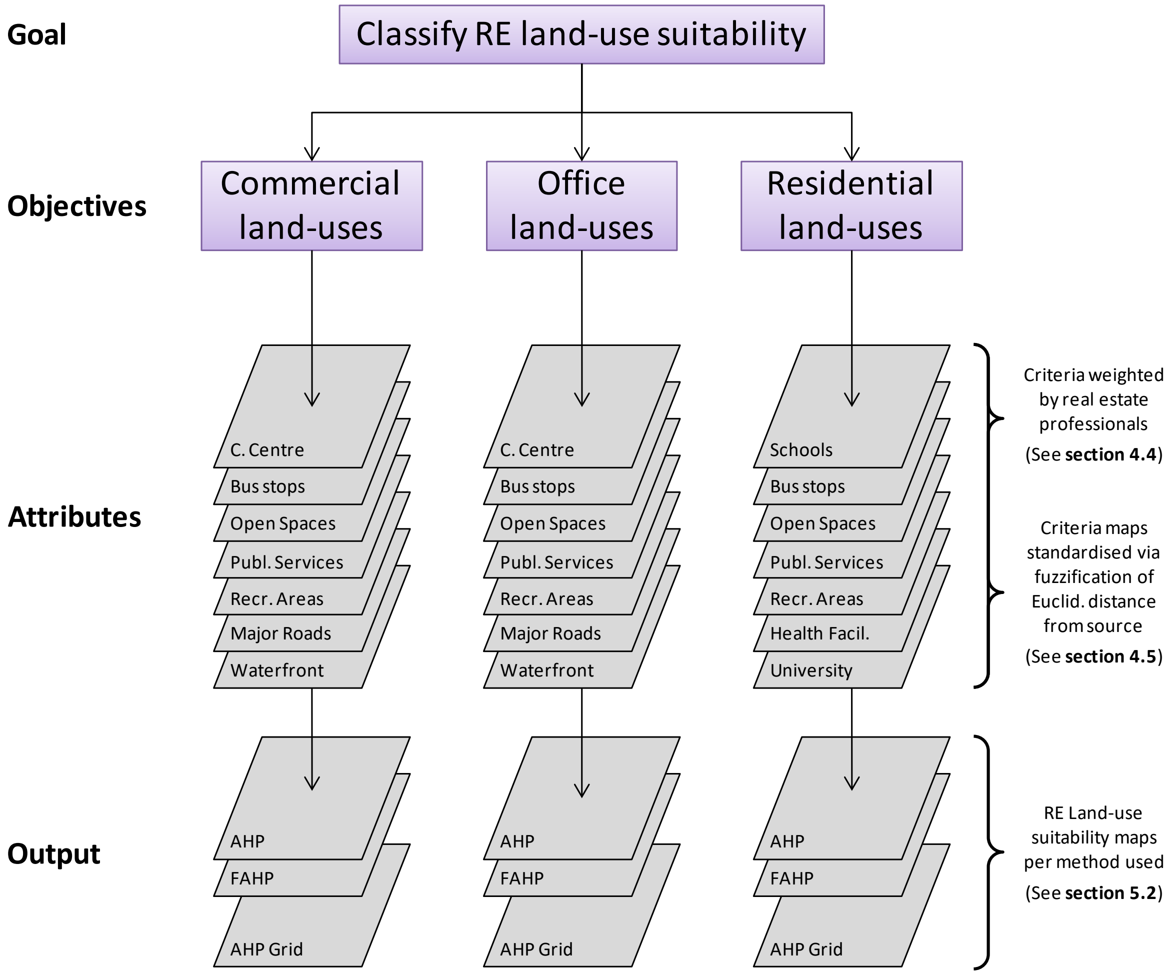

Figure II.1 - Analytic Hierarchy Process (AHP) diagram

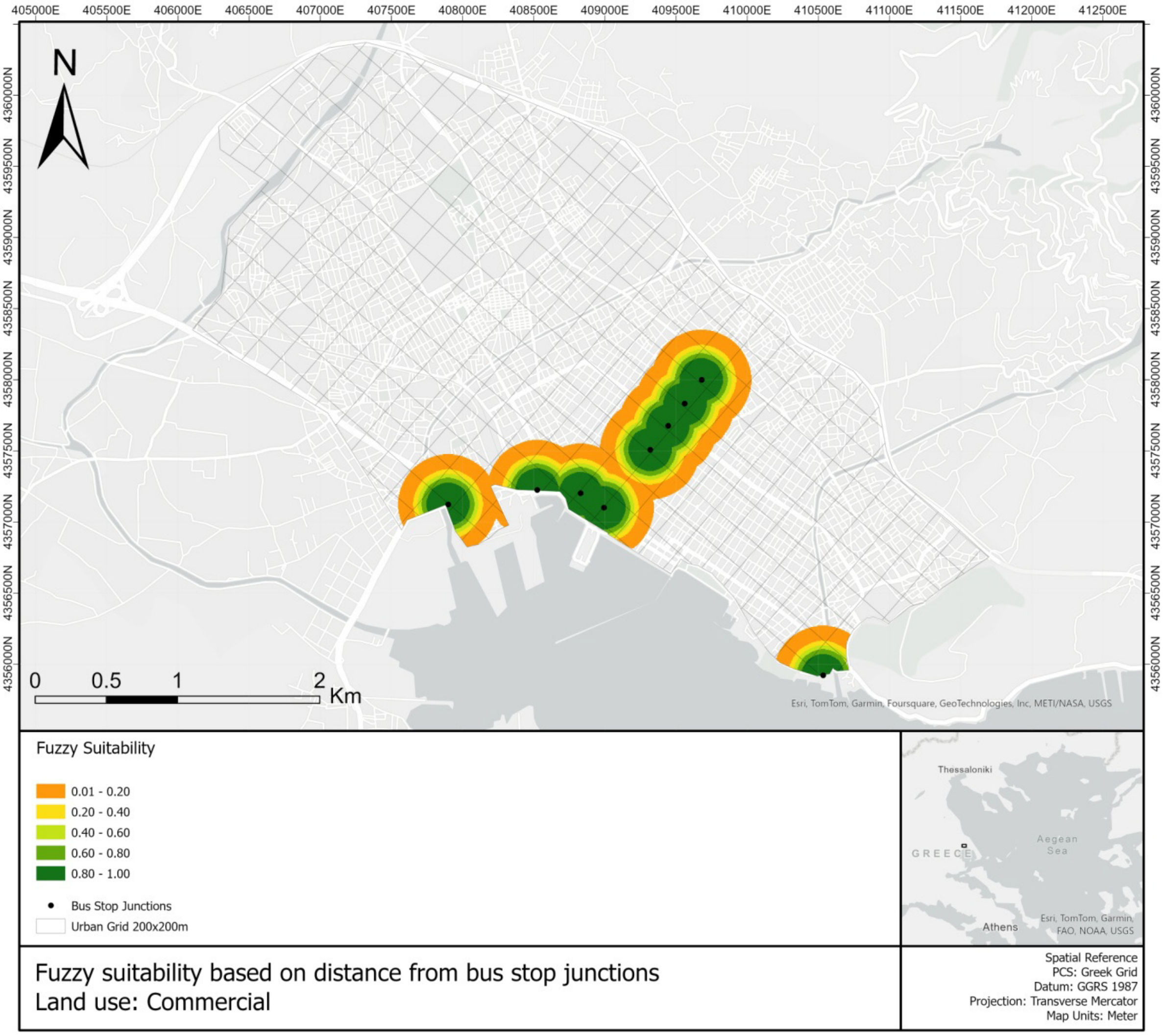

Figure II. 2 - Suitability map for distance from bus line junctions (commercial LUs)

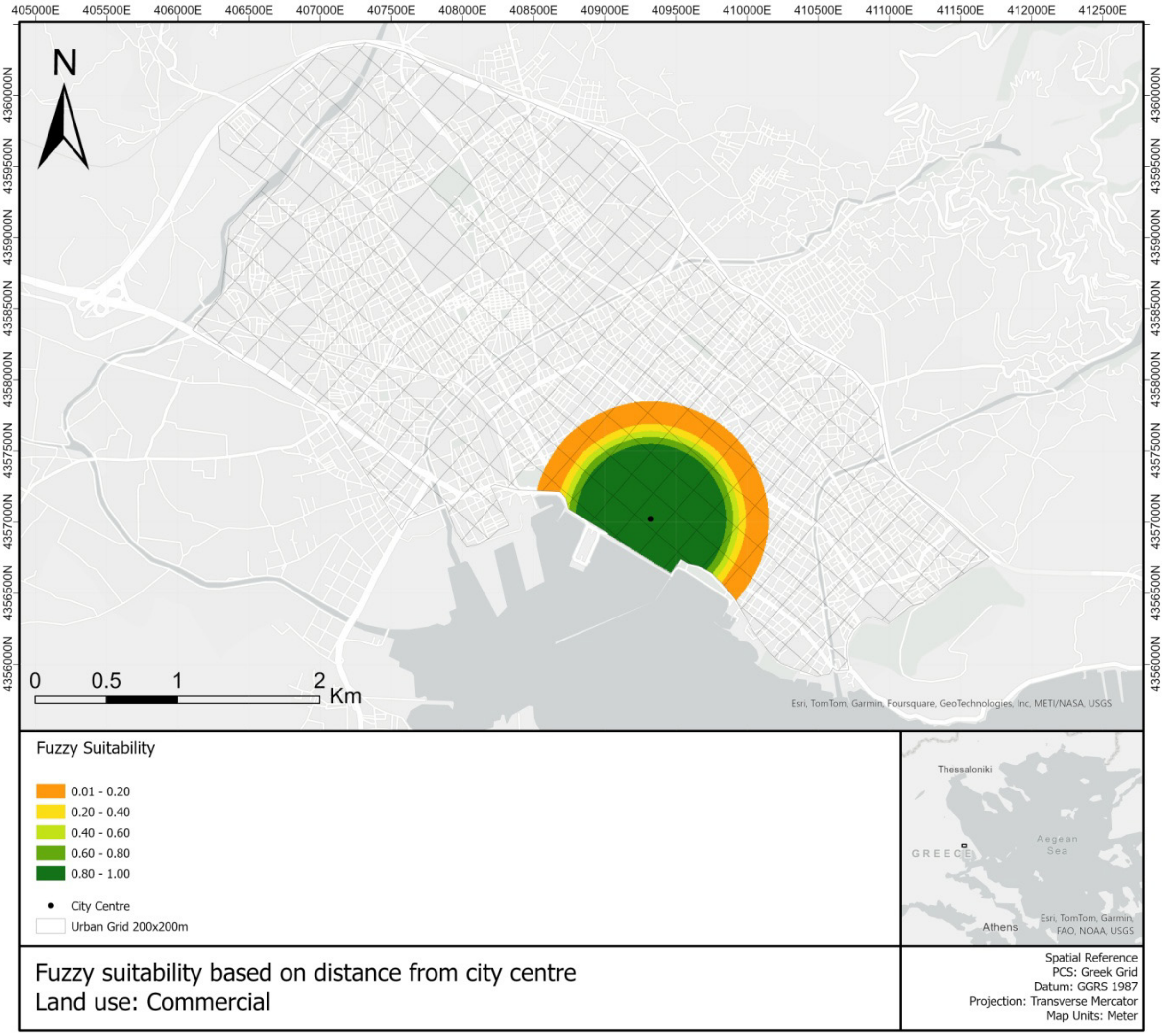

Figure II. 3 - Suitability map for distance from the city centre (commercial LUs)

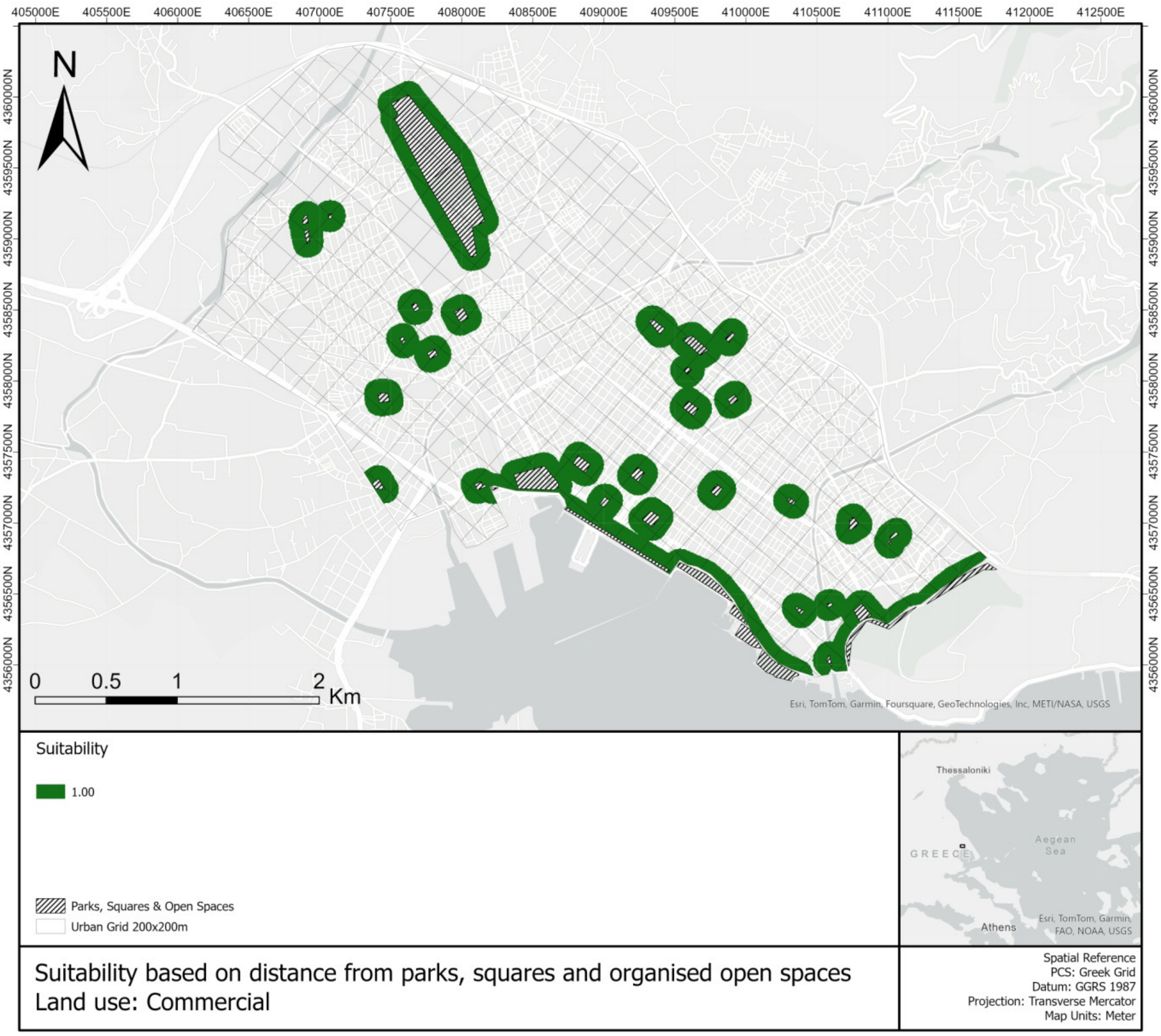

Figure II. 4 - Suitability map for distance from parks & squares (commercial LUs)

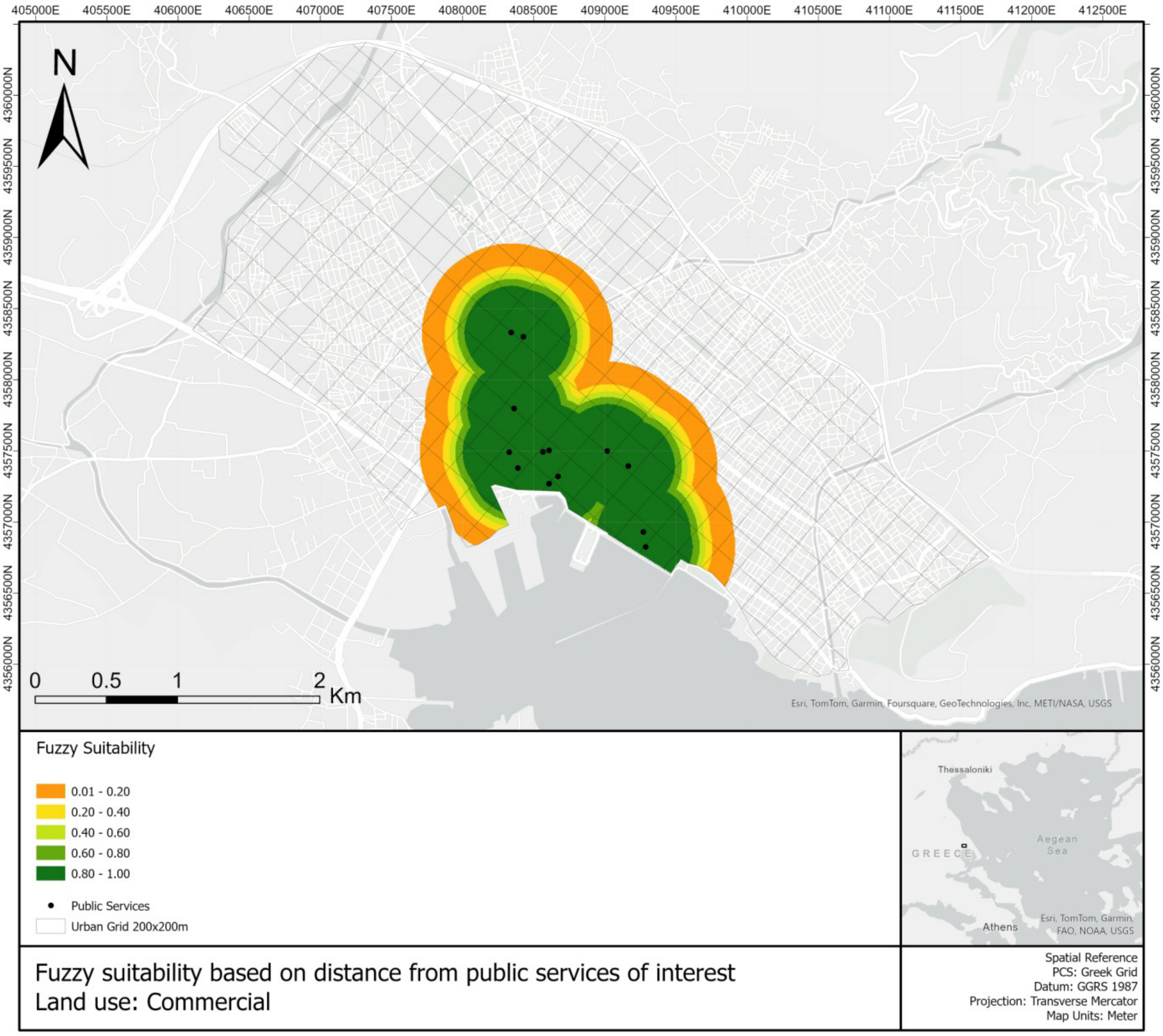

Figure II. 5 - Suitability map for distance from public services (commercial LUs)

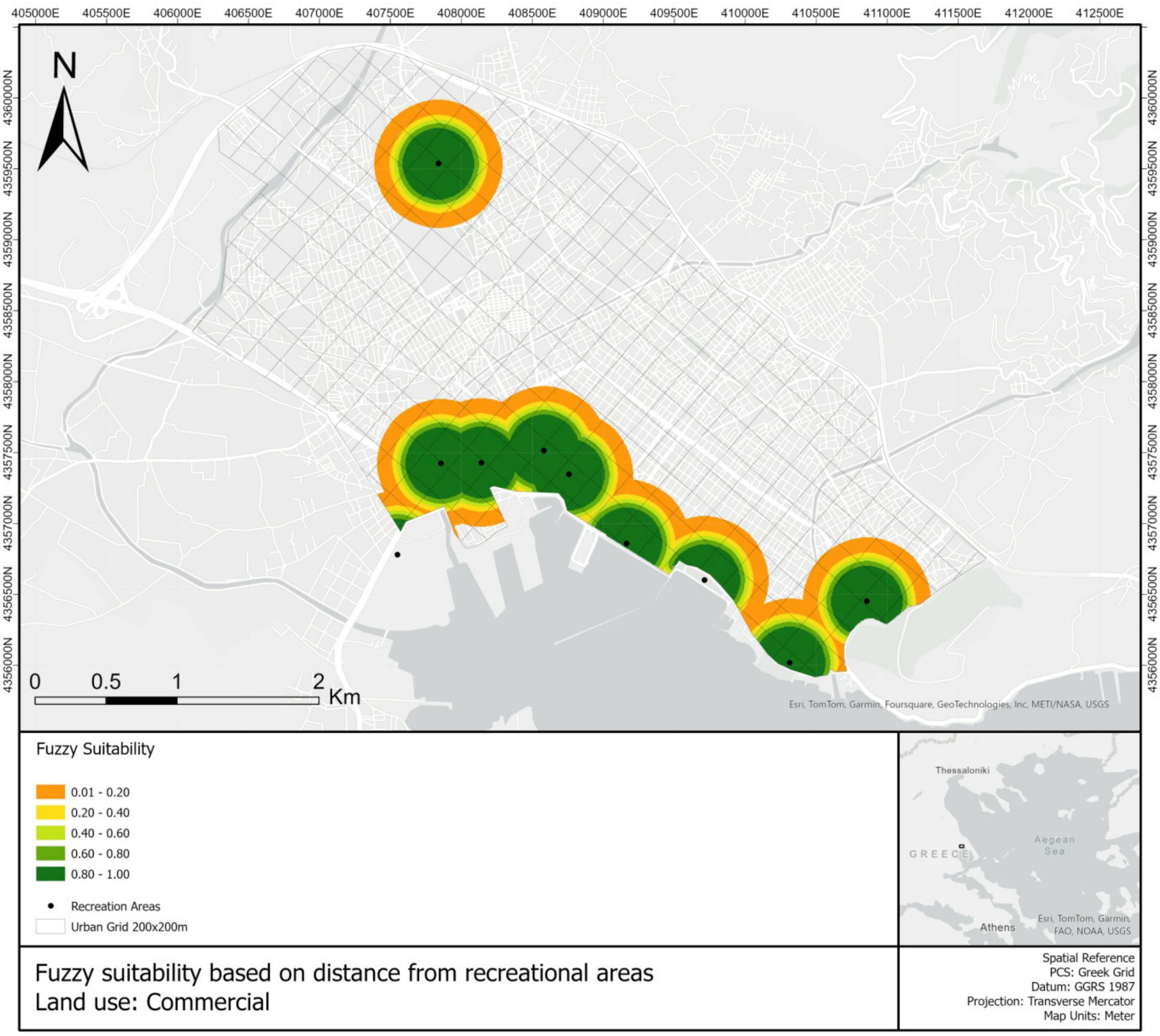

Figure II. 6 - Suitability map for distance from recreation areas (commercial LUs)

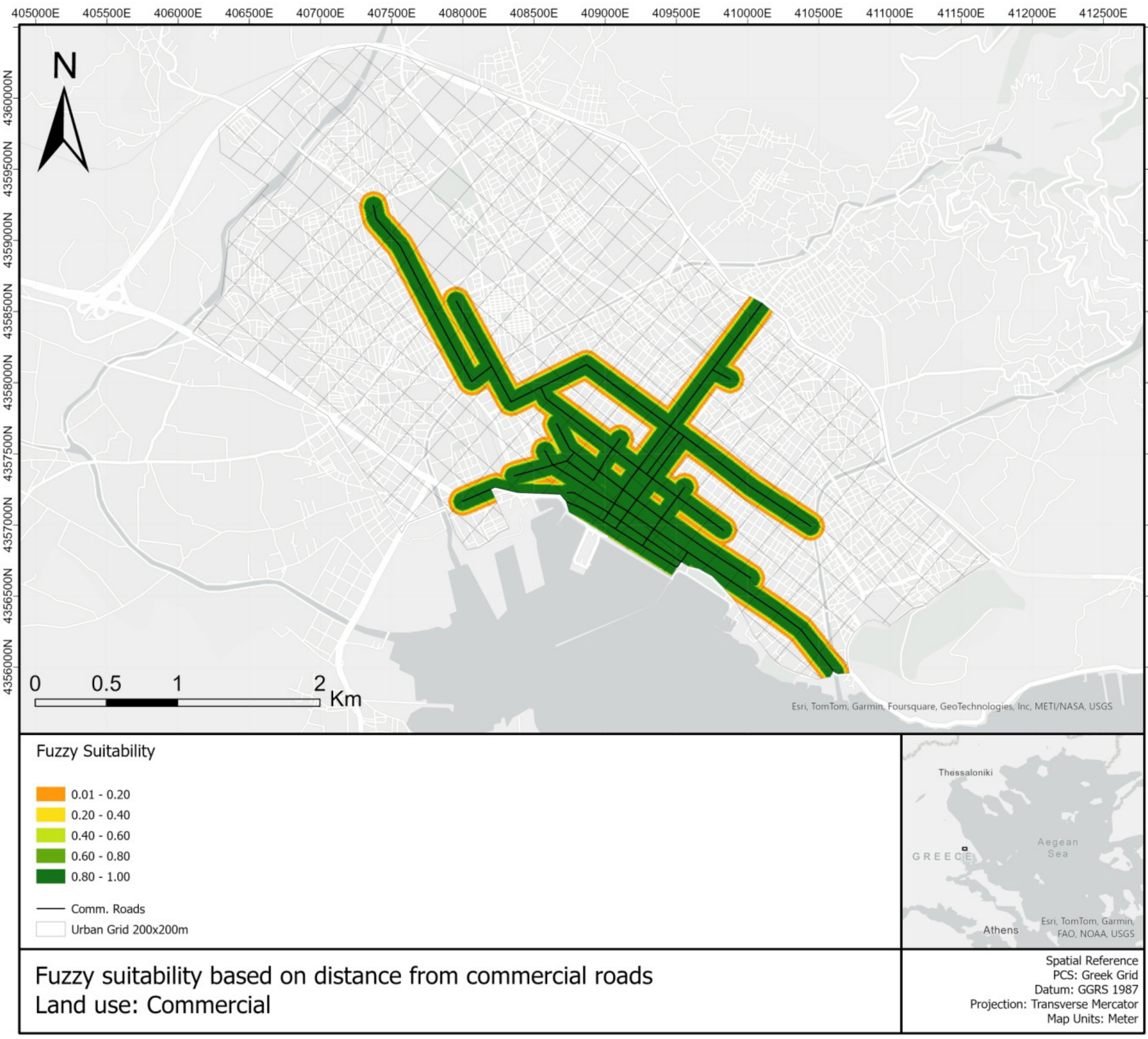

Figure II. 7 - Suitability map for distance from commercial roads (commercial LUs)

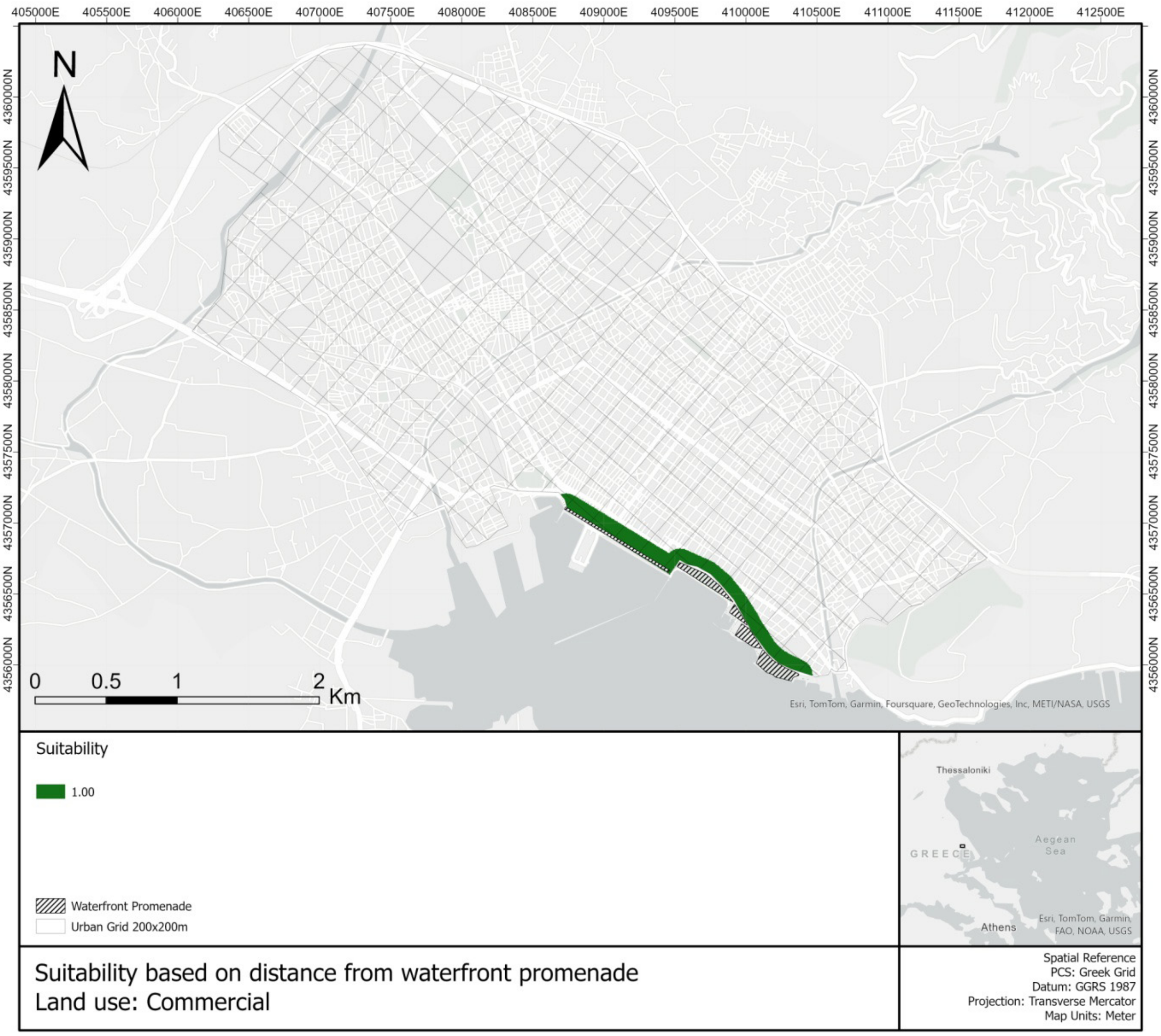

Figure II. 8 - Suitability map for distance from waterfront (commercial LUs)

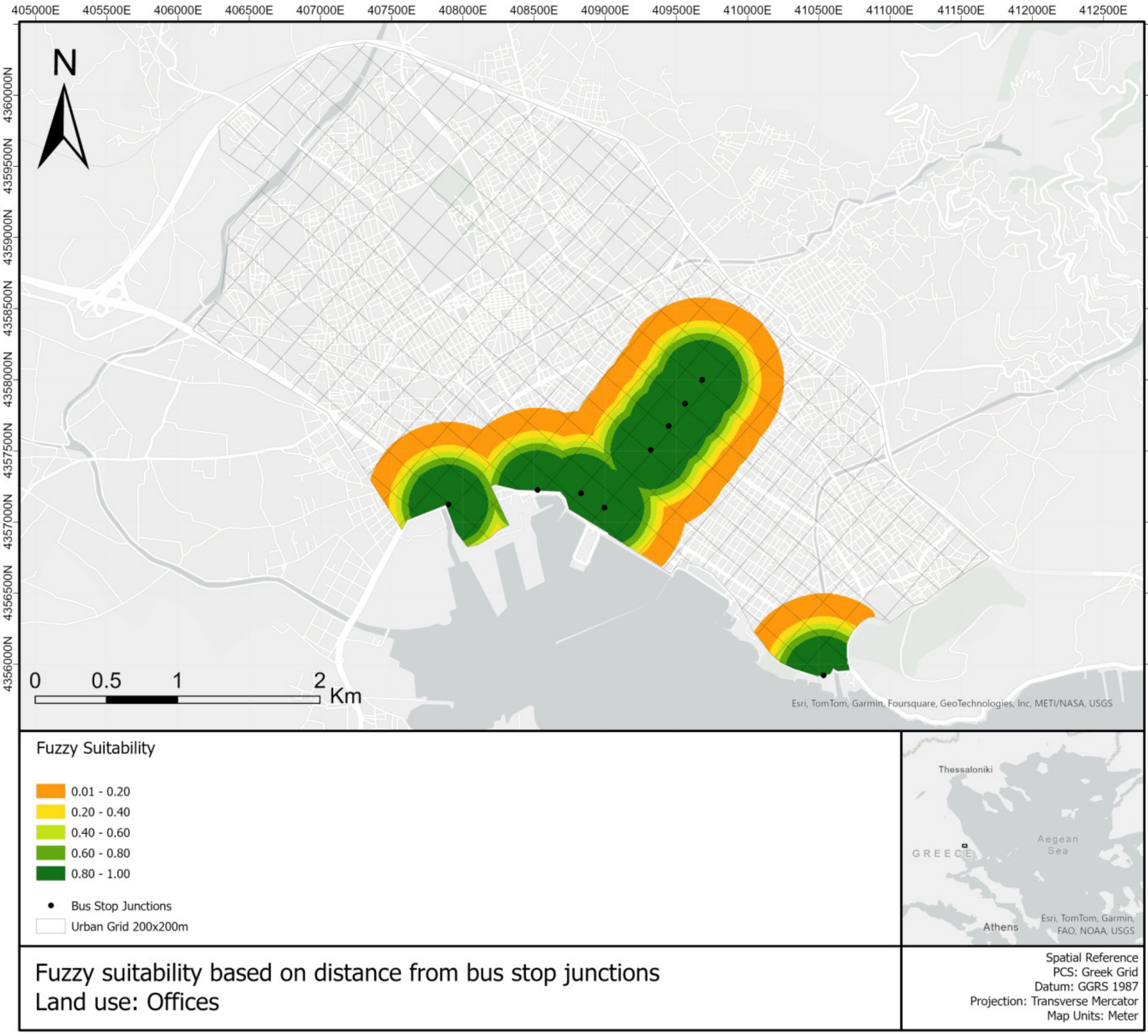

Figure II. 9 - Suitability map for distance from bus line junctions (office LUs)

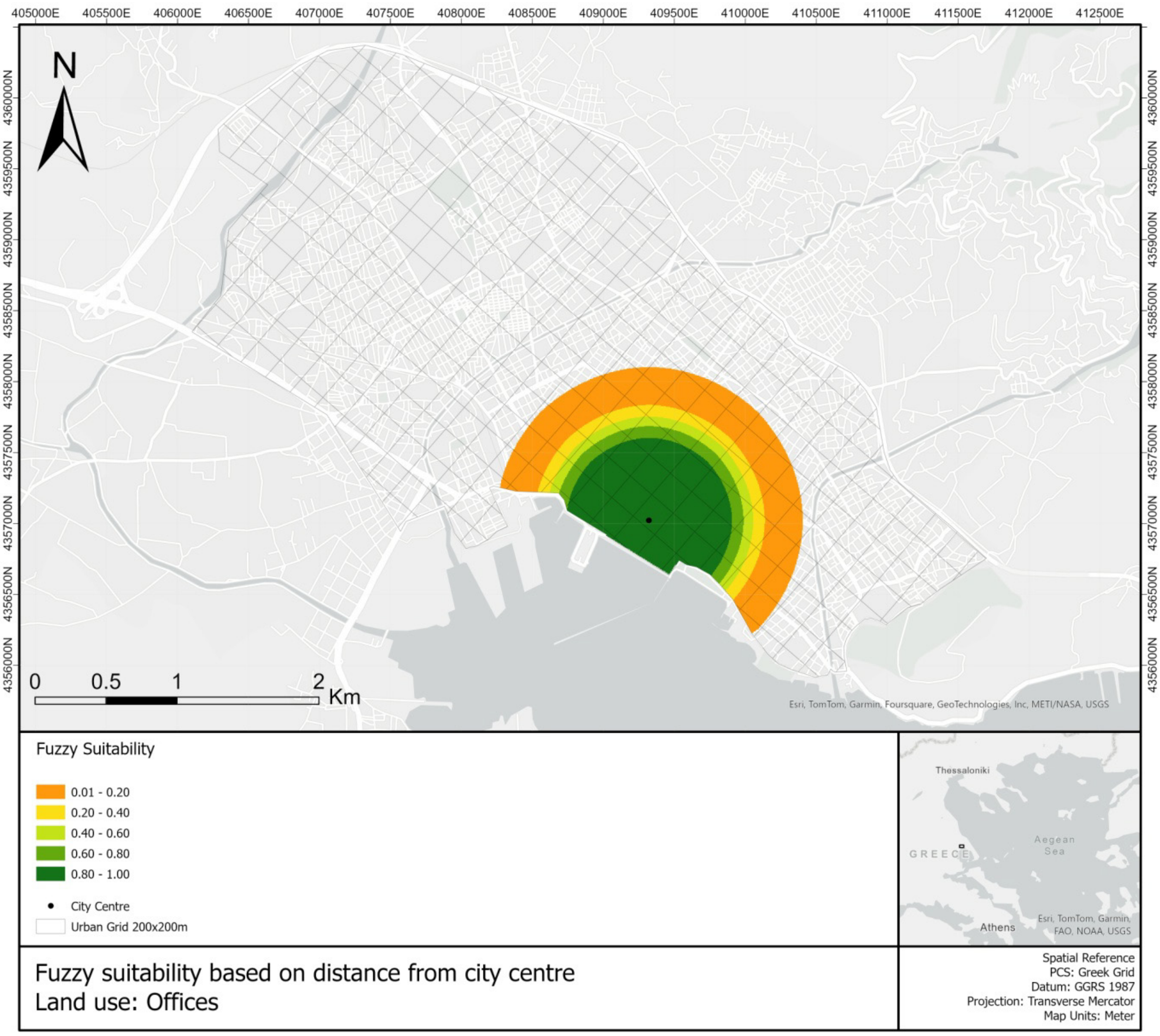

Figure II. 10 - Suitability map for distance from city centre (office LUs)

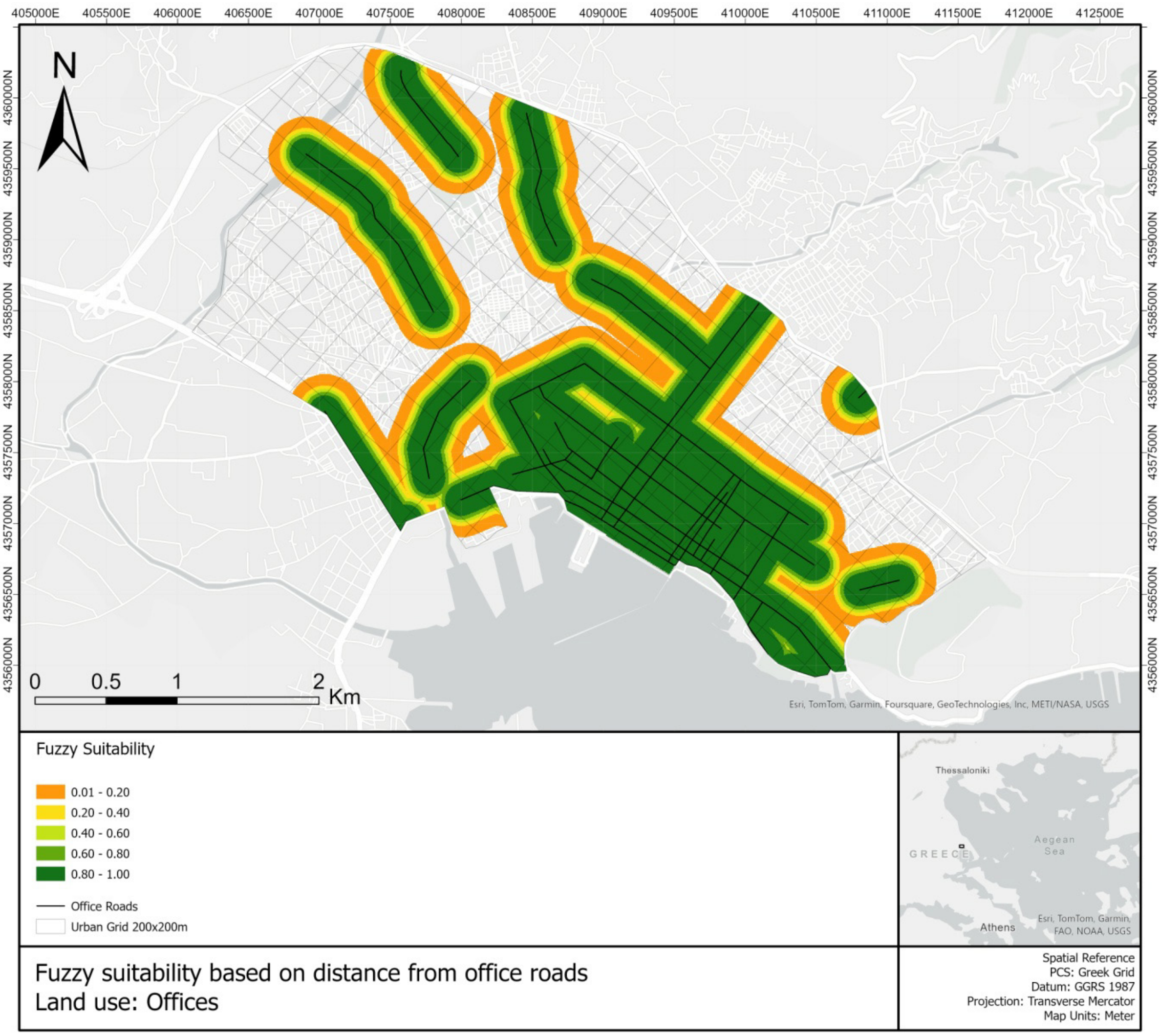

Figure II. 11 - Suitability map for distance from office roads (office LUs)

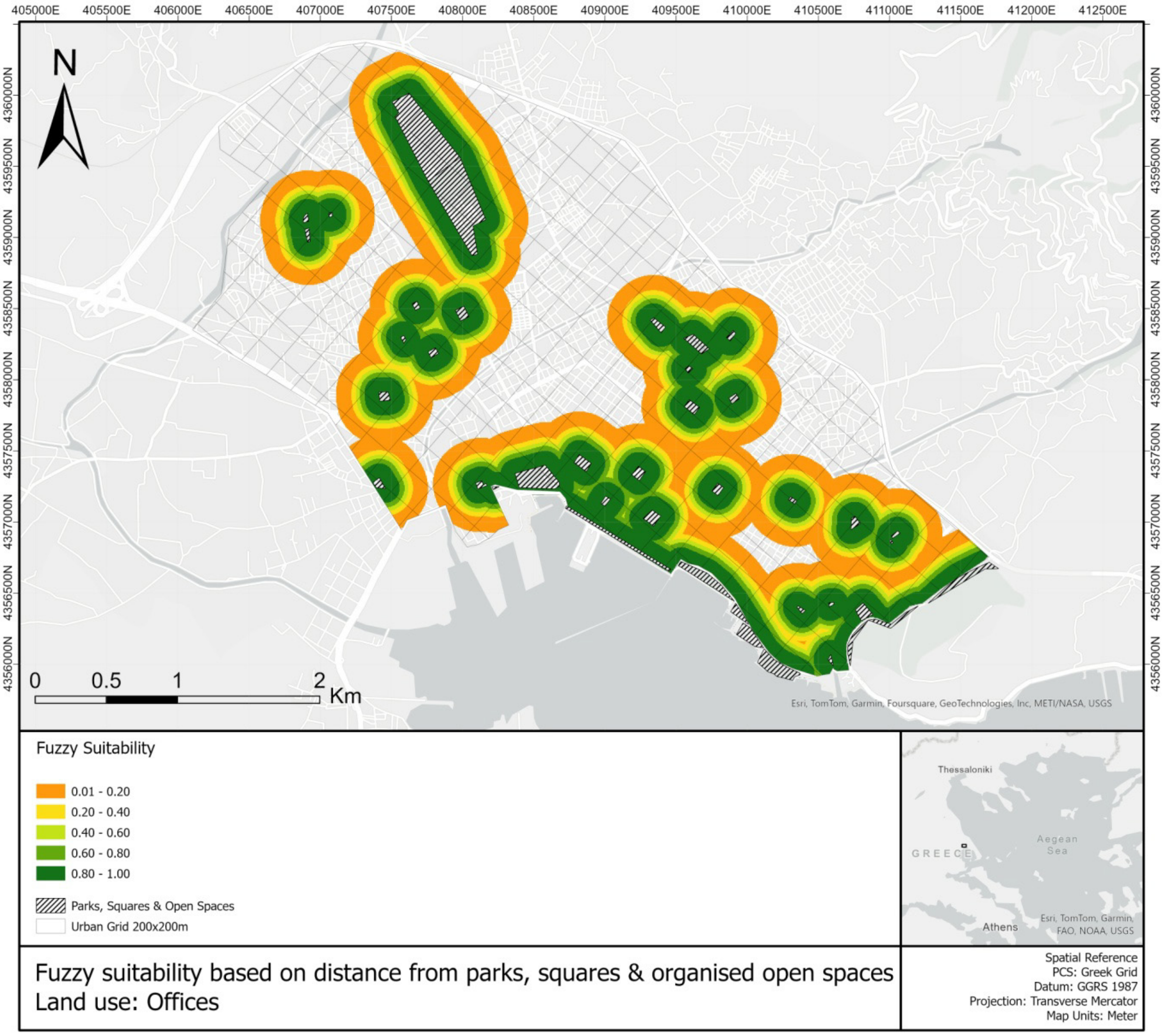

Figure II. 12 - Suitability map for distance from parks & squares (office LUs)

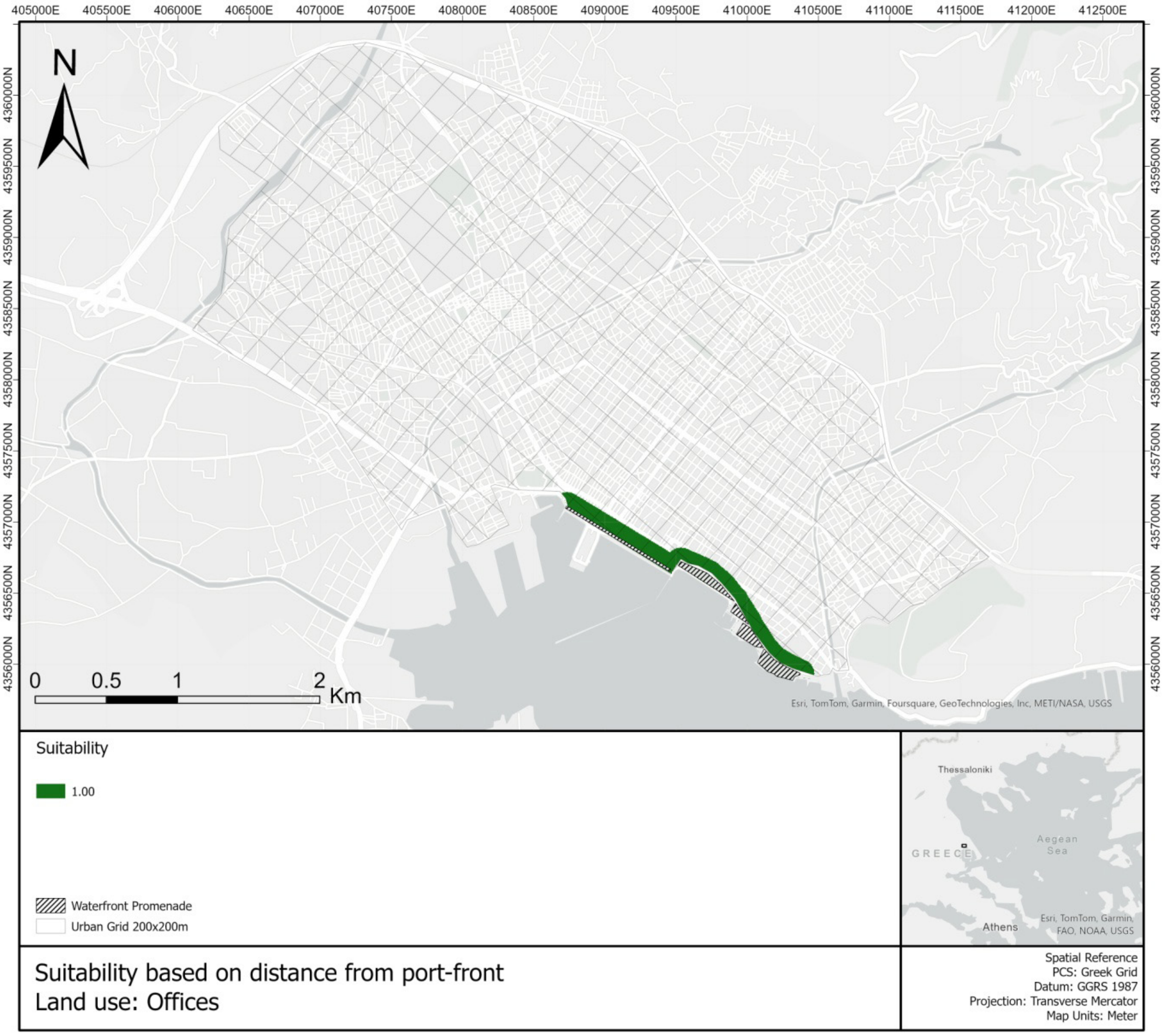

Figure II. 13 - Suitability map for distance from port-front (office LUs)

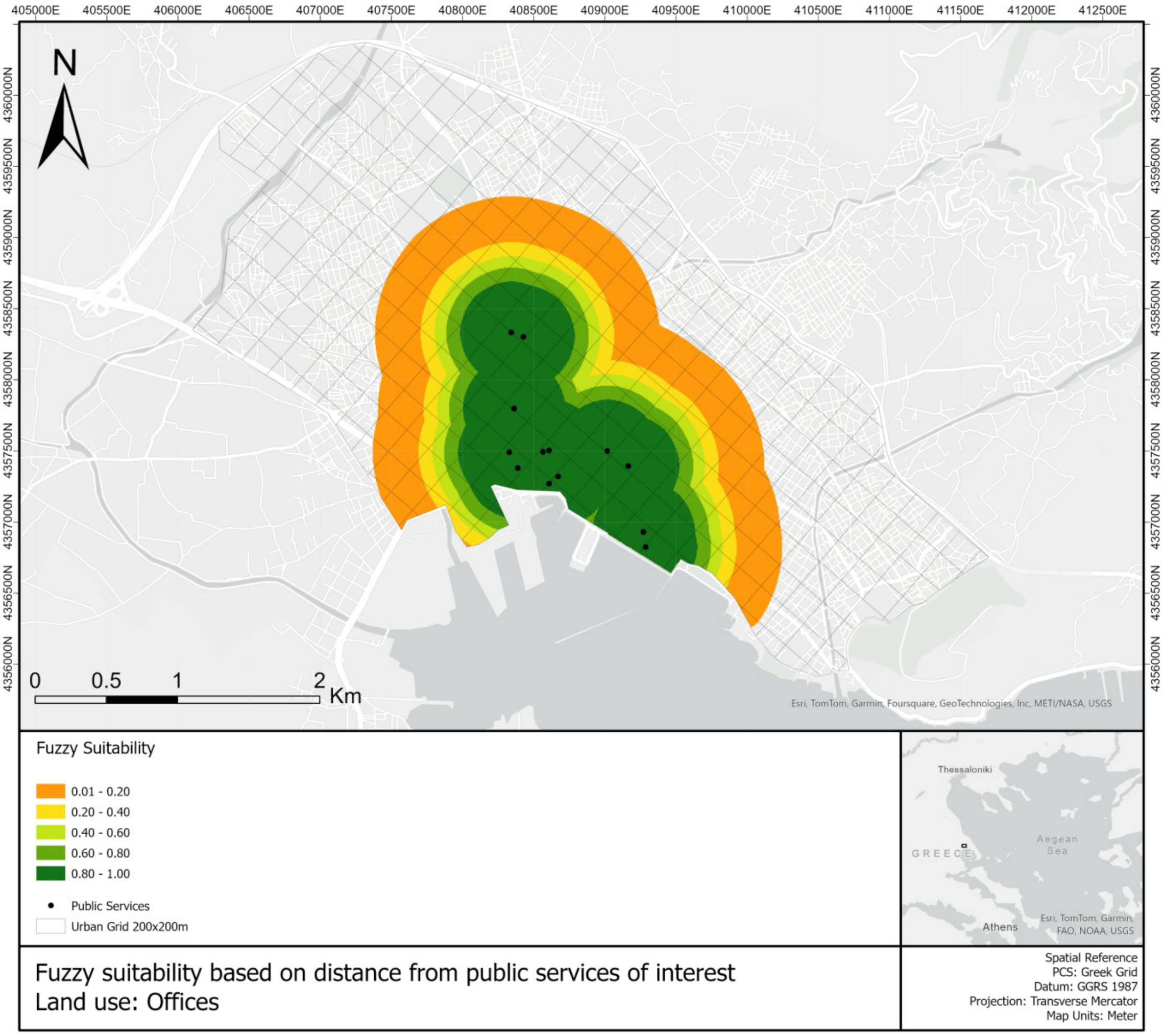

Figure II. 14 - Suitability map for distance from public services (office LUs)

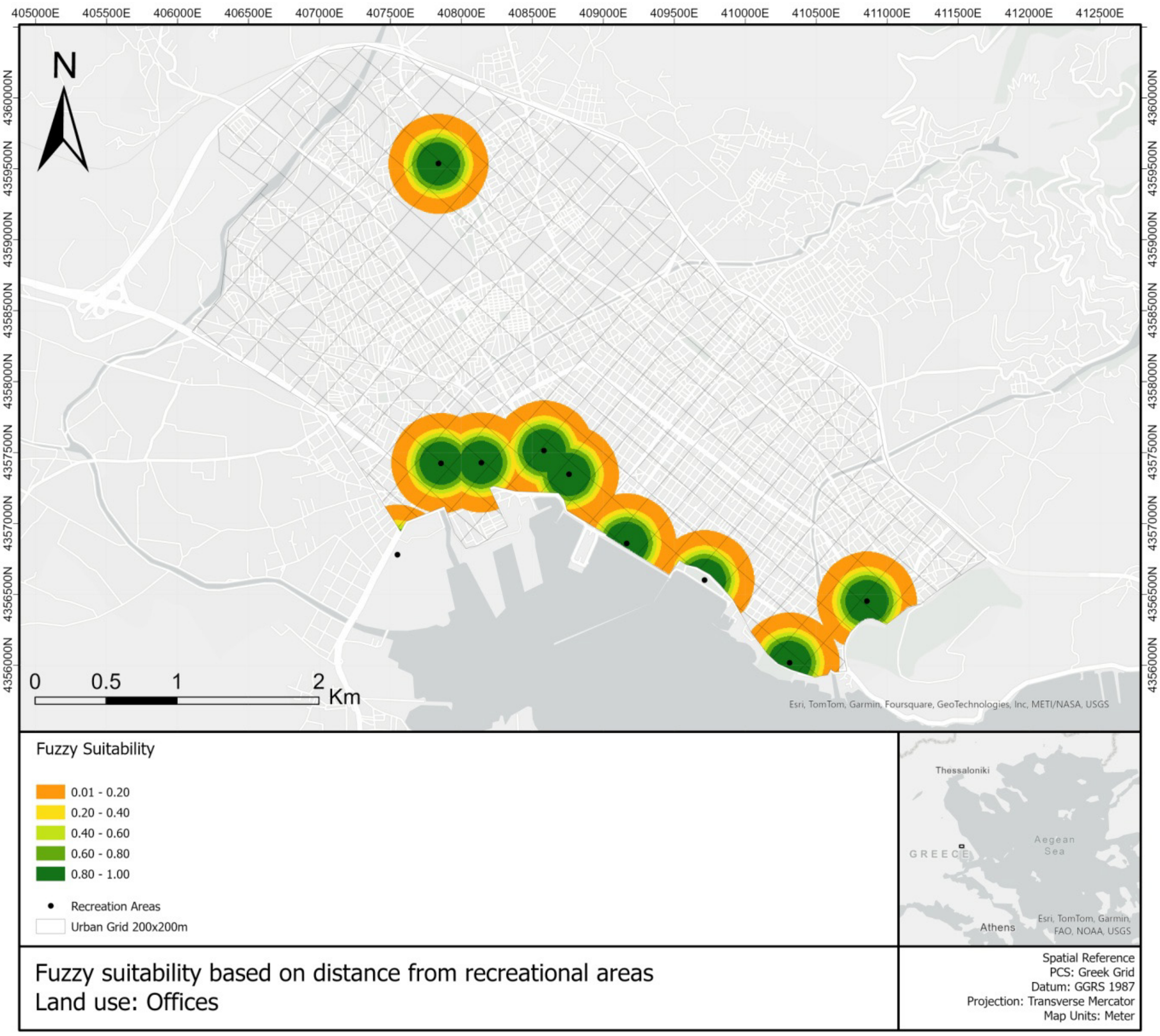

Figure II. 15 - Suitability map for distance from recreation areas (office LUs)

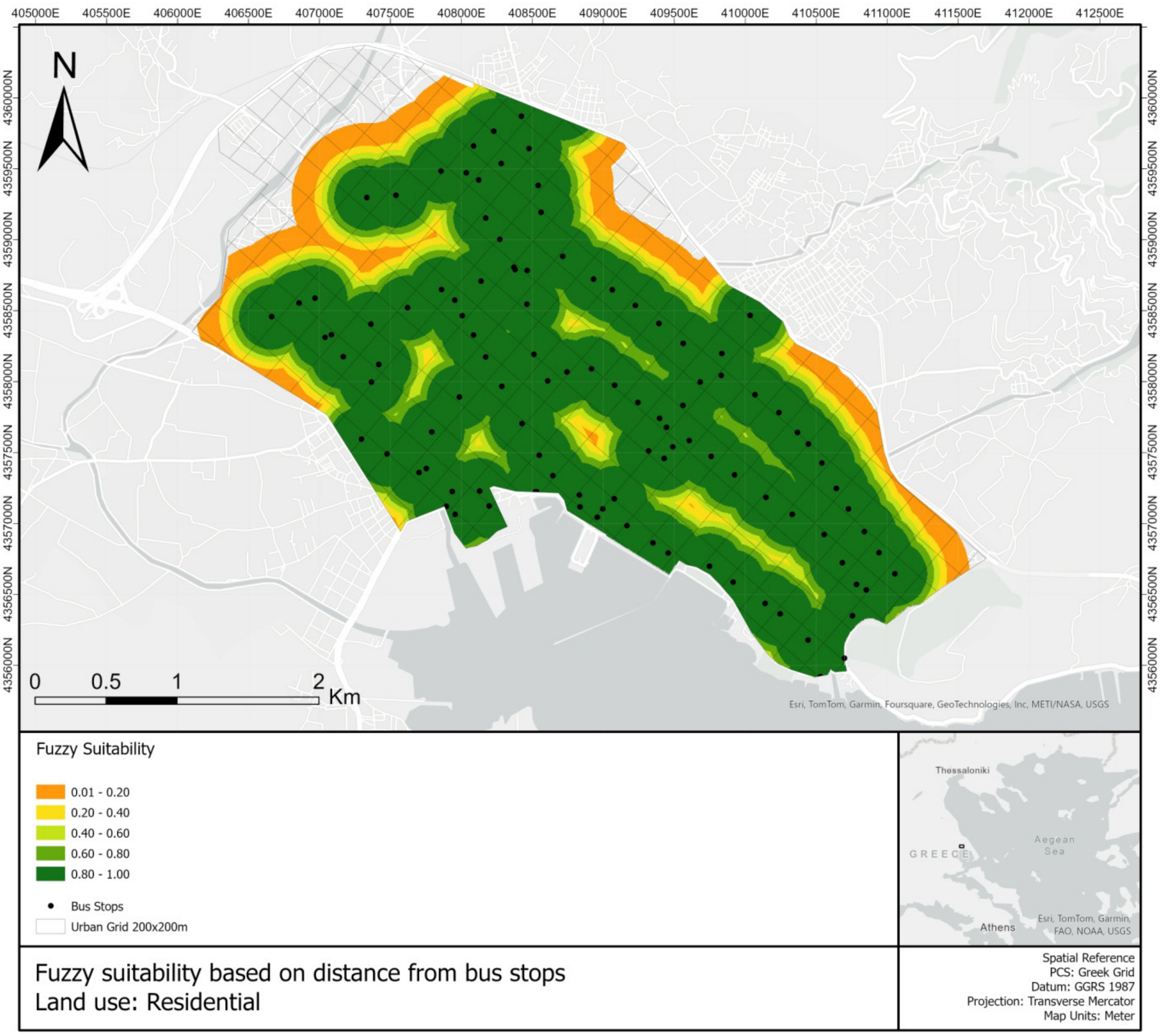

Figure II. 16 - Suitability map for distance from bus stops (residential LUs)

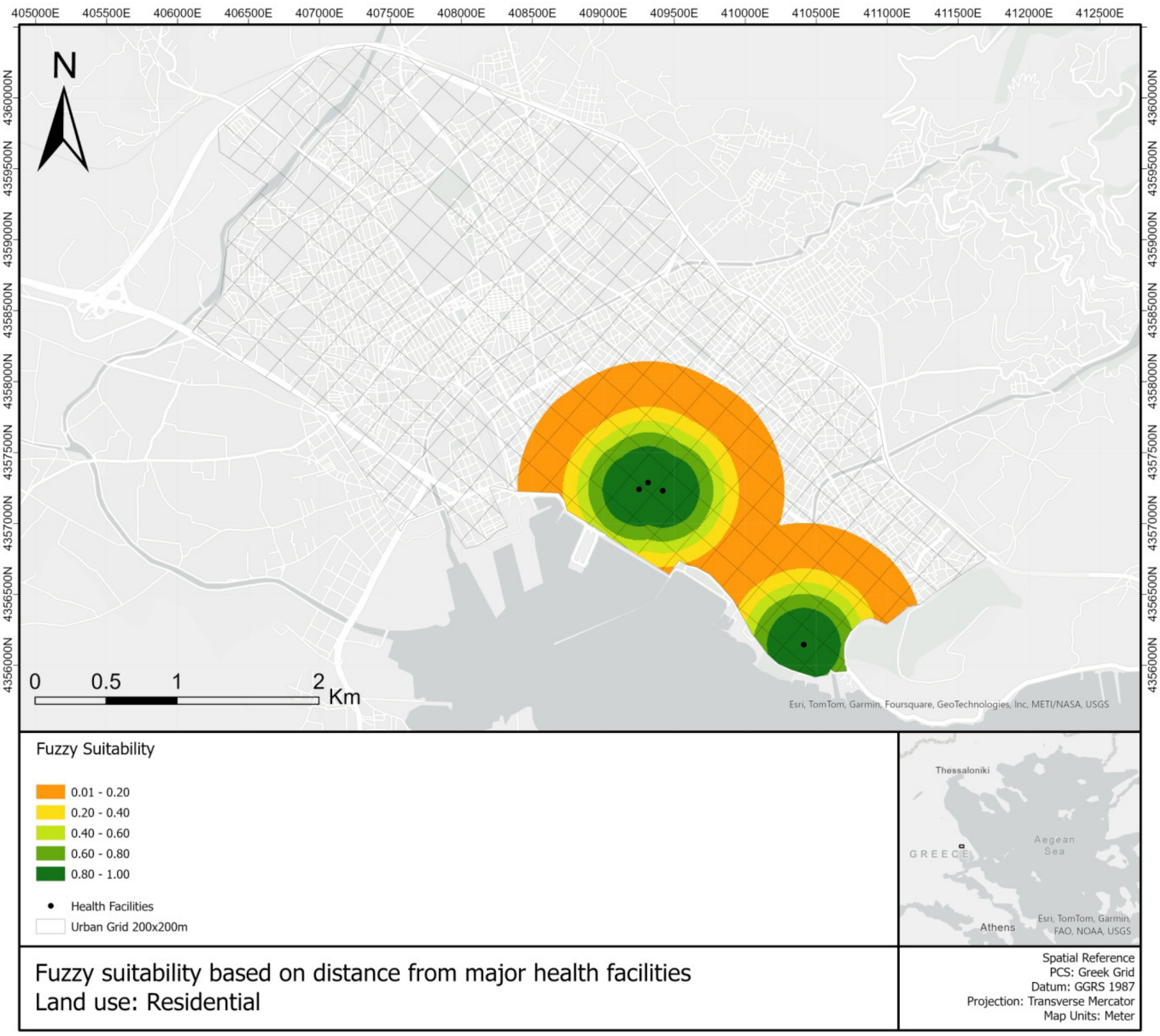

Figure II. 17 - Suitability map for distance from health facilities (residential LUs)

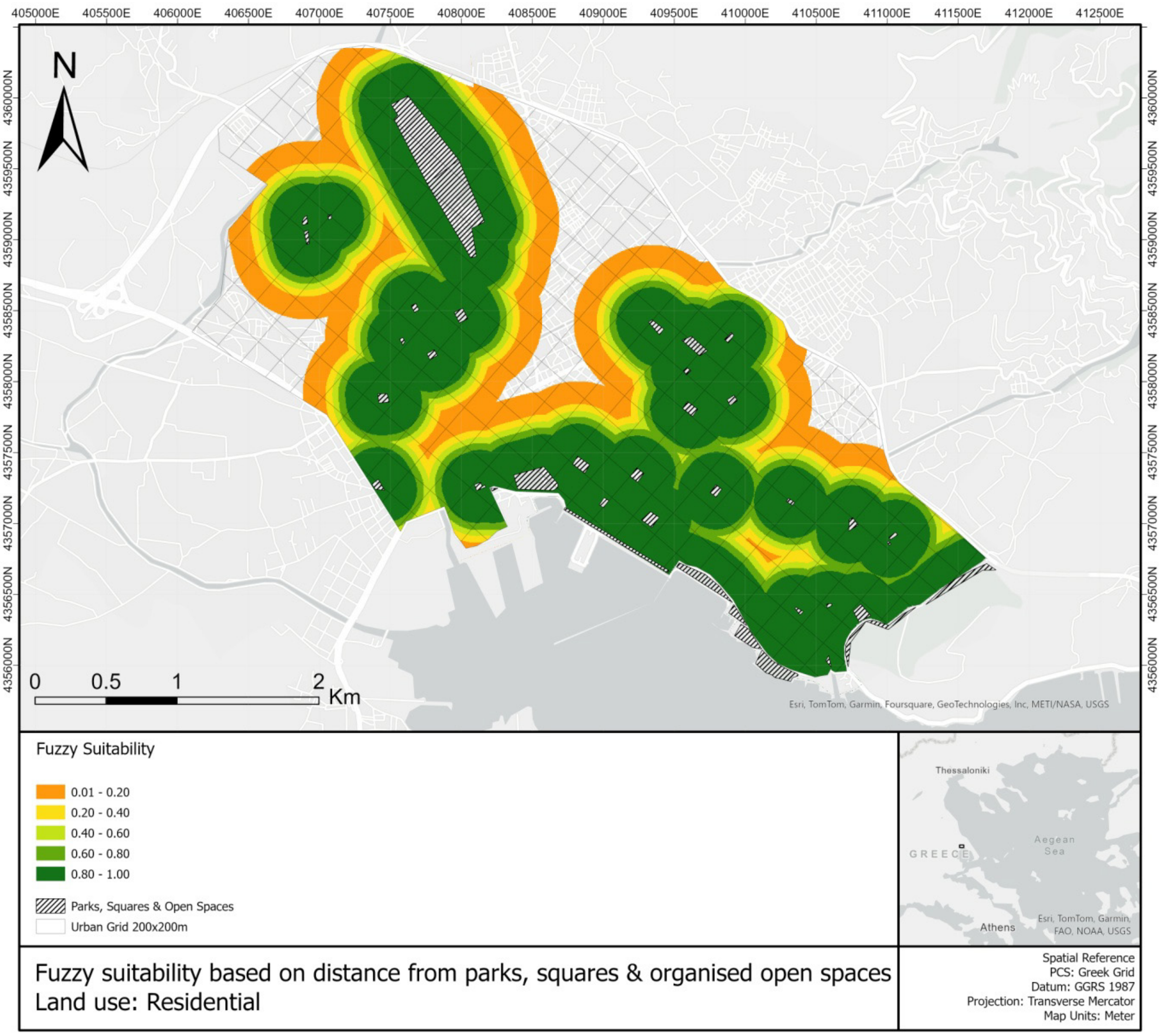

Figure II. 18 - Suitability map for distance from parks & squares (residential LUs)

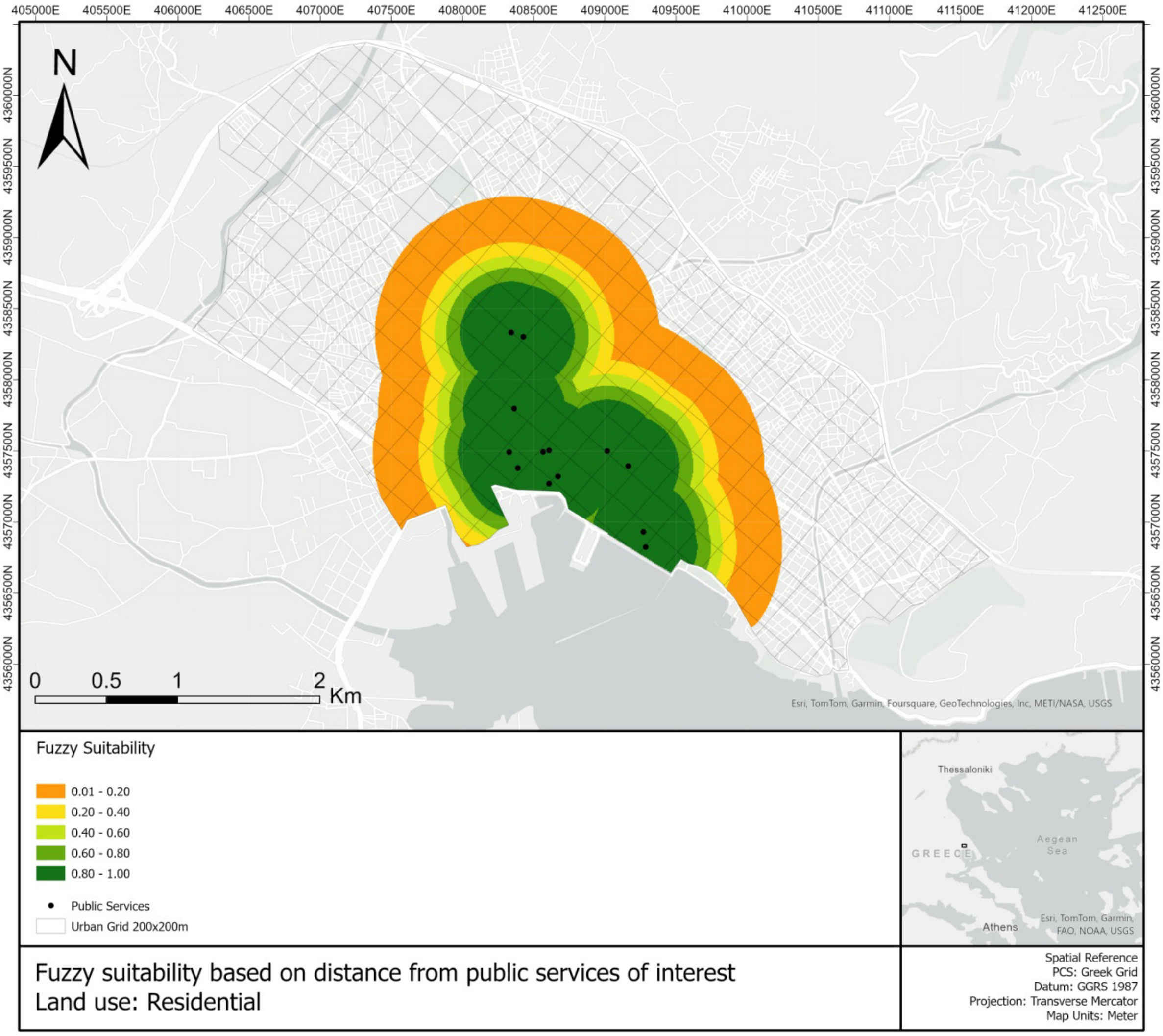

Figure II. 19 - Suitability map for distance from public services (residential LUs)

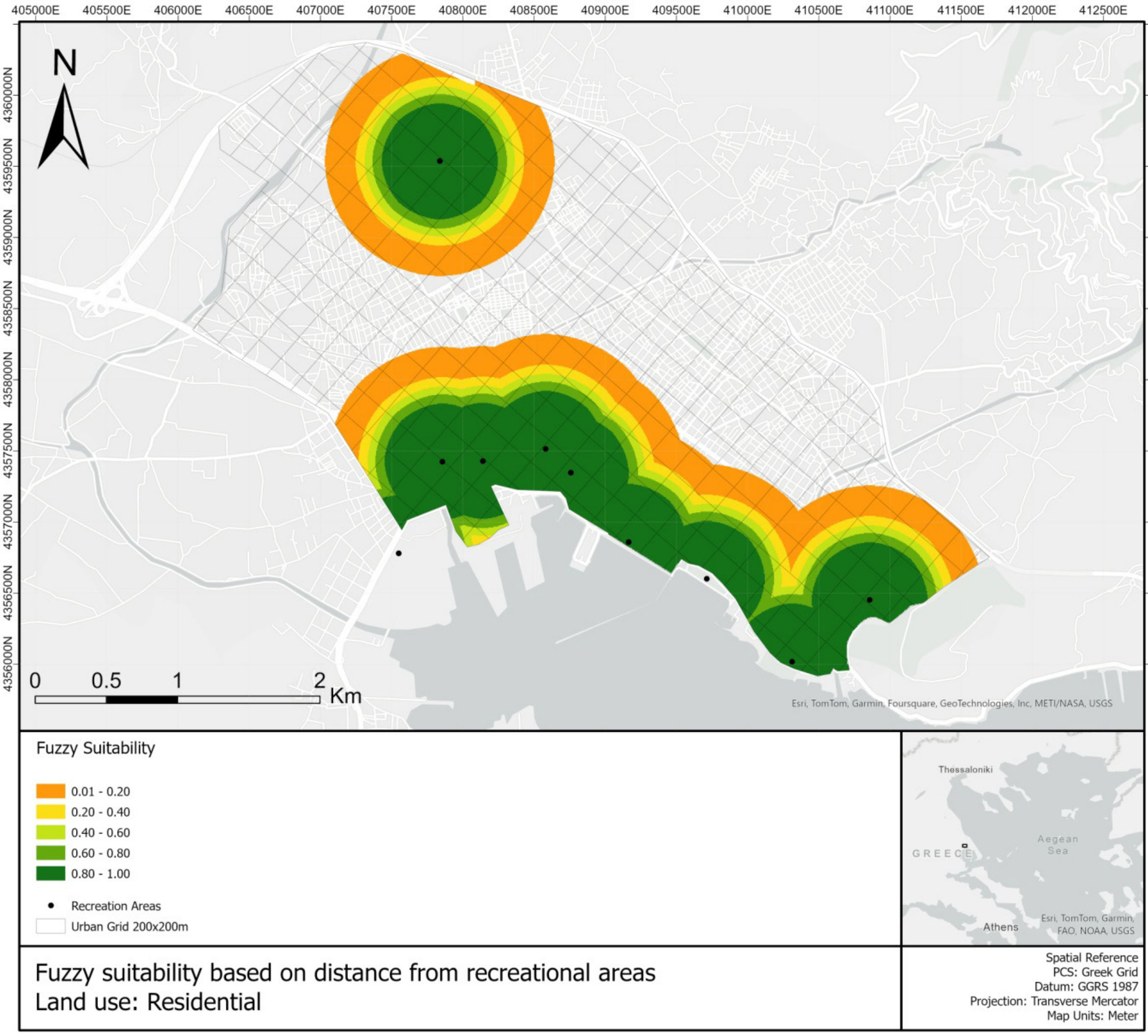

Figure II. 20 - Suitability map for distance from recreation areas (residential LUs)

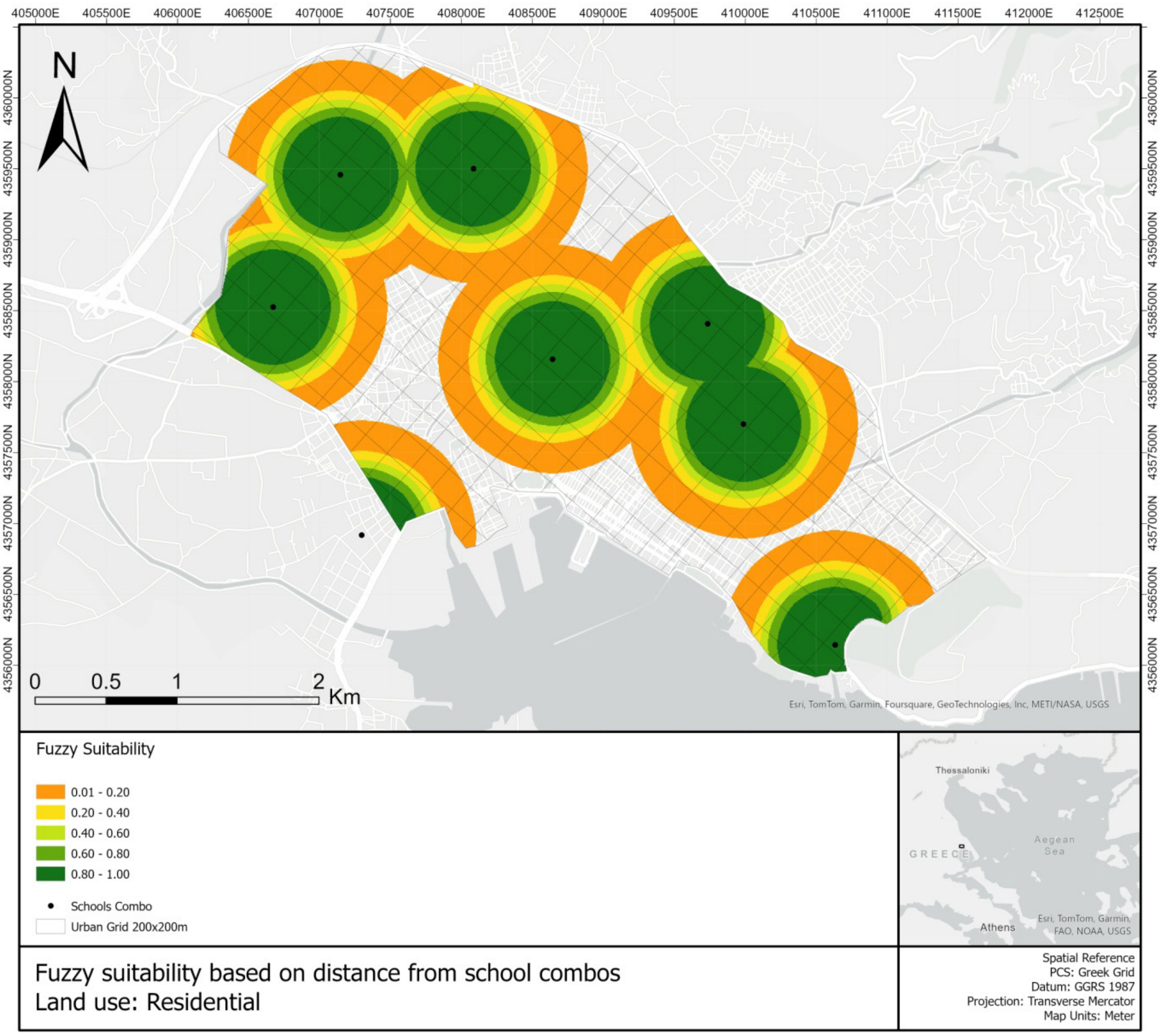

Figure II. 21 - Suitability map for distance from school junctions (residential LUs)

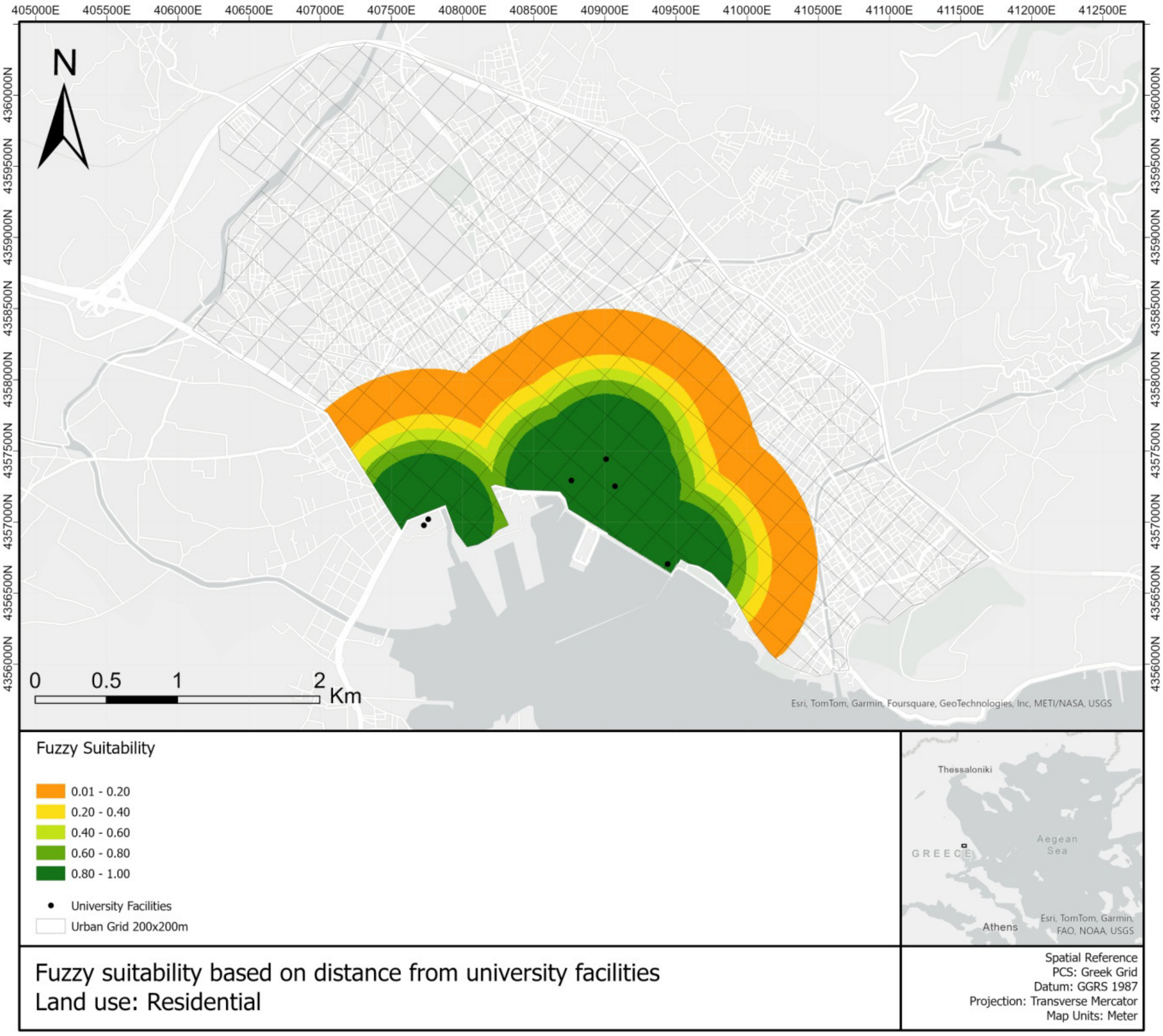

Figure II. 22 - Suitability map for distance from university facilities (residential LUs)

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