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Using Multi-criteria GIS analysis in nature conservation planning in Lilla Edet municipality

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Abstract
The challenge of nature conservation for municipalities usually revolves around limited resources and available data. A method that could predict the potential for nature values in different areas would help municipalities focus the available resources they have where they are most needed. In this study, such a model has been developed and tested for Lilla Edet municipality using MCA (Multi-criteria analysis) in GIS with data that are available to municipalities. The model results show a 92% level of agreement in relation to validation data using all criteria and pass the validation test. The results from the sensitivity analysis show that the most sensitive criteria groups are “Soil”, “Distance to roads” and “Forest value cores” with a resulting change of up to 4% on the results when adjusting the criteria group weights 20%. This indicates acceptable robustness in the sensitivity analysis and validity in the form of validation data agreement testing. In other words, it replicates the more resource demanding established methods sufficiently and can be used as an indicator tool for nature values in municipality conservation planning in Lilla Edet municipality. Further research is needed to verify how this model would perform in other geographical areas or with alternative variables and criteria in the methods.

Abstrakt
Utmaningen för många kommuner med att skapa naturvårdsplaner är brister på resurser och tillgängligt underlag. Att ha en modell som kan uppskatta potentialen för naturvärden hade hjälpt kommunerna att fokusera sina resurser. I den här studien tas en sådan modell fram i Lilla Edets kommun med hjälp av MKA (Multikriterieanalays) i GIS genom att använda data som är tillgängligt för kommuner. Modellens resultat visar en överensstämning på 92% med valideringsdata för alla kriterier och klarar därmed valideringstestet. Resultaten från känslighetsanalysen visar att de känsligaste kriteriegrupperna är ”Jordart”, ”Avstånd till vägar” och ”Värdekärnor skog” med en påverkan på upp till 4% på resultatet när kriteriegruppernas vitk justerades 20%. Detta indikerar indikerar på acceptabel robusthet i känslighetsanalysen och pålitlighet i relation till valideringsdata. Med andra ord så replikerear modellen de mer resurskrävande, etablerade metoderna på ett tillfredställande sätt och kan användas som ett indikeringsverktyg för naturvärden i samband med naturvårdsplanering i Lilla Edets kommun. Vidare studier krävs för att verifiera hur modellen presterar i andra geografiska områden eller med andra variabler och kriterier i metoden.

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Glossary

MCA – Multi criteria analysis, a collection of methods used in decision-making when there is a need to combine multiple decision criteria. When used in a spatial context it can also be called SMCA – Spatial multi criteria.

Standardizing – The part of an MCA where scores are assigned to criteria.

Weighting – The part of a weighted MCA where weights are assigned to criteria.

Nature values – A descriptive term for areas with qualities that are important for biodiversity, the more qualities of this kind that are present in an area, the higher the nature value is. Further description is provided in section 2.1 on page 4.

Nature conservation plan – A non-mandatory, governing document which is politically decided in a municipality.

Zoning plans – A legally binding document with maps and text created by municipalities to divide a specified area into zones. The zones are assigned regulations on allowed usage in relation to land use and construction of buildings for example.

Validation data – A data which can be considered “true” or “reality” for the purposes of validation analysis. It is used to compare the results of an analysis to.

Sensitivity analysis – A type of validation analysis that investigates how sensitive different variables in the MCA are to changes.

WLC – Weighted Linear Multi-Criteria Analysis, an MCA method which combines criteria scores and weights into a total result score.

Participatory approach – An approach to MCA where stakeholders, decision-makers or experts for example are included in the process of designing the MCA model.

Compensatory approach – An approach to MCA where one criterion with a low value should not offset the results significantly.

1. Introduction

Biodiversity is a term used to describe the variation of life, ecosystems, species and their genetic variation (Swingland, 2013). It is a fundamental requirement that there is enough biodiversity for life to exist and thrive. Some examples of vital resources that are dependent on biodiversity are drinking water and crops (Naturvårdsverket, 2023).

At a global level, biodiversity is included in the Sustainable Development Goals set by the United Nations (UN) member states in 2015 (United Nations, Department of Economic and Social Affairs, 2015) and the Convention on Biological Diversity ratified by Sweden in 1993 (United Nations, 1992). At a national level in Sweden there are environmental quality standards (Boverket, PBL Kunskapsbanken, 2025) which the municipalities are required to follow. Municipalities can also have a nature conservation plan that regulates how the municipality will work to protect nature values. All these goals, standards and documents are part of the larger physical planning process (Boverket, 2023).

When something is being built or developed in Sweden there are several processes that should be implemented. One of the most common steps is applying for building permits, which is only one part of a much larger process of societal physical planning. There are different levels of zoning plans and other documents from which the building permit should not deviate, and most of these documents are created by municipalities (Boverket, 2023). When producing these plans or other documents included in the larger physical planning process previously mentioned, Swedish municipalities must consider many different interests. This includes social and economic aspects, but also the ecological ones. One of the main parts of guarding ecological interests is biodiversity (Boverket, PBL Kunskapsbanken, 2025).

It is a large task for municipalities to ensure the protection and improvement of biodiversity through nature conservation plans, both in terms of importance and resources. To help municipalities on the way, there are regional plans in parts of the country that some county administrative boards provide. For example, the county administrative board of Västra Götaland has created a regional action plan for green infrastructure (Länsstyrelsen Västra Götaland, 2019). Even with this supporting document, it is still a resource-intensive task to investigate and collect field data needed to fulfill goals and plans related to ecology in physical planning such as building permits or zoning plans. Many municipalities create a nature conservation plan which identify especially sensitive areas and areas with high nature values in the municipality. However, it is also a resource-intensive document to create, especially for smaller municipalities. This leaves many municipalities in need of a more resource-effective method.

Nature conservation plans are very much linked to spatial data and GIS analysis. Geographical Information Systems (GIS) can sort, manipulate, analyze and display spatial data using computers (Khater et al., 2022). GIS is often used as a tool in various physical planning processes and can be a powerful tool when creating a nature conservation plan and many different data sources need to be combined such as both habitat variables data and pre-identified nature values data. Habitat variables data in this study refers to data that describe qualities of habitats which affects the potential for nature values while pre-identified nature values refer to data where a value judgement related to nature values has already been added into the data. Combining data in more complex ways requires additional techniques. Multi-criteria analysis (MCA) is a collection of methods that can be used in decision-making when there are multiple input factors that affect the decision, and the decision-makers want to combine these. These methods can identify and compare alternatives and combine data with different units (Feick & Hall, 2004). Applying MCA in a GIS is a very useful way of comparing different alternatives or identifying areas of interests in the context of physical planning.

MCA and other GIS analysis techniques are commonly used in studies related to nature values and biodiversity. There are some studies, such as the one by Donoso and Kjellström (2023) where a MCA GIS-model was developed to investigate ecosystem evaluation, specifically for urban environments in connection with detailed zoning planning processes. For example, Bubnicki et al. (2024) predicted the conservation value in forest at 1 hectare which can be valuable data in nature planning although it does not cover land outside forests. MCA has also been used for habitat suitability analysis to identify suitable habitats for specific species as Kangas & Store (2001) carried out to identify most suitable old-forest areas for the tree species *S. odora* in Finland. However, there seems to be a gap in the research field of such studies focusing on general biodiversity in the context of nature conservation plans in Sweden without focusing on specific land or species types. This gap also indicates that there is a lack of studies that validates the results of an MCA against nature conservation data and which variables that most affect the results. This is why it is of interest to investigate to what extent such a model can predict the potential for nature values. This research gap also relates to the lack of studies testing how different sub-groups of criteria affect the result. It is not uncommon in MCA to divide the criteria into sub-groups, for example economic, environmental and social objectives as Dean (2022) exemplifies. Store & Kangas (2001) also divided their input data into the two groups of vegetation and soil characteristics. However, it is not as common to also test how including only one or both sub-groups affect the results which is done in this study.

1.1 Research questions

This study aims at creating a flexible, user-friendly, weighted MCA model which assigns weight to all criteria and combines them to predict the potential of nature values. The model should be based on open-source software and openly available data using the municipality of Lilla Edet as a study area. The research questions are described below.

Research questions:

1. To what extent does the MCA model accurately predict areas with high nature values?
2. Does the model predict areas with high nature value more accurately when adding the pre-identified nature values data to the habitat variables?
3. What are the most influential variables in the MCA model?

These research questions will be used to address the research gaps described above and help reach the aim of this thesis. This is the first attempt (to the best of my knowledge) at evaluating two subgroups of input data categorized by habitat variables and pre-identified nature values in an MCA specifically. To determine the effect the two sub-groups have on the results, there will be two iterations of the MCA. The first iteration will only include the sub-group Habitat variables and the second iteration will include both sub-groups. The second research question addresses this by comparing these two iterations in a validation process. The third research question will use sensitivity analysis to investigate which variables that are most influential in the MCA.

2. Background

2.1 Nature conservation planning

The ecological aspect is one of the three main aspects previously mentioned that need consideration in physical planning processes. At a municipal level, it is common to create documents that detail the long-term plan of different nature-related aspects such as water management, recreation and wildlife or nature conservation. There are different types of documents that address these and a nature conservation plan is one of them (Boverket, 2023). A nature conservation plan is a non-mandatory, governing document which is politically decided upon at the municipality level. The document typically describes the nature of the municipality and specific objects or areas with high nature values. Furthermore, it contains goals and plans for how to preserve these nature values (Lilla Edets kommun, 2024). Nature values are defined in the Swedish standard for *Biodiversity assessment – Survey and mapping of habitats and species* as having especially important meaning for biodiversity (SIS, 2023). Areas with high nature values refer to areas with qualities that are valuable for biodiversity, and this can be presented in different ways depending on the context. The areas with high nature values are often presented on a map with classifications according to SIS (2023) and an accompanying list in the nature conservation plan. The classification of nature values according to SIS is based on what habitat characteristics and species that are found and identified. There are four classes of nature values in this standard which are in a ranked order going from class 1; highest nature value to class 4; some nature value. Areas without nature values are not included in this classification level (SIS, 2023). In other contexts, nature values might be discussed in a more general sense where nature values are either present or not present in an area.

The process of creating a nature conservation plan usually starts with planning and inventory of existing data and information. This is followed by collecting newer data through field visits or other methods. All this data can then be used to identify areas with nature values classified according to the SIS-standard (2023) and create a plan of how to protect these values (Boverket, 2023). A common method for identifying areas with high nature values in the context of a nature conservation plan is visual analysis in a GIS where these areas are also classified according to SIS standards (2023). This is how Lilla Edet municipality created both their old plan from 2009 and how the new plan for 2027 is being produced (Lilla Edets kommun, 2024).

2.2 MCA

Multi criteria analysis (MCA) is a collection of methods commonly used to evaluate different alternatives in decision-making. In combination with GIS, it is possible to identify geographical areas of interest or compare spatial alternatives in decision-making. MCA is useful when there is more than one criterion that needs to be applied, and even more so if these criteria are not equally important (Feick & Hall, 2004). Examples of applications of MCA methods include identifying suitable areas to construct wind farms using spatial data such as wind speed, population, roads etc.

Another example is evaluating alternative locations for new roads by analyzing the consequences of each alternative. A MCA model can be adjusted to fit different scenarios and circumstances which makes it suitable for the purposes of this study. In a case such as nature conservation analysis, there are many criteria of interest. MCA has commonly been used for over 20 years in nature conservation analysis (Esmail & Galetti, 2018) and allows many types of data input to play a role. It is also in these suitability analysis applications that Fuzzy logic is suitable because nature values and their potential are vague by nature (Romero et al., 2023). Using a weighted MCA could be somewhat comparable to fuzzy overlay even if Fuzzy logic and overlay are not specifically applied in this study. Some other commonly related terms are MCDA (Multi-Criteria Decision Analysis), SMCA (Spatial Multi-Criteria Analysis), and SDSS (Spacial Decision Support Systems) (Rahman et al., 2012 and Keenan, 2006). The MCA used in this study is a type of MCDA and SMCA while a SDSS is a more complex software-based system which is not used in this study.

Dean (2022) describes two main groups of MCA methods which include formal and simplified methods. Formal methods are more advanced and often require more knowledge and experience in mathematics than simplified methods. The simplified methods are more popular as they are generally accessible to a larger number of people. These methods are often more flexible than formal methods, which is why this group of methods is more suitable for the purposes of this study. Some examples of simplified methods that Dean (2022) are listed in Table 2.1 below:

Table 2.1 - Examples of MCA applications from Dean (2022).

Method	**Description**	**Example**
Simple multi-criteria summary charts	Lists the impact of different criteria for one or several alternative scenarios. There is no ranking of the alternative scenarios, the impacts are simply presented.	There are 3 different alternatives for a new wind power plant location. Each of these alternative locations has a column in the summary chart. Each row presents the impact for each alternative from criteria such as ecology, energy potential and economic efficiency.
Simple additive weighting methods	Ranks different options. The criteria are assigned a weight and a score for each option. The score and the weight of each criterion and option are multiplied into a weighted score. The weighted score of each criterion is then multiplied for each option, and a total score is presented for each option. The options are then ranked based on the total score.	A company is purchasing new software; there are 3 possible options to choose from. The company is interested in finding the option with the smallest cost, functions most adapted to their business and the most user-friendly interface. Each of these 3 criteria are assigned a weight, the cost is the most important for the company, so this criterion gets the highest weight assigned. The criteria are also assigned a rank based on their performance. The total score is

		calculated, and the three options are ranked accordingly.
Multi-criteria checklists	Screens one criteria at a time for the different alternatives as either a “yes” or a “no”. The options that fulfill a criterion and are classified as a” yes” move on to the screening of the next criterion until all criteria have been screened or one option remains.	A new plant for cleaning wastewater needs to be built and there are 5 suggested sites. To narrow these down, the first criteria, legal constraint rules out any option that is affected by protected areas. The remaining options are checked for area feasibility, the options with an area over 500 m² pass this check and move on to the next step. If the remaining options are closer than 50m from an existing road, they have passed the checklists and are considered viable locations for the wastewater plant.

The simple multicriteria summary charts and the multi-criteria checklists are optimal for use in the starting phase of a project to present or narrow down the options for a decision. The simple additive weighting methods are the most well known and most used of these three types of MCA. This type of MCA requires setting a score (standardizing) and setting a weight (weighting) for each criterion in the analysis. These terms are explained in more detail below.

To make the criteria comparable it is necessary to standardize their values into the same system or unit. This is commonly done by setting a score on each criterion based on how desirable it is in context of the MCA goal. Some examples of approaches to this are presented in Table 2.2:

Table 2.2 - Examples of standardization techniques.

Standardization approach	**Value ranges**	**Applications**	**Advantages/ Disadvantages**
Boolean score	Only 0 and 1 can be assigned, the criteria are either suitable or not.	Boolean values are a suitable approach if input data can only be assessed as suitable or not suitable without any degree of suitability. (Geneletti, 2019)	This approach allows for a simple standardization process but also limits the nuance of the criteria’s influence on the results.
Range score option 1	The score can be any whole number between 0-100 depending	This approach has a wide range of scores which allows for nuanced scoring but	This approach can give each criteria a very nuanced effect

	on the degree of suitability for the criteria.	can also cause difficulty setting the scores. Wide ranges can make the distinction in classes less clear to the researcher or participant.(Dean, 2022)	on the result but also introduces error sources in the more complex standardization process.
Range score option 2	The score can be any whole number between 0-5 depending on the suitability of the criteria	This approach has a smaller number of possible scores which allows for a text definition of each score. This can facilitate a more consistent scoring of all criteria. However, it might also decrease the nuance in suitability scoring. (Dean, 2022)	This approach allows for both nuance and a relatively simple standardization process, but it still limits the influence that each criterion has on the results somewhat.

Criteria in an MCA may have varying importance and this is addressed in a weighted additive MCA method by assigning each criteria a weight. Weighting can be done in different ways. One way is to divide weighting techniques into two main groups: compensatory and non-compensatory techniques (Dean, 2022). Compensatory techniques imply that a low score on one criterion can be offset by higher scores on other criteria when calculating the total weighted score, as each score is multiplied by its weight and summed. In contrast, non-compensatory techniques do not allow such compensation - a low score on one criterion will strongly limit the overall result regardless of high scores on other criteria. Some of the most common weighting approaches are listed in Table 2.3 below:

Table 2.3 - Examples of weighting techniques.

Weighting technique	**Weight value assignment**	**Application**	**Advantages/ Disadvantages**
Trade-off (Compensatory)	Weight values for each criterion are calculated using formulas for pairwise comparison between a reference criterion and every other criterion separately. Each criterion is compared to all other criteria separately and a preferred trade-off between the reference	This technique is suitable for compensatory MCA methods such as simple additive weighting. (Dean, 2022)	This approach allows for a nuance in the form of trade-offs between criteria. However, it implies a relatively complex weighting process which requires some experience

	criterion and the other criteria is decided. The weights are finally calculated by solving a system of formulas for each criterion. A commonly used scale of weight values with this technique is 0-100. (Dean, 2022), (Geneletti, 2019)		from the persons involved in the process
Swing (Compensatory)	Weights are decided by creating the same number of scenarios as the number of criteria where one criterion is “swung” from the worst to the best possible value. Each option has one criterion with the best value while the others have their worst. These options are then ranked and assigned a point from 0-100 where 100 is the best. These assigned points are then normalized so that they add up to 1 in total, these normalized values are the assigned weights. (Dean, 2022), (Geneletti, 2019)	This technique is suitable for compensatory MCA methods such as simple additive weighting. (Dean, 2022)	This approach implies a straightforward weighting process for the participants but can also introduce uncertainties due to the wide range of weight values.
Simple rating (Non-compensatory)	A scale of discrete value range such as 1-5 or 1-10 are listed and each number is assigned a level of importance. Each criterion is simply assigned the number that matches its level of importance, and these values are then normalized so they add up to 1 or 100 in total. (Dean, 2022)	This technique is suitable for non-compensatory MCA methods and when a simpler technique is desired. (Dean, 2022)	This approach implies a simple weighting process for the participants but can also over-simplify the resulting weights which introduces uncertainties.
Point allocation (Non-compensatory)	Each criterion is assigned a weight from a pool of 100 points. Thus, no normalization is needed as the sum of all criteria weights is already 100. A suggested approach in cases with a larger number of criteria is to first evenly distribute the points and then adjust accordingly. (Dean, 2022)	This technique is considered non-compensatory although it could be argued to contain some trade-off aspects which is a compensatory technique quality (Dean, 2022)	This approach allows for a relatively straight forward weighting process with a large number of criteria but will likely require several rounds of adjustments when distributing the points.

AHP (Non-compensatory)	Weights are decided through a matrix where each criterion is compared to every other criterion separately pairwise. Each pair is compared in terms of importance and assigned a point from 1-9. The assigned points are then normalized into a range of 0-1 or 0-100 which is the assigned criteria weight. (Dean, 2022), (Geneletti, 2019), (Ron & Store, 2001)	This technique is suitable for non-compensatory MCA methods. (Dean, 2022)	This approach allows for nuanced and balanced weight but requires knowledge and experience of the analyst involved in the process.

Not all MCA methods include standardizing and weighting, but when they are relevant, it is important to consider the biases and competence of the person or persons making the value judgements. In some cases, these value judgements are made by the analysist/analysists and are generally referred to as non-participatory approaches. Meanwhile, stakeholders, experts or other parties are included in the value judgement in other cases. This is referred to as participatory approaches. Arguments for non-participatory methods include obtaining more impartial and independent values, while also allowing for more complex methods of weighting as the specialist are trained in this kind of analysis (Dean, 2022). Conversely, participatory approaches increase the chance of result acceptance as a more democratic approach and can also include expert knowledge on the subject (Dean, 2021). The most suitable approach depends on the subject investigated in the MCA. In the application of habitat analysis, Store & Kangas (2001) used a participatory approach, including ecology experts, in their MCA. The authors noted that this approach enabled them to produce suitability indices for larger areas effectively. Only one expert was used in this case study, but the authors suggest using a group of experts as an alternative approach.

When the MCA methods and techniques for standardization and weighting have been decided for a project, it is also important to consider the uncertainties that each of these introduce into the MCA results (Geneletti, 2019). Elaborating on the uncertainties of the chosen methods is necessary to establish confidence in the MCA and its results. Furthermore, the MCA results should also be evaluated through validation and sensitivity analysis in order to assess robustness (Feick & Hall, 2004).

2.3 Model validation

To test the validity of a MCA model there are different approaches, the results can be compared to independent data or field data collection, for example, to produce a level of agreement. However, this type of independent validation data is not always available and sometimes it is of interest to see how well a model performs compared to established methods. To test the performance of a MCA model with established methods, the results could be compared to the results of an established model to produce a level of agreement between these. Validation testing is an important step in the assessment of an MCA because it reveals information about how well the model can predict, identify or compare data. This strengthens confidence in the MCA model (Qureshi et al., 1999).

What is considered suitable validation data depends on the type of MCA and its focus. An MCA that predicts potential geothermal areas could be tested against observed geothermal areas for example (Kiavarz & Jelokhani-Niaraki, 2017). If the MCA is comparing different alternatives for physical constructions to be used by humans, it can be a suitable approach to compare the results to public opinion instead (Mahmoody Vanolya et al., 2019).

The method of validating the MCA results can vary from statistical testing to visual comparison of the MCA results to the validation data. It is important to note that validation does not simply state that the MCA results are correct, but rather how well they agree with the validation dataset. The degree of agreement should be evaluated as acceptable or not (Qureshi et al., 1999).

2.4 Sensitivity Analysis

In the design process of a MCA there are often many value judgements that introduce uncertainties. Scores and weights are estimated by the analyst or experts and there can be varying confidence in how these are set. Sensitivity analysis is a method of testing MCA model robustness, besides testing model validity as described in the previous section. Sensitivity analysis instead examines how the MCA results change when parameters or variables are systematically varied in the MCA model to see how this affects the result. This kind of testing gives an indication of the stability of the MCA model and can strengthen confidence in it by investigating the relationship between input and output of the MCA (Qureshi et al., 1999) (Chen et al., 2010). Performing both a model validation test and a sensitivity analysis provides a more nuanced evaluation of the MCA. However, this is often overlooked in applications of MCA methods (Esmail & Geneletti, 2018), (Qureshi et al., 1999).

There are many different techniques of performing a sensitivity analysis. Some less common methods systematically change the standardized scores of the criteria and other methods systematically change the weight of the criteria. The most common type of sensitivity analysis for GIS-based MCA is testing the sensitivity of the weights (Chen et al., 2010). This will produce many different MCA results which can be compared to the original MCA result in an evaluation to see how sensitive the result is to changes in weights for each criterion (Dean, 2022). How much the weight varies depends on the chosen method. The Monte Carlo simulation randomly chooses the variation values from a probability distribution for each criterion within a chosen range; this is referred to as a probabilistic method and often generates a very large number of iterations of the MCA. Conversely, non-probabilistic methods implement a more systematic change to the weight for each criterion with a chosen value. This method changes the weight of one criterion in both a positive and a negative direction separately while the rest of the criteria are adjusted accordingly so the sum of the weights stays the same. The process will be repeated for each criterion separately so that there are two runs of the MCA for each criterion (Chen et al., 2010).

3. Methods

The methods used in this study are presented in this section.

3.1 Case study

The case study is carried out on Lilla Edet Municipality, and the data selection has been based on availability for this area. Lilla Edet was chosen for this study due to the municipality showing interest in the thesis idea and was planning to produce a new conservation plan in the municipality concurrently which allows for cooperation with the experts involved. Since this study aims at creating a model that would work for any municipality, no specific requirements were needed in the choice of study area.

Study area

Lilla Edet is one of 290 municipalities in Sweden with about 14 500 inhabitants (SCB, 2025) within an area of about 350 km². The municipality is in the south-west part of the country, 54 km north of Gothenburg at 58° 07' 60.00" N, 12° 07' 60.00" E. See Figure 3.1 for an overview of the area. While the municipality includes a few smaller urban areas, Lilla Edet center is the largest of these and located next to the river named Göta älv.

Most of the land in Lilla Edet is forest or agricultural land and its topography is partly defined by the large river Göta älv flowing through the municipality north to south with valleys and flat agricultural lands surrounding it. There are many smaller water streams flowing from this river and several lakes spread out through the area. The hills provide nice views and there are hiking trails offering good opportunities for recreational activity. The highest point of the municipality is about 200m above sea level. The Köppen-Geiger climate class of the area is Cfb which translates to a temperate oceanic climate (World Bank Group, 2020).

There are several protected nature areas in Lilla Edet, including nature reserves, Natura2000 areas and biotope protection areas. The current nature conservation plan (Lilla Edets kommun, 2009) lists the nature values in the municipality which are mainly linked to water environments such as lakes and streams and large areas of continuous forest and with varying elevation levels. The forests are mainly coniferous or mixed type where old and dead wood are present which is important for biodiversity. The municipality does have a few species that are more present in the municipality than in other Swedish municipalities such as the slender St. John's wort and does have a combined landscape which is favorable to biodiversity, but is generally representative of southern Swedish municipalities otherwise. Parallel to this project, a new nature conservation plan is being created to supersede the old one. The project area extends a few kilometers outside of the municipality borders as nature and ecosystems do not generally align with administrative borders. Therefore, extending the study area allows for identification of areas overlapping the municipality border.

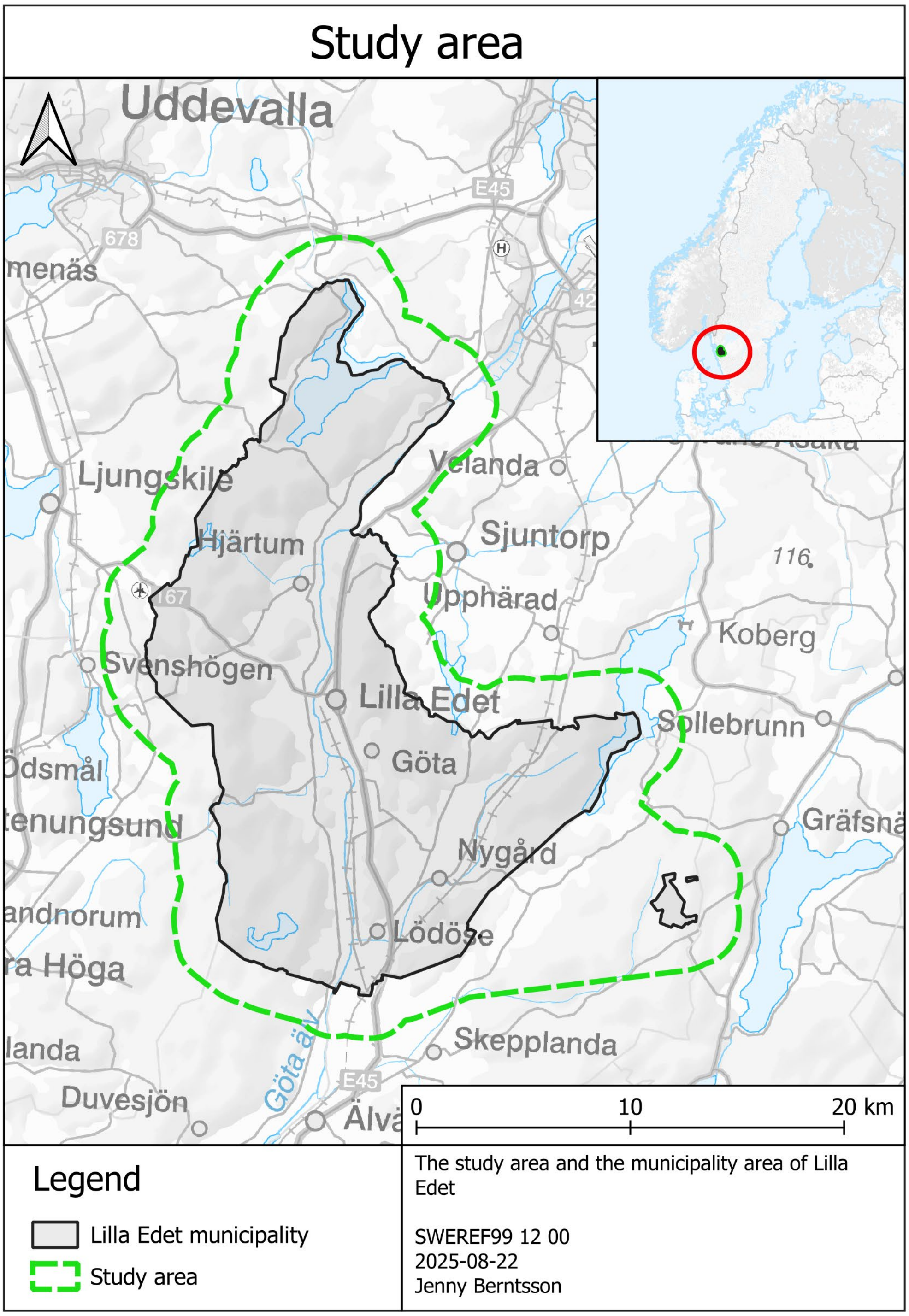

Figure 3.1 - Study area shown in a smaller scale while a larger scale map is also provided at the top to show the location of the study area in relation to whole country.

3.2 Data

3.2.1 Data collection

The input data used in this study were collected from datasets which are publicly available. The sources include Lantmäteriet (Swedish national mapping, cadastral and land registration authority), Naturvårdsverket (Swedish Environmental Protection Agency), NVDB (Swedish National Road Database), SGU (the Geological Survey of Sweden), Länsstyrelsen (The Country Administrative Board), Länstyrelsen Västra Götalands län (The Country Administrative Board of Västra Götaland county) and Mittuniversitetet (Mid Sweden University). Table 3.1 provides links to these sources.

Table 3.1 - URL links to the sources.

Source	**URL**	**Datasets**
Lantmäteriet	https://www.lantmateriet.se/sv/geodata/vara-produkter/geotorget/	Slope, Aspect, Distance to nearest water stream, Distance to nearest lake
Naturvårdsverket	https://www.naturvardsverket.se/verktyg-och-tjanster/kartor-och-karttjanster/nationella-marktackedata/	Land use raster
NVDB	https://lastkajen.trafikverket.se/login	Distance to nearest gravel road, Distance to nearest paved road,
SGU	https://www.sgu.se/produkter-och-tjanster/kartor/kartvisaren/jordkartvisare/jordarter-125-000-1100-000/ and https://ext-geodatakatalog-forv.lansstyrelsen.se/PlaneringsKatalogen/GetMetaDataById?id=2410c2e5-2a0e-4a47-9273-b7b77517420a_C	Soil type
Länsstyrelserna	https://ext-geodatakatalog.lansstyrelsen.se/GeodataKatalogen/srv/swe/catalog.search#/home	Mixed forest value cores, Historic wetlands from 1800, Historic wetlands from soil type data
Länstyrelsen Västra Götalands län	https://ext-geodatakatalog.lansstyrelsen.se/GeodataKatalogen/srv/swe/catalog.search#/home	Identified trees worthy of protection, Hay meadow value element, Rich marsh, Trivial deciduous forest value cores Deciduous forest analysis, Broad leaf forest value cores, Coniferous forest value cores, Valuable grassland 2022, Valuable grassland 2018
Mittuniversitetet	https://researchdata.se/en/catalogue/dataset/2024-49/1	High conservation values forest (HCVF)

Using openly available data is part of the aim for this thesis which is fulfilled by making sure the data are available without cost with licenses that allow free modification and distribution. Data were chosen based on relevancy to ecology and divided into two sub-groups to divide pure habitat variables and pre-identified nature values from existing analyses. This was done during the process of selecting input data when the participants noted this natural division which is relevant in the context. Other possible options were to divide the data by source for example, but this was not as relevant of an option to investigate.

The data sets used in this project are openly available with either CC0 1.0 or CC0 4.0 licenses online which allows for copying, modifying and distribution of the data freely with some requirements of referencing. The data sets are briefly explained here but Appendix A provides a more detailed overview. Initial selections were inclusive, where all potentially relevant datasets were collected in collaboration with ecological experts including the municipality ecologist of Lilla Edet municipality and two ecologist consultants. As Store & Kangas (2001) suggest, using a group of experts instead of just one can improve the quality of the analysis. The list was then filtered by the experts to only include the datasets with relevance to identifying nature values. The relevance in this case was evaluated by the experts based on ecological importance. The resulting list of input can be viewed in Table 3.4 and Appendix A.

The experts noted that there were two types of data in the final list. These include observational data which describe the characteristics of habitats and data which were the results of previous analysis to identify nature values. Therefore, the list of input data was divided into two sub-groups, *Habitat variables* and *Pre-identified nature values*. This grouping made it possible to test whether the *Pre-identified nature values* provide added value in the MCA through the second research question. This could provide valuable information on how different types of input data affect the result.

'Value elements' and 'value cores' are two terms commonly used in data from the sub-category *Pre-identified nature values* in Table 3.4. Naturvårdsverket describe these terms in their guidance document (2017). A value element refers to elements with a positive effect on biodiversity such as a collection of species or a habitat. Value cores refer to an area in nature with a high nature value, and this implies a presence of value elements to create the conditions for these high nature values. The criteria *Hay meadow value element* and *Mixed forest value cores* are two examples where the terms are used in the data name while the terms are instead used in the attributes in the criterion *Valuable grasslands 2022*, see Table 3.4.

All input data introduces further uncertainty into the MCA results. The data have varying quality and uncertainty, and their respective backgrounds and documentations are summarized in Appendix A.

3.2.2 Pre-processing of data

Geographical data often vary in format which is problematic when it is to be combined in analysis. Some pre-processing is often needed before the datasets can be used in any analysis, including MCA. The data used in this study were pre-processed in QGIS as listed and explained in Table 3.2. Figure 3.2 also presents a flowchart of the pre-processing along with the tools used. Appendix B offers a more detailed description of each criterion, their processing and qualities.

Table 3.2 - Summary of pre-processing of the input data.

Pre-processing	**Motivation**
Reprojected into SWEREF99 12 00	This is the established reference system used in the study area.
Clipped to the study area extent	Data outside of the study area is not of interest in this study and would add unnecessary data volume and computation load.
Rasterized if the original was in vector format	Raster is generally considered the most suitable GIS-format for MCA because of its ability to present continuous data, hence why it was chosen.
Resampled to a cell size of 1m and aligned to the DEM	The finest resolution in the raster input data was the DEM with 1m, the finest resolution in the vector data were road lines. A resolution of 1m was therefore chosen to preserve as much spatial resolution as possible in the results. Although one of the 21 criteria has a coarser resolution of 100 m, this single dataset is not likely to dictate the resolution of the MCA results. It was deemed more important to preserve the finer resolution in most input data which is why the finest resolution was chosen.
No-data-values set to 0	The no-data values were set to 0 to avoid interference with the analysis. The cells with no-data value will therefore have a final score of 0 which indicates low potential of nature values. See further details on this in the MCA section of the Methods.

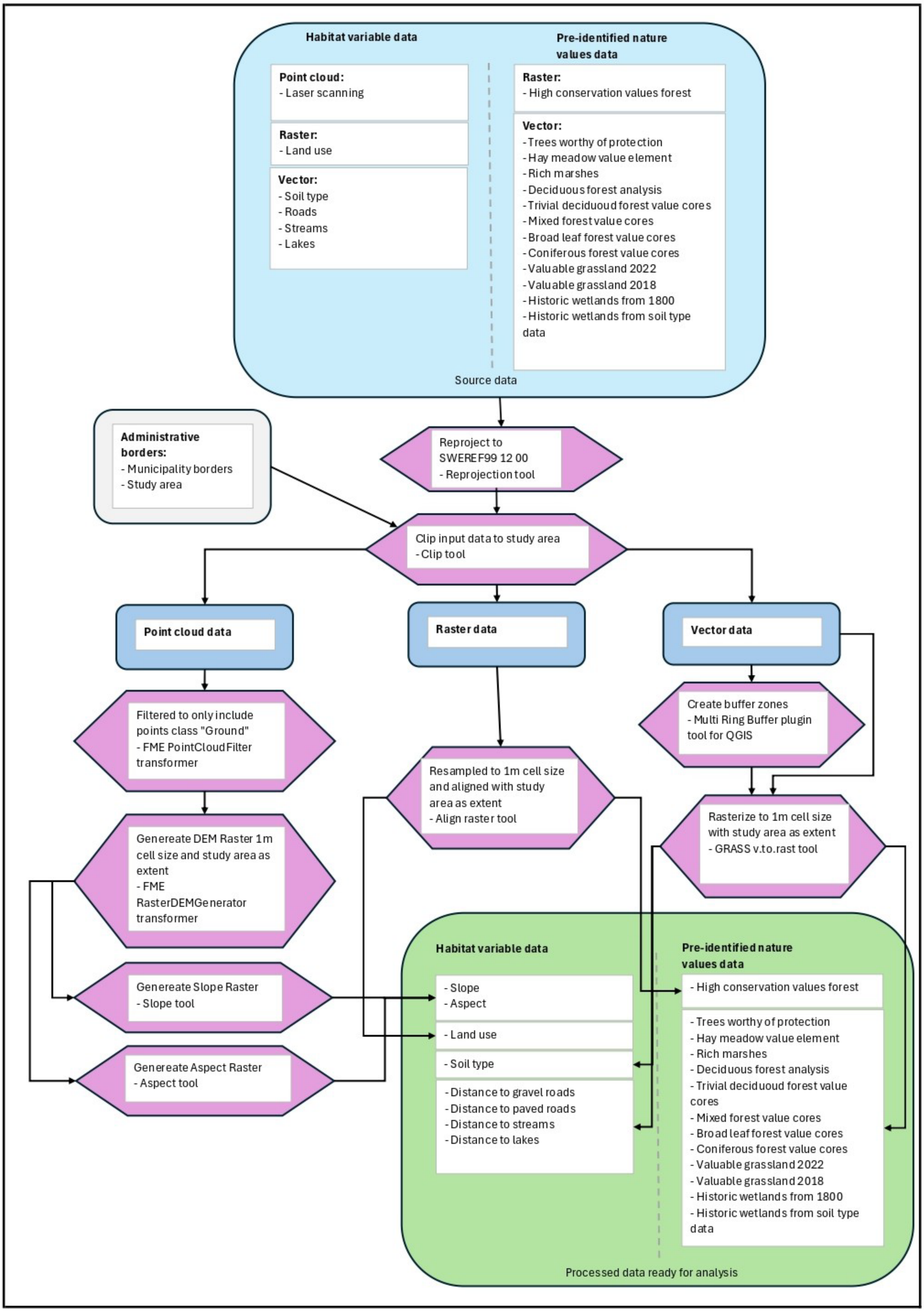

Figure 3.2 - Flowchart of the pre-processing of input data which is presented in Appendix A.

3.3 MCA analysis

The MCA method chosen for this study is weighted linear multi-criteria analysis (WLC) with a participatory approach. WLC is a type of Simple additive weighting method as mentioned in the background. For the purposes of this study, it is of interest to identify possible areas with high nature values where conservation efforts can be focused. This is done by using various data inputs related to describing habitat characteristics and existing areas of interest for biodiversity preservation. WLC was chosen partly due to its simplicity, which makes it more accessible and flexible for replication in other municipalities. Furthermore, WLC is a compensatory approach which is suitable for suitability analysis where one criterion with a low value shouldn't offset the results significantly (Dean, 2022). The different steps of the chosen MCA method and validation tests are described separately below and are also visually summarized in Figure 3.3 below.

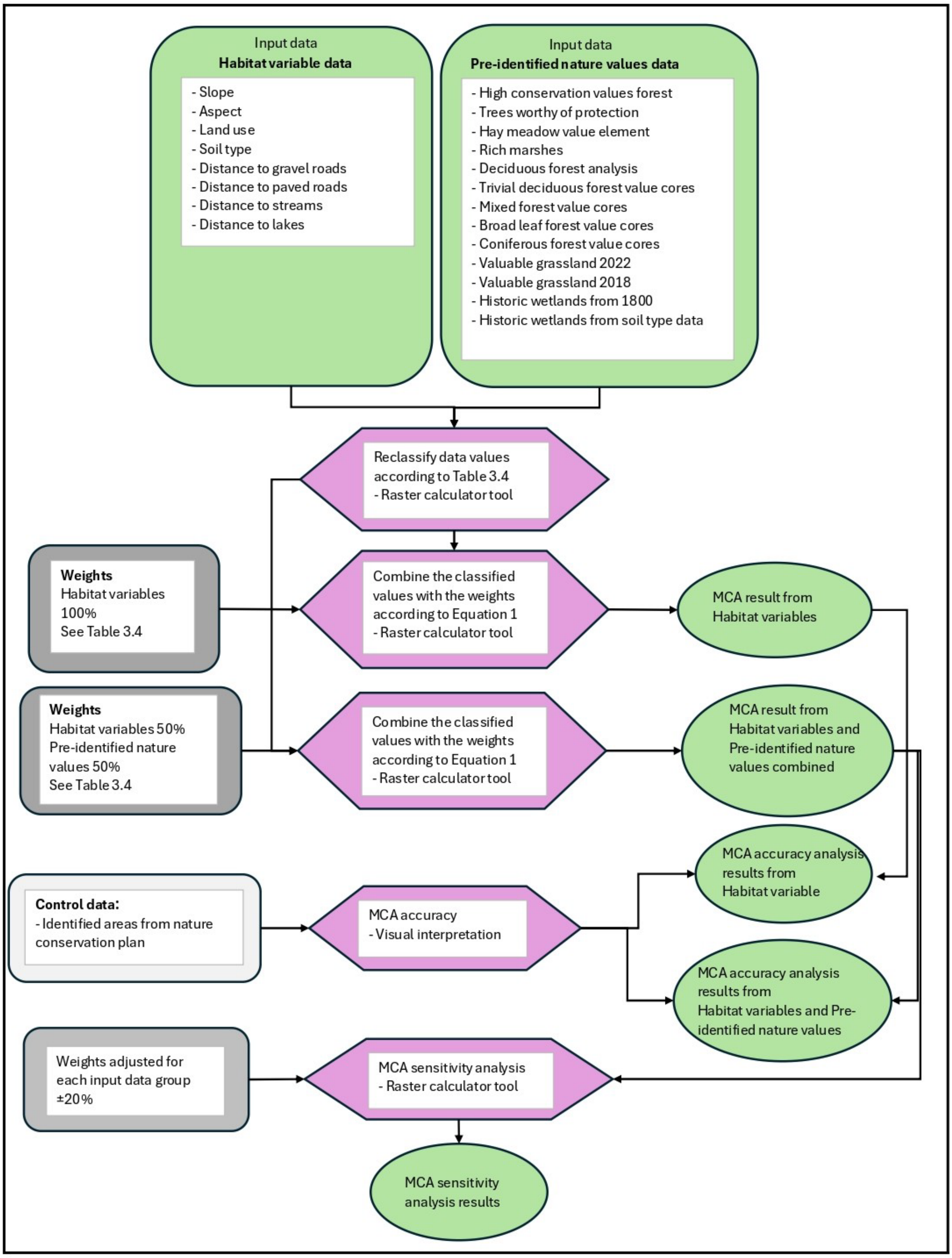

Figure 3.3 - Flowchart of method.

3.3.1 Participatory approach

The municipal ecologist and two consultants with similar competence and knowledge were consulted in a qualitative participatory approach to set the standardized attribute classes, scores and weights. Their input was also used for the design of sensitivity and method validation analysis together with previous research and literature. In MCA applications such as suitability analysis, it is appropriate to use a participatory approach. Store and Kangas (2001) found it an effective approach for larger areas and suggest using a group of experts instead of just one. This study can be considered a suitability analysis and uses a participation approach with more than one expert. The approach incorporates both local knowledge of ecology as well as general expert knowledge into the MCA results.

The cooperation between analysts and experts was done through an in-person meeting where a suggested plan for the MCA analysis was presented and explained to the participants as well as a presentation of MCA in general. The participants were given the material to consider in their own time before having a follow-up meeting in a digital format where the participants presented and discussed their suggested changes and input on the methods. The input was incorporated into the plan after the meeting along with consulting of previous research and literature and an updated plan was created. A second follow-up meeting was then held digitally where the participants were presented with the updated plan which they discussed and approved of from their ecological perspective. The standardized values were set based on the experts' knowledge of qualities that favor probability of nature values, and the weights were based on their estimations of each criteria's relative importance compared to the other criteria. The participants had general agreement on the resulting variable values set in the model.

3.3.2 Standardization

As is described in the background, there are different ways to standardize values in an MCA. A range score option was chosen for this study, specifically the approach named Range score option 2 in Table 2.2. This approach assigns scores as a whole number withing the range 0-5 based on the suitability of the criteria. Because borders of landscapes, ecosystems and habitats do not normally have distinct lines but rather fuzzy borders, and the fact that the magnitude of nature values in an area can vary, it is less desirable to use Boolean logic to standardize the input data in this study (Store & Kangas, 2001). A larger range could have been used which would have allowed for a more nuanced scoring but would also have risked a less consistent scoring due to vague score definitions (Dean, 2022). A range of 0-5 enables clearer and more consistent standardization. A '0' indicates no favorability for nature values, '3' indicates moderate favorability for nature values and '5' indicates very high favorability for nature values, see Table 3.3 below.

Table 3.3- Standardization of values

Standardized score	Description
0	No favorability
1	Very small favorability
2	Small favorability
3	Moderate favorability
4	High favorability
5	Very high favorability

The input data classes, and their scores were set with a participatory approach with the three experts. Firstly, the classes were defined for each score number based on the level of favorability a criterion could contribute to an area in relation to high nature values. Secondly, the attributes for each criterion were divided into sub-groups under each criterion to assign separate attributes standardized scores. Different soil types may have different levels of favorability for biodiversity, for example. A standardized score was assigned to each criterion sub-group based on the experts' knowledge and their combined judgements on how favorable each separate criteria attribute group is for biodiversity. The scores were first set in a preliminary draft and then adjusted after the experts' individual consideration and discussion. Table 3.4 shows the scores for each criterion and their attribute groups.

3.3.3 Weighting

Weights in an MCA determine the relative influence that each variable has in the analysis. For this study, weights were chosen between 0-1 where the sum of all the weights of the variables included is 1. As an MCA method which uses trade-off coefficients has been chosen for this project, it would be suitable to choose a weighting technique with compensatory qualities for this study (Greene et al, 2011). The weighting technique chosen is 'Point Allocation' as described in Table 2.3 which could be considered to have both non-compensatory qualities as well as some compensatory trade-off aspects since it allows relative importance while still limiting the effect of one low criteria (Dean, 2022). However, the weights in this study were set with relative importance to all other criteria, making the application consistent with trade-off coefficients which is a suitable combination with compensatory MCA methods according to Dean (2022).

Since the input data have been divided into two separate sub-categories, *Habitat variables* and *Pre-identified nature values*, there are two sets of weights. The first set includes both sub-categories and the second one only includes the *Habitat variables*. Both sets separately have a sum of 1 and are presented in Table 3.4. The weights were set in cooperation with the municipality ecologist and the two consultants. The weights were chosen based on the knowledge, estimations and discussions of the experts. The first draft of the weights was produced by the experts and analyst. The final weights were decided and agreed on by all participants after individual consideration and discussions of the first draft and are presented in Table 3.4 below.

Table 3.4 - Standardized values and weights of the input data.

Data name	**Data classes**	**Standardized values (0-5)**	**Weight Habitat variable: 50% Pre-identified nature values: 50%**	**Weight Habitat variable: 100%**
Slope raster	0-15	0	0.08	0.15
	15-30	1		
	30-45	3		
	45-90	5		
Aspect raster	North (337.5-22.5)	0	0.08	0.15
	Nort East (22.5-67.5)	0		
	East (67.5-112.5)	0		
	South East (112.5-157.5)	1		
	South (157.5-202.5)	2		
	South West (202.5-247.5)	1		
	West (247.5-292.5)	0		
	North West (292.5-337.5)	0		
Land use raster 2023 v 0.1	Open wetlands	5	0.08	0.15
	Arable land	1		
	Non-vegetated open land on solid ground	1		
	Vegetated open land on solid ground	1		
	Building	0		
	Constructed. not building or road/railway	0		
	Road or railroad	0		
	Inland water	5		
	Forest on solid ground	1		
	Temporarily non-forest on solid ground	0		
	Forest on wetland	3		
	Temporarily non-forest on wetland	1		
Soil type	Filling	0	0.08	0.15
	Glacial fine clay	0		
	Glacial clay	0		
	Glacial silt	0		
	Gyttja	2		
	Gyttja clay (or clay gyttja)	1		
	Ice river sediment	3		
	bog peat	4		
	Moraine	0		
	Moss peat	4		
	Postglacial fine sand	2		
	Postglacial rough clay	0		
	Postglacial clay	0		
	Postglacial sand	3		
	Postglacial silt	1		
	Sandy moraine	2		
	Swell-sediment. gravel	3		
	Flooding sediment. clay-silt	0		
	Flooding sediment. sand	4		
	Primary bedrock	2		

	Water	5		
	Other	0		
Distance to nearest gravel road	0-20 m	0	0.05	0.10
	20-100 m	1		
	100-200 m	1		
	200+ m	2		
Distance to nearest paved road	0-50 m	0	0.05	0.10
	50-100 m	1		
	100-200 m	1		
	200+ m	2		
Distance to nearest water stream	0-10 m	5	0.05	0.10
	10-50 m	3		
	50-100 m	1		
	100+ m	0		
Distance to nearest lake	0-10 m	5	0.05	0.10
	10-50 m	3		
	50-100 m	1		
	100+ m	0		
High conservation values forest	no data	0	0.04	-
	0-10	1		
	10-20	2		
	20-30	2		
	30-40	3		
	40-50	3		
	50-60	4		
	60-70	4		
	70-80	4		
	80-90	5		
	90-100	5		
Identified trees worthy of protection area	Yes	5	0.04	-
	No	0		
Hay meadow value element	Yes	5	0.04	-
	No	0		
Rich marsh	Yes	5	0.08	-
	No	0		
Trivial deciduous forest value cores	Yes	3	0.04	-
	No	0		
Deciduous forest analysis	Deciduous forest on moist land	4	0.02	-
	Deciduous forest. several types	2		
	Deciduous forest. areas from older surveys	2		
	Trivial deciduous forest	2		
	Trivial deciduous forest with features of broad leaf trees	3		
	Broad leaf trees	3		
	Meadow- and pastureland. 9070	5		
	Nothing	0		
Mixed forest value cores	Yes	3	0.04	-
	No	0		
Broad leaf forest value cores	Yes	5	0.04	-
	No	0		
Coniferous forest value cores	Yes	4	0.04	-
	No	0		
	Support habitat	2	0.04	-

Valuable grassland 2022	Value core	4		
	None	0		
Valuable grassland 2018	Support habitat	2	0.04	-
	Value core	4		
	None	0		
Historic wetlands from 1800	Lake	3	0.02	-
	fen land	2		
	fen meadow	3		
	None	0		
Historic wetlands from soil type data	Yes	2	0.02	-
	No	0		

3.3.4 Calculating the suitability score

As previously mentioned, WLC is the chosen MCA method for this study. The last step of the WLC MCA is calculating the combined score using the standardized scores and weights of each criterion. Equation 1 defines the formula associated with the WLC method. *n* represents the total number of criteria used in the MCA, *i* represents the criterion being evaluated, p_i is the standardized score of criterion *i* and w_i is the weight of criterion *i*.

$$Suitability\ score = \sum_{i=1}^{n} p_i w_i \tag{1}$$

The combined score of each cell is presented in a new raster file which is visualized in a map. The suitability score is categorized into groups of potential of nature values for easier interpretation of the result into the values presented in Table 3.5. The ranges were set in cooperation with the experts by reviewing the results together with local knowledge of known areas with low and high nature values respectively.

As explained previously, the analysis will be performed in two separate iterations, one where only the *Habitat variables* are included and one where both *Habitat variables* and *Pre-identified nature values* are included. The weights of the input data are different for these two iterations as Table 3.4 shows. However, the formula for the suitability score in Equation 1 and the ranges classifying the potential for nature values in Table 3.5 are the same in both iterations to enable comparison between them. The value breaks were chosen as *a posteriori* based on the quantile classification method in the GIS and rounded off to even numbers for simpler interpretation. While it is generally preferable to choose these classes a priori, these classes do not represent true biological threshold, but rather estimated potential for nature values. Furthermore, this approach also allows for easier readability of the results.

Table 3.5-The value ranges of the combined score classes of the MCA.

Suitability score range	**Potential of nature values**
0.0 – 0.4	Low
0.4 – 0.6	Moderate
0.6 – 0.8	High
0.8 +	Very high

3.4 Validation

There are several assumptions, estimations and uncertainties in an MCA analysis. Therefore, it is useful to validate the model in some way. The validation methods chosen in this study are model validation and sensitivity analysis which both provide different aspects that can elevate the quality and confidence in the MCA model and its results. Both methods are described further below.

3.4.1 Model validation test

Visual and quantitative model validation approaches were chosen to test the validity of the MCA results, the level of agreement with validation data. This is done by comparing the MCA results to a validation dataset. The validation dataset has been produced with the same goal and data as the MCA results, but with a completely different method than the MCA. These validation data were produced through manual and visual analysis and classification of data by the same experts that participated in the MCA. This means that the validation data are not independent which normally would cause issues in a validation process. However, this study aims at creating a model that can replicate the manual methods of identifying areas with high nature values by estimating the potential for nature values. Therefore, it is more suitable with an internal validation approach to estimate how well the model can perform the same tasks that are currently done by manual analysis, which would make the process much more resource efficient.

The validation data contains polygons which have been classified according to SIS standards (2023) where all classes indicate some level of nature value. Therefore, the areas from these data will only be presented as polygons without displaying their different standard classes. This is because all identified areas have some level of nature value and will be considered corresponding classes to the MCA result classes 'High potential of nature values and 'Very high potential of nature values'. It tests the MCA model performance in comparison to the established method used for nature conservation plans in the municipality. The degree of agreement between the MCA results and the validation data will be measured quantitatively by evaluating the number of cells of the MCA results which falls withing the polygon areas from the validation data as proportions. There should be a large proportion of cells classified with ‘High’ or ‘Very high potential for nature values’ to indicate that the results of the MCA are consistent with the validation data. At least 75% of the cells should be classified as ‘High’ or ‘Very high potential of high nature values’ to be acceptable. This threshold was set to include a majority while also allowing for some error, in the context of the study aim and purpose it is considered a reasonable acceptance limit.

3.4.2 Sensitivity Analysis

Sensitivity analysis of an MCA examines how results change when MCA parameters are systematically varied. A weight sensitivity technique has been chosen for this study because the experts expressed larger uncertainty in their estimations of the weights. Therefore, it is useful to test how changes in these affect the results. A non-probabilistic approach was applied in the sensitivity analysis as the uncertainties of the weights are unknown; this means changing the weight of each criterion a set number in both positive and negative direction while the other criteria are rebalanced to still have the same sum when added together (Chen et al., 2010). An important clarification to make is that the weight sensitivity analysis was performed on groups of criteria instead of separate criterion this study, similar to how Store & Kangas (2001) did in their case study of habitat suitability. This means that slope and aspect were grouped as well as both historic wetlands criteria for example. The reasoning behind this comes from the method with which the weights were assigned in the MCA. The experts assigned each group of criteria a weight before splitting it into the separate criterion. Therefore, it will make the result easier to interpret and will be more consistent with the experts’ original weight estimation to perform the sensitivity analysis on the grouped weights. The groups and their weights are presented in Table 3.6 below. If the result of the sensitivity analysis indicates robustness issues in any of the groups, it is possible to then perform the sensitivity analysis on the separate criteria in that group to discern which criterion or criteria in the group that are causing disruption in the robustness separately. This approach can save time and storage.

Weights were changed by ±20% for each criteria group and iteration. This percentage is standard for this application when the exact uncertainty is unknown (Chen et al., 2010), (Zajac et al, 2015). The weight uncertainties will be considered acceptable for a criteria group if the class proportions are not affected more than ±5% per class as it is a relatively small change that can be considered acceptable for the purposes of a nature conservation plan. For the most sensitive criteria, the results are also mapped to visualize the effect that the changes in weight effect the MCA results.

Table 3.6 - Sensitivity analysis groups and original group weights.

Group	**Data**	**Original weights**	**Group weights**
DEM	Slope	0.075	0.150
	Aspect	0.075	
Land use	Land use	0.075	0.075
Soil	Soil	0.075	0.075
Distance to roads	Distance to the nearest gravel road	0.050	0.100
	Distance to the nearest paved road	0.050	
Distance to water	Distance to nearest water stream	0.050	0.100
	Distance to nearest lake	0.050	
High conservation values forest	High conservation values forest	0.040	0.040
Valuable trees	Identified trees worthy of protection area	0.040	0.040
Hay meadow	Hay meadow value element	0.040	0.040
Rich marsh	Rich marsh	0.080	0.080
Deciduous forest analysis	Deciduous forest analysis	0.020	0.020
Forest value cores	Trivial deciduous forest value cores	0.040	0.160
	Mixed forest value cores	0.040	
	Broad leaf forest value cores	0.040	
	Coniferous forest value cores	0.040	
Valuable grassland	Valuable grassland 2022	0.040	0.080
	Valuable grassland 2018	0.040	
Historic wetlands	Historic wetlands from 1800	0.020	0.040
	Historic wetlands from soil type data	0.020	

4. Results

4.1 MCA

The results of the MCA model are presented in this section, both for the version only using the *Habitat variables* sub-group and the iteration using both *Habitat variables* and *Pre-identified nature values* as input. Both versions are presented in maps as well as the proportions of classes on a combined table towards the end. Possible reasons for the findings in this section are presented and discussed in the Discussion section.

4.1.1 Habitat variables

In general, most areas are classified as having ‘Low’ or ‘Moderate potential for nature values’ while a minority are classified as having ‘High’ or ‘Very high potential for nature values’. The pattern varies overall with both ‘High’ and ‘Low potential value’ classes throughout the study area as Figure 4.1 shows. Areas of ‘Low potential’ areas along the Göta älv river running vertically through the municipality. The river itself is classified as ‘Very high potential for nature values’ creating an abrupt division from the ‘Low potential’ areas surrounding it. The larger areas with ‘Very high potential for nature values’ are generally located along the outskirts of the municipality area. The main urban areas are located along the Göta älv river, coinciding with areas classified as ‘Low potential of nature values’. Most of the larger forests and lakes in the municipality are located further away from the river, these generally coincide with areas classified as ‘High’ and ‘Very high potential’ along the outskirts of the municipality. This is also where the greatest variation of classes occurs, in contrast to the somewhat homogenous distribution of ‘Low potential’ areas closer to the river. There are no clear smaller ‘Low potential’ areas as the concentrated area along the river is more continuous. However, there are a few clear areas with ‘Very high nature values’, these include the lake Öresjö on the north border of the municipality and the lake Vanderydsvattnet on the east municipality border.

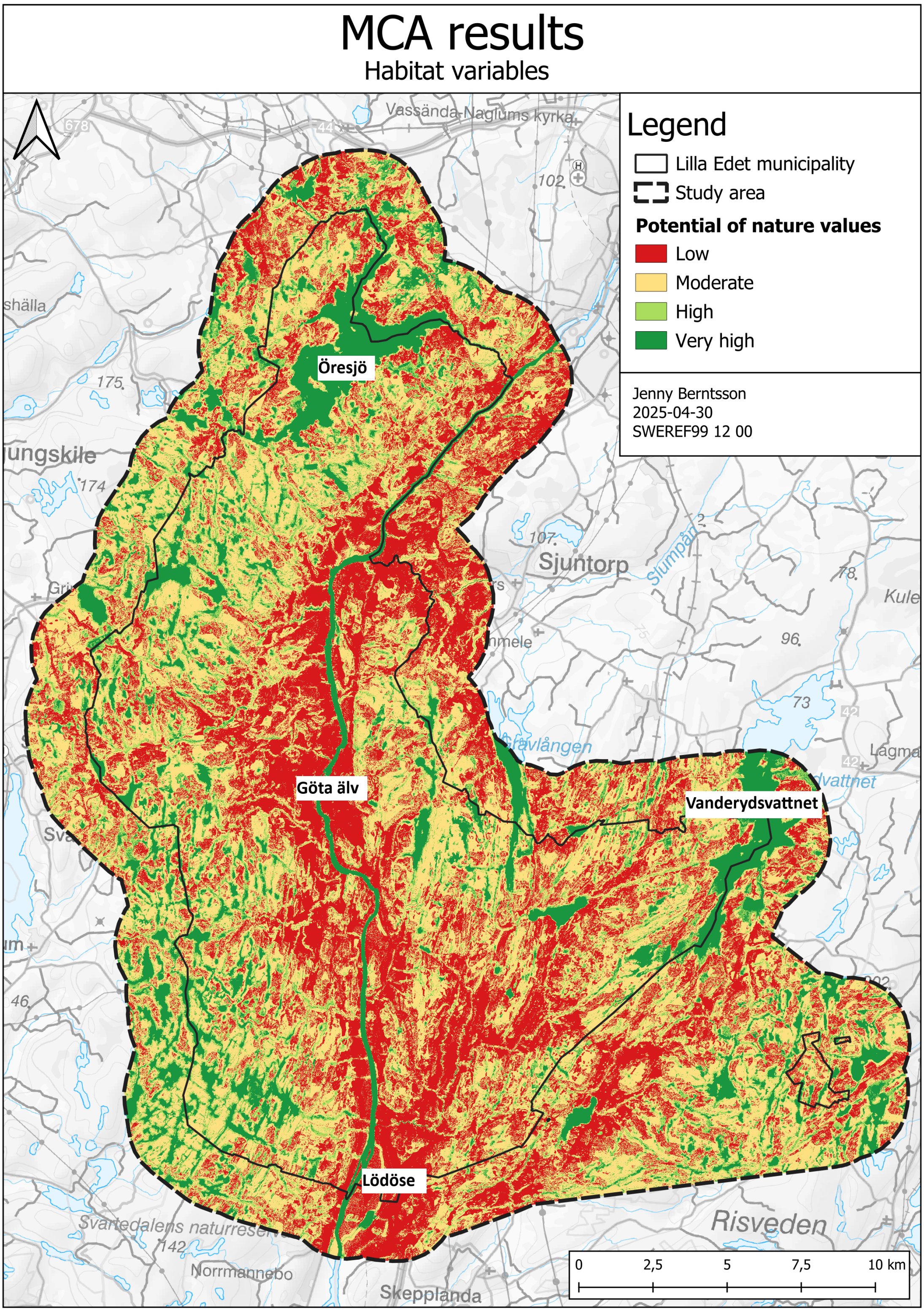

Figure 4.1 - Map result of the MCA using only the Habitat variables sub-group as input. The map shows a domination of the low and moderate potential class while High and Very high potential classes are present mainly in lakes and forests.

4.1.2 Habitat variables and Pre-identified nature values

Overall, it seems like the class ‘Moderate potential for nature values’ is the dominant class followed by the ‘Very high potential’ class. Figure 4.2 shows the results of the MCA using all criteria, both *Habitat variables* and *Pre-identified nature values* from Table 3.4. The calculated suitability scores are presented as classes of potential for nature values as specified in Table 3.5. The general pattern is more variable along the outskirts of the study area with a concentration of ‘Low potential’ areas near the Göta älv river. The river itself is classified as ‘Very high potential’ in stark contrast to the ‘Low potential’ areas in the nearby surroundings. Otherwise, there is generally a smooth transition between areas classified with ‘Low’ and ‘Very high potential for nature values’.

The urban areas in the municipality coincide with ‘Low potential areas’ while lakes and larger forests generally coincide with ‘Very high’ or ‘High potential’ classed areas further away from the river along the outskirts of the study area. Clusters of ‘Low potential’ areas are present in the central urban area located in the center of the municipality along the river. Furthermore, Lödöse is another large urban area in the south border of the municipality where there is a concentrated area of ‘Low potential for nature values’. Concentrated areas of ‘Very high potential’ areas include the largest lake in the municipality Öresjö and a larger lake named Vanderydsvattnet on the east municipality border. Another location for both ‘High’ and ‘Very high potential’ areas is the forest on the south-west edge of the study area.

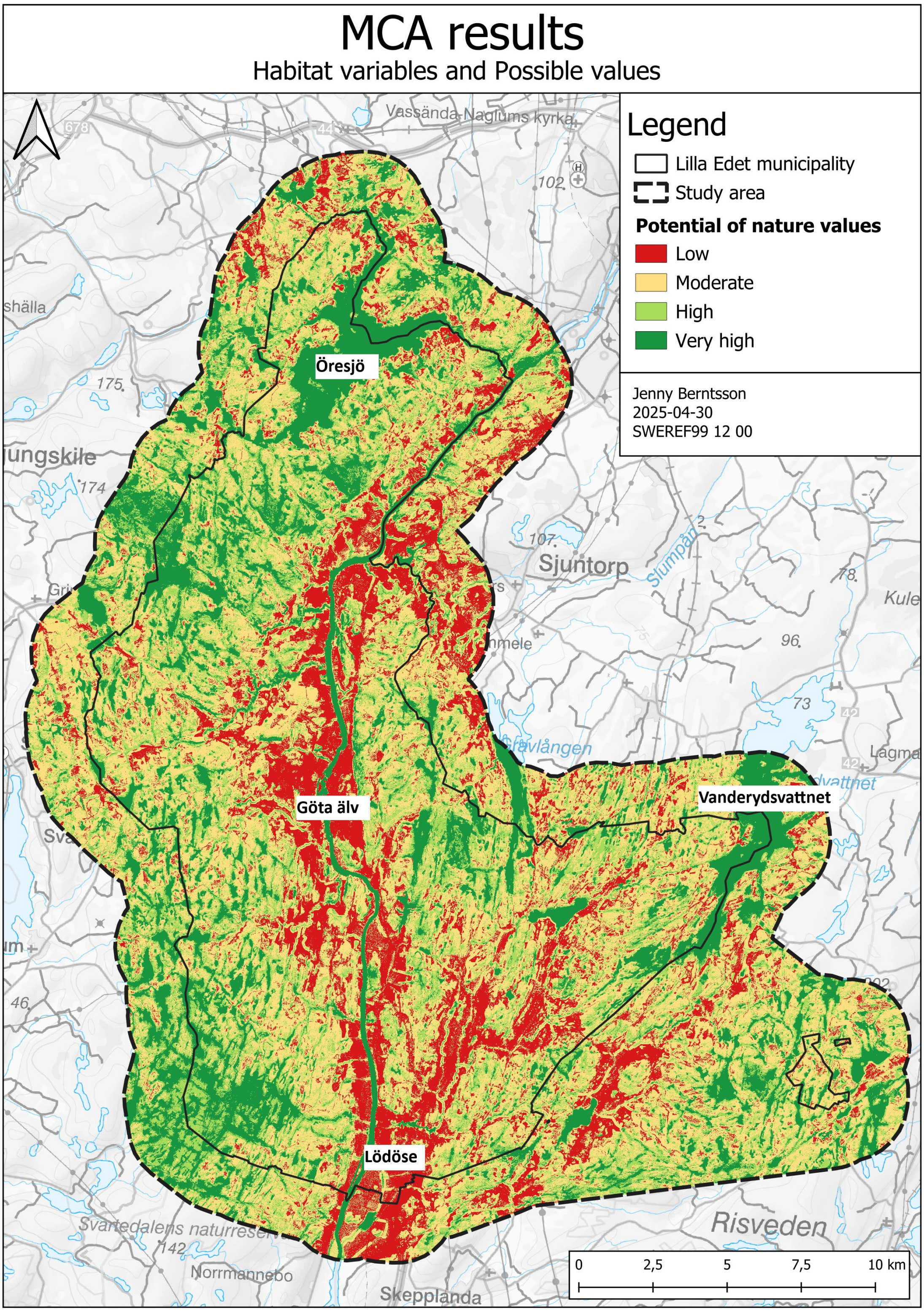

Figure 4.2 - Map results of the MCA using both sub-groups Habitat variables and Pre-identified nature values. There is generally a balance of the potential for nature value classes but the very high potential classes coincide with water bodies and lakes while low potential classes coincide with mainly urban areas.

Overall, it seems like the iteration using both sub-classes of input data in the MCA identifies more potential for nature values than the iteration using only *Habitat* *variables*. It is of interest to compare the two iterations of the MCA with each other; this can be done by looking at the proportions of the various result classes to see how differently they identify potential of nature values. Table 4.1 below shows the proportions for the two iterations and how they compare to each other. There is an increase in the 'High' and 'Very high potential for nature values' classes and consequently a decrease in the number of cells classified with a 'Low' or 'Moderate potential of nature values' when the MCA includes the *Pre-identified nature values*. This is consistent with the general observations in the respective maps. Adding the *Pre-identified nature values* criteria identify more concentrations of 'High' or 'Very high potential of nature values' areas.

Table 4.1 - Proportions of potential nature value classes for both iterations of the MCA.

	Proportion (%)	
Potential of nature values	**MCA using only Habitat variable data**	**MCA using both Habitat variable data and Pre-identified nature values data**
Low (0.0-0.4)	32	17
Moderate (0.4-0.6)	41	38
High (0.6-0.8)	13	24
Very high (0.8-2.1)	14	21

4.2 Model validation

4.2.1 MCA using only Habitat variables

Most larger areas in the validation data are consistent with the results from the MCA results using only *Habitat variables* in the qualitative, visual part of the analysis. The results of this MCA are presented in Figure 4.3 together with the validation data areas which are outlined in the map. These areas have all been classified as 1, 2 or 3 in the manual process according to SIS standards which implies that all areas in the validation data contain high nature values (SIS, 2023). Therefore, it is only their outlines and not their original classifications which are presented on the map. Instead, the results classes of the MCA can be seen within these areas to enable visual interpretation of how well the MCA has identified the potential for high or very high nature values within these areas. In general, the largest areas of high nature values in the validation data have been identified in the MCA results as areas with the classes 'High' or 'Very high nature potential'. However, there are also many smaller areas in the validation data that have been consistently classified as having 'Low potential' in the MCA results. Furthermore, there are several smaller areas in the MCA results with 'Very high' nature value potential which have not been identified at all in the validation data.

The model seems to match well with the validation data in the larger areas such as Öresjö in the north and Vanderydsvattnet in the east have been correctly identified by the MCA model as having 'High' or 'Very high potential'. The same can be said for Göta älv river which is also clearly identified with 'Very high potential' in the MCA. All these larger areas also have roughly the same spatial extent in the MCA results and the validation data.

An area where the MCA doesn't perform as well is the forest in the south-east where the MCA has correctly identified some parts of the area with 'Very high potential' but has also classified large parts as 'Moderate potential'. Areas in the validation data located nearby the Göta älv river are seemingly mis-classified in the MCA. Their spatial extent falls within larger areas classified with 'Low potential' in the MCA. There are also areas classified with 'Very high potential' in the MCA, but those have not been identified in the validation data and are mainly located along the outskirts of the study area.

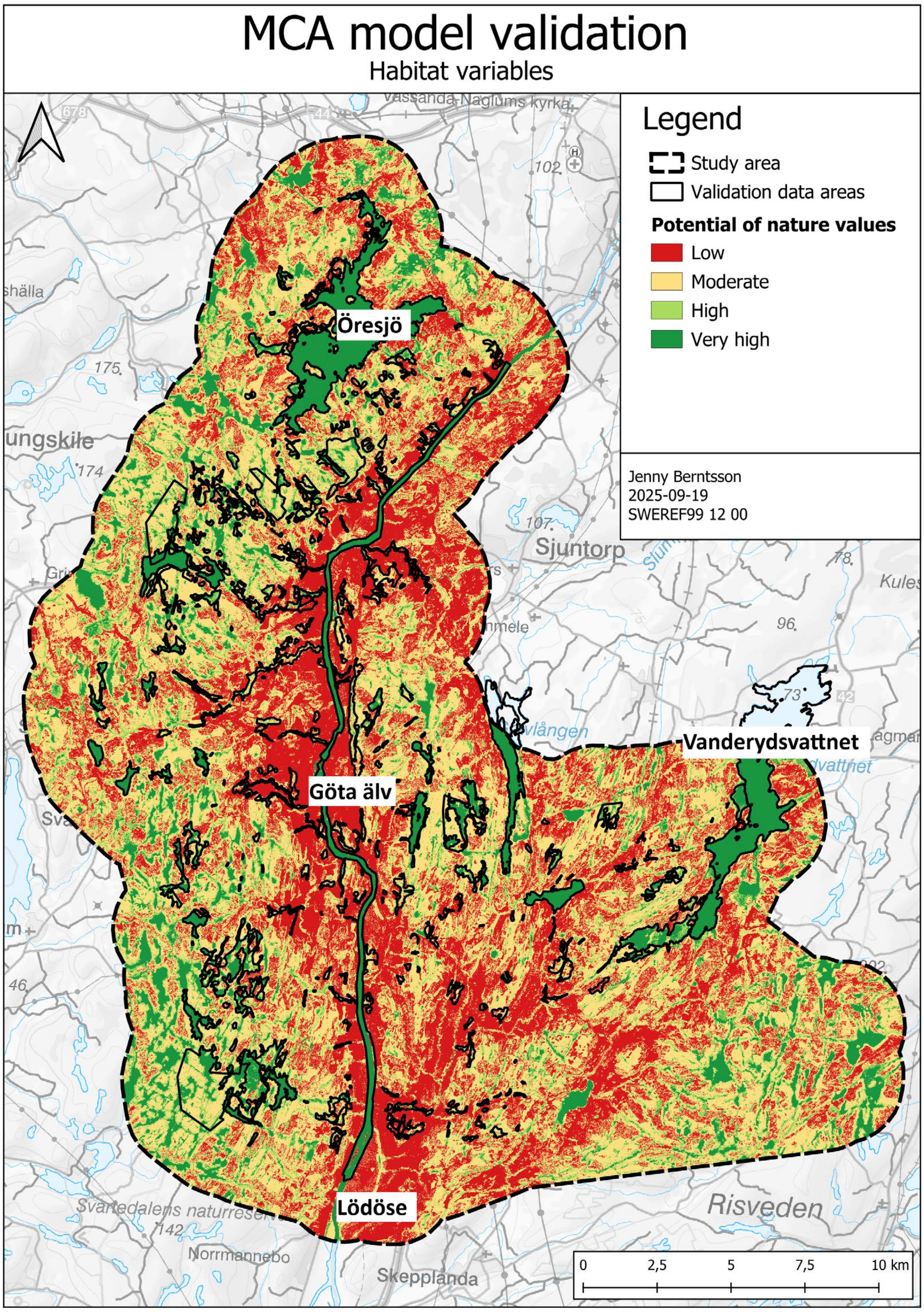

Figure 4.3 - Map showing the result of the MCA analysis using Habitat variables under the black polygon lines outlining the areas identified in the validation data. The classifications from the MCA results can be seen through the validation data polygons. Most larger validation areas are classified with very high potential but a few are classified with low or moderate potential.

The quantitative agreement part of the validation analysis shows the proportions of the MCA result classes within the validation data areas where the largest proportions are found in the 'High' and 'Very high potential of nature values' classes. Table 4.2 describes the proportion of the MCA result classes within the areas identified in the validation data.

Table 4.2 - Proportion of potential for nature value classes from the model validation test of the iteration including Habitat variables.

Potential of nature values	Proportion (%)
Low (0.0-0.4)	8
Moderate (0.4-0.6)	24
High (0.6-0.8)	14
Very high (0.8+)	55

However, the table does not provide any insight into areas outside the identified areas in the validation data which the MCA has classified with 'Very high potential'. The table shows that the MCA has classified 69% of the cells within the validation data polygons as having 'High' or 'Very high potential'. This is less than the set threshold of 75%.

4.2.2 MCA using both sub-categories

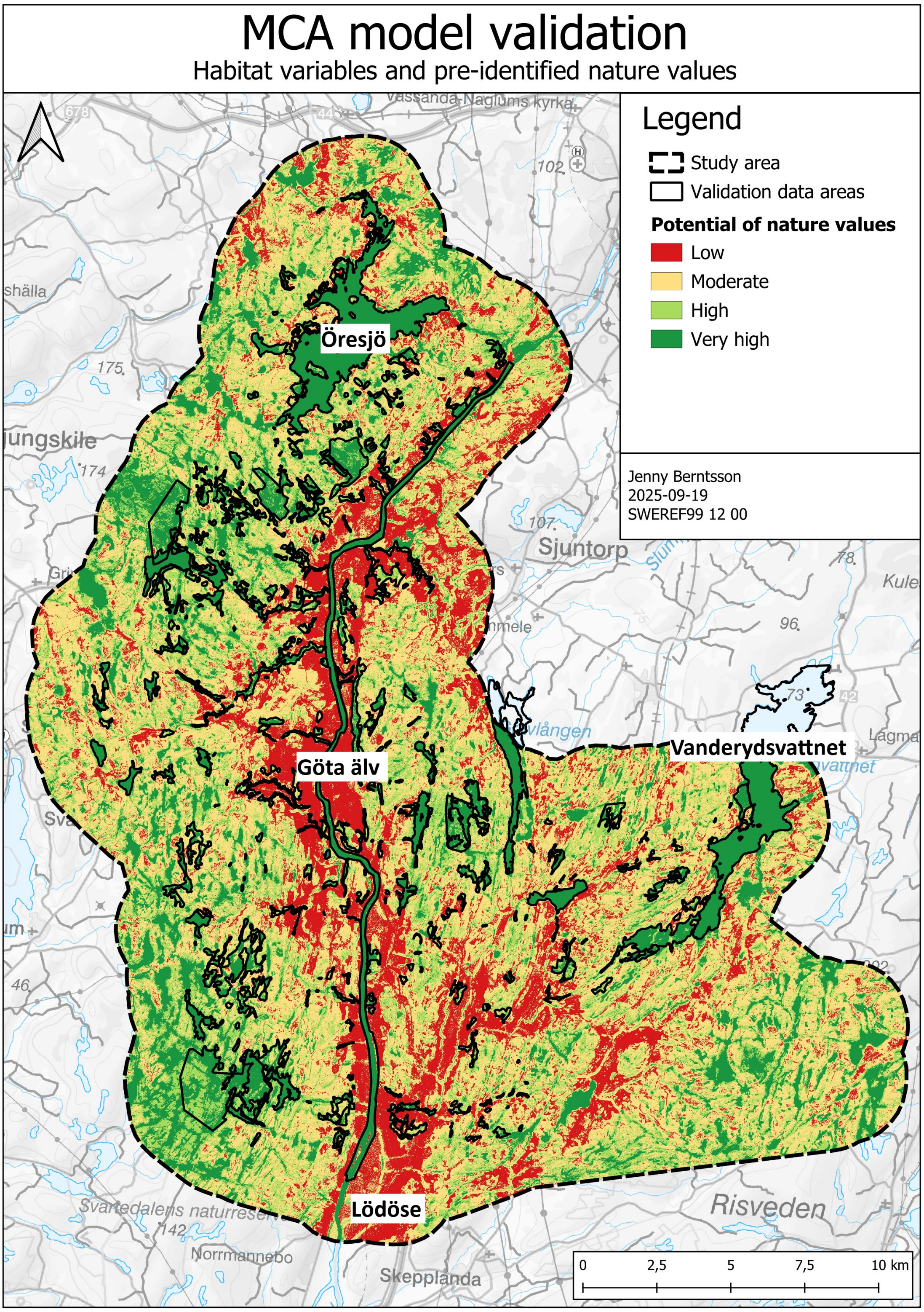

Figure 4.4 - Map showing the result of the MCA analysis using all variables under the black polygon lines outlining the areas identified in the validation data. The classifications from the MCA results can be seen through the validation data polygons. Most validation areas are mainly classified with very high potential while a small number are classified with low potential.

Overall, most areas from the validation data have been accurately classified with 'High' or 'Very high potential of nature values' in the MCA results. The results of the MCA using all criteria, both *Habitat variables* and *Pre-identified values* are presented in Figure 4.4 together with the validation data which are outlined in the map and represent validation areas where high nature values have been found in the manual analysis. The result classes of the MCA can be seen within these validation data areas so that it is possible to visually interpret if the MCA model accurately classified these areas with 'High' or 'Very high potential for nature values'. While most areas in the validation data agree with the results from the MCA, a few areas have been inconsistently classified with 'Low potential' in the MCA but are identified with 'High nature values' in the validation data, specifically two larger areas near Göta älv in the center and north part of the municipality. Furthermore, there are areas classified with 'High' or 'Very high potential for nature values' in the MCA which have not been identified in the validation data, especially in the outer edges of the study area.

The MCA model classifies areas such as Öresjö in the north, Vanderydsvattnet in the east, the forest in the south-west and Göta älv river with 'High' or 'Very high potential for nature values'. These areas generally have similar spatial extents except for the forest in the south-west. The area in the validation data has a much smaller spatial extent than what the results of the MCA show.

There are a few areas near the Göta älv river where the MCA results do not conform with the validation data areas. These cover parts of the larger areas in the MCA classified with 'Low potential' and are scattered along the river from north to south.

The quantitative part of the validation analysis shows the proportions of the MCA result classes within the validation data areas where the largest proportions are found in the 'High' and 'Very high potential of nature values' classes. Table 4.3 describes the proportion of the MCA result classes within the areas identified in the validation data.

Table 4.3 - Proportion of potential for nature value classes from the model validation test of the iteration including both Habitat variables and Pre-identified areas with high nature value.

Potential of nature values	Proportion (%)
Low (0.0-0.4)	2
Moderate (0.4-0.6)	7
High (0.6-0.8)	17
Very high (0.8+)	75

However, the table does not provide any insight into areas classified with 'Very high nature potential' in the MCA that goes beyond the borders of the spatial extent of the areas in the validation data. The table shows that the MCA has classified 92% of the cells within the validation data areas with 'High' or 'Very high potential'.

4.3 Sensitivity analysis

Generally, the changes in the weights have not had a large effect on the resulting proportion of classes. The criteria groups “Soil”, “Distance to roads” and “Forest value cores” had the largest impact on the result which is why these are presented spatially in Figures 4.4 – 4.6 below. The value thresholds of the classes describing the difference in the result between the original MCA and the result from the sensitivity analysis is shown in Table 4.4.

Table 4.4 - Classes of change to describe how the result of the MCA changed in the sensitivity analysis. The values represent the difference between the original MCA results and the sensitivity analysis results.

Value range	Class name
<= -0.1	Large negative change
-0.1 - -0.05	Slight negative change
-0.05 – 0.05	Very small change
0.05 – 0.1	Slight positive change
>0.1	Large positive change

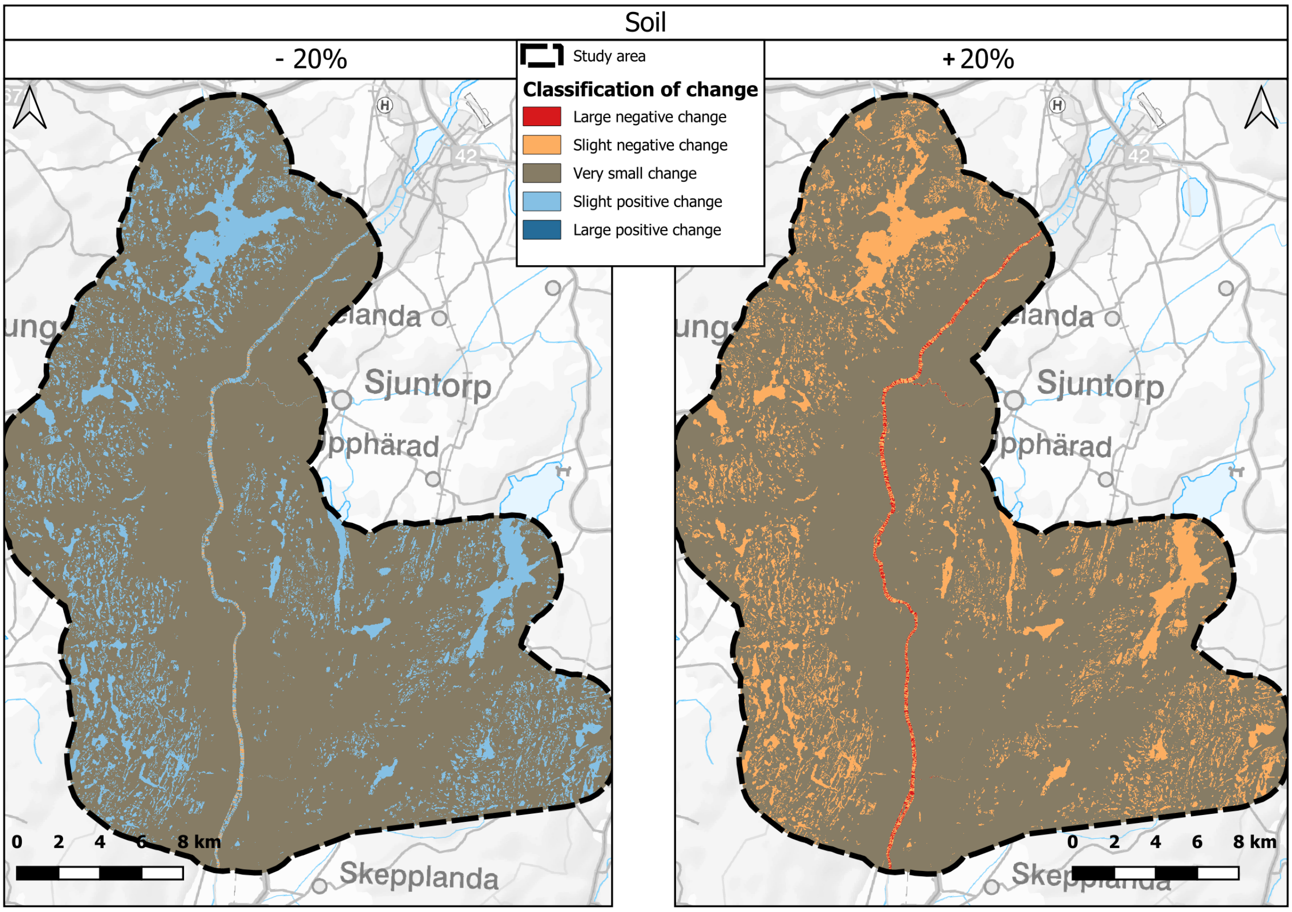

Figure 4.4 – Map showing the spatial distribution of change between the original MCA result values and the results from the sensitivity analysis for the Soil criteria group.

The general change seems to be mostly very small, slightly positive when decreasing the weight and slightly negative when increasing the weight of the "Soil" criteria group. There is also an overall negative change in the main river. Figure 4.4 shows that the areas with slight changes on both sides coincide with lakes in the municipality. The "Soil" data contain a water attribute which seems to be more sensitive to changes in weight than other soil data classes. The main river has a mix of slightly negative changes and slightly positive changes when decreasing weight, going against the general pattern of mainly positive changes. When increasing weight, the negative change is even stronger in the main river area.

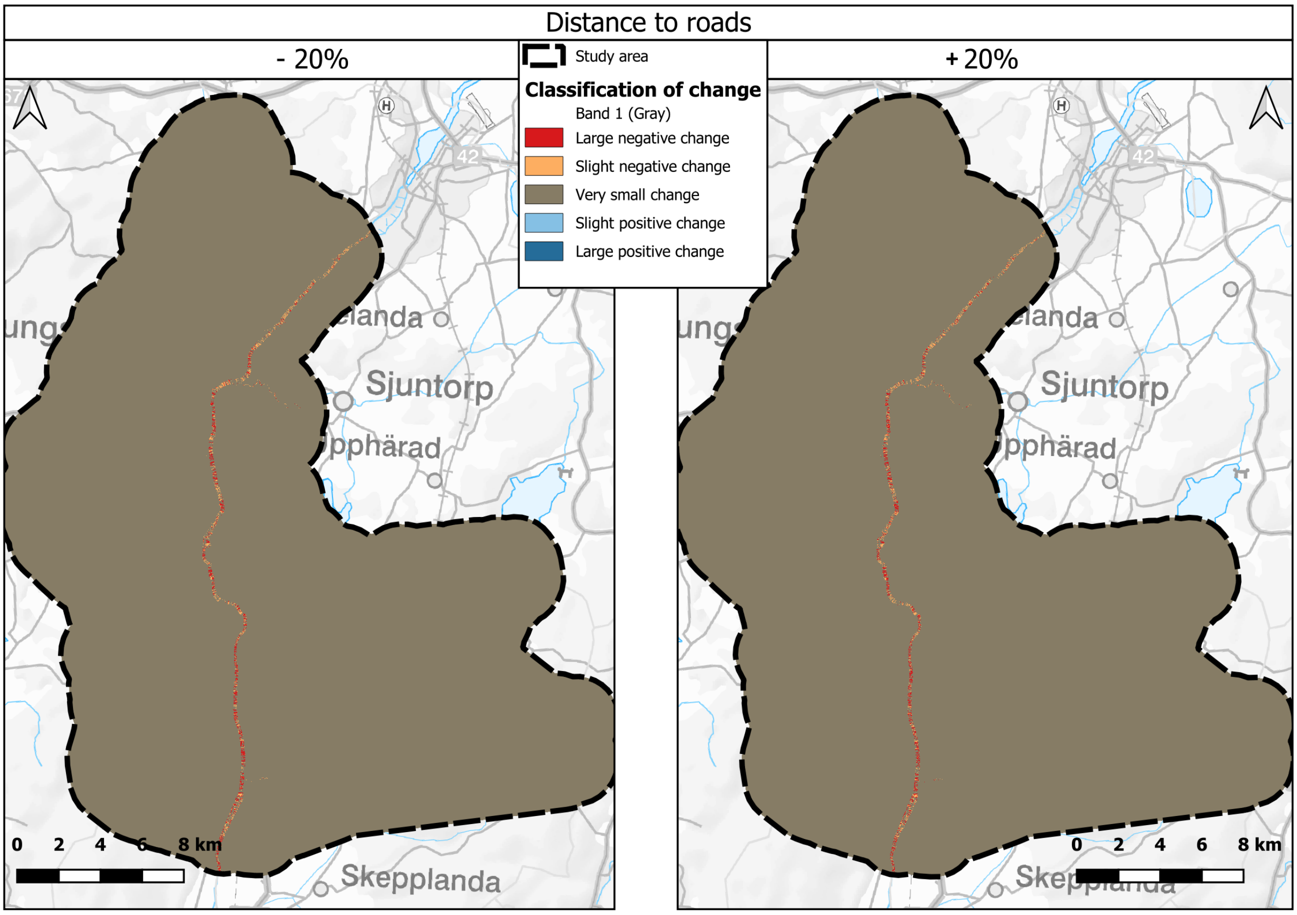

Figure 4.5 - Map showing the spatial distribution of change between the original MCA result values and the results from the sensitivity analysis for the Distance to roads criteria group.

The effect of the sensitivity analysis for the criteria group "Distance to roads" is very small overall with negative change in the main river. Figure 4.5 reveals that the criteria group "Distance to roads" is mostly not very sensitive to change except for the main river. The river has a mix of slight and large negative changes when both decreasing and increasing weight.

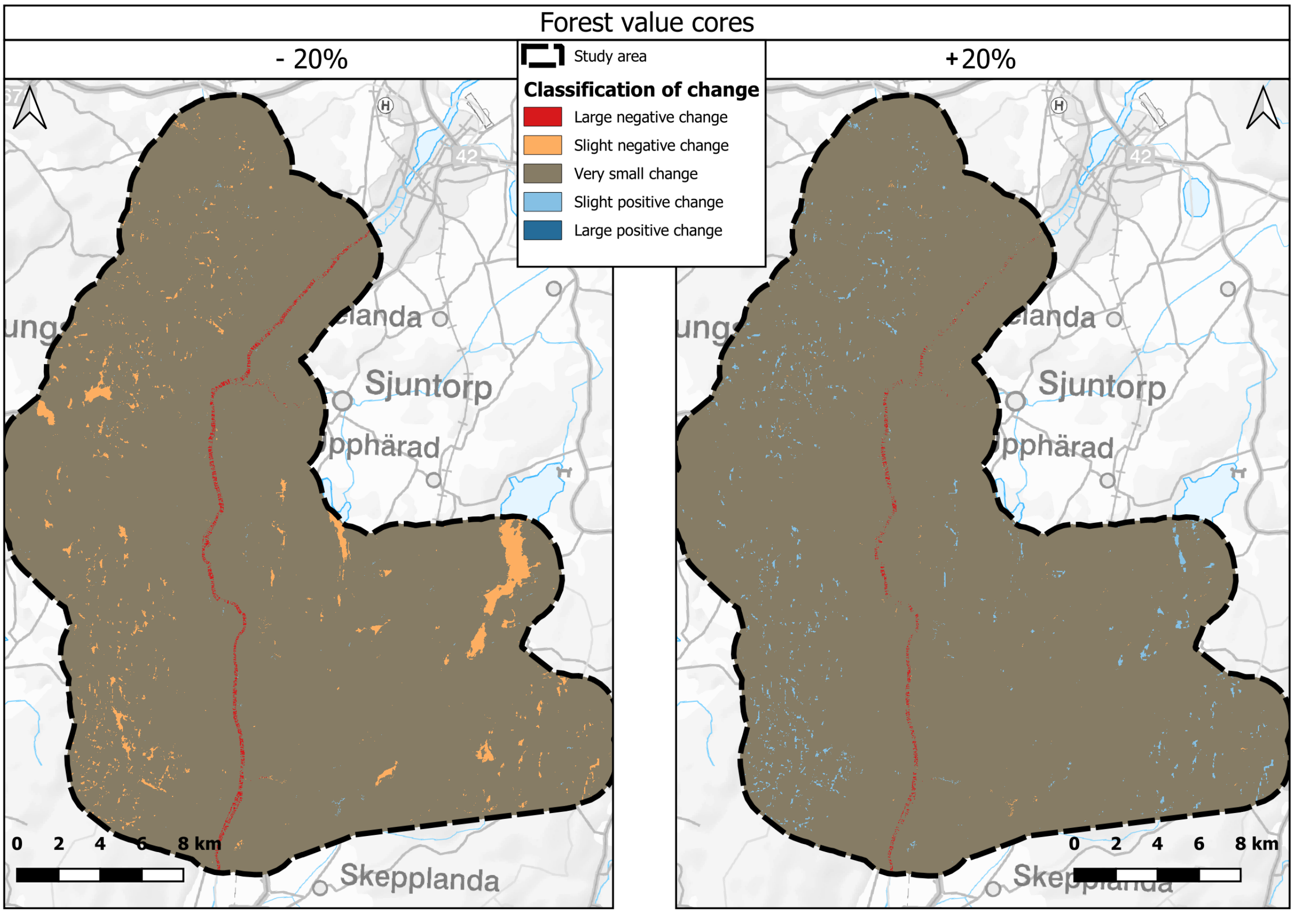

Figure 4.6 - Map showing the spatial distribution of change between the original MCA result values and the results from the sensitivity analysis for the Forest value cores criteria group.

Overall, change is very small, decreasing the weight of the "Forest value cores" criteria group causes a slight negative result while increasing the weight has a slight positive change. However, the main river contains large negative changes. Figure 4.6 shows that the areas with slight negative change when decreasing weight have a scattered pattern with slight coincidence with some water bodies. The areas with slight positive change in the map where the weight is increased are even smaller and more scattered. The only clear pattern on both maps is the large negative change occurring in the main river.

General proportions of MCA result classes in the whole study area for each criteria group only change with a few percentages. As stated earlier, the largest changes can be seen in the "Soil", "Distance to roads" and "Forest value cores" criteria groups. Results from the sensitivity analysis performed on the version of the MCA using all criteria are presented in Table 4.5. The result is presented in a table showing the proportion of the resulting suitability score classes for each iteration of the sensitivity analysis. This shows how much the weight change of each criteria group affected the MCA result classes. The proportion of each iteration can be compared to the original run of the MCA to reveal how sensitive each criterion is to changes in weight estimations. The largest differences have been marked blue in the result table. For the most sensitive criteria, the results are also mapped to visualize the effect that the changes in weight effect the MCA results.

Most criteria groups only affect the resulting proportions by 1-2% while a few groups affect the proportions by up to 4%. Three of these criteria groups have more than one blue-colored cell in the table, indicating that it had the largest effect out of all criteria groups in more than one result class. These three criteria groups are “Soil”, “Distance to roads” and “Forest value cores”. It should be noted that Table 4.4 only shows how the general proportions change and does not provide any insight into the spatial changes, this is why Figures 4.4-4.6 are presented above.

Table 4.5 - Proportion of all raster cells in the entire study area and how these proportions change for each run of the MCA in the sensitivity analysis. The weights for each criteria class were adjusted for each run where one criteria at a time is changed by ±20% and the remaining criteria groups were adjusted accordingly to still have a sum of 1 since the MCA method is compensatory. This means that if one weight is adjusted, the other weights must also be adjusted to compensate. The numbers represent the change in classification across the entire study area and have been rounded and the highest difference from the original MCA for each class has been marked with blue.The criteria groups Soil, Distance to roads and Forest value cores clearly have the most blue markings, indicating that these are the most sensitive criteria groups.

	Proportion (%)														
		DEM		Land use		Soil		Distance to roads		Distance to water		HCVF		Valuable trees	
Potential nature values	Original weights	-20%	+20%	-20%	+20%	-20%	+20%	-20%	+20%	-20%	+20%	-20%	+20%	-20%	+20%
Low (0.0-0.4)	17	16	18	18	16	20	16	21	15	17	18	18	17	17	17
Moderate (0.4-0.6)	38	37	38	39	38	39	35	38	36	38	38	39	35	38	38
High (0.6-0.8)	24	25	23	23	24	21	26	20	27	23	23	22	25	23	24
Very high (0.8+)	21	22	21	21	22	19	24	20	23	21	21	20	23	22	21

	Proportion (%)												
		Hay meadow		Rich marsh		Deciduous forest analysis		Forest value cores		Valuable grassland		Historic wetlands	
Potential nature values	Original weights	-20%	+20%	-20%	+20%	-20%	+20%	-20%	+20%	-20%	+20%	-20%	+20%
Low (0.0-0.4)	17	17	17	17	18	17	17	15	21	17	18	17	17
Moderate (0.4-0.6)	38	37	38	37	39	38	38	35	38	37	39	38	38
High (0.6-0.8)	24	24	24	24	23	24	24	27	21	24	23	23	24
Very high (0.8+)	21	22	21	22	20	21	21	23	20	22	20	22	21

Conclusively, as the largest difference observed in the proportions was 4%, this is within the acceptable range of ±5% chosen for this model.

5. Discussion

This study applies GIS-based MCA in nature conservation planning in cooperation with Lilla Edet municipality which is the study area. The methods, results and uncertainties associated with these are discussed below.

5.1 MCA

The MCA method chosen for this study is a weighted linear multicriteria analysis (WLC) where standardized scores and weights are combined in a linear equation to produce the resulting score. The resulting score represents the potential for nature values. The process of assigning standardized scores and weights to the criteria was done with a participatory approach using the range score technique and the Point allocation technique respectively as described in Table 2.2 and 2.3. The MCA aims at filling the gap of an early-stage analysis tool in nature conservation planning which targets biodiversity in general. As Quereshi et al. (1999) points out, MCA models are by nature simplified representations of reality which can be very useful. However, the tradeoff is that they also carry the risk of potentially large uncertainties. This is discussed further in section 5.4.

The standardized scoring technique used in this study is less nuanced and simpler than the weighting technique used as the first is a whole number between 1-5 while the second is a decimal number between 0-1. Therefore, the participating experts found the standardization process easier to perform as it could be based on existing data about how different aspects affect biodiversity and there were relatively few scores to choose from. On the other hand, they found the weighting process more difficult as the weight of an aspect in biodiversity is harder to define in such a nuanced range of values. Although, Dean (2021) found in his study that using a simple 3 level weighting system was too narrow and suggest using a more nuanced system such as 0-100 as it was likely to produce better results. Therefore, it could be argued that the chosen technique in this study is suitable for its context, especially as there were several rounds of edits of the weights together with the experts before they were decided.

Overall, most areas are classified with ‘Low’ or ‘Moderate potential for nature values’ in the first iteration presented in section 4.1.1. Adding the Potential for nature values sub-group in the second iteration causes a general increase in potential for nature values which is clearly visible when comparing Figures 4.1-4.2 in section 4.1.2. The spatial pattern of the result is mostly expected as lakes and forests generally have high potential for nature values and biodiversity (Naturvårdsverket, 2025). Furthermore, urban areas are known to have less potential for nature values, however, there seem to be other factors causing large areas outside of urban areas to also be classified with low potential for nature values. For example, the criteria distance to roads and/or “Slope” or “Aspect” could cause this effect because ‘Low’ areas somewhat coincide with the network of roads which is generally clustered around urban areas and the fact that the criteria “Distance to roads” have scores and weights affecting the potential for nature values negatively in the MCA. Secondly, the results of the MCA using both sub-categories including *Pre-identified nature values* show a more even balance in the proportions of the results in general, as confirmed in Table 4.1. The large forests and lakes which were classified with higher potential for nature values in the first iteration expanded spatially while areas classified with lower potential for nature values have shrunk. ‘Low potential for nature values’ classified areas more clearly coincides with urban areas and somewhat with roads which strengthen the postulation that the “Distance to roads” criterion affects the spatial pattern of these values. The expansion of areas classified with ‘High’ or ‘Very high potential for nature values’ is an expected result due to the nature of ecosystem and habitat borders being generally fuzzy and not strict boundaries. The results of the MCA do not claim to identify where high nature value areas are located, but rather to estimate the potential for such areas. This is an important point to keep in mind when looking at or using these results. It also explains why the classes of areas are not completely homogenous but rather vary throughout the study area which allows for identification of concentrated areas rather than clearly outlined areas of interest. The results can serve as an early-stage indication of where to focus resources in nature conservation planning or possibly other general planning processes at a municipal level like the one created by Donoso & Kjellström (2023). As they also state, their MCA model could be used to motivate deeper investigations into certain areas, similar to how the MCA model in this study could provide more efficient planning of resources in planning projects.

5.2 Model validation

As explained in section 3.4.1 the chosen validation method is an internal visual and quantitative testing of model validation by comparing the MCA results to validation data. This is considered an internal validation approach and can be compared to what Quereshi et al. (1999) describe in their article about how validation is often done to see how well a model mimics the real system. There are two main purposes of model validation in this study. Firstly, it is to see if both iterations of the MCA perform at an acceptable level of 75% agreement and secondly, to test if both iterations of the MCA perform at different levels of agreement. One aspect which has become topical in recent years is the use of AI and machine learning which increasingly is being used in geospatial analysis (Oladoja et al., 2025). There are examples where it has been used to choose weights in GIS MCA (Zhao et al., 2024) and could be used for pattern detection when comparing the results of an analysis to a validation dataset, but it is not an established method for validation. It was not implemented in this project since machine learning and AI would likely not add much value due to the validation being internal and not external.

Overall, the results show that the first iteration using only Habitat variables does not pass the threshold of 75% as only 69% of the cells within the validation data areas were accurately classified. Meanwhile, the iteration using both sub-categories passed the test with 92% of cells withing the validation areas being accurately classified. This means that the established manual method used to create the validation data translates rather well into the MCA results when both sub-categories are included and that adding the *Pre-identified nature values* increase the validation of the MCA results. If the goal of the study had been to independently identify and predict new areas with high nature values this validation result would indicate that the model has failed to do so without using the pre-identified nature values datasets. But since the goal is to make the manual analysis process in nature conservation planning more efficient by replicating this process in the MCA model, adding the pre-identified nature values data sets does not substantially reduce the validity of the MCA model since the same data sets are used in the established methods as well. However, it is still of interest to analyze why the iteration using only habitat variables fails to identify some areas which the second iteration succeeds with as it gives some insight into the predictive potential of the model even if this is not the primary aim of this study. This is likely due to the habitat variables data being indirect indicators of nature values where key aspects such as tree age are not included. The datasets are relatively coarse and non-specific which makes the use of them to identify more specific areas with high potential for nature values more difficult. The possible uncertainties of the remaining 8% of cells which were inaccurately classified in the second iteration can come from both the uncertainties of the MCA and the uncertainties of the validation data, as discussed further in section 5.4. For example, some areas in the MCA that fall outside the validation data areas have been classified as 'High' or 'Very high potential for nature values' which either means that the MCA model has inaccurately identified these areas with higher potential for nature values or that the validation data failed to identify them. One possible cause of this could be the uncertainties in the validation data. It is hard to draw any conclusions since this validation method is internal and there is no independent data to compare to. Although the validation data is supposed to represent the "true" values, it still contains uncertainties. Model validation in this study does not provide any insight into this, but it could be further investigated in future studies by performing external validation and comparing the results to independent validation data for example.

5.3 Sensitivity analysis

Sensitivity analysis is not always applied in MCA but is an important part of validation (Chen et al., 2010), (Feick & Hall, 2004). The sensitivity analysis method chosen for this study is performed on the weight of the criteria by adjusting the weight of each criteria group by ±20% one by one. The remaining weights are adjusted accordingly in a compensatory manner which means that when one criteria group's weight is decreased or increased by 20%, the adjustments made on the remaining criteria will affect the resulting total score.

Generally, the sensitivity analysis in section 4.3 shows that the MCA model using both sub-categories is sufficiently robust at the 5% threshold for all criteria groups. The maps reveal that though there are relatively small changes, it seems to generally increase the potential for nature values when a criteria group has its weight decreased by 20% and gives the opposite result when increasing the weight by 20%. This is expected as the MCA uses a linear weighted model. However, the river Göta älv seems to consistently shift in a negative direction in all maps. The “Soil” criteria group shown in Figure 4.4 shows no deviation from the general trend of relatively small changes. However, Göta älv only has a large negative change when increasing the “Soil” group unlike the other criteria groups where the large negative change is consistent. The patterns of the changes for “Soil” also seem to coincide with water bodies for the “Soil” criteria group. This is likely caused by double counting of the influence of water bodies in both “Soil” and “Land use” which gives is more influence on the result than it should. This is not an expected result and as Dujmović et al. (2009) states, criteria should not be redundant with respect to each other in suitability analysis, and as such, it indicates an issue in the current model design. The general trend in the case of Soil in this study is slightly positive when decreasing the weight and slightly negative when increasing the weight of the “Soil” criteria group. This is unlike what Chen et al. (2010) found in their case study when they changed the weight of the “Soil” criteria by ±20%. They found that decreasing the weight of this criteria group generally decreased the number of cells classified with higher suitability instead of increasing it like in this study, although, their study has a different MCA approach and a different aim than this study. Nevertheless, they also found “Soil” to be one of the most influential variables. Other criteria that both analyses have in common is “Slope”, which was found to not be one of the most influential criterion in both cases. The criteria group “Distance to road” map in Figure 4.5 did not reveal anything other than a general large negative change in the Göta älv river. This indicates that the influence of the road data was mainly based on the river being over-valued in the original MCA results as was indicated in the results for “Soil” as well. This is likely a consequence of double counting the bodies of water such as the river. The third criteria group which had one of the largest effects on the results is “Forest value cores” displayed in Figure 4.6 and shows a scattered and uneven result between the increase and decrease of the weights. The map counters the general results and instead shows an increase in potential for nature values when increasing the weight and a decrease when decreasing the weight. As forest is one of the most geographically dominant landscapes in the study area, increasing this criteria group’s weight by 20% and adjusting the rest means that the MCA model might assign less potential for nature values on areas that are not forest. Oppositely, decreasing the influence of forest value cores criteria group by 20% allows for other criteria groups to gain more influence in the results. The model is compensatory which means that this is an expected effect. The map reveals that water bodies might have a larger influence on the results when the weight of "Forest value" cores is decreased. However, when increasing the weight, this effect is not as obvious. It seems that the criterion group "Forest value cores" overshadow the influence of water bodies when increasing the weight by 20%. Future studies on this topic might want to adjust the model so that water bodies are not double-counted and see how the results change.

5.4 Limitations and uncertainties

Uncertainties are present in any analysis and can stem from various sources and it is important to be aware of them when using the results even if all uncertainties cannot be estimated. Common sources of uncertainties in MCA analysis include input data, standardization and weighting techniques, MCA equation and validation data.

Criteria

The choice of criteria, the spatial aspect or the attribute aspect of the input data all carry uncertainties (Malczewski & Rinner, 2015), (Chen et al, 2010). In this study, the input data used mainly come from authorities such as Lantmäteriet and Länsstyrelsen where an estimation of the uncertainties is not provided. However, the data were generally created with the purpose of being used in planning processes such as this one. Appendix A and B provide more specific details on this for each dataset. Therefore, it can be argued that the input data are of sufficient quality for general planning purposes such as this one even if they carry unknown uncertainties. Another aspect is the number of criteria which could be considered too large by some for this study. There are 21 criteria which are grouped into 13 general criteria groups. Dujmović et al (2009) state that generally, any number of criteria should be supported in MCA for suitability analysis. At the same time, more criteria mean more uncertainties introduced into the results. Store & Kangas (2001) used a smaller number of criteria in their habitat suitability analysis; however, they investigated the habitat suitability of one species while this study aims at estimating the potential for nature values which is a much wider aim. There are a larger number of factors that go into a general ecological analysis, so it could be argued that a larger number of criteria are motivated in a study such as this one. On the other hand, it also increases the risk of double counting which did occur in this study, but it could be amended in future developments of the MCA model. Nevertheless, it is of interest to see how the model performs with such a large number of input criteria and possibly compare it to future iterations using a smaller number of criteria in the future. Ultimately, it did perform at an acceptable level despite the high number of criteria.

MCA methods

In general, the method used in this study is relatively simple to fulfill its aim of being a user-friendly model that can be applied in municipalities without expert knowledge. Dean (2021) points out that using simpler methods and techniques in an MCA can be useful but also risk causing issues such as double-counting, rough scoring and weighting as well as questionable aggregation. The MCA methods and techniques always introduce uncertainties, especially in the scores and weights as Malczewski & Rinner (2015) state. This study applies a participatory approach for the selection of criteria, standardization and weighting processes which means that the uncertainties from these aspects mainly lie in the participatory approach. This can include the method with which it was performed and the judgments made by the experts. The participatory approach was carried out in a suitable way that allowed discussion and several iterations of the scores and weights to try and minimize the associated uncertainties.

The participatory approach used in this study could be classified as the l type according to the classification system that Dean (2021) presents. The l type of participatory approach indicates that participants were involved in the criteria selection, the scoring and the weight process. Anderson et al. (2022) found in their review that the most common case of GIS MCA application is that the analyst and the planner are different physical people and roles. This presents a challenge as close cooperation is required to design and perform the analysis with both set of skills. Such is the case in this project for example, the author of this thesis is the GIS analyst and does not possess knowledge of competence in ecology or nature conservation planning. This is why a participatory approach was selected even if it presents some uncertainties of its own. This project had the advantage of a smaller group of participants which already had planned meetings in the municipality project of the nature conservation plan. The participation of the experts could therefore be performed in connection with these meetings. This was something that Dean (2021) found challenging in his case study, for example, as there were many stakeholders and few were willing to take time to participate in the study.

It is hard to estimate the uncertainties affecting the result, but the sensitivity analysis performed attempts to provide some insight into this, and future studies may use other experts to see if they reach similar conclusions in these processes. It should be mentioned that in habitat analysis and ecology there are not often exact and true values in reality as these are ambiguous and vague by nature (Feick & Hall, 2004). Therefore, some uncertainty must be accepted in these applications.

Model validation

Model validation mainly introduces uncertainties through the validation data, especially in this case as the validation data used are considered to be preliminary. The same experts were used in the process of creating the MCA model as the validation data, this means that the validation data is not independent. Therefore, an internal validation method was chosen which means that this issue does not present a problem. However it still presents the risk of uncertainties if the experts judgements were not consistent in both processes for example. There are risks of incompleteness on top of the uncertainties introduced by the assumptions and estimations made by the experts. There were indications of uncertainties in the model validation in the form of concentrations of ‘High’ or ‘Very high potential for nature values’ outside of the validation areas. It means that the MCA model identified areas with high potential that were not identified in the validation data. This could be something that will be identified in the validation data in their final version, or perhaps the MCA model over-estimated the potential of those areas.

Sensitivity analysis

As mentioned previously, the sensitivity analysis attempts to provide insight into the uncertainties associated with the chosen weights of the criteria in the MCA by estimating the effect that these uncertainties have on the results (Malczewski & Rinner, 2015), (Dean, 2022). As the results of the sensitivity analysis showed that the MCA model had acceptable robustness with changes being under 5%, it could be stated that the uncertainties of the weighting process can be considered acceptable in this case. However, this does not mean that every aspect of the model is sufficiently robust, the standardized scores were not tested for example. It is possible that testing the sensitivity of the standardized scores might reveal that they are not considered robust in this study and change the conclusions made about robustness of this MCA model. Conversely, if the sensitivity analysis of the standardized scores showed that the model is sufficiently robust it would strengthen the conclusion that the MCA model is indeed robust enough. This could be further investigated in future studies.

6. Conclusions

This study aimed at creating a MCA model which estimates the potential for nature values in the context of nature conservation planning using the municipality of Lilla Edet as a study area. The model should be compatible with openly available data and software, as well as be flexible and relatively user-friendly. This was done using a participatory approach to the standardizing and weighting process and a simple linear, compensatory approach to the MCA. The method was designed with flexibility and simplicity in mind to facilitate the participatory approach and fulfill the aim of the project.

In relation to the research questions, the results show that the MCA has an estimated level of agreement of 69% using only *Habitat variables* and 92% using all criteria. This indicates that including the *Pre-identified values* in the MCA increases the validity, adding value to the analysis and allowing it to pass the model validation test of 75%. The sensitivity analysis revealed that the most sensitive variables were the three criteria groups “Soil”, “Distance to roads” and “Forest value cores”. However, the effect of these variables did not exceed the acceptable limit which was set to 5%. Therefore, the MCA model can be considered accurate and robust to an acceptable degree for the intended purpose as an indication tool. In other words, it replicates the more resource demanding established method to an acceptable degree and fulfills the research gaps addressed in the research questions.

The model should be used as an indicator of areas with nature values in nature conservation planning to allow for more efficient focus of resources such as field visits for example in the beginning of the project. Further research on this subject could include testing this model in another municipality to see if it performs at the same level as the geography changes. The scores and weights could also be set by different experts in future studies to test the uncertainties of their estimations. Finally, the study could be replicated using alternative techniques to evaluate how the chosen methods influence the results and reliability. This could be done by applying it in another geographical area, decreasing the number of criteria, other techniques for standardizing scores or weights or perhaps trying another MCA equation to combine the scores and weights. Comparing the results of this study to future studies such as these could provide valuable insight into best practices of nature value analysis.

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Appendix A

Name	Resolution (m)	Source	Documentation on quality and creation	Sub-category
Slope raster **Lutningsraster** See source license	-	Lantmäteriet Laser data **Original title: Laserdata Nedladdning, skog** License: CC0	Produced from a DEM created for this project from .las files available to municipalities through Lantmäteriet. QGIS software was used in this process.	Habitat variable
Aspect raster **Väderstreck lutning** See source license	-	Lantmäteriet Laser data **Original title: Laserdata Nedladdning, skog** License: CC0	Produced from a DEM created for this project from .las files available to municipalities through Lantmäteriet. QGIS software was used in this process.	Habitat variable
Land use raster 2023 v 0.1 **Original title: Markanvändning 2023 v 1.0** License: CC0	10	Naturvårdverket	This full-coverage land use data was created using satellite data (Sentinel-2), laser data from Lantmäteriet and various thematic datasets from different authorities. It is dated 2023 because that is the date of the latest satellite images used. However, the images used for the study area of this thesis are mainly from 2020 and 2021.	Habitat variable
Soil type **Original title: jordarter 25 000 - 100 000** License: CC0 1.0	-	SGU	This dataset has been produced and updated over many years based on data from 1960 and onwards, this means that the quality varies geographically. Interpretation from aerial images and field data collection are the main methods that this dataset is based on. The field observations have been done about 50cm below the surface level. The purpose of this data set is among other things to perform analysis on nature values.	Habitat variable
Distance to nearest gravel road **Avstånd till grusväg polygon** See source license	-	NVDB **Original title: NVDB_DK_O_88_Vagtrafiknat** License: CC0 1.0	The data in NVDB is continuously updated by the relevant municipality, the quality of the data can therefore vary. There is geometrical quality and quality of completeness. The municipality of Lilla Edet has completed Blåljuskollen which indicates good quality on completeness while the geometrical quality is dependent on the quality and accuracy of orthophotos from Lantmäteriet.	Habitat variable

Distance to nearest paved road **Avstånd till närmsta belagd väg** polygon See source license	-	NVDB **Original title: NVDB_DK_O_88_ Vagtrafiknat** License: CC0 1.0	The data in NVDB is continuously updated by the relevant municipality, the quality of the data can therefore vary. There is geometrical quality and quality of completeness. The municipality of Lilla Edet has completed Blåljuskollen which indicates good quality on completeness while the geometrical quality is dependent on the quality and accuracy of orthophotos from Lantmäteriet..	Habitat variable
Distance to nearest water stream **Avstånd till närmsta vattendrag polygon** See source license	-	Lantmäteriet - **Original title: Topografi 50** License: CC0	This is a generalized dataset that is updated in an automatic process as new data is collected. It is based on the previous terrängkarta from Lantmäteriet. The quality varies and the data is produced with the intention of usage on a scale of 1:15 000 - 1:50 000.	Habitat variable
Distance to nearest lake **Avstånd till närmsta sjö polygon** See source license	-	Lantmäteriet - **Original title: Topografi 50** License: CC0	This is a generalized dataset that is updated in an automatic process as new data is collected. It is based on the previous terrängkarta from Lantmäteriet. The quality varies and the data is produced with the intention of usage on a scale of 1:15 000 - 1:50 000.	Habitat variable
High conservation values forest License: CC BY 4.0	100	Mittuniversitetet	This dataset predicts the relative probability of value cores in Swedish forests. The model is based on training data such as land cover data and forest value cores from 2016 from Naturvårdsverket and DEM from Lantmäteriet among other sources. The model has been validated with forest management data and the Swedish National Forest Inventory (NFI).	Pre-identified nature values
Identified trees worthy of protection area **Skyddsvärda träd buffertzon** Licence: CC0 1.0	-	Länsstyrelsen Västra Götalands län, Lilla Edets municipality	This data is based partly on inventory made by Länsstyrelsen and inventory done by Lilla Edet municipality and has been compiled and evaluated by the municipality. Buffer zones of 5m have been created around the tree points. This dataset was finalized at the beginning of 2025.	Pre-identified nature values

Hay meadow value element **Original title: Slåtteräng värdeelement** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	This data was created as part of the green infrastructure project using the following datasets and selections: * Selection of 'Slåtteräng särskilda värden' from dataset SJV Markklasser 2014 and 2017. * Selection of 'äng' from SJV Ängs- och betesmarksinventeringen naturtyper	Pre-identified nature values
Rich marsh **Original title: Rikkärr** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	The data is based on inventory data from the 1970s and later. The dataset was first created in 1995 and has since been updated as new inventory data has been added.	Pre-identified nature values
Trivial deciduous forest value cores **Original title: Triviallövskog värdekärnor** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	The data contains value cores, areas with a concentration of several types of high nature value elements. The data is part of the Green Infrastructure project in 2018 and is based on datasets such as key biotopes, protected areas up until 2015 and forest types from KNAS.	Pre-identified nature values
Deciduous forest analysis **Original title: Lövskog analys** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	The data is part of the Green Infrastructure project. This dataset is the result of an analysis made to present different types of deciduous forest environments with high nature values. The analysis is based on various inventory data from 1983-2013 and was analyzed together with other datasets such as Land use data from Naturvårdsverket among others in 2022. The results from the analysis has been verified by comparing to IR satellite imaging and manual cleaning of objects that are no longer relevant.	Pre-identified nature values
Mixed forest value cores **Original title: Blandskog värdekärnor** License: CC0 1.0	-	Länsstyrelserna	The data describes areas with a higher concentration of values than their surroundings. This is a dataset that combines datasets containing different value areas for different nature types and was created as part of the Green Infrastructure project. The quality may vary in the different districts.	Pre-identified nature values

Broad leaf forest value cores **Original title: Ädellövskog värdekärnor** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	The data contains value cores, areas with a concentration of several types of high nature value elements. The data is part of the Green Infrastructure project in 2018 and is based on datasets such as key biotopes, protected areas up until 2015 and forest types from KNAS.	Pre-identified nature values
Coniferous forest value cores **Original title: Barrskog värdekärnor** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	The data contains value cores, areas with a concentration of several types of high nature value elements. The data is part of the Green Infrastructure project in 2018 and is based on datasets such as key biotopes, protected areas up until 2015 and forest types from KNAS.	Pre-identified nature values
Valuable grassland 2022 **Original title: Värdefulla gräsmarker 2022** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	The data contains information on support habitat and value cores and was created as a part of the Green infrastructure project. It is based on various datasets from 2021 and 2022 including meadow and pasture data, land classes and data on agricultural blocks among other datasets.	Pre-identified nature values
Valuable grassland 2018 **Original title: Värdefulla gräsmarker 2018** License: CC0 1.0	-	Länsstyrelsen Västra Götalands län	The data contains information on support habitats and value cores for grasslands and was created as a part of the Green Infrastructure project. The value cores consists of classes 'meadow' and 'pasture' from an inventory from 2016. The classes 'pasture', 'hay meadow special value', 'forest pastures' and mosaic pastures from land classes by Jordbruksverket. The support habitats consist of the classes 'restorative land', 'pasture' and hay meadow' from an inventory from 2016.	Pre-identified nature values
Historic wetlands from 1800 **Original title: historiska våtmarker 1800-talet** License: CC 4.0	-	Länsstyrelsen	This dataset is the result of a project from 2004 where historical wetlands were mapped from the historical map product generalstabskartan.	Pre-identified nature values

Historic wetlands from soil type data **Original title: historisk våtmark från jord och bergartskartan** License: CC0 1.0	-	Länsstyrelsen	This dataset shows historical wetlands based on soil type data from SGU done in 2008	Pre-identified nature values

Appendix B

All geoprocessing was done in QGIS 3.34.14 unless specified otherwise.
Slope and Aspect
The datasets on slope and aspect originate from laser data from the Swedish national mapping, cadastral and land registration authority. The point cloud from Lantmäteriet was filtered to only include points classified as Ground and then a DEM was generated using the PointCloudFilter and RasterDEMGenerator transformers in FME Software. However, there is also a DEM with the same resolution available for municipalities to download from Lantmäteriet. The reason that laser data was used in this study is because the 1m DEM was not available at the time of this phase of the project. A slope and an aspect raster were generated from the DEM using the terrain analysis tools Slope and Aspect. The Slope tool uses the algorithm "native:slope" which calculates the angle in degrees of inclination of the terrain from the DEM. The Aspect tool uses the algorithm "native:aspect" which calculates the aspect from the DEM and produces a raster with values ranging from 0-360 expressing the slope direction.
The uncertainties of these datasets mainly include error sources from the laser scanning data collection and the classification of points from the source data. Only the ground points were extracted and used in this study which means that incorrect classification will affect the quality of the resulting rasters. The generation of the DEM and subsequent Slope and Aspect rasters also introduce further uncertainties coming from geoprocessing.

Land use
The land use raster was aligned to the DEM and resampled into 1m resolution from the 10m dataset 'Markanvändning' available through the Swedish Environmental Protection Agency website. The alignment and resampling were done using the Align rasters tool.
The main uncertainties of the input data come from the method with which the dataset was created in the original source. It is based on satellite data, laser data and various thematic datasets from different authorities which all bring their separate uncertainties into the dataset. The result of the original analysis performed by Naturvårdsverket is validated by comparison to NILS (Riksskogstaxeringen) and is presented with different qualities for different classes of the land use raster. Forest, open wetlands, arable land and water generally was found to have very good conformity (80-100%) while land use classes related to urban areas had good (70-80%) and very good conformity.

Soil
The soil type dataset was rasterized using the v.to.rast tool. The original dataset 'jordarter 25 000-100 000' was accessed through from the Geological Survey of Sweden website. This dataset introduces uncertainties which are hard to define due to the varying amount and age of data used to create it ranging from 1960 to present day. However, the main method used is interpretation from aerial images and field data collection. The interpretation of aerial images introduces uncertainties through the method used. The field collection of data was done at a depth of about 50cm which may be a reasonable approach but also introduces uncertainties due to the limitation of depth being sampled. As already stated, the quality and presence of error sources and uncertainties vary greatly, but the publisher does state that more thorough

methods have been used in urban areas in the south of Sweden. The study area is in the south of Sweden and contain several urban areas.

Distance to nearest road
The original dataset consists of vector road lines with attributes describing the type of road. Gravel and paved road types were separated into separate layers, and the plugin tool Multi Ring Buffer was used to create multiple buffer zones around these. The buffer sizes were chosen in collaboration with experts in relation to the effect on ecosystems for different distances.
Data were accessed through the web service Laskajen hosted by Trafikverket and is dated to February 2025. The source data are created and updated continuously by the responsible party. This includes Trafikverket, municipalities or private people. Most roads in the study area are updated by the municipality and some by Trafikverket. The road lines represent the middle of the road and have often been interpreted from aerial images. The municipality of Lilla Edet has completed the project called Blåljuskollen which is a way for municipalities to improve the quality of datasets such as roads for example. This gives a rough indication that there is reasonable quality to the data. However, it still introduces uncertainties to this study, which is geographically estimated by the municipality to be roughly up to 5m of the road lines.

Distance to nearest water
The two datasets of distance to water streams and lakes respectively were created with data from the product 'Topografi 50'. The buffer zones were created in QGIS and then rasterized using the same method as for distance to roads. The buffer zones were also created and set using the same method as the distance to roads. The chosen buffer distances were set by the expert, similarly to how the distance to roads distances were set. Distance to roads and distance to water have different effects on habitat conditions relating to high nature values which is why the buffer zone sizes differ between these datasets. Using the knowledge of the municipality ecologist and the consultants the buffer sizes were set separately for distance to water and distance to roads.
The original data were accessed through Geotorget by the Swedish national mapping, cadastral and land registration authority. The dataset contains varying quality and is updated continuously, Lantmäteriet states in the documentation that the data have been generalized and partly contains larger uncertainties. However, the categories used in this study relating to water are not affected by this to the same degree and therefore contain smaller uncertainties than other classes in the dataset.

High conservation values forest
One of the datasets containing pre-identified nature values is a result of a recent study (Jonsson et al., 2024) where a model created a dataset predicting relative likelihood of value cores in Swedish forests as a raster with 100m resolution. The model was trained by data such as land cover data and forest value cores from 2016 from Naturvårdsverket and DEM from Lantmäteriet among other sources. To assess the extent of the relative likelihood of nature values, the results were validated through comparison and statistical significance testing to independent datasets such as forest management data and the Swedish National Forest Inventory (NFI). The result of both validation tests showed that the model accurately identified significantly higher likelihood of value cores in areas where high conservation values have been observed in the independent data sets.

Identified trees worthy of protection
The dataset containing valuable trees as vector points has been produced by Lilla Edet municipality in 2025 and is based partly on data from Länsstyrelsen and field inventory of trees collected and assembled by the municipality. To use this dataset in the MCA, it was decided in cooperation with the municipality ecologist and the two consultants that it is a reasonable approach to create buffer zones around these areas as valuable trees often also contribute to higher nature values in the close surrounding area. The buffer zones were set to 3m. This distance was set as an estimated parameter around a tree that could reasonably effect surrounding ecosystems in a significant way. Buffer zones were created using the Buffer tool before the data was rasterized with a 1m resolution using the GRASS tool v.to.rast. In the case that such a dataset is not available to a municipality or other party for a different study area, it is also possible to use the dataset containing trees worthy of protection produced by Länsstyrelsen instead. The trees in this dataset have been surveyed using instruments in the field and introduce geographical error sources related to this, but these should be relatively small in the context of the application of this study. Other possible error sources include the classification of the trees as valuable, this has been done through consideration of qualities such as age, diameter, species found etc. The largest uncertainty of this dataset is incompleteness as it only presents the valuable trees that have been identified by manual collection of data.

Green infrastructure data
Several of the datasets used in this study have been produced as a part of the Green Infrastructure project by Länsstyrelsen. This includes Hay meadow elements, trivial deciduous forest value cores, Deciduous Forest analysis, Mixed Forest value cores, Broad leaf forest value cores, Coniferous Forest value cores, Valuable grasslands 2022 and Valuable grasslands 2018. These datasets have been produced through analysis of various materials and data to identify different types of nature values in the region. Uncertainties are introduced from the data used in the analysis by the publisher and the analysis methods which mainly consist of selections from the source data and compilations of these. It is difficult to state exact errors which these may introduce into the study, but they have been produced by a government authority with the purpose of applications such as this study.

Rich marshes
The data covering the presence of rich marshes are an important part of the analysis because of their high nature value, the data used have been produced and updated by Länsstyrelsen. It has been rasterized using the v.to.rast tool with 1m resolution. Similarly to the valuable tree data, this datasets have a large uncertainty in terms of incompleteness. The data have been collected through field visit inventory of rich marshes which indicates a good level of geographical accuracy, the uncertainties introduced here are mainly related to the method used collecting the data in the field.

Historic wetlands
There are two different datasets covering historic wetlands. These have been produced based on two different approaches and therefore have slightly different results. This is why both are included in this study. One of them covers historic wetlands from the 1800's and is based on a historic military map, it was produced in 2004. The historic military map introduces larger possible uncertainties as well as

uncertainties from the method used to derive information from this historic source material. Georeferencing older maps can introduce large errors. The second dataset is based on soil type data and was produced in 2008. The source data for this dataset are of more recent and better quality than the historic map used for the older version, it is based on soil type data which is also included in the Habitat variable sub-category of this study. Hence it introduces the same uncertainties as the soil type data already did together with the uncertainties of the method used to interpret historic wetlands. Both have been rasterized with a 1m resolution using the v.to.rast tool.

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