STRATEGIC AFFORESTATION PLANNING IN DENMARK

A Multi-Criteria Framework Integrating Large Language Models for AHP-Based Expert Elicitation

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AI generated image

Summary

This thesis addresses the strategic implementation of Denmark's Green Tripartite Agreement, which mandates the afforestation of 250.000 hectares by 2045 to enhance CO_2 sequestration and biodiversity. The primary objectives were twofold: first, to develop a spatially explicit framework for prioritizing these afforestation areas while balancing environmental goals with agricultural and local planning considerations (RQ1); and second, to explore the potential of Large Language Models (LLMs) as a novel tool to support expert elicitation within the Analytic Hierarchy Process (AHP) used for this prioritization (RQ2).

A Geographic Information System (GIS)-based Multi-Criteria Decision Analysis (MCDA) was conducted, employing a Weighted Overlay Analysis (WOA) on a 100m grid resolution across Denmark. Nine spatial criteria, derived from the Green Tripartite Agreement through systematic content analysis and refined based on MCDA principles, were integrated into the model. The AHP methodology was used to: (1) derive criterion weights, benchmarking a human expert panel (five peers) against three LLMs (ChatGPT-o3, Gemini 2.5 Pro, Grok 3) emulating three stakeholder roles; and (2) generate category normalization scores within each criterion layer using the same LLM setup. Legal and physical constraints were applied as a binary mask to exclude unsuitable areas.

The results for RQ2 demonstrated that the LLM composite weight vector exhibited strong rank-order agreement (Spearman's $\rho = 0.69$) with the human expert-derived vector, and most LLM-generated matrices showed acceptable internal consistency. This suggests LLMs can produce plausible, policy-relevant AHP judgments and offer significant efficiencies, serving as a time- and cost-efficient complement, though not a full substitute, for human expertise. For RQ1, the WOA, utilizing the LLM-derived inputs, produced a national suitability map identifying 1.873 million hectares of suitable land post-constraints, with 1.058 million hectares classified as high priority (scores 8-9). A 250.000 hectare prioritized afforestation portfolio was subsequently delineated, primarily from high-suitability areas (scores 9, 8, and necessarily 7) located adjacent to existing forests to enhance landscape coherence. Local qualitative validation supported the model's spatial logic.

This thesis concludes that the developed GIS-based MCDA framework provides a transparent and adaptable tool for strategic afforestation planning. Furthermore, it demonstrates that LLM-assisted AHP can be a viable and efficient complementary method for expert elicitation, potentially reducing reliance on extensive external expert panels provided that significant human expertise is retained for prompt design, rigorous validation, and critical interpretation of LLM outputs. The study delivers a spatially explicit portfolio to inform Danish policy implementation, while also highlighting the importance of methodological limitations, dynamic policy contexts, and practical challenges such as existing subsidy schemes.

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Preface

This thesis represents the culmination of my education, providing an opportunity to delve into a current and complex interplay of policy, land use, and technology. My aim has been not only to answer the specific research questions but also to demonstrate how Geographic Information Systems (GIS) can be applied as a tangible tool to analyze and operationalize political objectives, such as those set forth in the Green Tripartite Agreement. The chosen Weighted Overlay Analysis is one example of such a GIS approach; the problem could have been viewed from other perspectives, and different modelling choices might have yielded different results. A central part of this process for me has also been to explore and test the potential of the latest technological tools, including Large Language Models (LLMs), to support decision-making processes. I hope that the described method for their application in this specific context may serve as an inspiration.

Finally, I would like to extend my sincere gratitude to those who have supported me throughout this thesis process. A special thanks to my supervisor, Professor Dr. Jamal Jokar Arsanjani, for his guidance, insightful feedback, and encouragement.

I would also like to thank my peers - and friends - Sarah, Lukas, Christian, Annie and Simon, who dedicated their time to act as experts in the AHP evaluations; their input was essential for this part of the research. Lastly, my deepest appreciation goes to my husband, Lars, for his unwavering support, patience, and for being an indispensable sparring partner, particularly with the mathematical and statistical aspects of this work.

Christina Elmegaard-Fessel

Contents

Acronyms

AHP	Analytic Hierarchy Process
BPS	Basic Payment Scheme
CAP	Common Agricultural Policy
CHR	Central Register of Livestock
CR	Consistency Ratio
DKK	Danish Krone
ETRS89	European Terrestrial Reference System 1989
EU	European Union
GCI	Geometric Consistency Index
GEUS	Geological Survey of Denmark and Greenland
GIS	Geographic Information Systems
GTA	Green Tripartite Agreement
HA	Hectare
LLM	Large Language Model
LULUCF	Land-Use, Land-Use Change and Forestry
MCDA	Multi-Criteria Decision Analysis
MLG	Multilevel Governance
MRE	Mean Relative Error
NCS	Natural Climate Solutions
NGOs	Non-Governmental Organizations
RQ1	Research Question 1
RQ2	Research Question 2
SQL	Structured Query Language
SVM	Coalition of Coalition of the Social Democrats, Liberal Party and Moderates
UTM	Universal Transverse Mercator
WOA	Weighted Overlay Analysis

1. Introduction

1.1 Purpose

In November 2024 the Danish government in collaboration with the Socialist People's Party (SF), Liberal Alliance (LA), the Conservative People's Party (C), and the Social Liberal Party (R), passed the Agreement on the Implementation of a Green Denmark (Agreement on the Implementation of a Green Denmark, 2024). Denmark is facing a severe transformation of its landscape- and use as part of this. With the agreement of a Green Denmark, which from here on will be referred to as the green tripartite agreement, a number of central actors commit to convert large agricultural areas to forest and carbon-rich lowland soils to reduce CO_2 emissions, strengthen the biodiversity, and to protect clean water resources (Agreement on a Green Denmark, 2024).

The agreement articulates three mutually reinforcing objectives:

1. Rapid decarbonization of the land sector
2. Restoration of ecological integrity
3. Long-term resilience of rural economies.

To operationalize these objectives, the parties have agreed on the following quantified action points:

- **Afforestation:** Establishment of 250.000 hectares of new forest by 2045, of which at least 100.000 hectares will remain untouched; the State will contribute a minimum of 30.000 hectares through strategic land purchases.
- **Conversion of carbon-rich lowland soils**: Convert 140.000 hectares by 2030, financed through a dedicated 9.4 billion DKK envelope and reinforced by a graded CO_2-equivalent tax from 2028.
- **Extensive land-use management**: Incentivize low-intensity agriculture, meadows and wetlands on selected land to curb nutrient runoff and enhance semi-natural habitats.
- **Expansion of protected nature:** Designate protected areas covering at least 20 % of Denmark’s terrestrial area, to be detailed in a national biodiversity plan due in 2026.
- **Local participation and multilevel governance**: Empower municipalities, watershed councils and a National Steering Group to coordinate land-conversion projects and monitor progress, to align with EU directives and national targets

(Agreement on a Green Denmark, 2024)

Afforestation plays a key role by both storing carbon and providing the foundation for more connected forest areas. Therefor this thesis focuses on how the 250.000-ha target can be spatially prioritized by determining where land should be converted, ensuring compliance with EU regulations and balancing environmental priorities with agricultural livelihoods.

1.2 Background

The adoption of the Danish Green Tripartite Agreement unfolded against a political backdrop characterized by mounting pressure to address the agricultural sector's substantial climate impact, previous incomplete policy initiatives, and pronounced conflicts of interest. Agriculture accounted for a significant share of Denmark's total greenhouse-gas emissions, and attainment of national and international climate goals—including the 70% target for 2030—was under pressure (Klimarådet, 2022) (Klimarådet, 2023).

Previous Agreements and Insufficient Reductions

The run-up to the tripartite agreement was not without prior political attempts to regulate the sector. The "Agreement on the Green Transition of Danish Agriculture" of October 2021 set a binding reduction target of 55–65 per cent for the land- and forestry sectors by 2030 relative to 1990 levels (Christensen, et al., 2023). The agreement included measures such as the retirement of low-lying peat soils and a focus on nitrogen reduction (A. Holm, et al. , 2024). Although reports continued to indicate that substantial additional reductions were required to meet overarching climate objectives and that further agriculture-specific measures were necessary (Klimarådet, 2023). The think-tank CONCITO warned that agriculture's share of total Danish emissions was expected to rise if action were not taken, thereby generating political momentum for new, more far-reaching initiatives (Hasforth, 2023).

Persistent Pressure from the Danish Council on Climate Change

As an independent expert body, the Danish Council on Climate Change played a central role in shaping the political climate. For years the Council had recommended a uniform greenhouse-gas levy (extending to agricultural emissions) as a key and cost-effective policy instrument (Klimarådet, 2020). These recommendations were continually reinforced through analyses and status reports that underscored the need for concrete action and regulation of agriculture to ensure target compliance (Nielsen, 2025). The Ministry of Taxation appointed an expert group on green tax reform that analyzed various models for a carbon tax on agriculture, further intensifying the political debate. The idea of a carbon tax on agriculture became a central point in the political landscape leading up to the tripartite negotiations (Joan Faurskov Cordtz, 2025).

Stakeholder Positions and Political Dynamics

The political climate was strongly influenced by the various stakeholder organizations. On one side stood "Landbrug og Fødevarer", representing farming interests and advocating a transition that would not undermine the sector's competitiveness while acknowledging its role in food production (Andersen, 2024). On the other side were environmental NGOs such as the Danish Society for Nature Conservation and Greenpeace, which pressed for more ambitious reductions, an effective carbon tax, and greater consideration of nature and biodiversity (A. Holm, et al. , 2024) (Barber, 2024). The Danish Society for Nature Conservation, for example, cited Council analyses as a roadmap for addressing both climate challenges and the nature crisis through extensive land-use changes. These opposing interests generated considerable political tension and underscored the need for a negotiation process capable of bridging the divide - a role the tripartite model aimed to fulfil. The Council for Green Transition also contributed to the debate, emphasizing the EU's role and the need to integrate climate, nature, and water-environment efforts (Jørgensen, 2024).

After the 2022 election, the SVM coalition's program reaffirmed the green transition. Together with five other parties, social partners, and stakeholder groups, the government forged the Green Tripartite Agreement (Agreement on the Implementation of a Green Denmark, 2024). Prolonged negotiations reconciled divergent interests in climate, industry, and rural development, reflecting strong political and public pressure—amplified by media scrutiny of agricultural emissions and looming targets—to break years of deadlock (Folketinget, 2020).

Overall, inadequate past measures, sustained expert pressure, entrenched stakeholder conflicts, and broad public concern coalesced into the political will that made the tripartite approach the chosen path toward a more climate-friendly agricultural sector.

1.3 Problem Statement

As the Green Tripartite Agreement moves from negotiated text to on-the-ground implementation, its success will hinge not only on *how much* land is converted, but *where* those conversions occur. A central element of the agreement is the need for a strategic prioritization of where these initiatives should be implemented and how they can contribute to the defined climate and environmental goals (Agreement on a Green Denmark, 2024, p. 6).

Poorly sited plantations risk forfeiting carbon gains on peat-rich soils, fragmenting existing habitats, or colliding with high-value farmland—re-igniting precisely the conflicts the Agreement seeks to resolve. Conversely, judicious placement can multiply benefits: maximizing long-term CO_2 sequestration, reinforcing ecological corridors, safeguarding groundwater recharge zones and, crucially, minimizing opportunity costs for Danish agriculture.

This thesis seeks to convert broad political goals into a spatially explicit action plan through a transparent, multi-criteria approach that can integrate heterogeneous evidence—biophysical, legal and socio-economic—while remaining auditable to stakeholders with divergent mandates. This study develops and tests such a framework, including a pilot use of emerging AI-based expert-elicitation tools, in order to underpin strategic afforestation decisions.

1.3.1 Research Questions

To address the problem statement, this thesis focuses on the following research questions:

1. **Which locations in Denmark offer the highest combined potential for carbon sequestration, biodiversity gain and operational feasibility—while ensuring landscape coherence with existing forest and minimizing conflicts with agricultural production?**

2. **To what extent can large language models (LLMs) effectively substitute or complement human expert judgement in Analytic Hierarchy Process (AHP) scoring for spatial afforestation planning?**

1.4 Structure of the Thesis

To answer these questions, the thesis is structured in six chapters, each building on the previous to move from policy motivation to spatial decision support. The structure can be seen in below structure diagram.

1. Introduction Frames the problem and research questions

1.1 Purpose; context of the Danish Green Tripartite Agreement (GTA)
1.2 Background - rationale for focusing on the 250.000 hectares afforestation target
1.3 Problem statement and research questions

2. Litterature review Provides the theoretical foundation for the methological and analytical workflow

2.1 Afforestation as a climate-policy instrument and its co-benefits
2.2 Multilevel-governance and implementation theory — legal constraints and stakeholder diversity
Implementation
2.3 Spatial MCDA: Weighted-Overlay Analysis (WOA) +
Weighing with the Analytic Hierarchy Process (AHP)
LLM assisted weighting
Criterion identification
2.4 Synthesis and implications for methods

3. Methods Converts the framework into a reproducible methological and analytical workflow

3.1 Data sources and preprocessing
3.2 Suitability modelling with WOA (criteria, reclassification, legal mask)
3.3 Analysis design - Criterion weighting with AHP
3.3.1 Human-expert matrices
3.3.2 LLM-assisted matrices (three stakeholder roles, prompt design, consistency screening)
3.4 Stage 1 AHP Application and LLM-evaluation
3.5 Stage 2: Suitability analysis for afforestation
3.6 Post-processing the Suitability output

4. Analysis and Results Presents what the workflow produces

4.1 Evaluation of AHP-derived weights and the Complementary Role of Large-Language Models
4.1.1 Human derived AHP weights and key observations
4.1.2 LLM-derived AHP weights and key observations
4.1.3 Human vs LLM priority vectors
4.2 Results and analysis of the WOA - National suitability map, constraint effects

5. Discussion Interprets findings, assesses methods, and places them in policy context

5.1 Principal Findings
5.2 Methodological Considerations
5.3 Policy implementation challenges
5.4 Study limitations
5.5 Future research directions

6. Conclusion Answers the research questions and offers recommendations

2 Literature Review

This chapter reviews the literature that anchor the thesis and justify the analytical choices made later on. The aim is not to deliver an exhaustive catalogue of studies but to assemble the conceptual building-blocks needed to turn the Green Tripartite Agreement's afforestation mandate into a transparent, spatially explicit decision tool. For a quick overview, the four strands that are covered can be seen in Figure 2.1:

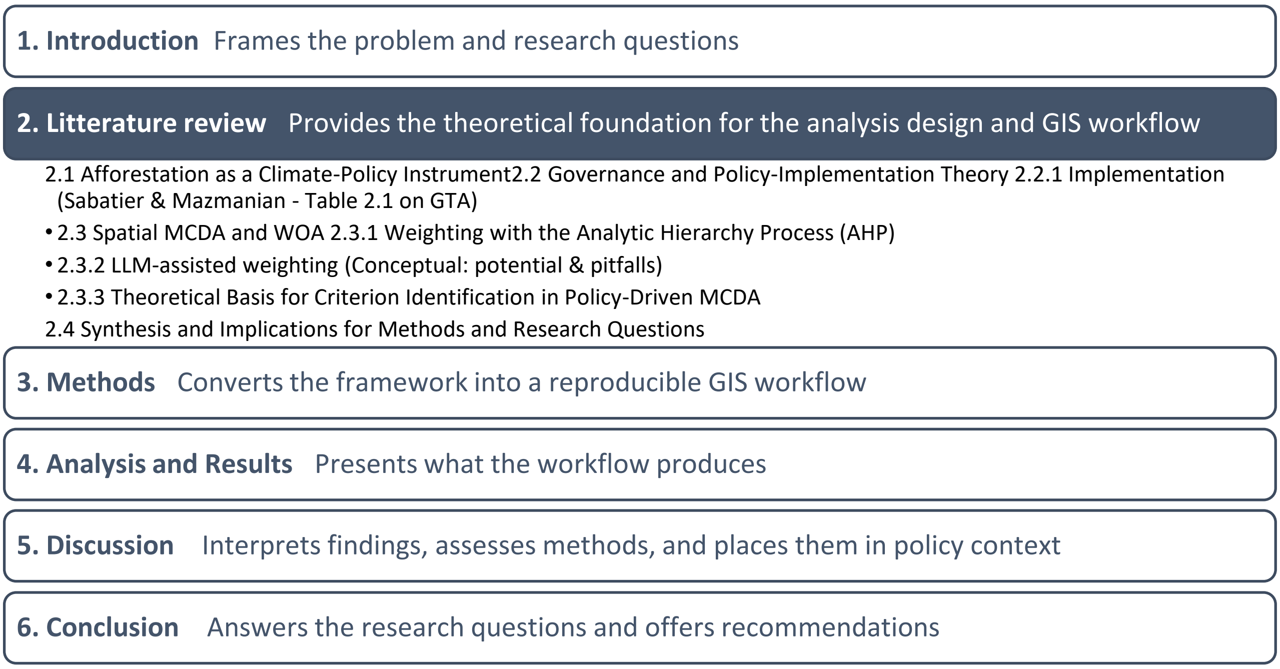

Figure 2.1 Thesis structure diagram with the literature review highlighted in Figure.

2.1 Afforestation as a Climate-Policy Instrument

Afforestation is now recognized as one of the most cost-effective natural climate solutions (NCS).
W. G Bronson et al. have found that expanding global forest cover could deliver up to 6.0 Gt CO_2 yr^{-1} of additional removals in 2030 – roughly one quarter of the mitigation required to remain on a 1.5°C pathway (W. G. Bronson et al., 2017). Within the European Union, the Land-Use, Land-Use Change and Forestry Regulation LULUCF (EU) obliges member states to maintain a net carbon sink from 2021-2030 and explicitly encourages new forests as a key lever for long-term negative emissions (European Parliament , 2018). The most recent European Parliamentary briefing on LULUCF shows that forest removals already offset ~7 % of total EU emissions, but that sink is projected to decline without additional planting (European Parliamentary Research Service, 2023).
Denmark has advanced its net-zero target to 2045 and aims for a 110 % reduction by 2050. National scenarios assume an average annual forest sink of ~2.2 Mt CO_2 to meet that ambition (Agreement on a Green Denmark, 2024). Nordic studies indicate that carbon-oriented forest management could enhance the regional mitigation effect by 10-20 % relative to "business-as-usual" harvesting regimes (Pukkala, 2018).
Afforestation is therefore framed not only as land-use change, but as a cornerstone of Denmark's and the

EU’s wider climate-neutrality strategy. Achieving that land-sector contribution will depend on how effectively the EU, the Danish state, municipalities and individual landowners can translate the 250.000 hectares target into concrete planting decisions—a governance question explored in the next section.

2.2 Multilevel Governance and Policy-Implementation Theory

The 250.000 hectares afforestation mandate in the Green Tripartite Agreement (GTA) is enforceable only if every tier of authority—from the EU down to individual landowners—pulls in the same direction. Multilevel Governance (MLG), as conceptualized by Gary Marks, describes a system of diffused authority where decision-making competence is shared across multiple, interconnected levels of governance, spanning sub-national, national, and supranational entities (Marks, 1993). The planning of afforestation initiatives operates within such an MLG framework, as seen in fig. 2.2. For instance, in the EU context, afforestation policies and funding are often decided at the European level, adapted by national governments, and finally implemented by regional and local authorities in cooperation with diverse stakeholders.

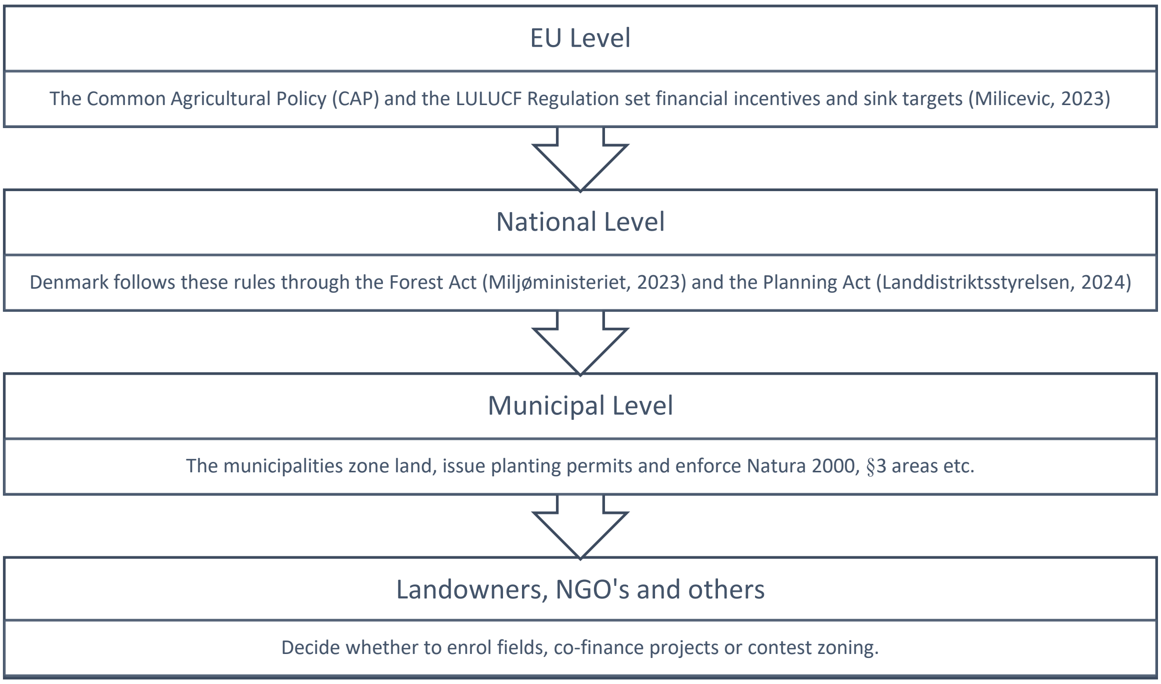

Figure 2.2 Governance chain for afforestation in Denmark. EU legislation (CAP and LULUCF) establishes financial incentives and sink targets; Denmark implement these rules via the Forest Act (2023) and Planning Act (2024); municipalities administer zoning, permits and Natura 2000 enforcement; landowners, NGOs and other stakeholders decide whether to participate or oppose projects.

2.2.1 Implementation

Sabatier and Mazmanian describes in their research that implementations in an MLG setting only succeed when four conditions are met; Clear and consistent policy goals will ensure that all involved actors understand and strive towards the same objectives. Adequate resources, is described as the necessity of financial, human, and informational resources. Supportive constituencies, refers to the presence of political and societal actors who advocate for the policy's success, and sufficient administrative capacity, being the organizational structures and expertise to effectively manage the process (P. A. Sabatier, 1983).

In table 2.1 these conditions have been applied to the afforestation pillar of the Green Tripart Agreement:

Implementation condition	Status in the green tripartite agreement
Clear, measurable goal	250.000 hectares of additional forest by 2045 (100.000 hectares untouched; 30.000 hectares state-purchased)
Adequate resources	DKK 9.4 bn earmarked for land conversion + EU co-financed CAP measures
Supportive constituencies	Divergent preferences of farmers, municipalities, NGOs and state agencies
Administrative capacity	98 municipalities issue planting permits and enforce Natura 2000; national agencies oversee subsidies

Table 2.1 Sabatier and Mazmanian's Implementation Conditions within the Green Tripartite Agreement.

The assessment in Table 2.1 indicates that while the GTA presents clear, measurable goals and has allocated significant resources, potential challenges for its successful implementation lie particularly within achieving broad supportive constituencies given divergent interests, and ensuring streamlined administrative capacity across all relevant governance levels.

2.3 Spatial MCDA and WOA

To operationalize the governance logic just outlined, the thesis now turns from "who must act" to "how their priorities can be translated into spatial choices". Spatial Multi-Criteria Decision Analysis (MCDA) is an applicable method. It offers a systematic way to compare across Denmark against the policy-derived criteria and stakeholder weights, while it integrates legal constraints imposed through the MLG. (J. Malczewski, 2015).

Among the various spatial MCDA techniques available within Geographic Information Systems, the Weighted Overlay Analysis (WOA) is particularly relevant for its intuitive implementation and capacity to integrate diverse spatial datasets based on their relative importance (Zope, 2021) (Ajaykumar Kadam, 2020).

The method has already informed Danish forestry policy for several years. For example county-level plans in the 1990s applied a seven-layer overlay (soil, groundwater, landscape, recreation, etc.) and identified 2–7 % of each county as legally designated afforestation areas, while 10–35 % were demarcated as 'negative areas' where planting is prohibited (Madsen, 2002). Subsequent studies in Sweden (Haraldsson, 2020, pp. 175-190) and Latvia (Janis Krumins, 2025) confirm WOA's portability across Nordic/Baltic landscapes.

In a weighted overlay analysis multiple raster layers, each representing a specific criterion relevant to the decision-making process are combined. Each criterion layer undergoes a transformation process involving two steps: reclassification (normalization) and weighting (Yağcı, 2021). Each criterion layer is converted to a common ordinal scale—typically 1 (least suitable) to 9 (most suitable) (Saaty, 1977).

The weighting step assigns a relative importance to each criterion layer based on its contribution to the overall afforestation objectives. These weights, typically expressed as percentages that sum to 100%, reflect the decision-maker's or stakeholder's priorities. The determination of these weights can be informed by expert knowledge, literature reviews, statistical analysis, or participatory methods such as the Analytic Hierarchy Process (AHP), which is the method chosen for this study, with its full application described in chapter 3.4 (Yağcı, 2021).

When performing a WOA, the final suitability map is generated by multiplying the reclassified values of each pixel in each layer by its assigned weight and then summing these weighted values across all layers. Mathematically, the suitability score S_{ij} for a given pixel ij can be represented as:

$$S_{ij} = \sum_{k=1}^{n} \left(v_{kij} \cdot w_i \right)$$

Equation 2.1

Where:

- n is the total number of criteria included in the analysis
- v_{kij} is the normalized value of pixel (i, j) in the k^{th} criterion layer.
- w_k is the weight assigned to the k^{th} criterion layer.

The weighted sum yields a continuous suitability surface. Pixels can then be ranked and clipped to meet the 250.000 hectares policy target, or queried at any aggregation level required for municipal planning (Malczewski, 1999).

2.3.1 Weighting with the Analytic Hierarchy Process

Within WOA the Analytic Hierarchy Process (AHP) is one of the most widely adopted weighting-tools, because it transforms complex questions into pairwise judgements, derives a priority vector through the principal-eigenvalue method, and tests logical coherence via the Consistency Ratio (CR) (Saaty, 1977) (J. Malczewski, 2015).

Despite its widespread adoption AHP has however faced several critiques in the decision-making literature. A primary concern revolves around the inherent subjectivity introduced through the reliance on human judgments in pairwise comparisons, which can be influenced by individual biases and inconsistencies (Dyer, 1990). Another significant limitation is the rank reversal phenomenon, where the addition or removal of an alternative can alter the relative ranking of existing options, raising questions about the stability and validity of AHP results (Belton, 1986). Furthermore, the linguistic vagueness used to express preferences can lead to inconsistent interpretations and contribute to the overall subjectivity of the weighting process

(A. Ishizaka, 2011). Furthermore AHP becomes resource-intensive when many criteria or stakeholder groups must be represented, because each additional participant multiplies the number of vetting, contact and coordination. Additionally pairwise judgements that have to be collected, validated and reconciled will increase. Organizing reiterations in case of unacceptable consistency ratios below the accepted 0.10 threshold, until agreement is reached can demand substantial time and budget—resources that are often scarce in land-use planning projects (J. Malczewski, 2015).
These limitations have motivated the exploration of more data-driven and hybrid approaches to criteria weighting in Multi-Criteria Decision Analysis.

2.3.2 LLM-assisted weighting

In response to the aforementioned limitations of traditional AHP, this study explores the potential of Large Language Models (LLMs) to act as informed decision-makers within the AHP framework.
LLMs, which are built on the transformer architecture, can interpret and generate human-like text, enabling them to synthesize vast, multi-disciplinary information which is a valuable capability in complex decision processes (A. Vaswani et al., 2017). Given their training on very large amounts of text, LLMs possess a broad knowledge base that can encompass diverse domains relevant to complex planning scenarios like afforestation (L. Floridi, 2020). Furthermore, LLMs can potentially simulate the perspectives of various stakeholders by being prompted with specific roles or viewpoints. Their linguistic flexibility enables them to articulate preferences and justifications that align with different interests, such as those of farmers, environmental organizations, or policymakers (OpenAI, 2023).
The ability of LLMs to synthesize information from multiple sources within their training data positions them as valuable tools for informed decision-making in AHP. When comparing the relative importance of different criteria for afforestation, an LLM can draw upon its synthesized understanding of ecological principles, economic factors, and policy implications to provide well-reasoned judgments (T. B. Brown et al., 2020). Moreover, their capacity to identify complex patterns and subtle relationships within the data could lead to more nuanced and insightful pairwise comparisons than might be apparent to human experts (Davis, 2019).

This capability could offer a novel way to incorporate a range of values and priorities into the AHP weighting process and potentially make it more inclusive and representative. The application of LLM's as "experts" or stakeholders in AHP are promising. Carefully designed prompts and validation could secure the broad knowledge and analytical capabilities of LLMs to enhance the robustness and inclusivity of the AHP weighting process in complex decision making scenarios such as afforestation.

However, there are some potential pitfalls. Just as human experts can introduce personal bias into AHP comparisons, LLMs can encode systematic bias from their training data and may occasionally fabricate plausible-sounding but false statements – so-called "hallucinations" (Davis, 2019). Consequently, human oversight is essential when considering the use of LLMs in critical decision-making processes like AHP.

2.3.3 Criterion identification

The selection and definition of criteria are foundational to MCDA, especially when supporting policy implementation such as that of the Green Tripartite Agreement. To ensure policy relevance, transparency, and legitimacy, criteria should ideally be derived directly from the formal objectives and specific language outlined in guiding policy documents. Systematic methods, such as the inductive content-analysis protocols described by Hall and Steiner (2020) for environmental policy, offer a structured approach to translate policy language into analytical themes, thereby enhancing objectivity and comprehensiveness in capturing policy intent (D. M. Hall, 2020).

MCDA theory further guides the refinement of these initially identified themes into a robust set of operational criteria. This involves assessing candidates against key characteristics such as their direct relevance to decision objectives, comprehensiveness in scope, non-redundancy to avoid skewed importance, measurability using available spatial data, and clear interpretability for decision-makers and stakeholders (Malczewski, 1999). Adherence to these principles aims to produce a criteria set that is both theoretically sound and practically applicable for spatial analysis. The specific application of this theoretically-informed approach to derive and refine the criteria used in this thesis is detailed in Chapter 3 (Section 3.4.1).

2.4 Synthesis and Implications for Methods and Research Questions

This chapter has so far reviewed the policy context for afforestation in Denmark (Section 2.1), explored key theories of governance and policy implementation relevant to the Green Tripartite Agreement (Section 2.2), and detailed the principles of spatial Multi-Criteria Decision Analysis (MCDA), Weighted Overlay Analysis (WOA), the Analytic Hierarchy Process (AHP), and the potential role of LLM-assisted weighting (Section 2.3). This synthesis now draws these diverse strands together to articulate the specific methodological framework adopted in this thesis, a framework designed to address the identified research questions and the practical challenges inherent in translating policy into spatial action.

The literature review confirms that while Weighted Overlay Analysis coupled with AHP is a prevailing technique in recent European afforestation studies, the reliance on conventional expert panels for deriving criterion weights presents known challenges regarding time, cost, and potentially the breadth of perspectives incorporated. Furthermore, to the best of the author's knowledge, no published study has yet systematically employed Large Language Models as synthetic experts within the AHP.

To address this identified research gap, and to operationalize the critical implementation conditions outlined by Sabatier and Mazmanian (Section 2.2.1), this thesis develops and applies a methodological framework for afforestation prioritization (table 2.2). While the framework incorporates established GIS and MCDA practices, its primary methodological innovation lies in the development and testing of a hybrid human–LLM AHP weighting protocol. This specific protocol is designed to explore potential efficiencies and new forms of expert elicitation by leveraging LLMs to emulate diverse stakeholder roles, with their outputs benchmarked against and validated by a panel of human experts. The aim is to combine the potential breadth of LLM insights with the depth and critical oversight of human expertise, as detailed in Chapter 3.3.

Implementation condition	**Operational response in the present study**
Clear, measurable goal	The 250.000-ha target and 2045 deadline define the *area threshold* for the suitability model. After the Weighted Overlay Analysis (WOA) is computed, pixels are ranked and the top-ranked 250.000 hectares are clipped to produce a policy-ready priority map (chapter 3.4).
Adequate resources	The project explores an innovative process of using LLMs to generate pairwise AHP matrices. If LLM assistance can deliver weights that are consistent and defensible, the time- and cost-savings address the resource constraint identified by Sabatier and Mazmanian.
Supportive constituencies	Divergent stakeholder priorities (e.g., carbon storage, groundwater protection, farm income) are addressed by employing a hybrid Analytic Hierarchy Process (AHP) weighting scheme. This approach is designed to transparently incorporate and balance multiple perspectives by drawing on both human expert judgments and an experimental application of Large Language Models emulating different stakeholder roles. The aim is to ensure the weighting process is methodologically rigorous, politically balanced, and auditable (full procedural details in Chapter 3.3).
Administrative capacity	Legal instruments such as Forest Act, Planning Act, Natura 2000, municipal “desired / undesired afforestation” maps, are converted into a binary constraint mask. Urban zones, § 3 lakes, water-abstraction buffers and municipally flagged “no-planting” areas are removed before the final suitable areas are calculated (chapter 3.2.3).

Table 2.2 Sabatier and Mazmanian’s Implementation Conditions within this study.

By explicitly linking its methodological design to established implementation theory, as summarized in Table 2.2, this study aims to move beyond a purely biophysical suitability exercise. The goal is to develop a policy-relevant decision tool that is sensitive to the governance realities of the Green Tripartite Agreement and offers a transparent, theoretically grounded approach to spatial prioritization.

3. Methods

Building on Chapter 2’s outline of the policy context and theoretical foundations this chapter, now transitions from this conceptual framework to the practical execution of the research. It provides a detailed look of the methods used to identify and prioritize suitable areas for afforestation across Denmark, thereby addressing the research questions and aiming to meet the 250.000-hectare national target.

Figure 3.1 below offers a visual guide to this chapter’s position within the overall thesis structure and outlines the key methodological stages that will be detailed.

1. Introduction Frames the problem and research questions

2. Litterature review Provides the theoretical foundation for the analysis design and GIS workflow

3. Methods Converts the framework into a reproducible GIS workflow

- 3.1 Data sources and preprocessing (100 m ETRS89/UTM 32 N grid)
- 3.2 Spatial framework and data classification (criteria, reclassification, legal mask)
- 3.3 Analysis design
- 3.4 Stage 1. Analytical Hierachy Process
  - 3.4.1 Using AHP with peers to derive criterion weights
  - 3.4.2 LLM-assisted AHP weighting
  - 3.4.3 Dianostics for evaluating AHP outputs
  - 3.4.4 AI experiment design using LLMs to derive normalization scores (
- 3.5 Stage 2: Suitability Analysis
  - 3.5.1 Criterion Identification
- 3.6 Post-processing

4. Analysis and Results Presents what the workflow produces

5. Discussion Interprets findings, assesses methods, and places them in policy context

6. Conclusion Answers the research questions and offers recommendations

Figure 3.1 Thesis structure diagram with the Methods section highlighted in figure.

3.1 Data sources and preprocessing

This study focuses exclusively on afforestation and its environmental effects, as outlined in The Green Tripartite Agreement. The study does not include other land-use changes such as wetland restoration or extensive land management. The analysis is limited to areas designated for afforestation in Denmark’s policy framework. Landowner willingness, economic incentives, and market-driven afforestation dynamics are not explicitly modeled. The study primarily focuses on physical and policy-based site selection, rather than financial viability. The study covers only Denmark and does not consider afforestation efforts in Greenland or the Faroe Islands.

3.2 Spatial framework and data standardization

Throughout, all geoprocessing is carried out in ArcGIS Pro 3.3 using a uniform ETRS89 / UTM 32N grid at 100 m resolution. For SQL-based data manipulation, querying, and preparation tasks, PostgreSQL was used**.** A dummy “snap raster” with these properties was generated and used to rasterize every vector layer to minimize resampling issues. NoData cells were reclassified to 9 where the lack of feature implied no restriction, or to the neutral value 5 where uncertainty might bias results; geographical NoData (sea, foreign territory) was masked.
Data sources, parameter settings and full AHP matrices are documented in Appendix A-1 and B.

3.3 Analysis Design

This thesis adopts an analytical framework to identify suitable afforestation areas in Denmark (RQ1), as mandated by the Green Tripartite Agreement. Central to this is a Weighted Overlay Analysis, which relies on criterion weights and normalization scores from the Analytic Hierarchy Process (See equation 2.1). A key part of this AHP application is addressing RQ2: evaluating if Large Language Models (LLMs) can effectively support AHP scoring. This LLM evaluation is thus an integral methodological step for the spatial prioritization. The framework consists of two interconnected stages:

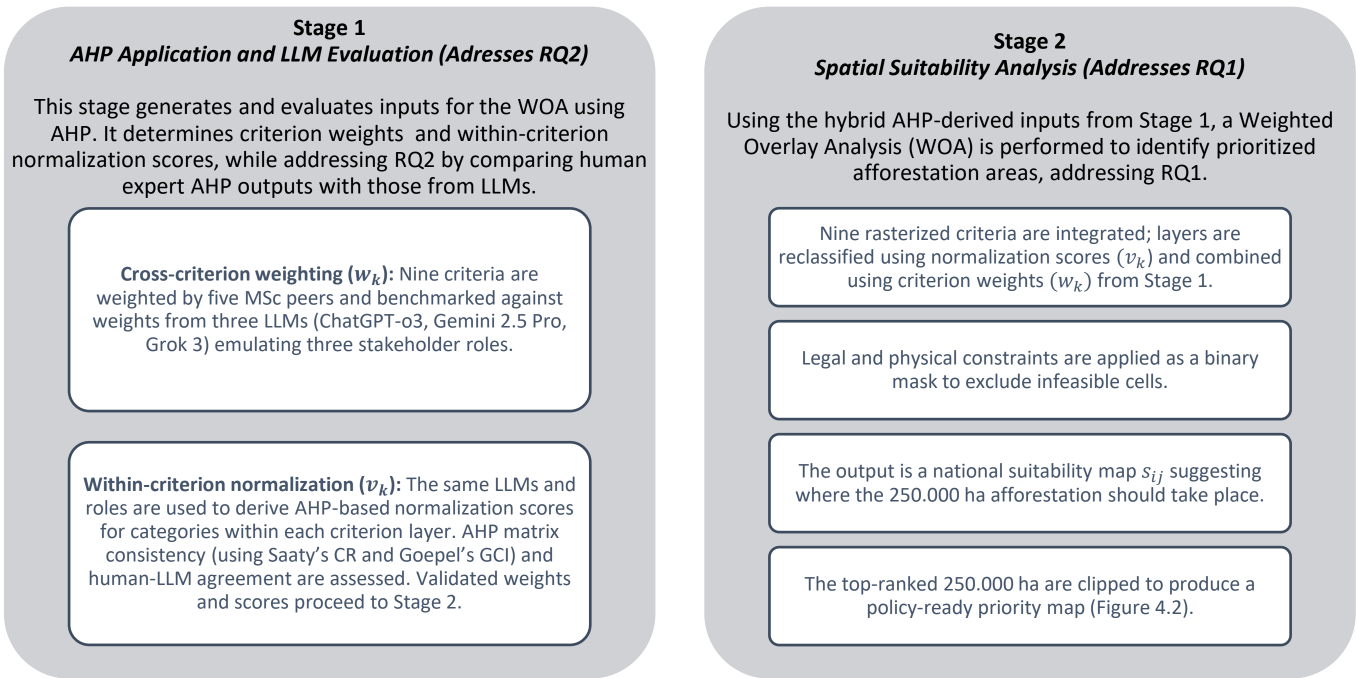

Figure 3.2 The two-stage analytical framework for afforestation prioritization. Stage 1 details the AHP application and LLM evaluation for deriving criteria weights and normalization scores, while Stage 2 outlines the spatial suitability analysis (WOA) for identifying priority areas.

This two-stage design ensures the spatial prioritization (RQ1) relies on a rigorously evaluated weighting methodology, incorporating an investigation into LLM utility (RQ2). Chapter 3.4 will describe the methods used for stage 1 and chapter 3.5 will describe the methods used for stage 2.

3.4 Stage 1: AHP Application and LLM Evaluation

This initial stage of the analytical framework (as outlined in Section 3.3) focuses on the application of the Analytic Hierarchy Process (AHP) and the experimental use of Large Language Models (LLMs) to derive the essential inputs - criterion weights and category normalization scores - for the subsequent suitability analysis. A primary objective of this stage is to address the second research question:

> **RQ2: To what extent can large language models (LLMs) effectively substitute or complement human expert judgement in Analytic Hierarchy Process (AHP) scoring for spatial afforestation planning?**

To investigate this, and to generate the necessary AHP-derived inputs, the Analytic Hierarchy Process (Saaty, 1970) is employed for two key tasks within this study:

1. **LLM assisted weighting experiment.**
   To benchmark the LLM workflow, 9 criterion AHP weight vectors from five human experts were compared with nine vectors generated by three large-language models (ChatGPT o3, Gemini 2.5 Pro and Grok 3) under three stakeholder-role prompts. The LLM's was assigned the roles as conservation biologist, agricultural economist and a municipal planner (see chapter 3.4.3). Internal coherence was checked with the Consistency Ratio (CR), while cross-group agreement was evaluated with Spearman's ρ and Kendall's τ b, and a jack-knife sensitivity test was performed on the five human expert vectors. Results, presented in Chapter 4, show that the LLM workflow reproduces human judgement within the predefined acceptance margins.
2. ***Category normalization.***
   Having validated the LLM approach, it was applied to the more granular task of scoring every category within each input layer (Type of crops, BPS, livestock density, etc.). Each layer received the same role-specific prompts; the resulting matrices passed the CR ≤ 0.10 gate and were averaged to a single normalization vector v_k.

All AHP calculations were carried out in the open-source Excel template by Goepel (2013), which provides automatic CR and GCI (Geometric Consistency Index) diagnostics as well as geometric-mean aggregation for groups.

3.4.1 Using AHP with peers to derive criterion weights

Five peers, each with a background in surveying and land management or geography was recruited as experts for the pair-wise comparison of criteria. Each had prior coursework in MCDA.
A one-page instruction sheet was e-mailed to every expert including (Appendix B-2):

- A short reminder of the decision context (afforestation under the Green Tripartite Agreement).
- The 9 criteria that appear in the LLM prompt, with the Saaty 1–9 scale of pairwise comparisons.
- The prepared Goepels AHP spreadsheet and instructions.

Once the completed AHP spreadsheets were returned by the experts, each was processed using the functionalities within the Goepel (2013) template itself. This template automatically calculates the Consistency Ratio (CR) (Saaty, 1970) for each individual expert's set of judgments. A CR value of ≤ 0.10 was considered the threshold for acceptable consistency. The established procedure, should an individual matrix exceed this CR threshold, was to provide targeted feedback to the respondent. This feedback would highlight the three pairwise comparisons – as identified by the Goepel template – that contributed most significantly to the inconsistency, along with a request to reconsider and potentially revise these specific judgments.

Following the individual consistency screening, the expert matrices deemed acceptable were further processed for group-level analysis, again utilizing the Goepel (2013) AHP template. The template automatically aggregates these individual matrices using the geometric mean to produce a single human composite matrix and its corresponding group priority weight vector w_H.

The methodological plan then involved evaluating the reliability and stability of this collective result by interpreting several diagnostic metrics, many of which are also automatically generated by the Goepel template. Specifically, the consistency of the composite group matrix was to be confirmed using its Composite Consistency Ratio, with the same acceptance threshold of CR < 0.10. Inter-expert agreement was planned to be assessed based on the template's output for Goepel's Ψ consensus index, aiming for a Ψ value greater than 25% as an indicator of reasonable consensus. To further examine the stability of the composite weight vector and to ensure that no single expert's judgments had an undue influence on the final group outcome, a leave-one-out jack-knife procedure was performed. This procedure involves interpreting shifts in criterion weights and overall rank stability that result from systematically omitting one expert at a time from the group aggregation, a process that can also be supported by AHP software outputs.

The final human composite vector (w_H), derived through this template-assisted aggregation and assessed for robustness according to these planned checks, was designated as the primary benchmark for comparison with the LLM-derived weight vectors, with the outcomes of these comparisons reported in Chapter 4.

3.4.2 LLM-assisted AHP weighting

To generate criterion weight vectors using LLMs, a structured experimental design was implemented. Three leading public Large Language Models were selected for this purpose: ChatGPT-o3 (OpenAI), Gemini 2.5 Pro (Google), and Grok 3 (xAI). For each of these models, a single prompt template was utilized, but issued under three distinct stakeholder perspectives to emulate a range of expert viewpoints. These roles were:

- **Conservation biologist:** Focused on Natura 2000 habitat protection and ecological connectivity.
- **Agricultural economist:** Specialized in land rents, commodity prices, and CAP subsidies.
- **Municipal planner:** Representing Aarhus Kommune, tasked with balancing environmental targets against local socio-economic development and Planning Act constraints.

This approach yielded nine independent sets of pairwise comparisons for the criteria (three LLMs × three stakeholder roles). The final prompts used for this process were developed through an initial, iterative testing phase to ensure clarity and minimize potential misunderstandings by the models. Each prompt (full text provided in Appendix C-1) systematically:

- Summarized the Green Tripartite Agreement and its afforestation goals.
- Listed the 9 afforestation criteria to be compared pairwise.
- Explained Saaty's 1–9 scale for pairwise comparisons and enumerated the required criterion pairs.

During the response generation, the LLM indicated which criterion in a pair was more suitable/important and the corresponding intensity score (1–9). To ensure the independence of each generated matrix and avoid conversational bias, no follow-up dialogue or iterative refinement with the LLMs was permitted during this initial response generation.

The aggregation of the LLM-derived judgments followed a two-step procedure, also performed within the Goepel template:

- **Within-role aggregation:** For each of the three stakeholder roles, the AHP vectors from the three LLMs emulating that role were first geometrically averaged. This produced three distinct role-specific vectors: a Conservation Biologist vector, an Agricultural Economist vector, and a Municipal Planner vector.
- **Across-role aggregation:** Subsequently, these three role-specific vectors were themselves geometrically averaged to form a single, overall LLM composite weight vector (w_{LLM}).

This w_{LLM} vector, along with the individual role-specific vectors, was then systematically compared against the human benchmark vector (w_H) using various agreement metrics and sensitivity analyses as described in the following chapter.

3.4.3 Diagnostics for evaluating AHP outputs

To ensure the reliability and validity of all AHP-derived outputs in this study, both individual and aggregated matrices (from human experts and LLMs) were evaluated using a comprehensive set of internal and external diagnostic metrics. Internally, metrics automatically generated by the Goepel (2013) AHP spreadsheet, such as the Consistency Ratio (CR) (Saaty, 1970), the Geometric Consistency Index (GCI), and the Shannon-based consensus index (Ψ), were utilized.
For external assessment and cross-matrix comparisons, particularly between human and LLM outputs, analyses Python was used to calculate Spearman's ρ and Kendall's τb (Zar, 2010) for rank correlation, and Kendall's W (Landis, 1977) for group concordance. Robustness of expert-derived weights was further assessed via a leave-one-expert-out jack-knife procedure (B. Efron, 1994).
Standard AHP practice thresholds were adopted: for example, CR ≤ 0.10, and W ≥ 0.60 to denote strong group consensus, with W < 0.40 triggering a divergence review. Table 3.1 provides a detailed list of each metric employed, its specific purpose in this study, and the interpretation rules or decision thresholds applied in the subsequent analysis presented in Chapter 4.
Table 3.1 lists each metric, its purpose, and the decision rule that guides the later analysis.

Metric	Source	Rationale	Acceptance rule
Priority weights (eigenvector)	*AHPcalc* (Summary sheet)	Final relative importance of the 9criteria; used in the GIS overlay.	No threshold; all vectors retained.
λmax	*AHPcalc*	Intermediate value for CR-formula; monitored for numerical stability.	Informational only.
Consistency Ratio (CR)	*AHPcalc*	Internal logical coherence of a single judgement matrix (Saaty 1980).	Target CR ≤ 0.10. Values 0.10–0.15 tolerated if localised and explained; > 0.15 triggers a focused revision round.
Geometric Consistency Index (GCI)	*AHPcalc*	Alternative consistency check less sensitive to matrix size.	Monitored; no hard cut-off.
Mean Relative Error (MRE)	*AHPcalc*	Sensitivity band on each weight; informs robustness discussion.	Informational only.
Ψ-index (Shannon consensus)	*AHPcalc* (group matrix)	Degree of agreement among k decision makers; 100 % = perfect, 0 % = none (Goepel 2013).	Ψ < 40 % flagged as "low consensus"; used narratively, not as exclusion.
Spearman rank correlation (ρ)	Python	Monotonic agreement between two weight vectors (e.g., human composite vs. LLM composite).	ρ ≥ 0.60 interpreted as "strong" alignment; statistical significance reported at α = 0.05.
Kendall's τb	Python	Pair-wise rank agreement, more robust to ties.	Provided alongside ρ for completeness; same qualitative bands.
Kendall's W	Python	Overall concordance across ≥ 3 weight vectors (e.g., five experts; nine LLM personas).	W ≥ 0.60 = strong agreement; W < 0.40 triggers commentary on divergence.
Jack-knife range	Python	Leave-one-out variation on each weight; tests influence of single stakeholder.	No formal cut-off; used to flag any criterion whose weight shifts > 0.05.

Table 3.1 Overview of Diagnostic Metrics, Their Sources, Rationale, and Acceptance Rules for AHP Evaluation.

3.4.4 AI experiment design – using LLMs to derive normalization scores (v_{kij})

Building upon the LLM-AHP workflow established for criterion weighting (Section 3.4.2), a similar approach was adopted to derive category normalization scores (v_{kij}) within each of the nine spatial data layers. The same LLMs (ChatGPT-o3, Gemini 2.5 Pro, Grok 3) were used.

The prompts, refined through iterative testing and detailed in Appendix C-1, maintained common elements such as the GTA context and Saaty's 1–9 scale. However, for this task, each prompt focused on a single data layer, instructing the LLM to perform pairwise comparisons between the *internal categories* of that specific layer (e.g., comparing different crop types within 'Crops and land-use'). As before, LLMs provided a suitability judgment and an intensity score (1–9) for each pair, with no follow-up dialogue to ensure response independence.

These category-specific pairwise comparison matrices were then processed in the Goepel (2013) AHP Excel template, undergoing the same consistency screening (CR ≤ 0.10, with one regeneration permitted if initially exceeded) as the criterion weight matrices.

Weights in the Excel sheet are expressed as percentages. These were converted to integers compatible with Saaty's fundamental scale via a min–max linear transformation:

$$s_i = 1 + 8 \times \frac{w_i - w_{min}}{w_{max} - w_{min}}$$

where w_i is the proportion, and w_{min}/ w_{max} the minimum/maximum within that matrix. Resulting scores were rounded to the nearest integer and capped to stay within the 1–9 range. A SQL update wrote the final normalization scores to each raster layer, completing data standardization for the Weighted Overlay Analysis.

3.5 Stage 2: Suitability Analysis for Afforestation

The primary aim of this suitability analysis is to identify the most suitable areas for afforestation in Denmark based on a set of environmental, legal, and agricultural criteria. The theoretical procedure is described in Chapter 2.4 and analysis provides the foundation for an evaluation of where new forests can optimally be established while balancing nature conservation, environmental protection, and existing land use interests in accordance with the Green Tripart Agreement. The analysis explicitly seeks to answer the first of the research questions:

> **RQ1: Where should afforestation take place to maximize environmental benefits while minimizing conflicts with agriculture and existing land use?**

3.5.1 Criterion Identification

The criteria for the Weighted Overlay Analysis (WOA) were selected based on the theoretical principles outlined in Section 2.3.3, emphasizing direct derivation from the Green Tripartite Agreement (GTA) and systematic refinement.

Initially, the GTA was systematically reviewed, in line with policy content analysis principles (D. M. Hall, 2020), to identify all formal objectives, commitments, and constraints relevant to afforestation. These policy-derived themes were then translated into potential spatial criteria by sourcing corresponding national GIS datasets from official Danish geodata portals.

This initial pool of potential criteria underwent a refinement process. This involved assessing each candidate criterion for its direct relevance to the GTA's afforestation goals, its accessibility, data quality, and the need to avoid significant redundancy with other criteria. While several data layers were initially considered, this refinement led to a focused set of criteria.

A significant final step in defining the criteria set involved incorporating the "National Afforestation Preference Map" (Plan og Landdistrikstyrelsen, 2025). This dataset, indicating areas where new forest is explicitly desired or undesired by municipalities, was found to already integrate considerations for §3 protected nature types and other general protected areas. To avoid redundancy and directly include these crucial local planning perspectives, this map was adopted as a key criterion, leading to the final set of nine (9) criteria used for the Weighted Overlay Analysis.

These nine criteria, detailed in Table 3.5.1, represent the core environmental, agricultural, and policy-based considerations for strategic afforestation in Denmark.

No.	***Criterion (Layer Name)***	***Published Dataset (Native Title)***	***Provider / Portal***	***Year***
1	Peat-rich lowland soils	Tørverige lavbundsarealer	Miljøstyrelsen	2024
2	Forrest	Danske skovområder	Data-Science.dk	2025
3	Ecological Areas	Økologiske arealer	Miljøstyrelsen	2025
4	National Afforestation Preference Map	Skovrejsningsområder, vedtaget	Plandata.dk	2024
5	Targeted N-reduction need	Målrettet kvælstofregulering – indsatsbehov	Miljøstyrelsen	2025
6	Zoning map	Zonekort (land-/by-/sommerhus)	Plandata.dk	2025
7	Crops and land-use	Afgrøder (Markblokke)	Landbrugsstyrelsen	2024
8	Livestock production density	CHR 2023	Landbrugsstyrelsen	2023
9	Basic Payment Scheme subsidy	Grundbetaling (Markblokke)	Landbrugsstyrelsen	2024

Table 3.5.1: Final Criteria Used in the Afforestation Suitability Analysis."

Each of these criteria was subsequently processed for the WOA, involving category normalization (as detailed in Section 3.4.4) and weighting (as detailed in Sections 3.4.1 and 3.4.2).

3.6 Post-processing the Suitability Output

Following the Weighted Overlay Analysis detailed in Section 3.5, which produces a continuous national suitability surface for afforestation, this section outlines the post-processing steps undertaken to translate this surface into the final 250.000-hectare national afforestation portfolio. This operational step ensures the analytical output directly addresses the Green Tripartite Agreement's quantified target.

To derive a spatially explicit portfolio meeting the 250.000-hectare national target, a rule-based, two-step procedure was applied to the constraint-filtered suitability surface generated by the WOA:

1. **Selection of Forest-Adjacent, High-Suitability Areas:** Initially, the analysis focused on areas with high suitability scores (specifically scores 7, 8, and 9) located within a 100-meter buffer of existing forest. This step aligns with the Green Tripartite Agreement's objective of promoting spatially coherent expansion of forest areas.

2. **Reaching the 250.000 ha:** From this subset of forest-adjacent, high-suitability cells, all cells with a suitability score of 9 and all cells with a score of 8 were unconditionally selected. To reach the cumulative national target of 250.000 hectares, additional cells with a score of 7 were then drawn at random from the remaining pool of forest-adjacent, score-7 cells, using the 'Create Random Points' tool in ArcGIS Pro (or equivalent GIS functionality).

The precise area counts for each suitability class included in the final portfolio and the spatial distribution of this priority-layer are presented and discussed in Chapter 4 (specifically Table 4.2 and Figure 4.2.3).

4. Analysis and Results

Having detailed the comprehensive methodological framework in Chapter 3 - which encompassed the establishment of the spatial framework and data standardization procedures, the overall analysis design, the application of the Analytic Hierarchy Process (AHP) for criterion weighting and category normalization including the experimental use of Large Language Models (LLMs) (Stage 1, chapter 3.4), and the procedures for the Weighted Overlay Analysis (WOA) for suitability mapping (Stage 2 chapter 3.5) and post-processing (Chapter 3.6)—this chapter now presents the Analysis and Results. The following sections will systematically report and initially interpret the findings generated from the application of this multi-stage methods-chapter.

The results are presented in two main parts, directly corresponding to the study's research questions and analytical stages. Firstly, the chapter details the outcomes of the AHP evaluations (Section 4.1). This includes the human expert-derived criterion weights, the LLM-derived criterion weights, and a comparative analysis of these, thereby addressing the second research question (RQ2) concerning the utility of LLMs in AHP scoring. Secondly, the chapter presents the results of the national-scale Weighted Overlay Analysis (Section 4.2). These findings directly address the first research question (RQ1) by identifying and prioritizing suitable areas for the 250.000 hectares afforestation target, culminating in the national suitability map and the delineated 250.000 hectares afforestation portfolio. This part also includes considerations of model sensitivity and uncertainty.

Figure 4.1 below offers a visual guide to this chapter's position within the overall thesis structure

1. Introduction Frames the problem and research questions

2. Litterature review Provides the theoretical foundation for the analysis design and GIS workflow

3. Methods Converts the framework into a reproducible GIS workflow

4. Analysis and Results Presents what the workflow produces

- 4.1 Evaluation of AHP-Derived Weights and the Complementary Role of Large-Language Models
  - 4.1.1 Human-derived AHP weights
    - 4.1.1.1 Key observations
  - 4.1.2 LLM-derived AHP weights
    - 4.1.2.1 Key observations
  - 4.1.3 Human vs LLM priority vectors
    - 4.1.3.1 Interpretation of Comparative Findings
- 4.2 Results of WOA
  - 4.2.1 The National Afforestation Suitability Map
  - 4.2.2 Strategic Prioritization of Coherent Forrest
  - 4.2.3 The 250.000 hectare National Afforestation Map
    - 4.2.3.1 Local Qualitative Validation
  - 4.2.4 Summary of Suitability Analyses Outcome
  - 4.2.5 Sensitivity and uncertanty considerations
  - 4.2.6 Conclusion on Suitability analysis for afforestation

5. Discussion Interprets findings, assesses methods, and places them in policy context

6. Conclusion Answers the research questions and offers recommendations

4.1 Evaluation of AHP-Derived Weights and the Complementary Role of Large-Language Models

4.1.1 Human-derived AHP weights

The five domain experts each supplied 45 pairwise judgments concerning the relative importance of the nine afforestation criteria. An overview of their individual consistency ratios (CR) and their top-ranked criteria is presented in Table 4.1. Detailed weights for all nine criteria from each participant are available in Appendix B-1.

Expert	CR	Top-3 criteria (descending weight)
E1	0.115	Peat-rich lowlands, National Afforestation Preference Ecological Areas
E2	0.105	National Afforestation Preference Peat-rich lowlands Ecologival Areas
E3	0.089	Peat-rich lowlands National Afforestation Preference Ecological Areas
E4	0.100	National Afforestation Preference Peat, -rich lowlands Ecological Areas
E5	0.110	Peat-rich lowlands National Afforestation Preference Ecological Areas

Table 4.1: Individual Consistency Ratios and Top-Ranked Criteria from Human Experts

The consistency analysis of the individual expert matrices showed final CR values ranging from 0.089 to 0.115 (Table 4.1). Although three matrices slightly exceeded Saaty's 0.10 guideline for ideal consistency (by a maximum of 0.015), no second round of revisions was performed. This decision was made as these minor exceedances were deemed acceptable in the context of the overall group analysis that followed.

Following the geometric aggregation of the five expert matrices, the resulting human composite matrix yielded a Composite CR of 0.049 and a Goepel's Ψ consensus index of 38%. Both these values meet the predefined acceptance criteria (CR < 0.10 for the composite matrix; Ψ > 25 % for consensus), indicating good internal consistency and a reasonable level of agreement within the expert group regarding their collective judgments. Furthermore, Kendall's W coefficient of concordance for the group was calculated to be 0.71, signifying strong agreement among the five experts.

The robustness of the composite vector was further assessed using a leave-one-out jack-knife analysis. This analysis showed that the maximum weight shift for any single criterion, when one expert was omitted from the aggregation, was only ±0.026. Critically, the ranking of the top-five criteria remained unchanged across all iterations of this test, indicating that no single expert disproportionately dominated the collective outcome.

The final human composite weight vector (w_H), derived from this aggregation process and confirmed as consistent and robust, is presented in Table 4.2. This vector represents the consolidated judgment of the human expert panel on the relative importance of the nine criteria for strategic afforestation.

Criterion	Human composite
Peat-rich lowlands	**0.242**
National Afforestation Preference	**0.230**
Ecological Areas	**0.235**
Targeted N reduction	**0.081**
Existing forest proximity	**0.079**
Zoning map	**0.058**
Crops and land-use	**0.033**
Livestock density	**0.024**
Basic Payment Scheme	**0.020**

Table 4.2: Human Composite Weight Vector (wH) for Afforestation Criteria

This w_H vector subsequently served as the primary benchmark against which the LLM-derived weights were compared, as detailed in the following sections.

4.1.1.1 Key Observations from the Human Expert AHP Evaluation

The evaluation of the AHP matrices derived from the five human experts reveals a number of key patterns and insights into their collective prioritization of afforestation criteria:

- **Individual Consistency:** While all experts demonstrated a foundational understanding of the AHP comparison process, three out of five experts slightly exceeded Saaty's 0.10 CR guideline (Table 4.1). However, these deviations were minor (maximum 0.015 above the threshold) and considered acceptable

- **Dominant Criteria:** A strong consensus emerged regarding the most important criteria. All five experts consistently ranked 'Peat-rich lowlands', 'National Afforestation Preference Map', and 'Ecological Areas' within their top three, merely interchanging the exact order of the first two. This is clearly reflected in the human composite weight vector (w_H), where these three criteria receive the highest weights (table 4.2).
- **Lower Prioritization of Agro-Economic Criteria:** Conversely, criteria directly related to agricultural economics, such as Basic Payment Scheme (0.020) and Livestock density (0.024), were consistently ranked lower by all experts, appearing no higher than seventh in any individual ranking and receiving the lowest weights in the composite vector. This suggests a primary focus on environmental and planning directives among the expert panel when considering afforestation priorities.
- **Strong Group Agreement and Robustness:** Despite minor variations in individual consistency, the overall group consensus was strong. The composite CR for the aggregated human judgments was excellent at 0.049, and Goepel's Ψ consensus index was 38%, both meeting the predefined acceptance criteria. Furthermore, a Kendall's W coefficient of concordance of 0.71 ($p < 0.05$, as per methodology) confirmed this strong agreement among the experts. The leave-one-out jack-knife analysis further underscored the robustness of the aggregated weights, with minimal shifts (±0.026) and no change in the top-five criteria ranking when any single expert was omitted.
- **Implication for Benchmark Vector:** Given the strong overall agreement, acceptable group consistency, and demonstrated robustness, the derived human composite vector (w_H) is considered a reliable representation of the collective expert judgment. This allows it to serve as a solid benchmark for the subsequent comparison with LLM-derived weights.

4.1.2 LLM-derived AHP weights

Three language-model families, Gemini 2.5 pro, ChatGPT o3 and Grok 3, each supplied pair-wise judgements in three professional roles.
Table 4.3 reports the internal consistency (CR) of the nine matrices and the three criteria each persona ranked highest.

Role	Model	CR	Top-3 criteria (descending weight)
Senior conservation biologist	Gemini	0.066	Peat-rich lowlands Ecological Areas National Afforestation Preference
	ChatGPT	0.028	Peat-rich lowlands Ecological Areas National Afforestation Preference

	Grok	0.048	Peat-rich lowlands National Afforestation Preference Ecological Areas
Agricultural economist	Gemini	0.124	Basic Payment Scheme Peat-rich lowlands National Afforestation Preference
	ChatGPT	0.008	Basic Payment Scheme Livestock density Zoning map
	Grok	0.053	Peat-rich lowlands Basic Payment Scheme National Afforestation Preference
Municipal planner	Gemini	0.022	National Afforestation Preference Peat-rich lowlands Zoning map
	ChatGPT	0.009	National Afforestation Preference Peat-rich lowlands Ecological Areas
	Grok	0.115	National Afforestation Preference Peat-rich lowlands Ecological Areas

Table 4.3 Internal consistency and highest-ranked criteria from the LLM's

To assess the level of agreement among the three different LLMs when emulating the same stakeholder role, Kendall's coefficient of concordance (W) was calculated for each set of three nine-criterion rank vectors (k=3, n=9). The results are displayed in Table 4.4.

Role	W	Interpretation
Senior conservation biologist	**0.99**	High agreement
Agricultural economist	**0.89**	High agreement
Municipal planner	**0.89**	High agreement

Table 4.4 Kendall W inside each role (n = 9, k = 3)

The final LLM composite weight vector (w_{LLM}), derived from this aggregation process and confirmed as consistent and robust, is presented in Table 4.5. This vector represents the consolidated judgment of the LLM expert panel on the relative importance of the nine criteria for strategic afforestation.

Criterion	LLM composite
Peat-rich lowlands	**0.22**
National Afforestation Preference	**0.235**
Ecological Areas	**0.209**
Targeted N reduction	**0.077**
Existing forest proximity	**0.075**
Zoning map	**0.078**
Crops and land-use	**0.031**
Livestock density	**0.031**
Basic Payment Scheme	**0.043**

Table 4.5: LLM Composite Weight Vector (w_{LLM}) for Afforestation Criteria

4.1.2.1 Key Observations from the LLM AHP Evaluation

The evaluation of AHP matrices generated by the Large Language Model personas provides some important insights into their performance and characteristics:

- **Individual Persona Consistency:** The majority of LLM personas demonstrated good internal consistency in their judgments. Seven out of the nine generated matrices met Saaty's CR ≤ 0.10 threshold for acceptable consistency. The two matrices that slightly exceeded this guideline (Gemini/Agricultural Economist: CR = 0.124; Grok/Municipal Planner: CR = 0.115) were considered acceptable as the deviations were minor.

- **Strong Within-Role Agreement:** A high degree of consensus was observed *within* each of the three stakeholder roles, despite these judgments being generated by three different LLM families. Conservation biologist personas exhibited almost unanimous agreement (Kendall's W ≈ 0.99), while both agricultural economist and municipal planner personas also showed high agreement (W ≈ 0.89 for both). This strong concordance within roles suggests that the specific framing of the stakeholder perspective in the prompt was a more dominant factor in shaping the weighting profile than the particular LLM used.

- **Influence of Role Framing on Priorities:** The assigned stakeholder roles clearly influenced the LLM-derived weight vectors, demonstrating the models' capacity to adopt and reflect different perspectives. For instance, only the agricultural economist personas significantly elevated the 'Basic

Payment Scheme' criterion. In contrast, the conservation biologist and municipal planner personas tended to converge in prioritizing criteria such as 'Peat-rich lowlands', 'National Afforestation Preference', and 'Ecological Areas'.

- **Commonly Prioritized Criteria by LLMs:** Despite the role-specific nuances, a common set of high-priority criteria emerged across most LLM personas, largely mirroring the emphasis also identified by the human expert panel. Specifically, eight of the nine LLM personas included 'National Afforestation Preference', 'Ecological Areas', and 'Peat-rich lowlands' within their top three ranked criteria.

Given the generally good internal consistency of individual LLM matrices and the strong agreement found within defined roles, the LLM-generated judgments can be considered a logically consistent and role-sensitive representation of AI-simulated stakeholder views. This forms a solid basis for the subsequent comparison of the aggregated LLM priority vector (w_{LLM}) with the human expert composite vector (w_H) in Section 4.1.3.

4.1.3 Human vs LLM priority vectors

Having established the human expert composite weight vector (w_H) in Section 4.1.1 (Table 4.2) and the LLM composite weight vector (w_{LLM}) in Section 4.1.2 (Table 4.5), this section now undertakes a direct comparison to quantify their mutual alignment and highlight substantive convergences and divergences. Both composite vectors were confirmed to be internally coherent, providing a solid basis for this comparative analysis.

Both composites vectors remain internally coherent with a CR 0.049 for w_H and CR = 0.052 for w_{LLM}.

Table 4.6 summarizes the cross-group agreement metrics between the human composite vector and the LLM composite vector.

Metric	Value	Interpretation
Spearman’s ρ	**0.69**	Strong monotonic agreement
Kendall’s τb	**0.55**	Confirms strong correspondence; c. 80 % of criterion pairs share the same order
Top-5 overlap	4 / 5 identical	Only *Zoning map* enters the LLM top-five but not the human top-five

Table 4.6 Key Metrics for Evaluating the Alignment Between Human-Derived and LLM-Derived Composite Criterion Weights.

While the metrics in Table 4.6 provide a quantitative summary of the overall agreement, a visual comparison of the two composite weight vectors can offer further insight into the specific similarities and differences for each criterion. Figure 4.2 below presents a side-by-side bar chart of the human composite vector (w_H) and the LLM composite vector (w_{LLM}) for all nine criteria.

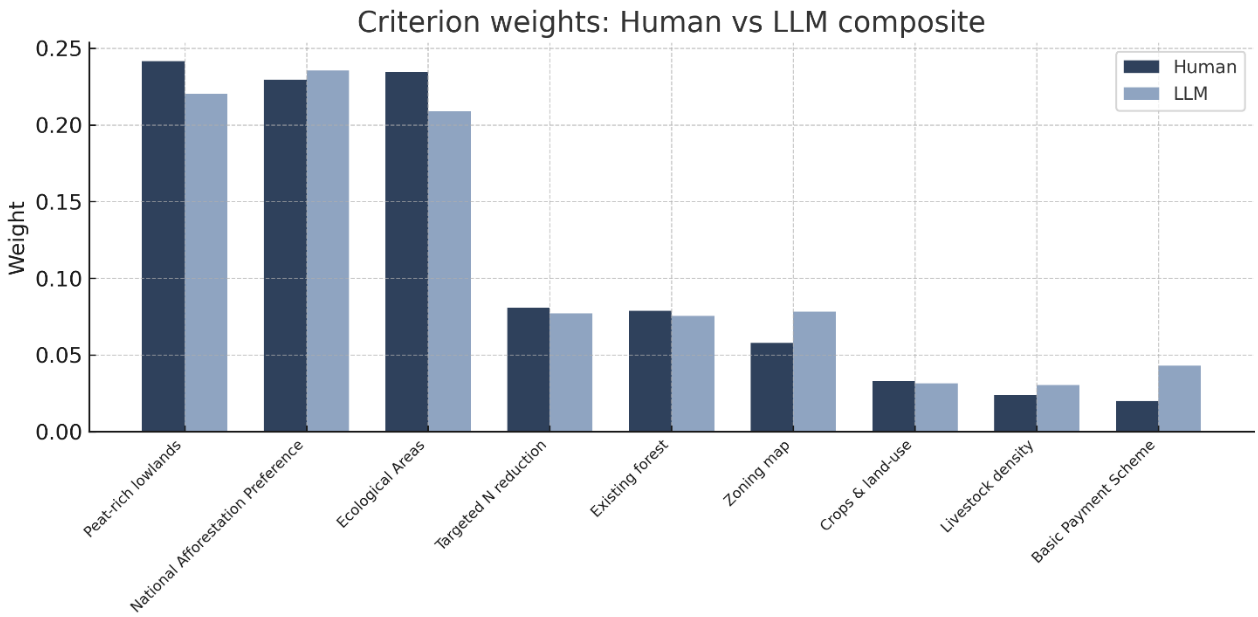

Figure 4.2 side-by-side bar chart of the two weight vectors.

4.1.3.1 Interpretation of Comparative Findings

The cross-group agreement metrics presented in Table 4.6 collectively indicate a substantial and positive correlation between the priorities derived from the human expert panel and those from the LLM composite. A Spearman's ρ of 0.69 and a Kendall's τb of 0.55 both signify strong monotonic agreement in the overall ranking of the nine criteria, suggesting that the relative order of importance for most criterion pairs is consistent between the two groups. This general alignment is further underscored by a 4 out of 5 overlap in the top-five ranked criteria, with the 'Zoning map' criterion being the only one to enter the LLM top-five without being similarly prioritized by the human experts.

The visual comparison provided by the side-by-side bar chart (Figure 4.2) reinforces this general pattern of similarity, while also clearly highlighting specific areas of convergence and divergence. Both the human expert composite vector (w_H) and the LLM composite vector (w_{LLM}) assign the highest importance to criteria such as 'Peat-rich lowlands' and 'National Afforestation Preference'. However, Figure 4.2 also visually illustrates the nuanced differences: the LLM composite tends to assign somewhat greater weight to criteria associated with implementation practicalities or broader planning considerations, such as 'Zoning map', and to a lesser extent 'Basic Payment Scheme', when compared to the human expert panel. Conversely, 'Ecological Areas' received a slightly lower weighting from the LLM composite than from the human experts. These observations suggest that while the core priority structure is largely congruent, the LLM personas, influenced by their assigned roles (particularly planner and economist), introduce subtle shifts in emphasis. The detailed numerical breakdown of these criterion-by-criterion differences is available in Appendix D-1.

4.1.3.2 Sub-conclusion for Research Question 2

The comparative experiment shows that large-language models can function as credible partners in the AHP weighting process for determining criterion importance. Rank-order agreement between the LLM composite vector and the human-expert composite vector is substantial (Spearman $\rho = 0.69$; Kendall's $\tau b = 0.55$). Furthermore, the LLM-generated matrices generally demonstrated acceptable internal consistency. The most pronounced divergences in weighting priorities, such as for the 'Zoning map' and 'Basic Payment Scheme' criteria, appear to stem directly from the different stakeholder roles encoded in the LLM prompts, rather than from erratic model behavior. These divergences highlight the LLMs' capacity to reflect varied perspectives.

In short, LLM personas were found to deliver internally consistent and policy-relevant judgments regarding criterion importance. They effectively broadened the set of perspectives considered without fundamentally compromising the strong ecological and planning emphasis established by the domain specialists. The findings therefore support the use of LLM-assisted AHP as a time- and cost-efficient complement—though not a full substitute to traditional human expert elicitation in the context of nationwide afforestation planning.

4.2 Results of the Weighted Overlay Analysis and Afforestation Prioritization

The validation exercise in chapter 4.1 showed that pure large-language-model (LLM) judgements are internally consistent and align closely with human expert judgements. On that basis the LLM weight vector and normalization scores were used for the Weighted-Overlay Analysis (WOA) to identify and rank afforestation opportunities across Denmark. The following section presents the spatial outcome of applying those LLM-derived inputs to identify and rank candidate afforestation areas across Denmark.

This presentation is structured in four main parts: the national suitability map (Section 4.2.1), the forest-adjacent refinement (Section 4.2.2), the derivation of the 250.000 hectares portfolio (Section 4.2.3), and a brief synthesis of these spatial outcomes (Section 4.2.4).

4.2.1 The National Afforestation Suitability Map

The final WOA model integrates nine spatial criteria, relevant to the Green Tripartite Agreement's goals for CO_2 sequestration, biodiversity, and agricultural considerations. These criteria were reclassified to a common 1–9 suitability scale (where 9 is most suitable) and weighted using insights from the Analytic Hierarchy Process (AHP) described in Section 4.1.

A critical step in the analysis was the application of constraint filtering. This process excluded areas where afforestation is legally or physically prohibited. These constraints are shown in (Table 4.7).

Constraint type	Datasource	Description
Urban zones	Zonekortet (Plandata.dk)	Removed all cells classified as urban zones.
Lakes	Paragraf3_soer_i_IMK_2025 (Plandata.dk	Excluded lakes.
Ground-water abstraction wells	Vandboringer (LandbrugsGIS)	Pixels containing a water well so the well protection buffer was included.
Forest-prohibition reserves	Fredning (Plandata)	Excluded only those protected areas where afforestation is explicitly forbidden.

Table 4.7 Constraints type, source and description

After applying these constraints, the resulting national suitability surface for afforestation ranged from a score of 3 to 9. The total area remaining after constraint filtering was 1.873 million ha. Within this area, high-priority zones, defined as those with suitability scores of 8 and 9, covered approximately 1.058 million ha.

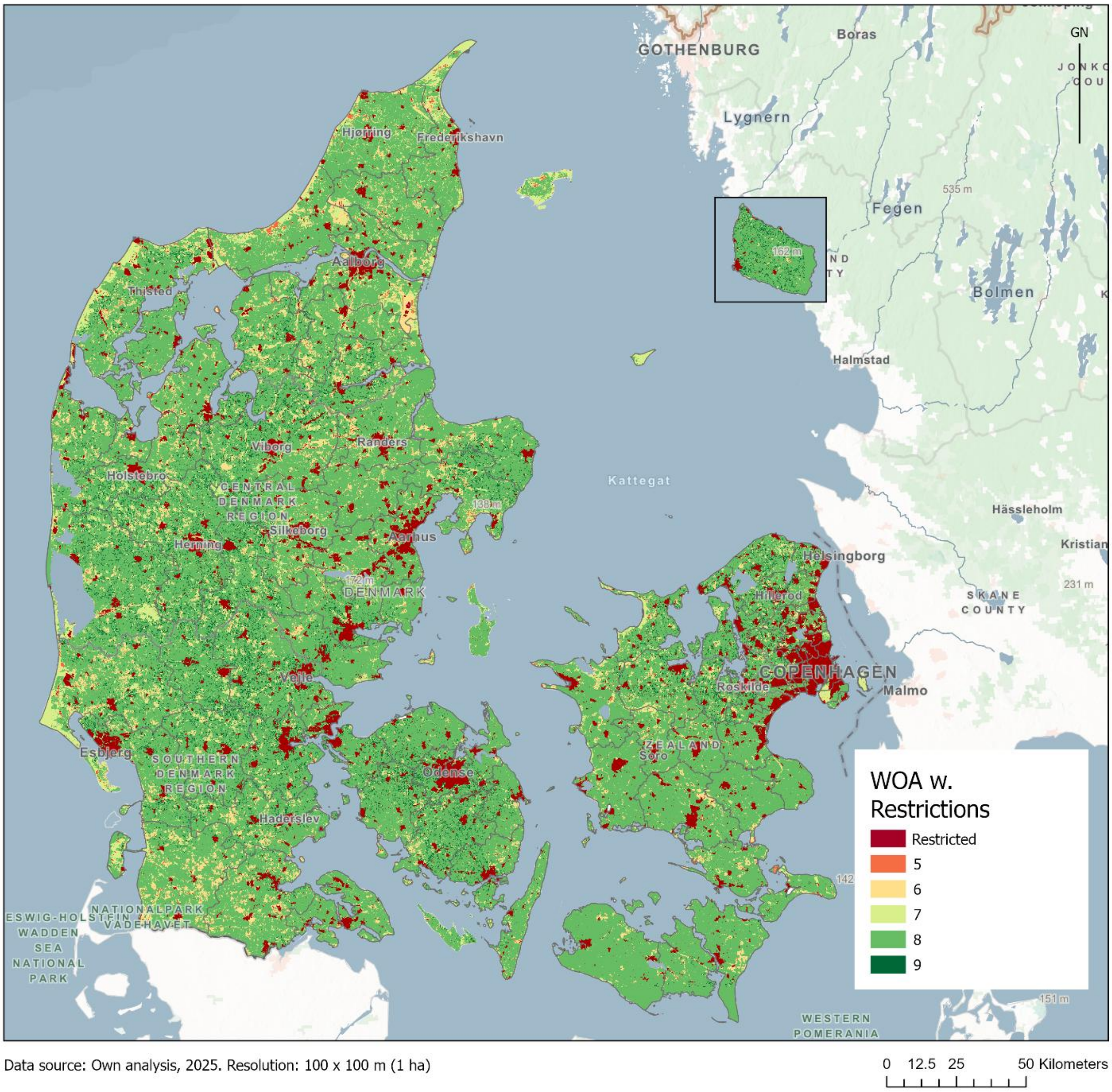

Figure 4.2.1 National suitability map for afforestation in Denmark after the application of legal and physical constraints. Suitability scores range from 3 (least suitable) to 9 (most suitable).

The suitability map (fig. 4.2.1) forms the basis for identifying specific areas for the national afforestation target.

4.2.2 Strategic Prioritization for Coherent Forest Landscapes

To promote the creation of larger, more coherent forest landscapes – a principle aligned with the policy objectives of enhancing biodiversity corridors and structural habitat integrity as discussed in Section 2.1 regarding afforestation's co-benefits, and central to the Green Tripartite Agreement's ambitions – a spatial refinement was applied. A 100-meter buffer was used to identify high-suitability cells (primarily scores 8 and 9) that are located directly adjacent to existing forest areas. This forest-adjacent high-suitability subset, identified through methods consistent with landscape-scale planning often influenced by multi-level governance frameworks (see Section 2.2), was then used as the primary pool from which to select the national afforestation portfolio (fig. 2.4.3). This approach ensures that new forests are strategically placed to contribute to expanding and connecting current woodland, thereby maximizing their ecological impact.

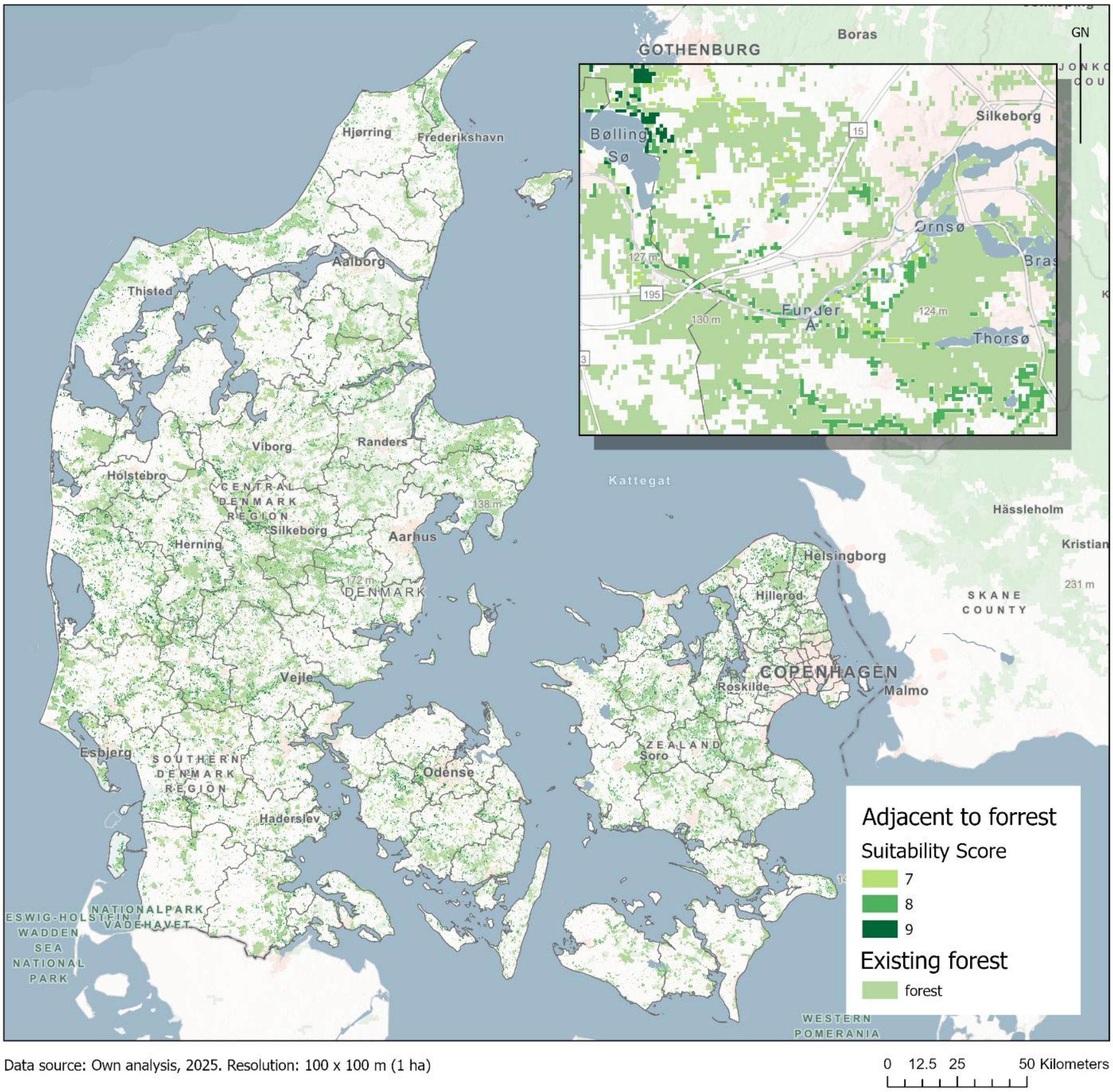

Figure 1.2.2 Map illustrating high-suitability areas (scores 8 and 9) located within 100 meters of existing forests, forming the primary selection pool for the afforestation portfolio (with a zoom on Silkeborg-area for clearer view.). This operationalizes the goal of enhancing landscape coherence.

4.2.3 The 250.000-Hectare National Afforestation Portfolio

The final 250.000-hectare implementation portfolio, directly addressing the quantifiable national target outlined in the Green Tripartite Agreement, was derived from the forest-adjacent, high-suitability subset identified in Section 4.2.2. A rule-based selection process was applied to ensure the portfolio meets the national afforestation target while prioritizing the most suitable and strategically located areas:

1. All 57.884 hectares with a suitability score of 9 were selected. These represent the most optimal areas for afforestation based on the criteria established.
2. All 156.979 hectares with a suitability score of 8 were selected. These areas are also highly suitable and were prioritized.
3. To reach the 250.000 hectares national target, an additional 35.137 hectares with a suitability score of 7 were randomly selected from the remaining pool of forest-adjacent, score-7 cells.

This rule-based selection operationalizes the principles of Spatial Multi-Criteria Decision Analysis (MCDA) and Weighted Overlay Analysis (WOA) discussed in Section 2.3, ensuring a transparent and systematic approach to prioritizing land. The prioritization ensures that the selected areas are not only highly suitable according to the model criteria and spatially connected to existing forests but are also in full compliance with current legal and policy constraints, reflecting the constraint mask approach discussed as an operational response to administrative capacity in Section 2.2.1 and further elaborated in Section 4.2.1. The composition of this 250.000-hectare National Afforestation Portfolio is detailed in Table 4.2.

Suitability Score	Selected Area (ha)	Share of Portfolio (%)
9	57,884	23.2%
8	156,979	62.8%
7	35,137	14.1%
Total	**250.000**	**100.0%**

Table 4.2: Composition of the 250.000-hectare National Afforestation Portfolio

This selection of a top-quota area aligns with the methodological implications for creating policy-ready outputs discussed in Section 2.4. The spatial distribution of this final 250.000 hectares afforestation portfolio across Denmark is visualized in Figure 4.2.3. To provide a more detailed illustration of how these prioritized areas appear at a local level and interact with existing landscape features, Figure 4.2.4 presents a closer view of a selected region, specifically the area around Silkeborg. This detailed map highlights the individual pixels designated for afforestation, differentiated by their suitability scores (7, 8, and 9 where possible), and clearly shows their adjacency to existing forest areas, which was a key element in the strategic prioritization process.

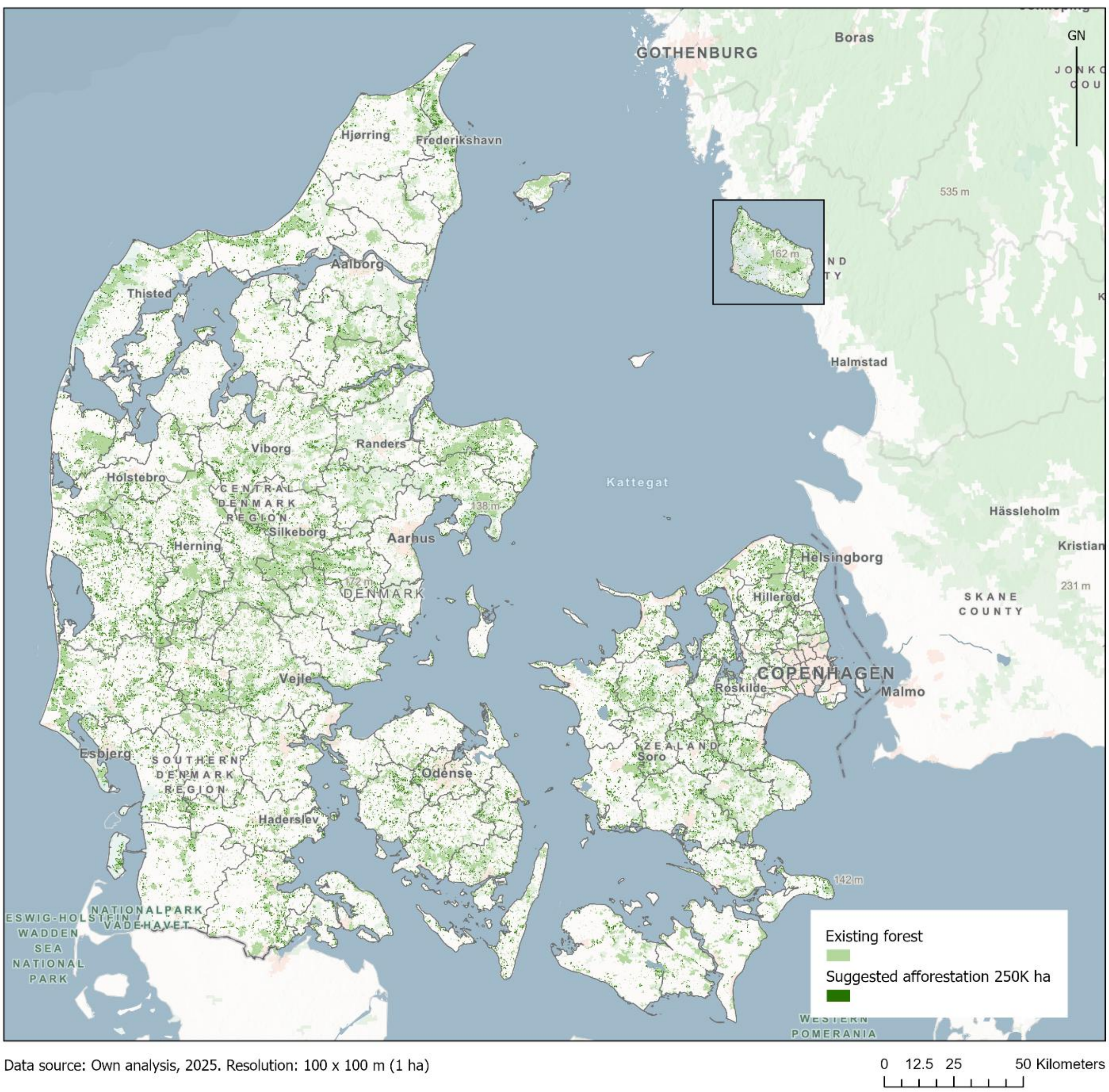

Figure 4.2.3 National overview of the 250.000-hectare Priority 250.000 afforestation portfolio.

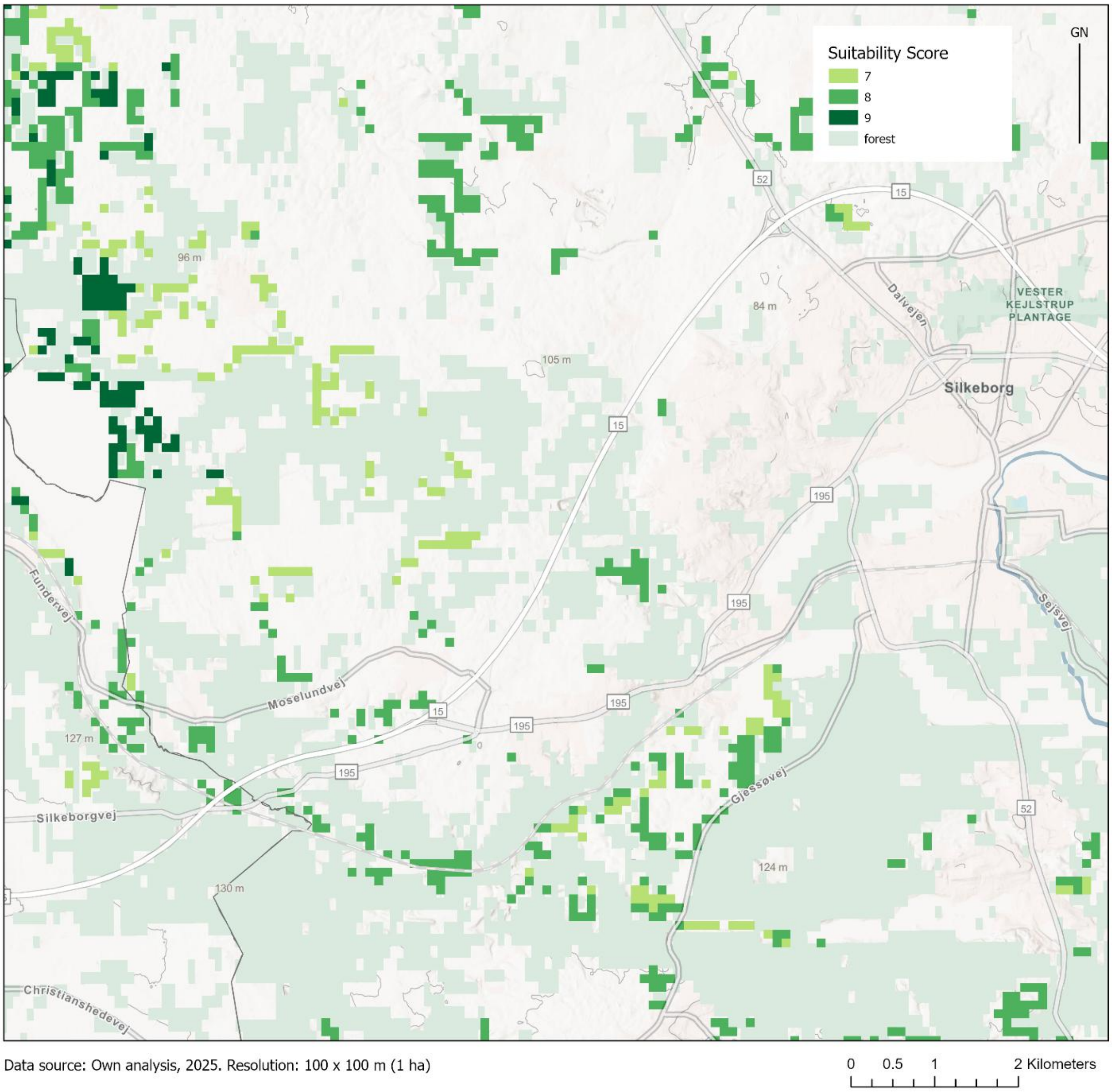

Figure 4.2.4. Detailed view of Silkeborg region showing the portfolio pixels (differentiated by scores 7, 8, and 9 where possible) and their adjacency to existing forest areas, illustrating the outcome of the strategic prioritization.)

4.2.3.1 Local Qualitative Validation of Suitability Outputs

To assess the practical applicability and spatial logic of the generated suitability scores, a qualitative visual inspection was conducted on selected subregions, comparing model outputs with known land-use patterns and landscape features. This involved examining areas like the Silkeborg region (as illustrated in Figure 4.2.4) and the distinct landscape of Nationalpark Thy (Figure 4.2.5).

Case I: Silkeborg Region (Central Jutland)

The Silkeborg region, characterized by a dynamic mix of forest, agriculture, and peri-urban development, served as an initial validation area. The suitability surface here (Figure 4.2.4) exhibited several noteworthy traits:

- Cells with the highest suitability score (9) were almost exclusively located directly adjacent to existing forest, consistent with the model's 100-meter buffer criterion designed to promote coherent forest landscapes as per the Green Tripartite Agreement's intentions.
- A notable cluster of score-7 and score-8 cells formed a mosaic pattern in the southern part of the inspected area, suggesting a high degree of fine-grained variability in the underlying suitability drivers. This may reflect the model's sensitivity to local differences in specific input criteria, such as crop types or subsidy levels.
- Conversely, some high-suitability cells identified near urban edges (east of Silkeborg) raised questions regarding immediate planning realism. While potentially suitable based on the land-use inputs, their practical availability for afforestation might be contingent on further land conversion assessments or the establishment of specific buffer zones not captured in the national-scale model.

These initial findings from the Silkeborg area generally support the spatial coherence and plausibility of the model's output for mixed-use landscapes, while also highlighting the importance of subsequent local-scale interpretation and policy alignment, especially in peri-urban contexts.

Case II: Nationalpark Thy Region (Northwest Jutland)

To further evaluate the model's performance across different Danish landscapes, a second local validation focused on the area around Nationalpark Thy (Figure 4.2.5). This region presents a markedly different land-use context, characterized by low population density, minimal urban development, and extensive, continuous tracts of existing forest, heathland, and dune systems.

In this relatively open and less fragmented environment, the model performed with notable consistency. High-suitability cells (scores 8 and 9) typically appeared in large, spatially clustered formations, primarily adjacent to or forming logical extensions of existing forest areas. This pattern reflects both the functional influence of the forest proximity criterion within the model and the inherent large-scale land-use structure of the Thy region. Unlike in more heterogeneous landscapes, the high-suitability zones here often formed substantial, coherent blocks rather than scattered patches, suggesting a strong alignment between the model's logic and the prevailing landscape conditions.

Score-7 pixels in the Thy region were also frequently arranged in more linear patterns, often forming distinct edge zones along existing forest margins or connecting natural areas. This pattern indicates the model's ability not only to identify isolated suitability hotspots but also to delineate potential buffer zones or corridors where afforestation could significantly enhance ecological connectivity.

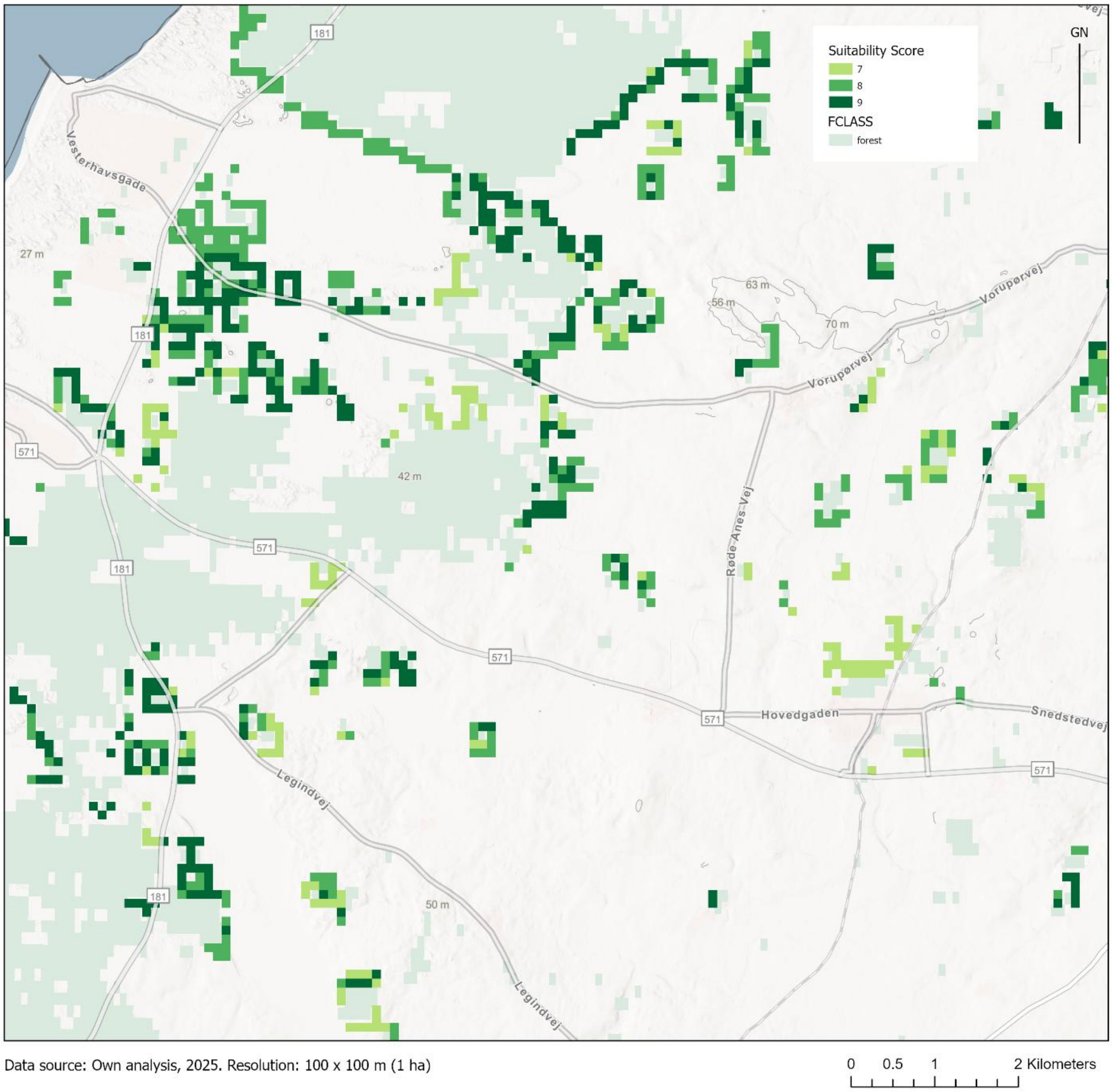

Figure 4.2.5: Detailed view of the Nationalpark Thy region showing prioritized afforestation pixels and their relation to existing natural landscapes.

Summary of Local Qualitative Validation

Overall, the qualitative visual inspection of these contrasting regions suggests that the suitability model is robust and its outputs generally align with landscape logic and national afforestation goals. The model appears particularly effective in identifying coherent afforestation opportunities in open, low-conflict landscapes like Nationalpark Thy, while in more mixed-use and peri-urban areas like Silkeborg, its outputs provide a solid strategic basis that would benefit from further local-scale planning refinement.

4.2.4 Summary of Suitability Analysis Outcomes

The Weighted Overlay Analysis, incorporating nine suitability criteria as justified by the policy review (Section 2.1) and weighted via AHP (Section 2.3.1), alongside essential legal and physical constraints reflecting governance realities (Section 2.2), has successfully identified a substantial land resource available for afforestation in Denmark. After filtering, 1.873 million hectares were deemed suitable (scores 3-9), with 1.058 million hectares classified as high-priority (scores 8-9). The local qualitative validations conducted (Section 4.2.3.1) further support the general spatial logic and plausibility of these suitability outputs in varied landscape contexts.

The strategic selection process, emphasizing adjacency to existing forests to foster ecological coherence (a key theme from Section 2.1), culminated in a 250.000-hectare portfolio. This portfolio is primarily composed of very high (score 9: 23.2%) and high (score 8: 62.8%) suitability areas, supplemented by moderately high (score 7: 14.1%) suitability areas to meet the national target. This spatially explicit portfolio provides a robust, data-driven foundation for planning the implementation of the Green Tripartite Agreement's afforestation goals. It directly reflects the integration of policy objectives (Section 2.1), governance constraints (Section 2.2), and MCDA methodology (Section 2.3), thereby balancing ecological benefits, agricultural considerations, and diverse policy directives.

4.2.5 Sensitivity and uncertainty considerations

The final suitability model and afforestation portfolio were built through a transparent, structured spatial analysis process. However, a number of assumptions influences the outcome:

- **Category scoring (normalization):**
  Suitability scores (1–9) were assigned using AHP matrices generated by large language models (LLMs). Alternative LLM configurations—or the use of human expert scoring—might result in different prioritization between land-use categories, particularly in complex layers like “Crops and Land-use.”
  This is not unique to LLM-generated scores: AHP by human experts is also inherently subjective and rarely produces identical results across respondents. The findings support that LLMs can serve as valid contributors in structured decision processes, but their outputs should, like human inputs, be treated as context-dependent and non-deterministic.
- **Criterion weighting:**
  Weights were derived from five peer experts using AHP. Two criteria (peat-rich lowlands and ecological areas) together account for nearly half the total weight (47 %), meaning small changes in these could affect the spatial pattern of high-suitability areas.
- **Constraint data:**
  Legal and regulatory constraints were applied using the latest available datasets (e.g., zoning, §3 lakes, forest bans). Outdated or incomplete registrations could lead to false positives or negatives.
- **Qualitative review:**
  The qualitative review in selected areas (Section 4.2.3.1) also highlighted that while national constraint data is applied, local planning realities, especially in peri-urban zones, may necessitate further scrutiny beyond the model's technical suitability assessment.

- **Random draw in suitability class 7:**
  To reach the 250.000 hectares portfolio, a random selection of 35,137 pixels with suitability score 7 (adjacent to forest) was made. Different random seeds would result in slightly different spatial layouts, though total statistics would remain stable.

Overall, the model was found to be methodologically robust and consistent with spatial logic across various landscape types.

4.2.6 Conclusion: Suitability Analysis for Afforestation

The weighted overlay analysis (WOA) provided a structured and transparent approach for identifying the most suitable and practically realizable areas for afforestation in Denmark, consistent with the principles of Multi-Criteria Decision Analysis (MCDA) outlined in Section 2.3. By integrating nine carefully selected spatial criteria (identified through the process described in Section 3.5.1) – each reclassified to a common 1-9 scale and weighted through an AHP-based procedure (detailed in Sections 3.4) – the model captures a wide range of environmental, regulatory, and land-use considerations linked to the policy goals discussed in Section 2.1.

The final suitability surface reflects both thematic suitability and legal feasibility, as it was constrained by regulatory layers such as zoning, lakes, protected areas, and officially undesired afforestation zones. This application of a "legal constraint mask," as conceptualized in Section 2.2.1 and methodologically implemented as part of the WOA in Section 3.5, ensures that high-scoring areas are not only environmentally appropriate but also legally implementable.

To support landscape connectivity, a key ecological objective identified in Section 2.1, an additional proximity filter was applied (see method in Section 3.6 or as described in Section 4.2.2) to identify suitability hotspots adjacent to existing forest. From this subset, a 250.000-hectare afforestation portfolio was constructed by selecting all high-priority cells (suitability 9 and 8) and a random subset of score-7 cells to meet the national afforestation target – a target central to the Green Tripartite Agreement (see Section 2.1).
The specific selection rules (detailed in Section 4.2.3) operationalize the aim of creating an actionable output, as discussed in Section 2.4. The qualitative validation in diverse local contexts (Section 4.2.3.1) further indicated that while the portfolio provides a robust strategic foundation, local-scale interpretation remains important, particularly in complex landscapes. The resulting portfolio provides a robust spatial foundation that can inform discussions on implementation strategies and serve as a basis for potential future scenario modelling (further explored in Chapter 5: Discussion).

The WOA model thus successfully addresses the first research question (RQ1), as formulated based on the policy context in Section 1.3.1 and linked to the analysis design in Section 3.3, by identifying where afforestation can be prioritized to maximize ecological benefit while respecting current land use and policy constraints. Its spatial logic, alignment with national goals (discussed in Section 2.1 and 2.2), and transparent methodology make it a solid basis for informing policy decisions and for guiding potential future scenario-based analyses beyond the immediate scope of this thesis.

5. Discussion

This thesis addressed the strategic implementation of Denmark's Green Tripartite Agreement afforestation target by: 1) developing a spatial framework to prioritize 250.000 hectares for afforestation (RQ1), and 2) exploring Large Language Models (LLMs) in AHP-based expert elicitation (RQ2). This chapter discusses the findings in relation to these questions, critically reflects on methodological choices and their implications, considers limitations and policy relevance, and suggests future research. The aim is to contextualize the results within environmental planning, policy implementation, and AI in decision support.

1. Introduction Frames the problem and research questions

2. Litterature review Provides the theoretical foundation for the analysis design and GIS workflow

3. Methods Converts the framework into a reproducible GIS workflow

4. Analysis and Results Presents what the workflow produces

5. Discussion Interprets findings, assesses methods, and places them in policy context

- 5.1 Principal Findings in light of research questions
- 5.2 Methodological Considerations
- 5.3 Policy implementation challenges
- 5.4 Study limitations
- 5.5 Future research directions

6. Conclusion Answers the research questions and offers recommendations

Figure 5.1 Thesis structure diagram with the literature review highlighted in Figure.

5.1 Principal Findings in Light of Research Questions

5.1.1 Discussing RQ1: The Nature and Implications of the Spatial Afforestation Prioritization

The application of Weighted Overlay Analysis (WOA) resulted in the identification of 1.873 million hectares of suitable land post-constraints, with 1.058 million hectares classified as high priority (scores 8-9). The subsequent delineation of the 250.000 hectares portfolio from forest-adjacent, high-suitability cells (scores 9, 8, and necessarily score 7) reflects a pragmatic, rule-based approach to meeting the national target. A notable implication of this spatially explicit selection strategy is the observed tension between the goal of enhancing landscape coherence through adjacency criteria and the potential constraint this places on accessing exclusively the highest-suitability land; the inclusion of score 7 areas became a necessity to fulfill the quota under this condition.

The WOA model's design, which integrated nine criteria intended to reflect CO_2, biodiversity, agricultural, and local planning considerations (such as 'Peat-rich lowland soils', 'Ecological Areas', and the 'National

Afforestation Preference Map'), represents an attempt to navigate and spatially manifest the multi-faceted objectives of the Green Tripartite Agreement. The resulting portfolio can therefore be interpreted as a spatial representation of these embedded, and sometimes competing, priorities and trade-offs. The local qualitative validation (Section 4.2.3.1), examining areas like Silkeborg and Nationalpark Thy, generally confirmed the spatial logic of these outputs, although it also highlighted areas where national-scale modelling meets local complexities, particularly in peri-urban zones.

5.1.2 Discussing RQ2: Reflections on LLM-Assisted AHP

The second research question (RQ2) explored the potential of LLMs in AHP scoring for spatial afforestation planning. The findings from the AHP experiment (Section 4.1), which indicated strong rank-order agreement (Spearman $\rho=0.69$, Kendall's $\tau b=0.55$) between LLM and human composite weight vectors and generally acceptable internal consistency for most LLM matrices, suggest that LLMs *can indeed* produce plausible and coherent AHP judgments.

A significant implication arising from this is the potential for LLMs to enhance the efficiency of traditionally resource-intensive expert elicitation processes. The observed rapid generation of pairwise comparison matrices for diverse criteria and stakeholder roles (as per methods in Sections 3.4.2 and 3.4.4) points towards a substantial opportunity for streamlining AHP workflows, potentially allowing for broader scenario exploration within practical project constraints.
However, the practical application also underscored that effective LLM use necessitates thorough and iterative prompt engineering to achieve desired levels of contextual understanding and output relevance, a process undertaken in this study (Section 3.4.2). Furthermore, while the results are encouraging, they strongly support the notion of LLMs as a *complement* to, rather than a wholesale replacement for, human expertise in such critical decision-making. The indispensability of human oversight for validation, nuanced contextual interpretation, and mitigating potential biases or "hallucinations" remains paramount. Consequently, a hybrid approach – where the efficiency of LLMs for initial input generation is combined with the critical review and validation by human experts (in this case the author of this study) – appears to be the most prudent and promising path forward in this emerging field.

The systematic approach presented herein for applying and benchmarking LLMs within an AHP framework potentially holds broader relevance beyond mere afforestation planning. The rigor pursued in prompt design, role emulation, and validation against human experts can serve as a foundation for the practical application of LLM-assisted multi-criteria analysis in other industries where complex, data-informed decisions must be made, including potentially within the surveying profession.

5.2 Methodological Considerations and Framework Adaptability

5.2.1 The GIS-Based Suitability Framework: Reflections on design choice, limitations, and alternatives

The GIS-based framework used in this study offered a clear and structured way to approach the problem. The choice of a 100m grid resolution provided a good balance for national-level strategic planning, though it naturally led to some generalization of the landscape. Translating the broad objectives of the Green Tripartite Agreement into nine specific spatial criteria was also a key step involving interpretation.
Weighted Overlay Analysis (WOA) was selected as the core MCDA technique, primarily due to its transparency and its established use in Danish forestry planning. While WOA is a valued and understandable method, its compensatory nature – where a low score on one criterion can be offset by high scores on others – is an important detail to consider in the interpretation of results. Alternative MCDA techniques, such as outranking methods or machine learning models, could have been explored in order to find different ways to handle interactions between criteria or manage uncertainties.
Similarly, the application of a binary constraint mask (areas are either in or out) was an effective way to incorporate definite legal restrictions.
Furthermore, the local qualitative validation (Section 4.2.3.1) provided practical examples of these considerations. For instance, while the model identified technically suitable areas near urban edges in the Silkeborg region, their real-world planning feasibility highlighted the importance of integrating fine-grained local knowledge with broader strategic assessments.
For future work, or for specific types of constraints, exploring only using 'soft' constraints (e.g., representing areas as less suitable rather than entirely excluded) could potentially offer more nuanced results and represents an area for methodological refinement.

5.2.2 Portfolio Delineation and Alternative Spatial Strategies

The GIS framework's adaptability is a key strength, as the model's output is shaped by design choices. The 250.000 hectares portfolio, for instance, prioritized areas adjacent to existing forest to enhance landscape coherence and create larger forest blocks. This represents one of several possible strategies. An alternative, aiming at enhancing connectivity in fragmented landscapes, could prioritize smaller, "patchy" forests as "stepping stones" between isolated nature areas, utilizing the same suitability surface but different GIS post-processing (e.g., network analysis). This flexibility demonstrates that the GIS framework is not a definitive answer but a tool for exploring varied policy scenarios based on differing ecological or socio-economic goals.

5.2.3 The Dynamic Nature of Policy Context and Constraints

Defining and using constraints, like the "National Afforestation Preference Map", is important. However, these constraints exist in a policy world that is always changing. For example a political initiative reported by TV2 on May 22, where SF, R, and C proposed a redefinition of 'protected nature,' arguing that areas like golf courses, old industrial sites, and cultivated fields are currently misclassified, and demanding that future classifications reflect more 'real' protection (Brusgaard, 2025). This political discussions about land classification highlight that what constitutes 'protected' or 'undesirable' for afforestation can evolve. Such policy shifts could alter the available land base and optimal portfolio configurations, underscoring the need for adaptable decision-support systems capable of incorporating updated constraints and facilitating scenario analysis based on different policy interpretations.

5.3 Policy Implications and Practical Implementation Challenges

The 250.000 hectares portfolio provides a data-driven, spatially explicit input for national and municipal planners implementing the Green Tripartite Agreement, guiding strategic land purchases and local planning. However, translating this plan into on-the-ground afforestation faces several challenges, notably concerning existing agricultural subsidy schemes.
A central, unmodelled factor in practical afforestation is the existing agricultural subsidy landscape. Current Danish schemes supporting environmentally friendly practices can paradoxically create barriers if landowners already receive support for alternative, eco-friendly land uses, disincentivizing a shift to forestry. Farmers' motivation heavily depends on financial incentives; existing subsidies can create an economic lock-in, meaning highly suitable areas for afforestation (regarding carbon, biodiversity, water protection) may remain unavailable. Thus, analytically optimal areas may not be practically attractive. The "Agreement on a Green Denmark" acknowledges this by prohibiting overcompensation, forcing landowners to choose between schemes. This economic decision point can deter afforestation unless it is clearly more attractive, making existing subsidy structures a critical implementation condition. Addressing this requires making afforestation economically attractive, perhaps via flexible transition or compensation models, or by adapting existing schemes to be complementary. This demands a coordinated political approach and thorough economic analysis. Policymakers must recognize existing subsidies as a potential barrier to achieving the GTA's ambitious objectives.

5.4 Limitations of the Study

Several limitations should be acknowledged. The study focused exclusively on afforestation, excluding other GTA land-use changes. The analysis prioritized physical and policy-based site selection; detailed economic viability and landowner willingness were not explicitly modelled beyond proxy criteria (e.g., 'Basic Payment Scheme subsidy'), meaning actual uptake depends on uncaptured socio-economic factors. As discussed in Section 4.2.5 (Sensitivity and Uncertainty), assumptions regarding LLM-based category scoring, the influence of heavily weighted criteria, constraint data currency, the random selection of some portfolio areas, and the 100m grid resolution (generalizing local conditions) all introduce uncertainties. These factors warrant caution in fine-scale application without further validation. Finally, LLM application, despite its potential, has limitations including potential training data biases, and a lack of true contextual grounding, reinforcing the need for human oversight.

5.5 Future Research Directions

This study opens several avenues for future research:

- **Diverse Afforestation Scenarios:** Systematically develop and compare alternative 250.000 hectares portfolios based on varied strategic objectives (e.g., the "stepping stone" biodiversity model (Section 5.2.2), minimized agricultural opportunity costs, maximized carbon sequestration etc.).
- **Advanced LLM Integration:** Investigate refined prompt engineering, domain-specific fine-tuning of LLMs for AHP, and comparative studies of different LLM architectures.
- **Socio-Economic Integration:** Incorporate detailed economic modelling (cost-benefit analyses) and landowner willingness-to-participate assessments for a more holistic prediction of land-use change.
- **Dynamic Land-Use Change Modelling:** Develop dynamic models simulating afforestation pathways over time, considering market dynamics, policy shifts, and forest maturation.
- **Finer-Scale Validation:** Apply and validate the model at regional/municipal scales using higher-resolution data and detailed local knowledge.

6. Conclusion

This thesis set out to address the critical challenge of strategically implementing Denmark's Green Tripartite Agreement, focusing specifically on the 250.000 hectare afforestation target. The primary objectives were twofold: firstly, to develop and apply a spatially explicit framework to identify and prioritize suitable areas for afforestation across Denmark (RQ1); and secondly, to explore the potential of Large Language Models (LLMs) as a novel tool to support the expert elicitation process within the Analytic Hierarchy Process (AHP) used for this prioritization (RQ2). The study successfully developed and tested such a framework, yielding both a national afforestation portfolio and significant insights into the utility of LLM-assisted AHP.

Addressing Research Question 1:

Which locations in Denmark offer the highest combined potential for carbon sequestration, biodiversity gain and operational feasibility—while ensuring landscape coherence with existing forest and minimizing conflicts with agricultural production?

Regarding the first research question this thesis has demonstrated a robust, data-driven approach. The Weighted Overlay Analysis (WOA), integrating nine policy-derived criteria and essential legal constraints, identified 1.873 million hectares of suitable land for afforestation, with 1.058 million hectares classified as high priority. From this, a 250.000 hectares prioritized afforestation portfolio was delineated, focusing on high-suitability areas adjacent to existing forests to promote landscape coherence.
This portfolio, composed primarily of areas with high (scores 9 and 8) and moderately high (score 7) suitability, represents a spatially explicit plan that balances the multi-faceted objectives of the Green Tripartite Agreement concerning CO_2, biodiversity, and agricultural considerations. The qualitative validation further supported the spatial logic of the model's outputs in diverse landscape contexts. The WOA model thus provides a transparent and theoretically grounded methodology for identifying where afforestation can be prioritized to maximize ecological benefits while respecting current land use and policy constraints.

Addressing Research Question 2:

To what extent can large language models (LLMs) effectively substitute or complement human expert judgement in Analytic Hierarchy Process (AHP) scoring for spatial afforestation planning?

In response to the second research question this study provides compelling evidence for the utility of LLMs. The AHP experiment revealed a strong rank-order agreement (Spearman $\rho = 0.69$; Kendall's $\tau b = 0.55$) between criterion weight vectors derived from LLM personas and those from human experts, with most LLM-generated matrices demonstrating acceptable internal consistency. The findings indicate that LLMs can produce plausible, policy-relevant, and logically consistent AHP judgments, capable of reflecting diverse stakeholder perspectives when appropriately prompted. While LLMs offer significant potential for enhancing the efficiency of resource-intensive expert elicitation processes, the study also underscores the continued indispensability of human oversight for validation, contextual interpretation, and mitigating potential biases. Therefore, this research concludes that LLM-assisted AHP can serve as a time- and cost-efficient *complement* to, but not a full substitute for, traditional human expert elicitation in the context of complex environmental planning. A hybrid approach, combining LLM efficiency with human expert validation, appears to be the most promising path forward.

Principal Contributions and Outlook

This thesis contributes a spatially explicit framework and a tangible 250.000 hectare afforestation portfolio that can directly inform national and municipal planning efforts for the Green Tripartite Agreement. Methodologically, it provides one of the first documented applications of LLM-assisted AHP in a nationwide environmental planning context, demonstrating both its potential and current limitations. The developed framework is adaptable, allowing for the exploration of alternative prioritization scenarios and the incorporation of updated policy contexts or constraints. While the study highlights the importance of addressing practical implementation challenges, such as existing agricultural subsidy schemes, the provided analytical tools and findings offer a robust foundation for more strategic, transparent, and potentially more efficient afforestation planning in Denmark.

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Appendix

Appendix A-1 – All data, sources, categories, normalization scores and final weights

Datalayer	Category	Normalization score (1-9)	Source	Year	Weight (%)
Zoning map*	Rural Zone	9	Zonekortet (Plandata.dk)	2025	6
	Summerhouse Zone	5			
	Urban Zone	1			
Basic Payment Scheme	No Subsidy	9	Markblokke_2024 (LandbrugsGIS)	2024	2
	Low Subsidy	7			
	Moderate Subsidy	4			
	High Subsidy	2			
	Very High Subsidy	1			
Crops and landuse	Root Vegetables and Greens	2	Markblokke_2024 (LandbrugsGIS)	2024	3
	Cereals and Seeds	6			
	Grassland & Meadows	4			
	Fruit	3			
	Fallow & Natural Areas	9			
	Other/Undefined	5			
Targeted Nitrogen Regulation	*Need for intervention:*		Indsatsbehov_maalrettet _kvaelstofregulering_2025	2025	8
	0%	2			
	0,01 – 12,3 %	3			
	12,3 – 16,1 %	4			
	16,1 – 18,0 %	5			
	18,0 – 20,9 %	6			
	20,9 – 26,8 %	7			
	26,8 – 33,7 %	8			
	33,7 – 41,4 %	9			
	41,4 – 45,2 %	9			
Groundwater Abstraction Wells*	Pixels containing waterwell	1	Vandboringer_i_IMK_2024 (LandbrugsGIS)	2024	0
	Pixels not containing waterwell	9			

National Afforestation Preference	Afforestation wanted		Skovrejsningsområder vedtaget (Plandata.dk)	2025	24
	Afforestation not wanted				
Organic Agriculture	Organic farmland	1	Oekologiske_arealer_2024 (LandbrugsGIS)	2024	23
	No Organic farmland	9			
Peat-Rich Lowland Soils	Peat-rich lowland soil	4	Toerverig_lavbund_2024 (LandbrugsGIS)	2024	24
	No Peat-rich lowland soil	5			
Livestock Production	Livestock production	3	CHR23 (LandbrugsGIS)	2023	2
	No Livestock production	9			
Existing Forrest	0–100 m from existing forrest	9	Data-Science.dk (Skove_Danske_Skovomåder)	2025	8
	100–500 m	8			
	500–1000 m	6			
	>1000 m	5			
Lakes*		0.00	§3 søer (LandbrugsGIS)		0
**** are layers used for masking***					
***** are layers used for final selection of 250.000 ha***					

Appendix B-1 – Weights from human experts

AHP Participants Reformatted Data

Sarah

i	j	Criteria A	Criteria B	more important ?	Scale
1	2	Zoning map	Basic Payment Scheme	A	5
1	3	Zoning map	Crops and landuse	A	3
1	4	Zoning map	Ecological areas	B	3
1	5	Zoning map	Targeted nitrogen regulation	A	3
1	6	Zoning map	Peatrich Lowland Soils	B	5
1	7	Zoning map	Livestock production	A	5
1	8	Zoning map	National Afforestation Preference	B	5
2	3	Basic Payment Scheme	Crops and landuse	B	3

2	4	Basic Payment Scheme	Ecological areas	B	7
2	5	Basic Payment Scheme	Targeted nitrogen regulation	B	5
2	6	Basic Payment Scheme	Peatrich Lowland Soils	B	7
2	7	Basic Payment Scheme	Livestock production	A	3
2	8	Basic Payment Scheme	National Afforestation Preference	B	7
3	4	Crops and landuse	Ecological areas	B	5
3	5	Crops and landuse	Targeted nitrogen regulation	B	3
3	6	Crops and landuse	Peatrich Lowland Soils	B	5
3	7	Crops and landuse	Livestock production	A	3
3	8	Crops and landuse	National Afforestation Preference	B	5
4	5	Ecological areas	Targeted nitrogen regulation	A	3
4	6	Ecological areas	Peatrich Lowland Soils	B	3
4	7	Ecological areas	Livestock production	A	5
4	8	Ecological areas	National Afforestation Preference	B	3
5	6	Targeted nitrogen regulation	Peatrich Lowland Soils	B	5
5	7	Targeted nitrogen regulation	Livestock production	A	3
5	8	Targeted nitrogen regulation	National Afforestation Preference	B	5
6	7	Peatrich Lowland Soils	Livestock production	A	5
6	8	Peatrich Lowland Soils	National Afforestation Preference	A	3
7	8	Livestock production	National Afforestation Preference	B	5
Simon					
i	**j**	**Criteria A**	**Criteria B**	**more important ?**	**Scale**
1	2	Zoning map	Basic Payment Scheme	A	3
1	3	Zoning map	Crops and landuse	A	3
1	4	Zoning map	Ecological areas	B	5
1	5	Zoning map	Targeted nitrogen regulation	B	3
1	6	Zoning map	Peatrich Lowland Soils	B	7
1	7	Zoning map	Livestock production	A	3
1	8	Zoning map	National Afforestation Preference	B	5
2	3	Basic Payment Scheme	Crops and landuse	B	3
2	4	Basic Payment Scheme	Ecological areas	B	7
2	5	Basic Payment Scheme	Targeted nitrogen regulation	B	5
2	6	Basic Payment Scheme	Peatrich Lowland Soils	B	7
2	7	Basic Payment Scheme	Livestock production	B	3
2	8	Basic Payment Scheme	National Afforestation Preference	B	7
3	4	Crops and landuse	Ecological areas	B	5
3	5	Crops and landuse	Targeted nitrogen regulation	B	3
3	6	Crops and landuse	Peatrich Lowland Soils	B	7
3	7	Crops and landuse	Livestock production	A	3
3	8	Crops and landuse	National Afforestation Preference	B	5
4	5	Ecological areas	Targeted nitrogen regulation	A	3
4	6	Ecological areas	Peatrich Lowland Soils	B	5

4	7	Ecological areas	Livestock production	A	5
4	8	Ecological areas	National Afforestation Preference	A	3
5	6	Targeted nitrogen regulation	Peatrich Lowland Soils	B	5
5	7	Targeted nitrogen regulation	Livestock production	A	3
5	8	Targeted nitrogen regulation	National Afforestation Preference	B	5
6	7	Peatrich Lowland Soils	Livestock production	A	7
6	8	Peatrich Lowland Soils	National Afforestation Preference	A	5
7	8	Livestock production	National Afforestation Preference	B	5

Lukas

i	j	Criteria A	Criteria B	more important ?	Scale
1	2	Zoning map	Basic Payment Scheme	A	5
1	3	Zoning map	Crops and landuse	A	3
1	4	Zoning map	Ecological areas	B	3
1	5	Zoning map	Targeted nitrogen regulation	B	5
1	6	Zoning map	Peatrich Lowland Soils	B	5
1	7	Zoning map	Livestock production	A	5
1	8	Zoning map	National Afforestation Preference	A	3
2	3	Basic Payment Scheme	Crops and landuse	B	3
2	4	Basic Payment Scheme	Ecological areas	B	5
2	5	Basic Payment Scheme	Targeted nitrogen regulation	B	7
2	6	Basic Payment Scheme	Peatrich Lowland Soils	B	7
2	7	Basic Payment Scheme	Livestock production	A	3
2	8	Basic Payment Scheme	National Afforestation Preference	B	5
3	4	Crops and landuse	Ecological areas	B	3
3	5	Crops and landuse	Targeted nitrogen regulation	B	5
3	6	Crops and landuse	Peatrich Lowland Soils	B	5
3	7	Crops and landuse	Livestock production	A	3
3	8	Crops and landuse	National Afforestation Preference	B	3
4	5	Ecological areas	Targeted nitrogen regulation	B	3
4	6	Ecological areas	Peatrich Lowland Soils	B	3
4	7	Ecological areas	Livestock production	A	5
4	8	Ecological areas	National Afforestation Preference	A	3
5	6	Targeted nitrogen regulation	Peatrich Lowland Soils	B	3
5	7	Targeted nitrogen regulation	Livestock production	A	5
5	8	Targeted nitrogen regulation	National Afforestation Preference	A	3
6	7	Peatrich Lowland Soils	Livestock production	A	5
6	8	Peatrich Lowland Soils	National Afforestation Preference	A	3
7	8	Livestock production	National Afforestation Preference	B	3

Christian

i	j	Criteria A	Criteria B	more important ?	Scale
1	2	Zoning map	Basic Payment Scheme	A	5
1	3	Zoning map	Crops and landuse	A	3

1	4	Zoning map	Ecological areas	B	3
1	5	Zoning map	Targeted nitrogen regulation	B	5
1	6	Zoning map	Peatrich Lowland Soils	B	5
1	7	Zoning map	Livestock production	A	3
1	8	Zoning map	National Afforestation Preference	A	3
2	3	Basic Payment Scheme	Crops and landuse	B	3
2	4	Basic Payment Scheme	Ecological areas	B	5
2	5	Basic Payment Scheme	Targeted nitrogen regulation	B	5
2	6	Basic Payment Scheme	Peatrich Lowland Soils	B	5
2	7	Basic Payment Scheme	Livestock production	B	2
2	8	Basic Payment Scheme	National Afforestation Preference	B	3
3	4	Crops and landuse	Ecological areas	B	5
3	5	Crops and landuse	Targeted nitrogen regulation	B	3
3	6	Crops and landuse	Peatrich Lowland Soils	B	5
3	7	Crops and landuse	Livestock production	A	2
3	8	Crops and landuse	National Afforestation Preference	B	3
4	5	Ecological areas	Targeted nitrogen regulation	A	3
4	6	Ecological areas	Peatrich Lowland Soils	B	5
4	7	Ecological areas	Livestock production	A	5
4	8	Ecological areas	National Afforestation Preference	A	5
5	6	Targeted nitrogen regulation	Peatrich Lowland Soils	B	3
5	7	Targeted nitrogen regulation	Livestock production	A	3
5	8	Targeted nitrogen regulation	National Afforestation Preference	A	3
6	7	Peatrich Lowland Soils	Livestock production	A	5
6	8	Peatrich Lowland Soils	National Afforestation Preference	A	5
7	8	Livestock production	National Afforestation Preference	B	3

Annie

i	j	Criteria A	Criteria B	more important ?	Scale
1	2	Zoning map	Basic Payment Scheme	A	5
1	3	Zoning map	Crops and landuse	A	3
1	4	Zoning map	Ecological areas	B	4
1	5	Zoning map	Targeted nitrogen regulation	B	5
1	6	Zoning map	Peatrich Lowland Soils	B	5
1	7	Zoning map	Livestock production	A	3
1	8	Zoning map	National Afforestation Preference	A	4
2	3	Basic Payment Scheme	Crops and landuse	B	3
2	4	Basic Payment Scheme	Ecological areas	B	5
2	5	Basic Payment Scheme	Targeted nitrogen regulation	B	5
2	6	Basic Payment Scheme	Peatrich Lowland Soils	B	5
2	7	Basic Payment Scheme	Livestock production	B	3
2	8	Basic Payment Scheme	National Afforestation Preference	B	3
3	4	Crops and landuse	Ecological areas	B	5

3	5	Crops and landuse	Targeted nitrogen regulation	B	3
3	6	Crops and landuse	Peatrich Lowland Soils	B	5
3	7	Crops and landuse	Livestock production	B	2
3	8	Crops and landuse	National Afforestation Preference	B	3
4	5	Ecological areas	Targeted nitrogen regulation	A	3
4	6	Ecological areas	Peatrich Lowland Soils	B	5
4	7	Ecological areas	Livestock production	A	5
4	8	Ecological areas	National Afforestation Preference	A	5
5	6	Targeted nitrogen regulation	Peatrich Lowland Soils	B	3
5	7	Targeted nitrogen regulation	Livestock production	A	3
5	8	Targeted nitrogen regulation	National Afforestation Preference	A	2
6	7	Peatrich Lowland Soils	Livestock production	A	6
6	8	Peatrich Lowland Soils	National Afforestation Preference	A	4
7	8	Livestock production	National Afforestation Preference	B	3

Appendix B-2 – Mail for Human Experts

Hi [Peers name]

Thank you so much for agreeing to help me! I need your expertise to help evaluate GIS criteria for new forest planting, supporting the goals of the green tripart agreement in regards to afforestation of 250.000 hectares. I have prepared Goepel’s AHP Spreadsheet, which you might have seen before and attached it here for your to fill in your inputs. Please use the best of your knowledge from school to score how strongly each criterion below supports afforestation. The scoring-system is described in the spreadsheet.

You will be evaluating the following criteria. I have added one line to each layer for context:

Zoning map: Municipal land-use zones; rural zones are generally easier to convert than urban or summerhouse zones.

Basic Payment Scheme (BPS): EU farm-subsidy level; high subsidy can signal strong agricultural dependency and conversion cost.

Crops and land-use intensity: Current cultivation intensity; higher intensity ⇒ greater opportunity cost.

Ecological Areas: prioritized under the Green Tripartite Agreement to remain unchanged

Targeted nitrogen-reduction zones: Areas prioritised for nitrate load reduction; trees are a favourable mitigation measure.

National Afforestation Preference: Municipal designations of areas desired for forest planting or where planting is not desired (e.g., Natura 2000 areas).
Peat-rich lowlands: High carbon storage potential; afforestation helps avoid peat oxidation (if certain plants are selected)

Livestock production density: Proxy for ammonia pressure; higher density can complicate forest establishment – expensive to convert.

Existing forest proximity: Adjacency facilitates ecological connectivity and management.

Thank you for your help! Please return the completed spreadsheet as soon as possible. Let me know if you have any questions.

Best regards,
Christina Elmegaard-Fessel

Appendix B-3 – Summary of human expert replies

AHP Analytic Hierarchy Process (EVM multiple inputs)

K. D. Goepel Version **07.07.2022** Free web based AHP software on: https://bpmsg.com

Only input data in the light green fields and worksheets!

n=	9	Number of criteria (2 to 10)	Scale:	1		AHP 1-9
N=	5	Number of Participants (1 to 20)	α:	0.1	Consensus:	38.0%
p=	0	selected Participant (0=consol.)	2	7		#REFERENCE!

Objective Evaluate GIS criteria for new forest planting, supporting the goals of the green tripart agreement in regards to afforestation of 250.000 hectares.

Author CEF

Date 25-Apr-25 Thresh: 1E-08 Iterations: 14 EVM check: 9.3E-09

Table

	Criterion	Comment	Weights	+/-
1	Zoning map		5.7%	1.0%
2	Basic payment sch		2.0%	2.0%
3	Crops and landuse		3.3%	0.6%
4	Ecological areas		23.5%	4.2%
5	Targeted nitrogen r		8.0%	4.7%
6	Peatrich Lowland S		24.2%	4.4%
7	Livestock productio		2.4%	0.4%
8	National Afforestatio		23.0%	4.1%
9	Existing forrest		7.9%	1.4%
10		question section ("+" in row 66)	0.0%	0.0%

Result

Eigenvalue				Lambda:	10.410		MRE:	18.0%
Consistency Ratio	0.37	GCI:	0.04	Psi:	0.4%	CR:	4.9%	

Appendix C-1 – Prompt for LLM's

You are

(1) [a senior conservation biologist working for Denmark's Nature Agency. Your primary objectives are biodiversity protection, habitat connectivity, and compliance with Natura 2000 obligations.]

(2) [an agricultural economist at Copenhagen Business School, specialising in land rents, commodity prices, and CAP subsidy impacts on Danish farming.]

(3) *[a municipal planner from the City of Aarhus with 15 years' experience in spatial zoning, groundwater protection zones, and recreational land policy. Your mandate is to balance environmental goals with local socio-economic development and legal constraints under the Planning Act.]*

Goal: Score how strongly each GIS criterion below supports new forest planting, using Saaty's 1–9 preference scale: 1 = equal importance, 3 = moderate preference, 5 = strong preference, 7 = very strong preference, 9 = extreme preference. If the second criterion in a pair is more supportive, output the reciprocal 1/2, 1/3 … 1/9. Output exactly 45 lines (numbers only, no extra text), one for each pair in the order given.
Criterion definitions:
A Zoning map: Municipal land-use zones; rural zones are generally easier to convert than urban or summerhouse zones.
B Basic Payment Scheme (BPS): EU farm-subsidy level; high subsidy can signal strong agricultural dependency and conversion cost.
C Crops & land-use intensity: Current cultivation intensity; higher intensity ⇒ greater opportunity cost.
D Protected areas: Natura 2000, Ramsar, etc.; afforestation must align with conservation objectives.
E Targeted nitrogen-reduction zones: Areas prioritised for nitrate load reduction; trees are a favourable mitigation measure.
F Waterwells (ground-water protection): Wellhead protection zones where chemical input must stay low; new forest is preferred to farming, but strict buffers apply.
G § 3 sites: Danish Nature Protection Act habitats; planting allowed only if it enhances habitat value.
H Peat-rich lowlands: High carbon storage potential; afforestation helps avoid peat oxidation.
I Livestock production density: Proxy for ammonia pressure; higher density can complicate forest establishment.
J Existing forest proximity: Adjacency facilitates ecological connectivity and management.
Pairs to evaluate: 1 A vs B, 2 A vs C, 3 A vs D, 4 A vs E, 5 A vs F, 6 A vs G, 7 A vs H, 8 A vs I, 9 A vs J, 10 B vs C, 11 B vs D, 12 B vs E, 13 B vs F, 14 B vs G, 15 B vs H, 16 B vs I, 17 B vs J, 18 C vs D, 19 C vs E, 20 C vs F, 21 C vs G, 22 C vs H, 23 C vs I, 24 C vs J, 25 D vs E, 26 D vs F, 27 D vs G, 28 D vs H, 29 D vs I, 30 D vs J, 31 E vs F, 32 E vs G, 33 E vs H, 34 E vs I, 35 E vs J, 36 F vs G, 37 F vs H, 38 F vs I, 39 F vs J, 40 G vs H, 41 G vs I, 42 G vs J, 43 H vs I, 44 H vs J, 45 I vs J

Appendix C-2 – LLM Replies to prompt

senior conservation biologist			Agricultural Economist			Municipal planner		
Gemini	ChatGPT	GROK	Gemini	ChatGPT	GROK	Gemini	ChatGPT	GROK
4	2	3	1/5	2	3	4	5	3
2	2	3	1/3	2	3	3	2	3
1/8	1/5	1/5	1	1/2	2	1/3	1	1/5
1/2	1/3	1/5	1/7	1/2	1/3	1/5	1/2	1/5
1/2	1/2	1/3	1/3	1/2	1	1/4	1	3
1/8	1/4	1/5	7	1	2	1/2	2	1/3
1/4	1/3	1/5	1/5	1/2	1/3	1/4	1	1/5

8	5	3	5	2	5	2	2	5
1/9	1/3	1/7	3	1	1/2	1/2	1	3
1/2	1	1	1/3	1	1	1/3	1/3	1/3
1/9	1/9	1/7	1/3	1/3	1/2	1/7	1/4	1/7
1/8	1/4	1/7	1/7	1/4	1/5	1/9	1/9	1/7
1/8	1/3	1/5	1/5	1/4	1/3	1/7	1/6	1/5
1/9	1/7	1/7	3	1/3	1/2	1/6	1/3	1/5
1/9	1/5	1/7	1/5	1/5	1/7	1/7	1/6	1/7
2	4	3	1	1	2	1/2	1/2	3
1/9	1/5	1/9	1/3	1/3	1/3	1/7	1/7	3
1/9	1/9	1/7	1	1/3	1/2	1/4	1	1/7
1/4	1/4	1/7	1/5	1/4	1/5	1/6	1/3	1/5
1/4	1/3	1/5	1/3	1/4	1/3	1/5	1/2	1/5
1/9	1/7	1/7	5	1/3	1/2	1/2	1	1/5
1/8	1/5	1/7	1/3	1/5	1/7	1/5	1/2	1/7
4	4	3	3	1	2	2	1	3
1/9	1/5	1/9	1	1/3	1/3	1/3	1/2	3
4	3	1	1/5	1	1/3	1/2	1/2	3
4	4	3	1/3	1	1/2	1/2	1	3
1	2	1	7	1	1	2	1	1
2	3	1	1/3	1/2	1/5	1/2	1	3
9	9	5	5	3	3	5	2	7
1/2	2	1/3	3	1	1/2	2	1/2	5
1	2	3	3	1	2	2	2	3
1/4	1/3	1	9	2	1/3	3	3	3
1/2	1	1	3	1	1/2	2	2	1
9	9	5	7	4	7	9	4	7
1/8	1/2	1/3	5	2	2	3	1	5
1/4	1/3	1/3	9	1	2	3	2	3
1/2	1/2	1/3	1/3	1	1/3	1	1	1
9	9	3	7	4	5	7	2	7
1/8	1/3	1/5	5	1	1	2	1	5
2	2	1	1/9	1/2	1/5	1/3	1/2	1/3
9	9	5	1/5	3	3	3	1	7
1/2	1	1/3	1/7	1	1/2	1/2	1/2	5
9	9	5	9	5	7	7	3	7
1/4	1/2	1/3	7	2	3	2	1	5
1/9	1/9	1/9	1/3	1/3	1/5	1/4	1/3	1/3

Appendix D-1 – Criterion-by-criterion differences between human experts and LLM's

4.1.3

Criterion-by-criterion differences

Criterion	w_H	w_{LLM}	**Δ**	Comment
Peat-rich lowlands	0.242	0.231	−0.011	Near-identical top rank
Afforestation planned / not wanted	0.230	0.247	+0.017	Planners boost municipality planning decisions
Ecological Areas	0.235	0.219	−0.016	Slight downgrade by economists
Targeted N reduction	0.081	0.081	—	Unchanged
Existing forest	0.079	0.079	—	Unchanged
Zoning map	0.058	0.082	+0.024	Elevated by planner personas
Crops and land-use	0.033	0.033	—	Unchanged
Livestock density	0.024	0.032	+0.008	Small upward shift
Basic Payment Scheme	0.020	0.045	+0.025	Driven by economist personas

No absolute difference exceeds 0.03, confirming that overlay outcomes are robust to substitution.