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Towards holistic forest monitoring in Europe: An exploration of forest definitions, cultural ecosystem services and their interactions in Germany’s Natura 2000 sites

GEO 511 Master's Thesis

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30.09.2025

Abstract

Forests play a vital role in supporting terrestrial biodiversity and a variety of important ecosystem services. To protect and conserve forests, comprehensive forest monitoring systems are needed; however, current and planned monitoring approaches have been criticised for under-representing socio-cultural indicators. This is also the case for Europe's Natura 2000 network, the largest network of protected areas in the world. In this thesis, I explored two socio-cultural elements of forest monitoring – forest definitions and cultural ecosystem services (CES) – for a case study in Germany's Natura 2000 sites. To explore how forest definitions influence measurements of forest cover, I compared forest cover and the degree of consensus for six geospatial datasets, each based on a different forest definition. I then applied natural language processing (NLP) and machine learning techniques to derive CES from social media data to gain insights into how people value forests. Finally, to understand the interactions between forest definitions and CES, I compared CES in different areas of forest consensus. My results show that forest cover in Germany's Natura 2000 sites can differ by up to 0.29 million ha depending on the forest definition – nearly twice the amount of net forest change reported for the six-year period from 2012 to 2018. Lack of consensus had a notable influence on forest cover estimates at the site level; at over 600 sites the majority of the site's area showed some degree of disagreement on forest presence. I found that recreationists valued CES associated with historical or religious values, aesthetic beauty and views or outlooks, and appreciated a variety of large natural landscape features in addition to forests. While I observed some differences in CES between non-consensus areas and full consensus forest, these results were inconclusive due to the lack of data in non-consensus areas. My findings demonstrate the considerable impact that the choice of forest definition can have for forest cover measurements, suggesting that forest definition selection should be considered carefully for monitoring in Natura 2000 sites. By contributing to our understanding of the CES experienced by recreationists in Natura 2000 forests, my findings may inform management and conservation strategies that preserve positive human-nature interactions. While my work highlights how social media data can be analysed in an efficient and scalable way with NLP and machine learning to derive CES at the national level, it also shows that these approaches can be limited for use-cases with a high spatial and/or temporal resolution. Future research could focus on how differences in forest definitions can be more clearly represented in monitoring and reporting, as well as how CES derived from social media can be integrated with traditional sources of information such as surveys. Overall, attention to forest definitions and a comprehensive understanding of CES are key for holistic forest monitoring in the Natura 2000 network.

Keywords: forest monitoring, Natura 2000, forest definitions, cultural ecosystem services (CES), natural language processing (NLP), social media analysis, Germany

Acknowledgements

This work would not have been possible without the guidance and support of my supervisor, Prof. Dr. Ross Purves. Our regular meetings were always helpful for sparking new ideas, considering different angles and, perhaps most importantly, building my confidence in my work. Thank you so much for your time, encouragement and insights.

Thank you also to Dr. Abdesslam Chai-allah for sharing public access to his code for downloading Wikiloc data, and for providing background information and encouragement at the start of my project.

I am very grateful for the support from friends in Switzerland, Scotland, Canada and around the world – I am so lucky to have so many people to cheer me on! In particular, I would like to thank my oldest friend Emily for leading the way, Sandra for always lending an ear, Belle for her spontaneous visits and Jil for her encouragement and Friday catch-ups – not to mention her helpful feedback.

I would also like to thank Ava for her incredible wisdom and kindness and for helping me to ‘see the forest’, rather than just the trees.

Getting to this stage would not have been possible without the support of my family, especially my parents. Thank you for always being there for me, even when I am so far away.

Finally, a very heartfelt thank you to my partner, Jakob, who has been incredibly kind, patient and encouraging throughout my entire Master’s degree. Thank you for going through the ups and downs with me, for all your advice and support, and for always making me laugh.

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1 Introduction

Human society depends on forests in many ways. Forests support the most biodiversity of all terrestrial ecosystems (Millennium Ecosystem Assessment, 2005), and this biodiversity provides a large range of ecosystem services, including soil conservation, watershed stabilisation, climate regulation and carbon storage, as well as employment and livelihoods, and benefits to human health and well-being (FAO & UNEP, 2020; IPCC, 2023; Jenkins & Schaap, 2018). Although global forest loss has slowed since 1990, deforestation and forest degradation are continuing to have significant impacts on forest biodiversity (FAO & UNEP, 2020). Furthermore, in ecosystems like forests, climate change is increasing the risk of species extinction and irreversible biodiversity loss (IPCC, 2023). In response, ongoing global initiatives like the New York Declaration on Forests (UN Climate Summit, 2014), the UN REDD and REDD+ programmes (FAO et al., 2008, 2016), the UN Sustainable Development Goals (UN, 2015), and the UN Strategic Plan for Forests (UN Forum on Forests, 2017) aim to protect and restore forests and the ecosystems services they provide.

In Europe, forests are under pressure from land use change, unsustainable human activities and climate change (Directorate-General for Environment, 2023). Although the area of forest in Europe has been steadily increasing over the last 35 years (European Commission, 2015; FOREST EUROPE, 2020), the average state of forests is deteriorating, raising significant concerns about forest health and economic sustainability (FOREST EUROPE, 2020). Even within the Natura 2000 network – a large network of conservation areas across the European Union (EU) – the majority of protected forest habitats are considered to be in either ‘poor’ or ‘bad’ condition (EEA, 2020). In addition to global strategies, Europe-based initiatives like the EU Biodiversity Strategy for 2030 (European Commission, 2020) and the EU Nature Restoration Law (EU, 2024) are intended to protect and restore European forests.

In order to assess whether the objectives of forest action programmes are being met, comprehensive monitoring approaches are required; however, forest monitoring in Europe currently faces many challenges. The European Commission (2023) has described how significant knowledge gaps for forests exist because of a combination of disorganised, outdated and incomplete data, compounded by inconsistent terminology used across the EU. In their most recent report summarising the status of the Natura 2000 network, the European Environment Agency (EEA; EEA, 2020) also acknowledged that their findings were limited by poor data quality and incompleteness. Although new forest monitoring requirements are being developed to address these problems, some argue that important aspects are still missing, particularly in terms of indicators explicitly related to ecosystem services and socio-cultural themes (Chambers, 2024). For the Natura 2000 network, scientists are concerned about gaps in our understanding about social processes that effect protected areas, calling for better integration of social sciences research in an arena which tends to focus more on ecological knowledge (Blicharska et al., 2016; Orlikowska et al., 2016; Popescu et al., 2014). Because social and natural systems are so closely linked (Kareiva & Marvier, 2012), more holistic monitoring and evaluation approaches are now seen as essential for lasting and successful conservation in protected areas like the Natura 2000 network (Blicharska et al., 2016; Tsianou et al., 2013; Vlami et al., 2020).

In an effort to contribute to a more comprehensive understanding of forests in Europe, I aim to provide insights on two socio-cultural aspects of forests in Natura 2000 areas in this thesis: 1) how forests are defined; and 2) how they are valued in terms of cultural ecosystem services (CES). In addition, I explore how these two components interact by examining CES in areas with different levels of consensus on forest presence. Using Germany as a case study, I investigate the differences across six commonly-used definitions of forests and the way they are operationalised as geospatial datasets. I then apply natural language processing (NLP) and machine learning techniques to examine CES in forested areas based on crowdsourced text from social media. Finally, I conduct a comparison of CES in areas of forest consensus (where forest definitions agree on forest presence) and non-consensus (where forest definitions do not agree).

In the next chapter (Chapter 2), I provide further details on the background of my research, as well as the knowledge gaps and research questions that I aim to address. In Chapter 3, I describe my methodological approaches for exploring forest definitions via geospatial analysis, deriving CES through text analysis of social media data, and combining these outputs to examine their interactions. This is followed by an explanation of my results in Chapter 4, and a discussion of the key outcomes and their implications in Chapter 5. The latter chapter also includes an explanation of the main limitations of my thesis and opportunities for future work. Finally, I provide a summary of the goals and outcomes of my thesis in Chapter 6.

2 Research context

In this chapter, I provide further context for my research. First, I explore an example of a holistic forest monitoring framework and its connections to other academic research. I then describe the Natura 2000 network in greater detail, including a summary of the status of EU-level monitoring and the state of academic research for these areas. I conclude this chapter by discussing the current research and knowledge gaps around the themes of forest definitions and CES, ending with a more detailed explanation of my research questions.

2.1 Holistic forest monitoring

High-quality, comprehensive forest monitoring is important for forest conservation and maintaining the environmental, economic and social services that forests provide (Directorate-General for Environment, 2023). Before considering specific metrics and indicators, a conceptual framework or model for holistic monitoring can help call attention to the complexity of forests and the aspects that are important to measure (Kull, 2017). Kull (2017) proposes a compelling example of one such framework which takes inspiration from forest transition studies, land change science and critical social science. Although developed for assessing forest transitions, in which an area transitions from net forest loss to forest gain (Rudel, 1998; Rudel et al., 2005), Kull's approach can be logically applied to the broader topic of forest monitoring due to its core focus on assessing changes in forest conditions.

Kull (2017) proposes that four aspects of forests can be measured to provide a more comprehensive assessment of forests and forest transitions. The first two aspects, *forest quantit*y and *forest characteristics*, relate to well-established forest indicators, including the spatial extent of forest cover and measurements related to ecological quality such as tree density, species composition, genetic diversity and biomass (Kull, 2017). Kull's (2017) third aspect focuses on the ecological, socio-economic and political *processes and relationships* which define a forest. This aspect captures a wide scope of factors ranging from biogeochemical cycles, herbivory and climate forces to human uses, management regimes, policy decisions and market demand (Kull, 2017). Finally, Kull's fourth aspect, *forest meanings and discourses*, concentrates on "how forests, their characteristics, and their processes are categorized, classified, labelled, valued, judged, and narrated" (2017, pp. 469). Here, Kull (2017) emphasises the close relationship between how forests are defined and the values, ideas and meanings associated with them. Considering all four aspects as interconnected and inseparable, Kull (2017) describes how their combined use can help analysts move beyond land cover statistics to explore how discourses, values and politics also play an important role in understanding forests.

Kull's (2017) emphasis on integrating human processes and relationships into our understanding of forests is echoed in other research and academic literature. Acknowledging that forest ecosystems exist in a constantly evolving social context, Daume et al. (2014) explore how traditional forest monitoring can be supplemented with information about the role and perception of forests gathered from social media data. In Switzerland, Hegetschweiler et al. (2020) demonstrate how socio-cultural forest monitoring efforts, like online surveys about forest preferences, can be combined with information about physical forest characteristics from the Swiss National Forest Inventory. The authors argue that this work is important for successful forest planning and management which requires information about both physical and social aspects of forests (Hegetschweiler et al., 2020).

2.2 The Natura 2000 network

The Natura 2000 network is the largest network of protected areas in the world (European Commission, 2024a). Consisting of over 27,000 sites across Europe, Natura 2000 operates under the legal framework of the EU's Nature Directives (the Birds and Habitat Directives) with the main goal to protect important European wildlife and habitats (European Commission, 2024a). With nearly half a million km^2 (50 million ha) of forest – roughly 27% of the EU's total forested area – the Natura 2000 network includes a significant portion of Europe's forests (EEA, 2020). Indeed, based on the total number of habitats protected under the Habitat Directive, forests represent the largest share at 35% (EEA, 2020). Furthermore, the corresponding area of protected forest may expand in the near future as the EU seeks to extend the coverage of protected areas as part of the EU Biodiversity Strategy for 2030 (European Commission, 2020).

2.2.1 EU-level forest monitoring

Currently, the required reporting for each Natura 2000 site involves regular monitoring for specific metrics which are summarised every 6 years in a 'State of Nature' report (EEA, 2020; European Commission, 2024b). As each Natura 2000 site is created to protect a specific species or habitat, monitoring focusses on information about the conservation status of that species or habitat. In the context of habitats like forests, the conservation status is monitored using standardised metrics for: (a) changes in the range and area/extent of the habitat; (b) changes in the ecological structure and functioning of the habitat; and (c) future prospects in terms of threats and pressures on the habitat (EEA, 2020). The most recent State of Nature report found that, while forests are improving more than other habitats, over 50% of assessments classified forest habitats as having 'poor' conservation status, and approximately 25% were classified as 'bad' (EEA, 2020). Complicating these findings, concerns about data quality and completeness are raised throughout the report and its associated methodological paper. Only 23% of numerical estimates and trends in the report originate from a “complete survey or a statistically robust estimate” (Röschel et al., 2020, Table 7.2, pp. 38). Instead, the majority (43%) are estimated from limited data and another 22% are derived from very limited data using expert opinion (Röschel et al., 2020). Overall, the EEA (2020) has called for fit-for-purpose monitoring schemes in all EU Member States to support monitoring needs in the Natura 2000 network.

Although not directly tied to Natura 2000, the European Commission has proposed a new law to help tackle the issues around monitoring for forests. Similar to the EEA, the Commission recognises that the current information gathered about the status of EU forests and their associated ecosystem services is patchy, inconsistent, untimely and incomplete (Directorate-General for Environment, 2023). The proposed EU Forest Monitoring Law, which is, at the time of writing, being examined by the European Parliament and Council (European Commission, 2023), aims to create more comprehensive and consistent forest monitoring systems and will expand the monitoring requirements for all European forests, including those within Natura 2000 sites. The law aims to regulate reporting for a variety of forest metrics ranging from forest area, tree density, forest connectivity and forest type, to forest fires and information about harvestable materials (Directorate-General for Environment, 2023 [Annex I-IV]). While the Forest Monitoring Law is being examined under the ordinary legislative procedure, several organisations and interest groups have recognised the opportunity to provide feedback to help shape the final outcome. As notable examples, both the World Wildlife Fund (WWF) and the international NGO Fern, have called for the Forest Monitoring Law to include specific social indicators that are currently missing from the proposed law (Chambers, 2024; Fern, 2024). The WWF has especially stressed the importance of incorporating social indicators, ecosystem service provision monitoring, and the intersection of the two, such as cultural and recreational services (Chambers, 2024).

2.2.2 Academic research

In terms of academic research on Natura 2000 sites, the literature has mainly focused on ecological topics (Orlikowska et al., 2016; Popescu et al., 2014). In a meta-analysis of over 572 peer-reviewed studies about the Natura 2000 network, Popescu et al. (2014) found that 452 (79%) could be categorised as ‘ecological’, whereas only 120 (21%) were labelled as ‘policy and social’. In a separate study focused solely on ecological publications, Orlikowska et al. (2016) found that most studies concentrated on single-site or regional spatial scales, were often based in the Mediterranean, and tended to use quantitative empirical methods. Proportional to the amount of area within the Natura 2000 network, alpine, agricultural, forest and marine habitats were under-represented, as were boreal regions (Orlikowska et al., 2016). A more recent study focusing on physical aspects of forests in Natura 2000 found that forest cover has increased for the period between 2012-2018, likely because of the abandonment of open spaces, but note that the associated increase in homogeneity may have negative consequences for biodiversity (Santoro et al., 2024).

Amongst the smaller proportion of publications focused on social themes in Natura 2000 sites, an additional meta-analysis by Blicharska et al., (2016) found that most research was related to themes of ‘Conservation conflicts’ and ‘Implementation challenges/solutions’; out of the 149 publications assessed, 44 (~30%) were assigned to one of these two categories. Social science studies related to ‘Perceptions, attitudes and values’ made up 11% of publications, however, most explored stakeholder attitudes towards Natura 2000, while very few were found to have looked at the benefits of Natura 2000, including ecosystem services (Blicharska et al., 2016). More recent publications have begun to address this knowledge gap, with several studies now focusing on ecosystem services in the Natura 2000 network. For example, single-site studies using high-resolution Earth Observation (EO) data have been undertaken in several Natura 2000 sites, including an assessment of the impact of land use and land cover change on regulating ecosystem services in Romania (Popescu et al., 2024), and ecosystem type and service mapping in Greece (Chrysafis et al., 2024). Issues related to nature-based tourism and visitor carrying capacity (e.g., Ćulibrk et al., 2025; Rocchi et al., 2020) have also emerged as important social science topics in recent studies focused on Natura 2000.

2.3 Research gaps and opportunities

Despite the body of work highlighting the importance of holistic forest monitoring and the push for more comprehensive monitoring systems in the EU, there are still significant gaps for forest monitoring in the Natura 2000 network. Socio-cultural themes, including those related to Kull’s (2017) *forest meanings and discourses*, are often under-represented in academic research and EU policy. This knowledge gap is especially important given that the way we define and value forests has implications for how and what we monitor; indeed, “…the ways in which forests are measured, categorized, and conceived affect the processes that shape forests and the forests themselves.” (Kull, 2017, pp. 470-471). In this section, I narrow my focus to two specific social science themes of forest monitoring – forest definitions and forest values (CES) – and elaborate why further research is important in these areas.

2.3.1 Forest definitions

There are currently over 800 official definitions of the term *forest*, with some collections including over 1,700 (Lund, 2024; Sexton et al., 2016). These definitions vary depending on whether the meaning is based on land cover or land use, as well as criteria such as the percentage of tree cover, actual and potential tree height, and parcel size (Lund, 2002, 2024; Sexton et al., 2016). Technology and the way these definitions are operationalised as maps also play an important role in determining what is counted as forest and what is not (Estoque et al., 2022; Robbins, 2001; Sexton et al., 2016). In practice, different definitions can have a considerable impact on our understanding of forests and are a major source of inconsistencies in forest estimates (Estoque et al., 2022). Notably, for definitions based on *land use*, there may be a complete absence of trees on land classified as forest because the definition is based on the human use of the land (i.e., for forestry) rather than what is physically present. Differences in tree cover thresholds can also lead to large discrepancies in terms of the amount of forest recorded, as well as any derived calculations such as biomass or monetary value (Sexton et al., 2016). Furthermore, the tree cover threshold applied in a forest definition influences what is counted as deforestation. For example, when the tree cover threshold is low, severe degradation can occur within a forest without being classed as deforestation (Sasaki & Putz, 2009; Zalles et al., 2024). In this sense, forest definitions can also represent an extension of politics and power, and can be (mis)used to achieve particular goals or political agendas (Chazdon et al., 2016; Côte et al., 2018; Kull, 2017; Peluso & Vandergeest, 2001; Robbins, 2001). As a further example, the decision to include plantations in a national definition of forests can be politically motivated by states attempting to profit from carbon markets or escape censure for deforestation (Kull, 2017). As pointed about by Zalles et al. (2024), when plantations are included in a forest definition, a natural forest can be cleared and replaced with a timber or rubber plantation without any deforestation officially occurring. Overall, forest definitions can differ significantly across institutions and countries, even varying at the sub-national level (Aspøy & Stokland, 2022; Lund, 2002; Zalles et al., 2024). As these differences can create major inconsistences for various forest measurements, as well as provoke political controversy (Aspøy & Stokland, 2022), understanding the magnitude of these differences is important for forest monitoring efforts.

To date, several publications have examined differences across forest definitions and the way they are operationalised as geospatial datasets. At the global scale, Sexton et al. (2016) compared eight satellite-based datasets from circa 2000 to produce a forest consensus map which indicates where forest definitions/operationalisations agree and disagree on forest presence and absence. Discrepancies in forest cover estimates, largely driven by differences in tree cover thresholds, were found across all biomes, with the largest differences in areas of intermediate tree cover (Sexton et al., 2016). Similarly, in a comparison of tree cover datasets from circa 2010 in western USA, Tang et al. (2019) found that datasets derived from satellite imagery are more likely to disagree on tree cover in sparsely vegetated areas, typically caused by differences in definitions and tree cover estimation errors. Exploring more recent datasets, Majasalmi & Rautiainen (2021) compared tree cover estimates from global land cover datasets to Finnish national forest inventory data from 2017, and found that global land cover products varied considerably in their cover estimates for Finland, especially for the distributions of conifer and deciduous species.

Despite these efforts, little has been done to explore forest definitions and their implications in the context of the Natura 2000 network. The official Natura 2000 documentation indicates that, for some assessments, a subset of forest classes from the CORINE (Coordination of Information on the Environment) land cover dataset has been used to define forests (e.g., EEA, 2020; European Commission, 2015), however, to the best of my knowledge, no academic or governmental publications have explored the impact of forest definition selection for Natura 2000 sites.

2.3.2 Forest values: cultural ecosystem services

While Natura 2000 sites are designated for the purpose of protecting vulnerable species and habitats, there are many ways in which these sites are valued which go beyond ecological conservation. In Europe, the vast majority of forested lands are accessible to the public (FOREST EUROPE, 2020) and CES generated by human interaction with these sites, including services related to recreation, cultural heritage, aesthetics, spirituality and education, are often described in Natura 2000 and EU literature (European Commission, 2015; FISE, 2024). Importantly, the relationship between biodiversity and CES goes both ways; not only is biodiversity important for supporting CES, but CES have an important role to play in helping to improve biodiversity conservation efforts by "provid[ing] the stimulus for conserving nature" (Haslett et al., 2010, pp. 2968). In other words, experiencing CES can help protect ecosystems by motivating and sustaining public support for their conservation (Daniel et al., 2012). Understanding and bringing awareness to the values people hold about Natura 2000 sites (and the forests within them) is therefore important for ensuring that these values are reflected in policies and decisions regarding the protection of these areas (Vlami et al., 2020). Furthermore, many landscapes within the Natura 2000 network are the product of centuries-old relationships with humans (Catsadorakis, 2007) and the ways people value and interact with these landscapes are therefore inextricably linked to their condition.

Despite acknowledgments that the intangible and subjective nature of CES can make them difficult to measure (Daniel et al., 2012), a variety of approaches have been developed to overcome these challenges. Surveys and questionnaires, such as a study by Frick et al. (2018) using telephone and online surveys to assess how people value and perceive forest in Switzerland, represent a common approach for measuring CES. Geographical mapping approaches have also been employed, often using multiple geospatial layers and proxies to develop indices and indicators (e.g., Paracchini et al., 2014). Rapid advances in the application of automatic image recognition and natural language processing (NLP) have also made it possible to estimate ecosystem services from crowdsourced information such as social media (Ghermandi & Sinclair, 2019; Schirpke et al., 2023). These approaches have been applied to study CES in a variety of ways including content classification of geotagged photos from Flickr (e.g., Richards & Friess, 2015), topic modelling using text from travel blogs (e.g., Adams & McKenzie, 2013), and annotating photo tags from Flickr (e.g., Komossa et al., 2023). Several studies have used imagery or text from multiple platforms to estimate CES, such as Külling et al.'s (2024) use of imagery from both Flickr and iNaturalist to model landscape potential for picture-taking. Others combine traditional survey methods with social media data to take advantage of the strengths of both methods (e.g., Olafsson et al., 2022). While the majority of such studies have used Flickr or Twitter/X (Ghermandi et al., 2023), outdoor recreation and route sharing platforms like Strava and Wikiloc have also been used to assess CES based on imagery (Callau et al., 2019; Norman & Pickering, 2019) or text (Chai-allah et al., 2023).

Regarding Natura 2000, several publications have focused on CES, though these have mainly relied on more traditional methods of measurement, rather than those incorporating social media. Both survey and mapping approaches have been implemented in Natura 2000 sites, including, for example, an on-site survey study for Natura 2000 sites in Italy (Schirpke et al., 2018) and an effort to estimate the spatial distribution of CES via proxy indicators for Natura 2000 sites in Greece (Vlami et al., 2020). To date, NLP approaches using data from social media have not yet been applied in the context of CES in Natura 2000, and CES related to forests in Natura 2000 remain under-explored.

2.4 Research questions

In order to address the knowledge gaps related to forest definitions and values in the Natura 2000 network, the goal of my thesis is to answer the following research questions in a case study focussed on the Natura 2000 sites in Germany:

1) **How do forest definitions influence forest cover?** How do forest cover measurements change across different forest definitions and their geospatial operationalisations in Germany’s Natura 2000 sites? How much consensus is there on forest presence and absence?
2) **How do people value forests in terms of cultural ecosystem services (CES)?** What CES are experienced by people recreating in forests in the Natura 2000 network in Germany? In particular, what can we learn about CES using natural language processing techniques with data from the route sharing platform Wikiloc?
3) **How do the ways people value forest relate to forest definition?** Do the observed CES differ between areas where there is consensus on forest presence and areas where there is no consensus?

Through the process of answering these research questions, I aim to explore how future monitoring could be supplemented to achieve a more holistic view of the forests in the Natura 2000 network. With my first research question, my goal is to examine how the choice of forest definition impacts basic metrics like forest cover. In this way, I aim to understand to what degree quantitative forest monitoring indicators can depend on social constructs in the context of the Natura 2000 sites. Through my second research question, my goal is to provide new insights into the CES which are experienced in the forests of Germany’s Natura 2000 sites. By using social media data and NLP techniques, I also seek to explore the value of these methodological approaches to study CES in Natura 2000 sites at the national level. Finally, by integrating both themes in my final research question, my goal is to determine whether the choice of forest definition can also create measurable differences in metrics beyond forest cover, such as evaluations of CES.

3 Methods

In this chapter, I describe the study area, and the materials and methods used to answer each of my research questions. I performed the analysis for all three research questions in a Python (version 3.12.7) conda environment, using Jupyter Notebooks to document and explain my code. Additionally, I used either Python, R (version 4.3.1) or QGIS (version 3.34.14) to create the final figures. The environment set-up and scripts for all automated processes are publicly available on GitHub[1].

3.1 Study area: Germany's Natura 2000 sites

To explore forest definitions, CES and their interactions for the Natura 2000 network, I narrowed my focus to use the Natura 2000 sites in Germany as a case study. I accessed the complete shapefile of all Natura 2000 sites from the EEA Datahub[2] using the most recent version available at the start of my analysis (version 2022: published in April 2024 with temporal coverage for 2022). This dataset contains 5,200 German Natura 2000 sites which have a combined area of approximately 113,054 km^2 or 11.31 million ha. However, for the purposes of this thesis, my analysis only corresponds to non-marine Natura 2000 sites or non-marine portions of Natura 2000 sites. In other words, I only assessed the parts of the Natura 2000 sites which were within the footprint of the datasets used for Research Question 1 (see Section 3.2.2 for details). This resulted in a total of 5,184 sites covering approximately 72,477 km^2 or 7.25 million ha (Figure 1). Due to the nature of the Natura 2000 network's designation types, this area included a spatial overlap between sites of roughly 23.85%, meaning the total unique coverage of the 5,184 sites was approximately 55,193 km^2 or 5.52 million ha. These designation types correspond to the specific directive(s) which each site is protected by, with Type A corresponding to Special Protection Areas (SPA) from the Birds Directive, Type B indicating Sites of Community Importance (SCI) or Special Areas of Conservation (SAC) designated under the Habitats Directive, and Type C corresponding to where the same boundary is designated under both directives (EEA, 2025). Of the 5,184 terrestrial sites, the vast majority were designated as Type B (4,445 sites or 85.74%) and only 654 (12.62%) as Type A and 85 (1.64%) as Type C. The range and variation in individual site sizes was large. The smallest sites, often dedicated to protecting specific species roosting in old buildings, were less than 18 m^2 (0.0018 ha) whereas the largest sites were up to 803 km^2 (~80,275 ha). Finally, it is important to note that the Natura 2000 designation does not prevent economic activities from taking place (European Commission, 2015). This point has direct relevance to my first research question where forest definitions may include or exclude land uses such as active timber harvesting.

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[1] https://github.com/n-mo92/nm_forest_thesis

[2] https://www.eea.europa.eu/en/datahub/datahubitem-view/6fc8ad2d-195d-40f4-bdec-576e7d1268e4

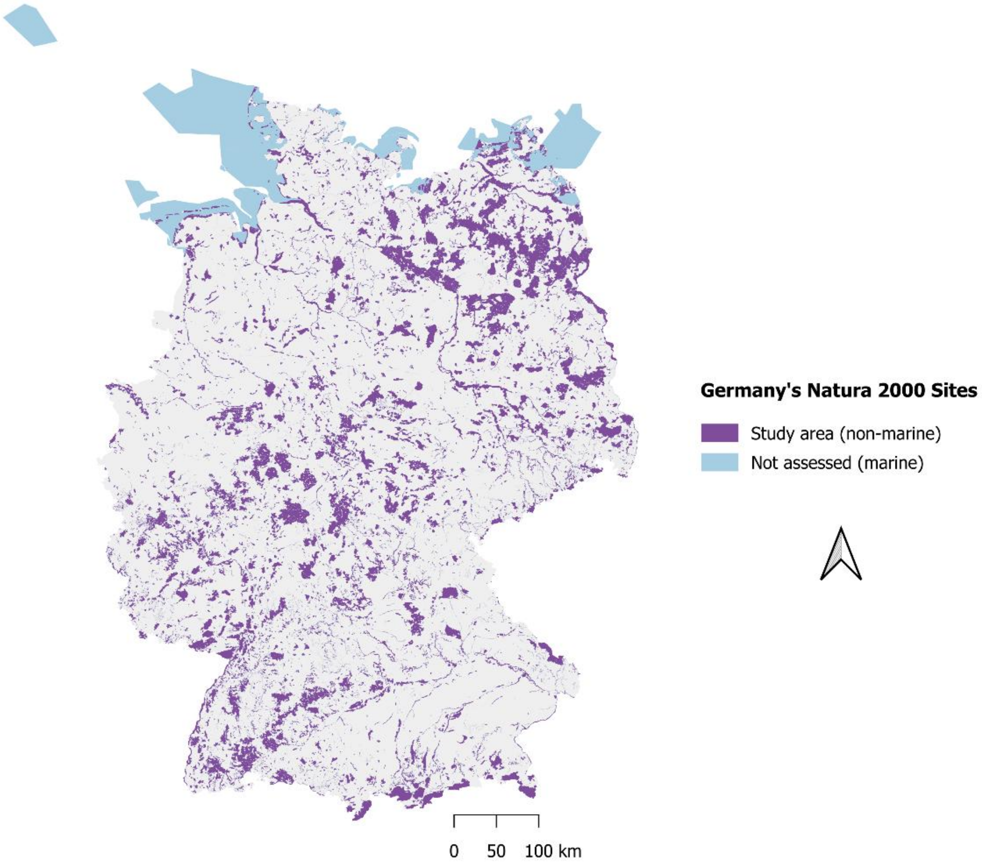

***Figure 1**. Germany's Natura 2000 sites. The study area comprises the non-marine portions of the Natura 2000 sites (purple), whereas Natura 2000 sites or parts of Natura 2000 sites over the ocean (light blue) were not relevant for this thesis.*

3.2 Forest definitions: estimating forest cover and consensus

To understand how forest definitions and their geospatial operationalisations compare in Germany's Natura 2000 network, I followed Sexton et al.'s (2016) approach for developing forest/non-forest (FNF) and forest consensus maps using six different geospatial datasets. In this context, I use the term 'geospatial operationalisation' to refer to a digital map which represents a forest definition; it is a forest definition translated into a geospatial dataset which can be used for analysis. Because the process of representing a forest definition as map can vary, the same forest definition can be operationalised in different ways – for example, by using a different satellite sensor for data collection, or by using a different approach to process the data. In the following sections, I elaborate on the steps I took to explore this research question, including the selection process for the six geospatial operationalisations (hereafter referred to as forest products), data processing and harmonisation steps to create comparable FNF raster maps, the development of an FNF map aligned with the Food and Agriculture Organization (FAO) definition of forest, the final summation of these layers into a forest consensus map, and the analysis steps used to explore differences across the Natura 2000 sites in Germany (Figure 2).

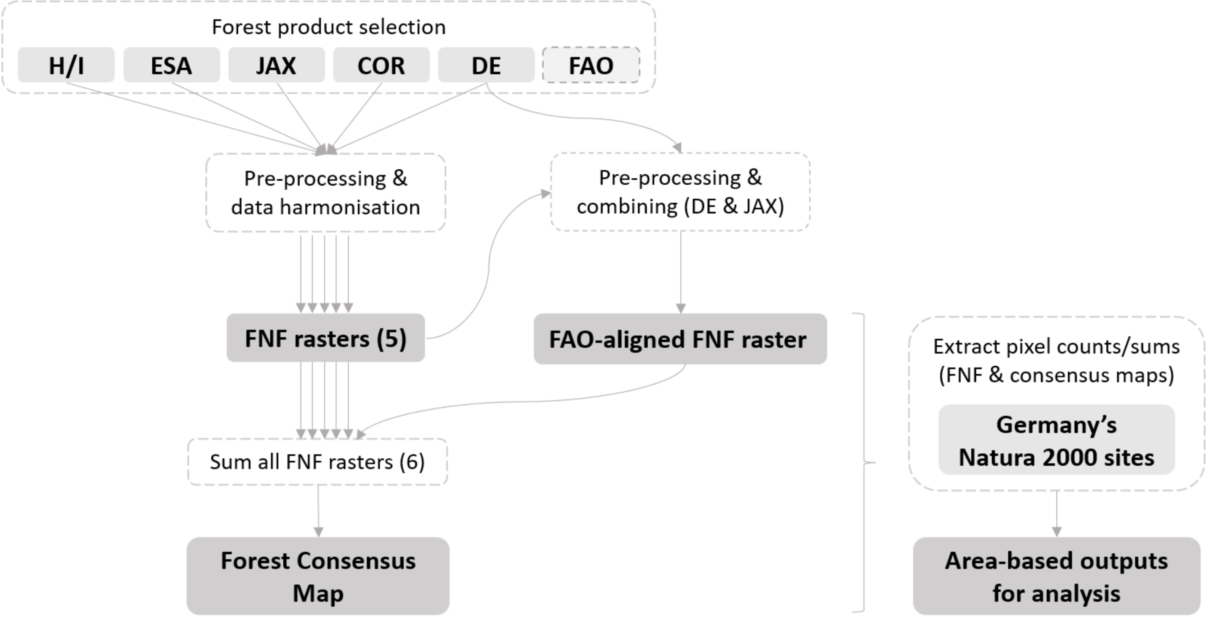

***Figure 2**. Generalised workflow for exploring and comparing forest definitions for Germany's Natura 2000 sites. Abbreviated forest product names are explained in Section 3.2.1. A more detailed illustration is available in Appendix 8.1.*

3.2.1 Forest product selection

As there is a large range of forest definitions and products, I began by selecting a set of six forest products for comparison. During this selection process, I aimed to cover a diverse range of land cover and land use-based forest definitions with varying tree cover thresholds. At the same time, I prioritised products that were created by authoritative sources and which use official definitions that are relevant to policy and decision-making. Furthermore, I ensured that the selected products have clear update cycles – meaning they are maintained regularly and more likely to be used in the future – and are supplied as free, open-access datasets. Because of my focus in Germany's Natura 2000 network, it was also important to include some forest products which are specific to Germany and which are used for Natura 2000 assessment reports. Finally, to ensure comparability, I aimed to find a set of six products which provided forest cover information for the same year.

For my final selection, I chose to focus on a set of three land cover-based products (Table 1) and three land use-based products (Table 2). These included: (1) the Hansen Global Forest Change product with the International Geosphere-Biosphere Programme (IGBP) definition of forest (referred to as H/I); (2) the European Space Agency's (ESA) Climate Change Initiative (CCI) Land Cover product using the Intergovernmental Panel on Climate Change (IPCC) land category classification for forests (referred to as ESA); (3) the Japan Aerospace Exploration Agency's (JAXA) ALOS-2 PALSAR-2 Forest/Non-Forest product (referred to as JAX) ; (4) the Coordination of Information on the Environment (CORINE) program's

Land Cover product using Natura 2000 forest classes (referred to as COR); (5) the Federal Agency for Cartography and Geodesy (BKG) Land Cover Model Germany (LBM-DE) / CORINE Land Cover 5 ha product using Natura 2000 forest classes (referred to as DE); and (6) a forest product aligned with the FAO definition of forest created using the methodology from Johnson et al. (2023; referred to as FAO). I selected the year 2018 for the forest cover assessment period as this was the latest date available across all forest products. It is important to note that while some forest definitions are built-in to the geospatial product directly (e.g., JAX), others involve decisions from the user in terms of the tree cover threshold applied (e.g., H/I) or which land cover/use classes are included to describe forests (e.g., ESA, COR and DE) – see details in Tables 1 and 2, as well as Appendix 8.1.

Table 1*. A summary of the three land cover-based forest products selected for analysis. Details about the precise classes used to define forests for the ESA forest product are available in Appendix 8.1.*

Reference Name	Forest Product	Forest Definition (Land Cover-Based)	Spatial & Temporal Details	Reference & Download Information
H/I	**Hansen Global Forest Change:** Produced by the Global Land Analysis and Discovery (GLAD) laboratory at the University of Maryland (UMD), in partnership with Global Forest Watch (GFW). The product is derived from Landsat time-series imagery.	This product provides canopy closure (%) for all vegetation taller than 5 m. I applied a **>60% tree cover** threshold in line with the International Geosphere-Biosphere Programme (IGBP) definition of forests (Loveland & Belward, 1997).[3]	*Resolution:* 30 m *Extent:* global *Selected year:* 2018 *Update frequency:* yearly	Hansen et al., 2013 Downloaded on 15.01.2025 from: https://glad.earthengine.app/view/global-forest-change
ESA	**ESA CCI Land Cover:** A land cover product developed by the European Space Agency (ESA) as part of the Climate Change Initiative (CCI). The land cover classes are defined according to the FAO's Land Cover Classification System (LCCS). The product includes inputs from Medium Resolution Imaging Spectrometer (MERIS), Advanced Very-High-Resolution Radiometer (AVHRR), SPOT-Vegetation (SPOT-VGT), PROBA-Vegetation (PROBA-V) and Sentinel-3.	This product includes several land cover categories related to tree cover. I applied the forest classification used for the Intergovernmental Panel on Climate Change (IPCC) land categories as explained in the Product User Guide for the ESA CCI product (UCL-Geomatics, 2017). This definition includes tree cover classes with a **>15% tree cover** threshold.	*Resolution:* 300 m *Extent:* global *Selected year:* 2018 *Update frequency:* yearly	Copernicus Climate Change Service, Climate Data Store, 2019 Downloaded on 14.01.2025 from: https://cds.climate.copernicus.eu/datasets/satellite-land-cover
JAX	**JAXA ALOS-2 PALSAR-2 Forest/Non-Forest:** Produced by the Japan Aerospace Exploration Agency (JAXA) using the Advanced Land Observing Satellite-2 (ALOS-2) with the PALSAR-2 radar sensor. The forest/non-forest (FNF) classification is based on region-specific thresholds related to surface characteristics.	Forests are classified directly in the product as land of at least 0.5 ha covered by trees with a **>10% tree cover** threshold.	*Resolution:* 25 m *Extent:* global *Selected year:* 2018 *Update frequency:* yearly	Shimada et al., 2014 Downloaded on 15.01.2025 from: https://www.eorc.jaxa.jp/ALOS/en/dataset/fnf_e.htm

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[3] While the IGBP ended in 2015, its global vegetation classification scheme is used for a variety of remotely sensed products, including NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) land cover products (Sulla-Menashe & Friedl, 2018).

Table 2*. A summary of the three land use-based forest products selected for analysis. Details about the precise classes used to define forests for the COR and DE products are available in the Appendix 8.1. Further explanation of the FAO-aligned product is included in Section 3.2.3*

Reference Name	Forest Product	Forest Definition (Land Use-Based)	Spatial & Temporal Details	Reference & Download Information
COR	**CORINE Land Cover:** A land cover and land use product developed under the Coordination of Information on the Environment (CORINE) program launched by the European Commission. The product is a key part of the European Environment Agency's Copernicus Land Monitoring Service and is created from both Sentinel-1 (radar) and Sentinel-2 (optical) imagery.	This product includes several land cover and land use categories related to tree cover. I applied the forest classification used in Natura 2000 literature (e.g., EEA, 2020 and European Commission, 2015). This definition includes tree cover classes with a **>30% tree cover** threshold with a minimum tree height of 5m, as well as transitional forest. Transitional forest comprises areas characterised by: natural or anthropogenic regeneration or degradation; clear-cutting or selective harvesting; or afforestation.	*Minimum Mapping Unit:* 25 ha (250000 m^2 or 500 m resolution) *Extent:* Europe *Selected year:* 2018 *Update frequency:* every 6 years	Copernicus Land Monitoring Service, 2020 Downloaded on 16.01.2025 from https://land.copernicus.eu/en/products/corine-land-cover/clc2018
DE	**LBM-DE / CORINE Land Cover 5 ha:** This product applies the CORINE Land Cover classification system to the Land Cover Model Germany dataset (LBM-DE). Developed by the Bundesamt für Kartographie und Geodäsie (BKG; Federal Agency for Cartography and Geodesy), LBM-DE uses satellite imagery (from RapidEye and Sentinel-2) for land cover and ATKIS® Basis-DLM (Official Topographic-Cartographic Information System: Basic Digital Landscape Model) for land use.	See forest definition for COR (generally **>30% tree cover** threshold and minimum tree height of 5m, with exceptions for transitional forest). Note that while this product uses the same definition as the COR product, it is operationalised in a different way.	*Minimum Mapping Unit:* 5 ha (50000 m^2 or ~225 m resolution) *Extent:* Germany *Selected year:* 2018 *Update frequency:* every 3 years	Bundesamt für Kartographie und Geodäsie, 2022 Downloaded on 14.01.2025 from https://gdz.bkg.bund.de/index.php/default/corine-land-cover-5-ha-stand-2018-clc5-2018.html
FAO	**FAO-Aligned Forest:** Using inputs from the JAX and DE forest products, I created this product to approximate the FAO definition of forests following the method from Johnson et al. (2023) – see Section 3.2.3 for details.	This product combines the DE and JAX products to create a final output with a **>10% tree cover** threshold. In addition, predominantly urban and agricultural areas (as defined by the LBM-DE model) are removed from the JAX product in order to account for land use criteria in the FAO definition (as per Johnson et al., 2023).	N/A	N/A

3.2.2 Forest/non-forest (FNF) maps

Following the methods of Sexton et al. (2016), several pre-processing and data harmonisation steps were required to convert the forest products into comparable FNF maps which could then be used for forest cover comparisons and for the assembly of the forest consensus map. These intermediate FNF maps are binary rasters where each pixel is either classified as forest or non-forest.

After manually downloading all the necessary datasets, the initial pre-processing steps varied according to the forest product. For the products which were downloaded as a set of tiles over Germany (H/I and JAX), I created mosaics to output a single raster for each product. As the ESA product was accessed as a netCDF file, I converted this to a raster by extracting the relevant land cover class layer. For the H/I product, additional pre-processing steps were required as the data is supplied as three separate tile sets corresponding to percentage tree cover for the year 2000, forest loss per year from 2001-2023 and forest gain for 2001-2012. Starting with the mosaicked raster for tree cover, I reclassified the percentages into a simple FNF map by applying the >60% tree cover threshold from the IGBP forest definition (see Table 1). The next step was to update this FNF map to 2018 by adjusting for changes in the loss and gain mosaics – however, due to the format of the gain raster, several complications arose at this stage. While the forest loss data is supplied as loss per year, the gain data is stored as a binary map with values corresponding to gain occurring between 2001-2012 or no gain. This meant that the FNF map could not be updated in a step-wise fashion (i.e., alternating between loss and gain on a yearly basis) and forest gain information was missing for 2013-2018. To understand the impact of this issue on my assessment, I generated estimates for the total forest in the study area in 2018 where only loss is taken into account versus the total forest where both loss and gain are considered (for details, see Appendix 8.2). Based on the extrapolation of the recorded forest gain, which includes the assumptions that the rate of forest gain is constant over time and that the gain does not occur in areas which are later recorded as forest loss, there could be up to 2.45% more forest in the study area in 2018 compared to when only loss is considered. However, as forest loss and gain often occur in the same places – for example at forest edges (Precinoto et al., 2022) or in managed forests – I expect the true extent of forest for this product is below this margin of error due to some of the loss occurring after the gain. As a result of these findings, I updated the 2000 FNF for the H/I product to 2018 by adjusting for areas of loss only (i.e., converting all loss pixels recorded from 2001-2018 to non-forest). This approach allows me to be transparent with the margins of error while avoiding the uncertainty which would arise by integrating forest gain since it is not possible to account for the order of loss and gain in time.

The remaining steps for creating the FNF maps consisted of data harmonisation processes to ensure the forest products were consistent and comparable with each other. In general, I aimed to adjust the products with the fewest transformations possible in order to minimise any artifacts introduced by the processes. First, I selected the most common projection across the forest products and Natura 2000 shapefile *(Lambert Azimuthal Equal Area Europe* or EPSG:3035), and reprojected any forest products not already using this system. Next, I rasterised the two vector-based products (COR and DE, using their corresponding land cover/use attribute column) and resampled the remaining raster-based products (H/I, ESA, JAX) to 5 m resolution (5 m x 5 m pixel size). As all products have an approximate resolution that is divisible by 5 m, using this common denominator allowed me to harmonise the resolution across products while avoiding the loss of information from downsampling and minimising any alteration in the coverage of the pixels (Figure 3). It is important to note that some transformation still occurs in this step especially in the case of the global products (H/I, ESA and JAX) as their resolutions are only accurate at the equator and are therefore not precisely divisible by 5 m for the study area in Germany. The raster-based products were resampled using the nearest neighbour interpolation algorithm which is often used for resampling categorical data to ensure that the values of the cells are retained from the input layer.

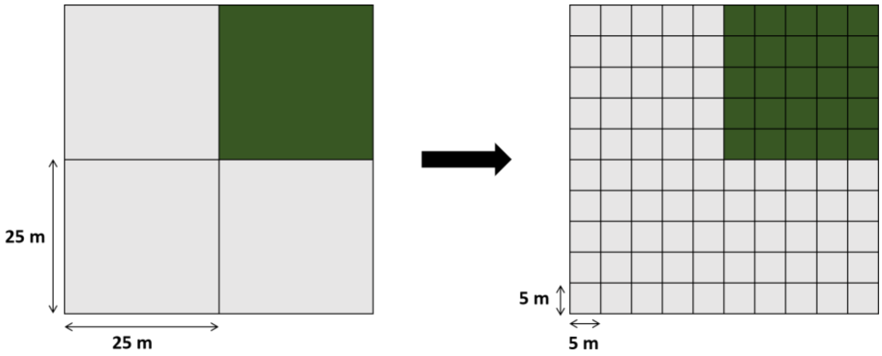

***Figure 3**. A simplified illustration of upsampling from a 25 m raster (e.g., JAX product) to a 5 m raster. In this approach, manipulation of the original data is minimised, but some transformation still occurs.*

After rasterisation and resampling, the forest products were ready to be reclassified into binary forest/non-forest outputs. This step varied depending on the product, with some products requiring no further reclassification and most requiring a careful selection of forest classes as per the relevant forest definitions described in Tables 1 and 2. A detailed description of the precise input classes counted as 'forest' for each product is provided in Appendix 8.1. Finally, all FNF maps were warped to a standard grid and then clipped to the same footprint so that pixels across each product were aligned and the data coverage was the same across all maps. For these steps, I used the COR product for the baseline for grid alignment and clipping as its footprint matched well with the other products in terms of data coverage. It is worth noting that a small portion of data on the eastern edge of Germany was missing from the DE product, including in the original source files. However, the impact of this discrepancy is likely to be extremely small as only 0.2 ha of forest was recorded by the other products in the affected Natura 2000 sites. As this amounts to only 3.62e-8% of the ~5.52 million ha covered by the Natura 2000 network, I determined that this small margin of error in the DE product would not have a significant impact on the final outputs.

3.2.3 FAO-aligned FNF map

In addition to the five FNF maps processed from pre-existing datasets, I also created a sixth FNF map to capture the definition of forest used by the FAO. The FAO defines forest as “Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use” (FAO, 2023, pp. 9). This definition of forest is important to include in my analysis because of its wide use and integration into several important monitoring systems. The FAO itself coordinates forest monitoring around the world through its forest resource assessment (FRA) reports which require countries to follow the FAO’s definition of forest (FAO, 2023). These FRA reports are then used to measure progress towards targets such as the UN Sustainable Development Goal (SDG) 15 which aims to “protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss” (UN, 2015, pp. 29).

To create an FAO-aligned FNF map, I adapted the methodology proposed by Johnson et al. (2023) to my use-case in Germany. In their approach, they combine forest identified in JAXA’s ALOS-2 PALSAR-2 Forest/Non-Forest product (i.e., the JAX product in this thesis) with a national Land Use and Land Cover (LULC) map to create an integrated output (Johnson et al., 2023). Taking the national LULC map as the starting point, their workflow aims to supplement this map with forest areas that meet the FAO definition criteria from the JAXA product (Johnson et al., 2023). While Johnson et al. (2023) distinguish between forest and other FAO categories for ‘Other wooded land’ and ‘Other land with tree cover’, for the purposes of producing a FNF map, I only focus on forest and non-forest classes.

For my work, the DE forest product represents the national LULC map used for the starting point. With its 5 m height threshold for most forest categories and the ‘Transitional woodland-shrub’ category for trees “able to reach” the height and cover thresholds of the FAO definition, the DE product captures a significant amount of FAO-aligned forest. However, its >30% canopy cover threshold for most forest categories means that forests in the 10-30% tree cover range are missing. Following Johnson et al. (2023), these ‘missing’ forests can then be added using the JAX product, but because the JAX product does not take land *use* into account, it first must be adjusted to remove any forests which are classified as mainly agricultural or urban land use – as per the FAO requirements. In terms of the technical steps to complete this workflow, I began by preparing a mask layer which could be used to remove areas of agricultural or urban land use from the JAX product. To create a mask layer, I identified all non-urban and non-agricultural areas (i.e., classes 3xx and 4xx) from the original DE land cover product and rasterised these land cover classes to 5 m to match the resolution of my FNF maps. In this mask layer, all non-urban and non-agricultural pixels were given a value of 1, with all other pixels (including 'nodata' pixels) reclassified to 0. After clipping and warping to ensure alignment, I then multiplied this mask layer with the JAX FNF map to essentially remove agricultural and urban areas. I then summed the *adjusted* JAX FNF map with the DE FNF map, and reclassified the output to values of 0 (non-forest) and 1 (forest) to create the final FAO-aligned FNF map. This workflow is also summarised in Appendix 8.1.

3.2.4 Forest consensus map

To generate the forest presence/absence consensus map in-line with Sexton et al (2016), the final data processing step was to simply sum the six FNF maps together. In this way a single output map was generated where values of 0 correspond to complete consensus on forest absence (non-forest) and values of 6 correspond to complete consensus on forest presence (forest). This means that values of 3 indicate areas of least consensus, with half the forest products estimating forest presence and the other half estimating forest absence. To create an accessible map figure for communicating these results I used QGIS to design the final map figures and applied a colour-blind safe palette (generated with Adobe's Accessibility Tools[4]) which aims to highlight non-consensus areas compared to consensus forest.

3.2.5 Analysis for Germany's Natura 2000 sites

With the map outputs finalised, the final step for this research questions was to assess the FNF and forest consensus maps in the context of Germany's Natura 2000 sites. For this analysis step, I used two different geometry sets: one original version of the Natura 2000 sites and a second adjusted version where areas of overlap were removed so that results for those overlaps were only counted once. To create this adjusted version, I used the *GeoPandas dissolve* function to merge all geometries, and *explode* function to separate the large output into individual non-overlapping polygons. Then, starting with the FNF maps, I extracted pixel counts and pixel sums for both geometry sets (original and adjusted for overlap) for each FNF map using the *zonal_stats* function from the *rasterstats* Python module. By multiplying these outputs by the pixel size (25 m^2 or 0.0025 ha), the pixel count could then be understood as the total area assessed for each Natura 2000 site, while the pixel sum corresponds to the total forest within each Natura 2000 site for each FNF map. Note that this approach means that any portion of a Natura 2000 site which was outside the footprint of the FNF map in question, was not included in the

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[4] https://color.adobe.com/create/color-accessibility

final outputs. In practice, this means that the marine Natura 2000 sites which are not relevant for this assessment were excluded, and Natura 2000 sites which were partly over the sea were only assessed for their land component. Next, I summed the area-based results across the geometries which were adjusted for overlaps to get the total results for all Natura 2000 sites for each FNF map. For this step, it was necessary to use the adjusted geometries to avoid double-counting. I also calculated the mean forest area across all six maps, and the difference from each map to this average. Finally, I experimented with some statistical testing to explore whether any of the differences in per-geometry forest area between FNF map pairs was statistically significant (i.e., significantly different from a value of 0). For this analysis I chose to explore both the absolute forest difference (comparing the total area of forest for each Natura 2000 site), as well as the relative forest difference (comparing percentage of forest cover for each Natura 2000 site). For this part of the analysis, I used the results calculated from the original Natura 2000 geometries. Since the probability plots of each absolute and relative difference indicated these differences were not normally distributed, I used the non-parametric Wilcoxon signed-rank test (from SciPy's *stats* module) for paired comparisons of Natura 2000 sites for two FNF maps at a time. Because I was performing multiple tests, I set a stricter significance threshold with the commonly-used Bonferroni correction: with a starting alpha of 0.05, this is converted to an alpha of 0.0033 for the 15 paired tests (0.05 / 15 = 0.0033). Finally, I created box plots to visually explore the statistical results and how the absolute and relative differences between each FNF map pair across all Natura 2000 sites compare to zero.

For the forest consensus map, I applied the *zonal_stats* function again to extract data for Germany's Natura 2000 sites. As with the FNF maps, I generated results for both the original Natura 2000 sites and the adjusted version with overlaps removed. Because the forest consensus map is a categorical dataset, I extracted the pixel counts for each forest consensus class for each Natura 2000 geometry set. I then converted the pixel counts to the area per class by multiplying by the pixel size and calculated the percentage coverage of each class for each original geometry. Using this coverage information, I also recorded the class with the highest percentage coverage (i.e., the dominant consensus class) for each original Natura 2000 site. To summarise the results across all Natura 2000 sites, I then summed the area results across all adjusted geometries for each consensus class, and also calculated the percentage coverage of each class for all Natura 2000 sites as a whole. Again, the adjusted geometries were used for this step in order to avoid double-counting. In order to understand the combination of FNF maps which make up each forest consensus class, I created a series of treemaps for each relevant consensus class. With this approach I aimed to produce a breakdown of the precise combination of FNF maps which tend to agree on forest presence or absence. This involved some additional processing steps to create a series of mask layers and FNF combination maps. For the mask layers, I created five rasters which isolated the area for a single consensus class for classes 1-5. I did not create any layers for classes 0 and 6 as the FNF maps in these classes completely agree on either non-forest or forest, respectively. For the FNF combination maps, I created 56 additional layers, each of which represents the forest areas for every possible combination of either two FNF maps (for class 2), three FNF maps (for class 3), four FNF maps (for class 4) or five FNF maps (for class 5). For class 1, where only 1 FNF map indicates forest presence, I simply used the original FNF maps themselves. Next, I used the class mask layers to isolate the area within each consensus class from the relevant combination maps. I then ran *zonal_stats* on all 62 map layers (56 combination maps plus the 6 original FNF maps for class 1) to extract the pixel sums for all geometries adjusted for overlap. These pixel sums were then multiplied by the pixel size to convert to the area of forest and then summed across geometries to get the total forest area per map or map combination. Finally, I imported the area results into R where I used the *treemap* package to create a series of treemaps, including one to show the overall area in each class, and five others to visualise the breakdown of the area of agreement for each FNF map combination for each consensus class. For consistency, I colour-coded the treemap outputs to match the class colours of the consensus map.

3.3 Forest CES: Wikiloc text analysis

To address my second research question and gain insights about CES in Germany's Natura 2000 sites, I applied NLP and machine learning techniques to geotagged, crowdsourced text from social media. Several recent studies have shown that text from social media can provide a valuable dataset for understanding the way people value and perceive a landscape, particularly when analysing text from people recreating outdoors (e.g., Chai-allah et al., 2023; Fox et al., 2021; Komossa et al., 2023). Note that while recreation itself can be considered to be an example of CES, in this thesis I mainly treat the activity as a pathway to other CES (Fox et al., 2021). For the purposes of this thesis, I use text from the route sharing platform, Wikiloc, and build upon the work of Chai-allah et al. (2023) who produced the first study using textual data from Wikiloc, finding the platform to be "a rich source of textual data to study human-nature interactions" (pp. 8). Using their case study in rural France as a starting point and methodological guide, my approach for this research question includes collecting data by web-scraping content from Wikiloc, filtering trails temporally and spatially, text pre-processing including translation and tokenisation, and semantic clustering based on vectors created from a pre-trained word2vec model (Figure 4). With these clusters, I aim to learn which topics and themes arise from those recreating in forests in Germany's Natura 2000 sites.

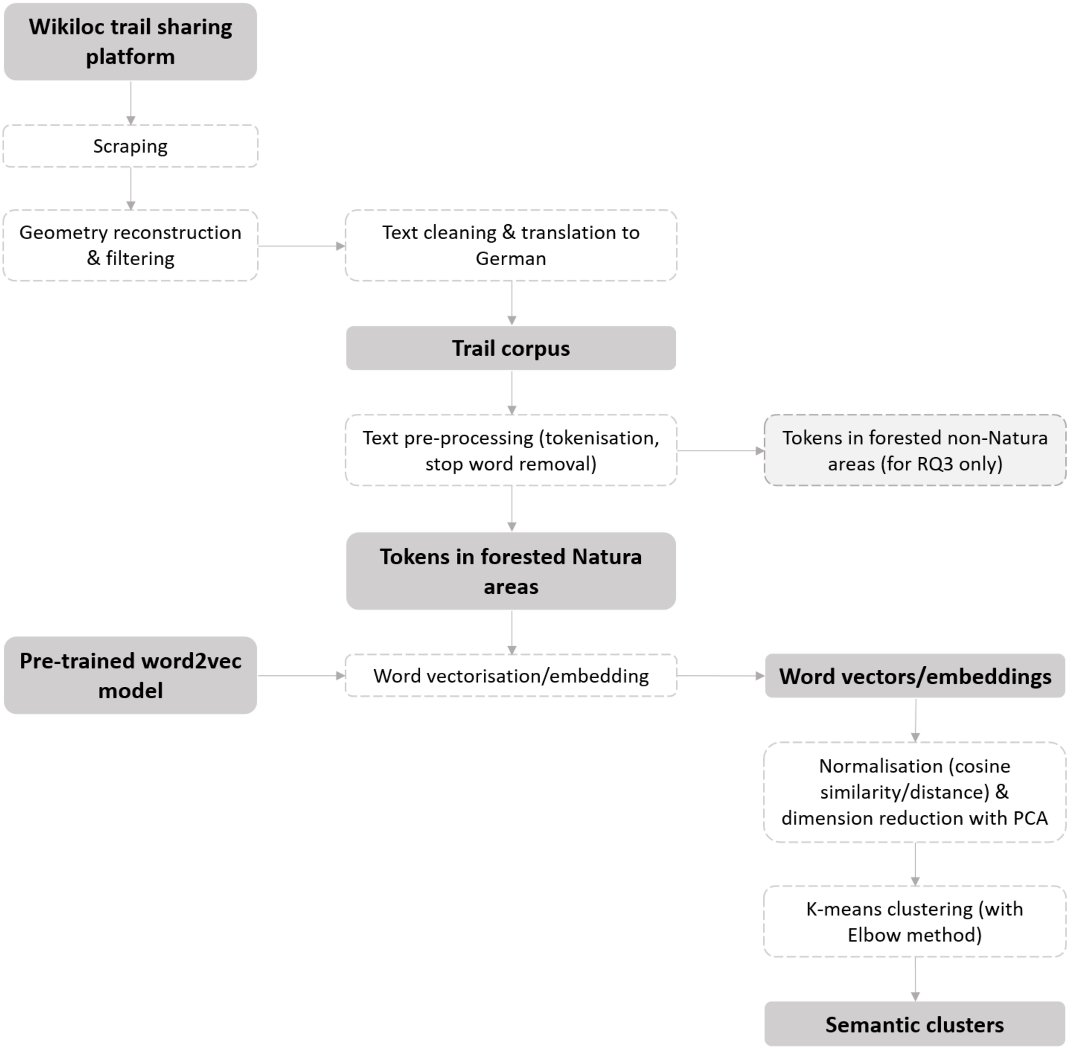

***Figure 4**. Generalised workflow for exploring CES from Wikiloc textual data using natural language processing and machine learning techniques. The additional step to produce tokens in non-Natura 2000 sites for my third research question is explained in more detail in Section 3.4.1.*

3.3.1 Data collection (Wikiloc)

Since 2006, Wikiloc[5] has provided an online space for users to share spatially-referenced trails alongside images, descriptions, photo captions and other details (Wikiloc, 2025a). The platform has grown steadily over time and in the last four years Wikiloc grew from hosting 9 million members, 30 million trails and 52 million photographs in 2021 (Wikiloc, 2025b) to nearly 18 million members who have shared over 66 million trails and 122 million photographs to date (Wikiloc, 2025a). For Germany, there were over 440,000 trails at the time of data collection, and while there were 70 different activity types recorded across the country, most trails (~75%) were categorised as either hiking, road biking, running or mountain biking trails.

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[5] https://www.wikiloc.com

To collect the textual data from Wikiloc trails in Germany, I built on the web-scraping tools used in Chaiallah et al. (2023) which are publicly available in their Wiki4CES repository on GitHub[6]. Their approach employs Python's *Scrapy* framework to develop 'spiders' for crawling and scraping information from the web. For the purposes of my work, I adapted two of their spiders, the first of which downloads URLs for each trail in each state or region of a country, and the second then uses those URLs to scrape the relevant textual data and metadata for each trail. Before the scraping could be executed, these Wiki4CES spiders required several updates and modifications. Recent changes to the Wikiloc website meant that the XPath path expressions (which correspond to the paths leading to the desired nodes of information on the website) were no longer able to retrieve any information. I therefore updated all path expressions for both spiders by inspecting the website HTML to derive the new path for each component. I also repeated this process partway through the scraping after Wikiloc released an update to the website which broke several previously-used path expressions. Next, to tailor the scraping for my project, I modified the content scraping spider by including scraping steps for extra textual data and metadata, including the date the trail was recorded, trail start coordinates, captions and coordinates for photos/waypoints and comments from other users, if available. I also removed scraping processes for unneeded attributes such as trail difficulty ratings and counts for views and downloads. To mitigate any privacy concerns, I did not download any information related to user identification. Finally, I adjusted my project settings to add default request headers (to simulate the scraping request coming from a browser), and enabled autothrottle features which add automatic delays to the scraping requests. The latter adjustment was important to ensure that there was minimal impact to the Wikiloc website servers, thus making the scraping more 'polite'.

After several rounds of testing, I observed that many trail URLs were not being extracted for larger, more popular states in Germany. This was due to a feature of the Wikiloc website itself which sets a pagination cap of 1,000 pages, meaning that when cycling through pages of trails, the website only allows a maximum of 1,000 pages: any remaining trails beyond this limit can only be accessed by applying more/different filters. To work around this pagination cap, I created another *Scrapy* spider for handling large regions specifically. Instead of supplying a starting URL to a German state and filtering all trails within that state by activity before scraping (as with the original Wiki4CES spider), this approach used a directory of places within a state, accessing each place in turn. For each place within a state, the scraper checked whether further filtering is possible by activity type: if available, the scraper filtered the trails for the place by activity, then extracted the trail URLs for each activity, and if not, it extracted the trail URLs directly. For large states, I found that the best results were achieved by combining the outputs of both

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[6] https://github.com/achaiallah-hub/Wiki4CES

the original spider and this additional spider, with any duplicate URLs removed. This approach was only necessary for four states: Baden-Württemberg, Bavaria (Bayern), North Rhine-Westphalia (Nordrhein-Westfalen) and Rhineland-Palatinate (Rheinland-Pfalz).

I performed the final scraping between April and June 2025 using the Anaconda Prompt command-line-interface in my conda environment to run the spiders for each state in Germany. I extracted a total of 432,936 trail URLs across all German states. I then downloaded the trail name, activity type, description text, trail distance, date recorded, comments and photo/waypoint caption text for these trail URLs. In addition, I extracted the latitude and longitude coordinates for the trail-start location, as well as the coordinates for each photo/waypoint. Unfortunately, the trail-end point could not be accessed as it was not exposed in the HTML of the website. Based on the number of trails per state displayed on Wikiloc at the time of download, I gathered 95-99% of the URLs per state, and scraped the content for >99% of these trail URLs. This resulted in a finally tally of 432,288 trails with their associated textual data and other metadata.

3.3.2 Data filtering & geometry reconstruction

In order to extract the trails that were relevant for answering my specific research question, I implemented several data filtering steps, including both attribute-based and spatial filtering. Beginning with the attribute-based filtering, I first used the 'date recorded' metadata to only extract trails recorded in the year 2018. This was to ensure that the Wikiloc data matched the same time period as the forest definition outputs from my first research question; as I later filter the trail data according to the categories of my forest consensus map, it was necessary to ensure that the two datasets aligned temporally. Next, I filtered the trail dataset to remove all trails which had a recorded trail distance greater than 175 km. This removed a small proportion of outlier trails which often corresponded to user error or long motorised transport journeys.

Before the spatial filtering could be performed, I first needed to reconstruct the trail geometries. Because the official trail geometries could not be scraped in a non-invasive way from Wikiloc, I instead relied on the trail start coordinates, combined with any additional coordinates for photographs or waypoints along the trail route, as available. In the cases where multiple sets of coordinates were available, I used functions from *pandas* and *shapely* to pair latitudes and longitudes into coordinate sets and generate line segments (LineStrings) following the sequence of coordinates in the order in which they were provided. This approach makes the assumption that the photo/waypoint coordinates were always supplied in the same order as the trail route itself. Though this was true in the majority of cases (based on a visual assessment), there were some instances where the trail geometries were inaccurate due to the order of the coordinates. Because of this assumption, combined with the lack of a trail-end coordinates, and the sometimes coarse granularity of photo/waypoint placement, the geometries were an approximation of the actual trail routes. Indeed, for cases where no photos or waypoints were contributed by the user, the trail geometries consisted of a single coordinate set for the start location, converted into a Point geometry with *shapely*.

As simple line and point geometries do not capture the field of view of a person on a trail, the next step for constructing the trail geometries was to apply a buffer. I used a buffer of 30 m on each side of the line geometries and for the radius of point geometries. This buffer size represents the approximate average between a minimum sight distance of 15 m used in Xiang (1996) "for hikers' unobstructed forward and rear view of the surroundings" (pp. 19) and a buffer of 50 m used in Torkko et al. (2023) which was found to most accurately capture perceived greenery in urban areas. The 30 m buffer is likely a small overestimation of sight in dense forest, but a large underestimation for high, open viewpoints where people may have expansive views ranging several kilometres. I opted for the more conservative approach with small buffers in an effort to increase the chance that the textual content is relevant to forests in the subsequent forest masking step. As a final step before the main spatial filtering, I ran additional area-based filtering on the buffered geometries. Although I had previously filtered the data to remove extremely long trails, this did not catch all cases as the distance attribute on Wikiloc was sometimes entered incorrectly. To accommodate for this issue, I manually assessed the extreme cases in QGIS (including trails which were flights or long distances outside of Germany) and removed all trail geometries over 65 km^2.

With the trail geometries prepared, I could now apply the spatial filtering steps to extract the trails that are relevant to forests in the Natura 2000 network. To ensure the trails passed through a Natura 2000 site, I added a column to the trail datasets which indicated whether the trail intersected with at least one Natura 2000 site (hereafter referred to as Natura trails). Any trails which did not intersect with a Natura 2000 sites were labelled as 'non-Natura'. I retained the non-Natura trails in my dataset for further processing, as this was necessary for my third research question (see Section 3.4.1), but removed them before the final semantic clustering analysis. To assess trails which were relevant to forests, I used the forest consensus map from my first research question as a filtering tool. I began by calculating the pixel counts for each forest consensus class for each buffered trail geometry. After converting the pixel counts to measurements of area and percentage coverage (with the same approach as described in Section 3.2.5), I then determined which consensus class comprised the dominant category for each trail, and used this attribute to remove trails in non-forest classes. For the purposes of this research question, I considered all classes where less than half of the forest definitions agree on forest presence as non-forest classes. This means that trails with a dominant class of 0 to 2 (where <50% of forest products agree on forest presence) were removed, leaving trails with dominant classes of 3 to 6 (where ≥50% of forest products agree on forest presence). Note that I carried this dominant class information through the subsequent text pre-processing steps to later separate the words from class 3 (non-consensus) and class 6 (full consensus forest) trails for Research Question 3 (see Section 3.4).

To prepare for the next processing steps which focus more on the textual data, I created a master dataset which included the full textual data for all states in Germany, with the trail URLs serving as a unique identifier. Because of the substantial filtering up to this stage, I was left with 2,646 Natura trails – or 0.61% of the total trails downloaded during data collection. An additional 2,526 non-Natura trails were carried through for text pre-processing as part of my third research question.

3.3.3 Text pre-processing

For the next stage of processing, my goal was to break down the textual data from the filtered Wikiloc trails into individual words or tokens, which could then be filtered and vectorised for use in the semantic clustering analysis. I began by combining the trail description and the captions provided for all photographs and waypoints for each trail to create a single entry of text per trail. Note that although I also scraped the comments for each trail, I decided not to use this for the analysis as there was no way to determine whether the comment was a reflection of the commenter's own experience of the route. Next, I removed some special characters, as well as the placeholder text I had added previously for any empty fields. During this cleaning step I also noticed that there were some trails with duplicate textual data despite having different trail URLs. When this occurred there were often other small differences in the trail metadata, but the user sharing the trail was the same. As I determined this was likely an issue with the user uploading the same trail twice, I removed any trails with duplicate description text so that only one unique version was retained.

Although the majority of the textual data was written in German, trails were recorded in a variety of languages. In a manual assessment of 662 Natura trails (which were selected in a stratified approach to ensure coverage across all German states), roughly 70% were in German, with other dominant languages including English (~10%), Dutch (~8%) and Spanish (~7%)[7]. Rather than removing non-German text, I translated the textual data to German using automatic language detection and translation tools. After experimenting with several different approaches for translation, I found that the *deep-translator* tool using Google Translate as the translating service had the highest success rate (89.62% for a testing subset of 289 trails[8]) in terms of both correctly recognising German text and successfully translating non-German text (see Appendix 8.3 for details). To prepare the text for translation, two

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[7] This subset of Natura trails was based on a preliminary selection and may include a small number of trails which were not part of the final analysis.

[8] As above, this subset may also include trails which are not represented in the final analysis.

additional filtering and modification steps were needed. First, because most language detection algorithms struggle with detecting and translating short text segments, I used *spaCy's* German language *de_core_news_sm* model to tokenise the text for each trail, counted the unique tokens per trail and then removed any trails which had less than three unique tokens (not including punctuation). Note that since I used a German language model across multi-language text, this initial tokenisation was an approximate process which was only used to estimate the number of tokens per trail. A more formal tokenisation process took place after the translation step. Second, I truncated trail text with over 5,000 characters in order to meet the requirements of the *deep-translator* tool. To account for cases where the truncation resulted in partial words at the end of the trail text, I removed the remaining characters after the last white space in the text segment. As this only impacted one trail in the dataset, this truncation did not dramatically reduce the amount of text remaining for analysis.

At this stage, I used *deep-translator* to auto-detect the language and translate non-German text to German for all remaining trails. Because of the additional filtering to remove trails with less than three unique tokens, the final translated trail corpus was comprised of text from 1,631 Natura trails (for this research question), with an additional 1,031 non-Natura trails for Research Question 3. During translation for the Natura trails, the algorithm recognised 959 trails (58.80%) as already being in German, and translated the text for 672 trails (41.20%). For non-Natura trails, 640 (62.08%) were detected as German and 391 (37.92%) were translated. It is important to note that while running this translation process multiple times during testing, I observed that *deep-translator* does not always produce the same translation. For example for one trail written originally in Dutch, the word for 'boss' or 'owner' was translated in one iteration as *Eigentümer*, and in a second iteration as *Besitzer*. While both translations could be considered correct, this does affect the reproducibility of the final results. To accommodate for this issue, I included a CSV of the final translated text results in my GitHub repository[9].

The final steps of the trail text pre-processing included tokenisation, normalisation and stop word filtering. Using the *spaCy de_core_news_sm* model, I tokenised the translated text for each trail to break down the textual data into individual words. This German language model is based on written text from German news and media. For this process, I also tested the *de_core_news_lg* model, but found the results did not change dramatically when only tokenising. Next, I normalised the text by converting all tokens to lowercase. Note that for the remainder of this thesis, all tokens are reported using these normalised terms. I then removed stop words based on the *de_core_news_sm* model (e.g., *und* 'and', *ist* 'is' and *aber* 'but') as these words were not of interest for the semantic analysis. In addition, I removed words like *foto* 'photo', *null* 'null' and *wegpunkt* 'waypoint' as these were often used as placeholder text

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[9] https://github.com/n-mo92/nm_forest_thesis/tree/main/other

in the photo/waypoint captions. I also removed punctuation, numbers, alphanumeric tokens, blank spaces and URLs to clean the final set of tokens. After the final token filtering, my dataset consisted of 19,603 tokens (8,927 unique tokens) for the 1,631 Natura trails.

3.3.4 Text analysis: semantic clustering

To understand the themes and topics which arise for people recreating in forests in Germany's Natura 2000 sites, I followed a similar methodological approach to Chai-allah et al. (2023) to generate semantically similar clusters of words based on word embeddings. Word embedding is a common NLP method which uses numerical vectors to represent words. These vectors can be thought of as coordinates in multi-dimensional space, with words that are closer together in this vector space having similar meanings. By calculating the similarity or 'distance' between vectors, we can create clusters or groups of semantically similar words.

To create these word embeddings, or 'vectorise' the words, Chai-allah et al. (2023) apply the pre-trained *baroni* word2vec model which is trained on a corpus of 2.8 billion words from Wikipedia, the British National Corpus (BNC) and the British Web corpus (ukWaC) (Günther et al., 2015). This model uses a Continuous Bag-of-Words (CBOW) algorithm and includes 400-dimensional vectors for 300,000 different words (Günther et al., 2015). In order to replicate this process for my thesis, my aim was to select a similar word2vec model, but one which can be used for the German language. After some exploration, I selected the *de_wiki* word2vec model which is provided in the same space as the *baroni* word2vec model[10] (Günther et al., 2015). The *de_wiki* model is trained using a corpus from Wikipedia, uses a CBOW algorithm and contains 400-dimensional vectors for over 500,000 words (Günther et al., 2015). Although the *de_wiki* model is provided as an R Data File, I converted the model for use in Python by exporting it as a text file (using R), and then loading the model into Python using the *gensim* library. After running the model with my token dataset, I was left with 15,873 vectors or word embeddings. This means that a total of 3,730 (19.03%) tokens were not available in the *de_wiki* model.

To group the word embeddings into themes containing words with similar meanings, I used the K-means algorithm for clustering based on the cosine distance between vectors. K-means is an unsupervised machine learning approach which has been used with word2vec word embeddings/vectors in other similar studies (e.g., Huai & Van de Voorde, 2022). In order to generate the clusters based on vector similarity, I normalised the token vectors. While normalisation sets the magnitude of each vector to a value of 1, it preserves the angle of the vector which is important for establishing semantic similarity. When using the K-means algorithm (which defaults to Euclidian distance), the effect of normalisation

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[10] https://sites.google.com/site/fritzgntr/software-resources/semantic_spaces

on the vectors is to replicate the cosine distance; in other words, the clustering is based on the cosine distance between vectors when normalised vectors are input into the K-means algorithm. Next, I experimented with performing Principal Component Analysis (PCA) for dimension reduction. After running through the complete clustering process several times, I observed that the outputs were somewhat sensitive to the initial (random) state parameter which initialises the cluster centroids, meaning the cluster themes and composition varied when different initial states were provided. As PCA can help address cluster instability by reducing some of the noise in the dataset, I tested reducing the dimensions to retain either 90% or 95% of the variance. The cluster outputs were the most stable for the version where 90% of the variance was retained. I therefore continued the processing steps using the normalised vectors which had been reduced to retain 90% of the variance, which transformed the 400-dimensional vectors into 275-dimensional vectors. As a final preparation step for the K-means clustering, I estimated the appropriate number of clusters using the elbow method with the within-cluster sum of squares (inertias). Since a clear ‘elbow’ was difficult to discern, I experimented with numbers of clusters between 10 to 14. I settled on a final value of 12 clusters to avoid undesired merges between themes when there were too few clusters, and relatively empty clusters when there were too many.

To generate the 12 clusters, I implemented an iterative approach in which the algorithm was automatically run with 50 different centroid seeds and the best of these runs (in terms of inertia or within-cluster sum of squares) was returned. As with the dimension deduction, this was performed in an effort to bring more stability to the clusters. Based on the output of the algorithm, each token included in the word2vec model was assigned a cluster number. Following a similar approach to Chai-allah et al. (2023), I then manually created and assigned labels or titles to these clusters, with the aim to summarise the most frequently occurring words in each cluster. For the clusters related to CES, I used labelling which roughly aligns with commonly accepted CES categories such as those applied by Vlami et al., (2020) for Natura 2000 sites, which in turn are based on guidance from the Common International Classification of Ecosystem Services (CICES; Haines-Young & Potschin, 2018). In a further effort to understand the impact of the initial cluster centroid, I ran the clustering with five different initial states, applying the same labelling for each iteration to see how the clusters varied in each output. While there was still some variation in these outputs, the cluster themes were fairly consistent across all iterations (see Appendix 8.4). For the final results, I selected the best output based on a manual interpretation of the clustering with the closest associations between words. To explore the clustering outputs, I assessed the frequency of words per cluster and created word cloud and bar chart visualisations for the frequency of the top ten words in each cluster. Finally, I assessed the spatial distribution of the top ten words in each cluster by linking these words back to the original trail text. For each cluster, I generated a map showing the centroids of all the trails containing the most frequent words in that cluster.

3.4 Forest definition & CES interactions

For my final research question, my aim was to explore the interactions between the outcomes of my first two research questions; by breaking down the CES themes revealed in the semantic analysis into different areas of forest consensus, I hoped to explore the potential influence of forest definition on how forest is perceived and valued. In particular, I used the clusters generated from the second research question for labelling tokens in non-consensus areas (class 3) and full consensus forest (class 6) and then compared the composition of the clusters related to CES for these two forest consensus areas (Figure 5).

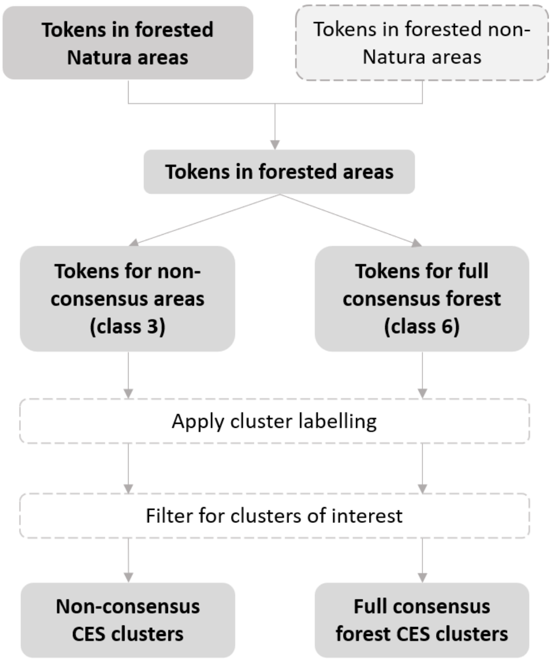

Figure 5. *Generalised workflow for exploring the interaction of forest definition in terms of forest consensus (Research Question 1) and CES (Research Question 2).*

3.4.1 Addition of non-Natura 2000 textual data

An important caveat must be made for this research question regarding the area of analysis. Until this stage, my thesis has focused on exploring different aspects of forest monitoring for Germany's Natura 2000 sites. While it was my intention to maintain this approach across all research questions, the additional filtering according to the dominant forest consensus class resulted in a dataset for the non-consensus areas that was too small to produce meaningful results (50 trails, whereas the full consensus forest had 1,318 trails). In an effort to address this issue, I expanded the textual data to include text from trails that do not intersect with Natura 2000 sites, which I generated during the processing for Research Question 2 for this reason (see Section 3.3.2). As described in the following sections, the clusters are still based on the outputs from my second research question, so any new tokens that were not included in the Natura-only clustering are not represented here. In this way I was still able to explore the clusters and tokens that were relevant to the Natura 2000 sites, while applying them to trails outside Natura 2000 as well. By expanding outside Natura 2000 sites, I increased the number of trails to 151 in non-consensus areas and to 1,979 trails in full consensus forest areas.

3.4.2 Labelling non-consensus & full consensus tokens

As the tokens for both Natura and non-Natura trails had been extracted in Research Question 2, these two sets could be merged and then filtered according to their dominant forest consensus class (also recorded during Research Question 2; see Section 3.3.2). More specifically, the tokens were separated into two subsets, one for non-consensus areas (class 3) and one for full consensus forest (class 6). I then assigned each token from the two subsets to their associated cluster label. This was done by using the labelled tokens from Research Question 2 as a dictionary to look up and match the cluster labels to the new subsets. Since the cluster labels were built using tokens from Natura trail text, any new tokens in the expanded subsets (which included both Natura and non-Natura tokens) could not be matched to clusters, and were therefore removed from the analysis.

3.4.3 CES cluster comparison

In order to compare the values and perceptions related to CES in non-consensus areas and full consensus forest, I generated visualisations for the frequency of words per cluster in each consensus subset, as well as the frequency of the top ten words in each cluster in each consensus subset. These comparison visualisations were only created for the four clusters which were of interest for CES.

4 Results

In this chapter, I present the results for each research question, including my comparison of six different forest definitions in Section 4.1, followed by the outputs for my analysis of forest CES in Section 4.2. Finally, the results for my assessment of the relationship between forest definition and CES are presented in Section 4.3.

4.1 Forest definitions

A total of 5,173 Natura 2000 sites in Germany were assessed for forest coverage and forest consensus. The number of assessed sites was slightly smaller than the initial study area (5,184 sites) as 11 sites were below 25 m^2 and did not overlap with any pixel centroids, thus not returning any results during the calculations for zonal statistics. The total terrestrial coverage of the assessed sites was approximately 7.25 million ha when including overlaps across Natura 2000 designation types, or 5.52 million ha when overlapping areas are only counted once.

The average forested area in Germany's Natura 2000 sites across all FNF maps was approximately 2.83 million ha. The smallest forest area was recorded by the H/I product (about 2.63 million ha) and the largest forest area was recorded by the FAO product (about 2.92 million ha; Figure 6). This corresponds to a difference of roughly 0.29 million ha (or 2867 km^2) between the smallest and largest estimates. If adjustments of +2.45% for forest gain are applied to the H/I product (see Section 3.2.2), the H/I product remained the output with the least amount of reported forest (approximately 2.70 million ha). The next lowest estimates for forest were 2.82 million ha by the COR product and 2.84 million ha by the DE product, putting these two products within +/- 0.5% of the average. Meanwhile, the ESA and JAX products both estimated slightly more forest than the average with approximately 2.87 million ha and 2.88 million ha, respectively. For more detailed forest area results, see Appendix 8.5.

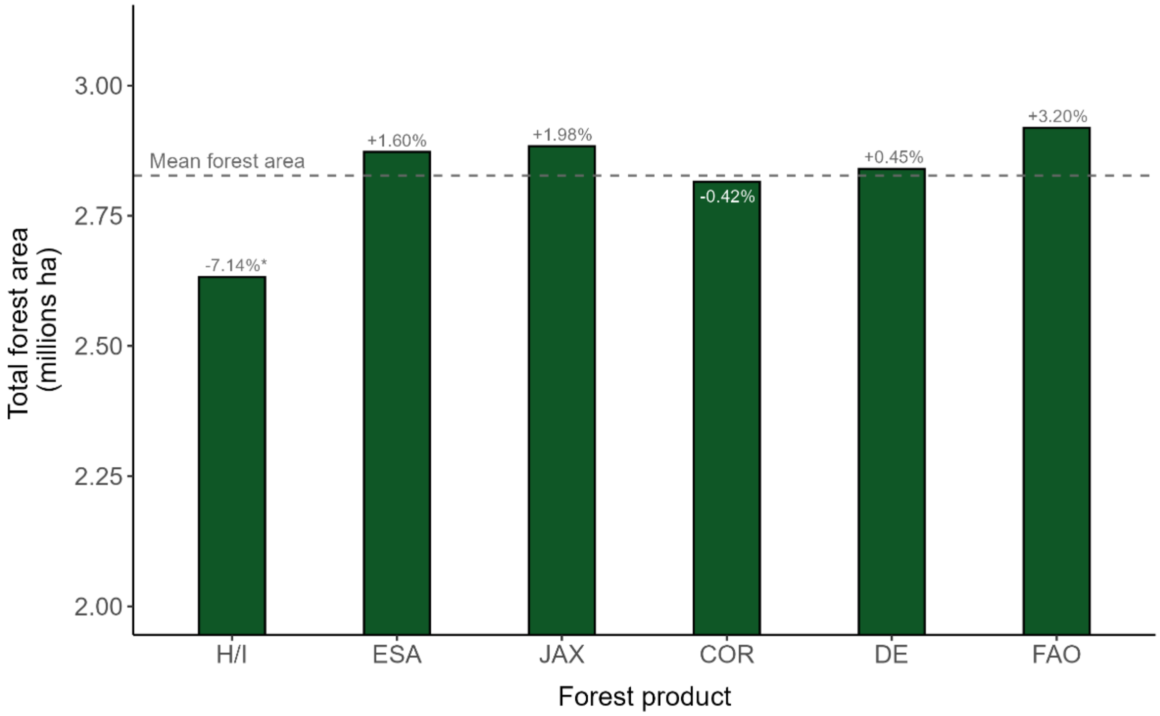

Figure 6. *The total forest area across Germany's Natura 2000 sites according to each forest product. The mean forest area across products is indicated by the dashed line. Bar labels correspond to each forest product's relative difference to the mean forest area. Areas where Natura 2000 sites overlap have been adjusted to avoid double-counting. *Please note: The H/I product results may be up to 2.45% higher than the values reported here (see Section 3.2.2).*

The statistical comparison of absolute and relative forest area for Natura 2000 sites using paired FNF maps showed that most map pairs were significantly different for a = 0.0033 (corresponding to a = 0.05 with the Bonferroni correction for 15 tests; see Section 3.2.5 for details). However, due to the large sample size and differences in the distributions of forest cover between the maps, these results should be interpreted with caution (see Appendix 8.6 for further details and the full results of the statistical tests). Instead, the box plots presented in Figure 7 provide more meaningful insights into the differences between the pairs of FNF maps.

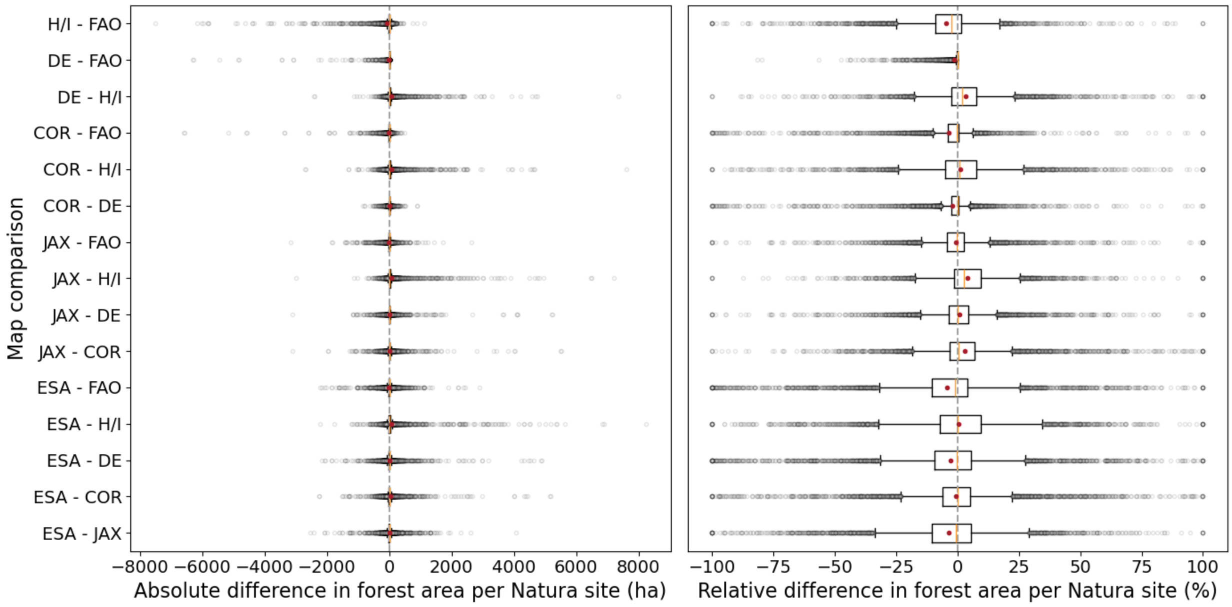

Figure 7. *Box plots showing the absolute (left) and relative (right) differences in forest area per Natura 2000 site for each FNF map pair. The box represents the interquartile range, whiskers correspond to values within 1.5 times the interquartile range and the grey circles represent the outliers beyond this range. The mean is indicated with a red point and the median is shown as an orange line. Differences are compared to a value of zero represented by the grey dashed line.*

The absolute differences presented in Figure 7 show that the mean, median and interquartile range were gathered very closely around zero, but the many outliers indicate that the differences were often positively or negatively skewed. The relative differences also highlighted the presence of outliers, but indicated that when Natura 2000 sites are treated equally (no matter the size of the forest within the site) the differences between FNF maps are more likely to deviate from zero. Exceptions include comparisons between the DE, FAO and COR maps which tended to be more similar to each other – especially the DE – FAO comparison which demonstrated the close relationship between these two maps (i.e., that the FAO map is created from the DE map, but with additional forest added). Meanwhile, the strongest differences were observed for comparisons between the H/I and FAO outputs, the H/I and DE outputs and the H/I and JAX outputs.

The forest consensus map consisted of seven different classes related to the degree of consensus on forest presence or absence. Areas of full consensus corresponded to places where all six FNF maps agreed on either forest presence or absence with a ratio of 0:6. Areas of high consensus corresponded to places where only one FNF map disagreed on presence/absence (ratio of 1:5) and areas of low consensus represented areas where the agreement ratio between FNF maps was 2:4. In areas where there was no consensus (referred to as non-consensus areas), half the FNF maps indicated forest presence, while the other half indicated forest absence (3:3). The majority of the area within Germany's Natura 2000 sites was classified as full consensus forest (approximately 2.11 million ha or 38.18%), closely followed by full consensus non-forest (about 2.10 million ha or 37.97%; Figure 8). The remaining classes, with varying degrees of disagreement on forest presence or absence, comprised approximately 1.32 million ha or 23.85% of the area covered by Natura 2000 in Germany (without double-counting for overlapping areas). More specifically, high consensus forest covered roughly 0.50 million ha (9.07%), high consensus non-forest covered ~0.33 million ha (5.91%), low consensus forest covered ~0.19 million ha (3.37%), low consensus non-forest covered ~0.16 million ha (2.98%) and non-consensus areas covered ~0.14 million ha (2.53%). For more detailed results on the forest consensus area, see Appendix 8.7.

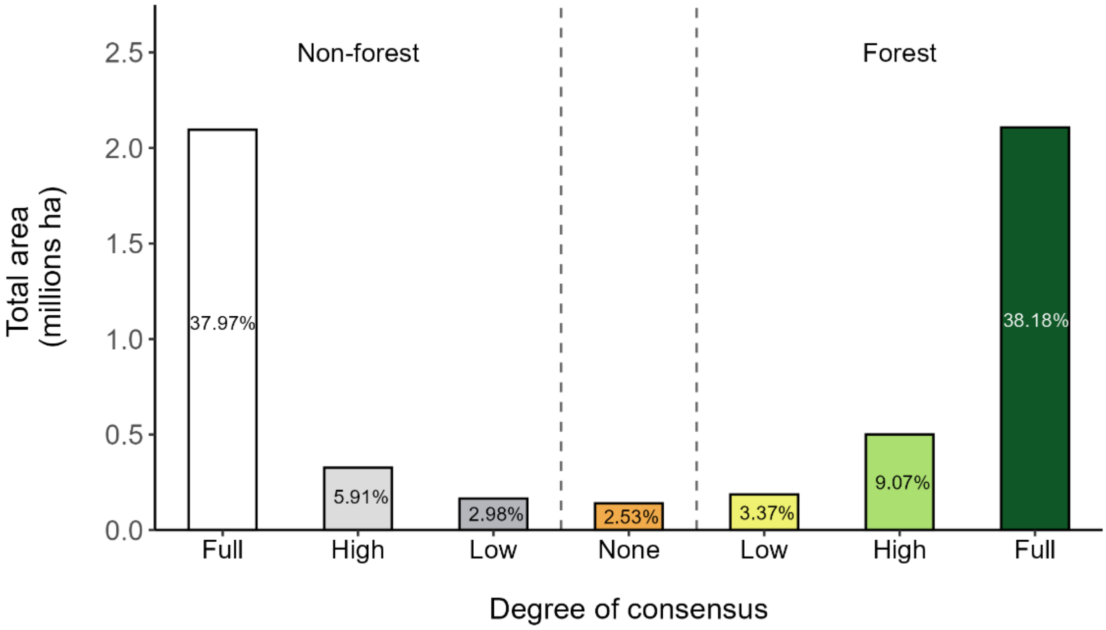

Figure 8. *The total area in Germany's Natura 2000 sites according to forest consensus class. In full consensus areas all forest products agree on either forest presence or absence. The high consensus class indicates that only one forest product disagrees with the others, whereas two forest products disagree in low consensus areas. In areas of no consensus (non-consensus class), half the forest products indicate forest presence and the other half indicate forest absence. Percentages represent the percentage of the class coverage across all Natura 2000 sites. Areas where Natura 2000 sites overlap have been adjusted to avoid double-counting.*

Exploring the forest consensus map visually, the dominance of full consensus forest and full consensus non-forest areas can be easily observed; however, there are also cases where Natura 2000 sites were mainly characterised as non-consensus (Figure 9).

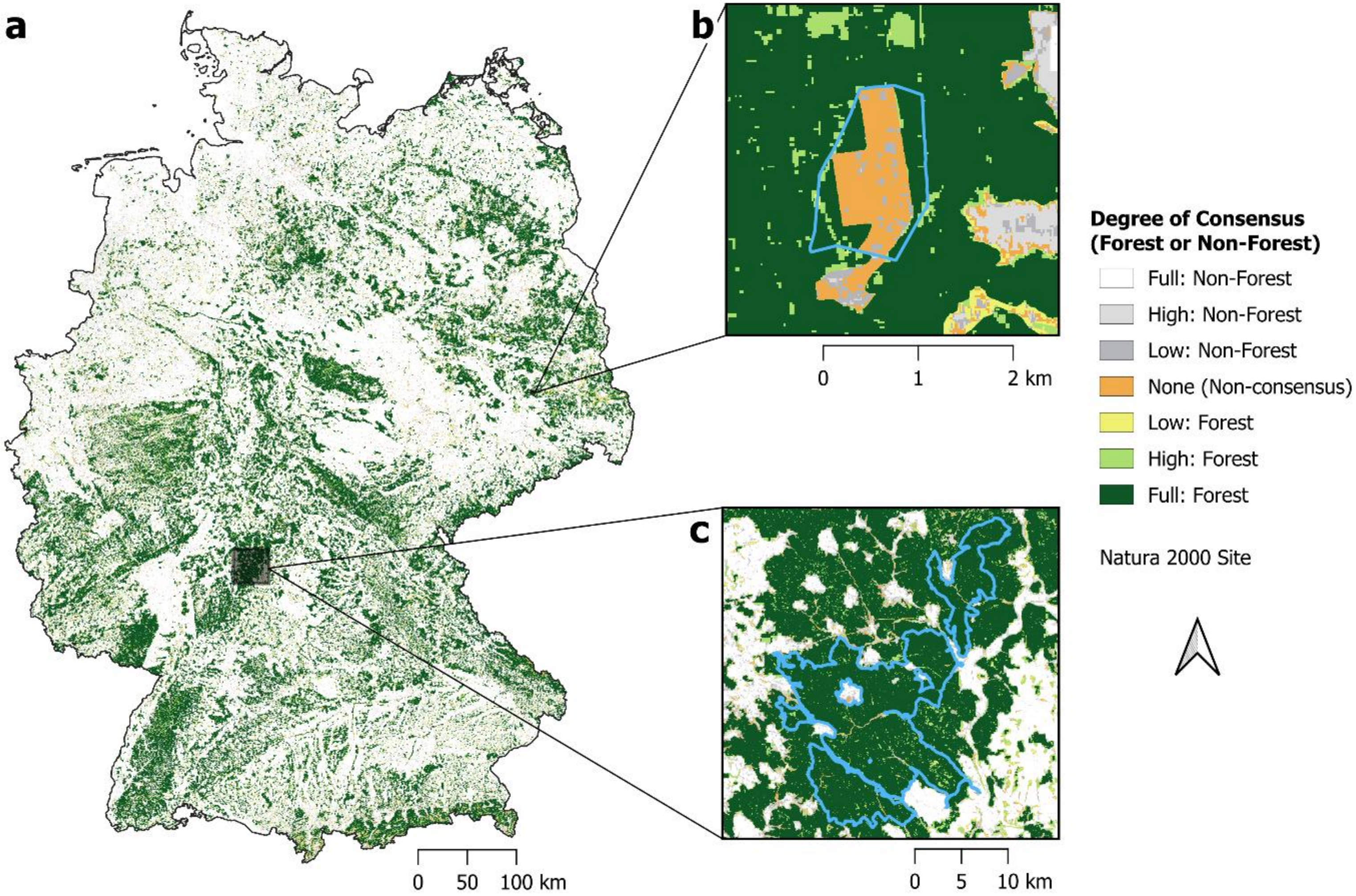

Figure 9. *The forest consensus map (**a**) generated by comparing six forest products. The 'Hohenleipisch' Natura 2000 site (**b**) provides an example of a site where the majority (about 84 ha or 49.93%) is classified as non-consensus. In contrast, the 'Spessart' site (**c**) showcases a large Natura 2000 site where the majority (about 26,672 ha or 93.75%) is classified as full consensus forest.*

In terms of the percentage coverage per site, 2,366 (45.74%) Natura 2000 sites had the highest percentage coverage in the full consensus forest class and 2,121 sites (41.00%) were dominated by full consensus non-forest. The remaining 686 sites (13.26%) were characterised by the highest percentage coverage in either high, low or no consensus, with 249 sites (4.81%) dominated by high consensus forest, 206 sites (3.98%) by high consensus non-forest, 107 sites (2.07%) by low consensus forest, 64 sites (1.24%) by low consensus non-forest, and 60 sites (1.16%) by no consensus. It is worth noting that although some Natura 2000 sites were heavily dominated by a single class, many others were made up of a range of different consensus classes and less dominant classes would sometimes still cover large areas (Figure 10).

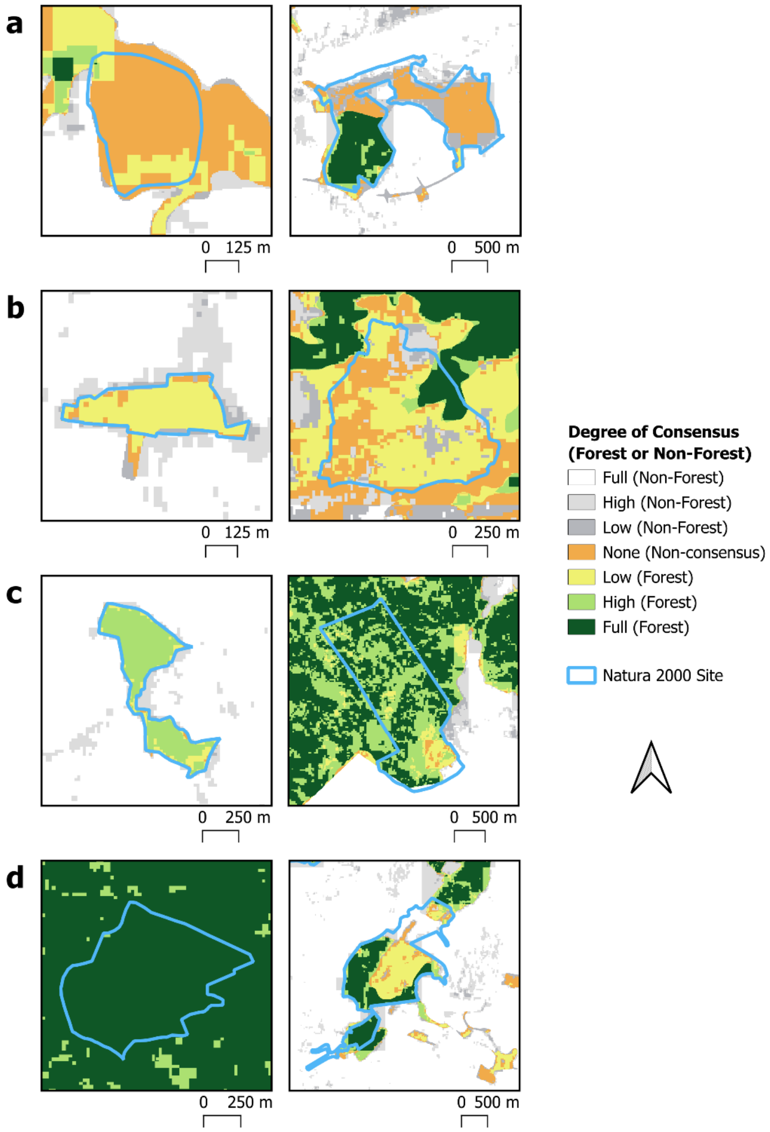

Figure 10. *Examples of paired Natura 2000 sites in which both sites had the same dominant class. The left column demonstrates examples where the degree of consensus was fairly consistent across the sites, whereas the right column shows cases where the degree of consensus was more mixed. Paired examples include sites that were dominated by non-consensus areas (**a**), low consensus forest (**b**), high consensus forest (**c**) and full consensus forest (**d**).*

By visualising the combinations of FNF maps which tended to agree on forest presence versus those which predicted forest absence, the treemap series (Figure 11) provides several insights regarding the relationships between FNF maps and the composition of the forest consensus classes. In high consensus non-forest areas, the ESA product was most likely to estimate forest presence in areas where all other maps agreed on forest absence. Conversely, for areas of high consensus forest, the H/I product was most likely to be the source of disagreement: the ESA, JAX, COR, DE and FAO products often agreed on forest presence in places where the H/I product indicated forest absence. Areas of low consensus (both forest and non-forest) were not characterised by a single dominant combination of FNF maps, but rather had several combinations of FNF maps which contributed more or less equally to these areas. This was also the case for the non-consensus category where there was the most uncertainty about forest presence. In general, the non-consensus class was often characterised by agreement on forest presence between the COR, DE and FAO products in places where the H/I, ESA and JAX products indicated forest absence, or vice versa, where the H/I, ESA and JAX products indicated forest presence, while the COR, DE and FAO products agreed on forest absence.

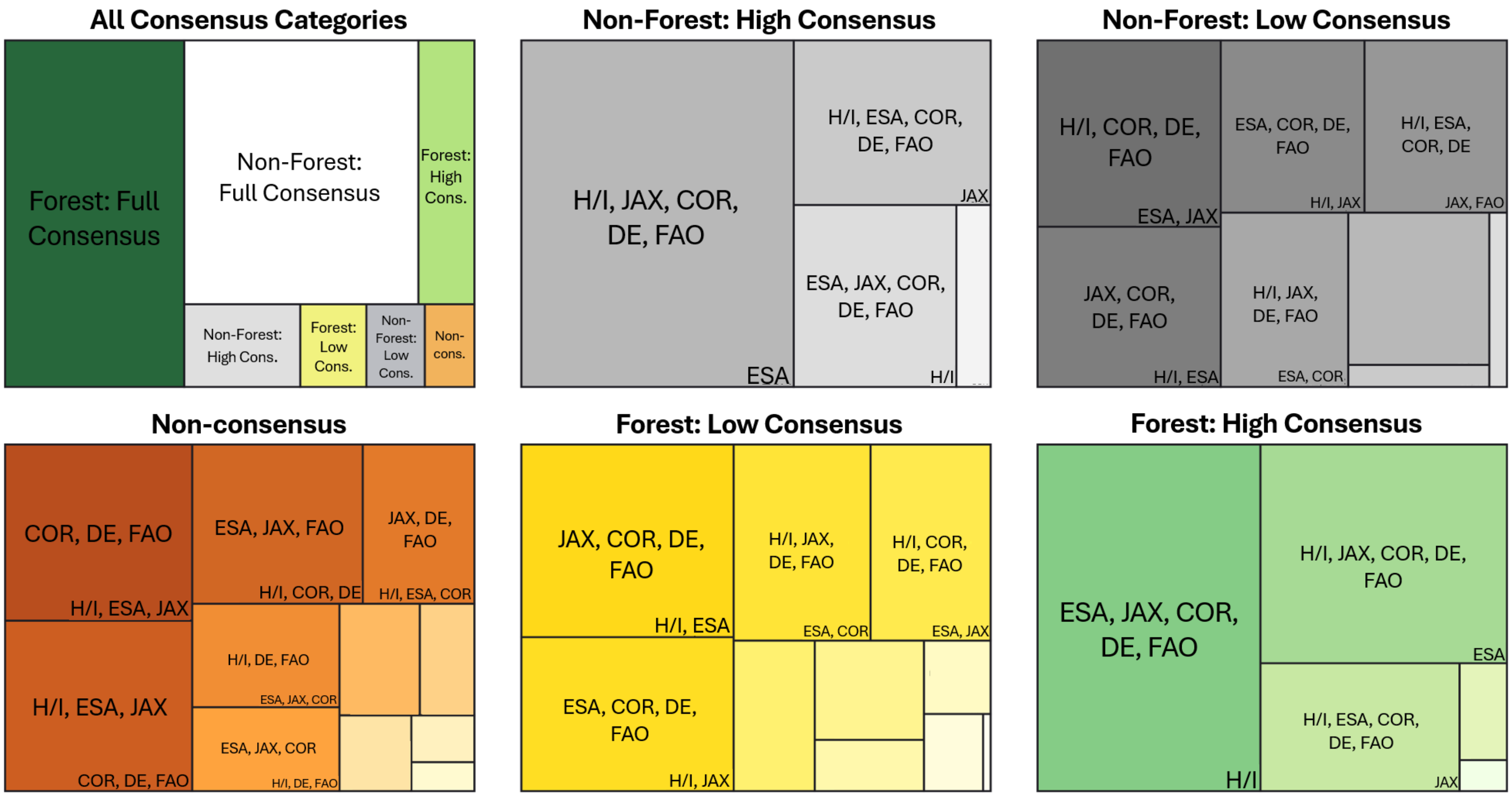

Figure 11. *Treemaps for exploring the relationships between FNF maps, broken down by each relevant consensus class. The area of land in each category is represented by the size of the box. Areas where Natura 2000 sites overlapped have been adjusted to avoid double-counting. The first treemap (top left) shows the breakdown of area in each consensus class. The centre label on subsequent treemaps show the FNF maps which agreed on forest absence (for low and high consensus non-forest classes) or forest presence (for non-consensus and low and high consensus forest classes). The label in the bottom right corner of each box corresponds to the map or map combination which indicate the opposite to the main label. For example, for the high consensus forest class, the ESA, JAX, COR, DE and FAO maps tended to agree on forest presence in areas where the H/I map indicated forest absence. For readability, labelling is provided for the most dominant combinations for each treemap.*

4.2 Forest CES

The final semantic analysis was performed with the textual data from 1,631 unique trails. These trails intersected with at least one Natura 2000 site, were primarily characterised by forest (where ≥50% of forest products agree on forest presence) and their associated text included descriptions and photo/waypoint captions with at least two tokens. These trails were spread across Germany, with all states represented except for Bremen (Figure 12). Most of the trails used in the final analysis were located to the south and west of Germany with 336 trails from Baden-Württemberg, 333 from Rhineland-Palatinate (Rheinland-Pfalz), 229 from North Rhine-Westphalia (Nordrhein-Westfalen) and 225 from Bavaria (Bayern). The final trail dataset intersected with a total of 752 Natura 2000 sites – or roughly 15% of the total number of Natura 2000 sites.

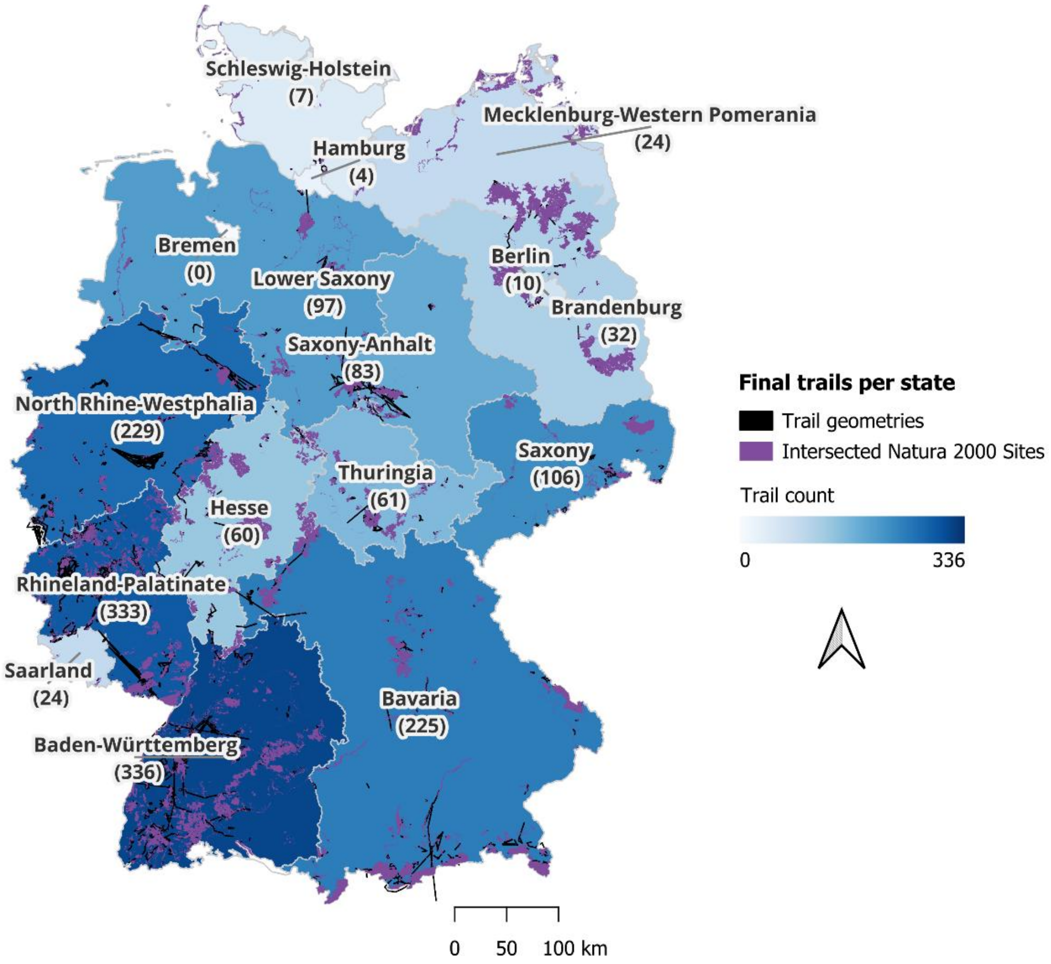

Figure 12. *The assessed trails in Germany per state. The number of trails per state is displayed in brackets below each state name and is also represented by the colour of the state, with darker colours representing more trails. Reconstructed trail geometries are shown in black. Intersected Natura 2000 sites (in purple) are intersected by at least one trail geometry.*

After transforming the trail tokens using the word2vec model, the final dataset consisted of 15,873 tokens with their associated vectors/word embeddings – of which 6,136 tokens were unique. All terms in this dataset, including proper nouns and German nouns, were normalised to lowercase. The most frequent tokens were *weg* ‘path/way’ (mentioned 181 times), *blick* ‘view’ (120), *aussicht* ‘prospect/view’ (103), *parkplatz* ‘parking lot/car park’ (95) and *schöne* ‘beautiful’ (87). The clustering analysis grouped the tokens into 12 semantic clusters, which I labelled according to the overall theme of the highest frequency words. Of the 12 clusters, four were relevant for CES: *Natural features, Historical & religious values*, *Aesthetic values (beauty & enjoyment)* and *Aesthetic values (views & outlooks)*. Note that while the *Natural features* cluster did not contain values explicitly related to a CES category, it provided insights into the types of ecosystems and natural features which may facilitate CES and was therefore grouped with the other CES clusters. The remaining clusters consisted of words related to specific places (*Placenames*), persisting English words (*English words*), a group of abbreviated words (*Units & Abbreviations*) and five semantically similar clusters with words related to trail features and directions (*Route features & directions 1 – 5*).

Looking across all clusters, the *Route features & directions 1* cluster was by far the most dominant with a total of 4,461 tokens (Figure 13). The *Placenames* cluster was also relatively large with 2,503 tokens. Of the CES clusters, the *Natural features* cluster was the most frequent with 1,360 tokens, followed by the *Historical & religious values* cluster and the *Aesthetic values (beauty & enjoyment)* cluster which were similarly sized at 487 and 434 tokens, respectively. The *Aesthetic values (views & outlooks)* cluster was the smallest cluster overall with a total of 273 tokens.

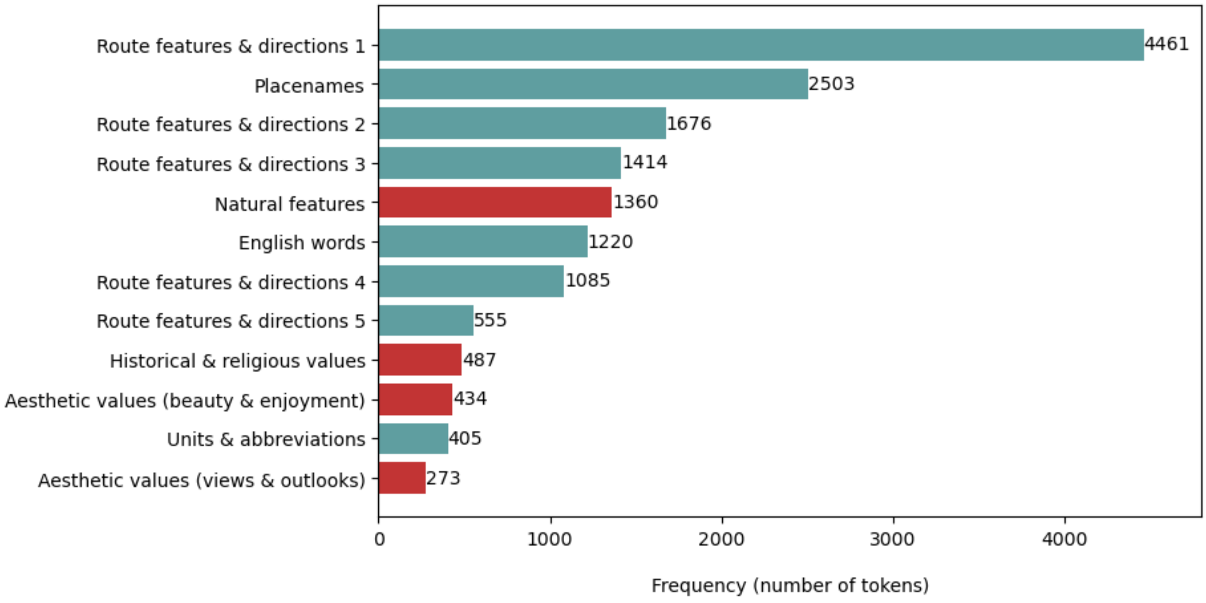

Figure 13. *The frequency, or number of words/tokens, for each cluster. Clusters related to CES are indicated in red.*

Regarding the composition of the non-CES clusters, the *Route features & directions 1 – 5* clusters were made up of a variety of words related to trails (e.g., *weg* 'path/way', *route* 'route'), trail features and infrastructure (e.g., *bank* 'bench', *parkplatz* 'parking lot/car park', *straße* 'street'), and directions or descriptions for navigation (e.g., *punkt* 'point', *entlang* 'along', *rechts* 'right', *links* 'left'; Figure 14). The *Placenames* cluster was dominated by the word *bad* 'bath/spa' which is used as part of a placename to refer to a spa town (e.g., Bad Griesbach, Bad Säckingen). This cluster may also provide some insights into areas that were especially popular places amongst Wikiloc users, such as the Harz Mountains (*harzer*), the Kyll River (*kyll*), the Rhine River (*rhein*, *rheinsteig*), the Eifel Mountains (*eifel*) and the popular tourist town, Cochem, in the Moselle Valley (*cochem*). The *English words* cluster mainly consisted of English words which were not caught in the translation step such as stop words like *of*, *the*, and *no*, but also included the word *view* which was one of the most frequently used German words. Finally, the *Units & Abbreviations* cluster was mainly composed of words or abbreviated words related to distances (e.g., *m*, *km*, *meter*, *kilometer*).

In terms of the clusters linked to CES, the words within the *Natural features* cluster were mainly related to general ecosystem and landscape features such as *wald* 'forest', *felsen* 'rock/cliff', *heide* 'heath/moor' and *landschaft* 'landscape', as well as water features like *see* 'lake', *wasser* 'water', *bach* 'stream' and *fluss* 'river' (Figure 14). Meanwhile, the *Historical & religious values* cluster was comprised of words related to man-made buildings and monuments which can be important in a historical or religious sense. More specifically, the cluster was dominated by *burg* 'castle' and *schloss* 'palace', as well as *ruine* 'ruin' and *kapelle* 'chapel'. The *Aesthetic values (beauty & enjoyment)* cluster was dominated by words related to beauty (*schöne*, *schöner*, *schönen*, *schön*, *schönes* and *schönem* are all variants of the word 'beautiful') or generally positive adjectives such as *tolle* 'great' and *super* 'super'. Finally, the *Aesthetic values (views & outlooks)* cluster contained a total of only seven unique words and was heavily dominated by the words *blick* 'view' and *aussicht* 'prospect/view' – both of which were mentioned over 100 times. For each of the four CES clusters, a list of all words which occurred at least three times is available in Appendix 8.8. Due to the large number of unique words for some clusters, a set of CSVs with all tokens for all clusters is available as supplementary material in my GitHub repository.[11]

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[11] https://github.com/n-mo92/nm_forest_thesis/tree/main/other/cluster_tokens

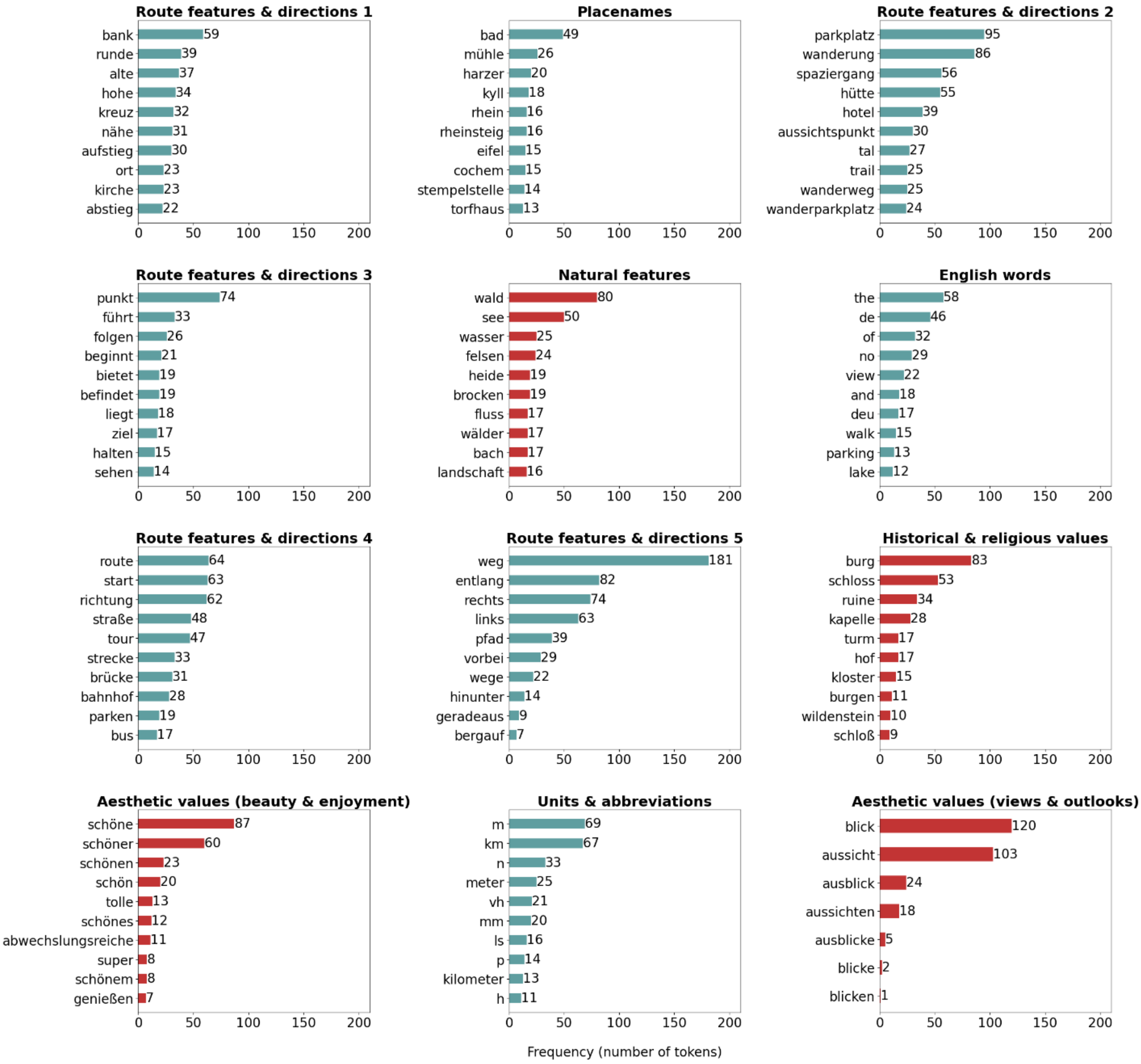


Figure 14. *The top ten words/tokens observed in each cluster. Clusters related to CES are indicated in red. To access the English translations for all words, see Appendix 8.9. A word cloud version of this figure is available in Appendix 8.10.*

Based on visual assessment, the spatial distributions of the top ten words in each cluster were fairly similar across many clusters (Figure 15), perhaps suggesting that these distributions mainly reflect where Wikiloc users prefer to recreate in general. However, some clusters did exhibit subtle differences. The words in the *Placenames* cluster, for example, tended to be more commonly located in the Harz Mountains in Lower Saxony (Niedersachsen), the area around the Moselle Valley and Eifel Mountains in Rhineland-Palatinate (Rheinland-Pfalz) and North Rhine-Westphalia (Nordrhein-Westfalen), as well as two concentrated hot spots in the region of the Black Forest in Baden-Württemberg. While these areas represented hotspots in most other cluster distributions, the *Placenames* cluster can be distinguished by the fact that it was associated with relatively few trails outside these regions. The *English words* cluster was also less spatially distributed than most other clusters, with concentrations of locations in the in the Harz Mountains and areas along the borders with France and Austria.

For the clusters related to CES, all four clusters were associated with hotspots in the Harz Mountains, the Moselle Valley and Eifel Mountains, the Black Forest, the Alps along the border with Austria and the Saxon Switzerland Mountains (Sächsische Schweiz) near the border with Czechia in Saxony (Sachsen; Figure 15). Additional hotspots were apparent along the Rhine River for the *Historical & religious* values cluster and in the region of Nuremberg (Nürnberg) for the *Aesthetic values (beauty & enjoyment)* cluster. Compared to the other three CES clusters, the *Natural features* cluster had the largest geographic spread and was associated with many additional areas outside the aforementioned hotspots.

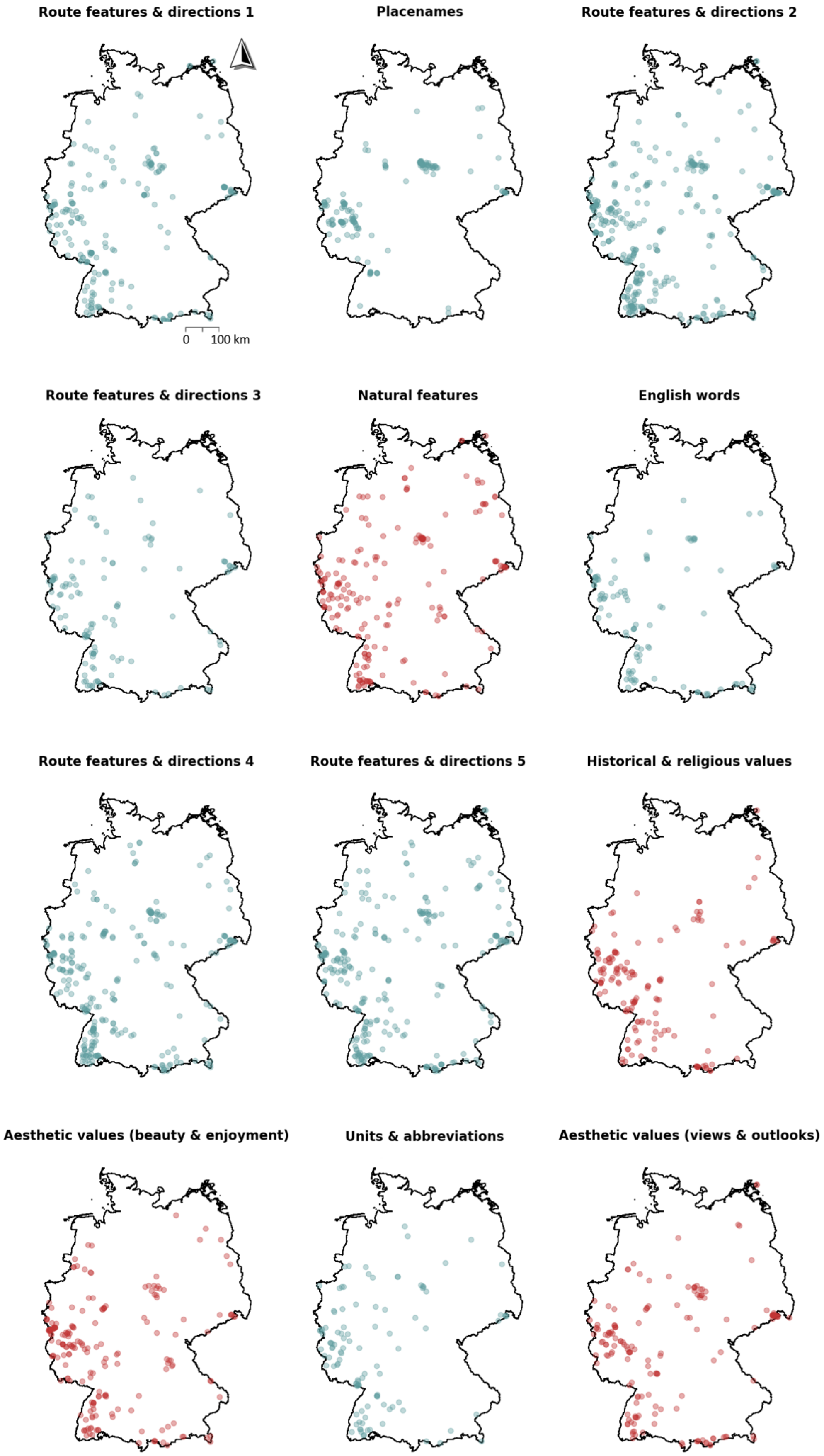


Figure 15. *The spatial distribution of the top ten words observed in each cluster. Clusters related to CES are indicated in red. Trails associated with each word/cluster are represented by their centroid.*

4.3 Forest definition & CES interactions

The comparison of CES clusters for different forest consensus categories involved 151 trails for non-consensus areas and 1979 trails for full consensus forest. Of the non-consensus area trails, 50 (33.11%) intersected with at least one Natura 2000 site while 101 (66.89%) did not. For the full consensus forest trails, 1,318 (66.60%) trails intersected with at least one Natura 2000 site, with 661 (33.40%) outside the Natura 2000 network. After tokenisation, there were a total of 1,032 tokens for non-consensus areas and 23,290 tokens for full consensus forest.

Once the trail tokens had been associated with their relevant clusters from the second research question, a total of 690 tokens remained for non-consensus areas and 17,062 remained for full consensus forest. Tokens were lost from both categories at this stage either because they were missing from the word2vec model or because they were not included in the Natura 2000-only clustering for Research Question 2. The most frequent tokens for non-consensus areas were *wanderung* 'hike' (18), *weg* 'path/way' (13), *runde* 'round/tour' (9), *schöne* 'beautiful' (8) and *route* 'route' (7) and the most frequent tokens for full consensus forest were *weg* 'path/way' (204), *blick* 'view' (142), *wald* 'forest' (131), *m* (most likely an abbreviation for 'metres'; 119) and *parkplatz* 'parking lot/car park' (118)

In terms of the frequencies for the four CES-related clusters, in total there were 130 tokens for non-consensus areas and 2,737 tokens for full consensus forest. Both categories were dominated by the *Natural features* cluster which corresponded to 66 tokens (50.77%) in non-consensus areas and 1,412 tokens (51.59%) in full consensus forest (Figure 16). For full consensus forests, the next most frequent cluster was the *Historic & religious values* cluster (531 or 19.40%), closely followed by the *Aesthetic values (beauty & enjoyment)* cluster with 476 tokens (17.39%). This is slightly different for non-consensus areas where the *Aesthetic values (beauty & enjoyment)* cluster was the second most frequent cluster with 37 tokens (28.46%), followed by the *Historic & religious values* cluster with 18 tokens (13.85%). The *Aesthetic values (views & outlooks)* cluster was the least frequent cluster for both categories, however it was proportionally more frequent in the full consensus forest class with 318 tokens (11.62%), compared to 9 tokens (6.92%) in the non-consensus class.

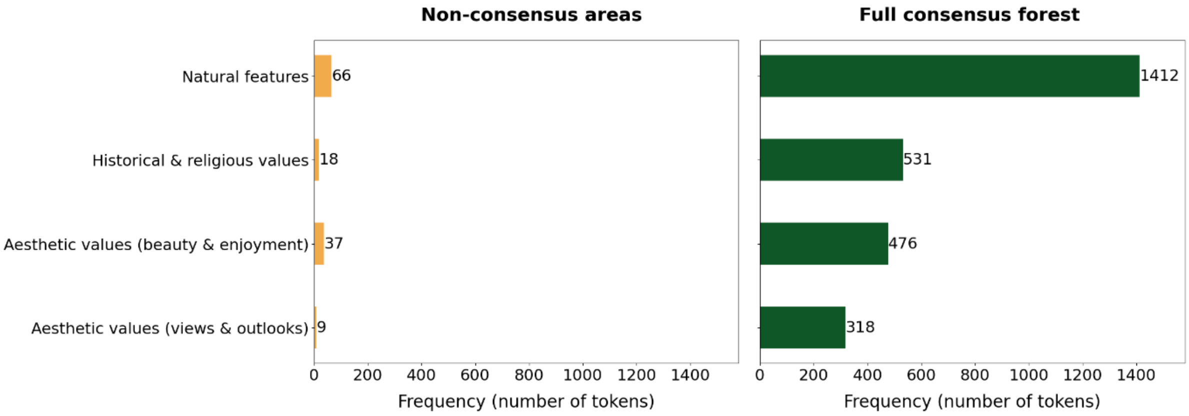
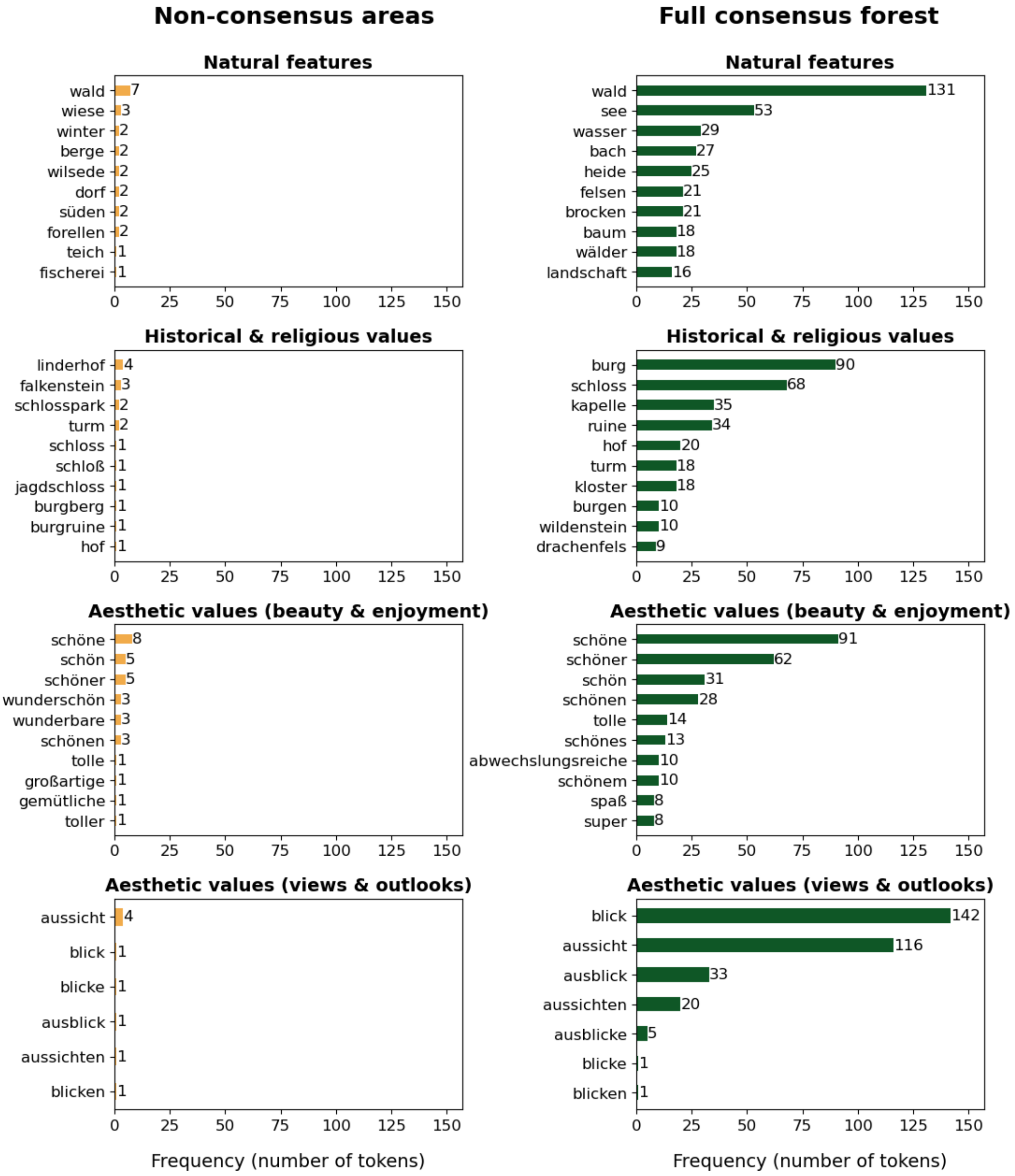


Figure 16. *The frequency, or number of tokens, for the CES-related clusters, comparing results for non-consensus areas (left) and full consensus forest (right). Note that these results include text from trail geometries which did not intersect with Natura 2000 sites.*

Regarding the cluster contents, the token frequencies for non-consensus areas were very low, making it difficult to assess whether any comparisons are truly meaningful. In general, the cluster contents for non-consensus areas and full consensus forest were similar for the two *Aesthetic values* clusters, with some variation for the *Natural features* and *Historic & religious values* clusters (Figure 17). For the *Aesthetic values (beauty & enjoyment)* cluster the most frequent words for both non-consensus areas and full consensus forest were variations of *schöne* 'beautiful'. Similarly, for the *Aesthetic values (views & outlooks)* cluster both categories were characterised by variations of the words *blick* 'view' and *aussicht* 'prospect/view'. The word *wald* 'forest' was the most frequent word in the *Natural features* cluster for both non-consensus areas and full consensus forest. For full consensus forest, the next most frequent terms were *see* 'lake', *wasser* 'water' and *bach* 'stream', whereas in non-consensus areas the next most frequent words included *wiese* 'meadow', *winter* 'winter' and *berge* 'mountains'. Finally, for the *Historic & religious values* cluster, *burg* 'castle', *schloss* 'palace', *kapelle* 'chapel' and *ruine* 'ruin' were the most frequently occurring words for full consensus forest, whereas words like *linderhof* (a palace in Bavaria), *falkenstein* (a name applying to several castles, palaces and ruins in Germany) and *schlosspark* (the park or gardens associated with a palace/castle) were among the most frequent in non-consensus areas.



Non-consensus areas

Full consensus forest

Natural features

Historical & religious values

Aesthetic values (beauty & enjoyment)

Aesthetic values (views & outlooks)

Figure 17. *The top ten words/tokens observed in each CES cluster, comparing results for non-consensus areas (left) and full consensus forest (right). Note that these results include text from trail geometries which did not intersect with Natura 2000 sites. To access the English translations for all words, see Appendix 8.11. A word cloud version of this figure is available in Appendix 8.12.*

5 Discussion

In this chapter, I examine my results in greater detail, focusing on the outcomes which help to answer my research questions while linking my findings to the pre-existing literature. After exploring each research question, I discuss the implications of my findings for forest monitoring and the Natura 2000 network, endeavouring to distil my work into useful insights to support decision-making and future work in these areas. I conclude this chapter by considering the limitations of my work and the opportunities for improvement and further research.

5.1 Differences across forest definitions

The analysis of the FNF and forest consensus maps demonstrates that forest definitions have a clear impact on forest cover measurements. The difference between the lowest and highest estimates of forest cover (approximately 0.29 million ha) corresponded to about 5.19% of the total area covered by the Natura 2000 sites assessed in this thesis. For context, this difference equates to an area slightly larger than size of the state of Saarland in southwest Germany (see Figure 12). Furthermore, the observed difference in forest cover between forest definitions considerably outweighs measurements of change in Germany's Natura 2000 sites. Between 2012 and 2018, the net forest cover in Germany's Natura 2000 sites increased by approximately 0.15 million ha, including 0.12 million ha of forest loss and 0.27 million ha of forest gain (Santoro et al., 2024). These changes are concerning because forest-surface expansion can lead to the homogenisation of landscapes with a subsequent negative impact on biodiversity (Santoro et al., 2024), but my analysis demonstrates that the forest definition can have almost twice the impact on estimated forest cover compared to actual net change over a six-year period. It is worth noting that measurements of forest change, including deforestation and forest gain, also depend on the choice of the forest definition. For their measurement of change, Santoro et al. (2024) use a forest product based on the FAO forest definition, meaning their analysis excludes changes in cultivated and urban areas, but includes change in lower density forests, which would not be considered as forest in definitions with high tree cover thresholds like the H/I product.

Although there are large areas of agreement on forest presence and absence, nearly a quarter (~23.85% or 1.32 million ha) of the area covered by the Natura 2000 network in Germany is associated with some level of disagreement on whether forest is present or not. These findings are especially relevant when considering smaller-scale analyses of individual Natura 2000 sites where differences in forest definition may have an even more prominent impact. For example, approximately half of the *'Hohenleipisch'* site (Figure 9b) is classified as non-consensus, with about 40% classified as full consensus forest. This means that some forest products would assume that 90% of the site is covered in forest, whereas others would only report about 40% of the site as forest. Since there are 60 Natura 2000 sites where the non-consensus class is the dominant class, and over 600 additional sites that are dominated by some level of disagreement between forest definitions, these kinds of discrepancies may occur for a large number of sites. Furthermore, sites dominated by one forest consensus class may still include large areas of other classes (Figure 10), meaning that forest cover measurements may still differ across forest definitions even in sites which are mainly classified as full consensus forest or non-forest.

The differences in the total forest cover across forest products can largely be explained by the tree cover threshold component of the forest definition – as the forest cover estimate increases, the tree cover threshold decreases. The H/I forest product has, by far, the highest threshold for what is considered to be forest (>60%) and it correspondingly has the lowest estimated forest cover of all the products explored in this thesis. On the other side of the scale, the FAO product estimates the most forest cover and has one of the lowest tree cover thresholds (>10%). The JAX product indicates the second highest amount of forest cover, also with a >10% threshold, with differences perhaps attributed to differences between land use- and land cover-based definitions. The JAX product forest cover estimates are closely followed by the ESA product (>15% threshold) and the DE and COR products (both with >30% threshold). The frequent disagreement between the H/I product and the other forest products in terms of where forest is present, also emphasises the relationship between tree cover threshold and total estimated forest cover. For example, the treemap series (Figure 11) shows how the H/I product is the source of disagreement in high consensus forests: in places where five forest products agree on forest presence, the H/I product is most often the one which indicates absence. This is also the case for low consensus forest and non-consensus areas where the H/I product often indicates forest absence. This trend can also be observed when exploring the forest cover differences on a per site basis, where the H/I product again stands out as being the most different from the other forest products (Figure 7). Overall, these findings fit in well with the previous literature which points to the strong role of tree cover threshold for driving differences across forest definitions (e.g., Lund, 2002; Sexton et al., 2016).

5.2 Recreationists' values related to CES

Following Chai-allah et al. (2023) and Wan et al. (2021), the cluster and word frequencies can be interpreted as what people value about their outdoor experiences when recreating in Natura 2000 forests. Of the four clusters connected to CES in my analysis, words associated with the *Natural features* cluster were the most frequent. The most common terms in this cluster focus on large landscape elements like forests and lakes as opposed to individual plants or animals (Figure 14). These findings are echoed in similar studies where large landscape features such as forest, lakes, mountains and/or rivers are often described in text or portrayed in photographs on social media (e.g., Chai-allah et al., 2023; Fox et al., 2021; Pickering et al., 2020). The token *wald* 'forest' was particularly dominant in this cluster (and indeed across the whole corpus) indicating that the spatial filtering for forested land in my analysis is reflected in the textual data. Additionally, tokens for *wald* 'forest' were much more common than tokens for *baum* 'tree', highlighting that my analysis captures what recreationist consider to be forests, rather than individual trees. Overall, *baum* 'tree' and its other forms *bäume*/*bäumen* were mentioned a total of 25 times, whereas *wald* 'forest' and its other forms *wälder*/*wäldern*/*waldes* were mentioned 107 times (see Appendix 8.8 for details), making the latter over four times as frequent.

In addition to large natural features, the recreationists represented in this analysis also frequently used words associated with sites of historical or religious importance (Figure 13). It is important to note here that CES can be co-produced through a variety of human-nature relationships, including via culturally important buildings and historical knowledge itself (Fischer & Eastwood, 2016). Repeated use of words for historical buildings like *burg/burgen* 'caste/castles' and *schloss*/*schloß* 'palace', as well as frequent use of the term *ruine* 'ruin', suggests that recreationists appreciate sites which can "relate people to the past and history of the area" (Chai-allah et al., 2023, pp. 6). The same could be said for high frequency words like *kapelle* 'chapel' and *kloster* 'cloister/monastery', which also have a potential element of religious or spiritual connection. These quantitative results are echoed in my own exploration of Wikiloc content, where I noticed many trail descriptions included details about the history of sites along the route. Overall, these findings correspond to other social media studies which also identified the importance of historical monuments and other human-made landscape features related to cultural heritage to those interacting with natural landscapes (e.g., Chai-allah et al., 2023; Oteros-Rozas et al., 2018; Van Berkel et al., 2018).

Words from the *Aesthetic values (beauty & enjoyment)* cluster were used almost as much as those from the *Historical & religious values* cluster (Figure 13). When the former are considered together with the *Aesthetic values (views & outlooks)* cluster, a cumulative frequency of 707 tokens emphasises the importance of CES related to aesthetic experiences. In terms of individual word frequencies, *blick* 'view' and *aussicht* 'prospect/view' from the *Aesthetic values (views & outlooks) cluster*, as well as *schöne* 'beautiful' from the *Aesthetic values (beauty & enjoyment)* cluster represent the top three words for all four CES clusters – and are also among the top five words across *all* clusters. Furthermore, by combining different forms of *schöne* (including *schöner*, *schönen*, *schön*, *schönes* and *schönem*) the word for 'beautiful' becomes the most frequently used term across the entire corpus. Other studies have also noted the importance of CES related to aesthetics. In the first study of textual data from Wikiloc, Chai-allah et al. (2023) found that the words for 'view' and 'beautiful' were among the most frequently used words by hikers in the Auvergne region of France. Furthermore, the semantic cluster related to aesthetics was the most dominant perception-based cluster of their study (Chai-allah et al., 2023). Outside of social media, aesthetic values were the most frequently mentioned CES in an interview-based study of people in villages in eastern Saxony in Germany (Plieninger et al., 2013).

Regarding the locations where these CES are experienced, the hotspots seem to correspond with internationally well-known destinations, (e.g., the Black Forest) and national parks (e.g., the Harz National Park within the Harz Mountains). Northern parts of Germany tend to be less well represented by the clusters related to CES, however this can be explained by the lack of large forested areas in the north (Figure 9a), as well as the small size of the Natura 2000 sites in this area, particularly in the north-west (Figure 1). Indeed, the coarse spatial assessment of CES provided in Figure 15 may be more of a reflection of the location of forests and Natura 2000 sites in Germany, combined with areas which are popular with Wikiloc users in general, rather than providing insights into places with higher levels of CES.

5.3 CES for non-consensus areas & full consensus forest: similarities & differences

Based on the available textual data for Natura and non-Natura trails, both similarities and differences can be observed for the CES clusters in non-consensus areas compared to full consensus forest. However, it is difficult to say whether any comparisons are truly meaningful due to the low amount of trail data for non-consensus areas.

On the whole, the two aesthetic clusters were fairly similar across non-consensus areas and full consensus forest. In both categories, the *Aesthetic values (beauty & enjoyment)* cluster was dominated by words associated with beauty and the *Aesthetic values (views & outlooks)* cluster was characterised by words related to views (Figure 17). As similar values are reported in other studies which do not focus solely on forests (e.g., Chai-allah et al., 2023; Plieninger et al., 2013), the similarities here are perhaps unexpected; since aesthetic values tend to be prominent across a diverse range of ecosystems, comparing non-consensus areas and full-consensus forest is therefore less likely to reveal strong differences (see Section 5.5.3 for further discussion on how this issue could be addressed). There were some differences, however, in terms of the proportion of tokens in each cluster across the two consensus categories. For example, the *Aesthetic values (beauty & enjoyment)* cluster was more frequent in non-consensus areas (28.45%) compared to full consensus forest (17.39%), and the *Aesthetic values (views & outlooks)* cluster was less frequent in non-consensus areas (6.92%) than in full consensus forest (11.62%). However, these differences may not be significant when taking the low number of tokens for non-consensus areas into account. Furthermore, aesthetic values were the most frequently expressed values related to CES in both non-consensus and full consensus forests when considering both aesthetic clusters together.

The *Natural features* cluster had the highest cumulative frequency in non-consensus areas and full consensus forest (Figure 16), making up roughly 50% of the total words in CES-related clusters in both categories. The word *wald* 'forest' was the most common word in both categories, with a very clear majority in full consensus forests (Figure 17). However, this was the only shared word for the two categories in the top ten words of the *Natural features* cluster. The next most frequent tokens in full consensus forest tended to focus on words related to water or aquatic landscape features (e.g., *see* 'lake', *wasser* 'water' and *bach* 'stream'), whereas the next most common words in non-consensus areas included a mixture of landscape or ecosystem words like *wiese* 'meadow' and *berge* 'mountains', as well as the word *winter* 'winter'. While this could suggest that there are differences regarding the natural features that are most valued in non-consensus areas and full consensus forest, it is difficult to establish whether these differences are meaningful due to lack of data in non-consensus areas.

Similar to the *Natural features* cluster, differences in non-consensus areas and full consensus forest can also be observed for the *Historical & religious values* cluster. In full consensus forest, words in this cluster were related to general historical/religious places (e.g., burg 'castle', schloss 'palace'), whereas words used in non-consensus areas often refer to specific places (e.g., *linderhof* and *falkenstein*, which are both placenames related to palaces/castles). Overall, the *Historical & religious values* cluster is slightly less frequent in non-consensus areas (13.85%) compared to full consensus forest (19.40%), but it is surpassed by the *Aesthetic values (beauty & enjoyment)* cluster for non-consensus areas (28.46%). Again, the very low frequency of words in this cluster for non-consensus areas (less than four for each token) raises the question of whether these patterns would also be discernible for a larger dataset.

While the low quantity of trail data for non-consensus areas makes it difficult to interpret why these similarities and differences occur, there is a possibility that the lack of data reveals something about the value of non-consensus areas for recreation. Based on the number of trails and the area of coverage in each category, there were 6.25 trails for every 10,000 ha (100 km^2) of full consensus forest, and 3.59 trails for every 10,000 ha of non-consensus land. This means that, for this study, there were almost twice as many trails for full consensus forest than for non-consensus areas, even when taking into consideration the relatively small coverage of non-consensus areas in Natura 2000 sites. The proportionately low quantity of trails recorded in non-consensus areas could suggest that these areas are less important for recreation and that people prefer to recreate in full consensus forests. However, more work is needed to understand whether the difference in data availability is statistically significant, and – at this stage – the findings from this research question are inconclusive.

5.4 Implications for forest monitoring & Natura 2000

By examining forest definitions and CES in Germany's Natura 2000 sites, my aim has been to provide insights for forest monitoring in the Natura 2000 network. Beginning with forest definitions, my analysis demonstrates that the choice of forest product has a considerable impact on measurements of forest cover – in some cases, even outweighing net forest change over multiple years. Based on the understanding that the COR product is normally used for Natura 2000 reporting, official monitoring could be seen as over-estimating forest compared to the H/I product by as much as 0.22 million ha (~3.97% of the total non-marine Natura 2000 area), or under-estimating forest compared to the FAO product by up to 67,846 ha (~1.23%). As Natura 2000 reporting is performed for individual sites, these large discrepancies can also have significant implications for site-specific reporting where forest definitions sometimes disagree on forest presence for large portions of a single site (e.g., Figures 9b,10). While I have not intended to supply an answer in terms of the 'best' or 'most accurate' forest definition for monitoring in the Natura 2000 network, my results bring attention to the consequences of an issue which is often ignored. As described by Lund (2002) in relation to forests: "Definitions are among the most difficult things to resolve, especially when time is limited. Any discussion of the meaning of terms is usually put off until later or not addressed at all" (pp. 24). Indeed, to the best of my knowledge, this thesis represents the first exploration of the influence of forest definition on forest monitoring in the Natura 2000 network. My results demonstrate the considerable impact of forest definition on our understanding of forests in Germany's Natura 2000 network, suggesting that discussions around forest definition selection should have higher prominence in future forest monitoring efforts.

In terms of CES, my findings contribute to a more holistic understanding of forests in Germany's Natura 2000 sites by providing initial insights into how forests in these areas are valued. By first building our understanding of what people find to be important, this information can then be used to help guide planning and management to ensure that these important CES are maintained (Chai-allah et al., 2023; Vlami et al., 2020). In turn, this means that positive human-nature interactions can be preserved, resulting in benefits for both people, who experience CES, and nature, as the human experience of CES can help to motivate conservation and protection (Daniel et al., 2012; Haslett et al., 2010). My analysis suggests that forests in Germany's Natura 2000 sites are valued for their connections to cultural heritage (history and religion) and for being places of aesthetic beauty where views and outlooks are especially appreciated. In addition, my findings suggest that other natural landscape features, including rocky areas, heathland and fresh water habitats like lakes, rivers and streams, are also valued in forested areas. Based on these findings, strategies like providing information and signage to encourage engagement with historical sites, maintaining clear view points and look-outs and supporting diverse landscapes could be included in future planning for Germany's Natura 2000 sites. Despite the importance of CES for both people and nature, this type of information is currently missing from Natura 2000 reporting requirements (EEA, 2020). Indeed, CES are generally less well integrated into the ecosystem services framework, partly because their intangible nature means they can be more difficult to measure and quantify (Daniel et al., 2012). In this context, the results of my thesis also help to demonstrate how combining NLP and machine learning techniques with social media textual data can provide useful insights for Natura 2000 forests in an efficient and scalable way at the national scale. As these approaches have not been previously applied in the context of CES in Natura 2000, this thesis may contribute to establishing methods for more holistic forest monitoring systems which are able to incorporate socio-cultural dimensions like CES.

Regarding the interaction between forest definitions and CES, the lack of trail data for non-consensus areas means that it was difficult to determine the degree of influence of forest definition on CES from my analysis. My work showed some subtle differences between non-consensus areas and full consensus forest, which may suggest that, for example, values related to history and religion are less important in non-consensus areas compared to full consensus forest or that non-consensus areas are less valued for recreation than full consensus forest. However, the lack of data means that these differences are not conclusive. Although this outcome does not help to shed light on the influence of forest definitions on measurements of CES, it may still help to inform forest monitoring efforts regarding the use of social media data for CES. The analysis for this research question was quite restricted in terms of the spatial scale (only trails which are dominated by non-consensus areas), with the temporal scale also being somewhat limited (only the year 2018). As I will discuss in Section 5.5.3, the lack of meaningful results for this research question may provide evidence that this type of fine scale analysis is not always possible with social media data and other approaches may be better suited for forest monitoring efforts which require a high level of spatial or temporal precision.

5.5 Limitations & future work

Throughout this thesis, limitations related to the scope, data and methodology provide opportunities for refinement and further research. In this section I discuss the limitations and possibilities for future work for each research question.

5.5.1 Forest definitions

For the exploration of forest definitions, one of the key limitations of my analysis was that I only compared a selection of six different forest products (all satellite-based), when in reality there many more data products which may be useful for forest monitoring in Natura 2000. In particular, expanding my thesis to include additional land use-based definitions could be useful to help understand the influence of the type of definition (i.e., land use or land cover) on forest cover estimates. Comparing land cover- and land use-based definitions with the same tree cover thresholds could especially help to tease apart potential factors which drive differences across forest cover measurements. For example, in my analysis the land use-based FAO product predicts more forest cover than the land cover-based JAX product, even though they both have the same >10% tree cover threshold. Whether this difference is largely due to the inclusion of land use-based forest categories, or whether other factors such as those related to data collection or processing play a larger role, could be an interesting area of future research. This is especially relevant as other forest definition comparison studies have mainly focussed on land cover products (e.g., Majasalmi & Rautiainen, 2021; Sexton et al., 2016; Tang et al., 2019).

By focusing this thesis on Germany's Natura 2000 sites, the scope of the work also excludes forest definitions from other regions where differences may more extreme. For example, in countries like Costa Rica, Jamacia, Malawi, South Africa and Zimbabwe, national criteria for tree cover thresholds are set at >70% or higher (Lund, 2024) meaning differences compared to international reporting requirements like the FAO (>10%) could be even more pronounced. Future research could therefore look beyond Natura 2000 and Germany to compare different national definitions of forest and their discrepancies with definitions from international institutions.

Looking at the bigger picture, the most important remaining questions are related to how we can move forward with forest monitoring in light of the differences between forest products. How can forest cover be measured in an appropriate and transparent way when the forest definition makes a considerable difference to the final outcome? Are some forest definitions better than others – and in what contexts? While several studies explore different aspects of these issues, for example by critically examining the limitations of current international forest definitions (Sasaki & Putz, 2009; Zalles et al., 2024) or by exploring how forest cover measurements can be complemented with statistics derived directly from tree canopy cover datasets (Estoque et al., 2021), the problem of forest definitions and the efficacy of potential solutions remains an important area for future research.

Regarding the technical implementation of the forest products there are several issues which place some limitations on the interpretation of the final results. For example, the uncertainty in the H/I product caused by the missing forest gain information (described in Section 3.2.2) means that the forest cover results could be higher than those presented in this thesis. While I estimated that impact of this issue would be relatively small with the forest cover for this product likely not more than 2.45% higher than my estimate (see Appendix 8.2 for details), this assessment is also limited in that it assumes the gain does not overlap with areas of loss and that the gain is constant over time. Future work could resolve the missing forest gain with the help of another dataset or by using another product with a >60% tree cover threshold in order to maintain alignment with the IGBP definition of forests (Loveland & Belward, 1997). However, as the original Hansen Global Forest Change product (Table 1) is a prominent dataset in the forest monitoring community (Global Forest Watch, 2025), I felt it was useful to include this product in my analysis, despite its limitations.

My results are also marginally affected by the missing data on the eastern edge of the DE and FAO products (see Section 3.2.2), as well as the missing results for 11 Natura 2000 sites which were below 25 m^2 and did not overlay any pixel centroids. While these issues have minimal impact on the final results across all Natura 2000 sites, it is worth noting that they do affect the individual site results, meaning that my approach for assessing forest cover differences may not be suitable for a small subset of Natura 2000 sites.

Future research could also include an exploration of other approaches for creating an FAO-aligned forest product. For my thesis, I followed a recent approach developed by Johnson et al. (2023), however, as they point out in their study, neither input dataset used in this method is completely consistent with the FAO definition. In particular, some areas where the tree cover does not meet the FAO requirements at the time of measurement, but may be able to reach those thresholds in the future, are likely to be missing from the area labelled as 'forest' (Johnson et al., 2023). As a result, my FAO product represents an approximation of an FAO-aligned forest product and future work could therefore include a comparison with other methodological approaches.

Finally, it is important to acknowledge that although my spatial analyses were carried out at a high resolution (5 m), the results are only representative of the original resolutions of the input datasets (i.e., between 25 m – 500 m). I selected the 5 m resolution in an effort to reduce the data manipulation as much as possible and to preserve the level of detail in the higher resolution input datasets – as has also been done in other forest cover studies such as Santoro et al. (2024). Furthermore, the impact of the resampling is likely small in the case of my analysis where the main focus is to draw comparisons across forest products. However, it is worth noting that the FNF maps are not able to distinguish landscape features, such as portions of forest, that are 25 m^2 in size. Instead, the smallest distinguishable features for each FNF map depends on the pixel size or the minimum mapping unit of the corresponding input dataset.

5.5.2 Forest CES

A significant limitation of my approach for exploring forest CES concerns the various forms of bias which are inherent in social media data. First, not all demographic groups are well represented by social media data (Oteros-Rozas et al., 2018). While issues around anonymity and privacy often make it difficult to determine the representativeness of social media data (Guerrero et al., 2016), several studies have explored the question of who tends to be included or excluded from these types of datasets. For example, Kubota et al. (2024) found that geotagged social media data regarding a national park in Japan was more representative of foreign visitors and people in their 30s and 40s compared to non-geotagged social media. The type of social media platform may also be related to demographic biases, with a recent study of the outdoor activity-sharing platform Strava indicating the tendency to exclude the young, the elderly and lower-income demographic groups (Venter et al., 2023). In addition to demographic bias, positivity bias is another known issue with social media data. Shared content on social media has been shown to skew towards more positive experiences (Reinecke & Trepte, 2014), meaning analyses which rely on social media data may be more likely to be missing negative perceptions. In the context of my work, this could help to explain why the most frequent words related to aesthetic values were all positive or neutral, with only six out of 707 tokens (0.85%) being negative (see supplementary material in my GitHub repository[12] for full lists of tokens). Finally, different landscapes and ecosystem services may not be equally represented in social media, with some platforms like Flickr shown to capture CES better than others (Oteros-Rozas et al., 2018) and biases towards accessible and well-known spaces observed in crowdsourced data for protected areas (Levin et al., 2017). Overall, these biases form an important limitation of my work, which can only be said to represent the values of recreationists using Wikiloc to share their experiences through geotagged routes. Future improvements to address some of these biases could therefore include an expansion of the data source(s) and methods to use a combined approach. This could include combining social media data with other more traditional sources like surveys as recommended by Toivonen et al. (2019), or the analysis could be enriched by using both image and text content as in Fox et al. (2021). Combining social media data with public participation geographic information systems (PPGIS) as recommended by Olafsson et al. (2022) could represent another pathway forward which would help address some of the shortcomings of social media data.

Comparing social media data with more direct communication from Natura 2000 visitors could also help examine the assumption that the frequencies of words and clusters correspond to the values of the Wikiloc users. Currently my analysis relies on interpreting the use of words as an indicator of value or appreciation. For example, when the word *burg* 'castle' is used in a textual description, I have understood this as an indication that they value the presence of the castle. While this interpretation has been made in other similar studies (e.g., Chai-allah et al., 2023; Wan et al., 2021), future work to compare my analysis with the results of surveys or participatory mapping exercises (as in Komossa et al., 2020, for example) would help to assess the validity of this assumption.

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[12] https://github.com/n-mo92/nm_forest_thesis/tree/main/other/cluster_tokens

Another important limitation of my work is that my approach does not explore the semantic context of the words or clusters. Currently, my analysis treats each word separately, clustering them into themes based on their semantic meaning. However, the context of each word in its original trail description may be important for understanding peoples' values and perceptions. To address this limitation, other studies have performed more advanced analyses by examining words in the context of their neighbouring words or by establishing associations between semantic clusters. For example, Chai-allah et al. (2023) use the Phi coefficient to measure how often pairs of semantic clusters appear together to better understand the associations between clusters. Their findings help to draw connections between clusters which deal with values or perceptions and clusters concerning physical elements in the landscape, thereby linking particular values with specific elements of a recreational experience. Interestingly, they found that more perceptions related to aesthetics, joy and restoration were expressed about ecosystems, animals and plants than about geomorphological and hydrological features, despite words in the latter cluster theme being more frequently used (Chai-allah et al., 2023). This highlights the importance of going beyond simple word and cluster frequencies to examine patterns and relationships in the textual data. An expansion of the work in this thesis could therefore include a similar analysis to Chai-allah et al. (2023) to understand connections between different CES clusters, as well as associations between CES and non-CES clusters.

Issues related to language also place some limitations on the final outcomes of this research question. My approach was affected by several technical challenges specific to NLP tasks in German. Because of the more complex pre-processing and reasoning steps required for lemmatisation in German (Wartena, 2019; Widmann & Wich, 2023), I did not apply lemmatisation in my approach. This means that my final clusters do not combine frequencies for words with the same lemma. For example, *schöne* and *schöner* are counted as separate words, even though they are variations of the same root word *schön* 'beautiful'. My outcomes were also affected by the relatively large number of tokens (about 19% of the total pre-processed tokens) which were missing from the *de_wiki* word2vec model and therefore not included in the final analysis. A large proportion of these missing tokens were compound words (e.g., *talwiese* 'valley meadow'), which present a common problem for machine learning and NLP tasks in languages like German (e.g., Do et al., 2017; El-Desoky Mousa et al., 2010; Hirschmann et al., 2016). To help address these challenges, future work could include more exploration and testing with different lemmatisation approaches, as well as further experimentation with different word2vec models. Although this was outside the scope of my thesis, training a word2vec model with a domain-specific corpus could help to ensure that more tokens are retained through to the clustering step. In addition, compound splitting tools such as those described in Hirschmann et al. (2016) could also help to address issues with missing tokens in the word2vec model.

In addition to these German-specific challenges, other language issues which are likely to have affected my outputs are related to translation. In order to assess all the text in the same language, I employed language recognition and translation tools to handle non-German text. Here, I encountered issues including the inconsistent translation described in Section 3.3.3, as well as problems with handling translations for text which included multiple language for the same trail entry. In these cases, the translating algorithm sometimes failed to fully translate the text, resulting in mixed language outputs which were sometimes carried through to the final clustering – as can be seen with the *English words* cluster. German placenames in non-German trail text also caused problems for the translating tools. For example, for text mainly written in English, German placenames starting with *Bad* 'bath/spa' such as *Bad Iburg*, were incorrectly translated to *schlechtes* based on the English meaning of the term 'bad'. Finally, machine translation itself is an imperfect process which is not yet able to achieve human-quality translations (Hirschberg & Manning, 2015), meaning nuance is likely being lost during this step. To address these issues with translation, future work could involve performing a multi-language assessment whereby each original language is preserved, and the vectorisation process is handled with different language-specific word2vec models. In this way, translation could be avoided entirely, and the final clustering outputs could be explored across different languages, allowing one to also examine cultural differences in how forests are valued (Komossa et al., 2023).

Additional technical limitations which may have impacted my results include the lack of filtering for unique users which has been implemented in other studies (e.g., Komossa et al., 2023) to ensure that the textual data captures a broad range of perspectives. In an effort to entirely eliminate any privacy concerns, I removed all scraping associated with the authorship of the trail. Unfortunately, this meant that I did not have the information necessary to determine the proportion of trails that were shared by unique users and I was therefore unable to determine how many perspectives are represented in the outputs for this research question. This could be corrected by re-scraping the data with the users' details included. After anonymising these details, trails associated with the same user could then be removed to correct for this issue.

Another technical limitation is that the trail geometries were significantly affected by what could be non-invasively scraped from Wikiloc. In this case, only the trail-start and photo/waypoint coordinates could be retrieved, meaning the geometries are missing their trail-end coordinates, and their precision depends on the frequency of the waypoints provided by the user. The trail geometries are also limited by user errors, which include issues of duplicate waypoints and waypoints which are out of order with the route that was actually taken, as well as assumptions about the trail buffer which is not able to completely replicate an individual's view. To help address some of these challenges, future work could explore methods for applying a viewshed analysis (e.g., Van Berkel et al., 2018) and national trail datasets such as the hiking trails from Geodata Portal Germany[13] could be integrated with the trail coordinates scraped from Wikiloc to interpolate more accurate trail geometries.

Caveats must also be made regarding the spatial filtering steps and the coverage of Natura 2000 forests. Two main spatial filters were applied in order to extract the trails which intersect with at least one Natura 2000 site and to ensure that the trail area was mostly comprised of forest cover (where >50% of the forest products agreed on forest presence). However, as these filters will still include portions of trails outside of Natura 2000 forests, these filters do not guarantee that all the textual data, and therefore all the values related to CES, are specifically about forests in Natura 2000 sites. Furthermore, the final trails and their associated text only covered 752 Natura 2000 sites, meaning the results for this research question are limited to a relatively small percentage (~15%) of the total Natura 2000 network in Germany. These issues are mainly the result of the limited spatial scale of analysis (forests within Natura 2000 sites) and the ability of social media data to fit these detailed requirements. As these factors are exacerbated during the analysis for my third research question, I elaborate on this problem and describe potential ways forward in Section 5.5.3.

Some of the disadvantages associated with the K-means clustering approach could also be addressed in future work. As K-means is a nondeterministic algorithm, the random initialisation step which produces the initial cluster centroids is controlled by the random state supplied by the user (scikit-learn, 2025). Since K-means is very sensitive to the selection of the initial cluster centroid (Celebi et al., 2013), changing the random state parameter can affect the cluster assignments (see Appendix 8.4). In addition, the accuracy of my clustering outputs with K-means could also be improved. For example, the word *aussichtspunkt* 'viewpoint' was grouped into the *Route features & directions 2* cluster, however, more accurate clustering would ideally place this word alongside words like *aussicht* 'prospect/view' in the *Aesthetic values (views & outlooks)* cluster. While this may also depend on the word embeddings from the word2vec model, general improvements to the stability and accuracy of the clustering could be explored by testing other clustering approaches. In particular, deterministic approaches such as hierarchical clustering using Ward's distance method as per Chai-allah et al. (2023), could provide a useful starting point.

Finally, it is worth noting that problems with consistent data access to Wikiloc may suggest that this platform is not sustainable for future use via scraping. While Wikiloc has been suggested as a new platform to address social media data availability issues as platforms like Flickr decline in popularity (Chai-allah et al., 2023), continued updates to the website structure and the pagination cap described in Section 3.3.1 make it difficult to scrape content in a consistent and thorough manner. For future work

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[13] http://data.europa.eu/88u/dataset/e528a2a8-44e7-46e9-9069-1a8295b113b5

with Wikiloc, direct contact with the website providers may be a more practical way forward. Through this contact, potential access to the original trail geometries may have the added benefit of addressing the issues with geometry reconstruction described above.

5.5.3 Forest definition & CES interactions

When assessing the relationship between forest definitions and CES, the most significant limitation of my approach was the lack of data for non-consensus areas. Because of the low quantity of trails in this category, I expanded this research question to also consider non-consensus areas outside of the Natura 2000 network. Despite this modification, there was still an insufficient amount of data in these areas, meaning the results were somewhat inconclusive. This outcome highlights how social media data does not suit every type of analysis; when the scale of analysis is very specific, individual social media data platforms may not be able to provide enough content to derive meaningful results. These findings are echoed in a methodological overview of the application of social media data in conservation science (Toivonen et al., 2019), where the authors describe how meaningful analysis with social media data is not always possible when working on limited spatial and temporal scales. In the case of this research question, the specific focus on comparing trails which were dominated by non-consensus areas against those mainly composed of full consensus forest, combined with the relatively narrow temporal focus on the year 2018, meant that the quantity of trail data from Wikiloc was insufficient. Indeed, this issue is also relevant for the second research question where the total number of trails used for the semantic analysis represented less than 1% of the total trails for Germany. Because of these limitations, more work is needed to determine whether differences in forest definitions have a significant impact on the CES experienced by recreationists. While I have speculated that there could be some differences between CES in non-consensus areas and full consensus forest, including the possibility that lower consensus on forest presence could be related to lower popularity for recreation, future work which brings in additional data sources could help to determine whether these differences persist in larger datasets. This could include supplementing the current Wikiloc textual data with data from other social media platforms, expanding the spatial scale to group non-consensus areas and low consensus forest, or adapting the temporal scale to consider multiple years. As a priority, my analysis could be supplemented with inputs from more traditional methods such as surveys in order to address the limitations of social media data in terms of both coverage, as well as demographic and positivity bias (as described in Section 5.5.2).

An additional limitation regarding this research question is that comparing word frequencies in non-consensus areas and full consensus forest may not be enough to tease apart differences in CES. This is because some CES, such as those related to aesthetic values, can be frequent across both forest and non-forest ecosystems (e.g., Chai-allah et al., 2023 and Plieninger et al., 2013, who do not distinguish their results based on forest presence), meaning relatively small distinctions between different forest consensus classes are unlikely to result in differences across the most frequent terms. In order to resolve this issue, future work could include an initial evaluation of token rarity on a corpus of all trails in both forested and unforested areas. In this approach, the Inverse Document Frequency (idf) from the commonly used Term Frequency–Inverse Document Frequency (tf-idf) weighting approach could be calculated for each word across the corpus. Words which are common across both forested and non-forested areas could then be removed before applying the original word frequency approach to explore differences in non-consensus areas and full consensus forest. In this way, we may be able to tease apart CES which are specific to these areas, thus providing greater insight into the impact of forest definition on CES. This approach could also be a useful addition to my second research question in order to supply further insights into CES which are uniquely prominent in forests.

6 Conclusion

In this thesis, my aim has been to contribute to a more holistic understanding of forests in Europe by concentrating on aspects of forests which are currently under-represented in forest monitoring efforts. In particular, I focussed on two socio-cultural aspects of forests in Germany's Natura 2000 network: how forests are defined and how forests are valued in terms of CES. I also investigated the interaction of these two themes by comparing CES in areas where forest definitions agree on forest presence with CES in areas where there is a lack of consensus.

Methodologically, I implemented a different approach to help answer each research question. To compare forest definitions, I selected six well-known definitions and used geospatial processing techniques to compare forest cover and consensus. To examine CES and provide insights into recreationists' values, I web-scraped textual data from the outdoor route-sharing platform Wikiloc and used NLP and machine learning techniques to generate semantic clusters. Finally, to explore the influence of forest definition on CES, I compared CES clusters in full consensus forests and non-consensus areas by applying cluster labelling to textual data which was spatially linked with different degrees of forest consensus.

My results highlight the importance of forest definitions and contribute to our understanding of what recreationists value about forests in Germany's Natura 2000 sites. First, my analysis of forest definitions demonstrated that the choice of definition can have a considerable impact on measurements like forest cover. Comparing these differences to actual change in Germany's Natura 2000 sites, discrepancies between forest definitions were nearly twice as high as the previously reported net change over a six-year period. This translates to a considerable amount of disagreement across the six forest definitions assessed in this thesis – an outcome which is even more salient at the site level where well over 600 sites were characterised by some level of disagreement. Second, my assessment of CES in Germany's Natura 2000 sites highlights that forests in these areas were valued for their association with sites of historical or religious importance, such as castles, palaces and ruins, as well as their aesthetic qualities including beauty and the availability of views and outlooks. In addition to forests, other large natural landscape features, such as lakes, rocky areas, heathland, rivers and streams, were also valued. Third, my analysis of the interactions between forest definitions and values related to CES was inconclusive due to the lack of social media textual data in non-consensus areas. While I observed some subtle differences between full consensus forest and non-consensus areas, further work is needed to determine whether these differences are truly meaningful.

These findings provide several insights for forest monitoring efforts in Germany's Natura 2000 network. My outcomes demonstrate that, although often overlooked, it is extremely important for forest monitoring systems to consider how forests are defined. Given the magnitude of difference across definitions shown in my work, future forest monitoring efforts could prioritise action in this area – especially in the case of Natura 2000 where the choice of forest definition had not been previously assessed. In this thesis, I also helped to build an understanding of the CES that are valued in forests in Germany's Natura 2000 sites and how they can be monitored. Knowledge about how people value forests in specific areas can help decision-makers preserve and facilitate positive human-nature interactions in a way that is tailored to these areas. Based on my results, CES related to historical and cultural values, as well as aesthetics, could form a focal point for planning and strategies in Germany's Natura 2000 sites. Furthermore, my thesis provides an exploration of modern methods for assessing CES and demonstrates that NLP and machine learning techniques may be useful for monitoring forest CES in Natura 2000 sites at the national level. Finally, the lack of data for non-consensus areas limited my ability to assess the impact of forest definition on measurements of CES, highlighting that social media data may not be well suited for all aspects of forest monitoring, particularly those with a high spatial or temporal resolution (Toivonen et al., 2019).

Comprehensive monitoring approaches are vital for protecting forests and maintaining the important ecosystem services that they provide (Directorate-General for Environment, 2023). These approaches are also necessary for informing enduring and successful conservation in protected areas like the Natura 2000 network (Blicharska et al., 2016; Tsianou et al., 2013; Vlami et al., 2020). However, social science themes such as those described by Kull (2017) are currently not included in official Natura 2000 reporting (EEA, 2020) and are under-represented in academic literature about the Natura 2000 network (Blicharska et al., 2016; Orlikowska et al., 2016; Popescu et al., 2014). My work presented in this thesis represents a useful starting point and case study for addressing these knowledge gaps. By providing initial insights into the impact of forest definition and what people value about forests, my work provides a step towards more holistic forest monitoring in Europe's Natura 2000 network. Future work including research concentrating on how differences in forest definitions can be clearly communicated in forest monitoring, as well as efforts to compare and integrate social media analysis and other approaches for deriving CES, have great potential to contribute further in this area.

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8 Appendix

8.1 Detailed workflow for forest/non-forest and forest consensus maps

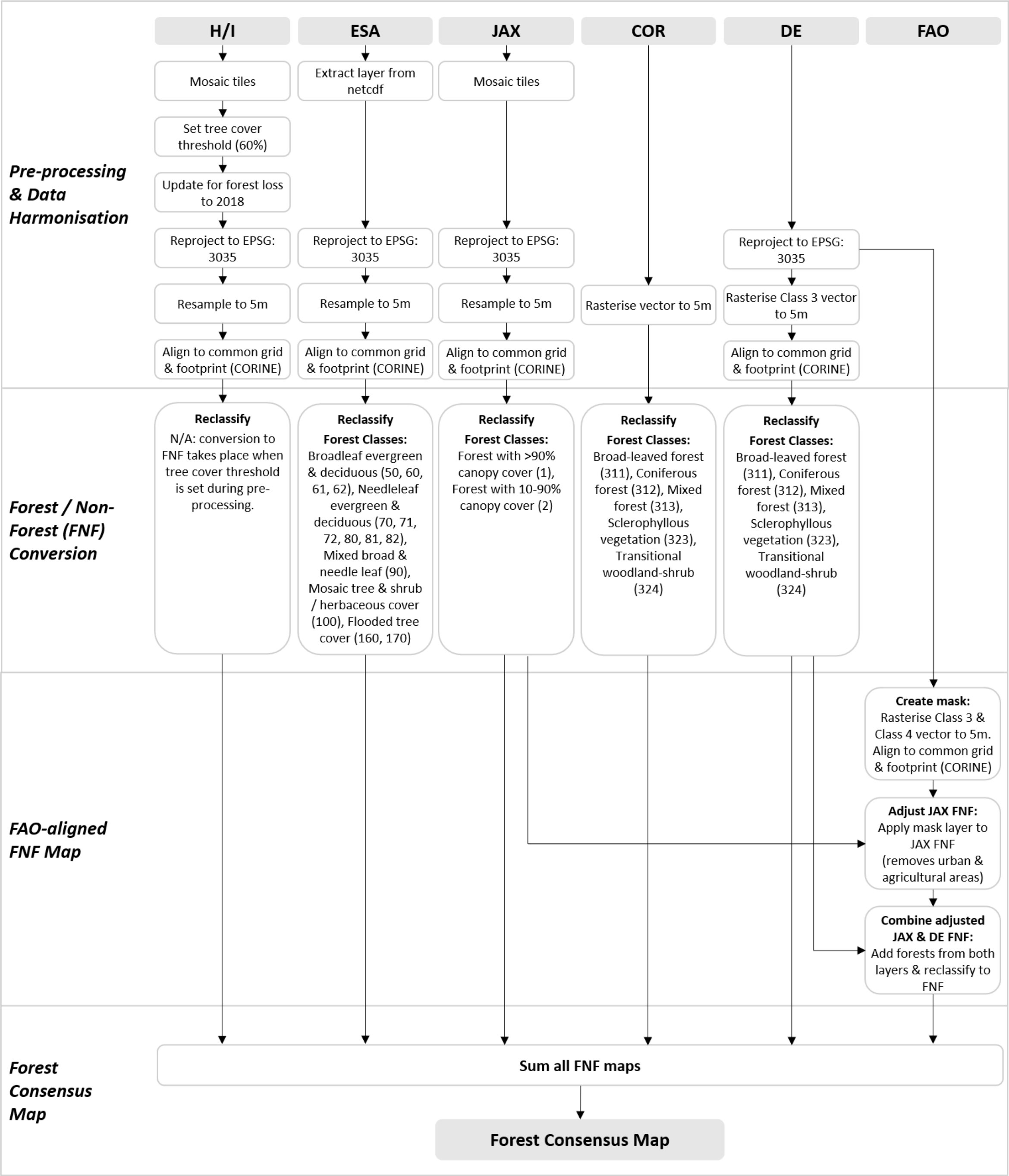

Figure A1. *A detailed illustration of the steps taken to produce the forest/non-forest and forest consensus maps, including specifics related to the pre-processing and data harmonisation steps, how the datasets were reclassified and how the FAO-aligned map was created. Abbreviated dataset names are explained in Section 3.2.1. Numbers in brackets in the reclassification step refer to raster or class column values from the original datasets. Note that the class Sclerophyllous vegetation (323) in the COR and DE products, as well as the classes for mangroves (160, 170) in the ESA product, are not present within Germany.*

8.2 H/I forest loss and gain adjustments

To update the H/I forest product to a specific year from its base year (2000), datasets for forest loss per year from 2001-2023 and forest gain for 2001-2012 are available from the original data providers. However, the forest gain dataset is not provided as a yearly value and is missing data after 2012. As I needed to update the product to the year 2018, I compared two approaches: 1) updating the forest product for loss only; and 2) incorporating both loss and gain, but with several assumptions to accommodate the limitations of the gain dataset. Note that the area calculations for these two approaches (described below) are based on estimates from pixel counts generated using QGIS. I treated pixels as 25 m x 25 m which is an approximation of the 0.00025 degree pixel size of the original dataset. All values were rounded to the nearest whole number and correspond to Germany's Natura 2000 sites.

First, I extrapolated the forest gain for the missing years from the available data. On average, 65 km^2 of forest was gained per year from 2001-2012. Assuming that the rate of forest gain was constant, over the course of 17 years (2001-2018) approximately 1,105 km^2 would be gained. Next, the amount of forest loss up to 2018 could be calculated by isolating the loss which occurred from 2001-2018 directly from the raster. This corresponded to 2,022 km^2 of forest loss. Finally, using the tree cover raster with the >60% tree cover threshold, I calculated that the total forest cover in the year 2000 was 46,867 km^2.

Combining these results to explore the impact of the extrapolated gain information shows that the difference in total forest cover between the two approaches was less than 3% (Table A1). However, in addition to assuming that the gain was constant over time, this difference also makes the assumption that areas of forest gain and loss do not overlap. As areas of loss and gain are often spatially linked (Precinoto et al., 2022), the second assumption means that the percentage difference recorded here is likely the *maximum* amount of difference. I expect that the true total forest cover results for this product are somewhere in between the two estimates in Table A1.

Table A1. *A breakdown of the estimates for the H/I total forest cover for 2018 depending on whether only loss is considered or whether both loss and gain are taken into account. Note the area assessed is for the original Natura 2000 sites (i.e., overlapping areas have not been removed).*

Area Assessed	Total Forest 2018 - with loss -	Total Forest 2018 - with loss AND gain -	Difference
Germany Natura 2000 sites	44845 km^2	45956 km^2	1111 km^2 (2.45%)

8.3 Comparing language detection and translation approaches

After preparing my textual data for translation, my initial approach was to use the *langdetect* package to detect whether the trail text was already in German, and then pass any non-German text to the *deep-translator* tool for translation. However, I found that this method sometimes failed to translate where needed or the language detection would fail to successfully detect German and an unnecessary translation would be applied – sometimes translating into English instead of German. I therefore tried an alternative approach where I used *deep-translator* for both language detection and translation. I compared the results from the two different approaches by manually assessing the original language and the translation for a preliminary subset of 289 trails. Note that these trails were part of an initial filtering effort and may include a small number of trails which are not part of the final analysis. Overall, I found that the approach which only used *deep-translator* produced the best results (Table A2). This approach produced a total of 259 successful outcomes (211 trail texts correctly identified as German and 48 trail texts successfully translated), resulting in a success rate of 89.62%.

Table A2. *A comparison of two language detection and translation approaches. Values represent the count of trails in each category based on a manual assessment of a subset of 289 trails.*

Outcome	**Details**	**Approach 1: langdetect & deep-translator**	**Approach 2: deep-translator only**
Success	German recognised	201	211
Success	Correct translation	33	48
Partial	Incomplete translation	20	13
Failure	Translation did not occur at all	14	6
Failure	Incorrect translation	7	4
Failure	Unneeded & incorrect translation	14	7

8.4 Comparing initial states for K-means clustering

During the processing and analysis steps for my second research question, I observed that the K-means clustering was sensitive to the random state parameter which initialises the cluster centroids. After taking steps to help address this instability, such as dimension reduction through PCA and increasing the number of iterations with different centroid seeds (after which the algorithm selects the best output in terms of inertia), I aimed to explore the cluster stability through a simple comparison. I ran the clustering several times, each time varying the input for the initial/random state. The results of this process are presented in Table A3. While the cluster compositions varied somewhat, the overall cluster themes remained fairly consistent across each iteration. Most of the variation occurred in the clusters related to route features and directions, whereas the clusters related to aesthetic values, historical and religious values and natural features (i.e., CES clusters) tended to be more stable. The *Aesthetic values (views & outlooks)* cluster was particularly stable, with all five iterations returning the same results. From these iterations, I selected the output which resulted in the most accurate clustering based on semantic similarity, focussing particularly on clusters related to CES.

Table A3*. A comparison of five iterations of K-means clustering using different initial/random states (RS). The top ten most frequent words/tokens are shown for each variation. Words in bold appear in at least four of the five variations. The iteration in bold borders (RS=14839) represents the clustering results reported in this thesis.*

Cluster	RS = 632	RS = 38503	RS = 237	RS = 14839	RS = 45
Route features & directions 1	**bank**	**bank**	punkt	**bank**	punkt
	runde	**runde**	**bank**	**runde**	**bank**
	alte	**kreuz**	**runde**	alte	de
	kreuz	nähe	alte	hohe	**runde**
	kirche	aufstieg	hohe	**kreuz**	n
	stadt	wasser	führt	nähe	**kreuz**
	nummer	**kirche**	**kreuz**	aufstieg	nummer
	brocken	abstieg	aufstieg	ort	brocken
	haus	stadt	folgen	**kirche**	ls
	denkmal	nummer	**kirche**	abstieg	stück
Placenames	**bad**	**bad**	**kyll**	**bad**	**bad**
	mühle	**harzer**	**rhein**	mühle	mühle
	harzer	**kyll**	**rheinsteig**	**harzer**	**harzer**
	kyll	wandernadel	**eifel**	**kyll**	**kyll**
	rhein	**rhein**	**cochem**	**rhein**	**rhein**
	rheinsteig	**rheinsteig**	abzw	**rheinsteig**	**rheinsteig**
	eifel	**eifel**	zwingenberg	**eifel**	**eifel**
	cochem	**cochem**	winterberg	**cochem**	**cochem**
	kloster	**stempelstelle**	heimbach	**stempelstelle**	**stempelstelle**
	stempelstelle	torfhaus	monschau	torfhaus	forsthaus
Route features & directions 2	**wanderung**	**wanderung**	**wanderung**	parkplatz	parkplatz
	route	**spaziergang**	route	**wanderung**	**spaziergang**
	spaziergang	**hütte**	**spaziergang**	**spaziergang**	**hütte**
	tour	see	**hütte**	**hütte**	hotel
	strecke	hotel	tour	hotel	**aussichtspunkt**
	aufstieg	**aussichtspunkt**	**aussichtspunkt**	**aussichtspunkt**	bahnhof
	aussichtspunkt	tal	tal	tal	ort
	trail	**trail**	**trail**	**trail**	restaurant
	wanderweg	**wanderweg**	**wanderweg**	**wanderweg**	familienzimmer
	wanderparkplatz	**wanderparkplatz**	**wanderparkplatz**	**wanderparkplatz**	gasthaus
Route features & directions 3	punkt	punkt	hotel	punkt	alte
	hohe	hohe	nähe	**führt**	hohe
	führt	**führt**	brücke	**folgen**	**führt**
	folgen	**folgen**	bahnhof	**beginnt**	**folgen**
	ort	ort	ort	**bietet**	**beginnt**
	beginnt	**beginnt**	stadt	**befindet**	direkt
	direkt	direkt	restaurant	**liegt**	vh
	bietet	**bietet**	familienzimmer	ziel	**bietet**
	befindet	**befindet**	parken	halten	**befindet**
	liegt	**liegt**	haus	sehen	**liegt**
Natural features	**wald**	**wald**	**wald**	**wald**	**wald**
	hütte	**heide**	**see**	**see**	**see**
	see	**wälder**	**wasser**	**wasser**	tal
	tal	bach	**felsen**	**felsen**	**wasser**
	wasser	landschaft	**heide**	**heide**	**felsen**
	felsen	baum	brocken	brocken	berg
	berg	teich	wasserfall	**fluss**	**heide**
	heide	naturschutzgebiet	**fluss**	**wälder**	wasserfall
	wasserfall	wiese	**wälder**	bach	**fluss**
	fluss	wald	bach	landschaft	**wälder**

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English words	**the** **de** **of** **no** **view** **and** **deu** **walk** **parking** lake	**the** **de** **of** **no** **view** **and** **deu** **walk** **parking** to	**the** **de** n **of** **no** **view** **and** **deu** ls **walk**	**the** **de** **of** **no** **view** **and** **deu** **walk** **parking** lake	**the** **of** **no** **view** **and** **deu** **walk** **parking** lake to
Route features & directions 4	parkplatz **entlang** **rechts** **links** **straße** hotel nähe brücke vorbei bahnhof	parkplatz **entlang** **rechts** route start **links** **richtung** **straße** tour strecke	**entlang** **rechts** **links** **richtung** **straße** pfad vorbei hinunter abzweigung kreuzung	route start **richtung** **straße** tour strecke brücke bahnhof parken bus	**entlang** **rechts** **links** **richtung** **straße** nähe vorbei hinunter abzweigung kreuzung
Route features & directions 5	**weg** richtung **pfad** **wege** weges	**weg** **pfad** **wege**	**weg** **wege**	**weg** entlang rechts links **pfad** vorbei **wege** hinunter geradeaus bergauf	**weg** wanderung route start tour **pfad** strecke aufstieg trail wanderweg
Historical & religious values	**burg** **schloss** **ruine** **kapelle** **turm** burgen wildenstein schloß burgruine drachenfels	**burg** **schloss** **ruine** **kapelle** mühle gasthaus **turm** hof kloster forsthaus	**burg** **schloss** bad **ruine** **kapelle** mühle harzer gasthaus **turm** hof	**burg** **schloss** **ruine** **kapelle** **turm** hof kloster burgen wildenstein schloß	**burg** **schloss** **ruine** brücke **kapelle** kirche stadt **turm** denkmal kloster
Aesthetic values (beauty & enjoyment)	**schöne** **schöner** **schönen** familienzimmer **schön** **paar** **tolle** **schönes** **abwechslungsreiche** **super**	**schöne** **schöner** alte **schönen** familienzimmer **schön** **paar** einfach **tolle** **schönes**	**schöne** **schöner** **schönen** **schön** **paar** **tolle** **schönes** **abwechslungsreiche** **super** schönem	**schöne** **schöner** **schönen** **schön** **tolle** **schönes** **abwechslungsreiche** **super** schönem genießen	**schöne** **schöner** **schönen** **schön** **paar** **tolle** **schönes** **abwechslungsreiche** **super** schönem
Units & Abbreviations	**m** **km** start n **meter** vh **mm** ls p **kilometer**	**m** **km** n **meter** vh **mm** ls p **kilometer** h	parkplatz **m** **km** start strecke **meter** **mm** **kilometer** minute höhenmeter	**m** **km** n **meter** vh **mm** ls p **kilometer** h	**m** **km** **meter** **mm** **kilometer** h metern kmh min meilen
Aesthetic values (views & outlooks)	**blick** **aussicht** **ausblick** **aussichten** **ausblicke** **blicke** **blicken**	**blick** **aussicht** **ausblick** **aussichten** **ausblicke** **blicke** **blicken**	**blick** **aussicht** **ausblick** **aussichten** **ausblicke** **blicke** **blicken**	**blick** **aussicht** **ausblick** **aussichten** **ausblicke** **blicke** **blicken**	**blick** **aussicht** **ausblick** **aussichten** **ausblicke** **blicke** **blicken**

8.5 Total forest per forest product

Table A4. *The total forest across Germany's Natura 2000 sites according to each forest product. Values in hectares are rounded to the nearest integer and percentages are rounded to two decimal places. The mean forest area across all products is 2,827,078 ha. Areas where Natura 2000 sites overlap have been adjusted to avoid double-counting. *Please note: the H/I product results may be up to 2.45% higher than the values reported here (see Section 3.2.2 and Appendix 8.2).*

Forest Product	**Total forest**		**Difference from mean**	
	hectares	*percent*	*hectares*	*percent*
H/I	2632242*	47.69*	-194836*	(-) 7.14*
ESA	2872677	52.05	45599	(+) 1.60
JAX	2883517	52.24	56439	(+) 1.98
COR	2815114	51.00	-11964	(-) 0.42
DE	2839957	51.45	12879	(+) 0.45
FAO	2918960	52.89	91882	(+) 3.20

8.6 Wilcoxon test for FNF map comparison

For the Wilcoxon signed-rank statistical test, I compared the forest results for all Natura 2000 geometries for two FNF maps at a time – either using the total area of forest for each geometry (absolute comparison) or the percentage of forest for each geometry (relative comparison). The null hypothesis is that the FNF maps are not significantly different from each other, or in other words, the absolute or relative difference is not significantly different from zero when looking across all Natura 2000 geometries.

While the results indicated that most (but not all) FNF maps were significantly different from each other in terms of both the absolute and relative differences (Table A5), there are two reasons why these results may be somewhat misleading. First, the sample size was very large (n = 5173) which could lead to false positives. Second, the Wilcoxon test is not very meaningful when the differences between paired samples are not distributed on either side of zero. For example, the DE – FAO comparison (in which the DE forest results are subtracted by the FAO forest results) returned a negative difference for all Natura 2000 geometries because the FAO product is essentially a version of the DE product *plus* additional adjusted JAX forest; for every Natura 2000 geometry there is always more forest in the FAO product than the DE product. Since the Wilcoxon test statistic corresponds to either the sum of the positive ranks or the absolute value of the sum of the negative ranks (whichever is lower), the test statistic for cases like the DE – FAO comparison will always be zero because the sum of the positive ranks is zero (there are no positive ranks). This outcome can be seen in Table A5 where the test statistic for the DE – FAO comparison is 0.0 and the p-value indicates the difference is significant, even though we might expect these maps to be fairly similar. For these reasons, I have focused on what can be learned from the box plots (Figure 7) in terms of the relationships between FNF maps, rather than these statistical results.

Table A5. *Wilcoxon signed-rank test results for absolute and relative differences in forest area in Natura 2000 sites for FNF map pairs. Comparisons with a starred p-value are significant for a = 0.0033 (based on Bonferroni correction for a = 0.05 for 15 tests).*

FNF map comparison	**Absolute difference**		**Relative difference**	
	test statistic	***p-value***	***test statistic***	***p-value***
ESA – JAX	5584135.5	7.697842e-10*	5126382.0	1.593503e-26*
ESA – COR	4720804.5	1.081384e-01	4666489.0	2.447185e-02
ESA – DE	4927662.0	4.337044e-11*	4740694.0	8.203388e-18*
ESA – H/I	5567080.5	3.245677e-11*	5948866.5	3.834814e-03
ESA – FAO	4500667.0	1.918883e-32*	4345812.0	1.498541e-41*
JAX – COR	5329547.5	1.726864e-16*	5070397.0	3.220739e-27*
JAX – DE	6057842.0	1.958046e-01	5958801.5	2.313679e-02
JAX – H/I	3831667.5	4.545881e-129*	3766722.0	8.610620e-136*
JAX – FAO	4968567.0	1.548425e-32*	5290864.5	3.667737e-18*
COR – DE	4290127.0	1.621291e-31*	4056887.5	4.674074e-46*
COR – H/I	5083201.0	2.419099e-28*	5435198.5	3.645185e-14*
COR – FAO	3291995.0	1.687492e-121*	3174495.5	7.337621e-135*
DE – H/I	4137167.5	2.604551e-93*	4330253.0	3.706409e-77*
DE – FAO	0.0	5.274665e-286*	0.0	5.274716e-286*
H/I - FAO	3427076.5	9.842722e-167*	3642817.0	2.409660e-142*

As a side note, there is a difference between the tests results for absolute and relative comparisons because the statistical test uses a ranking system which splits positive and negative differences (signed-rank). Since either the sum of the positive ranks or the absolute value of the sum of the negative ranks (whichever is lower) is used as the test statistic, this effects the p-value and whether the difference is found to be significant or not.

8.7 Total area per forest consensus class

Table A6. *The total area in Germany's Natura 2000 sites according to forest consensus class. Areas where Natura 2000 sites overlap have been adjusted to avoid double-counting. Values in hectares are rounded to the nearest integer and percentages are rounded to two decimal places.*

Forest Presence / Absence	**Degree of Consensus**	**Total Area**	
		hectares	*percent*
Non-Forest	Full Consensus (0:6)	2095617	37.97
Non-Forest	High Consensus (1:5)	326374	5.91
Non-Forest	Low Consensus (2:4)	164250	2.98
--	Non-consensus (3:3)	139435	2.53
Forest	Low Consensus (4:2)	185844	3.37
Forest	High Consensus (5:1)	500607	9.07
Forest	Full Consensus (6:0)	2107145	38.18

8.8 High frequency tokens for CES clusters

Table A7. *The unique tokens which occur at least three times for the clusters related to CES, with their corresponding frequencies in brackets. The lists have been truncated to show higher frequency terms due to the large amounts of unique tokens for some clusters (e.g., the* Natural features *cluster includes a total of 573 unique tokens). A set of CSVs with all tokens for all clusters is available as supplementary material in my GitHub repository.*[14]

Cluster name	Tokens and their frequencies
Natural features	wald (80), see (50), wasser (25), felsen (24), heide (19), brocken (19), fluss (17), wälder (17), bach (17), landschaft (16), baum (16), teich (14), naturschutzgebiet (13), stein (13), harz (12), dorf (12), wiese (11), wilde (11), natur (10), winter (9), dschungel (9), sonne (9), brunnen (9), höhle (9), berge (8), felder (8), wiesen (8), regen (8), elbe (8), linde (7), donau (7), fichten (7), wetter (7), hügel (7), sees (6), alpen (6), wäldern (6), bäume (6), steinbruch (6), höhlen (6), ufer (6), flusses (6), seen (6), hexentanzplatz (5), kreisförmiger (5), alb (5), tannen (5), forst (5), naturpark (5), eichen (5), steinen (5), sophienhöhle (5), graben (5), schneise (5), nadelwald (5), weiher (4), süden (4), gegend (4), dschungels (4), schluchten (4), holzkohle (4), boden (4), eiche (4), hirsche (4), landschaften (4), wild (4), hochwald (4), waldes (4), insel (4), klippen (4), mammutbaum (4), heidefläche (4), wilder (4), höhen (4), schilderwald (4), wilsede (3), elbsandsteingebirges (3), nationalpark (3), schnee (3), rothirsch (3), jahreszeit (3), eisenerz (3), rennöfen (3), flüssen (3), stauseen (3), mulde (3), hinab (3), grauwacke (3), bäumen (3), bachlauf (3), pferde (3), moor (3), gletscher (3), natürlichen (3), hasel (3), weinbergen (3), zauberwald (3), wasserlauf (3), bergen (3), naturparks (3), fels (3), buchenwälder (3), bärlauch (3), teiche (3), östlichsten (3), obelisk (3), tempelanlage (3), hgs (3), landschaftsschutzgebiet (3), quirl (3), umwelt (3)
Historical & religious values	burg (83), schloss (53), ruine (34), kapelle (28), turm (17), hof (17), kloster (15), burgen (11), wildenstein (10), schloß (9), burgruine (9), drachenfels (9), bastei (7), falkenstein (6), altstadt (6), ruinen (5), klosters (5), rathaus (5), pfarrkirche (5), linderhof (4), schanze (4), neuschwanstein (4), guttenberg (4), rheinfels (4), burghof (4), felsenburg (4), wartburg (4), restauriert (3), türme (3), klosterkirche (3), abtei (3), unterburg (3), oberburg (3), zeughaus (3), raubschloss (3), steinerne (3), drachenstein (3)
Aesthetic values (beauty & enjoyment)	schöne (87), schöner (60), schönen (23), schön (20), tolle (13), schönes (12), abwechslungsreiche (11), super (8), schönem (8), genießen (7), wunderschöne (7), wunderschöner (6), spaß (6), wunderschön (5), wunderschönen (5), nette (5), schönsten (5), angenehm (5), herrlichen (4), netter (4), abwechslungsreicher (4), angenehmer (3), tollen (3), großartig (3), romantischer (3), großartige (3), interessante (3), schönste (3), angenehme (3), wunderschönes (3)
Aesthetic values (views & outlooks)	blick (120), aussicht (103), ausblick (24), aussichten (18), ausblicke (5)

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[14] https://github.com/n-mo92/nm_forest_thesis/tree/main/other/cluster_tokens

8.9 English translations for cluster results

Table A8. *English translations for the top ten most frequent words/tokens observed in each cluster. Translations are based on a combination of my own knowledge of basic German, DeepL and leo.org.*

Cluster	Original tokens	English translations
Route features & directions 1	bank	bench
	runde	round/tour
	alte	old
	hohe	high
	kreuz	cross
	nähe	near
	aufstieg	ascent
	ort	place
	kirche	church
	abstieg	descent
Placenames	bad	bath/spa (often part of placename)
	mühle	mill
	harzer	(ref. to place – Harz region)
	kyll	(placename – Kyll River)
	rhein	(placename – Rhine river)
	rheinsteig	(ref. to place – hiking trail by Rhine River)
	eifel	(placename – Eifel Mountains)
	cochem	(placename – town in Moselle Valley)
	stempelstelle	stamping point
	torfhaus	(placename – village in Harz Mountains)
Route features & directions 2	parkplatz	parking lot/car park
	wanderung	hike
	spaziergang	walk
	hütte	hut/cabin
	hotel	hotel
	aussichtspunkt	viewpoint
	tal	valley
	trail	trail
	wanderweg	hiking trail
	wanderparkplatz	parking lot/car park for hiking trail
Route features & directions 3	punkt	point
	führt	lead/leads
	folgen	follow
	beginnt	begins
	bietet	provides
	befindet	located
	liegt	lies/located
	ziel	goal
	halten	stop
	sehen	see
Natural features	wald	forest
	see	lake
	wasser	water
	felsen	rock/cliff
	heide	heath/moor
	brocken	chunks of rock
	fluss	river
	wälder	forests
	bach	stream
	landschaft	landscape
English words	the	--
	de	(abbreviation for Germany)
	of	--
	no	--
	view	--
	and	--
	deu	(abbreviation for Germany)
	walk	--
	parking	--
	lake	--

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Route features & directions 4	route	route
	start	start
	richtung	direction
	straße	street
	tour	tour
	strecke	stretch
	brücke	bridge
	bahnhof	(train) station
	parken	park (as in to park a car)
	bus	bus
Route features & directions 5	weg	path/way
	entlang	along
	rechts	right
	links	left
	pfad	path
	vorbei	over/finished
	wege	paths/ways
	hinunter	down/under
	geradeaus	straight ahead
	bergauf	uphill
Historical & religious values	burg	castle
	schloss	palace
	ruine	ruin
	kapelle	chapel
	turm	tower
	hof	courtyard/farm
	kloster	cloister/monastery
	burgen	castles
	wildenstein	(placename – castle)
	schloß	palace
Aesthetic values (beauty & enjoyment)	schöne	beautiful
	schöner	more beautiful
	schönen	beautiful
	schön	beautiful
	tolle	great
	schönes	beautiful
	abwechslungsreiche	diverse/varied
	super	super
	schönem	beautiful
	genießen	enjoy
Units & Abbreviations	m	(metres)
	km	(kilometres)
	n	--
	meter	metre
	vh	(unknown)
	mm	(millimetres)
	ls	(unknown)
	p	--
	kilometer	kilometre
	h	--
Aesthetic values (views & outlooks)	blick	view
	aussicht	prospect (view)
	ausblick	outlook (view)
	aussichten	prospects (views)
	ausblicke	outlooks (views)
	blicke	view
	blicken	views

8.10 Word clouds for token frequencies

Figure A2. A word cloud representation of the top ten words/tokens observed in each cluster. The size of the word corresponds to its relative frequency within the cluster. English translations are available Appendix 8.9.

8.11 English translations for cluster results – non-consensus & full consensus forest

***Table A9**. English translations for the top ten most frequent words/tokens observed in each CES cluster for non-consensus areas and full consensus forest. Translations are based on a combination of my own knowledge of basic German, DeepL and leo.org. Note that these results include text from trail geometries which did not intersect with Natura 2000 sites.*

Cluster	Non-consensus areas: original tokens	Non-consensus areas: English translations	Full consensus forest: original tokens	Full consensus forest: English translations
Natural features	wald	forest	wald	forest
	wiese	meadow	see	lake
	winter	winter	wasser	water
	berge	mountains	bach	stream
	wilsede	(placename)	heide	heath/moor
	dorf	village	felsen	rock/cliff
	süden	south	brocken	chunks of rock
	forellen	trout (plural)	baum	tree
	teich	pond	wälder	forests
	fischerei	fishery	landschaft	landscape
Historical & religious values	linderhof	(palace name)	burg	castle
	falkenstein	(placename)	schloss	palace
	schlosspark	palace park/garden	kapelle	chapel
	turm	tower	ruine	ruin
	schloss	palace	hof	courtyard/farm
	schloß	palace	turm	tower
	jagdschloss	hunting lodge	kloster	cloister/monastery
	burgberg	(placename)	burgen	castles
	burgruine	castle ruin	wildenstein	(placename)
	hof	courtyard/farm	drachenfels	(placename)
Aesthetic values (beauty & enjoyment)	schöne	beautiful	schöne	beautiful
	schöner	more beautiful	schöner	more beautiful
	schön	beautiful	schön	beautiful
	wunderschön	beautiful/gorgeous	schönen	beautiful
	wunderbare	wonderful	tolle	great
	schönen	beautiful	schönes	beautiful
	tolle	great	abwechslungsreiche	diverse/varied
	großartige	great/awesome	schönem	beautiful
	gemütliche	cosy	spaß	fun
	toller	great	super	super
Aesthetic values (views & outlooks)	aussicht	prospect (view)	blick	view
	blick	view	aussicht	prospect (view)
	blicke	view	ausblick	outlook (view)
	ausblick	outlook (view)	aussichten	prospects (views)
	aussichten	prospects (views)	ausblicke	outlooks (views)
	blicken	views	blicke	view
			blicken	views

8.12 Word clouds for token frequencies – non-consensus & full consensus forest

Figure A3. *A word cloud representation of the top ten words/tokens observed in each CES cluster, comparing non-consensus areas (left) and full consensus forest (right). The size of the word corresponds to its relative frequency within the cluster. English translations are available Appendix 8.11. Note that these results include text from trail geometries which did not intersect with Natura 2000 sites.*

9 Personal Declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

Zurich, 30.09.2025

Nina Moffat