Development and improvement of the Dutch SEEA EA condition account.

Shaya van Houdt, Sylvia Bleker, Patrick Bogaart, Corine Driessen, Ewan van Eijden, Frank Prins

This research was funded by Eurostat.

Citation:

Statistics Netherlands, 2023, Development and improvement of the Dutch SEEA EA condition account.

CBS Den Haag
Henri Faasdreef 312
2492 JP The Hague
P.O. Box 24500
2490 HA The Hague
+31 70 337 38 00

www.cbs.nl

project number 2022-NL-EGD

22 December 2023

Index

Acknowledgements

We would like to thank Eurostat for their financial support of this project. Their contribution has been essential in enabling the research and its subsequent findings.

1. Introduction

1.1 Relevance

Ecosystem condition is a comprehensive term that encompasses the current state and health of an ecosystem, including both its abiotic (non-living), biotic (living), and landscape characteristics. This concept is measured through a set of condition indicators, which provide a quantifiable assessment of various aspects such as biodiversity, soil quality, and water purity. These indicators are essential for monitoring the ecosystem's capacity to sustain its functions and for measuring any degradation that may occur over time. The quality of these components, both abiotic and biotic, is a critical aspect of the evaluations, offering insights into the overall health of the ecosystem.

Ecosystem condition has two primary qualities: intrinsic and instrumental. The intrinsic quality, often referred to as ecosystem integrity, comprises the composition, structure, and functioning of the ecosystem. It reflects the internal dynamics and health of the ecosystem itself. On the other hand, the instrumental quality relates to the ecosystem's capacity to provide services and support various forms of life, including human communities. The use of these services may sometimes turn into pressures to the state of the ecosystem. State indicators, such as soil organic carbon, the presence of dead wood, or biodiversity levels, provide a snapshot of the ecosystem's current condition. In contrast, pressure indicators like pollution, recreation, or land-use changes highlight external factors impacting the ecosystem. By systematically assessing the health of ecosystems spatially, condition indicators can help identify areas of ecological degradation guiding conservation efforts and policy decisions for sustainable environmental management.

1.2 Condition account

The Ecosystem Condition Account forms a central component of the System of Environmental-Economic Accounting Ecosystem Accounting (SEEA EA). Defined by the United Nations in 2017, it serves as a measure of an ecosystem asset's overall quality, based on its inherent characteristics. This account comprehensively encapsulates key indicators that reflect the current state and functioning of ecosystems, focusing on their ecological condition and their capability to provide ecosystem services.

This account is a critical element of the SEEA ecosystem accounts framework, building on the foundational extent account. The extent account offers insights into the size and changes in different types of ecosystems, serving as a baseline for all subsequent accounts including condition, physical and monetary services, assets, carbon, and biodiversity. The condition account uniquely captures both the current state of ecosystems and the external pressures they face.

The SEEA EA framework emphasizes the integration of environmental data with economic accounts, enabling a more holistic understanding of the interactions between the environment and the economy. A condition account, in this context, serves as a crucial tool for measuring changes in ecosystem attributes and for tracking the impacts of human activity and natural processes on these ecosystems. By providing a detailed and standardized methodology for assessing ecosystem conditions, these accounts are instrumental in informing sustainable policy and decision-making processes, aimed at balancing economic development with environmental conservation and resilience.

1.3 Guidance note on condition accounts

In pursuing the development and improvement of the Dutch SEEA EA condition account, Statistics Netherlands is committed to advancing the field of ecosystem accounting, aligning its efforts with the environmental strategies of the European Union. This initiative focuses on developing a report that delves into the creation of five new condition indicators, soon to become mandatory for reporting to Eurostat. Originally, it was envisaged that the reference year for these indicators would be set in 2024, with the first cycle of reporting anticipated in 2026. However, there is an ongoing debate about whether this timeline should potentially be delayed.

As of now, the guidelines for these new indicators are still under development. The taskforce on ecosystem accounting, a group dedicated to refining and enhancing the SEEA EA, is actively working on these guidelines. The intricacies and specification of these new indicators are crucial for ensuring their relevance and effectiveness in capturing the nuanced aspects of ecosystem conditions.

For this research, we have based our methodologies and assumptions on the guidance notes as published on October 5th, 2023. Consequently, we have not incorporated the latest updates released on November 28th-29th, 2023.

Our report is a key component of a broader initiative funded by a European Green Deal grant. This grant symbolizes the commitment to fostering sustainable practices and policies across Europe. Through this project, we aim to explore and enhance the Dutch SEEA EA condition account, using the proposed – albeit incomplete – guidelines as a reference. Our focus will be exclusively on the indicators slated for mandatory reporting; we will not delve into those classified as voluntary. This targeted approach ensures that our efforts are aligned with the most pressing and regulatory requirements set forth by Eurostat and the broader European environmental agenda.

The development of these indicators is not just a statutory exercise, but also a vital input for the Taskforce on Ecosystem Accounting to further develop their guidelines for condition accounting under the system of ecosystem accounting. Through this report, we hope to lay the groundwork for informed condition accounting and informed policy-making, ensuring the preservation and enhancement of natural heritage for future generations.

1.4 Data and indicators

In this report, our attention will be primarily centered on five key indicators: tree cover density, urban green spaces, dead wood, soil organic carbon, and artificial impervious area in coastal regions. These indicators have been identified as essential elements in understanding and managing ecosystem condition. Our goal is to develop and refine these indicators for both national and regional scales, offering a detailed and nuanced perspective of the country's ecological state. While soil organic carbon is among the proposed mandatory indicators, our focus in this report will be different for this indicator. Instead of developing an indicator, we will conduct a comprehensive analysis of the existing data. This will enable us to assess the current state of knowledge and data availability concerning soil organic carbon in the Netherlands, providing a foundation for future indicator development.

The Netherlands sources its data for the condition account from a diverse array of systems. Key among these are the numerous environmental monitoring programs in place, such as the National Forest Inventory. These systems, in many cases, were established as a response to both national and international legal mandates that require monitoring of specific environmental elements. Pertinent to the ecosystem condition indicators discussed here are a variety of European directives: the EU Habitat Directive (EU, 1992), the EU Biodiversity Strategy (EU, 2011), the EU Water Framework Directive (EU, 2000), the EU Marine Framework Directive (EU, 2008), EU Green infrastructure Strategy (EU, 2013), EU Urban Agenda (EU, 2016), EU Soil Strategy for 2030 (EU, 2021).

The final output from this report will be an Ecosystem Condition Account, compiled by ecosystem type. Recognizing that each ecosystem type possesses unique characteristics vital for assessing its condition, we organized the data into accounting tables that categorize information on indicators by the main ecosystems (built-up, grasslands, forests, etc.) and by the various sub-ecosystem types (such as urban areas, agricultural land, and others).

2. Tree cover density

The health of people, animals and ecosystems relies heavily on the functions that trees provide. Trees provide cleaner air by filtering particulate matter and sequestering carbon, they are a nature-based solution to increasing temperatures by cooling down cities, and they provide habitats for unique species.

It is therefore important to monitor the health and pervasiveness of our forests and woodlands. Thus, the EU task force on ecosystem accounting has asked countries to develop an indicator for this purpose: the tree cover density.

Tree cover density describes the percentage of the earth's surface that is covered vertically by tree crowns. Tree cover density thereby holds vital information on the ability of forests to perform their essential functions.

The EU task force on ecosystem accounting states that the tree cover density is used (amongst others) to monitor the health of forests and woodlands, as well as urban green. The tree cover density is determined based on two different data sources, which are described below.

2.1 Spatial delineation

The spatial delineation of tree cover density is a critical aspect of understanding and managing forest ecosystems. The approach adopted here is that we consider the average percentage measured across all forests as defined in the ecosystem extent account.

However, a significant challenge in this process is the recognition that trees are not uniformly distributed and do not exist exclusively in natural areas. Trees can be found in a variety of settings, including urban environments. Measuring tree cover density in all places where trees exist might not always be relevant or practical, especially when the focus is on forests in their more natural states. For this reason, the delineation process often excludes certain types of tree populations particularly those in urban settings, such as parks and trees along roads. These areas, while they do contain trees, typically do not represent the natural or semi-natural forest environments that are the primary focus of such studies.

Measuring tree cover density in natural and semi-natural areas is integral to assessing ecosystem health and functionality. This approach offers crucial insights into the biodiversity, resilience, and ecological services of these ecosystems, such as carbon sequestration, water regulation and habitat provision.

On the other hand, measuring tree cover density in urban areas while beneficial for urban planning and local environmental management, is not as useful for assessing broader ecological health and forest ecosystem integrity. Urban trees, often planted and maintained for aesthetic, recreational, or microclimate purposes, do not accurately reflect natural ecological process or biodiversity. The structured and controlled environment of urban landscapes, with its artificial maintenance and limited species diversity, contrasts sharply with the complex, dynamic ecosystems found in natural and semi-natural forests. Therefore, including urban tree cover in assessments meant to gauge the health of natural ecosystems could lead to skewed data and misrepresentations of forest ecosystem conditions.

The emphasis, therefore, is placed on areas that provide at least semi-natural forests. Within the Dutch ecosystem classification, this categorization currently includes natural forests, production forests, and other types of forests. Natural forests are those that have developed primarily through natural processes, such as the dune forests that have developed as a result of succession. Tree species are mostly native to Europe and timber harvest does not occur, or very little, compared to the additional growth. Production forests, on the other hand, are managed for timber but still maintain a considerable tree cover and forest characteristics. Other forests might include those that have been altered or managed for specific purposes but still retain a forest-like environment. These forest types are currently not further distinguished based on species composition, and may consist of either deciduous or coniferous species, or a mixture of these types.

2.2 Assessing tree cover density

2.2.1 Data types

Dutch National Forest Inventory (NBI)

The Dutch National Forest Inventory (NBI) is a periodic survey to assess and monitor the status of the country's forests. The latest edition (NBI-7) covers the years 2017-2021 (Schelhaas et al., 2022), while the previous edition (NBI-6) covers the years 2012-2013 (Schelhaas et al., 2014). These two editions are very similar in approach and method, while the forest inventory before that (MFV, 2001-2005) has some design differences. The inventories use a systematic sampling approach where specific plots within the forest are selected for detailed assessment (see Figure 1).

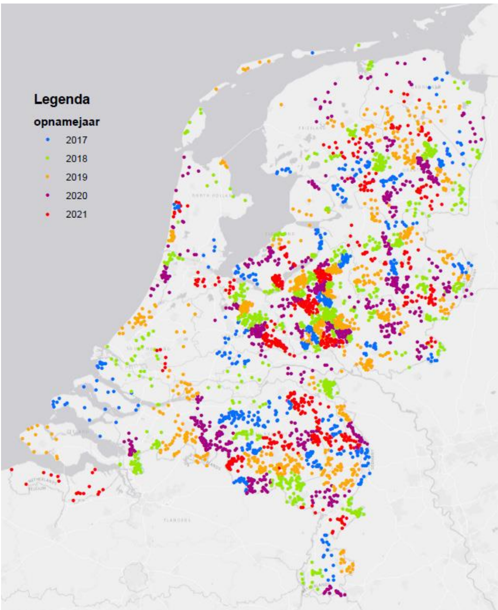


Figure 1. Geographic range of point samples in the NBI-7, with a separate colors for each year.

Important aspects that are investigated include forest area, standing stock, biomass, growth and felling. Detailed information on forest type, forest age, tree species, ownership, dead wood and vegetation cover are also recorded. Tree cover and shrub cover are recorded for each site in an 8m radius plot. Table 1 shows the results from the forest inventories as described in Schelhaas et al. (2022).

Table 1. Share of forest- and shrub-layer cover in the MFV, NBI-6 and NBI-7.

	Bedekkingsgraad	MFV	NBI-6	NBI-7
Struiklaag	0-1%	25,5%	29,8%	19,5%
	1-10%	27,0%	26,1%	26,4%
	10-25%	11,2%	14,0%	18,1%
	25-50%	10,7%	13,1%	16,3%
	>50%	14,8%	9,5%	9,5%
	Niet bezocht/ontbost	4,9%	7,5%	10,2%
Boomlaag	0-25%	7,4%	8,3%	9,2%
	25-50%	9,2%	11,4%	13,6%
	50-75%	23,2%	26,9%	26,8%
	>75%	49,4%	45,9%	40,1%
	Niet bezocht/ontbost	4,9%	7,5%	10,2%

*Note: Struiklaag = shrublayer, Boomlaag = treelayer, Bedekkingsgraad = cover, Niet bezocht/ontbost = Not visited/ deforested.

The NBI offers benefits due to its comprehensive data collection, encompassing a wide array of variables such as dead wood volume, tree cover density, and other ecological indicators. Additionally, being a nationwide indicator, it provides a broad overview of forest conditions across the country. The data is collected by on-the-ground personnel, which often ensures accuracy and reliability. However, the NBI also has its disadvantages. The data is point-based, and we lack access to exact locations, only knowing the one-kilometer grid cell they belong to. This limitation can pose challenges for precise spatial analysis. Furthermore, while the data is comprehensive over a more extended period, such as from 2017 to 2021 for NBI-7, it is not necessarily representative on an annual basis. This temporal spread means that the data isn't always reflective of year-to-year changes, potentially overlooking short-term ecological shifts.

Copernicus Land Monitoring Service

Additionally, there is the Copernicus Tree Cover Density data from the Copernicus Land Monitoring Service (European Union Copernicus Land Monitoring Service, 2018a), which provides information on the percentage of tree cover density across Europe (ranging from 0 to 100). The data is available with a resolution of 20 meters for the years 2012 and 2015 (Figure 2), and with a resolution of 10 meters for the year 2018. The layer is derived from multispectral high resolution satellite data including Sentinel-2A and Landsat 8. The data also aids in reporting for Land Use, Land Use Change, and Forestry (LULUCF), and supports the European Environmental Agency's State of the Environment reports.

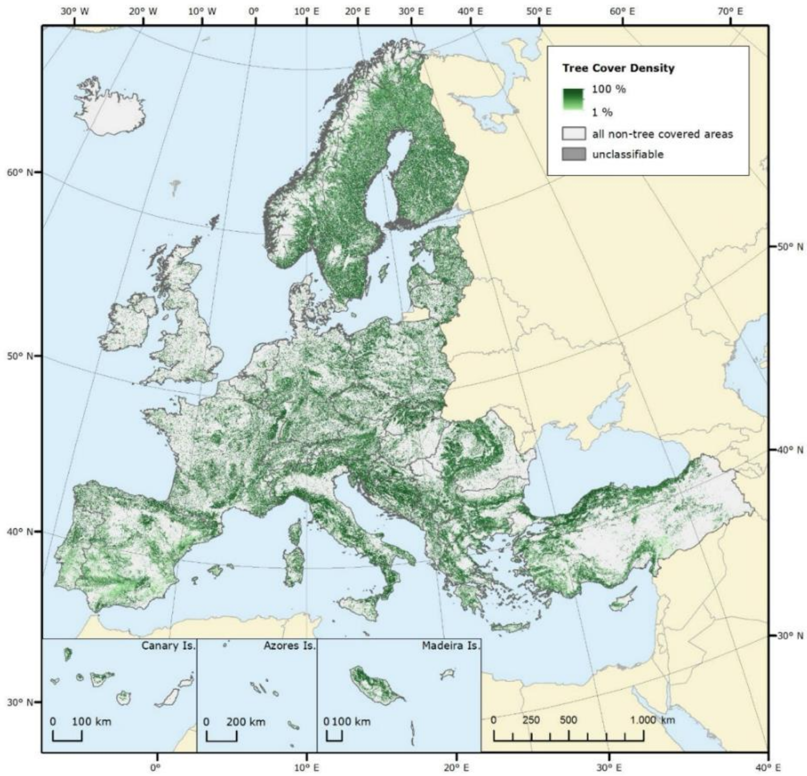


Figure 2. Pan-European illustration of the Tree Cover Density 2015 (Source: Copernicus).

The Copernicus data on tree cover density, with its high resolution and nationwide coverage, offers a detailed and comprehensive resource for ecological analysis. However, a significant drawback is the methodological change that occurred between 2015 and 2018, potentially affecting data consistency and comparability. Additionally, while more regularly updated than the NBI, with updates every three years, it still falls short of providing annual updates.

National Flora Monitoring Scheme

The National Flora Monitoring Scheme for Environmental and Nature Quality (LMF – M&N; LMF in short) is one of the major floristic monitoring schemes in the Netherlands. LMF is part of the Network Ecological Monitoring (NEM), which is a collaborative effort by several (semi-) governmental institutions (ministries; provinces; PBL Environmental Assessment Agency and Statistics Netherlands). The goal of the NEM and LMF is to provide data on nature and biodiversity to support (ex post) policy evaluation. Currently, as a result of decentralization of nature-related policies, the provinces are the most important stakeholders. The formal goal of the LMF is

> *"The supply of national and regional trends in floral composition, within the context of acidification, eutrophication and desiccation".*

The data collection on behalf of the LMF consists of vegetation relevés from permanent plots, which are sampled every 3 or 4 years[1] (Table 2).

---

[1] Originally relevés were taken every 4 years. The 3-year interval has been introduced to match the 6-year interval of reporting under Article 17 of the EU Habitat Directive.

Table 2. LMF plots per stratum. N2000 are the Natura 2000 sites; NNN (Nature Network Netherlands) are protected nature areas outside of Natura 2000 areas.

LMF-Type		**Strata**			
		N2000	**NNN**	**Other**	**Total**
Heathland	Dry	242	58		300
	Moist	231	69		300
Costal dunes	Fry	288	12		300
	Moist	146	4		150
Forest	**Dry**	**133**	**134**	**83**	**350**
	Moist	**70**	**168**	**62**	**300**
Grasland	Dry; poor	76	76		152
	Moist; poor	112	138		250
	Rich	106	194		300
Swamps		197	103		300

The LMF consists of a total of 2702 permanent plots, from which 650 (24%) are “forest” plots (Table 2). Plot size differs between ecosystem type. For forest plots, the size should be in the range 100–250m^2. For each of the plots general data is collected on vegetation structure (cover by trees; shrubs; herbs; moss and litter), abiotic conditions (relief, aspect, etc.) and general habitat. Tree cover density is estimated per species as a class, and averaged across species as a percentage. Vegetation type is classified using a three-level dedicated classification system (IPI), the top-level types are shown in Table 3.

Table 3. 'IPI' Vegetation classification. Left: level 1. Right: Level 2 (forest only).

IPI	**Classication**	**IPI**	**Classification**
100	Forest, Thicket, Tree lines etc.	110	Riparian and swamp forest
200	Open Natural (coastal dunes; heatland; wetlands)	120	Coniferous and mixed forest
300	Lakes, ponds etc.	130	Deciduous forest (dry)
400	Agricultural	140	Deciduous forest (moist)
500	Built-up and ruderal	150	Thicket
600	Infrastructure	160	Coppice
700	Linear water features	170	Wooded bank
800	Springs	180	Wils shoots
900	Bank, shores and associated wetlands	190	Clearcut, burnt etc

In this study, we only consider IPI 1xx (Forest etc.).

2.2.2 Methods

2.2.2.1 Calculating tree cover density from the National Forest Inventory

The forest inventories record tree cover within categories that represent a range of tree covers. To calculate an average tree cover for the condition account we, therefore, first converted the ranges to a single number. This was done by taking the average of the lower and upper boundary (Table 4). It should be noted though, that especially for the categories 6 and 7, which represent a substantial amount of the measured plots, this gives a high degree of uncertainty.

Table 4. Tree cover categories recorded in the National Forest Inventory, and values used for calculating an average.

Category in NBI	**Description**	**Value used for calculation**
0	0%	0
1	0.0-0.1%	0.05
2	0.1-1%	0.55

3	1-5%	3
4	5-10%	7.5
5	10-25%	17.5
6	25-50%	37.5
7	50-75%	62.5
8	75-90%	82.5
9	90-100%	95
10	Not visited/deforested	Not used

We then calculated the national tree cover of forests by multiplying the counts by the averages of the groups (values used for calculation in Table 4). These values were then summed to get a total percentage. Finally, we summed the counts and then divided the total percentage by the total number of counts. A similar approach was used to calculate the tree cover density per provinces, however, the counts were grouped by province.

We subsequently made a selection of forest appearance types recorded in the NBI. For this subset, only the regular forest types (all 'Opgaand bos' types), as well as spontaneous forest in natural areas ('Spontaan bos in natuurterrein') were selected. Special forest types that are probably part of other ecosystems, such as for example parks, tree lines and garden forests were excluded. However, since there is no detailed spatial information available of the plot locations, we cannot be sure how well the plots exactly align with the forest ecosystems of the extent map. Even within the provided one-kilometer grid cells, the types of forests often differ.

For the condition account we are also interested in tree cover density on a smaller time scale and a more detailed geographical distribution. However, the question is whether the forest inventory has enough representative sample plots for calculating, for example, yearly or provincial averages. Therefore, we also calculated the tree cover and observations per year and per province.

2.2.2.2 Calculating tree cover density from the Copernicus layer

To calculate a tree cover density indicator for the Netherlands and regionally, we also used the Copernicus tree cover density layer. We combined this layer with our ecosystem extent map to extract the data from forested ecosystems only (Natural forest, production forest, other forest, and all three together). It must be noted that for the year 2012, we used the forest polygons from our 2013 ecosystem extent map, due to data limitations. Finally, we calculated the averages for the whole of the Netherlands and for the different provinces to get a national and a provincial tree cover density indicator. All calculations we scripted in code using ArcPython.

2.2.2.2 Calculating tree cover density from Meetnet Flora

Using the 2021 data from Landelijk Meetnet Flora (LMF), we conducted a two-step process to analyze tree cover density. Initially, all forest plots labeled as IPI 1xx which include the main forest types (120, 130, 140), were examined. Subsequently, the focus shifted to specific LMF points meeting two criteria: a) they belong to the core IPI forest types (120, 130, 140), and b) they are located within recognized ecosystem types ("Natural Forest", "Swamp Forest", "Tree Line", and "Production Forest"). Additionally, further data segmentation was possible by combining ecosystem types with IPI classifications.

2.2.3 Results

2.2.3.1 National Forest Inventory data

We first looked at the average tree cover density of all sampled plots, excluding deforested areas. For the MFV, the average tree cover density was 70.2%. For NBI-6 the average tree cover density was 64.6%, and for NBI-7 the average tree cover density was 62.9%. While the difference is small, a decrease in tree cover density is consistent with what is reported in the latest report (Schelhaas et al., 2022).

Table 5 shows the average tree cover density per province from the NBI-7. The number of observations is highly variable between provinces, which also has to do with the amount of forest surface area each province has. Subdividing this further into separate yearly averages would likely result in sample sizes that are too small for a number of provinces.

Table 5. Average tree cover density per province (NBI-7, 2017-2021) and corresponding number of observations.

Province	Tree cover(%)	Observations
Drenthe	69.7	299
Flevoland	53.9	132
Friesland	66.1	95
Gelderland	59.1	818
Groningen	73.1	45
Limburg	70.8	274
Noord-Brabant	66.9	584
Noord-Holland	70.8	109
Overijssel	56.6	301
Utrecht	66.6	150
Zeeland	68.6	18
Zuid-Holland	64.4	54

The second calculation focused on a selection of forest appearance types recorded in the National Forest Inventory. Tree cover density for this subset of plots was slightly higher than for all plots (Table 6).

Table 6. Average tree cover density per forest inventory.

Period	All plots	Selected plots[1]
MFV (2001-2005)	70.2%	70.3%
NBI-6 (2012-2013)	64.6%	67.3%
NBI-7 (2017-2021)	62.9%	63.9%

1. Only regular forest and spontaneous forest included here.

Finally, as is clear from Table 7, the number of observations per year are not distributed evenly. Particularly, NBI-6 seems skewed towards 2013. Interestingly the differences in tree cover do not vary significantly with the number of observations.

Table 7. Average tree cover per year and corresponding number of observations.

Year	Tree cover (%)	Observations
2001	65.1	675
2002	71.1	641
2003	71.5	649
2005	73.4	665
2012	64.6	445

2013	67.8	2360
2017	68.1	425
2018	62.0	682
2019	61.6	637
2020	64.9	653
2021	64.3	482

2.2.3.2 Copernicus tree cover density layer

The analysis of national tree cover density using the Copernicus Tree Cover Density layer revealed a relatively stable trend overall. This stability is observed when considering the combined data from production forests, natural forests, and other forest types (Figure 3). The aggregated density was 51.8% in 2012, 52.6% in 2015, and 51.4% in 2018.

Notably, production forests consistently exhibited the highest tree cover density across the three assessment years. In 2012, the tree cover density in production forests was recorded at 56.8%, which slightly increased to 58.5% in 2015, before marginally declining to 57% in 2018.

In contrast, natural forests, while initially having a lower tree cover density compared to production forests, showed a more significant increase over time. The density in these forests was 52.1% in 2012, marginally increased to 52.3% in 2015, and notably rose to 60% by 2018. The tree cover density in natural forests closely mirrored the figures observed for the aggregated density.

Other forest types, categorized separately from production and natural forests, consistently showed much lower tree cover densities throughout the study period. In 2012, these forests had a density of 21.9%, which slightly decreased to 21.6% in 2015 and then marginally increased to 22.6% in 2018.

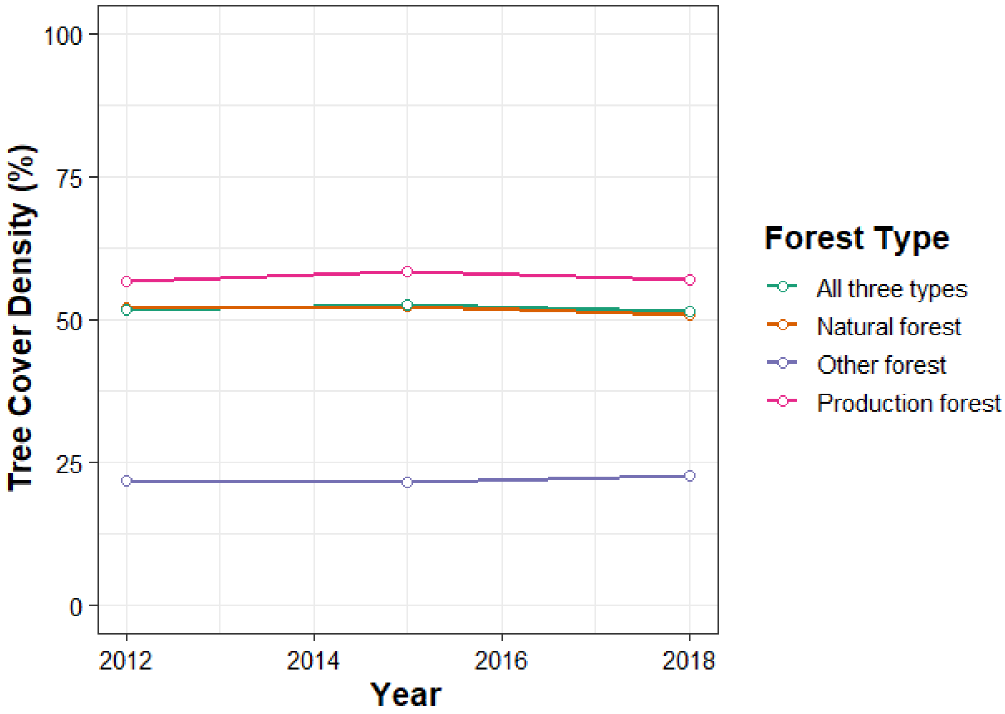


Figure 3. Tree Cover Density over multiple years by forest type and based on Copernicus data.

The analysis of tree cover density at the provincial level reveals similar trends (Figure 4). Generally, production forests maintain the highest tree cover density across most provinces, with notable exceptions in Friesland an Noord-Holland. The trends observed in other types of forests typically align with the national pattern.

Gelderland and Utrecht stand out for having the highest tree cover densities for both production and natural forests. The data from 2012 to 2018 highlights this trend clearly. For natural forests, Utrecht had a density of 55.4% in 2012, which slightly increased to 59.2% in 2015 and then decreased to 54.6% in 2018. Gelderland, on the other hand, started with a higher density of 57.1% in 2012, peaked at 59.5% in 2015, and then slightly decreased to 56.1% in 2018.

The pattern is similar in production forests. In Gelderland, the tree cover density was 61.2% in 2012, rose to 63.6% in 2015, and slightly decreased to 61.0% in 2018. Utrecht followed a similar trend, starting at 60.5% in 2012, peaking at 64.8% in 2015, and slightly decreasing to 61.0% in 2018.

Contrastingly, the lowest tree cover densities were observed in provinces like Zuid-Holland and Groningen for natural forests and in Friesland for production forests. Zuid-Holland had the lowest density for natural forests in 2012 at 36.9%. Groningen followed suit with 37.8% in 2015 and 39.0% in 2018. These numbers are significantly lower compared to figures from Gelderland and Utrecht. For production forests, Friesland recorded the lowest density in 2018 at 40.27%, a figure that stands out when compared to the higher densities observed in other provinces.

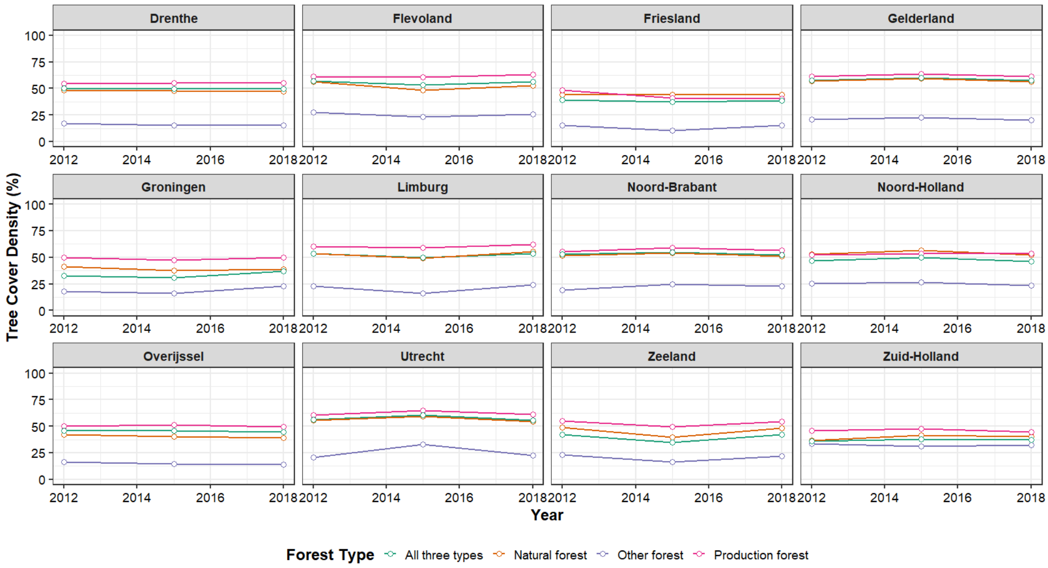


Figure 4. Tree Cover Density over multiple years by forest type and province.

Finally, we investigated the total area covered by natural, production, and other types of forests for the years 2013, 2015, and 2018, based on the ecosystem extent map (Figure 5). Production forests, interestingly, exhibit a slight decrease over the studied period. In contrast, the areas of natural and other forests show remarkable stability across these years.

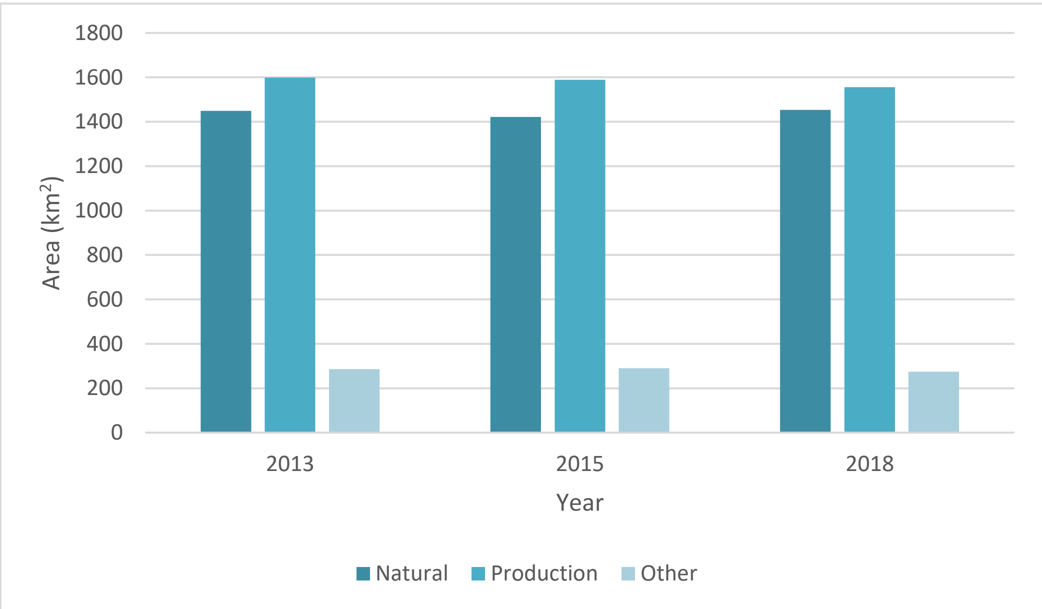


Figure 5. The total area of natural, production and other forest in the years 2013, 2015, and 2018.

Landelijk Meetnet Flora

The mean tree cover density of all subtypes 1xx (forest etc.) of the LMF relevés are shown in Table 8. Of the main forest types (120, 130, 140), dry deciduous forest has the highest tree cover density (55%), followed by moist deciduous forest (49%) and coniferous forest (41%). Note, however, that the variance in the data is very high, with coefficients of variation (cv) typically about 50%.

Table 8. Tree cover density for all 'forest' plots in the LMF flora monitoring network.

Forest type	n	Tree cover density		
IPI		mean	sd	cv
110 Riparian and swamp forest	92	45%	25%	56%
120 Coniferous and mixed forest	255	41%	21%	52%
130 Deciduous forest (dry)	241	55%	22%	40%
140 Deciduous forest (moist)	222	49%	24%	49%
150 Thicket	65	4%	13%	327%
160 Coppice	19	44%	22%	50%
170 Wooded bank	86	57%	25%	44%
180 Wils shoots	2	38%	0%	0%
190 Clearcut, burnt etc	10	12%	16%	130%

After refining the selection to include only specific sites, the tree cover densities for coniferous and dry deciduous forest remained unchanged, but increased from 49% to 51% for moist deciduous forest (Table 9).

Table 9. Tree cover density for LMF 'forest' sites within forest-ecosystem types.

Forest Type		Tree cover density		
IPI	n	mean	sd	c.v.
120 Coniferous and mixed forest	210	41%	20%	49%
130 Deciduous forest (dry)	200	55%	21%	39%
140 Deciduous forest (moist)	180	51%	24%	47%

Classifying all LMF sites according to their ecosystem type suggested that the mean for tree cover density for natural forest (50%) is higher than for production forest (45%), although again the variance is high (Table 10). A two-sided t-test confirmed that this difference is significant ($p<0.01$).

Table 10. Tree cover density for forest-ecosystem types.

Forest Type		Tree cover density		
ecotype	n	mean	sd	c.v.
Natural forest	389	50%	23%	45%
Swamp forest	20	45%	18%	41%
Production forest	157	45%	21%	47%
Other forest	24	49%	25%	50%

In contrast, when the data were subdivided by both ecosystem types and IPI classifications, the statistical analysis did not find these significant differences in tree cover densities (p values of 0.2, 0.5, and 0.6 for IPI 120, 1340, 140, respectively) (Table 11).

Table 11. Tree cover density for selected combinations of ecosystem type and IPI.

Forest Type		Tree cover density			
ecotype	IPI2	n	mean	sd	c.v.
Natural forest	120 Coniferous and mixed forest	119	43%	22%	51%
Natural forest	130 Deciduous forest (dry)	144	55%	21%	39%
Natural forest	140 Deciduous forest (moist)	126	52%	24%	46%
Production forest	120 Coniferous and mixed forest	86	40%	17%	43%
Production forest	130 Deciduous forest (dry)	45	53%	22%	41%
Production forest	140 Deciduous forest (moist)	26	49%	27%	54%

2.3 Discussion

2.3.1 Spatial delineation

The delineation of forests, particularly in the context of analyzing tree cover density, is a critical factor influencing the accuracy and relevance of the data obtained. We compared natural, production, and other forest types in this analysis. Each category represents distinct characteristics and serves different ecological roles.

Natural forests are primarily characterized by their minimal human intervention. They are key in maintaining biodiversity, providing habitats for wildlife, and preserving natural ecological processes. The high tree cover density in natural forests, as indicated by our results, could reflect that their health and resilience. However, it should be noted that tree cover density also relates to the type of forest (coniferous vs. deciduous) and age-structure.

Production forests are managed for economic purposes, primarily timber production. In the Netherlands, production forest also often have an additional function for nature recreation. The slightly declining extent in production forests could be indicative of harvesting practices or other management inventions. While they contribute to the economy, their ecological value might be different from natural forests, especially in terms of biodiversity and natural habitat preservation. The high tree cover density shown in the results is likely the result of the way production forests are managed. Typically, fast growing species with high-density stands are planted.

Other forests include forests that do not neatly fall into the natural or production categories, but are also not urban parks. The lower tree cover density observed in these forests suggests a varied set of ecological conditions and management practices and we can also see the, resulting lower tree cover density in our results.

In terms of measuring ecosystem condition using the tree cover density indicator, it would be most relevant to stick to the natural forest type. Tree cover density serves as an indicator of ecosystem health, resilience, and integrity. Assessing tree cover density in natural forests provides a more accurate picture of ecological conditions, while assessing the same indicator in production or other forests may result in misleading outcomes. Therefore, we would advise to focus on natural forests when reporting on this indicator and using it in condition accounts.

2.3.2 Assessing tree cover density

The Dutch National Forest Inventory, Copernicus Tree Cover Density, and Meetnet Flora data offer different perspectives on tree cover density. The NBI, with its systematic sampling approach and detailed plot assessments, provides in-depth information on various forest attributes, including tree and shrub cover. This approach is particularly beneficial for capturing subtle changes within specific plots or regions, offering insights into the dynamics of forest ecosystems at a micro level.

However, this method, especially in earlier editions like the MFV, has its limitations in terms of similar sample sizes and geographical representation over different years. These limitations could impact the comprehensiveness of the data. Moreover, the NBI tends to report a higher percentage of tree cover density, which may be attributed to the method's high degree of uncertainty, especially in the interpretation of range-based data. Though at the same time, it may also be attributed to the way tree cover density is measured. In-situ measurements are generally more representative of the real situation than satellite based measures. This is because the satellite can only see what happens above the trees.

In order to align the tree cover density condition variable based on the NBI data with the ecosystems from the extent account, it would be ideal to overlay the locations of the plots with the ecosystem type map. That way, it would be feasible to calculate a value for each (forest) ecosystem type, as long as there is a representative plot sample size. However, due to restrictions related to privacy, the exact location of the plots is not publicly available. Instead of the exact coordinates, the location of the 1km square is provided, but this does not give enough detail to compare the NBI data with the extent account. It must, therefore, also be noted that the data per province may have a higher uncertainty due to the coarse resolution.

The Copernicus data, derived from high-resolution satellite imagery, offers a broader spatial coverage. This is beneficial for large-scale assessments and policy-making. However, the Copernicus data may lack the finer details captured by ground-based inventories like the NBI. The resolution difference, especially in the data from 2012 and 2015 (20-meter resolution) compared to 2018 (10-meter resolution), adds a layer of complexity when comparing data across years. This variation in resolution implies that the data between years are not entirely comparable, although general trends remain consistent.

The differences in assessment methods could explain the variations in the results obtained between the NBI and Copernicus data. For instance, the decrease in tree cover density reported in the latest NBI could be due to its more detailed and localized data capturing changes not as easily detected by broader-scale satellite imagery of Copernicus. However, more likely is that the data from the NBI is just based on the top layer and not on the other lower layers, which are also part of the tree cover density. Also, it must be noted that a lower tree cover density is most likely the result of a change in structure.

An interesting observation is the contrast in provincial data. For example, Flevoland shows very low tree cover density according to the NBI, while Copernicus data indicates high tree cover density. This discrepancy underscores the different capabilities and focus areas of each method.

The LMF offers yet another perspective on tree cover density in the Netherlands, however, its approach has notable strengths and limitations when compared to the NBI and Copernicus datasets. A key strength of the LMF is its continuous collection of data. The NBI, on the other hand, is being done in cyclic events of multiple years. The LMF method is particularly beneficial for obtaining a macro-level overview of tree cover density across different forest types, such as dry deciduous, moist deciduous, and coniferous forests.

However, the LMF has limitations that affect its suitability for certain applications. Unlike the NBI, the LMF does not offer the same depth in terms of systematics sampling and detailed plot assessments. The NBI has a focused sampling method with regular sampling points and points in underrepresented habitats, whereas the LMF measures the same plots every time. This lack of detailed, plot-level data limits its ability to capture subtle changes and nuances within specific forest areas, which are crucial for in-depth ecological studies and localized forest management. Additionally, the high variance in the LMF data indicates a considerable level of uncertainty, which could impact its reliability for detailed scientific analysis.

Moreover, when compared to the Copernicus data, derived from high-resolution satellite imagery, the LMF lacks the spatial coverage and resolution that are vital for comprehensive national assessments. The Copernicus data, with its broader spatial extent, is more suited for aligning with national forest trends and providing a clear picture of tree cover density across the Netherlands.

Given these considerations, the Copernicus data seems most suitable for assessing tree cover density in the Netherlands. This decision, based on expert judgement, takes into account the most forested areas in the country, where high tree cover density is expected. On a provincial scale, Copernicus data aligns more with the general trends of well-forested areas, despite showing a lower general density than the forest inventory. The decision to prioritize Copernicus data is reinforced by its broader spatial coverage and consistency with observed trends in key forested regions like the Veluwe in Gelderland and the Utrechtse Heuvelrug in Utrecht. Additionally, the tree-year timing of Copernicus, aligns with the reporting period of the condition indicators to Eurostat.

2.3.3 Relevance to condition

Understanding tree cover density is crucial for assessing the condition of forest ecosystems. The stability observed in natural and other forests, as indicated by both NBI and Copernicus data, suggests a relative resilience in these ecosystems. However, the slight decrease in production forests' area and tree cover density raises concerns about sustainable forest management practices and their ecological impacts.

The observed slight decrease in tree cover density in production forests is a point of concern. It might indicate over-harvesting or inadequate regeneration practices, which could lead to reduced forest health and productivity over time.

The stability in tree cover density in natural forests suggests a relatively healthy condition of these ecosystems. This stability is indicative of effective natural regeneration processes and minimal human disturbance, which are crucial for maintaining biodiversity, ecological balance and provisioning of ecosystem services such as carbon sequestration and habitat provision.

The variations in tree cover density across provinces point to regional differences in forest management and ecological conditions. The Netherlands is not known for its forests and actually largely consists of open grasslands, wetlands and heathlands. However, some regions like the Veluwe are forested. Monitoring the change in tree cover density may inform management and policy making for this area.

Looking at the NBI data, the general decrease between inventories is not a concern. Local assessors stress that the lower tree cover density is a result of increased variation of structure in the forest. Where previously, the Dutch forests were dominated by one type of tree species, they are now more properly mixed between coniferous and deciduous trees. Also the variation in size and age is much more varied. Increased variation in structure of the forest is beneficial for the local microclimatic conditions of biota (Ehbrecht et al., 2017) and provides diversity in the types and thus number of niches available for organisms (Sukma et al., 2019). Thereby, it can increase biodiversity in the area and improve the functioning of the ecosystem.

Though not measured in this study, measuring tree cover density could actually be useful for urban areas too. Urban areas often suffer from urban heat island effect, where the concentration of buildings and pavement increases temperatures compared to surrounding rural areas. Trees in urban areas can mitigate this effect by providing shade and through evapotranspiration, thus reducing energy costs and improving urban climate. Reducing the urban heat island effect through tree cover helps maintain a more natural temperature balance in urban ecosystems. This is crucial for the survival of many species that are sensitive to temperature changes and for maintaining the natural rhythms of urban wildlife and plant life. However, these systems are significantly different to natural forest systems and should therefore be assessed separately and should definitely not be compared or used to measure tree cover density as a national indicator together.

3. Urban green

Green areas such as public parks, trees and other recreational or ornamental vegetated areas are an important part of urban zones. They provide spaces for recreation and leisure activities, play an important role in local climate regulation and deliver a positive contribution to human health and well-being. Monitoring the extent of urban green is therefore essential to inform policy makers, especially those that are involved in spatial planning on a local and regional scale. The proposal for the Nature Restoration Law requires that there is no net loss of urban green space by 2030 compared to 2021, and requires that the area of urban green increases with targets set for 2040 and 2050. In this chapter we assess the different methods to calculate urban greenspace and develop an initial version of this indicator. We also discuss the current limitations and possible future improvements for measuring urban green.

3.1 Spatial delineation

Within the new European Regulation on ecosystem accounting there are two options considered for the delineation of urban areas. The first option is to use Local Administrative Units (LAU) of cities. For the Netherlands this would mean that municipalities with a high degree of urbanization would be selected. However, many municipalities that contain large cities also contain rural areas, which results in the municipality as a whole to be not considered "urban" according to the LAU classification. Therefore it was decided to use a delineation of urban areas that is based on city limits instead of the LAU. While this delineation is not perfect it does give a better approximation of urban areas. Figure 6 and Figure 7 below show the difference between the two types of delineation.

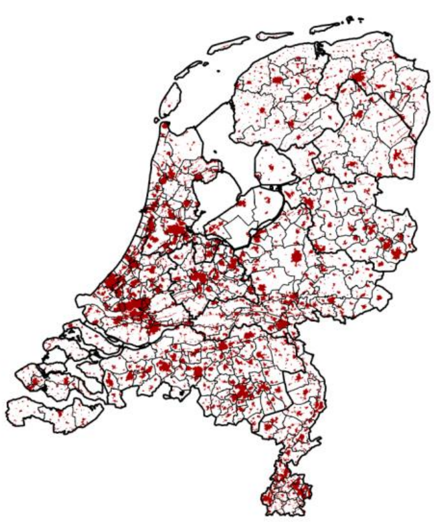


Figure 6. Delineation of urban area (red) based on city limits.

Figure 7. Delineation of urban area (red) based on the Classification of Local Administrative Units (LAU) with the highest degree of urbanization.

The second option is to take all the Settlements and artificial areas (EU typology lvl1) as a spatial delineation. The disadvantage is that this includes all road networks, industrial areas and rural buildings that are located outside of cities and are thus not very characteristic of urban areas. For the purpose of this report we used both options in order to compare results.

3.2 Assessing urban green

3.2.1 Demarcation of urban green space - method

Apart from the delineation of urban areas, it is important to establish what constitutes urban green space. Ideally what this indicator should capture is all area covered with trees, bushes, shrubs, grasses and other permanent herbaceous vegetation. To measure these green areas, we first looked at the Dutch ecosystem type map as a data source.

Within the EU Ecosystem typology there is the level 2 ecosystem type 'Urban Greenspace', which includes parks, sports and recreation sites, and other urban green. Within the Dutch ecosystem type map there are currently two ecosystem types that fall into this category, namely 'Urban green' (parks and other green in the public space) and 'Sports and Recreation sites' (sport parks, camping sites, zoos, botanical gardens, etc.). These two ecosystem types may overestimate urban green, since they are not completely covered in vegetation. It is also possible these ecosystems may underestimate urban green, because they do not include private gardens for example. Because in the past not all public parks and greenspace were included in the ecosystem map, we implemented new data from the detailed topographic map (BGT) and improved the algorithms for determining parks and public green (Statistics Netherlands and WUR, 2022). Depending on the delineation of urban areas it can also be important to include other nature ecosystem types such as forests and grassland. For the purpose of this report we looked at the effect of all these inclusions separately.

A second option is to use Earth Observation data from the Copernicus Land Monitoring Service. Several vegetation variable products are available, such as daily Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI). The High Resolution Vegetation Phenology and

Productivity product also has a yearly Season Maximum Value of the Plant Phenology Index (PPI) in 10m resolution. This indicator might be most comparable between years and there would be no need to aggregate data, as is the case for NDVI. However, the data is only available from 2017 onwards, so a longer time series would be more difficult to construct. Due to time limitations and data complexity it was decided to look at the improved ecosystem map to determine urban green space for now.

3.2.2 Data Processing

We calculated the total urban area and the surface area of all ecosystem types within this urban area for the years 2013-2021. To calculate relevant surface areas we used raster calculations on a 10m x 10m scale. Very small strips of green may not be detected this way, but overall a 10m resolution was considered to be fit for purpose for this indicator. Additionally we calculated a breakdown per province to assess regional differences.

3.2.3 Results

The results for the urban delineation using city limits are shown in Table 12. Because of changes in these city limits, the total urban area increases between 2013 and 2021. There is an outlier for urban area in 2014, likely due to a particular town that is included in that year but not in other years. Parks and other public green space make up around 12% of the urban area. The share of sports and recreation sites is much less (± 3%) and other nature occurs even more rarely (± 1%).

Table 12. Urban area and urban green for the Netherlands from 2013 to 2021, based on city limits.

SCOPE: city limits	2013	2014	2015	2016	2017	2018	2019	2020	2021
Urban area (km2)	4938	5273	4994	5034	5032	5087	5144	5144	5180
Parks, public green space.	601	641	610	618	621	626	632	634	641
Parks, public green space. (%)	12.2%	12.2%	12.2%	12.3%	12.3%	12.3%	12.3%	12.3%	12.4%
Sports & Recreation sites	143	145	140	148	143	143	154	160	163
Sports & Recreation sites (%)	2.9%	2.8%	2.8%	2.9%	2.8%	2.8%	3.0%	3.1%	3.1%
Other nature (forest,	47	50	46	44	42	43	45	47	47
Other nature (forest,	0.9%	0.9%	0.9%	0.9%	0.8%	0.8%	0.9%	0.9%	0.9%
Total (%)	16.0%	15.9%	15.9%	16.1%	16.0%	16.0%	16.1%	16.3%	16.4%

The results for the wider scope using all settlements and artificial areas is shown in Table 13. The resulting urban area is much larger due to the inclusion of roads and other artificial areas outside of the city limits. The urban area also increases over time. A larger share is taken up by sports and recreation sites (± 7.5%) than in the smaller scope. This is because a lot of these areas, for example camping grounds and golf courses, are located outside of cities. The area of parks and public green space is also higher, likely due to parks that lie next to or in close proximity to cities.

Table 13. Urban area and urban green for the Netherlands from 2013 to 2021, based on all settlements and artificial areas.

SCOPE: Settlements and Artificial areas (EU typology lvl1 - 1)	2013	2014	2015	2016	2017	2018	2019	2020	2021
Urban area (km2)	8142	8230	8212	8209	8209	8245	8289	8317	8336
Parks, public green space	749	791	754	770	768	773	790	798	808
Parks, public green space (%)	9.2%	9.6%	9.2%	9.4%	9.4%	9.4%	9.5%	9.6%	9.7%
Sports & Recreation sites	616	616	616	616	616	616	616	616	616
Sports & Recreation sites (%)	7.6%	7.5%	7.5%	7.5%	7.5%	7.5%	7.4%	7.4%	7.4%
Total (%)	16.8%	17.1%	16.7%	16.9%	16.9%	16.9%	17.0%	17.0%	17.1%

An additional regional analysis using the urban area based on city limits shows that there are some differences between provinces. Table 14 shows the results per province for the year 2021. Zeeland, Flevoland and South-Holland have a lot of urban green relatively to total urban area, though for Zeeland it matters a lot whether you include sports and recreation sites. While sports and recreation sites may contain a lot of vegetation, this is not necessarily always the case and may depend a lot on the specific type of site, for example a golf course opposed to a bungalow park.

Table 14. Urban area and urban green per province in 2021, based on city limits.

2021								
SCOPE: city limits	Urban area (km2)	Parks, public green space. (km2)	Parks, public green space. (%)	Sports & Recreation sites (km2)	Sports & Recreation sites (%)	Other nature (forest, grassland, etc.) (km2)	Other nature (forest, grassland, etc.) (%)	Total (%)
Groningen	234	31	13%	7	3%	1	1%	17%
Fryslân	276	32	12%	13	5%	1	0%	16%
Drenthe	231	30	13%	7	3%	3	1%	17%
Overijssel	383	47	12%	14	4%	3	1%	17%
Flevoland	89	15	17%	2	2%	1	1%	19%
Gelderland	717	89	12%	25	3%	6	1%	17%
Utrecht	326	43	13%	10	3%	3	1%	17%
Noord-Holland	649	79	12%	29	4%	5	1%	17%
Zuid-Holland	820	113	14%	34	4%	8	1%	19%
Zeeland	156	16	10%	13	8%	4	3%	21%

Noord-Brabant	865	101	12%	25	3%	4	0%	15%
Limburg	435	45	10%	12	3%	8	2%	15%

3.3 Discussion

In measuring urban green the delineation of urban areas is a very determining factor. The indicator is influenced not only by the amount of vegetation but also by the development of urban areas themselves. When new urban areas are developed that have more green space than average, the urban green indicator shows a positive trend. However, this urbanization often takes place at city edges and such a trend may not be indicative of the more densely populated areas. If the goal of the indicator is to measure greenery in the immediate living environment of citizens, it would be insightful to take population density into account as well. Additionally, depending on the definition urban, entire areas may suddenly fall into or out of this category and can potentially add a lot of noise to the general trend. One option to mitigate this is to use the most recent urban delineation for all years, thereby keeping the urban area the same. This way the trend in the indicator reflects only the changes in greenery, which is something that is easier to interpret and may align better with the wishes of policy makers and other applications. Still, such an approach also has its downsides, especially for longer time series where the most recent urban delineation deviates a lot from the historical situation.

The two delineations that we tested for in this study both show an increase in urban area and a stable or slightly positive trend of urban green. The first delineation based on city limits is more indicative of densely populated areas, with a greater contribution of parks and public green space to the total urban green. It is more suitable to use as a national or regional indicator, since the city limits are also defined nationally. The second delineation, containing all settlements and artificial areas, is potentially more useful in international context since it would be more comparable across different countries. The results from this study show similar trends for both delineations, giving an indication that green area measured across all artificial areas is also indicative of green area in the more densely populated areas. Further research could be done into the effect of infrastructure on this indicator, especially on a regional scale. For now we decided to include urban green based upon the first delineation (city limits) in the condition account.

To calculate a more precise number and also get a better indication of the percentage of green within sports and recreation sites, it is necessary look further into the available vegetation indices from the Copernicus Land Monitoring Service. This would potentially give a more precise measurement, because it would also include green within business parks and private gardens for example. However, one drawback is that the canopy cover from trees would cover impervious area as well when looked at from Earth Observation data. It would be useful if there was a standardized way to use the Season Maximum Value of the Plant Phenology Index, for example by using a cut-off value to separate vegetated areas from non-vegetated areas.

4. Dead wood

As part of Eurostat's ongoing efforts to expand its set of regular statistics on ecosystem condition, there is a growing interest in incorporating the assessment of dead wood. The Eurostat Guidance Note on Condition Accounts defines dead wood as follows:

> "*Dead wood is the amount of non-living standing and lying woody biomass in forest and other wooded land*"

Dead wood, or standing and fallen dead trees and woody debris, plays a crucial role in indicating the structural state and overall health of ecosystems. The presence, quantity, and quality of dead wood can be indicative of various ecological processes and dynamics within a given environment. Ecosystems thrive when the structure, function and composition are in balance and dead wood plays an important role in keeping this balance.

For example, it provides habitat niches for various organisms including insects, fungi and small mammals, contributing to the overall biodiversity and structural complexity of ecosystems. Additionally, dead wood contributes to vertical and horizontal structural diversity within ecosystems. This spatial variation supports a wide range of flora and fauna, influencing species distribution and interactions.

Dead wood also plays a crucial role in nutrient cycling. As dead wood decomposes, it releases nutrients back into the soil, enhancing soil fertility and supporting primary productivity. Nutrient cycling is therefore a vital part of ecosystem functioning, just like carbon storage. Dead wood can sequester carbon for extended periods. Its presence aids in carbon storage and mitigates the release of greenhouse gases into the atmosphere, helping to combat climate change. Additionally, dead wood can influence the ecological response to disturbances, such as fire and insect outbreaks. Its presence or absence can modulate the resilience and recovery of ecosystems following such events.

A key driver of species richness and composition is dead wood. It provides a specialized niche for various fungi, insects, and other decomposers. These organisms, in turn, attract predators and scavengers, contributing significantly to the composition and diversity of an ecosystem's biota. Certain species of fungi and insects are actually closely associated with specific types of dead wood. Monitoring these indicator species can provide insights into the composition and health of an ecosystem.

Understanding the quantity, quality and spatial composition of dead wood enables policymakers to gain a deeper understanding of the state of ecosystems. A sudden change may signal disturbances or alterations in ecological processes.

4.1 Assessing dead wood

4.1.1 Data types

The SEEA EA guidance note on condition accounts states that a dead wood indicator is provided by Forest Europe, UNECE and/or FAO as the Global Forest Resources Assessment (FRA). The data is retrieved from both country reports and remote sensing. The indicator can be easily retrieved from the FRA website [FRA platform (fao.org)].

The FAO defines dead wood as

“All non-living woody biomass not contained in the litter, either standing, lying on the ground, or in the soil. Dead wood includes wood lying on the surface, dead roots, and stumps larger than or equal to 10 cm in diameter or any other diameter used by the country”.

The Netherlands also provides national data to the Forest Resources Assessment (FRA). An extensive program has been set up to inspect and monitor dead wood and other forest information nationally. This inventory is named the National Forest Inventory (NBI) and is the same inventory as mentioned earlier for use on calculating tree cover density (see the chapter on tree cover density for further details). Three inventories were done between 2001 and 2021. The dataset consists of data on the volume of standing dead biomass and lying dead biomass. Dates and geographic points comparable to a one-kilometer grid cells are also available.

Though the input data from both sources should be similar, the FRA currently asks countries for input every five years and countries do not always have all the data available yet. Therefore, some of the data may be extrapolated. Therefore, we decided to compare the NBI with the FRA. The SEEA EA also advises to report the final indicator in cubic meters per hectare. The national data is reported in cubic meters per hectare, however the FRA indicator on dead wood is reported in tonnes per hectare. If we convert the FRA indicator to cubic meters per hectare, we can compare the two sources.

4.1.2 Methods

First, we looked at the NBI data to investigate the amount of dead wood present in the Netherlands. The most recent available data dates back to 2021, however the estimation is reported for the last six years. It is essential for our analysis to assess the estimation of dead wood on an annual basis. To facilitate this, we initiated our investigation by scrutinizing the comparability of the years under consideration. We sought to determine whether these years exhibited consistent trends or if they presented distinct variations, potentially attributable to geographical disparities among data collection points. By eyeballing the map each year’s data points seem reasonably distributed across the entirety of the Netherlands, suggesting a uniform representation of the geographic range in our dataset (Figure 1). Therefore, we decided to investigate each year separately.

By adding the standing and lying biomass together and taking the mean of all the points for each year, we can determine the national average of dead wood for every year. We also calculated the average for every complete NBI in order to analyze and compare trends.

We made the same selection of forest appearance types recorded in the NBI as for tree cover density. Only the regular forest types (all ‘Opgaand bos’ types), as well as spontaneous forest in natural areas (‘Spontaan bos in natuurterrein’) were selected. Again, the special forest types which might be part of other ecosystems, such as parks, tree lines and garden forest were excluded. However, again, we must note that we are not certain how well the plots exactly align with the forest ecosystems of the extent map since there is no detailed spatial information available of the plot locations. Even within the provided one-kilometer grid cells, the types of forests often differ.

The NBI was meant to be used as a national indicator by taking all the points over the studied period (e.g. for NBI-6 two years). To make sure we used the NBI data the way it was meant to be used, we took the average year of each NBI and calculated the mean dead wood of both standing and lying dead wood. For NBI-6, as this inventory only included two years, we took the year 2012 as the average year between the last year from the MFV (2005) and the first year from NBI-7 (2017) is 2011, and therefore 2012 is closest. We then used a linear interpolation in R to calculate the dead wood indicator for the missing years.

We also calculated dead wood indicator from the Global Forest Resources Assessment. The data was sourced from a comprehensive online database [FRA platform (fao.org)], which provided an accessible platform for retrieving detailed forest resource information. Our selection criteria centered on the geographical region of the Netherlands, targeting the recent data spanning the years 2015-2020.

Upon accessing the website, we navigated to the section dedicated to dead wood statistics. The platform allowed for a streamlined extraction process, enabling us to select the Netherlands as the region of interest and dead wood as the specific variable. The data were presented in a tabula format, detailing various indicators related to dead wood volumes, all quantified in tonnes per hectare.

To convert the data from tonnes per hectare to cubic meters per hectare, we employed a standard conversion formula, factoring in the density of dead wood. Recognizing the variability in wood density we conducted the conversion using two distinct density values: 0.3 tonnes per cubic meter and 0.9 tonnes per cubic meter. These values were chosen to represent a plausible range of densities accounting for different conditions and types of wood (Leban et al., 2020).

The conversion was achieved using the following formula:

$$Cubic\ meters\ per\ hectare\ \left(\frac{m^3}{ha}\right) = Tonnes\ per\ hectare \times \frac{1}{wood\ density\ (tonnes/m^3)}$$

This approach enabled us to calculate two sets of values for each indicator, corresponding to the two different densities, thereby providing a comprehensive range of estimates for dead wood volume in cubic meters per hectare.

4.1.3 Results

4.1.3.1 National Forest Inventory

The analysis of the NBI data on dead wood volume (measured in cubic meters per hectare) for different years and time periods reveals notable variations and trends. The data encompasses a range of values (Table 15 and Table 16), with dead wood volumes fluctuating from 8.92 m3/ha in 2002 to a peak of 22.22 m3/ha in 2020.

There is a notable trend between the different inventories, where it is clear that the amount of dead wood is increasing over time (Table 15). Within those inventories the yearly differences also show this trend, except for NBI-7 (Table 16). In NBI-7 there are some yearly fluctuations without a clear trend.

Table 15. Dead wood indicators for the three different inventories.

Years	Dead wood m3/ha (standing + lying)
MFV (2001-2005)	9.81
NBI-6 (2012-2013)	13.67
NBI-7 (2017-2021)	19.70

Table 16. Dead wood indicators for each year separately.

Years	Dead wood m3/ha (standing + lying)	Observations
2001	9.62	675
2002	8.92	641
2004	10.18	649
2005	10.51	665
2012	13.17	445
2013	13.76	2360
2017	21.47	425
2018	15.38	682
2019	20.04	637
2020	22.22	653
2021	20.40	482

We looked into the comparability of the data within NBI-7 and created a boxplot. We saw some significant outliers and decided to remove the outliers (Figure 8a). Our decision to remove the outliers was based on the fact that they caused too much noise in the comparison of the different years. By removing the outliers, we could focus on the central trend of the data. The resulting figure of boxplots show that the ranges of data in each year overlap significantly (Figure 8b). Though, the maximum and minimum of each year may be different, the quantile ranges all lie within similar ranges and are not significantly different (Figure 8b). We quickly tested this through a simple one-way ANOVA test using the 'stats' package in R (version 4.2.3). The test confirmed no differences ($p = 0.446$).

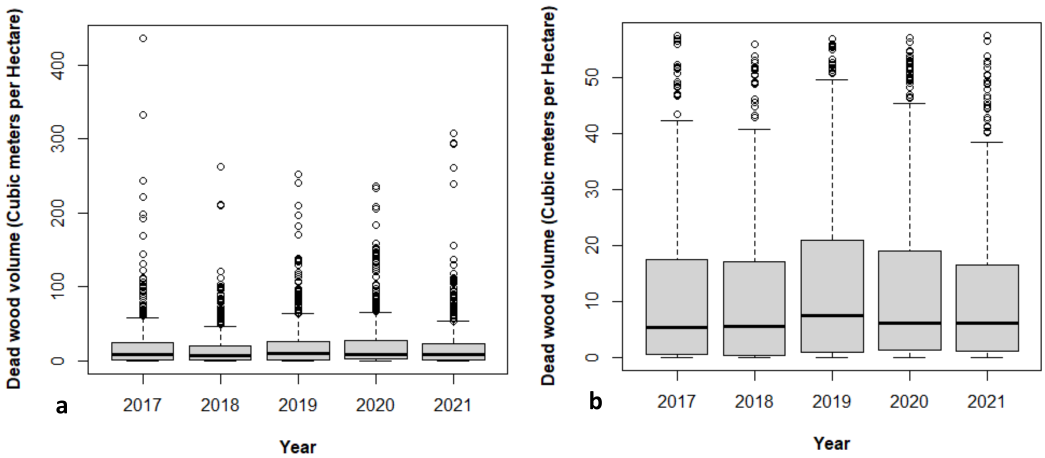


Figure 8. Boxplots of the forest inventory data per year a) raw and b) with outliers removed.

In Figure 9, we observed a distinct upward trend in the amount of dead wood over the years. The graph, which is based on interpolated values, indicates a clear increase in dead wood across the time frame considered. However, a notable change in the pattern is evident around the year 2012. Prior to 2012, the increment rate of dead wood is relatively moderate; the slope of the line in the graph is less steep, suggesting a gradual increase during this period. In contrast, post-2012, there is a marked shift in the steepness of the trend. The line becomes noticeably steeper, indicating a more rapid increase in dead wood from 2012 onwards.

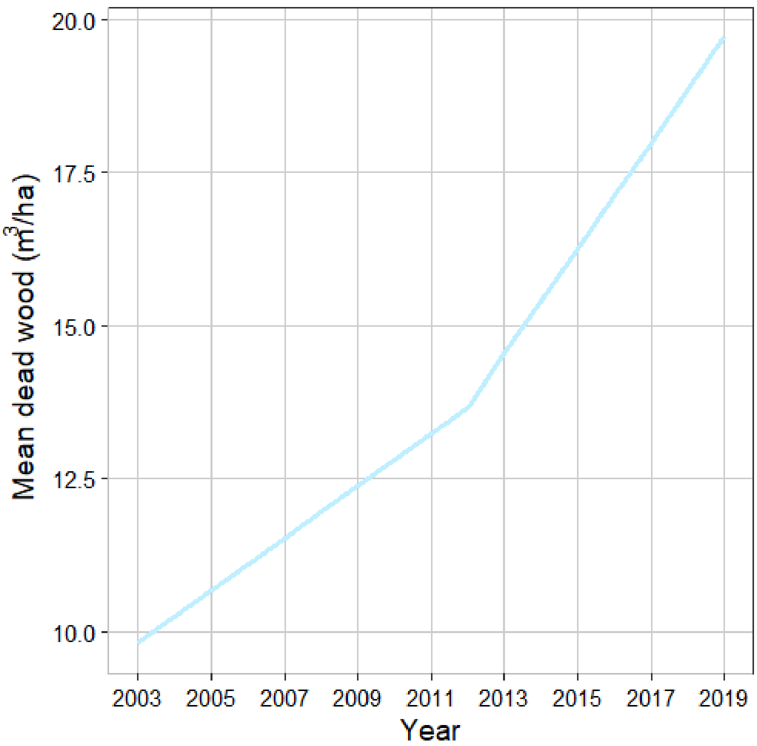


Figure 9. Mean dead wood per year based on interpolation between the average years of the three different inventories of the NBI.

4.1.3.2 Global forest resources assessment

The analysis of the data from the FRA reveals a notable trend in the accumulation of dead wood in Dutch forests over the years 1990 to 2020. This trend is evident in the increasing values across different metrics: tonnes per hectare (tonnes/ha), cubic meters per hectare at a density of 300 kg/m3, and cubic meters per hectare at a density of 900 kg/m3 (Table 17).

Table 17. Dead wood indicator by the Global Forest Resources Assessment (FRA) from 1990 to 2020 in tonnes per hectare and in cubic meters per hectare with different densities.

Year	tonnes/ha	m3/ha (density 300kg/m3)	m3/ha (density 900kg/m3)
1990	1.00	3.33	1.11
2000	1.00	3.33	1.11
2010	3.00	10.00	3.33
2015	3.85	12.83	4.28
2016	3.96	13.20	4.40
2017	4.07	13.57	4.52
2018	4.18	13.93	4.64
2019	4.29	14.3	4.77
2020	4.41	14.6	4.9

Between 2015 and 2020 there was an overall increase in dead wood of approximately 14.5% when looking at the data in tonnes per hectare. Notably, between 1990 and 2020, this increase even reached 341%.

When looking at the data in cubic meters per hectare, the density of 300 kilograms per cubic meter for dead wood most closely aligns with the data from the NBI, albeit the FRA figures are notably lower.

4.2 Discussion

4.2.1 Spatial delineation

Though intuitive, the spatial delineation to measure dead wood will focus particularly on forests. Specifically in this study, we used regular and spontaneous forest as the focus of the dead wood indicator is on measuring the provision of habitat for biodiversity in forests. Urban areas often have different objectives like aesthetics, safety and providing shade, rather than biodiversity. For example, falling branches or trees may pose safety risks to people living in the area and may therefore be removed. By understanding where dead wood is concentrated, we can identify key areas for protection and areas in need of management. In addition, in high temperature and dry areas, knowing where dead wood is concentrated may inform fire risk management. In the Netherlands fire risk because of dead wood is not an issue yet. However, in the future, without sufficient measures to mitigate climate change, it may become a risk.

The NBI provides geographical data points that could be integrated with the INSPIRE spatial grid of the Netherlands. This grid is divided into one-kilometer cells. This coarse resolution presented a significant challenge. For example, aligning the NBI data with our own extent would result in inherent uncertainty, as the resolution was not sufficiently detailed for comparison with forested areas mapped in the Dutch ecosystem extent. Additionally, the coarse resolution makes the calculation of dead wood on a provincial scale even more uncertain.

In the future, if we could obtain the microdata from the NBI, we could acquire actual coordinates for all data points. This could significantly enhance the resolution and accuracy of our spatial analysis. Moreover, we would be able to reduce the uncertainty of calculating a dead wood indicator at a provincial level and be certain if our points are in a forest or in an urban park. Distinguishing these areas may provide better trends of dead wood.

The FRA dataset posed a different set of challenges, primarily due to the absence of geographical data. This limitation meant that spatial delineation using FRA data was not feasible, restricting our analysis to a national-level assessment. While this provided an overview of dead wood distribution across the country, it lacked the spatial specificity needed for regional or local-level insights.

As we only have one dataset with geographic coordinates, we decided to only provide a national scale indicator on dead wood. At this point we are not able to compare two provincial indicators, which provides and inherent uncertainty and no validation of the quality of the data.

4.2.2 Assessing dead wood

The analysis of dead wood in Dutch forests, using data from both the NBI and the FRA, presents a complex picture with several notable points of discussion.

The NBI data shows a clear increasing trend in dead wood volume between the different inventories. The Netherlands started recognizing the importance of dead wood over ten years ago (Van der Maaten-Theunissen and Schuck, 2013). Dead wood from parts of felled trees and storm damage were previously immediately removed in order to prevent outbreaks of insect pests (Wijdeven et al., 2010). The significant increase is, therefore, as expected and could be a sign of good management.

However, within NBI-7 there is substantial variability between different years. The differences in sample sizes and geographic coverage between years within the same inventory potentially undermine the comparability of the data. This issue is exacerbated by the large uncertainty inherent in sampling over multiple years. By not considering the full extent of the study area, the year-to-year data variability becomes less significant, making it difficult to establish a reliable trend. The overlapping quantile ranges in NBI-7 further suggest that the year-to-year fluctuations in dead wood volume are within a similar range, not pointing to any definitive trend.

Though the year-to-year data is not suitable for monitoring dead wood in the Netherlands, we are still able to make use of the NBI data. The data was never produced to be used on a year-to-year basis. A full inventory represents the current state of dead wood in the Netherlands. However, we still want a year to year comparison or at least three-yearly to comply with the reporting period from Eurostat. We provided in the results by interpolating between the average years of the inventories. It seems clear that management is improving the volume of dead wood in the Dutch forests.

The FRA data shows a clear and consistent upward trend in volume of dead wood. This trend is significant and indicates a shift in the forest ecosystem over this period. Again this is in line with the expected trend after implementation of management of dead wood through a subsidy program (Van der Maaten-Theunissen and Schuck, 2013).

The FRA asks countries to report on dead wood every five years. Local forest assessors noted that these data were usually reported before the actual inventories were conducted. Therefore, the data in the FRA are usually extrapolated data from older inventories and thus less reliable than the actual NBI data.

4.2.3 Relevance to condition

The presence and amount of dead wood in a forest are critical indicators of its ecological health. Dead wood plays a vital role in nutrient cycling, provides habitat for numerous species, and contributes to overall biodiversity. An increasing trend could indicate maturation of natural forests, a change in management practices, or a change in ecological conditions. It is most likely that the increase in dead wood in Dutch forests is the result of change in management practices whereby there is reduced intervention by humans (Van der Maaten-Theunissen and Schuck, 2013).

The fact that the converted indicator from the FRA with a density of 300 kilograms per cubic meter aligns more closely with the data from the NBI is a good sign. A higher density usually indicates wood that is less decomposed (Herrmann et al., 2015), potentially implying that it is newer or less affected by decay organisms. A lower density, contrarily, suggests more decomposed wood, which is a crucial part of the forest ecosystem, providing habitat for various species and contributing to nutrient cycling as it breaks down. Old growth forests usually have more decomposed wood available (Öder et al., 2021). Less decomposed wood could be indicative of recent tree mortality, which might be a concern if it is due to disease or pest. The Netherlands seems to have a relatively low density, which reduces the level of concern for the state of dead wood.

However, though dead wood is increasing in the Netherlands, natural forests generally have over 100 m3 of dead wood per hectare on average (Wijdeven, 2006). The indicators for the Netherlands are far below that. In fact, neighboring countries even advise to retain at least 30 m3 per hectare in order to preserve dead wood dependent organisms. Still, the Netherlands is far below that amount.

Continuous monitoring and reporting will be necessary in order to keep track of the impact of management practices.

5. Soil organic carbon

5.1 Introduction

Soil organic matter (SOM) content is the single most relevant soil quality indicator. It contributes to soil physical structure, plays a major role in soil fertility due to its capacity for nutrient retention and supply, water holding capacity and many more soil functions. Apart from these local ecological functions, the storage of carbon in the soil also plays a major role in the global carbon cycle (soils are the second largest carbon pool, after oceans). While in reality soil organic matter has different forms, e.g. particulate organic matter (POM) and the more stable mineral-associated organic matter (MAOM), most soil quality statistics focus on either soil organic matter (SOM) in any form, or just the carbon content, as soil organic carbon (SOC). POM is less decomposed and consists of larger organic particles. MOAM is more stable and finely divided, often attached to mineral particles. SOM or SOC measurements are simpler and less expensive than distinguishing between POM and MAOM. Additionally, SOM and SOC are standard measurements in soil science and they provide a general overview of the soil's organic content. This could make it easier to compare data across different studies or regions.

SOM can be measured in different units. Common units are in mass concentration (g/kg or percentage) or in areal stocks (ton/ha). The choice for a certain unit will be dependent on the application. For example, mass concentration is commonly used in laboratory analyses and provides a direct measure of SOM concentration in the soil sample. Areal stocks are often used in agricultural and environmental management to estimate the total amount of organic matter in a larger, specific area of land.

In this study, we considered two data sets: the national soil sampling program, and the European LUCAS survey. To estimate soil organic carbon for both grassland and cropland as defined by Eurostat:

> *"Soil organic carbon stock in topsoil shall be reported in tonnes/ha, as a national average for the reporting period"*

5.2 Assessing soil organic carbon

5.2.1 Soil organic matter vs Soil organic carbon

While Soil organic matter (SOM) is the more relevant parameter from a soil quality perspective, its carbon content, i.e. Soil Organic Carbon (SOC) is especially relevant from a carbon cycle and climate regulation point of view. The choice by Eurostat to select SOC as the condition variable for cropland and grassland is thus somewhat surprising.

In practice, the difference between SOM and SOC is largely semantic because SOM is often estimated by first measuring SOC (by dry combustion) after which a carbon ratio is used to derive SOM from SOC.

The 'classic' ratio for SOC/SOM is the so-called " van Bemmelen factor" of 0.58 (Minasny et al., 2020), although this value has been since long been criticized, and instead a factor of 0.5 is proposed (Pribyll et al., 2010). In the Netherlands LULUCF context this value is used as well (Lesschen et al, 2012). While the national soil sampling program (discussed in the next paragraph), by measuring SOC and SOM independently from each other (SOC by dry combustion; SOC by dry ignition) found a ratio of 0.54, it was argued that more insight in uncertainties and links to different soil types would be required before adjusting the values of 0.5 as used in a LULUCF context. In the current study we used a value of 0.5 in all cases.

5.2.2 Data

The national Soil Sampling Program (SSP)

In the Netherlands, SOM measurements are routinely carried out as a part of soil quality data monitoring. Most of this data is, however, commissioned by farmers and/or land owners, private and not available for official statistics. Publicly available SOM data are collected as part of the national Soil Sampling Programme (SSP). This program was originally set up 30 years ago to provide data to describe the soil properties of the map units of the then national 1:50 000 soil map. To this end, 1396 randomly selected sites were sampled between 1994 and 2001. In 2018, 1152 of these sites were re-visited[2]. SOM and SOC content was measured using standard procedures (Knotters et al., 2022).

European: LUCAS

LUCAS (Land Use/Cover Area frame statistical Survey) is a pan-European network of land and soil monitoring. The LUCAS program is organised and managed by Eurostat to monitor changes in Land Use (LU) and Land Cover (LC) over time across the EU. Since 2006, Eurostat has carried out LUCAS surveys every three years. The surveys are based on the visual assessment of environmental and structural elements of the landscape in georeferenced control points. The points belong to the intersections of a 2 x 2 km regular grid covering the territory of the EU. This results in around 1 000 000 georeferenced points. In every survey, a subsample of these points is selected for the collection of field-based information (Fernandez-Ugalde et al., 2022).

The soil assessment module of LUCAS is the only mechanism that currently provides a harmonised and regular collection of soil data for the entire territory of the European Union, addressing all major land cover types simultaneously, in a single sampling period (April – October).

In total, 27 069 locations across Europe were identified for soil sampling during the 2018 survey, of which 19 777 locations were actually sampled. Of these, 99 were located in the Netherlands. On average, the median sampling density was approximately 250 km^2 per sample, which is at the lower limit for applications related to trends in SOC. In the Netherlands, the density is > 400 km^2 for most provinces, with Flevoland (100-200 km^2) as an exception, which would suggest that the LUCAS soil survey is too sparsely.

At each location a 500 g composite soil sample was taken between 0-20cm depth. Each composite sample consists of five subsamples, taken at a distance of 2m from the main point. Soil organic content is determined by standard procedure (dry combustion; ISO 10694:1995) and reported in g /kg (with 1 decimal precision)

In addition, the depth of the organic horizon was measured at each LUCAS point that had an OC content of >200 g /kg and/or was classified as wetland in the LUCAS survey.

For a subset of sites bulk density was measured for various depths (0–10cm, 10–20cm, 20–30cm).

In the Netherlands, in total 99 soil samples were taken, of which 47 in cropland, 33 in grassland, 13 in woodland and the remaining samples in other land cover types.

---

[2] The remaining sites were either urbanized, inaccessible, or no permission was granted.

5.2.3 Methods

SSP

SSP data were not analyzed directly. Instead, results were taken from the associated publications, i.e. van Tol-Leender et al., (2019); Knotters et al., (2022). It seems worthwhile to mention that two different approaches were used to classify individual soil samples as either "mineral" or "organic":

- By matching sample location and soil map unit (geomatching).
- By classification on the basis of soil profiles observed at the sampling location (class matching).

Where SOM was reported instead of SOC a SOC/SOM ratio of 0.5 was used.

LUCAS

LUCAS data for 2018 were downloaded from the ESDAC website[3] and analysed. For sites where bulk density was measured for both 0–10cm and 10–20cm, reported mean bulk density density for 0–20cm were used to convert organic carbon content (g / kg) to soil organic carbon in the requested units (ton / ha).

5.2.4 Results

National: SSP

On average, the SOC content of the topsoil (0-30cm) for the non-built-up area of the Netherlands is 3.22%. However, there is considerable variance between the major soil types. For mineral soils, SOC is lower (2.06%) while for organic soils SOM is much higher (8.05%). For soils that have organic horizons, but do not classify as organic soils, SOC in the top soil depends on the depth of the organic layers. If this is in the top 30cm, SOC is 3.96%, between the values for of mineral and organic soils, while if the organic layers are deeper in the profile, SOC (2.09%) resembles that of mineral soils (Table 18).

Table 18. SOC by soil type. Modified after van Tol-Leender et al. (2019).

Strata	Area	Soil Organic Carbon							
		0-30cm				30-100cm			
	ha	ton/ha		percent		ton/ha		percent	
Netherlands, non urban	**2.870.671**	**92,91**	**(1,22)**	**3,22%**	**(0,07%)**	**120,47**	**(2,20)**	**2,56%**	**(0,08%)**
of which:									
Mineral soils	1.039.521	74,235	(1,77)	2,06%	(0,07%)	81,225	(2,97)	0,89%	(0,04%)
Organic soils	393.685	162,84	(4,28)	8,05%	(0,40%)	264,875	(7,72)	9,75%	(0,49%)
Organic top soil (0-30cm)	393.685	108,265	(3,95)	3,96%	(0,20%)	143,46	(7,25)	2,89%	(0,24%)
Organic sub soil (30-100cm)	941.203	76,1	(1,59)	2,09%	(0,05%)	91,155	(3,04)	1,20%	(0,07%)

[3] https://esdac.jrc.ec.europa.eu/content/lucas-2018-topsoil-data

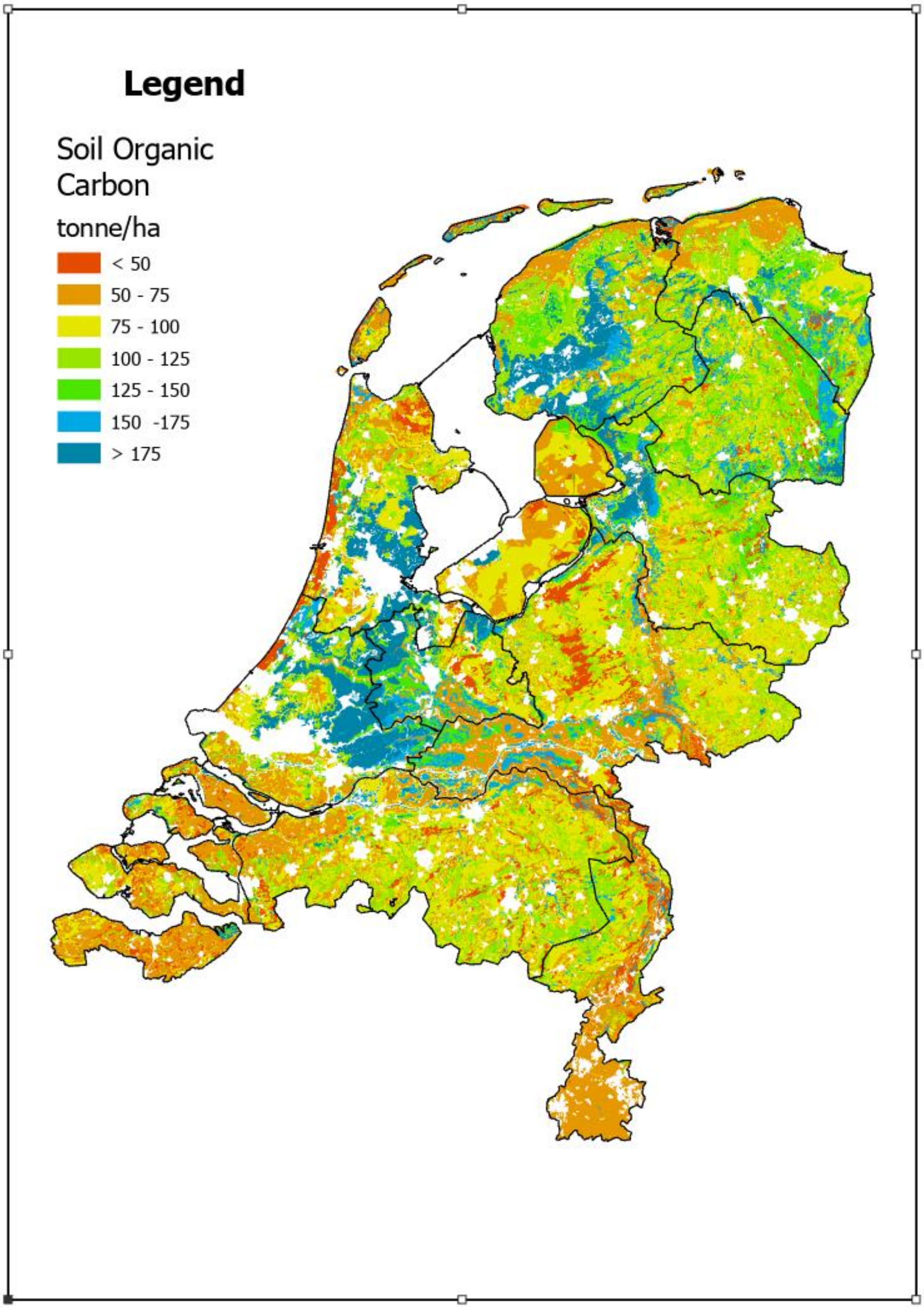


Figure 10. Soil Organic Carbon (tonne/ha for the top 30cm) in the Netherlands, 2018. Data: National Soil Survey Program.

In the Netherlands, land use (cropland or grassland) is correlated with soil type (Table 19). Especially peat soils and peaty soils are dominated by agricultural grassland (89% and 65% of these soil types, respectively).

Table 19. Land use per major soil type. Modified after van Tol-Leender et al. (2019).

Soil type	**Land cover**									
	Agricultural				**Nature**				**Total**	
	Cropland		Grassland		Forest		Other			
Sandy soil (thick earth layer)	97.896	36%	151.390	55%	23.466	9%	2.496	1%	**275.248**	**10%**
Sandy soil (other)	241.080	21%	500.967	44%	318.606	28%	81.626	7%	**1.142.279**	**41%**
Clay soils	399.855	40%	574.408	57%	20.785	2%	5.337	1%	**1.000.385**	**35%**
Loam soils	17.731	37%	18.992	39%	11.828	24%	-	0%	**48.551**	**2%**
Peaty soils	19.166	18%	68.648	65%	10.564	10%	7.652	7%	**106.030**	**4%**
Peat soils	16.750	7%	219.638	89%	5.919	2%	5.392	2%	**247.699**	**9%**
Total	**792.478**	**28%**	**1.534.043**	**54%**	**391.168**	**14%**	**102.503**	**4%**	**2.820.192**	

It was also found that SOC content stratified by soil type varied by method (Table 20). Classifying individual samples by soil profile characteristics (classmatching) resulted in higher SOC than if samples were classified by soil units (geomatching). This phenomenon was explained by the partial impurity of the soil maps (Knotters et al., 2022). Note that the fact that SOC increases for both soils when using classmatching could be explained by assuming that the 'erroneous' samples are organic-rich that classify as organic when using geomatching but as mineral when using classmatching. These soils can be expected to have a relatively high SOM for mineral soils (hence increasing their mean SOC) and a relatively low SOC for organic soils (hence increasing the average SOC for the remaining samples).

Table 20. SOC content for mineral and organic soils using geomatching and clasmatching. Significant changes are in bod (at a 5% significance level). Modified after Knotters et al. (2022).

Soil type	**Depth**	**Method**	**SOC content (g/kg)**					
			1998		2018		Change	
Mineral	0–30 cm	Geomatching	19,93	(0,55)	20,595	(0,62)	0,665	(0,64)
		Classmatching	24,86	(0,65)	23,92	(0,71)	-0,945	(0,49)
	30–100 cm	Geomatching	9,14	(0,40)	8,915	(0,39)	-0,225	(0,44)
		Classmatching	17,1	(0,84)	14,01	(0,74)	**-3,09**	(0,68)
Organic	0–30 cm	Geomatching	79,59	(6,04)	81,575	(4,08)	1,985	(5,09)
		Classmatching	93,18	(7,53)	90,705	(5,64)	-2,475	(5,72)
	30–100 cm	Geomatching	140,385	(8,17)	104,1	(5,24)	**-35,785**	(7,40)
		Classmatching	163,385	(10,91)	115,745	(7,52)	**-47,64**	(7,91)

The ecosystem map developed for 2018 as part of the Netherlands Ecosystem Account was used to compute SOC by ecosystem type. For cropland mean SOC is 88 ±70.5 tonne/ha (median: 84.0), while for grassland mean SOC is 125.5 ± 120.7 tonne /ha (median: 112.6). The large standard error suggests that variability within land use is considerably. Knotters et al., (2022) list SOC for cropland (69.5 tonne/ha) and grasslands (100.8 tonne/ha) on mineral soils only.

LUCAS

In total, data on soil organic carbon was available for 74 sites. For 21 of these (28%), bulk density was available to allow the conversion of organic carbon content as mass fraction to mass per area for the top soil.

Across all land use classes, the mean SOC is 33.4 ± 75.7 g/kg (n=74; median=18.9), or 92.8 ±140.7 ton/ha (n=21; median=69.7), which is lower than average for the Atlantic climatic zone (mean: 41.5 ± 134 g/kg; median: 22.6), as reported by LUCAS, and sites in between the values for mineral and organic soils, as found in the National surveys for mineral soils (Table 20).

Cropland

All 47 cropland samples were taken on agricultural land. Based on the raw LUCAS data, the organic content in the top soil (0-20cm) is 21.2 ± 39.8 g/kg (median 15.5), which suggests a huge variation. Close inspection of the underlying distribution shows that the vast majority of the samples have SOC < 25 g/kg (Figure 11). After removal of the samples with (much) higher SOC, the mean SOC is 15.9 ± 8.8 g/kg (median 14.9), although the underlying distribution suggests a bimodal distribution with peaks at approximately 14 and 23 g/kg (Figure 11). Throughout the LUCAS region, SOC for cropland is generally somewhat higher (mean: 18.3; median: 14.7 g/kg).

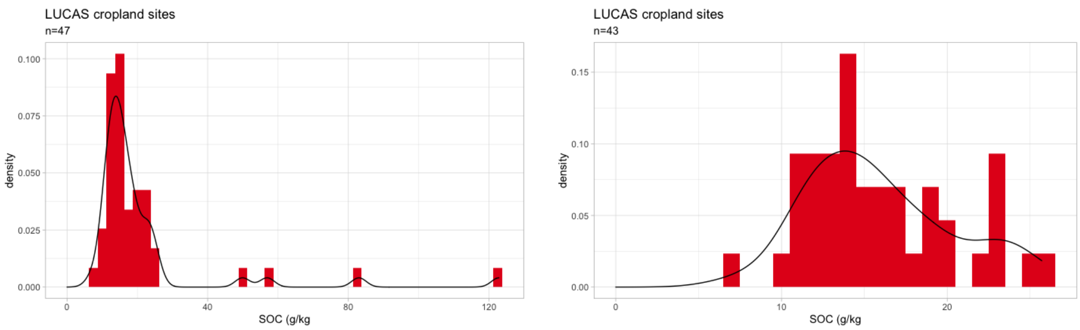


Figure 11. Distribution of SOC for cropland locations. Left: all data points. Right: for SOC < 25 g/kg.

Conversion of organic carbon content (g/kg) to ton/ha was possible for 11 out of 43 sites (26%) where bulk density was available, resulting in a mean value of 48.7 ± 27.3 ton/ha (median 41.0) for the top 20 cm.

Regional differences

Some attempt has been made to describe the regional variability in SOC (Table 21). For NUTS level 1, SOC on croplands is higher than average in the Eastern and Southern parts of the Netherlands. These are the regions that are overall characterized by more sandy soils. On the peat and clay soils of the West and North, SOC is lower.

The sample picture emerges when looking at NUTS level 2 (provinces). SOC levels are highest in provinces with a large amount of sandy and loamy soils (Drenthe, Gelderland, Overijssel) and lowest in provinces with a lot of clay soils, like Flevoland and Friesland. The province of Limburg (sand and loess soils) seems to be an anomaly, but since n = 1 it would be difficult to draw any conclusions. For the provinces of Utrecht and Zuid-Holland no data are available at all. In addition For thee out of the remaining ten provinces less than 3 sample sites were available, limiting the assessment of uncertainty in the mean values on that level.

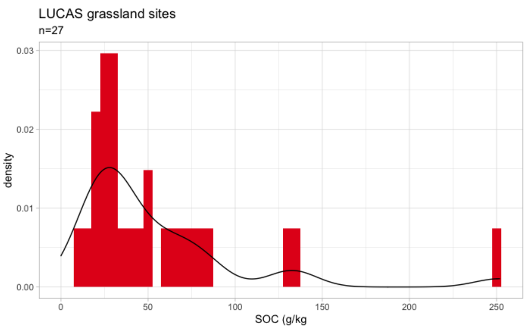
Bulk density, required to convert organic carbon content to ton per hectare, was only available for seven out of twelve provinces. On the NUTS-1 level, for two out of four regions only one data point was available.

Table 21. Soil organic matter statistics for cropland sites on various spatial scales.

Land use	NUTS level	Region		SOC (g/kg) n	mean			median	SOC (ton/ha) n	mean			Median
Cropland	0	NL	Netherlands	43	15,9	±	8,8	14,9	11	48,7	±	27,3	41,0
	1	NL1	North	9	15,0	±	11,2	12,0	3	46,4	±	40,3	35,7
		NL2	East	22	16,9	±	7,5	15,8	6	50,6	±	27,1	45,4
		NL3	West	6	13,1	±	3,8	12,5	1	39,6			39,6
		NL4	South	6	16,5	±	11,4	18,1	1	52,7			52,7
	2	NL11	Groningen	3	16,7	±	16,3	14,5	1	69,6			69,6
		NL12	Friesland	5	12,4	±	3,6	12,0	2	34,8	±	2,5	34,8
		NL13	Drenthe	1	22,8			22,8	0				
		NL21	Overijssel	4	16,7	±	8,9	15,4	3	51,1	±	21,6	49,8
		NL22	Gelderland	3	22,0	±	7,2	23,5	1	71,5			71,5
		NL23	Flevoland	15	16,0	±	5,9	15,2	2	39,4	±	0,9	39,4
		NL31	Utrecht	0					0				
		NL32	Noord-Holland	1	11,3			11,3	0				
		NL33	Zuid-Holland	0									
		NL34	Zeeland	5	13,4	±	3,8	12,9	1	39,6			39,6
		NL41	Noord-Brabant	5	18,3	±	7,8	18,9	1	52,7			52,7
		NL42	Limburg	1	7,3			7,3	0				

Grassland

Of the 33 grassland samples, 27 samples were taken on locations with agricultural land use. The remaining land uses were road and water transport (i.e., probably verges), sport, (semi-) natural and abandoned land. For the agricultural sites, SOC = 54.6 ± 50.9 g /kg (median SOC = 33.5 g /kg) (Figure 12). Again, this large variance is partly due to some high SOC values. For the 17 samples with SOC < 100 g /kg the mean SOC = 27.6 ± 9.7 g /kg (median 27.5). Again, there are some indications for a bimodal distribution (peaks at ~ 18 and 29 g /kg) (Figure 12). Throughout the LUCAS region, SOC for grassland is generally somewhat higher (mean: 40.2) or similar (median: 27.7 g/kg), depending on the metric.



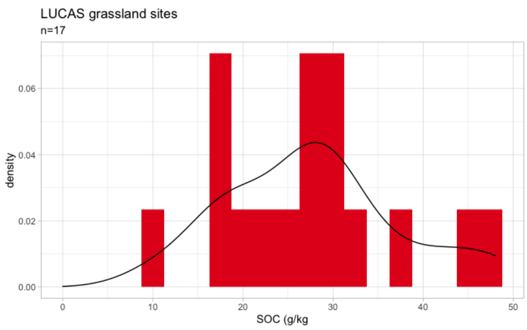


Figure 12. Distribution of SOC for grassland locations. Left: all data points. Right: for SOC < 25 g/kg.

Conversion of organic carbon content (g/kg) to ton/ha was possible for only 3 out of 17 grassland sites (18%) where bulk density was available, resulting in a mean value of 66.5 ± 45.8 ton/ha (median 77.5) for the top 20 cm.

Regional differences

For grassland sites, SOC is higher than average in the Northern and Southern parts of the country, which cannot be easily explained in terms of soil type. On the province level (NUTS 2), SOC appears to be highest in Noord-Brabant and Gelderland (both provinces with a lot of sandy soils) and lower in Overijssel (also sandy soil) (Table 22). Again, it would be difficult if not impossible to explain these differences in terms of geology and soil type, also because of the small number of samples (one sample each for six out of twelve provinces; two provinces, Drenthe and Zuid-Holland don't have any samples).

The data coverage for bulk density was even worse. This was available for only two out of four NUTS-1 regions and three out of 12 provinces.

Table 22. Soil organic matter statistics for grassland sites on various spatial scales.

Land use	NUTS level	Region		SOC (g/kg) n	mean			median	SOC (ton/ha) n	mean			Median
Grassland	0	NL	Netherlands	17	27,7	±	19,4	27,5	3	66,5	±	45,8	77,5
	1	NL1	North	4	33,6	±	19,6	30,0	0				
		NL2	East	6	25,8	±	12,8	27,2	2	79,7	±	6,0	79,7
		NL3	West	2	14,0	±	8,8	14,0	1	40,2			40,2
		NL4	South	5	30,7	±	20,4	28,1	0				
	2	NL11	Groningen	1	30,0			30,0	0				
		NL12	Friesland	1	48,0			48,0	0				
		NL13	Drenthe	2	28,1	±	5,4	28,1	0				
		NL21	Overijssel	3	23,2	±	17,8	18,2	1	81,8			81,8
		NL22	Gelderland	2	29,1	±	4,4	29,1	1	77,5			77,5
		NL23	Flevoland	1	26,8			26,8	0				
		NL31	Utrecht	0					0				
		NL32	Noord-Holland	1	10,9			10,9	0				
		NL33	Zuid-Holland	0									
		NL34	Zeeland	1	17,1			17,1	1	40,2			40,2
		NL41	Noord-Brabant	4	33,5	±	18,8	33,4	0				
		NL42	Limburg	1	19,7			19,7	0				

Comparison between grassland and cropland

Overall, according to the LUCAS 2018 soil survey, SOC on grassland (~28 g/kg) is (much) higher than on cropland (16 g/kg), as confirmed by a t-test ($p<0.001$), although the spatial variability is large (COV is 30% for cropland and 38% for grassland). This disparity in SOC levels can be attributed to various factors. Grasslands typically have more permanent vegetation cover, leading to greater accumulation of organic matter, compared to croplands which often undergo tillage and crop rotation, disrupting soil structure and hastening organic matter decomposition. Different soil types also play a role, with certain soils inherently better at storing organic carbon.

Additionally, the extensive root systems of grassland vegetation contribute more organic residues to the soil than the shallower root systems of many crops. Furthermore, crop residue management practices on croplands, where residues are often removed or minimally incorporated, limit organic matter inputs to the soil. In contrast, in grasslands, the decomposition of plant material directly enhances the soil organic matter pool. These management and environmental factors collectively contribute to the observed differences in SOC levels between these two land use types.

5.3 Discussion

First of all we note that the current legal text for this condition variable requires the measurement of soil organic *carbon* (SOC) instead of soil organic *matter* (SOM), which is arguably more relevant from an ecosystem functioning point of view. At the same time, we note that difference is perhaps just semantic because in practice fixed (but ill-defined) SOC/SOM ratios are being used.

Data from the LUCAS soil survey was found to enable the computation of soil organic carbon on various levels, although the relative scarcity of bulk density limited the reporting in the requested units (tonne /ha) for cropland on the NUTS-1 level, and for grassland on the NUTS-0 (national) level (Table 23). While strictly speaking this would be sufficient for reporting to Eurostat, this data scarcity would severely limit the applicability for application for national and regional policy development or evaluation. It is thus recommended to measure and report soil bulk density for all sites where soil organic carbon content is measured.

Table 23. Data availability for soil organic carbon based on the LUCAS 2018 soil survey

Ecosystem Type	Unit	NUTS level		
		0	**1**	**2**
Cropland	g/kg			
	tonne/ha			
Grassland	g/kg			
	tonne/ha			

At least 3 data points available

1 or 2 data points available

No data available

Furthermore, the current legal definition of the condition indicators does include units (tonne/ha) but fails to define the thickness of the “top soil”. Since LUCAS SOC data are measured for the top 20 cm, we used that thickness in the analysis of that data. In the national soil survey a different thickness of 30cm was used, severely limiting the direct comparison of the two data sets. We therefore recommend including the thickness into the definition for the condition variable.

However if we would assume the 0-30cm root zone to be homogenous, we could compare the national SSP values (0-30cm) with the LUCAS data (0-20cm) by adjusting for this difference. Doing so results in approx. 59 tonne/ha for cropland (all soils) or 46.4 tonne/ha (mineral soils, based on Knotters et al., (2022), for the soil survey data, and 48.7 tonne/ha for LUCAS. For grassland, these values are 84 tonne/ha (SSP, all soils), 67.2 tonne/ha (SSP, mineral soils, adapted from Knotters et al., 2022), and 66 tonne/ha (LUCAS), respectively. It thus seems that the LUCAS data, after censoring for high values that are likely associated with organic soils, correspond fairly well with the SSP national survey data. Nevertheless, we recommend to report SOC values stratified by ecosystem type and soil type, and ensure enough data points for each combination.

6. Artificial impervious area cover in coastal areas

Artificial impervious areas, characterized by surfaces that do not absorb water – such as roads, buildings, and other urban infrastructures – play a significant role in environmental and urban planning, especially in coastal areas. These surfaces alter natural land cover, impacting water runoff patterns, reducing soil permeability, and potentially exacerbating flooding, which is a critical concern in low-lying coastal regions like the Netherlands. Moreover, the increase in impervious surfaces is often a direct indicator of urban expansion and development, reflecting socioeconomic dynamics. In coastal zones, where ecosystems are sensitive and land use pressure is high, monitoring the growth of artificial impervious areas is essential for sustainable coastal management, balancing developmental needs with environmental conservation and resilience against climate change impacts such as sea-level rise. Understanding the extent and expansion of these areas are crucial for informed decision making regarding urban planning, environmental protection, and disaster risk mitigation in these vulnerable regions.

In this chapter we explore the different ways to define the coastal area, calculate the amount of impervious area using different data sources, and discuss the importance and limitations to this indicator.

6.1 Spatial delineation of coastal areas

6.1.1 Previous attempts by Statistics Netherlands

Statistics Netherlands has undertaken previous approaches to delineate the Dutch coastal zone for other studies. These approaches differ from the proposed method by Eurostat. Rather than using an administrative units perspective, previous attempts of delineating the Dutch coastal zone were done following a more nature-based perspective. These approaches are briefly described below.

In 2020, Statistics Netherlands published a report named the *Economic description of the Dutch North Sea and coast: 2010, 2015 and 2017*[4]. This study presents an economic valuation of activities related to the Dutch North Sea. Besides accounting for economic activities that take place on the North Sea, such as shipping, fishing or oil and gas production, also the activities on land related to the coastal area of the North Sea, such as hotels and restaurants and recreational, cultural and sporting activities, were included in this study. For this analysis, a coastal area was defined to select the relevant economic activities related to the Dutch North Sea coast.

For the 2020 study, the coastal area was defined as the one-kilometer wide strip of land *behind* the Dutch North Sea coastline and the Wadden Islands. The decision to use a one-kilometer wide strip is a pragmatic choice, based on the trade-off between the desire to fully represent the Dutch North Sea economy and, at the same time, not accounting for economic activities that are not considered part of the Dutch North Sea economy. In this demarcation, the coastline included the North Sea shoreline and the adjacent 'dry natural open area' according to the 2015 land-use map of Statistics Netherlands (*Basisbestand Bodemgebruik*)[5]. In the land-use map, the 'dry natural open area' category included dry heather, grass like natural areas, dunes, sand drift, sandbars and beaches.

[4] https://www.cbs.nl/en-gb/custom/2020/19/economic-description-of-the-dutch-north-sea-and-coast
[5] https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/bestand-bodemgebruik (Dutch only)

In 2023, Statistics Netherlands published an update of the report of the economic description of the Dutch North Sea and coast[6]. In this study, the spatial demarcation of the North Sea coastal area was changed compared to the previous report. The methodology for the spatial delineation was changed in two significant aspects.

Firstly, the ecosystem type map of Statistics Netherlands[7] - created for ecosystem accounting – was used instead of the land-use map. This change was made because the ecosystem type map contains a more recent and detailed mapping of the different natural ecosystems of the Netherlands than the land-use map. Consequently, the ecosystem type map enabled a more precise delineation of the Dutch natural coastal area. Four different ecosystem types were categorized as coastal ecosystems: beaches, coastal dunes, salt marshes and dune forests. Including these four ecosystems resulted in a greater area than the previous delineation based on the 'dry natural open area' bordering the North Sea shoreline. This is predominantly due to the inclusion of dune forest, which was not included in the 'dry natural open area' category. Including dune forests in the delineation extends the coastal area further inland.

Secondly, the 'one-kilometer rule' of the 2020 study was evaluated. Under this rule, the coastal area is defined as a one-kilometer wide strip of land behind the beaches and sand dunes. This approach, however, excluded economic activities from the analysis that may take place on the beach or in the dunes. Therefore, in the 2023 update, the coastal area of the Netherlands was defined as the North Sea shoreline, the four coastal ecosystems and a one kilometer strip of land. As in previous studies, the Wadden Islands were included in their entirety.

6.1.2 Testing and development of the coastal extent

In order to assess the condition of ecosystems, it is essential to accurately delineate coastal areas, as they represent the dynamic interface between land and water, significantly influencing both natural and human activities. The development of the guidelines by the Taskforce on Ecosystem Accounting have seen multiple definitions of the coastal area extent. In the second version, a clear definition of coastal areas was provided, categorizing them as local administrative units (LAUs) that either border or are in close proximity to a coastline, with at least 50% of their surface area situated within a 10-kilometer distance from the coastline.

However, the guidelines undergo constant evolution and the definition of the coastal extent changed to a focus on using beaches, coastal dunes, and wetlands near the Sea. It did not include the use of LAUs anymore.

In an attempt to create an extent that is pragmatic, but also a compromise with our previous work by Statistics Netherlands and the Eurostat definitions, we also created an extent based on a 10 kilometer buffer form the North Sea. This way the extent would be more constant and comparable over the longer term, but still 10 kilometers wide.

In the latest version of the guidelines, published on the 28th-29th of November 2023, the definition of the coastal extent changed again. The coastal extent has been defined as *"1 km inland from the seas's medium high water line".* Given that these new guidelines were published at a stage when our research was already significantly advanced, we made the decision not to include this version of the guidelines in our report.

6.1.3.1 Method based on LAUs

[6] https://www.cbs.nl/en-gb/background/2023/26/economic-description-of-the-dutch-north-sea-and-coast
[7] https://www.cbs.nl/en-gb/society/nature-and-environment/natural-capital/ecosystem-types

The guidelines in version two defined the coastal extent based on LAUs and proximity to the North Sea. The coastline itself is defined as the demarcation where land and water surfaces meet during mean high tide, while LAUs that do not meet these criteria are classified as non-coastal.

To achieve a precise delineation of coastal extents for our project, a tailored geospatial methodology was developed using Python and ArcPython. This methodology comprises the following steps:

Our initial step involved gathering essential datasets:

- **Municipality polygons (2022)**: We collected and processed all municipality polygons for the year 2022, converting them into a feature layer.
- **Provincial polygons**: We dissolved provincial boundaries to create a unified national polygon.
- **National Ecosystem Extent Map**: We extracted the North Sea region from the national ecosystem extent map.

Next, we created a 10-kilometer coastal buffer zone:

We buffered the North Sea polygon by 10 kilometers, effectively establishing a coastal buffer zone. To ensure alignment with administrative boundaries, this buffer was then clipped by the dissolved provincial polygons.

Our methodology then involved the calculation of overlapping areas:
The clipped buffer zone was intersected with the municipalities, enabling us to compute the exact overlapping area in square meters. Data attributes were seamlessly integrated into the intersected features using the JoinField function, facilitating a comprehensive analysis of overlap.

We classified and exported the results based on the degree of overlap:
Councils with more than 50% overlap with the 10-kilometer buffer were selected and exported as a distinct category. Councils with less than 50% overlap but still bordering the North Sea were clipped using the 10-kilometer buffer from the North Sea. These clipped councils were further refined through location selection, with a tolerance of 0 meters from the North Sea, resulting in the identification of councils solely within the 10-kilometer buffer. To ensure a unified coastal extent, we merged these two sets of council features (those fully within the buffer and those bordering the North Sea).

We further refined the coastal boundary:
The original 10-kilometer buffer, which had not been clipped, was overlaid with the merged coastal polygon. We used the Erase function to remove the overlapping portion, ensuring the buffer precisely aligned with the merged coastal extent. For accurate ecosystem extent mapping, we selected relevant ecotype categories from the national ecosystem extent map, including North Sea, Wadden Sea, Estuary, Other Sea, Intertidal, and brackish water.

Finally, due to the islands of the Wadden Sea, the 10-kilometer buffer assigned the coastal extent to some parts of the mainland in the North of the Netherlands. This issue arose due to some municipalities including water from the Wadden Sea. Therefore, the polygons bordered the North Sea, while the actual land did not. To solve this issue, we converted the coastal polygon into multiple polygons and removed the incorrect polygons by hand. The resulting extent is shown in Figure 13.

Figure 13. Coastal extent of the Netherlands based on the LAU system.

6.1.3.2 Method based on ecotype

In the guidelines, a refined approach to coastal extent delineation included recognition of the significance of certain ecotype categories. To comply with these new guidelines we initiated the process by identifying the relevant polygons and regions that are most pertinent to our assessment, specifically focusing on the North Sea and intertidal zones.

The relevant datasets were:

- **National Ecosystem Extent Map**: We extracted the North Sea region from the national ecosystem extent map as well as the intertidal zone bordering the North Sea. These were then merged into one big polygon. We continued to utilize the national ecosystem extent map, extracting only the ecotype categories of coast, dunes and wetlands to narrow our focus.

We employed a methodology that specifically identified polygons from the national ecosystem extent map within 5 km of the North Sea and intertidal zone. The resulting polygons were then selected based on ecotype. Only the ones with ecotype ‘beach’, ‘dune’, or ‘wetland’ were kept, as specified in the amendment to the guidelines. The resulting extent is shown in Figure 14.

Figure 14. Coastal extent of the Netherlands based on the ecosystem approach.

6.1.3.3 Method based on buffer

The final methodology, while innovative, diverges from the guidelines from the Taskforce on Ecosystem Accounting, recognizing the inherent challenges associated with the guidelines for the coastal extent. To overcome inconsistencies in resolution of ecosystem extent maps and size of LAUs and ecosystems which change over time, we devised an approach for creating a 10-kilometer buffer form the North Sea and subsequently clipping it by the polygons delineating the Netherlands (Figure 15).

The relevant datasets are:

- **Provincial polygons**: We dissolved provincial boundaries to create a unified national polygon.
- **National Ecosystem Extent Map**: We extracted the North Sea region from the national ecosystem extent map.

Figure 15. Coastal extent of the Netherlands based on the ten-kilometer buffer approach.

6.2 Assessing artificial impervious area in coastal areas

6.2.1 Data types

Our study employed two distinct datasets to assess the extent of impervious surfaces in the Dutch coastal regions. The first dataset is from the Dutch Top10NL dataset, a component of the Dutch national database of topographic information. The dataset comprises polygons representing buildings, which are key indicators of impervious surfaces. The dataset is available for each year of our study period, allowing for a consistent annual analysis of built-up areas. The polygonal data also ensures accurate and detailed outline of the built structures. This level of detail is essential for precisely calculating the extent of impervious surfaces within our defined buffer zones.

The second dataset is the Copernicus imperviousness dataset. This dataset, part of the Copernicus Land Monitoring Service, provides detailed information on the degree of imperviousness. The years 2012 and 2015 are available with a spatial resolution of 20 meters. This resolution is sufficiently detailed to capture significant urban features and allows for a comprehensive analysis of impervious surfaces. It is less well suited for detecting smaller areas of imperviousness. The 2018 dataset provides an improved resolution of 10 meters. This enhancement provides a more detailed view of impervious surfaces, allowing for finer-scale analysis and potentially revealing smaller-scale changes not captured in the earlier data. A caveat in the results is then that increased impervious area in the results over time could be due to resolution and not due to actual increased imperviousness.

6.2.2 Methods

The initial step in our assessment involved choosing the appropriate coastal extent. After evaluating the three options in 6.1.3, we decided to use the 10-kilometer buffer approach. This method was selected for its comprehensive coverage, in line with Eurostat's first approach, and the possibility to use extent accounts as a measure of imperviousness without subjectivity to how defined an extent is.

We then employed two distinct methods to assess imperviousness within the defined coastal extent. The first approach involved an overlay of the 10km buffer with the TOP10NL buildings layer. This process was conducted for the years 2013, 2015, 2018, 2020, and 2021. The missing years could not be computed due to data limitation for the Dutch extent map. By overlaying the buffer with building polygons, we were able to calculate the percentage of the buffer area covered by buildings.

The second approach, while utilizing the same 10km buffer, differed in its data overlay. Instead of the buildings layer, we overlaid the buffer with Copernicus data on imperviousness for the years 2012, 2015, and 2018. This method offered a different perspective, leveraging the European Union's Earth observation program to quantify imperviousness. More years were available for the imperviousness dataset by Copernicus (2006 and 2009), however we decided not to use these layers, as the Dutch extent map from which we can calculate our coastal extent only goes back to 2013. Therefore, for the year 2012, we also used the extent from 2013.

For both methods, the analysis was conducted using ArcPython, which facilitated complex geospatial calculations and manipulation. The results were then visually assessed in ArcGIS.

6.2.3 Results

6.2.4.1 Overlay with buildings layer (Top10NL)

In our analysis of impervious surface areas within the 10-kilometer coastal buffer using the Top10NL buildings layer, we observed a gradual increase in imperviousness over the period from 2013 to 2021 (Figure 16). The percentage of impervious areas rose from 5.22% in 2013 to 5.33% in 2021, demonstrating a consistent yet subtle upward trend. The data for the intermediate years further underscored this progression: 5.23% in 2015, 5.26% in 2018, and 5.31% in 2020. These figures reflect a steady increase in built-up areas along the coastal region of the Netherlands. Despite the relatively small annual changes, the cumulative effect over the eight-year span highlights a notable expansion in urban development and changes in land use within the studied coastal buffer zone.

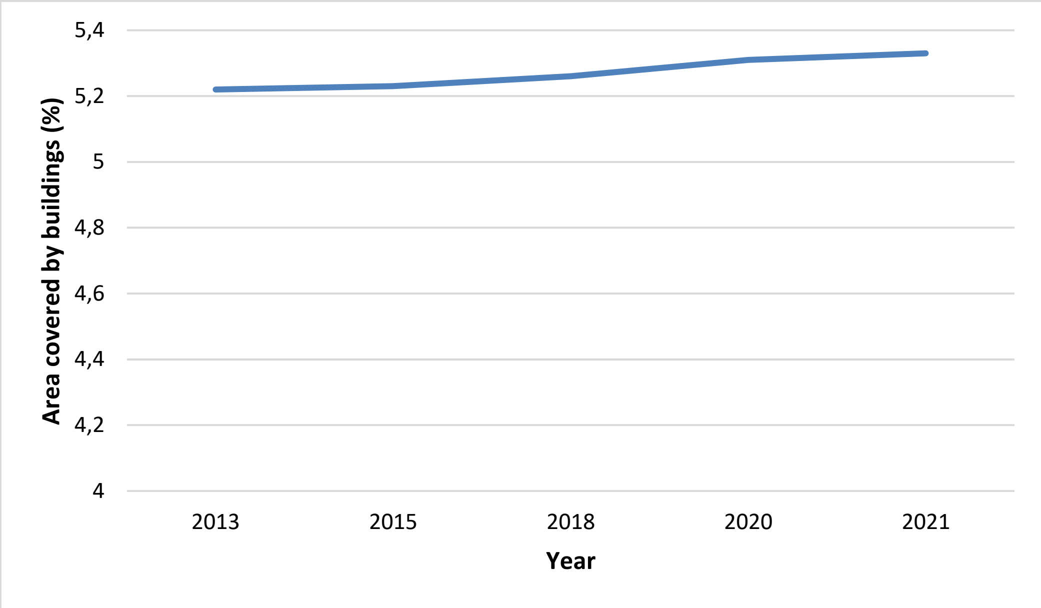


Figure 16. The percentage of coast in The Netherlands (10km buffer from the North Sea excluding areas beyond the Wadden Sea) which was covered by buildings for each year.

6.2.4.2 Overlay with Copernicus imperviousness data

The imperviousness density of the Copernicus datasets shows an upward trend between the years 2012 and 2015 (Figure 17), just like the method using the building polygons. However, the percentage of cover by impervious areas is about twice the size of the building polygons cover, according to the Copernicus dataset. In 2012, the Copernicus dataset reports 10.78% and in 2015 it reports 11.85%. Additionally, there is an imperviousness indicator for the year 2018. However, contrary to the trend before 2018, the imperviousness now drops significantly to 9.24%.

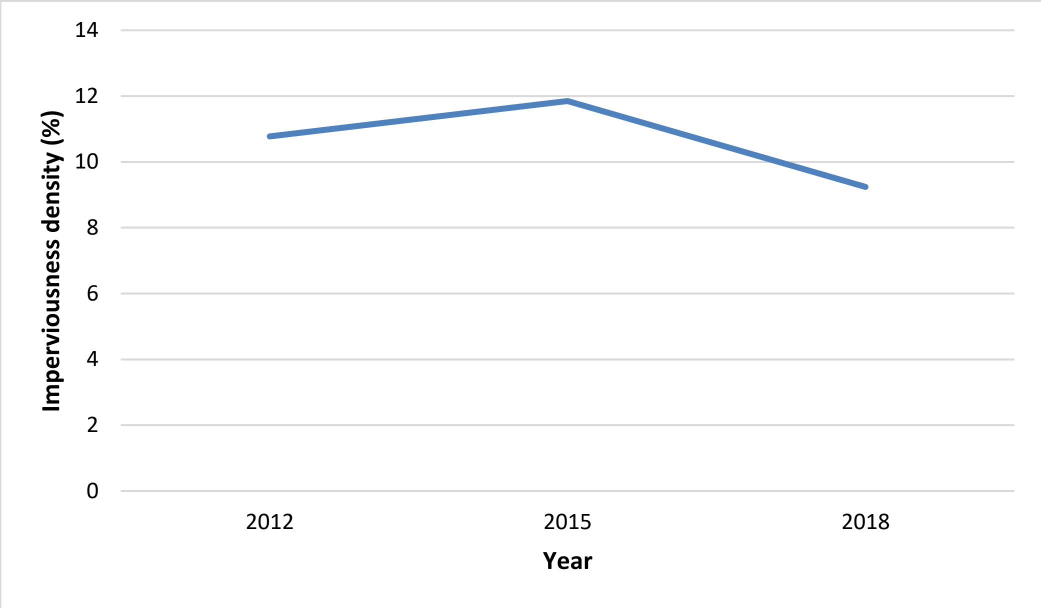


Figure 17. The percentage of coast in The Netherlands (10km buffer from the North Sea excluding areas beyond the Wadden Sea) which was covered by impervious surfaces for each year.

6.3 Discussion

6.3.1 Coastal extent

In the pursuit of constructing a reliable indicator to monitor artificial impervious area within coastal zones, the definition of the coastal extent might become a pivotal consideration. In this study we compare three different approaches based on; LAUs, ecotype, and a buffer.

The overarching objective is to capture the transformation of coastal ecosystems due to the encroachment of artificial, impervious surfaces. It would therefore be a primary indicator of ecosystem degradation. The approach to use the ecotypes coastal beaches, dunes and wetlands, as the foundation for delineating coastal extent aligns most closely with this overarching objective. By focusing on specific natural features vulnerable to change by human activities, including infrastructure development, this approach offers a direct and ecologically meaningful representation of coastal ecosystems. It enables nuanced assessments of preservation or conversion, thereby enhancing our understanding of the ecological integrity of coastal zones.

However, varying resolutions in the ecosystem extent across different countries can introduce discrepancies when identifying artificial impervious areas. This issue can arise in the LAUs method as well as in the ecotype method. To ensure comparability and consistency in the assessment process, it is advisable to establish a set resolution within the guidelines for all participating countries. This standardization not only mitigates the potential bias stemming from differing resolutions but also fosters robust cross-country and longitudinal comparisons, helping to improve the reliability of the indicator.

As described above, previous attempts of delineating the Dutch coastal zone differs from the proposed approach by Eurostat. The different approaches will likely lead to different results.

In general, the ‘ecosystem-based’ approach as used in the Statistics Netherlands (2023) report leads to a smaller delineation of the coastal zone compared to the Eurostat approach. This is especially the case in areas where natural coastal ecosystems are scarce, for example, in urbanized coastal areas (e.g., Scheveningen) or areas with sea-dikes (e.g., Hondsbossche Zeewering). In these areas, the coastal zone consists effectively of a 1 kilometer buffer from the North Sea, whereas the Eurostat definition often leads to a delineation of the coastal zone consisting of a 10 kilometer buffer from the North Sea. Only for the Dutch Wadden Sea islands (with the exception of Texel), the 'ecosystem-based' approach of Statistics Netherlands (2023) and the proposed Eurostat definition leads to the inclusion of the same area for the coastal zone.

Whereas the delineation of the coastal zone with the 'ecosystem-based' approach is dependent on the occurrence and extent of natural coastal ecosystems, the coastal zone based on the 'administrative-based' approach proposed by Eurostat is dependent on the geographic division of administrative units. The size and shape of LAUs bordering or close to the coastline ultimately determine the area which is included in the coastal zone. Hence, the delineation of the coastal zone is highly susceptible to administrative changes. In the Netherlands, due to municipal reorganizations, the number of municipalities is strongly declining since the 1980s[8]. These administrative reorganizations also occur in the coastal zone; changing the delineation of the coastal zone following the proposed methodology by Eurostat.

For example, if you would use the administrative-based approach for the municipal division of the Netherlands for 2003 and 2023, the results could show that due to the reorganization of municipalities, the delineation of the coastal zone is changed even though the 'ecological situation' in this area has not changed. This difference raises questions whether using LAUs is a robust demarcation of the coastal zone. Alternatively, a 10-kilometer buffer from the coastline could be used for a consistent delineation over time, not susceptible to administrative changes in e.g., municipalities.

The approach which implements a standardized buffer zone from the North Sea and intertidal areas mitigates challenges associated with tracking artificial impervious areas over time due to shifts in spatial delineations. For example, employing a 10-kilometer buffer zone ensures a consistent coastal extent across multiple years, enhancing the reliability of the indicator. At the same time though, this approach offers more noise to the data as all sorts of ecosystems are included. Therefore, you would not only track important coastal habitats but also urban areas.

It must be noted that shortly before finishing this report a new version of the Guidance Note on Condition Accounts was published using a 1 kilometer buffer. Due to limited time, we were unfortunately unable to test this approach. However, it closely aligns with our 10-kilometer approach. The one-kilometer approach will likely result in a lower overall percentage of imperviousness. We expect an underestimation of the imperviousness as most of the buildings, roads and pavements are built alongside the dunes and beaches, but not per se on or through them.

6.3.2 Imperviousness data

In assessing the extent of artificial impervious areas in coastal regions of the Netherlands, two distinct datasets were used, each presenting its own advantages and limitations. The first method which used building polygons offers a high-resolution image of the built environment, delineating the footprint of infrastructure. The high resolution is vital for local-scale analysis and planning, providing detailed insights into the spatial distribution of impervious surfaces.

[8] https://www.cbs.nl/nl-nl/nieuws/2022/52/aantal-gemeenten-daalt-tot-342-op-1-januari-2023#:~:text=Het%20aantal%20gemeenten%20in%20Nederland,worden%20toegevoegd%20aan%20grotere%20gemeenten.

Nevertheless, this approach primarily focusses on built structures, omitting other impervious elements such as roads, parking lots, and pavements, which are integral components of the anthropogenic footprint. This exclusion results in an underrepresentation of the actual impervious area of the coastal area in the Netherlands.

Conversely, the Copernicus dataset provides a broader perspective, incorporating various forms of imperviousness and thus offering a more comprehensive view of human alterations to the coastal terrain. Including all artificial impervious surfaces is essential for regional planning and environmental impact studies, as it gives a full overview of the local pressures to the environment. However, the temporal availability of Copernicus data poses significant constraints. Datasets are available for the years 2006, 2009, 2012, 2015, and 2018. Our coastal extent is only available from 2013, which limits the use of the Copernicus data to the last three years with a work around for the year 2012. Therefore, a long-term and consistent trend is not available. Additionally, the methodological enhancements in Copernicus data between 2015 and 2018 further complicate comparisons over time. The shift from a 20-meter to a 10-meter resolution could reflect a change in impervious area extent. Though such variations may not necessarily correspond to actual alterations on the ground. Instead, they may reflect improved detection capabilities of the finer resolution.

The change in the recording of imperviousness, from a gradational percentage per pixel to a binary categorization of built or non-built, introduces another layer of complexity. The previous method allowed for a nuanced understanding of the imperviousness gradient within each pixel, crucial for accurately evaluating the permeability of the surface. The binary classification, while simplifying the data, might not capture the partial imperviousness of certain areas, leading to a loss of detail and potentially overestimating imperviousness. Therefore, while the Copernicus dataset offers a broader picture, the shift in methodology underscores the need for careful interpretation of the data when comparing years before 2018 with the year 2018.

From the results we can also see these caveats of the Copernicus dataset. There is a clear drop in the year 2018 for impervious density in Dutch coastal areas. This is likely due to the increased resolution for the year 2018, which lead to a more accurate classification of land cover and resulted in a lower overall value of impervious area. Copernicus also stated that the higher resolution and reduced density mixing within each pixel, resulted in a more detailed density structure, especially in urban areas (European Union Copernicus Land Monitoring Service, 2018b). The first two years of the Copernicus dataset are, however, comparable and they show a similar trend as the building polygons. This underpins the assumption with results that impervious areas are increasing in coastal areas of the Netherlands.

6.3.3 Relevance to condition

The results from both the polygonal buildings method, as well as the Copernicus method suggest an overall increase in imperviousness over time in coastal areas of the Netherlands. Comparing the results of the two methods suggests that not buildings, but other types of impervious areas like roads and pavements are causing the high increase in imperviousness. Reason being, that the difference in imperviousness using the polygon method is much smaller than the difference using the Copernicus method, which uses NDVI to calculate imperviousness and thus includes all types of impervious areas.

One possible explanation could be the growth of recreational activities in coastal areas. The development of infrastructure to support recreational activities, such as parking lots, walkways and other facilities, often leads to an increase in impervious surfaces. Multi-day tourism in the area may also be growing in coastal areas as the share of buildings is also increasing. However, it seems that recreational activities might be growing at a much faster rate compared to tourism.

Though the increase in recreational and tourism activities is a positive contribution to the Dutch economy, they may also pose a significant pressure on ecosystems. The influx of tourists and the associated development of recreational infrastructure can lead to habitat disruption and fragmentation. Ecosystems are complex networks where each component, including flora and fauna, plays a vital role in maintaining ecological balance.

For example, in the case of birds, the construction of facilities like hotels, pathways, and other amenities often encroaches on their natural habitats, leading to a loss of nesting sites and food sources. Additionally, the presence of a higher number of people in these areas can lead to increased disturbance as birds are often sensitive to human presence and noise, which can disrupt their natural behaviors and breeding patterns. This is particularly critical in the Netherlands, where many coastal and wetland areas serve as crucial stopover points for migratory birds.

Each animal and plant plays a crucial role in their ecosystem, such as pollinating plants, dispersing seeding and controlling invasive species. The decline of any species could have significant effects on the balance that exists within an ecosystem, thereby affecting the overall health. A healthy ecosystem can provide critical services such as flood protection, water purification, and climate regulation. The disruption of these ecosystems due to increased tourism and recreation can therefore have significant environmental, economic, and social impacts.

In the context of the Netherlands, coastal protective structures such as dikes and revetments are indispensable for managing coastal erosion and sea-level rise. These structures are crucial given a substantial protection of the Netherlands lies below sea level making it particularly vulnerable to coastal erosion and sea-level rise. While these protective constructions are necessary, it is also important to consider the increasing imperviousness of the landscape. Impervious surfaces, which do not absorb rainwater, can contribute to increased runoff and flooding risks. This is especially critical in coastal areas, where the combination of sea-level rise and increase runoff can lead to more frequent and severe flooding. Therefore, it is essential to strike a balance between constructing necessary protective structures and preserving natural, water-absorbent surfaces to maintain ecological balance and resilience against flooding.

6.3.4 Impervious surfaces in Zeeland: An ecologist's view

To gain a clearer understanding of the ecological impacts of expanding artificial impervious areas, our team visited Zeeland, a southern coastal province in the Netherlands. During our visit, we spent a day with a local ecologist to observe the region's environment. The increase in artificial impervious surfaces along the coast has had various effects on both the natural environment and the balance of ecosystems.

A significant factor in the increase in impervious areas is the growth in recreational homes in Zeeland. The influence of these homes extends to the surrounding natural areas, as residents engage in leisure activities. This increased human activity is affecting local ecology, as demonstrated by several examples we noted in the region.

Sport fishing, popular due to the recreational appeal of the area, has been observed to impact the local wildlife. Fishing activities have deterred waterfowl and disrupted habitats crucial for feeding, resting, and breeding. Additionally, the construction of beach pavilions near key wintering sites for birds has had noticeable effects, such as an instance where a pavilion's proximity to a tern roost coincided with a decline in the tern population.

Another example is the construction of a cycle path near a salt marsh on the Western Scheldt, an important tidal resting place for various bird species. This cycling path, providing access for recreationists, has encroached on space essential for bird species like the ringed plover, affecting their foraging behavior and chick survival rates. The correlation between restricted areas and increased breeding success highlights the interaction between human activities and wildlife.

Although individual developments may seem insignificant, their combined effect exceeds initial expectations. These changes are altering the region's ecosystems and pose challenges to the stability of the coastal environment. The implications are significant, emphasizing the need for careful consideration of coastal development and impervious area expansion. Accurate reporting of these indicators is vital for raising awareness and encouraging actions to safeguard the health of our coastal ecosystems.

7. Condition Account

The condition of Dutch ecosystems reveals mixed trends with both positive and negative implications for biodiversity and ecosystem health (Table 25).

7.1 Forests

Forests in the Netherlands show conflicting trends regarding tree cover density. While Copernicus data suggests an increase, the NBI indicates a decrease. Despite this discrepancy, local assessments generally report improvements in forest conditions. A notable positive development is the increased diversity within these forests. The mix of coniferous and deciduous trees contributes to a richer and more resilient ecosystem. Dutch forests, historically younger, are now maturing. This aging process is beneficial for biodiversity, as older forests typically support a wider variety of species and habitats. However, a significant challenge facing these forests is the rejuvenation issue, largely attributed to overgrazing by large grazers like deer. This impacts the natural regeneration of the forests, posing a threat to their long-term health and sustainability.

Another encouraging sign in Dutch forests is the increase in dead wood. This trend is a key indicator of forest ecosystem health, as dead wood plays a crucial role in supporting biodiversity. It provides habitats for numerous insects and fungi, contributing to the nutrient cycling and overall ecological balance. The rising presence of dead wood suggests a move towards more natural forest conditions, where ecological processes can function effectively.

7.2 Urban areas

In the Netherlands, the condition of urban green spaces is generally stable with a slight increase, despite the concurrent expansion of urban areas. This trend is beneficial for multiple reasons: urban green spaces improve air quality by filtering pollutants, mitigate the urban heat island effect, aid in water management, and provide habitats for urban wildlife, thereby supporting biodiversity within cities. Furthermore, these areas are crucial for human health and well-being, offering residents reduced stress, improved mental health, and opportunities for physical activity.

7.3 Soil

Based on the national soil survey, initially carried out in 1998 and repeated in 2018, it has been found that the change in SOC depended on depth and method used to match the two surveys:

For cropland on mineral soils, SOC significantly decreased for all depth intervals (0–30cm; 30–100cm; 0–100cm). However, this was only when classmatching was applied, not geomatching. For grassland on mineral soils; SOC decreased for the subsoil layer (30–100cm) only. Changes in the topsoil (0–30cm) were not significant (Table 24; Knotters et al., 2022).

Nevertheless, for the purpose of this account, we assumed that all changes were significant, and applied linear interpolation to estimate SOM and SOC values for all accounting years.

Table 24. SOC contents (g/kg) and SOC stocks for cropland and grassland on mineral soils, based on classmatching. Standard errors are in parentheses. Significant changes are in bold (at 5% significance. level). Modified after tables 3 and 4 of Knotters et al., (2022).

Land use	Depth	Soil Organic Carbon contents						SOC stock					
		g/kg						tonne/ha (0-30cm)			(0-20cm)		
		1998		2018		Change		1998	2018	change	1998	2018	change
Cropland	0–30 cm	19,2	(1,22)	17,3	(1,21)	**-1,9**	(0,7)	78,6	69,5	-9,1	52,4	46,4	-6,0
	30–100 cm	14,1	(1,38)	9,8	(0,86)	**-4,3**	(1,2)	123,8	93,5	-30,2	82,5	62,4	-20,2
	0–100 cm	16,3	(1,86)	13,6	(2,11)	**-2,8**	(0,7)	199,5	163,1	-37,6	133,0	108,7	-24,3
Grassland	0–30 cm	28,2	(1,12)	27,9	(1,17)	-0,4	(0,7)	103,7	100,8	-2,8	69,1	67,2	-1,9
	30–100 cm	18,9	(1,22)	16,5	(1,14)	**-2,4**	(0,9)	144,7	127,2	-17,6	96,5	84,8	-11,7
	0–100 cm	24,6	(3,26)	21,2	(1,88)	-3,4	(2,3)	248,9	228,6	-20,2	165,9	152,4	-13,6

Knotters et al. (2022) further conclude that the accuracy of the bulk density data needs to be improved in future measurements to increase the accuracy of calculations of the SOC stock changes.

7.4 Coastal areas

Coastal ecosystems face challenges due to the expansion of artificial impervious areas. The increase in buildings and infrastructure, especially in coastal regions is driven by urban expansion and tourism development. This growth has several detrimental effects on the ecosystem. It leads to habitat loss, particularly of crucial natural areas like dunes and wetlands, which are vital for a range of species. Furthermore, the proliferation of impervious surfaces exacerbates issues like water runoff and pollution, negatively impacting both soil and water quality. This runoff can carry pollutants into coastal ecosystems, harming aquatic life. Additionally, the degradation of these national buffers increase the vulnerability of coastal areas to climate change impacts, such as sea-level rise and storm surges.

Table 25. Condition account with the five indicators per ecosystem over different years.

	Unit	Year	Forest and woodland	Heathlands and other sparsely vegetated ecosystems	Marine waters, inlets and transitional waters	Coastal beaches, dunes and wetlands	Inland wetlands	Lakes and reservoirs	Cropland	Grassland	Rivers and canals	Settlements and other artificial areas	Urban green and recreational sites	TOTAL
Extent														
Extent	km2	2012*	3.523	389	4.111	510	468	2.742	11.070	9.619	970	6.776	1.365	41.543
	km2	2013	3.523	389	4.111	510	468	2.742	11.070	9.619	970	6.776	1.365	41.543
	km2	2014	3.498	402	4.112	494	485	2.746	11.164	9.438	976	6.804	1.423	41.543
	km2	2015	3.485	394	4.111	507	482	2.729	10.771	9.866	990	6.821	1.388	41.543
	km2	2016	3.468	397	4.121	503	495	2.736	10.684	9.948	984	6.804	1.404	41.543
	km2	2017	3.479	402	4.117	509	483	2.742	10.676	9.939	988	6.817	1.390	41.543
	km2	2018	3.484	404	4.114	507	485	2.764	10.723	9.830	987	6.850	1.395	41.543
	km2	2019	3.483	406	4.112	505	490	2.762	10.704	9.808	986	6.882	1.407	41.543
	km2	2020	3.487	406	4.110	498	484	2.766	10.600	9.885	992	6.900	1.414	41.543
	km2	2021	3.498	405	4.120	490	483	2.767	10.609	9.843	993	6.930	1.406	41.543
	% of The Netherlands	2012*	8,5	0,9	9,9	1,2	1,1	6,6	26,6	23,2	2,3	16,3	3,3	100,0
	% of The Netherlands	2013	8,5	0,9	9,9	1,2	1,1	6,6	26,6	23,2	2,3	16,3	3,3	100,0
	% of The Netherlands	2014	8,4	1,0	9,9	1,2	1,2	6,6	26,9	22,7	2,3	16,4	3,4	100,0
	% of The Netherlands	2015	8,4	0,9	9,9	1,2	1,2	6,6	25,9	23,7	2,4	16,4	3,3	100,0
	% of The Netherlands	2016	8,3	1,0	9,9	1,2	1,2	6,6	25,7	23,9	2,4	16,4	3,4	100,0
	% of The Netherlands	2017	8,4	1,0	9,9	1,2	1,2	6,6	25,7	23,9	2,4	16,4	3,4	100,0
	% of The Netherlands	2018	8,4	1,0	9,9	1,2	1,2	6,7	25,8	23,7	2,4	16,5	3,4	100,0
	% of The Netherlands	2019	8,4	1,0	9,9	1,2	1,2	6,6	25,8	23,6	2,4	16,6	3,4	100,0
	% of The Netherlands	2020	8,4	1,0	9,9	1,2	1,2	6,7	25,5	23,8	2,4	16,6	3,4	100,0
	% of The Netherlands	2021	8,4	1,0	9,9	1,2	1,2	6,7	25,5	23,7	2,4	16,7	3,4	100,0
Condition														
Tree cover density														
National	% tree cover density	2012	52,0											
	% tree cover density	2013	.											
	% tree cover density	2014	.											
	% tree cover density	2015	52,0											
	% tree cover density	2016	.											
	% tree cover density	2017	.											
	% tree cover density	2018	60,0											
	% tree cover density	2019	.											
	% tree cover density	2020	.											
	% tree cover density	2021	.											
Urban green														
Extent urban green	km2	2012										.		
	km2	2013										791		
	km2	2014										836		
	km2	2015										796		
	km2	2016										809		
	km2	2017										806		
	km2	2018										812		
	km2	2019										830		
	km2	2020										840		
	km2	2021										851		
	% of Urban area	2012										.		
	% of Urban area	2013										16		
	% of Urban area	2014										15,9		
	% of Urban area	2015										15,9		
	% of Urban area	2016										16,1		
	% of Urban area	2017										16		
	% of Urban area	2018										16		
	% of Urban area	2019										16,1		
	% of Urban area	2020										16,3		
	% of Urban area	2021										16,4		
Dead wood														
National	m3 of dead wood per hectare	2012	12,7											
	m3 of dead wood per hectare	2013	13,6											
	m3 of dead wood per hectare	2014	14,6											
	m3 of dead wood per hectare	2015	15,5											
	m3 of dead wood per hectare	2016	16,5											
	m3 of dead wood per hectare	2017	17,4											
	m3 of dead wood per hectare	2018	18,3											
	m3 of dead wood per hectare	2019	19,3											
	m3 of dead wood per hectare	2020	.											
	m3 of dead wood per hectare	2021	.											
Soil organic carbon														
SOM content	SOM (g/kg) between 0-30cm	2012							35,7	55,9				
	SOM (g/kg) between 0-30cm	2013							35,5	55,9				
	SOM (g/kg) between 0-30cm	2014							35,3	55,9				
	SOM (g/kg) between 0-30cm	2015							35,1	55,8				
	SOM (g/kg) between 0-30cm	2016							34,9	55,8				
	SOM (g/kg) between 0-30cm	2017							34,7	55,7				
	SOM (g/kg) between 0-30cm	2018							34,6	55,7				
	SOM (g/kg) between 0-30cm	2019							34,4	55,7				
	SOM (g/kg) between 0-30cm	2020							34,2	55,6				
	SOM (g/kg) between 0-30cm	2021							34,0	55,6				
SOC stock	SOC (ton/ha) between 0-30cm	2012							72,2	101,7				
	SOC (ton/ha) between 0-30cm	2013							71,8	101,5				
	SOC (ton/ha) between 0-30cm	2014							71,3	101,4				
	SOC (ton/ha) between 0-30cm	2015							70,9	101,3				
	SOC (ton/ha) between 0-30cm	2016							70,4	101,1				
	SOC (ton/ha) between 0-30cm	2017							70,0	101,0				
	SOC (ton/ha) between 0-30cm	2018							69,5	100,8				
	SOC (ton/ha) between 0-30cm	2019							69,1	100,7				
	SOC (ton/ha) between 0-30cm	2020							68,6	100,6				
	SOC (ton/ha) between 0-30cm	2021							68,2	100,4				
Artificial impervious area cover in coastal areas														
Impervious area	% of The Netherlands	2012				.								
	% of The Netherlands	2013				5,22								
	% of The Netherlands	2014				.								
	% of The Netherlands	2015				5,23								
	% of The Netherlands	2016				.								
	% of The Netherlands	2017				.								
	% of The Netherlands	2018				5,26								
	% of The Netherlands	2019				.								
	% of The Netherlands	2020				5,31								
	% of The Netherlands	2021				5,33								

*The 2013 extent is used for 2012.

8. Conclusions and recommendations

Using the Ecosystem Condition Accounts Guidance Note, we compiled a condition account on the newest indicators set to become mandatory for reporting to Eurostat within a few years. This report gives a good overview of the data types available and the methods which could be used to compile these indicators. In this chapter we will give some further recommendations about how the guidance note could be improved based on our experience.

8.1 Data sources and limitations

Compiling a condition account for environmental factors like tree cover density, urban green, dead wood, soil organic carbon, and artificial impervious areas involves various data sources, each with its own limitations. In the Netherlands, data on tree cover density is widely available with good spatial coverage, but it lacks yearly updates.

Urban green data is more frequently updated (yearly), but may suffer from under or overestimations due to spatial resolution and inclusion of recreation. Despite this, it is considered reliable for detecting significant urban green areas. One potential enhancement for future studies is utilizing NDVI (Normalize Difference Vegetation Index) data or Plant Phenology Index data from the Copernicus Land Monitoring Service. This could help in detecting greenery within artificial ecosystems. A standardized way of using these data sources may help to make the data more internationally comparable and is also useful for countries that don't have detailed topographic data.

Dead wood data is regularly available with good spatial coverage. However, similar to tree cover density, it is not updated annually. This necessitates interpolation for missing years, increasing data uncertainty. Quality of data between countries depends on national inventory standards, with direct national data being preferable over extrapolated sources like the FRA.

Soil organic carbon data faces challenges with its limited availability, dependency on soil type, and infrequent updates, impacting trend analysis and ecosystem condition assessment. Data on artificial impervious areas, while available internationally through Copernicus, has good spatial but limited temporal coverage. Countries with local yearly data offer better temporal insights but may not match Copernicus in spatial detail.

8.2 Indicators – Recommendations for future compilation

In our report, we compiled five indicators, which could be reported to Eurostat when they become mandatory. Yet, there is potential for further refinement of these indicators. We identified several areas for improvement below.

Tree cover density is an indicator which can easily be measured by satellites and which may be useful for monitoring forests. However, a reduction in tree cover density does not necessary mean a reduction in the health of the forest. Given the challenges in interpreting tree cover density, an alternative indicator, like basal area, is recommended for assessing forest health. Basal area measures the cross-sectional area of tree trunks in forest at breast height and is crucial for evaluating forest density and timber volume. This metric, measured in square meters per hectare, can provide a more nuanced understanding of forest health and growth compared to tree cover density and is advised for use by local assessors of Dutch forests.

The indicator for measuring tree cover density, as it is calculated in this report, contains data which is too uncertain to report over continuous years. Though recommended to use Copernicus tree cover density data, this data has not been updated regularly and has severe discrepancies between publications in resolution. When new updates are published with a similar resolution as the 2018 data, the older data should therefore also be discarded. However, again, we stress to change this indicator for basal area.

Additionally, our study showed notable differences between different types of forests. Future indicators of tree cover density should therefore always differentiate between forest types. Uncertainty is increased when measuring tree cover density over different types of forests.

The urban green indicator that is calculated in this report could be further refined in terms of measuring vegetated areas more precisely. To make the indicator policy relevant it is also important to reflect on the inclusion of sports and recreation sites. Not all of these places are publicly accessible, and there could consequently be different kinds of benefits involved from these urban green areas. Overall, the indicator shows a plausible time series and trend, and can also be broken down per province and per municipality without too much uncertainty.

In the Netherlands, the assessors from the National Forest Inventory are keen to start reporting on a five year basis, with permanent assessment plots around the Netherlands. This approach would likely provide a more accurate and consistent representation of the state of dead wood in Dutch forests. Therefore, utilizing NBI data for future reporting is recommended for a more accurate depiction of dead wood status in Dutch forests.

Additionally, we would recommend the Taskforce on Ecosystem Accounting to revise their guidance notes. Currently, the guidance suggests utilizing FAO data for creating the dead wood indicator, but there exists a discrepancy in the units of measurement: the FAO reports dead wood volume in tonnes per hectare, whereas the guidance notes recommend reporting in cubic meters per hectare. To resolve this inconsistency and enhance the usability of the guidance, it would be beneficial either to align the recommended reporting units with those used by the FAO, or to provide a clear and standardized method for converting from tonnes per hectare to cubic meters per hectare. This adjustment would ensure more accurate and streamlined data usage, facilitating better comparability and ese of interpretation in ecosystem accounting.

In order to develop the account for soil organic matter, we found that the best data source (the national soil surveys) were not easily converted to the requirements for ecosystem condition accounting. For example, not all changes between the 1998 and 2018 surveys were found to be statistically significant, leaving the question open, which values to use for these years, and how to estimate values for intermediate years. We further found that the European LUCAS soil survey had a very low density (~100 points, compared to the ~1000 points of the national survey) and (currently) at different reporting depth (0-20cm, rather than 0-30cm for the national survey).

Measuring artificial impervious area in coastal areas is complex. The discussions during the taskforce on ecosystem accounting, as well as the frequent changes in the guidance on calculating the coastal extent highlight this complexity. After compiling different types of coastal extents, we recommend using the 10-kilometer buffer approach. This extent is comprehensive in coverage, in line with Eurostat’s first approach (the LAU approach), and there is the possibility to use country extent accounts as a measure of imperviousness without subjectivity to how defined the extent of the country is.

Further compilation of the imperviousness in the extent should be calculated using the Copernicus imperviousness layer. This dataset is more inclusive of imperviousness than the buildings layer alone. However, to produce time series of this indicator, new products of the Copernicus imperviousness layers should be produced in similar resolutions and layers from before 2018 should be discarded. Therefore, to produce a time series in this report now, we used the imperviousness by buildings in coastal areas in order to provide a condition indicator. In the future, if the Copernicus dataset is not updated, we could also enhance our own dataset by including different layers from the ecosystem extent map of the Netherlands or from topographic maps. We could, for example, add layers of roads, walkways, parking lots, airports and railroads.

9. References

BGT. Basisregistratie: Grootschalige Topografie (https://data.overheid.nl/dataset/0c9799f5-7906-49a5-950d-69e495e1a260)

Ehbrecht, M., Schall, P., Ammer, C., Seidel, D. (2017). Quantifying stand structural complexity and its relationship with forest management, tree species diversity and microclimate. *Agric For Meteorol* 242:1–9. https://doi.org/10.1016/j.agrformet.2017.04.012

European Union Copernicus Land Monitoring Service, (2018a). High Resolution Layer Tree Cover Density. DOI: https://doi.org/10.2909/486f77da-d605-423e-93a9-680760ab6791

European Union Copernicus Land Monitoring Service, 2018b. Lot1: Imperviousness 2018, Imperviousness Change 2015 – 2018 and Built-up 2018, European Environment Agency (EEA)

EU, 2011. EU Biodiversity strategy (COM(2011) 244). Website: http://ec.europa.eu/environment/nature/biodiversity/strategy/index_en.htm

EU, 2013. EU Green Infrastructure Strategy (COM(2013) 249). Website: https://environment.ec.europa.eu/topics/nature-and-biodiversity/green-infrastructure_en

EU, 1992. EU Habitats Directive (1992/43/EEC). Website: http://ec.europa.eu/environment/nature/legislation/habitatsdirective/index_en.htm

EU, 2008. Marine Strategy Framework Directive (2008/56/EC). Website: https://www.eumonitor.eu/9353000/1/j4nvk6yhcbpeywk_j9vvik7m1c3gyxp/vitgbgiogxml#:~:text=The%20marine%20strategy%[…]ans%20of%20an%20ecosystem%2Dbased

EU, 2021. EU Soil Strategy for 2030 (COM(2021) 699). Website: https://environment.ec.europa.eu/publications/eu-soil-strategy-2030_en

EU, 2016. EU Urban Agenda. Website: https://ec.europa.eu/regional_policy/policy/themes/urban-development/agenda_en

EU, 2000. Water Framework Directive (2000/60/EC). Website: https://environment.ec.europa.eu/topics/water/water-framework-directive_en

Fernandez-Ugalde, O., Scarpa, S., Orgiazzi, A., Panagos, P., Van Liedekerke, M., Marechal A. & Jones, A. (2022). *LUCAS 2018 Soil Module. Presentation of dataset and results*, EUR 31144 EN, Publications Office of the European Union, Luxembourg. 2022, ISBN 978-92-76-54832-4, doi:10.2760/215013, JRC129926

Herrmann, S., Kahl, T., and Bauhus, J. (2015). Decomposition dynamics of coarse woody debris of three important central European tree species. *Forest Ecosystems*, 2, 1-14.

Leban, J., Kerfriden, B., Lacarin, M., Taupin, A., and Hervé, J.C. (2020). La biomasse des forêts méditerranéennes Les premiers résultats du projet XyloDensMap. Forêt Méditerranéenne, XLI(4), 267-274.

Lesschen, J. P., Heesmans, H. I. M., Mol-Dijkstra, J. P., van Doorn, A. M., Verkaik, E., van den Wyngaert, I. J. J., & Kuikman, P. J. (2012). *Mogelijkheden voor koolstofvastlegging in de Nederlandse landbouw en natuur.* (Alterra-rapport; No. 2396). Alterra. https://edepot.wur.nl/247683

Minasny, B., McBratney, A. B., Wadoux, A. M. C., Akoeb, E. N., & Sabrina, T. (2020). Precocious 19th century soil carbon science. *Geoderma regional*, *22*, e00306. DOI: 10.1016/j.geodrs.2020.e00306

Öder, V., Petritan, A. M., Schellenberg, J., Bergmeier, E., and Walentowski, H. (2021). Patterns and drivers of deadwood quantity and variation in mid-latitude deciduous forests. *Forest Ecology and Management*, 487, 118977.

Pribyl, D. W. (2010). A critical review of the conventional SOC to SOM conversion factor. Geoderma, 156(3-4), 75-83. DOI: 10.1016/j.geoderma.2010.02.003

Schelhaas, M.J., A.P.P.M. Clerkx, W.P. Daamen, J.F. Oldenburger, G. Velema, P. Schnitger, H. Schoonderwoerd & H. Kramer, (2014). Zesde Nederlandse Bosinventarisatie; Methoden en basisresultaten. Wageningen, Alterra Wageningen UR (University & Research centre), Alterra-rapport 2545. 98 blz.; 8 fig.; 36 tab.;12 ref.

Schelhaas, M.J., Teeuwen, S., Oldenburger, J., Beerkens, G., Velema, G., Kremers, J., Lerink, B., Paulo, M.J., Schoonderwoerd, H., Daamen, W., Dolstra, F., Lusink, M., van Tongeren, K., Scholten, T., Pruijsten, I., Voncken, F., Clerkx, A.P.P.M. (2022). Zevende Nederlandse Bosinventarisatie; Methoden en resultaten. Wettelijke Onderzoekstaken Natuur & Milieu, WOt-rapport 142. 127 blz.; 15 fig.; 57 tab.; 17 ref; 9 bijlagen.

Statistics Netherlands (2020). Economic description of the Dutch North Sea and coast: 2010, 2015 and 2017. Den Haag/Heerlen.

Statistics Netherlands and WUR (2022), Natural Capital Accounting in the Netherlands – Technical report. *Statistics Netherlands (CBS) and Wageningen University and Research (WUR)*

Statistics Netherlands (2023). Economic description of the Dutch North Sea and coast: 2015, 2017, 2019 and 2021. Den Haag/Heerlen.

Sukma, H.T., Di Stefano, J., Swan, M., Sitters, H. (2019) Mammal functional diversity increases with vegetation structural complexity in two forest types. *For Ecol Manag* 433:85–92. https://doi.org/10.1016/j.foreco.2018.10.035

UN, (2017). SEEA Experimental Ecosystem Accounting: Technical Recommendations Consultation Draft V4.1

Van der Maaten-Theunissen, M. and Schuck, A. (2013). Integration of Nature Protection in Forest Policy in the Netherlands. INTEGRATE Country Report. EFICENT-OEF, Freiburg.

van Tol-Leender, D., Knotters, M., de Groot, W., Gerritsen, P., Reijneveld, A., van Egmond, F., Wösten, H., & Kuikman, P. (2019). *Koolstofvoorraad in de bodem van Nederland (1998-2018): CC-NL*. (Wageningen Environmental Research rapport; No. 2974). Wageningen Environmental Research. https://doi.org/10.18174/509781

Wijdeven, S.M.J. (2006). Factsheets Dood hout in het bosbeheer. Alterra-rapport 1430. Wageningen: Alterra.

Wijdeven, S.M.J., Moraal, L.G. and Veerkamp, M.T. (2010). Dood hout. In: Den Ouden, J., Muys, B., Mohren, F. and Verheyen, K. (eds.), Bosecologie en Bosbeheer. Leuven/Den Haag: Acco, pp. 425-435.