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A nature-inclusive future with healthy soils? Mapping soil organic matter in 2050 in the Netherlands

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Abstract

Nature-inclusive scenarios of the future can help address numerous societal challenges related to soil health. As nature-inclusive scenarios imply sustainable management of natural systems and resources, land use and soil health are assumed to be mutually beneficial in such scenarios. However, the interplay between nature-inclusive land use scenarios and soil health has never been modelled using digital soil mapping. We predicted soil organic matter (SOM), an important indicator of soil health, in 2050, based on a recently developed nature-inclusive scenario and machine learning in 3D space and time in the Netherlands. By deriving dynamic covariates related to land use and the occurrence of peat for 2050, we predicted SOM and its uncertainty in 2050 and assessed SOM changes between 2022 and 2050 from 0 to 2 m depth at 25 m resolution. We found little changes in the majority of mineral soils. However, SOM decreases of up to 5% were predicted in grasslands used for animal-based production systems in 2022, which transitioned into croplands for plant-based production systems by 2050. Although increases up to 25% SOM were predicted between 0 and 40 cm depth in rewetted peatlands, even larger decreases, on reclaimed land even surpassing 25% SOM, were predicted on non-rewetted land in peat layers below 40 cm depth. There were several limitations to our approach, mostly due to predicting future trends based on historic data. Furthermore, nuanced nature-inclusive practices, such as the adoption of agroecological farming methods, were too complex to incorporate in the model and would likely affect SOM spatial variability. Nonetheless, 3D-mapping of SOM in 2050 created new insights and raised important questions related to soil health behind nature-inclusive scenarios. Using machine learning explicit in 3D space and time to predict the impact of future scenarios on soil health is a useful tool for facilitating societal discussion, aiding policy making and promoting transformative change.

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KEYWORDS
agroecological farming, digital soil mapping, land use, nature-inclusive, rewetting peatlands, scenario modelling, soil health, soil organic matter, space–time modelling, spatial planning

1 | INTRODUCTION

International organizations such as the Intergovernmental Panel on Climate Change (IPCC) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) call for urgent action and transformative change to address the challenges that negatively affect our planet, such as climate change and loss of biodiversity (IPBES, 2019; Pörtner et al., 2021). For transformative change, we need approaches that address the interdependent challenges in an integrated way to avoid negative trade-offs and feedbacks (Larrosa et al., 2016). One such approach is envisioning nature-inclusive scenarios for the future to help us resolve challenges we are facing today (Keesstra et al., 2018; Sowińska-Świerkosz & García, 2022).

In the Netherlands, a scenario of a nature-inclusive society for the National Nature Outlook 2050 was jointly developed by the Netherlands Environmental Assessment Agency and Wageningen University & Research (Breman et al., 2022). In this scenario, a narrative was developed in which more nature-inclusive types of land use could help to tackle several topical and urgent societal challenges, such as (1) nature conservation and biodiversity, (2) climate change, (3) quality of living, (4) farming transition, (5) energy transition and (6) water quality. Nature-inclusive transformations could have a big potential in the Netherlands. For example, a farming transition has the potential to increase the functioning of ecosystem services and improve the quality of life. In the Netherlands, historic land use changes were mainly conducted with the aim to intensify agriculture. A total of 17% of the present day land surface was reclaimed from water and 70% of peatlands have disappeared in the past 2000 years (Erkens et al., 2016; Vos et al., 2020). Today, the Netherlands is the second largest exporter of agricultural products in the world (Jukema et al., 2023) and has the highest livestock density of all EU member states (Eurostat, 2022, p. 32). While this resulted in short-term economic growth, it had numerous negative effects for the environment and human well-being, such as nitrogen pollution and water eutrophication (de Vries et al., 2021; Stokstad, 2019). Consequently, parts of society are demanding a transformation to more sustainable practices (Aarts & Leeuwis, 2023; Erisman, 2021). The nature-inclusive scenario for 2050 addresses these and other challenges in an integrated way and would allow an increase in the provision of multiple ecosystem services and the quality of the human environment (Breman et al., 2022).

Highlights

- We explored whether nature-inclusive land use was beneficial for soil health in the Netherlands
- We predicted soil organic matter in 3D space in 2050 between 0 and 2 m depth at 25 m resolution
- Soil organic matter increased due to nature-inclusive practices but decreased in non-rewetted peat
- Scenario modelling in 3D space and time is a tool to aid policymakers and promote positive change

Soils play a pivotal role in the delivery of ecosystem services and the quality of the human environment. An increase in the provision of multiple ecosystem services largely depend on the soil's capacity to function within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality and promote plant and animal health (Creamer et al., 2022; Lehmann et al., 2020). Understanding the spatial variability, the current condition and the potential of the soil is essential for adopting nature-inclusive planning. In return, more nature-inclusive land use could also enhance soil health, defined as the continued capacity of soils to support ecosystem services (European Commission, 2021), as such an approach implies sustainable management of and investing in natural systems and resources (Doorn et al., 2016). Thus, nature-inclusive scenarios may be beneficial for implementing pressing soil health initiatives like the Soil Deal for Europe and the recent Directive on Soil Monitoring and Resilience (European Commission, 2021, 2023b). In summary, soil health and nature-inclusive land use are deemed mutually beneficial.

To the best of our knowledge, the interplay between soil health and nature-inclusive land use scenarios has not been studied using digital soil mapping (DSM). DSM is the computer-assisted production of soil type and soil property maps, using statistical models to infer the relationship between a soil property and spatially exhaustive environmental explanatory variables (McBratney et al., 2003; Scull et al., 2003). Though mechanistic models such as CENTURY (Parton et al., 1987), RothC (Coleman & Jenkinson, 1996) and Millenial (Abramoff et al., 2018, 2022) are often used for modelling soil carbon trends (e.g. Kaczynski et al., 2017), the prediction accuracy of spatial patterns is typically higher when using a DSM approach (Zhang et al., 2024). Although some DSM studies have mapped temporal changes in soil properties (Gasch et al., 2015; Helfenstein et al., 2024; Hengl et al., 2017; Huang et al., 2019; OpenGeoHub et al., 2021, 2022; Sanderman et al., 2017; Stockmann et al., 2015; Stumpf et al., 2018; Szatmári et al., 2019), few have used DSM for modelling future scenarios. Gray and Bishop (2016, 2019) used DSM to map soil properties in south-eastern Australia until 2070 based on projected climate change scenarios. Yigini and Panagos (2016) mapped soil organic carbon stocks in Europe in 2050 based on climate and land use scenarios. These studies were based on likely climate, and for the latter, land use projections, as opposed to scenario modelling based on future visions assuming the immediate adoption of sustainable practices.

In this study, we used the nature-inclusive land use scenario for 2050 (Breman et al., 2022) and a DSM model in 3D space and time (3D + T; Helfenstein et al., 2024) to predict soil organic matter (SOM) and its uncertainty at 25 m resolution between 0 and 2 m depth for 2050 in the Netherlands. SOM is linked to six of the eight mission objectives of the Soil Deal for Europe (European Commission, 2021), increasing SOM is one of the main challenges related to soil health (Vanino et al., 2023). Moreover, in this study we demonstrate how it also links to various societal priorities addressed in the National Nature Outlook 2050. SOM and absolute changes in SOM between 2022 and 2050 (ΔSOM) were expressed as mass percentages. Our aim was to explore whether a nature-inclusive scenario for 2050 is conducive to enhancing SOM-related soil health.

2 | METHODS

2.1 | Nature-inclusive scenario for 2050

The nature-inclusive outlook was one of three scenarios that were developed to explore the future of nature and related ecosystem services in the Netherlands (Breman et al., 2022; Hinsberg et al., 2020). In contrast to the other scenarios that focused mainly on biodiversity goals by protecting natural habitats and species, in the nature inclusive scenario, nature and its related ecosystem services were to be enhanced as much as possible throughout the entire country, not only in protected nature areas. The starting point was the upscaling of existing and promising nature-inclusive practices, such as:

- Greening of cities and ecological design and management of urban green spaces.
- Rewetting peatlands to mitigate further land subsidence and CO_2 emissions (Figure 1c).
- Stream valley restoration for increasing water storage, reducing flood risk, improving water quality and enhancing biodiversity.
- Transition to more agroecological and plant-based production systems where possible, to improve the efficiency of food production, enhance biodiversity (at soil, crop, parcel and landscape level) in agricultural systems and reduce emissions from animal-based production systems.
- Adding trees, hedges and ponds to the landscape to sequester carbon, store water and create corridors and stepping stones for biodiversity.
- Increasing plant biodiversity along river dikes, roadsides and train tracks to enhance drought resistance, strengthen natural corridors and biodiversity as a whole.

In the nature-inclusive scenario, these existing nature-based solutions were upscaled and implemented to a national level in 2050, based on detailed knowledge of landscapes and soils and the overarching principle that "function follows form". For example, peatlands were mainly rewetted where the starting depth of a peat layer was within the uppermost 40 cm depth (Figure 1d), based on the soil landscape map (Delft & Maas, 2022). Plant-based agricultural production was concentrated in areas with fertile soils suitable for crop growth, whereas animal-based production was concentrated in less productive areas where it can often be combined with other functions (Breman et al., 2022).

2.2 | 3D + T SOM model

In this study, we used an existing high-resolution soil modelling and mapping platform for the Netherlands. Over the last few years, we have developed 3D maps for a wide range of soil properties, such as soil pH (Helfenstein et al., 2022). More recently, we extended the model to predict changes in SOM between 1953 and 2022 in 3D + T (Helfenstein et al., 2024). The 3D + T SOM model is based on well-established DSM practices, while also developing innovative and improved methods, such as assessing map accuracy using design-based statistical inference (Helfenstein et al., 2022) and developing novel covariates, or spatial-explicit environmental variables, to map SOM in 3D + T (Helfenstein et al., 2024). In the 3D + T SOM model, some of the covariates are static,

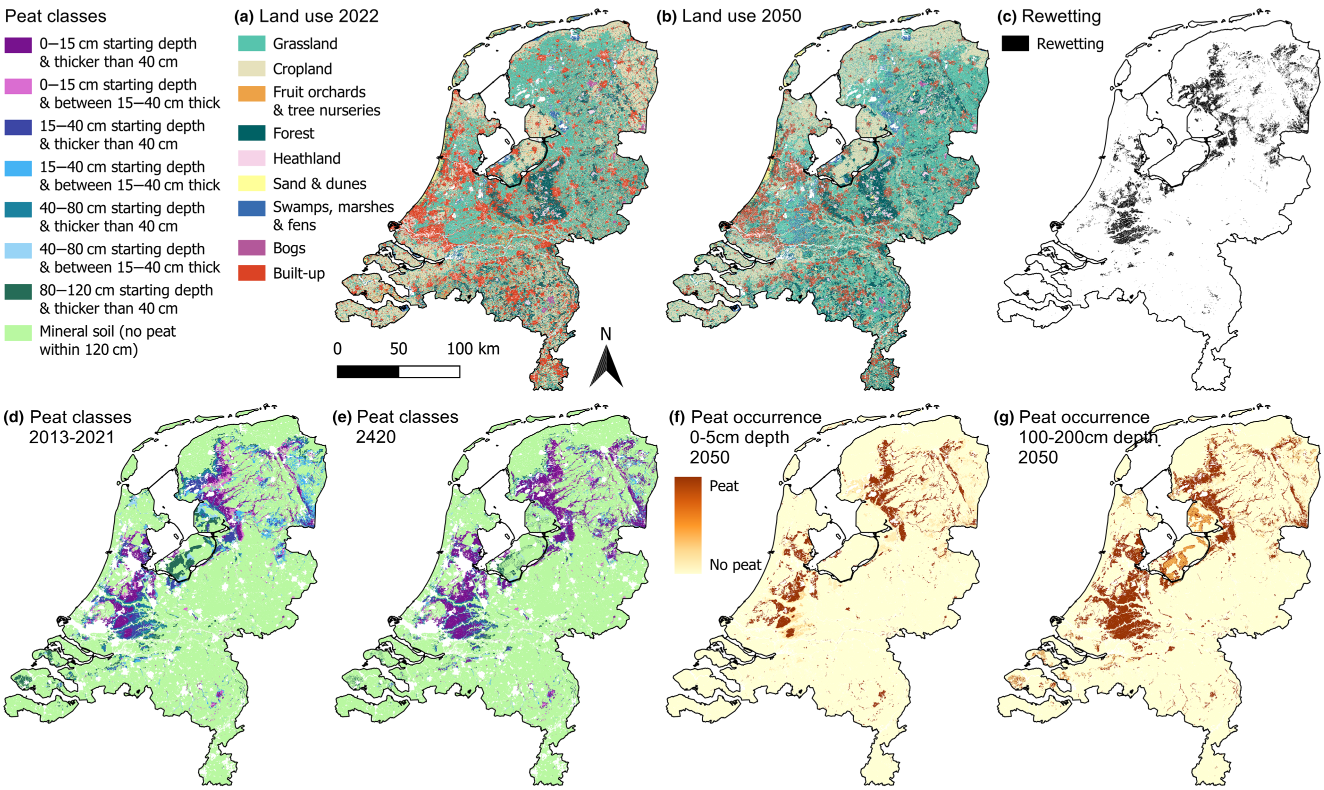

FIGURE 1 Land use in 2022 derived from Hazeu et al. (2023) (a) and in 2050 derived from Breman et al. (2022) (b), rewetted peatland areas (c), peat classes based on the 2021 version of the national soil map of the Netherlands (1:50000; de Vries et al., 2003) (d), peat classes in 400 years (e), and peat occurrence in 2050 for 0–5 cm depth (f) and 100–200 cm depth (g). Land use in 2050 and rewetted peatlands are based on the nature-inclusive vision for the Netherlands in 2050 (Breman et al., 2022). Land use and rewetting in 2050 were in turn used to modify the map of peat classes for 400 years from now (e) and derive 3D + T dynamic peat occurrence covariates for 2050 (f, g).

such as soil-forming factors representing climate, topography and parent material. However, other covariates in the model are dynamic in 2D space and time (2D + T) or 3D + T. For example, land use change and peat occurrence were covariates which have a greater propensity for change over several decades than climate, topography and parent material and were important for quantifying temporal SOM dynamics. In the model, land use (Figure 1a,b) and peat classes (Figure 1d,e) were variable in 2D + T, while peat occurrence was variable in 3D + T (Figure 1f,g).

The 3D + T SOM model was calibrated using 869,094 SOM observations from 339,231 point locations in the Netherlands (approximately 10 locations per km^2) and 33 covariates, the latter of which were selected based on rigorous model tuning of hundreds of covariates relating to the soil-forming factors (Helfenstein et al., 2024). We used quantile regression forest (QRF; Meinshausen, 2006) to infer the relationship between SOM observations and the covariates. Ensemble decision tree models such as QRF have repeatedly outperformed other DSM models (e.g. Nussbaum et al., 2018) and QRF has the unique advantage that it delivers a probability distribution of the modelled response. Thus, the 90th prediction interval (PI90), calculated as the difference between the 95th and 5th quantiles, serves as a measure of prediction uncertainty.

The performance of the 3D + T SOM model is summarized by depth layer in Table 1 based on design-based statistical inference and location-grouped 10-fold cross-validation (Helfenstein et al., 2024). Depending on the depth layer and statistical validation method, the mean error (ME) was between 0.00 and 1.97, the root mean squared error (RMSE) was between 4.87 and 10.33 and the model efficiency coefficient (MEC) was between 0.29 and 0.65. Accuracy metrics based on an additional validation dataset from 2018 were not displayed here since they were likely less indicative of model performance due to positional errors, differences in sampling support, changes in laboratory methods between the calibration and validation data and because no data from that dataset was available for 100–200 cm depth (Helfenstein et al., 2024). The prediction interval coverage probability (PICP) of the PI90 implies that the uncertainty in the 3D + T SOM model was overly-optimistic at 0–30 cm depth and slightly pessimistic at 100–200 cm depth. All information about the soil point data, covariates, model selection,

TABLE 1 Accuracy metrics of the 3D + T SOM model, summarized from Table 3 in Helfenstein et al. (2024). Metrics were computed using either location-grouped 10-fold cross validation or design-based statistical inference.

Depth (cm)	ME	RMSE	MEC	PICP of PI90
0–30	1.29–1.97	4.87–9.04	0.49–0.65	0.76–0.88
30–100	0.20–0.38	9.79–10.02	0.50–0.65	0.87–0.91
100–200	0.00–0.82	9.63–10.33	0.29–0.52	0.88–0.96

Note: See Helfenstein et al. (2024) for more information.
Abbreviations: MEC, model efficiency coefficient; ME, mean error; PICP of PI90, prediction interval coverage probability of the 90th prediction interval; RMSE, root mean squared error.

tuning and calibration and model accuracy assessment using design-based statistical inference and spatially explicit prediction uncertainty is further described by Helfenstein et al. (2024). In this study, we take the 3D + T SOM model a step further and explore to what extent it has the potential to simulate a future scenario.

2.3 | 2050 Scenario modelling

Using the 3D + T SOM model, we predicted SOM in 2050 by deriving simulated, dynamic land use and peat covariates based on the nature-inclusive land use scenario for 2050. The nature-inclusive land use map for 2050 (Breman et al., 2022) needed to be reclassified to the same general land use classes that were used when calibrating the 3D + T SOM model (Figure 1a; Helfenstein et al., 2024, Table 6), which resulted in the map shown in Figure 1b. The 3D + T SOM model uses dynamic covariates of land use variable in 2D + T during year *t*, as well as the land use class that occurred most frequently in the 5, 10, 20 and 40 years prior to and including *t*. These modal classes were assigned to account for the delayed response of SOM to land use change (Helfenstein et al., 2024). However, since the land use between 2022 and 2050 was unknown in this simulated future scenario, we simply used the re-categorized nature-inclusive land use map for 2050 for all dynamic 2D + T land use covariates. This assumes that the envisioned land use changes were implemented already several years prior to 2050.

Reclassifying land use led to the oversimplification of nuanced, nature-inclusive practices envisioned for 2050, particularly with regards to crop diversity and management practices. For example, it was not possible to distinguish land use and management practices such as strip cropping, biodiversity strips and alternative crops within the general "cropland" and "grassland" classes used in the 3D + T SOM model. In general, we were not able to incorporate numerous aspects of the nature-inclusive practices (Section 2.1) if they were not directly linked to land use, peat classes or peat occurrence as these were the only dynamic covariates used in the 3D + T SOM model. The 3D + T SOM model was not able to incorporate management practices as covariates because most management data is not spatially explicit. Although it is possible to use remote sensing products as proxies of management practices (e.g. Stumpf et al., 2020), high resolution remote sensing products are not available prior to the 1980s, whereas the 3D + T SOM model was calibrated over the time period from 1953 to 2022 (Helfenstein et al., 2024).

Deriving simulated peat classes in 2D + T and future peat occurrence in 3D + T for 2050 proved more challenging than deriving land use and required making several general assumptions. In the 3D + T SOM model, covariates of 2D + T peat classes and 3D + T peat occurrence were derived from the peat class categories found in the national soil map of the Netherlands (1:50000; de Vries et al., 2003). In the national soil map, soil type was mapped region by region between the 1960s and 1990s. Some regions, especially areas with peat soils, were updated between 2014 and 2021. For the 2050 scenario, we used the 2021 updated map of peat classes (Figure 1d) as a starting point and assumed a peat growth rate of 1 mm yr^{-1} only in areas subject to peatland rewetting strategies in the nature-inclusive scenario for 2050 (Figure 1c). Based on the literature, peat accumulation rates vary between 0.5 and 10 mm yr^{-1} (Charman, 2002; Craft, 2022; Höper et al., 2008; Joosten & Clarke, 2002; Stivrins et al., 2017; Witte & Van Geel, 1985), but 1 mm yr^{-1} is most commonly used as a general estimate. A detailed comparison between the 2021 map of peat classes and the rewetting areas chosen based on the soil landscape map (Section 2.1; Delft & Maas, 2022) revealed some discrepancies. For example, although all areas with peat starting at a depth between 0 and 15 cm and 15–40 cm were rewetted, only part of areas with peat starting between 40 and 80 cm depth and thicker than 40 cm was rewetted. Furthermore, none of the areas with peat starting between 40 and 80 cm depth and between 15 and 40 cm thick and peat starting between 80 and 120 cm depth were rewetted. In summary, peat growth was assumed only in areas where both of the following conditions were true: there already was a peat layer (Figure 1d) and where rewetting occurred (Figure 1c).

Based on the peat growth rate of 1 mm yr^{-1}, to change from peat starting between 15 and 40 cm depth to 0 and 15 cm depth (Figure 1d), up to 25 cm of peat would need to grow under rewetted circumstances, which would take approximately 250 years. Similarly, to change from peat class starting between 40 and 80 cm depth to 15 and 40 cm depth, up to 40 cm of peat would need to form over approximately 400 years. As the latter was the longest time needed of any change between classes, a map of peat classes in 2420 was made (Figure 1e). The 1 mm yr^{-1} peat accumulation rate is itself highly uncertain, partly because the estimated rate is based on natural peatland growth. Also, the land use oversimplification contributes to uncertainty, as some areas in the rewetted peatlands in the nature-inclusive scenario could be used for the production of crops suitable to these conditions, such as cattail, cranberries, reed and rice (Breman et al., 2022). Although crop growth under water saturated conditions would decrease the rate of or hinder peat mineralization, it is generally thought unlikely to lead to additional peat growth (Tanneberger et al., 2022).

Using the 2021 updated and the 2420 simulated peat classes maps (Figure 1d,e), we derived 2D + T peat class covariates and 3D + T peat occurrence covariates of any year up to 2420 using fuzzy memberships, in the same manner as during model calibration between 1953 and 2022 and explained in Section "Dynamic 2D+T and 3D +T covariates" of Helfenstein et al. (2024). For our purpose, we thus derived 2D + T peat class covariates and 3D + T peat occurrence for 2050, the latter of which are shown for 0–5 cm depth and 100–200 cm depth in Figure 1f,g.

The calibrated model from 1953 to 2022, the static covariates and the dynamic 2D + T and 3D + T land use and peat covariates for 2050 were used to predict SOM and its uncertainty for 2050 across six standard depth layers (0–5 cm, 5–15 cm, 15–30 cm, 30-60 cm, 60–100 cm and 100–200 cm).

To address the aim of whether nature-inclusive practices were conducive to enhancing SOM-related soil health based on this scenario model, we calculated spatial averages of SOM differences between 2022 and 2050 over areas in which we were able to localize the nature-inclusive practices listed in Section 2.1. For urban greening, we averaged SOM changes in areas classified as built-up in 2022 that were converted to grassland or forest by 2050. For rewetting peatlands, we averaged SOM changes in areas where rewetting occurred. Since it was not feasible to localize stream valley restorations and the addition of trees, hedges, and ponds separately, we grouped these areas together. This grouping was based on regions where agricultural land (grasslands and croplands) transformed into forests, swamps, marshes, and fens. Transitioning to agroecological and plant-based production systems was localized where grasslands were converted into croplands, fruit orchards or tree nurseries. Unfortunately, we could not localize the increase in plant biodiversity along river dikes, roadsides, and train tracks, as this could not be linked to specific land use classes or peat occurrence.

3 | RESULTS

3.1 | SOM trends at the national scale

We predicted decreases of more than 1% SOM on 22% of the land surface (7390 km^2) and corresponding increases of more than 1% SOM on 14% of the land surface (4740 km^2) between 2022 and 2050 based on the nature-inclusive scenario. Additionally, we predicted decreases of more than 10% SOM on 4% of the land surface (1300 km^2) and concurrent increases of more than 10% SOM on 2% of the land surface (670 km^2) over these 28 years. Thus, under the nature-inclusive land use scenario for 2050, the prevalence of areas predicted to experience SOM decreases exceeds those showing an increase. ΔSOM maps shown for 0–5 cm (Figure 2c), 15–30 cm (Figure 3a) and 100–200 cm (Figure 3b) support these findings.

3.2 | SOM trends in mineral soils

For the majority of the regions with mineral soils in the Netherlands (Figure 1d,e), there was little to no change in SOM between 2022 and 2050 (Figures 2c and 3a,b). However, in the uppermost centimetres of some mineral soils, SOM decreased by up to 5%, for example in the northern province of Friesland (Figure 2). These were usually areas where grassland was turned into cropland based on the reclassified land use categories of the 3D + T SOM model. In areas where cropland in 2022 was also cropland in 2050, SOM remained constant or decreased by <2.5%. However, along narrow strips bordering crop parcels designated as grassland, SOM mostly remained constant or increased slightly if it was cropland in 2022. In the nature-inclusive scenario, these narrow borders were mostly envisioned as buffer and biodiversity strips along the edges of agricultural parcels (Breman et al., 2022). In addition, SOM increased up to 10% between 2022 and 2050 in areas turned into nature reserves such as swamps and marshes in stream valleys and along waterways in the nature-inclusive scenario. Furthermore, SOM remained constant or slightly increased in built-up areas such as towns, cities and infrastructure, which can be explained by land use change from built-up to either grassland or forest as a result of greening in cities and alongside roads (Breman et al., 2022).

3.3 | SOM trends in peatlands

In peatlands (Figure 1d,e), we predicted more changes in SOM between 2022 and 2050 than in mineral soils (Figures 2c and 3a,b). In peatlands that were rewetted in the nature-inclusive scenario (Figure 1c), SOM increased

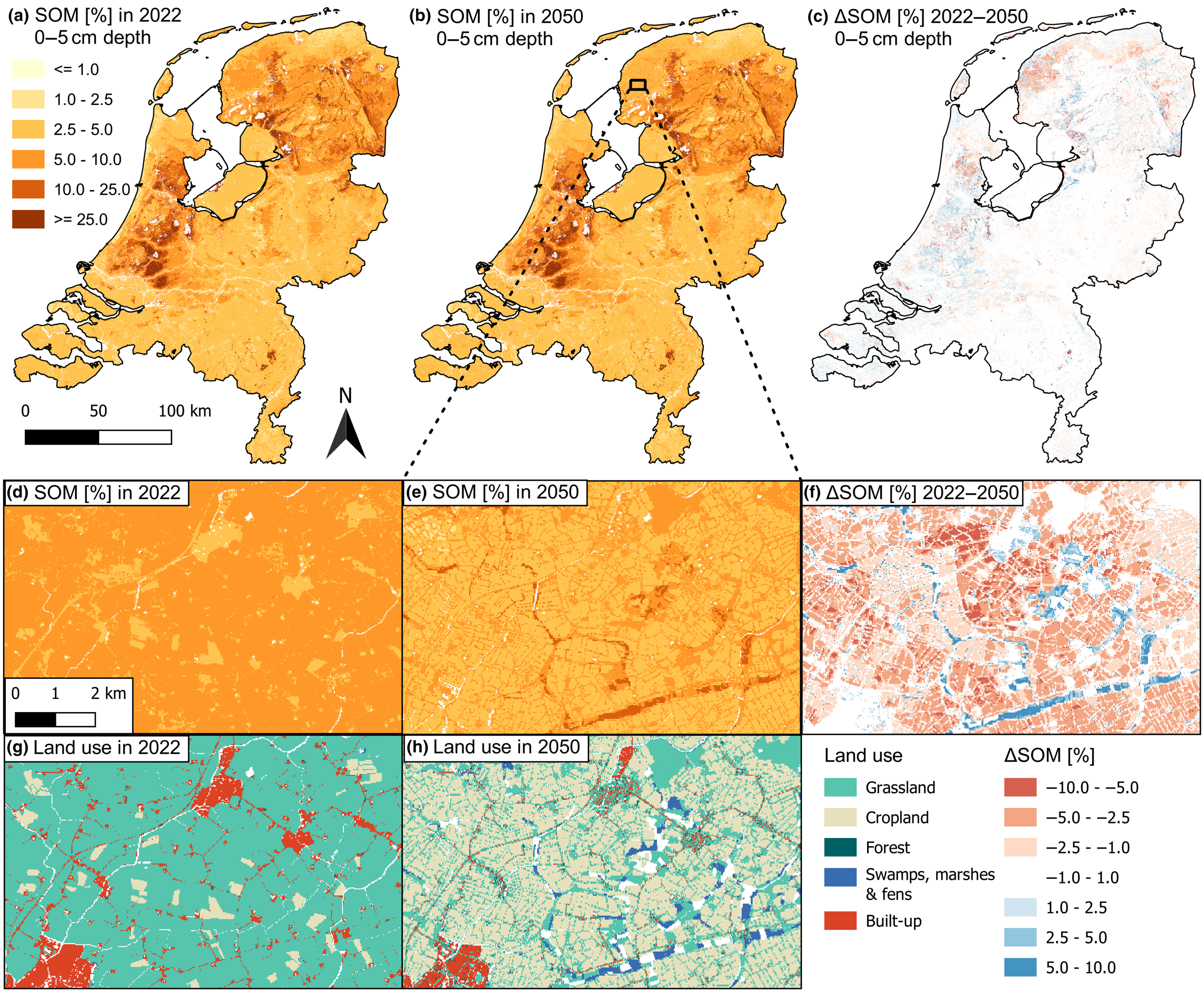

FIGURE 2 Predicted soil organic matter (SOM) [%] from 0 to 5 cm depth in 2022 (a), 2050 (b) and the difference in SOM between 2050 and 2022 (ΔSOM; c); zoom-in maps from the same depth layer and years (d–f) alongside land use (g, h) for an area in the province of Friesland.

by up to 25% in the upper 40 cm (Figure 3a,d). However, below 40 cm in rewetted peatlands, there was no clear pattern of SOM changes; SOM sometimes decreased and sometimes increased (Figure 3b,d).

The 3D + T SOM model predicted the largest changes in SOM in areas with peat layers that were not rewetted (Figures 1c and 3b,e). More specifically, these were in some of the areas where peat started between 40 and 80 cm depth and all areas where peat started below 80 cm depth (Figure 1d). For example on reclaimed land in the province of Flevoland (e.g. Helfenstein et al., 2024, Figure 1c), land subsidence caused peat layers below 80 cm to shift upwards (Brouwer et al., 2018), leading to SOM increase below 150 cm (Figure 3e). However, above 150 cm depth, this shifting up of peat layers resulted in large decreases of SOM above 10% and even above 25% farther North along the transect in Figure 3e.

3.4 | Model uncertainty

Prediction uncertainty, provided by the PI90 of the predicted probability distribution of QRF, was very high for 2050 (Figure 3c). Uncertainty was especially high where SOM predictions were high, for example in peatlands, and generally increased with increasing depth. One of the main limitations of the 3D + T SOM model is that it cannot provide uncertainty of ΔSOM and of spatial aggregates (e.g. Table 2) because it does not account for cross- and spatial correlation in prediction errors (Helfenstein et al., 2024). These correlations can be

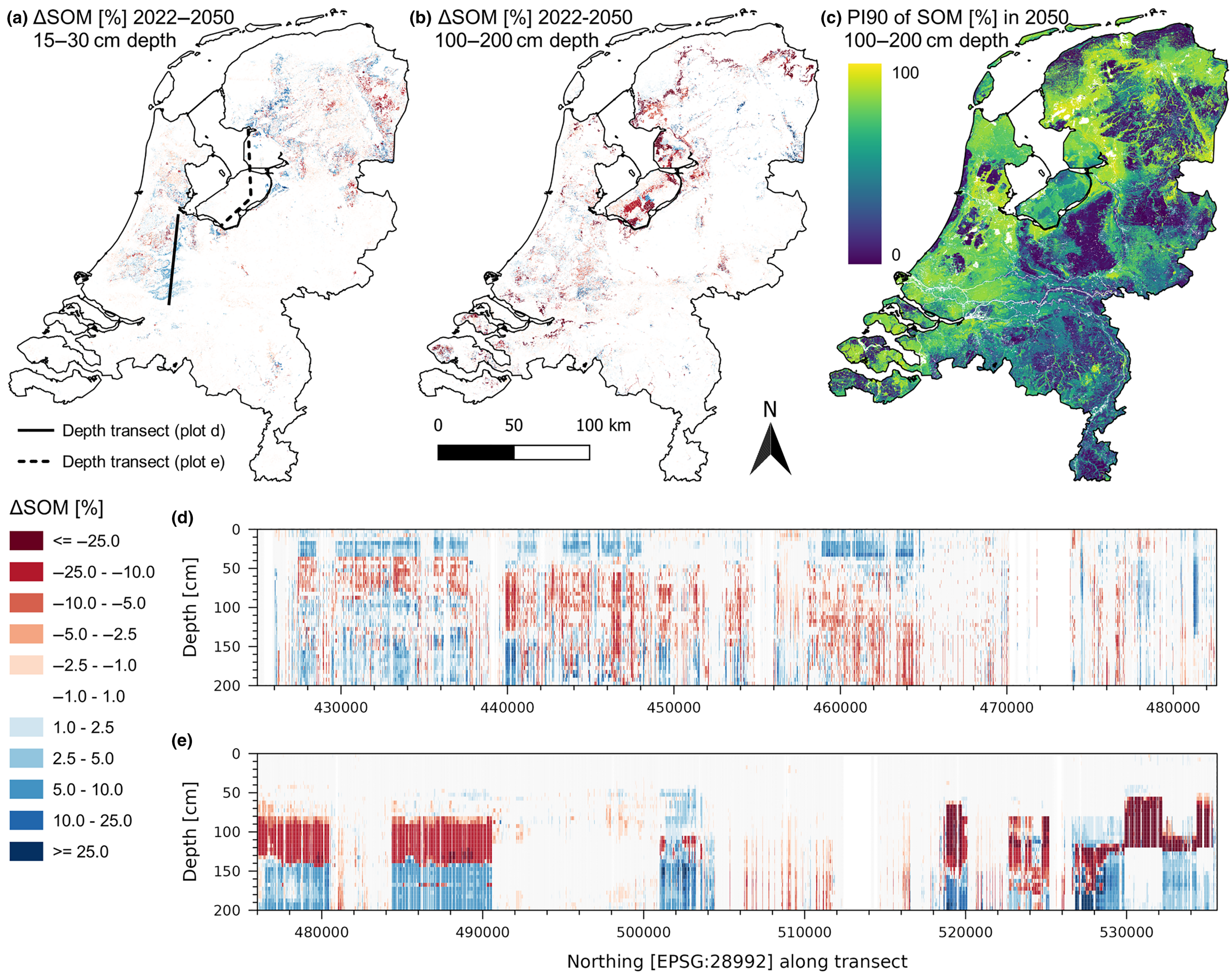

FIGURE 3 Predicted difference in soil organic matter (SOM) between 2050 and 2022 (ΔSOM) at 15–30 cm depth (a) and 100–200 cm depth (b); the 90th prediction interval (PI90) for SOM predictions [%] at 100–200 cm depth as a measure of uncertainty (c); ΔSOM depicted over depth [cm] vs. Northing [EPSG: 28992] in a region in the low-lying fen peatlands (d) and on reclaimed land in the province of Flevoland (e). The location of the depth transects (d, e) are shown in map a.

TABLE 2 Overview of the impact of nature-inclusive practices on soil organic matter (SOM) changes [%] between 2022 and 2050 separated by soil depth [cm].

Nature-inclusive practice	0–5 cm	5–15 cm	15–30 cm	30–60 cm	60–100 cm	100–200 cm
Greening of cities	0.4	0.4	0.0	0.2	0.3	0.2
Rewetting peatlands	0.6	0.5	1.4	1.5	−0.7	0.4
Stream valley restoration, adding trees, hedges & ponds to the landscape	0.8	0.4	0.6	0.4	−0.3	0.3
Transition to agroecological & plant-based production systems	−1.0	−1.0	0.0	0.0	−0.1	−0.2
Increasing plant biodiversity along river dikes & transportation infrastructure	–	–	–	–	–	–

Note: These spatial averages were calculated by localizing land use changes based on nature-inclusive practices (Section 2.3). Note that stream valley restoration and adding trees, hedges and ponds to the landscape were grouped. We were not able to link increasing plant biodiversity with any dynamic covariates in the 3D + T SOM model and therefore no average SOM changes are presented for this nature-inclusive practice.

accounted for by choosing a multivariate or geostatistical approach (Szatmári et al., 2021; van der Westhuizen et al., 2022; Wadoux & Heuvelink, 2023), but it is unclear how to do so in 3D space and time. Fitting a semivariogram in 3D + T is extremely challenging given that space–time and lateral-vertical anisotropies would have to be accounted for, while also the conventional geostatistical assumptions on multivariate normality and second-order stationarity would have to be questioned (Helfenstein et al., 2024). Quantifying the uncertainty of SOM changes in 3D + T at management and policy-relevant scales is crucial for future research, since uncertainty in soil monitoring has raised substantial doubts about the feasibility of measuring and verifying changes in SOM and soil organic carbon (Moinet et al., 2023; Paul et al., 2023). However, due to the challenges and complexity involved, this analysis was beyond the scope of this study. Nonetheless, while not demonstrated using our approach, we expect the uncertainty of ΔSOM to be high where the PI90 of SOM predictions for 2050 were also high (Figure 3c).

3.5 | Average SOM trends as a result of nature-inclusive practices

This study found that a majority of the nature-inclusive practices led to small increases in SOM and were therefore beneficial for soil health (Table 2). SOM increased in areas designated as grasslands, forests, swamps, marshes, fens or bogs in 2050 as a result of the greening of cities, stream valley restoration and adding trees, hedges and ponds to the landscape. However, rewetting peatlands and transitioning to agroecological and plant-based farming systems were only partially beneficial for SOM-related soil health. Due to rewetting peatlands, SOM on average increased by 0.4–1.5% between 0 and 60 cm and 100 and 200 cm depth, but on average decreased by 0.7% between 60 and 100 cm depth (Table 2). For example, SOM increased by as much as 25% in the top 40 cm where peatlands were rewetted, but this effect varied at lower depths in the low-lying fens in the West of the Netherlands (Figure 3d). Furthermore, the conversion of cropland to grassland in mineral topsoils showed an increase in SOM, whereas the reverse land use change during the farming transition resulted in a notable decreases up to 5% SOM (Figure 2) and average decreases of 1.0% SOM between 0 and 15 cm (Table 2). It is crucial to acknowledge that the partially beneficial outcomes observed in rewetting peatlands and farming transitions may be influenced by limitations inherent in our scenario modelling method, as discussed further below.

Additionally, the 3D + T SOM maps unveiled substantial SOM losses, sometimes exceeding 25%, in expansive regions with peat layers below 40 or 80 cm depth. Largely located on reclaimed land, these areas were not rewetted and the subsoil was not influenced by other nature-inclusive practices, resulting in SOM loss due to factors such as land subsidence and peat oxidation. In summary, model predictions underscore the importance of implementing nature-inclusive practices for sustainable soil management. Moreover, SOM maps in 3D + T emphasize the potential consequences of neglecting nature-inclusive practices and their limitations for positively contributing to soil health at lower depths in the soil profile.

4 | DISCUSSION

The nature-inclusive practices related to rewetting peatlands and transitioning to more agroecological and plant-based farming systems require a more nuanced evaluation. In the rewetted, low-lying, fen peatlands in the West of the Netherlands (Figure 3d), increases up to 25% SOM above 40 cm were due to dynamic peat class and peat occurrence covariates, which indicated that peat was accumulating (Figure 1d–g). However, since peat started below 15 or 40 cm in these areas already in 2022, dynamic peat occurrence remained constant and indicated the presence of peat below these depth thresholds in 2050, while dynamic peat class covariates in 2050 were changing because of increasing peat thickness as a result of slow peat growth. Consequently, SOM decreases below 40 cm depth are likely attributed to the dynamic peat class covariates and are deemed implausible within this scenario. While the validity of this assumption could be examined by excluding 2D + T peat class covariates and relying solely on 3D + T peat occurrence, such an analysis was not conducted in this study, as the inclusion of both peat class and peat occurrence improved model performance during the calibration period (Helfenstein et al., 2024). When considering these constraints, the modelling results support the notion that rewetting peatlands tends to increase SOM, a conclusion supported by numerous empirical field experiments (e.g. Ballantine & Schneider, 2009; Negassa et al., 2019).

Another major limitation was the 3D + T SOM model's inability to incorporate agroecological farming methods in plant-based production systems envisioned in the nature-inclusive scenario for 2050 (Breman et al., 2022). Methods such as conservation tillage, mulching, cover crops and especially growing crops where less soil disturbance is needed, such as perennial crops, have shown to achieve improvements in maintaining SOM in croplands compared to conventional methods (Crews & Rumsey, 2017). However, crop type and management practices such as tillage were not included as covariates. Moreover, the model was calibrated without accounting for sustainable management practices, as such practices were not the standard during the model calibration period (1953–2022; Helfenstein et al., 2024, Table 2). Extrapolating this conventional farming scenario into the future likely caused an overestimation of SOM losses in croplands and with the conversion of forest or grassland into cropland. In essence, the model represented a simplified version of the past reality, limiting its ability to predict a highly complex vision of a potential future reality. Yet, it also shows that if we do not transition to nature-inclusive farming systems, on the long term our soils will be less capable to provide multiple ecosystem services needed to sustain plant and animal productivity, maintain or enhance water and air quality and promote plant and animal health.

Limitations related to land use and management practices also applied to peatlands. Some rewetted peatlands areas in the nature-inclusive scenario would be used for paludiculture or crops suitable for growth under water saturated conditions (Breman et al., 2022). While this may prevent peat mineralization and lead to constant SOM levels, it is unlikely that new peat grows in these areas (Tanneberger et al., 2022). In summary, in its limited ability to account for nature-inclusive land use practices, our approach may have overestimated SOM decrease in mineral croplands and SOM increase in rewetted peatlands.

Another methodological limitation in our study was that climate was a static covariate. We included long-term minimum, maximum and average temperature and precipitation data between 1981 and 2010 as static covariates in our modelling approach (Helfenstein et al., 2022, Table 2). Hence, the temporal dynamics inherent in climate covariates, such as precipitation and temperature, were not accounted for in either the model calibration period (1953–2022) or the projection for the 2050 scenario, even though climate change affects carbon dynamics in the soil (Beillouin et al., 2022, 2023). While other DSM studies modelling future scenarios accounted for climate change (Gray & Bishop, 2016, 2019; Yigini & Panagos, 2016), we posited that, within our specified timeframe and under the prevailing conditions, the impacts of temperature and precipitation on SOM dynamics were of lesser consequence compared to changes in land use, peat class, and peat occurrence. The current time-frame is <30 years in the future, with an expected increase of 1.6°C and decrease of 17 mm (−2%) in rainfall under a high emissions and dry scenario projected for the Netherlands (KNMI, 2023; van Dorland et al., 2023). Nonetheless, we recommend studies, especially ones over longer scenario timeframes, to include dynamic changes in covariates related to the climate. For our model, it would have required deriving dynamic covariates based on temperature and precipitation maps between 1953 and 2050 and recalibration of the model, which was outside of the scope of this study.

Despite the limitations in the model, mapping SOM in 3D space in 2050 and assessing SOM changes compared to 2022 in the context of a nature-inclusive scenario yielded valuable insights. Although regional soil conditions were considered for developing the nature-inclusive outlook for 2050 (Breman et al., 2022), this study creates new insights and raises important questions related to soil health about some of the notions and assumptions behind the scenario. For example, switching from animal-based to plant-based production systems is expected to bring many advantages for the environment and human well-being (Breman et al., 2022), such as less greenhouse gas emissions from animal husbandry. Yet even with the adoption of agroecological practices, achieving SOM levels akin to those in permanent grasslands (e.g. pastures) within croplands presents a formidable challenge (Crews & Rumsey, 2017). This links to the policy target of the European Union to reverse soil organic carbon losses in croplands to an increase of 0.1–0.4% yr^{-1} on average by 2030 (Veerman et al., 2020). Conversely, the conversion of less suitable croplands into grazing lands for extensive animal production systems is expected to offset this challenge.

Another valuable insight is that rewetting peatlands as a nature-inclusive practice prevented the continuation of substantial SOM decreases in expansive areas in the majority of fen peatlands in the West and bogs and brook valleys in the East that were predicted between 1953 and 2022 (Helfenstein et al., 2024). The major potential in rewetting peatlands lies in its potential to impede rapid and sustained SOM decrease, as we found that SOM mainly decreased where soils were not rewetted (Figure 3b,e). Although preventing further SOM loss can be immediate or within a few years, peat growth in rewetted peatlands takes decades to centuries, operating on time-scales over multiple generations. Moreover, it is also dependent on the land use, for example natural peatland vs. peatland under paludiculture. The modelled scenario is only around 25 years in the future, but for some aspects of soil health to substantially change, so that humans and other organisms in return benefit from the ecosystem services that soils provide, a longer time window might be necessary.

Consistent with mapping SOM in 3D + T between 1953 and 2022 (Helfenstein et al., 2024), we also predicted substantial decreases in SOM on reclaimed land in the nature-inclusive scenario for 2050. It is improbable that nature-inclusive farming methods alone will suffice to prevent SOM decrease in these regions, given ongoing land subsidence, compaction and upward shifting of peat layers, and lower groundwater levels for part of the year, all of which contribute to SOM mineralization. Soils in areas with deep peat layers, not designated as peat soils in the soil landscape map (Section 2.1; Delft & Maas, 2022), may currently by suitable for crop production. However, our 3D + T approach showed that nature-inclusive scenarios only based on the dominating soil conditions in the topsoil may have severe consequences and lead to soil health deterioration if adopted by policy makers. In line with Helfenstein et al. (2024), this highlights the strengths of the 3D + T approach and inadequacy of evaluating soil health at point scale or static mapping at a single depth for policymaking.

Although negative trends in SOM-related soil health found over the last 70 years (Helfenstein et al., 2024) continued up to 2050 on reclaimed land, nature-inclusive practices benefited SOM in many areas, suggesting that a nature-inclusive transition can improve soil health, thereby also benefiting society. The quantitative modelling of prospective scenarios, facilitated by our innovative 3D + T method, yields insights that may be valuable for guiding strategic spatial planning decisions. This is particularly relevant in the context of aligning with targets delineated in national policies such as the Climate Agreement of the Netherlands (Dutch government, 2019), as well as adhering to international frameworks like the European Soil Deal (European Commission, 2021), Green Deal (European Commission, 2023a), and Sustainable Development Goals (United Nations, 2015). Our findings underscore the potential of envisioning nature-inclusive transitions as a proactive and impactful approach to address soil health concerns and contribute to broader sustainability goals.

5 | CONCLUSION

In this study, we demonstrated that 3D + T mapping of SOM for a future scenario is a pivotal tool to move from soil health-related proceedings to actions on a national scale. Beyond functioning as visual aids to underscore the societal importance of soils, our approach generated novel insights and prompted pertinent questions within the context of nature-inclusive scenarios. These insights require thoughtful consideration for the enhancement of soil health and the facilitation of broader societal transformations. By linking the nature-inclusive outlook to soils and thereby capturing the potential benefits and overlooked opportunities within spatial planning for soil-based ecosystem services, we have introduced an innovative and indispensable tool for policymakers. Space–time scenario modelling of soils not only aids in developing future plans but also provides a framework for gauging the temporal efficacy of implemented practices. However, it is equally imperative to emphasize the necessity of field monitoring and measurement to ensure the effectiveness of these practices over time.

In alignment with Breman et al. (2022), adopting nature-inclusive forms of spatial planning across the entirety of the Netherlands represents a major challenge. Key factors in realizing this agenda will include a clear spatial policy strategy, sustainable business models, and a structured behavioural change. Despite the recognized challenges, we contend that ambitious visions stimulate a broader dialogue on the significance of soil health in the context of sustainable development and are catalysts for societal transformation.

AUTHOR CONTRIBUTIONS

Anatol Helfenstein: Conceptualization (lead); data curation (lead); formal analysis (lead); investigation (lead); methodology (lead); project administration (equal); software (lead); validation (lead); visualization (lead); writing – original draft (lead). **Vera L. Mulder:** Conceptualization (supporting); formal analysis (supporting); funding acquisition (lead); investigation (supporting); methodology (supporting); project administration (equal); resources (lead); supervision (lead); validation (supporting); writing – original draft (supporting); writing – review and editing (lead). **Mirjam J. D. Hack-ten Broeke:** Conceptualization (supporting); formal analysis (supporting); investigation (supporting); methodology (supporting); project administration (supporting); resources (supporting); supervision (supporting); validation (supporting); writing – review and editing (supporting). **Bas C. Breman:** Data curation (supporting); formal analysis (supporting); investigation (supporting); methodology (supporting); validation (supporting); writing – review and editing (supporting).

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

See Helfenstein et al. (2024) for the data and code of the 3D + T SOM model. Data for the nature-inclusive land use scenario for 2050 and code for the 2050 scenario modelling of SOM is available upon reasonable request.

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