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Research article

Land degradation neutrality: Testing the indicator in a temperate agricultural landscape

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ABSTRACT

Land degradation directly affects around 25% of land globally, undermining progress on most of the UN Sustainable Development Goals (SDG), particularly target 15.3. To assess land degradation, SDG indicator 15.3.1 combines sub-indicators of productivity, soil carbon and land cover. Over 100 countries have set Land Degradation Neutrality (LDN) targets. Here, we demonstrate application of the indicator for a well-established agricultural landscape using the case study of Great Britain. We explore detection of degradation in such landscapes by: 1) transparently evaluating land cover transitions; 2) comparing assessments using global and national data; 3) identifying misleading trends; and 4) including extra sub-indicators for additional forms of degradation. Our results demonstrate significant impacts on the indicator both from the land cover transition evaluation and choice or availability of data. Critically, we identify a misleading improvement trend due to a trade-off between improvement detected by the productivity sub-indicator, and 30-year soil carbon loss trends in croplands (11% from 1978 to 2007). This carbon loss trend would not be identified without additional data from Countryside Survey (CS). Thus, without incorporating field survey data we risk overlooking the degradation of regulating and supporting ecosystem services (linked to soil carbon), in favour of signals from improving provisioning services (productivity sub-indicator). Relative importance of these services will vary between socioeconomic contexts. Including extra sub-indicators for erosion or critical load exceedance, as additional forms of degradation, produced a switch from net area improving (9%) to net area degraded (58%). CS data also identified additional degradation for soil health, including 44% arable soils exceeding bulk density thresholds and 35% of CS squares exceeding contamination thresholds for metals.

1. Introduction

Progress towards Land Degradation Neutrality (LDN) underpins global stability and environmental sustainability (Cowie et al., 2018). The concept of Land Degradation Neutrality (LDN) was established to “maintain or enhance land-based natural capital and its associated Ecosystem Services” (Cowie et al., 2018). Urgent global action to limit land degradation within the next ten years is a central requirement for meeting most of the United Nations Sustainable Development Goals (SDG) (IPBES, 2018). In particular, SDG 15.3.1 sets out to “combat desertification, restore degraded land and soil” and “achieve a land degradation-neutral world” by 2030. The importance of LDN was recently recognised by the UN Decade on Restoration (2021–2030). Land degradation directly affects between 25% and 33% of land (IUCN, 2015), and costs around US$ 300 billion annually (Nkonya et al., 2016). The economic benefits of reversing degradation trends can be around five times greater than the costs (Nkonya et al., 2016), and avoiding or reversing degradation can combat climate change and reduce political instability (Cowie et al., 2018).

Reliable, timely assessment of progress towards LDN is critical, due to long lead in times for new interventions, and time lags for recovery (IPBES, 2018). Assessment is based on SDG indicator 15.3.1, which comprises three sub-indicators: 1) land cover; 2) productivity; and 3) soil organic carbon (SOC). Each sub-indicator is intended to provide a proxy for change in the capacity of land to deliver ecosystem services and biodiversity (Sims et al., 2021). The indicator uses a

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Table 1
Sub-indicators in the UNCCD (2015) Land Degradation Neutrality (LDN) indicator, showing data availability, rate of response, the ecosystem services (and biodiversity) represented by each sub-indicator, and trade-offs between these.

Sub-Indicator	Data availability	Rate of response	Links to ecosystem services as selected by UNCCD expert workshop*	Ecosystem services and biodiversity opportunity costs/ trade-offs
Land cover	Globally available with varying confidence, resolution and levels of classification.	Annual	Biodiversity Cultural heritage Regulation of: extreme events; pests and diseases; water Pollination Provisioning of: food; water; fibre and wood; medicinal resources	Inherent trade-offs: different land cover types provide different services Trade-offs between provisioning and biodiversity common (Reidsma et al., 2006)
Productivity	Proxy data globally available as NDVI.	Sub-annual	Provisioning of: food; fibre and wood Primary production Regulation of: climate; water Nutrient cycling	Short term high provisioning may have trade-offs with biodiversity and regulating services (Reidsma et al., 2006; Akhtar-Schuster et al., 2017), and threaten longer term provisioning through impacts on soil health (Kopittke et al., 2019) and carbon (Smith et al., 2007)
Soil organic carbon (SOC)	Limited, due to short-range variation, generally slow rates of change and rarity of comprehensive repeat surveys (Lorenz et al., 2019).	Decadal or slower	Primary production Nutrient cycling Water cycling Soil formation Climate change mitigation Regulation of: extreme events; pests and diseases Provisioning of: food; water Biodiversity	Trade-offs between short term provisioning and soil carbon (Smith et al., 2007) with impacts on other services (Kopittke et al., 2019)
Additional nationally relevant forms of degradation may be included			Specific to the form of degradation and local or national ecosystem services concerns	Trade-offs with the ecosystem services represented by the core sub-indicators may be relevant

'one-out-all-out' principle, and reports separately for each land cover class. The indicator was defined by the United Nations Convention to Combat Desertification (UNCCD, 2015), reflecting concern for land degradation in drylands, particularly in countries with high rates of agricultural expansion and large populations engaged in subsistence agriculture, where societal impacts may be more severe (IPBES, 2018). However, the European Court of Auditors (2018) recommended the indicator as a starting point for consistent monitoring of degradation across the region, so suitability outside of drylands should also be considered.

Each sub-indicator is related to multiple ecosystem services (Table 1), and trade-offs between these can create subjectivity in assessment of change as "degraded" or "improving". Combined with trade-offs between the sub-indicators, and issues of data interpretation, this can lead to "false-positives" of apparent improvement trends for degrading areas (and conversely false-negatives; Table S1) which should be identified in reporting (Sims et al., 2020). In addition to the sub-indicators in Table 1, the UNCCD guidelines encourage countries to incorporate additional metrics, which may account for locally important degradation concerns (Cowie et al., 2018). This has particular importance in temperate regions and established agricultural landscapes, where the primary forms of degradation may differ from the indicator development context.

The aim of this study is to explore the ability of indicator 15.3.1 to detect degradation in temperate agricultural landscapes, through an application in Great Britain (GB). Recent analysis for the EU has demonstrated indicator sensitivity to choice of data (Schillaci et al., 2023). Here we expand on this with the following objectives: 1) construct a transparent evaluation of land cover transitions; 2) compare assessments using global and national data; 3) identify misleading trends; and 4) include extra sub-indicators for additional forms of degradation. Objective 1 allows us to demonstrate inherent trade-offs which must be considered in land cover degradation assessments. Objective 2 is addressed separately for land cover and SOC, and demonstrates the impacts of using country specific datasets. Objective 3 is addressed for the sub-indicators separately and in combination to identify potential bias from trade-offs between sub-indicators, i.e. whether readily detectable trends in one sub-indicator may conflict with difficult to detect trends in another. We explore the resulting challenges in detecting degradation for GB, an issue which may extend to other temperate agricultural landscapes.

The additional forms of degradation we assessed for objective 4 were soil health, soil erosion, and critical load exceedance by nitrogen and acid deposition. The EU mission board for soil health and food identifies soil health metrics that may indicate degradation, although data are limited for many of these, particularly spatially (Veerman et al., 2020). Data to assess some of these soil health trends are available for GB from Countryside Survey (Carey et al., 2008). Soil erosion has been identified as a complementary or alternative land degradation indicator with global data available (Olsson et al., 2019; Wuepper et al., 2021). Critical load exceedance by nitrogen and acid deposition is also recognised as an important form of degradation of soils and vegetation, with impacts on vegetation productivity, species composition, ecosystem function and resilience (Bobbink et al., 1998), and data are available for GB (from Rowe, 2021).

2. Methods

We calculated the LDN indicator for GB using methods based on the Good Practice Guidance (GPG) for SDG Indicator 15.3.1 (Sims et al., 2021), testing both global and GB specific datasets. In line with UNCCD guidance, we also tested the inclusion of datasets on other nationally relevant forms of degradation in addition to the core sub-indicators.

The GPG provides steps and data requirements for calculating the proportion of total land area degraded, using the three sub-indicators (Table 1). Proportion of total land area degraded is calculated separately for each land cover type. Productivity should be calculated separately for areas with land cover change, since this will have misleading effects on the productivity trend. Land cover change will contribute to degraded or improved area depending on whether the change is classified as degradation in the national context. Soil carbon change may only be assessed where land cover change occurs, unless tier 3 assessment is possible. The GPG provides guidelines for selecting data, as well as lists of available datasets. The LDN target requires no net increase in the proportion of degraded land. The GPG guidelines (version 2) specify monitoring over a 16-year moving window, to identify change in extent of degradation relative to the baseline period (2000–2015) (Sims et al., 2021).

Here, we assessed the baseline period. We first calculated each sub-indicator, tested multiple datasets and interpretations where appropriate, and explored the relationship of the sub-indicator to the ecosystem services represented. We then explored potential false-positives and trade-offs between sub-indicators to investigate potential biases. Next, we completed assessment for additional forms of degradation. Finally, we calculated the overall indicator and explored the impacts of the additional forms of degradation.

We used the Trends. Earth tool (demonstrated by Giuliani et al., 2020) to calculate the productivity sub-indicator. For the remaining spatial analysis, we used a simple approach of creating raster composites and calculating zonal statistics to assess the other sub-indicators, compare datasets, construct the combined indicator and examine the impact of data on additional forms of degradation. We assessed a period broadly representative of the 2000–2015 baseline period, however some national data were not available for this exact range of dates. All datasets used are listed in Table S2.

2.1. Land cover change

2.1.1. Land cover change assessment as degraded or improved

To assess landcover change, we first identified all possible land cover transitions and evaluated whether each may represent degradation, by constructing a bespoke transition assessment matrix in line with the GPG. The GPG (Sims et al., 2021) provides an example matrix assigning each possible land cover change an assessment as degradation, stable or improvement. This should be adapted to account for context and country specific concerns, using a transparent approach and accounting for trade-offs, ideally with multi-stakeholder input. We accounted for impacts on: biodiversity, provisioning and regulating ecosystem services. These broadly relate to the four main forms of land cover change degradation identified in the GPG. Multi-stakeholder consultation was out of scope for this work, instead, assessments were made using expert opinion, supported by GB relevant literature. Each transition was then assigned an overall assessment of degradation or improvement, based on an equal weighting of the impacts. We then compared this overall assessment to the example six class transition assessment provided in the GPG.

2.1.2. Impacts of choice of land cover data

The GPG highlights the importance of spatial resolution of data, recommending 300 m or finer, since detection of change may be more challenging for mixed pixels. We therefore compared land cover change degradation assessments using land cover change maps at 25 m from UKCEH for 1990–2015 (Rowland et al., 2020) and globally available data at 0.00278° (approximately 160 b y 300 m) from the climate change initiative (CCI) of the European Space Agency (ESA, 2017) for 1992–2015. Comparison was performed at the 25 m pixel resolution and degradation was assigned based on the bespoke transition assessment matrix constructed per section 2.2.1.

Use of annual land cover data is recommended to reduce the risk that dynamic land cover (e.g. periodic inundation, crop/grass rotation) is mistaken for a transition between stable states. Here, we compared land cover between individual years, which may introduce some error in terms of areas mapped as changing, however the net area erroneously mapped as degrading should be small, since erroneous transitions can be expected to occur in both directions.

2.1.3. Impacts of differing land cover change assessments for LDN

Having identified the transitions occurring, we then analysed the impact on net area degrading from using the bespoke transition assessment matrix (from section 2.2.1) compared to the example six-class transition assessment provided by the GPG.

2.2. Productivity degradation

The GPG allows assessment of relative change in productivity levels using the Normalised Difference Vegetation Index (NDVI) using global (Tier 1) or national (Tier 2) data, without calculating biomass (required for Tier 3) (Sims et al., 2021). Here, we used 250 m NDVI data from MODIS (Didan, 2015) for the recommended baseline period (2000–2015).

We assessed productivity degradation using approaches provided in the Trends. Earth tool for trajectory, state and performance. Productivity trajectory assessment applies linear regression at the pixel level to identify areas as degrading or improving based on changes in annual integral of NDVI, using a Mann-Kendall non-parametric significance test (Z score < -1.96 for improving, >1.96 for degrading). Alternative trajectory analyses accounting for climate are explored in Supplementary section S4. Productivity state is assessed by comparing a historical mean (2010–2012) to the most recent period (2013–2015), to capture recent changes in productivity. Here, we applied the approach in Trends. Earth of assessing change in percentile class between the time periods to assign each pixel as degraded or improved. Productivity performance is assigned as degraded where mean productivity is $<$ 0.5 max productivity, defined as the 90th percentile NDVI for similar land class, assigned here using soil taxonomy units (SoilGrids 250 m resolution Hengel et al., 2017) and land cover (ESA CCI ~300 m resolution, ESA, 2017). Trajectory, state and performance were combined spatially in accordance with the GPG (Supplementary Table S6). Overall productivity trends were combined with the UKCEH land cover data at 25 m resolution to calculate the trends by land cover class. The balance between area degrading and improving is used to calculate net area degrading for each land class.

2.3. Carbon

2.3.1. Identifying baseline carbon stocks, and comparing datasets for area degrading

Numerous spatial datasets are available to provide a baseline for carbon stock. Here, we used global 250 m 0–30 cm data for 2015 based on SoilGrids and CCI landcover (from Wheeler and Hengl, 2018). To explore the issues detecting degradation for this metric, we also demonstrated assessment of change over the baseline monitoring period. Data to assess change in soil carbon are very limited due to monitoring challenges, including slow rates of change and large short-range variation. As a result, estimates of changes in soil carbon are commonly based only on the expected changes for land cover change, using a space for time approach under Tier 1 (global soils data) or Tier 2 (national soils data). Here we identified areas gaining or losing carbon stock from: 1) land cover change maps at 25 m for 1990–2015 (Rowland et al., 2020); and 2) ~250 m SOC change from CCI landcover 2000–2015 (Wheeler and Hengl, 2018).

2.3.2. Use of inventory data to quantify change in stock

The GPG points to the IPCC guidance for Land Use, Land-use Change and Forestry (LULUCF) for quantification of change in stocks, and recommends aligning with the latest approaches and data. Here, we compared likely changes in soil carbon associated with land use changes based on a LULUCF inventory for the 1990–2015 period (data from Brown et al., 2023), with the change identified in the global data 2000–2015 (from Wheeler and Hengl, 2018).

2.3.3. Use of field survey data to identify carbon trends where there is no land cover change

The GPG notes other sources of SOC degradation, including unsustainable agricultural management (Sims et al., 2021). Although carbon losses may be smaller than for land cover change, this may lead to degradation of large areas, and is thus a key component of the indicator, but would not be detected by tier 1 and 2 approaches. Tier 3 approaches, including repeated soil surveys and process-based modelling, can help to understand where this type of degradation may be occurring. Therefore, we also used data from the Countryside Survey (CS) to identify trends in habitat level carbon for intervals between 1978 and 2007, and 1998 and 2007 (Carey et al., 2008).

2.4. Trade-offs and false-positives

We discuss how trade-offs between the sub-indicators, and the relative availability of data on each (see Table 1), affect the ability of the indicator to identify important forms of degradation in GB. We then extracted our core sub-indicators to data on peat extent (from Evans et al., 2017) to interpret land cover change and NDVI trends on peat and to reassess where this may represent false-positives or negatives.

2.5. Additional forms of degradation tested for GB

We also explored the use of data on additional forms of degradation: 1) degradation due to contaminated soils and other soil health metrics; 2) areas with degradation from soil erosion; 3) areas with degradation from critical load exceedance (data sources are described below). Where historic data are available, we assessed change to identify degradation. Where data are only available for one time period, we used thresholds to identify baseline degraded area. Where data are available spatially, we combined these with the core sub-indicators, to establish whether they represent additional degraded area.

2.5.1. Soil health metrics

Soil health was assessed using Countryside Survey data. For pH, bulk density and Olsen P (OP) in improved habitats, we compared our data to prompt values to assess condition and identify the proportion of sites within prescribed ranges for different soil health concerns (see Supplementary section S6.1 forthresholds, from Bhogal et al., 2008). For soil contamination, areas that may be degraded were identified from Countryside Survey data for 2007, using the multisubstance Potentially Affected Fraction (msPAF) for metals nickel, copper, zinc, cadmium and lead in soils (Lofts et al., 2005). Complete spatial maps are not available to overlay with our other data.

2.5.2. Erosion

Soil erosion by water has been modelled at high resolution (100 m) across Europe for 2010 (Panagos et al., 2015a), and we used these data to identify areas exceeding a sustainable soil loss rate of 1 t/ha/yr (suggested by Verheijen et al., 2009 from a European wide synthesis of soil formation rates). Change data are not currently available. However, we estimated potential changes in erosion rates over time using crop statistics from DEFRA and information on management practices from Eurostat and the literature. We did this using methods previously applied to Europe (Panagos et al., 2015b), to calculate the "C-factor", which represents the protection conferred by vegetation cover and management to soils from erosion.

2.5.3. Critical load exceedance

Critical load exceedance has been modelled for different time steps, so we used these data to identify areas that may be subject to degradation from exceedance of N deposition, eutrophication, nutrient nitrogen deposition or acid deposition thresholds. We used Average Accumulated Exceedance (AAE) data combined for all terrestrial habitats for 1998–2000 and 2014–2016 gridded at 1 km (Rowe, 2021). Calculations consider total degraded area, newly degraded area and recovered area.

2.6. Overall indicator

The overall assessment assigns a unit of land as degraded if any of the sub-indicators show degradation (a one-out-all-out approach) and calculates the proportion of land degraded for each land cover type assessed.

3. Results and discussion

3.1. Land cover change

3.1.1. Land cover change assessment as degraded or improved

Our land cover change assessment highlights trade-offs between provisioning services and biodiversity and regulating services, such as hydrological function (Table 2). The net outcome is based on equal weighting of biodiversity, provisioning and regulating outcomes. Our assessment shows low agreement with the example six-class land cover change matrix from the GPG. There is only agreement for transitions between cropland and tree-covered land, and for wetland to cropland or tree-covered. Some of the disagreements may reflect preferential weighting of production in the GPG six-class matrix. When the trade-offs for cropland transitions are considered, cropland only benefits production, whereas grassland, wetland and forest have better outcomes for biodiversity and regulating ecosystem services (Reidsma et al., 2006; Moreno-Mateos et al., 2012; Panagos et al., 2020; McElwee et al., 2020). Provisioning may be given preferential weighting in some socio-ecological contexts, particularly countries with food security concerns. The GPG acknowledges that desirability of trends is context specific, depending on stakeholders and national priorities (Sims et al., 2021). Transparency around why a land cover change is being assigned as improvement or degradation is critical for the LDN indicator to be implemented appropriately. Additionally, it is recommended that counterbalancing of habitat loss be implemented at appropriate scales, with consideration of biodiversity value for existing habitat relative to new habitats (IUCN, 2015).

The disagreement between our bespoke land cover assessment and the six-class GPG default also reflects variation within the broad land cover classes. These may contain habitats with wide ranging values, e.g. in the UKCEH landcover data used, the "grassland" land cover category contains bogs and intensively managed systems, while "tree-covered" could be native trees or plantation, and "wetland" includes a range of flooded vegetation types. The updated GPG provides an example matrix for a 13-class landcover dataset which would better categorise the context specific transitions in Table 2, and which classifies conversion of cropland to native grassland as improvement, reducing some of the production bias in the six-class matrix (Sims et al., 2021). Again, this should be adapted to the national context.

The outcomes in Table 2 may also be affected by changes in land management (e.g. Reidsma et al., 2006) or landscape composition and configuration (e.g. Haines Young, 2009; Bodin et al., 2006), which would be missed by this indicator. We have not assessed impacts on pollination, regulation of pests and diseases or cultural heritage, since these are harder to generalise due to the importance of site factors or effects of landscape spatial configuration. For the remaining steps of the analysis, the net outcome based on our bespoke land cover change assessment matrix was used.

3.1.2. Impacts of choice of land cover data

Both land cover datasets assessed (Fig. 1a) suggested net area reduction of grassland, net area increase of tree-covered land, and slight net area reduction of cropland (Fig. 1b). The CCI data indicated net area reduction of wetland, whereas wetland classes are not separately identified in the UKCEH data. The UKCEH data have finer resolution at 25 b y

Table 2
Land cover change matrix with breakdown of Ecosystem Service trade-offs specifically defined for UK and comparison to Good Practice Guidelines (GPG) 6 class matrix (Sims et al., 2021).

from/to		Cropland	Grassland	Tree-covered	Wetland
Cropland	biodiversity	Context specific: Gain if reduced intensity or conversion to organic (1)	Improvement: Increased species diversity and richness for some groups (1,2,3)		
	provisioning	Context specific: Loss if reduced intensity (1)	Degradation: (1,6)	Context specific: May gain timber production, impacts on water provisioning	Degradation
	regulating	Context specific: Management can improve regulating services (6)	Improvement: Increased erosion control (5)	Improvement: Impacts on temperature regulation (7)	Improvement: Impacts on temperature and water regulation (6,7)
	net		Improvement	Improvement	Improvement
	GPG matrix	Stable	Disagreement (Degradation)	Agreement	Disagreement (Degradation)
Grassland	biodiversity	Degradation: Loss of species richness and abundance (1)	Context specific: Losses if increased intensity, worse for more extensive systems. (1)	Context specific: Increased species diversity and richness for some groups, depending on species composition (1,2)	Context specific: Dependant on type of wetland (1,3)
	provisioning	Improvement: (1,6)	Context specific: Loss if reduced intensity (1)	Context specific: May gain timber production, impacts on water provisioning	Degradation
	regulating	Degradation: Reduced erosion control (5) reduced regulation of climate and water quantity (6)	Context specific: Management can improve regulating services (6)	Improvement: Impacts on flood regulation (8)	Improvement: Impacts on temperature and water regulation (6,7)
	net	Degradation		Context specific	Context specific
	GPG matrix	Disagreement (Improvement)	Stable	Disagreement (Improvement)	Disagreement (Degradation)
Tree-covered	biodiversity	Degradation: Loss of species richness and abundance (1)	Context specific: Dependant on vegetation species composition (1,2)	Context specific: Loss if native forest to plantation (2)	Context specific: Dependant on type of wetland (1,3)
	provisioning	Context specific: May lose timber production but gain of agricultural production. Impacts on water provisioning		Context specific: Gain if native forest to plantation	Context specific
	regulating	Degradation: Impacts on water and extreme event regulation (4, 8). Reduced erosion control (5)		Stable	Context specific: Impacts on water regulation
	net	Degradation	Trade off		Context specific
	GPG matrix	Agreement	Disagreement (Degradation)	Stable	Disagreement (Degradation)
Wetland	biodiversity	Degradation: Loss of species richness and abundance (1) Negative impacts on sensitive species (2)	Context specific: Dependant on vegetation species composition (1)	Degradation: Negative impacts on sensitive species (2)	Stable
	provisioning	Improvement: (6)	Improvement: (6)	Context specific: May gain timber production	Stable
	regulating	Degradation: Damage to water, climate, air quality and extreme event regulation (4,6, 7)		Degradation: Damage to water regulation	Stable
	net	Degradation	Trade off	Degradation	
	GPG matrix	Agreement	Disagreement (Degradation)	Agreement	Stable

References: 1 Reidsma et al., 2006; 2 Burton et al. (2018); 3 Moreno-Mateos et al. (2012); 4 Findell et al. (2017); 5 Panagos et al. (2020); 6 McElwee et al. (2020); 7 Gohr et al. (2021); 8 Monger et al. (2022).

25 m, whilst CCI data are coarser, and transitions were assigned as degraded or not based on our bespoke transition assessment matrix. In terms of land cover areas (mapped in Fig. 1a), the UKCEH data identified 2 Mha less cropland, counterbalanced by more grassland (0.3 Mha), tree covered (0.4 Mha) and artificial land (0.4 Mha), as well as more other land and water, than the CCI data. The CCI data identified 1 Mha of wetland which was not mapped in the UKCEH data.

Comparing assessments of degradation for the land cover sub-indicator, both datasets identified more land degrading than improving (Fig. 1c). The CCI data showed 2.4 Mha more land as stable (i.e. with no land cover change); the vast majority (0.8 Mha) of land changing was classified as degrading, with only a small area (0.1 Mha) identified as improving. In comparison, the UKCEH data has approximately 1 Mha more land improving, 0.8 Mha more land degrading and 0.4 Mha more land where net outcomes are context dependent. These disagreements in areas transitioning would affect the overall inventory, with net additional 0.2 Mha land cover degradation identified by the UKCEH data.

Beyond the direct impacts on the land cover sub-indicator, calculation of the other sub-indicators was affected by (dis)agreement spatially, i.e. where different land cover types are present, and where transitions occur. Land cover class is used to subset trends for other sub-indicators. Additionally, land cover change affects interpretation of the production sub-indicator and, under tier 1 and 2 approaches, affects calculation of the SOC sub-indicator. The datasets largely agree on spatial locations of stable land cover but disagree for 4 Mha (Fig. 1d). Failing to correctly map land cover change may create spurious results for productivity trends and would omit changes in SOC.

The finer spatial resolution of the UKCEH data may be expected to improve performance relative to the CCI data, particularly in landscapes with high heterogeneity. The differences in findings between these land cover change datasets will also reflect the classification approaches. Quality and resolution of land cover data used in LDN assessments should be considered critical to the confidence in the indicator values.

3.1.3. Impacts of differing land cover change assessments for LDN

We compared areas assigned as improving and degrading by our bespoke land cover transition assessment matrix relative to the six-class GPG matrix. The results of this comparison were dependent on the underlying land cover data used. Low agreement between land cover change assessments (Table 2) had a major impact on the area of land identified as degrading due to land cover change. It is therefore critically important that the land cover change matrix is constructed with consideration of the ecosystem services this sub-indicator is intended to

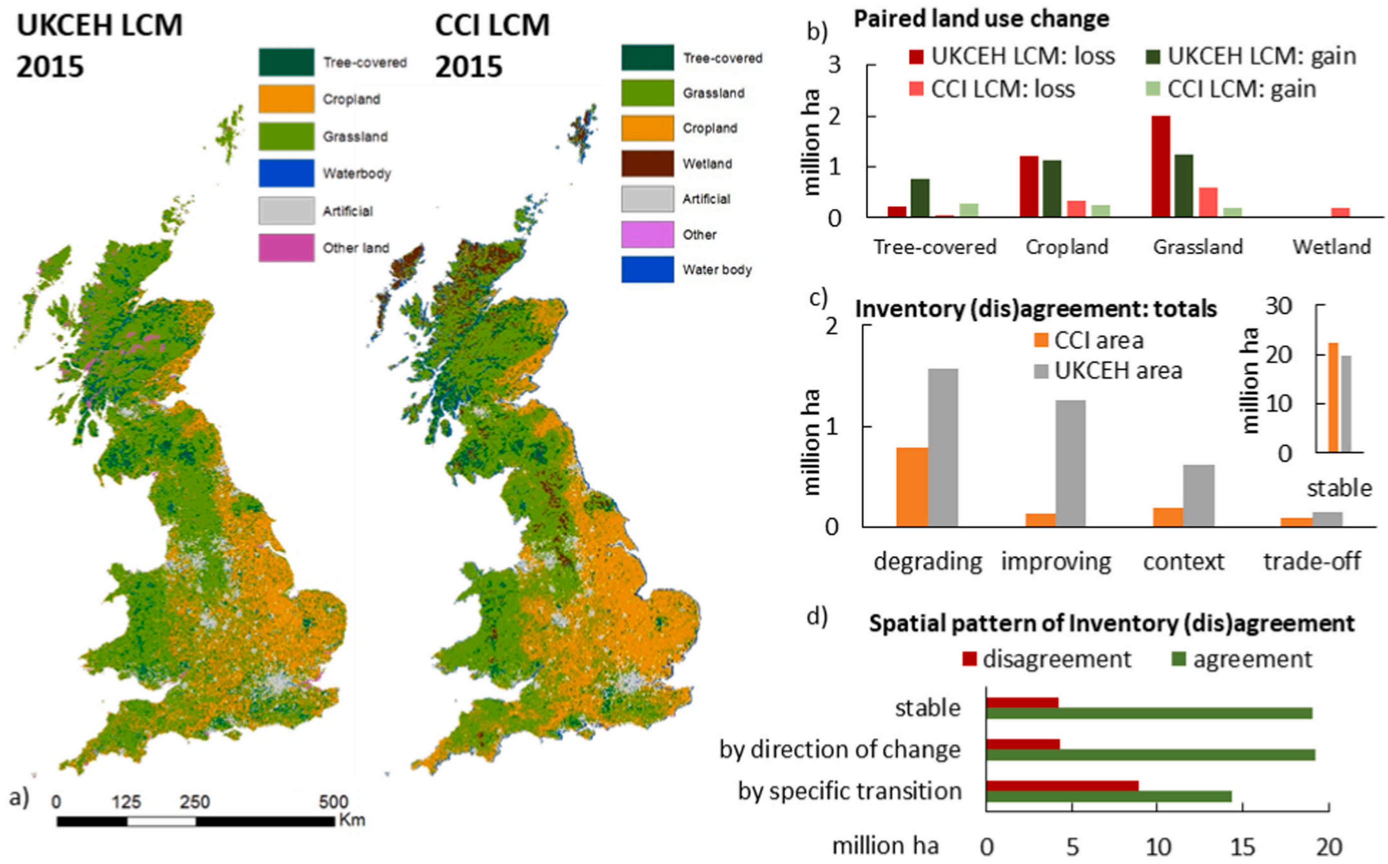

Fig. 1. Effect of land cover change dataset choice on the LDN land-cover sub-indicator: comparing data from UKCEH (UKCEH LCM: Rowland et al., 2020), and European Space Agency Climate Change Initiative (CCI LCM: ESA, 2017); a) maps of land cover for 2015; b) plot of paired land cover change (1990–2015); c) plot of inventory disagreement for the land cover sub-indicator; d) plot of spatial pattern of the disagreement in land cover change.

represent, and how they are affected by different types of land cover change in the country being assessed.

Using the UKCEH land cover data, the area assigned as improving for the land cover sub-indicator reduced by 0.7 Mha when using our bespoke land cover transition assessment to assign land as improving or degrading (instead of the GPG matrix). Not all of this area is identified as degrading based on our bespoke assessment: 0.6 Mha grass to trees was classed as context dependent instead of improvement. When using the CCI land cover data, there were around 0.3 Mha of disagreement between the assessments, including 0.16 Mha grass to trees classed as context dependent instead of improvement and 0.07 Mha wetland to grassland classed as a trade-off instead of degradation.

3.2. Productivity degradation

There was no consistent regional pattern of productivity degradation (Fig. 2a). Areas with significant increase and decrease were distributed across the country. Overall, there was a much greater area with improving productivity trajectory than degrading. When compared between vegetation types (Fig. 2b), grassland had by far the greatest area improving, then cropland, then tree-covered. When considered as a proportion of the total area, around 18% of tree-covered was improving, compared to 12% of grassland and 8% of cropland, whilst around 1% of grassland and cropland was degrading, and 3% of woodland.

The productivity sub-indicator primarily relates to food production, so its accuracy and relationship to this ecosystem service can be explored through comparison to agricultural statistics. For cropland, NDVI increases are in line with a trend of increased average cereal yield reported in UK agricultural statistics over this period (DEFRA, 2021), suggesting improvement for the provisioning services represented by the indicator. For grassland, the relationship between the sub-indicator and provisioning ecosystem services is more complex. Increasing NDVI in grassland may reflect reduced grazing intensity, although there is disagreement in the literature over the relationship between NDVI and grazing (e.g. Miau et al., 2020; Xu et al., 2019). Agricultural data for this period show that cattle numbers increased, while sheep numbers were stable (DEFRA, 2021), nutrient inputs on grassland continued an earlier trend of decline (DEFRA, 2020) and total grassland area and grassland utilisation percentage also declined (DEFRA, 2020). These trends may be explained by the increased offshoring of impacts of livestock through feed imports (McKay et al., 2019) which may have led to reduced exploitation of UK grasslands. This interpretation would suggest that NDVI has largely increased due to a reduction in the in-situ provisioning of food, hence the sub-indicator does not capture the trend for the primary ecosystem service it is intended to represent. This analysis highlights the importance of considering the links between each sub-indicator and the ecosystem services represented. It is also clear that trends in the sub-indicators must be considered in the global context, since improved land condition in one country may be linked to degradation in another. For tree-covered land, the relationship between NDVI and provisioning services is again difficult to interpret given differences between coniferous and broadleaf, as well as influence from heterogeneous management and age.

3.3. Carbon

3.3.1. Identifying baseline carbon stocks, and comparing datasets for area degrading

Assessment of baseline (2015) soil carbon stocks using global data indicates greatest carbon stocks in grassland, then cropland, then tree-

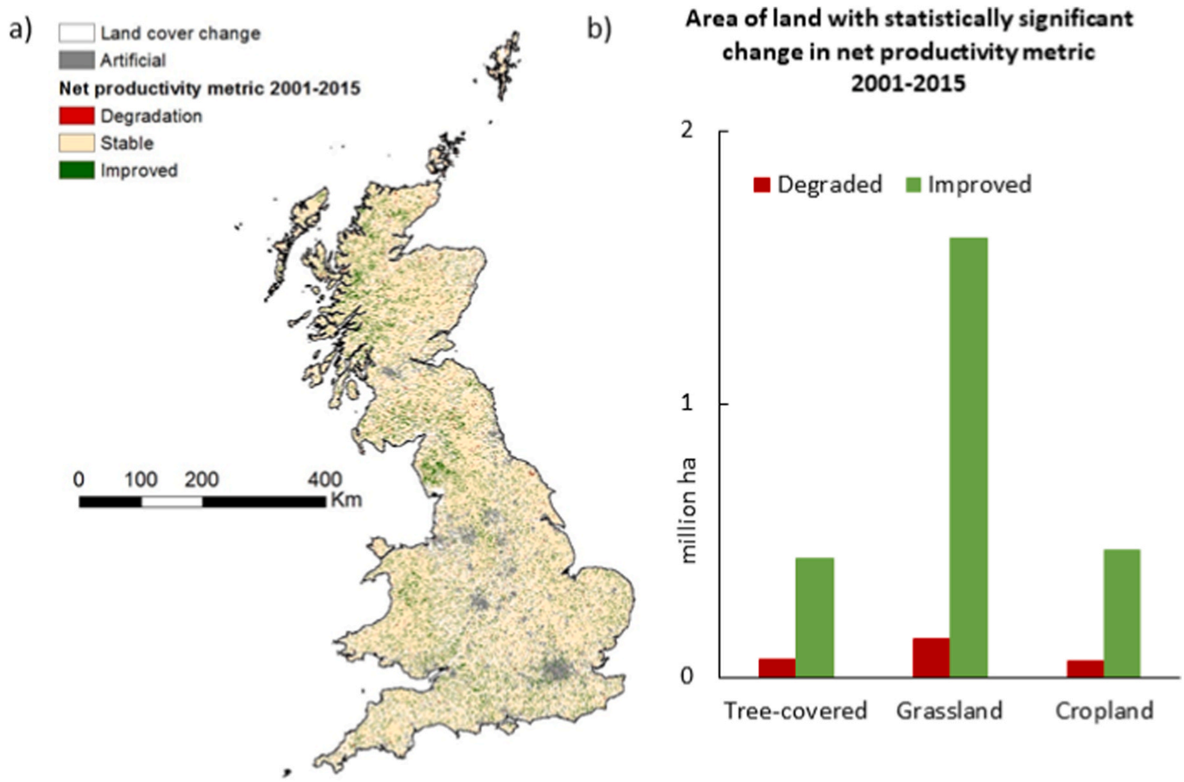

Fig. 2. Productivity sub-indicator data: a) mapped net productivity metric; b) plot of net productivity metric by land cover type. Net productivity is a composite of trend, state and performance. Areas of land cover change are masked out in the map because productivity change in these areas are likely to reflect differences between vegetation types.

covered land. We found there was a greater area degrading (losing soil carbon) than improving (gaining soil carbon) with both datasets and methods (Table 3) with a greater area affected in the UKCEH data, and differences for some landcover classes. Using the global data (carbon change from Wheeler and Hengl, 2018 and CCI landcover data) there was a greater area of grassland improving than degrading. Using the GB data (UKCEH landcover map and assessment of the effects of land cover change on carbon in Table S4) there was a greater area of tree-covered improving. Note that whilst these area-change data are for differing time periods (here we use the CCI trend for 2000–2015 to enable use of carbon stock change data) section 3.2.2 sh ows that the CCI data also identify less land cover change for a consistent period.

3.3.2. Use of inventory data to identify change in stock

The LULUCF inventories provide a robust, standardised existing dataset which accounts for magnitude of carbon change, not just area affected. Because soil carbon changes slowly over time, the LULUCF inventory accounts for this rate to calculate cumulative carbon changes over a time period. Therefore, the inventory data for 2000–2015 accounts for the timing of a change, how much carbon change would have occurred by 2015, and includes ongoing carbon changes from land cover changes since 1950. These data (summarised in Table 3, full data Table S5) suggest that land use change was responsible for net soil carbon losses of 25,363 kt C across the three landcover classes over the 2000–2015 period. This was around three times greater than losses were modelled using the global data (from Wheeler and Hengl, 2018), extracted to the same landcover classes in the CCI data at 250 m resolution. This reflects the greater depth represented by the LULUCF data, and the much greater area of change identified in the LULUCF datasets (Supplementary Table S3), as well as methodological differences which enable LULUCF to capture carbon change from historic landcover change. There was also disagreement in areas transitioning between the LULUCF inventory and the spatial datasets used to identify area degrading for carbon for the 1990–2015 period (see Supplementary Table S3). Overall, these differences highlight the importance of selecting appropriate methods and data, and the value of considering a range of evidence where available. The LULUCF inventory has undergone several major methodological improvements in recent years, including improved areas and UK-specific emission factors for organic soils and improved tracking of land-use change, using multiple data

Table 3
Carbon indicator for baseline and area and carbon trends from global data (Wheeler and Hengl, 2018; CCI) compared to the area trends from UKCEH landcover data (Rowland et al., 2020) and LULUCF inventory (Brown et al., 2023). Area degrading is shown by base class, and area improving by new class. Losses of soil carbon stocks are expressed as negative values.

Land class	2015 baseline soil carbon stocks (KtC) from global data	Area trends from global data (Mha) 2000–2015		Area trends from UKCEH data (Mha) 1990–2015		Soil carbon trends by baseline class (KtC)	
		Area degrading	Area improving	Area degrading	Area improving	Global data 2020–2015	LULUCF inventory 2020–2015
Tree-covered	434,732	0.02	0.00	0.08	0.13	−1449	−1813
Grassland	2,270,818	0.10	0.12	1.37	1.09	−4955	−38,156
Cropland	746,930	0.11	0.00	0.12	0.03	−1211	14,605

sources (Brown et al., 2023). Use of the most recent data here is in line with the GPG recommendation of using the latest LULUCF data and methods where possible. LULUCF assessments generally do not include spatially explicit assessment of where carbon stock changes occur, hence it is likely that studies elsewhere will have similar challenges reconciling inventories with the overall LDN assessment of net area degrading by any metric.

3.3.3. Use of field survey data to identify carbon trends where there is no land cover change

Land use and change are major controls on soil carbon (Ostle et al., 2009; Thomas et al., 2020). Hence, in countries undergoing expansion of agricultural land or urban areas, land cover change is likely to dominate trends of carbon change. However, in countries where landscapes are agriculture dominated, land management may dominate the overall trend, particularly in terms of area affected. Soil carbon will be affected by changes in: crop type, tillage, residue incorporation, nutrient inputs, cutting, grazing, and species composition (Smith et al., 2007; Guo and Gifford, 2002; Thomas et al., 2020). In GB this is highlighted by the 30-year trend of declining soil carbon in croplands (11% since 1978, which may affect 4.4 Mha, see Table 4, section 3.5.1 and Carey et al., 2008). These carbon trends may be driven by land management changes. For example, increasing straw removal and reduced nutrient inputs (see Figure S7, DEFRA, 2020; DEFRA, 2021) may be expected to drive losses of soil carbon, although increases in conservation tillage since 1990 may offset this (Eurostat, 2016). Ongoing data collection in GB will soon provide a new data point to identify if the carbon trend for arable land has continued.

Identifying key degradation processes is highlighted as a good practice principle in the GPG, and tier 3 methods including process modelling or monitoring are recommended for improved representation (Sims et al., 2021). It is clear from our data that the use of land cover change as a proxy for the SOC sub-indicator would omit a key degradation process, and lead to incomplete representation. However, measured data on soil carbon trends are unavailable for most countries, or are insufficient to resolve spatial or regional trends (Lorenz et al., 2019), and measuring or modelling SOC change in the absence of land cover change is notoriously challenging (e.g. Smith et al., 2010). Any available data on status and change can be useful for targeting on the ground data collection, e.g. soil data collection might be targeted to areas with high carbon stocks and evidence of changes in productivity or land cover change.

Table 4
Change in soil health metrics from Countryside Survey data for GB. Using data from all sites for 1978 to 2007 and 1998 to 2007 aggregated by broad habitat types. OP thresholds are assessed only for soils with pH > 7 where they are relevant for production.

Habitat	metric/time period	% within prescribed range (threshold type(s) in brackets)
Arable	pH 1978	73 (production)
	pH 2007	93 (production)
	OP 1998	47 (production), 70 (water quality)
	OP 2007	50 (production), 79 (water quality)
	Bulk Density 2007	56 (production)
	Soil Carbon	Statistically significant decline in stock and concentration 1978–2007 & 1998–2007
Improved grass	pH 1978	65 (production)
	pH 2007	90 (production)
	OP 1998	23 (production), 81 (water quality)
	OP 2007	23 (production), 88 (water quality)
	Bulk Density 2007	94 (production)
	Soil Carbon	No statistically significant trends
Neutral grass	pH 1978	53 (habitat support)
	pH 2007	77 (habitat support)
	OP 1998	18 (habitat support), 90 (water quality)
	OP 2007	37 (habitat support), 90 (water quality)
	Soil Carbon	No statistically significant trends
Shrub heath	pH 1978	92 (habitat support)
	pH 2007	81 (habitat support)
	Soil Carbon	No statistically significant trends
Acid grass	pH 1978	89 (habitat support)
	pH 2007	69 (habitat support)
	Soil Carbon	Statistically significant decline in concentration 1998–2007 but not stock
Broadleaf woodlands	Soil Carbon	Statistically significant increase in concentration 1978–2007 but not stock
Coniferous woodlands	Soil Carbon	Statistically significant decrease in concentration 1998–2007 but not stock

3.4. Trade-offs and false-positives

3.4.1. Trade-offs between the main sub-indicators leading to false-positives

Trade-offs between production and regulating services are particularly common. Whilst LDN aims for balance between economic, social and environmental sustainability (Orr et al., 2017) it has been criticised for favouring production (e.g. Akhtar-Schuster et al., 2017). This may occur due to the relative ability to detect trends for different ecosystem services from available data. Our findings show that available data can more easily detect changes in productivity than changes in SOC, and these may have opposing trends where unsustainable management increases production whilst degrading SOC. The trend of cropland soil carbon loss suggests sustainability issues with management, which may undermine the classification of these areas as improving by the productivity sub-indicator. This creates false-positives, where the LDN indicator classes land as improving due to increased production while associated degradation of SOC is not detected. Since SOC underpins productivity, later productivity declines may occur, showing alignment of the sub-indicators in cases of severe degradation. Trends were more difficult to interpret for grassland. Carbon trends were inconsistent across grasslands, with decline in concentration for acid grassland 1998–2007 (Table 4, and Carey et al., 2008), which again could suggest production increasing at the expense of other ecosystem services. Alternatively, increased grassland NDVI over this period may reflect improvement in grassland condition under less intensive management identified in the agricultural data, with positive implications for long-term sustainability of local land use.

Whilst food production is important to the SDGs, prioritising provisioning over regulating and supporting services can undermine the ecological function required to maintain provisioning services in the longer term (Akhtar-Schuster et al., 2017). Intensification of land management to increase production can be detrimental to biodiversity (Reidsma et al., 2006), soil erosion (Panagos et al., 2015b, 2020), soil carbon stocks (Smith et al., 2007) and ecosystem services underpinned by soil health (Kopittke et al., 2019), yet may be recorded as improvement by the LDN indicator due to increased NDVI. Relative prioritisation of these issues will vary between socioecological settings. Impacts of management trends are variable, e.g. analysis for England suggests declining nutrient inputs over this period reduced other aspects of degradation including water and air quality (McKay et al., 2019). Understanding the implications of SOC trends for LDN is further complicated by the difficulty of quantifying the links between SOC loss, degradation, and the soil health metrics underpinning ecosystem service delivery (Lorenz et al., 2019). Interpretation of land cover change for LDN (section 3.1.1, Table 2) also exposes a conflict between "production-advocacy" and the conservation of natural ecosystems, particularly for transitions between natural and agricultural systems (Kust et al., 2017).

3.4.2. Using peat extent as contextual data to interpret change for the main sub-indicators

Land cover change data within the peat extent (Table S7), indicate net decrease in grassland and to a lesser extent cropland, balanced by an increase in tree-covered land of around 145 Kha. These transitions may be detrimental on peat, but would be assigned as improving (cropland to tree-covered) or context dependant (grassland to tree-covered) using our bespoke land cover change matrix (Table 2).

Similarly, the NDVI data indicate around 0.3 Mha grassland where NDVI is increasing on peat, which may indicate degradation due to encroachment of inappropriate species, and 0.02 Mha where reduced productivity may indicate favourable shifts in species (Cowie et al., 2018; Šimanauskienė et al., 2019). This may be driven by changes in e.g. grazing intensity, drainage or temperature, which can shift the species composition of bog towards grassier species (Bobbink et al., 1998, Baritz et al., 2021). The assessment of trends conflicts with the standard assignment for changes in productivity, indicating the value of contextual data for interpretation.

This demonstrates that contextual data such as maps of peat can be useful in spatially identifying false-positives and negatives, in line with the GPG.

3.5. Additional forms of degradation tested for GB

3.5.1. Soil health metrics

Table 4 identifies a mix of improving and degrading trends in soil health. Although important for land degradation, these trends may only be detected from soil surveys and therefore cannot be mapped nationally with a high level of confidence. Use of such data to assess LDN is further complicated by a lack of consensus on thresholds in relationships between soil properties and degradation of functions, due to limited process understanding (Lorenz et al., 2019; Baritz et al., 2021). These are included with a breakdown of habitat types classed as grassland in the overall assessment, due to variation in the relevant thresholds for soil health metrics.

Overall, data indicated all habitats exhibit decline and/or a large proportion degraded for at least one soil health metric. There was a decline in proportion of sites with good pH performance against habitat support metrics for acidic habitats but improvement in pH against production thresholds for arable and improved grass. A large proportion of arable soils exceed the bulk density production threshold, whereas the majority of improved grass soils were within the prescribed range. Olsen P (OP) performance against production metrics was poor, but most soils were within the prescribed range for OP impacts on water quality.

Critically, these data also identified habitat level degradation trends for the core sub-indicator of soil carbon which would be missed by the tier 1 and 2 approaches (as discussed in section 3.3.3), and conflict with assessment based on NDVI. Arable data showed decline in soil carbon concentration and stock (1978–2007, 1998–2007, $p < 0.05$ statistically significant). This 30-year trend of soil carbon loss (11% since 1978) may affect 4.4 Mha (Carey et al., 2008). Declines in soil carbon were also recorded for concentration only in acid grass and coniferous woodland (1998–2007). A statistically significant increase was recorded for broadleaf woodland soil carbon concentration (1978–2007) but not for soil carbon stock.

For soil contamination, the proportion of CS squares exceeding the critical msPAF threshold for metals was 35% (78 of 225 squares for

Table 5
Overall Land degradation indicator for baseline setting period 2000–2015: summary by degradation type as proportion of habitat area.

Habitat type	Land cover change	NDVI change	Carbon change		Total
	Degrading (loss to alternative)	Degrading (decrease)	Total	Additional	Degrading
			Degrading (loss)		
Tree-covered	3.5%	2.7%	3.5%	0.0%	6.2%
Grassland	10.2%	1.0%	10.2%	0.0%	11.3%
Cropland	2.1%	1.1%	2.1%	0.0%	3.2%
Overall	7.3%	1.2%	7.3%	0.0%	8.6%
	Improving (creation from alternative)	Improving (increase)	Improving (increase)		Improving
Tree-covered	5.3%	18.0%	5.3%	0.0%	23.2%
Grassland	8.1%	12.0%	8.1%	0.0%	20.2%
Cropland	0.6%	8.2%	0.6%	0.0%	8.7%
Overall	5.9%	11.7%	5.8%	0.0%	17.6%
	Net degrading	Net degrading	Net degrading		Net degrading
Tree-covered	−1.8%	−15.2%	−1.8%	0.0%	−17.0%
Grassland	2.1%	−11.0%	2.1%	0.0%	−10.0%
Cropland	1.5%	−7.1%	1.5%	0.0%	−5.5%
Overall	1.5%	−10.5%	1.5%	0.0%	−8.9%
Additional degradation metrics: data here are not mutually additive but do account for the core sub-indicators. Calculation of remaining core indicator net degradation applies the one-out-all-out principle, i.e., areas improving for the core-sub indicators are excluded if they are degraded in the additional data.					
	Erosion	**N deposition**		**Acid deposition**	
Additional degradation (no core indicator degradation)	Degraded (threshold exceeded)	Total degraded	New degradation	Total degraded	New degradation
Tree-covered	18.8%	83.3%	0.0%	64.7%	1.0%
Grassland	39.8%	59.1%	0.4%	47.9%	1.3%
Cropland	18.8%	57.6%	0.1%	27.7%	0.4%
Overall	31.9%	61.5%	0.3%	44.5%	1.0%
Additional improving (stable for core indicator)		Improving (threshold no longer exceeded)		Improving (threshold no longer exceeded)	
Tree-covered		3.5%		11.4%	
Grassland		3.9%		11.0%	
Cropland		0.9%		6.1%	
Overall		3.0%		9.7%	
Net new degradation	Net degrading	Net degrading	Net new degradation	Net degrading	Net new degradation
Tree-covered	18.8%	83.3%	−3.4%	64.7%	−10.5%
Grassland	39.8%	59.1%	−3.5%	47.9%	−9.7%
Cropland	18.8%	57.6%	−0.8%	27.7%	−5.7%
Additional metrics: overall	31.9%	58.4%	−2.8%	34.7%	−8.7%
Remaining core indicator net degradation	−4.3%	−0.5%	−8.9%	−2.6%	−8.9%
Overall net	27.6%	57.9%	−11.7%	32.1%	−17.6%

which there are data where metals were analysed with msPAF $\geq$0.05, suggesting a potential risk to $\geq$5% of the soil ecosystem). Whilst these squares may be degraded, site-specific investigation is necessary to groundtruth the prediction of possible impact. This suggests pollutants may degrade additional area (see Supplementary section S6.2 for maps and further details of methods).

3.5.2. Erosion

Overall, 6.6 Mha were identified as degraded due to exceeding erosion thresholds, primarily (5.2 Mha) on grassland. Combining these data with our other sub-indicators (see Table 5, Table S11), a large area not otherwise classed as degraded would be classified as degraded through exceedance of erosion thresholds, in particular around 0.8 Mha grassland classed as improving for productivity.

Although crop erosion factors fluctuated (Figure S8), land management data indicate an overall reduction in the erosion factors due to improvements in management practices and changes in land use composition (Table S12). Trends over our study period would also be affected by climate: increase in erosion and fluctuating trends identified elsewhere have been attributed to rainfall variation (McKay et al., 2019). Influence of climate and topography may create regional variation in potential for management changes to address erosion losses. The issue may be expected to worsen with increased rainfall intensity with climate change (Borrelli et al., 2020). Tolerable soil erosion thresholds also vary spatially due to factors including variations in soil profile depths and soil formation rates (Evans et al., 2020). Previous analysis suggests that the tolerable erosion threshold for some soils may be an order of magnitude lower than the blanket value we applied (Verheijen et al., 2009). While we have applied a single tolerance threshold due to limited spatial data on soil formation rates, using site-specific tolerance thresholds would improve accuracy of future LDN assessments.

3.5.3. Critical load exceedance

Whilst large areas remain in exceedance of critical loads, there has been a trend of recovery from critical load exceedance from 2000 to 2015, affecting 0.65 Mha for N deposition and 2.08 Mha for acid deposition on land which was stable for the core indicator. For both pollutants, this was greater than the area newly exceeding thresholds, but smaller than the total area where critical loads were exceeded. Combining data on ongoing exceedance of critical loads with our other sub-indicators (Table 5, Table S11) identifies large areas not otherwise classed as degraded are degraded through ongoing critical load exceedance. It should also be noted that the critical load exceedance data were at 1 km resolution, so may overestimate the area affected, since not all of each grid square contained sensitive habitats. For grassland classed as improving for productivity, around 1.1 Mha is exceeded for N (of which 2.8 kha is new degradation). N deposition may be supporting increased production, with theoretical benefits for LDN goals. However, this may be at the expense of other aspects of ecosystem function or resilience, and may reflect detrimental shifts in species composition (e.g. Bobbink et al., 1998).

3.6. Overall indicator

The overall indicator is calculated from the core sub-indicators, using tier 1–2 approaches as the proportion of total area degraded over the baseline period (2000–2015), with a breakdown by land cover and sub-indicator (Table 5), in line with the GPG recommendations. This is calculated as the net of areas degraded by any sub-indicator, and areas improving by any sub-indicator (but not degraded by any sub-indicator). Because carbon change is only calculated here for areas of land cover change, it may not contribute additional area of degradation (i.e. this area may already be degrading or improving for the land cover sub-indicator). Therefore carbon change data are displayed separately for the total and additional.

Overall, 18% of land was identified as improving for the core sub-indicators, with net negative area degrading for all three land classes. This reflects the large areas classed as improving for productivity. Underestimation of net cropland area degrading by the core sub-indicators is likely using tier 1–2 assessment of carbon, since the use of tier 3 approaches (see sections 3.3.3 and 3.5.1) highlight a trend of carbon loss. Therefore, using only NDVI data to assess area degrading or improving for cropland remaining cropland may be creating false-positives. Survey data are appropriate for habitat level assessment, but do not enable us to consider the SOC loss spatially in relation to the NDVI trends, hence this cannot be explicitly mapped and included in the analysis in Table 5. However, trends in soil health could be projected from data on land management trends: for example, the area intensifying or area under sustainable land management.

Accounting for the additional degradation metrics indicates there may be net area degraded in all three land cover types, up to 55% net area degraded overall. Additional degradation was only identified for areas not degraded by the core sub-indicators, and additional improvement was only identified for areas stable for the core sub-indicators (i.e. not improving or degraded). For each extra metric, overall net degradation was calculated by combining additional net degradation with remaining net degradation from the core sub-indicators (i.e. excluding areas improving for the core sub-indicators which are degraded for additional metric).

As noted in section 3.5.3, differing interpretation of degradation by critical load exceedance reversed impacts on the inventory. Using total area exceeding thresholds (total degraded) suggested net degradation. However, using new area exceeding thresholds (new degradation over baseline period), suggested net improvement.

3.7. Limitations, challenges and insights for assessment in other contexts

Availability of appropriate data on consistent timescales to enable spatial assessment which captures false-positives and false-negatives is a key challenge for calculating the LDN indicator. The GPG points to various global and regional datasets for the core sub-indicators which would support analyses similar to this study in other countries, enabling comparisons between datasets (Sims et al., 2021).

Previous analysis for the EU comparing these datasets identified greatest impacts on overall assessment from choice of method and data for the productivity sub-indicator (Schillaci et al., 2023). This is perhaps unsurprising, since relatively smaller areas are subject to land cover change (and hence detectable SOC change). However, our study identifies that the trade-off between productivity changes and carbon changes may be masking degradation, highlighting the importance of tier 3 approaches for SOC in areas potentially under unsustainable management. Whilst our analysis was only for GB, soil survey data from LUCAS are available across Europe (Orgiazzi et al., 2018), and have been used to model trends (Panagos 2020). Similarly, agricultural statistics data are available in many regions to validate findings on productivity trends against the provisioning services they are intended to represent.

Land cover change assessments may also be improved through new datasets developed and validated at regional or national levels, which may be expected to perform better at identifying local habitats (Tulbure et al., 2022; Rayner et al., 2021). Tools are now available to support the development of bespoke land cover maps to better capture nationally or regionally important land cover and transitions (Morton and Schmucki, 2023). Improved land cover data would also support better interpretation of productivity trends, through identification of form of production affected, and of spurious trends due to landcover change.

Ideally, multi-stakeholder engagement would be used to evaluate whether land cover transitions are considered an improvement or degradation. However, our assessment in Table 2 demonstrates a transparent approach which could be applied elsewhere, incorporating stakeholder input to select and prioritise ecosystem services, alongside locally relevant evidence of impacts.

Our findings on the impacts of different approaches to incorporate additional forms of degradation highlights the need for guidelines on this, to ensure inventories are as consistent and representative as possible. With the inclusion of additional metrics, the one-out, all-out approach becomes increasingly conservative (Cowie et al., 2018). However, disregarding nationally important additional degradation issues may give an inaccurate picture of land condition and trajectories of change.

Although relative importance of different forms of degradation will be specific to our assessment, the trade-offs and potential biases identified here may have wider implication for global LDN monitoring.

4. Conclusions

Our assessment for GB shows that choices of datasets and methods can have large impacts on the LDN assessment. Testing multiple datasets as demonstrated here may be more appropriate than calculating a single definitive value. Our work also shows that monitoring LDN through SDG indicator 15.3.1 is better able to identify land cover change and productivity loss than degradation of soil carbon, particularly with tier 1 and 2 implementations. This can create false-positives for areas currently being over-exploited for agriculture, since intensive management may drive opposing trends for productivity and soil carbon. The importance of this depends on the socioecological context of the assessment. However, in well-established agricultural landscapes, land management may dominate ecosystem services trends. Inclusion of additional data will be more important in such landscapes. In GB, inclusion of survey data for soil carbon in line with tier 3 approaches identified false-positives from the trade-off between increased productivity and 30-year soil carbon loss trends in croplands, representing degradation of regulating services. This trade-off between regulating and provisioning ecosystem services creates a risk the LDN indicator will be biased towards provisioning; hence, trade-offs must be considered explicitly in assessments. Inclusion of data on additional forms of degradation may reverse findings from the core indicator, as we show from the inclusion of erosion and deposition data in the analysis for GB.

CRediT authorship contribution statement

Amy Thomas: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Laura Bentley:** Writing – review & editing. **Chris Feeney:** Writing – review & editing. **Stephen Lofts:** Formal analysis, Writing – review & editing. **Ciaran Robb:** Writing – review & editing. **Ed Rowe:** Formal analysis, Writing – review & editing. **Amanda Thomson:** Formal analysis, Writing – review & editing. **Eleanor Warren-Thomas:** Writing – review & editing. **Bridget Emmett:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data used is either publicly available, or available with license.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jenvman.2023.118884.

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