Integration of wetlands in Ecological Footprint

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Glossary

EFB Ecological Footprint and Biocapacity
EEA European Economic Area (27 member states of the European Union, plus Iceland, Liechtenstein, and Norway)
CLC CORINE Land Cover
GLWD Global Lakes and Wetlands Database
EWM European Wetland Map
NEP Net Ecosystem Productivity

Introduction

The goal of this summer project is to provide an analytical overview of data availability towards the integration of wetlands as a land component of the Ecological Footprint and Biocapacity (EFB) environmental accounting framework. The most important characteristics of wetlands to consider in relation to EFB accounts are area spatial coverage and carbon accumulation rates. Many maps of wetlands are available, however the global extent varies from 3% to 21% of the land surface area depending on the definition of wetland used and limitations in observation or modeling systems (Tootchi et al., 2019). Additional uncertainty is added when considering carbon accumulation rates at the global scale required for EFB as the geographic availability of input data is limited, in particular for certain regions like the Arctic and the tropics (Li et al., 2025). Generally, there is high uncertainty in wetland C estimates due to a lack of field and laboratory data to parameterize, calibrate, and validate models for many wetland types and locations (Bansal et al., 2023). That being said, recent years have marked vast improvements in both wetland mapping capacity and data availability relating to carbon fluxes in wetlands, which may provide the basis for integration of wetlands into frameworks used to constrain the global C budget such as EFB accounts (Li et al., 2025).

Given the vast range of interpretations available, it is crucial to understand both the characteristics of the input data and of the system it's applied towards, and it's the purpose of this report to outline the current state of research and a path forward towards a more representative attribution of the terrestrial C sink in the EFB methodology.

Methods

Spotlight country selection. While the scope of this project is the EEA, 5 states were defined as spotlight countries to make the analysis feasible given the timeframe. Countries were prioritised based on prevalence of wetlands/peatlands, the top four being Ireland, Sweden, Finland and Norway (Eurostat, 2018; UNEP, 2024). Iceland was included as the final country of interest due to its high relevance given the context of this project.

Wetland area dataset selection. A list of wetlands datasets was compiled in Table 1 to create an overview of data availability. Key characteristics of the datasets such as spatial coverage, spatial resolution, temporal coverage, time range, inputs, outputs, wetland types and version history were included. Pros and cons for selecting the dataset as a representation of wetlands in EFB accounts were listed. Addition of wetlands datasets to the list was based on a Zenobo search using the keyword ‘wetland’ and the resource type ‘dataset’. Zenobo is a multi-disciplinary open repository maintained by CERN and a catch-all for EU funded research (EUI, 2024). Datasets focused on land cover and GHG emissions (CO2 and CH4) were included if the spatial coverage was either global or Europe-wide. CH4-related datasets were included provided that these captured wetland spatial extent. Additional datasets were added because they are either already used in EFB accounts (CORINE land cover) or because they are frequently cited in literature (GLWD, PEATMAP, etc). Datasets published before 2015 have been excluded as these are likely to be outdated given the vast improvements in remote sensing and computational capacity over the last decade.

Table 1 in this version has been abbreviated and the full table is available in the project GitHub repository. The overview of wetland datasets in this report is representative of the data published in Europe and globally over the last decade. Further lists inclusive of older wetland maps or source data for larger datasets can provide useful information on the history of wetland science or the data necessary for the generation of a comprehensive global dataset (Lehrer et al. 2025, Tootchi et al., 2019).

Deriving national data from selected datasets. Three datasets, CORINE Land Cover (CLC) 2018, European Wetland Map (EWM) and Global Lakes and Wetlands Database (GLWD) v2, were selected for the analysis stage during which data was extracted for the five spotlight countries, Ireland, Sweden, Finland, Norway and Iceland.

CORINE Land Cover 2018. CORINE Land Cover (CLC) is available for download as both a vector and a raster format at a spatial resolution of 100 m. The data was downloaded from an interactive data viewer that provides direct access to statistics derived from the CORINE land cover data series (EEA, 2023).

European Wetlands Map**.** The European Wetland Map includes data for 43 European countries with a downloadable layer for each state. Files are available both in a vector and raster format. Data was derived from the vector files of Ireland, Sweden, Finland, Norway and Iceland using the Statistics by Category algorithm from the Vector Analysis toolbox in QGIS, which calculates summary statistics (count, sum, mean, etc.) of numerical attributes (Shape_Area) grouped by a categorical field (wetland type). The ETRS89 / LAEA Europe (EPSG:3035) projected coordinate system was used, which minimizes area distortion across continental Europe and is an equal-area projection, resulting in total area values for each of the 10 wetland categories of the European Wetland Map in square meters (m^2).

GLWD v2. The Global Lakes and Wetlands Database v2 is available in raster format containing either (1) absolute wetland areas in hectares per grid cell for each of the 33 wetland classes, (2) wetland extents in percent coverage per grid cell for each of the 33 wetland classes, or (3) combined wetland extents of all 33 classes (in ha and percent) as well as the dominant wetland type per grid cell. Data was derived from the rasters of absolute wetland areas in hectares in two steps. In the first step, the QGIS Clip raster by mask layer tool is executed as a batch process to clip each of the 33 rasters using a polygon layer showing the national borders of the spotlight countries. The country border polygons are sourced from GADM version 4.1, administrative level 0 (GADM, n.d.). In the second step, the QGIS's Python environment (PyQGIS) is used to calculate pixel value statistics from the clipped raster files (code snippet is available in project GitHub). Each pixel value is equivalent to 0.1 ha according to the GLWD technical documentation.

Wetland carbon data selection. A literature search was performed using Google Scholar for articles published after 2010 using the keywords "wetlands" and "NEP" and "carbon" and "global". Papers were only included in the overview in Table 5 if they estimate NEP across multiple sites across the globe.

Results

Characteristics of wetland maps. Table 1 describes the key characteristics of 16 wetland databases identified in this report including spatial scope, resolution, time period, coverage, approach and inputs. Spatial scope can either be global, regional (e.g. Europe or tropics and subtropics) or national (e.g. Sweden). Resolution refers to the level of detail or the smallest measurable unit that can be observed or represented in geographic data. Time period describes which period the database is representative for on the basis of the source data. Temporal coverage distinguishes between static (fixed, unchanging) or semi-static (updated periodically/time series) or dynamic (near real-time). Dynamic wetland maps are rare due to the high computational demand and practically non-existent at the national/global scale considered in this report. Approach differentiates between top-down and bottom up maps, which is further elaborated on in the next section. Inputs describe the data used to generate the map product.

Bottom-up vs top-down maps. There are multiple methods that can be applied to map wetlands and these can be broadly grouped in two categories, the top-down (e.g. machine learning, remote sensing) and bottom-up (e.g. amalgamation of country data, hydrological modeling, land-surface models) approach (UNEP, 2022). It is possible that bottom-up approaches may have higher estimates of wetland coverage as these capture areas that have been degraded and converted to agricultural or forestry, whereas top-down land use maps frequently attribute former wetlands to the land class of conversion (Tegetmeyer et al., 2025). For example, a production forest planted on peatland may be difficult to discriminate from the surrounding landscape with remote sensing data as the characteristic feature, peat, is below the surface (UNEP, 2022). A validation of the European Wetland Map (bottom-up) against a 30 m resolution Land Cover map (top-down) resulted in a 67% accuracy estimate, which was deemed satisfactory and justified with the difference in ability to capture degradation/conversion of the top-down vs bottom-up approach (Tegetmeyer et al., 2025). Maps such as the Tootchi et al. (2019) Composite Wetlands (CW) are bottom-up and extend the definition of wetlands beyond inundated zones to include groundwater-driven wetlands, but correspond rather to potential wetlands as they neglect wetland losses due to human impact. The CW maps estimate that wetlands account for 21% of the global land area, which is at the high end of the 3% - 21% range in published literature (Tootchi et al., 2019). In comparison, the Global Lakes and Wetlands Database (GLWD) v2 has a mid-range wetland extent estimate of 13.4% of global land area.

Map resolution. Resolution is another key characteristic to consider as coarse resolution mapping products may omit small inundated areas (Xi et al., 2022). Global and more dynamic datasets tend to suffer from coarser resolution due to the quality of the input data (Zhen Zhang et al., 2021) and the computation cost (Xi et al., 2022, UNEP, 2022). Recent advances in remote sensing, computing power and storage abilities are increasing readiness for the generation of high resolution semi-dynamic maps. GWL_FCS30 is an example of a global wetland map with a 30 m resolution and yearly time step between 2000-2022, but omits peatlands (Zhang et al., 2020).

EFB considerations. With regard to the EFB framework, which includes agriculture and forestry land components, it's important to be mindful of double counting when integrating wetland data due to the long history of wetland conversion (Fluet-Chouinard at al., 2023). Drained and intensively used wetlands have distinct CO2 sequestration/emission profiles and may need to be considered separately, especially because carbon capture is a highly relevant wetland ecosystem service for EFB (Borucke et al., 2013). An additional consideration is that EFB accounts are produced on a yearly basis and are meant to reflect changes in supply and demand of the biosphere's capacity. High-resolution wetland maps are generally static and amalgamate data collected over decades and therefore reflect a baseline of wetland extent, but not interannual variability, which is a key requirement for estimating the changes in GHG fluxes from year to year (Bansal et al., 2023). Although CO2 is currently the only greenhouse gas considered in the EFB methodology, the inclusion of other GHG emissions has been outlined in the EFB research agenda. Wetlands play an important role in global methane dynamics and in fact the majority of annual/monthly wetland maps have been developed to aid CH4 modelling such as WAD2M, GIEMS-MC and the Zhang et al. TOPMODEL-based map. The consideration of future research priorities as well as the current focus on CO2 highlight the need to not only delineate wetlands from other land types, but to also consider different classes of wetlands due to the intrinsic variation in GHG fluxes (Bansal et al., 2023). High resolution maps provide the basis for distinguishing between classes, whereas coarse resolution maps show interannual variation. A combination of both may present the appropriate spatial consideration of wetlands for EFB accounts.

Table 1. Overview of wetland area datasets.

Name	Scope, resolution	Time period, temp. cover.	Approach	Inputs
Global Lakes and Wetlands Database (GLWD) v2 (Lehrer et al., 2025)	Global, 500 m	1984-2020 Static	Top-down	25 primarily global datasets ranging from broad representations of wetland ecosystems to individual types and ancillary information including PEATMAP, CIFOR, GIEMS-D3 (Table 1 in Lehrer et al., 2025)
European Wetland Map (EWM) (Tegetmeyer et al., 2025)	Europe, 1 arcsec, ~30 m	2012-2024 Static	Bottom-up	200 data sources including Riparian Zones Land Cover/Land Use 2018, Copernicus CORINE data Coastal Zones Land Cover/Land Use 2018, GWL_FCS30, EEA's Extended wetland ecosystem layer 2012, European Peatland Map from Tanneberger et al. (2017)

CORINE Land Cover (CLC) 2018 (CLMS, n.d.)	Europe, 100 m	2018 Semi-static, 6-yearly	Top-down	Country-specific topographic and remote sensing datasets for 39 countries; Sentinel-2 and Landsat-8 for gap filling
Extended wetland ecosystem layer (EEA, 2022)	Europe, 100 m	2018 Semi-static, 6-yearly	Top-down	Derived product of the CLC layer for the year 2018 (v20) reclassified into 20 wetland classes on the basis of ancillary spatial layers
ELC10: European 10 m resolution land cover map 2018 (Venter et al., 2021)	Europe, 10 m	2018 Static	Top-down	Random forest classification model trained on 70K ground truth points from the LUCAS (Land Use/Cover Area Frame Survey) dataset; Sentinel-2 optical and Sentinel-1 radar sensor data
Global Wetlands Map (CIFOR) (Gumbricht et al., 2017)	Tropics and subtropics, ~236 m	2011 Static	Top-down	Combination of MODIS satellite data (MCD43A4) and topographic convergence indices (TCIs) based on the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) at a 250 m resolution with precipitation climatology from the WorldClim global dataset
National Land Cover Database (NMD) 2018 (Naturvårdsverk et, 2019)	Sweden, 10 m	2018 Semi-static, 5-yearly	Top-down	Multispectral analysis of satellite data (mostly Sentinel-2) and elevation-derived variables collected from LiDAR-scans
Composite Wetlands (CW) (Tootchi et al., 2019)	Global, 15 arcsec, ~500 m	~1980–2016 Static	Bottom-up	Merging regularly flooded wetlands (RFWs), where surface water can be detected at least once a year through satellite imagery (ESA-CCI, GIEMS-D15, JRC surface water), and groundwater-driven wetlands (GDWs) based on groundwater modeling
Global Wetland Loss Reconstruction 1700-2020 (Fluet-Chouinard et al., 2023)	Global, 0.5° , ~55.5 km	1700-2020 Semi-static	Bottom-up	3,320 national and subnational drainage and land-use records from 154 countries and across four land uses (cropland, forestry, peat extraction and wetland cultivation)
WAD2M - Wetland Area and Dynamics for Methane Modeling (Zhen Zhang et al., 2021)	Global, 0.25°, ~25 km	2000-2018 Semi-static, monthly	Top-down	Based on the dynamic Surface Water Microwave Product Series v3.2 (SWAMPS) and static wetland maps to fill gaps (NCSCD, CIFOR, GLWD)
Dynamics of global wetlands based on TOPMODEL	Global, 0.25°, ~25 km	1980–2020 Semi-static, monthly	Bottom-up	Seven global soil moisture reanalysis data, observation-based wetland/flooded area data (GIEMS-2, RFW (Tootchi, 2019), WAD2M, CIFOR), TOPMODEL-based diagnostic model

(Xi et al., 2022)				
GIEMS-MC (Bernard et al., 2025)	Global, 0.25°, ~25 km	1992-2020 Semi-static, monthly	Top-down	Based on GIEMS-2, which is derived from passive microwave land surface emissivity, and ancillary data (GLWDv2, MIRCA2000)
GWL_FCS30 (Zhang et al., 2023)	Global, 30 m	2000-2022 Semi-static, annual	Top-down	Combination of an automatic sample extraction method, existing multi-sourced products, satellite time-series images (Landsat, Sentinel-1) and a stratified classification strategy
Peat-ML - global peatland extent created using machine learning (Melton et al., 2022)	Global, 5 arcmin, ~9.26 km	2001-2020 Static	Top-down	Generated using machine learning and drivers of peatland formation including spatially distributed climate, soil, geomorphology, and vegetation data. Trained using maps of peatland fractional coverage for 14 relatively extensive regions
Global Peatland Map 2.0 (GPM2.0) (UNEP, 2022)	Global, 500 m	~1958-2022 Static	Bottom-up	Compiled by amalgamating country level peatland maps and high-resolution peatland 'proxy' data contained in the Global Peatland Database (GPD)
PEATMAP - peatland distribution based on meta-analysis (Xu et al., 2022)	Global, variable	1999-2010 Static	Bottom-up	Produced by combining the most high quality available peatland map from a variety of sources that describe peatland distributions at global, regional and national levels

Database selection. Three databases were selected on the basis of absence of data gaps for the EEA region, accessibility and ability to describe multiple wetland types. The CLC 2018 map was selected as CORINE Land Cover is one most widely used land cover products for Europe (Bielecka at al., 2017) and is already used in the EFB methodology (Borucke et al., 2013). The European Wetland Map was included as the most recent standardised geospatial dataset on peatlands and wetlands in Europe (Tegetmeyer et al., 2025). The Global Lakes and Wetlands Database (GLWD) v2 was added as a potential data source for extending the scope beyond Europe as it's produced by fusing 25 primarily global datasets and differentiates between 26 wetland types, which may aid in removing double-counting issues or attributing emissions/sequestration fluxes.

Total wetland area by country. There are notable differences in the total wetland values derived from the three data sources and CLC 2018 consistently has the lowest estimate (Figure 1). The relative differences are listed in Table 2. CLC 2018 and GLMD v2 are nearly identical for Iceland and Ireland, but there's a large discrepancy for Finland (117%), Norway (66%) and Sweden (75%). EWM and GLMD v2 are more consistent relative to each other, especially in Norway (36%), Sweden (17%), and Finland (49%).

The production of CLC varies by country and uses mostly visual interpretation for land use/land cover (LULC) classification with semi-automatic techniques being more common in recent versions. The reported thematic accuracy of CLC 2018 is 85%, however a recent validation study revealed heterogeneous accuracies between classes with wetlands having the largest omission error as high as 60% (Varga et al., 2021). As such, CLC is very conservative in terms of classifying wetlands. Additionally, the CLC nomenclature guidelines include certain wetlands in non-wetland categories, e.g. small wetlands in agricultural areas, drained wetlands, dwarf-shrub covered peat (EEA, 2019). Zhang et al. (2019) points out that wetlands generally suffer from low accuracy if a classification algorithm is not specifically designed for the wetland environment, which highlights the importance of using wetland-specific dataset.

Nevertheless, it's interesting that in Ireland and Iceland CLC 2018 and GLWM v2 have a high consensus as both countries have a low forest cover. One possible explanation is that tree cover might be an important factor for CLC omissions as wetland visual clues may become obscured. On the other hand, GLWM v2 combines 25 datasets with broad to specific representations of wetlands and adds forest cover as an ancillary layer, presumably limiting omission risks.

As mentioned above, it’s expected that bottom-up maps such as the EWM may have higher estimates of wetland cover as they are more inclusive of areas that have been converted or drained. However, this expectation is not consistent between EWM and GLWD v2 in terms of total area as GLWD v2 has higher values for Finland and Norway. EWM was compiled from over 200 data sources with the peatland layer in particular including more than 100 regional and national datasets. Although this generally allows for finer resolution input data to be used, it also brings the issue of inconsistent definitions across inputs. Top-down datasets like GLWD v2 have the benefit of a consistent definition of wetland, which allows for coherent mapping across the globe (UNEP, 2022).

Table 2. Relative difference in % between datasets across countries.

	CLC vs EWM	**CLC vs GLWD**	**EWM vs GLWD**
Finland	80	117	49
Iceland	109	12	100
Ireland	64	1	63
Norway	32	66	36
Sweden	89	75	17

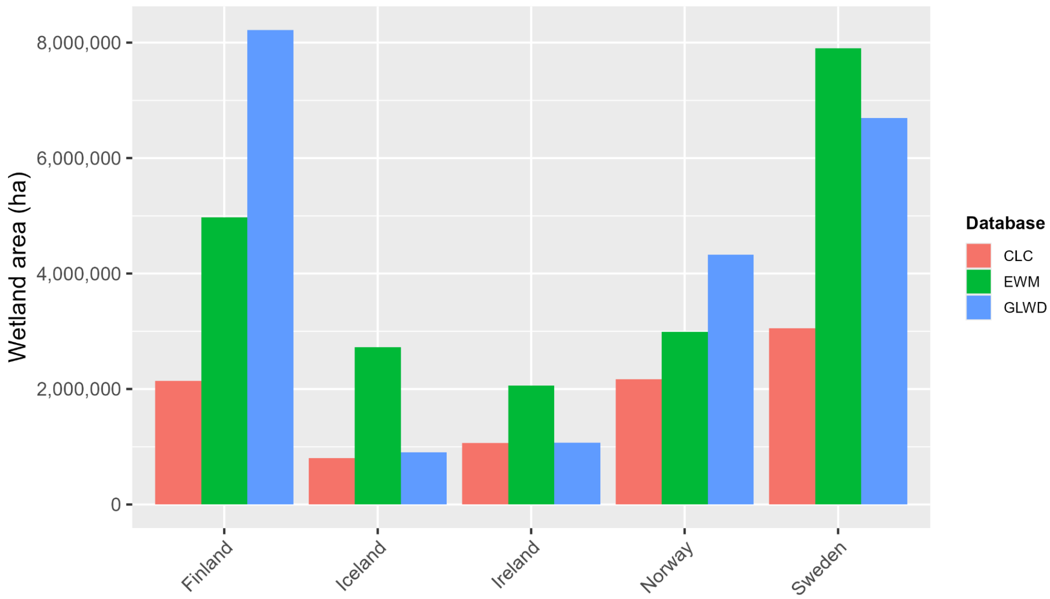

Figure 1. Total wetland area by country and database in hectares.

Wetland area by class and country. As the three datasets consider different numbers of classes, it is also important to analyse class-by-class differences for matching categories. In all cases, classes representing waterbodies (lakes, rivers) or non-wetlands are excluded as described in Table 3. GLWD is the most disaggregated and is broken down into 26 wetland classes. However, it can be aggregated based on flooding source (lacusterine, riverine, palusterine, coastal) and soil type (mineral, organic/peatland). The subdivision is based on inundation frequencies and forest cover, which can be an aid when dealing with double counting (Lehner et al., 2025).

*Table 3. Class number and excluded classes by database. *GLWD classes can be aggregated*

Database	Class number	Included	Excluded
CLC	44	6	Classes 1XX-3XX, 511 - Water courses, 512 - Water bodies
EWM	10	8	Floodplain, maximum extent Floodplain, potential floodplain extent
GLWD	33	26*	Dryland (non-wetland), Freshwater lake, Saline lake, Reservoir, Large river, Large estuarine river, Other permanent waterbody, Small streams

In Figure 2, the wetland class distribution across datasets and countries is illustrated as a pie chart. GLWD classes are aggregated into 8 categories to simplify visualisation. Peatlands are generally the wetland class with the largest surface area across the spotlight countries. Overall, CLC tends to attribute the largest percent of wetland area (83-98%) to peatlands whereas GLWD consistently has the lowest percent values (apart from Ireland).

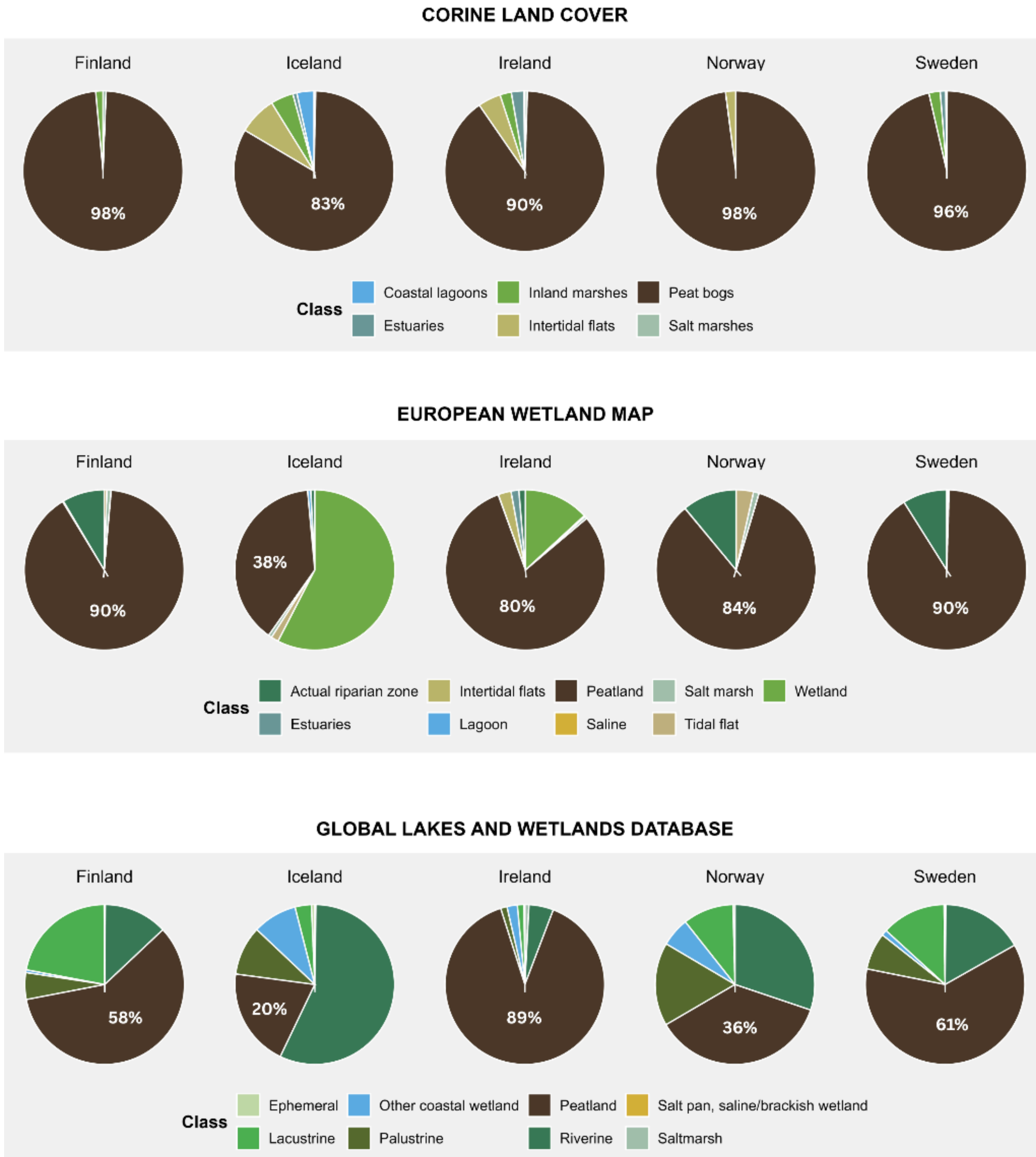

Figure 2. Pie chart of wetland class distribution per country and database with % value for peatland cover.

Country-specific comparison. When comparing the absolute values for peatland area, it emerges that EWM has the highest estimates across the three datasets (apart from Finland). This is consistent with the expectation that a finer-resolution, bottom-up map would capture small/degraded peatlands in a fragmented landscape. Table 4 presents a country-specific summary of the comparison between total wetland and peatland area estimated by the three datasets, as well as key differences between the two.

Table 4. Country-specific summary.

Country	Summary
Finland	High agreement in peatland estimates between EWM and GLWD (8% relative difference) in contrast with 49% difference for total wetland area, which seems to emerge from high GLWD estimates for riverine and lake-associated wetlands.
Iceland	Lack of agreement for peatland area. EMW notably attributes the majority of wetland area (57%) to wetlands that could not be clearly assigned. CLC assigns most wetland area to peatlands (83%) and GLWD to riverine wetlands (56%). Although CLC and GLWD have high agreement for total wetland area (12% relative difference), they disagree on what type of wetlands these are with a 115% relative difference for peatlands. Iceland has a unique soil profile and may need to be treated as a special case (Arnalds at al., 2016).
Ireland	High agreement across datasets regarding peatland ratio of all wetlands with 0% relative difference between CLC and GLWD with EWM values being 54% higher. Consistent with total wetland area differences.
Norway	High agreement between CLC and EWM for peatland area (17% relative difference). GLWD estimates highest total wetland area, yet lowest peatland area as it estimates for far larger coastal and inorganic wetlands.
Sweden	Lack of agreement for peatland area. CLC and EWM both estimate a high peatland ratio of total wetland area (90-96%), yet the EWM absolute value is 84% higher. GLWD estimates ~36% inorganic wetlands.

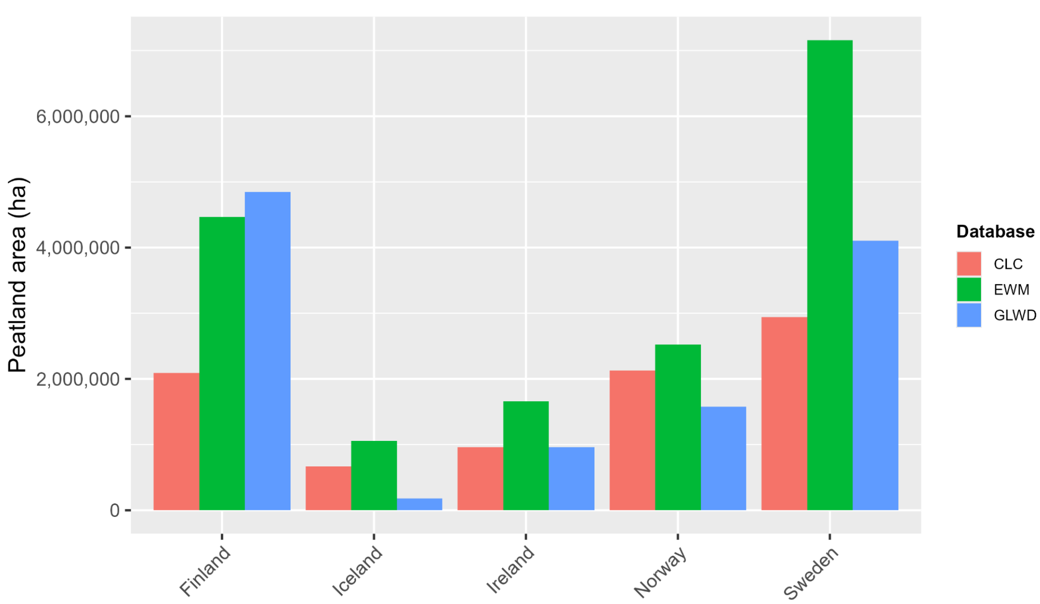

Figure 3. Total peatland area by country and database in hectares.

Carbon dynamics in wetlands. Wetlands have been estimated to contain 29-45% in global C stocks, however there are relatively few global estimates of wetland carbon balance (Li et al., 2023). Ecosystem carbon balance is represented by net ecosystem production (NEP), which is equal to the difference between CO_2 uptake by assimilation and CO_2 losses through ecosystem respiration. Table 5 provides an overview of publications of global wetland NEP since 2010. Earlier studies have been based on relatively small sample sizes and were skewed toward wetlands with high primary plant production and NEP such as marshes (Gilmanov et al., 2010, Mitsch et al., 2013, Lu et al., 2017). Recent papers leverage increased data availability and machine learning to extrapolate NEP based on the spatial variation of environmental factors (Li et al., 2023, Li et al., 2025). One of the key differences between the 2023 and 2025 studies is that Li et al. 2023 includes data on inland open waters (e.g. lakes, reservoirs) and human-influenced wetlands (rice paddies, drained wetlands), which can have low sequestration rates or be net sources of CO2. That being said, Li et al., 2025 excluded coastal wetlands, which generally have high sequestration. These omissions seem to balance each other out as the global mean NEP values of the two studies are strikingly similar: 56.4 and 57 g C m^{-2} yr^{-1}.

The 2023 and 2025 publications use GLWD v1 and v2 respectively to prescribe wetland extent. Li et al. 2023 integrates two additional maps, WAD2M v.2.0 and GIEMS v.2.0, to account for uncertainties in global wetland area estimates. As both publications generate a global NEP map of wetland carbon sequestration, it would be possible to estimate national averages as has been demonstrated in Li et al. 2023.

Table 5. Global wetland NEP publications.

Reference	NEP [g C m^{-2} yr^{-1}]	Description	Temporal coverage	Spatial coverage	Wetland type
Li et al., 2025	56.4	Machine learning, NEP from 222 sites scaled up with environmental data	Annual wetland NEP during 2000–2020	Global	Wetlands, Mineral soil wetland (marsh, swamp), peatland (swamp, bog, fen), floodplain, wet tundra
Li et al., 2023	57	Machine learning, NEP from 772 sites scaled up with environmental data	Aggregated NEP with input data from ~1970-2021	Global	Inland wetlands, peatlands and coastal wetlands
Lu et al., 2017	93.15	Meta-analysis, NEP averaged across 43 sites	Input data range 1998-2012	Sites across Asia, Europe, North America, and Australia	Inland wetlands, coastal wetlands
Mitch et al., 2013	118	Simulation, NEP averaged across 21 sites	NEP based on a 100-year simulation	Sites across North America, Central America, Europe, Asia, Africa	Wetlands
Gilmanov et al., 2010	137	NEP averaged across 9 sites from wetland flux towers	Input data range 2000-2006	Sites across Europe and Asia	Wetlands

Reported vs modelled values. It would be interesting to attempt to validate national values based on modelled data against reported values in CRF tables for national GHG emissions reporting in the UNFCCC. CRF tables are available annually from 1990-2023 for Annex I Parties under the UNFCCC, which includes most European states, Japan, Turkey, Australia, New Zealand, Canada and the USA (UNFCCC, n.d.). Data on emissions and removals/sequestration is available for the Wetland land-use category under Wetlands Remaining Wetlands and Land Converted to Wetlands. Data describing drained wetlands is reported under Land Converted from Wetlands.

Recommendations

When integrating wetlands as a land component of the EFB framework, it's important to assign a clear definition to wetlands, as well as to be transparent about the data sources used, because of the vast variation of estimates between different datasets and models. The definition of wetlands is generally inherited from the maps used as input data (Li et al., 2025, Fluet-Chouinard et al., 2023). The EFB framework measures the regenerative capacity of the biosphere and is applied on the global, national and subnational level. It allows for a comparison of a national economy's pressure on the environment over a time period and relative to other countries. As such, it's important to have a consistent definition across states, which is why it's preferable to use input data which is coherent and standardized across the globe. Based on this requirement, it's recommended to prioritise top-down datasets such as the Global Lakes and Wetlands Database (GLWD) v2 as opposed to bottom-up data like the European Wetland Map (EWM), which is an amalgamation of input data with non-uniform definitions. Non-wetland specific datasets (e.g. CLC 2018) can suffer from large omission errors for wetlands. Using data generated with wetland ecosystems in mind is generally more reliable.

Attributing carbon fluxes to wetland ecosystems brings significant challenges as there is limited scientific consensus on wetland sequestration rates. Similarly to wetland spatial coverage, it's preferable to use data consistent across the globe. Possible approaches are to use a global model that distinguishes between different wetland types and can be scaled down to national/regional annual carbon accumulation values such as Li et al. 2025 and Li et al. 2023. Alternatively, it's possible to use models that estimate carbon sequestration for a specific class of wetlands (e.g. peatlands, coastal wetlands), which may be a reasonable approach and needs to be investigated further. Reported values in CRF tables are subject to reporting guidelines and therefore may be a consistent data source, however these are only available for a limited number of countries and can't be applied on the global scale relevant to EFB accounts.

Lastly, it's important to note that all datasets and models make assumptions and may over- or underestimate the "true" extent of wetland ecosystems. Integrating wetlands into EFB accounts is subject to all the limitations of the input data, but so is all other input data of similarly global and amalgamated metrics. While the final outcome of such an effort is unlikely to be 100% true to reality, it would still make the EFB framework more representative of Earth's systems and would give visibility to an often overlooked and undervalued ecosystem. To generalize, having consistent definitions and data sources would allow for an easier interpretation of the output. The exception to this rule are countries with unique wetland ecosystems (e.g. Iceland), for which global classification schemes may be inappropriate, which need to be evaluated on a case-by-case basis.

Conclusion

Recent years have brought major advances in remote sensing and data analysis, which have resulted in the most comprehensive data of wetland spatial coverage and carbon dynamics yet. Therefore, the basis for wetlands to be integrated in systems from which they were previously omitted (such as the EFB framework) has been vastly improved. An absence of clear definitions, regional data unavailability (e.g. tropics) and a lack of consensus on global models still limit wetland data applications. However, it's possible to work around these constraints through transparency on the approach used. Further considerations for EFB accounts include the requirement that data must be obtainable as far back as 1961. Approaches to extrapolate backwards from the present data availability need to be investigated further.

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