Large-extent classification of wetland and management types using satellite remote sensing and auxiliary data

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SUMMARY

There have been few studies examining how effectively land use / land cover (LULC) classes of wetland types and their management can be detected with remote sensing and auxiliary data. We conduct wetland-specific present-day LULC classification and long-term change detection in seven European study areas. We assess how accurately LULC types and their changes can be detected with satellite remote sensing and to what extent auxiliary data improves classification accuracy. We conduct 10 m spatial resolution 27-class LULC classifications using Sentinel-1 and -2 satellite imagery and auxiliary GIS data about soil, LULC, and topography. For the change detection, we distinguish 8 LULC classes between 1985 – 2023 using Landsat imagery at a 30-meter resolution. The classification accuracy for the present-day analysis varies between 52–93 %, with the omission of auxiliary datasets reducing accuracy by up to 41 %-points. The change detection classifications have 73–94 % agreement with the Corine Land Cover data. Our results indicate that wetland and management types can be classified using 10-meter imagery, but the use of good quality auxiliary data is required to improve the classification accuracies. Additionally, 30-meter LULC changes are detectable using Landsat imagery. The developed approach allows for quick and straightforward implementation of LULC classification and change detection over large areas.

KEY WORDS: change detection, land cover, land use, peatland, satellite imagery

INTRODUCTION

The global extent of the wetlands and peatlands has declined, with recent estimates suggesting 21 % loss in global wetland cover and > 50 % loss in Europe, parts of Asia and the United States since 1700 (Fluet-Chouinard *et al*. 2023). Additionally, the ecological condition of remaining wetlands has deteriorated, with about 50 % of peatlands in the European Union being degraded (Tanneberger *et al*. 2021). The primary drivers of wetland loss and degradation have been drainage for agriculture and forestry, and conversion into urban areas (Fluet-Chouinard *et al*. 2023). To reverse this trend, restoration has been suggested (Temmink *et al*. 2023).

Geospatial information is crucial to monitor the extent and status of wetlands and detect long-term changes in their extent. Geospatial information is also important to classify different wetland types (*e.g*., peatland vs. mineral soil wetland types) as the ecosystem structure and processes vary between the types (Minasny *et al*. 2023). Furthermore, identifying management, drainage, and restoration is essential to monitor the ecological status and functioning of the wetlands and to guide management (Minasny *et al*. 2023). Large-scale wetland mapping has relied on various methods, including (1) bottom-up compilation of existing local, regional, and national wetland databases (Tanneberger *et al*. 2017; UNEP 2022; Xu *et al*. 2018), (2) top-down prediction of

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wetland extent using remote sensing and other GIS information (Hu *et al*. 2017; Melton *et al*. 2022), (3) development of wetland type maps targeted to previously identified wetland areas (Minasny *et al*. 2023), and (4) construction of wall-to-wall land use / land cover (LULC) databases with remote sensing and GIS data (Pontone *et al*. 2024).

The existing wetland mapping methods enable the detection of wetland and peatland types and their management, but these approaches present caveats. Existing wetland databases often contain information only about the extent of wetlands, not about their types and status (*e.g*., Tanneberger *et al*. 2017, Melton *et al*. 2022) and there is also uncertainty in the wetland extent estimates (Fluet-Chouinard *et al*. 2023). Furthermore, detailed information of wetland types and particularly their degradation, management, and restoration status are currently poorly presented in the current LULC products. For instance, while there are several LULC classifications available for the European Union (*e.g*., Corine Land Cover products), these maps do not contain a good understanding of peatland and wetland types (*e.g*., Minasny *et al*. 2023).

To develop new wetland map products, the use of wall-to-wall remote sensing products is essential. Satellite remote sensing can be used to produce both present-day maps and track changes that have happened during past decades (Chasmer *et al*. 2020). Optical data can be used to depict spectral properties of land cover (Zelioli *et al*. 2025), while synthetic aperture radar (SAR) signals are sensitive to soil moisture and surface structure (Millard *et al*. 2020), both being widely used in wetland applications (Thompson *et al*. 2016; Amani *et al*. 2017; Millard *et al*. 2020; Pontone *et al*. 2024, Zelioli *et al*. 2025). Furthermore, the use of multi-sensor and multi-season data boosts classification accuracies in wetlands, as different sensors capture different aspects of the landscape (Pontone *et al*. 2024, Zelioli *et al*. 2025) and the seasonality differs between LULC types (Millard *et al*. 2020). As wetlands have fine-scale spatial heterogeneity, high-spatial resolution (≤ 30 m pixel size) data is required to accurately map the different wetland types (Treat *et al*. 2018). To date, suitable satellite remote sensing datasets that are openly available include the 10 – 60-meter Copernicus Sentinel-1 C-band SAR and Sentinel-2 optical data for present-day wetland classification, while 30-meter resolution Landsat-5–9 optical data can be used for tracking long-term wetland changes since 1984.

The differentiation of mineral soil wetlands and peatlands from other LULC types using satellite remote sensing is challenging. Satellite remote sensing captures the spectral and backscatter properties of the surface of the land cover; however, it is complicated to capture the water below the vegetation (Gallant, 2015), processes that occur belowground, and soil properties such as carbon content (*e.g*., Minasny *et al*. 2023). Therefore, auxiliary GIS data, such as topographic information and existing maps and databases of for example soil, LULC types, and wetland management (*e.g*., drainage) can improve the classification accuracy. However, there have been lack of multi-site studies assessing how well wetland types and management can be classified with satellite remote sensing and whether different types of auxiliary data improve classification accuracy.

To address the limitations in existing wetland map products, our main objective is to develop and implement a method for LULC classification and change detection using openly available Sentinel-1, Sentinel-2, and Landsat data, as well as different auxiliary geospatial datasets. This method is designed to accurately recognise different wetland types and their management statuses over large spatial extents. We implement our approach in seven study areas across Europe to test its robustness and whether results are similar in different contexts. Our detailed research questions include:

1. How effectively can the LULC classes of different wetland types and management be classified using satellite remote sensing and auxiliary GIS datasets?
2. To what extent does the use of auxiliary datasets improve classification accuracy compared to satellite remote sensing alone?
3. How accurately can changes in LULC be traced over time using satellite remote sensing data?

METHODS

We developed a LULC classification and change detection algorithm in the Google Earth Engine platform (Gorelick *et al*. 2017) (Figure 1). The 10-meter present-day LULC classification relied on Copernicus Sentinel imagery and auxiliary datasets, the 30-meter resolution long-term change detection was conducted with Landsat imagery available for the whole target period (1985–2023). We conducted the LULC classifications in seven study areas located throughout the EU (Figure 2, Supplementary text). All study areas were a combination of multiple river catchment areas and were chosen so that they include a mosaic of different LULC and wetland types and management

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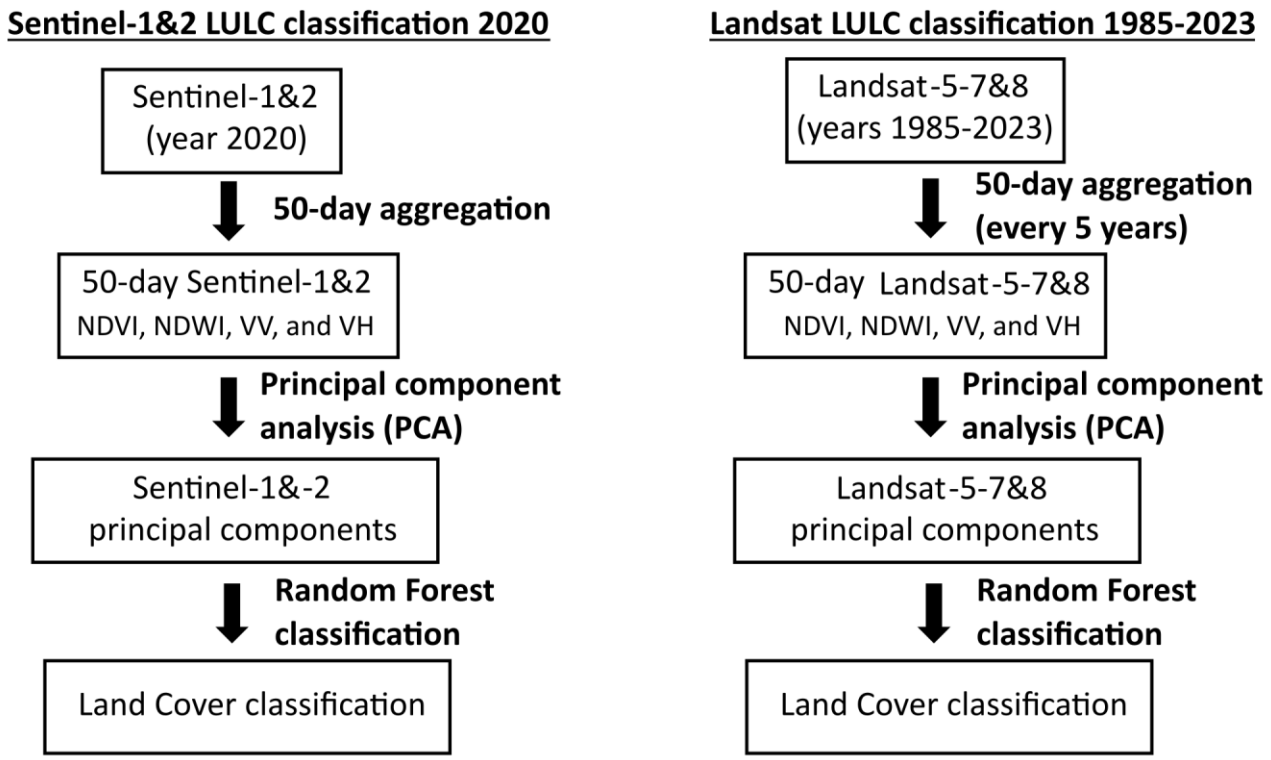


Figure 1. Workflow for the classification of 10-meter resolution LULC classes (left panel) and 30-meter LULC change detection analysis (right panel).

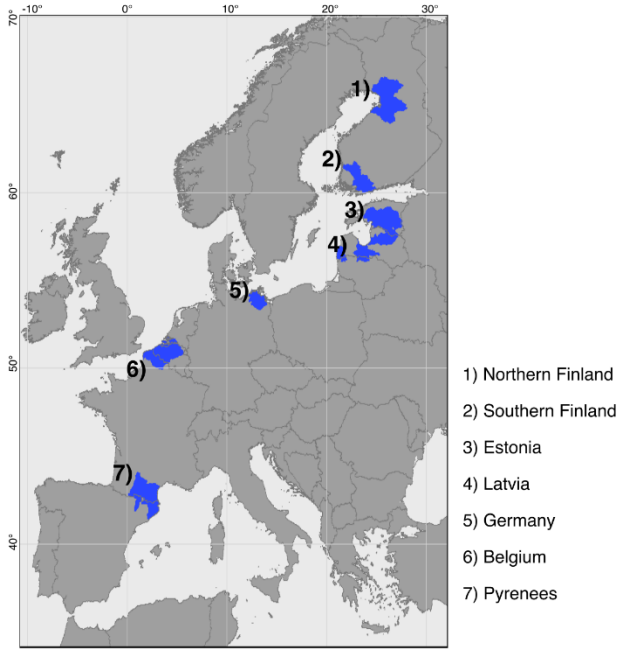


Figure 2. Location of the study areas representing selected river catchments.

LULC classes

For the 10-meter resolution approach, we included a total of 27 LULC classes. They were not present or identified in all the study areas, so the number of classes range between 9–25 across the areas. LULC classes covered different wetland and peatland types under different land use and drainage statuses (Table 1). For the 30-meter resolution change detection analysis, we grouped the LULC classes to broader eight classes that are detectable by using solely 30 m optical data from Landsat (Table 1).

We divided peatlands into minerotrophic (groundwater fed) fens dominated by sedges, minerotrophic *Sphagnum* mosses and/or wet brown mosses, and ombrotrophic (rainwater fed) bogs, dominated by shrubs and ombrotrophic *Sphagnum* mosses (*e.g.*, Kuhn *et al*. 2021, Karlson & Bastviken 2023, Pontone *et al*. 2024). Additionally, we specified classes for both treeless and treed peatlands, of which the latter consisted of usually sparsely treed ombrotrophic bogs with Scots pines and more densely treed typically minerotrophic fen and swamp forests (*e.g.*, Hörnberg *et al*. 1998) with different classes for deciduous, coniferous, and mixed tree stands. We included different types of forested peatlands because of the remote sensing approach with satellite imagery detecting mostly the top-of-canopy vegetation. Moreover, we differentiated classes for pristine peatlands, peatlands drained for different purposes (forestry, agriculture, peat production), and rewetted peatlands. In addition to peatlands, we included coastal wetlands that are found on the water-land-ecotone and can be both on peat and mineral soil (Kennedy *et al*. 2014).

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Table 1. LULC classes used in this study, along with their soil type, drainage status, and generalised land uses for the change detection. The specific classes used in each study area are given in Table S7.

LULC class name (for detailed Sentinel LULC classification, 2020)	Soil type	Drainage status	LULC class name (for generalised Landsat LULC classification, 1985–2023)
fen	peat	undrained	open peatland
bog	peat	undrained	open peatland
treed bog	peat	undrained	open peatland
deciduous swamp forest	peat	undrained	forest
coniferous swamp forest	peat	undrained	forest
mixed swamp forest	peat	undrained	forest
coastal wetland / grassland	peat	undrained	open peatland
drained pine bog	peat	drained	forest
drained deciduous swamp forest	peat	drained	forest
drained coniferous swamp forest	peat	drained	forest
drained mixed swamp forest	peat	drained	forest
forest clear-cut	peat	drained	clear-cut
agriculture: cropland	peat	drained	agriculture
agriculture: grassland	peat	drained	agriculture
peat extraction	peat	drained	peat extraction
coastal wetland / grassland	peat	drained	agriculture
revegetated peat extraction site	peat	restored	low vegetation
rewetted for nature development	peat	restored	low vegetation
coastal wetland / grassland	mineral	NA	agriculture
coniferous forest	mineral	NA	forest
deciduous forest	mineral	NA	forest
forest clear-cut	mineral	NA	clear-cut
Mediterranean shrubland/forest	mineral	NA	low vegetation
agriculture: cropland	mineral	NA	agriculture
agriculture: grassland	mineral	NA	agriculture
water	NA	NA	water
built-up	NA	NA	built-up

Additionally, we included mineral soil classes other than wetlands to enable the construction of wall-to-wall datasets that consisted of forests, agricultural areas, built-up areas, and open water.

High-resolution 10-meter classification

For the 10-meter LULC classification, we used a multi-sensor approach, by including Sentinel-1 and Sentinel-2 satellite imagery for the year 2020 for each study area (Figure 1 and 2). We used Level-2A orthorectified surface reflectance for the optical Sentinel-2 data and ground-range detected, thermal

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noise removed, radiometrically calibrated and terrain corrected product for the synthetic aperture radar Sentinel-1 data. For Sentinel-2, we masked out non-valid observations (clouds, cirrus, snow, and defective pixels) with the Scene Classification Layer, which is a layer included in the Level-2A product. As multi-season data typically boosts classification accuracy (Senf *et al*. 2015), we divided the data into 50-day time periods which represent different seasonal stages and are sufficiently long to produce a robust dataset including valid observations. We calculated mean values of individual spectral bands and two widely used spectral indices (normalised difference moisture index (NDMI, Gao *et al*. 1996), and normalised difference vegetation index (NDVI, Rouse *et al*. 1973)) for the Sentinel-2 data and two polarisations (vertical transmit vertical receive, VV; vertical transmit horizontal receive, VH) for the Sentinel-1 data. To derive the main spatiotemporal patterns from the 50-day image composites and to reduce noise in the composites, we calculated six principal components of the data that were used as explanatory datasets. Then, we employed random forest algorithm (Breiman, 2001), which has been successfully used in LULC classifications (Belgiu & Drăguţ 2016). We optimised the model parameters using an exhaustive grid search, resulting in 100 decision trees and 3 variables tested at each tree node.

For each study area, we generated 50 – 100 points for each class used for training and validation. We generated the points with a visual interpretation of very high spatial-resolution satellite and aerial imagery (pixel size < 5 m; *e.g*., satellite imagery in Google Earth and ESRI World Imagery, and aerial imagery provided by national land surveying agencies) and using auxiliary information from existing maps and GIS data sources. To avoid problems with spatial autocorrelation (Sheykhmousa *et al*. 2020) and unrepresentative training data, when generating the points we included a diverse set of training points for different classes and spread the points for each class throughout the study areas. This way, the model training and validation were more representative of the overall variability within the areas. Nevertheless, in the training and validation data generation, we focused on such areas that we either knew well based on our field and local expertise or that had existing high-quality peatland or habitat type data available. In Belgium, we could utilise an existing LULC map available for part of the area; therefore, instead of using visual interpretation, we randomly generated the points with the help of GIS data sources of the different classes and visually checked them afterwards.

To train and validate the models, we implemented a spatial block cross-validation based on a regular grid of spatial blocks. Each grid cell covered approximately 25 × 25 km and contained a variable number of training points. To assign the grid cells to a fold, we applied a greedy balancing procedure in which each grid cell was sequentially assigned to the fold with the lowest cumulative number of training points. This approach generated approximately ten folds with similar sample sizes. The cross validation consisted of taking the points included within the grid cells of one-fold as a test set and the remaining points as training data. We calculated the mean overall accuracy and class-specific user's and producer's accuracies (1-commission error, and 1-omission error, respectively).

Auxiliary datasets

For the 10-meter resolution classification, we tested whether the classification accuracy improved when including different types of auxiliary GIS datasets. These auxiliary datasets included soil, LULC, and topography information (Tables A1 – A6). The auxiliary data was primarily used to discriminate peat/organic soils from mineral soils. We included also other available wall-to-wall datasets that were considered relevant, and except for Belgium, we did not include higher accuracy LULC products available only for part of the study areas that were used to help training and validation data generation. All used auxiliary datasets had some uncertainties, so they were not used to force the classification but were part of predictor set. We used both global/European data available for all study areas and local data available only for specific study areas. In Belgium, the local auxiliary data only partially covered the study area, and the validation for the 2020 LULC classification only encompassed the area covered by these local auxiliary data. Random forest can predict LULC classes when some input variables are missing but, in that case, the results are expected to be less accurate. This feature of random forest explains why we can provide a LULC map for areas that are not covered by auxiliary data in Belgium. For the study area Pyrenees, we did not include any local auxiliary data as relevant auxiliary data was not available.

To test the effect of the different auxiliary data sources, we applied six different classification options:

1. Only Sentinel satellite imagery
2. Sentinel satellite imagery and topography information from Copernicus DEM
3. Sentinel satellite imagery and global canopy height model

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4. Sentinel satellite imagery and global land cover and peatland maps
5. Sentinel satellite imagery and site-specific auxiliary datasets
6. Sentinel satellite imagery and all auxiliary data
7. All auxiliary data but no satellite imagery

Change detection in 30-meter spatial resolution

We used a similar mapping approach for the 30-meter LULC change detection as for the 10-meter resolution classification, but instead of using Sentinel satellite imagery, we used cross-harmonised 30 m spatial resolution optical USGS/NASA Landsat-5, -7, and -8 satellite imagery. We calculated the eight-class LULC classification aggregated for 5-year intervals for the years between 1985 and 2023, with the last interval being 2020–2023 (Figure 1). We calculated the percentage of area experiencing LULC change during the study period and examined which kind of changes occurred within the period.

We used the point-based data as training data separately for each time period's classifications. To test the robustness of the classifications and validate them, we cross-compared the classifications with the best-available European LULC classification Corine Land Cover (minimum mapping unit 25 ha; Copernicus 2024) available for the Finnish sites from 1995 and other sites for the whole change detection period. We did not generate separate validation data nor use the training points for validation as high-resolution imagery would have been needed for visual interpretation of LULC classes and such imagery was not available for the entire 1985–2023 period.

RESULTS

The overall classification accuracy in the 10-meter resolution classifications varied notably between sites, with the highest accuracy being in the Pyrenees (92.7 %) and the lowest in Germany (52.0 %) (Table 2, Figure 3). The accuracy was relatively high (> 80 %) in the Finnish and Estonian areas, while moderate 69 – 74 % accuracy was obtained in Latvia and Belgium. There was also a notable variation in the class-specific users' and producers' accuracies. In all sites, some of the classes were classified with high accuracy, but particularly in Germany, Latvia and Belgium, there were difficulties in classifying the drained peatland forest classes (Table A7).

The inclusion of global and European auxiliary datasets increased the classification accuracy moderately (-0.6 – 15.8 %-points; Table 2). The inclusion of site-specific auxiliary datasets boosted the classification accuracy for Finland, Estonia, Latvia, and Germany both when global/European auxiliary data was not used (12.2 – 39.2 %-points) and was used (12.3 – 39.9 %-points). For Belgium, the impact of site-specific auxiliary data was more moderate (5.5 – 6.8 %-point increase). The added value of global and European auxiliary datasets was also considerable (1.9 – 6.3 %-points) when the local auxiliary data were also included. In the classifications with all auxiliary data but no satellite imagery, the accuracies were 0.5 – 31.2 %-point higher than in the classifications with satellite imagery only and 6.8 – 13.2 %-point lower than in the classifications with satellite imagery and all auxiliary data.

Table 2. The overall classification accuracy (OA) in different classification options in the different study areas. The accuracies were obtained for the 10-meter classification based on 2020 Sentinel-1 and -2 data.

Region name	OA1 (%)	OA2 (%)	OA3 (%)	OA4 (%)	OA5 (%)	OA6 (%)	OA7 (%)
Northern Finland	47.4	53.4	47.5	56.3	80.8	85.4	78.6
Southern Finland	44.2	48.8	45.5	47.6	83.4	85.4	73.3
Estonia	48.6	52.4	49.8	56.7	77.2	80.8	73.7
Latvia	47.4	49.8	48.0	55.0	63.0	69.3	56.1
Germany	37.9	39.7	37.3	38.3	50.1	52.0	43.7
Belgium	65.3	67.4	68.6	67.4	71.7	74.2	65.8
Pyrenees	76.9	83.0	77.2	88.0	NA*	92.7	80.0

OA1 = Classification with satellite imagery
OA2 = Classification with satellite imagery + topography
OA3 = Classification with satellite imagery + canopy height model
OA4 = Classification with satellite imagery + global land cover maps
OA5 = Classification with satellite imagery + local auxiliary data
OA6 = Classification with satellite imagery + all auxiliary data
OA7 = Classification with all auxiliary data but no satellite imagery
*No local auxiliary data was used.

For each study area, there were LULC changes in less than 10 % of the area since 1985 (Figures 4 and 5). The agreement with Corine Land Cover was moderate to high (73.4 – 93.5 %) in all study areas and time periods (Table 3, Figure 6). For Northern Finland, the agreement was notably higher after 2010 than before that while for the other study areas, no temporal trends in the agreement were found. Most of the observed changes were between forest, clear-cut, agriculture, and built-up classes (Figure 7).

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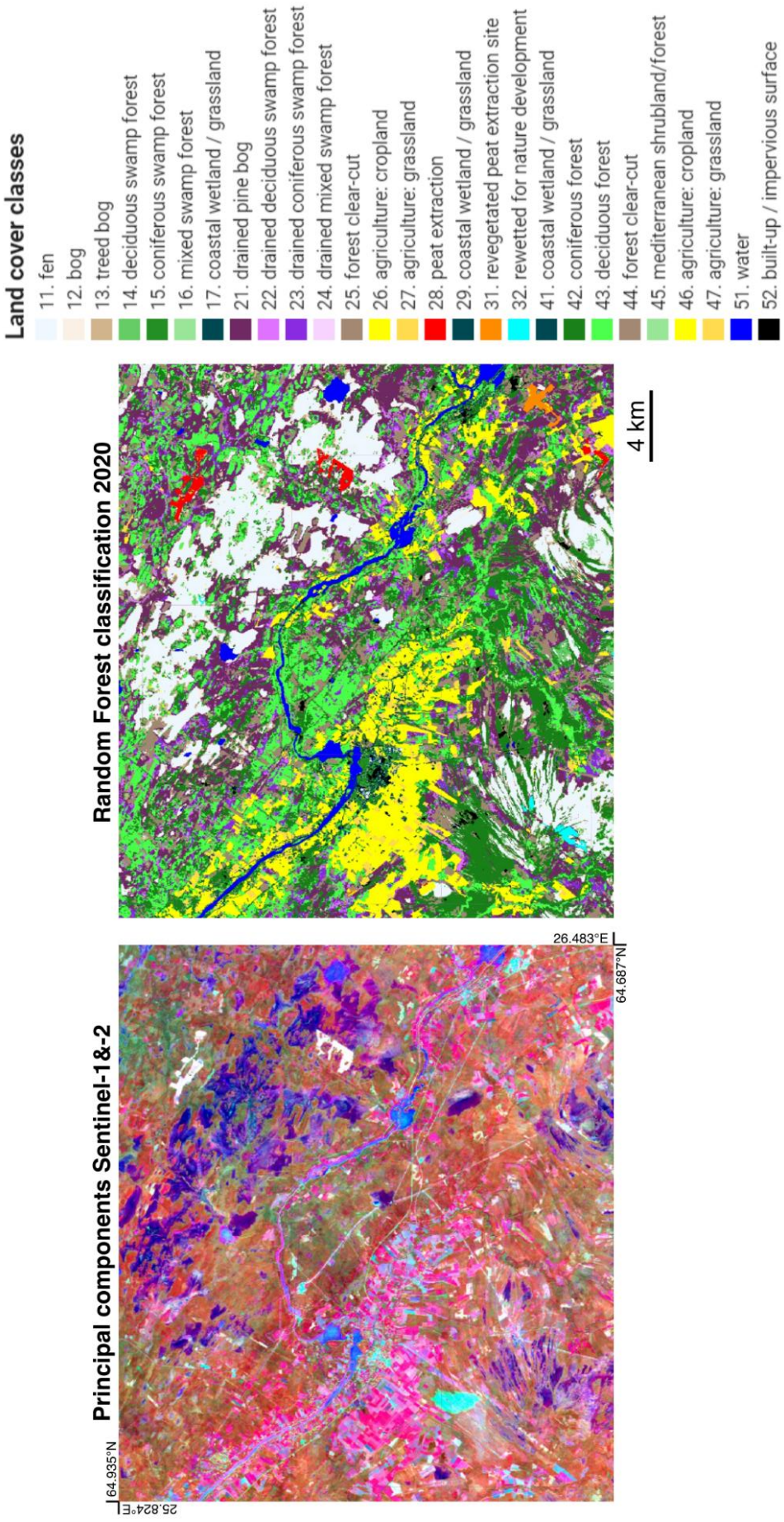


Figure 3. Left) A principal component image calculated from the Sentinel satellite imagery (RGB image consist of the first, second, and third principal components in the red, green, and blue channels); Right) the final LULC classification for a sub-area within the Northern Finland study area. Classes 11–17 are undrained peatlands, 21–29 drained peatlands, 31–32 restored peatlands, 41–47 mineral soil classes, and 51–52 other classes.

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Table 3. Agreement between the 30-meter resolution Landsat-based classification of this study and Corine Land Cover classification for the different time periods. Corine Land Cover is not available for the study areas in Finland before 1995.

Study area	**1985–1989 (%)**	**1990–1994 (%)**	**1995–1999 (%)**	**2000–2004 (%)**	**2005–2009 (%)**	**2010–2014 (%)**	**2015–2019 (%)**	**2020–2023 (%)**
Northern Finland	NaN	NaN	74.5	74.5	77.6	83.6	84.4	84.1
Southern Finland	NaN	NaN	89.2	89.3	88.8	88.9	88.5	88.7
Estonia	88.8	89.1	88.5	88.0	87.5	87.9	87.9	87.8
Latvia	90.7	90.7	90.1	89.8	89.4	87.5	87.3	87.2
Germany	93.2	92.8	92.6	92.4	92.9	92.9	93.5	93.2
Belgium	88.0	87.0	85.7	86.4	87.7	86.6	87.2	87.5
Pyrenees	73.8	73.9	73.5	73.4	74.2	74.9	74.2	74.4

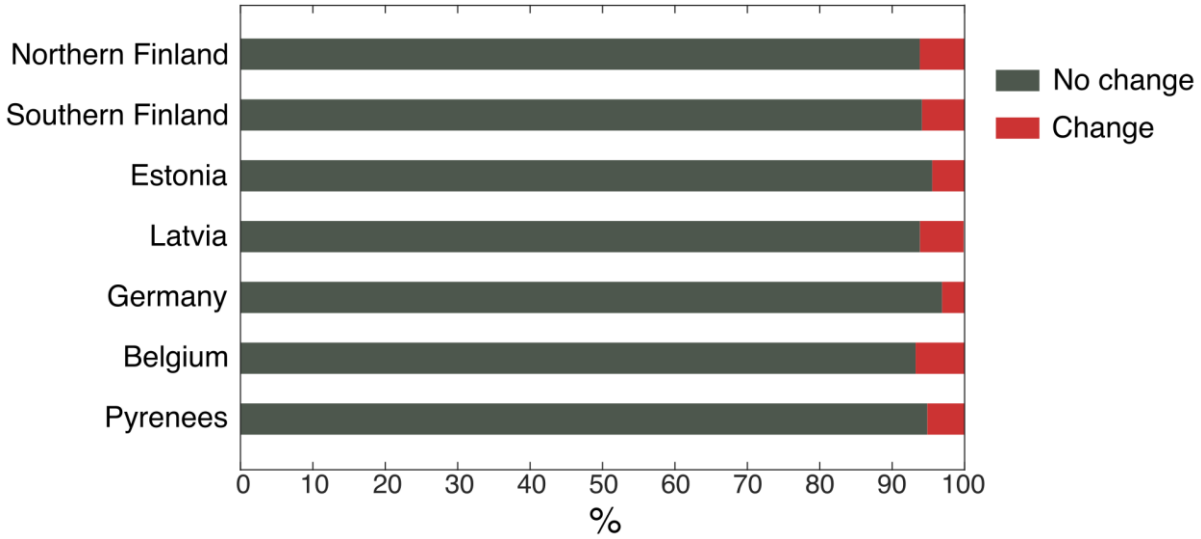


Figure 4. The percentage of area that has experienced changes in land use or land cover in each study area between 1985–2023.

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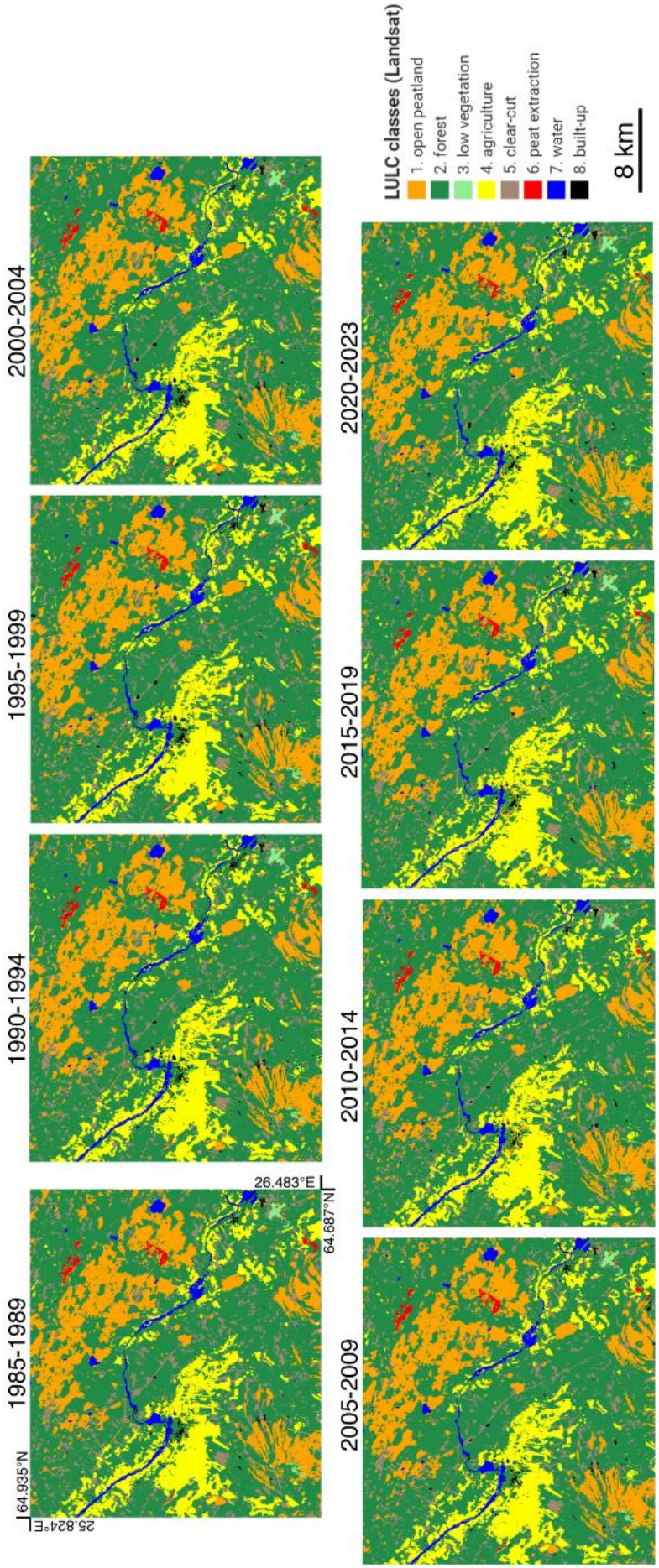


Figure 5. Landsat-based LULC classifications for a sub-area within the northern Finland study area between 1985–2023.

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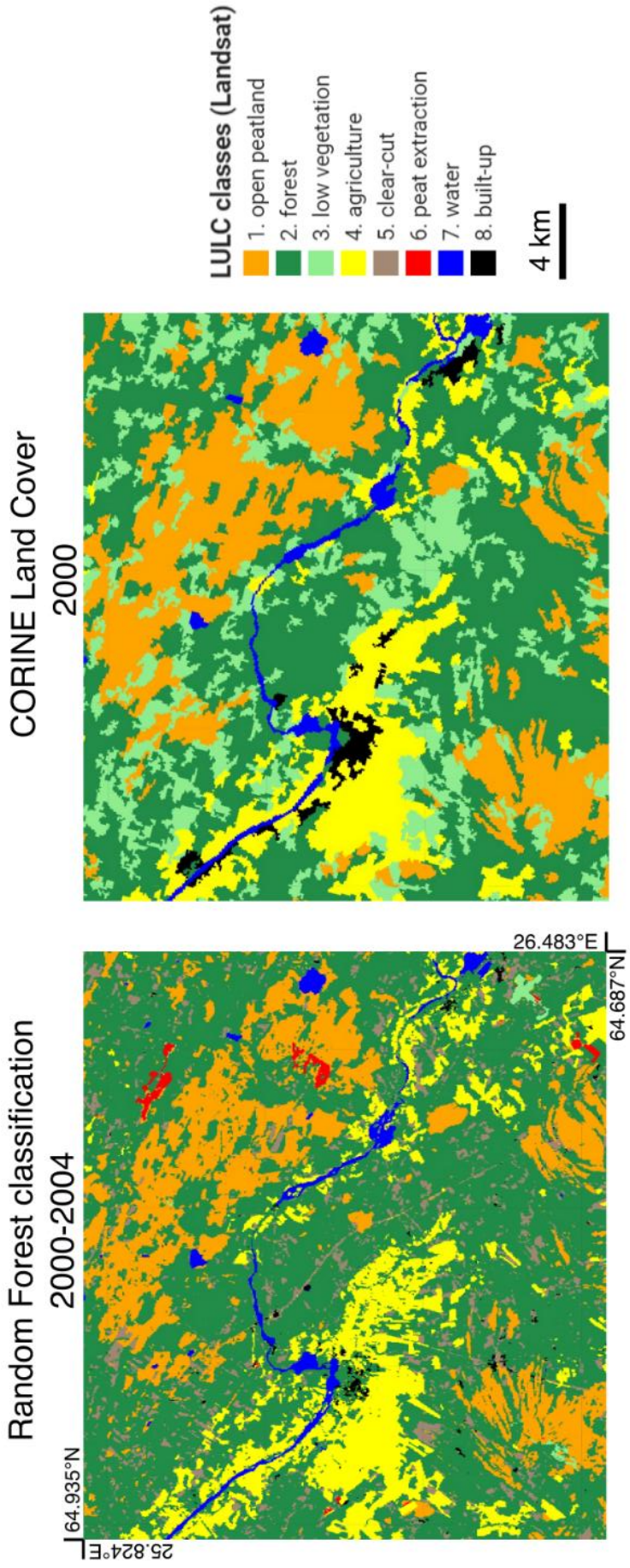


Figure 6. Landsat-based LULC classification for a sub-area within the northern Finland study area for years 2000–2004, and Corine Land Cover for the same area. The low vegetation class of CORINE Land Cover consists mostly of class 3.2.4 "Transitional woodland/shrub" which in northern Finland corresponds to drained peatland forests in which forest growth has been limited and to sparsely forested areas on mineral soils. These areas are classified as forests in our 30-m LULC change detection, but for the sake of consistency, we classified the transitional woodland/shrub as low vegetation in all study areas.

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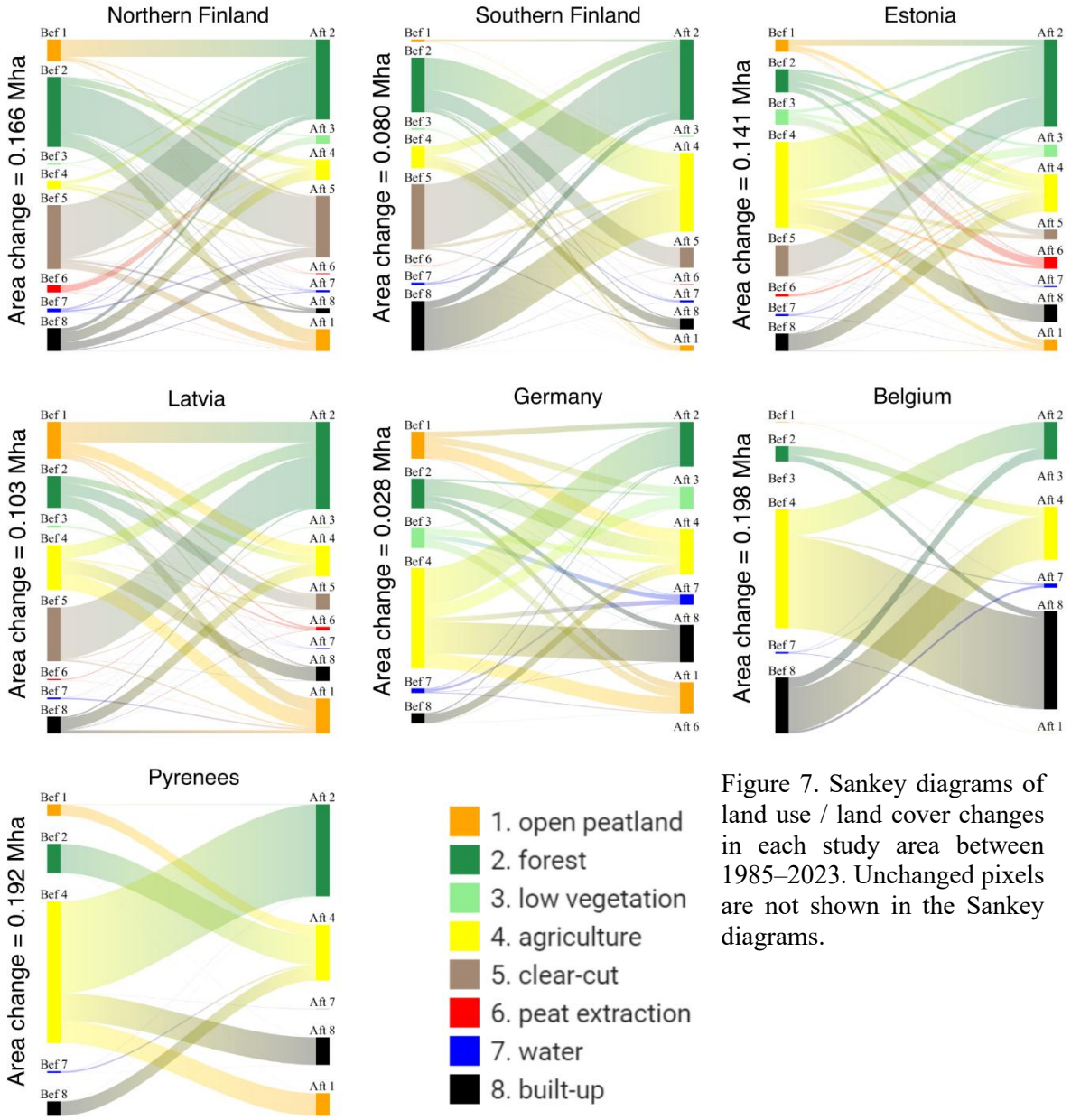


Figure 7. Sankey diagrams of land use / land cover changes in each study area between 1985–2023. Unchanged pixels are not shown in the Sankey diagrams.

DISCUSSION

We have developed a method for LULC classification focusing specifically on wetland types (incl. peatlands, coastal and mineral wetlands) and their management. Our results indicate that wetland and other LULC classes can be classified with a relatively high accuracy using a classification approach that combines Copernicus Sentinel-1 and Sentinel-2 data with auxiliary datasets. Our approach enables relatively fast and easy implementation of LULC classification over large areas. The approach can be replicated and scaled to other regions, potentially even to continental scale, such as across Europe, provided that sufficient training, validation, and auxiliary data are available for the entire target area.

Classification accuracies

Our classification accuracies are approximately at the same level as in previous studies. For instance, in previous multi-source remote sensing studies, Zelioli *et al*. (2025) have obtained 37 – 55 % accuracies in separating peatland site and fertility types in Finland, while Pontone *et al*. (2024) have obtained > 70 % accuracies in differentiating peatland sub-classes in the Canadian boreal forest region. Nevertheless, in the Pontone *et al*. (2024) study, there are problems with spatial coverage and thematic quality of training and validation data; particularly, there is no randomly sampled validation data.

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Previous studies show a large variation between wetland classes in classification accuracy (Karlson & Bastviken 2023; Pontone *et al*. 2024, Zelioli *et al*. 2025), which is evident also in our results. Particularly, the presence of rarer classes is typically underpredicted unless their relative proportion in the training data is significantly higher than on the ground (Mellor *et al*. 2015; Maxwell *et al*. 2018). In our case, we have sampled 50 – 100 training and validation points for each class to mitigate this effect; consequently, the classification accuracy of the rarer classes is approximately like that of more common classes. However, there are some other problems in class-specific predictions that are probably related to the between-class similarity in remote sensing data signatures and their temporal variation (*e.g*., Karlson & Bastviken 2023), as well as to the lack of suitable auxiliary data for some of the LULC classes. Furthermore, there is also large heterogeneity in the spectral signatures within the different LULC types. For example, bogs and fens have high internal variability and fine-scale spatial heterogeneity that complicates their classification. Nonetheless, the 10 m spatial resolution of Sentinel imagery smooths the fine-scale spatial structures and, thus, enables classification of broader types while its spatial resolution is too coarse for detailed classification of peatland microforms (Räsänen & Virtanen 2019). The different peatland types could also be separated into a larger number of subtypes, but typically the classification accuracy is low in classifications with multiple peatland types due to high similarity between the types when observed from above (Zelioli *et al*. 2025).

Our results indicate large differences in classification accuracy between the separate study areas, potentially due to the differences in the detectability of classes and to the quality in the training and validation data (Mellor *et al*. 2015; Karlson & Bastviken 2023), a common problem in remote sensing studies. We have used visual interpretation and purposeful sampling in all other sites than Belgium where we have used the recommended stratified random sampling procedure (Maxwell *et al*. 2018) followed by a visual verification of the points using high-resolution imagery. In Belgium, we could use an existing and reliable LULC classification available for a large part of the study area whereas in other sites, there is no such dataset available. Therefore, we could not produce independent high-quality validation data through stratified random sampling, as soil and management types cannot be distinguished with visual interpretation of high-resolution imagery and uncertain auxiliary data. Nevertheless, the overall and class-specific classification accuracy in Belgium is in-between that of the other study areas suggesting that sampling procedure per se does not affect the accuracy.

Non-random sampling may lead to artificially high accuracy if the training and validation points are selected so that they are homogeneous and easily interpretable. We have tried to avoid this problem by collecting points throughout the study areas, by including a versatile set of points for each class, and by conducting a spatial block cross-validation. Furthermore, the classification accuracies are < 93 % and even lower than in many of the earlier studies (Karlson & Bastviken *et al*. 2023; Pontone *et al*. 2024), suggesting that the classification accuracy is not artificially high. However, the quality of training and validation data should be targeted in future work to get more realistic estimates for the LULC classes and their classification accuracy.

The role of auxiliary data

While moderate classification accuracy can be achieved using only satellite imagery, integrating local auxiliary data, such as information on peat soils and land management, is crucial to improve the accuracy and provide more realistic estimates of LULC. This underscores the importance of (existing) field-based GIS databases, which are critical for differentiating various LULC classes, including wetland types and their management statuses. However, many of the auxiliary datasets that improve classification accuracy are local and cannot be used in global estimations of wetland types, which restricts the generalisability of the approach. Furthermore, also the auxiliary datasets have uncertainties and potential errors which may be propagated to the final maps. Such problems can be mitigated through using multiple predictors calculated from various remote sensing and auxiliary data sources (Pontone *et al*. 2024, Zelioli *et al*. 2025) and the use of machine learning algorithms, such as random forest, that can deal with various types of predictors (Breiman 2001).

The large improvement in classification accuracy after the inclusion of auxiliary data evidences the problems in developing high-thematic resolution wetland LULC classifications with satellite remote sensing only. This aligns with earlier observations that have discussed the problems in classifying wetland and peatland types (Minasny *et al*. 2023). The main problem is the similarity in remote sensing data signatures of wetland types compared to non-wetland classes related to the similarities in canopy, vegetation, and land cover observable from space (Amani *et al*. 2017).

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Notably, in our analysis, the classifications with auxiliary data only produce higher classification accuracies than classifications with satellite imagery only. However, this does not mean that satellite imagery is not useful in classifying wetland types and their management statuses, as accuracies are the highest when both satellite imagery and auxiliary data are included.

Surprisingly, topography or canopy height information does not increase classification accuracy notably, even though previous studies have suggested that particularly topographical information is of high importance in wetland specific LULC classifications (Karlson & Bastviken 2023), while the usefulness of the inclusion of forest structure variables has also been highlighted (Thompson *et al*. 2016). This suggests that these datasets offer little additional information when using both multi-season optical and SAR satellite imagery and further emphasises the usefulness of multi-sensor satellite information (Amani *et al*. 2017). Similarly, the added value of global land cover datasets is limited, pointing to the fact that wetland and peatland types are poorly represented in these datasets (Kou *et al*. 2022).

Based on the improvements on classification accuracies, the most important auxiliary datasets are the good quality local datasets depicting information of soil, land cover, land use, and drainage status. These data are typically produced utilising a large amount of field work and local expert knowledge and cannot be easily transformed into large area wall-to-wall products. Despite the enormous work required to produce the local-to-regional geospatial information, there are uncertainties also in these datasets, as the interpretation of LULC types and other information on the ground is partly subjective and there are differences between observers (Eriksen *et al*. 2018). The uncertainties and quality of the auxiliary data is exemplified also in the differentiated improvement in classification accuracy; the increase is notable particularly in Finland but more moderate in some of the other study areas. While the local datasets have been composited into global or regional products of peatland or wetland extent (Tanneberger *et al*. 2017; Xu *et al*. 2018), future work could further develop methods to constrain uncertainties in the local products and combine them with remote sensing data sources to produce high thematic and spatial resolution regional to global maps for wetlands.

Change detection

Changes in LULC over time can be detected using long-term Landsat imagery with good agreement with Corine Land Cover data. However, our analysis focuses on eight broad LULC classes and does not include a detailed change analysis of wetland management and status. This limitation is due to the relatively low spatial resolution and revisit time of Landsat imagery throughout the 1985 – 2023 period. Future studies could focus on developing more refined methods to detect changes in specific LULC types at local scales, in addition to providing comprehensive wall-to-wall estimates over large areas. Nevertheless, generating classifications for past time periods would require, in addition to high-quality remote sensing and auxiliary data, proper training and validation data. We used our point-based data only for training the classifications but also this decision causes some uncertainties, as LULC classes might have changed over the study period even though we tried to select such training point locations in which LULC changes between the eight broad classes have not happened.

Our results indicate that less than 10 % of areas have experienced land cover change during this ~40-year study period. Previously, it has been estimated that land cover changes represent 17 % of the world's land surface between 1960 – 2019 (Winkler *et al*. 2021), with the corresponding estimate being 15.5 % for Europe between 1950 – 2010 (Fuchs *et al*. 2013). As our study period is approximately two thirds of the study period in the respective studies and as our study areas are mostly located in areas experienced little changes according to Fuchs *et al*. (2013), the analysis can be considered robust.

We have compared the classifications with Corine Land Cover data. It needs to be acknowledged that like all LULC products, Corine data has uncertainties. Earlier literature has indicated both high and low classification accuracies for wetland and peatland classes in Corine data (Bronge & Näslund-Landenmark 2002, Aune-Lundberg & Strand 2021), and there are likely differences between countries and years in how accurate the mapping of different classes is in Corine.

The observed change types, majority of which are between forest, clear-cut, agriculture, and built-up classes, are in concordance with the typical LULC changes in Europe observed within the period of study (Fuchs *et al*. 2013). Particularly, in northern countries (Finland, Estonia, Latvia), a major proportion of the changes have happened between forest and clear-cut which aligns with the forestry practices in these countries and is in line with previous research (Gerard *et al*. 2010).

There are also some changes from open peatlands to other classes, maybe referring to direct peatland drainage, and LULC changes from other classes to the open peatland and water classes, either referring

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to peatland restoration (*e.g*., in the Peene River catchment significant areas in valley peatlands were restored during the last 30 years; Zerbe *et al*. 2013) or to misclassifications. The changes between forest, agricultural, and built-up areas are related to urban and agricultural dynamics in the study area. A small proportion of them can have happened in wetlands, including peatlands.

Unfortunately, the particular wetland areas under land use change cannot be properly validated due to lack of reliable and detailed data across our large study areas. Large-scale drainage of wetlands and peatlands in temperate and boreal Europe have happened before 1980s (Fluet-Chouinard *et al*. 2023), before Landsat imagery became available. Most of the fine-resolution studies have analysed wetland degradation and change over relatively small areas (*e.g*., Hu *et al*. 2020; Liu *et al*. 2020). Thus, future studies could further develop methods to estimate changes in wetland and peatland drainage status and management over large extents in a detailed manner.

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AUTHOR CONTRIBUTIONS

AR, AD, EU, PR, JP and AB contributed to the study conception and design. Material preparation, data collection and analysis were performed by AD while AR, EU, PR, TDB, EMU and AB contributed to the data collection. AR wrote the first draft of the manuscript. All other authors commented on previous versions of the manuscript and approved the final manuscript.

DATA AVAILABILITY STATEMENT

Data availability: The resulting LULC maps at 10-meter resolution for year 2020 and LULC maps at 30-meter resolution for the period 1985-2023 can be accessed through Zenodo (https://doi.org/10.5281/zenodo.10665475) and Google Earth Engine assets (https://ee-descalsgeu.projects.earthengine.app/view/alfawetlands-lulc-1985-2023).

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