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Trends in Extent and Size of European Ecosystem Units From 2000 to 2018

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ABSTRACT

Introduction and Aim: The mapping and monitoring of ecosystem size and extent is critical for assessing changes in the environment. Mapping approaches typically include the use of expert-based assessments and remotely sensed products. In this work, we present a new annual high-resolution time series dataset of ecosystem units for Europe that integrates a range of different data sources. In total, 411 different distinct ecosystem units were identified in the EU27+, with large patches of woodland and forest in cold climates and temperate climate croplands on plain terrain as the two most commonly occurring types in 2000. Over the 18 year period, only 56 ecosystems remained stable, with area increases in 192 ecosystem types but losses in area in 163 of them. Furthermore, we highlight gaps in representation for 16.8% of all ecosystem units in the current protected area network.

Main Variables Included: Corine Land cover time series, Landforms, climate, patch size.

Time Coverage: 2000 to 2018.

Spatial Coverage: 100 m spatial resolution at pan-European extent.

Taxa: Ecosystem assessment.

Applications: The dataset is consistent with previous EU ecosystem accounting assessments, while providing additional detail on climate, landform and fragmentation. It can serve as a data source, for example, for ecosystem accounting, conservation planning, or species distribution modelling.

1 | Introduction

Ecosystems, defined as systems formed by organisms within specific vegetation types interacting with both the biophysical and human environment, are diverse and inherently dynamic (Keith et al. 2013; Pimm 1984). They provide valuable services to humans including food production, clean air and water, and spaces for recreation (Maes et al. 2014). Yet, many ecosystems are at risk due to human modification (Bergstrom et al. 2021; Theobald et al. 2025), which has recurrently highlighted the conservation necessity of preventing ecosystem loss and degradation (Nicholson et al. 2021; Watson et al. 2020). This makes spatially explicit information for monitoring changes in ecosystems indispensable.

Remote sensing has transformed the way that ecosystems are monitored, providing high resolution information on land cover, land use and terrain (Álvarez-Martínez et al. 2018; Murray et al. 2018). Combined with other types of geospatial data, such as gridded climate datasets, integrative or machine learning based approach have been applied for different ecosystem classifications (Jung, Dahal, et al. 2020; Keith et al. 2022; Maes et al. 2016; Sayre et al. 2020). For example, the Global Ecosystem Typology (GET) developed by the

International Union for Conservation of Nature (IUCN) is utilising a standardised typology (Keith et al. 2022), nested by realm, biome and ecosystem functional groups. Other thematic systems have relied on habitats used by species (Jung, Dahal, et al. 2020) or differentiated them by vegetation communities (Halvorsen et al. 2020; Mucina et al. 2016). Since ecosystems can be distinguished by a multitude of factors and at different spatial–temporal scales, the use of any specific classification system is usually determined by their applications.

Integrative ecosystem mapping approaches are those that create novel mapping layers by aligning and combining different, previously scientifically validated datasets into novel products (Jung, Dahal, et al. 2020; Mücher et al. 2010; Price et al. 2023; Sayre et al. 2020; Weiss and Banko 2018). For example, Sayre et al. (2020) identified a total of 431 distinct classes at 250 m resolution using a combination of global datasets on climate, landforms and land cover (ESA CCI 2017). Such integrated maps can be more than the sum of their parts. By separating land cover information by landforms, several studies have recently shed a new light on the distribution and loss of rare ecosystems in mountainous regions (Chen et al. 2024; Theobald et al. 2024). Others have used macroclimatic information to assess state and change to differentiate different types of natural vegetation at high resolution (Gopar-Merino et al. 2024). Lastly, integrated approaches provide an opportunity to expand on accepted thematic classifications and datasets, for example, those used in ecosystem accounting practices (Bruzón et al. 2022; Maes et al. 2016, 2023). To date, however, there do exist similar integrative ecosystem maps for Europe at high spatial and temporal resolutions. Existing categorisations are often comparatively coarse in spatial scale and are not consistent with European land-cover change accounts from Corine. Expanding the thematic legend of ecosystem accounts to include features such as climate and landform will allow for further nuance in assessing environmental change.

The extent of ecosystems does not only change in total amount, but also in individual size and in-between distance. There is a wealth of evidence highlighting the fragmentation of European ecosystems (Jaeger et al. 2016), often with consequences on biodiversity, climate and society (Brodie et al. 2025). For example, patches from small to large sizes have varying use in maintaining healthy populations of species (Fahrig 2003; Papp et al. 2022; Riva and Fahrig 2022). Ecosystem patch size can also approximate important information on land use (such as farm size), land-use change and governance (Lesiv et al. 2019; Nagendra et al. 2004). Meanwhile Island ecosystems, which are per se also isolated from nearby ecosystems, usually have distinct biodiversity and climatic features (Russell and Kueffer 2019). Reporting only on total ecosystem extent in national accounts might hide such important aspects.

Ecosystem accounting is a key approach used by policy makers to monitor the extent, size and condition of ecosystems as well as estimating their ecosystem service value (Maes et al. 2014, 2016; United Nations 2021). As part of Target 2 Action 5 of the European Union's (EU) Biodiversity Strategy to 2020, EU member states (MS) were required to map, monitor and assess their ecosystem extent using the Mapping and Assessment of Ecosystems and their Services (MAES) framework (Maes et al. 2014), and a second, follow-up MAES assessment is currently under way. MAES is based on the broader System of Environmental-Economic Accounting (SEEA) framework developed by the United Nations Statistical Division (UNSD) and uses a remapped Corine Land Cover as one key input to track changes in ecosystem extent. Although mapping ecosystem condition has been highlighted as a fundamental topic in upcoming assessments (Maes et al. 2023), robust spatial–temporal ecosystem extent information at high resolution will remain central to any future assessments.

Thus, the aim of this work is to present a new high resolution time series dataset for ecosystem units for Europe. We followed the approach by Sayre et al. (2020), but here we integrate higher resolution data from the European Corine Land Cover dataset, as well as recently updated and released data on climate and terrain. We furthermore extend previous ecosystem mapping classifications by also distinguishing by patch size as well as islands, offering a perspective not only on total area extent but also on patch size as an important dimension. The resulting annual time series of high-resolution maps is provided together with summary statistics of ecosystem changes. We critically assess gaps and describe potential use cases of these new maps for conservation planning, ecosystem accounting and assessments of ecosystem loss.

2 | Methods

To construct these European ecosystem layers, we build on a previously published global approach (Sayre et al. 2020). This approach harmonises sets of different input layers, categorises each layer to a reduced thematic resolution and then builds an integrated layer and legend through a geospatial overlay (Figure S1). We adapted the approach to European data, using a new thematic legend, a higher spatial resolution, and an assessment of spatial patterns of change over time. To do so, we preprocessed a range of input layers covering climate, landforms, land cover and derived ecosystem patch size. We generally differentiated ecosystems in this context as a combination of macroclimatic patterns, terrestrial landforms and land cover, while also further distinguishing between the size of ecosystem patches. We recognise that the integrated data only represents an abstraction of European ecosystem extents, and other factors such as lithology and soil, or land-use intensity and management are additional important factors delineating ecosystem units (Dou et al. 2021; Jung et al. 2022). The datasets were chosen based on the best available data and to represent a parsimonious perspective on European ecosystems, in line with European ecosystem accounting practices (Maes et al. 2014, 2020). It is broadly consistent with the EU Ecosystem Typology at level 1 (EUROSTAT Technical Note, 2024), while providing additional nuance with regards to climate, landform and patch size. All input datasets were carefully processed to ensure consistency in the legend and to avoid misalignments at fine spatial grain. For example, we ensured that coastal cells and small islands are covered by all input layers, applying a nearest neighbour region grow algorithm in the case of macroclimate and landform.

For the climatic sub-division, we used the latest data on terrestrial Köppen-Geiger climate zones at a 1 km spatial resolution (Beck et al. 2023). Here we used a 30-year climatology closely matched to the land-cover data availability (1991–2020) and clipped the data to a European extent. We used the Köppen-Geiger classification instead of more commonly used EU climatic stratification information (Metzger et al. 2005), to (a) benefit from improved downscaled climate data that became available in recent years, (b) have a temporally consistent climatology, and (c) mitigate uncertainties related to clustering in these data. Similar to previous work (Sayre et al. 2020), the original Köppen-Geiger climate zones were then remapped to more parsimonious characterisations of the European macroclimate (full crosswalk in Table S1). We took special care to ensure that small islands across the EU are appropriately covered. For the climate layer we buffered the extent of climate zones to neighbouring grid cells using the most common class ('mode') of neighbouring climatic zones. To avoid hard boundaries owing to differences in spatial resolution, we converted the layer to a vector format and applied a Gaussian kernel smoother with a bandwidth of 2 to the polygon edges using the '*smoothr*' R-package (Strimas-Mackey 2023) before rasterising the map at 100 m again. This procedure only minimally affected the distribution of climate zones, although we recognise the uncertainties at high resolution particularly in the climatic data (see 4. Discussion).

To capture differences in topography and elevation, we used a recently released layer on Global Basic Landform Units (GBLU) at a 30 m spatial resolution (Yang et al. 2024a, 2024b). We clipped the global layer to a European extent and aggregated it to a spatial resolution of 100 m for consistency with other datasets using the modal value. The full legend of the GBLU has 23 thematic classes, separating land by ruggedness and height (Yang et al. 2024a). We reclassified the level 3 geomorphological units of the GBLU to three landform classes across Europe—flat, hill and mountain (Table S2). Where necessary, for example in cases of small missing coastal grid cells or islands, we spatially extended the landform layer by a factor of 1 km using a modal filter to the nearest grid cells to fill missing data values.

The land cover data were derived from a novel annual time series from the year 2000 to 2018 of the European Corine Land Cover Accounting layers at 100 m spatial grain (See et al. 2024). The Corine Accounting Layers were made available by the European Environment Agency (EEA) for 2000, 2006, 2012 and 2018. Corine accounting layers integrate change transitions into the original Corine Land Cover to provide layers that are spatially and temporally consistent. We made updates to the Corine Accounting layers, by interpolating the missing intermediate annual layers to determine the year in which a land change occurred. Three different methods were used: The first involved determining the year of change based on the integrated annual land cover time series produced by Witjes et al. (2022), in those cases when the type of change was consistent with the Corine Accounting Layers between the 6 year steps. Here it was possible to identify the year of change in 82.9%, 80.5% and 80.4% of cases for 2000–2006, 2006–2012 and 2012–2018, respectively. Second, where possible, the remaining changes were then determined by using MODIS time series information of NDVI between 2000 and 2019. We then applied the BFAST-Lite algorithm (Masiliūnas et al. 2021) to determine abrupt changes in the time series for intermediate year periods. Here, changes could be identified in 7.0%, 11.2% and 7.5% of all cases for 2000–2006, 2006–2012 and 2012–2018, respectively. Thirdly, any remaining changes that could not be identified using the first two approaches were assigned randomly to a year within the six-year time period, which applied to 10.1%, 8.3% and 12.1% for 2000–2006, 2006–2012 and 2012–2018, respectively. Finally, a set of rules for possible land cover transitions was applied to ensure that any abrupt changes had smooth land cover transitions in the intervening years of each six-year period. These transition rules differed between land cover and land use types, considering for example all logical transitions (e.g., urban to forest) and vegetation succession. Both the filled years and the change estimates between years were separately validated (but see See et al. 2024).

Using previously applied crosswalks (Table S3), we reclassified the original Corine thematic legend to the MAES ecosystems classification at level 2 (Maes et al. 2014; Weiss and Banko 2018). The MAES level 2 classification legend differentiates between nine ecosystem classes (not including Marine) mapped at a 100 m resolution. A special case was the Principality of Andorra, which is otherwise a blank spot with missing data, so we filled the gap using similarly reclassified land cover information from the 2019 Copernicus land cover product (Buchhorn et al. 2020). It should be noted that the land cover in this small area is assumed to be static over time, which is in our opinion defensible, given that any land-cover changes in Andorra are not considered in European ecosystem accounting. Nevertheless, we caution against overinterpreting changes in land cover at fine local scales, in which case customised local datasets and input layers are likely to be more accurate (see also the discussion).

The size of ecosystem patches is a key measure of structural fragmentation, a concept which has been frequently used in landscape ecology (Hesselbarth et al. 2024), while being seldomly assessed at European level, possibly as the identification of unique patches is computationally intensive at high spatial resolution. In this dataset we differentiate between four discrete types of patch size as well as islands (see below). Individual ecosystem patches were identified through a connected component labelling approach using a square kernel as implemented in Google Earth Engine (Gorelick et al. 2017). All patches with a size smaller or equal to 1 km^2 were reclassified as 'tiny' ($>$ 0–1 km^2), 'small' ($>$ 1–10 km^2), 'medium' ($>$ 10–100 km^2) and anything larger as 'large' patches ($>$ 100 km^2). We acknowledge that this discrete categorisation is arbitrary and does not explicitly quantify patch configuration or their position within a landscape per se, both of which are important aspects of ecosystem fragmentation. Instead, the names are intended to reflect a relative gradient that could be further broken down depending on specific use cases.

In addition to patch size, we added a class that differentiates between mainland and island ecosystems. Islands in a European context were defined as a landmass surrounded by marine ecosystems according to the Global Islands database (Sayre et al. 2019). We clipped the Global Islands database (version 3) to a European extent and furthermore filtered the data based on a size criterion. Specifically, in an European context we considered only land masses smaller than 5000 km^2 as a separate 'island' class, while larger outlier islands such as mainland Great Britain or mainland Ireland were instead considered as landscapes with their own nested patch distributions. The resulting filtered polygon layer was then projected and rasterised at 100 m to the same spatial grid as the Corine Accounting layers.

All layers were composited together in a hierarchical thematic legend, where X000 describes the macroclimate, 0X00 the landform, 00X0 the land cover type and 000X the patch size and fragmentation (Figure S1). For example, a small (4) patch of temperate (2), hilly (1) forest (3) would receive the code 2134. Patch size and whether a class was situated on an island were calculated based on the combination of macroclimate, landform and land cover (Figure S1). We constructed a visually appealing legend that shades the multiple combinations of classes on a gradient that varies by hue and intensity (Figure 1). We summarised ecosystem changes using data on European countries and biogeographical regions (Roekaerts 2002), calculating total measures of extent and inequality (using an unbiased Gini coefficient), assessing their change over time (Figure S2) and representation within the European protected area network, including Natura 2000 sites and other areas in non-EU countries. Basic chi-square tests were used to test for differences inside and outside the current protected area network. All individual layers are made openly available on Zenodo as cloud-optimised GeoTiffs (Jung, Cornford, et al. 2025, https://doi.org/10.5281/zenodo.14996728). Layers are made available both as rendered colour-coded format (e.g., RGB, allowing quick load into web or desktop applications), and as raw thematic layers accompanied with a legend in QGIS QML format.

3 | Results

We identified a total of 411 distinct ecosystem units for the EU27+ (Figure 1). In 2000, the two most common classes are large patches of woodland and forest in cold climates on plain terrain (0.46 million km^2) and temperate climate croplands on plain terrain (0.31 million km^2), while the two rarest classes were tiny patches of cropland in polar climate and plain terrain and marine inlets in mountain terrain and polar climates (both 0.01 km^2, Table S1). Among EU 27+ countries, Italy ($N = 249$) and France ($N = 244$) had the largest number of unique ecosystem units (Table S4), which can to some extent be expected by their size (although larger countries like the UK had some of the lowest numbers). Similarly, the Alpine ($N = 270$) and Mediterranean ($N = 254$) biogeographic regions had the largest number of unique ecosystem units (Table S5). The areal extent of ecosystem units was the most unequal in Finland (Gini = 0.93) and Sweden (Gini = 0.92).

Between the year 2000 and 2018, a total of 192 ecosystem unit classes increased in area extent (range 0.1–3496 km^2), 163 classes decreased (range −0.1 to −7072 km^2) and 56 remained stable over time. The largest loss of area was for large patches of cold, plain terrain grasslands. The country with the most overall transitions was Italy ($N = 190$), although Poland observed the largest absolute single loss of ecosystem unit extent (−2750 km^2, driven by loss of large patches of temperate, plain terrain woodland and forest) and Portugal the largest single increases (3006 km^2, driven by increases in medium patches of arid, plain terrain cropland). Similarly, between 2000 and 2018 the Mediterranean biogeographic region experienced the most transitions between ecosystem units ($N = 223$) and the largest absolute single decreases (−6037 km^2), while the Continental region had the largest absolute single increase (2538 km^2). In terms of relative changes, urban land cover increased the most between 2000 and 2018, particularly so in

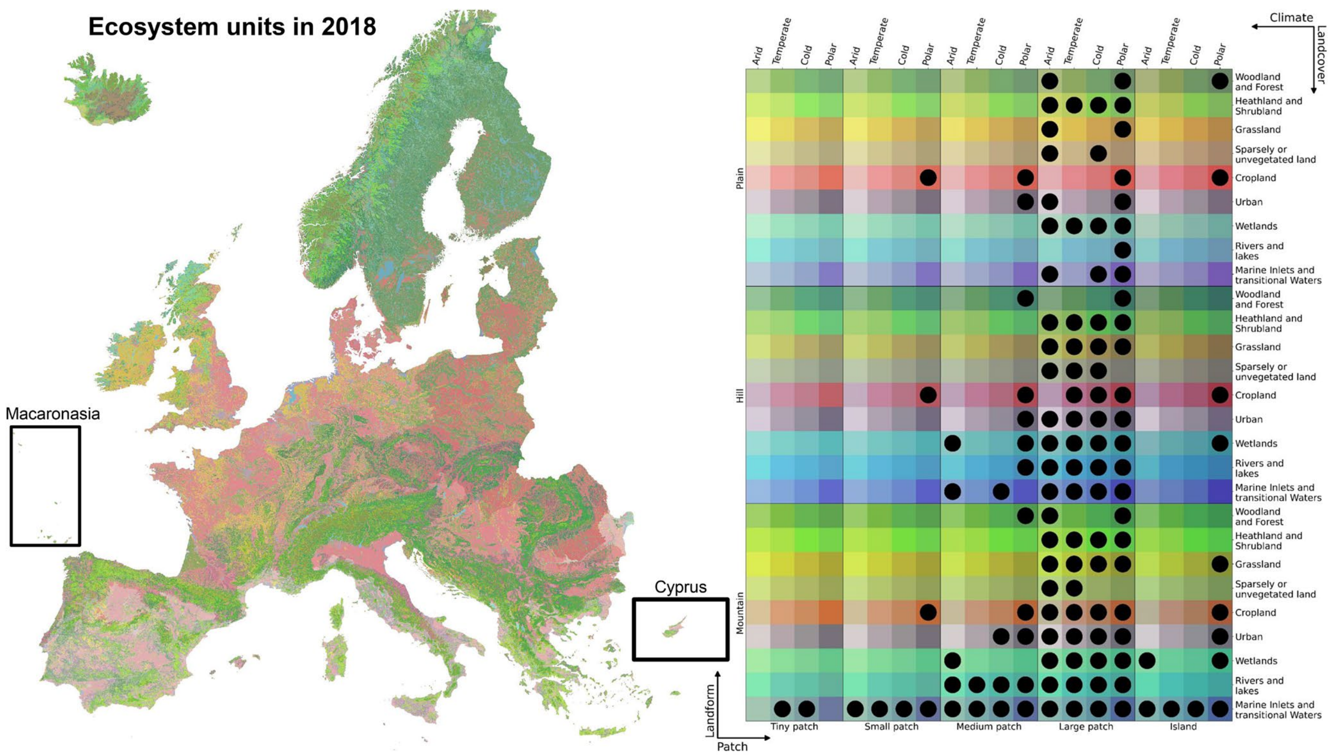

FIGURE 1 | European Ecosystem map including all 411 classes for 2018 and legend. Classes with a black dot indicate classes that were not present in 2018. Seperate insets shown for Macaronesian Islands and Cyprus.

arid regions and mountains, closely followed by rivers and lakes (Figures 2 and 3). Large patches of urban area grew substantially (Figure 2), possibly driven by both increases in cities and infrastructure, while tiny patches of grassland and sparse vegetation tend to change frequently in between years (Figure 2). In terms of relative and absolute decreases in ecosystem unit extent, we found grasslands, forests and wetlands in plain landforms to have decreased the most (Figure 3), driven by loss and fragmentation.

Differentiating ecosystem units by landform, climate and patch size provides a more nuanced view of distribution and changes across Europe. For example, the most observed European land cover was woodland and forest (36.8% of all land), yet cropland ecosystem units were slightly more common in plain landforms and temperate climate (Figure 4A). Further, across Europe in 2018, cropland and woodland & forest cover had almost equal shares of large consecutive patches. Between the year 2000 and 2018 most land transitions took place between cropland to urban and grassland to cropland, particularly in plain, temperate and arid regions (Figure 4B). Interestingly, where ecosystem unit transitions occurred between 2000 and 2018, cropland patches shrank in size (large to medium and medium to small), possibly reflecting

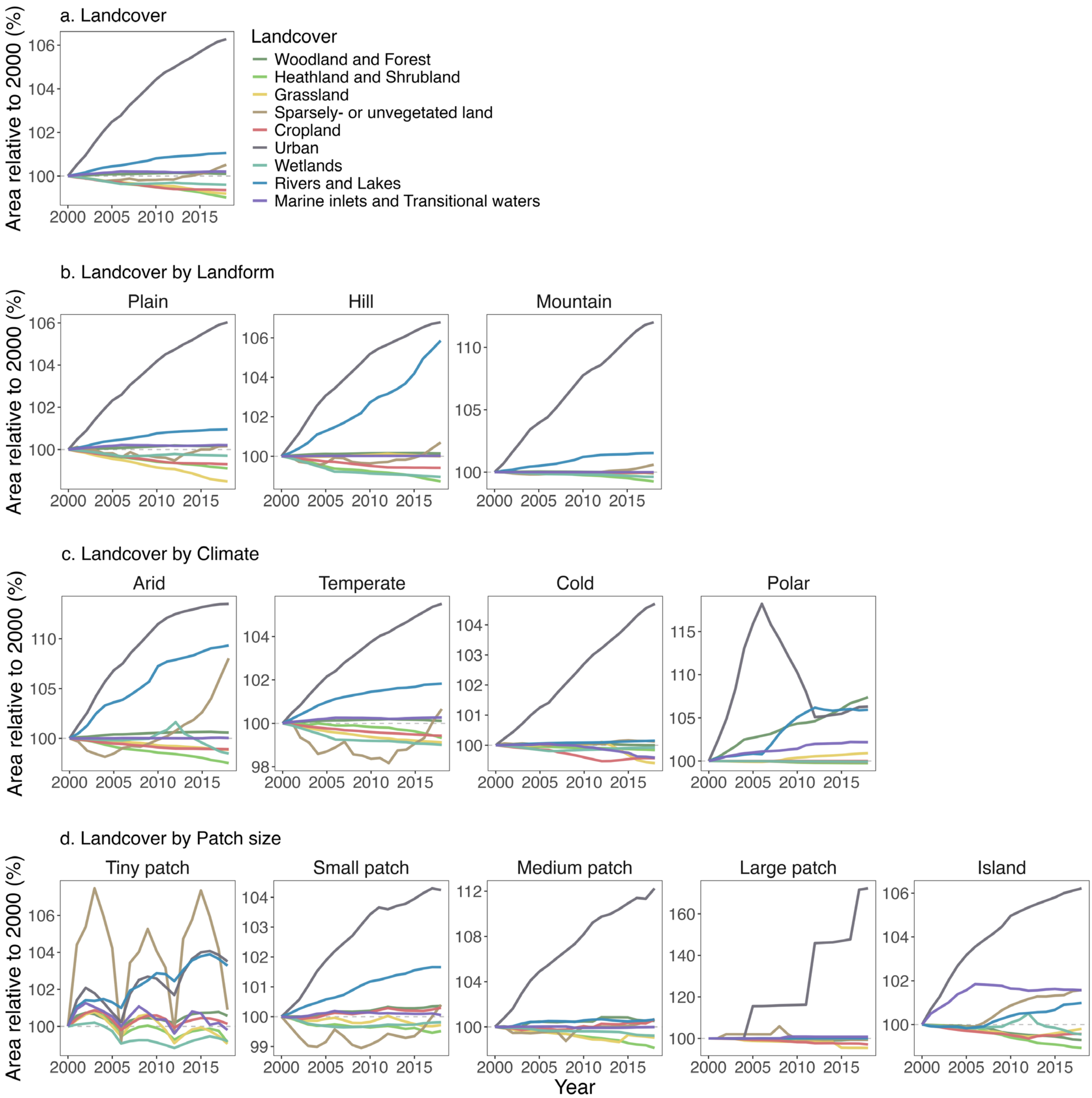

FIGURE 2 | Temporal changes in European Ecosystem unit extents, coloured by landcover and relative to their extent in 2000. Urban landcover displays the greatest increase in relative extent between 2000 and 2018, with strong relative increases also seen for 'Rivers and Lakes' in Hills and Arid environments.

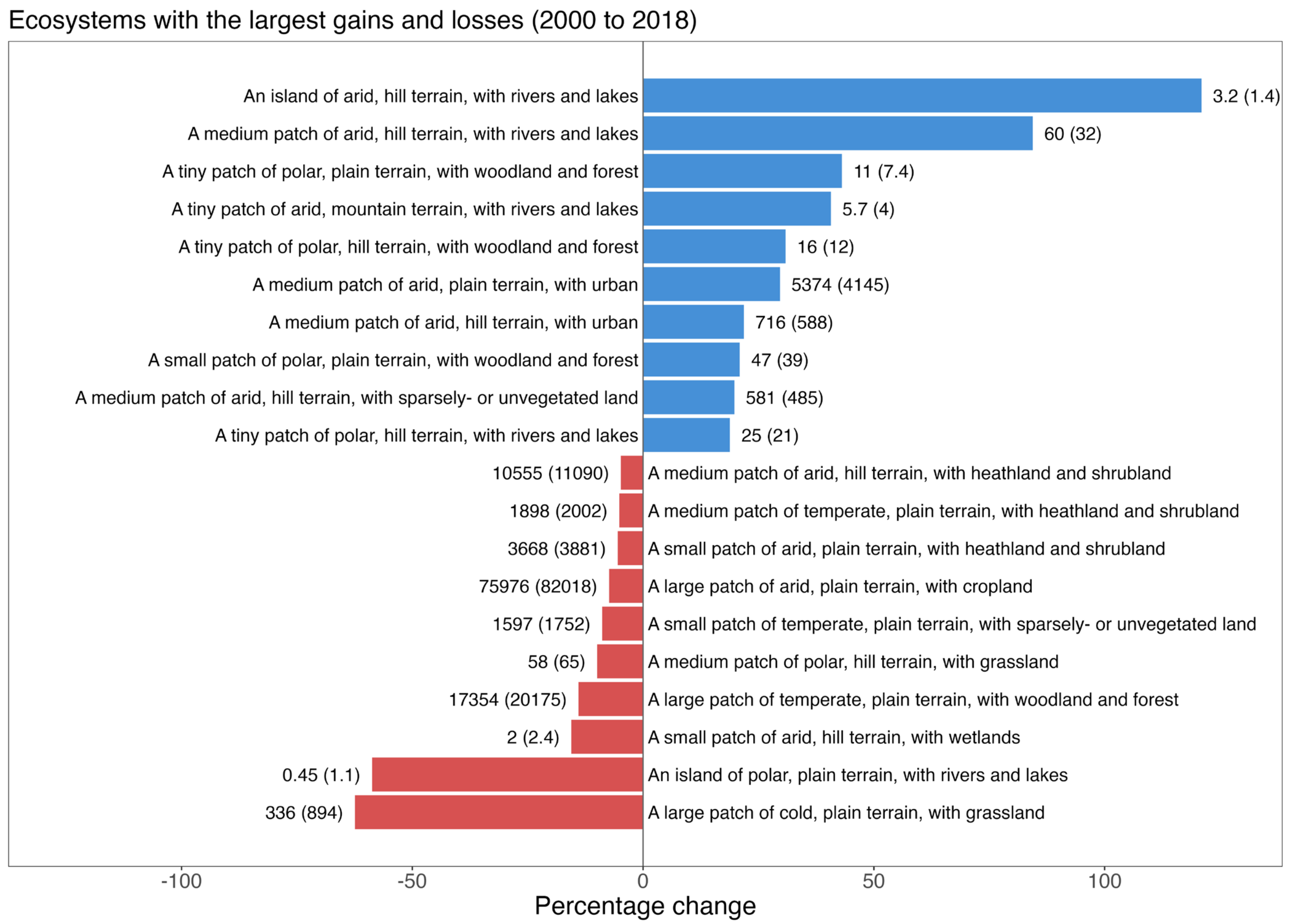

FIGURE 3 | European Ecosystem units with the largest percentage change between 2000 and 2018. Only ecosystems with a total area of at least 1 km^2 in either 2000 or 2018 are presented. Numbers adjacent to bar tips represent the ecosystem area (km^2) in 2018, with the value for 2000 in brackets.

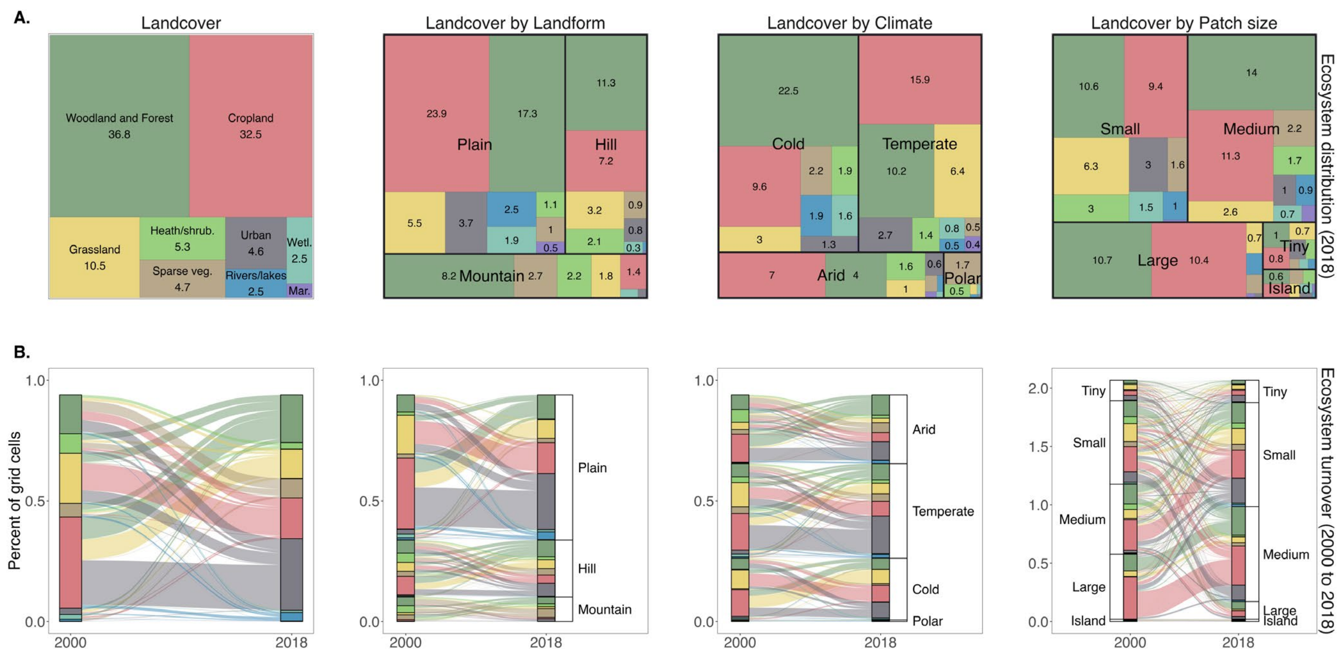

FIGURE 4 | Distribution of European Ecosystems in 2018 (A, top row), and grid-cell level Ecosystem turnover between 2000 and 2018 (B, bottom row). In the upper row (A), solid black rectangles delineate Ecosystem group types (e.g., Mountain, Hill, Plain), numbers indicate percentage cover and are shown where space allows. Mar., Marine inlets and transitional waters; Wetl., Wetlands.

increasing fragmentation (Figure 4B). Most afforestation events of agricultural land between 2000 and 2018 occurred in plain and arid environments, although mostly creating only small patches of forests.

The current protected area network covers a range of unique ecosystem units. Special protected areas (SPAs) and Special Areas of Conservation (SAC) contain up to 90 (median 11) and 85 (median 4) unique ecosystem units in 2018. The most common observed ecosystem units within European protected areas were medium patches of woodland & forest in mountain terrain for SPAs and large patches of woodland & forest in plain terrain and cold climate for SACs. Out of 411 ecosystem units, a total of 69 (16.8%) do not intersect any currently protected areas, among them being large to medium patches of plain terrain and sparse vegetated land or shrubland (Table S6). In contrast, a total of 18 (4.3%) were fully protected by the existing protected area network, among them particularly marine inlets in temperate and arid climates on plains (Table S6).

Interestingly, out of 26,842 protected areas in Europe, cropland was the predominant land cover in 3881 (14.5%), and urban most prevalent in 581 (2.2%). Further 837 (3.1%) protected areas were situated within, or largely intersect, large consecutive patches of cropland and urban areas in 2018. When comparing the coverage of ecosystem units between protected and non-protected areas, we find that their distribution was significantly different ($\chi^2 = 8907.7$, $df = 326$, $p < 0.0001$), even when differentiating only by land cover and patch size ($\chi^2 = 6299.9$, $df = 42$, $p < 0.0001$). This indicates that the current protected area network is biassed towards specific environmental conditions and ecosystem units.

4 | Discussion

Here we provide a new depiction of European ecosystems at high spatial and temporal resolution. These new data of European ecosystem units (1) cover a total of 411 new composite thematic classes at 100 m spatial resolution, (2) are available at an annual temporal resolution compared to previous six-year intervals, and (3) provide an unprecedented level of detail on ecosystem fragmentation by specifically including the patch size into the thematic legend. It goes beyond previous classifications by integrating novel datasets on climate, landforms and annual land cover change at a high spatial resolution (Mücher et al. 2010; See et al. 2024). The land cover classification system used here is consistent with previous EU ecosystem accounting assessments, while providing additional details on climate, landforms and fragmentation. Similar to previous ecosystem assessments for Europe, we found that urbanisation is the largest driver of ecosystem change (Bruzón et al. 2022; Maes et al. 2016, 2020). Yet, by considering patch size at a high resolution, we are also able to capture not only changes in extent but also layout. For example, we show that Forests and Woodlands as well as cropland contain the largest consecutive patches while overall patch size is also decreasing across ecosystems over time (Figure 4). The finding that tiny grassland patches have changed frequently on an annual basis is interesting (Figure 2d), and could be explained by inter-annual transitions between cropland and fallow land (Parente et al. 2024). Overall, these new data provide a fresh perspective on changes in extent and fragmentation of European ecosystem units.

4.1 | Applications and Future Developments

The resulting layers of European ecosystem units can be used to assess changes in extent and patch size across Europe, and we provide an overview of these changes in this work (Figures 2–4 and Tables S4 and S5). Given the hierarchical system of the thematic legend, it is furthermore possible to obtain specific combinations (e.g., mountain forest and woodland only), which can enrich future ecosystem accounting assessments (Bruzón et al. 2022; Maes et al. 2016). These new data could also be utilised to make species habitat availability assessments following, for example, an area of habitat (AOH) concept within species distributions (Brooks et al. 2019); or the different patches of habitat could, as recently proposed (Riva et al. 2024), be directly included in species distribution modelling efforts as covariates or a mask (Jung 2023). Homologous units of similar ecosystems could be used to guide ecosystem-specific conservation planning applications (Chapman et al. 2025; Jung, Coll, et al. 2025), for example, by using discrete classes in a given region directly as planning units (e.g., areas which are prioritised for certain actions) for decision making. Further, identifying when inter-annual transitions in ecosystem units occurred can potentially improve down-stream ecological and socio-economic impact analyses by identifying specific transitions and years of change (Jung, Scharlemann, and Rowhani 2020).

Both the thematic legend and the layers themselves could be further improved or supplemented by additional evidence in the future. For example, lithology and soil formation patterns could be added as an additional hierarchical level (Hengl et al. 2017), although such expansions can come at a cost of interpretability given the potential huge number of classes. Clustering methods could be used to reduce the thematic resolution of such classes by creating composites of landform and lithology. Moreover, changes in land cover will not have any information on the associated management, any many species might have reduced value from increases in heavily managed ecosystems (Jung et al. 2022). In particular, the labelling of patch size can be affected by changes in land use, as patches appear to be larger than they are, for example, semi-natural forests being surrounded by intensive forestry plantations, despite providing different value for species and habitat connectivity. Additional research emphasis could be placed on covering future trends in macro- and microclimatic zoning across Europe, as new data on projected land cover becomes available. Lastly, many ecosystem assessments have increasingly focused on ecosystem condition or degradation as an additional dimension (Gianoli et al. 2023; Maes et al. 2023), and dedicated layers for different classes could be developed to support future assessments. Promising could be the application of potential natural vegetation (PNV) concepts to assess deviations from vegetation cover by ecosystem class, and time series of high spatial and temporal resolution have recently become available (Hackländer et al. 2024; Jung 2025).

4.2 | Data Gaps and Possible Input Data Improvements

The time series presented here integrates a range of previously released datasets that have either been validated already or have been aggregated for the purpose of creating the thematic legend. However, not all input layers are temporally changing or are available at the same spatial resolution. In particular, data on macroclimatic conditions is—to our knowledge—only available at a downscaled 1 km resolution across Europe regardless of data source (Beck et al. 2023; Karger et al. 2017). Although downscaling of macroclimatic data to a finer spatial resolution is statistically possible, it can contribute to substantial biases and misrepresentations (Lafferty and Sriver 2023). There are also limitations in temporal resolution and what can be reliably identified from annual remote sensing data, with particular grassland and cropland transitions likely occurring on much more intra-annual intervals. Grid-cell level interpretations of ecosystem unit transitions should thus be interpreted with care and further externally validated (See et al. 2024). Future research efforts could be made on integrating remotely sensed climatic information (sensors, satellite detected precipitation and cloud-cover) into novel products. Novel clustering and machine learning approaches could potentially help to identify macro- and microclimatic zones at high resolution (Demuzere et al. 2019).

In this work we relied on available Corine Land Cover time series at 100 m for Europe, which remain the standard for EU MS to report on changes in ecosystem extent (European Environment Agency 2019; See et al. 2024). Yet, many particularly small ecosystem patches have likely been missed, which could have, in theory, been improved by the new 10 m Corine CLC+ data (Probeck et al. 2021) but is not yet, however, available for longer time periods. Particularly, small land use and land cover transitions (e.g., grassland or shrubland changes) might be missed at a coarser grain. Future work could aim at downscaling and harmonising changes in the Corine Accounting layer with other products and utilise novel Corine CLC+ products for higher spatial resolution.

Author Contributions

All authors contributed to investigation, writing, and editing the manuscript. Additionally: M. J. contributed to conceptualization, funding acquisition, methodology, project administration, resources, and supervision. R.C., Z.R. and O. Y. contributed to formal analysis, validation, and visualization, M.H.K.H. contributed to validation, and methodology. L.S. contributed to funding acquisition, supervision, methodology and validation.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are available in Jung, Cornford, et al. (2025). https://doi.org/10.5281/ZENODO.14996728.

Peer Review

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/ddi.70179.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting information.