



GHLC: global harmonized land cover datasets for 2020–2024 at 10 m and 30 m resolution based on a rule-based ensemble approach

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Abstract. The paper describes the production and assessment of GHLC: a global harmonized land cover product at 10 meter spatial resolution for 2020 and at 30 meter resolution for 2020–2024. GHLC is generated using a rule-based ensemble approach that integrates 24 individual land cover and auxiliary layers from different projects. Because each class label is assigned based on an explicit, documented rule rather than a trained model, every classification decision in GHLC can be traced to a specific input dataset and threshold, making the product transparent, reproducible, and straightforward to update as improved input datasets become available. These 24 layers are combined around a primary spatial backbone provided by ESA WorldCover and GLAD GLCLUC (Global Land Cover and Land Use Change). The documented sequence of conditional rules describes how other thematic datasets (e.g., Global Mangrove Watch for mangroves, WorldCereal for maize, South American maps for soybeans, and GLC_FCS30D for detailed forest subtypes) are fused with ESA WorldCover and GLAD GLCLUC. The target legend is structured hierarchically to balance thematic detail with global mapping feasibility (Level 1 consists of 10 broad classes; Level 2 consists of 40+ distinct classes, including specific crop types, varying grassland management types, and forest types). The map was validated against a large pool of independent reference samples from the Global Ensemble Land Cover (GELC) database, matched to each product's mapped years. At the broadest level, the GHLC product achieved an overall accuracy of 0.92 for the 10 m and 0.86 for the 30 m maps, respectively. Forests, forest plantations, and woodland ($F1 \geq 0.94$) and water bodies ($F1 \geq 0.85$) performed best across both resolutions due to their high spectral distinctiveness and spatial coherence. Cropland classification was more accurate in the 30 m product ($F1 = 0.81$) than in the 10 m product ($F1 = 0.72$), as the 30 m GLAD GLCLUC backbone provides a stronger cropland signal. Macro-averaged F1 across all classes was effectively identical between 10 m (0.63) and 30 m (0.62), demonstrating that spatial resolution alone does not govern overall accuracy. The poorest performance was registered for sparsely vegetated ecosystems and inland wetlands. Urban ecosystems appear to be overestimated in the 30 m map. The datasets can be used for reporting on ecosystem extent and ecosystem services in ecosystem accounting. The biggest limitations of the GHLC are (1) that it is based on manual rules that may be subject to errors, and (2) that it relies on 24 independently derived external layers, each produced and maintained by separate research groups or agencies. If those external groups cease updating or maintaining their specific datasets, the corresponding GHLC rules cannot be applied, causing the classification system to degrade.



25 1 Introduction

Land cover mapping plays a fundamental role in understanding the Earth's surface and the interactions between natural and human systems. Land cover and land use are among the key UN-GGIM's Global Fundamental Geospatial Data Themes (Selmy et al., 2024). By providing spatially explicit information on the distribution of vegetation, water bodies, built-up areas, and other surface types, land cover maps support a wide range of policy applications, including land use planning, environmental
 30 monitoring, and natural resource management (Foley et al., 2005; Turner et al., 2007). Accurate and up-to-date land cover information is essential for quantifying ecosystem services, modeling biogeochemical cycles (Sellers et al., 1997), and advancing progress towards sustainable development goals (Anderson et al., 2017).

One key application of land cover data is ecosystem accounting, which follows the UN System of Environmental-Economic Accounting (SEEA) methodological framework (United Nations et al., 2025). Within this framework, ecosystem extent serves
 35 as a fundamental reporting unit, and spatially explicit land cover information is a primary input for delineating ecosystem extent and, in turn, for modeling ecosystem condition and ecosystem services. However, ecosystem accounting draws on a typology distinct from conventional land cover mapping. Although ecosystem types share some categories with land cover classes, they are also defined by additional ecological properties that are not captured by land cover alone. For example, while land cover maps can distinguish forests primarily by leaf type (e.g., deciduous versus needle-leaved), ecosystem typologies can
 40 further differentiate forest types based on species composition (Keith et al., 2020). Despite these differences in terminology and conceptualization, detailed land cover maps remain indispensable inputs for ecosystem accounting, as most ecosystem typologies ultimately rely on land cover classifications.

Over the past few decades, global land cover mapping has advanced substantially, driven by the increasing availability of earth observation data, improvements in sensor technology, and the development of sophisticated classification algorithms.
 45 Numerous global land cover products have been produced from satellite observations, drawing on data from the Landsat, MODIS, and Sentinel missions, among others. An in-depth review of time-series of global land cover/land use maps is also provided by Mora et al. (2014), Liu et al. (2021), and García-Álvarez et al. (2022). García-Álvarez et al. (2022) also includes all legends for the main global land cover products. Among the main current (state-of-the-art) global land cover products at spatial resolutions of 100 m or finer, the following three can be singled out: (1) GLAD GLCLUC (2000–2024), (2) ESA
 50 WorldCover (2020–2021), and (3) GLC_FCS30D (1985–2022). The GLAD (Global Land Analysis and Discovery) GLCLUC (Global Land Cover and Land Use Change) product, developed at the University of Maryland from Landsat satellite data at approximately 30 m resolution, provides one of the longest and most temporally consistent global time series available (Potapov et al., 2022). The European Space Agency (ESA) WorldCover product, produced by the Flemish Institute for Technological Research (VITO) using the Sentinel-1 and Sentinel-2 satellite constellations, instead prioritizes spatial resolution and thematic
 55 consistency, providing annual, globally consistent land cover maps with 11 classes at 10 m resolution (Zanaga et al., 2021). At a coarser resolution, the ESA Climate Change Initiative (CCI) land cover product offers a longer multi-decadal time series at 300 m resolution, with a comparatively larger number of classes tailored to climate modeling applications (European Space Agency, 2017). More recently, the Chinese Academy of Sciences (CAS) has sought to combine the thematic richness of CCI



with finer spatial detail in the Global Land Cover Fine Classification System (GLC_FCS30D; Zhang et al., 2024), which
 60 downscales the CCI legend to produce a global 30 m dataset with additional forest-type detail.

These global land cover datasets differ in spatial resolution, thematic detail, temporal coverage, and methodological approach, reflecting the different priorities each was designed to serve. However, none combines the thematic detail (i.e., number of land cover classes), accuracy, and spatial resolution (preferably 30 m or finer) required for applications such as land use planning, monitoring of natural resource use, or ecosystem accounting. For example, in most policy applications, it is critically
 65 important to differentiate between natural forests, plantation forests, and perennial crops such as oil palm, since these types of land cover are frequently aggregated into a single *tree cover* or *forest* class despite representing fundamentally different land uses (Abramowitz et al., 2023). The EU Deforestation Regulation illustrates the practical stakes of this distinction by restricting the import of commodities such as cocoa when produced on land that was deforested after 2020 (European Parliament and Council of the European Union, 2023), a requirement that depends on land cover data capable of distinguishing natural
 70 forests from tree-crop plantations at the parcel level. A similar distinction matters in ecosystem accounting, where the services provided by tree crop areas differ substantially from those of natural forests (Dislich et al., 2017), and it likewise matters for annual croplands, where knowing which specific crop is grown is often more informative than a single generic *cropland* label. Taken together, these examples show why thematic detail, spatial resolution, and classification accuracy must be considered jointly, rather than as independent design choices, when developing land cover products intended for policy and accounting
 75 applications.

Given the flood of new global land cover products and the increasing complexity of navigating through all these, several researchers have invested efforts to produce a multisource combination *the-best-of-the-best* ensemble land cover dataset. Xu et al. (2014) developed a Bayesian-based data fusion method to synthesize a synergetic global land cover map by combining existing products. Lu et al. (2020) developed a 30 m cropland dataset based on a global synergy/data-fusion framework.
 80 Li et al. (2023) integrates three multiple-class 30 m products (GlobeLand30, FROM_GLC, and GLC_FCS30), four high-quality single-class products (Global Forest Change, Global Annual Urban Dynamics, JRC Global Surface Water, and Global Mangrove Watch), and three national-scale products (such as NLCD 2016, China land-use/cover dataset, and the annual China land cover dataset) using a pixel-level, multisource product-fusion approach based on the Dempster–Shafer theory of evidence to produce a single ensemble 30 m global land cover map representing the year 2015. Rieutord et al. (2024) recently produced
 85 ECOCLIMAP-SG-ML, a 60 m resolution ensemble land cover map designed specifically for numerical weather prediction and land surface models. Bratic et al. (2023) developed a new benchmark dataset, MOLCA (Map of Land Cover Agreement), and a generic legend that should align with most high-resolution global datasets and consists of nine distinct land cover classes. The most comprehensive recent global training datasets for land cover mapping to date (approximately 2M training points covering years 1984–2020) are provided by the Global Land Cover Estimation (GLanCE) project (Stanimirova et al.,
 90 2023). Shi et al. (2023) produced Globe230k, a benchmark dataset for global land cover mapping that includes approximately 230,000 annotated images with a size of 512×512 pixels and a spatial resolution of 1 m. In the cropland domain specifically, Tang et al. (2024) developed CROPGRIDS using a comparable logic, a documented multi-criteria ranking scheme, combining endogenous quality indicators (synchrony with the reference year, spatial resolution, validation level) and exogenous agreement



with an independent cropland mask and FAOSTAT statistics, to select the best-fit source among 28 heterogeneous crop-specific
 95 datasets for each crop-country combination. This shows that transparent, criteria-driven selection logic, rather than a trained
 fusion model, can scale to highly heterogeneous, multi-resolution inputs beyond the land-cover domain.

Beyond thematic detail and resolution, transparency and reproducibility are also relevant considerations for global land cover
 products. Many recent classifications are based on machine learning algorithms. However, their internal decision-making pro-
 cess is often opaque, making it difficult to trace why a given pixel was assigned a particular class or update the classification
 100 when improved input datasets become available (Adadi and Berrada, 2018). A rule-based ensemble approach, in which an en-
 semble of existing land cover and thematic datasets (rather than a data-driven model) assigns each class through a documented
 sequence of conditional rules applied to existing input products, makes the classification logic explicit and traceable to its un-
 derlying data sources. As noted above, this property may be particularly useful for applications such as ecosystem accounting,
 where land cover serves as a key input to the SEEA framework, and for regulatory contexts such as the EU Deforestation
 105 Regulation, where the ability to explain a classification decision can be as relevant as its accuracy. A rule-based structure may
 also facilitate future updates, since individual rules can potentially be revised or extended as new or improved thematic layers
 become available, without necessarily requiring the entire classification to be retrained.

In this paper, we make two related contributions. We first develop a rule-based ensemble method to combine multiple land
 cover and thematic datasets into a single classification, integrating 24 individual land cover, ancillary, and auxiliary layers.
 110 We then produce a series of global harmonized land cover products that combine greater thematic detail with high spatial
 resolution. We refer to the harmonized land cover ensemble product at 10 m spatial resolution as “GHLC10” (2020) and the
 product at 30 m (2020–2024) as “GHLC30”. These products feature a broad range of classes (40+ classes) and are expected
 to be more fit-for-purpose than, e.g., products with simplified legends such as ESA WorldCover. We describe in detail the
 steps we developed to produce these maps, present the resulting products with selected regional zoom-ins, and assess their
 115 performance against reference samples from the Global Ensemble Land Cover (GELC) dataset, filtered to exclude any source
 sharing lineage with the input layers, ensuring the assessment is independent of the classification it evaluates. Finally, we
 discuss the strengths and limitations of the resulting products and outline key steps toward developing the next generation of
 global land cover maps. The resulting maps, the underlying protocol, and an interactive platform for visualizing the products are
 available at <https://source.coop/opengeohub/ogh-ghlc10>, <https://codeberg.org/landmetric/ghlc>, and <https://app.landmetric.org>,
 120 respectively.

The remainder of this paper is organized as follows. Sect. 2 describes the input datasets used to generate the land cover
 products, including the primary backbone products, thematic ancillary layers, auxiliary layers, and the independent validation
 reference data. Sect. 3 presents the methods, covering the overall workflow, the hierarchical legend design, the rule-based
 ensemble classification logic, and the validation approach. The resulting land cover maps, area statistics, temporal dynamics
 125 for the 30 m product, validation results, and regional zoom-in comparisons are presented in Sect. 4. Finally, Sect. 5 discusses
 the strengths and limitations of the proposed approach and outlines the directions for future development, and Sect. 6 concludes
 the paper.



2 Data

Harmonized land cover products were generated by integrating multiple existing global land cover products with complementary thematic ancillary and auxiliary datasets (Table 1). This section describes these input datasets, their key characteristics, and their specific role in the rule-based classification. We first introduce the three primary land cover products that serve as the spatial basis of classification (Sect. 2.1), followed by the thematic ancillary layers used to refine specific land cover classes (Sect. 2.2) and the auxiliary layers used to account for the topographic, spectral, and coastal context (Sect. 2.3). Finally, we describe the independent validation dataset (Sect. 2.4).

2.1 Primary land cover products

Three global land cover products serve as the backbone of land cover classification, each contributing unique strengths in spatial resolution, temporal coverage, and thematic detail. ESA WorldCover anchors the 10 m product with high spatial resolution and thematic consistency, GLAD GLCLUC anchors the 30 m product with a long, temporally consistent annual time series, and GLC_FCS30D provides detailed forest subtype information used to refine tree cover classes in both products. Together, these three products define the spatial and temporal structure of the classification described in the following sections.

The ESA WorldCover is a 10 m global land cover dataset derived from Sentinel-1 radar and Sentinel-2 multispectral imagery, classifying land into 11 discrete classes following the FAO Land Cover Classification System (LCCS), namely tree cover, shrubland, grassland, cropland, built-up, bare/sparse vegetation, snow and ice, permanent water bodies, herbaceous wetland, mangroves, and moss and lichen. The product was generated using a CatBoost classifier, achieving an overall accuracy of 74.4% based on a stratified random sample of validation points, with versions available for the reference years 2020 and 2021 (Zanaga et al., 2021). In this study, ESA WorldCover (2020) serves as the primary spatial backbone for the 10 m product, providing a globally consistent, high-resolution base classification that is subsequently refined using the thematic layers described below.

The GLCLUC dataset produced by GLAD provides annual land cover information at 30 m resolution derived from Landsat imagery (Potapov et al., 2022). Covering the period from 2000 to 2024, it represents one of the longest and most consistent global land cover time series at medium resolution, updated every 5 years before 2015 and annually thereafter. GLAD GLCLUC employs a hierarchical classification with seven classes, three expressed as continuous gradients, and four as discrete categories. Vegetation density is represented as continuous fields of tree height (3–25 m) and short vegetation cover (0–100%), while inland surface water is characterized by water cover frequency (0–100%); the remaining discrete classes cover snow and ice, ocean, built-up areas, and cropland. In this study, GLAD GLCLUC serves as the primary spatial backbone for the 30 m multi-temporal product, owing to its temporal consistency, annual coverage, and detailed representation of vegetation dynamics.

The GLC_FCS30D is a multi-temporal global dataset that maps land cover changes at 30 m spatial resolution over the 38 years 1985–2022, at five-year intervals with annual products available from 2000 onward (Zhang et al., 2024). GLC_FCS30D provides detailed thematic information across 35 land cover classes, which can be aggregated into 10 major classes. At the highest level of detail, it differentiates forest types by leaf type (broadleaved, needleleaved, mixed), phenology (evergreen, deciduous), and canopy closure (open >15%, closed >40%). The dataset was produced using a combination of Landsat im-



agery, ancillary environmental data, and a random forest classification approach, and was validated with more than 84,000 global samples, achieving an overall accuracy of 80.88% for the 10 main land cover classes. In this study, GLC_FCS30D provides detailed forest-subtype information to refine areas classified as tree cover by the primary backbone products, thereby distinguishing forest types that would otherwise be aggregated into a single *tree cover* class.

165 2.2 Thematic ancillary layers

Thematic layers were integrated to enhance the classification of specific land cover types beyond those represented in the primary products, with a focus on cropland systems, grassland management types, forest disturbance dynamics, and coastal ecosystems. Unlike the primary products described above, which provide a general-purpose backbone classification, these thematic layers are tailored to a specific land cover type, allowing individual classes to be refined using the most relevant and up-to-date source available for that class.

The first group of thematic layers targets cropland areas, where several crop-specific products were integrated to increase thematic detail beyond the generic cropland classes provided by the primary backbone products. Soybean cover for South America was extracted from the Commodity Crop Mapping and Monitoring in South America project, which provides annual maps spanning 2000 to 2019, generated by integrating Landsat and MODIS data with extensive field observations (Song et al., 2021). Maize cover was similarly obtained from the WorldCereal dataset, produced by VITO, which integrates Sentinel-1, Sentinel-2, and Landsat 8 thermal time series using a CatBoost classifier that accounts for regional variations in crop phenology through agroecological zone stratification (Van Tricht et al., 2023). Rice paddies were identified using regional products that exploit the distinctive backscatter patterns of flooded rice fields in Sentinel-1 time series, with separate products for East Asia and India tailored to local cropping calendars (Han et al., 2021; Chen et al., 2024). Finally, perennial crop probabilities for coffee, cocoa, rubber, and oil palm were obtained from the Forest Data Partnership (FDP), which provides continuous probability values ranging from 0 to 100%, indicating the likelihood that a pixel contains each crop type for the years 2020 and 2024 (Forest Data Partnership, 2025).

Beyond cropland, grassland types were distinguished using the Global Pasture Watch (GPW) products introduced by Parente et al. (2024). This dataset provides separate probability layers for cultivated grasslands, natural and semi-natural grasslands, and open shrublands, derived through a random forest classification trained on harmonized reference data from multiple sources. These probability layers allow distinction between grassland management types, with pixels assigned to cultivated or natural grassland depending on which probability is higher, provided that at least one exceeds a minimum threshold. The grassland classification was further refined using bare soil fraction data to distinguish semi-arid shrublands from vegetated grasslands in transitional environments (Consoli et al., 2024).

A further set of thematic layers addresses forest and coastal environments, targeting two specific cases in which the primary backbone products may require correction. Forest cover was characterized using the GLAD Global Forest Change dataset (GFC), which maps global tree cover and forest loss dynamics at 30 m spatial resolution (Hansen et al., 2013). This dataset provides a globally consistent baseline of tree cover percentage for 2000, along with annual forest loss from 2001 to 2024. In this study, these layers were used to correct built-up pixels in the backbone classification that, in fact, retain substantial



195 tree cover and show no recent loss, such as street trees and urban parks, reclassifying them as tree cover. A comparable
correction was applied in coastal environments, where mangrove extent was obtained from the Global Mangrove Watch (GMW)
dataset, which provides global maps of mangrove distribution based on radar and optical imagery, combining radar backscatter
characteristics with optical vegetation indices to identify mangrove forests (Bunting et al., 2018). Baseline extent maps are
available for multiple years between 1996 and 2020; in this study, the most recent available version (2020) is used as the source
200 for mangrove identification in coastal areas, where the primary backbones may otherwise confuse mangroves with other flooded
forest types. In addition, aquaculture ponds were mapped using the Coastal Land-based Aquaculture Ponds (CLAP) dataset at
30 m resolution (Yufeng et al., 2020). The CLAP product spans four time periods (1990, 2000, 2010, and 2020) and covers
coastal regions of East Asia, developed using long-term Landsat archives and an object-oriented hierarchical classification
approach, with validation results achieving an overall accuracy of over 0.90.

Table 1. Summary of input datasets used in the ensemble land cover classification. GLCLUC = Global Land Cover and Land Use Change; GLAD = Global Land Analysis and Discovery; GLC_FCS30D = Global Land Cover Fine Classification System; CAS = Chinese Academy of Sciences; GPW = Global Pasture Watch; CLAP = Coastal Land-based Aquaculture Ponds; UMD = University of Maryland; GEDTM30 = Global Ensemble Digital Terrain Model; VITO = Flemish Institute for Technological Research; ESA = European Space Agency; OGH = OpenGeoHub Foundation.

Dataset	Data provider	Resolution	Temporal coverage	Reference
WorldCover	VITO/ESA	10 m	2020–2021	Zanaga et al. (2021)
GLAD GLCLUC	UMD GLAD	30 m	2000–2024	Potapov et al. (2022)
GLC_FCS30D	CAS	30 m	1985–2022	Zhang et al. (2024)
GLAD soybean	UMD GLAD	30 m	2000–2019	Song et al. (2021)
WorldCereal	VITO/ESA	10 m	2021	Van Tricht et al. (2023)
Rice paddies	–	30 m	2017 and 2020	Han et al. (2021); Chen et al. (2024)
Perennial crops	Forest Data Partnership	10 m	2020 and 2024	Forest Data Partnership (2025)
GPW	OGH	30 m	2000–2024	Parente et al. (2024)
GFC	UMD GLAD	30 m	2000–2024	Hansen et al. (2013)
GMW	–	30 m	1996–2020	Bunting et al. (2018)
CLAP	–	30 m	1990, 2000, 2010 and 2020	Yufeng et al. (2020)
GEDTM30	OGH	30 m	Static	Ho et al. (2025)
GLAD Landsat ARD	OGH	30 m	1997–2024	Consoli et al. (2024)

205 **2.3 Auxiliary layers**

Our rule-based classification also incorporated auxiliary layers to account for landscape contexts in which topography, spectral characteristics, or coastal proximity influence land cover patterns. These layers do not represent land cover directly, but instead



provide a continuous spatially explicit context used to refine specific classes, namely elevation and terrain position, bare soil fraction, and distance to the coast.

210 Topographic information was obtained from the Global Ensemble Digital Terrain Model (GEDTM30), a global 30 m terrain model produced by the OpenGeoHub Foundation (OGH) using an ensemble machine learning approach that integrates multiple elevation sources, including Copernicus DEM, SRTM, ASTER GDEM, and ALOS (Ho et al., 2025). Elevation was combined with distance-to-coast metrics to support coastal wetland classification, while a derived topographic position index helped identify rocky mountain peaks.

215 A second source of continuous information came from spectral characteristics, incorporated via annual bare soil fraction layers produced by OGH and derived from GLAD Landsat Analysis Ready Data (Consoli et al., 2024). Bare soil fraction quantifies the proportion of bare soil in each pixel, ranging from 0% (fully vegetated) to 100% (bare ground), capturing gradual variations in vegetation cover that categorical land cover classes cannot represent. A four-year average for 2020–2023 was used to distinguish semi-arid shrublands from vegetated grasslands during the classification.

220 Finally, coastal zones were delineated using a buffered land mask derived from the ESA WorldCover dataset. Distance-to-coast buffers were calculated to identify coastal zones and distinguish landforms such as beaches, dunes, and coastal wetlands from inland areas. By combining these distance-to-coast buffers with the elevation thresholds described above, coastal environments were consistently identified across diverse geographic settings. In addition, a harmonized land mask, prepared by integrating multiple existing land layers, was applied identically to the 10 m and 30 m classification streams to ensure a
225 consistent ocean extent across both products.

2.4 Validation reference data

Validation reference data were obtained from the Global Ensemble Land Cover (GELC; Simoes et al., 2025) dataset, a harmonized global compilation of land cover reference samples spanning 2000–2022. GELC integrates data from multiple sources, including GLanCE (Friedl et al., 2022), Dynamic World (Tait et al., 2021), GPW (Parente et al., 2024), MangrovesDB (Maxwell
230 et al., 2023), and WorldCereal (Oliveira et al., 2024). These source datasets were standardized into a unified 15-class legend encompassing major land cover types such as cropland, bare soil, forest, shrubland, wetland, water, and urban areas, among others, providing a harmonized reference dataset that supports consistent large-scale validation across global land cover products. After matching each reference sample to the corresponding product year, 627,335 samples (2020) were used to validate the 10 m product, and 816,573 samples (2020–2022) were used to validate the 30 m product.



235 3 Methods

3.1 Workflow overview and legend

The land cover products were generated using a rule-based ensemble approach that integrates multiple existing land cover datasets with thematic ancillary and auxiliary layers, as illustrated in Fig. 1. The workflow consists of three main stages, namely data preparation and legend design, rule-based ensemble classification, and validation.

240 Two parallel processing streams produce the 10 m and 30 m products, respectively. Both streams share the same classification logic, ancillary and auxiliary layers, and follow a widely shared hierarchical legend (Table 2), differing primarily in their spatial backbone, temporal coverage, and the small number of Level 2 classes available only in the 10 m product. The 10 m product uses ESA WorldCover as its spatial backbone and produces a single map with 44 classes for the reference year 2020, while the 30 m product uses GLAD GLCLUC as its spatial backbone and produces annual maps with 40 classes for the period 2020–
 245 2024. In both streams, the backbone defines an initial coarse land cover assignment that is subsequently refined class-by-class using thematic ancillary and auxiliary layers, as described in Sect. 3.3. After this, the classified tiles are merged and exported as Cloud Optimized GeoTIFF (COG) files. The resulting maps are validated against harmonized reference samples as described in Sect. 3.4.

3.2 Legend design

250 The target legend (Table 2) was designed to balance thematic detail with mapping feasibility across diverse global environments. The legend follows a hierarchical structure with two levels. Level 1 provides 10 broad land cover categories—built-up, cropland, grassland, forest, forest plantations and woodland, shrubland and heathland, sparsely vegetated ecosystems, inland wetlands, water bodies, coastal ecosystems, and aquaculture—suitable for general applications and compatible with existing global products (Herold et al., 2008; Di Gregorio and Jansen, 2005). Level 2 expands to 44 and 40 classes for the 10 m and
 255 30 m products, respectively, subdividing each Level 1 category based on ecologically and economically relevant distinctions.

The subdivision criteria differ by Level 1 class, reflecting the thematic priorities of each ecosystem type. Among managed land covers, cropland is subdivided by crop type into annual crops (soybean, maize, rice, and other) and perennial crops (coffee, cocoa, rubber, and oil palm). Grassland is subdivided into cultivated and natural grassland based on management type. Shrubland and heathland follows a comparable logic, distinguishing a general shrubland and heathland class from other, less
 260 clearly defined shrub vegetation. Forest receives the most detailed treatment of any class, subdivided by a combination of leaf type (broadleaved, needleleaved, mixed), phenology (evergreen, deciduous), canopy closure (open, closed), and hydrological regime (flooded), yielding 14 Level 2 classes, reflecting the wide ecological and economic significance of forest subtypes. At the drier end of the vegetation gradient, sparsely vegetated ecosystems are subdivided into true deserts, semi-arid, semi-arid shrubland, rocks and mountain peaks, snow and ice, and moss and lichen. Conversely, at the wetter end, inland wetland
 265 is subdivided by dominant vegetation structure into sparse vegetation, grassland, and shrubland. Finally, water and coastal environments are subdivided by their own defining characteristics, water into permanent and seasonal categories based on seasonality, and coastal environments into mangroves, coastal wetlands, and beaches and dunes.

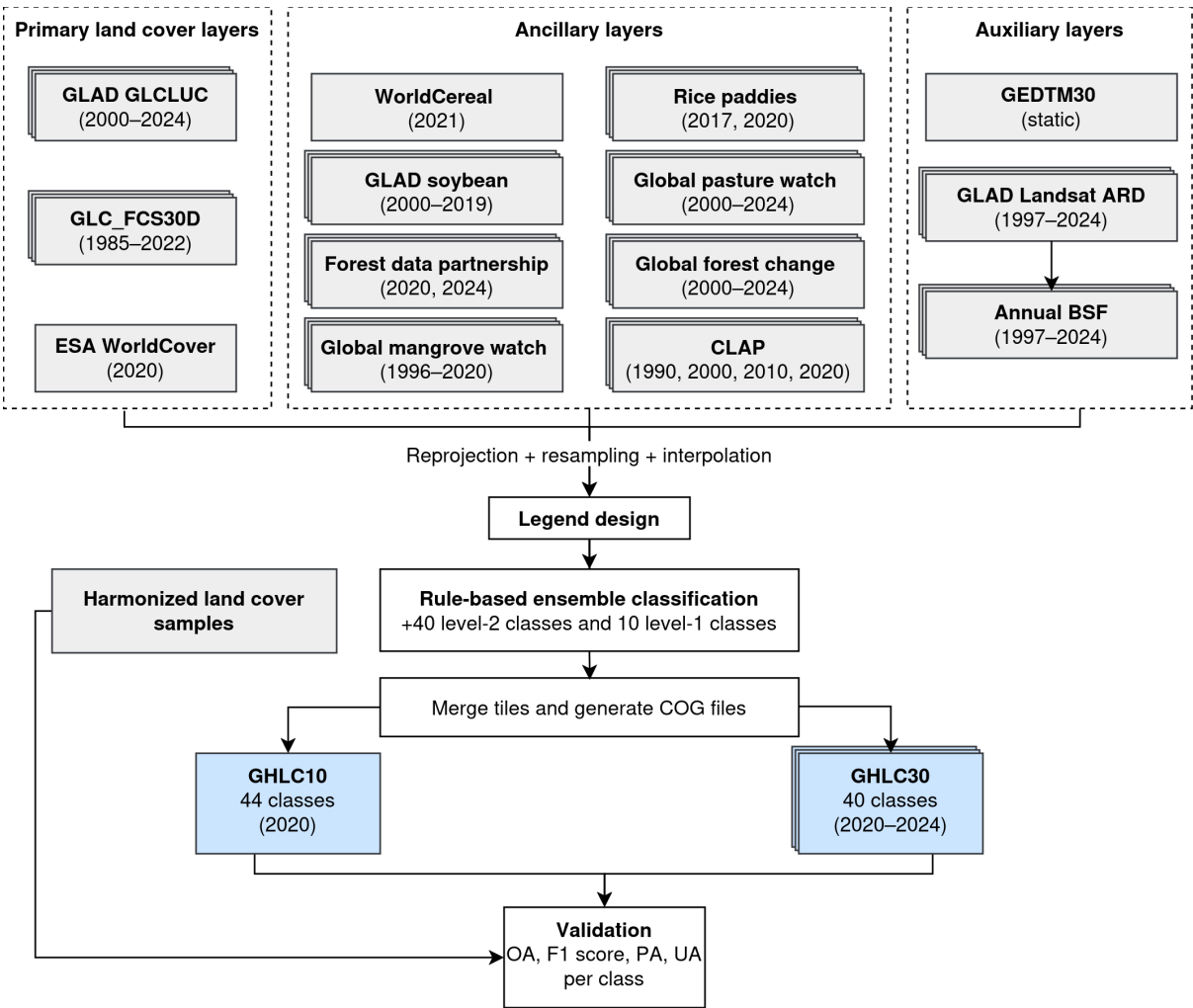


Figure 1. Overview of the proposed workflow illustrating the main sequential steps.

Both products share the same Level 1 classification, enabling direct comparison and aggregation across resolutions. Minor differences at Level 2 reflect the capabilities of their respective input datasets, with the 10 m product including four additional classes, namely other grassland (3.3), other shrubland (5.2), moss and lichen (6.6), and wetland other (7.4), which rely on ESA WorldCover classes not available in the GLAD GLCLUC backbone used for the 30 m product (indicated by dashes in Table 2).

3.3 Rule-based ensemble land cover classification

Combining multiple existing land cover classifications into a single composite product has been explored under various names, including decision fusion, geographic stacking, and hybrid mapping (Jung et al., 2006; Tuanmu and Jetz, 2014; Li et al., 2023). These approaches generally exploit disagreement among independently produced classifications to construct a composite that



Table 2. Legend for the 10 m and 30 m land cover products. bl: broadleaved; nl: needleleaved; ml: mixed leaf type; eg: evergreen; dc: deciduous. Classes absent in the 30 m product (–): Other grassland (3.3), Other shrubland (5.2), Moss and lichen (6.6), and Wetland – other (7.4), which rely on input layers exclusive to the 10 m product.

Class	10 m	30 m	Class	10 m	30 m
1. Built-up			5. Shrubland and heathland		
1.1 Built-up	1	1	5.1 Shrubland and heathland	27	26
			5.2 Other shrubland	28	–
2. Cropland (annual and perennial)			6. Sparsely vegetated ecosystems		
2.1 Annual crops – soybean	2	2	6.1 True desert	29	27
2.2 Annual crops – maize	3	3	6.2 Semi-arid	30	28
2.3 Annual crops – rice	4	4	6.3 Semi-arid shrubland	31	29
2.4 Annual crops – other	5	5	6.4 Rocks and mountain peaks	33	30
2.5 Perennial crops – coffee	6	6	6.5 Snow and ice	32	31
2.6 Perennial crops – cocoa	7	7	6.6 Moss and lichen	34	–
2.7 Perennial crops – rubber	8	8	7. Inland wetlands		
2.8 Perennial crops – oil palm	9	9	7.1 Wetland – sparse veg.	35	32
3. Grassland			7.2 Wetland – grassland	36	33
3.1 Cultivated grassland	10	10	7.3 Wetland – shrubland	37	34
3.2 Natural grassland	11	11	7.4 Wetland – other	38	–
3.3 Other grassland	12	–	8. Water bodies		
4. Forest, forest plantations and woodland			8.1 Water – permanent	39	35
4.1 Tree cover, bl eg open	13	12	8.2 Water – seasonal	40	36
4.2 Tree cover, bl eg closed	14	13	9. Coastal ecosystems		
4.3 Tree cover, bl dc open	15	14	9.1 Mangrove	41	37
4.4 Tree cover, bl dc closed	16	15	9.2 Coastal wetlands	42	38
4.5 Tree cover, nl eg open	17	16	9.3 Beaches and dunes	43	39
4.6 Tree cover, nl eg closed	18	17	10. Aquaculture		
4.7 Tree cover, nl dc open	19	18	10.1 Aquaculture	44	40
4.8 Tree cover, nl dc closed	20	19			
4.9 Tree cover, ml open	21	20			
4.10 Tree cover, ml closed	22	21			
4.11 Flooded tree cover, open	23	22			
4.12 Flooded tree cover, closed	24	23			
4.13 Other flooded tree cover	25	24			
4.14 Other tree cover	26	25			

may be more accurate, or more thematically detailed, than any single input. Prior implementations range from data-driven decision fusion using voting algorithms or trained meta-classifiers (Tuanmu and Jetz, 2014; Li et al., 2023) to expert-defined semantic rule sets that synthesize biophysical information across products with differing legends (Pérez-Hoyos et al., 2012).



The approach adopted here is closer to the latter than to statistically learning how to combine inputs; each output class is assigned through a documented, deterministic sequence of conditional rules applied to the input products described in Sect. 2.

The rule-based ensemble follows a hierarchical decision tree, in which rules are applied in a fixed order of priority. A pixel is assigned by the first rule whose condition evaluates to true and cannot be reassigned by any later rule, so earlier rules take precedence. This ordering allows specialized thematic layers, such as crop-specific or mangrove extent maps, to override the more general backbone classification when they are expected to provide higher thematic accuracy. The design was chosen over data-driven alternatives to ensure transparency, interpretability, and ease of updating as input datasets improve (Rudin, 2019). Rule conditions were themselves developed iteratively, through multiple rounds of refinement, by comparing classification outputs with existing detailed regional and national land cover maps, high-resolution satellite imagery, and expert visual interpretation across a range of representative landscapes worldwide; this calibration process is separate from the classification logic itself, individual rules and thresholds, once set, are fixed and documented as described above. The classification logic is identical for the 10 m and 30 m products, differing only in how backbone classes are encoded and in the number of years processed. Simplified examples are shown in Fig. 2, and the complete rule set is available in the code repository (<https://codeberg.org/landmetric/ghlc>).

The chain begins with mangroves (GMW), followed immediately by specialized crop layers, then proceeds from the most thematically specific classes to the more structurally defined ones. Cropland is resolved first among the vegetated classes. Soybean is assigned from the South America soybean product and maize from the WorldCereal layer, both treated as authoritative within their domains and therefore not gated to the backbone cropland class. In contrast, rice is assigned where a regional rice product coincides with backbone cropland. Backbone cropland matching none of these defaults to a generic annual crops class. Perennial crops follow a separate logic, since rather than originating from the backbone cropland class, they are identified within tree-cover areas wherever the corresponding FDP probability exceeds a crop-specific threshold, and are evaluated before the general tree-cover rules. Grassland is then split into cultivated and natural types using the GPW probability layers, subject to a minimum threshold; a cross-cutting rule reclassifies pixels with a high multi-year mean bare soil fraction as semi-arid shrubland, illustrating how continuous auxiliary variables can redirect assignments away from categorical backbone classes.

Tree-cover pixels are refined into 14 forest subtypes by leaf type, phenology, and canopy closure using GLC_FCS30D, with flooded forest identified by cross-referencing GLAD GLCLUC wetland codes. A reverse correction reclassifies backbone built-up pixels that retain substantial tree cover with no recent loss, from GFC, as tree cover, addressing commission errors over street trees and urban parks. The remaining classes follow the same first-match logic along the rest of the gradient, from shrubland and sparsely vegetated ecosystems, using vegetation density, topographic position, and distance to coast, to wetlands, refined by vegetation structure and coastal proximity, and water bodies, refined by seasonality. Aquaculture, confirmed by CLAP, is assigned near the end of the chain, and built-up is assigned last, directly from the backbone, so that every thematic rule takes precedence and only unclaimed pixels default to built-up. Several thematic layers are regional rather than global (Table 1); soybean covers South America, rice covers South and Southeast Asia, and aquaculture covers coastal East Asia. Outside these regions, the corresponding Level 2 classes cannot be assigned, and affected pixels fall through to the relevant generic class.



Examples of rule-based classification (30 m product)

2.2 Annual crops - maize (3rd rule): A pixel is labeled as such only if no prior rule has been matched (including mangrove and soybean), and if:

```
worldcereal_maize = TRUE
```

4.1 Tree cover, broadleaved, evergreen, open (13th rule): A pixel is labeled as such only if no prior rule has been matched (including mangrove, all cropland, rules 2–9, and grassland, rules 10–12), and if:

```
glad_glcluc = tree cover and glc_fcs30d = broadleaved evergreen open
```

7.1 Wetland - sparse vegetation (33rd rule): A pixel is labeled as such only if no prior rule has been matched (including mangrove, all cropland, grassland, tree cover, shrubland, sparse vegetation, water, and wetland grassland rules, 1–32), and if:

```
glad_glcluc = wetland sparse vegetation
```

Figure 2. Simplified examples of the hierarchical rule-based classification for three selected classes in the 30 m product. A pixel is assigned to the first rule whose condition evaluates to true; once labeled, any subsequent rule cannot reassign it.

For the 30 m product, the full chain is applied independently for each year from 2020 to 2024 using the annual GLAD GLCLUC layer and year-specific ancillary layers where available. Datasets without annual coverage are applied at their nearest available version. GMW (2020) and CLAP (2020) are held constant, the WorldCereal maize layer corresponds to 2021, the soybean product ends in 2019, and the rice products correspond to 2017 and 2020; FDP perennial-crop probabilities (2020 and 2024) are linearly interpolated for intermediate years. Because CLAP is held constant, the interannual variation in aquaculture area (Sect. 4.3) does not originate in the aquaculture layer, as aquaculture is evaluated near the end of the chain, its area varies between years only through the pool of pixels left unclaimed by earlier rules.

A relevant consideration is that the backbone GLAD GLCLUC does not cover large areas at high northern latitudes, Greenland, and a number of islands, mostly in the Pacific Ocean, leaving corresponding gaps in the GHLC30 time series. To overcome this issue, the resulting GHLC10 product for 2020 was first crosswalked from the 44-class legend to the 40-class GHLC30 legend, with the four classes exclusive to GHLC10 mapped to their nearest GHLC30 equivalent: other grasslands to natural grassland, other shrubland to shrubland and heathland, moss and lichen to natural grassland, and other wetland to wetland-sparse vegetation, and then aggregated to 30 m resolution. The resulting crosswalked and aggregated product was used to fill the missing areas in the GHLC30 time series.



3.4 Validation approach

Validation was performed using reference data from the GELC compilation. Because GELC integrates, among other sources, GPW (Parente et al., 2024) and WorldCereal (Oliveira et al., 2024), and because the corresponding products are used here to classify grassland management type and maize (Sect. 2.2), all reference samples originating from these two sources were excluded before accuracy assessment. This removes any shared lineage between the reference labels and the layers used to produce the maps; the retained samples are independent of all input datasets, and the backbone products contribute no samples to GELC.

GELC spans 2000–2022. To align the reference data with the mapped years, only samples from 2020 onward were retained, and each sample was compared against the product for its own acquisition year, 2020 for the 10 m product, and the corresponding annual layer for the 30 m product. No reference data are available for 2023 or 2024, so the 30 m assessment draws on samples from 2020–2022; validation figures are reported accordingly for that period.

Reference labels were harmonized to the target legend by mapping GELC classes to the corresponding Level 1 classes. Sample sizes vary substantially between classes, reflecting the composition of the underlying GELC sources rather than a designed allocation; comparatively few samples represent classes such as built-up and sparsely vegetated ecosystems, and their per-class metrics should be read accordingly (Sect. 5.2). GELC provides Level 2 labels for some classes, but coverage across all Level 2 classes is insufficient to support a reliable class-by-class assessment, so validation is restricted to Level 1. Aquaculture is not assessed, as the reference pool contains no aquaculture samples.

Accuracy was assessed using overall accuracy (OA), producer’s accuracy (PA), user’s accuracy (UA), and the F1 score for each class. Overall accuracy is the proportion of correctly classified pixels across all classes. Producer’s accuracy, equivalent to recall, is the probability that a reference pixel of a given class is correctly classified (i.e., 1 minus omission error); user’s accuracy, equivalent to precision, is the probability that a classified pixel of a given class matches the reference label (i.e., 1 minus commission error). The F1 score, the harmonic mean of PA and UA, was computed per class, together with its macro-averaged (unweighted mean across classes) and weighted-averaged (weighted by class support) variants (Sokolova and Lapalme, 2009). As set out in the Discussion (Sect. 5.1), the reference pool is not distributed in proportion to mapped area, so overall and weighted accuracy are weighted towards the best-sampled classes; the macro-averaged F1 is therefore reported alongside as a less pool-dependent summary. Metrics were computed separately for the 10 m and 30 m products, as these constitute two distinct datasets.

4 Results

This section presents the resulting land cover products and assesses their consistency, dynamics, and accuracy. We first describe the global patterns captured by the 10 m and 30 m maps (Sect. 4.1) and summarize their area statistics (Sect. 4.2). We then examine temporal dynamics in the 30 m product between 2020 and 2024 (Sect. 4.3), report validation results against independent reference data (Sect. 4.4), and illustrate the spatial detail captured at the local scale through four regional zoom-in comparisons (Sect. 4.5).



360 **4.1 Land cover maps**

Global land cover maps at 10 m and 30 m resolution for the reference year 2020 are shown in Fig. 3 and Fig. 4, respectively. Both maps capture the broad latitudinal zonation of global land cover, with needleleaved evergreen forests (classes 4.5 and 4.6) dominating the northern high latitudes, broadleaved evergreen closed forest (4.2) concentrated across the tropical belt of the Amazon, Congo, and Southeast Asia, and true desert (6.1) and semi-arid (6.2) classes occupying the arid interiors of Africa, the Arabian Peninsula, and Central Asia. Cropland classes are most prominent across the mid-latitudes of North America, Europe, South Asia, and East Asia, with commodity crops such as soybean (2.1) and maize (2.2) clearly identifiable in their main production regions. The 10 m product shows consistent global patterns with the 30 m product while providing finer spatial detail in fragmented landscapes and mapping four classes not present in the 30 m product: other grassland (3.3), other shrubland (5.2), moss and lichen (6.6), and wetland other (7.4).

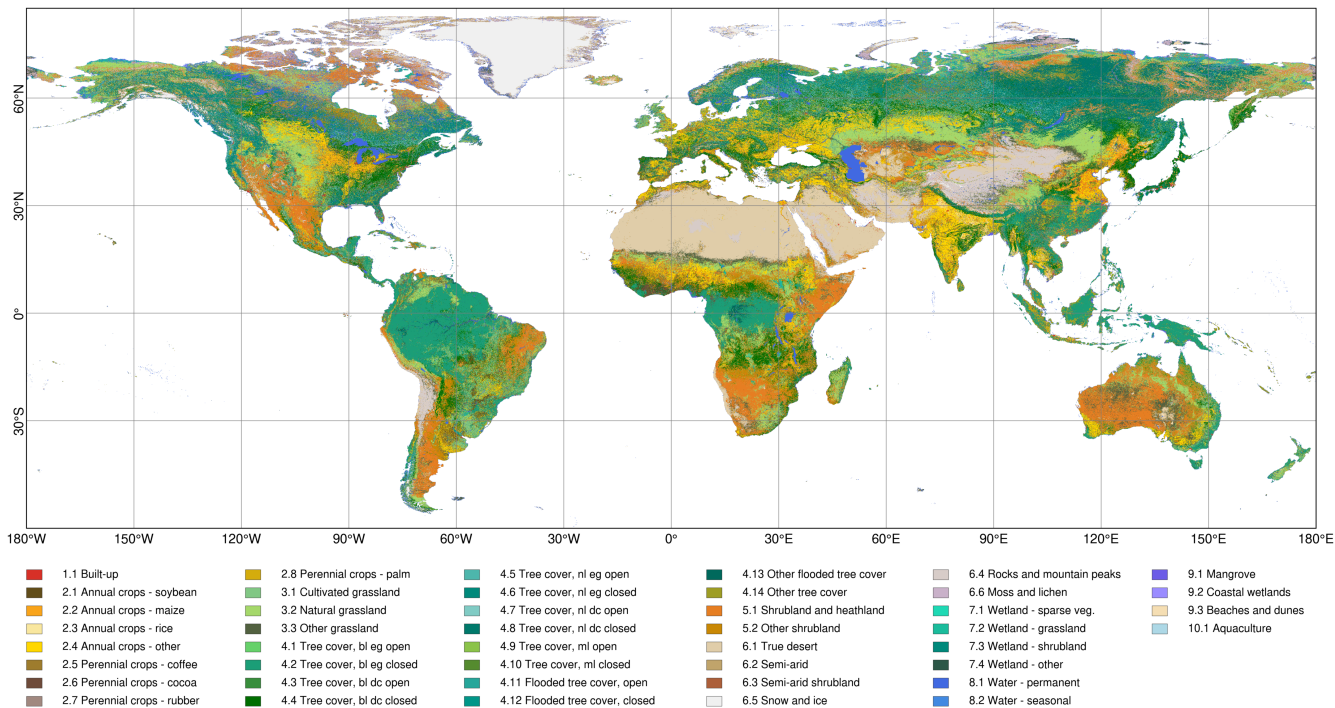


Figure 3. Global land cover map at 10 m resolution for the year 2020, produced using the rule-based ensemble classification approach. Classes follow the two-level hierarchical legend described in Table 2.

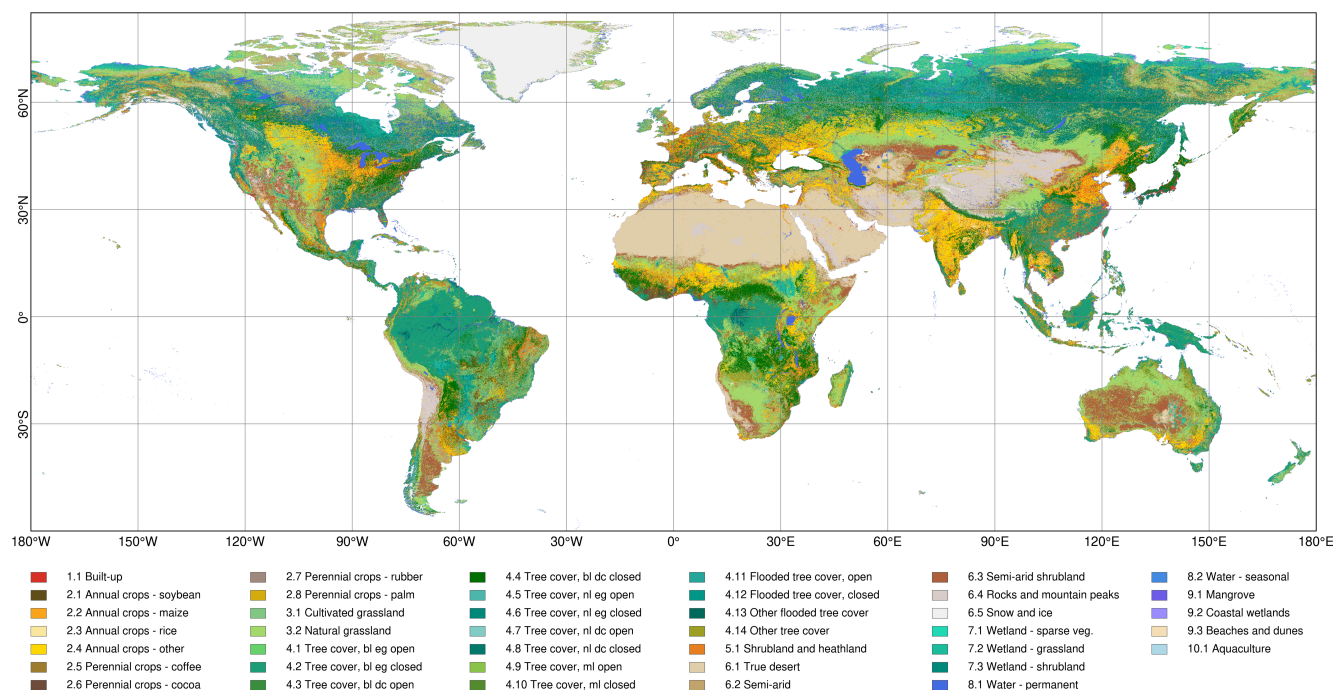


Figure 4. Global land cover map at 30 m resolution for the year 2020, produced using the rule-based ensemble classification approach. Classes follow the two-level hierarchical legend described in Table 2.

370 4.2 Area statistics

Area statistics per Level 1 class for both products are summarized in Table 3. Forest, forest plantations and woodland is the largest class in both, covering approximately 4,269 Mha (31.3%) in the 10 m product and 4,192 Mha (30.7%) in the 30 m product, followed by sparsely vegetated ecosystems (2,440 Mha, 17.9%, and 3,342 Mha, 24.5%) and grassland (2,642 Mha, 19.3%, and 2,551 Mha, 18.7%). Cropland covers approximately 1,366 Mha (10.0%) and 1,327 Mha (9.7%) in the 10 m and 375 30 m products, respectively.

The two products show only modest differences at the level of individual classes, and total mapped area is nearly identical between them (13,659 Mha at 10 m versus 13,660 Mha at 30 m), reflecting the harmonized land mask applied consistently to both classification streams (Sect. 2.3). The residual 1 Mha difference arises from the area computation itself rather than from differences in the mapped extent, area statistics were derived from reduced-resolution COG overviews, specifically overview 380 level 5 (64× reduction, corresponding to an effective pixel size of 640 m) for the 10 m product and overview level 4 (32× reduction, corresponding to an effective pixel size of 960 m) for the 30 m product, and this difference in effective resolution introduces a small amount of rounding at the pixel-aggregation stage. Water bodies, in particular, differ only modestly (537 Mha, 3.9% at 10 m, versus 494 Mha, 3.6% at 30 m), a result of the shared land mask rather than of the differing native water definitions of the two backbones.



Table 3. Area per Level 1 land cover class for the 10 m and 30 m products (2020), reported in million hectares (Mha) and as a percentage of each product's total mapped area. Estimates use latitude-weighted pixel areas to account for the varying pixel size of the underlying geographic grid.

Class	10 m (2020)		30 m (2020)	
	(Mha)	(%)	(Mha)	(%)
1. Built-up	160	1.2	322	2.4
2. Cropland	1,366	10.0	1,327	9.7
3. Grassland	2,642	19.3	2,551	18.7
4. Forest, forest plantations and woodland	4,269	31.3	4,192	30.7
5. Shrubland and heathland	2,000	14.6	734	5.4
6. Sparsely vegetated ecosystems	2,440	17.9	3,342	24.5
7. Inland wetlands	185	1.4	599	4.4
8. Water bodies	537	3.9	494	3.6
9. Coastal ecosystems	59	0.4	99	0.7
10. Aquaculture	0.1	<0.01	0.2	<0.01
Total	13,659	100.0	13,660	100.0

Other differences reflect genuine disagreement between the backbones over transitional classes. Shrubland and heathland accounts for 14.6% of the 10 m product (2,000 Mha) but only 5.4% of the 30 m product (734 Mha), reflecting differences in how the two backbones divide the grassland–shrubland–sparse vegetation gradient rather than a difference in coverage (Sect. 5.2). Built-up area also differs markedly (160 Mha at 10 m versus 322 Mha at 30 m). Because built-up is assigned last in both products, from the backbone alone, this contrast reflects a known difference between the backbones, the GLAD GLCLUC built-up class tends to represent urban extent as spatially continuous cover and to over-estimate its area, whereas ESA WorldCover produces a sparser, more fragmented built-up signal; the low user's accuracy of the 30 m built-up class (Table 4) is consistent with the former. Coastal ecosystems are, conversely, larger in the 30 m product (59 Mha versus 99 Mha), because the coastal-wetland and beach rules are conditioned on additional ESA WorldCover classes in the 10 m stream and are therefore more restrictive there.

These estimates are broadly consistent with other recent global cropland assessments for the same reference year. CROP-GRIDS (Tang et al., 2024) reported a global crop (physical) area of approximately 1,387 Mha in 2020 (167 Mha permanent crops and 1,220 Mha temporary crops). Independently, the cropland area mapping (CAM) aggregation dataset (Tubiello et al., 2023) estimated global cropland area at $1,500 \pm 400$ Mha for the same year, a range within which both GHLC estimates fall.

4.3 Temporal dynamics

Area trajectories per Level 1 class for the 30 m product between 2020 and 2024 are shown in Fig. 5, with corresponding absolute and relative changes summarized in Fig. 6. Overall, most classes changed by approximately 2% or less over the five years, with built-up and aquaculture standing out as clear exceptions. Built-up area increased most markedly in relative terms,



from 322 Mha in 2020 to 383 Mha in 2024 (+18.9%); given the low user's accuracy of this class (Sect. 5.2) and the tendency of the backbone to over-map continuous built-up (Sect. 4.2), this figure should be read as an upper bound rather than a direct estimate of urban expansion. Meanwhile, aquaculture showed the largest relative increase (+40.9%) despite its negligible total extent (0.22 to 0.31 Mha). Among the classes that declined, Forest, forest plantations and woodland showed the largest absolute loss, decreasing by 41.7 Mha (-1.0%) from 4,192 Mha to 4,150 Mha, with losses occurring in every year of the time series. Grassland followed a similar downward trajectory, decreasing by 27.2 Mha (-1.1%), while sparsely vegetated ecosystems and inland wetlands declined more modestly (-13.8 Mha and -4.4 Mha, respectively). Coastal ecosystems, though comparatively small in total area, showed the largest proportional decline of any class (-2.3%), falling from 99.2 Mha to 96.9 Mha.

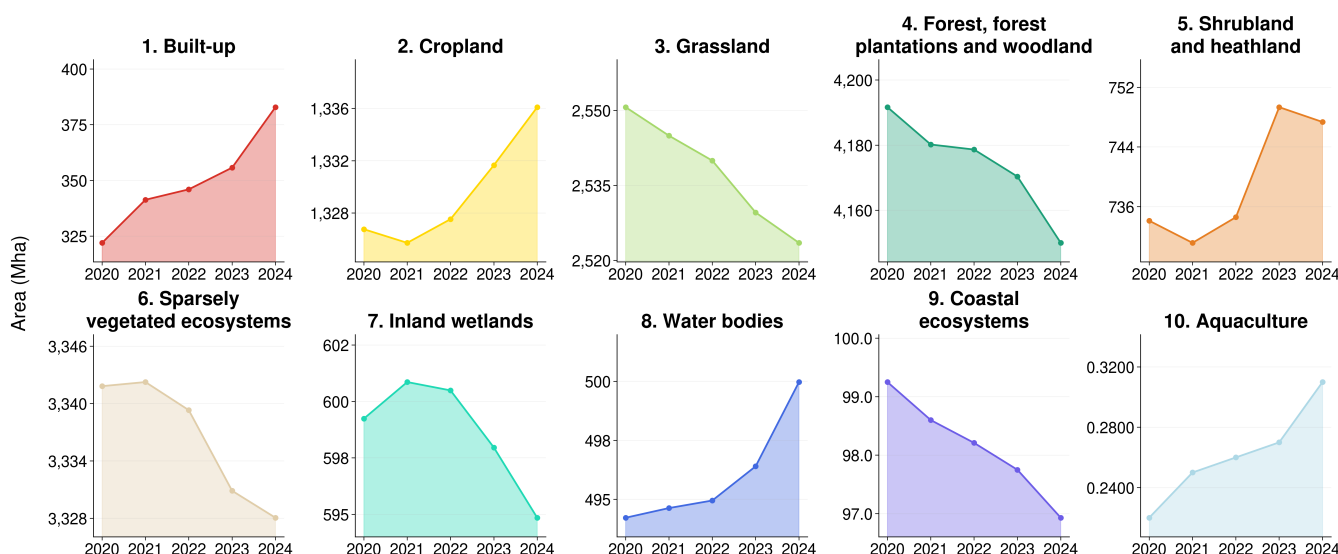


Figure 5. Area dynamics per Level 1 land cover class for the 30 m product, 2020–2024 (million hectares). Each panel shows the annual area trajectory for one class, with the first and last-year values labeled.

In contrast, cropland, shrubland and heathland, as well as water bodies, increased over the period, albeit only marginally, by +0.7%, +1.8%, and +1.2%, respectively. The increase in water bodies likely reflects a combination of reservoir construction and interannual variability in surface water extent, as captured by the GLAD GLCLUC backbone, rather than a systematic hydrological trend. However, given that changes across most classes remain small relative to the total mapped area, longer time series would be needed to confidently distinguish genuine land cover change from interannual classification noise, particularly for classes with more moderate absolute changes.

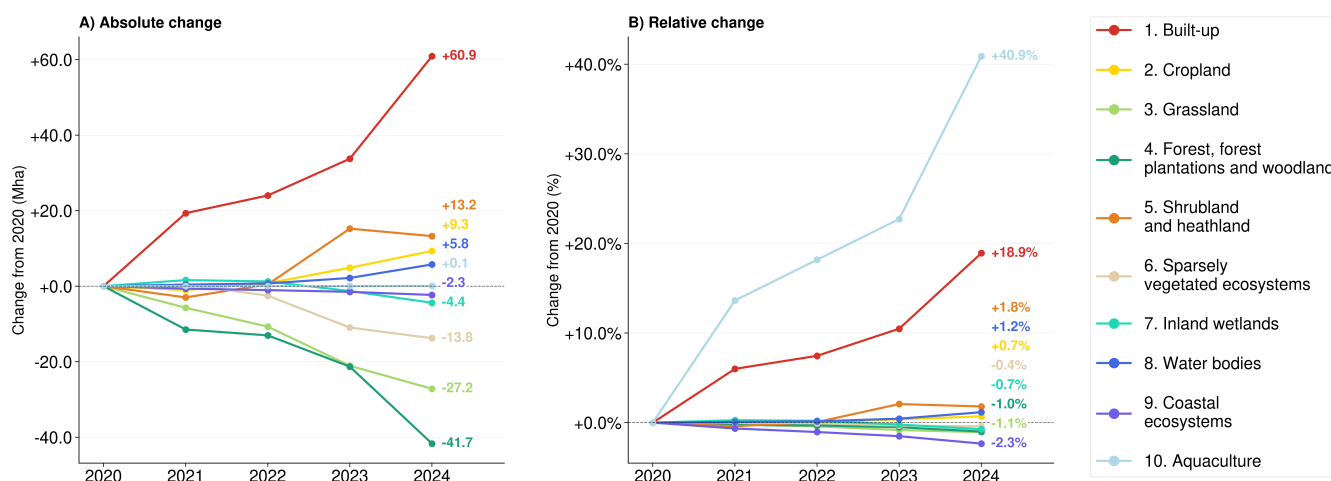


Figure 6. Change in area per Level 1 land cover class for the 30 m product between 2020 and 2024, relative to the 2020 baseline area, showing (a) absolute change (million hectares) and (b) relative change (%). Positive values indicate net gains and negative values indicate net losses.

4.4 Validation

Table 4 summarizes the validation results for both products. The 10 m product achieved an overall accuracy of 0.92 with a weighted F1 score of 0.92, while the 30 m product achieved an overall accuracy of 0.86 and a weighted F1 score of 0.86. Both products performed best for Forest, forest plantations, and woodland ($F1 \geq 0.94$), and for water bodies ($F1 \geq 0.85$), reflecting the spectral distinctiveness and spatial coherence of these classes. Cropland classification was markedly less accurate in the 10 m product ($F1 = 0.72$) than in the 30 m product ($F1 = 0.81$), likely due to the stronger cropland signal in the GLAD GLCLUC backbone. Conversely, several classes showed lower accuracy in both products. Sparse vegetation exhibited low F1 scores (0.17 for 10 m, 0.26 for 30 m), primarily due to low producer's accuracy, indicating that sparse vegetation pixels are frequently misclassified as other classes. Shrubland showed high commission errors in the 10 m product ($UA = 0.36$) and high omission errors in the 30 m product ($PA = 0.36$), reflecting the inherent difficulty of distinguishing shrubland from adjacent grassland and sparse vegetation classes. Built-up areas showed notably low user's accuracy in the 30 m product ($UA = 0.36$), suggesting commission errors in which other land cover types are incorrectly classified as built-up; however, this result should be interpreted with caution, given the limited representation of built-up areas in the GELC reference dataset.

4.5 Regional detail

To illustrate the spatial detail captured by the ensemble classification at the local scale, Fig. 7 presents four regional zoom-in panels covering a $0.5^\circ \times 0.5^\circ$ area centered on a representative landscape in Brazil, Italy, Sudan, and Vietnam. For each region, Sentinel-2 imagery is shown alongside the corresponding 10 m and 30 m land cover products, allowing visual cross-checking of the classification against the underlying satellite imagery.



Table 4. Validation results for the 10 m (2020) and 30 m (2020–2022) land cover products. UA: user’s accuracy; PA: producer’s accuracy; F1: F1 score; n : number of reference samples.

Class	10 m (2020)				30 m (2020–2022)			
	UA	PA	F1	n	UA	PA	F1	n
Built-up	0.60	0.77	0.67	881	0.36	0.81	0.50	2,101
Cropland	0.63	0.83	0.72	7,635	0.80	0.82	0.81	30,342
Grassland	0.63	0.64	0.63	25,309	0.73	0.66	0.69	75,716
Forest, forest plantations and woodland	0.96	0.97	0.96	439,058	0.91	0.97	0.94	507,353
Shrubland and heathland	0.36	0.75	0.48	12,478	0.48	0.36	0.41	34,443
Sparsely vegetated ecosystems	0.41	0.10	0.17	7,290	0.27	0.25	0.26	7,680
Inland wetlands	0.32	0.22	0.26	2,193	0.25	0.60	0.36	6,575
Water bodies	1.00	0.88	0.93	124,139	0.99	0.75	0.85	127,311
Coastal ecosystems	0.89	0.84	0.87	8,352	0.70	0.80	0.75	25,052
OA / F1 _{macro} / F1 _w / n total	0.92 / 0.63 / 0.92 / 627,335				0.86 / 0.62 / 0.86 / 816,573			

435 The four regions span contrasting landscape types. The Brazil panel shows a fragmented cropland-forest mosaic in the Cerrado, where soybean fields (2.1) and other annual crops (2.4) are interspersed with remnant forest patches (4.* classes); both products closely track the field boundaries visible in the Sentinel-2 imagery. The Italy panel, centered on Lake Garda, captures a transition from Alpine forest in the north to a densely built-up and agricultural landscape in the south, with built-up areas (1.1) clearly delineating urban centers along the lake shore and surrounding valleys. The Sudan panel illustrates an
 440 arid-to-hyper-arid landscape along an irrigated agricultural strip, where a narrow band of other annual crops (2.4) and built-up areas (1.1) follows the water source, against a backdrop of true desert (6.1) and semi-arid land (6.2) that dominate the rest of the panel. The Vietnam panel, located in the Mekong River delta, shows an intricate network of rice paddies (2.3) and built-up areas (1.1) following the river channels and canals.

Across all four regions, the 10 m and 30 m products show strong overall agreement in dominant land cover patterns, while
 445 the 10 m product resolves finer features such as narrow water channels, more refined built-up areas, and small field parcels that are locally aggregated or smoothed in the 30 m product. This is particularly visible in the Vietnam panel, where the dense built-up network is more distinctly separated from surrounding cropland at 10 m resolution, and in the Sudan panel, where the 10 m product delineates the cropland strip with sharper boundaries. While the two products show minor differences in class boundaries at Level 2—expected given the roughly nine-fold difference in pixel area—aggregation to Level 1 shows close agreement
 450 in the dominant land cover pattern across the four regions, indicating that resolution primarily affects boundary precision and the detection of rare or spatially confined classes rather than broad thematic consistency. Both products nonetheless maintain a similar thematic structure and class boundaries when compared with the Sentinel-2 imagery, supporting the consistency of the underlying rule-based classification across resolutions.

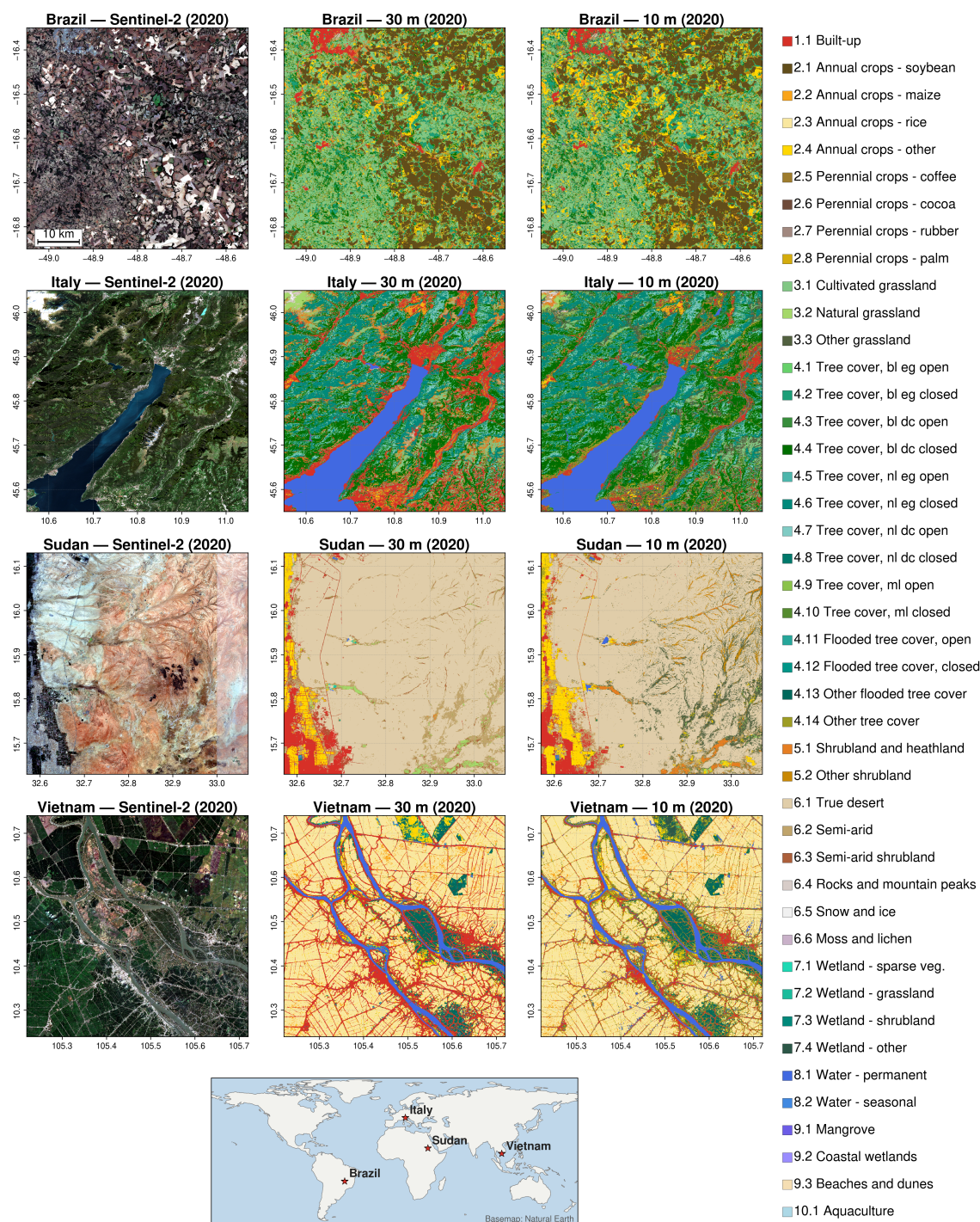


Figure 7. Regional zoom-in panels for four representative landscapes (Brazil, Italy, Sudan, Vietnam), each covering a $0.5^\circ \times 0.5^\circ$ area. For each region, Sentinel-2 imagery is shown alongside the corresponding 10 m and 30 m land cover products. Classes follow the two-level hierarchical legend described in Table 2. The bottom panel shows the geographic location of the four study regions on a Natural Earth basemap.



5 Discussion

455 This study presented GHLC10 and GHLC30, two globally consistent land cover datasets, a 10 m map for 2020 with 44 classes and a 30 m annual time series for 2020–2024 with 40 classes, produced by combining 24 existing land cover, thematic, and auxiliary layers through a documented sequence of conditional rules rather than a trained classifier. In the next sections, we discuss the strengths and limitations of the resulting GHLC, as well as the remaining challenges and opportunities.

5.1 Strengths and performance

460 The central claim of this study is that substantially greater thematic detail can be obtained from existing global products at comparable spatial resolution, without degrading the backbone classification (Level 1), using no trained classifier. The design delivers three properties. First, the classification is transparent, since each pixel's label traces back to a specific rule, condition, and input dataset, and the complete rule set is available in the accompanying code repository (<https://codeberg.org/landmetric/ghlc>) rather than summarized here. Second, it is reproducible, since the rule chain is deterministic and the products can be
 465 regenerated exactly from the published inputs and code. Third, it requires no retraining to update, since a new release of a single thematic layer propagates through the chain by rerunning the classification, without any model needing recalibration. These properties matter for the applications set out in Sect. 1, where the ability to explain why a pixel received a given label can be as important as the label's accuracy, and where products must be refreshed on a reporting cycle rather than rebuilt as research exercises.

470 The way this differs from the established literature on product fusion determines how the products should be evaluated. Most prior fusion work is reconciliation-based, in which several products mapping the same classes disagree with each other. The method decides between them on a fixed target legend by weighting each input according to its estimated reliability, as in consensus weighting (Tuanmu and Jetz, 2014), Dempster–Shafer evidential reasoning (Li et al., 2023), and affinity-based synthesis (Luo et al., 2024). Because the output legend matches the input legend, the success criterion is unambiguous; the
 475 fused product should beat the best single input. The approach taken here is instead compositional, using thematic layers to subdivide a backbone into classes that no single input provides, 44 classes from a backbone of 11 at 10 m, and 40 from a backbone of seven at 30 m, to increase thematic resolution while preserving the backbone's spatial structure. This has a direct consequence for interpreting Sect. 4.4. At Level 1, where the products are aggregated back to categories that the backbones already resolve, agreement with the backbone is what the method is designed to produce. The Level 1 results therefore serve as
 480 a consistency check, confirming that the rule chain does not degrade the backbone; the distinctive contribution lies at Level 2, which we were unable to validate independently (Sect. 5.2).

Within that frame, the Level 1 results require careful reading, because both the headline figures and the difference between them are governed by the composition of the reference pool rather than by the maps. The 10 m product reports higher overall accuracy than the 30 m product (0.92 vs. 0.86), suggesting that the finer product is more accurate; however, the per-class results
 485 do not support this inference. Macro-averaged F1 is effectively identical (0.63 against 0.62), and neither product dominates the other, with the 30 m product performing better for cropland, grassland, sparsely vegetated ecosystems, and inland wetlands.



Forest, forest plantations and woodland together with water bodies, the two classes on which both products perform best, account for 89.8% of the samples available for the 10 m product but 77.7% for the 30 m product, contributing to the apparent accuracy gap. The two products should be considered equivalent at Level 1. More generally, the GELC pool is not distributed in proportion to the mapped area; forest, forest plantations and woodland constitutes 31.3% of the 10 m map but 70.0% of its reference samples. In contrast, sparsely vegetated ecosystems constitute 17.9% of the mapped area but only 1.2% of the samples, so overall accuracy here is not an unbiased estimator of map accuracy but a weighted average of per-class performance, with the weights derived from the reference collection rather than the landscape. The macro-averaged scores are the more defensible summary. The classes they penalize, sparsely vegetated ecosystems, inland wetlands, and shrubland and heathland, are transitional classes defined by gradients rather than boundaries, known to be weakly separated across the global land cover literature (Herold et al., 2008; Fritz et al., 2011), and also the classes this pool samples most sparsely, so their low scores conflate thematic difficulty with sampling sparsity. For the same reasons, the figures reported here are not comparable to the published accuracies of the input products, which were obtained against different reference data, under different legends, and, in the case of ESA WorldCover, under a probability sample designed specifically for unbiased global estimation (Zanaga et al., 2021); we make no claim that these products are more accurate than their own inputs. Estimators that account for the inclusion probabilities of the reference sample (Olofsson et al., 2014) would be required to produce figures unbiased with respect to the mapped area, and we regard this as the highest-priority extension of the present validation.

Finally, the relevance of the products depends on how they relate to the ecosystem typologies used in ecosystem accounting under the SEEA framework, which differ conceptually from land cover legends. The IUCN Global Ecosystem Typology (GET; Keith et al., 2020) groups ecosystems at its upper levels by convergent ecological function and at its lower levels by contrasting species assemblages, criteria not represented in any input dataset used here, so GHLC cannot be meaningfully crosswalked to it without substantial additional information. The EU Ecosystem Typology (EUET; Eurostat, 2026), by contrast, is a closer match; its Level 1 terrestrial classes correspond closely to GHLC's own Level 1 categories, while water and coastal environments are subdivided differently between the two. At Level 2, the two typologies remain broadly comparable in kind; both EUET and GHLC define their Level 2 classes primarily through structural and thematic criteria, such as crop type, leaf type, and management intensity, rather than species identity. It is at EUET's Level 3 that the two diverge, introducing genuine species- and community-level detail, drawn from dense in-situ ecological surveys; GHLC has no equivalent third tier. GHLC's Level 1 classification is therefore well-suited as a direct input to EU ecosystem extent accounting and, more broadly, offers a level of structural detail at a global, consistent, and reproducible scale that existing ecosystem typologies do not themselves provide.

5.2 Limitations

The produced rules and global datasets have numerous limitations that should be noted. First, our estimate of data quality is limited. Our validation focused on Level 1, where the products are least distinctive; the thematic detail that motivates this work remains unverified against independent reference data. Level 2 classes inherit whatever accuracy their source products possess. Nevertheless, an accuracy inherited from an input assessed on its own terms, to its own extent, is not equivalent to an accuracy established for the composed product, and it should not be assumed that agreement at Level 1 will transfer



downward. In addition, classes are sampled sparsely relative to their mapped extent; notably, built-up ($n = 881$ for the 10 m product) and sparsely vegetated ecosystems are insufficiently represented to support conclusions about map quality, and their per-class metrics principally describe the reference pool rather than the maps. This means that per-class accuracy estimates for sparsely sampled classes should be treated with greater caution than the headline metrics might suggest, independent of whether the true accuracy for those classes is higher or lower than reported.

Two further limitations are derived from our design. The classification is sequential and deterministic; each pixel takes the label of the first rule that it satisfies, and no later rule can revise it. This is what makes each label traceable, but the priority ordering is itself a modeling decision wherever two rules would both fire, errors in an input propagate directly into the output with no opportunity for downstream correction, and neither product carries a per-pixel measure of how close a pixel came to a different assignment. Probabilistic approaches such as evidential reasoning (Li et al., 2023) or accuracy-weighted consensus (Tuanmu and Jetz, 2014) yield a graded measure of agreement as a by-product, at the cost of the traceability sought here; its absence is a genuine limitation, particularly for ecosystem accounting, where the credibility of extent accounts rests on the auditability of their spatial inputs. Separately, several layers are static or are updated intermittently; for example, the perennial crop probabilities (2020 and 2024, interpolated between), and the mangrove and aquaculture masks (held at their most recent versions). Stability in the affected classes might be influenced more by the frequency of input updates than by the landscape. As mentioned in Sect. 4.3, the apparent 40.9% growth in aquaculture cannot originate in the aquaculture mask, which is kept constant, and must be attributed to changes elsewhere in the rule chain.

The two products (30 m and 10 m) are, unfortunately, not entirely interchangeable either. Their differing backbones still introduce one systematic difference in mapped area (Sect. 4.2), shrubland and heathland accounts for 14.6% of the 10 m product but only 5.4% of the 30 m product. This shrubland discrepancy is not attributable to a structural cause and instead reflects genuine disagreement about how to partition the grassland–shrubland–sparse vegetation gradient. Neither product’s absolute area for this transitional class should be treated as authoritative, and the two should not be combined in a single area time series. As with the transitional classes discussed in Sect. 5.1, this disagreement likely reflects inconsistent class definitions rather than mapping error. Tubiello et al. (2023) reached a similar conclusion for cropland extent, showing that disagreement across six independent land-cover products stemmed largely from inconsistent inclusion of pastures and shrub crops within each product’s cropland definition; a comparable definitional mismatch plausibly explains the shrubland–grassland–sparse-vegetation disagreement reported here.

A final limitation of GHLC is structural. In a conventional ML-driven classification, a trained model, once fitted, can be reapplied to new imagery indefinitely (this, in turn, depends on the continued operation of missions such as those run by ESA and NASA, which we take as a reasonable baseline assumption). The GHLC method depends on 24 derived layers, each of which exists only because a research group or agency chose to produce and maintain it. If those layers cease to be updated, the corresponding rules cannot fire, and the classification degrades class by class until, in the limit, the method has nothing to compose. This cannot be engineered away; it is intrinsic to compositional design and the price of not having to train, label, and validate our own global classifier. The ability of data-producing groups to actively maintain and improve their datasets is, today, at least as important as open licensing or professional technical documentation (Giner-Miguel et al., 2025).



We state it plainly because it carries an implication worth making explicit. Ensemble methods of this kind demonstrate that a single-purpose thematic product has value well beyond its original purpose; a rice mask produced for agricultural monitoring or a mangrove layer produced for coastal conservation becomes a load-bearing component of a general-purpose global land cover map, a role its authors probably never anticipated. That compounding value is largely invisible in the citation record and in the funding case for the original product. The persistent disagreement among general-purpose products that motivated two decades of fusion research (Fritz et al., 2011) is, from this point of view, partly a consequence of each attempt to do everything at once; the alternative demonstrated here instead depends on a healthy ecosystem of specialized layers, each doing one thing well. We therefore encourage continued production and, equally, continued maintenance of such layers. Maintenance is the harder half; open licensing alone does not guarantee long-term access. An empirical survey of research data repositories found that many had closed or become inaccessible over the past two decades, and that successor arrangements have often been absent (Strecker et al., 2023). Publishing the processing code alongside the data, so that products can be regenerated as inputs are revised, converts a static release into something maintainable (Ho et al., 2025), and we have followed this approach here.

A further challenge for the seamless integration of land cover products (global, regional, and national) is that we had to develop manual rules to integrate various land cover systems. FAO has recently promoted an international Land Cover Legend registry (LCLR; <https://data.apps.fao.org/lclr-tool/en/>), which should help harmonize legends across borders. Unfortunately, most global or continental land cover classification systems are not registered in FAO's LCLR system. In addition, our experience is that automated translation of legend entries is cumbersome, since each entry needs to be studied and analyzed in detail, and it can lead to different rules.

5.3 Future work and perspectives

Three future development priorities follow from the above. The first is a validation design that is compatible with the products. Accuracy should be estimated using estimators that account for the inclusion probabilities of the reference sample, so that the figures are unbiased with respect to the mapped area rather than how the reference pool happens to be composed (Olofsson et al., 2014); based on the present evidence, this will lower the headline figures and raise their credibility, which is the correct trade. Reference collection should be stratified by Level 2 rather than Level 1, and concentrated on the classes introduced by the thematic layers, for which no current global reference dataset provides adequate per-class sample sizes, and on the transition classes, where sampling sparsity and thematic difficulty are currently confounded. The input products should also be evaluated against the same reference sample under the same legend, which would establish where the composed product departs from its backbone and quantify what the thematic overrides contribute; the reference points already assembled here provide a starting point, making this a matter of extraction and crosswalking rather than new data collection.

The second is temporal depth, and here the compositional design meets a hard limit. Sect. 4.3 shows that five years is too short to separate genuine land cover change from interannual classification noise for most classes, and ecosystem accounting typically requires longer reporting periods. The backbone would permit extension, since the GLAD GLCLUC series dates back to 2000 (Potapov et al., 2022), but the composition as a whole would not; several layers supplying Level 2 classes do not exist for earlier years at all, including WorldCereal (Van Tricht et al., 2023), and the FDP crop probabilities (Forest Data



Partnership, 2025), and layers already held constant for five years could not credibly be held constant for twenty-five. Extending these products backward would therefore require abandoning the classes that those layers provide, thereby removing much of what distinguishes them. The temporal extent of a compositional product is set by its youngest essential input, and the period presented here is the period over which the necessary thematic layers exist. This constraint is not peculiar to the rule-based design adopted here. Still, it applies to any product assembled from existing maps, a data-driven ensemble of global land cover products that we are developing separately reaches no further back than the products it draws on and is similarly bounded. What differs among such approaches is where the binding constraint lies; the thematic layers that make the present legend possible are recent, whereas the general-purpose products that reach further back resolve fewer classes. In summary, the trade is between thematic richness and temporal reach rather than between methods, and neither approach is immune to the availability of its inputs.

The third is uncertainty. Recording which rule fired and how many competing rules were close to firing would partially recover the information that the deterministic design discards, while preserving the traceability that motivates it. Together with an explicit crosswalk to existing ecosystem typologies, this would substantially improve the usability of the products for ecosystem accounting, to the extent that accounts must be auditable rather than merely available. However, such a crosswalk remains laborious because the field lacks automated tooling to translate between legends. The FAO LCLR (Mushtaq et al., 2022) catalogs legends in a common formalism, structured according to the ISO 19135 registry standard and documenting classes in the Land Cover Meta Language (LCML; ISO 19144-2), while the Action Group on Land Monitoring in Europe (EAGLE) concept decomposes nomenclatures into elementary components so that classes can be compared through their constituent attributes rather than their labels, representing a paradigm shift away from traditional, paper-map-based land classification toward an object-oriented, descriptive characterization of the Earth's surface that underlies the CLC+ Backbone and CLC+ Core databases (Arnold et al., 2015, 2025). LCLR, LCML, and EAGLE are among the most comprehensive and best-documented frameworks for hierarchical land cover legends, taxonomies, and metadata, and together provide strong semantic foundations; what is missing is a means to derive and apply a crosswalk between two arbitrary legends programmatically. We see its development as a precondition for routinely assembling ensemble products of this kind rather than as a bespoke exercise, and we encourage groups working on legend harmonization to build on these frameworks.

6 Conclusion

We introduced a simple and robust framework for creating high-resolution global land cover products without training a machine learning classifier from scratch. Our results show that a substantially greater thematic detail (+40 Level 2 classes) can be obtained from existing datasets at high spatial resolutions (10 m and 30 m) using a transparent, deterministic sequence of conditional rules. We generated two new datasets:

1. **10-meter product (GHLC10, 2020):** which uses ESA WorldCover as its spatial backbone to produce a single global map with 44 thematic classes;



2. **30-meter product (GHLC30, 2020–2024):** which uses GLAD GLCLUC as its spatial backbone to generate annual multi-temporal maps with 40 thematic classes.

Both products achieve strong overall baseline accuracies at Level 1 (10 broad classes). GHLC10 achieved an OA of 0.92, and a weighted F1-score of 0.92, while GHLC30 achieved an OA of 0.86, and a weighted F1-score of 0.86. Forests, forest plantations and woodland ($F1 \geq 0.94$), as well as water bodies ($F1 \geq 0.85$) performed best across both resolutions due to their high spectral distinctiveness and spatial coherence. Cropland classification was more accurate in the 30 m product ($F1 = 0.81$) than in the 10 m product ($F1 = 0.72$), likely because the 30 m GLAD GLCLUC backbone provides a stronger cropland signal. Macro-averaged F1 across all classes was similar for the 10 m (0.63) and 30 m (0.62), demonstrating that spatial resolution alone does not determine overall accuracy.

The GHLC10 and GHLC30 datasets provide fine-grained thematic categories that serve as direct inputs for ecosystem extent reporting under the UN SEEA frameworks. Transitional vegetation classes remain challenging to classify, most notably sparse vegetation ($F1 = 0.17$ at 10 m and $F1 = 0.26$ at 30 m), shrublands, and inland wetlands. Future work should address spectral confusion and uncertain class boundaries in semi-arid and arid biomes by evaluating input products against standardized reference samples using harmonized legends, thereby quantifying the specific contribution of thematic overrides. Furthermore, validation designs specifically tailored to fine-grained thematic products are needed, including dedicated reference sampling for specialized crop types (maize, rice, soybean) and more detailed forest leaf/canopy subcategories.

Because GHLC relies on 24 external, independently derived layers maintained by separate agencies (e.g., WorldCereal, Global Mangrove Watch), GHLC faces a long-term maintenance risk. If external producers stop updating a layer, the corresponding rule cannot be run, causing the ensemble classification system to degrade class by class over time. Supporting a healthy ecosystem of specialized thematic layers and prioritizing long-term dataset maintenance over one-off mapping efforts are necessary. Furthermore, because GHLC10 and GHLC30 use different backbones (ESA WorldCover and GLAD GLCLUC), they exhibit structural differences that are unrelated to the classification rules. For example, ESA WorldCover maps shrubland across 14.6% of the globe at 10 m versus only 5.4% at 30 m. This indicates that future multi-resolution products need harmonized spatial masking to enable seamless cross-resolution time series. Manually curating deterministic rules is labor-intensive and difficult to standardize because most global classifications are not registered in automated tools such as the FAO LCLR. We therefore also call all data producers to leverage object-oriented ontologies, EAGLE, and the UN LCML, to derive and apply semantic crosswalks between arbitrary legends programmatically.

In the end, although we initially criticized the overwhelming number of land-cover products and initiatives at national, regional, and global scales, we believe that diversity of methods and creative solutions can, in fact, help produce a global, common land cover dataset that is *the-best-of-the-best* and outperforms any individual product. Whether such data fusion can be fully automated or will continue to require expert-based systems remains an open question.



Code and data availability. The GHLC10 and GHLC30 datasets, together with the source code implementing the GHLC framework and the deterministic classification rules used to generate these products, are publicly available at <https://source.coop/opengeohub/ogh-ghlc10> and
655 <https://codeberg.org/landmetric/ghlc>, respectively. The datasets can also be visualized through the <https://app.landmetric.org> web platform.

Author contributions. MM: conceptualization, data curation, formal analysis, methodology, validation, visualization, software, writing (original draft preparation). LP: conceptualization, data curation, formal analysis, funding acquisition, methodology, software, supervision. LH: conceptualization, funding acquisition, methodology, writing (original draft preparation). CB: conceptualization, methodology. QX: data curation, software. MSI: data curation, writing (original draft preparation). MIW: data curation, software. MP: conceptualization, writing
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