SCIENCE BASED TARGETS FOR LAND

VERSION 0.3 – SUPPLEMENTARY MATERIAL

SBTN NATURAL LANDS MAP: TECHNICAL DOCUMENTATION

STEP

3

MEASURE, SET & DISCLOSE

LAND

SCIENCE BASED TARGETS NETWORK

GLOBAL COMMONS ALLIANCE

Table of Contents

SBTN Natural Lands Map

Authors: Elise Mazur[1], Michelle Sims[1], Elizabeth Goldman[1], Martina Schneider[1], Fred Stolle[1], Marco Daldoss Pirri[2], and Craig R. Beatty[3]

1: World Resources Institute
2: Food and Land Use Coalition / SystemIQ
3: World Wildlife Fund – United States

1. INTRODUCTION

Natural lands are being lost and degraded at unprecedented levels (IPBES, 2019). Three-quarters of land and two-thirds of oceans have been significantly impacted by humans through pollution, urban expansion, conversion to crop or livestock production, intensive logging in natural forests, unsustainable fishing practices and other activities. The rate of species extinctions is also accelerating, with some experts warning that a sixth mass extinction may be under way. Wildlife populations have decreased by 69% since 1970 (WWF, 2022), and projections estimate that three-quarters of today's animal species could go extinct within 300 years (Barnosky et al. 2011).

Climate change is intertwined with natural land loss. According to the Intergovernmental Panel on Climate Change (IPCC 2019), emissions from the agriculture, forestry and other land use sector contribute 23% of all anthropogenic emissions. In 2018, the IPCC warned that to avoid the worst impacts of climate change, global warming must not exceed 1.5°C above pre-industrial temperatures. To achieve this, greenhouse gas (GHG) emissions must halve by 2030, and drop to net-zero by 2050. Many governments, corporations and other entities around the world have met this call to action with ambitious pledges to reduce and eliminate their share of GHG emissions. However, the sector-wide transformations needed to achieve net-zero by 2050 require coordination and guidance on how to do this effectively and efficiently.

Voluntary schemes have emerged to help entities fully understand their impact on nature and emissions contributions and determine a plan for reducing or eliminating this impact. The Science Based Targets Network (SBTN) is one such voluntary scheme. It builds on the progress of the Science Based Targets initiative (SBTi) which enables companies to set science-based greenhouse gas emissions reductions and net-zero targets. SBTN is a network of international environmental nonprofit organizations, international agencies and mission-driven entities developing methods and resources for science-based targets (SBTs) for nature for companies, and science-based targets for both climate and nature for cities. SBTN's goal is for the world's major companies and cities to have adopted science-based targets and taken action for climate, water, land, ocean and biodiversity by 2025. This will form a key part of progress towards meeting the commitments of the Paris Agreement.

SBTN's Land Hub has developed the first version of its voluntary corporate target setting methodology. These targets allow companies to engage in quantifiable and meaningful actions that address their main impacts on land systems. Besides their specific contributions to achieving global goals for nature, the design of the three land targets comprehensively addresses the avoidance and reduction of impacts and puts companies on a pathway to substantial engagement in landscape initiatives that regenerate, restore, and transform the interaction between nature and business. All three targets work in conjunction to prevent negative consequences from one of the targets alone. The targets are:

1. No conversion of natural ecosystems
2. Land footprint reduction
3. Landscape engagement

The first among these targets, no conversion of natural ecosystems, recognizes the value of *all* ecosystems. Until recently, commitments were primarily focused on forests and achieving zero-deforestation targets (Taylor et al. 2022). However, this ignores other valuable and vulnerable natural ecosystems. For example, grasslands and other short vegetation ecosystems like shrublands are one of the largest biomes on Earth and are rich in biodiversity, yet they are particularly susceptible to conversion because they are easier to clear than forests. Wetlands are vulnerable to development, despite their critical role in providing habitat, improving water quality, and preventing floods. All natural ecosystems store and sequester carbon, support biodiversity, regulate the climate, filter air and water, protect communities from flooding, regulate against diseases and pests, and provide food, medicine, fuel and shelter.

Preventing the conversion of natural ecosystems starts by knowing where natural lands exist by delineating them into a map – The SBTN Natural Lands Map. This map:

- Provides companies and other stakeholders with a baseline from which to estimate their conversion of natural lands from 2020 with their current production or sourcing site data.
- Provides a baseline for independent groups to monitor conversion of natural lands once monitoring datasets for lands outside forests become available.
- Features in the SBTN Land methodology and allows companies to understand their contributions to conversion and set no conversion of natural ecosystems targets.
- Provides a 2020 baseline for these calculations that is agreed upon by a broad membership of organizations, including those of the SBTN Land Hub and the Accountability Framework Initiative (AFi)

The SBTN Natural Lands Map does **not**:

- Inform scientific research and analysis that use different definitions of natural lands
- Quantify the area of natural and non-natural lands
- Supplant existing research and biophysical mapping and analysis on ecosystem science
- Define ecosystems and/or working lands
- Assess the importance of the natural land for biodiversity
- Assess the quality of ecosystems
- Replace the need for local validation to ground truth the data
- Represent an unbiased map of natural lands - a conservative approach overestimates the extent of natural lands, and while remote sensing can provide powerful insights, additional field work should be used for validation and to understand local dynamics

This technical note outlines the methods, results, and limitations of the first version of the 2020 Natural Lands Map. The map will be used by SBTN to permit companies to set No Conversion of Natural Ecosystems Targets and to understand and calculate the conversion of natural ecosystems for which they are responsible. It will be updated in the coming years as better data becomes available.

2. DATA AND METHODS

Our approach for identifying natural lands across the world was to combine the best available global spatial data on land cover and land use into a single harmonized map at a 30 meter resolution circa the year 2020. We aligned our definitions and approach to the extent possible with the Accountability Framework Initiative (AFi) definitions (AFi 2019) of natural ecosystems and AFi Operational Guidance on Applying the Definitions Related to Deforestation, Conversion, and Protection of Ecosystems (AFi 2019), recognizing the limitations on what can be directly mapped with earth observation data and relying on proxies to operationalize these definitions based on existing land cover/land use and supplementary data. We assessed and selected the land cover and land use data that were best suited for distinguishing between natural and non-natural land, using additional data where necessary and possible.

While a global approach to mapping natural lands can help produce consistent, comparable results, local ecosystems are not always well represented with global data. For example, the Cerrado Biome in Brazil has short trees which are sometimes missed with global forest data calibrated for vegetation higher than 5 meters. Where possible, the natural lands map incorporates and prioritizes local data to better represent local ecosystems.

2.1 Definitions

Science Based Targets Network (SBTN) adopted the AFi definitions of natural ecosystems and forests, which were used as guidance for developing the map. AFi defines a natural ecosystem as “one that substantially resembles - in terms of species composition, structure, and ecological function - what would be found in a given area in the absence of major human impacts”, and can include managed ecosystems as well as degraded ecosystems that are expected to regenerate either naturally or through management (AFi 2019). Because species composition and ecological function cannot be directly mapped with earth observation data, our approach operationalizes AFi definitions using proxies based on available data that align with AFi guidance to the extent possible. We used AFi Operational Guidance in Applying Definitions (AFi 2019) to guide our development of proxies (see Table 1).

While natural forests are of course part of natural ecosystems, a detailed forest definition is also provided by AFi, as adopted from the Food and Agriculture Organization of the United Nations (FAO). Forests are defined as “land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or other land use” (AFi 2019). When height or canopy cover thresholds used to define forests in local data sources differed from the AFi thresholds, we adopted the thresholds used in the local data. This approach aligns with guidance provided by AFi, which states that “quantitative thresholds (e.g., for tree height or canopy cover) established in legitimate national or sub-national forest definitions may take precedence over the generic thresholds in this definition” (AFi 2019).

Table 1. AFi operational guidance and description of how it was used to develop mapping approach. Specific data and methods used are described in section 2.2 and 2.3

AFi classification	Attributes and descriptions in AFi operational guidance, with italic indicating elements that cannot be directly mapped with remotely sensed data	Description of how AFi guidance was used to determine operational proxy	Limitations of proxy
NATURAL FOREST			
Unmanaged or minimally managed natural forest	Unmanaged or minimally managed natural forest, including with some human impacts	We used the definition of forests (tree cover greater than 5 meters in height and more than 0.5 hectares) and the process of elimination to map natural forests by labeling plantations, planted forest or tree crops as non-natural. Where definitions of forest used in local data differ from the AFi global forest definition with regard to height, canopy cover, or minimum mapping unit, we adopted the local definition. When evaluating supplementary data or local data, any class name or description that included “natural”, “native”, “naturally regenerating”, or “secondary” were considered natural.	May include tree plantations and tree crops when data is not available for specific regions or crop types. May include severely degraded forest. May include areas under shifting cultivation, regardless of the length of fallow period or impact. May include tree cover within agricultural mosaics, regardless of whether it is under agricultural use. May include agroforestry, regardless of intensity or whether crops are grown under forest canopy
Managed natural forest	Forests that are managed for harvest or services in a way that maintains most of the key elements of ecosystem composition, structure, and function over time Forests undergoing selective harvest where high value species are planted or promoted		
Regenerated natural forest	Forests that have regrown and now have ecosystem composition, structure and function similar to forest native to the site Regrowth of *native* vegetation for several years after agricultural abandonment Plantings of diverse native tree species through management for ecosystem restoration		
Non-permanent or low-intensity cultivation within a natural forest	Permanent, semi-permanent, or shifting cultivation that causes little disturbance of the canopy and retains a high proportion of species and main attributes of the forest's structure and function Swidden cultivation in small, isolated patches harvested for short periods and then left fallow Low-intensity forest farming such as some rustic coffee and rubber agroforestry systems *under forest canopy*		
NATURAL NON-FOREST ECOSYSTEM			
	• Largely “pristine” natural ecosystems that have not been subject to major human impacts in recent history • Regenerated natural ecosystems that were subject to major impacts in the past but where the main causes of impact have ceased or greatly diminished and the ecosystem has	• We used the process of elimination to map natural short vegetation by labeling all short	• May include unstocked forest. • May include pasture. • May include fields used for various

attained species composition, structure and ecological function similar to prior or other contemporary natural ecosystems. • Managed natural ecosystems (including many ecosystems that could be referred to as "semi-natural") where much of the ecosystem's composition, structure, and ecological function are present, including native grasslands or rangelands that are, or have historically been, grazed by livestock • Natural ecosystems that have been partially degraded by anthropogenic or natural causes (e.g. harvesting, fire, climate change, invasive species, or others) but where the land has not been converted to another use and where much of the ecosystem's composition, structure, and ecological function remain present or are expected to regenerate naturally or by management for ecological restoration. • Grasslands, savannahs, wetlands, and other areas that are not recently transformed or intensively managed, and maintain much of the ecosystem's structure, composition, and function • Includes many traditional pastoral systems and well-managed livestock grazing on native vegetation	vegetation with high densities of ruminant livestock, cropland, or tree crops as non-natural. • When evaluating local or supplementary data, any class name or description that included "natural, "native", "low-intensity grazing", "secondary", or "naturally regenerating" was considered natural.	purposes, including recreation or agricultural activities. • May include areas under shifting cultivation, regardless of the length of fallow period or impact. • May include severely degraded non-forest ecosystems.
TREE PLANTATION		
• Eucalyptus or rubberwood plantations • Monocultures of temperate or boreal species where such monocultures would not have naturally existed • Monoculture and/or even-aged management where such management does not approximate the spatial and temporal dynamics of a natural forest ecosystem • All or a substantial portion of planted trees are exotics • Regular herbicide or pesticide usage	• We used available data on tree plantations, wood fiber or timber plantations, and planted forests. • When evaluating local and supplementary data, any class name or description that included "plantation" or "planted" were considered non-natural.	• Tree plantations are not mapped comprehensively for all regions. Therefore, tree plantations may be mapped as natural forest. • Planted forests are not mapped comprehensively for all regions, and data on forest management is extremely limited and may not contain sufficient detail on management intensities. Therefore, some monoculture/even-aged management may be mapped as natural, and likewise some semi-natural planted areas may be non-natural, even if meeting AFi criteria for natural forest.

AGRICULTURE			
Permanent smallholder agriculture for local consumption and trade; permanent agriculture for commodity production	• Annual or perennial cropping systems (including most agroforestry systems) where the production is for subsistence use within the household, local trade among individuals, or trade involving local intermediaries for local markets • Annual crops, intensive livestock raising, perennials in monoculture or simple polyculture, tree crops • Soy, sugar, most cattle ranching, palm oil, coconut, fruit orchards, and coffee or cocoa grown with no shade or light to moderate shade For boundary cases, may include: • Intensification of swidden agriculture in which patches become larger, cultivation periods longer, fallows shorter • Cultivation leads to significant and long-term change in ecosystem composition, structure, and function	We used available data on: • Cropland • Tree crops • Specific crop types • High ruminant density areas • When evaluating local and supplementary data, any class name or description that indicated "mixed agriculture", "agricultural mosaic", "pasture", "high-intensity grazing", or "cultivated" was considered agricultural use and thus non-natural.	• Tree crops are not mapped comprehensively for all crop types or for all regions. Therefore, some tree crops may be mapped as natural forest. • Data on pasture and livestock is severely limited. Therefore, pasture may be mapped as natural. • Due to the dynamic nature of shifting agriculture, it is often not included in data on cropland. Therefore, shifting agriculture, regardless of length of fallow period or impact, may be mapped as natural.
SEVERELY DEGRADED LAND			
Land formerly meeting the definition of a natural ecosystem (either forest or non-forest) that has experienced severe and sustained degradation that alters ecosystem composition, structure, and function to the extent that regeneration to a prior state is unlikely. Degraded natural ecosystems (including forests) are generally presumed to be natural ecosystems unless: • The land is managed for uses other than natural ecosystem • Due to severe or sustained degradation, the ecosystem is not able to regenerate much of its prior ecosystem structure, composition, and ecological, biophysical, and cultural functions naturally and/or through assisted regeneration		Because ecosystem composition and function cannot be directly mapped with remotely sensed data, we only classified severely degraded areas as non-natural if they were mapped by existing data as within an agricultural or built-up extent.	• Severely degraded forest patches or other ecosystems within agricultural areas may be mapped as natural if they are not specifically mapped as agriculture by existing data. • In general, severely degraded ecosystems may be mapped as natural.

Note: AFi classification, descriptions, and attributes are from AFi definitions and Tables 1 and 2 from AFi Operational Guidance on Applying the Definitions Related to Deforestation, Conversion, and Protection of Ecosystems (AFi 2019).

We also considered AFi's conversion definition in anticipation of the relevance of these natural lands map for monitoring purposes, which includes "a change to another land use or profound change to composition, structure, or function" (AFi 2019). Conversion can happen regardless of whether or not the change was legal. In this technical note we do not map or monitor conversion.

Additional natural land cover classes beyond forests were included in the map: short vegetation, which includes grasslands and shrublands, water, snow/ice, bare land, and wetlands (Table. 2). In the absence of specific definitions for these ecosystems from AFi, we relied on definitions from available data sources. Here, short vegetation is defined as areas of land with vegetation shorter than 5 meters, and can include areas of land dominated by grass or shrubs. Water is defined as surface water present 20% or more of the year, outside of wetlands. Snow and ice include any permanent snow and ice. Wetlands are transitional ecosystems with saturated soil that can be inundated by water either seasonally or permanently, and can be covered by short vegetation or trees. Bare land is defined as areas with exposed rock, soil, or sand with less than 10% vegetated cover. Table 2 includes examples of the types of ecosystems which may be included under these broad land cover classes.

Table 2: Examples of ecosystem types that may be included under the map's natural land cover classes.

Natural land cover class	Class definition	Ecosystem examples
Forest	Areas with tree cover greater than or equal to 5 meters in height spanning more than 0.5 hectares.	Rainforests, dry forests, montane rainforests, heath forests, temperate forests, boreal forests, woodlands, some types of savannas.
Short vegetation	Areas of land with vegetation shorter than 5 meters, including areas of land dominated by grass or shrubs.	Grasslands, shrublands, heathlands, steppes, vegetated deserts and semi-deserts, some types of savannas.
Wetlands	Transitional ecosystems with saturated soil that can be inundated by water either seasonally or permanently and can be covered by short vegetation or trees.	Peatlands, mangroves, inland, coastal, saline, freshwater, brackish.
Water	Surface water present 20% or more of the year, where water is the dominant class.	Rivers, lakes, coastal inlets, bays, lagoons.
Snow/Ice	Areas covered by permanent snow or ice.	Glaciers, perennial snowfields.
Bare land	Areas with exposed rock, soil, or sand with less than 10% vegetated cover.	Sparsely-vegetated deserts, lava flows, screes, alpine rocky outcrops, sandy shorelines.

Note: The ecosystem examples included in this table are not an exhaustive list of all ecosystems included within each land cover class, but are illustrative examples of some types of ecosystems which may be included. Land cover classes are defined based on the biophysical presence and coverage of certain types of vegetation or landforms, and thus a similar type of ecosystem in different regions may fall into different land cover classes depending on the biophysical characteristics present. Please note that in cases where local data was incorporated, we adopted the local definition of the land cover, therefore there may be inconsistencies in how land cover classes are defined (e.g. with regard to tree height threshold for forests, etc.).

2.2 Datasets

The natural lands map combines data collected from a variety of sources that were assessed for quality and met certain criteria (Table 3). Additionally, all data – including local data sources – were subject to a visual inspection as an added assurance that the land cover classes selected matched our own understandings of these ecosystems.

Table 3: Selection criteria for natural lands map data.

Licensing	Data included in the map should be publicly accessible and licensing should allow for a wide variety of uses, including commercial.
Resolution	Data included in the map should have a spatial resolution of 30 x 30 meters or higher. If no 30 x 30 meter data are available, coarser resolution data can be included to fill any data gaps. Vector data are also suitable for inclusion if high resolution raster data is not available.
Timescale	Data included in the map should be as close to the year 2020 as possible, but not after it.

Accuracy	Data included in the map should have robust user and producer accuracy scores when available. When using a specific class within a dataset, we looked at individual class accuracy. Accuracy was considered, along with the other selection criteria, when comparing among available data.
Definitions	Class definitions are aligned with our mapping needs.
Coverage	Data included in the map should have a global extent to ensure all geographies have coverage. However, local data that meet the other requirements outlined in this table, and which define land cover classes and natural ecosystems in a way that is aligned with our mapping needs, should take precedence over global sources. While this map version considers a limited set of regional data for incorporation, future versions will likely include more regional data.

First, we assessed and selected global land cover data to establish the base land cover classes in the natural lands map. Because most global land cover maps define vegetated classes based on the biophysical presence of vegetation types and do not contain information on the degree of human impact or other characteristics that can be used to delineate natural ecosystems according to the AFi definition, we evaluated additional supplementary datasets to distinguish natural and non-natural lands for specific land cover classes. For this beta version of the map, we evaluated a limited set of regional data that met our criteria for inclusion due to time constraints. We are actively incorporating more local data for future versions of the map.

2.2.1 Land Cover Classes

The land cover classes included in the map are largely drawn from two maps of global land cover for 2020: (a) WorldCover, a 10 meter resolution dataset created by the European Space Agency (ESA) (Zanaga et al. 2021), and (b) Global Land Use and Land Cover Change, a 30 meter resolution dataset created by the Global Land Analysis and Discovery Lab at the University of Maryland (UMD) (Hansen et al. 2022; Potapov et al. 2022). Both share a similar classification scheme, and were compared to decide which land cover classes from each product were most appropriate for our map (Table 4A and 4B).

Table 4A: Breakdown of land cover classes and measures of user accuracy (UA) and producer accuracy (PA) as reported in their technical documentation. Bold indicates that the data were included in the natural lands map.

Map Class	ESA	UA | PA	UMD	UA | PA
FORESTS	Trees	80.8 | 89.9	Forest	94.6 | 94.8
SHORT VEGETATION	Shrubland	38.6 | 44.1	Short Vegetation	N/A
	Grassland	69.3 | 76.7		
WETLANDS	Herbaceous Wetland	27.8 | 40.6	Wet Short Vegetation	52.4 | 59.6
	Mangroves	68.6 | 51.5	Wet Forest	
	Open Water	88.5 | 85.0	Permanent Water	98.8 | 86.1
NON-NATURAL	Cropland	81.1 | 76.7	Cropland	88.5 | 86.4
	Built-up	67.7 | 67.9	Built-up	63.7 | 39.1
OTHER	Barren/Sparse Vegetation	87.5 | 81.4	Bare	N/A

	Snow and Ice	93.9 | 97.0	Ice	92.6 | 97.1

Table 4B: Summary of comparison between ESA WorldCover and UMD Land Cover data, notes from visual inspection of the data, and decision-making process.

Map Class	Comparison Description	Decision
Forests	The UMD forest class had higher accuracy than the ESA WorldCover tree class.	UMD
Short vegetation	The UMD short vegetation class was made by clipping out other classes from a global vegetation fraction dataset, and therefore is not intended to stand on its own. We defaulted to the ESA WorldCover shrubland, grassland, and herbaceous wetland classes which were independent classes in the WorldCover map. Although the UMD data were ultimately selected to delineate wetlands, the ESA WorldCover herbaceous wetland class was included in the short vegetation class because it contains areas with vegetative cover, which are included in our short vegetation definition.	ESA
Wetlands	The UMD wetlands data benefit from a higher accuracy score as well as a general "wet forest" class.	UMD
Cropland	The UMD cropland accuracies were higher than those of the ESA WorldCover cropland class. While UMD's cropland class is older (2016-2019), it classifies areas which had crop during any of those four years as cropland, allowing for a fallow period. By definition, the ESA cropland class does not include cropland that was in fallow in 2020. Because we aim to include all areas used for crop production– including both temporarily fallow and cultivated cropland– in our cropland class, the UMD data better suited our needs.	UMD
Built-Up	While the UMD accuracy scores are lower than ESA WorldCover, we selected the UMD built-up class because its definition includes any pixels that contain man-made constructions or surfaces, including lower density built-up areas such as airports and suburban neighborhoods. The ESA built-up class includes only pixels covered by buildings, roads, and other man-made surfaces, while excluding parks, sports facilities, and other urban green spaces. The UMD built-up class therefore includes more areas which fall under our definition of non-natural.	UMD
Bare Land	The ESA barren/sparse vegetation class definition includes areas with exposed rock, soil, or sand with less than 10% vegetated cover, whereas the UMD bare class is derived from the global vegetation fraction dataset and includes lands with less than 7% vegetated cover. Therefore, the ESA barren/sparse vegetation class classifies a larger area as bare land, including areas such as alpine rock faces, whereas these areas are classified as short vegetation with the UMD data. We therefore combined the UMD and ESA classes and used the extent of both to provide broader coverage of this class.	ESA and UMD
Ice and Snow	Both UMD and ESA snow and ice classes had high accuracies, however upon visual inspection, ESA seemed to overestimate snow and ice more, leading us to use the UMD class.	UMD
Water	The water class in the UMD water data had a higher User's Accuracy, and was adjustable based on the percentage of the year water was present.	UMD

Overall, we found that the UMD Land Cover data were a better fit for the map for most classes, with the exception of the short vegetation and bare classes. While the ESA data benefit from having a higher spatial resolution and therefore more precise data, accuracy metrics were generally lower. Further, we wanted to choose data where the spatial resolution was as consistent as possible; global data with a 10 meter spatial resolution are uncommon and would make resampling difficult.

2.2.2 Supplementary data

To distinguish natural from non-natural lands in the land cover classes that contain both, we incorporated additional data into the map (Table 5). While both the ESA and UMD Land Cover data include non-natural classes (cropland and built-up area), the other land cover classes selected from both the ESA and UMD Land Cover data include areas that do not adhere to AFi's definition of a natural ecosystem.

Table 5: Summary of supplementary data used to delineate natural and non-natural lands for land cover classes

Classification	Land cover class	Dataset name	Resolution	Year	Reference
NON-NATURAL	Tree cover, short vegetation	Spatial Database of Planted Trees (SDPT), version 2.0	Varies	Varies	Richter et al. in review
	Short vegetation	Gridded Livestock of the World (GLW), version 4.0	10 km	2015	Gilbert et al. 2018
	Cropland	USGS Global Cropland Extent Product at 30m Resolution (GCEP30)	30m	2015	Thenkabail et al. 2021
	Built-Up	IIASA Global Scale Mining Polygons	Vector	2019	Maus et al. 2022
NATURAL	Forests	Intact Forest Landscapes (IFL)	Vector	2020	Potapov et al. 2017
	Mangroves	Global Mangrove Watch (GMW), version 3.0	0.8 arc seconds	2020	Bunting et al. 2022

Forests

The UMD forest class includes all tree cover greater than or equal to 5 meters in height, regardless of whether it is planted or natural. Tree cover is a convenient metric for monitoring forests because it is easily measurable from space, but cannot be used to assess natural forests on its own. While no globally consistent planted or natural forest dataset exists, they can be delineated through the use of multiple ancillary datasets. Here we applied two additional datasets to identify non-natural and natural forest in the UMD forest class.

The Spatial Database of Planted Trees (SDPT), version 2.0

A global dataset of tree crops - defined as stands of perennial tree crops such as rubber, oil palm, coffee, coconut, cocoa, orchards, etc. - and planted forests - defined as stands of planted trees (other than tree crops) grown for wood and wood fiber production or for ecosystem protection against wind and soil erosion (Harris et al. 2019). This is a vector dataset of compiled and harmonized national or regional maps from a variety of sources, including national governments, nongovernmental organizations, independent researchers, or a combination of sources. As such, the resolution, methods, year, and accuracy of input data vary by source.

In version 2.0, the Spatial Database of Planted Trees incorporates a number of new data sources, including a global map of palm oil plantations (Descals et al. 2021), a map of rubber plantations across mainland Southeast Asia and the Yunnan province (Xiao et al. 2021), and the Global Forest Management (GFM) data (Lesiv et al. 2022), in addition to new and updated country-level data. The GFM data (Lesiv et al. 2022) was used to delineate planted forests and plantations in Europe, as well as any other country which did not have other sources of regional or national data available but which reported some area (greater than zero hectares) of plantations[1] or planted[2]

1 Plantation forest is defined by FAO as planted forest that is intensively managed and meets all the following criteria at planting and stand maturity: one or two species, even age class, and regular spacing. This specifically includes short rotation plantations for wood, fiber, and energy. This specifically excludes forest planted for protection or ecosystem restoration, or forest established through planting or seeding which at stand maturity resembles or will resemble naturally regenerating forest (FAO 2020).
2 Planted forest is defined by FAO as forest predominantly (more than 50%) composed of trees established through planting or deliberate seeding (FAO 2020).

forests or had no data available for the FAO 2020 Forest Resource Assessment (FRA). For these countries, the following classes in the GFM data were used: *planted forest*, defined as managed forest with signs that the forest has been planted within the 100 m pixel, with a relatively long rotation time (>15 years); *plantation forest*, defined as intensively managed forest plantations for timber with short rotation (<15 years). For a full list of data sources included in the SDPT v2, see Appendix D.

Tree crops and tree plantations do not meet the AFi definition of a natural forest. Although "planted forest" as defined in the SDPT may in some instances meet the AFi definition of natural forest (e.g. if natural species composition, structure, and function is maintained), the SDPT specifically includes plantations that were likely to be intensively managed and excludes areas of semi-natural forest with natural regeneration. Therefore, we consider "planted forests" in this dataset to represent a reasonable proxy of "tree plantations" as defined by AFi. Version 2.0 of this dataset is used to classify forests as non-natural (Richter et al. in review).

Intact Forest Landscapes (IFL)

Intact Forest Landscapes are defined as mosaics of forests and naturally treeless ecosystems within the zone of current forest extent that show no signs of significant human activity or habitat fragmentation and are large enough to maintain all native biodiversity (Potapov et al. 2017). These data map the extent of Intact Forest Landscapes globally in 2020. Forests within Intact Forest Landscapes are likely to meet the AFi definition of natural, as they show no signs of significant human activity. Therefore, we used the IFL extent in 2020 to apply an additional precautionary measure to ensure forests that fall within these boundaries are classified as natural.

Short vegetation

A key challenge in mapping natural short vegetation is distinguishing it from pasture. To identify pasture, we used the Gridded Livestock of the World 4.0 (GLW) dataset, a 10 kilometer spatialization of subnational livestock distribution data in 2015, presenting density of cattle, buffalo, goats, sheep (Gilbert et al. 2018). These data are the only global spatial dataset of livestock distribution and are used to derive a threshold for areas with high density ruminant livestock as a proxy for pastureland.

Wetlands

Wetlands are delineated in both the forest and short vegetation classes. These areas were further refined to delineate mangroves and peatlands; wetland types that are of high-interest to map users because of their high potential for carbon storage. Mangroves are designated as a unique class using data produced by Global Mangrove Watch (GMW) on mangrove extent for the year 2020 (Bunting et al. 2022). The GMW data was produced using L-band Synthetic Aperture Radar (SAR) global mosaic datasets from the Japan Aerospace Exploration Agency (JAXA) for 11 epochs from 1996 to 2020 to develop a time-series of global mangrove extent and change. Although the ESA WorldCover data include a separate class of mangrove forests, the GMW data were selected because of their high accuracy scores (86% producer's accuracy and 89% user's accuracy) (Bunting et al. 2022). Peatland extent was included by using a map developed by researchers at WRI modeling forest carbon emissions and removals (Harris et al. 2021). This map (WRI Peat) is a 30-m resolution composite of 5 peatland maps that were either converted from vector data to raster data, or were resampled from coarser resolution raster data. This composite includes 3 datasets with regional coverage and 2 with global coverage. This peat map was overlaid with the forests and short vegetation class to delineate peat forests and peat short vegetation.

Table 6. Input data used to create the composite peat map.

Coverage	Native Resolution	Source
Indonesia and Malaysia	Vector	Miettinen et al. 2015
Congo Basin	50-m	Crezee et al. 2022
Peru	50-m	Hastie et al. 2022
Land area below 40 degrees north	250-m	Gumbrict et al. 2017
Land area above 40 degrees north	Vector	Xu et al. 2018

Cropland

To supplement the UMD Land Cover cropland class, we used the USGS Global Cropland Extent Product at 30m resolution (GCEP30) for the year 2015 (Thenkabail et al. 2021). These data were developed through the classification of Landsat imagery using machine learning algorithms trained for 74 agroecological zones and compiled into one global map (Thenkabail et al. 2021). In this dataset, cropland includes the following: cropland cultivated one or more times throughout a 12-month period, cropland that is left fallow but is equipped for agriculture, and cropland that is permanently cropped with plantations (such as vineyards, orchards, coffee, tea, etc.). In Argentina, Australia, Brazil, Kazakhstan, and New Zealand, the data also include managed pasture, as is likely in much of South and Central America. Upon visual inspection in Mexico and Nigeria, we found the GCEP30 data included large areas of agricultural lands (possibly managed pasture, mixed crop/pasture, fallow fields or abandoned cropland) that were not included in the UMD cropland extent. Because the UMD data limit the fallow period to four years, we incorporated the GCEP30 data to include cropland that may experience longer fallow periods, as well as managed pasture in the regions where it is included.

Built-Up

To supplement the UMD Land Cover built-up class, we used the IIASA Global Scale Mining Polygons (Maus et al. 2022) for the year 2019 as additional built-up areas. These data outlining mining areas were created by digitizing a 2019 Sentinel-2 cloudless mosaic, checking high resolution imagery where needed to identify land cover types related to mining activities. Some mining areas contain a mix of mining activities and natural lands such as tree patches, so only the areas within mining boundaries that are bare and water land covers were used to identify non-natural areas.

2.2.3 Regional Data

We evaluated a limited set of regional data using our criteria for inclusion described in Table 3. These data were harmonized with our map classes and incorporated into the map, replacing our global data where available. In cases where regional data included only one or a few classes relevant for our natural lands map (e.g. cocoa, primary forest, and natural grassland/shrubland maps), these data were used to supplement or replace the relevant map class.

Table 7: Summary of regional datasets incorporated into the map

Region	Dataset Name	Year	Reference	Resolution
Brazil	MapBiomas Brazil Collection 7.0	2020	Souza et al. 2020	30m
Amazon	MapBiomas Amazonia Collection 4.0	2020	MapBiomas Amazonia 2023	30m
Chaco	MapBiomas Chaco Collection 3.0	2020	MapBiomas Chaco 2023	30m
Pampa	MapBiomas Pampa Collection 2.0	2020	Baeza et al. 2022	30m
Atlantic Forest	MapBiomas Atlantic Forest Collection 2.0	2020	MapBiomas Atlantic Forest 2023	30m
Indonesia	MapBiomas Indonesia Collection 1.0	2019	MapBiomas Indonesia 2023	30m
South Africa	South Africa National Land Cover 2020	2020	Department of Forestry, Fisheries, and the Environment, South Africa	20m

Côte d'Ivoire and Ghana	ETH/EcoVision Cocoa Map	2019-2021	Kalischek et al. in review	10m
New Zealand	LUCAS NZ Land Use Map	2016	Ministry for the Environment	vector
Europe	CORINE Land Cover	2018	Copernicus Land Monitoring Service	100m
Europe	European Primary Forest Database (EPFD) version 2.0	Varies	Sabatini et al. 2021	vector

MapBiomas Land Cover and Land Use products for Brazil, the Amazon, Chaco, Pampa, Atlantic Forest, and Indonesia are 30 meter resolution maps that contain detailed land cover/land use classes for natural forest and non-forest ecosystems, as well as agriculture, water, and non-vegetated areas. We used the year 2020 for Brazil, the Amazon, Chaco, Pampa, and Atlantic Forest, and the most recent year available (2019) for Indonesia.

The South Africa National Land Cover map for 2020 was produced using multi-seasonal 20m resolution Sentinel-2 satellite imagery. This map contains 73 classes that delineate natural and non-natural land covers.

The Ghana and Côte d'Ivoire cocoa map for 2019-2021 was produced using Sentinel-2 satellite imagery at a 10 meter resolution. The map delineates land under cocoa cultivation, including shade grown cocoa.

The Land Use and Carbon Analysis System (LUCAS) New Zealand Land Use data for 2016 are based on Sentinel-2 satellite imagery acquired in the summer of 2016/2017. There are 30 distinct land use classes, including classes for natural forests and natural grasslands.

The CORINE Land Cover dataset for 2018 is a complete land cover map over the participating counties of the European Environment Agency at a 100m resolution. We included CORINE data to improve the delineation of natural grasslands in Europe. We used three shrub classes: natural grassland, moors and heathland, sclerophyllous vegetation, as natural short vegetation.

The European Primary Forests Database (EPFD) defines primary forests as forests where the signs of human impacts, if any, are strongly blurred due to decades without forest management (Sabatini et al. 2021). These data combine and harmonize 48 datasets of primary forests in 33 countries in Europe, and were used to aid in the delineation of natural forests in Europe. While these data include both polygons and point features, only polygons were used for the natural lands map. Due to the variety of data sources used in these data, data quality, accuracy, and completeness vary.

While we only included a limited set of regional data for this version of the map, we intend to incorporate additional regional data in subsequent map versions where available. We welcome recommendations for additional global or regional land cover data to help delineate natural lands.

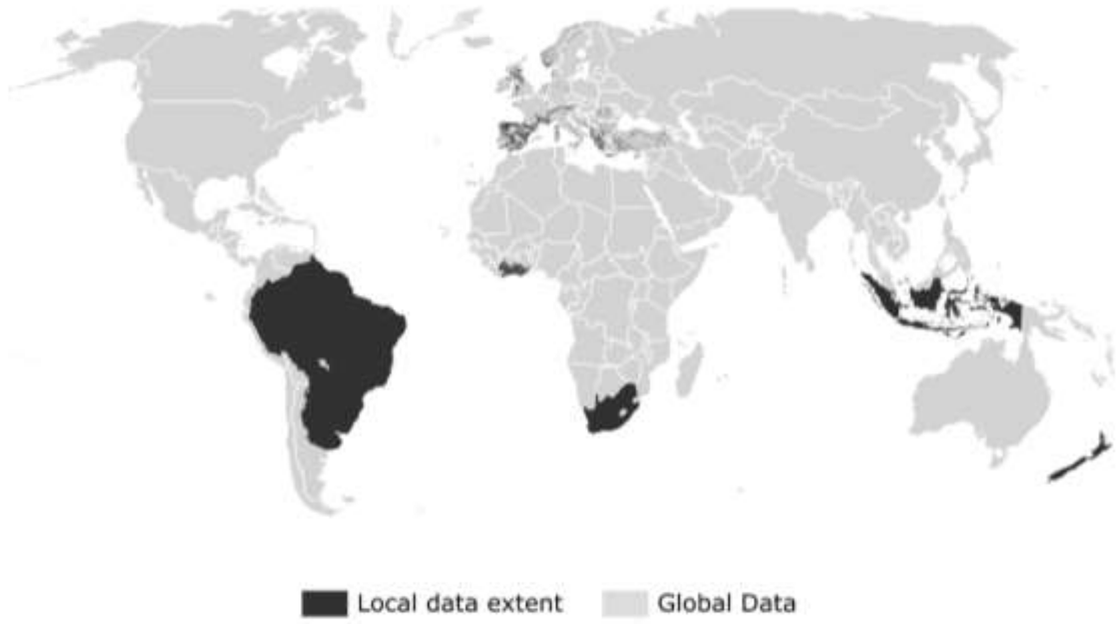

Figure 1: Extent of regional data included in the natural lands map

2.3 Methods

2.3.1 Methods for creating and combining map classes

To create the global 2020 natural lands map, we combined our input data through a series of overlays and decision rules (Figure 2). The map has a hierarchical legend, with level 1 distinguishing two classes – natural and non-natural – and level 2 distinguishing various land cover classes within the natural and non-natural classifications. The map includes both natural and non-natural forests, short vegetation, water, wet forests, peat forests, wet short vegetation, and peat short vegetation. Natural classes also include mangroves, bare land, and permanent snow/ice. Non-natural classes also include built-up and cropland.

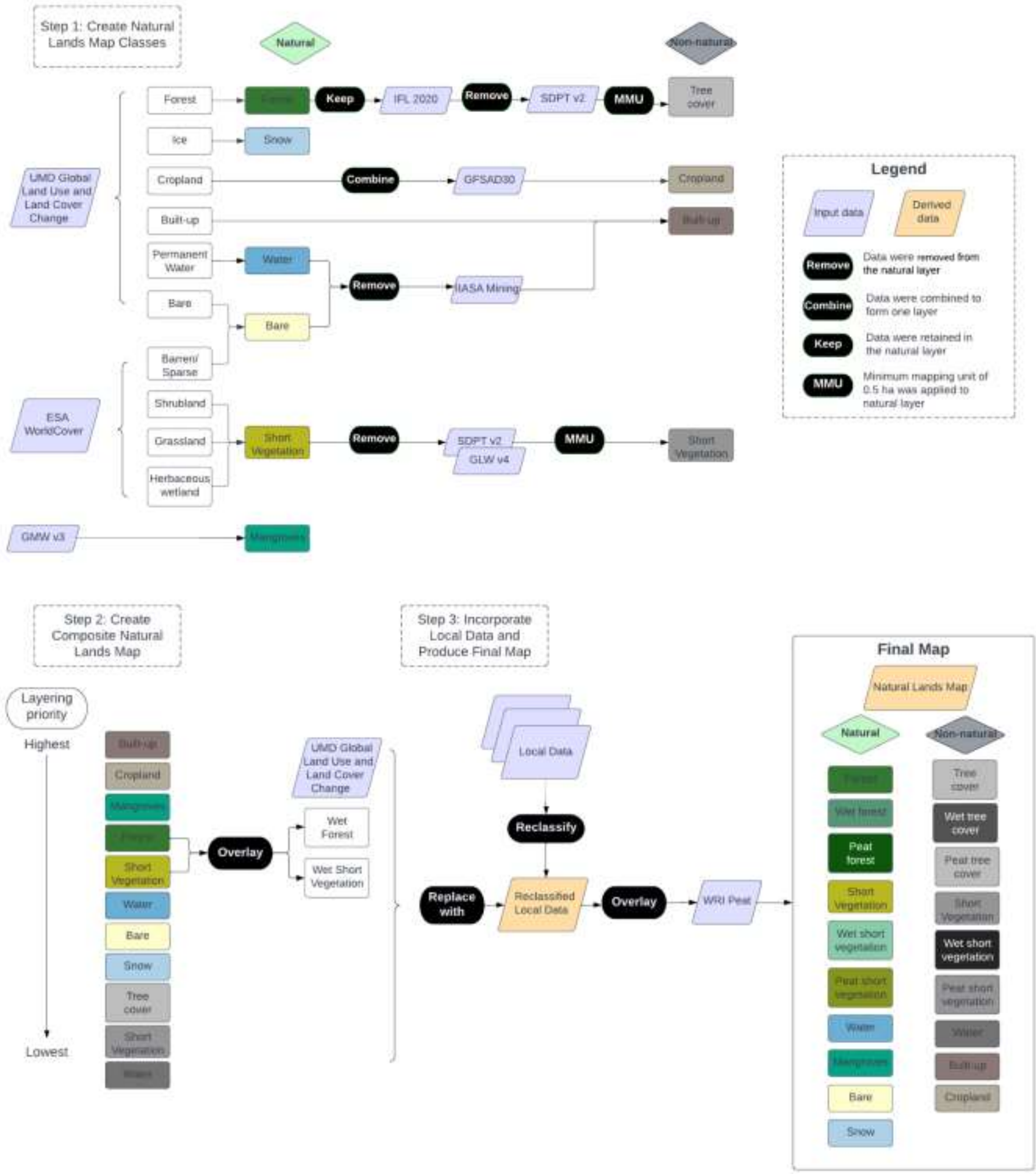

Figure 2: Process used to create the natural lands map

We applied a conservative approach in mapping non-natural lands, meaning that decisions were made with the aim to be precautionary in assigning a non-natural classification to an ecosystem. As a result, our final data may overestimate the area of natural lands in some regions. Due to the lower resolution and variation in accuracy of some of our input data, we used additional data where available to apply additional conditions before removing non-natural classes as an added precautionary step. Because our map may overestimate natural lands, it is essential that this map be strictly applied to setting a corporate “no conversion of natural ecosystems” target in SBTN Land and not used to quantify the area of natural or non-natural lands.

We adopted this conservative approach because the risk of underestimating natural lands is greater than the risk of overestimating natural lands for the protection of nature. If natural lands were underestimated, natural areas not included in the map may be at higher risk of conversion because they are not designated as “off limits” for conversion. Particularly considering the data limitations for certain land cover types– including grasslands and pasture– we considered it more appropriate to adopt a precautionary approach so that potential natural lands are rarely omitted from the map. This approach can be beneficial to companies and other entities, too, since a conservative approach makes it less likely to unknowingly convert natural lands. However, the overestimation of natural lands is unevenly distributed with more natural lands in areas with less data to distinguish between natural and non-natural.

All processing steps and analyses were conducted in Google Earth Engine (Gorelick et al. 2017).

Pre-processing

All data were converted to raster format and resampled to 30 meter resolution to match the resolution of the UMD Land Cover data, which were used as the base layer for the majority of our land cover classes. The data that had higher resolutions were resampled by using the median pixel value for binary data and mode for categorical data within each 30 meter pixel.

Forests

To delineate forests, we used the forest class from the UMD Land Cover data, which define tree cover as all woody vegetation greater than or equal to 5 meters in height. All forest within the UMD forest extent was assumed to be natural unless re-classified as non-natural. Because these data include both natural forests and non-natural tree cover, such as wood fiber plantations or tree crops, we relied on the SDPT version 2.0 (Richter et al. in review) to target non-natural tree cover.

To remove tree crops and planted forest from the natural forest class, we overlaid the SDPT v2 with the UMD forest class and reclassified any areas of overlap as non-natural tree cover. However, due to regional variations in the resolution and accuracy of the SDPT v2.0 source data, which limits the precision and accuracy by which non-natural tree cover can be delineated in certain cases, we used data on the extent of intact forest landscapes from the global IFL data in 2020 to apply additional conditions before removing UMD forest extent that overlapped with SDPT from our natural forest class. This data, which maps forests with no signs of human intervention, is likely to represent areas containing natural forests. In cases where the SDPT overlapped with areas designated as intact forest landscapes, the IFL area was masked (to keep the data classified as natural forest) before removing the SDPT from the UMD forest extent. Therefore, the IFL data were given priority and the area remained classified as natural forest.

Finally, to align with the AFi definition of forest, we applied a minimum mapping unit of 0.5 hectares to the natural forest class. 0.5 hectares is approximately 5.6 pixels, meaning that if there is a patch of natural forest smaller than 0.5 hectares (patches can be connected by any side or corner of the pixel), it is labeled non-natural tree cover, unless another class with higher priority re-labels it another class when the data are all compiled.

Short vegetation:

With limited global data available regarding natural and non-natural short vegetation (including grasslands and shrublands), we set a livestock density threshold on the short vegetation class as a proxy for pasture. We combined the ESA WorldCover grassland, shrubland, and herbaceous wetland classes as the extent of short vegetation. All short vegetation was assumed to be natural unless re-classified as non-natural. Using the GLW data, we classified areas of short vegetation that had high densities of ruminant livestock as non-natural. The cattle, buffalo, goats, and sheep data were rescaled from livestock per pixel to livestock per square kilometer. The top 5% density of cattle (above 45.15 per square kilometer), and top 1% of buffalo, goats, and sheep (above 35.74 per square kilometer, 103.65 per square kilometer, 110.00 per square kilometer respectively) were considered high density. The thresholds were decided through visual inspection for evidence of high livestock density, such as cattle tracks, as well as comparison to pasture class in the MapBiomas data. The high density extents for the four ruminant types were all mosaicked into one global image of livestock density. Any areas of short vegetation that overlapped with high density livestock were re-classified as non-natural, as well as any short vegetation that overlapped with plantations from the SDPT (with IFL masked), since orchards and other tree crops may be shorter than 5 meters in height and therefore classified as short vegetation. We applied a minimum mapping unit of 0.5 hectares to the natural short vegetation class to account for the low resolution (10 km) of the GLW data. The short vegetation class is explicitly shaped by livestock because of a lack of grassland or shrubland species and condition data.

Water

Natural was mapped with the water class from the UMD Land Cover data, which includes all water present 20% of the year or more in 2020. Non-natural water was labeled in some local land cover datasets.

Built-Up

The UMD Land Cover built-up class was used as the primary extent of built-up area. We also assigned the built-up class in areas within the IIASA Global Scale Mining Polygons that were labeled as water or bare as defined above. This combination covered most mining activities, while preserving areas of natural forest or short vegetation within the polygons.

Combining map classes

For our cropland class, we combined the UMD cropland class with the GCEP30 cropland data. All the final class layers as described above were compiled with the following priority from highest to lowest: built-up, cropland, mangroves, natural forest, natural short vegetation, natural water, bare ground, snow/ice, non-natural tree cover, non-natural short vegetation, and non-natural water. In cases where any classes overlap, the higher priority class takes precedence. The forest and short vegetation classes (both natural and non-natural) were overlaid with the WRI Peat data and the UMD wetland classes and assigned a peatland or wetland label where applicable. We used the UMD short vegetation class to fill in gaps caused by using land cover data from different sources, which defaulted to a natural label.

2.3.2 Methods for Incorporating Regional Data

In creating the natural lands map, we aimed to include regional or country-level data where available and appropriate. Therefore, where quality regional data are available that meet our criteria, we harmonized these data to our global classes and used them in place of our global data. For this version of the map, we incorporated MapBiomas data for Brazil, the Amazon, Chaco, Atlantic Forest, and Pampa in South America, and Indonesia. We also incorporated the South Africa National Land Cover Map for 2020, New Zealand LUCAS Land Use map, the grassland classes from the European CORINE Land Cover Data, the European Primary Forest Database, and the ETH/EcoVision Cocoa Map for Côte d'Ivoire and Ghana (see Table 7).

We reclassified each dataset according to the classes used in our global map (see Appendix A, B, and C). Where possible, we applied a direct reclassification to convert each class in the regional dataset to the class that was most closely aligned in our global dataset. For classes where the thresholds used for defining forest or short vegetation deviated from our global map definition (for example, by using a different height or canopy threshold for forests, by not including a maximum height limit for vegetation in grasslands or shrublands, or by allowing for a certain density of tree cover in grasslands or shrublands), we adopted the definition used in the regional data.

For some MapBiomas datasets, we found that some classes were too broad to be reclassified as a single class in our map, in some cases encompassing both natural and non-natural areas. In these cases, we used the UMD Land Cover data to assist in reclassifying the broad class into multiple classes that are harmonized with our global map. For example, the MapBiomas Pampa and Amazon datasets have a single class for agriculture, which includes both cropland and pasture. For this class, we reclassified it as non-natural short vegetation (e.g. pasture) unless it overlapped with the UMD cropland class, in which case we reclassified it as cropland. Similarly, the MapBiomas Pampa, Chaco, and Atlantic Forest datasets have a single class for non-vegetated areas, which can include both non-natural built-up areas or exposed soil in cropland, or natural areas of bare land, rock or sand. In these cases, we reclassified this non-vegetated class as natural bare land unless 1) it overlapped with the UMD built-up class, in which case we reclassified it as built-up; or 2) it overlapped with the UMD cropland class, in which case we reclassified it as cropland. This was also done with the New Zealand LUCAS Land Use data to separate the permanent snow and ice from the rest of the bare class. We plan to take a similar approach with any regional datasets incorporated in future versions of the map if needed.

For regional data with only one or few classes that correspond to the natural lands map (e.g. the ETH/Ecovision Cocoa map, the European Primary Forest Database, and the CORINE Land Cover data), these data were reclassified to the corresponding map class and incorporated into the map. Areas mapped as cocoa by the ETH/Ecovision Cocoa map were classified as non-natural tree cover , and then layered into the map following the same layering priority as described in section 2.3.1, with the built-up and cropland classes given priority in any areas of overlap. The CORINE natural shrub classes were overlaid with the short vegetation class and labeled as natural short vegetation, while the European Primary Forest Database was overlaid with the forest class and labeled as natural.

For future versions of the map, we anticipate including additional regional data, following the same general process:1) evaluation of the data to ensure it meets our criteria for inclusion in the map; 2) reclassification to harmonize the data with our map classes; 3) replace or supplement our natural lands map with the harmonized regional data.

2.3.3. Methods for creating the final map

After replacing our global data with local data where applicable, the forest and short vegetation classes (both natural and non-natural) were overlaid with the WRI Peat data and assigned a peatland label where applicable. The final result is a land cover map with forest, short vegetation, mangroves, water, bare, snow/ice, built-up, and cropland, where the forest, short vegetation, and water have both natural and non-natural classes, and forest and short vegetation are labeled as dry, wetland, or peatland. For the use of the SBTN no conversion target, the level 1 categories in the map can be used to create a binary image: natural and non-natural.

Table 8. Final map classes, values, and description

Level 1	Level 2	Class Value	Description
NATURAL	Forest	2	Tree cover greater than 5 meters in height and more than 0.5 hectares, excluding planted forests grown for wood or wood fiber production or perennial tree crops. Height or minimum mapping thresholds may vary based on local definitions.
	Short vegetation	3	Areas of land with vegetation shorter than 5 meters (including areas of land dominated by grass or shrubs), but excluding areas with high densities of ruminant livestock, cropland, or tree crops.
	Water	4	Surface water present 20% or more of the year, where water is the dominant class.
	Mangroves	5	Areas dominated by mangrove forests.
	Bare	6	Areas with exposed rock, soil, or sand with less than 10% vegetated cover.
	Snow	7	Land covered by glaciers and snow remaining during the entire year.
	Wet forest	8	Natural forests with saturated soil that can be inundated by water either seasonally or permanently
	Peat forest	9	Natural wet forests that have accumulated peat
	Wet short vegetation	10	Natural short vegetation with saturated soil that can be inundated by water either seasonally or permanently.
	Peat short vegetation	11	Natural wet short vegetation that have accumulated peat
NON-NATURAL	Cropland	12	Land used to produce annual and perennial crops. This may include herbaceous crops, land that is permanently cropped with plantation crops (such as vineyards, coffee, tea), some tree crops (such as orchards), and some pasture or mixed pasture/crop systems. It includes land that is left fallow but equipped for agriculture.
	Built-up	13	Man-made land surfaces associated with infrastructure, commercial, residential uses, and mining.
	Tree cover	14	Perennial tree crops (including rubber, oil palm, cocoa, orchards, etc.) and planted forests grown for wood or wood fiber production. This may include both intensively managed forest plantations for timber with a short rotation time, or managed forests with signs that the forest has been planted with a long rotation time (greater than 15 years).
	Short vegetation	15	Pasture, tree or plantation crops, or other areas with vegetation shorter than 5 meters and high density ruminant livestock.

Water	16	May include aquaculture, artificial dams, or other artificial areas with surface water.
Wet tree cover	17	Non-natural tree cover with saturated soil that can be inundated by water either seasonally or permanently.
Peat tree cover	18	Non-natural wet tree cover that have accumulated peat
Wet short vegetation	19	Non-natural short vegetation with saturated soil that can be inundated by water either seasonally or permanently.
Peat short vegetation	20	Non-natural wet short vegetation that have accumulated peat

2.4 Validation methods

International Institute for Applied Systems Analysis (IIASA) conducted an independent accuracy assessment of the natural lands map. They created a validation data set of natural and non-natural classes using a random sample of 4,943 points globally. Each of the 4,943 points were validated by two IIASA experts with visual inspection of very high resolution imagery in a Geo-Wiki web-application created with various supplementary data, including Google imagery, Microsoft Bing, Esri images, NDVI time series, Sentinel 2-time series, etc. The validation team followed the operational definitions used in the map for the natural/non-natural classes to guide decisions applied for the labeling of validation data. To account for geolocation errors in both the original map as well as the underlying very high-resolution imagery, additional neighboring pixels around the central pixel were classified and the majority class was used in the validation. Any disagreements in the classification of the two experts were revised by a third expert. In some locations, very high-resolution imagery was either not available or not frequently available, so it could be difficult to determine the class of a given validation point, and a label of "not sure" was given. Points with a "not sure" label were not included in the results of the accuracy assessment. The overall and per class accuracies were derived from confusion matrices at a global scale.

3. RESULTS

The natural lands map can be viewed at:
https://wri-datalab.earthengine.app/view/sbtn-natural-lands

3.1 Map Results

The natural lands map shows that large blocks of natural land still exist across most regions of the world. *Figure 3* shows the map of natural (green) and non-natural (gray) areas. The majority of non-natural land is built-up areas, cropland, and pastureland. There are also large contiguous regions of non-natural tree cover. As expected with our conservative approach in designating non-natural lands, visual inspection showed that the proxy we used to delineate pasture, combined with the low (10 km) resolution of the GLW input data, results in some pasture and other types of non-natural short vegetation being classified as natural because it did not meet the high density livestock threshold. Similarly, some areas of non-natural tree cover were classified as natural. However, our visual inspection indicated that there were not many obvious places where natural forests were classified as non-natural, indicating that our conservative definition of non-natural tree cover produced the intended result.

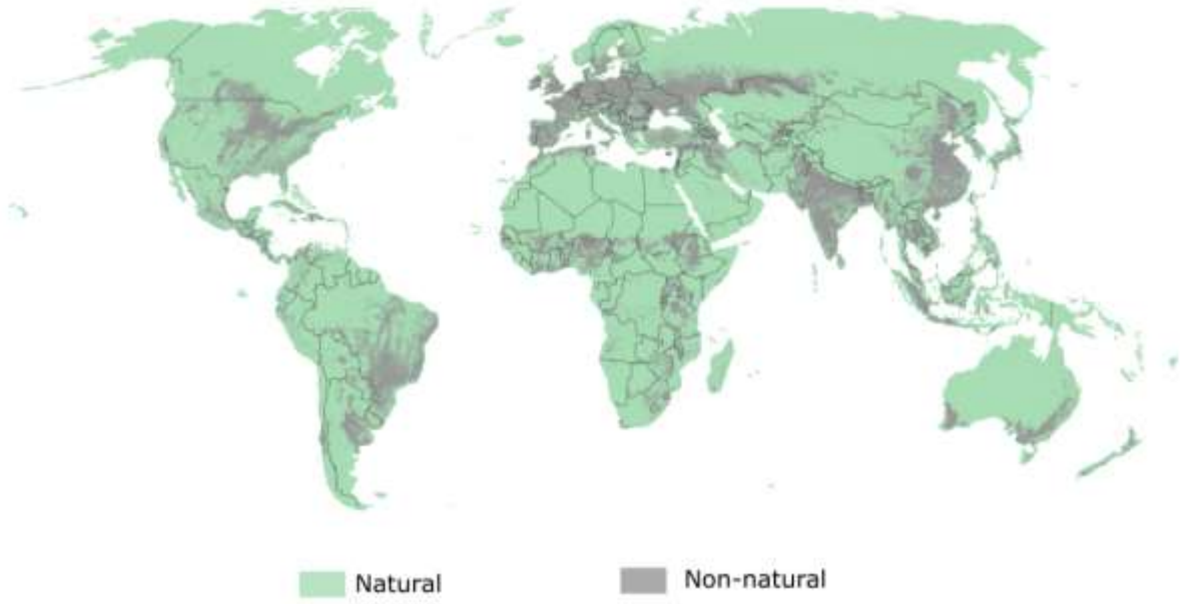

Figure 3: Global map of natural lands. Note: There is no data on the glaciers of Greenland.

In Figure 4 we highlight six regions around the world. The natural lands are broken out by land cover and the non-natural lands were combined into one class and shown in gray. Figure 3 a) shows the Cerrado in Brazil, which is a mix of short vegetation and low density forests, and non-natural areas, which are largely agricultural croplands, pasturelands and plantations. The north-west corner is the Amazon rainforest and the north-east corner is the arid Caatinga savanna. Figure 3 b) focuses on Colombia and depicts natural forests in the Amazon rainforest and the Andean region. There is natural short vegetation in the Orinoquia region in the northeast; however, there are also non-natural lands occupied by pasture. Figure 3 c) covers much of western/southern Europe centered on the Alps. The natural lands map classifies many areas of this region as non-natural, with the exception of some natural forests in Germany, France, Switzerland, and Italy, and the mountainous areas of the Alps, which are mostly bare land, permanent snow/ice, short vegetation, and forest. Figure 3 d) shows natural forests and short vegetation in West Africa, with built-up areas, cropland, and tree plantations - largely cocoa - categorized as non-natural land. Most of Figure 3 e) in the Congo basin is natural forest, with peat forest in the middle and some natural short vegetation to the south. There are non-natural areas in the northern part of the image that are mostly cropland with some built-up areas. Finally, Figure 3 f) shows Peninsular Malaysia's natural forests and the non-natural area, which is mostly oil palm plantations.

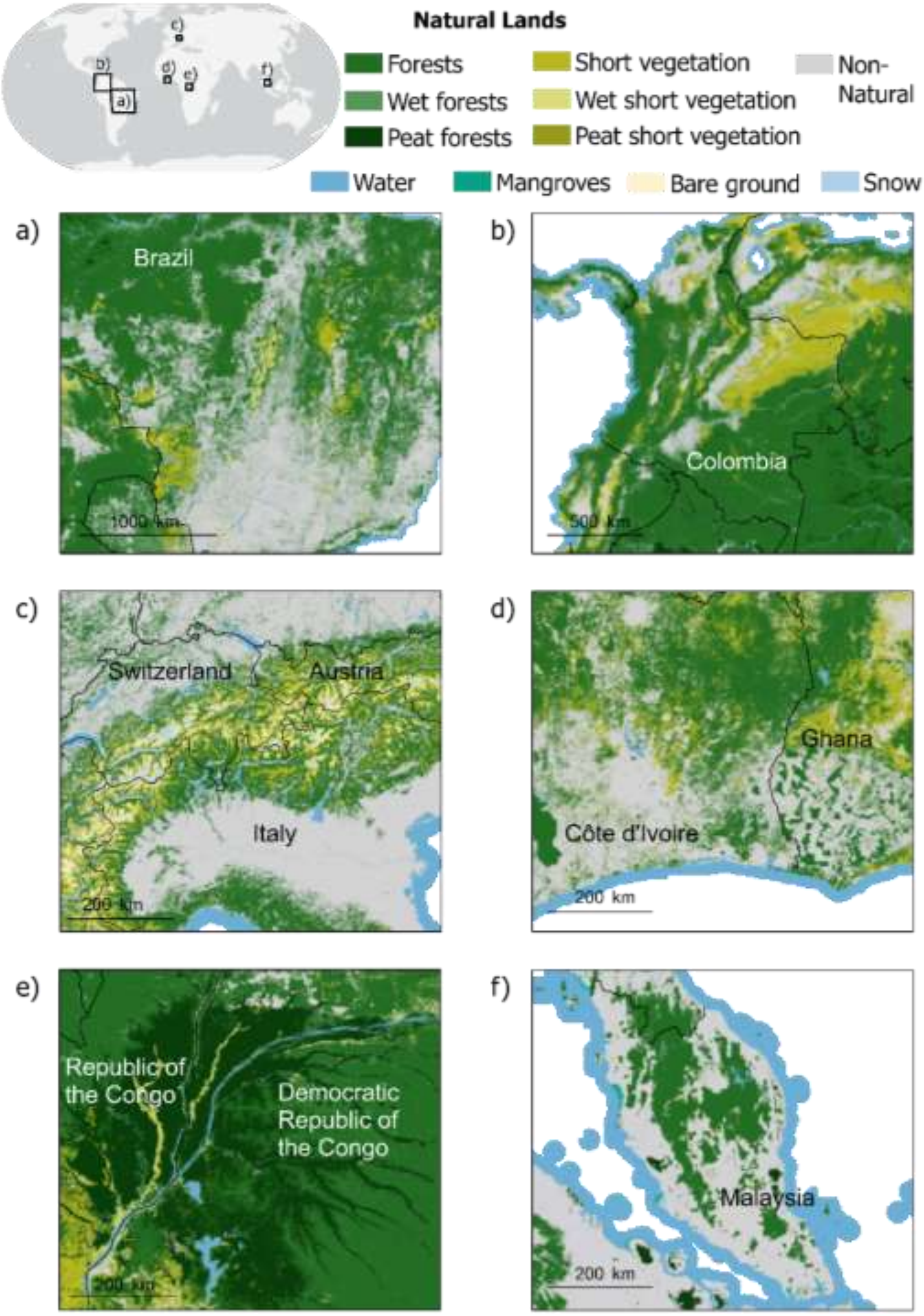

Figure 4: Natural land covers in: a) the Cerrado in Brazil; b) Colombia; c) western/southern Europe; d) Côte d'Ivoire; e) the Congo basin; f) Peninsular Malaysia.

Upon visual inspection, areas where we replaced the global data with local data improved significantly. Figures 5 a) and 5 b) depict the northwest part of the state of Rondonia, Brazil which is mostly deforested for pasture. Figure 5 a) shows the version with only global data, which has large areas of natural short vegetation and bare land, whereas 5 b) (after incorporation of Mapbiomas) designates these areas as non-natural. The livestock data used in the global map is from 2015 and because this area is rapidly being deforested, the livestock density did not represent recent changes in land use which were seen in the Mapbiomas data. Figures 5 c) and 5d) are centered on an area of southern Cote d'Ivoire and Ghana that have many cocoa plantations. Figure 5 c) shows the version with only global data, which has mostly natural forests in the area, whereas 5 d) (after incorporation of ETH/EcoVision Cocoa Map) designates lots of areas as non-natural. The cocoa data helps identify plantations in this area that were not captured by the Spatial Database of Planted Trees. Bringing in local data improved the natural lands map through the use of datasets with higher accuracy that were produced to suit the regional context and based on local knowledge of these landscapes.

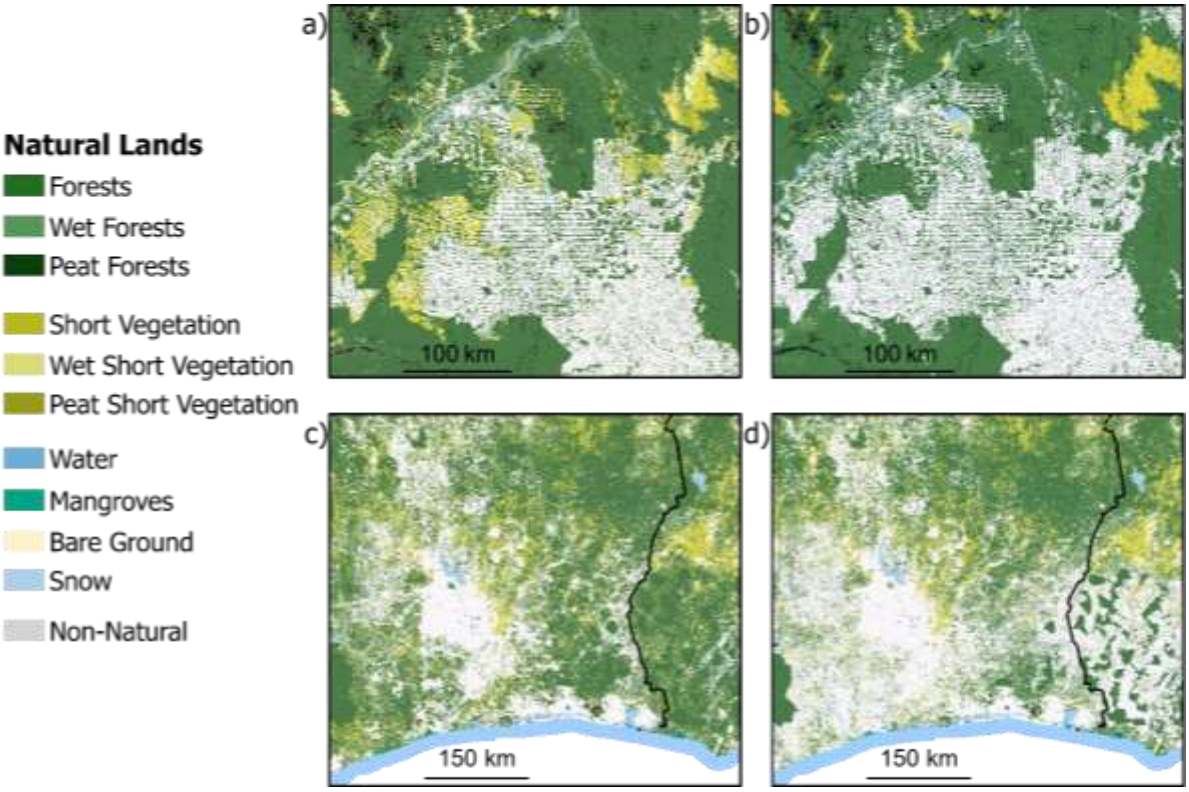

Figure 5: Comparison of area in a) Brazil with global data vs. b) Brazil with the incorporation of MapBiomas data; and the comparison of area in c) Côte d'Ivoire and Ghana with global data vs. d) Côte d'Ivoire and Ghana with the incorporation of ETH/EcoVision Cocoa Map data.

3.2 Validation and accuracy

The natural and non-natural binary map as validated by IIASA showed a 91.6% overall accuracy. Three percent of the validation points were classified as "not sure" because of a lack of high resolution imagery from 2020, and were removed before running the validation. The natural class had a 93.9% User's accuracy and 95.7% Producer's accuracy. These results show that the map mis-classifies 6% of the natural points as non-natural, and 18% of the non-natural points as natural. This result is expected, as our mapping approach was precautionary in assigning a non-natural label.

Table 9: Confusion matrix showing agreement between validation dataset and natural lands map

		MAP			
		Natural	Non-natural	Total	User's Accuracy
REFERENCE	Natural	3592	233	3825	93.9%
	Non-natural	162	743	905	82.1%
	Total	3754	976	4730	
	Producer's Accuracy	95.7%	76.1%		91.6%

3.3 Comparison with existing data

Gosling et al. (2020) produced a global map at 1 km resolution of natural and modified habitat for use in investment screening as part of Performance Standard 6 (PS6) of the International Finance Corporation (IFC) by combining eleven data layers. IFC PS6 defines natural habitats as "areas composed of viable assemblages of plant and/or animal species of largely native origin, and/or where human activity has not essentially modified an area's primary ecological functions and species composition" and modified habitats as "areas that may contain a large proportion of plant and/or animal species of non-native origin, and/or where human activity has substantially modified an area's primary ecological functions and species composition". Gosling et al. (2020) use these definitions to classify and combine input data, relying on human pressure as a proxy for the loss of ecological function and species composition. Aside from differences in input data used, Gosling et al.'s approach differs in a few ways: 1) they use only global data, whereas our approach incorporates regional or local data where available; 2) they overlay data representing natural and modified categories, and fill in remaining area (37.5% of global land area) using a categorized Human Footprint Layer (Venter et al. 2016); whereas our approach starts with land cover classes with global coverage and uses supplementary data to remove non-natural areas.

Gosling et al. used four categories in their map, representing a gradient between natural and modified: 1) likely modified, 2) potential modified, 3) potential natural, and 4) likely natural. We reclassified these four categories into two categories for better comparison with our map. Likely modified and potential modified were reclassified as "non-natural", and likely natural and potential natural were reclassified as "natural". We resampled our natural lands map to match the 1 km resolution of Gosling et al. map, taking the mode value of our binary layer.

Overall, the maps had high agreement: 59% of area was classified as natural by both maps and 19% of area was classified as non-natural by both maps, resulting in 78% overall agreement. However, a larger percentage of our map was classified as natural: 20% of the area classified as natural by our map was classified as non-natural by Gosling et al. Meanwhile, only 2.4% of the area classified as non-natural by our map was classified as natural by Gosling et al. Although Gosling et al. similarly take a precautionary approach by prioritizing natural categories when there is disagreement between the input datasets used, they incorporate the Human Footprint Layer, which uses data on population density and proximity to roads, variables which were not considered in our natural lands map. This is likely a source of disagreement between the two maps.

4. LIMITATIONS

Users of the map should be cautious of its limitations, and should take additional steps, such as validation with high resolution imagery or ground-truthing or use of additional data, to supplement the use of the map, especially for smaller scale applications. The natural lands map includes a number of important data limitations:

1. **Definitional inconsistencies**: The dataset definitions do not always match the definitions outlined by AFi. AFi provides robust definitions of natural ecosystems and forests; however, short vegetation, wetlands, water, and snow and ice lack the same level of distinction, and as a result we relied on definitions derived from the data used to create the map. There are also definitional inconsistencies across various sources used to create the natural lands map, which is a tradeoff for including local data when possible (see below for more detail). For example, the SDPT data used to exclude tree plantations from natural forests include dozens of local sources. While most capture short rotation plantations and tree crops, they also include mixed use areas dominated by tree plantations. Similarly, the MapBiomas data do not have a height threshold used to define forests, which may create inconsistencies with the delineation of forests within regions in which Mapbiomas data was used, versus those which relied on the UMD forest extent.

2. **Temporal inconsistencies**: While the map is as close to the year 2020 as possible, some data are from earlier time periods. For example, the livestock data used to differentiate natural from non-natural grasslands are from the year 2015, and the managed forest data used to differentiate natural from non-natural forest in countries without SDPT data are from 2015. Likewise, some source datasets for the SDPT and EPFD are from earlier time periods. See section 2.2 for more details.

3. **Resolution inconsistencies**: Most data in the map are at least 30 meter resolution, but some lower resolution data were used when higher resolution data were unavailable. These include the Gridded Livestock of the World data at 10 kilometer resolution and other countries/regions in the SDPT that included source data at varied resolutions (see Appendix D). This resolution inconsistency led to some data artifacts - meaning sharp boundary lines between natural and non-natural areas that are only due to the resolution (Figure 6).

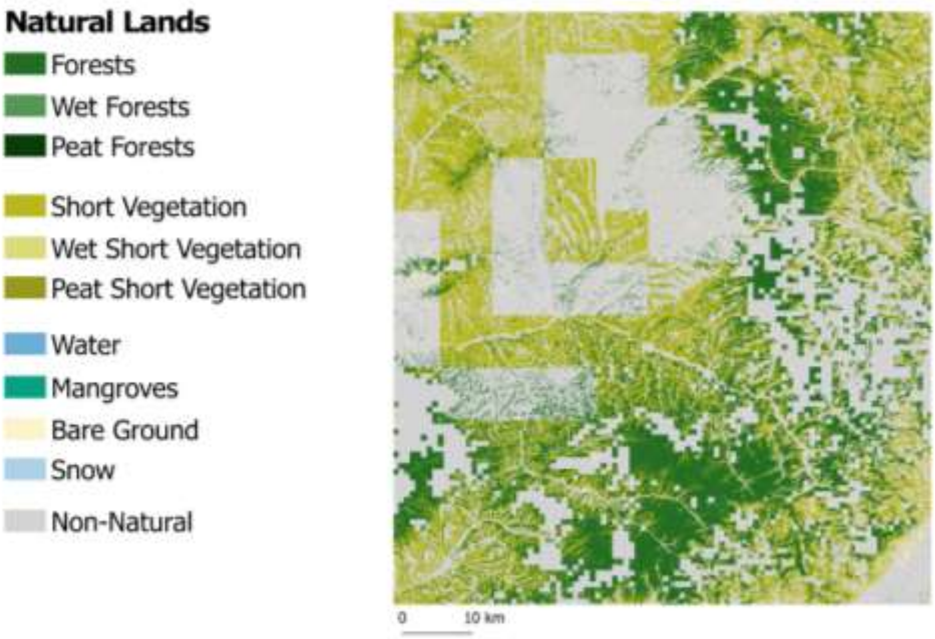

Figure 6: Example of data artifacts present in the map in China due to incorporation of lower resolution data. The larger non-natural areas are from incorporating 10 km GLW data and the smaller non-natural areas are from incorporating the SDPT, which includes source data at 1 km resolution for China.

4. **Insufficient data**: There are limits to what can currently be captured by earth observation data, including species composition, structure, and ecological function - the primary elements which define natural ecosystems in the AFi guidance. Some non-natural areas are somewhat easier to delineate with earth observation data though, such as tree plantations, built-up areas and cropland. Natural lands are thus deduced by removing these areas instead of including direct measurements of the definition. Even so, availability of data is not consistent across regions or types of plantations; for example, while there are multiple high-resolution maps of palm oil in some Southeast Asian countries, there is less data available for other palm oil producing regions or other crop types, such as coffee or cocoa. Additionally, certain ecosystems are easier to map than others. The distinction between natural and non-natural short vegetation and water is extremely difficult to identify using available datasets, and wetlands are more difficult to detect during dry periods.

As a result of the limitations described above, users should be aware of the following:

- Natural forests are overestimated in temperate and boreal regions, particularly Europe and Canada. In these regions, it can be challenging to differentiate plantation forests from natural forests, as rotation cycles are often long (greater than 20 years) and therefore not frequently discernable with earth observation data. Moreover, spatially-explicit data on forest management in these regions is limited. The SDPT v2 primarily uses the GFM data for Europe, Canada, and Russia, as it is currently the best available data for these regions. However, Lesiv et al. (2022) note that planted forests are underestimated in this dataset and as a result, natural forests in the natural lands map are overestimated in these regions.
- In some regions, small-scale agriculture– particularly mixed/rotational pasture and cropland– is classified as natural forest or short vegetation due to a lack of data that can be used to delineate these areas as non-natural. These heterogeneous agricultural mosaics are not always well-captured in existing cropland data, and due to the rotational nature of these systems, may not be included in existing data on plantations, tree crops, or planted trees.
- The threshold used for livestock density to classify short vegetation as non-natural was derived based on visual inspection, and does not represent the same intensity world-wide. AFi does not have a specific definition on natural short vegetation or grasslands, and because the only relevant global dataset was the GLW data, the operational definition of natural short vegetation was based on livestock density. This class has been improved in areas with local data and areas where the USGS Crop data includes pasture; however, the rest of the world relies on this definition derived from livestock density and data from 2015.

5. **Tradeoff between global and local data sources**: The use of local data sources can be beneficial, especially in overcoming limitations of global data sets and ensuring that local knowledge and conditions are well represented in the map. For example, local data allowed for better delineation of natural and non-natural short vegetation in Latin America. It also introduced local definitions of ecosystems, which better

account for the unique characteristics of a particular landscape. However, the use of local data introduces methodological and definitional inconsistencies with areas outside those regions. An organization using the natural lands map will need to use caution when comparing performance in supply chains across geographies with different data sources.

6. **Monitoring challenges**: The natural lands map is only available for the year 2020 and there are currently only limited monitoring systems in place for natural lands. Future mapping efforts should focus on producing dynamic maps which show change across multiple time periods or monitoring systems to evaluate change within the 2020 natural lands baseline. While we are aware of a number of regional land monitoring datasets (PRODES and DETER) and a larger scale dataset that is in development, even monitoring in forests, which have had monitoring systems in place for years, has proven to be challenging and only exists for the tropics. A natural forest basemap will help with a key barrier to uptake of monitoring data by corporate and other actors, which is the delineation of natural and non-natural forests. Another challenge which remains, however, is the lag time associated with deforestation and conversion. While we can now detect the initial forest disturbance quickly, it can take years to understand if the forest then regrew (not deforestation) or if it resulted in a change of land use (deforestation) using only remote sensing data. The land must be cleared and converted to another land use, then detected in a land cover/land use dataset to register deforestation, and this process takes time, often longer than annual reporting cycles.

7. **Equity impact**: The natural lands map and definitions overestimate natural areas, which is intended to protect land from potential conversion. However, a potential drawback of this approach is that areas with less available data to delineate non-natural lands may have a relatively larger overestimation of natural lands. Overestimation may also occur in areas where agricultural production systems do not clearly fall into the natural or non-natural land definitions, such as lower intensity, mixed, and shifting agriculture. Thus this limitation has important social and equity considerations. We recommend all companies who use the natural lands map to set no conversion targets validate the map with high resolution imagery or ground truthing, and engage with the local communities to understand the landscape. We recommend companies also set the SBTN land targets on land footprint reduction and landscape engagement to increase the effectiveness of the no conversion target and minimize unintended negative consequences for the communities where they are producing or sourcing.

5. FUTURE WORK

The natural lands map is intended to be a beta version using the best publicly available data. As new and improved (higher accuracy, finer resolutions) datasets are published, they will be incorporated into the map as future versions. New data for natural grasslands and planted forests in temperate and boreal regions would be especially valuable to future maps. New global grassland and pasture data at 30 meter resolution are expected from Land and Carbon Lab's Global Grassland Monitoring Consortium in late 2023 and will be incorporated into the next version of this map. We will also continue to incorporate national or regional data sources. If you know of local spatial data that may be able to help delineate natural and non-natural lands, please email Elise Mazur (elise.mazur@wri.org).]

Further work in this field is needed to define conversion, and identify and create data capable of monitoring the conversion of natural lands.

6. ACKNOWLEDGEMENTS:

We thank the team at IIASA for validating the Natural Lands map by collecting over four thousand visually inspected points. The team included Steffen Fritz, Myroslava Lesiv, Katya Perez Guzman, Linda See, Maria Shepaschenko, Ivelina Georgieva, Florian Hofhansl, and Juan Carlos Laso Bayas. We also want to thank our many reviewers for their time and detailed comments that improved the map and technical note, including Sarah Carter, David Gibbs, Viviana Zalles, Kemen Austin, Megan Critchley, Neil Burgess, Susana Baena, Sveltana Turubanova, and the many people who reviewed the map through the SBTN internal review and public consultation. While the contributions from reviewers are greatly appreciated, the approach presented in this report are those of the authors alone.

APPENDIXES

APPENDIX A: MAPBIOMAS RECLASSIFICATON

We reclassified each MapBiomas dataset to the value that aligned most closely with our natural land classification. Where definitions of ‘forests’ or ‘short vegetation’ differed from the AFi definition and/or the definition used in our global map (e.g. with regard to canopy cover and height thresholds, etc.), we adopted the regional definition of MapBiomas. In cases where the MapBiomas category was not specific enough to allow differentiation between natural/not natural categories or a specific class on our map, we overlaid the class with UMD Land Cover data to assign categories.

The MapBiomas classes present in each dataset are marked with an ‘X’ in Table A-1.

Table A-1: Reclassification table for MapBiomas datasets

MapBiomas Classification									Natural Lands Reclassification		
		Class Number	Brazil	Amazon	Chaco	Pampa	Atlantic Forest	Indonesia	Category	Class	Class number
NATURAL FOREST FORMATION	**NATURAL FOREST**	1									
	Forest Formation	3	X	X	X	X	X	X	natural	forest	2
	Savanna Formation	4	X	X	X	X	X		natural	forest	2
	Mangrove	5	X	X			X	X	natural	mangrove	5
	Sandy coastal plain vegetation	49	X				X		natural	forest	2
	Flooded/ wet forest	6		X	X				natural	wet forest	8

	Dispersed trees	45			X				natural	forest	2
NATURAL NON-FOREST FORMATION	**NATURAL NON-FOREST FORMATION**	10									
	Wetland	11	X	X	X	X	X		natural	wet short vegetation	10
	Grassland	12	X	X		X	X		natural	short vegetation	3
	Grassland with open vegetation	42			X				natural	short vegetation	3
	Grassland with closed vegetation	43			X				natural	short vegetation	3
	Grassland with dispersed vegetation	44			X				natural	short vegetation	3
	Hypersaline Tidal Flat	32	X				X		natural	wet short vegetation	10
	Rocky Outcrop	29	X	X			X		natural	bare	6
	Herbaceous Sandbank Vegetation	50	X				X		natural	wet short vegetation	10

	Other non Forest Formations	13	X	X			X	X*	natural	short vegetation	3
FARMING	**FARMING**	14									
	Pasture	15	X	X	X	X	X		non-natural	short vegetation	15
	Agriculture	18		X		X			non-natural	cropland	12
	Temporary Crop	19					X		non-natural	cropland	12
	One crop	57			X				non-natural	cropland	12
	More than one crop	58			X				non-natural	cropland	12
	Soybean	39	X						non-natural	cropland	12
	Sugar cane	20	X						non-natural	cropland	12
	Rice	40	X						non-natural	cropland	12
	Cotton	62	X						non-natural	cropland	12
	Other Temporary Crops	41	X						non-natural	cropland	12
	Perennial Crop	36			X		X		non-natural	forest	14
	Coffee	46	X						non-natural	forest	14

	Citrus	47	X						non-natural	forest	14
	Other Perennial Crops	48	X						non-natural	forest	14
	Oil Palm	35		X				X	non-natural	forest	14
	Other agriculture	21						X	non-natural	cropland	12
	Forest Plantation	9	X	X	X	X	X	X	non-natural	forest	14
	Mosaic of Uses	21	X	X		X	X		non-natural	cropland	12
NON VEGETATED AREA	**NON VEGETATED AREA**	22			X	X	X		natural/non-natural	Natural bare/ Built/Crop**	6/13
	Beach, Dune and Sand Spot	23	X						natural	bare	6
	Urban Area	24	X	X					non-natural	built	13
	Mining	30	X	X				X	non-natural	built	13
	Other non Vegetated Areas	25	X	X				X	natural/non-natural	Natural bare/ Built/Crop**	6/13
WATER	**WATER**	26			X				natural	water	4

	River, Lake and Ocean	33	X	X		X	X	X	natural	water	4
	Glacier	34		X					natural	snow/ice	7
	Aquaculture	31	X					X	non-natural	water	16
	6. Not Observed	27		X	X	X		X	Mask and take global map value}		

* MapBiomas Indonesia was the only dataset without a wetlands class, though wetlands are present in Indonesia. First, we reclassified the 'other non-forest formations' class (13) in Indonesia to natural grassland. We then overlaid this class with the UMD Land Cover data and reclassified it to natural wet grassland if it overlapped with the UMD wet short vegetation class.

**MapBiomas classes for non-vegetated areas can include non-natural built-up areas and transitional cropland, as well as natural bare land, sand, rock, and other non-vegetated cover. First, we reclassified the 'non-vegetated area' (22) or 'other non-vegetated areas' (25) to natural bare land. We then overlaid this class with the UMD Land Cover data and reclassified it to non-natural built if it overlapped with the UMD built-up class, and overlaid this class with the UMD crop data and reclassified it to crop if it overlapped with the UMD crop class.

APPENDIX B: SOUTH AFRICA NATIONAL LAND COVER RECLASSIFICATION

We reclassified the South Africa National Land Cover 2020 data to the value that aligned most closely with our natural land classification. Where definitions of 'forests' or 'short vegetation' differed from the AFi definition and/or the definition used in our global map (e.g. with regard to canopy cover and height thresholds, etc.), we adopted the regional definition of the South Africa National Land Cover classification.

Table B-1: Reclassification table for the South Africa National Land Cover 2020 Map

South Africa National Land Cover 2020 Classification		Natural Lands Reclassification		
Class number	Name	Category	Class	Class number
1	Contiguous Forest (combined very high, high, medium)	Natural	Forest	2
2	Contiguous Low Forest & Thicket	Natural	Forest	2
3	Dense Forest & Woodland	Natural	Forest	2
4	Open Woodland	Natural	Forest	2
5	Contiguous & Dense Planted Forest	Non-Natural	Forest	14
6	Open & Sparse Planted Forest	Non-Natural	Forest	14
7	Temporary Unplanted Forest	Non-Natural	Forest	14
8	Low Shrubland (other regions)	Natural	Short vegetation	3
9	Low Shrubland (Fynbos)	Natural	Short vegetation	3
10	Low Shrubland (Succulent Karoo)	Natural	Short vegetation	3
11	Low Shrubland (Nama Karoo)	Natural	Short vegetation	3
12	Sparsely Wooded Grassland	Natural	Short vegetation	3

13	Natural Grassland	Natural	Short vegetation	3
14	Natural Rivers	Natural	Water	4
15	Natural Estuaries & Lagoons	Natural	Water	4
16	Natural Ocean	Natural	Water	4
17	Natural Lakes	Natural	Water	4
18	Natural Pans (flooded)	Natural	Water	4
19	Artificial Dams	Non-Natural	Water	16
20	Artificial Sewage Ponds	Non-Natural	Water	16
21	Artificial Flooded Mine Pits	Non-Natural	Water	16
22	Herbaceous Wetlands (currently mapped)	Natural	Wet short vegetation	10
23	Herbaceous Wetlands (previous mapped extent)	Natural	Wet short vegetation	10
24	Mangrove Wetlands	Natural	Mangroves	5
25	Natural Rock Surfaces	Natural	Bare	6
26	Dry Pans	Natural	Bare	6
27	Eroded Lands	Natural	Bare	6
28	Sand Dunes (terrestrial)	Natural	Bare	6

29	Coastal Dunes & Beach Sand	Natural	Bare	6
30	Bare Riverbed Material	Natural	Bare	6
31	Other Bare	Natural	Bare	6
32	Cultivated Commercial Permanent Orchards	Non-Natural	Forest	14
33	Cultivated Commercial Permanent Vines	Non-Natural	Cropland	12
34	Cultivated Commercial Sugarcane Pivot Irrigated	Non-Natural	Cropland	12
35	Commercial Permanent (Pineapples)	Non-Natural	Cropland	12
36	Cultivated Commercial Sugarcane Non-Pivot (all other)	Non-Natural	Cropland	12
37	Cultivated Emerging Farmer Sugarcane Non-Pivot (all other)	Non-Natural	Cropland	12
38	Cultivated Commercial Annuals Pivot Irrigated	Non-Natural	Cropland	12
39	Cultivated Commercial Annuals Non-Pivot Irrigated	Non-Natural	Cropland	12
40	Cultivated Commercial Annuals Non-Pivot /Non-Irrigated	Non-Natural	Cropland	12
41	Subsistence Annual Crops	Non-Natural	Cropland	12
42	Fallow Land & Old Fields (Trees)*	Natural	Forest	2
43	Fallow Land & Old Fields (Bush)*	Natural	Short vegetation	3
44	Fallow Land & Old Fields (Grass)*	Natural	Short vegetation	3

45	Fallow Land & Old Fields (Bare)*	Natural	Bare	6
46	Fallow Land & Old Fields (Low Shrub)*	Natural	Short vegetation	3
47	Residential Formal (Tree)	Non-Natural	Forest	14
48	Residential Formal (Bush)	Non-Natural	Short vegetation	15
49	Residential Formal (low veg / grass)	Non-Natural	Short vegetation	15
50	Residential Formal (Bare)	Non-Natural	Built-up	13
51	Residential Informal (Tree)	Non-Natural	Forest	14
52	Residential Informal (Bush)	Non-Natural	Short vegetation	15
53	Residential Informal (low veg / grass)	Non-Natural	Short vegetation	15
54	Residential Informal (Bare)	Non-Natural	Built-up	13
55	Village Scattered	Non-Natural	Built-up	13
56	Village Dense	Non-Natural	Built-up	13
57	Smallholdings (Tree)	Non-Natural	Forest	14
58	Smallholdings (Bush)	Non-Natural	Short vegetation	15
59	Smallholdings (low veg / grass)	Non-Natural	Short vegetation	15
60	Smallholdings (Bare)	Non-Natural	Built-up	13

61	Urban Recreational Fields (Tree)	Non-Natural	Forests	14
62	Urban Recreational Fields (Bush)	Non-Natural	Short vegetation	15
63	Urban Recreational Fields (Grass)	Non-Natural	Short vegetation	15
64	Urban Recreational Fields (Bare)	Non-Natural	Built-up	13
65	Commercial	Non-Natural	Built-up	13
66	Industrial	Non-Natural	Built-up	13
67	Roads & Rail (Major Linear)	Non-Natural	Built-up	13
68	Mines: Surface Infrastructure	Non-Natural	Built-up	13
69	Mines: Extraction Sites: Open Cast & Quarries combined	Non-Natural	Built-up	13
70	Mines: Extraction Sites: Salt Mines	Non-Natural	Built-up	13
71	Mines: Waste (Tailings) & Resource Dumps	Non-Natural	Built-up	13
72	Land-fills	Non-Natural	Built-up	13
73	Fallow Land & Old Fields (wetlands)*	Natural	Wet short vegetation	10

*We classified fallow land and old fields as natural, rather than cropland, because the class description states that these are long-term, non-active, previously cultivated lands where the cultivated land unit is no longer detectable, and thus may meet the AFi definition of a regenerated natural ecosystem (which is included in the AFi natural ecosystem definition). These classes were mapped using historical field boundaries from the 1950s-70s.

APPENDIX C: LUCAS NEW ZEALAND LAND USE RECLASSIFICATION

Table C: Reclassification for the LUCAS New Zealand Land Use dataset

LUCAS NZ Land Use Classification				Natural Lands Reclassification		
ID	Class	Subclass	Subclass ID	Category	Class	Class number
71	Natural Forest	Shrubland	120	Natural	Forest	2
		Tall forest	121	Natural	Forest	2
		Wilding trees	122	Natural	Forest	2
72	Pre-1990 Planted Forest	Unknown	0	Non-Natural	Forest	14
		Pinus radiata	201	Non-Natural	Forest	14
		Douglas fir	202	Non-Natural	Forest	14
		Unspecified exotic species	203	Non-Natural	Forest	14
73	Post-1989 Forest	Wilding Trees	122	Natural	Forest	2
		Pinus radiata	201	Non-Natural	Forest	14
		Douglas Fir	202	Non-Natural	Forest	14
		Unspecified exotic species	203	Non-Natural	Forest	14
		Regenerating natural species	204	Natural	Forest	2

74	Grassland - with woody biomass	Unknown	0	Natural	Short Vegetation	3
75	Grassland - high producing	Unknown	0	Non-Natural	Short Vegetation	15
		Grazed - dairy	502	Non-Natural	Short Vegetation	15
		Grazed - non-dairy	503	Non-Natural	Short Vegetation	15
		Ungrazed	504	Non-Natural	Short Vegetation	15
76	Grassland - low producing	Unknown	0	Natural	Short Vegetation	3
		Grazed - dairy	502	Natural	Short Vegetation	15
		Grazed - non-dairy	503	Natural	Short Vegetation	15
		Ungrazed	504	Natural	Short Vegetation	3
77	Cropland - perennial	Unknown	0	Non-Natural	Cropland	12
78	Cropland - annual	Unknown	0	Non-Natural	Cropland	12
79	Open water	Unknown	0	Natural	Water	4
		Naturally occurring	901	Natural	Water	4
		Human induced	902	Non-Natural	Water	16
80	Vegetated wetland	Unknown	0	Natural	Wet Short Vegetation	10

		Peat mine	1001	Non-Natural	Wet Short Vegetation	17
81	Settlements	Unknown	0	Non-Natural	Built-up	13
82	Other	Unknown	0	Natural	Bare / snow/ice *	6/7

*The LUCAS 'Other' class can include natural bare rock and sand, as well as permanent ice/snow and glaciers. First, we reclassified the Other class as bare and then we overlaid this class with the UMD Land Cover and reclassified it to snow/ice if it overlapped with the UMD snow/ice class.

APPENDIX D: SDPT v2.0 DATA SOURCES

The Spatial Database of Planted Trees version 2.0 is currently in review. Table D lists the datasets used for each country, as well as new regional datasets incorporated.

Table D: Data sources in SDPT v2.0

Country	Year	Source	Native resolution	Regional - Oil Palm (Descals et al. 2021) 10m	Regional - Rubber (Xiao et al. 2021) 30m	Regional - Orchard (Open Street Map)
Algeria	2015	Lesiv et al. 2022	100 m			x
Angola	-	-		x		x
Argentina	2013	Argentina Ministry of Agroindustry	vector			x
Armenia	2015	Lesiv et al. 2022	100 m			x
Australia	2014-2015	Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES)	vector			x
Azerbaijan	2015	Lesiv et al. 2022	100 m			x
Bangladesh	-	-				x
Belize	2018	Belize Ministry of Agriculture, Fisheries, Forestry, the Environment, Sustainable Development, and Immigration	vector	x		x
Benin	2013	USGS LULC West Africa	2 km	x		x
Bhutan	2015	Lesiv et al. 2022	100 m			x
Bolivia	2015	Lesiv et al. 2022	100 m			x
Botswana	2015	Lesiv et al. 2022	100 m			x
Brazil	2013-2014	Petersen et al. 2016 (Transparent World)	vector	x		x

Brunei	-	-		x		x
Burkina Faso	2013	USGS LULC West Africa	2 km			x
Burundi	-	-		x		x
Cabo Verde	2013	USGS LULC West Africa	2 km			x
Cambodia	2013-2014 / 2015	Petersen et al. 2016 (Transparent World) / Debonne et al. 2019	vector / 1 km	x	x	x
Cameroon	2020	Cameroon Ministry of Forestry and Wildlife, Cameroon Ministry of Forestry and Wildlife/WRI	vector	x		x
Canada	2015	Lesiv et al. 2022	100 m			x
Central African Republic	-	-		x		x
Chile	2014 / 2016	Instituto Forestal de Chile (INFOR), Sistema Informationa de Territorial (SIT) / Zhao et al. 2016	vector / 30m			x
China	2016-2020	Abbasi et al. (in review)	1 km			x
Colombia	2013-2014/ 2002-2020	Petersen et al. 2016 (Transparent World)/ Instituto Amazónico de Investigaciones Científicas - SINCH	vector / vector	x		x
Congo	-	-		x		x
Costa Rica	2012	Sistema Nacional de Areas de Conservación (SINAC), Fondo Nacional de Financiamiento Forestal (FONAFIFO), Ministerio de Ambiente y Energia (MAE)	5 m	x		x
Cote D'Ivoire	2013-2015/ 2013	WRI/ USGS LULC West Africa	vector/ 2km	x		x
Cuba	2015	Lesiv et al. 2022	100 m			x

Cyprus	2015	Lesiv et al. 2022	100 m		x
Dominican Republic	-	-		x	x
DRC	2013/ 2018	Ministère de L'Environnement, Conservation de la Nature, et Développement Durable (MECNDD), Nature Conservancy and Sustainable Development (MECNDD)/ DRC Ministry of the Environment and Sustainable Development's Forest Atlas	vector/ vector	x	x
Ecuador	2018/ 2020	Ministry of Environment Land Use Map/ Ministry of Agriculture and Livestock	30m / vector	x	x
Egypt	2015	Lesiv et al. 2022	100 m		x
El Salvador	-	-		x	x
Equatorial Guinea	-	-		x	x
Eritrea	2015	Lesiv et al. 2022	100 m		x
Ethiopia	2015	Lesiv et al. 2022	100 m		x
European Union	2015	Lesiv et al. 2022	100 m		x
Fiji	2015	Lesiv et al. 2022	100 m		x
French Guiana	2015	Lesiv et al. 2022	100 m		
Gabon	2013-2015	WRI	vector	x	x
Gambia	2013	USGS LULC West Africa	2 km		x
Ghana	2013-2015/ 2013	WRI/ USGS LULC West Africa	vector/ 2 km	x	x

Guadeloupe	2015	Lesiv et al. 2022	100m			
Guatemala	1998-2020	Guatemala Forestry incentives database, Forestry Development Directorate - INAB 2020	vector	x		x
Guinea	2013	USGS LULC West Africa	2 km	x		x
Guinea-Bissau	2013	USGS LULC West Africa	2 km	x		x
Haiti	2015	Lesiv et al. 2022	100 m			x
Honduras	2013	National Institute of Conservation and Forest Development, Protected Areas, and Wildlife	5 m	x		x
India	2015	Roy et al. 2016	23.5 m	x		x
Indonesia	2013-2014 / 2015/ 2017-2019	Petersen et al. 2016 (Transparent World) / Austin et al. 2017/ Miettinen et al. 2016/ Gaveau et al. 2016/ Condro et al. 2020	vector/ 250 m/ 30 m / 60m/ 30m	x		x
Iran	2015	Lesiv et al. 2022	100 m			x
Iraq	2015	Lesiv et al. 2022	100 m			x
Israel	2015	Lesiv et al. 2022	100 m			x
Jamaica	2015	Lesiv et al. 2022	100 m			x
Japan	2016-2020	Abbasi et al. (in review)	1 km			x
Jordan	2015	Lesiv et al. 2022	100 m			x
Kazakhstan	2015	Lesiv et al. 2022	100 m			x
Kenya	2010	Kenya Forest Service	vector			x
Kyrgyzstan	2015	Lesiv et al. 2022	100 m			x
Laos	-	-			x	x

Lebanon	2015	Lesiv et al. 2022	100 m			x
Lesotho	2015	Lesiv et al. 2022	100 m			x
Liberia	2013-2014/ 2013	Petersen et al. 2016 (Transparent World)/ USGS LULC West Africa	vector/ 2 km	x		x
Libya	2015	Lesiv et al. 2022	100 m			x
Madagascar	2015	Lesiv et al. 2022	100 m			x
Malawi	2012/ 2015	Malawi Department of Forestry/ Food and Agriculture Organization (FAO)	vector/ vector			x
Malaysia	2013-2014/ 2015/ 2010/ 2016	Petersen et al. 2016 (Transparent World) / Gaveau et al. 2016/ Miettinen et al. 2016 / Gunarso et al. 2013/ Xu et al. 2020	vector/ 30 m/ 30 m/ vector/ 100 m	x		x
Mali	2013	USGS LULC West Africa	2 km			x
Mauritania	2013	USGS LULC West Africa	2 km			x
Mexico	2010-2021/ 2018	Dirección General de Gestión Forestal y de Suelos (DGGFS) of Mexico's Ministry of Environment and Natural Resources (Secretaría de Medio Ambiente y Recursos Naturales; SEMARNAT)/ Mexico Conafor Comision Nacional Forestal, INEGI	vector/ vector	x		x
Mongolia	2015	Lesiv et al. 2022	100 m			x
Morocco	2015	Lesiv et al. 2022	100 m			x
Mozambique	2015	Lesiv et al. 2022	100 m			x
Myanmar	2014	Bhagwat et al. (2015)	30 m	x	x	x
Nepal	2015	Ministry of Forest and Soil Conservation	vector			x
New Caledonia	2015	Lesiv et al. 2022	100 m			x

New Zealand	2016	New Zealand Ministry for the Environment LUCAS Land Use	vector		x
Nicaragua	2014	Furumo and Aide (2017)	250 m	x	x
Nigeria	2013-2015/ 2013	WRI/ USGS LULC West Africa	vector/ 2 km	x	x
North Korea	2016-2020	Abbasi et al. (in review)	1 km		x
Oman	2015	Lesiv et al. 2022	100 m		x
Pakistan	2015	Pakistan Forestry, Environment and Wildlife Department	vector		x
Palestine	2015	Lesiv et al. 2022	100 m		x
Panama	2021	Panama Ministerio de Ambiente	10 m	x	x
Papua New Guinea	2015/ 2015	Papua New Guinea Forest Authority (PNGFA)/ New Britain Palm Oil Ltd (NBPOL)	2 km/ vector	x	x
Paraguay	2015	Lesiv et al. 2022	100 m		x
Peru	2013-2014	Petersen et al. 2016 (Transparent World)	vector	x	x
Philippines	2003, 2017	National Mapping and Resource Information Authority (NAMRIA)	vector	x	x
Rwanda	2008	Government of Rwanda	vector	x	x
Sao Tome and Principe	-	-		x	x
Senegal	2013	USGS LULC West Africa	2 km		x
Sierra Leone	2013	USGS LULC West Africa	2 km	x	x
Solomon Islands	-	-		x	x

Somalia	2015	Lesiv et al. 2022	100 m			x
South Africa	2020	South Africa Department of Forestry, Fisheries, and the Environment Land Cover Map	20 m			x
South Korea	Unk./ Unk.	Korean Forest Service/ South Korea National Map of Planted Forests (Kim et al. 2009)	vector/ vector			x
South Sudan	2015	Lesiv et al. 2022	100 m			x
Sri Lanka	2013-2015	WRI	vector	x		x
Suriname	2015	Lesiv et al. 2022	100 m			x
Swaziland	2015	Lesiv et al. 2022	100 m			x
Syria	2015	Lesiv et al. 2022	100 m			x
Tajikistan	2015	Lesiv et al. 2022	100 m			x
Tanzania	-	-		x		x
Thailand	2000	Thai Royal Forestry Department	vector	x	x	x
Togo	2013	USGS LULC West Africa	2 km	x		x
Trinidad and Tobago	2007	Helmer et al. 2012	vector			
Tunisia	2015	Lesiv et al. 2022	100 m			x
Uganda	-	-		x		x
United States	2017 / 2014	United States National Agricultural Statistics Service; NASS / WRI analysis based on data from USDA Forest Service (ownership, forest type, timberland extent), US Geological Survey (protected areas), Pan et al. 2011 (stand age)	30 m/ 250m			x

Uruguay	2015/ 2021	Dirección Nacional de Ordenamiento Territorial (DINOT), within Ministerio de Vivienda, Ordenamiento Territorial y Medio Ambiente (MVOTMA) / Uruguay Ministry of Livestock, Agriculture, and Fisheries	vector/ vector			x
Uzbekistan	2015	Lesiv et al. 2022	100 m			x
Vanuatu	-	-		x		x
Venezuela	2014	Furumo and Aide (2017)	250 m	x		x
Vietnam	2016	Government of Vietnam	vector	x	x	x
Zambia	2015	Lesiv et al. 2022	100 m			x
Zimbabwe	2015	Lesiv et al. 2022	100 m			x

*Year represents the year of source plantation data and not the publication year.

REFERENCES

Accountability Framework Initiative (AFi), 2019. *Accountability Framework version 1.0.* https://accountability-framework.org/

Accountability Framework Initiative (AFi). 2019. *Operational Guidance on Applying the Definitions Related to Deforestation, Conversion, and Protection of Ecosystems.*

Baeza, S., E. Vélez-Martin, D. De Abelleyra, S. Banchero, F. Gallego, J. Schirmbeck, S. Veron, et al. 2022. "Two Decades of Land Cover Mapping in the Río de La Plata Grassland Region: The MapBiomas Pampa Initiative." *Remote Sensing Applications: Society and Environment* 28 (November): 100834. doi:10.1016/j.rsase.2022.100834.

Barnosky, A.D., N. Matzke, S. Tomiya, G.O.U. Wogan, B. Swartz, T.B. Quental, C. Marshall, J.L. McGuire, et al. 2011. "Has the Earth's sixth mass extinction already arrived?" *Nature* 471: 51-57.

Bunting, P., A. Rosenqvist, L. Hilarides, R.M. Lucas, N. Thomas, T. Tadono, T.A. Worthington, M. Spalding, N.J. Murray, and L.M. Rebelo. 2022. "Global Mangrove Extent Change 1996–2020: Global Mangrove Watch Version 3.0." *Remote Sensing* 14 (3657). https://doi.org/10.3390/ rs14153657

Cover, C.L., 2018. European Union, Copernicus Land Monitoring Service. Eur. Environ. Agency.

Crezee, B., G.C. Dargie, C.E.N. Ewango, E.T.A. Mitchard, O. Emba, J. Kanyama, P. Bola, J.B.N. Ndjango, N.T. Girkin, Y.E. Bocko, S.A. Ifo, W. Hubau, D. Seidensticker, R. Batumike, G. Imani, A. Cuni-Sanchez, C.A. Kiahtipes, J. Lebamba, H.P. Wotzka, H. Bean, T.R. Baker, A.J. Baird, A. Boom, P.J. Morris, S.E. Page, I.T. Lawson, and S.L. Lewis. "Mapping peat thickness and carbon stocks of the central Congo Basin using field data. *Nature Geoscience* 15: 639-644. https://www.nature.com/articles/s41561-022-00966-7

de Abelleyra, D., S. Verón, S. Banchero, M. Iturralde Elortegui, S. Valiente, O. Puig, F. Murray, J.P. Martini, K. Zelaya, D. Maidana, N. Varlamoff, J. Peiretti, P. Benedetti, J. Portillo, M. Melilli, E. Maidana, Y. Goytía, V. Sapino, A. Regonat, F. Cracogna, C. Espíndola, M. Parodi, F. Colombo, J. Scarel, J. Ayala, L. Martins, M. Basanta, A. Rausch, G. Almada, L. Boero, J. Calcha, A. Chiavassa, M. Lopez de Sabando, D. Kurtz, F. Marini, S. Sarrailhe, M. Petek, T. Propato, A. Ferraina, A. Pezzola, C. Winschel, S. Muñoz, J. Mesa, J. Volante. 2021."Mapa Nacional de Cultivos Campaña 2020/2021." Instituto Nacional de Tecnologia Agropecuaria.

de Abelleyra, D., S. Verón, S. Banchero, J. Mosciaro, A. Franzoni, M. Boasso, S. Valiente, O. Puig, Y. Goytia, M.R. Iturralde Elortegui, D. Maidana, J.P. Martini, F. Murray, F. Marini, T. Propato, A. Ferraina, C. Gomez, S. Sarrailhe, M. Petek, J.C. Mesa, D. Kurtz, R. Perucca, P. Benedetti, S. Muñoz, J. Volante. 2020."Mapa Nacional de Cultivos Campaña 2019/2020." Instituto Nacional de Tecnologia Agropecuaria.

Descales, A., S. Wich, E. Meijaard, D. L. A. Gaveau, S. Peedell, and Z. Szantoi. 2021. "High-resolution global map of smallholder and industrial closed-canopy oil palm plantations." Earth System Science Data 13(3): 1211-1231. https://doi.org/10.5194/essd-13-1211-2021

Forest Europe. 2020. "State of Europe's Forest 2020". Ministerial Conference on the Protection of Forests in Europe Liaison Unit Bratislava. https://foresteurope.org/wp-content/uploads/2016/08/SoEF_2020.pdf

Gilbert, M., G. Cinardi, D. Da Re, W.G.R. Wint, D. Wisser, T.P. Dominik. 2022. "Global cattle distribution in 2015 (5 minutes of arc)." Harvard Dataverse, V1. https://doi.org/10.7910/DVN/LHBICE

Gorelick, N., M. Hancher, M. Dixon, S. Llyushchenko, D. Thau, and R. Moore. 2017. "Google earth engine: Planetary-scale geospatial analysis for everyone." *Remote Sensing of Environment*. 202: 18–27. https://www.sciencedirect.com/science/article/pii/S0034425717302900

Gosling, J., M.I. Jones, A. Arnell, J.E.M. Watson, O. Venter, A.C. Baquero, and N.D. Burgess. 2020. "A Global Mapping Template for Natural and Modified Habitat across Terrestrial Earth." *Biological Conservation* 250 (October): 108674. doi:10.1016/j.biocon.2020.108674.

Gumbricht, T., R.M. Roman-Cuesta, L. Verchot, M. Herold, F. Wittman, E. Householder, N. Herold, and D. Murdiyarso. 2017. "An expert system model for mapping tropical wetlands and peatlands reveals South America as the largest contributor". *Global Change Biology* 23 (9): 3581-3599.

https://onlinelibrary.wiley.com/doi/full/10.1111/gcb.13689

Hansen, M.C., P.V. Potapov, A.H. Pickens, A. Tyukavina, A. Hernandez-Serna, V. Zalles, S. Turubanova, I. Kommareddy, S.V. Stehman, and X-P Song. 2022. "Global land use extent and dispersion within natural land cover using Landsat data." *Environmental Research Letters* 17 (3). https://doi.org/10.1088/1748-9326/ac46ec

Harris, N.L., E.D. Goldman, and S. Gibbes. 2019. "Spatial Database of Planted Trees Version 1.0." Technical Note. Washington, DC: World Resources Institute. https:// www.wri.org/publication/spatialdatabase-planted-trees.

Harris, N.L., D.A. Gibbs, A. Baccini, R.A. Birdsey, S. de Bruin, M. Farina, L. Fatoyinbo, M.C. Hansen, M. Herold, R.A. Houghton, P.V. Potapov, D. Requena Suarez, R.M. Roman-Cuesta, S.S. Saatchi, C.M. Slay, S.A. Turubanova, A. Tyukavina. 2021. "Global maps of twenty-first century forest carbon fluxes". *Nature Climate Change* 11: 234-240. https://www.nature.com/articles/s41558-020-00976-6

Hastie, A., E.N. Honorio Coronado, J. Reyna, E.T.A. Mitchard, C.M. Akesson, T.R. Baker, L.E.S. Cole, C.J. Cordova Oroche, G. Dargie, N. Davila, E.C. De Grandi, J. Del Aguila, D. Del Castillo Torres, R. De La Cruz Paiva, F.C. Draper, G. Flores, J. Grandez, K. Hergoualc'h, J.E. Householder, J.P. Janovec, O. Lahteenoja, D. Reyna, P. Rodriguez-Veiga, K.H. Roucoux, M. Tobler, C.E. Wheeler, M. Williams, and I.T. Lawson. 2022. "Risks to carbon storage from land-use change revealed by peat thickness maps of Peru". *Nature Geoscience* 15: 369-374. https://www.nature.com/articles/s41561-022-00923-4

Hill, S.L.L, J. Fajardo, C. Maney, M. Harfoot, M. Harrison, D. Guaras, M. Jones, M.J. Oliva, et al. In Review. "The Ecosystem Integrity Index: a novel measure of terrestrial ecosystem integrity with global coverage." *bioRxiv*. https://doi.org/10.1101/2022.08.21.504707

IPBES. 2019. "Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services." S. Díaz, J. Settele, E.S. Brondízio, H.T. Ngo, M. Guèze, J. Agard, A. Arneth, P. Balvanera, et al. (Eds.). Bonn, Germany: IPBES secretariat. https://doi.org/10.5281/zenodo.3553579

IPCC. 2019. "Climate Change and Land, an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse has fluxes in terrestrial ecosystems." P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Portner, D.C. Roberts, P. Zhai, R. Slade, et al. (Eds.). Cambridge, United Kingdom and New York, USA: Cambridge University Press. https://www.ipcc.ch/site/assets/uploads/sites/4/2022/11/SRCCL_Full_Report.pdf

Kalischek, N., N. Land, C. Renier, R.C. Daudt, T. Addoah, W. Thompson, W.J. Blaser-Hart, R. Garrett et al. In Review. "Satellite-based high-resolution maps of cocoa planted area for Côte d'Ivoire and Ghana." *Nature Food.* https://doi.org/10.48550/arXiv.2206.06119

Lesiv, M., D. Shchepashchenko, M. Buchhorn, L. See, M. Dürauer, I. Georgieva, M. Jung, F. Hofhansl, et al. 2022. "Global forest management data for 2015 at a 100 m resolution." *Scientific Data* 9 (199). https://doi.org/10.1038/s41597-022-01332-3

Ministry for the Environment. 2020. LUCAS NZ land use map 1990 2008 2012 2016 v008. Ministry for the Environment, Wellington

MapBiomas Amazonia Project - Collection 4.0 of Amazonian Annual Land Cover & Land Use Map Series, accessed 01/2023 through Google Earth Engine.

MapBiomas Chaco Project- Collection 3.0 of the Annual Series of Land Use and Land Cover Maps of Chaco, accessed 01/2023 through Google Earth Engine.

MapBiomas Indonesia - Collection 1.0 time-series maps of land-use and land-cover, accessed 01/2023 through Google Earth Engine.

MapBiomas Trinational Atlantic Forest Project - Collection 2.0 of the Annual Coverage and Land Use Series, acquired 01/2023 through Google Earth Engine.

Maus, V., Giljum, S., da Silva, D.M. et al. 2022. An update on global mining land use. Sci Data 9, 433 https://doi.org/10.1038/s41597-022-01547-4

Miettinen, J., C. Shi, and S.C. Liew. 2016. "Land cover distribution in the peatlands of Peninsular Malaysia, Sumatra and Borneo in 2015 with changes since 1990". *Global Ecology and Conservation* 6: 67-78.

https://www.sciencedirect.com/science/article/pii/S2351989415300470

Potapov, P., M.C. Hansen, L. Laestadius, S. Turubanova, A. Yaroshenko,C. Thies, W. Smith, I. Zhuravleva, A. Komarova, S. Minnemeyer, and E. Esipova. 2017. "The last frontiers of wilderness: Tracking loss of intact forest landscapes from 2000 to 2013." Science Advances 3 (1). https://www.science.org/doi/10.1126/sciadv.1600821

Richter, J., Harris, N.L., E.D. Goldman, and H.L. Harris J. Richter. In review. "Spatial Database of Planted Trees Version 2.0." Technical Note. Washington, DC: World Resources Institute.

Sabatini, F.M., H. Bluhm, Z. Kun, D. Aksenov, J.A. Atauri, E. Buchwald, S. Burrascano, E. Cateau, et al. 2021. "European primary forest database v2.0." *Scientific Data* 8 (220). https://doi.org/10.1038/s41597-021-00988-7

South Africa Department of Environment, Forestry, and Fisheries (DEFF). 2021. "South African National Land-Cover 2020 Dataset". Downloaded 02/2023 from https://egis.environment.gov.za/data_egis/data_download/current

Souza, Carlos M., Jr., Julia Z. Shimbo, Marcos R. Rosa, Leandro L. Parente, Ane A. Alencar, Bernardo F. T. Rudorff, Heinrich Hasenack, Marcelo Matsumoto, Laerte G. Ferreira, Pedro W. M. Souza-Filho, Sergio W. de Oliveira, Washington F. Rocha, Antônio V. Fonseca, Camila B. Marques, Cesar G. Diniz, Diego Costa, Dyeden Monteiro, Eduardo R. Rosa, Eduardo Vélez-Martin, Eliseu J. Weber, Felipe E. B. Lenti, Fernando F. Paternost, Frans G. C. Pareyn, João V. Siqueira, José L. Viera, Luiz C. Ferreira Neto, Marciano M. Saraiva, Marcio H. Sales, Moises P. G. Salgado, Rodrigo Vasconcelos, Soltan Galano, Vinicius V. Mesquita, and Tasso Azevedo. 2020. "Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine" *Remote Sensing* 12, no. 17: 2735. https://doi.org/10.3390/rs12172735

Taylor, R., A. Rosenbarger, L. Samberg, J. Milder. "It's Time for Supply Chains to Go Conversion Free — For the Climate's Sake." World Resources Institute. https://www.landcarbonlab.org/news-updates/supply-chains-zero-land-conversion-climate

Thenkabail, P.S., P.G. Teluguntla, J. Xiong, A. Oliphant, R.G. Congalton, M. Ozdogan, M.K. Gumma, et al. 2021. "Global Cropland-Extent Product at 30-m Resolution (GCEP30) Derived from Landsat Satellite Time-Series Data for the Year 2015 Using Multiple Machine-Learning Algorithms on Google Earth Engine Cloud." Report 1868. Professional Paper. Reston, VA. USGS Publications Warehouse. doi:10.3133/pp1868.

Venter, O., E.W. Sanderson, A. Magrach, J.R. Allan, J. Beher, K.R. Jones, H.P. Possingham, et al. 2016. "Sixteen Years of Change in the Global Terrestrial Human Footprint and Implications for Biodiversity Conservation." *Nature Communications* 7 (1): 12558. doi:10.1038/ncomms12558.

WWF. 2022. "Living Planet Report 2022 - Building a nature-positive society." R.E.A. Almond, M. Grooten, D. Juffe Bignoli, and T. Petersen (Eds). Gland, Switzerland: World Wildlife Fund. https://wwflpr.awsassets.panda.org/downloads/lpr_2022_full_report.pdf

Xiao, C., P. Li, Z. Feng, Y. Yang, Z. You, Y. Lin, and X. Zhang. 2021. "Latest 30-m Map of Mature Rubber Plantations in Mainland Southeast Asia and Yunnan Province of China: Spatial Patterns and Geographical Characteristics." *Progress in Physical Geography: Earth and Environment* 45 (5): 736–56. doi:10.1177/0309133320983746.

Xu, J., P.J. Morris, J. Liu, and J. Holden. 2018. "PEATMAP: Refining estimates of global peatland distribution based on a meta-analysis". *CATENA* 160: 134-140. https://www.sciencedirect.com/science/article/abs/pii/S0341816217303004#ec0005

Zanaga, D., R. Van De Kerchove, W. De Keersmaecker, N. Souverijns, C. Brockmann, R. Quast, J. Wevers, A. Grosu, et al. 2021. "ESA WorldCover 10 m 2020 v100." https://doi.org/10.5281/zenodo.5571936