Remote Sensing for Monitoring Impacts of Land-use Change on Biodiversity and Carbon Stocks

The role in the spatial planning process

Technical review
January 2023

About SPACES

SPACES is an emerging coalition that aims to mobilise financial and technical support for high-ambition countries to design and implement spatially-explicit strategies for delivering on the Kunming-Montreal Global Biodiversity Framework and related nature and climate objectives. SPACES had a scoping phase in 2022, coordinated by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and Systemiq, working with UNDP, IIASA and IIS, among other partners.

SPACES invites interested countries and national technical partners to explore participation in the coalition. Potential benefits include: (i) technical support and capacity building, including the development of national datasets, tools and databases, working with government departments and national institutions (ii) sharing of experiences between countries (iii) a route to short and medium-term financial support for the development of spatial plans, including stakeholder engagement across sectors.

For more information, please visit www.spacescoalition.org, or contact info@spacescoalition.org

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Contents

About this report

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Acronyms

AGB	Above-Ground Biomass
AFOLU	Agriculture Forestry, and Other Land Use
AOH	Area of Habitat
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High-Resolution Radiometer
BII	Biodiversity Intactness Index
CBD	Convention of Biological Diversity
CCI	Climate Change Initiative
DEM	Digital Elevation Model
EBV	Essential Biodiversity Variable
ETM+	Enhanced Thematic Mapper Plus
ESA	European Space Agency
FAO	Food and Agriculture Organization of the United Nations
GEDI	Global Ecosystem Dynamics Investigation
GEO BON	Group on Earth Observations Biodiversity Observation Network
GFW	Global Forest Watch
GLAS	Geoscience Laser Altimeter System HRV – High Resolution Visible
ICESAT	NASA's Ice, Cloud and Land Elevation Satellite IUCN – International Union for Conservation of Nature
ISRO	Indian Space Research Organization (ISRO)
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MRV	Measuring, monitoring and verifying
MSI	Multispectral Instrument
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NDC	Nationally Determined Contributions
NDVI	Normalised Difference Vegetation Index
NICFI	Norway's International Climate & Forests Initiative
NOAA	National Oceanic and Atmospheric Administration
OLI	Operational Land Imager
SAR	Synthetic Aperture Radar
SDM	Species Distribution Model
SDM	Structured Decision Making
SPOT	Satellite pour l'Observation de la Terre
SRTM	Shuttle Radar Topography Mission
TM	Thematic Mapper
TIROS	Television InfraRed Operational Satellite
TIRS	Thermal Infrared Sensor
UNFCCC	United Nations Framework Convention on Climate Change

Executive summary

Background

SPACES is an emerging coalition that aims to mobilise financial and technical support for high-ambition countries to design and implement spatially-explicit strategies for delivering on the Kunming-Montreal Global Biodiversity Framework and related nature and climate objectives. In the first half of 2022, SPACES assessed emerging datasets, tools, techniques and state of the art approaches relevant to spatial planning. It is also consulting widely on the climate and nature spatial intelligence needs of countries and businesses. One of the objectives of SPACES is to advance the integration of Remote Sensing and biodiversity data. Keeping that objective in mind, the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) in partnership with the International Institute for Applied Systems Analysis (IIASA) has produced this technical paper on the role of Remote Sensing in monitoring impacts of land-use change on biodiversity and carbon stocks.

Aim and structure

Focusing on freely available satellite data, this paper explores the opportunities that Remote Sensing technology provides for biodiversity and carbon monitoring at global scales. Aimed primarily at non-specialist users, it intends to pave the way to integrate Remote Sensing into biodiversity and carbon stock analysis systems. It also aims to strengthen insights into the biodiversity and carbon implications of land-use change. The paper further documents how this information can be used by governments, business and civil society for spatial planning.

Remote Sensing technology provides data that supports the different types of information that is needed during spatial analysis, as shown in figure 0.1. It provides the means to generate global land-cover maps, which can then be used to assess the impacts of land-cover change on biodiversity and carbon stocks. It can be used to directly monitor biodiversity across the landscape as well as to measure the carbon stored in different land-cover types. This paper shows how this remotely-sensed information, combined with land cover maps, can estimate changes in biodiversity and carbon stocks over space and time and how this information comes together in the spatial planning process.

This type of monitoring can be done at different scales. This paper focuses upon what can be achieved at global scales using open source and freely available data. Some chapters are more technical than others allowing for a deeper understanding of the underlying technologies. The aim of this paper is to inspire decision-makers to embrace the use of this technology.

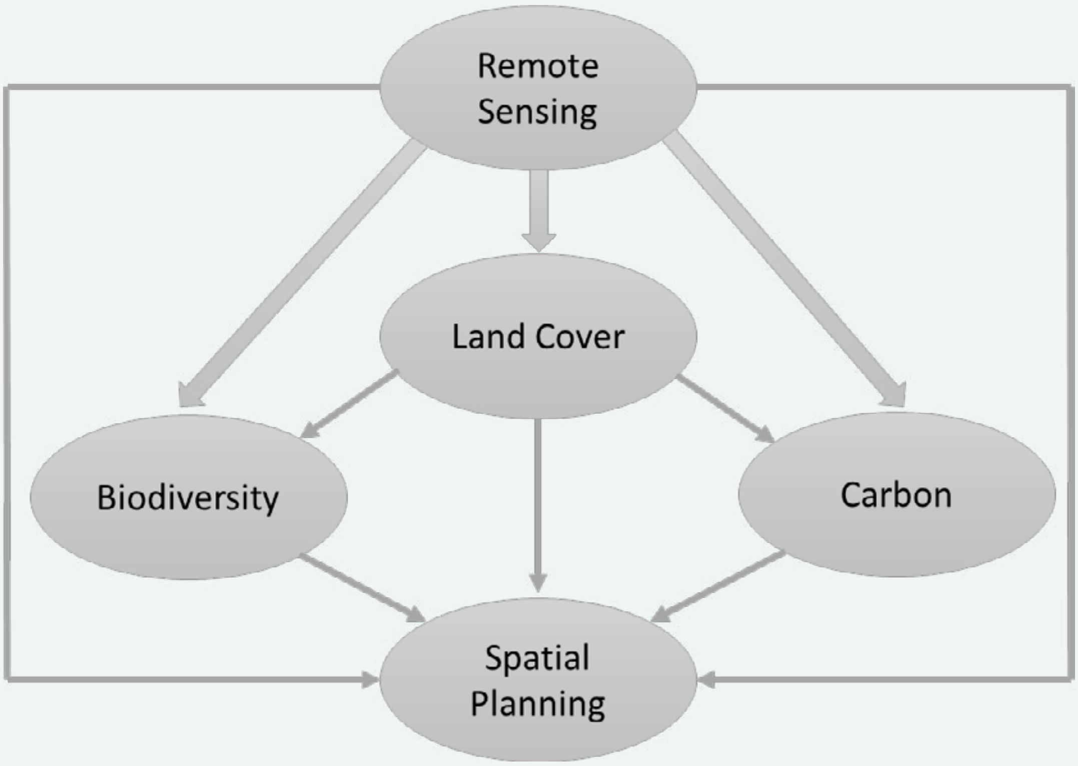

Figure 0.1: Integration of Remote Sensing in data needed for spatial planning for carbon and biodiversity assessments

Introduction

The rapid rate of biodiversity loss, particularly in tropical hotspots (Habel *et al.* 2019), has led to the declaration of a biodiversity crisis and the establishment of international policies to reverse this decline. In addition, the Earth's climate is changing at an unprecedented rate due to the continued rise of global greenhouse gas emissions (IPCC 2021). Again, international policy has been set to encourage countries to reduce carbon emissions and enhance carbon stocks.

Land-use change can be considered as the processes by which human activity modifies the natural landscape. Land use has changed dramatically in recent decades. According to the most recent research on the subject land-use change has had a significantly larger impact than previously thought, affecting almost a third of the world's land area over the past 60 years (Winkler *et al.* 2021). Land-use change has also become a key driver of both biodiversity loss and changes in carbon stocks caused by deforestation and forest degradation. Habitat loss from land conversion, including changes from forest to agriculture, causes fragmentation of populations, reducing genetic diversity and increasing the risk of extinction (Pardini, Nichols, and Püttker 2018). In addition, a shift from forest to agriculture increases CO_2 emissions and reduces carbon sequestration and storage, impacting global climate change (Don, Schumacher, and Freibauer 2011). Assessing the impacts of land-use and land-cover change on biodiversity and carbon stocks is therefore critical to making informed conservation and land management decisions.

Remote Sensing technology provides a consistent, rapid and scalable means of assessing these impacts. The technology is also swiftly advancing. An ever-increasing number of satellites are being launched and imagery constantly becoming more readily available at higher resolutions. In addition, novel ways of processing data through the use of artificial intelligence and cloud-based platforms are allowing large-scale monitoring of changes to the Earth's surface. As a result, the amount, regularity and quality of data obtained from Remote Sensing are increasingly enabling the improved monitoring and analysis of land-use change and enhancing understanding of land-use impacts.

Long-term monitoring of global biodiversity from space contributes to the knowledge of trends in biodiversity decline and aids decision-making to combat further loss. A range of different metrics encompassing many aspects of biodiversity can be derived using Remote Sensing. These metrics cover different facets of biodiversity ranging from ecosystem level (like land cover) to species level (like abundance and distributions). This allows for improved monitoring and reporting on the state of biodiversity (Skidmore *et al.* 2021).

Remote Sensing provides an invaluable tool to monitor carbon stocks and their response to human activities through different dynamics of land-use change. Both the soil and the above-ground biomass (in stems, branches and leaves) contain terrestrial carbon, but also the below-ground biomass (in roots) of vegetated biomes such as forests and grasslands store terrestrial carbon.

The above-ground biomass component of carbon stocks can be monitored from space (Goetz and Dubayah 2011) by measuring various vegetation attributes, including tree canopy height, three-dimensional forest structure and various spectral vegetation indices. Aboveground biomass measures are then used to estimate the amount of carbon stored in different types of land and vegetation. This information, combined with temporal land cover maps, provides a picture of how carbon stocks change over time.

Decisions about land use and changes to land management are made by governments and landholders, who can use this Remote Sensing derived information as part of their spatial planning process. For example, they can use it to identify critical hotspots or specific regions of interest for climate and nature actions. Spatial planning is a form of decision-making that uses spatially explicit data to navigate complex problems, often including multiple objectives and trade-offs between them. Spatial information, namely information on current or future land use and its relationship with biodiversity and carbon, can be useful in all steps of a decision-making process. This includes during social, economic, and political decisions on land use to achieve national development, climate and nature targets.

This report focuses on satellite Remote Sensing and describes the latest global land cover datasets available. It then describes how they can be used to assess the impacts of land-use change on biodiversity and carbon stocks. Expanding on these concepts, this paper provides details on how Remote Sensing technology plays a crucial role in monitoring global environmental changes affecting biodiversity and carbon stocks.

1

Remote sensing of global land use and land-cover

1.1 Background

In the broadest sense, Remote Sensing is about gathering information from a distance. More specifically, Remote Sensing systems acquire images of the Earth's surface from overhead using energy emitted or reflected from the Earth's surface (Campbell and Wynne 2011). From these images, land cover can be derived, which may then indicate how the land is used. Sustainable land management relies on information on the influence of past and upcoming land use changes as well as the current land use. As such, global datasets of land use and land-cover can help managers make decisions.

Land use and land cover are two closely related but separate terms. The physical and biological composition of the Earth's surface is referred to as "land cover" (C. P. Giri 2012). Land-cover categories may be natural or anthropogenic and may include water bodies, wetlands, artificial surfaces, croplands, snow and ice, forests, grasslands, shrublands, bare ground and tundra. Contrarily, land use describes how people use and manage land for various purposes. A land-cover type (like a forest) may have multiple land use purposes (like production of timber, recreation and conservation). It could also have varying management regimes (for example, minor or intense logging activity), which are often difficult to derive from Remote Sensing alone (C. P. Giri 2012). Decision-makers are interested in land use and land-use change. However, the Remote Sensing community is focused on detecting land cover and land-cover change. In this document, "land cover" will be used in the Remote Sensing context and "land use" in the context of decision making.

Since the first Landsat satellites launched in the early 1970s, satellite sensors have been monitoring the surface of the Earth (Figure 1.1). Prior to the satellite era, land cover was mapped using aerial photography, but these assessments were costly and could only be done for small areas (Woodcock, Strahler, and Franklin 1983). Remote Sensing using sensors mounted on satellites that orbit the Earth has enabled scientists to map large areas of the Earth's surface. Sensors record electromagnetic radiation emitted by the Earth's surface or reflected off of it at different wavelengths (Figure 1.2). Data recorded by the sensors are then transmitted to a receiver on the ground and processed into an image (Sherbinin *et al*. 2002). The image is interpreted using a range of techniques that classify aspects of the image into different land-cover categories. Over the past fifty years, the spatial resolution of openly available global satellite imagery has improved dramatically from 1 km to 10 m. Temporal resolution has also greatly improved, moving from land-cover maps that can only capture images annually to those that can capture many images regularly over a long period of time. In 2022, a dataset was released showing land cover at 10 m resolution in near-real time (Brown *et al*. 2022). Additionally, the spectral resolution of satellite sensors has also increased. This has made it possible for electromagnetic radiation to be detected in a greater range of wavelengths and has vastly improved land-cover identification (Acharya and Yang 2015).

Initially, land cover was mapped in collaboration with local stakeholders for local to regional areas only. Over the years, computer-assisted techniques to classify land cover from satellite images have been developed, land-cover mapping initiatives have grown and sensors have improved. This has driven the progression of land cover maps from local to regional and global scales (Loveland and Dwyer 2012).

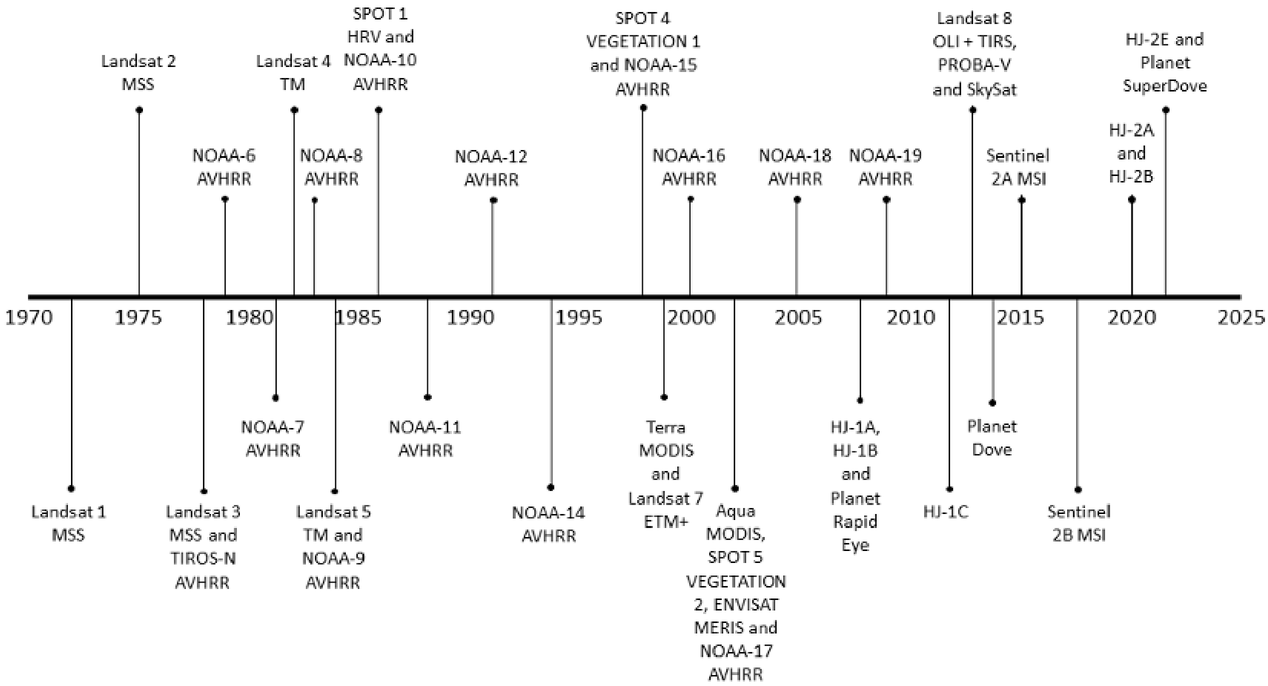

Figure 1.1: Launch of major satellites with sensors to monitor land-cover.

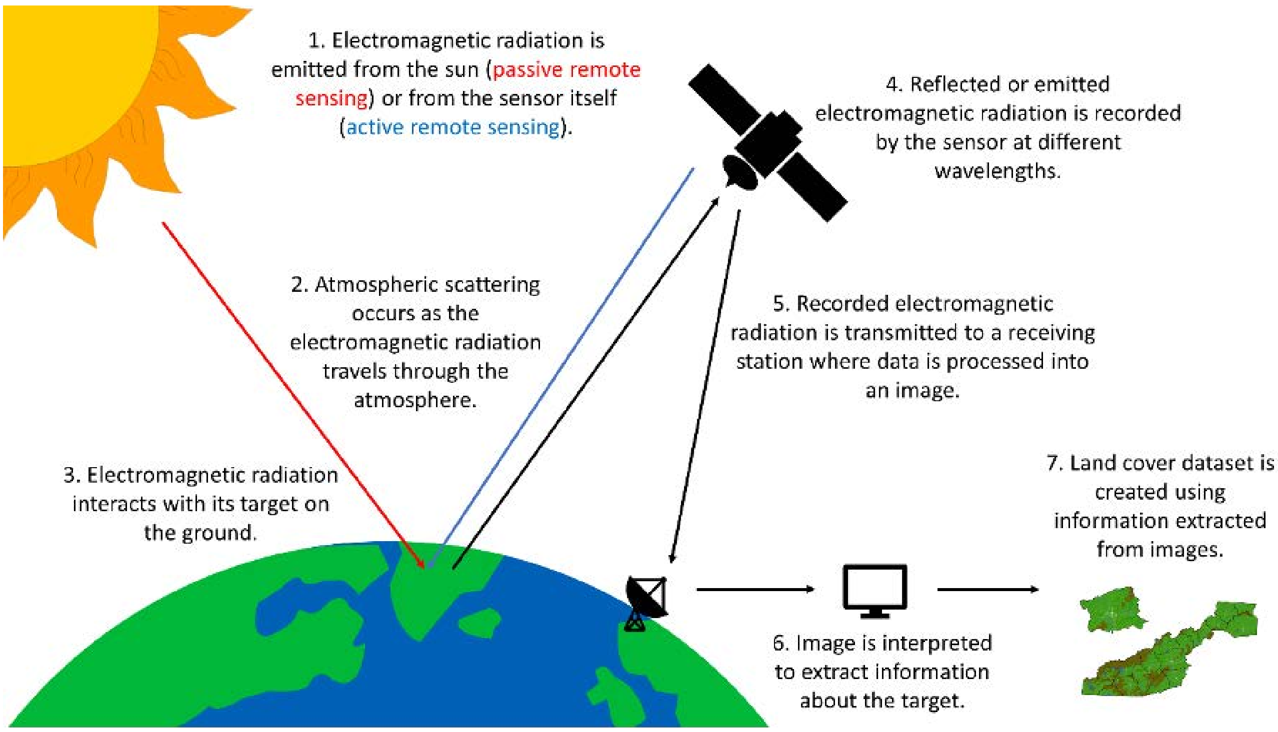

Figure 1.2: Step-by-step process for developing land-cover datasets using remote sensing (adapted from Sherbinin et al. (2002))

Frequently updated categorical land-cover data are useful for monitoring substantial shifts in land cover (e.g. forest to cropland) but do not capture more subtle changes (Rogan and Chen 2004). For example, measuring above-ground biomass may indicate where forests have degraded and now harbour lower levels of biodiversity and less carbon even though the forest itself is still there. Using data from different sensors (data fusion), such as combining optical and SAR data, is a technique that is increasingly being used to overcome some of these problems.

In addition, time series of continuous data are extremely useful for monitoring attributes like forest phenology, which allows, for example, the classification of deciduous versus evergreen forest (Cord *et al.* 2014). However, there are specific land-cover classes (such as natural grasslands or primary forests) that often cannot be easily identified using Remote Sensing techniques alone and frequently require incorporating other spatial data sources (data integration).

1.2 Global remotely sensed land cover datasets

1.2.1 Historical context

Despite the fact that Landsat provided the first terrestrial satellite Remote Sensing data in the early 1970's, global land cover products were not developed until lower spatial resolution data were made available from the Advanced Very High-Resolution Radiometer (AVHRR) in 1978. Data were freely available at that point, and because of the low spatial resolution, data could be more easily stored and processed over large areas (Hansen *et al.* 2000). Following different methodologies and classification schemes, a series of 1-km resolution global datasets were produced (DeFries and Townshend 1994; Hansen *et al.* 2000; T. R. Loveland *et al.* 2000). A description of these datasets is included in Table 1.1.

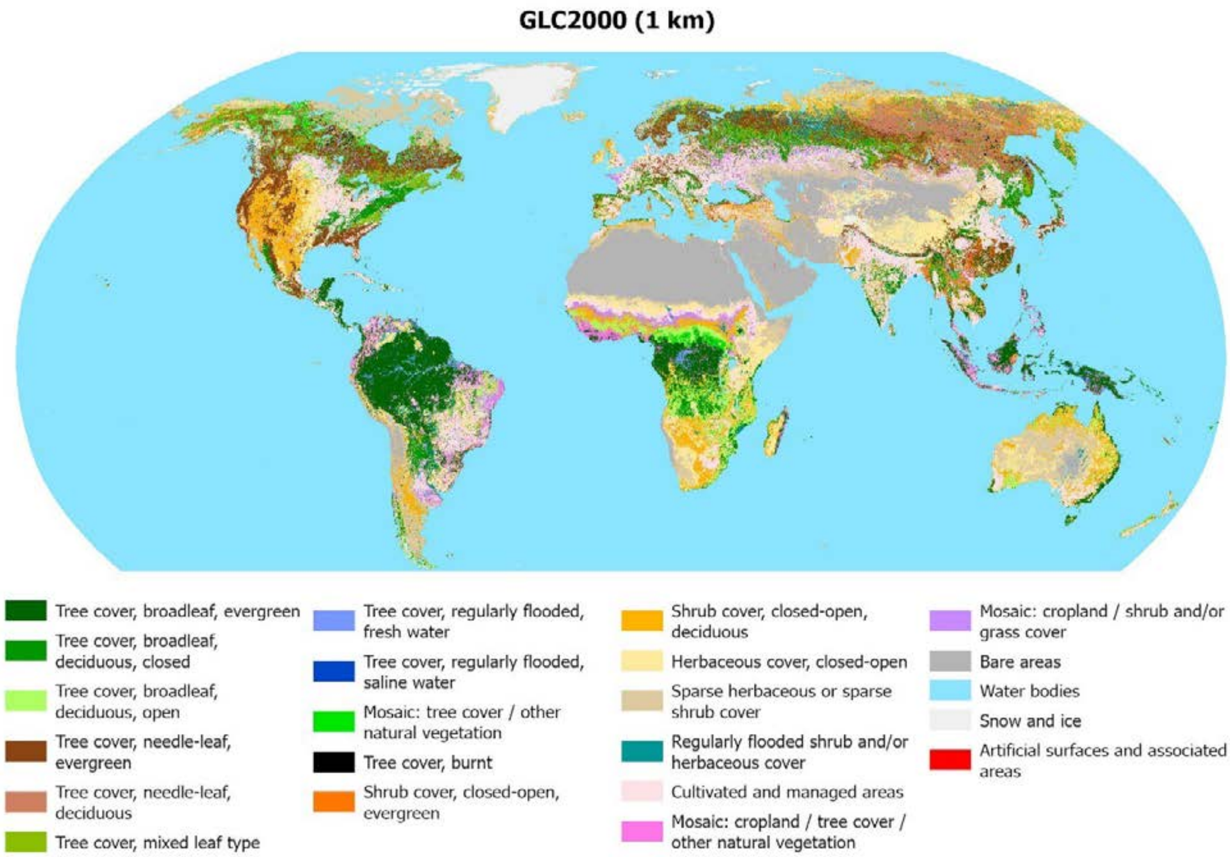

Figure 1.3: GLC2000 1-Km resolution land cover map for the year 2000 (Bartholome and Belward 2005).

1.2.2. Increasing spatial resolution

The launch of the Moderate Resolution Imaging Spectroradiometer (MODIS) in 1999 meant a shift to 500-m resolution with the Terra and Aqua sensors, resulting in the production of a global 500-m resolution land cover product (MCD12Q1) (Friedl *et al*. 2002). As opposed to previous 1-km resolution maps, which were produced for a single moment in time (circa 2000), this very successful initiative is producing yearly updates of global land-cover maps.

The European Space Agency (ESA), using Medium Resolution Imaging Spectrometer (MERIS) images, introduced two different 300-m resolution datasets (Table 1.1). The Climate Change Initiative Land Cover product (CCI LC) map is especially relevant as it has adopted a methodology for developing a time series that ensures temporal and spatial consistency between successive maps and therefore allows for changes to be more readily detected. This map series was initially produced because of the relevance of land cover as predictors in climate modelling, but the long-term consistency of the product has made it useful for a variety of other applications.

Providing higher resolution products, ESA as part of the Copernicus Global Land Service released the CGLS-LC100 (Buchhorn *et al*. 2020) at 100-m resolution. These series of land-cover maps are produced every year and primarily target the detection of land-cover change.

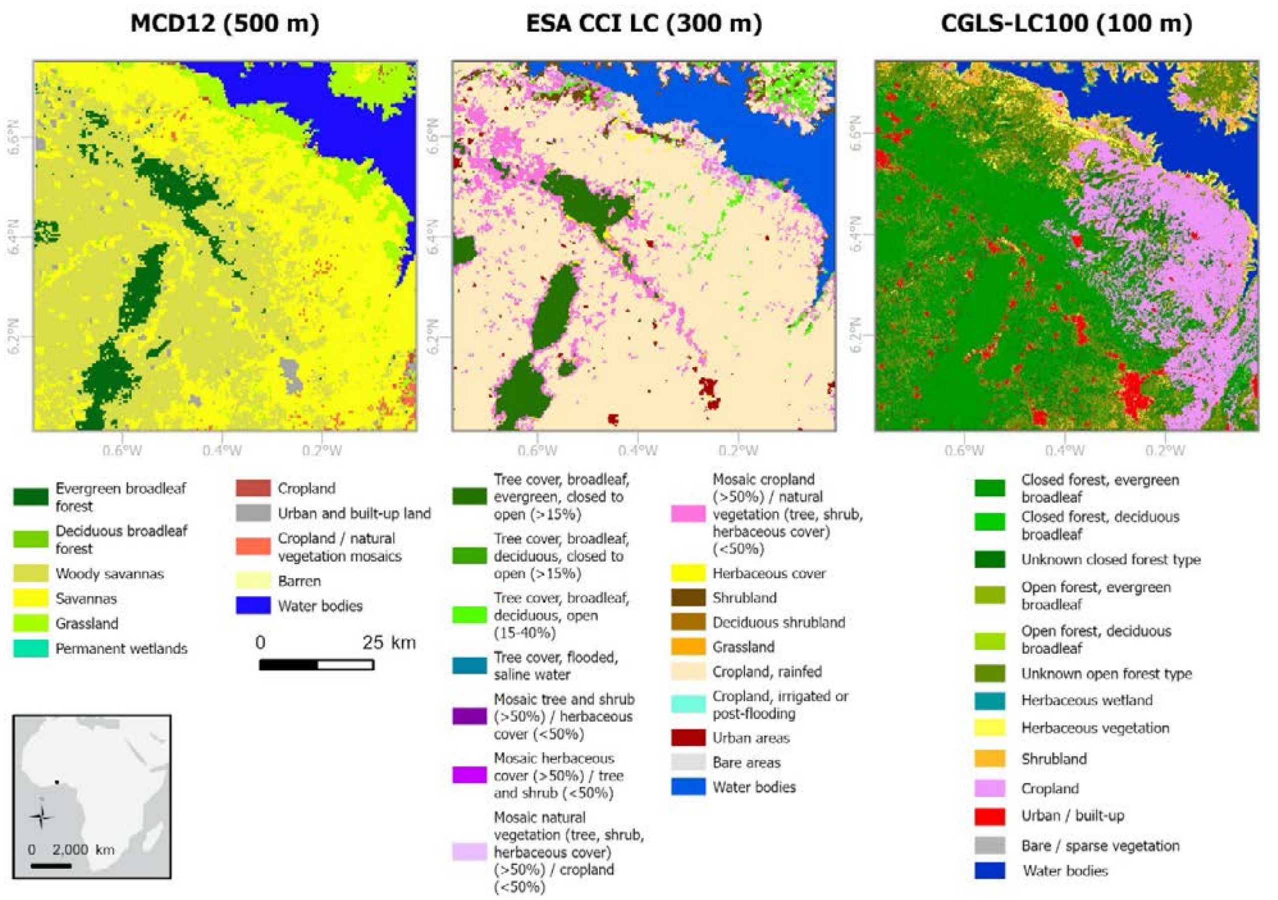

Figure 1.4: Land-cover maps of South-east Ghana at three spatial resolutions for the year 2015. MCD12 (Friedl et al. 2010), ESA CCI LC 300 m (Defourny et al. 2017) and CGLS-LC100 (Buchhorn et al. 2020).

Table 1.1: Global land cover datasets.

Dataset	Org.	Sensor	Res	Time period	Access	Citation
GLCC 2.0 IGBP DISCover	USGS	AVHRR	1 Km	1992-1993		(Loveland *et al.* 2000)
Hansen 2000	UMD	AVHRR	1 Km	1992-1993		(Hansen *et al.* 2000)
GLC-SHARE	FAO	Various*	1 Km	Many*	https://data.apps.fao.org/map/catalog/srv/eng/catalog.search#/metadata/ba4526fd-cdbf-4028-a1bd-5a559c4bff38	(Latham *et al.* 2014)
GLC2000	JRC	Vegetation	1 Km	2000	https://forobs.jrc.ec.europa.eu/products/glc2000/products.php	(Bartholomé and Belward 2005)
GLCNMO	ISCGM	MODIS	1 Km, 500 m, 500 m	2003, 2008, 2013	https://globalmaps.github.io/glcnmo.html	(Kobayashi *et al.* 2017; Tateishi *et al.* 2011, 2014)
MCD12	Boston Uni.	MODIS	500	2001-2020	https://lpdaac.usgs.gov/products/mcd12q1v006/	(Friedl *et al.* 2010)
ESA CCI LC	ESA	MERIS	300	1992-2020	https://www.esa-landcover-cci.org/?q=node/164	(Defourny *et al.* 2017)
GlobCover	ESA	MERIS	300	2004-2006, 2009	http://due.esrin.esa.int/page_globcover.php#:~:text=GlobCover%20is%20an%20ESA%20initiative,board%20the%20ENVISAT%20satellite%20mission	(Bicheron *et al.* 2008; Bontemps *et al.* 2011)
GLC250	CAS	MODIS	250	2001, 2010	http://data.ess.tsinghua.edu.cn/	(Wang *et al.* 2015)
CGLS-LC100	ESA	PROBA-V	100	2015-2019	https://lcviewer.vito.be/download	Buchhorn *et al.* 2020)
FROM-GLC30	Tsinghua Uni.	Landsat TM/ETM+	30	2010, 2015, 2017	http://data.ess.tsinghua.edu.cn/	(Gong *et al.* 2013)
GlobeLand30	NGCC	Landsat TM/ETM+, HJ-1	30	2000, 2010, 2020	http://www.globallandcover.com/defaults_en.html?src=/Scripts/map/defaults/En/download_en.html&head=download&type=data	(Chen *et al.* 2015)
GLC_FCS30	CAS	Landsat-8	30	2015, 2020	https://zenodo.org/record/3986872#.YuPniD3MK70	(Zhang *et al.* 2021)
Global land-cover and land use 2019	UMD	Landsat	30	2019	https://glad.umd.edu/dataset/global-land-cover-land-use-v1	(Hansen *et al.* 2022)
FROM-GLC10	Tsinghua Uni.	Landsat 8 / Sentinel 2	10	2017	http://data.ess.tsinghua.edu.cn/	(Gong *et al.* 2019)
Esri Land-cover 10 m	Impact Observatory	Sentinel 2	10	2017-2021	https://www.arcgis.com/home/item.html?id=d3da5dd386d140cf93fc9ecbf8da5e31	(Karra *et al.* 2021)
Dynamic World	WRI	Sentinel 2	10	2021-2022	https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_DYNAMICWORLD_V1	(Brown *et al.* 2022)
WorldCover	ESA	Sentinel 1/ 2	10	2020	https://esa-worldcover.org/en/data-access	(Zanaga *et al.* 2021)

*GLC-SHARE was developed using numerous national and regional land-cover maps spanning 1990-2012

1.2.3. Landsat derived land-cover datasets

Improved computing and storage capabilities have resulted in a surge of higher resolution land cover maps intended to offer sufficient spatial detail for more specific studies like urban expansion natural resource management (C. Giri *et al.* 2013; Gong *et al.* 2013). The Global Land Analysis and Discover (GLAD) lab part of the University of Maryland, following a long history of processing Landsat data and archives (Wulder *et al.* 2022), has produced a series of global land-cover-related products, including the Global Forest Change map (Hansen *et al.* 2013), a global change map depicting tree cover change (forest cover gain and forest cover loss) at 30-m resolution for 2000 – 2012. This data set, known as the Hansen Dataset, provides a free, transparent and globally available record of forest loss.

The Hansen dataset was followed by the development of a 30-m resolution global land-cover map for 2019 (Hansen *et al.* 2022). The dataset is also derived from Landsat satellite imagery alongside a series of other metrics for estimating the spatial distribution of different land-uses split by climate domain and ecozone. Both categorical and continuous variables (vegetation cover and height) are included in the dataset. This map is complemented by the global land-cover change product developed for 2000-2020. The map, which is also based on 30-m resolution Landsat, measures: “changes in forest extent and height, cropland, built-up lands, surface water and perennial snow and ice extent” globally for the last two decades (Potapov *et al.* 2022).

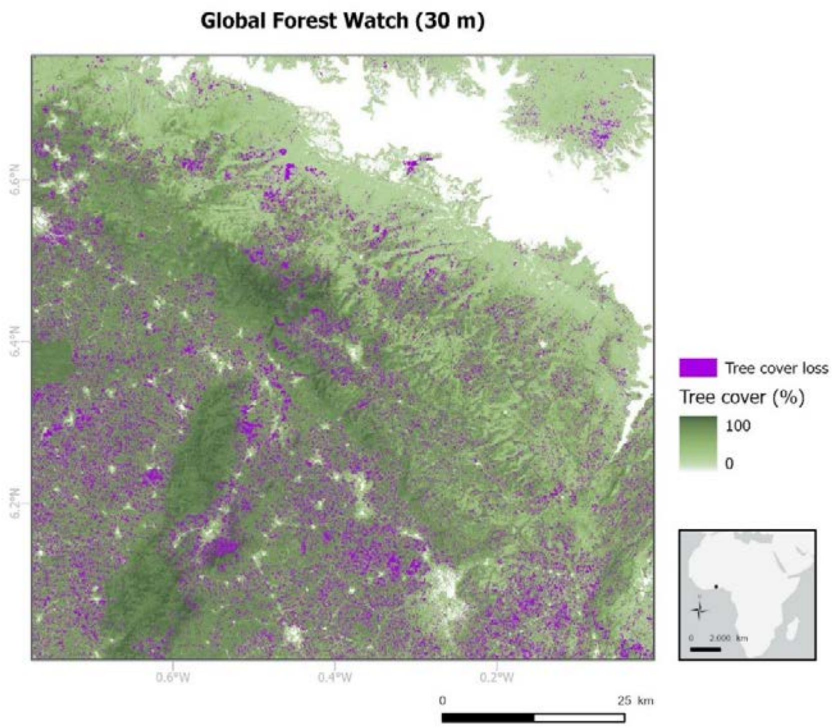

Figure 1.5: Global Forest Watch 30 m resolution map of tree cover in South-east Ghana in 2021 including tree cover loss (Hansen et al. 2013).

Furthermore, the Global Land, Analysis and Discovery (GLAD) Lab, in collaboration with Google and the World Resources Institute (WRI) as part of Global Forest Watch, has developed an alerting system for areas where 50% or more of the tree canopy has been lost (Hansen *et al.* 2016). Known as the GLAD alerts, this information is highly relevant for forest management activities and enforcement.

1.2.4. The Sentinels and the 10-m resolution challenge

The availability of Sentinel-2 satellite imagery at 10-m resolution has driven the development of finer resolution global land-cover maps. Four global 10-m resolution land cover maps have been released from four different partnership projects. Led by Tsinghua University, the first 10-m global land-cover map was released in 2019 (Gong *et al.* 2019). Land classification was performed on Sentinel-2 imagery using an algorithm trained on 30-m resolution Landsat data. Impact Observatory, Microsoft and Esri produced land-cover products from 2017 to 2021, prioritising the time series aspect. Land-cover classes were identified using the Impact Observatory deep learning artificial intelligence classification model (Karra *et al.* 2021). The third dataset is Dynamic World, developed by Google and the World Resources Institute (Brown *et al.* 2022). Like the previous dataset, Dynamic World was developed using deep learning artificial intelligence methods and a large training dataset. The dataset is updated in near real-time (every few seconds), providing the highest temporal resolution dataset currently available. In contrast to the previous three datasets, the WorldCover dataset produced by ESA is based on both Sentinel-1 and Sentinel-2 imagery, providing land-cover data with a slightly expanded classification scheme for the year 2020 (Zanaga *et al.* 2021).

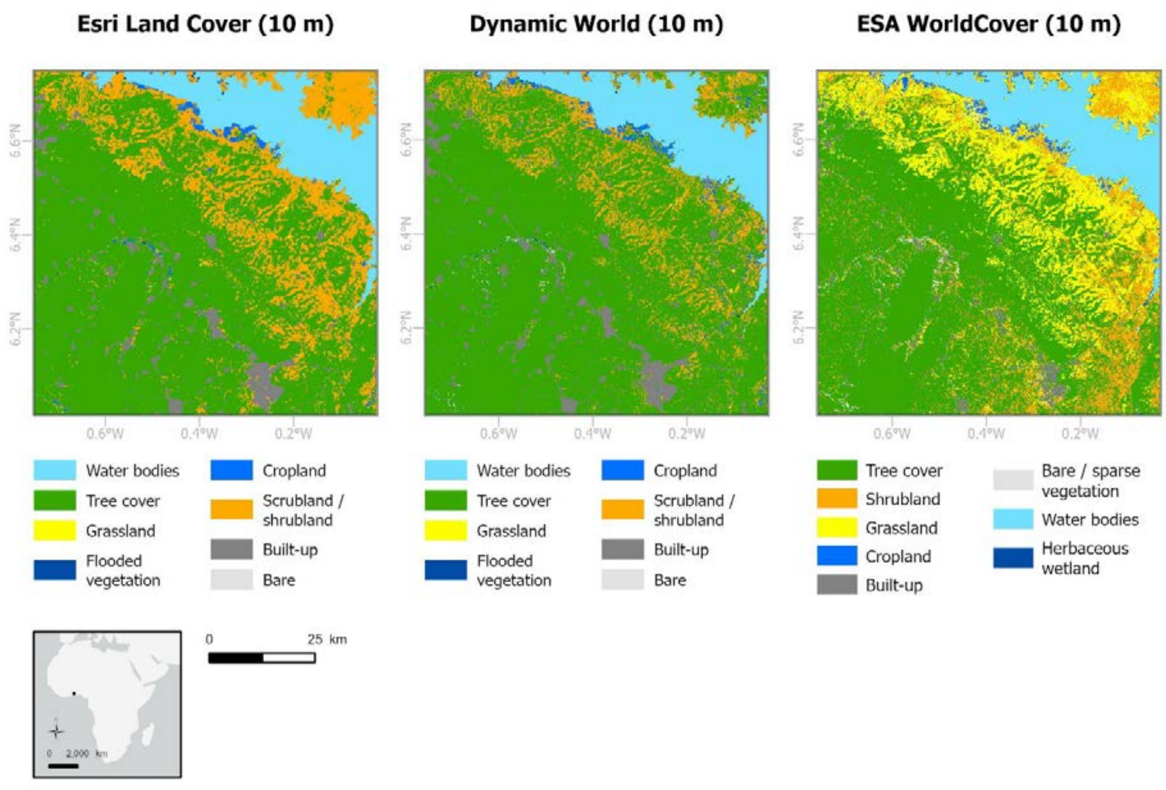

Figure 1.6: Land-cover maps of South-east Ghana at 10m spatial resolutions from 3 different sources for the year 2020: Esri Land-cover (Karra et al. 2021), Dynamic World (Brown et al. 2022) and ESA WorldCover (Zanaga et al. 2021).

1.2.5. Further considerations

Spatial resolution is an important aspect of land-cover maps, with a continuous trend towards developing higher and higher resolution maps. However, the highest resolution maps may not be the best alternative for all applications, and consideration must be given to other aspects, such as the classification scheme, the date/temporal resolution and the accuracy of the datasets. All remotely sensed global land-cover datasets have uncertainties. Evaluating the accuracy of land-cover data is critical part of the development process, which involves statistical validation using a sample of human-labelled reference images, often from other satellite sensors subject to their own spatial and spectral limitations (Congalton *et al*. 2014). Every reliable land-cover map will provide some kind of overall measure of accuracy aiming to meet the 85-95% Global Climate Observing System (GCOS) class accuracy requirements (Liu *et al*. 2021) (although overall accuracies rarely reach 80%). However, differences in validation methods between datasets, in addition to the different classification schemes used with different definitions for the different classes, make it difficult to compare land cover datasets and their accuracy (Congalton *et al*. 2014). It is common that reported accuracies get significantly smaller when independently validated (Grekousis, Mountrakis, and Kavouras 2015). For these reasons, it is important not to be tempted to compare individual reported accuracies but rather to rely on specific assessments for particular applications.

However, Remote Sensing technology continues to advance rapidly, increasing our ability to map global land cover and land-cover change at increasingly high spatial and temporal resolution. Future datasets are likely to have higher spatial resolution, improved accuracy, finer classification schemes and availability in near real-time. For example, very high-resolution (4.77-m) data for the tropics are available from Planet Labs imagery as part of Norway's International Climate & Forests Initiative (NICFI). Data are provided biannually from December 2015 to August 2020 and monthly from September 2020 to the present and are freely available to download for non-commercial purposes in support of NICFI's mission. NICFI aims to support projects that reduce tropical forest and biodiversity loss, mitigate climate change and protect the rights of indigenous peoples.

Cloud computing platforms, like Google Earth Engine, will continue to contribute significantly to the advancement of global land-cover datasets in the future due to advanced image processing and classification and increased computing power (Liu *et al*. 2021). In addition, integrating the multi-spectral data discussed in this chapter with other Remote Sensing data sources will further improve the classification of certain land cover types. Radar, Light Detection and Ranging (LiDAR) and hyperspectral data can capture land-cover characteristics not resolved using multi-spectral data alone. For example, the use of radar and night-time light sensors has improved the classification of built-up areas resulting in an overall accuracy of 95% (Zhang *et al*. 2020). These sensors, which are discussed in more detail in the following chapters, are becoming more common as Remote Sensing technology advances.

2

Remote Sensing of Biodiversity: Estimating impacts of Land-cover Changes

2.1 Introduction

There is growing recognition of the great value of biological diversity across the world[1]. However, pressures such as the destruction of natural ecosystems are causing rapid population declines and extinctions of species (Ng *et al*. 2003), together with loss of genetic diversity. In response to this biodiversity crisis, the Convention on Biological Diversity (CBD) set global targets to safeguard biodiversity. Between 2010 and 2020, international biodiversity policy was dominated by the CBD's Strategic Plan for Biodiversity 2011-2020, which included the Aichi biodiversity targets. This plan detailed an international commitments to halt biodiversity loss, with Target 5, for instance, aiming to halve global deforestation rates by 2020, Target 11 aiming to achieve the formal protection of at least 17% of all terrestrial areas and Target 12 seeking to prevent the extinction of known threatened species. Few of these targets were met (Cooper *et al*. 2020), despite many conservation successes at a smaller scale. The long-awaited Kunming-Montreal Global Biodiversity Framework (CBD 2022a) now sets goals and targets for 2020-2030. The 2030 mission of this ambitious framework is to "take urgent action to halt and reverse biodiversity loss to put nature on a path to recovery for the benefit of people and planet by conserving and sustainably using biodiversity, and ensuring the fair and equitable sharing of benefits from the use of genetic resources, while providing the necessary means of implementation".

[1] CBD: https://www.cbd.int/

According to IPBES, land-use change combined with the direct exploitation of nature due to activities like hunting, fishing, logging and harvesting is the main cause of declines in nature and biodiversity, being responsible for more than half of all the human pressures on terrestrial and freshwater ecosystems (Díaz *et al*. 2019). Habitat loss and fragmentation are the cause of declines in biodiversity and health of species and ecosystems worldwide (Davison *et al*. 2021). Habitat loss leads to direct and indirect impacts on species populations. Habitat fragmentation prevents species from moving between or dispersing to other vegetated patches shrinking their available habitat and reducing the gene pool (Elias 2018). It can also alter ecosystem structure and species composition. The effects of land-use change are also selective, affecting species differently because some are able to occupy many different habitat types, make use of a range of resources and move to new habitats, making them better able to survive land-use changes than those that are not so flexible (Oliver and Morecroft 2014).

In this context, Remote Sensing plays a crucial role in monitoring Earth's biodiversity. We have identified three areas of impact for this technology. First, it offers a way to keep track of biodiversity on a global basis using data that are directly recorded by satellite sensors or indirectly by means of statistical modelling. It also offers a valuable tool to report progress towards biodiversity targets. In addition, as demonstrated in previous sections, it is a crucial component for monitoring land use change, which in turn is a major driver of biodiversity loss. In the following section, further detail is provided on how this technology can be applied to monitor biodiversity, to report against biodiversity targets and to use remotely sensed land cover maps for making further biodiversity assessments across a changing landscape.

2.2 The role of Remote Sensing in monitoring biodiversity

Various types of sensors provide biodiversity information either directly or indirectly by using a proxy where direct measurements are not possible (Geller *et al.* 2017). Multi-spectral data are widely available and have been providing ecosystem-level measurements, such as land-cover classes of different vegetation types, for the past 50 years. Hyperspectral sensors detect energy in a greater number of spectral bands than multi-spectral sensors enabling specific species to be monitored. In addition, LiDAR (a Remote Sensing method that uses laser pulses to measure distances) is ideal for measuring tree height and tree canopy characteristics while synthetic aperture radar (SAR) estimate vegetation structure under cloudy conditions typical of tropical forest areas.

It has long been accepted that Remote Sensing is a useful technique for monitoring whether global targets to reduce biodiversity loss are being met. In this context, the Group on Earth Observations Biodiversity Observation Network (GEO BON) has produced a uniform system of “essential biodiversity variables” (EBVs) for monitoring biodiversity (Pereira *et al.* 2013). Members of the Remote Sensing community have embraced this framework as a means of assessing the potential of Earth observation products to track progress towards global conservation targets (Skidmore *et al.* 2015). Global EBVs are defined as the main biological metrics used to determine the Earth’s biodiversity. They provide a framework for monitoring biodiversity, although they are not analytical tools themselves. Their main aim is to coordinate biodiversity monitoring efforts on a global scale by producing a manageable list of priority variables. EBVs are split into six classes: “genetic composition, species populations, species traits, community composition, ecosystem function and ecosystem structure” (Pereira *et al.* 2013). All classes have the potential to be measured with the help of Remote Sensing data (Figure 2.1). Scientists are in the process of agreeing on and prioritising biodiversity variables under the EBV umbrella that can be monitored remotely (Skidmore *et al.* 2021).

Ecosystem structure is commonly measured using Remote Sensing. The concept covers the 2D spatial patterns of land cover and land-cover change and the 3D component of ecosystems’ vegetation structure. One aspect of the 2D ecosystem structure is land-cover change. For example, forest loss has a major impact on biodiversity, so monitoring forest loss over time is crucial for quantifying these impacts. Global Forest Watch[2] shows the global tree cover extent, loss and gain from 2001 to 2021 based on 30-m resolution Landsat data (Hansen *et al.* 2013).

[2] https://www.globalforestwatch.org/

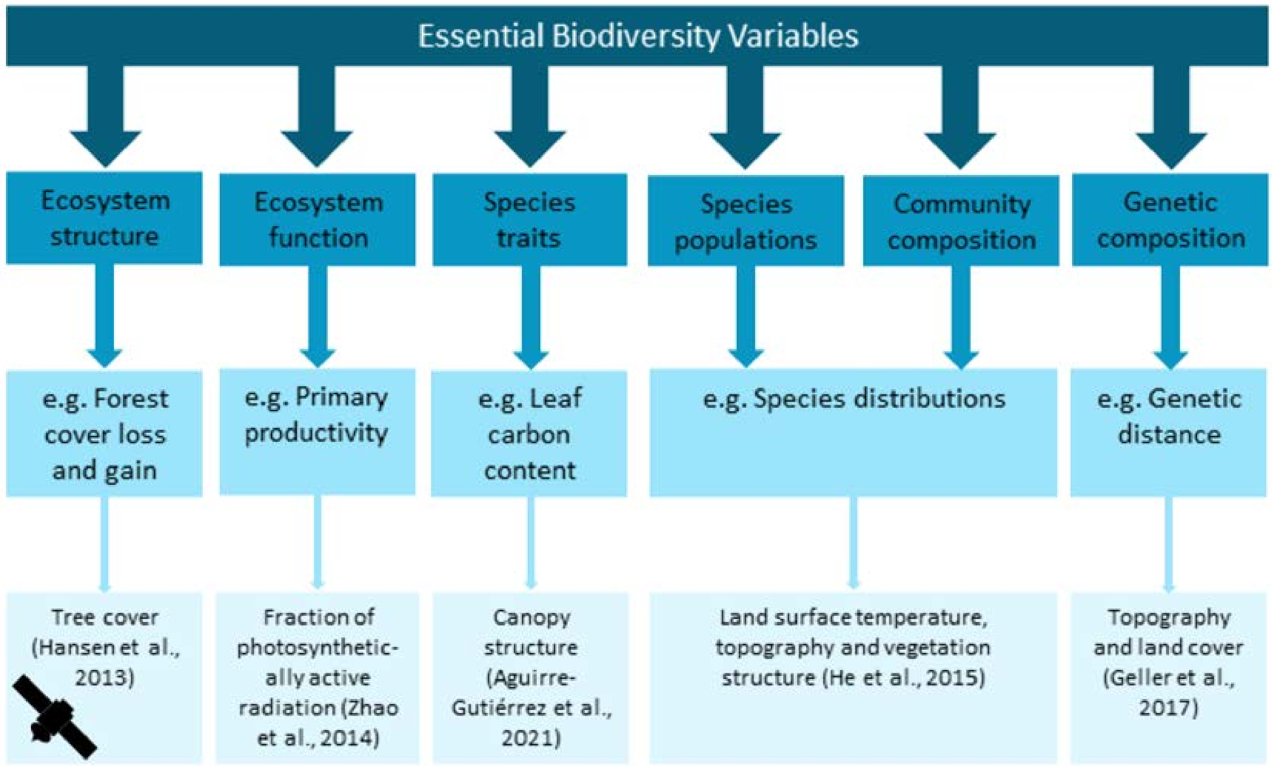

Figure 2.1: Example of EBVs that can be directly or indirectly measured using Remote Sensing.

Active sensors, such as radar and LiDAR, monitor 3D patterns of ecosystems, like tree height and canopy structure. For example, a space-based LiDAR sensor known as the Global Ecosystem Dynamics Investigation (GEDI) has been developed by NASA with the particular purpose of measuring the structure of the Earth's surface and providing detailed data on the 3D canopy structure of terrestrial vegetation (Dubayah *et al.* 2020). These LiDAR-derived structural parameters can be used to help reveal biodiversity patterns of plants and animals.

Some aspects of ecosystem function can also be estimated using Remote Sensing. For example, the normalized difference vegetation index (NDVI) is frequently employed as an indicator for Net Primary Productivity (NPP). In addition, net and gross primary production are modelled at 500-m and 1-km resolution and 8-day intervals using data from the MODIS (Zhao *et al.* 2005). These MODIS products are based on a range of remotely sensed inputs, including the fraction of photosynthetically active radiation, leaf area index (LAI) and land cover (Zhao *et al.* 2014).

Species traits, species populations, and community composition are also being directly or indirectly monitored using Remote Sensing. Using direct methods, key functional plant traits, such as leaf thickness and leaf carbon content, have been detected using satellite imagery from Sentinel-2 for tropical regions (Aguirre-Gutiérrez *et al.* 2021). In addition, for species' populations and community composition, very high spatial and spectral resolution sensors can monitor the distribution of certain large animals, such as elephants (Duporge *et al.* 2021), as well as tree species (Geller *et al.* 2017).

However, these direct methods are only relevant for a subset of species and, until recently, access to such high-resolution data has been very expensive. More commonly, indirect methods are used to estimate the current distribution of species using environmental data (e.g., temperature) in combination with reference data (presence/absence of species) to predict the species occurrence in a certain area. The environmental data are increasingly obtained using Remote Sensing, and there is also potential to use this technology as a source of reference data at high spatial resolution for large-bodied species. (He *et al*. 2015).

Of all the components of biodiversity, mapping and monitoring genetic diversity using Remote Sensing presents the greatest challenge. Current efforts correlate metrics measured using Remote Sensing, such as geographic distance, land-cover or topography, with genetic differences between individuals in different locations (Geller *et al*. 2017).

Despite these major advances using Remote Sensing for biodiversity monitoring, there is still poor alignment between the EBV framework and Remote Sensing products (Skidmore *et al*. 2021). Firstly, there are differences between the terminology used in the EBV framework and the Remote Sensing product names. This creates confusion on whether EBVs are represented by Remote Sensing datasets. Secondly, data from a range of sensors, such as hyperspectral or LiDAR, must be integrated as multi-spectral sensors alone cannot capture the many aspects of biodiversity. However, hyperspectral sensors are less common than multi-spectral sensors and require specialist expertise to process the data (Bioucas-Dias *et al*. 2013). Similarly, LiDAR data are not widely available (both in terms of spatial coverage and data accessibility), and radar data can be expensive and less user-friendly than multi-spectral data.

Ongoing cooperation between Remote Sensing scientists and ecologists is required to ensure that sensors meet biodiversity data needs. For example, merging some EBVs (like live cover fraction and ecosystem vertical profile) that can be captured by a single Remote Sensing product (like habitat structure) would streamline Remote Sensing data collection for biodiversity (Skidmore *et al*. 2021). In addition, as technological advances continue, more of the species-level EBVs currently measured using planes and unmanned aerial vehicle-borne sensors will be able to be monitored directly from space on a global scale. For instance, data integration with data provided by other in situ Earth observation systems, such as acoustic sensors or eDNA, can greatly improve the Remote Sensing monitoring capability at different scales.

2.3 Biodiversity Indicators: reporting progress towards biodiversity targets

Biodiversity is challenging to quantify because it is affected by a range of complex interactions that vary over space and time (Reddy *et al*. 2021). Developing meaningful biodiversity metrics is a challenging endeavour. Since many metrics have been developed that focus on individual aspects of biodiversity, it is important to choose the right ones that are meaningful for a specific situation.

The EBV framework mentioned in the previous section provides the context to study, report and manage biodiversity and has been embraced by members of the Remote Sensing community as a means to explore how this technology can be used to measure biodiversity. They bridge the gap between primary observations and the more complex indicators of biodiversity explored in this section.

The CBD has adopted a monitoring framework for its Kunming-Montreal Global Biodiversity Framework, with headline, binary, component and complementary indicators (CBD 2022b). Some, but not all of these indicators can benefit from remotely sensed information[3]. GEO BON has proposed a set of eight biodiversity indicators than can be developed using in-situ observations, remotely sensed derived information and modelling techniques[4]. These range from indicators specific to certain ecosystems (e.g., trends in forest extent) to others applicable across the entire planet (e.g., rate of invasive alien species spread). Overall, biodiversity indicators are a useful tool for planning conservation actions, assessing ecosystem health and monitoring progress towards national and global policy targets.

[3] https://www.post-2020indicators.org/

[4] https://geobon.org/ebvs/indicators/

The Biodiversity Intactness Index (BII) is an example of a biodiversity indicator focused on degradation status (Figure 2.2). BII is a measure of the change in average abundance of wild species in a location relative to a reference period or population free from anthropogenic disturbance (Scholes and Biggs 2005). BII synthesises “land use, ecosystem extent, species richness and population abundance data” (Scholes and Biggs 2005).

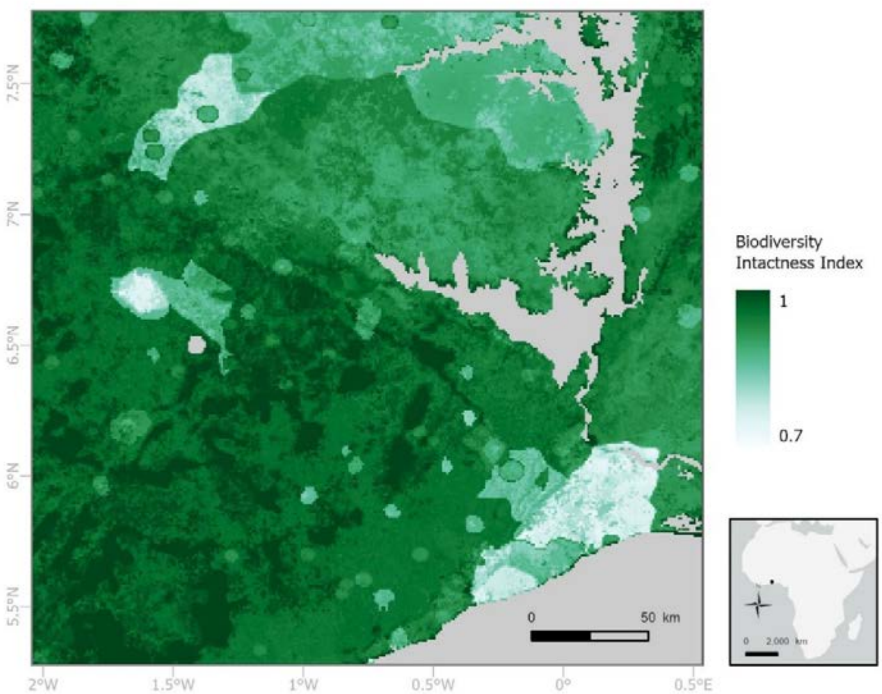

Figure 2.2: Biodiversity intactness index showing the modelled average abundance of species relative to their abundance in an intact ecosystem in South-east Ghana (Newbold et al. 2016).

The Biodiversity Intactness Index is calculated using data from the "Projecting Responses of Ecological Diversity In Changing Terrestrial Systems" (PREDICTS) project, a comprehensive database with the largest geographical and taxonomic extent currently available for undertaking community-level analyses (Hudson *et al.* 2017). Each site in PREDICTS is assigned a land use and land-use intensity based on the habitat present when the biodiversity sample was collected (reported within a peer-reviewed publication or through interviews with the sample collectors). The database contains information that allows many land-use types to be classified, but the generic land-use types most commonly used include primary vegetation, young, mature and intermediate secondary vegetation, plantations, annual croplands, perennial croplands, managed pastures, rangelands and urban landscapes (Hill *et al.* 2018). Each land-use type can also be further divided into high, medium and low use intensity. The occurrence of each land-use activity can also be determined using Remote Sensing land-use and ecosystem maps. A range of Remote Sensing land-use datasets are used in BII estimates, such as Global Land Cover 2000 (GLC2000) (Bartholomé and Belward 2005) and global downscaled 1-km land-use data (Hoskins *et al.* 2016).

BII is sensitive to habitat losses and declines in habitat condition, which impact species populations on various spatial and temporal scales relevant for policy-making, such as at local and national levels (Scholes and Biggs 2005). In addition, BII is robust to variations in data quality, such as the resolution of species richness data. However, various studies have raised concerns about the BII metric.

BII can inform policy decisions and monitor progress towards global biodiversity targets by providing an early indicator of species extinction risk (Stevenson *et al.* 2021). This statistic may be used to initiate preventative action to limit further biodiversity loss. However, the BII metric is only as good as the land-use/land use intensity layer that is combined with the PREDICTS models to provide spatially explicit layers. Remote Sensing data can help to improve land-use maps, especially when validated using reference data.

2.3 Mapping biodiversity across land cover types

As described in the previous section, Remote Sensing can be used to monitor biodiversity either directly, using measurements derived from satellite sensors, or indirectly, using proxies that relate to these measurements. One example of these proxies is the use of Remote Sensing derived environmental variables such as climatic parameters, vegetation indices or observations of the three-dimensional structure of the vegetation to biodiversity estimations using models, such as species distribution models. Some species distribution models can also make use of land-use data as environmental variables or predictors, but generally other more explicit methods are preferred when evaluating the impacts of land-use change on biodiversity.

Including information on land use in the biodiversity analysis is crucial to enabling estimates of significant anthropogenic impacts on habitat quantity and quality. It also allows assumptions to be made on how biodiversity alters with land-cover change, as well as extrapolating biodiversity values across the landscape. This section now explores metrics that consider land use in their biodiversity analysis workflow, including the Area of Habitat (AOH), an approach to mapping biodiversity across the landscape based on land-use maps.

The habitat inside a species' range is often referred as AOH (Brooks *et al.* 2019), and represents "the distribution of suitable habitats at suitable altitudes for a species inside its broad geographical range" (Dahal *et al.* 2022). It is a metric broadly used to monitor species-level biodiversity as it can quickly change over time as habitats are constantly being altered by land use and climate change. By assessing changes in AOH over time, it is possible to assess past habitat loss and fragmentation as well as estimate impacts on species using modelled land-use data for future scenarios. AOH can also be used to evaluate the amount of a species' habitat that is protected, feed into protected area network proposals and identify locations for potential field surveys that can inform conservation planning.

AOH is usually calculated by identifying the regions in a land-cover map inside a species' range, altitudinal limit and habitat preference (Brooks *et al.* 2019). Land-cover classes from datasets, such as Copernicus Global Land Service Land cover (CGLS-LC100) (Buchhorn *et al.* 2020), are matched to a species' preferred habitat type based on peer-reviewed literature and expert opinion. Digital elevation models, often derived from Remote Sensing, provide elevation data for selecting the area within a species' altitudinal limits.

In terms of species data, their ranges and maximum and minimum elevation values can be extracted from the International Union for Conservation of Nature (IUCN) Red List. Similarly, habitat preferences are often based on those identified as suitable or of major importance on the IUCN Red List. The next step is to overlay the digital elevation model and species ranges with the land-cover map. One of the key steps is to link the range or habitat maps (typically from the IUCN Red List database) to land cover classes to select suitable habitats from the land cover data for a given species. Typically, this is implemented through expert-derived 'crosswalks', which are effectively look-up tables (LUTs) with a column of IUCN habitats, and next to it all the corresponding land cover types/classes that would be considered to represent this type of habitat.

These identified areas within the species range and altitudinal limits and of the preferred habitat type are selected as the species' AOH. Ideally, AOH maps should then be validated using point data for each species.

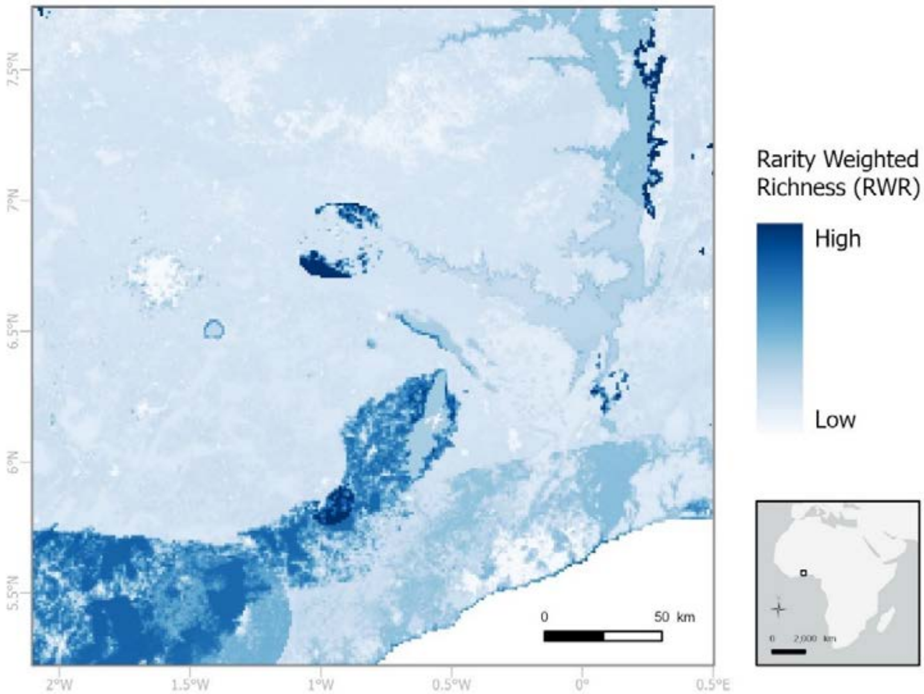

Figure 2.3: Rarity weighted richness (RWR) data based on area of habitat (AOH) maps for all amphibians, mammals and birds with range data on the IUCN Red List (IUCN 2017). RWR dataset from (Sassen et al. 2022) and log transformed for visualisation.

Although some conservation decisions focus on single species, most conservation problems concern multiple species and therefore require large numbers of AOH maps to be combined. Several metrics have been developed that represent various facets of biodiversity that benefit from AOH. On its own, the commonly known metric of species richness is not a useful measure for most conservation decisions. Metrics that include some weighting for range-rarity (i.e., a higher score for species with small AOH) are more relevant for conservation. Such metrics (Figure 2.3), aggregated across many species, may be known as rarity weighted richness (Williams *et al*. 1996) or weighted endemism (Guerin and Lowe 2015). These more closely depict the importance of a given area of habitat to that species, which reflects the potential magnitude of impact of future changes (loss or gain) of habitat occurring within the species range. For understanding change over time, calculating the proportional change in AOH for each species is similarly useful. Examples that use this approach include the biodiversity impact metric (Buchanan *et al*. 2011) and the InSIGHTS index (Baisero *et al*. 2020), among other analyses (Brock *et al*. 2021; van Soesbergen *et al*. 2017).

Recently two metrics have emerged that share similarities with the above examples but also help answer additional questions. Firstly, the species persistence score links changes in area of habitat to the probability of a species persisting over time (Durán *et al*. 2020). Secondly, the Species Threat Abatement and Recovery metric quantifies the reduction of extinction risk that can be achieved by abating threats and restoring habitats in specific places (Mair *et al*. 2021).

3

Estimating impacts of Land-cover Changes on Carbon Stocks

3.1 Policy framework – International agreements and relevant policies

23% of all carbon emissions[5] are produced by the Agriculture, Forestry and Other Land Use (AFOLU) sector with significant potential to reduce emissions and remove carbon from the atmosphere (like through halting and reversing deforestation). The importance of nature's contribution to climate change mitigation has been climbing up the political agenda with increasing pressure to set and meet ambitious targets. This has led to landmark agreements like the Glasgow Leaders Declaration on Forests and Land Use, the New York Declaration on Forests and initiatives like as the UN Decade on Ecosystem Restoration. Additionally, more than 60 countries have pledged to restore forest cover under the Bonn Challenge[6] with 210 million hectares pledged. Remote Sensing should play a key role in monitoring progress towards these commitments, measuring greenhouse gas benefits and improving the accuracy of the reported results.

3.1.1 National-level reporting

The United Nations Framework Convention on Climate Change (UNFCCC) was created in 1994 to protect the global climate system from harmful human interventions. A total of 198 countries are members (or "Parties") of the convention (UNEP and IUCN 2021). Key decisions adopted by UNFCCC parties include the 2015 Paris Agreement, which intends to keep global warming below 2°C (preferably 1.5°C). Developing country parties are advised to contribute to climate change mitigation through their forestry sector. Activities include lowering emissions caused by deforestation and forest degradation, protecting and improving carbon pools in forests and managing forests sustainably. These activities are commonly referred to as "REDD+".

At the national (or subnational) level, developing parties report to the UNFCCC on emissions and removals in forests, indicating where carbon from the atmosphere is sequestered into biomass and soils. This is usually done in two parts. First, a forest reference emissions level is set, which is typically based on the average historical emissions (and sometimes removals) over a given reference period. Future emissions (and removals, if relevant) are then compared to this reference level to estimate whether emissions reductions or removals exceeding this baseline have been achieved. These results may then be eligible for results-based payments and be used to demonstrate progress towards Nationally Determined Contributions (NDCs). Alongside reporting on emissions and removals, parties are asked to produce a national REDD+ strategy, a reliable, consistent and transparent forest monitoring system for reporting REDD+ results and a method for delivering evidence on how safety measures are being considered and maintain during the implementation of REDD+.

Remote Sensing is widely used in producing both the reference levels and the emissions and removals estimates during the reporting period. Typically, satellite images are used to determine areas of forest converted to other land use, areas of forest degradation, and areas of forest regrowth, known as the activity data.

[5] IIPCC 2019. Data for 2007 to 2016

[6] https://www.bonnchallenge.org/progress

Emissions and removal factors represent the volume of emissions or removals of certain greenhouse gases over one year that results from land use or land management change. These are then applied to the activity data to estimate the emissions or removals over that period. Emissions and removals factors are classed into three tiers, from Tier 1 (globally agreed means for broad habitat-region combinations, collated by the IPCC) to Tier 3, which are site-based measurements specific to the habitat studied (IPCC 2006). The accuracy of the results depends on both the activity data and the emissions and removals factors.

As Remote Sensing technologies improve (e.g., spatial and temporal resolution of satellite imagery), it is essential for countries to have access to this technology, to have the capacity to use it and to understand its limitations and inherent uncertainties. Furthermore, technologies such as LiDAR may be able to complement data collected on the ground through forest inventories by providing biomass estimates.

3.1.2 Voluntary carbon markets

Voluntary carbon markets are increasingly seen as a mechanism to facilitate the flow of finance from private sector actors ('buyers') to projects ('sellers') that reduce or remove emissions (also known as offsets or carbon credits). However, projects face numerous challenges, including high upfront and ongoing costs associated with measuring, monitoring and verifying their carbon credits. Improved Remote Sensing technology presents several opportunities to overcome these challenges. Remote Sensing technology could reduce the labour and prohibitive costs of measurement reporting and verification (MRV) of carbon credits. Historically, forestry projects have been restricted to using field measurements when conducting MRV (Cevallos *et al.* 2019), requiring samples and data taken from the site at regular intervals and verified by a third party. Carbon standards now typically use a mixture of Remote Sensing and on-site data during the MRV process. This can range from simple default methodologies, such as those specified in the IPCC guidelines, to complex models based on carbon cycling modelling and/or Remote Sensing to quantify potential emissions reductions and removals (Smith *et al.* 2014). Remote Sensing could reduce this burden by providing a low-cost method to collect activity data by using satellite imagery to estimate areas undergoing land-use change or degradation. Furthermore, modelling approaches and Remote Sensing data from satellite images and LiDAR can be used to establish baselines and monitor and measure the ongoing changes in carbon stocks from within projects. By addressing these barriers, Remote Sensing can help to enable the flow of finance to projects that contribute to climate change mitigation efforts.

3.2 The Carbon cycle

Carbon has been a central point for discussions in climate mitigation as the current flux of CO_2 and methane to the atmosphere via the burning of fossil fuels and other anthropogenic activities has been a leading cause of greenhouse gas emissions and climate change (Le Quéré *et al.* 2009).

The consequences of anthropogenic climate change on human survival and sustainability will be significant (Peters, Davis, and Andrew 2012). To halt and even reverse the contribution of land use/land-use change to these greenhouse gas emissions, it is crucial to assess the Earth system's carbon sources and sinks, understand the drivers of changes in carbon flows, inform management plans to safeguard carbon reservoirs and enhance sinks across the world (Gibbs *et al*. 2007; Le Quéré *et al*. 2009).

The largest carbon exchange between terrestrial systems and the atmosphere occurs when terrestrial ecosystems absorb carbon through photosynthesis. Among Terrestrial vegetation, the amount of carbon is almost half to one-third of carbon in soils (Anderson-Teixeira *et al*. 2021; Houghton 2003). Yet, forests are key carbon pools because compared to other types of vegetation, trees store far more carbon per unit of land. Forest ecosystems store up to 80% of total global above-ground carbon and contribute to about 70% of Soil carbon through photosynthetic capture by plants and deposition of carbon in soils (Simard *et al*. 2020).

The quantity of carbon held in a system or reservoir is referred to as a stock or pool and is determined by the carbon cycle, which comprises carbon exchange between different stocks in the land, ocean and atmosphere (Friedlingstein *et al*. 2022; Houghton 1999). In other words, carbon stocks are dynamic and are influenced by a range of activities, including photosynthesis and respiration, deforestation and fossil fuel combustion. These activities trigger the exchange of carbon between stocks, referred to as flux. The understanding of the drivers of carbon flux within and between ecosystems across the globe helps identify regions and reservoirs where carbon might be most vulnerable to release as CO_2 or methane to the atmosphere.

Both terrestrial carbon exchange and pools can be estimated using different Remote Sensing methods. The amount of carbon retained in an ecosystem, or NPP, is how much carbon is generated during photosynthesis (referred to as gross primary production or GPP), excluding the amount of energy used for respiration[7]. GPP and NPP are major components of terrestrial carbon fluxes. Traditionally, satellite-derived measurements, such as NDVI, were used to estimate GPP and NPP. More recently, Remote Sensing with machine learning approaches and other models have been used. When looking at carbon stocks, carbon in soils has been estimated at relatively small spatial scales and mainly for croplands (Xiao *et al*. 2019) but it has been frequently employed for quantifying biomass carbon stocks.

[7] UN-REDD programme

The quantification of biomass carbon stocks is highly relevant to estimating changes in carbon pools that come from land-use change. The next section will now focus on the applications of Remote Sensing to estimate carbon stocks through measuring above-ground biomass (AGB).

3.3 Quantifying Carbon stocks: The role of Remote Sensing

Land-use changes, such as deforestation and forest degradation, directly impact carbon stocks. Large-scale monitoring of AGB complemented by land cover is key to monitoring carbon stocks and carbon stock dynamics. This is critical for enabling land-use planning to identify feasible management alternatives that can reduce emissions. AGB comprises all vegetation above the ground, including shrubs and trees with stems and branches, as well as live foliage. Approximately 50% of its composition is considered to be carbon (Eggleston *et al*. 2006). Remote Sensing can provide a feasible and efficient alternative to more conventional methods of quantifying AGB, such as field measurements based on vegetation harvesting, which are often subject to severe limitations and costly in terms of time and budget (Ketterings *et al.* 2001). Other non-destructive methods are based on developing equations (called allometric equations) that establish a relationship between AGB and tree metrics like tree height and diameter at breast height that are frequently recorded in forest inventories. However, these equations have severe limitations as they are generally only developed for temperate and boreal forest ecosystems, are species-dependent and limited to relatively small geographic areas.

The cost-effective collection of data associated to the spatial distribution of AGB across vast areas is made possible by Remote Sensing technology, particularly space-borne sensors (Brewer 2012). However, the lack of geographically spread reference data for calibration, as well as the low sensitivity of satellite sensors to AGB makes estimating carbon stocks from satellite data a challenging task. In addition, variations in species, the consistency of their wood, the amount of moisture and different atmospheric conditions, makes the signal received by the sensors and the actual AGB display geographical variations (Rodríguez-veiga *et al*. 2017).

Different types of Remote Sensing data have been employed to estimate AGB, mainly including passive optical, microwave and LiDAR technology. Each type of data has advantages and disadvantages for the quantification of AGB. A brief description is now provided on how these technologies are used for quantifying AGB (Table 3.1).

3.2.1 Optical

Different vegetation canopy features are particularly responsive to optical Remote Sensing. Therefore, this technology is frequently used to assess AGB at various scales. Vegetation canopy properties, such as NDVI and LAI, can be easily detected and used as effective predictors through empirical models calibrated through ground measurements for AGB estimation. Low-resolution sensors like Advanced Very High-Resolution Radiometer (AVHRR) and MODIS have often been used to estimate AGB at global and regional scales for a variety of ecosystems such as forests (Chopping *et al*. 2011; Dong *et al*. 2003) and grasslands (John *et al*. 2018).

Medium-resolution sensors like Landsat and Sentinel-2 are generally preferred for regional to local scales but increasing processing power and cloud computing capabilities are expected to open the possibilities of these sensors for global AGB estimations. Lately, the Harmonized Landsat and Sentinel-2 (HLS) product developed by NASA which combines Landsat-8 and Sentinel-2 has been developed in near real-time (Claverie *et al.* 2018), allowing the acquisition of 30-metre resolution data at less than 5-day intervals.

3.2.2 Synthetic aperture radar

Synthetic aperture radar (SAR) instruments on board of satellites offers unique capabilities for forest biomass estimation. The sensitivity of SAR instruments depends on the wavelength or frequency at which they operate with X-, C-, S-, L- or P-band sensors enumerated in ascending wavelength order. Longer wavelengths can penetrate deeper into forest canopies, while shorter wavelengths are sensitive to smaller components of the canopy like leaves and small branches. Longer wavelengths are potentially better for evaluating AGB because stems and tree branches contain the largest proportion of AGB in forests (Sinha *et al.* 2015).

SAR backscattering is not a direct measurement of forest AGB. It provides a strong correlation that is used to model biomass, but it is also very sensitive to environmental factors like precipitation and soil moisture. The SAR backscattered signal increases with higher levels of biomass until it gradually saturates. The saturation point also varies with the radar frequency. It reaches its highest point with P-band sensors. However, there are no sensors currently in orbit (neither optical nor radar) that can deliver accurate estimates for the high AGB frequently observed in tropical areas.

3.2.3 Light Detection and Ranging (LiDAR)

LiDAR is a form of active Remote Sensing that measures the distance between a sensor and an object using laser pulses. LiDAR instruments can deliver precise information on the vegetation's 3-dimensional structure using this technology. LiDAR instruments provide canopy height information as well as other three-dimensional forest structure parameters that are used to estimate AGB through allometry (Rodríguez-Veiga *et al.* 2017). LiDAR data can be acquired from terrestrial, airborne and space systems characterizing the vertical vegetation information at various scales from individual trees to large areas. The use of terrestrial or airborne LiDAR is not viable for large-scale mapping, but it is widely used for mapping at local scales and for calibrating space-borne LiDAR, which has the capability to collect data routinely over large regions. Terrestrial LiDAR sensors provide such dense point cloud data that they can be used to provide very accurate 3-D models of individual trees. After classification into points from trunk, branch and leaves, biomass volume can be estimated, providing a non-destructive method for measuring AGB that can also be used to develop allometric equations. LiDAR data is mainly used in forest ecosystems, but has also been employed to calculate biomass in other environments, including shrublands (Li *et al.* 2017) and grasslands (Wu *et al.* 2009).

Table 3.1: Types and examples of sensors measuring vegetation attributes used to estimate AGB and their pros and cons.

Sensor type	Sensors	Measures	Pros	Cons
Optical	- AVHRR - MODIS - Landsat - Sentinel-2	Canopy properties (e.g., LAI, NDVI)	- Global coverage at a range of different resolutions - Freely-available data - Extensive archives that allow study of changes in vegetation overtime - High temporal resolution (e.g., 5-day intervals) improves chance of having cloud-free observations	- Cannot penetrate cloud cover - Common indices measured are mainly related to vegetation photosynthetic activity but Branches and trunks of trees, which are not photosynthetic, make up the majority of the forest AGB - Difficult to measure many vegetation attributes (e.g., tree height and stem diameter) - Saturation of the Remote Sensing (spectral) signal at high biomass implies limited correlation between the signal from the optical imagery and AGB after canopy closure
SAR	- L-band: JERS, ALOS, PALSAR, NASA/ ISRO NISAR (scheduled 2024) - P-band: ESA BIOMASS (scheduled 2023) - C-band: Sentinel 1	Tree trunks and ground surface (P-band), woody components of vegetation (L-band), upper surface of vegetation canopies (C-band)	- Able to penetrate through clouds in day and night making it the ideal candidate for tropical areas with persistent cloud cover - P-band data can penetrate deep into forest canopy - L-band sensors are able to measure woody vegetation - Global, high temporal and spatial resolution C-band data is available since 2014	-P-band data is not currently available at a global scale -Lack of systematic and dense L-band data for global AGB estimation
LiDAR	ICESAT, GEDI	3-D structure of vegetation, canopy cover, ground height and canopy height	- Not bound to signal saturation on estimation of AGB as high point density (or full waveform) measures through gaps in canopy - Characterises vertical vegetation information at different scales from individual trees or plots to large areas	- Short operational period - Spatial discontinuity (specific spatial sampling patterns) of the footprint - Discrete footprint biomass estimates alone are not suitable to map extensive areas but are usually combined with other Remote Sensing datasets to generate spatially continuous biomass

3.4 Mapping Above-Ground Biomass

The first global AGB maps did not use Remote Sensing technology, they were generated by downscaling (assigning values at finer scale from coarser scale maps) FAO forest inventory statistics and assigning IPCC default AGB averages (estimated from country-level carbon stocks) to global land cover maps. Methods to map AGB at a global scale using Remote Sensing have since been developed. The main constraint for large-area mapping is the non-availability of enough ground data to validate the methods. Medium to low resolution satellite data (both optical and SAR) combined with ground data are used to derive global AGB maps. These data integration approaches overcome the limitations of different sensors (such as signal saturation and cloud cover) while providing continuous global coverage.

There have been a number of initiatives to map biomass at a global scale using a combination of different Earth observation data sets. Table 3.2 lists the open-access global biomass maps currently available.

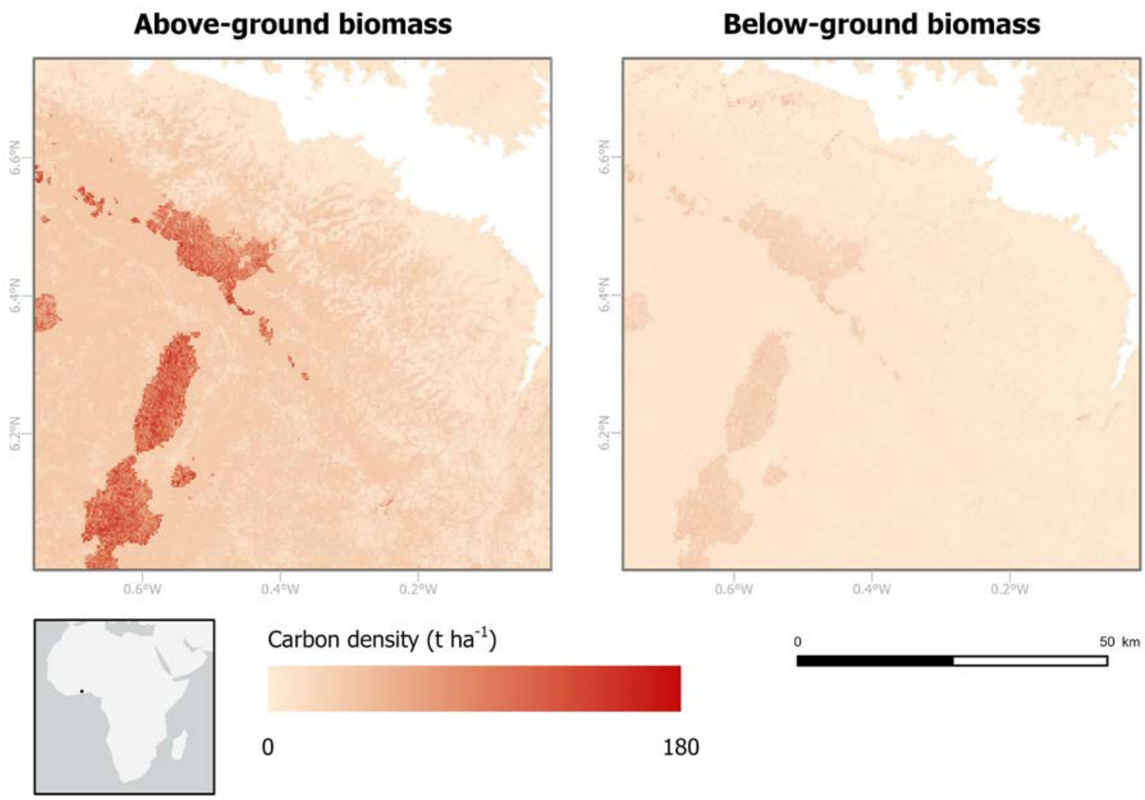

Figure 3.1: Carbon maps of South-east Ghana showing above- and below-ground biomass carbon density for the reference year 2010 at 300 m resolution (Soto-Navarro et al. 2020; Spawn et al. 2020).

Table 3.2: List of global and open access biomass maps adapted from (Hein et al. 2022).

AGB map	Spatial resolution (m)	Epoch	RS data	Reference
Baccini Global	30	2000	GLAS, Landsat, SRTM	(Baccini *et al.* 2012)
GEOCARBON	1000	2007 - 2010	ENVISAR, MODIS	(Pratihast *et al.* 2014; Maurizio Santoro *et al.* 2015)
GlobBiomass	100	2010	ALOS-PALSAR, ENVISAT	(Maurizio Santoro *et al.* 2021)
CCI Biomass	100	2017	ALOS-PALSAR, Sentinel 1	(Maurizio Santoro *et al.* 2021)

The Baccini Global map[8] (epoch 2000) was developed using a method (Baccini *et al.* 2012) that correlates AGB to spaceborne LiDAR data through models calibrated with field data directly underneath the LiDAR footprints. A statistical algorithm that estimates AGB from Landsat reflectance is then calibrated using these AGB estimates and therefore providing global coverage. Following a similar data fusion approach, a refined pantropical map (Avitabile *et al.* 2016) and a boreal map (Maurizio Santoro *et al.* 2015) were combined to generate the GEO-CARBON (2007–2010) map to achieve worldwide coverage. The GlobBiomass[9] (2010) and the CCI Biomass[10] (2017) were produced from SAR images (Santoro and Cartus 2021). The GlobBiomass and CCI Biomass maps contain non-forest areas, in contrast to the Baccini and GEOCARBON maps which only cover forested areas.

[8] Available at https://www.globalforestwatch.org/

[9] Available at https://climate.esa.int/en/projects/biomass/#resources

[10] Available at https://catalogue.ceda.ac.uk/uuid/bedc59f37c9545c981a839eb552e4084

The above-mentioned AGB maps have been derived using different sources of data and methodologies. This leads them to have strong discrepancies that hinder their reliability to derive carbon stocks for global, regional and country based applications (Hein *et al*. 2022). There are many potential sources of errors ranging from human bias on the 3-dimensional measurements (including the application of wrong allometric models) to those related to the Remote Sensing instrument or the environmental conditions. Consistent accuracy assessment of these products is required but limited by the lack of global reference data. National Forest Inventories are often unavailable (as is the case in many tropical areas), inaccessible (lacking open access) or incomplete.

Furthermore, the fact that these maps have been developed using different methodologies and data sources and are bound to different level of accuracy, makes them unreliable for biomass change analysis, even though they represent different time periods (Herold *et al*. 2019). This biomass change is key to monitoring the carbon emissions from the land surface. Currently, changes in carbon stocks (carbon stock dynamics) are estimated through land-use change, where the area of change is estimated using land cover maps (or any bespoke Remote Sensing product), and the biomass value is estimated through AGB maps or by assigning emissions and removal factors. However, when the change is not related to land use but to an increase in growth, forest degradation, natural disturbances or mortality events, this method becomes unviable. Thus, there is an increasing interest in evaluating the ability of Remote Sensing techniques to capture rates of regrowth and degradation (Goetz and Dubayah 2011). This kind of information is crucial for monitoring the effectiveness of large-scale restoration efforts as well as rates of forest regrowth and degradation.

3.5 Mapping carbon storage across land cover types

Most remotely sensed biomass carbon products focus on woody or forest biomass and therefore exclude carbon stocks associated with other non-woody vegetation types such as grasslands, croplands, and scrublands. The first attempt to cover above and below-ground biomass in all vegetation types was undertaken by the Centre for Sustainability and the Global Environment (SAGE), which produced the first IPCC Tier-1 Global Biomass Carbon Map for the Year 2000 (Ruesch and Gibbs 2008). The aim was to provide a benchmark for starting to look at carbon stocks and emissions in relation to land-use change using methods outlined in the IPCC Greenhouse Gas Inventory Guidelines (IPCC 2006). This method assigned default carbon stock values for above-ground biomass (provided by the IPCC) to 23 land-cover types within 20 different ecological zones (FAO 2012) and 7 continental regions. At the time of production, the best available and most widely accepted land-cover map was at 1-km resolution (GLC2000), derived from Remote Sensing and based on SPOT-VEGETATION satellite imagery. For Non-Forest classes, values were only assigned by continent, meaning that differences in carbon stocks in vegetation in different climatic zones were not accounted for.

Below-ground biomass (i.e., living biomass in the roots) was calculated using a root-to-shoot ratio (the relationship between the above-ground and below-ground biomass components) provided by IPCC. This was then applied to calculate below-ground biomass.

More recently, three more refined global maps and estimates of carbon storage within all vegetation types have been produced by (Soto-Navarro *et al*. 2020), (Spawn *et al*. 2020) and (García-Rangel *et al*. In prep). Each has followed a similar approach combining remotely sensed above-ground biomass datasets with global remotely sensed land cover maps to produce more refined global maps and estimates of carbon storage within all vegetation types plus additional soil organic carbon layers. All three teams used root-to-shoot relationships to estimate below-ground biomass, so the focus here is on these biomass carbon components. There were specific differences between the methodologies, but the broad methods included the selection of a global land-cover map as a starting point. Soto-Navarro and Spawn both used the 300-m ESA CCI land-cover map for the year 2010. In contrast, García-Rangel used a more recent Copernicus product at 100-m resolution for the year 2015. Land-cover types were used to select the most appropriate biomass dataset (based on literature review and selection criteria including resolution, accuracy, biomass definition). Each dataset was resampled to the resolution of the land-cover map and the above-ground biomass value was assigned from the chosen source to each grid cell within the land-cover type. The above and below-ground biomass maps (illustrated in Figure 3.1) were then combined to produce the harmonised global maps of above and below-ground carbon.

In terms of forest carbon change, the most widely used and recognized product is that produced by Harris *et al*. (2021). They used 30-m tree cover change data from (Hansen *et al*. 2013) to map annual greenhouse gas emissions and removals (losses and gains in sequestered carbon) that are related to forests, for both biomass and soil carbon integrating both ground and Remote Sensing data. Along with the 30-m change product, many ancillary datasets were required, including mangrove forest extent, primary forest extent, plantations/ tree crops, peatlands, above and below-ground live woody biomass density, ecological and climatic zones, activity data (such as burned areas) and emission and removal factors.

With the release of higher resolution land-cover products, UNEP-WCMC and Impact Observatory have been more recently exploring the potential use of 10-m near real-time land-cover change products for looking at the annual change in carbon stocks for all land-cover types. This builds on work initiated with the National Geographic Society and draws on the methods used for forests by (Harris *et al*. 2021). The outcome of this work is still to be determined, but the approach has been to identify areas where land cover change may result in significant changes in biomass carbon storage.

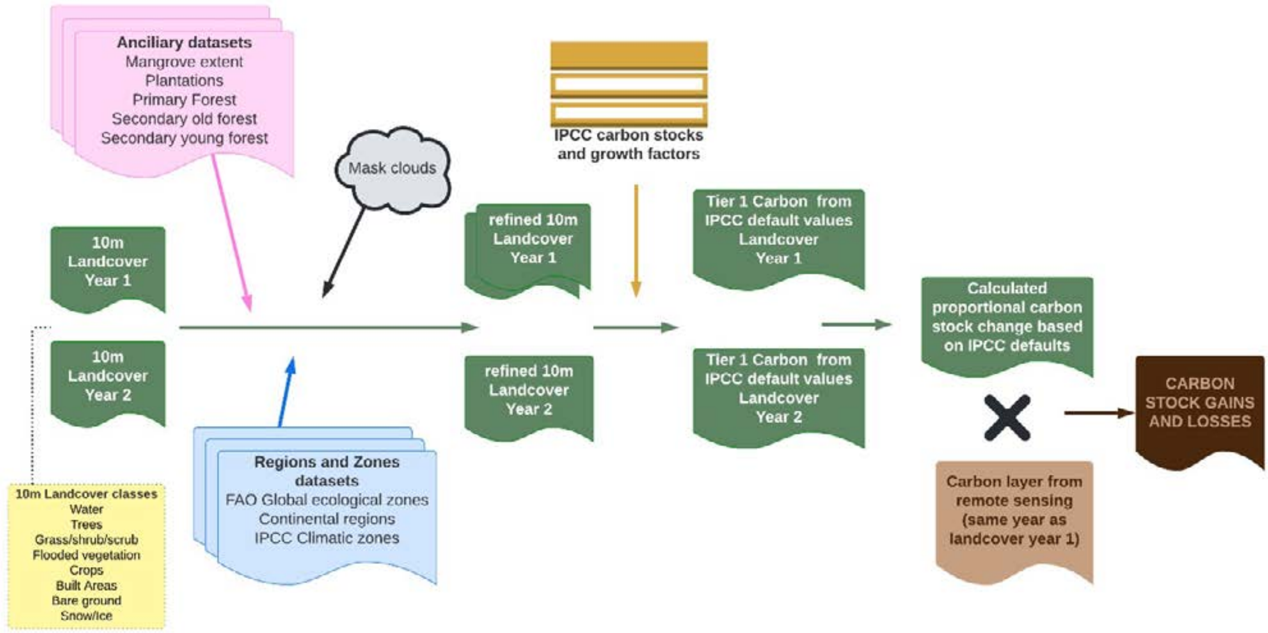

Figure 3.2: Broad overview of the combined approach in development with Impact Observatory exploring the use of high-resolution land cover change projects to assess changes in carbon stocks

The methodology combines both the IPCC Tier 1 approach with the more detailed maps of land cover and forest types obtained from Remote Sensing (Figure 3.2). A transitions table is compiled to apply IPCC default above-ground biomass carbon stock values to the different land-cover types in different climatic and ecological zones and, for secondary young forest, growth rates for calculating annual gains. Below-ground biomass is added using a root-to-shoot ratio (IPCC 2006, 2019). Estimating change in this way carries much uncertainty and the output from this type of mapping will only provide an indication of the trajectory of change rather than accurate measurements. Errors will come from a variety of sources including the default values applied, the remotely sensed biomass products used for the analysis and the proportions applied to obtain the estimate for year 2. By grouping the results into high, medium and low split into gains and losses, the results of such analysis can help inform potential changes in carbon based on the land-cover change.

One of the main limitations of the 10-m land-cover products for this type of work is that they all currently only show 10 broad land-cover types (e.g., trees, grass, crops). While these match with the broad IPCC land-cover classes, they do not provide adequate detail on their own to either enable the assignment of default IPCC carbon values or utilization of remotely sensed biomass datasets without heavy reliance on ancillary data (as per the approaches outlined above). Trees, for example, need to be split into primary forest, secondary old and secondary young forest and mangroves and then split by ecological zones. There is an added complication in that mangroves, in some cases, qualify as both trees and flooded vegetation. Other categories need to be split by climatic zone. This requirement for ancillary data (often at a coarser resolution than the 10-m products) eliminates some advantages of using these high-resolution layers for this type of work.

An example of the limitations of these broad land-cover types is the tree category that appears to include more than just forest. There is no distinction between natural primary/closed canopy forest and more open forest or plantations. This can be seen in Figure 3.3 below, which compares the IO ESRI land-cover dataset with national land cover product. The latter shows relatively few pockets of closed forest left and larger areas of open forest and Cocoa plantations.

Further validation and class refinement are necessary to make these high-resolution land-cover maps viable and more robust products for this type of work. For example, mangroves are included in both the 'Trees' and "Flooded Vegetation" categories, making the application of appropriate carbon stock values difficult. In addition to these issues with the land cover classes, while the IPCC provides detailed data for different types of forest in different ecological zones, data for other vegetation classes, such as grasslands and wetlands (other than mangroves) are less detailed. There are also fewer remotely sensed products for other vegetation types.

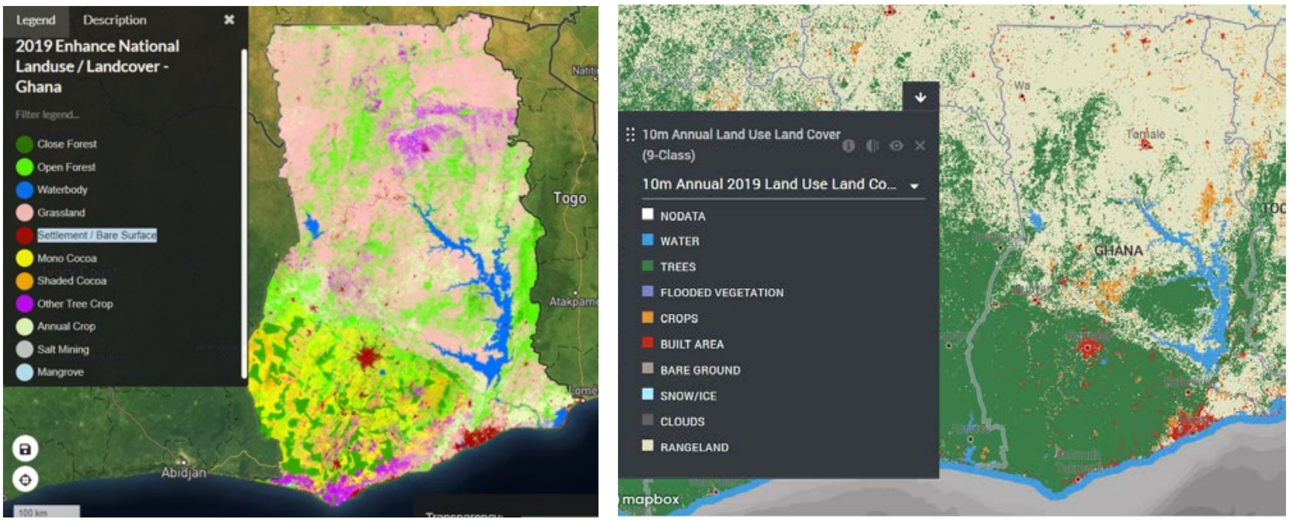

Figure 3.3 National land-cover map (left) produced by the Ghana Forestry Commission's Resource Management Support Centre (RMSC) compared to (right) IO ESRI 10m land-cover map (accessed on UN Biodiversity Lab September 2022)

4

Spatial planning and the use of Remote Sensing in decision-making for conservation of biodiversity and carbon stocks

4.1 Foundations of decision-making and spatial planning

Spatial planning is a form of decision-making that uses spatially explicit data in a structured process of finding solutions to complex problems. Most often, this type of planning occurs after a problem has been identified and involves choosing among options to alter current management regimes with the aim of achieving specific objectives. Most problems relating to land use, natural resource management and conservation are linked to one or more decisions that need to be made in the face of multiple management alternatives within the land- or seascape. In a conservation context, spatial planning often explores the issue of how to spend money and effort on conservation in both space and time. Decision-makers need to decide what they want to achieve, what they can do to achieve their aims and how they want to measure progress towards their aims (Groves and Game 2016; Rittenhouse 2017). Conflicting objectives, such as using land for agriculture or for conserving biodiversity, are common and introduce trade-offs.

Even though most decision contexts are unique, standards for rigorous, inclusive, defensible and transparent processes should guide all decisions, including spatial plans (Gregory *et al.* 2012) (Box 1, Figure 4.1). These standards include structuring the problem in a useful way to inform decision-making. A clear and transparent structure is key for an efficient planning process and provides a robust process to choose the most promising way forward among multiple options. In order to structure the planning process, the key points that are important to consider in any planning process can be seen as individual steps (Box 1, Figure 4.1). There are slight variations of the terminology, grouping and order of activities of different steps in strategic planning (Pressey and Bottrill 2009), and here we follow one of the most condensed versions with roots in decision science and multiple applications in complex real-world settings (Gregory *et al.* 2012) (Box 1). The steps provide an evaluation structure that helps decision-makers to clearly define relevant objectives and performance measures targeted to find solutions to a problem that tick all important boxes and foster learning and a shared understanding of the problem context through discussion and deliberative thinking. A more detailed description of each step in the context of Remote Sensing can be accessed in Telhado *et al. (in prep.)*.

One common spatial planning approach that can benefit from such a stepwise approach is to identify priority areas for specific actions based on analysis of spatial data. Spatial planning involves working with spatially explicit maps throughout the planning process. Early on, they can enable decision-makers to develop a thorough understanding of the problem context, and, later, the overall aims and details of alternative management actions. In the best case, the final map is much more than just a map of implementation plans and also documents the whole decision process. Remote Sensing products can be useful during all six steps (Figure 4.1), the scoping clarification of the decision context, the definition of objectives and measures, the development of alternative actions, the estimation of their consequences using the performance measures the evaluation of trade-offs, and the implementation, monitoring and review of the selected action.

BOX 1. Structuring a spatial planning process in six key steps to create a rigorously thought-out "actionable map" that documents a decision-making process.

Problem solving is easier when a problem is well structured. Spatial planning benefits from following this sequence of steps:

1. Consider the problem: What are the core elements, who are the stakeholders, what are the uncertainties and trade-offs?
2. Think about what you (the decision-maker and relevant stakeholders) want: What are the objectives and outcomes?
3. Think about what you can do: Which actions and strategies are possible?
4. Think about how you will monitor and measure the impact of the actions that you could take: Which metrics and indicators should be relied upon, based on which assumptions?
5. Choose the most promising way forward based on previous thinking, deliberation and modelling.
6. Implement the chosen action and monitor, based on the chosen metrics, what happens after the implementation, with the option to re-enter and update any of the above if you are not achieving the objectives as planned.

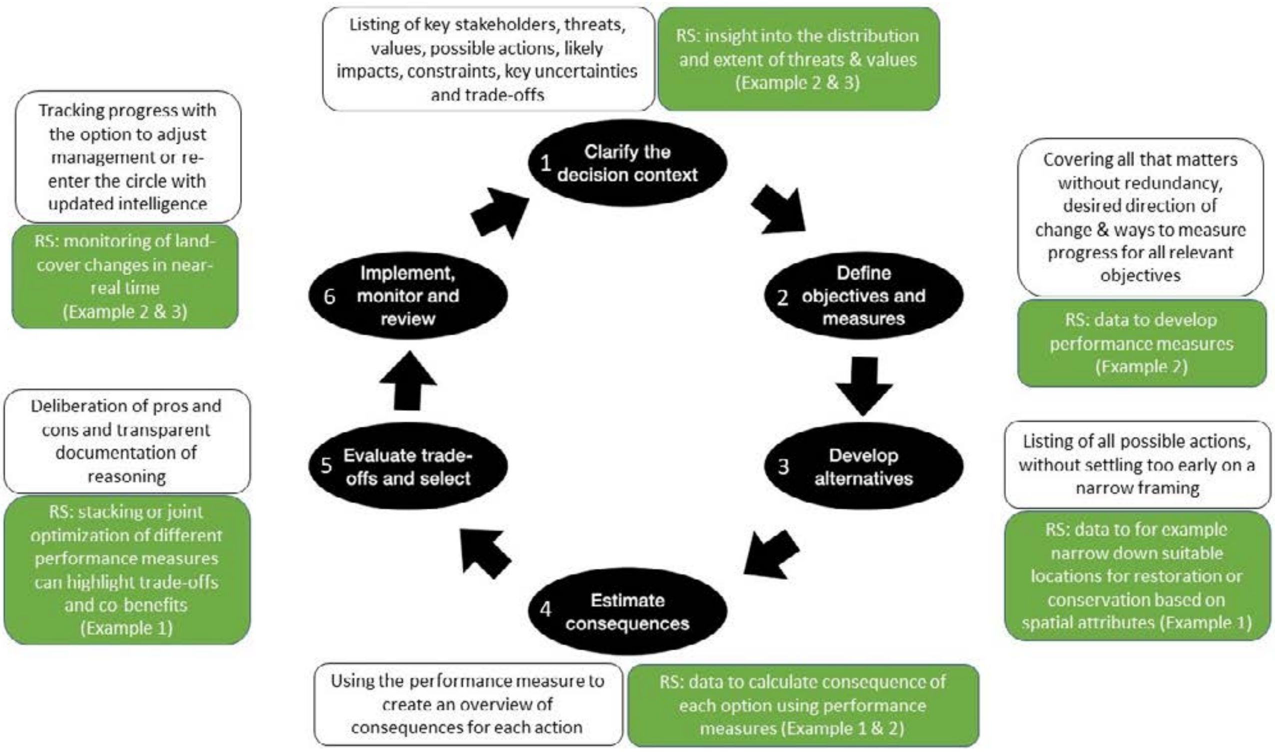

Figure 4.1: The six steps of a decision-making process and the usefulness of information derived from Remote Sensing

4.2 Examples of the use of Remote Sensing in real world applications

This section offers several examples of the use of specific Remote Sensing datasets for informing real-world conservation decision-making.

Example 1: Using Remote Sensing for developing alternative actions and estimating their consequences and trade-offs: Jung *et al.* 2021, *"Spatial optimization of areas of importance for biodiversity, carbon and water".*

Resolution: 100 m (biodiversity, above-ground biomass carbon), aggregated to 10 km (planning unit in prioritization)

Source: Copernicus land cover (ESA PROBA-V), Lesiv *et al.* (2021) forest management (ESA PROBA-V), ESA CCI Biomass (Sentinel 1, Envisat ASAR, JAXA ALOS-1 and ALOS-2), Bouvet *et al.* (2018) above-ground biomass of African savannahs and woodlands (JAXA ALOS PALSAR L-band), Santoro *et al.* (2021) global forest above-ground biomass (JAXA ALOS PALSAR L-band, Envisat ASAR C-band, Landsat 7)

Data analysis:

Jung *et al.* (2021) embedded Remote Sensing data within several steps of their global spatial optimisation for biodiversity, carbon and water. This work sought to identify the potential opportunities that could arise from coordinated action for biodiversity conservation and climate change mitigation. It aimed to provide broad spatial guidance showing the synergies that could arise from high-level conservation policy decisions rather than providing advice implementable on the ground.

Remotely sensed land-cover and climate data were used to create a map of IUCN Red List habitat types (Jung *et al.* 2020), from which species' ranges were refined to produce their Area of Habitat (see Chapter 2). Carbon data were similarly mapped from remotely sensed above-ground biomass, land cover data by García-Rangel *et al.* (in prep.; see Chapter 3). One key advantage of using Remote Sensing for this is that it provides objective, transboundary data that crosses social and political contexts. However, such data are only useful if they are accurate. Improving validation of these data in under-sampled regions of the world is key to ensuring their usefulness. Jung *et al.* then jointly optimized biodiversity and carbon (along with clean water provisioning) to minimize the number of species that are threatened and maximize carbon storage and regulation of clean water.

To develop different alternatives, they weighted species differently according to their conservation status, and evolutionary distinctness. They also varied the weighting of water and carbon relative to the combined species (biodiversity) weight in the prioritization. These different alternatives produced different rankings of the importance of each planning unit, with the consequence of each alternative being the estimated shortfall of the number of species remaining at the Red List's Least Concern status, and the amount of carbon and water left unprotected globally. For example, weighting biodiversity, carbon and water equally would adequately conserve 57.9% of species, but giving full weight to biodiversity would adequately conserve 81.3% of all species. This reveals the biodiversity trade-off depending on the action taken.

Other, more local prioritizations have considered the conflict between anthropogenic demand for land alongside the need to conserve land for biodiversity and carbon in their development of alternative actions. For instance, (Moilanen *et al.* 2011) prioritized land in Great Britain for biodiversity, carbon, urban development potential and agricultural value. Remote Sensing products were the basis of the land-cover maps used to assess the urban development potential of the land and create these alternatives actions.

How it has been used

Global analyses like Jung *et al.*'s work should not be implemented at local scales because they do not consider locally specific consequences and trade-offs. These can include views of stakeholders, as well as discrepancies between both local and global data. National level implementations using this framework are underway in Mexico[11], Colombia[12], and Argentina[13], to help designate new protected areas and other conservation actions to help the countries meet the nature conservation goals of the post-2020 global biodiversity framework (for instance, 30×30). Remote Sensing products could also be useful in monitoring the effectiveness of these actions.

[11] https://www.dof.gob.mx/nota_detalle.php?codigo=5634786&fecha=08/11/2021#gsc.tab=0

[12] http://portafolios.humboldt.org.co/

[13] https://naturemap-argentina.web.app/

Example 2: Using remote sensing for the conservation of forest and biodiversity: The development of the Hansen *et al.* 2013 data set on forest cover and loss to a real time monitoring platform of land-cover change.

Resolution: 30 m

Source: Landsat

Data analysis:

The initial dataset by Hansen *et al.* (2013) on global canopy cover and loss was developed to include a broader land cover status and land cover change product (Hansen *et al.* 2022), which analysed over 650,000 Landsat 7 Enhanced Thematic Mapper Plus (ETM+) scenes acquired during the growing season with Google Earth Engine.

How it has been used:

Updates of canopy cover and loss have been included in the Global Forest Watch data platform operated by the World Resource Institute and widely used by NGOs, policymakers, journalists and industry to inform decisions. The initial annual updates have developed into monitoring in real-time, with large implications for the use and application of conservation decisions.

<u>Defining problem contexts</u>

A) Actions resulting from prompt alerts about the problem context

NGOs such as the Amazon Conservation Association can now detect illegal gold mining and logging within days and alert authorities.

Journalists in Peru were able to incentivize government action on forest fires in protected areas through real-time reporting.

B) Derived data to inform about biodiversity significance

Forest biodiversity significance datasets were created for pixels identified by Global Forest Watch as either currently forested or having lost forest between 2000 and 2018. Ranges for forest-dependent mammals, amphibians and birds species as well as conifers were selected from the IUCN Red List. The area of forest within each species' range was calculated. This area value was then used to give an inverse weighting so that restricted species with smaller areas of forest habitat had higher scores. To distinguish plantations from forests, the spatial database on planted trees (Friedlingstein *et al.* 2022) was overlaid to remove areas with plantations from calculations for species only affiliated with natural forests.

The weighted maps for each species were then summed up to assign a rarity-weighted richness (significance) to each forest pixel. The resulting significance maps complement maps of forest intactness, as instead of providing an estimation of community-level intactness, they provide an understanding of where the risk of extinctions may be highest if habitat is removed. They have the potential to be especially useful for helping prioritize the conservation significance of ongoing forest loss events, such as those detected by the near real-time Global Land Analysis and Discovery alerts[14].

C) The potential of forest to contribute to nature-based solutions for climate change mitigation

Harris *et al.* (2021) used a derived approach from Hansen *et al.* to map forest extent globally. From this above-ground biomass carbon, they further applied root-to-shoot ratios to calculate below-ground biomass carbon. These data were then used to map the carbon fluxes of global forests, providing important information to scope the current contribution of forests to climate change mitigation.

<u>Development of performance measures</u>

The “GFW biodiversity project” aimed to assign values to each forest pixel to produce additional datasets showing different facets of biodiversity. To achieve this, two metrics were created. One was known as forest biodiversity intactness and based on BII and the other was the forest biodiversity significance discussed above. Both metrics, as well as the biodiversity datasets underpinning them, namely the PREDICTS database and the IUCN Red List, all required some ancillary data on land use to complement the remotely sensed imagery.

Forest biodiversity intactness was based on a subset of sites for forested biomes from the database, and biome-specific models were created with population density as a continuous variable. To project the values on to a map, a set of rules was used to group each pixel into the following categories: “Primary/mature secondary forest, Intermediate secondary forest, Young secondary forest, Cropland, Pasture and Urban” (Hill *et al.* 2019). The latter three anthropogenic classes were defined by overlaying forest loss pixels with downscaled land-use data from Hoskins *et al.* (2016). The distinction between different forest types, however, was dependent on comparing the cover in 2000 with a corresponding cover dataset for 2010. The resulting map characterized each pixel of forest cover and loss with a value of intactness. This reflects the proportion and abundance of the remaining original forest community at any location.

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[14] https://glad.umd.edu/dataset/glad-forest-alerts

The datasets have also been used for developing indicators for SDG 6.6.1 and in the UNFCCC's REDD+ initiative.

Assessing consequences

The food company Mars[15] has used the website to evaluate Palm Oil suppliers and inform decisions on where to source ingredients.

Impact on biodiversity conservation decisions

Analysis of the initial data (Hansen *et al*. 2013) has contributed to the most recent update of the IUCN red list assessment and the status of hundreds of forest-dependent species (Tracewski *et al*. 2016), while (Joshi *et al*. 2016) used the more recent data set for assessing forest loss in priority areas for tiger conservation and identifying palm oil plantation as a driver of ongoing loss of habitat. This can inform the planning of protection of key habitat and corridors. Expansion of palm oil plantations has also been linked to the loss of chimpanzee habitat in Africa. Here, the analysis of the Hansen *et al*. dataset was picked up by the Jane Goodall Institute to inform their monitoring and decision-making activities. Indicators of habitat condition were aggregated at the relevant level of management areas to inform decisions and evaluate management effectiveness. The monitoring revealed mixed success, which in turn informed the adoption of new or modified conservation strategies. One of the important insights of the project was the superiority of multiple indicators compared to a singular index of habitat health, as multiple aspects are necessary for a deeper understanding of drivers of healthy habitat condition and threats.

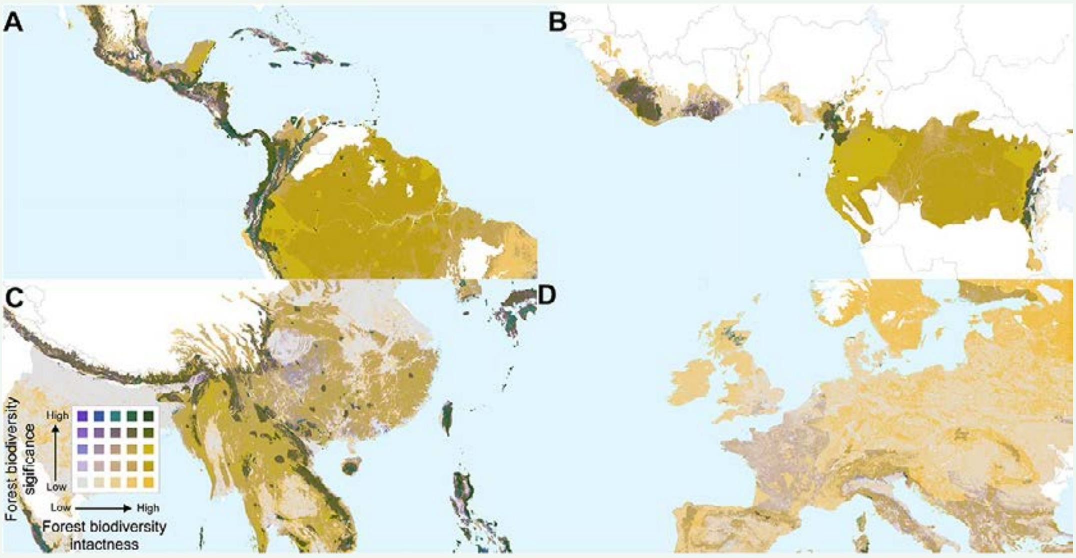

Figure 4.2: Bivariate maps of significance and intactness of forest biodiversity within forest biomes for 2018, with a focus on areas of (A) Central and South America, (B) Central and West Africa, (C) China and Southeast Asia, and (D) Western Europe. Panels reflect different spatial scales. Image taken from (Hill et al. 2019).

[15] https://www.mars.com/

Example 3: Using Remote Sensing for the conservation of intertidal habitat and the conservation of migratory shorebirds: The Murray *et al*. data set on tidal mudflats, wetlands and mangroves.

Resolution: 30 m

Source: Landsat

Data analysis:

The initial dataset (Murray *et al*. 2014) provided a classification of the intertidal zone by subtracting high and low tide image pairs to provide the first transparent and replicable evidence of large-scale losses of intertidal habitat in the Yellow Sea, an important part of a major migratory shorebird flyway. A number of datasets were consecutively developed (Murray *et al*. 2019) using Google Earth engine and machine learning to analyse over 700,000 satellite scenes to map tidal flats both in extent and change across 33 years (1984–2016) at a global scale.

How it has been used:

The initial analysis and subsequent products that have come out of ongoing development and elaboration have been used in different stages of decision-making and conservation planning, from describing problem contexts, to prioritizing areas to protect for conservation (developing alternative actions) and monitoring the protected area effectiveness.

Dissemination and communication of the loss of intertidal habitat with key stakeholders and decision-makers were key in the successful use of this data to influence conservation decision-making and spatial planning. The East-Asian-Australasian Flyway Partnership (EAAFP) disseminated key results to governments and NGOs in the region. The new insights into the ongoing loss of key habitat sparked new scientific collaborations. Many subsequent analyses of the dataset were focused on triggering conservation action, for example, a comparison of the performance of China and South Korea’s Protected Area Network. The finding that South Korea’s system effectively conserved intertidal habitat while China recorded ongoing loss was communicated as a clear pathway for action (improving management of protected areas) in workshops with government officials.

The dataset and related analysis also contributed to a major international IUCN report, which helped a motion at the 2012 IUCN World Conservation Congress in Jeju, South Korea, aiming at an agreement to take necessary action for the conservation of migratory shorebirds and their intertidal habitat.

This further sparked additional workshops and collaborations to take place that involved the coordination of conservation activities and agreement on a supplementary motion at the IUCN World Conservation Congress in Hawaii in 2016.

The evidence was a supporting factor for the listing of migratory shorebirds in Australia as threatened species and several bird species under the Convention for Migratory Species. It also led to the listing of the tidal flat ecosystem of the Yellow Sea on the IUCN Red List of Ecosystems.

The initial analysis of intertidal mudflats has been broadened to include wetlands and mangroves, as well as a long-running collaborative project providing data with financing by Google, the Australian Research Council and James Cook University[16].

4.3 Limitations of planning and decision-making with global data

Users of any map should ask whether the map provides clear and actionable messages that can inform decision-makers at the relevant spatial scale for their application. This is particularly relevant when considering the use of global data for national decision-making. For example, decisions to allow particular land-use changes are typically made at a sub-national scale, ideally using data at a fine spatial resolution and with a locally appropriate thematic classification (Ferrier *et al.* 2004). Other types of decisions, including on resource allocation, may apply to broader regions and may be better candidates for incorporating global data (Wilson *et al.* 2007). In many cases, other information might be more helpful, or at least needed to support the choices that must be made. Local and regional contexts often provide the necessary fine-scale information to fully understand biodiversity, which cannot be distilled into a singular indicator or performance measure (Wyborn and Evans 2021). Some authors of global maps provide guidance on appropriate and inappropriate uses of their data and may explicitly point out that these are not suitable to guide on-the-ground decisions (e.g. Jung *et al.* 2021; Strassburg *et al.* 2020). The pros and cons of using global data for national planning are discussed in more detail in UNEP-WCMC (in press).

No map, tool, data or modelling can lift the burden of choice during decision-making. Analyses can only inform a choice between options, based on available information for the values considered. It is up to decision-makers to justify the choices they make, and in many cases difficult trade-offs between competing objectives need to be evaluated.

[16] https://www.globalintertidalchange.org/

Spatial planning inevitably impacts on people at various scales, and those people need to be included in decision-making. Poorly considering the social impacts of conservation plans can lead to unintended negative consequences, particularly for already marginalized groups of people (Schultz *et al*. 2022). Meaningful conservation plans must therefore represent the needs and values of diverse groups of stakeholders. This should help ensure good outcomes for society, the economy and conservation, but is not always straightforward (Halpern *et al*. 2013).

Bringing together objectives from a range of stakeholders and sectors in a single analysis, allows spatial planners to estimate likely trade-offs between these objectives. These may include cultural heritage, nature's contributions to people and direct socio-economic costs to different groups, identifying who bears the costs and who benefits from planned changes (Klein *et al*. 2015). Data on costs and benefits should be subject to scrutiny and methodological rigour, particularly when planning across areas with large socio-economic disparities (Naidoo *et al*. 2010; Armsworth 2014; McCreless *et al*. 2013).The possible trade-offs can then be discussed among stakeholders to find acceptable, equitable solutions. The values and preferences that lead to the final choice of one option above others should be communicated clearly (Keeney *et al*. 2008; Keeney 1992). Fair, equitable planning that involves Indigenous peoples and local communities is discussed in more detail in Systemiq (2023).

5

Integrating remote sensing into biodiversity and carbon workflows: user uptake

In previous sections, this document has discussed how Remote Sensing can contribute to biodiversity and carbon assessments, how these datasets are produced at increasingly higher resolutions, accuracy, and frequency and how this information can be used in the spatial planning process. However, there is still the need to integrate data that often come from different sources, services, and software applications and make them available as useful information to the final users.

A series of web-based platforms, data portals and dashboards have been developed by different organizations aiming to integrate land cover maps and other Remote Sensing products into biodiversity and carbon workflows in a way that this information can be accessed, visualized and easily interpreted. Examples include the Map of Life project from Yale University[17], NatureServe's habitat modelling framework[18] and World Resources Institute's Global Forest Watch project[19]. Additionally, some organizations are developing biodiversity workflows based on species' area of habitat (AOH), including IUCN, BirdLife International and UNEP-WCMC. As for carbon workflows, Impact Observatory[20] are working on annual dynamic carbon change maps based on frequently updated land-cover maps. Similarly, WRI are working on producing carbon maps based on forest cover change[21].

However, despite the ongoing technological advances, growing data availability, increasing numbers of available workflows, and continuing scientific efforts in this field, biodiversity and carbon-related outputs are still insufficient, infrequently updated and often fail to reach the end user. One of the overarching scientific gaps is the lack of generally agreed and relevant Remote Sensing-derived metrics to monitor carbon fluxes and biodiversity trends. Only if there are clear objectives and clarity on what needs to be measured can decisions be made on whether the available Remote Sensing data is useful or if there are new methods or workflows that need to be developed to make it useful.

In addition, there are still outstanding technical limitations, including those around the value of the land cover classification scheme of currently produced land-cover maps for biodiversity and carbon analysis. There are several land-cover classes omitted in remotely sensed derived products, such as primary forest or pasture, that are key for biodiversity and carbon analysis. There is also a general mismatch between classification schemes used for biodiversity analysis (such as the IUCN Habitat Classification systems or those collated in the PREDICTS database) and those mapped in remotely sensed derived land-cover products. In addition, when it comes to analysing changes, short-term changes depicted in land-cover maps are often non-genuine, hampering the frequency with which there can be confidence in these products. These limitations reduce the suitability of these maps for direct input in biodiversity and carbon workflows.

Moreover, the growing need for near real time availability of biodiversity and carbon outputs requires the automation of these workflows. Currently, many of them require manual input or rely on additional data products with mismatching updating frequencies.

[17] https://mol.org/

[18] https://explorer.natureserve.org/

[19] https://www.globalforestwatch.org/map/ and https://gfw.global/3h5wYR1

[20] https://www.impactobservatory.com/

[21] https://www.nature.com/articles/s41558-020-00976-6

This means that even if the Remote Sensing derived products are available in near real-time, there will be a time gap until the value-added data product becomes available. This near real-time requirement also relies on datasets that are often generated by different organizations to be made readily available and accessible. This requirement comes with its own technological challenges, including limitations of licensing that are applied to the data, as well as data interoperability issues with workflows and datasets. Different data sources need to work together in a common framework, especially one that can provide both the processing and the subsequent dissemination of the products. A solution linking key land-use, biodiversity and carbon data sources could provide great scope and flexibility for answering new scientific questions as well as integrating novel datasets. Although originally targeted at the Remote Sensing community, platforms like Google Earth Engine (Gorelick *et al.* 2017) and its close relation SEPA[22] provide examples of some of the more mature and readily accessible systems that fit many of the needs for automated workflows.

Incorporating these high-resolution near real-time products in a robust spatial planning framework requires stakeholder uptake. The user needs to believe in the data. One of the issues hindering this uptake is the overwhelming amount of biodiversity and carbon products available. This results in information overload and a lack of understanding of which product is best for specific applications. In addition, these datasets are spread throughout different platforms with a lack of alignment between them in terms of the statistics that they report against seemingly the same dataset. This leads to a lack of trust. Also, an issue contributing to this lack of trust is the uncertainty of how long specific products are going to be available for, especially for time series of data that may not be available in the near future. Thus, from the user's perspective, there are real limitations in terms of availability, accessibility and reliability, as well as a lack of clarity on the intended scope of use.

The above-described bottlenecks and limitations are currently preventing this carbon and biodiversity information from reaching the diverse group of individuals and organizations making decisions in a way that is comprehensive, easily interpreted and relevant for their intended use. To overcome these limitations, more understanding of user needs is required. Communication with intended users of the data about their specific needs and for which specific decision contexts the information is required would ensure that the temporal, spatial and thematic resolution of the data matches their needs with an acceptable level of uncertainty.

Promoting institutional collaboration will help overcome data access and interoperability issues and prevent duplication of efforts in terms of developing workflows and producing datasets. In addition, this may also help ensure that the sustained set of funding needed to push all the above technical barriers forward is in place for the continuous development of high quality, freely available and frequently updated carbon and biodiversity monitoring products.

[22] https://sepal.io/

6

Conclusion

Remote Sensing technology continues to evolve and develop rapidly. The increasing availability of freely accessible data, along with advances in analytical developments, processing techniques and computational capabilities, has facilitated the production of a range of land-cover products available at increasingly high resolution in space and time. This trend is expected to continue in the future. However, further transparency and consistency in terms of methodologies, data limitations and accuracy assessment procedures are vital in order to meet the information requirements of all users of these data.

In addition, mapping land cover and land cover change will not continue to be unconnected activities but rather seen as complementary ones in which knowledge of land-cover change will be used to develop the next generation of land-cover maps. Similarly, complementing land cover with other remote-sensing derived data products provides a versatile source of information for different aspects of management-related decision-making. Traditionally, high levels of expertise were required to create products of Remote Sensing data that could be analyzed in more conventional software and workflows. However, with the expansion of analysis-ready data, these types of products become increasingly useful for a broad range of scientists and analysts, and less time and effort are required to use the data in planning contexts. There are already many examples of the successful use of these products and derived datasets in different stages of the decision-making process, with real impacts on conservation projects and management actions around the world.

Remote Sensing is set to continue to feed into many metrics describing the various facets of biodiversity. Currently, land-cover and land-use products are often linked to species range data or modelling community responses to land-use change at global and national scales. Increasingly, there also appears to be scope for integrating more direct Remote Sensing measurements of biodiversity proxies, such as some of the proposed essential biodiversity variables (EBVs).

Remote Sensing will also continue to play a pivotal role in monitoring progress towards global climate commitments, particularly those concerning land-use change, ecosystem restoration, biodiversity conservation, quantification of carbon stocks, carbon offsetting, deforestation and forest degradation. Furthermore, these technologies are likely to reduce upfront costs associated with measuring and verifying emissions reductions from carbon projects.

However, improving the availability of data and the technical capacity of data users will be key for the widespread use of remote-sensing derived data products. Data must be available to users and stakeholders across a variety of sectors, computational and internet capacities, and geographical scales. To make sure that these data are best-used, end users, especially local stakeholders, will need to be empowered through targeted technical capacity-building. They must also be provided with relevant information about the nature of their data, so they are aware of existing limitations and nuances. Broader dissemination of the sources and applications of Remote Sensing data for conservation decision-making can lead to better outcomes for the management of biodiversity and carbon stocks.

Remote Sensing technology and derived data sets on biodiversity and carbon stocks, along with food production and commodity supply chain data, will be crucial for understanding the interactions between different sectors and goals and how they overlap in space and time. Understanding these interactions will help decision-making activities such as mapping hotspots of trade-offs and synergies (co-benefits) between the goals (like biodiversity, food security and climate change mitigation) and assist in developing sustainable management strategies.

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