ECO-MOSAIC: Ecosystem Monitoring and Scaling for Climate Change Impacts

SCIENCE REQUIREMENT ANALYSIS

Consortium

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ACRONYMS AND ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
BioDT	Biodiversity Digital Twin
CBD	Convention on Biological Diversity
CCI	Climate Change Initiative
CHIME	Copernicus Hyperspectral Imaging Mission for the Environment
DEMs	Digital Elevation Models
DTMs	Digital Terrain Models
EBOCC	European Biodiversity Observation Coordination Centre
EBVs	Essential Biodiversity Variables
ECVs	Essential Climate Variables
eDNA	Environmental DNA
EnMAP	Environmental Mapping and Analysis Program
EO	Earth Observation
EOSC	European Open Science Cloud
ESA	European Space Agency
EU	European Union
FAIR	Findable, Accessible, Interoperable, and Reusable
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GBIF	Global Biodiversity Information Facility
GDDS	Green Deal Data Space
GCOS	Global Climate Observing System
GEDI	Global Ecosystem Dynamics Investigation
GFMs	Geospatial Foundation Models
iDiv	German Centre for Integrative Biodiversity Research
InSAR	Interferometric Synthetic Aperture Radar
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
ISDMs	Integrated Species Distribution Models
LAI	Leaf Area Index
LST	Land Surface Temperature
LiDAR	Light Detection and Ranging
MAMBO	Modern Approaches to the Monitoring of BiOdiversity
MODIS	Moderate Resolution Imaging Spectroradiometer
NBMCCs	National Biodiversity Monitoring Coordination Centres
NDVI	Normalised Difference Vegetation Index
NECST	Nature and Ecosystem Services Trade-offs
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SAGE	Sustainable Green Europe Data Space
SAR	Synthetic Aperture Radar
SDMs	Species Distribution Models
GEO BON	Group on Earth Observation Biodiversity Observation Network
UAVs	Unmanned Aerial Vehicles
UAVSAR	Uninhabited Aerial Vehicle Synthetic Aperture Radar

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1. KNOWLEDGE GAPS IDENTIFICATION

This report presents a comprehensive, state-of-the-art assessment of the impacts of climate change on terrestrial biodiversity, examining how data from the European Space Agency Climate Change Initiative (ESA-CCI) Programme can help address the key knowledge gaps identified in the ECO-MOSAIC project. To this end, we conducted a systematic review of the scientific literature and a thorough examination of major European and international research initiatives relevant to these themes, supported by an in-depth and targeted literature analysis.

1.1. Climate Change and Biodiversity

1.1.1. Impact of Climate Change on Biodiversity in Terrestrial Ecosystems

Climate change has profound impacts on biodiversity in terrestrial ecosystems and is currently recognised as one of the most significant drivers of biodiversity loss (Montràs-Janer et al. 2024). The increase in global temperature, coupled with irregular precipitation patterns, is leading to more intense and frequent extreme climate events that significantly affect fauna and flora, ecological communities, and ecosystem services (Weiskopf et al. 2020). Even ecosystems that are highly resilient to climate-induced changes are being impacted, as the frequency and magnitude of these changes exceed their capacity for recovery (Côté and Darling 2010). The primary mechanisms by which climate change-related extreme events impact biodiversity in terrestrial ecosystems are described in this section, including habitat shifts, phenological changes, alterations in species composition, and the loss of ecosystem services. As a result, we conducted a literature review to explore the impact of climate change on various aspects, including habitat shifts and loss, phenological changes, increased frequency and intensity of extreme events, changes in species composition, and reduced ecosystem services (Figure 1).

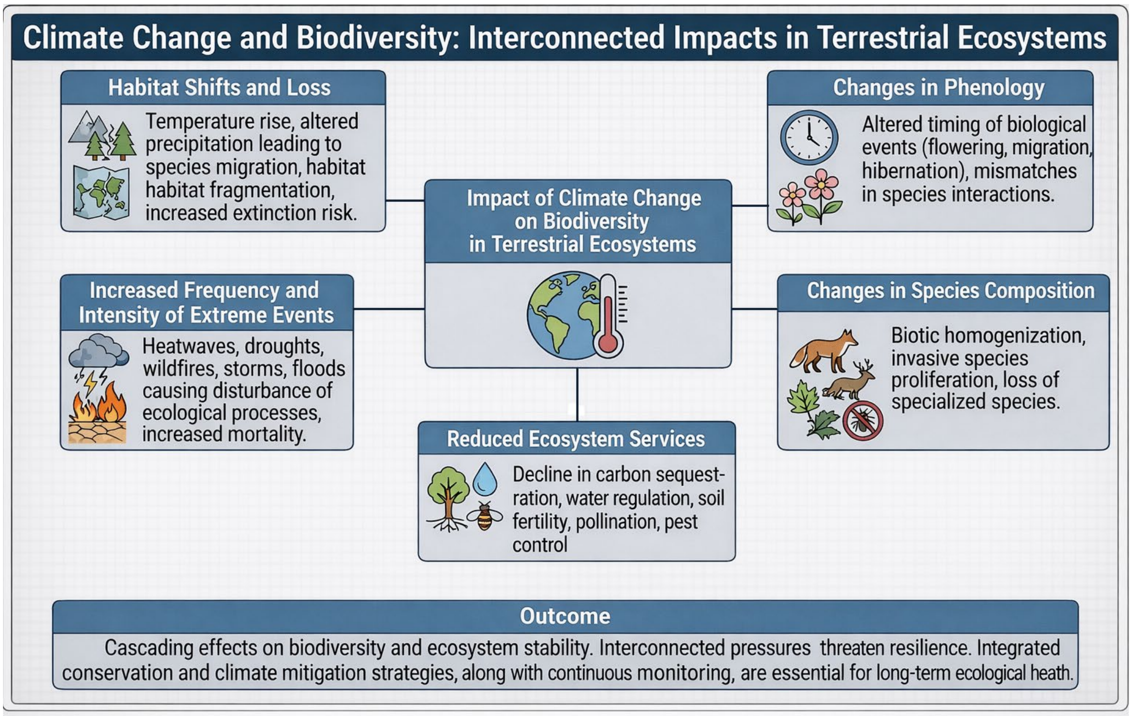


Figure 1. *Schematic representation by which climate change-related extreme events impact terrestrial biodiversity, including habitat shifts, phenological changes, species composition alterations, and loss of ecosystem services. Conceptual content provided by the authors; figure drafted with assistance from FigureLabs (figurelabs.ai).*

1.1.1.1 HABITAT SHIFTS AND LOSS

Due to rising temperatures, the niche of many terrestrial species is shifting to new geographic areas in response to altered climate conditions, resulting in a realignment of biogeographical ranges. This often implies moving to higher elevations or higher latitudes (Parmesan and Yohe 2003; Walther et al. 2002). For example, some European butterflies have moved tens to hundreds of kilometres northward in the past decades (Parmesan et al. 1999). A similar pattern is observed with some alpine plants in the Alps, which have shifted their habitats one to four meters uphill per decade (Gobiet et al. 2014). However, species that are adapted to high-altitude or high-latitude habitats face significant challenges as global warming progresses, as they have limited options for migration. This situation renders them particularly vulnerable and increases their risk of extinction (Parmesan et al. 2022). This phenomenon is exemplified by the American Pika (*Ochotona princeps*), which has vanished from certain areas in the United States due to warmer conditions exceeding its thermal tolerance (Beever et al. 2011).

Furthermore, the displacement of new species from lower-elevation areas can create competitive pressures for space and resources, thereby diminishing the availability of optimal habitat for specialised species. For instance, warmer-adapted species entering a historically cold-dominated environment alter the ecosystem structure (Flickinger and Dukes 2024). This displacement of new species can also introduce novel predators and pathogens, such as the mountain pine beetle (*Dendroctonus ponderosae),* which is causing large-scale pine mortality (Alexander et al. 2015; Root et al. 2003).

Moreover, not all species can shift quickly enough to survive as global warming progresses. Several factors may constrain the movement of affected species, including limited dispersal capacity, the presence of geographic barriers (e.g., rivers and mountain ranges), and landscape fragmentation. These constraints are further exacerbated by anthropogenic pressures such as deforestation, agricultural expansion, infrastructure development, and urbanisation (Opdam and Wascher 2004; Sala et al. 2000). For instance, small mammals or reptiles with limited dispersal ability can become trapped in isolated habitat patches, or some tropical tree species may be unable to disperse their seeds far enough due to road or infrastructure development. Additionally, several studies show that many species are shifting their distribution at a slower rate than necessary to keep pace with the current global warming (Chen et al. 2011). This means that species that depend on very specific habitats, such as amphibians, alpine plants, and high-elevation mammals, face a particularly high risk of extinction due to the decline in habitat availability (Hof et al. 2011; Laurance et al. 2011).

1.1.1.2 CHANGES IN PHENOLOGY

Phenology, understood as the timing of biological events such as flowering, leaf unfolding, fructification, breeding, hibernation, migration, and reproduction, among others, is highly sensitive to and dependent on temperature, photoperiod, and seasonal cycles (Cleland et al. 2007). Due to global climate change, natural rhythms are being altered, causing terrestrial species to initiate or end their activities earlier or later than expected (Parmesan 2007; Root et al. 2003). Some species are able to adapt more easily to changes in climate conditions, while others cannot keep pace with these phenological changes and face a high risk of extinction. For instance, in temperate species, due to rising temperatures, plant flowering, budburst, and leaf unfolding occur earlier. Observatory records from Europe and North America indicate that many species are now flowering two to five weeks earlier than they did 40 years ago (Fitter and Fitter 2002; Menzel et al. 2006). This phenomenon creates a mismatch with the peak activity of pollinators, such as bees or butterflies, which are not shifting their phenological cycles at the same pace. Consequently, this misalignment has an adverse effect on the reproductive success of these plants.

Likewise, particular bird species are severely impacted as they rely on seasonal food availability for their offspring. This mismatch between migratory periods and food availability places these species at greater risk. For instance, some studies have shown that the population of pied flycatchers (*Ficedula hypoleuca*) in Europe declines significantly when caterpillars emerge earlier in spring due to global warming, while the birds maintain their traditional migration schedule (Both et al. 2006). These phenological mismatches threaten species stability by reducing survival and reproductive success, thereby impacting entire ecosystems (Thackeray et al. 2016). Another example is documented in Arctic-breeding birds, where shifts in snowmelt and insect emergence occur earlier, resulting in a mismatch with the birds' nesting period (Jones and Cresswell 2010).

Changes in phenology also affect mammals, especially hibernating species. Warmer winters result in earlier emergence from hibernation, often coinciding with periods when food is not yet available, thereby increasing mortality risk for these species (Inouye et al. 2000). A similar pattern is observed in herbivores and their plant hosts, where the early onset of vegetation creates a mismatch between the peaks of food availability and the calving and lactation needs of herbivores (Post and Forchhammer 2008). As global warming driven by climate change intensifies, changes in phenology are expected to be one of the most significant ecological impacts, affecting various species interactions and ecosystem dynamics (Parmesan et al. 2022; Thackeray et al. 2016).

1.1.1.3 INCREASED FREQUENCY AND INTENSITY OF EXTREME EVENTS

Global warming is intensifying and increasing the frequency of extreme events, including heatwaves, droughts, wildfires, storms, and precipitation events (Parmesan et al. 2022). All of these extreme events have a profound impact on biodiversity in terrestrial ecosystems, causing disturbances that exceed the capacity of species to recover and disrupting ecological processes as well. Even species that are adapted to extreme events now confront conditions in which the intensity and frequency of these events surpass their adaptive capacity for survival (Jentsch and Beierkuhnlein 2008). For instance, drought increases vegetation stress, reduces primary productivity (Abdullah et al. 2025), and affects water availability, ultimately impacting the food supplies for herbivores. Consequently, predators face reduced prey availability. For instance, the prolonged droughts in the Amazon rainforest cause a large-scale tree mortality, affecting forest structure and increasing forest vulnerability to fires (Lewis et al. 2011; Phillips et al. 2009). More frequent and intense drought events are expected in the future due to climate change, suggesting that these impacts are likely to intensify further in the coming years (Parmesan et al. 2022).

Heatwaves have also increased rapidly in magnitude and duration over the last few decades, causing physiological stress in flora and fauna, reducing reproductive success, and increasing mortality in heat-sensitive species. For instance, heatwaves have led to the deaths of tens of thousands of flying foxes (*Pteropus spp.*) in Australia (Welbergen et al. 2008). In Europe, the significant heatwave in 2003 resulted in high mortality among trees, amphibians, birds, and invertebrates. This heatwave also caused a 30% reduction in gross primary productivity across Europe during the summer. Plant species experienced significant reductions in growth, tree mortality increased, and leaves senesced much earlier than usual (Ciais et al. 2005).

Shifting climate patterns and rising temperatures in recent years have also led to numerous record-breaking monthly temperatures across Europe (Semenza and Paz 2021). These conditions have facilitated the proliferation of European spruce bark beetles (*Ips typographus*), one of Europe's most destructive pest species, which has subjected Norway spruce (*Picea abies*) and compromised its health. Norway spruce is considered a vital coniferous species in Europe, with significant economic and ecological implications; ecologically, it provides a favourable habitat for numerous bird species (Ritter 2020). In addition to increases in outbreak frequency and severity, warmer temperatures have altered the development and number of generations per year (voltinism) of European spruce bark beetles. In Central Europe, European spruce bark beetle populations that historically completed one to two generations annually are now frequently producing two to three generations per year under current climatic conditions, driven by faster development and longer growing seasons (Hlásny et al. 2011). Similarly, in Scandinavia, notably in southern Sweden and parts of southern Finland, where beetles were once predominantly univoltine (one generation per year), ongoing warming is increasing the occurrence of a second generation within a single season. These shifts in voltinism amplify population growth rates and outbreak potential, further threatening spruce forests (Jönsson et al. 2009; Tikkanen and Lehtonen 2023).

Wildfires, although considered a natural component of some ecosystems, are experiencing a rapid increase in intensity and frequency due to global warming (Bowman et al. 2020). Even fire-resilient species, such as those found in Mediterranean or savanna ecosystems, are unable to recover quickly enough between fire events, resulting in the destruction of large areas of habitat. This leads to changes in vegetation composition, alters food availability, and affects soil chemistry, as well as increases water and air pollution, which in turn alters vegetation composition, affecting food availability and soil chemistry, increasing the risk of erosion. Bushfires that occurred in Australia in 2019-2020 burned over 19 million hectares and impacted nearly three billion species, including mammals, birds, reptiles, and amphibians (Ward et al. 2020). These wildfires have also led to long-term ecosystem challenges, including habitat loss, altered species interactions, and changes in soil and water quality.

Storms and extreme precipitation events have also been intensified due to global warming over the last decade. Severe storms increase tree mortality that modifies forest structure, and cause habitat loss and displacement of wildlife. For instance, Hurricane Maria in 2017 severely impacted Caribbean forests, resulting in high mortality rates among birds, frogs, and bats due to habitat destruction and altered microclimates (Knutson et al. 2020). Additionally, extreme flooding alters riverine habitats, leading to increased sedimentation and erosion. It is essential to recognise that the intensification and frequency of these extreme events, attributed to global warming resulting from climate change, compromise ecosystem resilience, making it more challenging for ecosystems to recover. This can lead to species shifting their distributions to new areas, leading to competition for space and resources (Holmgren et al. 2013; Scheffer et al. 2001).

1.1.1.4 CHANGES IN SPECIES COMPOSITION

As climate change alters habitat conditions and the spatial distribution of resources, species with broad climatic tolerances may survive or even expand their ranges, whereas more specialised and climate-sensitive species are likely to experience population declines. This contributes to what is called "biotic homogenization", where unique adapted species are lost, and the ecosystem is dominated by more generalist or disturbance-tolerant species (McKinney and Lockwood 1999). These changes may have a significant impact on ecosystem functioning and habitat structure. In addition, global warming particularly benefits invasive species. Warmer temperatures and longer growing seasons enable non-native species to create more favourable conditions for establishing and spreading into other habitats. This is especially evident in species whose distribution areas are strongly temperature-dependent. For instance, the mountain pine beetle (*Dendroctonus ponderosae*), which was historically limited by low temperatures, has expanded to higher latitudes due to warmer temperatures and is causing dramatic conifer mortality in western North America (Bentz et al. 2010; Kurz et al. 2008). A similar situation occurs in the temperate forests of Europe due to outbreaks of the European spruce bark beetle, which have intensified its activity under warmer and drier conditions, resulting in high tree mortality in Norway spruces across Europe (Hlásny et al. 2021; Seidl et al. 2017). These infestations also increase forest vulnerability to future disturbances, such as storms or wildfires.

Research has indicated that, although climate warming and heightened aridity have not affected net primary production in alpine grassland ecosystems, they have resulted in a shift in belowground resource allocation. This transformation is influenced by changes in community and species composition (Liu et al. 2018). Recent studies suggest that, over the medium to long term, climate change will intensify alterations in species composition within temperate forests of the Southern Carpathians in Romania. Particular species, such as European silver fir (*Abies alba Mill.*), are projected to expand their range, while others, including European beech (*Fagus sylvatica L.*), may experience population declines due to substantial mortality events. This shift is expected to be particularly pronounced under severe climate change scenarios (García-Duro et al. 2021). Moreover, climate change is concurrently driving significant alterations in the structure and functioning of high-altitude ecosystems. Such alterations in species composition have cascading effects on ecosystem functioning, including modifications to trophic interactions, nutrient cycling processes, and habitat structural complexity.

1.1.1.5 REDUCED ECOSYSTEM SERVICES

Many essential ecosystem services are closely linked to biodiversity, including carbon sequestration, water regulation, soil fertility, pollination, pest control, and climate regulation (Cardinale et al. 2012; Hooper et al. 2012). For instance, global warming is affecting ecosystem services by altering species composition and causing species extinctions. Species loss also affects ecosystem resilience, reducing the ecosystem's ability to recover after a disturbance, thereby compromising ecological integrity and human well-being (Isbell et al. 2011; Parmesan et al. 2022).

Biodiversity loss, induced by global warming, has a significant impact on forest carbon storage (Higgins and Scheiter 2012; Ploton et al. 2022). Tree mortality due to heat stress, drought events, or pest outbreaks reduces forest biomass and carbon storage. For instance, tree mortality in the Amazon rainforest due to the drought events that occurred in 2005 and 2010 resulted in the release of carbon to the atmosphere, transforming part of the forest from a carbon sink to a carbon source (Brando et al. 2014; Phillips et al. 2009). Likewise, the increase in wildfires in boreal forests in North America and Australia releases greenhouse gases, while also reducing forest carbon storage, thereby accelerating global warming (Bowman et al. 2020; Ward et al. 2020). The decline in plant species and microbial diversity due to global warming also reduces nutrient availability, decreases soil fertility, and alters nutrient cycling (Wagg et al. 2014). For example, some studies have shown that in grassland, the loss of plant species reduces nitrogen and lowers primary production (Isbell et al. 2011). In forests, high rates of tree mortality, along with the loss of vegetation cover, increase soil erosion and alter water cycle and microclimate conditions, resulting in land degradation and an increased risk of desertification in vulnerable regions (Laurance et al. 2011). In addition, as vegetation cover decreases, water regulation, water availability, and hydrological services are disrupted. For example, high rates of deforestation and tree mortality alter rainfall patterns, increase surface runoff, and increase the risk of flooding (Ellison et al. 2017). As mentioned previously, global warming affects the phenological cycle of plant species and pollinators, leading to mismatches between flowering and the peak of pollinator activity, which impacts food security (Klein et al. 2007; Potts et al. 2010).

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) emphasises that the decline in ecosystem services has a severe impact on regions already facing environmental stress, with significant effects on agriculture, livelihoods, and climate mitigation efforts (Brondízio et al. 2019; Parmesan et al. 2022). Without the necessary conservation and adaptation efforts, the degradation of ecosystem services will severely affect global food security, water supply, and carbon sequestration abilities. The interconnected pressures resulting from habitat shift and loss, phenological changes, increased frequency and intensity of extreme events, changes in species composition, and reduced ecosystem services due to global warming threaten the survival of many species and the stability of ecosystems. To address these challenges, it is crucial to integrate climate change mitigation strategies with effective conservation plans. This requires a precise, long-term monitoring approach, along with prediction, to forecast future changes and mitigate, or at least reduce, the effects of global warming as much as possible.

2. EXISTING METHODS AND TOOLS APPLIED

2.1. Species Distribution Models

Understanding the spatial distribution of species is essential in addressing the pressing questions faced in the field of ecology (Meyer et al. 2015). The primary tools to assess the relationship between climate and observations of species composition are species distribution models (SDMs). The sub-field of SDMs in ecology is vast and encompasses a wide range of statistical or machine learning methods applied across various software packages. Comprehensive reviews detailing the historical development and prevailing trends within this field are available in the scientific literature (Elith and Leathwick 2009; Franklin 2013; Sánchez-Mercado et al. 2010; Zurell et al. 2020). A central goal of SDMs is to estimate species-environment relationships and produce predictive raster maps illustrating relevant metrics of biodiversity indicators across a geographic domain. More importantly, these models are used extensively to address the myriad questions ecologists and biogeographers have regarding our natural world, such as conservation assessments for threatened species and the impacts of climate change on distribution patterns (Franklin 2013). The complexity of SDMs falls on a relatively large spectrum (Norberg et al. 2019). These models are typically applied to a single species and assume that the species is in equilibrium with its environment. However, more intricate models may be developed, such as joint SDMs (Pollock et al. 2014) and spatiotemporal models (Martínez-Minaya et al. 2018), to assess community-level relationships and temporal dynamics, respectively. A common issue faced across SDMs, however, is that of spatial autocorrelation; species observations closer together are more likely to exhibit similar values than observations further away (F. Dormann et al. 2007). If neglected, this causes violations of the assumption that model residuals are independent and identically distributed, which can inflate type I errors and lead to inverse slopes for the statistical effects. As a result, SDMs often include components such as spatial random effects (for example, conditional autoregressive models or Gaussian random fields) in their models to address this issue.

2.2. From Citizen Science to Global Biodiversity Information Facility

Our ability to estimate species distributions has never been greater, thanks to recent advancements in theoretical statistical ecology, computational resources, and the massive growth in data for both species' observations and environmental raster data. These factors have consequently enabled researchers to construct models and answer questions at scales previously unattainable. A significant reason for the growth in species occurrence data is due to the rise in smartphone applications and web platforms that allow users to record and submit data on biodiversity they observe within their proximate environment, and the development of large-scale biodiversity infrastructure to host these data at large (Heberling et al. 2021; LaDeau et al. 2017; McClure et al. 2020).

The most notable is the Global Biodiversity Information Facility (GBIF), which aggregates and provides free and open-access biodiversity data describing the locality of species within a standardised framework (GBIF 2025). According to this source, GBIF currently hosts information on 3.5 billion occurrence records from nearly 120,000 different datasets worldwide, although with a bias towards Western countries. As GBIF aggregates data from a wide range of independent sources, the records are generated using heterogeneous sampling protocols, capturing different aspects of species composition, and vary substantially in terms of data quality and reliability. A large proportion of these records originates from citizen-science platforms, such as eBird and iNaturalist. Although observations are subject to community-based review at the time of submission, these datasets present inherent challenges, including spatial sampling biases towards easily accessible areas and considerable variation in observer expertise.

2.3. From Remote Sensing to Species Distribution Models

Beyond species occurrence, inputs for SDMs include information about land cover, soil and rock type, elevation, slope characteristics, and climatology. To varying degrees of quality, much of this information can be derived from remote sensing products at various stages of processing. This section addresses the most critical remote sensing modalities, platforms, their spatial and spectral coverage, as well as the types of information they provide.

Multispectral orbital platforms, such as MODIS[1], Landsat, or Sentinel-2, provide synoptic observations at optical and infrared wavelengths. These platforms offer coarse to moderate spatial resolution ranging from approximately 10 m to 500 m, combined with revisit intervals of up to daily frequency. Multispectral data are primarily used to derive spectral indices that serve as proxies for biophysical and geochemical properties, including photosynthetic activity, above-ground biomass, soil and lithological composition, and surface moisture conditions. Such indices are typically formulated as ratios or normalised differences between reflectance values measured in distinct spectral bands. For comprehensive overviews of multispectral indices for vegetation, soil, and geological applications, refer to the literature (Mulder et al. 2011; Van der Meer et al. 2012; Yan et al. 2025).

[1] Moderate Resolution Imaging Spectroradiomete

Remote sensing products derived from multispectral satellite platforms are increasingly essential for SDMs, as they provide comprehensive, spatially detailed, and temporally consistent environmental information over extensive geographic areas. These products provide key predictor variables that describe both abiotic and biotic factors influencing species distributions, including climate indicators, vegetation structure and productivity, land cover changes, and measures of soil moisture and surface water (Doninck et al. 2020; Quintano et al. 2019). By delivering standardised measurements across vast regions and extended time periods, Earth observation (EO) products help to overcome the inconsistencies often found in ground-based data, facilitating large-scale, cross-boundary studies and long-term monitoring of distributional shifts driven by climate variability. The temporal resolution of these products further enables SDMs to capture dynamic habitat characteristics, such as seasonal phenology, disturbances, and fragmentation, improving the ecological realism and predictive power of the models. Additionally, remote sensing supports the scaling and transferability of models, allowing predictions developed at local scales to be applied regionally or globally and enhancing projections of species distributions under future climate scenarios. In areas with limited field observations, these products provide reliable environmental proxies that help fill critical data gaps.

Hyperspectral orbital platforms, such as EnMAP[2], PRISMA[3], and CHIME[4] offer extremely high spectral resolution, allowing for the acquisition of contiguous spectral information across a large number of narrow bands (Bhargava et al. 2024). The resulting data volumes impose trade-offs in terms of spatial resolution, swath width, and temporal revisit frequency, which are generally lower than those of multispectral systems. The high spectral fidelity of hyperspectral observations enables the accurate detection and classification of vegetation species (Adam et al. 2010; Thenkabail et al. 2018), as well as the detailed characterisation of soil (Minu et al. 2016) and lithological properties (Van der Meer et al. 2012). However, the exploitation of hyperspectral data requires advanced atmospheric correction and calibration methodologies to account for atmospheric absorption and scattering effects (Thenkabail et al. 2018). Hyperspectral sensors mounted on unmanned aerial vehicles (UAVs) can achieve substantially higher spatial resolution than spaceborne systems; however, their applicability is limited by the constraints of spatial extent, flight endurance, and operational coverage. Airborne hyperspectral platforms, while capable of providing both high spectral and high spatial resolution, are generally associated with high operational costs and typically offer limited temporal coverage, often restricted to single-epoch or campaign-based acquisitions. As passive optical sensors, hyperspectral systems rely on solar illumination and are therefore constrained by the availability of daylight and cloud cover.

Compared to multispectral products, hyperspectral data offer much higher spectral resolution, capturing information across hundreds of narrow wavelength bands. This allows for the detailed characterisation of vegetation traits and ecosystem properties that are often undetectable with multispectral sensors. In the context of SDMs, hyperspectral imagery can reveal subtle differences in plant functional traits, leaf chemistry, canopy architecture, and species composition—factors that are critical for assessing habitat suitability. The fine-scale discrimination provided by these datasets improves the ability of SDMs to identify niche differentiation, particularly for species with specialised ecological requirements. Additionally,

[2] Environmental Mapping and Analysis Program
[3] Preferred Reporting Items for Systematic reviews and Meta-Analyses
[4] Copernicus Hyperspectral Imaging Mission

hyperspectral data enhance the detection of stress responses, phenological changes, and ecological disturbances, which are essential drivers of species distributions under changing climatic conditions. Although processing hyperspectral datasets is more complex and computationally intensive, the detailed ecological information they provide significantly improves the accuracy, explanatory power, and predictive performance of SDMs, especially in heterogeneous or species-rich environments.

Synthetic Aperture Radar (SAR) systems employ active microwave illumination to measure surface backscatter, enabling the characterisation of surface roughness, geometric structures, and dielectric properties. Interferometric SAR (InSAR) exploits phase differences between multiple SAR acquisitions to derive digital terrain models (DTMs), estimate vertical structural attributes (e.g., vegetation canopy height), and detect surface deformation and temporal changes (Bae et al. 2019; Moreira et al. 2013; Novresiandi et al. 2023). Airborne SAR platforms (e.g., UAVSAR[5]) provide very high spatial resolution (sub-meter scale) but are constrained in spatial coverage. In contrast, spaceborne SAR missions (e.g., Sentinel-1, RADARSAT, TerraSAR-X) offer consistent, wall-to-wall coverage at regional to global scales, albeit with moderate spatial resolution on the order of several meters. Dedicated spaceborne InSAR missions, such as TanDEM-X[6] and ALOS PALSAR[7], enable the generation of global digital elevation models (DEMs) and large-scale forest structure and extent maps (Balzter 2001; Kumar et al. 2020; Novresiandi et al. 2023). Overall system performance depends on radar frequency band, polarisation configuration, and post-processing methodologies, including interferometric and polarimetric SAR techniques. As active sensors, SAR systems operate independently of solar illumination and are largely unaffected by cloud cover, enabling reliable day-and-night, all-weather observations.

Light detection and ranging (LiDAR) systems measure the time delay and intensity of reflected laser pulses to characterise surface and vegetation structure. Operational LiDAR platforms can generate three-dimensional point clouds, operate in photon-counting mode, or record and process the full return waveform. Airborne LiDAR systems, deployed on UAVs or crewed aircraft, primarily generate dense point clouds with typical sampling densities ranging from approximately 1 to 20 points per square meter (Garcia et al. 2017; Petras et al. 2023). Such data enable plot-scale reconstruction of three-dimensional canopy architecture, including leaf and branch distribution, understory structure, and fine-scale habitat heterogeneity (Bergen et al. 2009). In contrast, spaceborne LiDAR instruments, such as the Global Ecosystem Dynamics Investigation (GEDI) aboard the International Space Station, acquire waveform measurements over medium-sized footprints (~25 m diameter). These observations facilitate the retrieval of ground elevation and detailed canopy structural metrics—such as vertical foliage profiles, canopy cover, and above-ground biomass—potentially at near-global scales, depending on orbital configuration and sampling strategy (Dubayah et al. 2020). A key trend in remote sensing research is the fusion of complementary data modalities—including multispectral, SAR, and LiDAR observations—across satellite- and airborne-based platforms, as well as the integration of localised measurements derived from citizen science initiatives, in situ sensors, and field surveys (Lassalle et al. 2023). Such data integration aims to leverage the strengths of individual sensing technologies to improve the characterisation of environmental and ecological processes. However, a significant challenge

[5] Uninhabited Aerial Vehicle Synthetic Aperture Radar
[6] TerraSAR-X add-on for Digital Elevation Measurement.
[7] Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR).

lies in harmonising datasets acquired at disparate spatial, temporal, and spectral resolutions. Existing data fusion approaches include window-based spatiotemporal fusion techniques (Gao et al. 2006; Qiu et al. 2021; Tian et al. 2024), deep learning methods such as convolutional neural networks (Matyukira and Mhangara 2024), and the emerging use of geospatial foundation models (GFMs) for large-scale data integration and representation learning (Brown et al. 2025; Feng et al. 2025; Klemmer et al. 2025). In parallel, hyperspectral observations have demonstrated strong potential for mapping fine-grained taxonomic units, including plant and animal species, yet their direct integration into species and habitat distribution models remains challenging due to data dimensionality, limited coverage, and model transferability constraints (Kacic and Kuenzer 2022; Lyu et al. 2024; Wang et al. 2025).

3. TRENDS, GAPS, AND INNOVATIONS

3.1. Data Integration Methods

The heterogeneous nature of occurrence data typically results in a dilemma for modellers of species' distributions: use one dataset over the others, thereby reducing the quantity of data available for inference, or arbitrarily combine the data, thereby failing to account for their individual collection processes (Simmonds et al. 2020). Most SDMs are currently equipped with easy-to-use software packages, such as *MaxEnt* (Phillips and Dudík 2008) and *Biomod* (Thuiller 2003), which typically assume that the data are generated as presence-only processes, regardless of how the data were actually generated. Consequently, the outputs and predictions generated by these models are often subject to bias, which limits their reliability and renders them inappropriate for formal inference (Yackulic et al. 2013). In response to these challenges, the field of integrated species distribution modelling has experienced substantial growth (Fletcher Jr et al. 2019; Isaac et al. 2020; Miller et al. 2019). Integrated species distribution models (ISDMs) are a general class of SDMs that combine heterogeneous datasets that contain information collected through various sampling protocols together in a single-model framework. The primary objective of this approach is to apply all available occurrence data within a framework that respects the way it was generated, thereby leveraging the unique strengths and personalities of each. Additionally, these models enable practitioners to account for dataset-specific biases by incorporating observation-level effects or covariates (Simmonds et al. 2020).

Integration of disparate data has been addressed using various methods across literature, for example: by constructing an ensemble model (Case and Lawler 2017), using the results of one dataset as auxiliary information in the form of a covariate or offset (Regos et al. 2016), or by using information from one dataset as an informative prior for another in a Bayesian framework (Marcantonio et al. 2016). However, the predominant method used is the Poisson point-process framework for data integration (Fletcher Jr et al. 2019; Isaac et al. 2020; Miller et al. 2019). This methodology formulates state-space point-process models, which are a combination of a process model for the latent state (describing the actual ecological distribution) with multiple observation models for each dataset (describing the data-collection procedure), conditioned on the latent state. Using an inhomogeneous Poisson point process for the latent state provides an intuitive framework for understanding how different datasets, each collecting distinct metrics of species occurrence, can emerge from a single system. Simulation studies using this methodology have demonstrated that these models are preferred over single-dataset alternatives, as they reduce uncertainty, provide more robust estimates, and enhance model identifiability (Simmonds et al. 2020). However, these virtues are only valid if the biases inherent in the unstructured data are adequately accounted for using observation-level covariates or flexible spatial terms. These hierarchical models are typically fit in a Bayesian framework because it allows both the observed data and model parameters to be random variables, which results in a more accurate and realistic estimation of uncertainty (Martínez-Minaya et al. 2018). Furthermore, they are often estimated using flexible software packages, such as the R packages *R-INLA* (Martins et al. 2013) and *Nimble* (de Valpine et al. 2017). Moreover, ready-to-use software packages have been developed specifically to help users construct these types of models more conveniently, thereby facilitating the widespread adaptation among non-experts in the field of statistical ecology (Mostert and O'Hara 2023).

ISDMs have been formulated to address diverse problems across various ecosystems and ecologies, incorporating multiple observation processes to accommodate the heterogeneous nature of biodiversity data. Most notably, these models have been fitted to analyse unstructured citizen science data in combination with structured presence-absence data (Adde et al. 2021; Koshkina et al. 2017; Morera-Pujol et al. 2023). However, these models have also been used in combining data coming from other data sources commonly collected in ecology, such as line transect data (Martino et al. 2021), abundance data (Mäkinen and Vanhatalo 2018), density data (Cunningham et al. 2021), and expert range maps (Merow et al. 2017), emphasizing the utility and flexibility of employing this framework. In addition, these models have also been applied in other frameworks, such as community analyses (Zipkin et al. 2023), and more recently, in spatio-temporal analyses, which model the dynamics of species across time (Seaton et al. 2024; Wiethase et al. 2024). Naturally, spatio-temporal point process models modelled with flexible spatio-temporal random effects become increasingly computationally infeasible to estimate as the number of time periods and study domain increases. However, sequential modelling approaches, which break down large-scale spatio-temporal models into more computationally manageable components, have been proposed in the field of ecology, providing comparatively accurate results within a more realistic timeframe (Figueira et al. 2025).

In a Norwegian context, these models have been utilised in large-scale workflows to derive maps of relative taxa-specific richness by combining open-access species occurrence data obtained from GBIF with covariate data collected by European and Norwegian satellite systems (Finstad et al. 2024; Mostert et al. 2025). Maps like these illustrate broad patterns of biodiversity hotspots at a relatively high resolution and are essential for informing management decisions and conservation efforts. While integrated models have typically been formed by combining data from presence-only and presence-absence sources, other types of data can also be integrated into this framework. For instance, recent work has focused on incorporating movement data and individual-based data into this setup by constructing an appropriate observation process (Buderman et al. 2025). Moreover, novel data sources for species occurrence data, such as environmental DNA (eDNA) samples, satellite systems, aerial remote sensing, and UAV platforms (Altwegg et al. 2025), have the potential to further supplement integrated models. Naturally, some outstanding gaps and challenges still need to be addressed with ISDMs (Isaac et al. 2020; Zipkin et al. 2021). Although ISDMs provide more accurate estimates in comparison to single-dataset models, they tend to be more computationally demanding to estimate. Consequently, if the bias in the unstructured data is minimal, there may be little to gain using ISDMs. Moreover, work needs to be done to determine how to handle situations where there are significant data size imbalances between the datasets. Finally, there are still outstanding questions regarding the validation and assessment of model fit for integrated models, especially since traditional methods may be insufficient.

4. MAIN EUROPEAN AND INTERNATIONAL PROJECTS WITHIN THESE AREAS

Given the considerable work on modelling species distributions, numerous European and global projects are supported by institutions such as the European Union (EU), Biodiversa+, as well as organisations such as GBIF and the German Centre for Integrative Biodiversity Research (iDiv). Here, we list some of the most relevant projects most related to the ECO-MOSAIC project, rather than providing a comprehensive overview of the numerous projects within Europe.

Table 1. *Selected European and global projects related to species distribution modelling and the climate–biodiversity nexus, highlighting their ecosystem focus and key contributions relevant to this project*

Project	Ecosystem Focus	Key Contributions to the Climate/Biodiversity Nexus
wildE	Terrestrial	Rewilding land, climate mitigation/adaptation, biodiversity
BiodivClim	Cross-ecosystem	Research coordination on biodiversity & climate
WaterLANDS	Wetlands (terrestrial/coastal)	Ecosystem restoration, biodiversity, climate resilience
BioClima	Terrestrial (forests & grasslands)	Climate-smart biodiversity conservation, ecosystem resilience under climate change
OBSGESSION	Terrestrial & freshwater	Aims to improve understanding of biodiversity drivers by integrating Earth Observation, field data, and advanced ecological modelling
EO4Diversity	Terrestrial	Earth Observation tools to monitor biodiversity change and climate impacts
GlobDiversity	Terrestrial	Global biodiversity monitoring, climate-driven species distribution change
LIFE IP NATURA.SI	Terrestrial	Biodiversity conservation and ecosystem restoration under climate change
NATALIE	Terrestrial & freshwater	Nature-based solutions for climate resilience
Global Land Programme	Terrestrial	Land-use change, climate interactions, ecosystem services
Global Forest Watch	Forest ecosystems	Climate-driven deforestation monitoring and biodiversity loss
BioClimSol	Terrestrial & freshwater	Nature-based solutions for climate mitigation and adaptation while enhancing biodiversity
MoveOn	Terrestrial	Species range shifts and ecological connectivity in response to climate change.
SPONFOREST	Forest ecosystems	Climate change impacts on forest biodiversity and ecosystem functioning
SCALES[8]	Terrestrial	
BIOTraCes	Terrestrial & freshwater	Climate-driven biodiversity change and cascading ecosystem effects

[8] Securing the Conservation of biodiversity across Administrative Levels and spatial, temporal, and Ecological Scales

Among the projects listed in Table 1, three—EO4Diversity, OBSGESSION, and BioClima—are most relevant to ECO-MOSAIC in terms of investigating the impacts of climate-change extreme events on biodiversity using essential climate variables (ECVs) and essential biodiversity variables (EBVs) derived from EO data.

- **EO4Diversity**

The main goal of the EO4Diversity (Earth Observation for Biodiversity Modelling) project was to enhance terrestrial biodiversity monitoring and prediction by integrating EO data with advanced ecological models. The project identified and addressed significant biodiversity science gaps, particularly by selecting three biodiversity pilots focused on (1) ecosystem productivity and health, (2) including accounting, monitoring, and reporting towards policy obligations, and (3) ecosystem resilience to invasive species. Those pilots integrated environmental and climate variables using EBVs and ECVs derived from EO data into ecological models to produce consistent, large-scale information on biodiversity patterns, as well as changes over time. Results from this project help to improve the understanding of terrestrial ecosystem dynamics and the risk of degradation. Moreover, EO4Diversity helps identify and understand how climate drivers affect biodiversity across space and time, thereby supporting more accurate forecasting of climate impacts on terrestrial ecosystems. The project also provides a science agenda and scientific roadmap to support conservation strategies and environmental policies in the context of global climate change.

- **OBSGESSION**

OBSGESSION project (Observation of Ecosystem Changes for Action) is a European research initiative to improve the monitoring, understanding, and prediction of changes in biodiversity across terrestrial and freshwater ecosystems, integrating multi-sensor EO data, *in situ* measurements, and citizen science observations. By combining these multi-source data with advanced ecological models and explicitly accounting for uncertainties, this project aims to detect biodiversity trends better and identify and understand the underlying drivers. One of the key objectives of OBGESSION is to identify direct and indirect pressures on biodiversity, including land-use change, human activities, and climate change. Thus, climate change plays a central role in OBSGESSION's framework. By monitoring biodiversity responses to environmental and climatic changes over time, OBSGESSION will enhance our understanding of how climate change impacts terrestrial and freshwater ecosystems. Results from this project will provide robust, actionable information to strengthen the interface between science and policy, supporting European and international biodiversity strategies.

- **BioClima**

The BioClima project, strengthened through EU–China collaboration, is designed to advance the monitoring and understanding of biodiversity and climate dynamics by integrating cutting-edge artificial intelligence (AI) with both ground-based observations and remote sensing data systems. By leveraging AI-driven analytical tools, the project processes and interprets large and complex environmental datasets, generating novel insights into the structure, function, and dynamics of terrestrial ecosystems. Central to BioClima's approach is the use of EBVs and ECVs, which provide standardised indicators for assessing ecosystem changes and environmental trends. Within this framework, the project focuses on biodiversity conservation, examining spatial and temporal patterns to evaluate the impacts of climate change and identify effective adaptation strategies. Building on harmonised EBVs and ECVs, BioClima explicitly investigates the effects of climate change extreme events—such as heatwaves and droughts—on ecosystem structure, functioning, and overall health.

An additional set of European projects and initiatives includes climate and biodiversity as supported domains for data sets and models.

- **Destination Earth**

Destination Earth (DestinE) is a flagship EU–led initiative aimed at developing a high-precision digital replica of the Earth system—a so-called digital twin—by integrating EO data, numerical models, simulations, and advanced analytics. The initiative is designed to support the monitoring, simulation, and prediction of environmental change and anthropogenic impacts at multiple spatial and temporal scales. DestinE constitutes a core component of the European Commission's Green Deal Data Space (GDDS), providing critical digital infrastructure to enable evidence-based environmental policy, risk assessment, and decision-making (Figure 2).

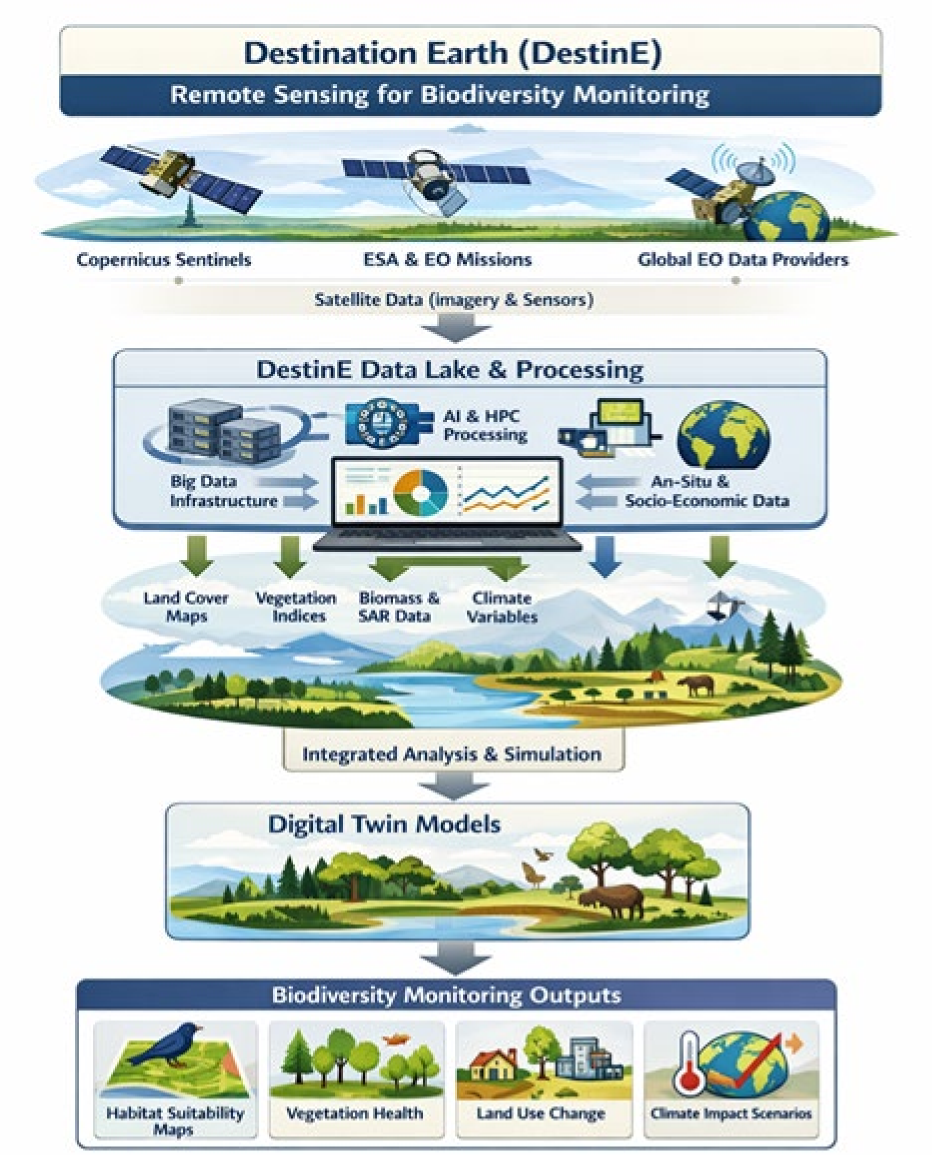


Figure 2. *Conceptual workflow of the DestinE framework for biodiversity monitoring illustrates how satellite EO data from Copernicus Sentinels, ESA missions, and global EO providers are integrated with in situ and socio-economic data within the DestinE Data Lake. (Conceptual content provided by the authors; figure drafted using ChatGPT (OpenAI).*

ECO-MOSAIC's remote sensing–based biodiversity monitoring use cases generate datasets that are well-suited for integration into DestinE's modelling and analytical framework. In particular, DestinE's Data Lake provides access to a wide range of EO data repositories that overlap conceptually and technically with ECO-MOSAIC's biodiversity products. Satellite-derived observations of habitat dynamics, vegetation indices, and species distribution patterns are directly relevant to DestinE's objectives and can contribute to enhancing the representation of ecosystems and biodiversity processes within Destination Earth models and tools.

- **European Data Spaces**

European data spaces are federated ecosystems (no single databases) that enable trusted data sharing across countries and sectors while respecting EU rules on privacy, sovereignty, and intellectual property. Some key features of data spaces include clear governance and access rules, common standards and metadata, interoperable infrastructure, and support for cross-domain use. The relevant data spaces for Bio-Clima are (1) Green Deal Data Space, (2) Earth Observation Space Data Ecosystem, and (3) Agriculture Data Space. Remote sensing biodiversity products exist, but they are scattered across various platforms in inconsistent formats and metadata, making it challenging to integrate with *in situ* observations. European data spaces can be relevant for ECO-MOSAIC case studies, enabling the discovery and access to data, and exposing data through standardised interfaces. A biodiversity researcher can combine sentinel imagery, habitat maps, and species observations without needing to negotiate separate access agreements for each source. Integrated data enhances biodiversity models and supports the development of EBVs.

- **Sustainable Green Europe Data Space- Use Cases**

The Sustainable Green Europe Data Space (SAGE) project is working towards a fully operational GDDS, designed to enhance the accessibility and usability of environmental and green data across the EU. Its objectives directly support key pillars of the European Green Deal, including zero-pollution ambitions, climate adaptation, biodiversity conservation, and circular economy action, by bringing together high-value datasets and translating them into practical, data-driven services and solutions, as demonstrated through ten pilot use cases. The Nature and Ecosystem Services Trade-offs (NECST) use case is one of several strategic actions within the SAGE framework, explicitly focusing on biodiversity conservation. The primary goal of the NECST use case is to provide a decision support tool that makes the trade-offs involved in managing natural resources more transparent. Ecosystem services often have complex relationships; increasing one service (e.g., food production via intensive agriculture) can decrease another (e.g., water quality or biodiversity). By leveraging the GDDS to integrate diverse data sources — including environmental, biodiversity, and geospatial datasets — with AI-based models and socioeconomic information, NECST aims to support evidence-based sustainability assessments for land use and natural capital planning. This use case is highly relevant to remote sensing–based biodiversity monitoring, demonstrating how EO data can be operationally integrated with biodiversity, ecosystem service, and socioeconomic information within an interoperable data space.

Through the GDDS, SAGE enables harmonised access to satellite-derived products, including land cover, vegetation condition, habitat extent, and environmental pressures, which are essential inputs for biodiversity indicators and ecosystem assessments. NECST builds directly on these capabilities by combining remote sensing–derived spatial layers with AI-driven models to quantify trade-offs among land use, economic activities, and ecosystem services, making biodiversity change observable, comparable, and decision-relevant at scale.

- **European Open Science Cloud**

The European Open Science Cloud (EOSC) is a European initiative designed to create a federated, trusted environment for sharing, accessing, and reusing research data, tools, and services across disciplines and countries. It is relevant to ECO-MOSAIC in how it enables FAIR[9] data practices, cross-disciplinary integration, and reproducible science. EOSC enables hosting interoperable datasets from different disciplines, provides shared metadata and semantic standards, and supports cross-domain data discovery. It allows researchers to publish data, codes, and workflows, run analyses, and share benchmark datasets and models. In the ECO-MOSAIC project, remote sensing provides the observations, while ecologists working on the use cases supply the models. EOSC can provide an environment for connecting, testing, and validating models.

The EOSC Node Data Terra serves as a French national research e-infrastructure within EOSC that federates high-quality, FAIR, multi-domain Earth system data — including land surfaces, atmosphere, oceans, solid Earth, and biodiversity — together with tools for cross-domain data analysis, virtual research environments, and interoperable workflows that connect researchers and stakeholders with satellite observations and *in situ* measurements across disciplines. Data Terra underpins European data ecosystems that support projects such as the NECST use case in the GDDS.

- **Biodiversity Digital Twin**

The Biodiversity Digital Twin (BioDT) is an EU-funded Horizon Europe project that aims to design and prototype a Biodiversity Digital Twin for Europe. The project combines observations, models, and simulations to allow users to monitor, understand, and forecast biodiversity change.
The project is currently working towards integration into DestinE infrastructure. BioDT rely on spatial data (including remote sensing) for dynamic ecological modelling, which, when integrated with DestinE, enhances biodiversity monitoring, forecasting, and decision-making. BioDT and DestinEs remote sensing for biodiversity monitoring systems are standard ecological remote sensing approaches (e.g., satellite EO, EBV derivation, AI-enabled species mapping) used internationally to monitor biodiversity change.

BioDT has achieved results relevant to ECO-MOSAIC through its efforts in combining high-resolution satellite imagery, including land cover and temperature, with ground data. Together with the DestinE integration, these projects provide ECO-MOSAIC with the following foundational infrastructure for large-scale biodiversity monitoring and forecasting:

  - DestinE's use cases (notably the Forest Biodiversity use case) show concrete methods for producing habitat suitability, carbon/biomass maps, and species-related indicators from EO + models. These act as blueprints for remote-sensing biodiversity monitoring.
  - Both DestinE and BioDT focus on integrating satellite observations with process and statistical ecological models (e.g., species distribution, forest growth), enhancing the use of remote sensing to inform forecasts and scenario testing.

[9] Findable, Accessible, Interoperable, and Reusable

- By combining long satellite time series with DestinE's computational and BioDT modelling, both initiatives support the robust detection of habitat change, phenology shifts, and long-term biodiversity trends across large regions.
- The project emphasises fusing field data (e.g., species occurrences, plot inventories) with satellite products to improve model calibration/validation and to scale local biodiversity information to regional/global extents.
- User exchange events and the BioDT ↔ DestinE synergy pages demonstrate active community engagement that disseminates best practices for EO-based biodiversity monitoring and pulls user needs into platform development.
- The Joint Research Centre/use-case work and BioDT prototypes directly tie remote sensing outputs to policy-relevant questions (e.g., forest management, biodiversity indicators), demonstrating how EO products can inform regulation and reporting.

- **GBIF and links to Geo BON and EuropaBON**

GBIF, GEO BON (Group on Earth Observations Biodiversity Observation Network), and EuropaBON are interconnected but play different, complementary roles in the biodiversity data and monitoring ecosystem. Their links primarily concern data flow, standards, and coordination, rather than governance or ownership. GBIF's role is primarily data infrastructure and access, with standardised biodiversity data publishing (Darwin Core). GEO BON is an international coordination network under the auspices of GEO. The group coordinates global biodiversity monitoring, defines EBVs, integrates in situ and remote sensing observations, and supports global biodiversity assessments (CBD[10], IPBES). In fact, GEO BON defines what to observe and how to observe it. In addition, EuropaBON is the European regional BON, aligned with GEO BON. Its goals include outlining European biodiversity monitoring needs, harmonising across EU Member States, and supporting EU policy (e.g., the Biodiversity Strategy and the Nature Restoration Law). The European Biodiversity Observation Coordination Centre (EBOCC) is the newly funded extension of the EuropaBON project. EuropaBON has defined 84 EBVs (including metrics, spatial, and temporal resolutions) suitable for European interest needs and policies for monitoring biodiversity. The project has identified gaps in monitoring community composition, ecosystem structure, and ecosystem functioning, where remote sensing can provide valuable assistance.

ECO-MOSAIC must relate to all three organisations. GBIF provides Darwin Core and data infrastructure. GEO BON defines the global framework for biodiversity monitoring. EuropaBON applies that framework in Europe and supports policy.

- **Biodiversa+**

Biodiversa+ is the European Biodiversity Partnership, established to advance high-quality biodiversity research with clear relevance for policy and societal needs. It was co-designed and launched in 2021 by BiodivERsA in collaboration with the European Commission under the EU Biodiversity Strategy for 2030. Through this framework, Biodiversa+ supports the broader goal of placing Europe's nature on a recovery trajectory by 2030 and enabling people to live in harmony with nature by 2050. Key priorities include harmonising biodiversity monitoring, strengthening the use of EO data, and improving knowledge of the drivers of ecosystem change. Some specific needs that are addressed are: harmonised biodiversity monitoring,

[10] Convention on Biological Diversity

improved use of EO data, and Knowledge on drivers of ecosystem change. The vision of Biodiversa+ is that EO should be a routine element for biodiversity monitoring, and remote sensing biodiversity data products should be readily available (via Copernicus), as well as support the measurement of EBVs. By 2040, ground and space observations will be integrated into models to support decision-making and forecast changes.

Biodiversa+ funded ~33+ transnational projects that directly target transnational terrestrial biodiversity observation (e.g., acoustics, radar, eDNA, soil/soil fauna, fungi, forest plots, grasslands, ponds, etc.). Their deliverables (standard protocols, harmonised datasets, EBV prototypes) provide the necessary inputs that EuropaBON needs to build a Europe-scale monitoring system. Two funded remote-sensing initiatives in this context include the Habitat pilot and MAMBO (Modern Approaches to the Monitoring of BiOdiversity). The Habitat pilot investigates how various remote sensing approaches can provide accurate, scalable information on the spatial distribution of habitat types, their condition, and associated structural and qualitative changes across seasonal cycles and longer time horizons. In parallel, MAMBO designs, evaluates, and operationalises enabling tools to monitor conservation status and the ecological requirements of species and habitats, with a particular focus on areas where substantial knowledge gaps remain.

Biodiversa+ outputs are being routed into EOSC (for FAIR data & workflows), the European data spaces/Copernicus ecosystem (for combined EO and *in situ* products), and into digital twin efforts (BioDT/Destination Earth) for modelling, scenario analysis, and policy-relevant products (Biodiversa+ 2022). One outcome has been a list of recommendations for the use of remote sensing in biodiversity monitoring. These recommendations for the use of satellite data include ground truth data, harmonised protocols, time series, collaboration among experts, open algorithms, and more analysis-ready data products. Additionally, they involve the preparation of novel sensors and the integration of observational data with models to detect changes and provide Knowledge for a sustainable future. The use of long-term, consistent, and harmonised EO time series to detect biodiversity trends, variability, and change over time requires sensor continuity, consistent preprocessing, temporal comparability across datasets, and the integration of satellite time series with *in situ* observations for validation and interpretation.

The ECO-MOSAIC project will also follow and harmonise with the developments by the preparatory Action project for the EBOCC. The project will pilot and test the biodiversity observation coordination centre and monitoring framework based on the EuropaBON proposal. In this way, the contract will contribute to the better availability, coherence, and accessibility of biodiversity data in support of EU biodiversity policy implementation at national, EU, and global levels, and support a coherent, structured, and cost-effective EU approach to systematic biodiversity observation. This will streamline biodiversity data flows and reduce the administrative burden in Member States regarding biodiversity monitoring and reporting.

At the European scale, the proposed EBOCC seeks to coordinate biodiversity monitoring activities through a common, harmonised framework. Its objectives include the provision of policy-relevant information on key EBVs, the adoption of FAIR (Findable, Accessible, Interoperable, Reusable) data principles, and the more effective use of existing data resources. In support of this approach, Biodiversa+ partners have introduced the concept of National Biodiversity Monitoring Coordination Centres (NBMCCs), conceived as a flexible, nationally anchored model aligned with the EBOCC framework. These centres are intended to contribute national monitoring data and perspectives, while benefiting from coordinated support for implementation, funding mechanisms, and EU-level reporting. Complementing this structure, Thematic Hubs operate as transnational expert networks that promote collaboration, harmonise monitoring protocols, strengthen capacity, and deliver analyses at the European level. The EBOCC pilot project will contribute to improving the availability, accessibility, and coherence of biodiversity data at national, EU, and global levels. It aims to reduce the reporting burden on Member States by streamlining biodiversity data flows and integrating existing monitoring efforts into a structured, cost-effective European framework. Ultimately, the EBOCC will support the implementation of the EU Biodiversity Strategy for 2030 and the European Green Deal. Building on the work of the EuropaBON consortium, the EBOCC is envisioned as a central coordination hub. It will address existing data gaps, harmonise biodiversity data collection, and foster collaboration among national and international monitoring initiatives. Its core objective is to deliver timely and policy-relevant biodiversity information, especially EBVs, to support evidence-based decision-making.

5. ESA-CCI PROGRAMME: DATA CONTRIBUTION

The ESA-CCI programme is one of Europe's most critical long-term efforts to monitor and understand climate change and its impacts on biodiversity, land, and coastal systems. It was launched in 2008 to produce reliable, consistent, and scientifically accurate data across the 27 ECVs defined by the Global Climate Observing System (GCOS). Individual CCIs do not rely on a single satellite but combine data from multiple ESA and non-ESA missions. Data is harmonised across different sensors and time periods, and biases are corrected to ensure consistency[11][12]. Partners include the European Commission, ESA, EUMETSET, and many institutes and universities. The following Table lists the CCIs that are directly related to terrestrial biodiversity ecosystems (Table 2).

Table 2. *ESA-CCI projects relevant to terrestrial biodiversity, highlighting their thematic focus and contributions to monitoring climate–biodiversity interactions and ecosystem change.*

Thematic Area	Project Name	Biodiversity/Climate Relevance
Land Cover	Land Cover-CCI	Provides global maps of land use and land cover changes — critical for tracking habitat loss, fragmentation, and ecosystem change.
Soil Moisture	Soil Moisture-CCI	Monitors drought conditions and vegetation stress affecting terrestrial species.
Fire	Fire-CCI	Tracks global fire occurrences and intensity — a key factor in studying the impacts on forests and grasslands.
Biomass	Biomass-CCI	Estimates above-ground carbon stock and vegetation productivity, supporting forest biodiversity monitoring.
Vegetation	Vegetation Parameters-CCI	Derives LAI and FAPAR to assess ecosystem productivity and climate impacts on vegetation.
Glaciers	Glaciers-CCI	Monitors glacier retreat affecting alpine and downstream freshwater ecosystems.
Permafrost	Permafrost-CCI	Develop and deliver permafrost maps to quantify the changes and variations in this ECV.

[11] https://climate.esa.int/en/about-us-new/climate-change-initiative/Climate-Change-Initiative/
[12] https://climate.esa.int/en/about-us-new/climate-change-initiative/essential-climate-variables/how-cci-ecvs-are-generated/

Snow	Snow-CCI	Establish robust, fully validated processing chains for key global seasonal snow parameters

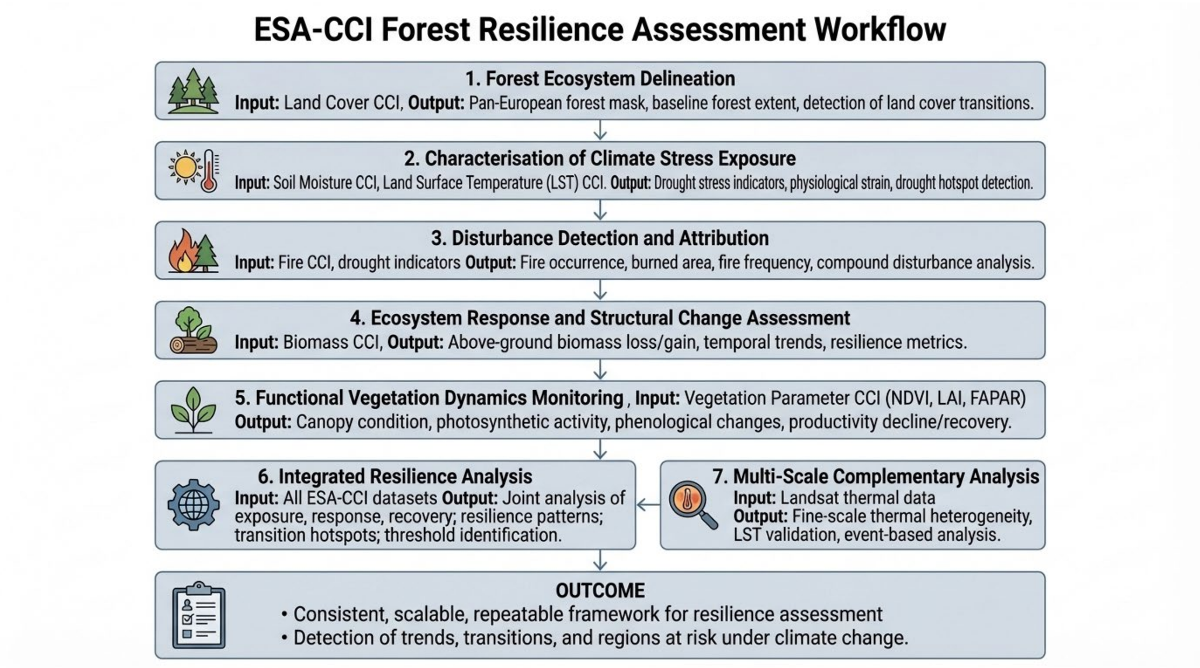
As these products are based on historical data and aim to establish a validated record, CCIs are inherently backwards facing. The ambition for a global snapshot that supports forward-looking modelling is addressed by the DestinE, which aims for a high-resolution Digital Twin of the Earth system[13]. This twin should support global now-casting and forecasting of the Earth system state. In this context, data from CCIs serve as validated initial conditions and calibrators for forward-looking models.

In the context of biodiversity, establishing a baseline link between EO products and biodiversity metrics can be supported by CCI products. Forward-looking and nowcasting approaches, once developed, should be related to the DestinE components.

5.1. Relevance and Applicability of ESA-CCI Data for the ECO-MOSAIC Project

5.1.1. Case study 1: Resilience of Transitional Forest Ecosystems in Europe

In this case study, transitional forest ecosystems are defined as forested areas undergoing structural and functional changes driven by climate-related disturbances, such as drought, wildfire, pest outbreaks, and subsequent regeneration processes. These ecosystems are susceptible to climate change, as increasing disturbance frequency and intensity may push forests beyond recovery thresholds, leading to long-term shifts in ecosystem state. ESA-CCI datasets provide a harmonised and long-term observational basis for analysing these dynamics at regional to continental scales. The pilot utilises multiple ESA-CCI ECVs to capture both ecosystem exposure to climate stressors and ecosystem responses, including degradation, resilience, and recovery.



[13] https://destination-earth.eu/destination-earth/destines-components/

Figure 3. *ESA-CCI–based workflow for Case Study 1: Resilience of Transitional Forest Ecosystems in Europe, illustrating how CCI products contribute to the integration of land cover, climate stress, disturbance, biomass, and vegetation dynamics data to analyse ecosystem responses and resilience to climate change across multiple spatial scales. Conceptual content provided by the authors; figure drafted with assistance from FigureLabs (figurelabs.ai).*

Biomass-CCI will be used to characterise long-term and spatial patterns of above-ground biomass dynamics associated with tree mortality and post-disturbance recovery, rather than to interpret short-term year-to-year biomass fluctuations. Temporal biomass trends will be analysed at multi-annual time scales to identify areas exhibiting sustained biomass decline or recovery trajectories potentially linked to drought stress, fire disturbance, or pest-related impacts.
Given known limitations in annual Biomass-CCI estimates, including interannual variability arising from observation density and data quality, individual-year anomalies will be interpreted cautiously and will not be directly attributed to actual biomass change without supporting evidence from complementary indicators. Instead, Biomass-CCI will be integrated with additional EO-derived variables (e.g. vegetation parameters, land cover change, and disturbance information) to support a robust, multi-indicator assessment of forest resilience, understood as both resistance to disturbance and the capacity for recovery.

Soil Moisture CCI and ***Land Surface Temperature (LST)-CCI*** will be jointly employed to characterise drought stress conditions affecting transitional forest ecosystems. Reduced soil moisture, combined with elevated LST, serves as an indicator of physiological stress, increased vulnerability to tree mortality, and heightened susceptibility to secondary disturbances, such as bark beetle outbreaks or wildfires. Seasonal and interannual analyses of these variables support the identification of recurrent drought hotspots and emerging patterns of climate stress.

Fire-CCI data will be applied to track fire occurrence, burned areas, and fire frequency within forested landscapes. In the pilot, fire history is analysed in combination with biomass and vegetation indicators to assess post-fire regeneration trajectories and to detect potential shifts from forested to non-forested states. This supports the identification of resilience thresholds and areas where repeated disturbances may inhibit recovery.

Land Cover-CCI will provide a consistent and harmonised delineation of forest ecosystems across Europe. In the pilot, it is used to define the spatial extent of forested areas and to identify land cover transitions related to disturbance, degradation, or regeneration. Its pan-European consistency is vital for analysing transitional forest dynamics across administrative and national boundaries.

ECVs under the terrestrial domain, related to vegetation parameters such as leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (FAPAR), will be used to monitor vegetation productivity, phenological dynamics, and functional responses to climate stress and disturbance. In transitional forest ecosystems, these indicators provide insight into changes in canopy condition, photosynthetic activity, and recovery processes following drought or fire events.

A key strength of this case study lies in the integrated use of multiple ESA-CCI datasets. By combining biomass, vegetation parameters, soil moisture, LST, fire, and land cover information, the pilot captures complementary structural and functional aspects of forest resilience. While the spatial resolution of CCI products limits the detection of fine-scale changes in forest structure, their long-term consistency and pan-European coverage make them well-suited for identifying large-scale patterns, trends, and hotspots of ecosystem transition. Overall, ESA-CCI data provide a robust foundation for assessing the resilience of transitional forest ecosystems in response to ongoing and future climate change.

Evaluation of ecosystem exposure and resilience in this case study will follow established EO-based approaches from disturbance ecology and forest resilience research, where resilience is assessed through the combined analysis of climate exposure, ecosystem response, and recovery trajectories rather than single indicators. Ecosystem exposure will be characterised using multi-year anomalies and extremes in climate-related variables such as land surface temperature, soil moisture, and fire occurrence, while ecosystem response and recovery will be evaluated through the temporal behaviour of biomass and vegetation parameters following disturbance events. This evaluation framework is consistent with recent studies that have applied long-term satellite observations to assess forest disturbance, recovery, and resilience across Europe and Central Europe, including the Czech Republic, where climate-driven drought and bark beetle outbreaks have led to pronounced forest mortality and heterogeneous recovery patterns (e.g. Hlásny et al., 2021; Abdullah et al., 2025). Resilience will be evaluated using relative changes, recovery rates, and the persistence of post-disturbance signals over multi-annual time scales, allowing the identification of areas exhibiting stable recovery, delayed regeneration, or potential transitions to alternative ecosystem states. Where available, uncertainty information and quality indicators associated with ESA-CCI products will be considered to support a cautious interpretation of results. Ecosystem exposure and resilience patterns will be assessed relative to and comparatively, with confidence supported by temporal robustness and consistency across multiple EO-derived variables. Complementary event-based analyses using higher-resolution datasets, such as Landsat thermal observations, will further support the interpretation of selected extreme events and the validation of large-scale ESA-CCI-derived patterns.

Complementary non-CCI datasets

To complement the coarse-to-moderate spatial resolution of ESA-CCI LST products, thermal observations from the Landsat programme are used in a complementary and exploratory role. Landsat thermal data enable higher-resolution characterisation of spatial thermal variability and canopy heat exposure, particularly in fragmented forest landscapes and areas with complex topography. In this case study, Landsat-derived thermal indicators are primarily used to support the interpretation and validation of LST CCI products, as well as to explore the added value of local-scale thermal information for assessing forest stress and post-disturbance conditions. This includes assessing thermal heterogeneity following extreme events such as droughts or fires and comparing local thermal patterns with broader-scale CCI-derived signals.

Due to limitations related to cloud contamination and revisit frequency, Landsat thermal data are not used as a continuous stress indicator; instead, they are utilised through compositing and event-based analyses. This ensures consistency with the long-term, harmonised nature of ESA-CCI datasets, which remain the primary climate data backbone of the pilot. The combined use of ESA-CCI ECVs and complementary higher-resolution datasets provides a multi-scale perspective on forest resilience. While differences in spatial resolution and temporal sampling require careful harmonisation and awareness of uncertainty, this approach strengthens the assessment of large-scale patterns, emerging hotspots of ecosystem transition, and potential resilience thresholds under ongoing and future climate change.

5.1.2. Case study 2: Biome-wide shifts of key tree species

In this case study, climate-sensitive forest ecosystems are defined as tree-dominated habitats occurring at the climatic margins of their distribution, where ecosystem structure and functioning are strongly constrained by temperature, water availability, and cryospheric processes. These forests are particularly vulnerable to climate change, as increasing temperatures, altered precipitation regimes, and more frequent extreme events—such as heatwaves, droughts, and permafrost thaw—can exceed species tolerance thresholds, triggering range shifts, forest decline, or ecosystem transformation. Harmonised, long-term EO datasets, including those from the ESA-CCI, provide a consistent observational framework for analysing these dynamics across European biomes. This case study exploits multiple EO-derived ECVs in combination with biodiversity information to characterise ecosystem exposure to climate stressors, assess climate-driven impacts on key tree species, and evaluate ecosystem responses in terms of stability, resilience, and potential regime shifts

- **Western Taiga Boreal Forest**

The integration of multiple EO-derived ECVs enables a process-based assessment of boreal forest vulnerability, moving beyond correlative distribution models toward a mechanistic understanding of how climate change and extreme events reshape ecosystem suitability, resilience, and biodiversity.

Permafrost-CCI is a critical control on boreal ecosystem functioning, influencing soil thermal regimes, hydrology, nutrient cycling, and root penetration. EO-derived permafrost products enable the spatial and temporal monitoring of permafrost extent, active-layer thickness, and thaw dynamics. Integrating these datasets allows assessment of whether climatically suitable areas for boreal tree species are also edaphically and hydrologically suitable. This is particularly relevant for evaluating potential northward range expansion, as permafrost degradation may simultaneously create new opportunities for tree establishment while increasing ecosystem instability.

LST-CCI capture fine-scale warming trends and extreme thermal events that directly affect physiological stress, phenology, and growing-season length. These datasets are crucial for identifying heat anomalies and rapid warming episodes that are not accurately represented in interpolated climate surfaces. When combined with permafrost information, surface temperature data help identify thresholds beyond which boreal forest structure and productivity may be fundamentally altered.

Snow-CCI duration and freeze–thaw cycles play a key role in insulating soils, regulating soil moisture, and protecting roots from frost damage. EO-derived snow products provide high-resolution information on interannual variability in snow persistence and melt timing, which are critical drivers of seedling survival and early growth. Changes in snow regimes can also accelerate permafrost thaw, indirectly affecting forest stability.

Soil Moisture-CCI, although boreal forests are generally moisture-rich, EO-derived soil moisture data reveal increasing variability and episodic drought conditions linked to warming and altered precipitation patterns. These datasets allow the detection of moisture stress events that can reduce tree growth, increase susceptibility to pests, and elevate fire risk.

- **Mediterranean pine forests with endemic Mesogean pines**

Mediterranean pine ecosystems are susceptible to climate extremes, and EO-derived ECVs are particularly valuable for capturing short-term variability, cumulative stress, and threshold-driven ecosystem responses. These variables provide direct measures of climatic stressors that drive forest decline and ecosystem transitions. EO-derived ECVs allow the identification of tipping points where climate extremes drive irreversible ecosystem transitions, such as shifts from forest to shrubland or grassland. This supports more robust risk assessments, adaptive management strategies, and conservation planning under future climate scenarios.

Soil Moisture-CCI offer continuous, spatially explicit monitoring of water availability, allowing the quantification of drought frequency, duration, and intensity. These datasets are crucial for evaluating hydraulic stress in thermophilous pine species and for pinpointing periods when drought conditions surpass physiological tolerance thresholds. Unlike precipitation-based indices, soil moisture directly reflects plant-available water, making it a more ecologically meaningful indicator of drought stress.

LST-CCI enables the detection of heatwaves and prolonged thermal stress, which interact strongly with drought to drive tree mortality. These products support the identification of compound extreme events (e.g., heat–heat-drought interactions) that are major drivers of ecosystem degradation but are often poorly represented in bioclimatic datasets.

The vegetation parameter CCI, such as LAI in conjunction with EBVs, provides early warning signals of declining forest health, reduced productivity, and canopy dieback. These indicators help link climate extremes to observable ecological responses, supporting the detection of both gradual degradation and abrupt regime shifts.

Fire-CCI, as an EO-derived climate indicator related to fuel dryness, temperature anomalies, and moisture deficits, enable improved assessment of fire risk. Post-disturbance EO data further allow monitoring of ecosystem recovery or transition toward non-forest states.

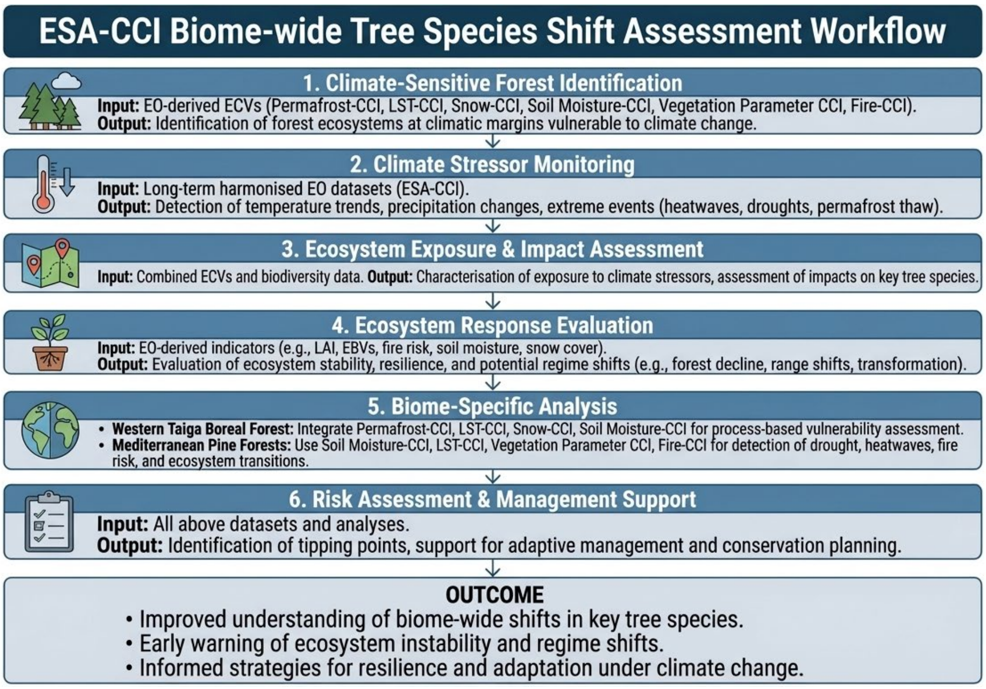


Figure 4. *ESA-CCI–based workflow for Case Study 2: Biome-wide shifts of key tree species, illustrating how CCI products contribute to characterise ecosystem exposures to climate stressors, assess climate-driven impacts on key tree species, and evaluate ecosystem responses in terms of stability, resilience, and potential regime shifts. Conceptual content provided by the authors; figure drafted with assistance from FigureLabs (figurelabs.ai).*

Assessing ESA-CCI Suitability for SDM and Resilience Analysis
Typical explanatory variables used in SDMs include WorldClim bioclimatic variables derived from interpolated station data, while resilience is assessed using vegetation time-series metrics such as resistance (impact magnitude), recovery time, and temporal autocorrelation as an early-warning signal of critical slowing down. We advance this by deriving parallel SDMs from ESA-CCI ECVs (e.g., LST, soil moisture, snow, permafrost) versus WorldClim predictors, comparing predictive performance (AUC/TSS, spatial realism) and alignment with observed range shifts or dieback. Exposure metrics (e.g., drought frequency, heatwave duration, thaw probability) and resilience indicators from CCI vegetation data will be benchmarked against independent forest inventories and disturbance records. ESA-CCI products include per-pixel uncertainty layers that we will incorporate into our analyses—via confidence intervals on trends/anomalies or sensitivity tests—to distinguish robust signals from data-limited regions, ensuring traceable risk maps.

5.1.3. Case study 3: Developing a suite of predictors for modelling species distribution across taxa

This case study aims to take the currently developed SDMs from Finstad et al. (2024) and replace the current environmental covariates, which are derived from data products specifically tailored to a Norwegian context, with data products developed from the ESA-CCI. By doing this, the current framework of developing maps of predicted species' distributions can be extended from a relatively local scale to a global scale. This would be beneficial as the results would provide a more detailed, accurate and robust illustration of the predicted niches of large groups of species, given that political borders do not constrain them. ECVs will be highly relevant to this case study, as they describe Earth's climate. On a large spatial scale, climate is known to be a major driver of species, and including this information in our models allows us to understand the extent to which a changing climate affects the dynamics of large groups of species. The case study will include the following data sets:

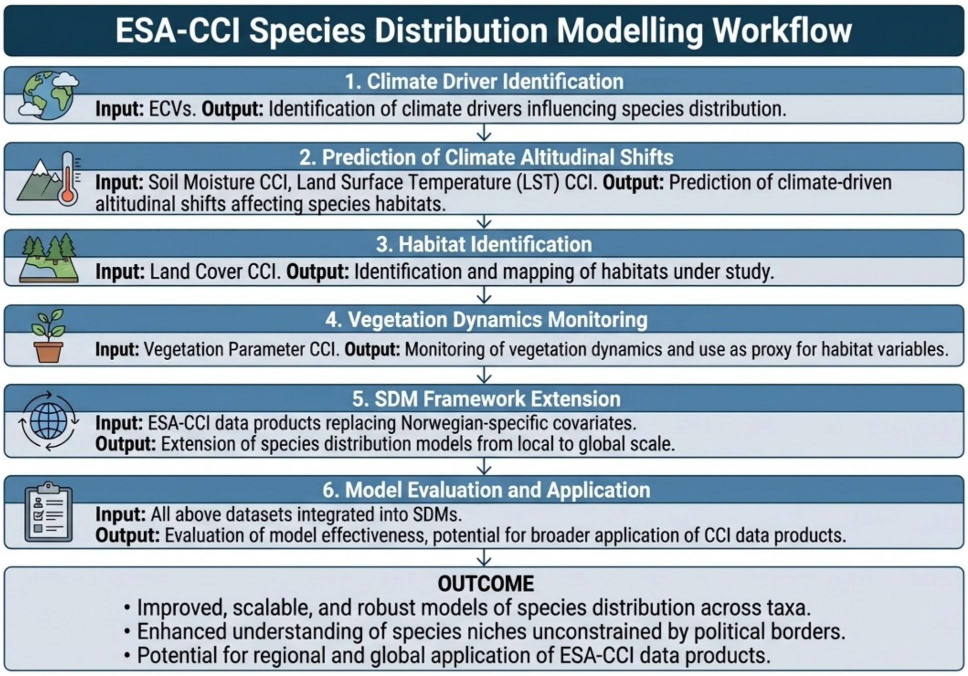


Figure 5. *ESA-CCI–based workflow for Case Study 3: Developing a suite of predictors for modelling species distribution across taxa. Conceptual content provided by the authors; figure drafted with assistance from FigureLabs (figurelabs.ai).*

Soil Moisture CCI and LST-CCI will be used to understand the impact that a changing climate has on species' distributions. Soil moisture may be a valuable covariate in the models used, as it represents water availability in an area, which is a major driver of habitat suitability for many species. LST is widely used in SDM analyses, as the variable is key in capturing broad-scale environmental patterns that structure the distribution of species, and is ultimately influential, given that it may drive species' survival, growth, reproduction, and dispersal abilities.

Land Cover-CCI will provide highly relevant and detailed information on the physical material on the Earth's surface. The models used in the Norwegian case study included land cover information obtained from local and regional sources (for example, Corine land cover); however, these covariates are not available on a global scale. Employing land cover CCI in the updated models would therefore allow us to extend the models to a far larger spatial scale than was previously possible.

The vegetation parameter CCI will be beneficial in the models, as it may aid in understanding the distribution of many species and can serve as a proxy for other relevant variables, such as habitat. Nevertheless, for some plant species (e.g., trees), using vegetation information will be circular since the variable will reflect the plants' own structure rather than independent environmental drivers.

The purpose of this case study is not only to provide improved models of Norwegian species, as derived in Finstad et al. (2024), but also to explore the implications of these models for the broader context. However, if ESA-CCI data are found to be as effective as or more effective than the Norwegian environmental data, it would suggest that CCI data products can be used more broadly, allowing regional and global models of species distribution to be developed based on a broader range of data products. Validation for the different models will be completed by predicting on independent species occurrence data not included in the models, and then computing some posterior predictive score or graphical method, such as area under the receiver operating characteristic curve, depending on which occurrence datasets are available in the study (Zurell *et al.,* 2020*)*. In addition, the sensitivity of the model parameters may be estimated by propagating the uncertainty estimated from the EO data. More sophisticated methods, such as incorporating uncertainty through a classical or Berkson error model could also be considered in this framework (Stocklosa *et al.,* 2015), although these would increase model complexity, and thus computational costs and potential model instabilities too.

6. KNOWLEDGE GAPS SELECTION

A persistent limitation in current biodiversity modelling frameworks for monitoring biodiversity is that structured biodiversity data remains sparse, unevenly distributed, and frequently lacks sufficient metadata to support robust integration across sources and scales. Although large volumes of biodiversity observations exist, particularly through citizen science initiatives and aggregated infrastructures, their usability in integrative modelling frameworks is constrained by heterogeneity in sampling design, spatial and temporal resolution, taxonomic coverage, and documentation of observation processes. This limitation directly restricts the scalability, transferability, and policy relevance of biodiversity models, especially when applied at continental or global extents.

When biodiversity data are sparse or incomplete, synthetic datasets can be generated to mimic the statistical properties of observed data, aiming to augment limited samples, improve model training, and support generalisation in machine learning–based approaches. Synthetic data can be helpful in methodological testing, sensitivity analyses, and exploratory modelling. However, they also introduce well-recognised risks, including the amplification of existing biases, the propagation of artefacts from poorly characterised training data, and the creation of false confidence in model performance when validation relies on simulated rather than empirical variability. Consequently, synthetic data cannot substitute for well-documented, harmonised, and ecologically meaningful observations when the objective is operational biodiversity monitoring and decision support.

In contrast, climate variables have benefited from decades of investment in globally consistent observation and reanalysis frameworks, enabling their routine use in species distribution and biodiversity models. For other key drivers of biodiversity patterns, such as land cover, habitat structure, fragmentation, disturbance regimes, and human pressure, data are typically developed at national or regional levels. These datasets often rely on country-specific definitions, classification schemes, processing chains, and validation strategies, which limit their direct usability beyond their region of origin.

Even when such variables are derived from EO systems, processing workflows and product specifications are frequently programme- or country-specific, resulting in inconsistencies that hinder application across large transboundary regions such as the EU. This leads to a critical and unresolved knowledge gap: to what extent do globally consistent EO-derived products exist that can replace or complement national and regional datasets beyond climate variables?

Addressing this question is crucial if biodiversity and SDMs are to be reliably extended to continental and global scales while retaining sensitivity to landscape-level drivers. Without such products, biodiversity models remain implicitly constrained by political boundaries rather than ecological gradients. For climate change studies, global data sets have been utilised to model species distributions for many years (Brun et al. 2022; Hijmans et al. 2005). However, other variables, such as land use, habitat, and human population, are developed nationally or regionally and will only be usable in those areas, with different countries developing their own metrics.

Closely linked to this challenge is the lack of a systematic framework for assessing and operationalising harmonisation in biodiversity datasets. Harmonisation encompasses the alignment of methods, units, sampling protocols, data structures, and semantic definitions so that observations from different sources can be reliably compared and jointly analysed. This includes the use of controlled vocabularies and ontologies, standardised data schemas, consistent provenance and metadata descriptions, and calibration or statistical harmonisation approaches such as rescaling, normalisation, and bias correction.

Despite broad recognition of its importance, harmonisation is rarely quantified, and its impact on model uncertainty and inference is seldom assessed explicitly. This represents a significant gap for integrated modelling approaches that combine *in situ* observations, citizen science data, EO-derived products, and model-based predictors. Without a transparent assessment of harmonisation, model outputs risk conflating ecological signals with artefacts arising from data incompatibility, undermining their credibility for operational monitoring and policy support.

6.1. Link to ECO-MOSAIC Case Studies

These knowledge gaps are directly relevant to, and will be addressed by, all three ECO-MOSAIC case studies:

- ***Case Study 1: Resilience of Transitional Forest Ecosystems in Europe***

Assessing forest resilience requires consistent, long-term, and spatially coherent information on biomass, vegetation condition, drought stress, fire disturbance, and land cover change across national boundaries. The reliance on harmonised EO products, such as ESA-CCI datasets, directly responds to the need for globally consistent landscape variables that can replace fragmented national datasets and support cross-border resilience assessments.

- ***Case Study 2: Biome-wide Shifts of Key Tree Species***

Modelling biome-wide distribution shifts demands predictors that are transferable across regions and stable through time. National land-use or habitat datasets are insufficient for this purpose. Identifying EO products that provide harmonised information on habitat structure, moisture stress, and vegetation dynamics is essential for extending SDMs beyond regional case studies to biome and continental scales.

- ***Case Study 3: Developing a Suite of Predictors for Modelling Species Distribution Across Taxa***

This case study specifically focuses on integrating heterogeneous predictors across taxa, regions, and data sources. The lack of harmonised EO-based landscape variables and the absence of metrics to evaluate harmonisation directly constrain predictor selection, model transferability, and uncertainty assessment. Addressing these gaps enables the development of scalable, repeatable, and policy-relevant predictor suites.

6.2. Why Does This Matter for the ECO-MOSAIC Project?

For the ECO-MOSAIC project, these knowledge gaps define the boundary between experimental modelling and operational biodiversity monitoring. The project's ambition to support large-scale, cross-border biodiversity assessment depends on identifying EO-derived products that are globally consistent, well-documented, and ecologically meaningful, and on establishing transparent approaches to data harmonisation and uncertainty assessment. By explicitly addressing these gaps, the ECO-MOSAIC project contributes to advancing biodiversity modelling frameworks that are scalable, reproducible, and aligned with European policy needs, supporting the development of interoperable monitoring systems that can inform EU biodiversity strategies, reporting obligations, and long-term environmental decision-making.

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