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1 Background

1.1 CIBER Science requirements and scope of report

This science requirements analysis is based on an in-depth review of the literature relevant for the subsequent work in CIBER with the objective to ensure a state-of-the-art project approach. This has included reviewing and analysing knowledge gaps, scientific challenges and research questions from different sources that **relay interactions between climate and biodiversity.**

This report first outlines background information for the importance and concepts of biodiversity and climate and for remote sensing of freshwater biodiversity as well as conceptualising fish community habitat templates (Chapter 1). Chapter 4.1.3 outlines scientific requirements and Chapter 3 summarizes freshwater climate-biodiversity knowledge gaps identified in recent scientific outcome reports from intergovernmental organizations and ESA projects (e.g. (Lever et al., 2024; Pörtner et al., 2021)) and other literature. Section 3.3 explains which science requirements the CIBER project aims to address from these knowledge gaps. Chapter 4 describes the data and methodological tools the CIBER project will use or develop to address the science requirements.

1.2 Methodology for review and identification of relevant scientific papers

Several sources have been utilised to identify knowledge gaps, scientific challenges and relevant research questions for CIBER. A main source is the review work done as part of the BIOMONDO project (Lever et al., 2024), see also Chapter 2, this document. Policy and science requirements related to freshwater biodiversity were extracted from strategies and policies, and from scientific literature with the aim to identify research areas for which there is potential for remote sensing data to support filling of knowledge gaps and address challenges. The policy documents reviewed included the main strategies as defined in the ESA ITT, but the review was extended to also include other relevant policy publications and reports. For scientific issues and challenges, a search of the Web of Science[1] was performed with several combinations of search terms {lake biodiversity}, {river biodiversity}, {wetland biodiversity}, {lake “remote sensing”}, {river “remote sensing”}, and {wetland “remote sensing”}. Based on the papers resulting from each of these searches, different fields of research were identified, and the results were analysed (network and cluster analysis) to determine groups of “research themes” using methods and approaches described by Newman (2006) and Calamita et al. (2024).

In CIBER, additional scientific papers were identified and reviewed by each partner for the different themes and document sections. Document searches in Google Scholar, Scopus and Web of Science, as well as AI tools including ChatGPT and Claude.ai, were used to identify relevant papers. To exclude marine studies, it is essential to always use the search term *“freshwater fish”* in these literature surveys. We combined (“freshwater fish” OR “lake fish”) in different combinations with the following search terms:

[1] www.webofscience.com

1) “database” OR “data base”, “biodiversity”, “functional diversity”, “trait”, “species distribution”, “Europe” OR “European” OR “Eurasia” OR “Asia”
2) habitat template OR habitat OR niche OR biogeography OR environmental filter* OR indicator species OR indicator tax*

Besides these online literature surveys, it turned out to also be highly valuable to perform inverse searches (checking literature cited or follow-on papers citing) of existing data repositories, publications and books, for example:

- Tedesco et al. (2017). *A global database on freshwater fish species distribution.* Scientific Data.
- Su et al. (2021). *Global patterns of freshwater fish diversity under climate change.* Science.
- Bayat et al. (2025). *Freshwater fish thermal tolerance and trait compilation.* Scientific Data.
- Souchon & Tissot (2012). *Synthesis of thermal tolerances of freshwater fish.* Knowledge and Management of Aquatic Ecosystems.
- Erős et al. (2009). *Trait-based approaches in freshwater fish ecology.* Freshwater Biology.
- Brosse et al. (2021). *Global biogeography of freshwater fish functional diversity.* Global Ecology and Biogeography.
- Cano-Barbacil et al. (2020). *Reliability analysis of fish traits reveals discrepancies among databases.* Freshwater Biology.
- Comte & Olden (2017). *Evolutionary and environmental determinants of freshwater fish thermal tolerance.* Global Change Biology.
- Mehner & Brucet (2022). *Structure of Fish Communities in Lakes and Its Abiotic and Biotic Determinants.* Encyclopedia of Inland Waters, Second Edition. Book Chapter 2022. DOI: 10.1016/B978-0-12-819166-8.00004-9

This list of studies is considered as a growing compilation and is continuously extended.

1.3 Importance of biodiversity and climate

Biological diversity is the variety of life on Earth and depends on the many different aspects that make organisms and the communities within which they coexist unique. We face global challenges linked to biodiversity decline worldwide, and there is extensive research and governance work on the linkages between climate and biodiversity.

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) and the Intergovernmental Panel on Climate Change (IPCC) have emphasized the inseparable connection between biodiversity and climate in a workshop report (Pörtner et al., 2021). The report highlights that current national and international policies address climate and biodiversity as separate issues, although the two are intertwined through mechanistic links and feedbacks that include “*temperature-induced changes in photosynthetic capacity and carbon storage, modified reflectivity of the land surface, altered formation of clouds and atmospheric dust, and shifted biogeochemical cycling of nutrients and carbon, which in turn influence he concentration of greenhouse gases in the atmosphere*”

(Pörtner et al., 2023). Biodiversity loss and climate change can therefore be considered both drivers and consequences of each other.

The EU has also traditionally adopted a ‘silo approach’, for example in the policy areas of climate change, biodiversity and circular economy, which does not reflect the actual interlinkages between these different domains (Paleari, 2024). However, the European Green Deal (launched in 2019), including the Nature Restoration Regulation (adopted in 2025), has been designed as a coherent growth strategy, aimed to transform the EU into a “climate neutral and resource efficient economy, while protecting, conserving and enhancing the EU's natural capital” (European Commission, 2019).

At the COP28UAE in 2023, a side event (Unpacking the biodiversity-climate nexus) highlighted and discussed the opportunities and challenges of the biodiversity-climate nexus with emphasis on mankind’s absolute dependence on nature for a sustainable future. Biodiversity and climate, together with water, food and health, constitute the five nexus elements included in the Nexus assessment recently undertaken by IPBES (McElwee et al., 2025). This report is a critical evaluation of the evidence of their interlinkages, and assesses the state of knowledge on past, present and possible future trends in the interlinkages with a focus on biodiversity and on nature’s contributions to people (NCP). Freshwater ecosystems are strongly linked to the nexus elements water, food, health, and biodiversity, and climate change has important and escalating interactions with all nexus elements. A nexus approach can help to avoid dangerous trade-offs and maximize co-benefits for humankind.

The Climate-Biodiversity-Health Nexus (CBH) or framework is another goal-oriented attempt to integrate approaches to planning and policy and support monitoring and development of indicators for global, regional and national strategies (Newell, 2023). Nexus approaches recognize that challenges within each element are interconnected with other elements across multiple spatial and temporal scales, which means that Earth Observation data can play an important role in providing essential information.

1.4 Biodiversity and climate change in freshwater ecosystems

Freshwater ecosystems, including rivers, lakes, and wetlands, are home to a rich diversity of species and habitats. Over 125,000 freshwater animal species are described to date, which roughly corresponds to 10% of the number of species described globally (Balian et al., 2008).

It is impossible to monitor all the different aspects of biodiversity on a global scale directly for several reasons, for example, objective metrics require subjective choices on how much we value one aspect of biodiversity relative to others. When determining biodiversity, we therefore must rely on estimates and approximations. In addition, facilitating global monitoring of the extent and condition of freshwater ecosystems is a big challenge, even though major drivers affecting their condition are quite clear and often straightforward to assess and monitor (Revenga et al., 2005). These geospatial indicators are referred to as proxies or surrogates, because they are indicators of current threat and give only indirect information about actual ecological integrity. To monitor freshwater ecosystems, we may thus have to rely on global, relatively easily detectable proxies, particularly those measuring changes of environmental conditions, and biodiversity models that use these proxies to extrapolate from local field observations to a regional or global scale.

The major impacts of climate change on inland waters include warming of rivers and lakes, which in turn can affect chemical and biological processes, reduce the amount of ice cover, reduce the amount of dissolved oxygen in deep waters, alter the mixing regimes, and affect the growth rates, reproduction, and distribution of organisms and species (IPCC, 2002; Till et al., 2019; Woolway et al., 2021). In addition, sea level rise will affect a range of freshwater systems in low-lying coastal regions. For example, low-lying floodplains and associated swamps in tropical regions could be replaced by salt-water habitats due to the combined actions of sea level rise and extreme sea levels during storm surges or tropical cyclones (Bayliss et al., 1997; Eliot et al., 1999). Plant species not tolerant to increased salinity or inundation could be eliminated, while salt-tolerant mangrove species could expand from nearby coastal habitats. Changes in the vegetation will affect both resident and migratory animals, especially if these result in a major change in the availability of staging, feeding, or breeding grounds for particular species (Boyd and Madsen, 1997; Zöckler and Lysenko, 2000). In addition to this, climate change affects other drivers and can be seen as a threat multiplier. In particular, drought or increased rainfall may lead to habitat change.

Global assessments of biodiversity set focus on the impact of different drivers on biodiversity rather than on monitoring a change in biodiversity per se (e.g., IPBES, 2018; Millenium Ecosystem Assessment, 2005). There are also scientific reasons for this approach. On one hand, drivers of global environmental change usually affect most aspects of biodiversity simultaneously. As such, they come as close to a compound proxy for change in biodiversity as we can get. On the other hand, a change in environmental drivers may precede biodiversity loss by several decades. Monitoring a change in environmental drivers can thus give us an early outlook on future changes in biodiversity to come.

Massive impacts of human activities on fish are very well documented (Su et al., 2021). Issues relating to how climate change currently is impacting freshwater fish biodiversity needs to be synthesized including how climate change impacts can be expected to change in the future. Links to mitigation measures and natural and human adaptation responses requires exploration with description of how such findings can help put nature on the path to recovery (nature-positive actions).

Biodiversity change indicators are needed to assess trends and determine areas of urgent action. They represent a way to simplify the relationship between observations and the detected changes for policy makers so that appropriate mitigation measures can be implemented with improved chances of meeting set targets. The key to a biodiversity monitoring system that provides useful scientific and policy output is, consequently, a system that assesses impacts and trends of drivers of global environmental change on biodiversity.

1.5 Remote sensing of freshwater biodiversity

CIBER explores how Earth Observation (EO) techniques and modelling can be used to assess climate impacts on freshwater ecosystems. Earth Observation (EO) is the process of gathering information about the Earth's surface, waters and atmosphere via ground-based, airborne and/or satellite remote sensing platforms. The analysis of the EO potential for monitoring of the main drivers of global environmental change (Thulin et al., 2022) demonstrated that satellite observations are increasing our understanding of the dynamics of water systems, their riparian borders and catchments. Satellite remote sensing is crucial for getting long-term global coverage and allows for time series analysis and change detection. It can rapidly reveal where to reverse the loss of biological diversity on a wide range of scales in a consistent, borderless and repeatable manner.

Remote sensing can be done over large areas, including remote areas, and at a relatively high temporal resolution. Remote sensing techniques are thus ideal when monitoring changes in environmental variables (see Table 1) over time and across space, whose signals can be measured in the domains of the electromagnetic spectrum at a relatively large spatial scale (Figure 1). In doing so, EO sensors can resolve processes and objects at meter to kilometre scale, i.e. ecosystem level, and signatures in the optical and thermal domain, e.g. photosynthetic pigments. Therefore, applications are often based on ecosystem-scale estimates of primary production or environmental drivers, from which other parameters of interest may be derived. Here we describe in a very abbreviated form the state of the art for the most common applications for freshwater ecosystems.

Table 1: List of lake properties, response variables (modified from Adrian et al., 2006) and related remote sensing indicators (modified from Dörnhöfer and Oppelt, 2016).

Lake properties	**Response variables**	**Remote sensing indicators**
Transparency	Dissolved Organic Carbon	Coloured dissolved organic matter
	Turbidity	Suspended particulate matter Turbidity Diffuse attenuation
	Transparency	Secchi depth Euphotic depth
Biota	Algal blooms	Chlorophyll-*a* (phytoplankton) Phycocyanin (cyanobacteria)
	Phenology	Time series analyses of chlorophyll-*a*
	Primary productivity	Trophic state index
	Species composition	Submerged aquatic vegetation
Hydrology	Water level	Bathymetry
Temperature	Epilimnic temperature	Surface temperature

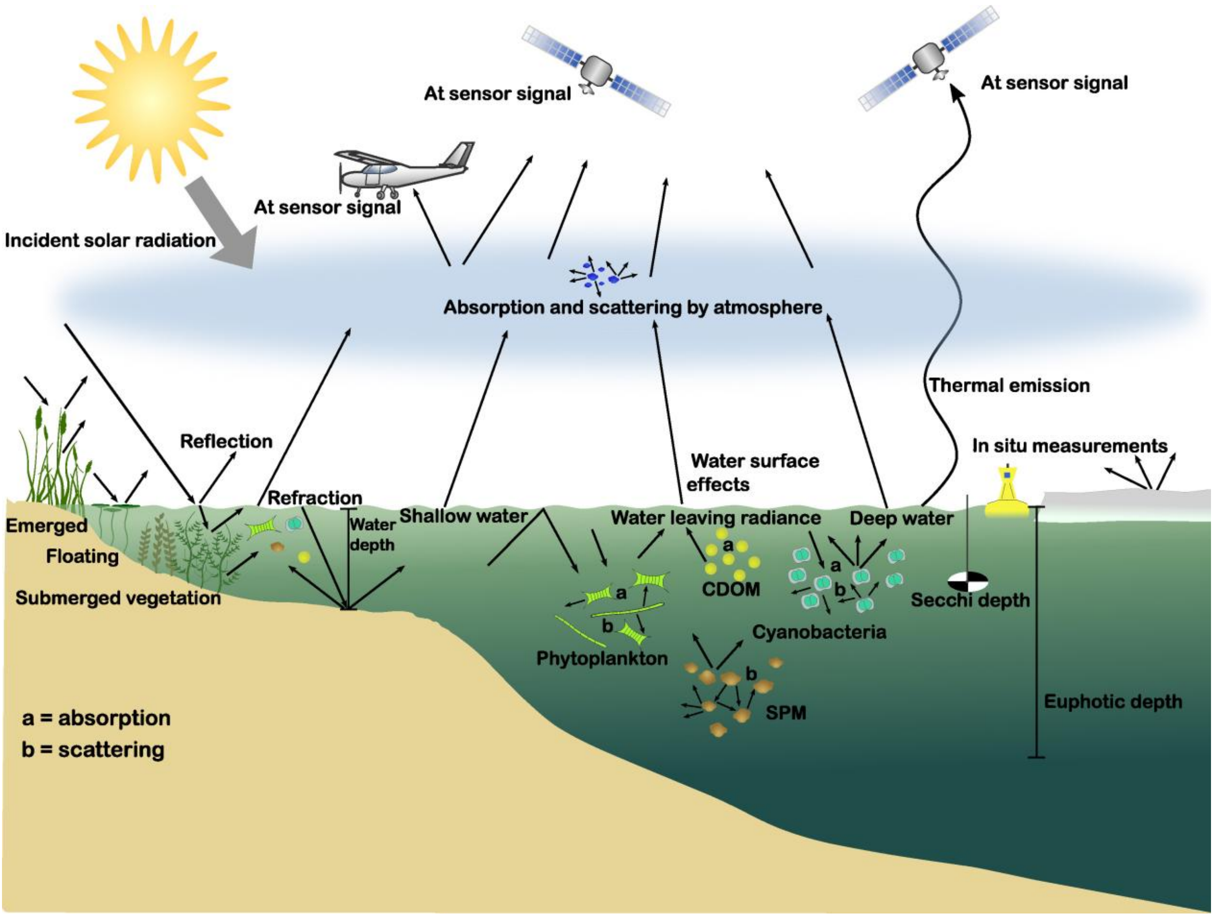

Figure 1: Interaction between radiation, remote sensing indicators of lake ecology, and sensors (from Dörnhöfer and Oppelt, 2016).

Below we summarise two key metrics of freshwater biodiversity that are detectable with satellite remote sensing: phytoplankton characterization (diversity, productivity, and phenology) and lake surface water temperature. Phytoplankton characterization is an important indicator of the biotic conditions in a lake, and lake surface water temperature provides valuable information on the abiotic conditions. Below, we describe state of the art approaches which are later referred to with regards to biodiversity knowledge gaps that EO can fill and subsequent scientific requirements to be addressed.

Phytoplankton diversity, productivity and phenology

Phytoplankton is an important component of freshwater lake ecosystems (Naselli-Flores and Padisák, 2023). Trends and anomalies in phytoplankton productivity or community composition directly impact resource availability for the entire lake system, including fish. The potential for characterizing phytoplankton and its growth in optically complex waters is basically the same as the applications known from Ocean Color remote sensing. However, the larger proportion and greater variability of Coloured Dissolved Organic Matter (CDOM) and Total Suspended Matter (TSM) make it difficult to determine almost all parameters. Therefore, it is currently common to use a pre-classification of optical water types (Moore et al., 2014; OWT; Spyrakos et al., 2018) for the production of global chlorophyll-*a* (chl-*a*, or, as an aggregate, Trophic State Index TSI) data products, for which various blended band ratio algorithms are applied. Other than that, the optical properties of cyanobacteria are sufficiently different from eukaryotes to facilitate a robust discrimination at moderate and high abundances (Matthews et al., 2012; Simis et al., 2005). The optical properties of many other phytoplankton taxa are well known (Lomas et al., 2024; Xi et al., 2017), but an estimation of their relative abundance is only possible with a high level of previous knowledge of the taxa present (Zheng and DiGiacomo, 2018). Therefore, the great success of remote sensing based marine Phytoplankton Functional Types (PFT), (see roadmap in Bracher et al., 2017) has not yet been transferred to inland waters. However, the increasing availability of hyperspectral data has the potential to enable PFT retrievals in inland waters when a priori knowledge of present phytoplankton species is available, e.g. from emerging automated underwater microscopes and machine learning classifications (Maire et al., 2025).

Phytoplankton phenology retrieval based on MERIS, MODIS or OLCI chl-*a* products have been for many lakes and lake regions (e.g., Benzouaï et al., 2020; Maeda et al., 2019; Palmer et al., 2015; Shi et al., 2019), and a study based on colorimetry rather than chl-*a* even identified phenology shifts across 26’000 lakes (Topp et al., 2021). However, there is no established standard method for lake phenology retrievals yet. This task is complicated by the shorter time scales and less regular seasonal patterns at which phytoplankton abundance varies, in comparison to terrestrial vegetation. We are currently investigating adequate methods for phytoplankton phenology retrievals on the basis of chl-*a* products from the ESA CCI processing chain[2].

Primary production can be modelled from a combination of two EO products, namely pigment concentration or absorption, and diffuse absorption or Secchi depth. Together with estimates of downwelling irradiance and a parameterization of photon use efficiency, photosynthetic light availability can then be modelled, in theory, at all depths and wavelengths, allowing for accurate retrievals based on semi-analytical models (Silsbe et al., 2016). In practice, simplified models assuming uniform spectral attenuation, vertical gradients and photon use can be used when previous knowledge of these variables is not available (Sayers et al., 2020). One main limitation for the broad use of such products is however that reference measurements of primary production require incubation of carbon isotopes during long periods, they are hence laborious and scarce, in particular in comparison to chl-*a* measurements. Operational products for lakes are therefore, to our knowledge, currently not available not even at the scale of regions or individual lakes.

Lake surface water temperature and thermal structure

Lake Surface Water Temperature (LSWT) is an Essential Climate Variable that can be routinely estimated using surface emitted radiance around 11 and 12 µm (A/ATSR, SLSTR, TIRS). Future satellites will explore also adjacent thermal infrared wavelengths, e.g. 8-9 µm in case of the French-Indian mission Trishna or the Copernicus Expansion Mission LSTM. Global and regional operational LSWT products are available from a range of sources, most prominently Copernicus and ESA CCI. Their main limitation is a spatial resolution of 1 km, which limits the application potential to the few thousand largest lakes in the world. 100 m resolution LSWT is distributed within Landsat Collection 2 products, but subject to longer revisit times of eight days for Landsat-8 and Landsat-9.

Water temperature largely determines lake water stratification, and stratification is key to near-surface nutrient availability and deep-water oxygen renewal. This is why vertical temperature gradients are a key information in lake research. However, LSWT only

[2] https://www.bgbphenology.com/

represents the top micrometers of seawater, but can be measured via satellite-based remote sensing, which why it was predominantly used for decadal warming trend estimations. But lately, it was reported how seasonal stratification and mixing in large temperate lakes can be estimated by means of a 4° LSWT threshold representing the temperature of maximum density (Fichot et al., 2019). This threshold, occurring as a longitudinal thermal bar in very large lakes, indicates vertical mixing when it passed the entire lake during a given winter. With this approach, 20 lakes that experienced mixing anomalies in the past 20 years (e.g. from dimictic to oligomictic) could be identified from the CCI LSWT products (Calamita et al., in preparation). Further detail on vertical temperature gradients in lakes, e.g. the thermocline depth, requires 1D hydrodynamic models. LSWT from EO can make a significant contribution to the calibration and validation of such models.

1.6 Conceptualising fish community habitat templates

Habitat templates (Kruk and Segura, 2012) aim to describe the features of the biotic and abiotic environment that support the survival, growth and reproduction of fish populations – usually for a given species. A template is a way of summarizing the necessary environmental conditions, or habitat properties, needed by a species (or higher taxonomic aggregations) to meet their physiological needs, to be able to reproduce, display appropriate behaviour and fulfil their life cycles. This is essentially a description of the physical, chemical, structural and biological features of an ecosystem (such as a lake) - across space and time – that are required and therefore can act as filters (necessary but not always sufficient) for determining whether a species can live there or not.

For fish, key abiotic environmental gradients include aspects of the physical and chemical environment: temperature, light, nutrients, water chemistry (conductivity and pH), flow or velocity of the water, mixing regimes, oxygen availability, depth, and the substrate or structure of the lake bottom (Cheng et al., 2012; Matuszek and Beggs, 1988). Lake structure can include the underlying geological formation, hydrodynamic impacts from bathymetry, the sediment or substrate type.

Fish also respond to the biotic environment in which they find themselves – characterized by the abundance of resources, competitors and predators. For many lake fish, resources consist of zooplankton species, community composition and their abundances, or the density of benthic macroinvertebrates (mussels, insect larvae, snails etc.). Fish populations can also be strongly controlled by fish predators and therefore may be closely related to predator density. Competition with other fish species within the same feeding guild may also reduce abundances. Lake productivity, often reflected in measures of chlorophyll-a, total nutrient concentrations, or "trophic state" also provide gross estimations of the energy available to the food web and consumers via internal carbon fixation and trophic transfer. However, how much of the total energy is available to individual fish taxa depends on the ecological context: which species contain the energy, how edible and nutritious they are, and how much energy is transferred across trophic levels. Finally, disease and parasitism can also be strong drivers of fish dynamics.

Fish interact with these environmental gradients in ways that are determined according to their own biological traits, behaviours, life history and physiology. These include aspects such as body size, growth rates, metabolic demands, feeding strategies, reproductive strategies and vulnerability to predation. Different environmental gradients may influence fish at different temporal and spatial scales. For example, many species may have similar thermal affinities and therefore co-occur across regional spatial gradients (i.e. across lakes), but they may partition food resources that vary across the benthic and pelagic environments of the same lake. With remote sensing-based products alone, we will inevitably be constrained to consider variability in the upper layer of the water column. We cannot characterize depth gradients that vary within lakes or on diel time scales, though they may be important for fish distributions and abundance. To supplement this EO constraint, we employ 1D lake models to capture depth-dependent gradients.

We will most likely constrain our analysis to variables observed at the whole lake ecosystem scale, and which vary on regional spatial and seasonal to interannual temporal scales. These may include effects of bathymetry, productivity, climate, mixing regime and water column stability, total organic carbon, dissolved oxygen, turbidity, total organic carbon, light availability, spatial connectivity, and land-use.

We can already hypothesize that we may observe key gradients of lake fish habitat, affecting the species which are present, and the composition of communities (Mehner et al., 2021). Gradients of importances will likely include measures of productivity and trophic state (i.e. oligotrophic and clear to eutrophic and turbid, (Heino et al., 2010)). Furthermore, lake morphology can interact strongly with lake productivity. These two gradients together are thought to shape food web structures, determining whether they are dominated by benthic or pelagic energy pathways, dominant foraging modes (planktivores or benthivores/plant-associated omnivores), and the body size and biomass distribution. Additionally, climate, lake size, basin depth and shape will control whether or not a lake is mixed, how often and for how long. This influences gradients of temperature and oxygen, and therefore the balance and extent of benthic versus profundal habitat. It will of course determine how much of the water volume of a lake is habitable, and which species can survive (e.g. in colder climates or under lower oxygen levels (Tonn, 1990)).

Some work on European fish has been done to show that particular traits of fish, or "trait syndromes" are associated with particular and dominant environmental conditions in lakes. For example, fish in small, shallow, or often disturbed lakes are often occupied by opportunistic fish species with rapid maturation, high fertility and low juvenile survivorship. Large, more seasonal systems, with predictable and highly productive periods, have fish with seasonal spawning whose timing match peak lake productivity – these are often larger bodied and more fecund fish species. Finally, stable and more structured lakes often have fish that are less fecund but invest more in their offspring (Blanck et al., 2007).

One example is a study in German lowland lakes where Mehner et al. (2005) found that community composition was largely explained by depth and chlorophyll-a, with deep cool lakes being dominated by vendace (*Coregonus albula*), perch (*Perca fluviatilis*) and smelt (*Osmerus eperlanus*), while shallower, more productive lakes were dominated by cyprinids. This was reiterated, in a second paper (Mehner et al., 2021) suggesting that lake depth and geography drive compositional changes in which cool, deep, less productive lakes are dominated by coregonids and salmonids, while warm, shallow, more productive lakes are dominated by cyprinids or percids. In a Finnish study (Heino et al., 2010) across multiple ecoregions, cool, deep lakes contained Arctic charr, salmonids and grayling, whereas more tolerant species were present in more shallow, nutrient rich lakes: e.g.

crucian carp. Perch, roach, ruffe and pike were characterized as generalists, and therefore not good indicators of any particular lake type. Indeed, a number of lake indices have been proposed that describe the status of the lakes based on the composition of the fish communities within them (Arranz et al., 2016; Blabolil et al., 2017; Emmrich et al., 2014; Specziár and Erős, 2020). Nevertheless, they often recapitulate the observed importance of coregonids in deep, cool, stratified oligotrophic lakes as compared to the dominance of cyprinid-percids in warmer, shallow, more eutrophic lakes. Finally, a species distribution modelling approach of 19 fish species in 772 European lakes showed that the abiotic environmental and spatial predictors contributed to the presence and absence of fish species, while lake size and productivity contributed more to the biomass of the community (Mehner et al., 2021).

2 Scientific requirements

The NASA Biological Diversity and Ecological Conservation program elements have released a detailed report on the value of remote sensing for understanding, monitoring, and forecasting biodiversity and supporting decision making. Developed by a working group of experts, the report demonstrates the value of remote sensing for biodiversity, explores new ideas, and identifies potential program opportunities for the next decade Geller et al., (2022). To predict changes in biodiversity and ecosystem services and to provide the best possible information to decision makers, they make several recommendations. These include improved integration of EO in ecological forecasting, coordination with stakeholders, iterative updating of forecasts, use of multisensor data and increased interaction with social scientists. They also called for the development of a shared, sustainable community infrastructure to facilitate ecological forecasting.

The ESA Scientific Strategy (European Space Agency, 2024) prioritizes understanding climate-biodiversity feedback, particularly how warming waters and altered hydrological regimes impact aquatic species distributions. ESA explicitly recognizes the monitoring of Ecosystem health as one of six core thematic objectives, with freshwater biodiversity constituting a critical component of this mandate. The emphasis is on understanding Earth system feedback mechanisms through advanced satellite monitoring, particularly focusing on aquatic ecosystems where biodiversity loss rates exceed those of terrestrial systems by 2-3 times (Haase et al., 2023). The EO science strategy specifically requires integrating EO-derived parameters like water temperature dynamics, sediment transport patterns, and wetland extent changes with biodiversity models and address critical knowledge gaps identified in recent studies showing stagnating recovery of European freshwater ecosystems despite restoration efforts (European Environment Agency, 2018; Haase et al., 2023). The ESA Scientific Strategy will be further analysed as the project progresses (e.g. in WP3) with focus on three of the six scientific themes, namely the Water cycle (ST-1), Ecosystem health (ST-IV) and Interfaces & coupling in the Earth system (ST-VI) and their interconnectedness.

In addition to the description in section 1.3 of the scientific outcomes of the IPBES-IPCC workshop, Pörtner et al. (2023) highlights the need for an integrative approach to strengthening of biodiversity in all systems and to achieve better detailed understanding of how climate and biodiversity is currently interacting and might do in the future.

The EU Biodiversity Strategy 2030 with the Nature Restoration Regulation, "sets binding targets to restore degraded ecosystems, in particular those with the most potential to capture and store carbon and to prevent and reduce the impact of natural disasters." Based on the assessments of European ecosystem condition, measures for restoration and protection of habitats and species and implementing the target of restoring 25,000 km of free-flowing rivers by 2030 (European Commission, Joint Research Centre and EEA., 2021; Paganini, 2022) have been included which requires spatial information and monitoring of freshwater ecosystem extent and condition. These strategies and laws also seek to contribute to achieving the EU's climate mitigation and climate adaptation objectives of the EU Strategy on Adaptation to Climate change (European Commission, 2021). It seeks to improve knowledge and data which is a key priority for building European climate resilience under the European Green Deal (European Commission, 2019).

Freshwater biodiversity constitutes a key indicator for achieving multiple UN Sustainable Development Goals (6, 13, 14 and 15) and information that can be utilised to obtain global understanding of changes to biodiversity are much needed.

At a global level the 2022 CBD Kunming-Montreal Global Biodiversity Framework (GBF) and monitoring framework with targets and indicators, aims at "holistically capturing the state and trends of biodiversity, interactions of nature and people, along with the drivers and pressures that are causing biodiversity loss and ecosystem degradation" (Kim et al., 2023). As it recognises inland water / freshwater ecosystems as a realm of its own it can help sustain water-related ecosystems and ecosystem services, as well as support SDG 6 and other Sustainable Development Goals. GBF targets relevant to the CIBER project include "Ensure Sustainable, Safe and Legal Harvesting and Trade of Wild Species" (Target 5), "Manage Wild Species Sustainably To Benefit People" (Target 8) and "Manage Wild Species Sustainably To Benefit People" (Target 9). By focusing on freshwater biodiversity indicators that in turn can inform GBF component- and complimentary indicators, there is potential to also link with the GEO BON essential variables frameworks, i.e. Essential Biodiversity Variables (EBVs) and Essential Ecosystem Services Variables (EESVs). Such indicators that are scalable and interoperable for multiscale analyses have the potential to play an important role to prioritise actions and to monitor progress towards reaching goals. In addition, they may inform the UN SEEA EA framework to consolidate national monitoring systems nationwide and account for natural capital including converting growth-oriented economic models to more sustainable and well-being-oriented models (United Nations, 2024).

The Science Agenda and Roadmap of BIOMONDO (Lever et al., 2024) fully endorsed the recommendations of Geller et al. (2022) and moved forward by outlining research gaps for freshwater biodiversity remote sensing related to the identified knowledge gaps including mutual dependencies that require specific consideration. In the sections below we emphasise the complex and multiple connections between climate and biodiversity.

The research priorities and scientific requirements derived from the knowledge gaps are summarised under the following headings below:

- Freshwater ecosystems and habitats
- Thermal structure
- Phytoplankton diversity, phenology, and productivity
- Ecosystem disturbances, regime shifts, anomalies, and resilience indicators (strong links to climate change and mitigation effects) including attribution of bd change

- Biodiversity – climate change feedback system

The relevance of the knowledge gaps and challenges for the work to be undertaken in CIBER, are further described in Chapter 3 with specific analysis to determine the ones with the highest priority.

2.1 Freshwater ecosystems and habitats

Geospatial information about the location, size, and geographic relations like connectivity of freshwater ecosystems and habitats are needed to assess their status and monitor changes with regards to biodiversity policy targets and goals. However, existing classification schemes and typologies have evolved over time with different objectives, and they are neither optimized for linking to global biodiversity assessments, nor suited to take full advantage of developments in remote sensing of recent years (e.g. MAES, IUCN and EUNIS classification schemes). With an increasing emphasis on and need for development of EBVs to inform biodiversity indicators, some of the typologies have recently been revised or are under revision. This will hopefully leverage the use of remote sensing and modelling.

The below listed information and knowledge are needed to monitor freshwater biodiversity in rivers and streams, lakes, reservoirs and ponds, wetlands:

- Time series data/maps of freshwater habitats (with flexible classifications that allow for global and regional/local utility, with appropriate resolution and accuracy/uncertainty estimates) to determine short-term and long-term trends
- Transparent connection between biodiversity (species records, abundance and distribution), habitat requirements (temperature, hydrology, depth etc) and habitat and ecosystem characteristics (e.g. structure, function)
- Scalable connection between habitat types[3] (e.g. EUNIS trophic state and vegetation) and ecosystem types (functional not trophic state)

Certain elements of the required information can be provided by remote sensing, of which some is already in use for determining, e.g. extent of lakes, rivers and streams, some aspects of water quality (trophic state, LCLU and change, net primary production, turbidity, chl-*a*), hydrographics and physical characteristics from sonar (depth), and extent attributes from radar.

EO based methods to map and monitor changes in the spatial extent of freshwater bodies are readily available (e.g., Verpoorter et al., 2014) and are highly relevant, in particular in permafrost regions and in arid climate zones where freshwater bodies may appear or disappear due to climate change, as well as in river basins where dams are placed affecting water flows and wetland formation. But there is no global dataset that classifies freshwater bodies according to lower classification levels, such as trophic state and depth, which are required for example in the EUNIS classification scheme.

[3] From EEA, https://www.eea.europa.eu/en/topics/in-depth/biodiversity/an-introduction-to-habitats: A habitat or a group of related habitats can be considered an ecosystem. Ecosystems are dynamic complexes of plant, animal and micro-organism communities and their non-living environment, which interact to form functional units.

To determine freshwater habitats and ecosystem classes is inherently complicated because of the position within the terrestrial realm where changes to the upstream landscape processes, catchments and hydrography can affect extent, structure, function and condition. Hydrography can be derived from spaceborne elevation data (Lehner et al., 2008) but other aspects have not been fully assessed when it comes to the support of EO and remote sensing. In condition assessments both environmental quality (physical and chemical quality) and ecosystem attributes (biological quality) are considered. These aspects also provide an opportunity for the expanded use of EO but may need to be explicitly required by framework guidelines to reach full potential.

To achieve a global coverage that can give comparable results and a better understanding of whether quality status or climate change mitigation measures are having desired outcomes, methods employed need to be flexible but transparent and work at different scales, which are design principles of the new IUCN Ecosystem typology. An important scale aspect is the relationship between habitats and ecosystems where the latter often consists of several habitats and different parameters have been used to characterise them depending both on geographic location but also on the resolution or grain of the input data. For wetland classifications this is especially difficult as many wetland habitats are complex with properties that can be assigned to combinations of terrestrial, freshwater and marine biomes.

As the ability to map the extent of and discriminate between different habitats and ecosystems has improved, and emphasis on biodiversity monitoring aspects has increased; the <u>condition</u> of the habitats and ecosystems is receiving growing attention. This is especially important for linking with the expanding field of ecosystem accounting and raises issues relating to the notion of high biodiversity per se as it is not always a good indicator of habitat and ecosystem condition – or how to monitor negative change in ecological status not reflected by biodiversity (number of species).

2.2 Thermal structure

Lake water temperature is linked directly to warming air temperatures, although it was reported that lake surface temperatures warm only at a rate of 0.24° per decade, while surface air temperatures increase at a rate of 0.29° per decade (Tong et al., 2023). The retrieval of LSWT from satellite EO is rather straightforward and accurate with uncertainties in the order of 1°. But LSWT is not an optimal environmental variable for aquatic biodiversity, which requires information on bulk surface (epilimnetic) temperatures or vertical stratification. Both can be achieved through skin-to-bulk conversion (e.g., Wilson et al., 2013) or thermal bar mapping approaches (Fichot et al., 2019), respectively, but further research is needed to make these tasks optimal and operational, and other variables, such as thermocline depth, require complementary model simulations.

Assessment of impacts of changes in thermal stratification and lake mixing regimes must address impacts on primary producers as well as impacts on consumers. Concerning the former, it should be investigated how changes in the seasonality of epilimnetic temperature and vertical mixing are related to phytoplankton growth by contrasting them with currently available TSI, or, preferably, gap filled chl-*a* products prior to temporal aggregation. In doing so, it should be considered that temperature and productivity may be related positively when lake water temperature is limiting, but negative when nutrient availability in the epilimnion is limiting (Bouffard et al., 2018). Furthermore, it must be taken into account that short term weather phenomena related to solar irradiance and wind forcing can cause algae blooms that exceed even the seasonal dynamic range (Irani Rahaghi et al., 2024). These combined effects, and the differences in their relative contributions and temporal and spatial scales, complicate systematic assessments significantly, while antecedent case studies with a focus on individual lakes and events are relatively straightforward.

Assessments of the impacts of extreme climate events, e.g. heatwaves and massive rainfall events, on biodiversity variables, can hence be understood as special cases if they focus on response variables related to primary producers.

2.3 Phytoplankton diversity, phenology, and productivity

Phytoplankton form the foundation of the aquatic food web, and its photosynthetic pigments allow direct retrievals of phytoplankton biomass. IF spectral resolution is sufficiently high, accessory pigments even enable to assess the diversity on different taxonomic levels from species to phylum (Maire et al., 2025), phenology and productivity using optical EO data. Therefore, phytoplankton is a key topic in aquatic remote sensing. The knowledge gaps relating to ecosystem functioning address various aspects of this topic, including phytoplankton-related links between ecosystem functioning and environmental variables. The dependencies of these knowledge gaps are depicted in Figure 2Figure 2.

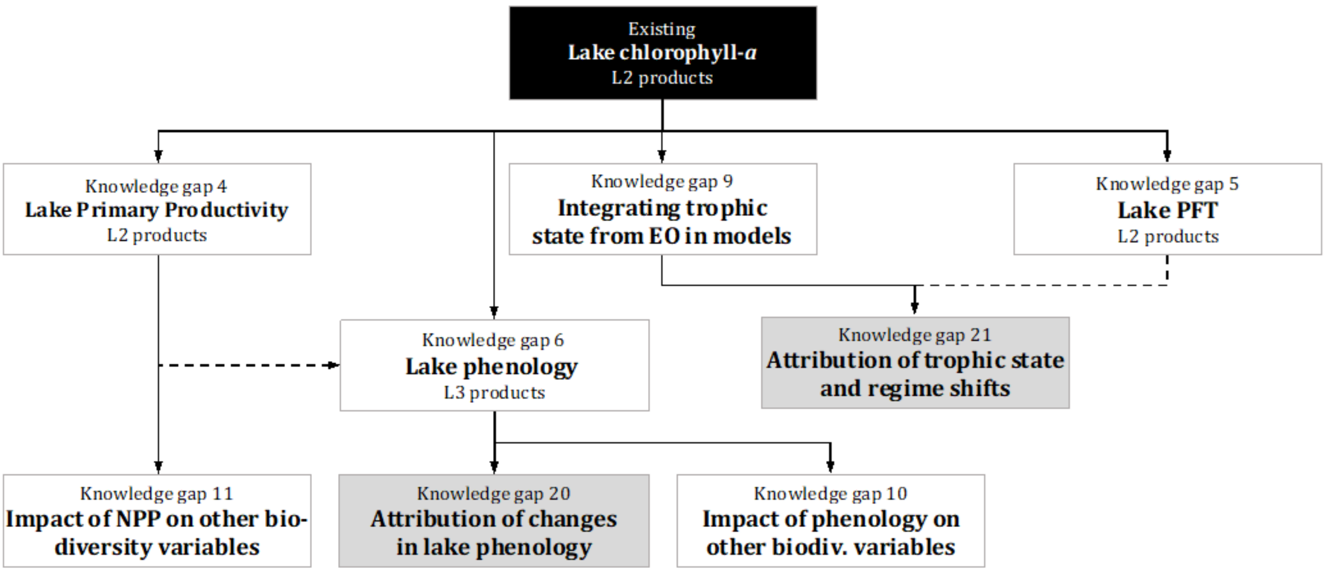

Figure 2: Hierarchy of research gaps related to phytoplankton diversity, phenology and productivity (updated from BIOMONDO Science Agenda and Roadmap, Lever et al., 2024). Starting from L2 product but could be replaced by L3 CCI lakes product. The knowledge gap numbering refers to the numbering in Table 2.

Net primary productivity and phytoplankton phenology (based on chl-*a* products) are proven applications of EO data. But the comprehensive upscaling of phenology products is limited to, e.g., the US-wide lake browning (Topp et al., 2021), and global, full mission phytoplankton phenology is missing. The upscaling of PP retrievals is limited to a simple, empirical approach for the eleven largest lakes in the world (Sayers et al., 2020).

Phytoplankton phenology products are currently in development at Eawag[4], based on CCI lakes chl-*a* products from MERIS and OLCI provided by the Plymouth Marine Laboratory (PML). These products are well validated, which is why only limited validation work is necessary. Contrariwise, PP products from analytical algorithms (e.g., CAFE model; Silsbe et al., 2016) still need comprehensive validation and high-quality PP reference measurements are much scarcer than chl-*a* measurements. However, the EO input products to PP algorithms (phytoplankton absorption, diffuse attenuation, downwelling irradiance) are well established, and operational PP products could be used far beyond the biodiversity community (e.g. in carbon assimilation models).

Lake Phytoplankton Functional Types (PFT) describe highly diverse phytoplankton taxa, which play different roles within ecosystems (e.g. as food for other species) and within the carbon cycle (e.g. the shells of some phytoplankton species may sink to the bottom after death, while others release a larger fraction of carbon back into the atmosphere). Different species may also respond differently to changing environmental conditions, and some species produce toxins that are harmful for ecosystems and water quality (e.g. cyanobacteria). Operational products are until now limited to cyanobacteria (e.g. CyanoAlert and CyanoLakes), which can be identified robustly by means of spectral reflectance features in red wavelengths (Matthews and Odermatt, 2015; Simis et al., 2005; Wynne et al., 2010). The use of cyanobacteria products for a dedicated phenology product is currently under development for ESA Lakes CCI. In addition, PACE, launched in 2024 is significantly improving the potential to distinguish PFT in lakes that are sufficiently large for the use of 1 km spatial resolution data (Dierssen et al., 2023). Methods to exploit the potential of the first daily hyperspectral satellite data exist already (e.g., WASI; Gege, 2014), and spectral absorption properties of some common lacustrine and marine algae taxa are available (e.g., Lomas et al., 2024; Soja-Woźniak et al., 2022), although further lab analyses are needed for less common lacustrine taxa and to clarify the sensitivity of spectral absorption properties to environmental conditions (Göritz et al., 2017).

Integrating trophic state from EO in models is a task that can be implemented on the levels of different parameters that are available from EO and ecosystem (water quality) model parameters, as well as in different work steps. At the current stage, readily available trophic state EO products can be used, and existing assimilation techniques could be used to connect these products with existing model simulations.

2.4 Ecosystem disturbances, regime shifts, anomalies, and resilience indicators

While the focus of section 2.3 is on the production of new time series (i.e. of lake primary productivity and lake PFT) and the extraction of seasonal dynamics (i.e. phenology), this section focusses on the cases in which these time series or dynamics show a substantial change, either in the form of longer-term regime shifts or relatively short-lived but large-scale anomalies. This is important because shallow lakes are known to typically show (at least) two alternative states, i.e. a clear-water state with submerged macrophytes and piscivorous fish, or a turbid state dominated by phytoplankton. Shifts between these states may occur relatively suddenly under the influence of gradual changes in nutrient inflows

[4] www.bgb-phenology.com

when ‘tipping points’ are passed (Scheffer et al., 1993). Deeper lakes may exhibit shifts in mixing regimes under the influence of climatic changes (Calamita et al., 2024), while the high rates of herbivory in freshwater systems makes them particularly susceptible to regime shifts arising from changes in biotic interactions (which, e.g., are dependent on phenology; Lever et al., 2023)). Anomaly detection is important because they are expected to increase in size and frequency under the influence of climatic changes with potentially catastrophic consequences for species and biodiversity. Such extreme events may also trigger regime shifts. At the same time, such anomalies may provide important information about the resilience of ecosystems under the influence of global environmental change. Resilience may be, among other possibilities, defined as the speed at which a system recovers from disturbances (i.e. engineering resilience), or as the amount of change a system can handle without going through a regime shift (i.e., ecological resilience; Holling, 1996). Loss of both types of resilience tends to go hand-in-hand and, therefore, an increasingly slow recovery from disturbances (e.g. after anomalies) can be used as an indicator of the loss of both types of resilience. Changes in the statistical properties of time series (e.g. increased variance and autocorrelation) may provide an indication that the speed of recovery from disturbances is slowing down. Monitoring of lake resilience using such ‘resilience indicators’ is important, in particular because it is not always easy to determine which environmental driver is undermining ecosystem resilience (Scheffer et al., 2009; van Nes and Scheffer, 2007).

Knowledge gaps on ‘lake regime shifts and anomaly detection’ and ‘lake resilience monitoring and resilience indicators’ are the key knowledge gaps related to the here discussed research themes. Dependencies on, and dependencies of other knowledge gaps are shown in Figure 3. This figure also shows the large number of gaps that may need to be filled to attribute observed regime shifts to environmental changes. When it is difficult to do attribution (e.g. because there are many drivers of change) direct monitoring of resilience indicators might be a particularly important alternative.

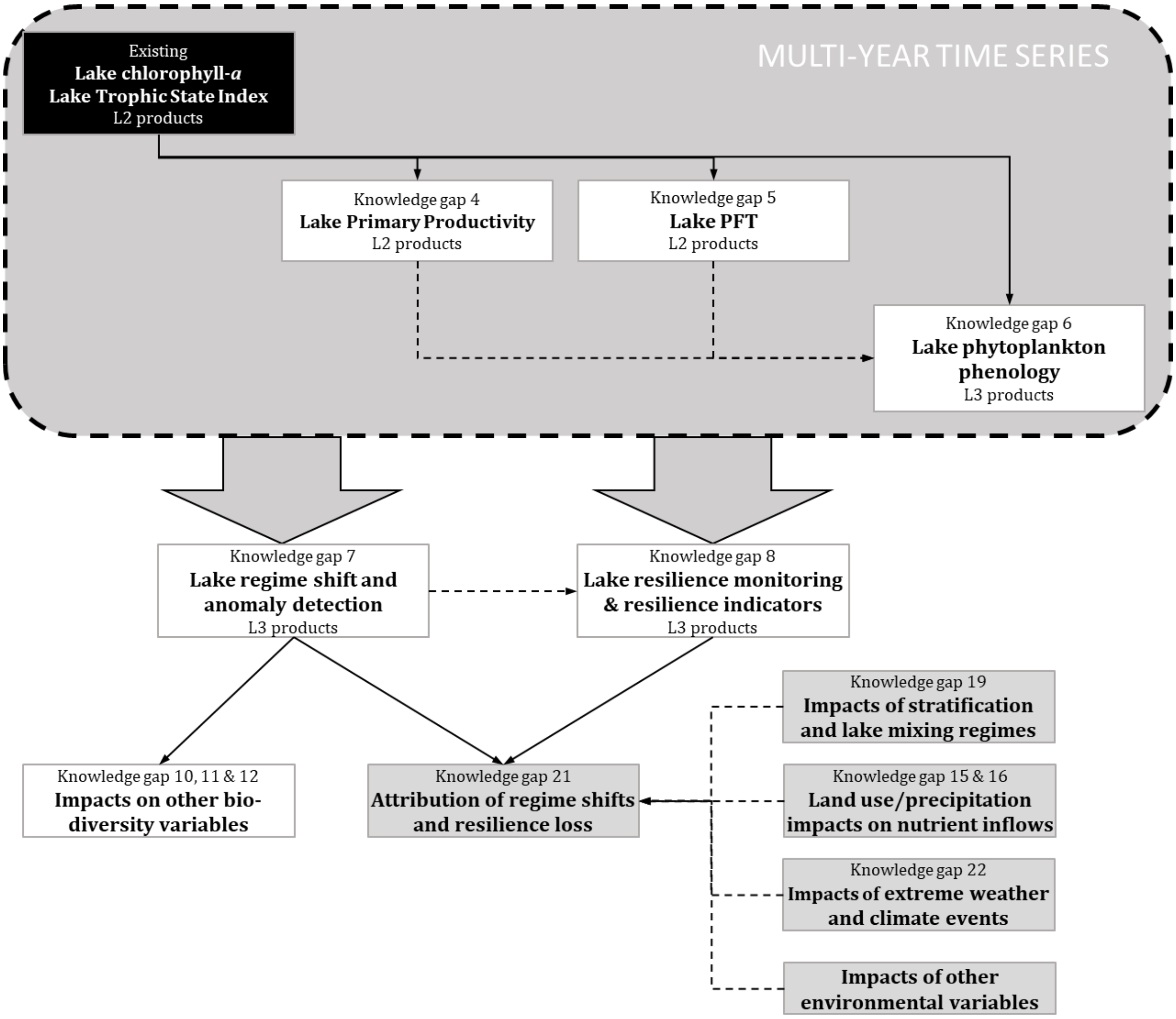

Figure 3: Hierarchy of knowledge gaps related to lake regime shifts, anomaly detection, and resilience monitoring. Existing variables are shown in black boxes, ecosystem functioning knowledge gaps are shown in white boxes, and knowledge gaps linking ecosystem to environmental variables are shown in grey. For more detail, see BIOMONDO Science Agenda, (Lever et al., 2024)

Studying regime shifts requires knowledge of when and where they may have happened which requires data preparation (e.g. gap filling) and decomposition of time series in seasonal, trend, and residual components. A wide variety of methods exist to do this (Bathiany et al., 2024). One of the most commonly applied methods when using satellite data is BFAST (Verbesselt et al., 2010) and the more recent BEAST (Zhao et al., 2019), although the most appropriate method depends on the nature of the data. This, in turn, allows for the detection of so-called 'change points', i.e. where a sudden change in the statistical properties of a time series occurs. To do this, classical change-point detection algorithms are increasingly often combined with supervised classification models to filter out false positives (Bathiany et al., 2024). Following earlier work on case studies (e.g., Gsell et al., 2016), a first global dataset of regime shifts, trends, and variability in lakes was produced by Gilarranz et al. (2022). This dataset can, however, be extended to include more recent years (e.g. using OLCI data, the current dataset uses MERIS only), to include more lakes, and to use other time series data (e.g., chl-*a* estimates, instead of TSI, and other spatial or temporal resolutions). When knowledge gaps related to Lake PP and PFT have been addressed primary productivity and PFT time series may be good candidates as well.

Anomaly detection is typically used to study 'disturbance regimes' in their own right and are often characterized by their size (i.e. the area affected), frequency, and the 'severity' of the anomaly (Senf and Seidl, 2021). It is expected that the values of these anomaly metrics will increase as the frequency and severity of extreme climatic events escalates. There is a wide variety of anomaly detection algorithms available (e.g. k-nearest neighbours mean distance, kernel density estimates, a recurrence approach, and ensemble approaches that combine them). For the detection of anomalies, the method to extract the key features (e.g. the seasonal, trend, and residual components as discussed above) may, however, be more important than the specific anomaly detection method chosen (Flach et al., 2017). (Changes in) anomalies can be studied for all the aforementioned time series as well as for metrics of phenology (after addressing knowledge gaps for lake phytoplankton phenology).

There is a rapid increase in studies that use of EO to monitor changes in the resilience of terrestrial ecosystems (e.g., Forzieri et al., 2022). For lakes, similar studies rely mostly on in-situ data (Carpenter et al., 2011; Gsell et al., 2016), with few exceptions that use EO (Gilarranz et al., 2022). Extracting resilience indicators from lake phytoplankton time series thus constitutes an important opportunity. To validate obtained results, known cases with and without regime shifts may be used. It might be more challenging to extract classical indicators of resilience (e.g., as in Scheffer et al., 2009) for lakes, because the seasonal dynamics of lakes are more complicated than those on land. Existing methods might therefore need to be updated to take this into account. Alternative methods could also involve the development of a metric of recovery after anomalies, or machine learning approaches (e.g., as in Bury et al., 2021), to close this gap.

2.5 Predicting responses of biodiversity to climate change

Climate change alters freshwater biodiversity by shifting thermal niches, restructuring communities, reducing cold-adapted species, and promoting warm-affiliated or invasive taxa (Blois et al., 2013; Walther et al., 2002). To understand these responses, we link observed species distributions to environmental gradients and project how these relationships may change under future climates.

Two key scientific gaps need to be addressed: (1) it is unclear how well EO-derived lake variables capture habitat constraints in data-poor regions (Heino et al., 2009) and (2) the ecological signal retained when modelling at genus or family level instead of species level remains poorly tested (Hortal et al., 2015). Combining fish occurrence records with EO-based descriptors provides a consistent basis for evaluating these relationships.

Species Distribution Models (SDMs), such as MaxEnt and Hierarchical Modelling of Species Communities (HMSC), statistically link species occurrences to environmental conditions for estimating habitat suitability and predicting biodiversity change (Royle et al., 2012; Tikhonov et al., 2020). Known relationships between species occurrences and past and current environmental conditions allow us to predict where species may occur in unsampled habitats and to forecast how their distributions may shift under future climate scenarios (Piirainen et al., 2023). Their reliability depends on assumptions about niche stability (Guisan and Thuiller, 2005) dispersal ability, and the adequacy of current occurrence data (Elith and Leathwick, 2009).

We will use presence-only GBIF data to create descriptions of fish habitat preferences. Aggregation to genus or family level will be applied when species-level data are sparse, when taxonomic resolution is unreliable, or when environmental predictors do not support species-level modelling.

Climate projections will then be used to estimate the environmental conditions of CCI lakes, incorporating all relevant biotic and abiotic variables that can be modelled under future climate scenarios, including thermal, optical, hydrological, biogeochemical, and phenological descriptors that structure freshwater habitats.

These variables may be derived from combination of EO-based products, physical lake models, biogeochemical models, and climate model outputs. To ensure that SDM predictors reflect ecologically meaningful habitat dimensions, species-level habitat requirements derived from traits, literature, and occurrence data must be explicitly linked to the EO-based lake descriptors as summarised in Table 1. Together, they allow consistent climate-driven projections for CCI lakes across multiple potential climate scenarios and timeframes.

We can then use the SDM approach to project the distributions of fish genera or families for lakes for which we do not currently have adequate data. Furthermore, we will project species distributions forward in time. Such approaches will also allow predictions of how biodiversity hotspots may move over the landscape under various scenarios of future climate. With a knowledge of species habitat preferences and traits, we can also subset our projections to observe how cold-adapted or stenothermic taxa will be affected by climate, versus, how more generalist (eurytherm) or warm stenothermic taxa will be affected.

The resulting information on shifting hotspots and dispersal corridors will support conservation planning by highlighting areas where connectivity is essential for enabling climate driven range adjustments. This approach allows for coherent and scalable anticipation of freshwater biodiversity responses to climate change.

To support the objectives of CIBER, the scientific requirements can be summarised as follows: (1) environmental predictors must capture the key thermal, hydrological, and biochemical gradients that structure freshwater habitats; (2) occurrence and environmental datasets must be harmonised at spatial and temporal scales relevant for detecting climate-driven ecological change; (3) modelling approaches must quantify uncertainties arising from scenario divergence, data limitations, and model structure; (4) and outputs must support assessments of species-level and community-level responses, including identification of vulnerable taxa, shifts in functional composition, and the movement or loss of biodiversity hotspots.

3 Knowledge gaps and challenges

3.1 Relevance of BIOMONDO knowledge gaps

The BIOMONDO science agenda (Lever et al., 2024) included a review of comprehensive lists of generic biodiversity knowledge gaps presented in the IPBES Global Assessment on biodiversity and ecosystem services (IPBES, 2019) and selected scientific publications (e.g., Harper et al., 2021; Maasri et al., 2022). From these lists, the BIOMONDO project extracted 23 knowledge gaps in aquatic biodiversity research and conservation activities that can be filled using EO data products (Table 2). The expected relevance of these knowledge gaps for CIBER is indicated in the table and further detailed in the subsections. We do not expand on the descriptions of knowledge gaps relevant to wetlands and river deltas, as these are beyond the scope of the lake ecosystems.

Table 2 List of knowledge gaps in the BIOMONDO science agenda and their relevance for the CIBER project. Knowledge gaps considered high priority are highlighted in bold.

No.	Knowledge gap	Relevance in CIBER
Ecosystem structure		
1	Freshwater habitat type and extent	Low
2	River delta extent	None
3	River habitat connectivity	**High**
Ecosystem functioning		
4	Lake net primary productivity	Low
5	Lake phytoplankton taxa	**High**
6	Lake phytoplankton phenology	**High**
7	Regime shift and anomaly detection	**High**
8	Monitoring lake resilience indicators	Low
9	Using EO-derived PP indicators in food web models	None
10	Impacts of phytoplankton phenology on other biodiversity variables	**High**
11	Impacts of net primary productivity on other biodiversity variables	Low
12	Impacts of anomalies in phenology and net primary productivity on other biodiversity variables	**High**
Interlinkages between ecosystem structure and functioning		
13	Monitoring the spread of invasive species	None
Environmental variables		
14	Impacts of hydraulic engineering on sedimentation processes	None
15	Impacts of land use/land cover on nutrient inflows	Low
16	Impacts of watershed precipitation on nutrient inflows	Low
17	Monitoring changes in thermal stratification and lake mixing regimes	**High**
Interlinkages between ecosystem and environmental variables		
18	Attribution of changes in wetland and river delta formation	None
19	Impacts of thermal stratification and lake mixing on PP	**High**
20	Attribution of changes in lake phytoplankton phenology	None

21	Attribution of changes in lake trophic state	None
22	Impacts of extreme weather, e.g. heatwaves and thunderstorms	Low
23	Impact of the hydroperiod of wetlands on biodiversity variables	None

3.1.1 Ecosystem structure

Only a limited level of detail on **freshwater habitat types and their extent** is available at continental scale. Among the criteria considered in the EUNIS habitat classification for standing surface waters, ice cover, water surface extent and trophic status are included as dynamic variables in the Lakes CCI product suite (Figure 4). Static bathymetry is also available for the Lakes CCI water bodies. Other variables, such as salinity or properties of the littoral zone are not available. And while available variables will be considered, CIBER will not contribute to an improved characterization of ecosystem structures as required for the corresponding EBV class. The overall relevance of this knowledge gap in CIBER is thus considered low.

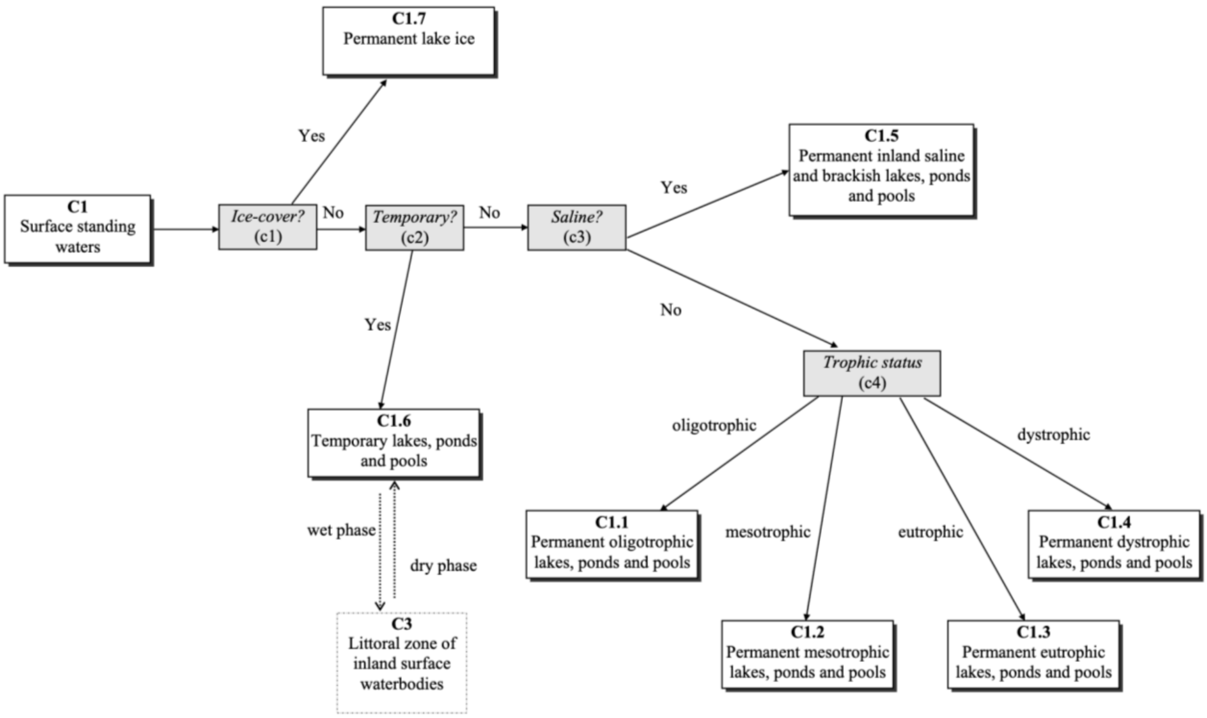

Figure 4: EUNIS habitat classification criteria for 'Surface standing waters' (type "C1"; from Davies et al., 2004). Level C is 'Inland waters', with C2 being 'Surface running waters' and C3 'Littoral zone of inland surface water bodies'.

Monitoring the **extent of river deltas** was considered an important knowledge gap in BIOMONDO, because they are important wetland habitats, and variations in their extent should be attributed to changes in sea level rise, subsidence and changes in river sedimentation. Since CIBER focuses on impacts on lakes rather than wetlands, a dedicated analysis of river deltas is not planned.

River habitat connectivity is a key prerequisite for fish migration, and hence for the main impact variable considered in CIBER. Connectivity is a combined spatial property based on river morphology, the construction of dams and the presence of fish ladders. Various geospatial datasets exist for these individual components. But an aggregated connectivity product is to our knowledge missing, and its feasibility requires dedicated investigations of ancillary data sources. The relevance of this variable for CIBER is considered high, but connectivity data are not available for the whole study region.

3.1.2 Ecosystem functioning

Lake net primary productivity, phytoplankton taxa, phytoplankton phenology are important indicators of the base of the food web in lake ecosystems, and past studies confirmed that they can be estimated from optical EO products. However, lake primary productivity studies are limited to selected lakes (e.g., (Sayers et al., 2020), phytoplankton taxa retrievals focus mostly on separating cyanobacteria and eucaryotes (Odermatt et al., 2018), and a phytoplankton phenology algorithm based on Lake CCI products is still under development. We will make use of these indicators as soon as they become available. The Lake CCI cyanobacteria index and phenology products for chl-*a* and cyanobacteria are expected to be completed during the first year of CIBER, while new primary productivity products are not expected. We consider this missing input as of low relevance, because biomass products (i.e., chl-*a*) are to some extent expected to make up for this gap. The use of new cyanobacteria and phenology products from Lake CCI, however, is an important innovation in CIBER, which is of high relevance both for the scientific objectives of CIBER and for proving their quality and information content.

Monitoring lake resilience indicators and **detecting regime shifts and anomalies** in lake ecosystem is an important component of understanding how climate change impacts fish biodiversity. They are in focus of the ESA RESETlakes project (PI: Eawag), which runs in parallel to CIBER. We thus expect relevant knowledge transfer across the two projects, in particular methods that indicate lake regime shifts and anomalies from Lake CCI products, and we. expect that they will be of high importance to the CIBER project, while lake resilience indicators are less likely to become available for the project, apart from the case where a regime shift indicates. failing resilience.

We do not plan to incorporate food web models into our analysis; thus, we will not **use EO-derived PP indicators in food web models**.

Assessing impacts of remotely sensed variables on other (higher trophic level) biodiversity variables is the main objective of CIBER. We can explicitly assess the **impacts of phytoplankton phenology** with the new CCI phenology products, which makes this knowledge gap highly relevant. Impacts of **net primary productivity (NPP)** can only be investigated based on phytoplankton biomass (chl-*a*) as a surrogate, which makes NPP as an explicit variable less relevant. Using our link to the RESETlakes project, we hope to be able to incorporate downstream products on **trends and anomalies in chl-a phenology** in our analyses of fish biodiversity, which gives it a potentially high relevance for CIBER. Decadal trends of the earlier emergence of seasonal blooms can be extracted directly from the phenology products, anomalies are deviations from these trends that can be associated to causes such as, e.g., preceding winters with anomalous mixing behaviour or lake ice cover.

3.1.3 Interlinkages between ecosystem structure and functioning

CIBER does not focus on invasive species specifically, and the expected taxonomic resolution of the habitat templates is at the genus or family level. However, the resilience of habitat templates of co-occurring fish taxa (e.g. one native and one invasive) under climate scenarios may inform the relative **spread of invasive species**. However, this would only provide a modelled estimate, not monitoring data. We hence don't consider this knowledge gap relevant for the satellite data analyses in CIBER.

3.1.4 Environmental variables

While the CIBER project will consider the turbidity and connectivity of lake ecosystems, we do not expect to directly address the **impacts of hydraulic engineering on sedimentation processes.**

We anticipate that we will use EO-derived land cover and watershed meteorologic conditions as inputs into the fish habitat template models. We include these as inputs because of the expected **impacts of land use/land cover, watershed precipitation on nutrient inflows.** However, we will not directly connect these basin characteristics with nutrient inflows, so this knowledge gap is of low importance.

Thermal stratification and lake mixing are important indicators of fish habitat suitability, which is why 1D lake model simulations will be performed alongside the use of new lake stratification information compiled from Lake CCI LSWT products (Calamita et al., submitted). Therefore, we have ideal prerequisites to incorporate **changes in thermal stratification and lake mixing regimes** in our analyses, and we consider this a highly relevant knowledge gap for CIBER.

3.1.5 Interlinkages between ecosystem and environmental variables

Thermal stratification is an important environmental variable in fish habitat suitability for several reasons. One reason is the **impacts of thermal stratification and lake mixing on phytoplankton growth**, a key part of the lake food web. We expect better understanding of the connection between phytoplankton growth and thermal stratification to be highly relevant to the CIBER project.

We anticipate that **assessment of the impacts of extreme weather and climate events on biodiversity variables** will be of low importance to the CIBER project. While these events can produce anomalies in lake ecosystems, we do not focus on the connection between lake ecosystem variables and meteorological events.

CIBER focuses on the relationship between remotely sensed habitat properties and fish taxa distribution, without investigating why habitat properties may change. The **attribution of reasons for changing wetland and river delta formation, changes in phytoplankton phenology or lake tropic state** are thus out of the scope of CIBER.

3.2 Other knowledge gaps

To our understanding, the BIOMONDO Science Roadmap presents a comprehensive assessment of knowledge gaps in remote sensing of freshwater biodiversity. As the project develops, we will complement this assessment with knowledge gaps in remote sensing for freshwater fish for the release of version 2 of this document.

3.3 Contributions by CIBER and expected challenges

3.3.1 Knowledge gaps to be addressed

Building on the knowledge gaps described in BIOMONDO, we have identified the knowledge gaps that we expect to address in the CIBER project ("high relevance" in Table 2). Distilled into three overarching categories, the knowledge gaps we plan to address relate to:

- thermal stratification,
- NPP/phytoplankton impacts on other biodiversity variables, and
- resilience, regime shift, and anomaly detection.

Advancements in monitoring of changes in thermal stratification and lake mixing regimes were achieved by Calamita et al. (submitted), who evaluated the stratification stability using CCI Lakes data and the thermal bar method (Fichot et al., 2019) and identified anomalies in the mixing behaviour of more than 600 dimictic lakes. Furthermore, we will compile our own 1D lake model simulations in CIBER, which provide even more detail on vertical temperature gradients, and the capacity to simulate these gradients for different climate change scenarios (see section 2.5). These new data sources contribute to the detection of regime shifts and anomalies in lakes, and they allow the assessment of impacts of thermal stratification on lake mixing and primary production. Thus, there has been significant progress in addressing these knowledge gaps, which CIBER can build on and confirm the benefits of.

Assessing the impacts of remotely sensed variables on biodiversity variables is the main objective of CIBER, using fish counts and diversity as the key impact variable. With most remotely sensed variables (phytoplankton and cyanobacteria biomass, phenology, lake stratification) being available, our research will largely focus on how they can be statistically related to GBIF data, and in this way improve our understanding of how basic physical and food web variables relate to higher trophic levels. With a comprehensive analysis of the biotic and abiotic variables impacting fish biodiversity, we expect to improve our understanding of resilience indicators in lake ecosystems. Connected to assessing resilience, we expect to apply regime shift and anomaly detection algorithms to phytoplankton time series and other variables that influence fish habitability. In this category of knowledge gaps, CIBER relies largely on the collaboration with the parallel ESA project RESETlakes.

3.3.2 Challenges

Our review of BIOMONDO knowledge gaps also revealed some gaps that we may not be able to account for in the CIBER project. It is uncertain if we can account for the impacts of river connectivity and invasive species on the lakes' fish communities with our habitat models. We are currently not aware of suitable global data sources, but might find case studies, e.g., on lakes that have a lot of revitalised rivers in their catchment, or lakes that are affected by a recent colonisation by benthic mussels. However, it currently seems that a systematic assessment of these impact variables is currently not feasible.

4 Data, models and methods for CIBER

To address the knowledge gaps and scientific requirements of the CIBER project, we will develop freshwater fish habitat templates using environmental variables from available data sources. In our context, the term "habitat template" refers to a quantitative description of the physical and chemical environment and additional lake variables (e.g. depth) that define the habitable environmental space of a given species or a species group (Southwood, 1977; Suren and Ormerod, 1998). For definition of freshwater fish habitat templates, existing literature and extractions from data repositories and scientific data bases will be used to access information on species' habitat requirements and geographical occurrences of fish species at the global scale. These data sources and further literature extractions identified provide the data basis for the identification of habitat requirements at high taxonomic resolution. These can be used as a basis for fish habitat template characterisations and corresponding species occurrence models.

Three data sources will generate the required information for specification of the habitat templates and habitat requirements:

A. Species Occurrence: Data on fish species in individual lakes as recorded in biodiversity data bases.
B. Lake habitat descriptors: Characterisation of the physical, chemical, biological, (hydrological,) and morphological properties of lakes in the target region derived from satellite-based EO, large scale data bases, and mechanistic models.
C. Trait-based species characterisation: Characterisation of the physiologically derived environmental preferences as provided by trait-oriented data bases.

The data sources for these three approaches, which will be explored simultaneously and in parallel, are provided in Table 3. The table is not exhaustive, and additional sources might be added.

When evaluating the overall data availability two workflow paths can be employed. First, by combining A and B based on individual lakes that appear in both collections, species-specific, i.e. typical, habitat descriptors can be identified for a given species. As soon as this link between species occurrence and lake descriptors is established, the identified transfer function is applicable to any other lake whenever the set of lake habitat descriptors is available. This follows the logic: "tell me the properties of the lake ecosystem and I tell you the species that likely appear". The more generic the identification of lake habitat descriptors is (e.g. by global-scale covering data bases, EO-based data, transferable models), the more applicable the emerging workflow will be.

Second, an alternative approach is to combine B and C in such a sense that the lake habitat descriptors identify a set of species whose physiological preferences fit into the range of lake habitat descriptors. This approach is less reliable simply because not all species whose physiological preferences are fitting necessarily occur in reality. On the other hand, this approach is very powerful to analyse the effects of a changing environment, e.g. by global warming or anthropogenic pollution by nutrients, as biodiversity loss can be predicted based on surpassing physiological thresholds of given species.

Table 3 Data sources supporting generation of habitat templates and habitat requirements.

Approach	Data sources
A	• Global Biodiversity Information Facility (GBIF Database): https://www.gbif.org/ • Freshwater biodiversity data portal, Biofresh-Project, https://data.freshwaterbiodiversity.eu/metadb/ • Worldbank Global Biodiversity Data, https://data360.worldbank.org/en/dataset/WB_GBIOD
B	• LakesCCI-Dataset for lake habitat descriptors like chlorophyll a, turbidity, secchi depth • Hydrolakes database (lake morphometry) • Water temperature dynamics along the vertical axis derived from applying a 1D hydrophysical model (e.g. Simstrat or GLM). Model simulations are either done in CIBER or taken from the ISIMIP lake sector • Oxygen conditions in the deep waters based on the model of Nkwale et al. (2023) using information on trophic state, stratification duration and deep water temperature (derived from the sources above) • Basic meteorological and climatological data (ERA5)
C	• Fwtraits, R-package described in Basooma et al. (2025). FishBase: https://www.fishbase.org

In addition, an extrapolation into future climatic conditions requires the inclusion of climate projections. Foreseen sources for biodiversity data, remote sensing based products and climate datasets are described and discussed in sections 4.1.1-4.1.3.

Appendix A.1 contains a draft work logic diagram in to visualize the connections between the datasets, models, and methods in CIBER.

4.1 Data sources

The definition of data needs and sources will be continuously assessed as the project developments progress. New sources will be added as needed.

4.1.1 Biodiversity data

The Global Biodiversity Information Facility (GBIF) is an online database of species occurrence records. GBIF provides a single portal to download data from a wide variety of regions and study types.

GBIF is the most comprehensive global database of occurrence records, but it is an imperfect data source. The data only assess the *presence* of a species, not the *absence* of a species in a water body. Absence data would allow a more complete picture for statistical analysis of habitat suitability, but absence requires much more exhaustive field methodology than presence. Also, as GBIF is a voluntary collection of studies, it has a nonuniform data distribution across countries and lakes. For example, Metropolitan France alone has more than 100x the data as the IPBES region of Central Asia despite being 0.15x the land area.

We will use the GBIF data in two steps. First, we will create rarefaction curves based on GBIF data to determine the resolution we will work at (taxonomic, spatial). Second, we will use GBIF to determine fish habitat preferences.

In addition to presence data, we will use existing trait data on fish to determine reasonable bounds on data-driven habit templates. We will use trait data and expert opinion to assess, for example, if the suitable water temperature range developed from the species distribution models (see Section 4.3) align with known temperature preferences of a given fish genus.

The FishBase and Freshwater Information Platform (FIP) are well-established, accessible repositories of fish trait data. As these databases are collections of data from many sources, the data are not uniformly distributed across lakes in the study area. We will need to rely on range maps and expert opinion should these databases have insufficient data density.

To assess river connectivity, we will also investigate using existing dam datasets, starting with Global Dam Watch (GDW, GlobalDamWatch.org). This dataset is coordinated with HydroLAKES and has georeferenced metadata on dam construction and intended use.

4.1.2 EO data products

The project will build on a range of operational EO data products and services. The European Space Agency's Climate Change Initiative (ESA CCI) provides a comprehensive suite of Essential Climate Variable (ECV) datasets designed to support climate research and applications (https://climate.esa.int). For this study, the focus is on ECVs that are directly relevant to freshwater ecosystems and fish biodiversity assessments. The Lakes CCI dataset serves as the primary remote sensing data source, offering long-term, globally consistent records of Lake Surface Water Temperature (LSWT), Lake Ice Cover (LIC), and Lake Water Leaving Reflectance (LWLR). These parameters are inputs for monitoring the thermal regime, ice phenology, and optical water quality characteristics of lakes. Derived products such as chlorophyll-a concentrations, turbidity, and harmful algal bloom (HAB) indicators from LWLR further enhance the ecological relevance of these datasets. The ECV products in the ESA CCI suites that we anticipate using and their connection to the science requirements, are identified in Table 4

The ESA CCI ECVs are the scientific foundation but will be complemented with data from Copernicus operational services, such as the Copernicus Land Monitoring Service (CLMS), which offers high-resolution and thematic products on land cover, land use, and specific ecosystems. In particular, the CLMS Riparian Zones product provides valuable spatial information on vegetation structure and dynamics along water bodies in Europe (https://land.copernicus.eu).

Beyond pre-processed ECV and CLMS products, satellite raw data sources, including Sentinel-1 (SAR), Sentinel-2 (optical), Sentinel-3 (ocean and land monitoring), and Landsat-8 will be evaluated for their potential to derive additional variables where required. For these cases, existing algorithms and processing frameworks will be applied to generate additional parameters.

The selection of datasets and data sources will remain adaptive throughout the project. If specific datasets prove to be redundant or unsuitable for the analyses, they will be replaced or neglected. New or emerging EO products may be integrated if they enhance the scientific objectives. This flexible and iterative approach ensures that the data foundation remains current, comprehensive, and fit for purpose.

Table 4: Preliminary list of relevant parameters and identified data sources

Parameter	Data Source (Sec.4)	Processing	Key Metrics	Science Req. (Sec.2)	Knowledge gap (Sec. 3)
Surface water temperature	ESA Lakes CCI (LSWT)	Data access	Range, extreme events	2.1-2.5	3.1.4-5
Deep water temperature	1D lake hydrophysical models simulations	Own processing	Seasonal stratification, thermocline depth, hypolimnion temperatures	2.3	3.1.4
Oxygen	1D lake hydrophysical models simulations and empirical oxygen model	Own processing	End-of-stratification dissolved oxygen concentration, deep water anoxia/hypoxia	2.1, 2.4	3.1.4-5
Turbidity/Transparency	ESA Lakes CCI (Turbidity)	Data access	Mean, range, trends, shifts	2.3	3.1.4-5
Phytoplankton abundance	ESA Lakes CCI v2.1/2.2 (Chlorophyll)	Data access	Mean, range, trends, shifts	2.2	3.1.2
Cyanobacteria abundance	ESA Lakes CCI v2.2 (cyanobacteria index), CyanoAlert (own processing)	Data access, own processing	Mean, range, trends, shifts	2.2	3.1.2
Phenology	BGB phenology algorithm	Own processing	Number, seasonal patterns and spatial extent of blooms	2.2	3.1.2
Bathymetry	Modelling, HydroLAKES	Data access, own processing	Hypsographic curves, structural complexity	2.3	3.1.4
Morphology	CLMS Riparian Zones	Data access	Shoreline complexity	2.3	3.1.1
Zonation/Basins	ESA CCI Land Cover, HydroLAKES, ISIMIP	Data access	Basin land cover types, Lake properties	2.4	3.1.1
Lake ice cover	ESA Lakes CCI (LIC)	Data access	Ice cover duration, seasonal trends	2.1, 2.4	3.1.4

Table 4 contains two different types of input sources. The first type corresponds to operational services. These need to be accessed via their individual interface, and individual preprocessing (subsetting, selection of desired variable, QC, spatial interpolation and remapping) needs to be applied. For cases where there are no operational services available, we can access the satellite data and process the required parameters in the team. It should be noted that it includes easy cases, like water quality parameters from Copernicus satellites. The second type are modelled parameters where interfaces will be implemented to a potential model, or the model output data will be cubed to the properties of the EO data cubes. The modelled data is further discussed in section 4.2.

The project's focus on creating data cubes of various datasets is in alignment with ESA's Earth Observation Science Strategy (European Space Agency, 2024). Those data cubes are essential for developing web tools to allow the public and other researchers to access and query the data compiled for this project.

To complement the lake-specific parameters, several additional CCI ECV datasets can be integrated for cross-variable analysis. Soil Moisture CCI data contributes to understanding wetland and catchment hydrology. River Discharge CCI supports the assessment of hydrological connectivity, freshwater inflows, and the influence of precipitation variability on habitat conditions. High- and medium-resolution Land Cover CCI products will be used to identify land-use changes such as deforestation, urban expansion, and agricultural intensification. Other potential relevant ECVs under consideration include Snow Cover CCI, which informs on seasonal runoff and thermal regimes; Fire CCI, offering information on disturbance events that affect erosion and nutrient cycling; and Vegetation CCI, which provides indicators of riparian and aquatic vegetation.

4.1.3 Climate ensemble projections

The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) is an established framework and international coordinator for climate modelling reanalysis and projections (see https://www.isimip.org/protocol/3/ and Frieler et al. (2024)). ISIMIP3b maintains a data repository and standardized protocol for global bias corrected climate projections using a multi-model ensemble of different GCMs. For ISIMIP3b, these bias-corrected CMIP6 climate forcing data are provided for the following scenarios: pre-industrial, historical, SSP1-RCP2.6, SSP3-RCP7.0 and SSP5-RCP8.5 conditions. Data are available at a 0.5°x0.5°C global grid and at daily time step. The new bias-adjustment has been developed by Stefan Lange and corrects the simulated data towards corrected ERA5 observational data (W5E5). Climate-input data for the climate ensemble projections in CIBER uses these climate forcings, interpolated to the specific location of the lake, as meteorological input for the lake model. Generally, for ISIMIP3b simulations, the lake model outputs produce daily and monthly projections from 2015 through 2100.

For some lakes, the ISIMIP lake sector provides already finished lake model outputs and CIBER has access to lake model projections from multiple models under various climate change scenarios. The overlap between the ISIMIP3-lake sector lakes and the CCI lakes will be a good starting point for the foreseen habitat templates analysis as no additional data processing is required. The model projection variables from these lake sector simulations are thermal stratification status, depth of the thermocline, temperature depth profiles, surface and bottom water temperature, lake ice cover, lake ice thickness, sensible and latent heat fluxes, and light extinction coefficient.

4.2 Lake models

We will complement the extensive number of datasets in the project with data from hydrodynamic 1D lake models. The 1D lake models will be used to generate more data on environmental conditions within lakes in the study region. We then use the EO products, model outputs, and fish presence data as the inputs into habitat suitability models (Figure 5 and Appendix A.1). With the habitat templates generated, we then assess changes in habitat suitability under climate projection inputs.

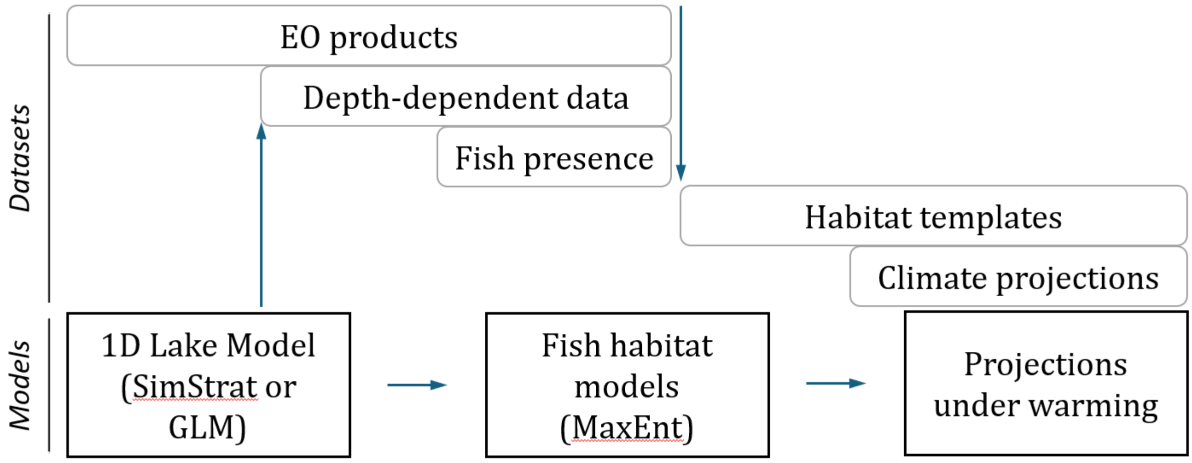

Figure 5: Overview of the models and datasets used for the project.

To augment the EO data products, we will use a 1-dimensional (1-D) hydrodynamic lake model. The project team has extensive experience with two existing models: Simstrat (at Eawag) and GLM (at UFZ). These 1-D models estimate the thermal structure of lakes at high temporal resolution. By capturing the vertical profiles of lakes, we can model difficult-to-observe variables relevant to fish habitat suitability, including dissolved oxygen and deep-water temperature (Table 4). The lake models not only extend current information on biodiversity indices but also provide projections of future climate impacts based on climate projections from the IPCC.

We use 1-D models for this project, as they provide an important balance between accessibility and accuracy (Gaudard et al., 2019). Using bathymetry data from HydroLAKES, we can capture structural complexity of lakes, without the computational intensity of a full 3-D simulation. This computational efficiency makes 1-D models well-suited for long-term analysis and for coupling with biological and water quality simulations (Gaudard et al., 2019). In this context, however, 1D physical models are highly appropriate because (1) the required input data can be provided from data bases and remote sensing, (2) they are fast and easy to apply, (3) they provide data that are relevant to fish but cannot be measured by satellites (temperature gradients, mixing regime, hypolimnion temperature), (4) they were proven to be transferable among different lakes (Bruce et al., 2018), and (5) their output can be used as proxy for further decisive lake characteristics (e.g. oxygen status). Using bathymetry data from HydroLAKES, we can capture structural complexity of lakes, without the computational intensity of a full 3-D simulation.

The Simstrat physical model has four classes of inputs (similar to GLM):

(1) Morphology – the area-elevation (hypsographic) curve derived from HydroLAKES

(2) Meteorological forcings – atmospheric conditions at the lake surface (wind speed, air temp, vapor pressure, cloud cover). Multiple forcing input combinations available. These inputs can be ERA5 reanalysis or climate projections.
(3) Hydrologic flows – inflow and outflow quantities, inflow temperature and salinity. Data source not yet determined. Global, dynamic discharge estimates are provided by ISIMIP2-data but for most lakes a simplified assumption is sufficient (e.g. assuming average, constant inflows/outflows or even assuming no inflow/outflow).
(4) Light attenuation – implemented as a function of time and depth. This variable couples with the biogeochemical module of the model or can be approximated by transparency, which is retrieved by satellites.

Simstrat has parameters such as 'UserDefinedWaterAlbedo' where EO data products can improve model accuracy.

In addition to the physical model, Simstrat and GLM can be coupled to the AED2 biogeochemical model which models dissolved oxygen, phytoplankton populations, and organic matter. These model outputs provide a useful validation (phytoplankton and CDOM) and extension (DO) of EO data products, but its application goes beyond the scope of this project and cannot be run for all CCI lakes. For oxygen, however, simplified empirical models can be linked to the 1D model outputs, e.g. the approach from Nkwalale et al. (2023).

4.3 Methods

Before development of habitat suitability models, we will first use rarefaction curves to assess the biodiversity data availability in the different lakes within the study area. Rarefaction curves indicate how well the samples taken represent the underlying diversity of an ecosystem (Hsieh et al., 2016). For example, Figure 6 shows the rarefaction curve for Bodensee in Bavaria, Germany. The in-situ samples in this lake have likely captured approximately 82% of the fish species present.

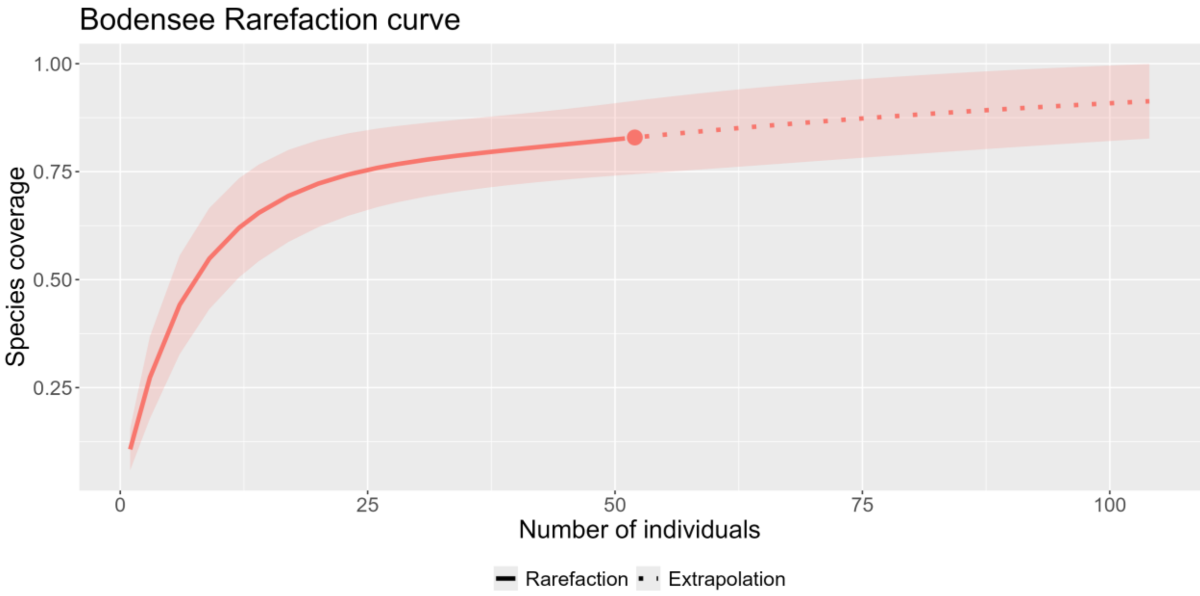

Figure 6: Rarefaction curve of GBIF fish occurrences for Bodensee, Germany.

An important preanalytical step for the evaluation of species occurrence data from data bases is the balance between taxonomic resolution and the sampling effort by rarefaction analysis. This is required because the observation of species depends on the sampling efforts. Since the entries in the databases are heterogeneous with respect to the underlying sampling intensity, a balancing by rarefaction is required. With these rarefaction curves, we will determine the taxonomic resolution for our analyses and rank lakes by sampling saturation.

To assess fish habitat suitability, we will use the MaxEnt algorithm to create species distribution models (SDMs) (Merow et al., 2013). These are also called environmental niche models and model habitat range at any taxonomic level, not just at the species level.

Many algorithms exist to calculate SDMs based on data-driven statistical or machine learning approaches. We will use the MaxEnt algorithm, which is based on machine, is established and accurate. Importantly, MaxEnt takes presence-only data as an input, the type of data available on GBIF. MaxEnt also takes gridded environmental variables as inputs, which is well-suited to the EO and model data products.

An initial data analysis may be complemented by standard multivariate statistics like cluster analysis, factor analysis or CCA.

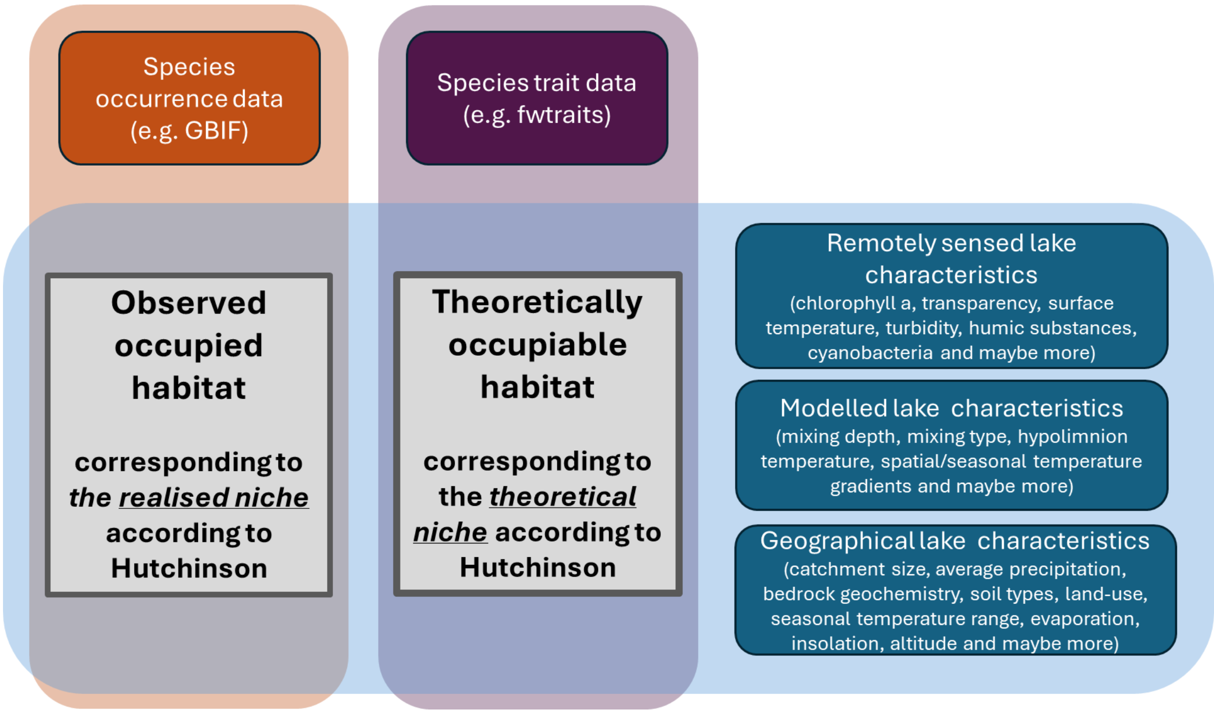

Figure 7. A conceptual plot for identifying the fundamental/theoretical ecological niche of given species based on the available data.

5 Conclusions

The conclusions from the review analysis, including main findings and the intended contribution by CIBER related to the identified knowledge gaps and scientific challenges, are summarized below.

Biodiversity and climate change are deeply intertwined. Climate change impacts freshwater ecosystems by altering thermal niches, community structures, and species presence and distributions. At the same time, the current biodiversity status of a given ecosystem is influencing its sensitivity to climatic changes. Direct global monitoring of freshwater biodiversity is challenging due to the complexity of ecosystems and the need for proxies to assess environmental conditions and biodiversity trends.

Key knowledge gaps include understanding the impacts of thermal stratification, net primary productivity (NPP), and phytoplankton phenology on fish biodiversity. There is also a need for improved methods to detect regime shifts, anomalies, and resilience indicators in freshwater ecosystems. Distilled into three overarching categories, the knowledge gaps we plan to address relate to:

- thermal stratification,
- NPP and phytoplankton impacts on other biodiversity variables, and
- resilience, regime shift, and anomaly detection.

EO techniques, and particularly satellite remote sensing, are critical for monitoring freshwater ecosystems. They provide scalable, consistent, and repeatable data on environmental variables such as lake surface water temperature, chlorophyll-a concentrations, turbidity, and phenology. The requirements analysis identified the need for scalable, transparent, and flexible data and models to support monitoring freshwater biodiversity. It also highlighted the importance of integrating EO-derived parameters with biodiversity models to address knowledge gaps and support decision-making.

In CIBER we will therefore utilize a combination of EO data products, 1D lake models (Simstrat and GLM), data from biodiversity databases (e.g., GBIF, FishBase) and fish habitat modelling (MaxEnt) to develop species distribution models and freshwater fish habitat templates to assess climate-driven changes in habitat suitability. We strive to identify suitable workflows to adopt this integrative approach. For that, we analyse to what extent the existing CCI datasets and products can be used together with the identified models and available in situ fish biodiversity data, for the IPBES region Europe and central Asia, to improve understanding of climate-biodiversity interactions. If not suitable or sufficient, we will investigate how the results can be leveraged with additional own processing of EO data, e.g. for lakes that CCI-ECVs do not cover or where improved spatial resolution or other temporal aggregation is needed. Adaption of models to the additional EO data products and their impact on resulting habitat templates will also be necessary.

In addition, recent advances related to improved monitoring of thermal stratification and mixing regimes in lakes, in combination with our 1D lake model simulations that provide detailed vertical temperature profiles and allow scenario-based simulations under climate change, will enhance the detection of regime shifts and anomalies. This will establish new workflows that combine modelling and EO and will support an assessment of how thermal stratification affects lake mixing and primary production and demonstrate substantial progress in addressing existing knowledge gaps.

Finally, the outcome of the developments and analysis of results should help to determine whether results for additional lakes can be achieved, including variations in regional spatial and seasonal to interannual temporal scales. It should also contribute to understanding remaining parameter needs and what additional environmental predictors are lacking and suggestions for how these needs can be addressed and by what means. Finally, it will also characterise the opportunities and limits of an EO centered approach towards biodiversity in ecosystems.

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A.1 Data and methods overview

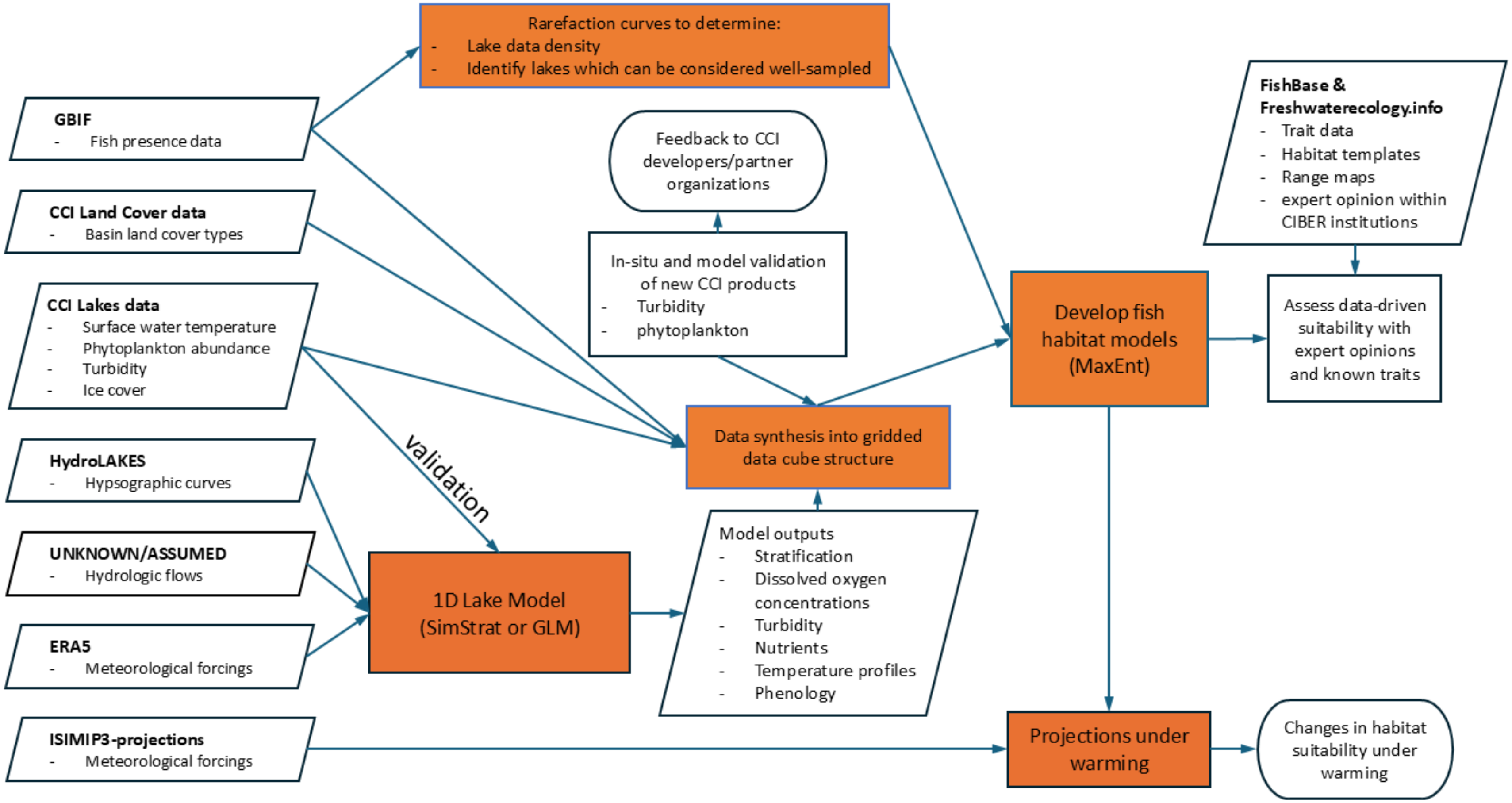

Figure 8 Very draft overview of project workflow with data, models, inputs and outputs.