Desktop Study East Atlantic Flyway

Monitoring of habitats and anthropogenic pressures via remote sensing

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1 INTRODUCTION

The 'East Atlantic flyway' (EAF) is one of the world's most prominently used migratory routes and serves as a critical pathway for a diverse array of avian migrants. Millions of Afro-Palearctic coastal waterbirds, mainly shorebirds (*Charadriiformes*), but also waterfowl (*Anseriformes*), some *Pelecaniformes* (Heron, Egret, Spoonbill, Pelican), flamingos, as well as cormorant and shags (*Phalacrocoracidae*), rely on the EAF for their seasonal journeys, making it a vital conduit for avian movement and migration studies (Boere et al., 2006). Its geographical extent spans from the Arctic in the Northern hemisphere, along the western European and African coasts to the tip of South Africa in the Southern hemisphere.

Since 2014 a flyway-wide simultaneous monitoring is conducted every three years in January, providing estimates for total population numbers. The results are published in a comprehensive report. The latest Flyway report based on the 2020 counts revealed that while a majority of the EAF water-bird populations show favourable long-term trends, 30% showed a long-term and 29% a short-term declining trend (of which 4% were even strongly declining in the short-term) (Schekkerman et al., 2022). Especially species depending on intertidal mudflats for foraging on benthic organisms, and generally many wader species, showed stronger declining tendencies than species relying on other habitats, foraging e.g., on plants or fish (Schekkerman et al., 2022). Also, a spatial pattern of more negative changes further south along the coastal EAF was found.

Staging sites along the flyway may be exposed to a range of pressures, including habitat degradation, pollution, climate change, and potential hazards posed by human activities, such as habitat fragmentation due to urbanization or agriculture (Navedo & Masero, 2007) which may contribute to these negative trends.

Currently, financial and personnel resources are a crucial limiting factor in carrying out ground-based monitoring activities along many parts of the flyway. At the same time the aim is to harmonize the monitoring programme along the flyway and integrate alternative approaches to improve the data quality. Thus, there is a need to review and assess the possibilities for implementing innovative techniques along the flyway. This opens a range of opportunities for monitoring habitats and anthropogenic pressures through novel developments in sensors, platforms and analytical tools, which is addressed within the Project "Innovation for migratory bird monitoring along the East Atlantic Flyway (FLYWAY)".

The overall task of this report is to assess the possibilities and opportunities to apply remote sensing solutions to monitoring of habitats and anthropogenic pressures along the EAF.

Assessment of habitats plays only a minor role in the current monitoring schemes, but some effort has been made to gather some information on the status of important staging sites. The local bird counters and site managers were provided with questionnaires, allowing them to record the situation on site. This approach mainly produces presence/absence data (is a particular habitat or pressure there?) and a scale of intensities (a score to express how strongly certain influences are estimated to affect the status of the local site). Although such reports can be good indicators of a general state or large-scale change of a habitat, their subjective nature and local restraint hinders quantitative analyses. For disentangling global and local effects of the environment on bird populations, data on the global scale of the complete flyway is required. To gain insights into these spatiotemporal dimensions, it is important to gather spatially explicit data, which might be available from some sites (e.g., via specific research projects), but still lacks on the global flyway scale.

In this study, we describe the habitats used by birds on the EAF, the parameters affecting their abundance and how to infer these parameters using remote sensing tools. One promising approach is the utilisation of satellite data, which offers global coverage and extends to poorly accessible areas. We give an overview of available satellite data and data products, indicating their main technical characteristics and limitations (technical overview). Taking the technical specifications and the monitoring demands into account, we will then formulate recommendations that can guide implementation of remote sensing based monitoring of habitats along the flyway.

2 LITERATURE REVIEW

The field of remote sensing is developing quickly, especially for satellite data, with many different types of open access and commercial data available. The need for collecting and assessing information about habitats comes with the challenges of selecting appropriate and relevant metrics as proxies for monitoring parameters of interest (e.g., habitat quality). Building on the information from the questionnaires of the 2020 flyway report, we first review the available scientific literature to extract the key environmental variables to best reflect meaningful proxies. In a next step, we synthesize the outcomings by discussing different remote sensing products (and how to obtain them, including limitations etc.) and link them back to their relevance for the monitoring along the flyway (by pointing out for which habitats/pressures the assessment of these parameters would be useful).

To address the extensive expanse of the East Atlantic Flyway (EAF), we adopt the common partition into six regions: The Arctic region, Northwest Europe, Iberia and North Africa, Gulf of Guinea, West Africa, and Southern Africa. This regional subdivision facilitates a more focused and systematic approach to the study and the conservation of avian migration within the EAF.

2.1 The Arctic

The Arctic plays a vital role as a summer breeding ground facilitating the survival and reproductive success of a diverse range of migratory bird species (Gaston, 2013). In accordance with the Circumpolar Arctic Vegetation Map (CAVM), the Arctic region is categorized into six distinct bioclimatic zones, primarily based on the prevailing vegetation coverage (Walker et al., 2005). However, the escalating impact of climate warming in the High Arctic (Stocker, 2014) is introducing a phenomenon known as 'shrubification', altering the local vegetation significantly (Pearson et al., 2013; Wauchope et al., 2017). Consequences may be shifts in predator-prey dynamics, alterations in the timing of egg-laying and trophic phenology of arthropods, and modifications in the overall habitat suitability for breeding birds (Høye et al., 2007).

Concurrently, the receding ice cover in the High-Arctic presents new opportunities for industrial development and resource extraction. This juxtaposition of avian breeding grounds and burgeoning human activities may induce new human-wildlife conflict(s), as the limited landmass available in the High Arctic intensifies competition for space and resources (Kullerud, 2011).

Icelandic lowlands are particularly affected by threats from expanding agricultural practices, afforestation initiatives, tree planting programs, and land reclamation endeavours aimed at facilitating summer recreational activities, such as the construction of summer cottages (Jóhannesdóttir et al., 2019; Pálsdóttir et al., 2022; Skarphéðinsson et al., 2016). Additionally, the conversion of grassland habitats and the alteration in vegetation structure resulting from afforestation can significantly impact the concealment of bird nests, potentially rendering them more vulnerable to predation.

In summary, monitoring changes in vegetation cover and type (2.7.5), ice cover extent and conversion of grasslands via remote sensing (2.7.5, 2.7.4), can inform about habitat availability for arctic breeders.

2.2 Northwest Europe

2.2.1 The Wadden Sea

Most arctic-breeding waders and waterfowl make stopovers of varying durations within the Wadden Sea, relying on the biomass of benthic macrofauna or availability of seagrass meadows (Bakker et al., 2021; Horn et al., 2021; Kraan et al., 2009; Scheiffarth & Nehls, 1997; Zoffoli et al., 2022). Other species utilise the area to undergo the process of moulting, which extends over a period of two to four months (Boere et al., 2006). However, long-term trends for migratory birds in Wadden Sea are negative for 35% of species, with benthic-feeding species showing less favourable trends on the global flyway scale than on the local scale (Bregnballe et al., 2018; Kleefstra et al., 2022).

Factors including eutrophication, climate change impacts, shellfish fisheries, disruptions linked to tourism, habitat degradation, and shifts in biological communities are likely to collectively contribute to negative population trends in the Wadden Sea ecosystem (Kleefstra et al., 2022; Thorup & Koffijberg, 2016; Van Roomen et al., 2012). As sea levels continue to rise, intertidal mudflats face submersion and erosion, potentially reducing available foraging habitats for migratory populations (Huismans et al., 2022; Wang et al., 2018).

As a popular recreational destination, human leisure activities in the Wadden Sea promote contentious interactions with avian species during their stopovers (Clausen & Bregnballe, 2022; Laursen et al., 2016). Additionally, disruptions to roosting habitats have been documented (see also Crowe et al., 2022, Chapter 3 Flyway report), significantly influencing avian foraging behaviour even when suitable foraging areas are in proximity, as discussed in the study by Horn et al. (2021).

Mapping the extent and types of intertidal mudflat habitats (including seagrass meadows) via remote sensing can inform about available foraging grounds for differently specialised shorebirds and how their main staging sites might be affected by e.g. sea level rise or erosion (2.7.3).

Investigating options to infer ship activities from remote sensing data could indicate intensities of recreational touristic activities (2.7.7).

2.2.2 France

In Northern France, dynamic coastal areas and specifically intertidal mudflats are predominantly used by migrating birds. Prominent sites are the Seine and Girone estuary as well as Mont Saint Michel Bay. However, as in many European countries, the intertidal wetlands in France have substantially decreased (Beck & Airoldi, 2007). The Gironde estuary, for example, is experiencing a notable reduction in its intertidal wetland areas. Decreased freshwater discharges into the estuary in conjunction with rising sea levels have likely impacted the local hydrosedimentary processes, facilitating habitat loss (Raphaël Musseau et al., 2017). The results of the 2020 questionnaires further report that coastal developments and defence pose negative impacts on soft-sediment wetland habitats (Crowe et al., 2022, Chapter 3 Flyway report).

Rice fields have been posited as a prospective alternative to natural wetlands, as they have been reported to be used by waders, herons, egrets and storks (Lourenço & Piersma, 2008). However, investigations in regions such as the Rhône River delta have revealed that these rice fields exhibit diminished biodiversity and a reduced level of species richness when compared to their natural wetland counterparts (Antón-Tello et al., 2021; Tourenq et al., 2001, 2003).

Salt pans are known to be used as foraging habitats by several waterbird species in Europe and across the globe (e.g., flamingos, waders) (Béchet et al., 2009, 2012; Green et al., 2015; Pedro & Ramos, 2009). The abandonment and thus absence of water management practices and artificial flooding can impact the suitability of these habitat for accommodating waterbirds (Béchet et al., 2009).

Furthermore, human activities, notably tourism and hunting, introduce additional disruptions (Eybert et al., 2003; Poirier Clément et al., 2023; Reise et al., 2023; Rolet et al., 2015).

Remote sensing monitoring of intertidal habitats, including sediment type, can inform about the status of the sites used by birds migrating along the EAF (2.7.3). Additionally, remote sensing can be used to infer (seasonal) availability of natural (estuaries) and artificial wetlands (rice fields and salt pans) (2.7.2, 2.7.6).

2.3 Iberia and North Africa

2.3.1 Iberia

Wetlands within the Iberian Peninsula, both of natural and anthropogenic origin, are recognized for their capacity to support a diverse array of migratory avian species, like waders, herons, egrets and storks (Lourenço & Piersma, 2008) as well as for their role in facilitating the mating and pairing processes of Anatidae (Parejo et al., 2015). The decrease in wader populations within the Iberian wetlands can primarily be attributed to anthropogenic influences, particularly the alteration of land use, a trend that is observable in various migratory bird flyways (Green et al., 2015). However, waterbirds, like waders, herons, egrets and storks do benefit from the secondary use of rice paddies in Iberia (Longoni, 2010; Lourenço & Piersma, 2008). These agricultural landscapes can be beneficial secondary habitats as the water extraction compounded with droughts in important protected areas such as Doñana in Spain limit both the feeding and roosting grounds for these birds (Camacho et al., 2022; Santamaría & Martin-Ortega, 2023). Even so, the limited productivity of rice fields restricts their utilisation by species that depend on wetlands (Antón-Tello et al., 2021; Sánchez-Guzmán et al., 2007).

The increasing abandonment of artisanal saltpans has resulted in proliferation of vegetation within the ponds, thereby rendering them unsuitable for utilization by both wintering and breeding waders (Herbert et al., 2018). The partial conversion of these saltpans into aquaculture ponds has led to an increase in their depth, posing a significant challenge, particularly for short-legged waders, which typically rely on these areas as roosting and foraging sites (Catry et al., 2011; João R. Belo et al., 2023; Pedro & Ramos, 2009).

In summary, monitoring natural wetlands (e.g. Doñana in Spain or Tagus estuary in Portugal) but also their artificial alternatives (rice fields and salt pans) via remote sensing, will allow to assess habitat availability throughout the Iberian Peninsula, which serves as an important stepping stone for migrants crossing the Mediterranean and the Sahara (Deboelpaep et al., 2022) (2.7.2, 2.7.6). Monitoring the expansion of greenhouses, often used for strawberry cultivation, may indicate the illegal extraction of water from natural wetlands, particularly in the vicinity of the Doñana National Park (Bosque, n.d.; Loch et al., 2020; Tittarelli et al., 2017) (2.7.6, 2.7.4).

2.3.2 North Africa

In Northwest Africa, the EAF extends along Morocco, Algeria, and Tunisia. These countries and their regional wetlands act as a stopover sites for birds crossing the Mediterranean or the Sahara, especially for birds migrating further south to compensate for energy loss (Deboelpaep et al., 2022; Vansteelant et al., 2017). Whenever the conditions are suitable, they may even overwinter (Draidi et al., 2023). Unfortunately, historical records indicate a concerning trend where approximately half of these wetland habitats were lost by the beginning of the 20th century (Perennou et al., 2012). In addition, impacts from pollution (littering and agricultural sources) and water extraction are thought to affect the local wetland ecosystems (Ayaichia et al., 2018; Crowe et al., 2022; Farrah Samraoui et al., 2011; Squalli et al., 2022). This decline, if it persists, could act as a spatial constraint for migrating bird populations, as they are critical stopover points along avian migration routes facilitating connectivity of the EAF (Aouadi et al., 2021; Deboelpaep et al., 2022).

Besides, local observers reported direct negative impacts of recreational tourism and poaching in the latest flyway assessment (Crowe et al., 2022).

Because of logistic demands, lack of funding and technical support, habitat monitoring along this part of the flyway is limited to irregular observation efforts of bird abundances (Van Roomen et al., 2022), therefore using remote sensing tools can help to fill the knowledge gaps. Assessing the extent and seasonality of the local wetland areas can help to manage and protect these important sites (2.7.2).

2.4 West Africa

The Banc D'Arguin National Park, located in Mauretania, is one of the key staging sites along the EAF (Deboelpaep et al., 2022). Its intertidal habitats carry the ecological capacity to support substantial populations of migrating shorebirds and breeding waterbirds, numbering in the millions (Delany et al., 2009; El-Hacen & Kidé, 2022).

Motorised boats are prohibited and fishing practices within the Banc D'Arguin National Park are restricted to artisanal activities from the local Imraguen people (PNBA). As the park is regularly entered illegally by fishers, authorities and fishery committees strive to enforce these restrictions by surveilling the marine areas of the park collaboratively. However, commercial fisheries outside of the park's borders target the international shark and ray market and pose a threat to these species, potentially leading to alterations in the local macrozoobenthic communities (www.ramsar.org).

Ongoing impacts of climate change likely exacerbate these processes, with recurring droughts and dust storms affecting the local seagrass beds either by desiccation or anoxia, further disrupting the macrozoobenthic assemblage (Brodersen et al., 2017; de Fouw et al., 2016; Honkoop et al., 2008).

Consequently, this complex interplay of ecological shifts has cascading effects on the availability of food resources for the shorebirds, culminating in an evident and concerning decline in the overall shorebird population within the Banc D'Arguin National Park as well as the survivability beyond the national park (Nagy et al., 2022; Oudman et al., 2020; van Gils et al., 2013).

In Senegal, natural wetlands, surrounding river deltas and protected natural parks serve as important staging and wintering sites, facilitating the overall migratory connectivity of the EAF (Deboelpaep et al., 2022). However, these sites are affected by conversion into agricultural landscapes, predominantly characterized by rice cultivation (Bos et al., 2006; Crowe et al., 2022; Zwarts et al., 2016). Consequently, the unpredictability of these agricultural runoff areas, in conjunction with the regulatory influence of dam-controlled water management, become discernible factors contributing to the decrease in the recorded waterbird counts (Aissatou Y. Diallo et al., 2023; Coulthard, 2001; Hooijmeijer et al., 2017; Triplet & Yésou, 2000; Zwarts et al., 2023). In the southern region of Senegal's wetlands, sites like Technopôle, Djoudj, and the Saloum Delta, are confronted with a variety of anthropogenic influences. These include the extraction of water resources for agricultural activities, the influx of agricultural runoff and pollutants as well as progressing urbanization (Diop et al., 2023; Sy et al., 2014). Additionally, these areas are considerably impacted by climate change with shifts in precipitation patterns and elevated sea levels perturbing the hydrological dynamics of these wetlands (Aissatou Y. Diallo et al., 2023; Diallo et al., 2019; Diop et al., 2023; Mohamed Ahmed Sidi Cheikh et al., 2023).

In summary, habitats in West Africa are facing a range of anthropogenic pressures that are difficult to quantify. Remote sensing techniques can help to gain a better understanding of the spatial and temporal extent of fishing practices, agricultural conversion and urbanisation (2.7.4, 2.7.6, 2.7.7). Besides, remote sensing monitoring allows for investigations of the key habitats' conditions, investigating for example the extent and changes in types of intertidal habitats or coastal wetlands and river deltas (2.7.2, 2.7.3).

2.5 Gulf of Guinea

The Gulf of Guinea is a critical region for avian migratory species due to its abundance of mangroves, intertidal mudflats and highly productive wetlands created by upwelling currents and river deltas. Migratory birds depend on these stopover habitats and conversion of these habitats to grasslands and sparse woodlands has been identified as a risk factor for non-breeding shorebirds in the Gulf of Guinea (Piro & Schmitz Ornés, 2022; Santos et al., 2023).

In Guinea Bissau, the Bijagós Archipelago is of outstanding importance along the East Atlantic Flyway, as it provides large areas of mangrove forests (ca. 524 km^2) and extensive intertidal mudflats (ca. 450 km^2). Although there is relatively low human disturbance, overexploitation of the shellfish *Senilia senilis* (Bloody Cockle) by the local communities has been reported recently (Henriques, Belo, et al., 2022). Poorly managed tourism could become an additional threat, if associated land use changes and urbanisation are unregulated (Henriques, Belo, et al., 2022). Furthermore, the area is expected to be particularly affected by rising sea levels, because it lies below sea level with no coastal slope (Catarino et al., 2015; Granadeiro et al., 2021; Monteiro et al., 2017; Raimundo Lopes et al., 2022).

Other mangrove ecosystems in the Gulf of Guinea are facing increasing deforestation pressures, primarily stemming from swamp rice farming and commercial forest logging (Crowe et al., 2022). Coastal erosion is a result of such degradations in vegetation cover, compromising numerous essential ecological services, such as providing food, shelter, and nurseries for various fish species (Alves et al., 2020; Andreetta et al., 2016; Fossi Fotsi et al., 2019; Giri et al., 2011; Mbevo Fendoung et al., 2022; Temudo & Cabral, 2017). These challenges are further compounded by the presence of the Nipa palm, *Nypa fruticans*. This invasive species does not only compete with native mangrove trees but also induces modifications in the chemical and physical composition of wetland sediments (Numbere, 2018; Onyena & Sam, 2020).

The coastal habitats face further pressures by oil exploration and extraction, especially in Nigeria and the Congo (Crowe et al., 2022; Onyena & Sam, 2020). Additionally, practices of overfishing top predators, as well as unsustainable industrial fishing along the coast (Kassouri, 2021; Mimbang, 2006), are intensifying the pressures on the intertidal mudflats' trophic levels and, consequently, the available prey items for shorebirds (Leeney & Poncelet, 2015; Leurs et al., 2021).

Habitats along the Gulf of Guinea are exposed to a diverse range of pressures. Monitoring the extent and types of available intertidal mudflats (2.7.3), but also wetlands (2.7.2) and mangroves (2.7.5) can inform about general habitat availability for migrating and wintering shorebirds. Changes in these habitats can inform about pressures like coastal erosion or agricultural conversion (2.7.4, 2.7.6). Additionally, remote sensing methods can be used to explore fishing activities and oil exploitation off the coast (2.7.7, 2.7.8).

2.6 Southern Africa

In Angola, coastal ecosystems range from mangroves in the North to arid zones in the South. Prevailing unregulated urban development has become a major driver of the destruction of the country's coastal habitats (Crowe et al. 2022, Singh 2019). Moreover, accumulating plastic waste and industrial pollution disrupt the foraging and resting grounds of the flyway species that depend on these areas for sustenance (Kirkman & Nsingi, 2019; Simmons et al., 2006; Tarr et al., 2007).

Namibia most important coastal wetlands are Walvis Bay (wetland and intertidal areas), Sandwich Harbour (lagoon), and Orange River Mouth (estuary). Walvis Bay is currently grappling with the effects of urbanization and ongoing housing development projects, which threaten its natural habitat and biodiversity (Crowe et al., 2022). Similarly, Sandwich Harbour is dealing with disturbances caused by tourism activities, including low-flying tourist planes and quad biking (Crowe et al., 2022; Garcia Moreno et al., 2019). While human activities are restricted in the National Park of Orange River Mouth, diamond mining, irrigation and large-scale water abstraction strongly influence the surrounding areas (Ramsar Site Information Service, rsis.ramsar.org).

In South Africa, intra-African migrant and Palearctic waders have experienced a decline, which appears to occur even in protected areas (Delany et al., 2009; Ryan, 2013). Coastal habitats face the dual threats of accelerated sea-level rise and human-driven development, including the construction of storm defences along coastlines. This phenomenon, often referred to as 'coastal squeeze,' endangers coastal waterbird species as their available habitats become increasingly limited (Doody, 2004; Silva et al., 2020; Torio & Chmura, 2013).

Remote sensing methods can help to quantify the extent of land conversion affecting the wetlands of Southern Africa, especially as this region of the EAF extends over a large geographical range (2.7.2). Particularly the pressure of urbanisation can be investigated by satellite data (2.7.4).

2.7 Satellite Remote Sensing Applications

2.7.1 Introduction to Satellite Remote Sensing

Earth Observation (EO) satellites are used to gather Earth's characteristics to infer weather data, environmental monitoring and mapping from space and have a range of applications (e.g. forestry, ecosystem services, agriculture, geology) (Zhao et al., 2022) and atmospheres.

They can be divided into geostationary and low earth orbit satellites (polar- and non-polar-orbiting) (https://eos.com/blog/types-of-satellites/). Different sensors can be used for EO. There are active and passive sensors. Active sensors transmit an electromagnetic pulse and detect the signal that is reflected or scattered back. Passive sensors measure the electromagnetic radiation emitted or reflected from the Earth's surface depending on their spectral resolution and coverage (Chuvieco, 2020; Erdle et al., 2011).

The spectral resolution of a sensor describes the width of the spectral bands and thus the ability to resolve features in the electromagnetic spectrum. The spectral coverage defines the area of the electromagnetic spectrum covered by the sensor. A sensor's spectral coverage varies from multispectral (typically two to ten bands, such as RGB with three bands) to hyperspectral (100-1000 spectral bands) (Panteras & Cervone, 2018; Pettorelli, 2019). Since all materials on the Earth's surface absorb incident sunlight differently depending on the wavelength, the recorded reflectance signal is characteristic for each material and can be used to establish classification approaches. (Richards & Jia, 2006).

The spatial resolution of a satellite describes the pixel size of the imagery acquired by a remote sensing sensor. Satellite platforms have fixed pixel sizes for their individual bands. The spatial coverage refers to the area covered and recorded by a sensor (Richards & Jia, 2006). Temporal resolution refers to the time it takes a satellite to pass over the same point on the Earth's surface. Most remote sensing satellites are in sun-synchronous orbit and have a revisit time of about 16 days. However, the temporal resolution may be higher, depending on the field of view and the spatial coverage of the sensor, or in the case of satellite constellations (e.g. WorldView 3, see A.1). Thus, there is a trade-off between the acquisition of high spatial resolution imagery and imagery of high temporal or spectral resolution. Geostationary satellites, on the other hand, have a very high temporal resolution (down to 15 minutes) but a much lower spatial resolution and coverage (Panteras & Cervone, 2018).

Typical sensors for EO are multi-spectral and hyper-spectral sensors (passive), microwave radiometer (active), spaceborne radar (active), and synthetic aperture radar (SAR) (active) as well as lasers (active) (Zhao et al., 2022).

There is a vast number of studies that have investigated satellite remote sensing possibilities of habitat mapping, and more are published to the day, exploring new techniques. Here, we thus aim to focus on the parameters that are most important to the EAF (extracted from the literature review and flyway monitoring results):

- Water coverage and availability of wetlands
- Extent and type of intertidal mudflats
- Land use change
- Vegetation cover and type
- Agriculture and rice fields
- Fishing activities
- Pollution

2.7.2 Water coverage and availability of wetlands

Wetlands are key resting and foraging sites along the EAF, facilitating migration of waterbirds, as they optimally provide predictable annually reoccurring resources (Deboelpaep et al., 2022). For a study of wetland connectivity along different flyways, Deboelpaep et al. (2022) used data on water occurrence from the "Global Surface Water Explorer" (Pekel et al., 2016). At 30 m resolution this tool provides spatially explicit data on different characteristics of the world's surface water, which include occurrence, seasonality (intra-annual variability), recurrence (inter-annual variability) and transitions, taking into account more than three decades of satellite data (currently from 1984 – 2021). Temporally, the resolution is limited to monthly data.

Higher temporal resolution was achieved by Cavallo et al. (2021), who combined open access raw data from Landsat-8 and Sentinel-2 satellites to reduce the effective revisit time. Using the information from the satellites' different spectral bands, they calculated three multispectral indices that are commonly employed for characterising water or vegetation surfaces: Normalised Difference Water Index (NDWI), Modulated NDWI (MNDWI) and Normalised Difference Vegetation Index (NDVI). Combining these indices, four different land cover classes were obtained by employing a rule-based classification. The classification results were validated by VHR-satellite imagery and ground-based surveys. This approach allowed for a representation of a wetlands water extent and how the available open water decreased over the course of a winter month, providing spatiotemporal features that could be linked with bird counts.

Doña Monzo et al. (2021) used Landsat-7 and Sentinel-2 imagery with the use of genetic programming algorithms to improve the quality of the spatial and the temporal resolution of temporary and permanent shallow lakes and wetlands.

All studies above use optical data, which is limited by lighting conditions and cloud cover. To extend the amount of usable data and thus potentially further refine the spatiotemporal resolution, there is the possibility to use active satellite sensors. An example is the study of Rapinel et al. (2019), who have used a combination of data and data products from active and passive sensors to derive information about potential, existing and efficient wetlands. The authors utilized LiDAR Digital Terrain Models (DTM) for defining potential wetlands based on topographical characteristics. Existing wetlands were mapped by employing Sentinel-1 (RADAR) and Sentinel-2 (visible and infrared bands) time series to gain land cover information. Using a MODIS time series product (MOD13Q1) for NDVI enabled the investigation of annual primary vegetation production, including aspects such as phenology and carbon flux and thus the assessment of efficient wetlands. These classifications were calibrated and validated with soil and vegetation samples from the study area.

2.7.3 Intertidal mudflats

Intertidal mudflats form essential foraging habitats along the entire flyway, including the three key sites Wadden Sea, Banc D'Arguin and Bejagos Archipelago. They provide resources for migratory species feeding on macrozoobenthos (bivalves, molluscs, worms, crustaceans, small fish, insects) but also for herbivorous species feeding on seagrass (Kraan et al., 2009; Scheiffarth & Nehls, 1997; Zoffoli et al., 2022).

To map the occurrence of intertidal mudflats there is an online tool available "Global Intertidal Change" (https://www.globalintertidalchange.org/about), which provides global information about the presence of intertidal habitats at 30 m resolution. The intertidal habitats are defined as either saltmarshes, mangroves or tidal flats and information on the change in these ecosystems is available over the period 1999 – 2019 (Murray et al., 2019; Murray, Phinn, et al., 2022; Murray, Worthington, et al., 2022). While intertidal mudflats are suffering from losses by land reclamation or rising sea levels globally, on the local scale the habitat's dynamics can facilitate sediment accumulation or redistribution that may counteract negative environmental changes (Murray, Worthington, et al., 2022). Using the global dataset that is the foundation of Global Intertidal Change, Murray, Worthington, et al. (2022) modelled the global spatiotemporal distribution of intertidal habitats and assessed the timing of losses, gains and their drivers between 1999 and 2019. Their results indicate global losses of intertidal wetlands of approx. 13,700 km^2, but also gains of around 9,700 km^2 over the complete study period, emphasizing that satellite remote sensing is a viable tool for monitoring the occurrence of these habitats on a global scale.

Although these historical data can offer valuable insights into the development of intertidal habitats and the causes of habitat losses in the past, it can be important to also map the topography of intertidal mudflats to learn about their potential vulnerability to erosion and flooding by sea-level rise in the future. Mapping topography of mudflats accurately remains challenging due to the habitat's frequent water coverage. Passive remote-sensing sensors struggle whenever there is a water layer, as water absorbs a big part of the electromagnetic radiation (especially in the infrared) instead of reflecting it. Active sensors like LiDAR are promising but limited in their ability to penetrate turbid waters and not always easily available for some parts of the world. Digital Elevation Models (DEMs) can be utilised for assessing not only vulnerability of intertidal mudflats, but also estimating their exposure periods.

Several studies have employed the so called "waterline method" to infer DEMs, assuming that the extent of water at different times can indicate topographic contours, e.g., using Synthetic Aperture Radar (SAR) or multispectral instruments (e.g., Sentinel-2 sensors) (see also Granadeiro et al., 2021). However, this method requires precise information on the height of the water at the specific time of image acquisition and thus problematic to implement for remote areas where gauges for determining water height are scarce. Granadeiro et al. (2021) further developed and refined a DEM and produced a detailed (10m resolution) map of exposure periods for the Bijagós Archipelago in Guinea-Bissau, aiming to improve DEMs in areas without tide gauges and thus minimize geographical bias in water level estimations. The use of Sentinel-2 imageries to retrieve NDWI maps, contributes to an accurate identification of intertidal areas. A Generalized Additive Model (GAM) was employed to estimate time differences in tidal stage for intertidal pixels. While primarily using Sentinel-2, the study suggests the potential of Landsat-8 for correcting tide-phase differences and enhancing intertidal DEM accuracy due to its extensive coverage (170 x 185 km) when the scenes are processed with the same methodological refinement and calibration.

Besides topography and mudflat extent, the intertidal habitat type is of interest, because it can be linked to prey availability and indicates suitability of foraging sites for birds along the EAF. Dube (2012) demonstrated that it is possible to map sediment properties from coarse-to-medium resolution satellite imagery, using ASTER (15m), Landsat TM5 (30m) and MERIS (300m) data. The spectral reflectance of sandy sediments differs from that of clay sediments, because it correlates with moisture content and grain size, allowing for classification of sandy and muddy sediment types (Fairley et al., 2018).

Henriques, Catry, et al. (2022) aimed to map different habitat types in the Bijagós Archipelago, combining data from active (SAR from Sentinel-1) and passive (multispectral from Sentinel-2) remote sensing sensors along with a DEM of the area. Using pixel-level random forest machine learning algorithms, they were able to classify rocks, shell beds and macroalgae as well as differentiate between bare sediment and fiddler crab areas. It was even possible to further distinguish sandy and mixed sediments (according to mud content) within the bare sediment category. The overall accuracy achieved with the final random forest model was 81%, and at least 70% accuracy were reported for most habitat types at the class level. Algorithms were trained and validated with extensive data from the field.

Lathrop et al. (2022) combined multispectral data from Landsat 8 with Sentinel-1 SAR backscatter and found data features of sand and mud sediments to represent opposite ends of a continuous gradient in feature space. Using spectral unmixing techniques via Google Earth Engine, the authors were able to map a range of sediment classes along the sandy – muddy gradient (i.e., sand, muddy sand, sandy mud, mud), even achieving an overall accuracy of 75%.

To map seagrass meadows within the intertidal habitats, the vegetation signal of multispectral optical data can be used. There are service providers offering such data products, mapping the extent and density of seagrass, which has already been employed in a pilot study of a subsection of the German Wadden Sea (Kohlus et al., 2020). Dalby et al. (2023) used multispectral Sentinel-2 imagery to infer distribution and density of seagrass meadows, achieving an overall accuracy of 77% - 85%. (Zoffoli et al., 2022) paired Sentinel-2 data with *in situ* radiometric and biological data (dry biomass) and trained algorithms to map seagrass percentage cover, leaf biomass and characterise seasonal dynamics. They did so with a remaining uncertainty of 14 % that might be due to errors in geolocation and heterogeneity within satellite image pixels (e.g. due to puddles). In a follow-up study Zoffoli et al. (2022) linked seagrass abundance and phenology to census data of Brent geese at a wintering site in France (Bourgneuf Bay). Satellite remote sensing data revealed an increase of density and extent in local seagrass (1985 – 2020) and a strong relationship with geese counts (especially in October and November). To improve the robustness of the training and validation, the authors suggest using UAVs with much higher spatial resolution, to better link remote sensing imagery and *in situ* samples. In fact, Duffy et al. (2017) used a lightweight drone to map intertidal sites and employed different classification methods to investigate local seagrass abundance. They achieved very high spatial resolution of around 4mm/pixel and were able to recognise lugworm mounds (at 43mm/pixel) and cockle shells (at <17mm/pixel). Using UAVs complementary to Satellite imagery can expand the possibilities of generating training and validation data, because it can be acquired for complete sites rather than only a limited number of ground samples. Furthermore, temporal mismatch between satellite image collection and in situ sampling may distort results of such classifications, especially in habitats that undergo regular inundation as is the case for intertidal mudflats (Lathrop et al. 2022). Airborne imagery (like UAV) could help mitigate this problem, as the images could be collected simultaneously to the ground truths.

2.7.4 Land use/cover change

Land use/ land cover change (LULCC) mapping is widely used in remote sensing to describe multi-temporal trends (Treitz & Rogan, 2004). LULCC can be applied by comparing satellite RAW data, principal component analysis (e.g. Tasseled cap with brightness, greenness, and wetness), derived indices (e.g. NDVI, NDWI), machine learning approaches (e.g. using phenology) or post classification results (e.g. vegetation vs. urban areas) (e.g., Alqurashi & Kumar, 2013; Rahman & Mesev, 2019). Using archival satellite data allows trans-decadal changes to be analysed (e.g., Thamaga et al., 2022 analyse land cover change on unprotected wetland ecosystems in South Africa over a period of 36 years (1983–2019)). LULCC can be used for numerous applications, e.g., urbanisation (Addae & Oppelt, 2019), droughts (Rahman & Mesev, 2019), snow/ ice coverage (Jin et al., 2017),changes in wetland (Thamaga et al., 2022) or deforestation (Kouassi et al., 2021).

A ready to use data product is the Copernicus CORINE Land Cover change layer which covers changes between 1990-2000, 2000-2006, 2006-2012 and 2012-2018, however, only for Europe. For a world-wide application the dynamic land cover from Copernicus can be used as an input for a change analysis (https://land.copernicus.eu/en/map-viewer), dating back to 2015 (in 100 m resolution). Alternatively, a global land cover product of ESA's Climate Change Initiative (CCI) is available in 300 m resolution, going back to 1992 (https://maps.elie.ucl.ac.be/CCI/viewer/index.php).

2.7.5 Vegetation cover and type

Information about vegetation cover can be derived from various land cover data products. These can give a good general indication of habitat loss and show long-term trends but are not very sensitive to more subtle changes.

Bellón et al. (2020) investigated landscape changes in Brazilian protected areas and their surroundings ("interface areas"). During their study period, 75% of the assessed vegetation cover had not undergone land cover changes, but had experienced changes in phenology, productivity or structural changes (e.g., homogenization of natural forests). Integrating landscape metrics based on vegetation indices (NDVI), allowed them to take into account spatial and temporal variation of the vegetation. (NDVI data was derived from MODIS time series vegetation data product (high temporal resolution) and Landsat scenes (high spatial resolution)).

Mangroves

The online tool "Global mangrove watch" shows the extent of mangroves around the globe, as well as their change, covering historical data from 1996 onwards (Bunting et al., 2023). To generate this extensive map, data from active and passive satellite sensors was combined. While L-band SAR data (here from the Japanese Aerospace Exploration Agency (JAXA)) are sensitive to mapping mangrove change, multispectral data from Sentinel-2 imagery are well suited for mapping the extent of mangrove forest (Bunting et al., 2023).

Nababa et al. (2020) used Landsat archival data of 25 years and Google Earth Engine to compute land cover dynamics in the Niger Delta region, specifically assessing the status and coverage of mangroves, differentiating degraded from intact mangrove forests. As reference data for validation, the study used very high-resolution satellite imagery of MAXAR, which is available within ArcGIS software (https://www.maxar.com/products/imagery-basemaps).

Not only degradation and land conversion are a threat to the mangrove ecosystems along the flyway, but also an increasing spread of the invasive Nipa Palm. Combining L-band SAR with Landsat data and a SRTM (shuttle radar topography mission) digital elevation model, Nwobi et al. (2020) were able to estimate the area of mangroves and Nipa Palm in the Niger Delta. They mapped the extent of these vegetation types with an overall accuracy of 93%, but higher uncertainty for the nipa palm.

Shrubification

Arctic habitat-change by shrubification was monitored by Nill et al. (2022) using multi-temporal Landsat data for six time-intervals between 1984 and 2020. The authors used a regression-based unmixing approach to show the increase in shrub coverage in the greater Mackenzie Delta Re-gion of the western Canadian Arctic. The unmixing approach allows to derive fractional cover of various surface types per pixel (Nill et al., 2022).

2.7.6 Agriculture and rice fields

Different land cover maps are freely available that include information on agricultural land use. Some products will only have one class indicating the extent of cropland (Dynamic Land Cover), while others extent to 11 classes, covering rice fields and pastures, but also categories like agroforestry (CORINE Land Cover).

Nguyen & Wagner (2017) have utilised Sentinel-1 SAR imagery to monitor the operational rice farms in Spain and other Mediterranean countries. They tested the applicability of an existing phenological classifying approach to backscatter data from Sentinel-1 (SAR). Generally, using time-series SAR data to identify rice fields has been explored extensively in existing literature, as temporal variation in backscatter from rice fields is higher than from any other crop (see Nguyen & Wagner, 2017 and their references; phenology-based classification strategy goes back to Nguyen et al., 2016). Nguyen & Wagner (2017) used SPOT 5 high resolution optical imagery and the CORINE Land Cover product for validating the classification results. An overall accuracy of 70% was achieved for all study sites. Notably the S-1 based maps provided more detail (spatial resolution 20 m) than the equivalent rice field land cover class of the data product.

In a similar approach (also using Sentinel-1 data), Arias et al. (2020) showed that it was possible to distinguish 14 different crop classes (supervised classification algorithm based on temporal backscatter signatures of the different crop types) and achieved an overall accuracy of at least 70%.

2.7.7 Fishing activities

Global Fishing watch is a free and open access data product to monitor and visualize commercial fishing activities using AIS and VMS data as well as satellite imagery. Global Fishing offers historical data from 2012 to the present for about 70,000 commercial fishing vessels.

The European Commission JRC developed a ship detecting algorithm (SUMO = search for unidentified maritime objects) that works with Synthetic Aperture Radar (SAR), utilizing the radar backscatter from the ships (Greidanus et al., 2017; Kourti et al., 2001). It is also available as a Java Software package (https://github.com/ec-europa/sumo). Santamaria et al., (2017) implemented this approach on a large scale, extracting ship positions automatically from more than 11,500 Sentinel-1 images and using repeated image sampling of the Mediterranean Sea area to improve their monitoring results. Comparing the ships' positions of the two-year monitoring period with data from AIS (Automatic Identification System) reports, they were able to produce density maps for the complete Mediterranean Sea.

Building on the approach from Santamaria et al.(2017), Kurekin et al.(2019) investigated illegal fishing activities in Ghana by utilizing SAR imagery from Sentinel-1 and multispectral imagery from Sentinel-2. In their study the signals from satellites are matched to AIS data, yielding a success rate of 91% for AIS-registered vessels. Over the 17-month observation period, unmatched detections with a vessel length of 20 m – 100 m in 75% of cases, indicating very high frequency of unregulated or illegal fishing activities.

However, these approaches are limited by the difficulty to ground-truth detections of non-registered vessels. Additionally, Kurekin et al. (2019) report that false alarms were triggered by, e.g., small clouds or cloud edges of high contrasts.

2.7.8 Pollution

Anthropogenic debris:

The pollution of the oceans by anthropogenic debris has a negative impact on marine animals and birds that can become entangled or can ingest plastic objects. Entangled birds may be unable to find food or avoid predators. Plastic ingestion can cause direct mortality or can affect animals through slower sub-lethal physical and chemical effects (Bergmann et al., 2015; Laist, 1997).

As marine litter is difficult to monitor directly, beach litter has become an indicator of the overall pollution of marine waters by artificial debris (OSPAR, 1992) and can be quantified by several monitoring methods (Alkalay et al., 2007; Bravo et al., 2009; Cheshire et al., 2009; Opfer et al., 2012; Wenneker & Oosterbaan, 2010). However, all methods require the presence of surveyors on the beaches and are therefore not efficient in remote areas that are difficult to access. They also require a great amount of manual labour for large-scale applications and can be cost-intensive.

Therefore, satellite imagery may be an effective way of assessing litter quantities and identifying hotspots of litter accumulation along the East Atlantic Flyway, as it allows for a large-scale monitoring, including remote areas, and can detect litter directly at sea as well as on beaches.

However, no ready-to-use data product is available yet. But several studies have shown potential approaches.

Maximenko et al. (2019) describe the general potential of active and passive sensors for marine plastic litter detection. Active sensors, such as radar sensors, can be used to monitor the dynamics of floating objects, such as drift speed or the generated wake, and can operate at sub-metre spatial resolution (e.g. platform PAZ, see A.1). Passive sensors can be used to detect plastic debris using optical data with spatial resolution down to 0.3 m. Topouzelis et al. (2019) and Biermann et al. (2020) successfully used Sentinel-2 imagery to detect floating plastics. Biermann et al. (2020) classified floating plastics at a sub-pixel level with an accuracy of up to 86%. The authors detected spectral characteristics of plastic in pixels filled by at least 30% of bottles or bags or 50% of fishing nets, indicating a minimum object size of 30m² for floating marine litter. Acuña-Ruz et al. (2018) applied satellite imagery to detect beach litter by using Worldview 3 imagery for the detection of plastic litter on beaches in Chile. Litter objects with a minimum size of 1 m² were detected with an overall classification accuracy up to 88%. However, Schnurawa et al. (2023) describe the limitations of Worldview 3 imagery to detect beach litter for less polluted beaches. On Arctic beaches with 10 (50m beach length) to 325 (200m beach length) pieces of litter, it was not possible to identify beach litter with Worldview 3 imagery.

Despite the great potential of satellites for the detection of marine debris, the spatial resolution is often still insufficient for the detection of litter objects or accumulations, and even less to identify them, which would be necessary for the identification of their sources. However, a high number of successful applications of drones to detect and identify beach debris (e.g., Gonçalves, Andriolo, Gonçalves, et al., 2020; Gonçalves, Andriolo, Pinto, & Bessa, 2020; Gonçalves, Andriolo, Pinto, & Duarte, 2020; Martin et al., 2018; Wolf et al., 2020) show what may be possible in the future as spatial resolution of satellites continues to improve.

Oil spills:

Oil spills can have direct negative impacts on birds due to feather fouling (harmful to thermoregulation and locomotion) or toxic effects from oral doses (King et al., 2021; Maximenko et al., 2019), but also indirect effects by harming their habitats like mangrove forests (Lassalle et al., 2023; Obida et al., 2021) or river deltas (Obida et al., 2021). To monitor the appearance, behaviour and effects of oil spills, satellites were used in several studies using optical and radar imagery (e.g., Kolokoussis & Karathanassi, 2018; Obida et al., 2021; Tysiąc et al., 2022). Whereas optical sensors are limited by cloud coverage and lack of contrast, radar sensors are widely used for oil spill remote sensing and most promising (Fingas & Brown, 2017). The effects of oil spills can be monitored using multi-temporal satellite imagery. Obida et al. (2021) used NDVI to measure Mangrove mortality due to a major oil spill event in 2008/ 2009 over an area of 393 km² in the Niger Delta. Ozigis et al. (2019) used optical Landsat 8 imagery and a machine learning approach (Random Forest) for the same study area classifying between oil-free and oil spill-impacted landcover. Both studies confirm the value of satellite remote sensing to provide a spatially comprehensive assessment in geographically remote and challenging environments.

Already implemented data services for oil spill monitoring are the Copernicus Maritime Surveillance Service (CMS) and the CleanSeaNet (CSN) service from the European Maritime Safety Agency (EMSA). CMS and CSN are based on SAR-satellite data such as Sentinel-1 and are provided to national authorities and EU bodies engaged in the maritime domain to monitor oil spills in near-real time (https://www.emsa.europa.eu/copernicus.html).

2.8 Conclusion

In summary, there are many potential applications for satellite remote sensing data as an innovative tool for the monitoring scheme along the EAF. Especially for reoccurring habitats of great importance, like wetlands or intertidal mudflats, using satellite data is a feasible approach to obtain spatially explicit data on such a large geographical scale. Additionally, it offers a range of opportunities to explore landscape dynamics gaplessly along the flyway and detect not only long-term changes, but also seasonal variations in habitat availability.

For certain types of anthropogenic pressures, like illegal fishery or plastic pollution, the possibilities of remote sensing data are currently still limited. However, rapid technical developments, particularly concerning spatial resolution (see chapter 3.3.), promise progress on this end.

3 TECHNICAL OVERVIEW

3.1 Data options

The required spatiotemporal resolution in combination with the available financial budget and expertise can provide guidance in choosing a fitting approach and data source. Here, we provide a broad overview, explaining the most important categories of satellite data.

Generally, satellite data falls into different dimensions of costs, resolution, and processing stage. The main options on the market can be broadly divided into open access and commercial data, as well as data products and raw data (Figure 3-1).

Open data products are pre-processed tools, targeting specific parameters, e.g., land cover maps and water maps. Their data is freely available for download and often GIS-plugins or -integrations are available. The available resolution depends partly on the degree of processing. Spatially it is limited by the spatial resolution of the corresponding open access raw data, while temporally it is restricted by processing effort and the need to pool data over time. Open data products are thus a useful tool to investigate the general state of an environment or long-term changes.

Open raw data is the data made directly available from satellite providers. It can be acquired with radiometric and geometrical corrections. While spatial resolution is similarly limited to the sensors' capabilities, high temporal resolution can be achieved, as it solely depends on the revisit time and can be increased by using data from several satellites (even across providers). Open access raw satellite data is well suited for applications that aim to perform their own classifications.

Commercial data products are pre-processed tools based on commercial satellite data. They come at a range of costs, depending on the degree of processing and effort of the developers. They can be useful for customized questions or whenever tailored analyses need to be commissioned (e.g., BioConsult SH's service SPACEWHALE).

Commercial raw data is available in very high spatial resolutions, reaching < 1m GSD easily. Their temporal resolution is limited equally like the open access raw data. Financial cost and processing effort are usually very high for these types of data and large computational capacities are needed.

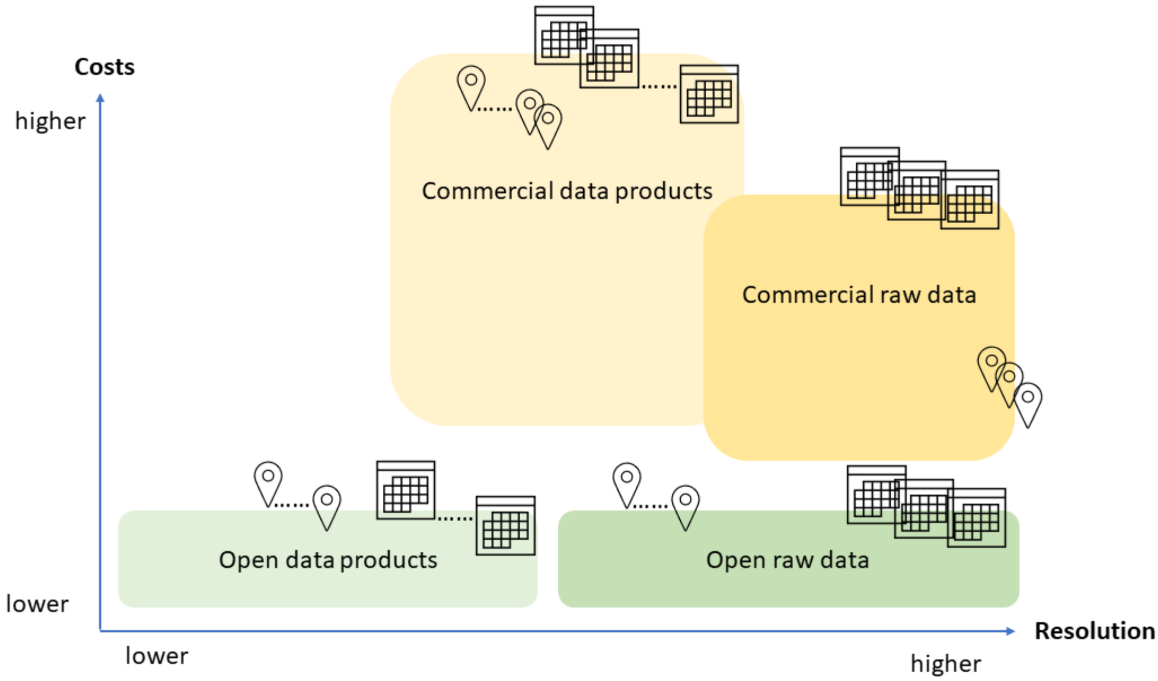

Figure 3-1 Schematic overview of categories of satellite data, along the dimensions of resolution and costs.

In the Supplementary material we provide a detailed overview over the most suitable (open access) data products (A.2) as well as a comprehensive list of relevant satellite platforms and their sensor products (A.1).

3.2 Google Earth Engine – a useful tool

Handling satellite remote sensing data and data products poses typical challenges of handling "big data". Notably procedures like storing, visualising or querying the data still require considerable computational resources and technical expertise. Cloud-based computation platforms can facilitate transfer, storage and diverse processing of big data, and there are several providers available (e.g. Amazon Web Services, Google Cloud or Azure from Microsoft).

Google Earth Engine (GEE) provides a cloud-based platform designed for efficient access and processing of large volumes of freely available satellite imagery (Gorelick et al., 2017). Using Google's computational capabilities and integrating them in the platform, it makes remote sensing data outputs and procedures more easily accessible, thereby enabling users with limited experience in such large-scale computations/computing resources. The platform grants direct access to the entire archives of Landsat, Sentinel-1 and Sentinel-2 datasets, as well as to a range of open access data products (e.g. vegetation indices, land cover products etc.). Application Programming Interfaces (APIs) facilitate the processing of these data by allowing for more commonly known coding languages, i.e. Python or JavaScript (Gorelick et al., 2017; Tamiminia et al., 2020). Since many datasets require some level of processing or classification before they can be visualised or included in statistical analyses, the "awesome-gee-community-catalog" was founded as an additional platform to share geospatial datasets with the community (https://gee-community-catalog.org/).

3.3 General limitations

There are factors that generally limit the availability of satellite data (Dubovik et al., 2021). One primary challenge is the impact of cloud cover, which significantly diminishes spatial and temporal resolution of data retrieved from passive sensors or, in some cases, leads to omission of data (Robinson et al., 2019). Revisit time is the main constraint to temporal resolution and depends on the orbit and constellation of satellites. This issue can be bypassed by acquiring data from several compatible satellite providers and platforms (Cavallo et al., 2021). However, inconsistencies might arise from differences in spectral coverage and resolution and should be taken into account (Beamish et al., 2020). There is archival data available from many open access satellite providers, but historical coverage depends on the respective launch date. For example, the commonly used Sentinel satellite series was only initiated in 2014 (Braun, 2021). Commercial data, however, is often acquired only on request and thus, historical data may not be accessible for most providers. Further complicating matters are restrictions in sensitive areas, like active military zones, especially for very high-resolution optical satellites.

Transferability of results should be validated using reliable reference data, thus, combination of field studies with remote sensing data may be required (Pettorelli et al., 2018), which in turn might not be feasible in remote or hard to access areas.

Whenever readily available data products are used, it is necessary to familiarize with uncertainties and constraints of that particular dataset and account for them appropriately, e.g., by propagating uncertainties in analyses (Murray, Worthington, et al., 2022); https://www.globalintertidalchange.org/data-usage).

3.4 Outlook

As satellite technology continues to improve, current limitations in spatial or temporal resolution, spatial or spectral coverage and even costs may be overcome in the future. Several satellite missions are already announced for the near future:

- Maxar: 6 VHR Satellites (World-View Legion) launch in 2024, 30 cm resolution/pixel https://www.maxar.com/worldview-legion
- Planet Labs: VHR satellites (Pelican constellation), launch soon, 30 cm resolution/pixel https://www.planet.com/products/pelican/
- Albedo: VHR satellites, launch in 2024, 10 cm resolution/pixel https://www.satimagingcorp.com/satellite-sensors/albedo-10cm/
- Aerospacelab: launch of VHR satellites
- Sentinel-2 C is expected to be launched in 2024 to replace Sentinel-2 A when it's decommissioned, ensuring the continuity of data. Sentinel-2 D will replace Sentinel-2 B in the

future, but is not scheduled yet. https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2/Gearing_up_for_third_Sentinel-2_satellite

With the development of sensor technology, also data products will further improve:

- Dynamic Land Cover soon available in 10m spatial resolution.

4 RECOMMENDATIONS

4.1 General recommendations

In conclusion, we recommend implementing satellite remote sensing for monitoring habitats and anthropogenic pressures along the EAF. There is a great potential of satellite data to obtain multi-dimensional and spatially explicit information, especially for the large-scale and international monitoring scheme of the EAF.

Not only the spatial or temporal resolution can guide the decision which data to use, but also costs and expertise at hand. Therefore, in the beginning, open access data products already offer a good range of information on a variety of parameters (Table 4-1). Data processing and analyses could subsequently be expanded by more parameters or including raw data. No additional sampling would be required, as several satellite providers offer archived data. Generally, open access products and data should cover most data needs for the monitoring along the flyway. Whenever a question requires a more customised, but also more complex data processing and analysis approach, we recommend reaching out and teaming up with expert research groups or specialised service providers. Such cooperations offer great opportunities to speed up developments and build expertise along the way.

In the light of aiming to harmonize the monitoring programme, we suggest to build expertise by topics rather than geographically, as many relevant parameters are reoccurring along the flyway. We further recommend establishing standardised protocols of obtaining, processing, and analysing satellite data. Workflows would optimally be tested, discussed, and then fixed to enable training of people involved in the monitoring and adequate knowledge transfer.

Accordingly, an ongoing exchange with the field observers is essential to guide questions that need urgent attending, but also to build on their local expertise whenever ground truthing is required. For EAF-wide data analysis, transferability is crucial and should always be considered. Results should be validated on a large-scale using reference data to ensure the transferability of the methods. Additionally, small-scale drone surveys could be conducted to address locally relevant questions or to facilitate ground truthing to better understand satellite-based results.

4.2 Specific recommendations

Here we provide an overview of EAF-relevant parameters and the satellite remote sensing approaches we render to be most feasible starting points to implement as monitoring variables.

For the use of Google Earth Engine, we recommend this introduction by the FU Berlin: https://www.geo.fu-berlin.de/en/v/geo-it/gee/1-introduction-to-gee/1-2-introduction-to-the-gee/index.html

On the website of the awesome-gee-community, you can find a guide to navigating the catalogue: https://gee-community-catalog.org/startup/navigation/

Furthermore, there is the community of the German Environmental Mapping and Analysis Program (EnMAP), which provides a platform for knowledge exchange about hyperspectral sensors, calibration, data evaluation and applications.

Table 4-1 Specific recommendations to guide implementation of satellite remote sensing methods to monitor relevant parameters of habitats and anthropogenic pressures along the EAF.

Parameters	Relevance to Flyway	Recommendation
Water Coverage	Availability of wetlands Flooding status of estuaries	Global Surface Water Explorer – coverage, seasonality, transitions Aqueduct – global water risk Global: Custom calculation of e.g. NDWI for higher temporal resolution of water coverage
Intertidal mudflats	Availability as foraging sites	Global Intertidal Change – long-term changes (approx. 30 years divided into three-year interval layer), solid spatial resolution (30m) Global: Custom calculation is challenging due to regular flooding of areas – we recommend partnering with expert research groups or consulting service providers
Land Use Change	Habitat loss/ changes e.g., Deforestation, droughts, urbanization	Europe: Copernicus CORINE Land Cover change – long-term changes – 100 m spatial resolution Global: Custom change analysis with Dynamic Land Cover from Copernicus as input. – yearly changes (from 2015 onwards), currently 100m resolution, from 2024 on release of 10m resolution. For global land cover data going back until 1992, CCI Land Cover (ESA) is a good option (300m resolution). Global: Custom change analysis with Satellite RAW data as input. – For inter-annual changes, e.g. Sentinel 2 data with 10 m-20 m spatial and six days temporal resolution. Simple classification using machine learning or thresholds for broader land cover classes (e.g., bare soil, grassland, shrubs, trees, water and urban areas)
Vegetation cover and type	Degradation and land conversion Availability as foraging sites	Europe: CORINE Land Cover – long-term changes, 100m and 10m resolution available Global: Dynamic Land Cover – yearly changes, currently 100m resolution, 2024 release of 10m resolution Global: The fraction of Vegetation Cover: interannual and intersessional changes of the spatial extent of vegetation - 300 m to 1 km resolution with data every 10 days Global: Custom calculation of NDVI using Sentinel 2 imagery

Mangroves	Phenology & productivity-changes Availability as foraging sites	Global Mangrove Watch – long-term changes, solid spatial resolution of 30m
Agriculture	Habitat conversion and degradation	Europe: CORINE Land Cover – long-term changes, 100m and 10m resolution available Global: Dynamic Land Cover – yearly changes, currently 100m resolution, 2024 release of 10m resolution
Rice Fields and salt pans	Habitat degradation, availability as artificial wetland	Europe: CORINE Land Cover; Fraction of vegetation Global: custom calculation, we recommend partnering with expert research groups or consulting service providers
Fishing Activities	Human pressure: Bycatch and food resources	Global Fishing Watch: Database of vessel characteristics, type and size, and authorizations based on AIS and VMS data Global: Ship detecting algorithm (SUMO = search for unidentified maritime objects) by the European Commission JRC is available as a Java Software package. Custom application is challenging – we recommend partnering with expert research groups or consulting service providers
Pollution	Human pressure: Health impact and habitat degradation	Anthropogenic debris: Global: Drones are recommended for beach litter detection and identification. Satellites only for hotspot detection and mainly over sea. Oil spills: Europe mainly: The Copernicus Maritime Surveillance Service and the CleanSeaNet service from the European Maritime Safety Agency provid oil spill data to national authorities and EU bodies. Global: Custom application of Radar data for oil spill monitoring is challenging – we recommend partnering with expert research groups or consulting service providers
Water Coverage	Availability of wetlands Flooding status of estuaries	Global Surface Water Explorer – coverage, seasonality, transitions Aqueduct – global water risk Global: Custom calculation of e.g. NDWI for higher temporal resolution of water coverage
Intertidal mudflats	Availability as foraging sites	Global Intertidal Change – long-term changes (approx. 30 years divided into three-year interval layer), solid spatial resolution (30m)

		Global: Custom calculation is challenging due to regular flooding of areas – we recommend partnering with expert research groups or consulting service providers
Land Use Change	Habitat loss/ changes e.g., Deforestation, droughts, urbanization	Europe: Copernicus CORINE Land Cover change – long-term changes – 100 m spatial resolution Global: Custom change analysis with Dynamic Land Cover from Copernicus as input. – yearly changes, currently 100m resolution, from 2024 on release of 10m resolution. Global: Custom change analysis with Satellite RAW data as input. – For inter-annual changes, e.g. Sentinel 2 data with 10 m-20 m spatial and six days temporal resolution. Simple classification using machine learning or thresholds for broader land cover classes (e.g., bare soil, grassland, shrubs, trees, water and urban areas)

5 LITERATURE

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A APPENDIX

A.1 Technical overview satellite platform

Table A.1 Technical overview of satellite platforms, their sensors, spatial resolution and coverage, as well as limitations and practicability.

Platform	Sensor (e. g. active/passive)	Spatial resolution & coverage	Temporal resolution & coverage	Agency/ Provider
Aqua (+)	Passive Multispectral (RGB, NIR, TIR) 36 bands	• AMSR-E: 5 – 10 km • MODIS: 250 – 1000 m • Swath width 1445 – 2330 km	• 16 days • 2002 - ongoing	• INPE • JAXA • NASA
DMC-1 (+)	Passive Multispectral (RG, NIR)	• 32 m (RG, NIR) • Swath width > 600 km	• On average 1 – 2 days (considering the entire constellation) • 2002 until 2005 - ongoing	• BLMIT • CNTS • NASRDA • UKSA
DMC-2 (+)	Passive Multispectral (Pan, RGB, NIR)	• 1 – 2.5 m (RGB, NIR) • 4 – 22 m (MS) • Swath width 650 km	• On average 1 – 2 days • 2009 - 2019	• UKSA
DMC-3 (-)	Passive Multispectral (Pan, RGB, NIR)	• 1 m (RGB, NIR) • 4 m (MS) • Swath width 23 km	• On average 1 – 2 days • 2015 - 2022	• NRSCC • UKSA • 21AT
EnMAP (+)	Passive Hyperspectral (420-2450 nm) 225 bands	• 30 m • Swath width 30 km	• 4 days • 2022 - ongoing	• DLR • GFZ
Envisat (+)	Passive/active C-Band SAR MERIS: Multispectral (RGB, NIR)	• AATSR: 1 km • ASAR: 30 – 150 m • MERIS: 260 – 1200 m • Swath width 57 – 1150 km	• 3 days • 2002 - 2012	• ESA
JASON-3 (+)	Active Altimeter	• 30 – 100 km	• 5 – 10 days • 2016 - ongoing	• EUMETSAT • NASA • NOAA • CNES
Landsat-1 to 3 (+)	Passive Multispectral (RGB, NIR)	• 68 m (IFOV) • 56 m (cross-track) • 79 m (along-track) • Swath width 185 km	• 6 days (considering the entire constellation) • 1972 - 1983	• NASA • USGS
Landsat-4 and 5 (+)	Passive Multispectral (RGB, NIR)	• 68 m (IFOV) • 56 m (cross-track) • 79 m (along-track) • Swath width 185 km	• 8 days (considering the entire constellation) • 1982 - 2013	• NASA • USGS
Landsat-7 (+)	Passive Multispectral (Pan, RGB, NIR, SWIR)	• 15 m (Pan) • 30 m (VNIR, SWIR) • 60 m (TIR) • Swath width 185 km	• 16 days • 1999 - ongoing	• NASA • USGS

Landsat-8 (+)	Passive 11 bands OLI: Multispectral (Pan, RGB, NIR, SWIR) TIRS: TIR	• OLI: 15 m (Pan), 30 m (RGB, NIR, SWIR) • TIRS: 100 m • Swath width 185 km	• 16 days • 2013 - ongoing	• NASA • USGS
Landsat-9 (+)	Passive 9 bands OLI 2: Multispectral (Pan, RGB, NIR SWIR) TIRS 2: Thermal	• OLI 2: 15 m (Pan), 30 m (RGB, NIR, SWIR) • TIRS 2: 100 m • Swath width 185 km	• 2021 - ongoing	• NASA • USGS
PAZ (*)	Active X-Band SAR	• 0.25 – 40 m • Swath width 4 – 200 km	• On average 24 hours • 2018 - ongoing	• Hisdesat
PlanetScope (*)	Passive Multispectral (RGB, NIR)	• 3.7 – 4.1 m (multispectral) • Swath width 25 km	• Daily • 2014 – ongoing • 430+ Dove and SuperDove satellites	• Planet Labs
Pleiades 1A and 1B (*)	Passive Multispectral (Pan, RGB, NIR)	• 0.5 m (Pan) • 2 m (multispectral bands) • Swath width 20 km	• 13 days (considering the entire constellation) • 2011/ 2012 - ongoing	• CNES
Pleiades Neo 3 and 4 (*)	Passive Multispectral (Pan, RGB, NIR)	• 0.3 m (Pan) • 1.3 m (multispectral bands) • Swath width 14 km	• Twice a day • 2021 - ongoing	• Airbus
SMAP (+)	Passive Active	• 3 - 36 km • L-band radar • L-band radiometer • Swath width 1000 km	• 2-3 days • 2015 - ongoing	• NASA
QuickBird-2 (*)	Passive Multispectral (Pan, RGB, NIR)	• 0.61 – 0.72 m (Pan) • 2.4 – 2.6 m (MS) • Swath width 14.5 km	• 1.5 – 2.8 days • 2001 - 2015	• MAXAR
RADARSAT-1 and 2 (*)	Active C-Band SAR	• 1 – 100m • Swath width 18 – 500 km	• 12 days (considering the entire constellation) • 1995/ 2007 - ongoing	• CSA • MDA
RapidEye (*)	Passive Multispectral (RGB, NIR)	• 6.5 m (multispectral bands) • Swath width 77 km	• 1 day (considering the entire constellation) • 2008 – 2020 • 5 satellites in total	• Planet Labs
Sentinel-1A and 1B (+)	Active C-Band SAR	• ≤ 5 m • Swath width 400 km	• 6 days (considering the entire constellation) • 2014/ 2016 - ongoing	• EC • ESA
Sentinel-2A and 2B (+)	Passive Multispectral (RGB, NIR, SWIR)	• 10 m (VNIR) • 20 m (NIR, SWIR) • Swath width 290 km	• 5 days (considering the entire constellation) • 2015/ 2017 - ongoing	• ESA

Sentinel-3A and 3B (+)	Active/passive OLCI SLSTR SRAL	• OLCI: 300m, swath width 1270 km • SLSTR: 500m (RGB, NIR), 1000m (MIR, TIR), swath width 1420 km • SRAL: ≥300m	• 3 – 4 days (considering the entire constellation) • 2016/ 2018 - ongoing	• ESA • EUMETSAT
SkySat (*)	Passive Multispectral (Pan, RGB, NIR)	• 0.57 – 0.86 m (Pan) • 0.75 – 1 m (multispectral bands) • Swath width 5.5 – 8 km	• On average 6 – 7 times a day (considering the entire constellation) • 2013 until 2020 - ongoing • 21 satellites in total	• Planet Labs
SPOT-1 to 3 (+)	Passive Multispectral (Pan, RG, NIR)	• 10 m (Pan) • 20 m (multispectral bands) • Swath width 60 km • Mainly Europe and Africa	• 9 days (considering the entire constellation) • 1986 until 1993 - 2009	• CNES
SPOT-4 (+)	Passive Multispectral (Pan, RG, NIR, SWIR)	• 10 m (Pan) • 20 m (multispectral bands) • Swath width 60 km • Mainly Europe and Africa	• 26 days • 1998 - 2013	• CNES
SPOT-5 (+)	Passive Multispectral (Pan, RG, NIR, SWIR)	• 2.5 – 5 m (Pan) • 10 m (multispectral bands) • 20 m (SWIR) • Swath width 60 km • Mainly Europe and Africa	• 26 days • 2002 - 2015	• CNES
SPOT 6 and 7 (*)	Passive Multispectral (Pan, RGB, NIR)	• 1.5 m (Pan) • 6 m (multispectral bands) • Swath width 60 km	• 13 days (considering the entire constellation) • 2012/2014 - ongoing	• Airbus
Terra (+)	Passive Multispectral (RGB, NIR, TIR)	• ASTER: 15 m (VNIR), 30 m (SWIR), 90 m (TIR) • MISR: 275 – 1100 m • MODIS: 250 – 1000 m • Swath width 60 – 616 km	• 16 days • 1999 - ongoing	• NASA • CSA • METI
TerraSAR-X and TanDEM-X (*)	Active X-Band SAR	• 1 – 16 m • Swath width 10 – 100 km (cross-track) • Swath width 5 – 1500 km (long-track)	• On average 24 hours • 2007/ 2010 - ongoing	• DLR
Vision-1 (*)	Passive Multispectral (Pan, RGB, NIR)	• 0.87 m (Pan) • 3.48 m (multispectral bands) • Swath width 20.8 km	• 1 – 8 days • 2018 - ongoing	• Airbus
WorldView-1 (*)	Passive Pan	• 0.5 m (Pan) • Swath width 17.6 km	• Up to < 1.7 day • 2007 - ongoing	• MAXAR
WorldView-2 (*)	Passive Multispectral (Pan, RGB, NIR)	• 0.46 m (Pan) • 1.8 m (eight VNIR bands) • Swath width 16.4 km	• Up to < 1.1 day • 2009 - ongoing	• MAXAR
WorldView-3 (*)	Passive Multispectral (Pan, RGB, NIR, SWIR)	• 0.31 m (Pan) • 1.24 m (eight VNIR bands) • Swath width 13.1 km	• Up to < 1.0 day • 2014 - ongoing	• MAXAR

+ open access, * partly available (e.g. for research purposes after successful proposal, or only limited data free available), commercial.

BLMIT (Beijing Landview Mapping Information Technology Ltd), CNES (Centre National d'Etudes Spatiales), CNTS (Algerian Centre National des Techniques Spatiales), CSA (Canadian Space Agency), DLR (Deutsches Zentrum für Luft- und Raumfahrt), EC (European Commission), ESA (European Space Agency), EUMETSAT (European Organisation for the Exploitation of Meteorological Satellites), GFZ (GeoForschungsZentrum), Hisdesat (Hisdesat Servicios Estratégicos, S.A.), INPE (Instituto Nacional de Pesquisas Espaciais), JAXA (Japan Aerospace Exploration Agency), MDA (MacDonald, Dettwiler and Associates), METI (Ministry of Economy, Trade and Industry), NASA (National Aeronautics and Space Administration), NASRDA (Nigeria Space Research & Development Agency), NOAA (National Oceanic and Atmospheric Administration), NRSCC (National Remote Sensing Center of China), UKSA (UK Space Agency), USGS (United States Geological Survey), 21AT (Twenty First Century Aerospace Technology)

A.2 Technical overview data products

Table A.2 Technical overview of satellite data products, including their spatiotemporal resolution and coverage, as well as limitations and practicability.

Product name	Usage	Spatial resolution & coverage	Temporal resolution & coverage	Limitations	Practicability & costs
CleanSeaNet	Detection of oil pollution on the sea surface	Variable satellite service providers- (12 optical and 8 SAR satellites) Covers European Union (EU), as well as associated countries and certain neighbouring regions.	Variable	The request for RPAS services can be made by Maritime Authorities of the European Union (EU) Member States, Candidate Countries and EFTA Member States, or other Member State Authorities through the European Agencies FRONTEX and EFCA.	Available to National Authorities of Coastal EU Member States
Copernicus: CLC+Backbone	European-wide land cover and land use inventory with 11 thematic classes	10 m, covers Europe	Every three years, from 2018 on, 2021 product available in Q1 2024	Publishing time (2021 product in Q1 2024) Covers only Europe	Free and open access
Copernicus: Dynamic Land Cover	Layer of Land Cover Class with 10 classes	100 m, 2024 release of 10m resolution, global coverage	Annually updated	Only from 2015 on Coarse spatial resolution No interannual changes	Free and open access
Copernicus: Imperviousness	Imperviousness Density: data on sealing density; Built-up: binary data on presence/absence of built-up areas	10 m – 100 m , covers Europe	Every three years, from 2006 on 2021 product will be available in Q3 2024	Publishing time (2021 product in Q1 2024) Covers only Europe	Free and open access
Copernicus: Water and Wetness	Water and wet surfaces data for environment, agriculture, regional development, transport and energy	10-20 m, covers Europe	Every three years, from 2015 on 2021 reference year will be available in Q4 2024	Publishing time (2021 product in Q4 2024) Covers only Europe Wetness information will not be included for the new product.	Free and Open Access.

Copernicus: Soil Moisture	Relative water content of the top few centimetres soil	5m. covers Europe	Since 2015- Oct 2016 (3-8) days. Since Oct 2016- Ongoing (1.5- 4) days.	Soil moisture cannot be retrieved over deserts and high vegetation areas like tropical forests. Covers Europe only. no reliable soil moisture measurements during frozen or snow-covered conditions.	Free and Open Access.
Copernicus: CORINE Land Cover	European-wide land cover and land use inventory with 44 thematic classes	100 m, covers Europe	Every six years, Archive data from 1990, 2000, 2006, 2012 and 2018 (2024 dataset will be produced in 2025)	Temporal resolution Coarse spatial resolution Covers only Europe	Free and open access
Critical Site Network Tool 2.0	Map for IBAs, KBAs and Ramsar sites from different migratory flyways.	N/A covers the flyway Ramsar, IBAs and Critical sites	N/A	Data accuracy depends on the frequency of the data provided. The depth of information varies	Free and Open Access.
ESA Climate Change Initiative (CCI) Land Cover	Layer of Land Cover Class with 38 classes	300m, global	Annual land cover maps dating back to 1992	Coarse spatial resolution	Free and Open Access.
Global Fishing Watch	Visualization tool to monitor commercial fishing activities.	Vessel coordinates AIS: global coverage VMS: covers 10 countries only	AIS live feed from fishing and commercial vessels. VMS data is published on a three-day delay	Limited to AIS and VMS equipped vessels Satellite data is limited in terms of spatial resolution and	Free and Open Access

		Satellite: global coverage		data needs validation	
Global Forest Watch	Mapping tool to visualize and analyse tree cover, land use and land cover change.	Depends on input imagery used (e.g., Planet Satellites, Google Satellite, Landsat 8 satellite), global coverage	Depends on the satellite revisit interval.	Cloud coverage or sensor specifications Limitations in distinguishing between natural forest cover and certain land uses as sustainable logging or agroforestry.	Free and Open Access.
Global Intertidal Change	Identifies the non-vegetated areas of Earth's coastline that undergo regular tidal inundation	30 m, global coverage	30-year span (1984-2016), divided into 10 three-year interval layers	Variability in spatial and temporal data over the years introduce inconsistencies in the analysis Site-level scale needs to be validated via ground truthing and needs local training data.	Free and Open Access.
Global Mangrove Watch	Detecting Mangrove habitat extent, biomass, mangrove alerts and blue carbon.	Global coverage, (10-30m). Using POLSAR for the synthetic aperture radar and Landsat for the optical.	N/A	Accuracy reached 87.4 % for the mangrove habitat extent (Bunting et al. 2023), meaning it is more accurate on the regional level but not on the site-level, thus ground-truthing and field validation is required.	Open access and Free.
Global Surface Water	Spatial and temporal patterns of surface water.	30 m, globally.	16 days. Monthly information spanning from 1984 to 2020	The accuracy and availability depend on the Landsat imagery data archive Data for periods in northern regions during winter are unavailable because of the low sun angle	Free and Open Access.
GlobWetland Africa	Open source and access toolbox (QGIS) for inventorying, mapping, monitoring, and	10 m to 300 m from Sentinel series or Landsat Series. Covers African westlands	Dependent on the status mapping, yet the temporal resolution is daily, every 3- 16 day, and since the 2000, but can	Only covers African wetlands. Possible misclassification between mangrove areas and	Free and Open Access

	assessing wetlands.		make use of the archival data, too.	invasive plants, such as the Nipa palm.	
Hansen Global Forest Change	Visualization of the loss/gain in forest cover around the globe	30 meters, global coverage	Landsat Series (16 days) Since 2000.	Limited spectral resolution. Temporal gaps between the decommissioning of Landsat 5 in 2011 and the launch of Landsat 8 in 2013	Free and Open Access.
Land Use Harmonization	land-use states, transitions, and gridded mgt layers	0.25 x 0.25 degree, global	Annually, data is modelled from 850 - 2100	Coarse spatial resolution. Use predictions (past and future) with caution, as modelling processes can always be biased by assumptions that might not hold for e.g. regional case studies.	freely available for use by the scientific community, with attribution (cite according to instructions on website)
LitterBase	Online visualization platform of projected plastic pollution around the globe	N/A but covers the globe.	N/A	Ground-based data. Data cannot be retrieved from the website Data from different years	Free and Open Access.
The Aqueduct	Water risk atlas visualizer, I.e., water stress, depletion, and availability.	Covers Asia, Africa and North America and	Monthly	Low quality data in regions with persistent cloud cover	Free and Open Access.
The Fraction of Vegetation Cover	Spatial extent of the vegetation, Emphasis on the Rice fields in Iberia.	300 m to 1 km, global coverage	Each 10 days. (1999-June 2020) for the 1 Km product, Since January 2014 300 m product.	Variations in sensor calibrations and atmospheric conditions may introduce errors in the estimates.	Free and Open Access.