Biodiversity and Artificial Intelligence

Opportunities & Recommendations for Action

November 2022

GPAI | THE GLOBAL PARTNERSHIP ON ARTIFICIAL INTELLIGENCE

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CONTENTS

1. Executive Summary	*4*
2. Introduction	*9*
3. Responsible AI for biodiversity	*17*
4. Using AI to understand biodiversity and biodiversity trends	*21*
5. Using AI to understand the drivers of biodiversity loss	*34*
6. Using AI to support policy action on biodiversity	*50*
7. Using AI to optimise action on biodiversity	*63*
8. Common Bottlenecks, Challenges and	*75*
9. Sector-wide AI for biodiversity Roadmap	*84*

1. Executive Summary

Biodiversity loss is one of the most critical issues facing humanity, requiring urgent and coordinated action. Despite ongoing conservation efforts, biodiversity has declined dramatically in recent decades. Artificial intelligence (AI) is one tool that offers opportunities to accelerate action on biodiversity conservation. However, it must be deployed in a way that supports a paradigm shift to new, sustainable models of development, rather than entrenching business as usual. Applications such as automated classification of species from citizen scientists and communities, automated monitoring of land use change, monitoring of fishing vessels, monitoring of the impact of different biodiversity policies, and the optimisation of biodiversity-positive business models for key sectors all enable enhanced transparency, accountability and action that can support biodiversity conservation. However AI is not a silver bullet and needs to be deployed as part of wider applications and efforts that support action.

This report offers actionable recommendations for how governments, NGOs, researchers and companies can use AI to support biodiversity conservation. These recommendations were developed following extensive consultation with a broad community of stakeholders.

Responsible AI for Biodiversity:

The application of AI to biodiversity challenges comes with three types of risk: impact, social and environmental risks. Impact risks include when AI is deployed where it does not add value, is applied incorrectly leading to poor, incorrect or biassed results, or is used as a form of greenwashing to distract from the need for more fundamental business model changes. Social risks include the risk that the technology increases inequality, undermines local community data rights, is deployed in a language not relevant to local communities, or is used to enable persecution of environmental activists. Environmental risks include AI being used to optimise and entrench unsustainable business models or to drive e-commerce consumerism, thereby increasing the demand for resources, the extraction of which impacts biodiversity.

Using AI to understand biodiversity and biodiversity trends:

Impactful conservation relies on solid biodiversity baseline measurements and change monitoring, which has traditionally involved time-intensive manual data collection and analysis. AI can support the development of an effective, automated, and globally distributed biodiversity monitoring system that provides verified information on the state of the biosphere in real time. Challenges to delivering such *a system include current data inequalities between regions, species and habitats; balancing collecting relevant data with the need to recognise the data rights of local communities, insufficient AI awareness and capacity, and a lack of trust in AI systems. We recommend practitioners ensure biodiversity monitoring follows both FAIR and CARE principles, invests in integration and maintenance of monitoring efforts and focuses on communication and explainability of data products.*

Using AI to understand the drivers of biodiversity loss:

A detailed understanding of the drivers of biodiversity loss is critical to conservation efforts. AI offers an opportunity to create a radically more transparent and precise understanding of its specific corporate and political drivers. However, full driver transparency cannot be achieved with existing open data streams, and satellite imagery is often too expensive for continuous driver monitoring. AI-derived insight on drivers is insufficient on its own to drive change. We recommend that governments support enhanced monitoring of drivers by adopting tools developed in the voluntary sector to monitor drivers (eg Global Fishing Watch), build networks of biodiversity driver monitoring sensors, and mandate data openness for supply chains that are high-risk drivers of biodiversity loss. Initiatives focussed on improving the transparency around drivers should consider including advocacy tools within their applications to drive action.

Finally we recommend the development of a new initiative to aggregate data and develop data modalities on the drivers of biodiversity loss across organisations and geographies.

Using AI to support policy action on biodiversity:

Good biodiversity policy making relies on good data analysis to support policy prioritisation, design, implementation, enforcement and impact monitoring. AI is not currently used significantly to support these processes, but it has the potential to create a step-change through all phases of the policy cycle. There is a lack of awareness amongst policy makers about how to apply AI to policy making. Biodiversity policy is often highly location and ecosystem specific, limiting the transferability of results from one region to another. We recommend that governments seek to deploy AI throughout the policy cycle, in particular in policy design optimisation, policy enforcement and policy impact monitoring. To enable this, governments should seek to develop their own data science capacity and seek external support. We recommend governments establish a set of Biodiversity Policy AI Labs around the world as centres of excellence to bring biodiversity policy makers and AI experts together to inform policy development.

Using AI to optimise action on biodiversity:

Addressing biodiversity loss is rising up the agenda for the private sector, in particular for *sectors that have a high impact such as the food, infrastructure, energy and fashion sectors. AI can be used to help optimise new business paradigms in these sectors such as plant-based diets, regenerative agriculture and circular economy fashion. We expect to see a Cambrian explosion of AI startups to support these paradigm shifts. AI can also help analyse where companies both impact and depend on biodiversity and nature, for example by improving supply chain mapping to enable biodiversity impact assessments. Such efforts will support corporations and financial institutions to respond to the Taskforce on Nature-related Financial Disclosures (TNFD). In the public sector, AI can be used to directly support the optimal management of conservation areas, and facilitate interaction with local communities and indigenous people. However, funding is limited, understanding of the potential of AI is still low, and there is a lack of standardised metrics for private sector biodiversity impact data. In conservation areas, a key challenge is how to ensure community (and especially indigenous peoples') data rights are respected when conducting data-led conservation projects. We recommend that governments and international funds increase funding for AI-for-biodiversity projects and initiatives. We propose that a series of sectoral action groups be established to examine how AI can support paradigm shifts in food, infrastructure, energy and fashion sectors and to establish data solutions that enable the pooling and sharing of relevant data. To support community data rights, we suggest a community-data dialogue be established to identify sensitive data and explore how different tools, such as federated learning, edge computing or privacy-enhancing technologies could enable data use and data sharing, whilst respecting community data rights.*

Common Bottlenecks, Challenges and Recommendations:

There are a range of issues holding back greater adoption of AI for biodiversity challenges that are common across many of the potential AI applications to biodiversity challenges. We have highlighted the top 3 areas around AI capacity and awareness, data-related challenges, and funding and investment:

AI capacity and awareness is low across most organisations involved in conservation efforts. *We recommend bespoke training is developed for executives and managers, and cross-disciplinary technical courses are offered to develop more technical data science and engineering talent with deep biodiversity domain expertise.*

Data-related challenges include: *Collection in biodiversity hotspots which could be deemed to be undermining local communities' data usage rights; limited geographical and species spread, primarily in the Global North and with more charismatic ecosystems and* *species; lack of biodiversity driver data, with the [Global Biodiversity Information Facility]() only pooling species occurrence data. Linking different data types together is also challenging and time-consuming. We recommend biodiversity initiatives that use AI should prioritise outreach to local communities and seek to deploy privacy enhancing technologies to protect data privacy where appropriate to protect community data rights. We also recommend that an international data task-force on the drivers of biodiversity loss be established, and that a new initiative is needed that aggregates and stores data and models on the direct and indirect drivers of biodiversity loss.*

Sourcing funding and investment is a challenge for many AI for biodiversity initiatives. *Philanthropic funding, the most common for AI and biodiversity projects, tends not to allow unsolicited applications, thereby limiting access to those with networks surrounding the fund. Most funding is also targeted at developing new technologies and startups, not at scaling-up of AI for biodiversity projects. This will change as biodiversity becomes more salient to citizens, politicians and companies, with the market for AI initiatives offering biodiversity services to private companies increasing, enabling financial scalability. We recommend philanthropic foundations consider a more open funding model that actively encourages applications from the Global South, and that large international public funds take a more active role in supporting AI-for-biodiversity initiatives to scale. We also recommend that AI for biodiversity projects explore the potential to offer services to the private sector as the market for supporting the transition to biodiversity-positive business models develops.*

2. Introduction

Aim of report and intended audience

Biodiversity is being lost rapidly creating an increasing risk of ecosystem collapse, which would undermine the critical life-supporting functions that biodiversity provides humanity. There is an urgent need for action to address this crisis. This will require unprecedented levels of coordinated action and a move away from business-as-usual approaches to biodiversity conservation.

Artificial Intelligence (AI) is one tool that we can use to support enhanced action on biodiversity loss. However it is not a silver bullet, and should only be applied where it can add value. The aim of this report is to help identify where AI can add value to biodiversity conservation, and to propose how we can advance the responsible application of AI in these areas.

The report offers an assessment of the current landscape of AI and biodiversity initiatives; it assesses where the gaps in this landscape exist, sets out a vision for how AI can be applied more widely to support conservation, identifies bottlenecks to such adoption, proposes recommendations to achieve the proposed vision, and puts forward a roadmap for how these recommendations can be delivered.

The report is relevant to:

- *AI practitioners, researchers, and data scientists interested in understanding how they can apply their skills to support action on biodiversity*
- *Researchers and research institutions working in biodiversity conservation or ecology research field who may benefit from using AI for science discovery or data analysis*
- *Biodiversity NGOs seeking to increase the impact of their work by applying AI,*
- *Private sector companies seeking an understanding of how they can apply AI to reduce their biodiversity risk and support biodiversity gain*
- *Government officials seeking to support the application of emerging technology such as AI to biodiversity challenges.*
- *Communities and citizens interested in understanding the application of AI to biodiversity challenges.*

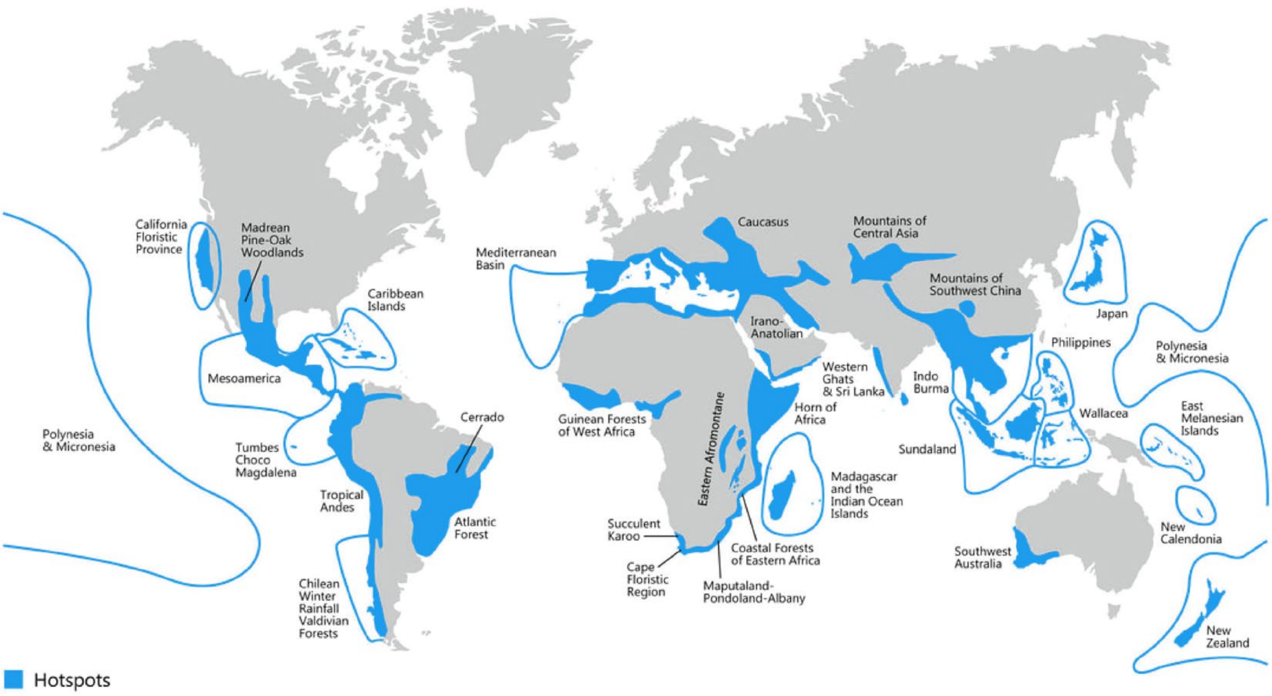
Biodiversity - current status

For readers with an AI background, this subsection offers a summary of the status of biodiversity and biodiversity loss.

Biodiversity is the variety and variability of life on Earth and acts as a measure of variation at the genetic, species, and ecosystem level[1]. Biodiversity is critical to human life on earth. The contributions it makes to humans are referred to as **'ecosystem services'.** *There are four major types of ecosystem services: provisioning (eg raw materials, food, shelter, energy), regulating (e.g. the regulation of air, water, soil, flood and disease), supporting (eg. nutrient cycling, primary production) and cultural (recreational, aesthetic, cognitive and spiritual)[2].*

Places on Earth that are both biologically rich and deeply threatened are known as **biodiversity hotspots.** *These areas have large numbers of endemic species - those found nowhere else. Many of these are heavily threatened by habitat loss and other human activities. Conservation International adopted Myers criteria (Myers et al 1988, 1990, & 2000) for identifying conservation hotspots and applied them to highlight [36 regions] where success in conserving species can have an enormous impact in supporting global biodiversity (see Figure 3.1). Their intact habitats represent just 2.5% of Earth's land surface, but they support more than half of the world's plant species as endemics and nearly 43% of bird, mammal, reptile and amphibian species as endemics.*

Figure 3.1: Biodiversity Hotspots



Source: [Tropical Conservation Fund]

[1] *Convention on Biological Diversity (CBD)*
[2] *Millenium Ecosystem Assessment (2005)*

Since the industrial revolution, human activities have increasingly destroyed and degraded forests, grasslands, wetlands and other important ecosystems, and in doing so have undermined the ecosystem services that support human well-being. Seventy five per cent of the Earth's ice-free land surface has already been significantly altered, most of the oceans are polluted, and more than 85% of the area of wetlands has been lost. This destruction of ecosystems has led to 1 million species (500,000 animals and plants and 500,000 insects) being threatened with extinction over the coming decades to centuries. However, many of these extinctions are preventable if we conserve and restore nature.[3] Remaining species populations have declined, on average, by 69% since 1970 ([Living Planet Report 2022]).

Drivers of biodiversity loss

There are a range of drivers that are causing biodiversity loss[4]:

Changes in land use, including habitat loss and degradation: *Changes to an environment where a species lives. Common changes in use are caused by unsustainable agriculture, logging, transportation, residential or commercial development, energy production and mining. Land use change and habitat loss is the largest driver of biodiversity loss, accounting for approximately 50% of all biodiversity loss since 1970 (IPBES).*

Species overexploitation: *Direct overexploitation refers to unsustainable hunting and poaching or harvesting, whether for subsistence or for trade. Indirect overexploitation occurs when non-target species are killed unintentionally, for example as bycatch in fisheries.*

Invasive species and disease: *Invasive species can compete with native species for space, food and other resources, can turn out to be a predator for native species, or spread diseases that were not previously present in the environment. Humans also transport new diseases from one area of the globe to another.*

Pollution: *Pollution can directly affect a species by making the environment unsuitable for its survival (this is what happens, for example, in the case of an oil spill). It can also affect a species indirectly, by affecting food availability or reproductive performance, thus reducing population numbers over time.*

Climate change: *As temperatures change, some species will need to adapt by shifting their range to track a suitable climate. The effects of climate change on species are often indirect. Changes in temperature can confound the signals that trigger seasonal events such as migration and reproduction, causing these events to happen at the wrong time.*

[3] WWF Living Planet Report (2020)
[4] Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES)

These direct drivers are in turn caused by underlying, indirect drivers. These include broad global trends such as population growth, expansion of global trade and travel, the growth of the global economy, and the rise in consumption and the associated demand for resources.

In practice there are often interactions between economic and political actors that enable biodiversity loss to occur.

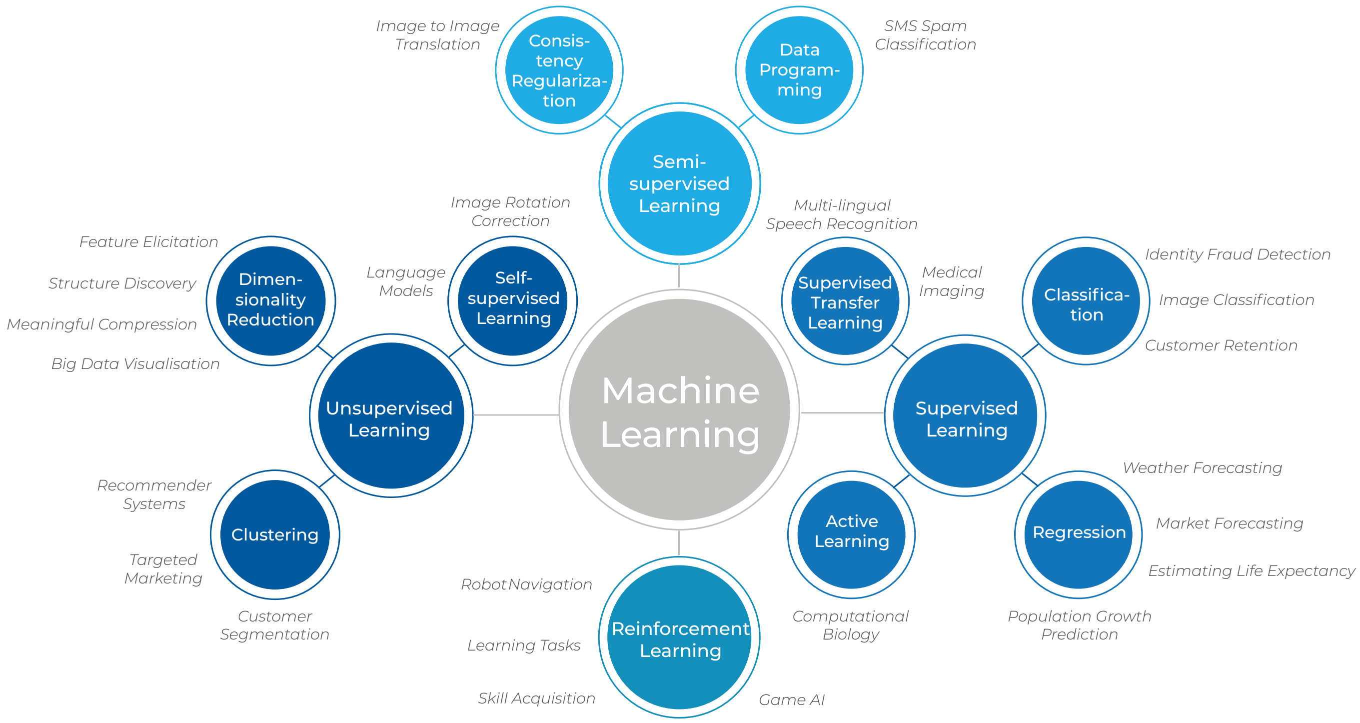
The wealth that can be generated by short-term exploitation of natural resources can undermine good, long-term biodiversity governance, either through wide-spread political pressure to allow exploitation, or through corruption. Understanding and addressing the underlying political and economic incentive structures that enable biodiversity loss will be critical to successfully reducing it.

AI

For readers from a biodiversity background, this subsection offers a summary of the types of Artificial Intelligence (AI) that exist, the kinds of challenges it is well placed to support, and some of its weaknesses.

AI encompasses any computer algorithm that makes predictions, recommendations or decisions on the basis of a defined set of objectives[5]. AI further encompasses machine learning which is particularly useful

Figure 3.2: A non-exhaustive taxonomy of machine learning methods in AI and example applications.



Source: Adapted from Morioh

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[5] OECD Definition

for identifying subtle or complex patterns in vast amounts of data. AI methods use models and data to draw results. These models broadly fall into four categories (see Figure 3.2) that can be learned from data. **Unsupervised learning** *models mine correlations within unlabelled data,* **supervised learning** *models find correlations between data labels and patterns within the data,* **semi-supervised** *learning uses both labelled and unlabelled data and* **rule-based systems** *use hand-made rules to draw results. A fifth category,* **reinforcement learning** *models, find optimal policies by rewarding desirable behaviours and punishing undesirable ones.*

AI problem types: *There are a range of challenges that AI is well placed to be able to help with:*

- *Classification: Based on training data, AI can classify input data as belonging to one of a set of categories, thereby supporting greater insight. For example an AI image processing algorithm might be able to identify and classify fishing vessels from satellite images.*
- *Prediction and forecasting: Based on training data, an AI algorithm can estimate the next value or values in a sequence. This type of use-case can go beyond forecasting future trends in time-series data, and can be applied to a wide range of data types to support pattern recognition and sequence prediction. For instance, AI can be used to predict deforestation risk.*
- *System optimisation: AI can support the operational optimisation of well-monitored systems by recommending a set of actions that optimise outcomes for a specific objective based on feedback from system monitoring. For instance, reinforcement learning may be used to design and monitor anti-poaching strategies.*
- *Anomaly detection: AI can help determine whether specific inputs are out of the ordinary when provided with historic data. For instance, detecting the presence of invasive species from photographs.*
- *Data generation: AI models are capable of generating novel examples from an existing distribution. For instance, historic agricultural system data might be used to generate new scenarios for how agricultural systems could operate.*

AI also has a series of weaknesses it is worth understanding. AI models find patterns in the data they are given, so if data is skewed or biassed towards certain contexts (for example, biological data can have regional, species, habitat, geographic, threat or language biases) they may fail to extrapolate or find only spurious correlations. AI methods are also often "black boxes" where the output is delivered by the model without much or any explanation of why it is true, or of how uncertain the answer is. Finally, current machine learning methods are also generally geared towards addressing specific challenges and are less able to solve problems that require broader conceptual understanding.

AI for Biodiversity

Approaches to addressing biodiversity loss include research on biodiversity to build an evidence base for action, citizens and local communities working directly to manage their ecosystems and resources; national and local governments and agencies developing biodiversity protection policy and biodiversity-aligned market frameworks; businesses and finance institutions working proactively, in advance of policy, to reduce the negative biodiversity impact of their products, services and investments; and non-governmental organisations (NGOs) supporting, raising awareness and providing pressure for all of the above. Despite ongoing efforts across all of these approaches, biodiversity has declined drastically in the last decades. The short-term financial benefits of exploiting natural resources have tended to win-out over long-term models of sustainable development. In exploring the potential to apply AI to biodiversity we need to recognise that current approaches have not been sufficient and simply applying AI to existing business-as-usual conservation methods is unlikely to be successful.

At present the majority of AI-for-biodiversity applications are focussed on enhancing current approaches to conservation, albeit at greater scale than previously conducted. The most common existing applications involve AI supporting biodiversity monitoring by helping classify species and landscapes captured through camera traps and satellite images, and to some extent, the monitoring of the drivers of biodiversity, for example by monitoring fishing trawlers or illegal timber logging.

These are important applications and AI can increase the scale, speed and accuracy of many of them. However, to create a step change in biodiversity conservation, these approaches need to be augmented with novel, innovative ways of shifting the politics of biodiversity conservation to increase its salience with electorates and politicians. This will require new ways of engaging and empowering citizens and communities to manage their land and to advocate for biodiversity; increasing transparency around the immediate political and financial drivers of biodiversity policy development; improved prioritisation on biodiversity strategy and policy; and driving transparency and optimisation across key commodity value chains and financial asset classes. AI has the potential to play a supporting role in all of these efforts.

Report structure

This report is a call-to-arms - a roadmap for guiding the emerging community working at the intersection of AI and biodiversity to focus efforts to apply AI on applications that can support a step-change in biodiversity conservation.

However, the application of AI to biodiversity challenges is not without risk. In **Section 3** *we summarise the risks that must be managed to support the* **responsible** *application of AI for biodiversity conservation.*

Sections 4 - 7 *offer an assessment of the current landscape of AI and biodiversity initiatives and the gaps in this landscape. The sections then set out a vision for how AI can be applied more widely to support conservation, identify bottlenecks to adoption, and propose recommendations to achieve the proposed vision. We have structured these sections as follows:*

- **Section 4**: *Using AI to understand biodiversity and biodiversity loss*
- **Section 5**: *Using AI to understand the drivers of biodiversity loss*
- **Section 6**: *Using AI to support policy action on biodiversity*
- **Section 7**: *Using AI to optimise action on biodiversity*

Section 8 *then seeks to assess the common challenges that arise in seeking to apply AI to biodiversity challenges across all of these opportunity areas and proposes recommendations for addressing these common challenges.*

Section 9 *captures the recommendations from sections 4-8 in a more detailed roadmap, describing who should take each recommendation forward, when they should be initiated, and an estimate of their duration and resource requirement.*

This report references relevant initiatives and organisations where these can support readers' understanding and notes tools readers could consider drawing on; however such references do not constitute an endorsement.

3. Responsible AI for biodiversity

There are potential pitfalls in using AI for biodiversity challenges that may create new risks and unintended consequences. AI needs to be developed, deployed and governed in a responsible manner to ensure it benefits biodiversity and society.

The principles outlined in the next section are applicable throughout this report and need to be assessed continuously. The responsible development and deployment of AI is not a static one-off process. The responsible use of AI requires active, on-going management of a range of risks to ensure that it is being used for the social good. These include risks that it will not have the hoped-for impact, and that it will create a range of social and environmental issues. These risks are detailed below.

Impact risk

The context in which AI technology is applied requires an understanding that:

- **AI is not a silver bullet but rather a specific capability that is relevant for certain applications.** *Whilst it has many benefits it should only be deployed where it is required and effective. In many instances, it cannot replace more traditional, low-tech historic approaches and risks distracting attention from them.*
- **AI is a component of an enabling technology, not a comprehensive solution.** *Its successful deployment depends significantly on the context and problems it is developed for. It is therefore important that the application of AI within a solution is carefully designed so that the interpretation of results provides meaningful and trusted input to decision-making. Poorly developed or deployed AI may lead to the incorrect conclusions and actions associated with biodiversity conservation.*
- **Greenwashing:** *there is a risk that companies seek to deploy AI to their operations, in a professed attempt to reduce the negative impact of their product or service on biodiversity, instead of taking more fundamental action to shift their business models.*

Social risk

Society needs to consider carefully how AI can be deployed:

- **AI can deepen inequality and injustice.** *AI is currently a tool of the wealthy whether tech companies, blue chip corporates, start-ups or researchers in leading universities. There is a risk it could accelerate inequality by giving powerful tools to the wealthy that* *allows them to further widen the wealth divide. AI-for-biodiversity applications are generally only available over the internet, and in many countries internet access can be prohibitively expensive, severely impacting data equity. For example, despite growing internet coverage, in Africa less than half of the population can afford to regularly use the internet to both obtain and communicate information.*

- **Data sovereignty:** *there is a risk that in seeking data for AI applications, organisations in the Global North seek to collect and aggregate large volumes of data from communities (including indigenous communities) in the Global South. This risks undermining the rights of communities who have been protecting biodiverse landscapes for many years. Engagement with local communities, especially those in the Global South, to support the democratisation of AI and aid its diffusion will be important to ensure that the benefits of AI are as wide as possible.*
- **Language:** *the proliferation of biodiversity related applications that use AI can create inequity if they are not accessible in a range of languages, and in particular those used in biodiversity hotspots. The availability of information and tools in natural languages and the accessibility of writing styles for non-experts, has importance for ensuring AI for biodiversity resources are available in languages relevant for countries with biodiversity hotspots. For example, there are over 2000 different languages spoken across Africa and India. The majority are low-resource languages (LRLs) which have a relatively small digital footprint for training AI language translation models.*
- **AI relies on quantity and quality of data.** *There is currently an inequality in the amount and quality of data being collected between the Global North and Global South. There is a risk that data availability will further exacerbate social inequality.*
- **AI can be used for repression and persecution:** *AI-enabled surveillance can be used to target environmentalists and local communities. Mechanisms to provide independent verification of issues such as through remote sensing or social media are able to use AI to support this democratisation and openness of data to support these causes.*

Environmental risk

The impact of the application of AI means that:

- **AI can optimise and accelerate business practices that have a negative impact on biodiversity.** *The benefits biodiversity offers humanity are mostly not captured by the market. Applying AI to industries that are having a negative impact on biodiversity risks accelerating and growing unsustainable business practices.*

Current models of resource extraction are often unsustainable, whether it is logging, mining, fishing or oil and gas exploration. AI is enabling more successful prospecting at a time when alternative solutions are needed. If we want to move away from "business as usual" we need to focus the use of AI in applications that have business models aligned with biodiversity net gain.

- **AI also risks increasing demand for resources that impact biodiversity.** *We have also seen a dramatic increase in consumerism across society driven by e-commerce platforms with AI-optimised recommendation engines that facilitate higher levels of consumption and hence resource demand.*
- **There is a direct risk to our natural environment through carbon emissions from energy usage and resource extraction for hardware materials associated with computing and data infrastructure.** *Efforts are being made to move towards energy recovery, with examples of liquid immersion cooling linked to district heating as a mechanism for heat recovery, but this needs to become widespread if society is to mitigate the impacts of increasing computing infrastructure.*

Tools

The challenge of implementing responsible AI is being addressed from both top down and bottom up perspectives.

Leading standards organisations (OECD, IEEE and NIST) are beginning to develop policies and standards concerning risk management and ethics for the implementation of AI. These are generic standards and need to be tailored for application to biodiversity and the natural environment to reflect impacts upon nature in addition to those on human beings. These standards have potential to affect those implementing AI in practice, but there needs to be a join up between these overall policies and practitioners if we are to see transformation of the community.

At a tech community and corporate level, a range of tools and toolkits have been developed to help researchers, organisations and communities to develop AI responsibly. These tools are still at an early stage of application and lack relevant examples in the environmental sphere. Tech companies with publicly available tools and examples of application include Google's Responsible AI Practices, Meta's Five Pillars of Responsible AI and Microsoft's Responsible AI resources. In the finance sector, global consultancies have taken the lead, with KPMG putting forward Five guiding pillars for ethical AI, PwC has a Responsible AI Diagnostic Toolkit, and Accenture has developed guidance on Scaling AI with confidence through Responsible AI. These approaches are complemented by the engagement of technology companies with responsible innovation and responsible AI initiatives globally, from the OECD AI Policy Observatory project to the cross-industry Partnership on AI.

4. Using AI to understand biodiversity and biodiversity trends

Context

Impactful conservation relies on solid biodiversity baseline measurements and change monitoring, requiring intensive observation and research. Traditionally, biodiversity monitoring has mostly involved manual methods for data collection and analyses, which are resource and time intensive, thus limiting the spatial, temporal and taxonomic coverage of biodiversity monitoring efforts. Artificial intelligence provides a potential breakthrough in this area, increasing the efficiency of both data collection and analyses at scale and is increasingly applied to monitor, model and understand patterns of biodiversity change in space and time. Three broad categories of applications of AI for understanding patterns of biodiversity and biodiversity change can be identified: 1) AI for automated direct species monitoring; 2) AI for predicting derived biodiversity metrics across space and time; and 3) AI for inferring environmental variables that are important for further understanding and managing these patterns of biodiversity. This report focuses on uses of AI for biodiversity, as biodiversity is strongly linked to overall ecosystem function and health (e.g. Hooper et al. 2005; Grace et al. 2016), and underpins many ecosystem services (Haines-Young & Potschin 2012). Biodiversity thereby forms a useful and observable measure of the state of nature.
The remainder of this chapter will discuss various examples of AI-driven biodiversity monitoring efforts. For more comprehensive overviews see e.g. Tuia et al. (2022), Shivaprakash et al. (2022) and Batist & Ermi (2022).

Figure 3.3: Data types commonly used in (AI-driven) biodiversity monitoring.

Source: Tuia et al. 2022.

Automated species identification

A large field of researchers and a growing community of applied conservationists are using AI for automated species monitoring. Using data from optical, acoustic or thermal sensors deployed in the field or mounted on drones, aircraft or satellites, algorithms are capable of providing species identification and sometimes population abundance estimations. A major benefit of using AI for these purposes is the vastly increased efficiency, repeatability, and accuracy of data processing compared to manual data analysis (Weinstein 2017).

One of the earliest and still most common applications of AI in this field is species identification in camera trap imagery. Multiple platforms exist that allow researchers, citizen scientists and wildlife enthusiasts to upload camera trap images in bulk, and then apply machine and deep learning-based algorithms for automated species identification (e.g., Kellenberger et al. 2020, Wildlife Insights, WildMe). Underlying many automated wildlife monitoring workflows is the Microsoft AI for Earth MegaDetector (Beery et al. 2019). The MegaDetector API detects animals (as well as humans and vehicles) in camera trap imagery, enabling batch filtering and croping of images containing animals for further processing. Animal species identification algorithms are still continuously improved, with newer applications focussing on automated identification in more complex images (e.g. birds in flight, Atanbori et al. 2016). Camera traps for insects now allow for detailed observation of insect populations remotely in the field and through bulk analysis in the laboratory. These systems include methods for moths (e.g. Bjerge et al. 2021), pollinators (e.g. Droissart et al. 2021), and freshwater species (e.g. Didry et al. 2019), often combining new sensors and computer species algorithms. For plants, a large body of work exists delivering detection and species identification using optical, multi- and hyperspectral data (e.g. Jensen et al. 2012; Zhang & Hu 2012) and LIDAR (e.g. Duncanson & Dubayah 2018) from satellite and airborne sensors (for comprehensive reviews see Fassnacht et al. 2016 and "Related work" in Beery et al. 2022). For coral reefs, solutions exist for automatic coral reef monitoring using photographic and videographic data. Computer vision technology enablesautomaticspeciesidentification, 3D modelling (photogrammetry), and analyses of benthic cover and species composition from user-uploaded materials (e.g. ReefSupport, ReefCloud). For the broader public, various applications also exist using AI algorithms for instant plant species identification in a user-uploaded photos (e.g., PictureThis, PlantNet, PlantStory, LeafSnap, Seek by iNaturalist (also for wildlife and fungi), and PlantSnap). Automatedanimalspeciesidentification for the general public is available through Merlin Bird ID (Van Horn et al. 2015) and iNaturalist (Van Horn et al. 2018).

Automated species identification from optical data is also increasingly relevant for museums and botanical gardens, to enable more rapid identification of new samples and thus enable faster description of new species. European museums are involved in the development of digital twins of samples to assist in remote research and analysis and a new EU-wide digital annotation *system making use of hybrid human and artificial intelligence ([Distributed System of Scientific Collections - DISSCO]())*

Besides optical data, a growing application of AI for biodiversity monitoring involves acoustic data. Reductions in size, weight and cost of acoustic sensors have given rise to a broad field of biodiversity monitoring applications via computational bioacoustics (e.g., Towsey et al. 2011, Aide et al. 2013, Ganchev 2017, Stowell 2022). Conservation NGO Rainforest Connection provides a platform to upload and analyse soundscape recordings for automated species identification (Rainforest Connection Arbimon). In the marine realm, acoustic monitoring is increasingly applied to improve understanding of cetacean population structure and communication (e.g. Deep Voice Foundation, Cetalingua Project, Project CETI). In French Polynesia, indigenous community conservation group the Coral Gardeners uses the AI-enabled platform ReefOS to monitor the health of transplanted heat-resistant coral species using a network of underwater acoustic sensors and cameras (ReefOS). Applications of bioacoustic monitoring by and for citizen scientists are also becoming more common. Soundscapes to Landscapes, for example, a citizen science project in Sonoma County, California, uses AudioMoth Open Acoustic Devices, crowd-sourced bird-call labels and machine learning models to assess avian diversity across varying parts of the region. Location-based assessments of diversity are then extrapolated across space using spatial modelling techniques by linking location-based diversity data to remotely-sensed climate data and other predictor information, to produce dynamic maps of species occurrence across the region. For amateur birders, the Cornell Lab of Ornithology has developed two applications applying deep neural network approaches to help users identify birds by sound (i.e., BirdNET, Merlin).

Thermal imagery is also employed in AI algorithms for species detection, for instance from airborne sensors (drones, UAVs) for automatic identification of for example koala (Corcoran et al. 2019), deer (Sudholz et al. 2021) and rabbits (Psiroukis et al. 2021).

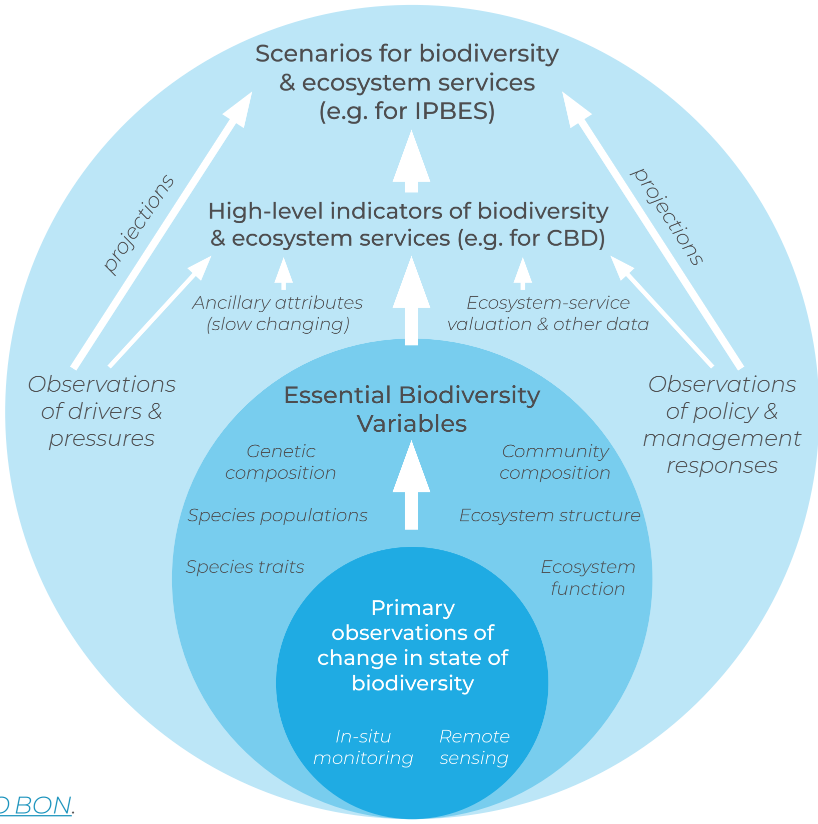
The growing availability of algorithms for automated species monitoring to the wider public is rapidly democratising biodiversity knowledge. Anyone with a smartphone can use the technology, and cheap tailored hardware is increasingly available (e.g. FieldKit, BirdBot), to improve understanding and awareness of local biodiversity, providing huge opportunities for citizens and community-led initiatives to participate in biodiversity monitoring efforts. Some challenges still lie ahead however, especially around spreading awareness of the available technology, reducing costs for data transfer (e.g. by improving on-device computations), and enabling those without access to necessary devices (smartphones, cameras, computers) to make use of the technology. A key consideration is that existing models are often derived from biased training data and might not generalise to new geographic or taxonomic domains. Low probability and erroneous species identifications in otherwise data-sparse domains could signal the need for future model refinement and development, with these new data employed as new training data.

Beyond identification: Essential Biodiversity Variables

Besides direct species observation and identification, AI is also increasingly used for predicting various derived measurements of biodiversity required to study, report, and manage biodiversity change across space and time. These derived measurements are referred to as Essential Biodiversity Variables (EBVs; [Pereira et al. 2013]).

Prediction of EBVs is a fast-growing field, with new data sets being produced regularly, such as increasingly fine-grained classifications of terrestrial and aquatic habitats, enabling better understanding of abiotic-biotic relationships and drivers of community composition.

Figure 3.4: Classification of Essential Biodiversity Variables.



Source: GEO BON.

AI offers particular advantages in classifying and monitoring species traits, such as animal behaviour (e.g. Rew et al. 2019, Bidder et al. 2020, Whitehead et al. 2020), especially when used in combination with animal-borne tags (biologgers) producing large volumes of data (Valeletta et al. 2017, Yoda 2018, Holton et al. 2021). Animal behaviour and other species traits can also be classified by AI from accoustic data (e.g. Mcloughlin et al. 2019) and occurrence data (e.g. Pontin et al. 2011).

At the population-level, AI models are commonly used in concert with remotely sensed data, to overcome heterogeneity and sparseness of raw biodiversity data, and to derive predictions that are contiguous in space and time and global in extent (Jetz et al. 2019). Automated *population abundance estimations often use satellite data in pixel-based classification and thresholding methods (Wang et al. 2019). Examples include counting wildebeests and zebras (Yang et al. 2014), elephants (Duporge et al. 2020), pack-ice seals (Goncalves et al. 2020), and albatros (Bowler et al. 2020). With very high-resolution satellite imagery becoming more widely available (e.g., WorldView-3, GeoEye) new algorithms for object-based methods are also being developed (e.g., whale species identification and population assessments, Cubaynes et al. 2022). Several applied conservation initiatives also leverage computer vision machine learning to automatically process crowd-sourced camera images to track individual animals in wildlife populations using natural markings, genetic identifiers, or vocalisations, matching individuals from within a database to enable population-level analyses (e.g. Blount et al. 2022, WildMe, BearID Project, Wildlife.ai). Researchers at Cornell's eBird Status & Trends programme use AI and vast amounts of bird presence and absence data from citizen science-derived species lists to model the full annual cycle distribution and population trends for over 1000 bird species (Fink et al. 2019). Finally, researchers are also using machine learning models to predict the distribution patterns of yet undiscovered biodiversity (e.g. Moura & Jetz 2021, Kass et al. 2022).*

At the community level, AI has been used to infer metrics of species diversity and richness (e.g. Yoo et al. 2013, Olaya-Marin et al. 2013). The mainstreaming of next-generation sequencing techniques in molecular ecology has also played a role here, giving rise to computational methodologies for population genetic inference employing artificial intelligence to make use of the enormous amount of genomic sequence data (see Schrider & Kern 2018 and Fountain-Jones et al. 2021 for comprehensive reviews). For example, researchers using machine learning methods are able to predict genetic diversity in amphibians (Barrow et al. 2020) and rodents (Kittlein et al. 2022) from species range data and life history traits, and very-high-resolution satellite data, respectively. AI is also applied to derive joint predictions of species abundance, genetic variation and functional traits (Overcast et al. 2021) and to infer past effective population size history (Sanchez et al. 2020). At the ecosystem-level, metrics of ecosystem functioning are also increasingly derived using AI, such as ecosystem degradation and integrity metrics (e.g. Garcia-Alaniz et al. 2017, iGamma White Paper).

Finally, AI is starting to play a role in improving scientific workflows around biodiversity data. AI-powered text-classification approaches have been used to identify relevant biodiversity articles in the published literature, to construct and enhance larger biodiversity datasets for use in further macroecological studies (e.g., Cornford et al. 2020). AI is also proposed to assist in developing better workflows to deal with the growing abundance and inconsistency of biodiversity data sources (e.g. Sen et al. 2021).

Biodiversity-relevant environmental covariates

Besides direct species and biodiversity monitoring, AI is also commonly used for inferring environmental variables relevant for further biodiversity modelling. Such variables include, for example, classifications of land use/cover, soil moisture content, aboveground biomass and carbon stock, and water quality.

The application of machine learning and artificial intelligence for the classification of satellite-based and airborne remotely-sensed imagery into large scale land cover and land use datasets is widespread and well-developed (e.g. Dynamic Earth, ESRI 2022, for more information see Chapter 6 of this report). Newer developments include subclass vegetation classifications from airborne hyperspectral and LiDAR data, sometimes going down to tree species-level (e.g., Mayra et al. 2021, Michalowska & Rapinski 2021) and mapping with multi-resolution data (e.g, Robinson et al. 2019).

Another application of satellite-based AI focusses on estimation of aboveground carbon stocks, for example mapping forest carbon fluxes (Harris et al. 2021), and automated large-scale high resolution carbon stock estimation (Lang et al. 2019, 2022; ETH, Avitabile et al. 2016). Freely available, high quality carbon stock estimates can provide broader insights into carbon stock losses and associated drivers (e.g. Feng et al. 2022), enabling better accountability in the interlinked climate and biodiversity crises.

Satellite imagery is also used in combination with artificial intelligence to improve fire monitoring (and management). Examples include fire susceptibility modelling (e.g., Pourtaghi et al. 2016, Kalantar et al. 2020, Zhang et al. 2021, Bera et al. 2022, Shmuel & Heifetz 2022); predicting fuel moisture content (Rao et al. 2020); and soil moisture content mapping (e.g., Srivastava et al. 2013). Improvements in IoT networks are also used for fire monitoring, enabling ultra-early fire-detection systems for public and private landowners (e.g. Dryad). One challenge is to scale such systems more widely, and provide access to less technologically advanced user groups such as local communities and indigenous peoples who manage large areas of fire-prone land.

Citizen science and monitoring by indigenous peoples and local communities

Citizens, local communities, and indigenous peoples all have unique connections to their environments, often giving rise to particular knowledge of or interest in local biodiversity patterns. Citizen science projects most often engage the public in data collection or classification, although public contributions to the scientific process are growing more diverse (Shanley et al. 2021). Examples of citizen science projects employing AI capabilities range from small scaleprojects to gain understanding of local biodiversity patterns (e.g. Soundscapes2Landscapes, Sri Lankan Turtle ID Project, Bat Detective) to global systems for systematic data collection (e.g. eBird, eMammal, Zooniverse). Citizens can also contribute to conservation monitoring efforts via hackathons (e.g. Earth Hacks). All these initiatives greatly democratise biodiversity data collection and analysis, providing citizens with insight into the state of biodiversity and opportunities for engaging in advocacy for better environmental decision-making. There is considerable scope however for further integrating AI and biodiversity citizen science. Combined human-machine teams (increasingly known as "humans-in-the-loop" research designs) can leverage the best of both worlds, leveraging the power of algorithms to detect patterns, while using human local ecological knowledge to make sense of anomalies (e.g. Branson et al. 2010, Reda et al. 2013). This is particularly important in identifying potential biases (Shanley et al. 2021). A systematic approach to data collection by citizens is the Citizen Science Global Partnership (CSGP). The CSGP is coordinating the collaboration of existing citizen science practitioners with international organizations and governments, and supports the use of citizen science data and tools as a key contributor to the global effort towards sustainable development. It establishes diverse and inclusive partnerships across geographies, cultures, and research domains, promoting citizen science as a unifying, enabling, and multiplying force for change.

Indigenous communities have an intergenerational connection to nature and often derive livelihood from it, providing them a wealth of knowledge of their local ecosystems that cannot be matched by modern science. This indigenous knowledge is important for understanding historic baselines and monitoring the status and trends of biodiversity and can help develop policies that are important for biodiversity while ensuring maintenance of indigenous community livelihood and culture. With escalating threats, many communities have taken to monitoring ecosystems and some efforts exist to bundle efforts and resources (e.g. Indigenous in AI, IndigenousAI). Incorporating indigenous knowledge into assessments and policy is not without its difficulties. Given that indigenous knowledge and science stem from very different knowledge systems, it is important that there is careful consideration in developing frameworks that bring these together. Working together, indigenous knowledge and AI can transform monitoring and put power in the hands of the local communities enabling them to use local indicators that they uniquely understand and value and gain insight into what is happening in the ecosystems. One such example is the partnership between Microsoft and CSIRO. In this project, drone footage is collected by indigenous rangers and computer vision is used to identify plants and animals and the results used for local decision making. While developing and deploying such AI-powered monitoring approaches, it is essential that local communities are involved, adequate training provided and considerations made to their ability to use it and maintain data sovereignty. There is an opportunity in scaling and standardising such efforts so that they can be used on multiple scales including globally and to inform policy.

Further opportunities

For the near-future, various growth areas exist for AI technology to further improve biodiversity monitoring efforts.

On the species monitoring side, a growth is expected in applications using edge analytics to process data upon capture. On-device, in-situ, local data analysis provides a solution to overcome data transferability and ownership issues when transferring data to remote computing resources is not possible, too costly, or otherwise undesirable. Processing data upon capture also results in lower data storage burdens as only processed data is stored and potentially transferred.

AI is also expected to be of increasing use in overcoming data bias and scarcity. AI algorithms can be applied to infer data in data-sparse systems, regions or timespans. This will lead to increased and improved forecasting and hindcasting of biodiversity baselines and trends where existing data is limited. A similarly growing application is that of developing conservation counterfactuals: inferring what the consequences of conservation inaction are likely to be where it is impossible or unethical to conduct research with empirical control groups.

Another trend in biodiversity monitoring is the increased availability and use of hyperspectral data. Analysis of such data is giving rise to monitoring at increased taxonomic and thematic resolutions. Analysis of satellite and airborne hyperspectral data is enabling, for instance, vegetation mapping at the species level. Hyperspectral data can also provide rich insights into many other environmental variables, such as soil carbon content, plant health, or levels of (micro-)pollutants.

AI is also increasingly important in integrating field-based species data archives (e.g., life history traits, habitat preferences) with remotely sensed data, to derive improved biodiversity metrics and variables (e.g. EBVs). This development will provide improved quality and depth of biodiversity monitoring data and enable faster scaling of ground-based observations across space and time. Relatedly, there is increasing interest in AI applications to monitor ecosystem degradation and restoration as derived metrics from empirical data.

Another trend in AI for biodiversity monitoring is the development and openly sharing of libraries of labelled training data for species monitoring (e.g. LILA BC). More and more such open libraries are becoming available for bioacoustic classification and camera trap image classification for example, whilst libraries for object-based species identification from very high-resolution satellite data or for hyperspectral remotely-sensed data are somewhat rarer. Increased availability of libraries of labelled training data will spur further analyses where topical data is unavailable.

Finally, there seems to be an increasing role for AI in enhancing the human experience in nature and its gamification. Augmented reality (AR) is increasingly applied to assist in detecting and classifying species in the environment in real-time (e.g., binoculars with bird identification abilities, mobile phone apps enabling real-time bird call or plant leaf identifications). It can also be used to enable local communities to explore future scenarios of land use change, such as increased tree planting (e.g. UKCEH E-Viewer). This is a field that could see an expansion of applications as nature enthusiasts seek new ways of connecting with their environments and may provide a tool in connecting new audiences with nature spurring demand for biodiversity protection.

Vision

Reliable biodiversity data is the backbone of conservation and restoration science. Without knowing what there is, or was, and how it's changing, it is impossible to design effective conservation policy and deliver conservation action and impact. The conservation community has long recognized the need for an effective, automated, and globally distributed biodiversity monitoring system that provides verified information on the state of the biosphere in real time (Scholes et al. 2008, 2012). AI has the potential to considerably accelerate such efforts (Tuia et al. 2022). A distributed system of automated sensors that couples different types of information streams (networks of in-situ, airborne, and satellite-based sensors) and algorithms, with traditional field-based observations and other new information streams (e.g. eDNA), holds the potential to provide a holistic picture of the state of biodiversity (e.g. a network of Automated Multisensor stations for Monitoring of species Diversity: AMMODs; Wägele et al. 2022). Such a system should be ruled by a set of data and ethical standards that ensure data quality and account for ethical and environmental risks of making certain types of data publicly available. A global biodiversity monitoring system should monitor species irrespective of size, rarity or charisma and in both easy- and hard-to-reach places. Resulting biodiversity information should be freely available not just for the research and conservation communities, but also for education and to the wider public to further democratise biodiversity science and facilitate political advocacy for better environmental decision-making and biodiversity protection.

Bottlenecks and challenges

Several bottlenecks and challenges exist providing potential hurdles in developing an autonomous real-time global biodiversity monitoring system.

1 *First, there are considerable challenges around data quality control, bias and interoperability. Although AI can assist in cases of low data quality or data bias, it cannot make up entirely for existing data skews. Current data biases are multidimensional, along axes of taxonomy, habitat, geography (Global North vs South), threat type, and language. More efforts need to be made to better direct monitoring efforts to places of high priority (e.g. DECIDE Tool).*

2 *Second, environmental data ethics, particularly around data sovereignty and privacy, can be complex, especially in the context of local communities and indigenous groups. The FAIR principles stipulate that data should be findable, accessible, interoperable, and reusable. Consideration should also be given however to potential unintended consequences of publicly sharing data, for instance pertaining to endangered species. The Global Indigenous Data Alliance further stipulates that projects should also consider the CARE principles: providing collective benefit, ensuring authority to control, responsibility and ethics. Both these sets of principles should be foundational to the development of any biodiversity monitoring efforts.*

3 *Third, there are considerable technical, financial, and knowledge barriers to using existing data and tools. Although technical knowledge often exists within technical private companies and university departments, considerable gaps still exist in more traditional conservation departments and organisations. The private sector is sometimes able to provide computational resources (e.g., cloud computing credits), but not expertise or hands-on support. Some efforts are already being made to better include applied domain knowledge in AI projects from the design phase (e.g. Karpatne et al. 2017, Reichstein et al. 2019). More ross-disciplinary programmes should be designed training technical students to work in biodiversity and conservation topics, but also including training in technical tools for students in biodiversity and conservation departments (e.g. CV4Ecology Summer School). Training is also often not available in languages other than English, limiting the opportunities for uptake of new technology by non-English speakers. Besides technical capabilities, the cost of applying AI solutions is often a barrier to entry. Training, running and maintaining AI solutions is expensive, both when using advanced local machines as well as when leveraging cloud computing resources.*

4

Finally, careful efforts should be made to ensure that data and insights derived from biodiversity monitoring using AI technologies is trusted and understood by a wide range of potential end-users. Currently, a certain degree of distrust of technical solutions by end-users and/or governments is sometimes experienced by experts working on AI solutions for biodiversity conservation. This is likely due to a limited focus on communicating and explaining models and model outcomes to non-technical audiences in the past. A related challenge pertains to effective ways of communicating uncertainty in AI-derived identification and analyses to different stakeholders.

Recommendations

- **Address bias in biodiversity data**

  Efforts should be made to improve the substantial taxonomic and geographic imbalance in available biodiversity training data by directing observation efforts towards underrepresented dimensions of biodiversity. Resulting biodiversity information should be well-annotated and machine-readable so that data is easily accessible and interoperable, and can find its way into diverse applications.

- **Ensure biodiversity monitoring follows both FAIR and CARE principles**

  The FAIR principles should be adhered to in all biodiversity monitoring efforts. Biodiversity monitoring data should be findable, accessible, interoperable, and reusable. Data collection should also provide collective benefits to researchers, policy-makers as well as indigenous peoples and local communities. All involved stakeholders should have the authority to control their data. Data collection should come with the responsibility to explain how data will be used. And the rights and wellbeing of data owners and providers should be of primary ethical concern.

- **Moving towards near-real time monitoring and prediction**

  Biodiversity monitoring holds a significant potential for rapid conservation action (see also chapter 8 of this report). Reactive conservation interventions will always be one step behind biodiversity destruction, however, if alerts of species declines, unauthorised activity or other forms of biodiversity risk are not delivered in a timely manner. AI should be further leveraged to increase the speed of analyses necessary for monitoring efforts, to enable (near-) real time biodiversity monitoring. On the ground, AI can be used for rapid identification of species or changes in environments, especially when employing on-device analyses through edge technology. When combined with AI-enabled data fusion, relevant information can be assimilated rapidly to support immediate action. In space, there is a move towards AI processing on board satellites to enable rapid disaster response and tasking of satellites for further observation (e.g. Mateo-Garcia et al. 2021). Further applications of such technology for biodiversity monitoring could be derived as well.

- **Invest in integration and maintenance of monitoring efforts**

  In addition to developing new and better monitoring tools, existing monitoring tools and datasets need to be better integrated in a unifying platform under an overarching framework. Governments can play a role in funding these efforts and ensuring agreement on data standards. More funding also needs to be directed to operationalisation and industrialisation of existing data sources, rather than funding projects primarily based on novelty. Collaboration on employing AI approaches to biodiversity challenges needs to be better stimulated. NGOs and private sector actors need to be more careful in avoiding replication of existing efforts. Community networks and fora for collaboration should be further mainstreamed. Both data and models need to be more openly shared and developed while upholding common standards of quality control.

- **Focus on communication and explainability of data products**

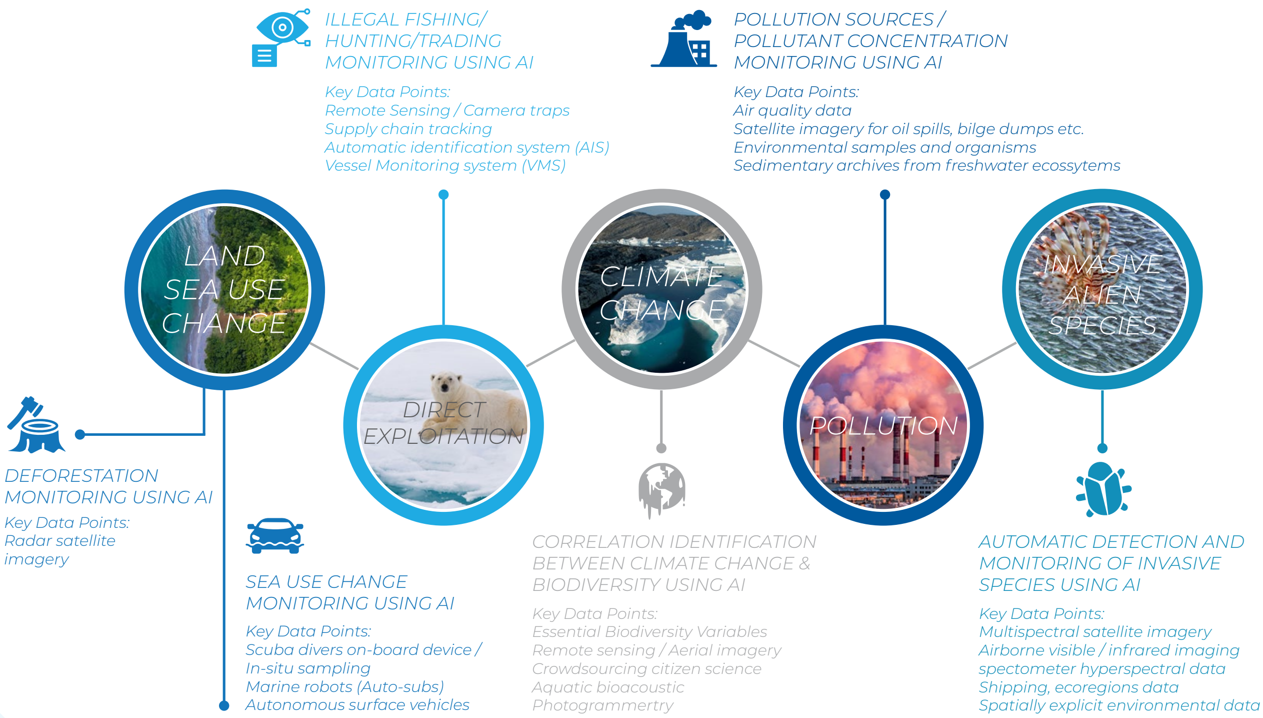
  Data monitoring and modelling efforts should improve on efforts to communicate and explain data and model outcomes outside of traditional scientific avenues to develop increased understanding of and thereby trust in AI-derived biodiversity information. A focus on developing new tools has given rise to a prolific sector developing new tools and models whenever possible, while sometimes more focus on communication and driving adoption of existing solutions might result in more conservation impact. Transparent communication on uncertainties at various stages of the monitoring and modelling process is key in this.

5. Using AI to understand the drivers of biodiversity loss

Drivers of biodiversity loss

As discussed in the introduction, the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystems (IPBES) identifies five direct drivers of biodiversity loss: 1) changes in land and sea use, 2) direct exploitation of organisms, 3) climate change, 4) pollution, and 5) invasion of alien species.[6] These direct drivers are in turn driven by underlying forces, or indirect drivers, which include production and consumption patterns, human population dynamics and trends, and technological innovations. The rate at which these drivers influence biodiversity change varies by region and can exacerbate one another through cumulative pressures, risking irreversible tipping points.

Applying AI to the monitoring of these drivers could represent a step change in our understanding of biodiversity loss, given its ability to identify patterns in large amounts of data and make recommendations. The drivers of biodiversity loss cross temporal and spatial boundaries and are each highly complex in their own right. AI can be a powerful tool for monitoring the drivers, their interrelationships and associated risks to ensure continued provision of the ecosystem services we depend on. Below, we discuss the drivers of biodiversity loss and how AI can support a better understanding of each.



[6] Global Assessment Report on Biodiversity and Ecosystem Services | IPBES

Direct drivers

Land- and sea-use change

Land- and sea-use change is the process by which human activities transform the natural landscape (Paul and Rashid 2017). The primary anthropogenic drivers of land-use change are agriculture, forestry and urbanisation. Agriculture covers more than one-third of the Earth's landmass, and urban areas have doubled since 1992. This growth in urban and other infrastructure is a key reason for the destruction of habitats such as forests and wetlands. Sea-use change is the second most significant driver of biodiversity loss in the ocean (after direct exploitation), and is caused by development along coastlines, aquaculture, bottom trawling, oil and gas extraction, among other activities

AI is already widely used to monitor land-use change, particularly in the creation of land cover and land use datasets, and in the monitoring of deforestation. Machine learning can help to classify satellite-based and airborne remotely-sensed imagery into land cover and land use datasets. For example, Google and the World Resources Institute have partnered to develop a dynamic dataset of the physical material on the surface of the Earth (Dynamic Earth).

One of the most common applications of AI in the realm of land use change is in the monitoring of deforestation. A novel development in this field is using AI to forecast future changes on the landscape. PrevisIA analyses a set of variables to indicate the areas at most significant risk of deforestation in the biome, including topography, land cover, official and unofficial roads, urban infrastructure and socioeconomic data. Forest Foresight uses radar satellite data and machine learning models to predict deforestation up to six months in advance, providing land-managing stakeholders the necessary time to carry out field investigations and ultimately prevent illegal deforestation before major damage is done. The system has been piloted with governmental stakeholders in Suriname, Gabon, and Indonesian Borneo who value the system for providing timely warnings of upcoming deforestation risk. Goldman et al. 2017 used a spatial modelling approach to identify the most important drivers of forest loss (biophysical conditions, accessibility, and land management status) and predict the likely location of future forest loss in landscapes managed by the Central Africa Regional Program for the Environment (CARPE).

There are fewer tools and approaches for monitoring sea-use change than for monitoring land use change. This may be because marine biodiversity data is more costly to collect, often requiring primary data from on-board devices and/or in situ samplings by scuba divers (Bicknell et al. 2016). However, AI is helping to meet this challenge. For example, marine robots such as autosubs[7] and autonomous surface vehicles[8] can survey large areas and record oceanographic data. And the EU Marine Spatial Planning Platform aims to create a Digital Twin of the Ocean to examine the impact of human activity

[7] Autosubs | National Oceanography Centre
[8] Autonomous Surface Vehicles | National Oceanography Centre

Direct Exploitation

The greatest driver of biodiversity loss in the ocean is the direct exploitation of marine resources. This includes unsustainable exploitation of fish stocks and illegal, unreported and unregulated (IUU) fishing. Direct exploitation of biodiversity on land includes hunting, harvesting, and logging. AI is currently being deployed to tackle overexploitation of organisms, and to monitor and prevent illegal activities such as poaching and illegal fishing. Illegal hunting and the trade of endangered wildlife poses a significant threat to biodiversity and is difficult to monitor and control manually, due to lack of resources and remote locations. Considering such rare species are often being traded online, in some cases AI has been used to investigate illegal wildlife trade on social media (Di Minin et al. 2018). However, given the breadth and depth of current social media, online markets, and e-commerce makes it difficult to deal with such a problem single handedly. WWF, TRAFFIC and IFAW launched the Coalition to End Wildlife Trafficking Online in 2018 and are collaborating with 47 of the world's biggest e-commerce, technology, and social media companies.

Use case: AI for sustainable fishing - OpenSC

Open supply chain (OpenSC), a joint venture by WWF Australia and BCG Digital Ventures[9], uses AI and blockchain technology to create transparency in the supply chain. OpenSC enables businesses to track their products by assigning a unique ID to an individual product at its point of origin, such as the moment a fish is caught at sea. The platform uses machine learning and real-time data such as the ship's GPS coordinates, direction and speed, and sea floor depth, to verify that the fish was caught in a sustainable way. This information is recorded using blockchain technology, a digital ledger that cannot be tampered with. Consumers can also use OpenSC to learn more about the products they purchase. For example, by scanning a product QR code with a smartphone camera, a consumer can see where a fish was caught, how it journeyed along the supply chain, and importantly, that it comes from a certified sustainable fishery and not an established marine protected area.

Use Case: Monitoring of Marine Protected Areas

Ocean Mind is a not-for-profit organisation which combats illegal fishing by using satellite imaging and artificial intelligence. Vessel tracking with OceanMind's artificial intelligence analysis allows rapid identification of fishing activities in marine protected areas. Remote sensing and satellite observations allow for the detection of "dark vessels" i.e. those that do not broadcast their locations. In-depth analysis by OceanMind's expert fisheries

[9] AI for sustainable fishing | OpenSC | WWF-Australia

to direct vessels to the highest threats.[10] *These capabilities have been applied across the globe with more than 20 countries with significant success in preventing illegal fishing, in particularly around UK overseas territories and in Thailand's exclusive economic zone.*

Similarly, Global Fishing Watch combines tracking data from publicly available automatic identification systems (AIS) and integrates that with information acquired through vessel monitoring systems (VMS) to identify fishing vessels and monitor their activity.

Climate Change

The changing climate directly affects biodiversity. Higher temperatures impact species distribution, phenology, population dynamics, community structure, and ecosystem function. These changes have knock-on effects on human health, food security through impacts on agriculture, aquaculture, fisheries, and the availability of other critical ecosystem services such as clean water provision and coastal protection from storm surges. Climate change also accelerates and exacerbates biodiversity loss through increased frequency and intensity of extreme weather events such as storms, fires, floods and droughts.

AI can help to find relationships between climate change and biodiversity. A team at the School of Biosciences of the University of Birmingham proposed a 'time machine framework' using AI to analyse historical data to find links between biodiversity, pollution events, and climate change (Eastwood et al. 2021).

As discussed in the section above on Essential Biodiversity Variables, AI can be used to track species populations, traits and distribution, including how these aspects change with climate change. These approaches can also be combined with crowdsourcing citizen science – e.g. Penguin Watch available through Zooniverse. The social impact organisation Coral Gardeners and partner Cornell University are using aquatic bioacoustics and photogrammetry programs to listen to restored reefs and determine whether they sound like healthy and stable reef systems, or whether additional restoration activities and interventions are needed[11].

Machine Learning can be helpful in analysing large amounts of data from climate and weather model simulations, identifying patterns and finding correlations quickly (incl. of Extreme events[12]*), provided the required input data to inform the learning process and iterative improvements are available. Human-induced changes in temperatures and other environmental*

[10] Marine Protected Area Enforcement | OceanMind

[11] AI for coral reef restoration | Coral Gardeners | Cornell University

[12] Franziska Gaupp, Jim Hall, Dann Mitchell, Simon Dadson, Increasing risks of multiple breadbasket failure under 1.5 and 2 °C global warming, Agricultural Systems, Volume 175, 2019, Pages 34-45, ISSN 0308-521X, https://doi.org/10.1016/j.agsy.2019.05.010.

conditions, such as salinity, can alter the suitability of habitats for species, leading to changes or reductions in their normal geographic ranges, and mean that some species have less and less area in which they can live and thrive. As species' ranges change, efforts to protect or restore these species and their habitats through designation of the boundaries of protected areas, for instance, may no longer be appropriately located or sufficient to protect species.

Pollution

Pollution of air, water and soil is one of the key drivers of biodiversity loss globally. The level and type of pollution varies by region, but the main sources are typically agriculture, transportation, electricity generation, and burning fuel for electricity and heat. Pollution affects ecosystems' ability to function and provide the key ecosystem services on which all life depends.

Fertiliser runoff from agriculture is a particular issue, as nitrogen and phosphorous can accelerate eutrophication, causing algal blooms and hypoxia (Chislock et al. 2013). In terrestrial ecosystems, ammonia increases soil acidity, harming plants and increasing their vulnerability to droughts and disease (Guthrie et al. 2018).

Air pollution can deposit in water, on vegetation and on soils as "acid rain"[13] and also has adverse effects on human health, through respiratory diseases. AI can be applied to monitor sources of pollution as well as pollutant concentration in air and water pollution, for example, by predicting ozone concentrations and oil spills. In Kampala, Uganda, cloud-based AI software is used to analyse air quality data and predict areas of severe local pollution through a project called AirQo.[14]

Globally, 80% of wastewater flows back into the ecosystem without being treated or reused, while soils are polluted with inorganic and organic compounds, some organic wastes and so-called "chemicals of emerging concern". Keramitsoglou et al. 2006 developed an automated approach for the identification of oil spills from satellite images based on AI fuzzy logic. AI has also been used for the detection of bilge dumps, gas flaring, algal blooms and other forms of pollution from satellite imagery (SkyTruth).

Plastics are another threat to biodiversity: there has been a tenfold increase in marine plastic pollution since 1980[15] and micro or even nano-plastics are now found all over the globe and within organisms. AI can be used to automatically detect microplastics in environmental samples (Meyers et al. 2022, Ai et al. 2022) and organisms (Botterell et al. 2022).

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[13] Air pollution, ecosystems and biodiversity | UNECE
[14] Using AI to reduce air pollution in Uganda | AirQo
[15] Global Assessment Report on Biodiversity and Ecosystem Services | IPBES

Use Case: Investigating the effects of chemical pollution and climate change on freshwater ecosystems

Eastwood et al. 2021[16] use AI time-series analysis to establish causal links between chemical pollution, climate variables, and biodiversity dynamics. They investigate sedimentary archives from freshwater ecosystems which can provide continuous records of biological and abiotic changes which occurred over time. They propose a 'time machine' framework for identifying the causes of ecosystem function loss and forecasting the future of ecosystem services under different climate and pollution scenarios. The approach is put to practice to identify taxa in watersheds affected by chemical pollution and climate change. AI is also used to model the dispersal of pollutants and can be used to establish source attribution.

Invasive Alien Species

The introduction of invasive alien species (IAS) is a growing trend that is driven by increased trade and human migration. IAS can have a significant detrimental effect on the invaded ecosystems by outcompeting native species and thereby decreasing their abundance and variety (Vilà et al. 2011). The introduction of alien species to a new environment is heavily driven by human movements such as trade and travel.

Machine learning can be used to automatically detect and monitor invasive plant species from remote sensing data. Jensen et al. 2020 tested the performance of several machine learning algorithms for the detection of invasive plants from multispectral satellite imagery and airborne visible/ infrared imaging spectrometer hyperspectral data. AI has also been applied for the detection of invasive plants along land transportation networks such as train tracks[17] and roads (Dyrmann et al. 2021).

AI can also be used to analyse the risk of aquatic alien species dispersal. Saebi et al. 2020 employ network analysis and data mining techniques to assess, visualise, and project the introduction and dispersal of invasive aquatic species within the Arctic from data about shipping, ecoregions and environmental conditions. The proposed approach can be used to inform risk-based assessment and management of ship-borne invasions. Meanwhile, Carter et al. 2021 present a workflow that generates rapid spatial risk assessments on aquatic invasive species using occurrence data, spatially explicit environmental data, and an ensemble machine learning approach to species distribution modelling. Trains

[16] Biodiversity "time machine" | University of Birmingham
[17] Using AI to detect IAS by railway tracks | UK Centre for Ecology & Hydrology

Use Case: Image Recognition for IAS monitoring

A collaboration between researchers from the University of Münster and the European Commission Joint Research Centre investigated how image recognition technology can be used for the automated image-based species recognition of IAS of European Union concern ([Jakuschona et al. 2022](), [Niers et al. 2022]()). The study analyses existing image-based plant and animal species recognition models such as the iNaturalist API and the Microsoft AI for Earth model and assesses their usability for an integration in a citizen science application to enable user conducted monitoring of IAS.

Indirect drivers

Indirect drivers describe the political, social, and economic forces that underlie the direct drivers of biodiversity loss described above. These include broad global trends such as the growth in global population, expansion of global trade and travel, and the growth of the global economy.

Production, consumption and the circular economy

Within each of these global trends, there are more nuanced changes in how our societies are constructed, how humans live and how we interface with nature. For example, global household numbers - the basic units of consumption - have increased much faster than global population, especially in countries with biodiversity hotspots, due to rising divorce rates and more single living.[18] Production is often geographically separated from the household - in other words our biodiversity footprint may be larger abroad than at home.[19] Many people not only consume imported products, but also travel to consume goods and services in other locations.[18] UNCTAD has noted that in order for trade to play a role in the battle against biodiversity loss, trade must be sustainable throughout the value chain, from the farm or factory to the store.

The patterns of consumption have changed, too. Humans now consume more calories per capita per day and meat and seafood consumption is on the rise.[20] The turnover rate of the products we use has also increased and their longevity decreased, for example in the fashion and electronics sectors.[18] In recent years, some countries have introduced policies relating to the circular economy. The circular economy represents a move away from the linear "take-make-use-

[18] Consumption patterns and biodiversity | Royal Society
[19] Why trade must be part of the solution to biodiversity loss | UNCTAD
[20] Global meat consumption, World, 1961 to 2050 (ourworldindata.org)

dispose" model towards a regenerative growth model in which the value of products, materials and resources is maintained in the economy for as long as possible, and the generation of waste is minimised.[21] While AI can have a significant role in promoting a circular economy or identify new patterns of consumption and help to influence them positively, as discussed in Section 7, it could also exacerbate the problem of overconsumption and overproduction and entrench the status quo. For example, when online shopping, matching algorithms make recommendations for customers on items that are frequently bought together. The often-seen prompt of "Customers who bought this item also bought" beneath an online purchase is designed to encourage further, potentially unnecessary, purchases.

Travel and tourism

The travel and tourism sector contributes to biodiversity loss through greenhouse gas emissions from air travel and other modes of transport; the clearing of land for tourism development and through physical disturbance to sensitive areas caused by tourism activities.[22] Furthermore, widespread and faster travel increases our vulnerability to pandemics, as it accelerates the spread of disease.[23]

Values

Human value systems and behaviours are also a critical driver of biodiversity loss. The recent IPBES Values Assessment[24] found that the short-term focus on profits and economic growth persists across political and economic decision-making, and that the multiple values of nature are excluded from these decisions. The report calls for new definitions of "development" and "good quality of life", and for societal goals to move away from individualism and materialism and align more strongly with values such as justice, stewardship, unity and responsibility, both towards other people and towards nature.

The System of Environmental-Economic Accounting (SEEA) is a framework that aims to bring nature into political and economic decision-making, providing a more comprehensive and multipurpose view of the interrelationships between the economy and the environment. SEEA provides standard concepts, definitions, classifications, accounting rules and tables for producing internationally comparable statistics and accounts.

AI is enabling a wider uptake of the SEEA framework through ARIES (ARtificial Intelligence for Environment & Sustainability). ARIES can generate ecosystem accounts for any user-specified terrestrial area in the world (such as a country, administrative region, watershed, etc.) by using freely available global remote-sensing derived data and models, and rapidly computing these accounts online using a web browser. ARIES uses semantics

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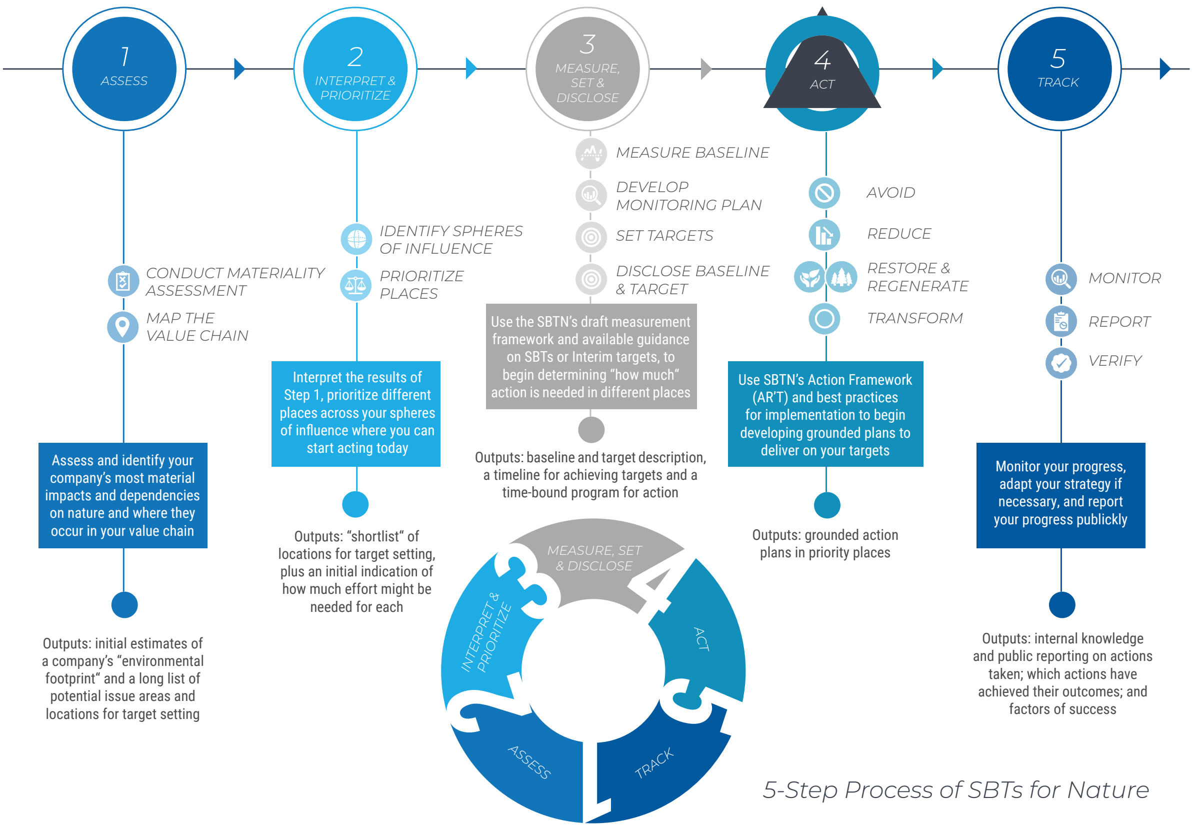
[21] Circular economy (europa.eu)
[22] No guilt trips: Tourism is part of the solution for nature | Convention on Biological Diversity (cbd.int)
[23] Annual report on global preparedness for health emergencies | Global Preparedness Monitoring Board
[24] Summary for policymakers of the methodological assessment of the diverse values and valuation of nature of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services | IPBES

and machine reasoning and automates model selection based on a user's specific request, choosing the "most appropriate" model for the location, spatiotemporal resolution and account specified (e.g., an ecosystem service or condition account for a given country and year) and depending on the models and data sources accessible to the system.

Capital markets

Through their lending and investment activities, capital markets are currently enabling biodiversity loss. The Draft Post-2020 Global Biodiversity Framework[25] calls on businesses to assess and report on their dependencies and impacts on biodiversity, and ensure that financial flows are aligned with nature-positive outcomes.

AI can also be used to support corporates and financial institutions to understand and publicly disclose their relationship with—and reliance on—nature. Several key frameworks and standards are currently in development, for example, the [Science-Based Targets Initiative](), which originally focused on corporate climate targets, has now created a [Science Based Targets Network]() which is developing guidance for companies to set science-based targets for freshwater, land, ocean and other nature-related areas. In particular, AI could support organisations with Step 5 of the SBTN framework, which focuses on collecting data for monitoring progress towards targets.



5-Step Process of SBTs for Nature

Source: TNFD

[25] [First draft of the post-2020 global biodiversity framework | CBD]()

Similarly, the Taskforce on Nature-related Financial Disclosures (TNFD), which is developing a risk management and disclosure framework for organisations to report and act on nature-related risks, has recently launched a Data Catalyst to address shortcomings in the current landscape of nature-related data, and encourage and improve the development of, and access to, nature-related data, analytics and tools. In particular, the Catalyst will focus on improving the quality of location-specific data linked to company supply chains.

Some tools (e.g., Global Forest Watch Pro) already exist to support businesses and financial organisations in identifying inherent risks within supply chains (e.g. water, forest risk), and quantifying impacts throughout the lifecycle of a product or service. There is potential for further applications of AI within these tools. For example, the company Rezatec uses geospatial AI data to enable remote monitoring of water infrastructure and water catchment areas. This allows organisations to monitor water quality, pipeline risk and prioritise where to direct ground-based engineering resources. Such technologies may allow companies to increase resource efficiency and avoid waste, however, as noted elsewhere, this will not have net positive impact for biodiversity if absolute resource consumption increases as a result of the efficiency gains.

AI is already widely applied to analyse corporate performance from a financial perspective, for example, using NLP to analyse the sentiment and content of quarterly earnings call (e.g. Acuity). As companies and financial institutions begin to establish organisational biodiversity policies and targets, stakeholders such as investors and customers may want to analyse performance against biodiversity targets, or evaluate the content of biodiversity policies for completeness and robustness. Automatic text summarization can be used to distil documents to retain only the most important information, or to combine information found in several related documents (multi-document summarization). Query-based summarization, commonly employed in search engines, provides the user with a document summary tailored to their search query. Text classification and topic modelling can be used to categorise policy documents and identify common themes. Finally, machine translation can be used to automatically obtain translations of policies published in another language. While the quality of the translation can vary depending on the complexity of the text and the language pair, it is usually sufficient to provide a basic understanding of the content and can thus be used as a first step for analysing documents from different jurisdictions.

Further opportunities

Land Use: *While there are many examples of AI being used to better understand land use change, there is less evidence of AI being used to understand the underlying drivers behind it, such as the political and economic incentives for agricultural expansion, urbanisation and the expansion of infrastructure.*

Direct Exploitation: *AI is already widely used to tackle money laundering and terrorist activities, for example by monitoring dark web activities and social media/online communication channels. These technologies could be applied to better understand the drivers behind illegal poaching and fishing activities. Furthermore, IPBES notes that funds channelled through tax havens support most vessels implicated in illegal, unreported and unregulated fishing.[26] AI could be used to track the flows of capital that enable these illegal activities.*

Climate change: *Further work could usefully be done to apply AI to help analyse individual species' vulnerability to climate change. This is a complex challenge requiring analysis across multiple variables. A recent study developed a Climate Risk Index for Biodiversity (CRIB) to assess the climate risk for nearly 25,000 marine species and their ecosystems ([Boyce et al. 2022]). While the study used a statistical approach rather than AI, future studies could incorporate AI methods to further improve species' climate vulnerabilities.*

Invasive Alien Species: *Further work on IAS could focus on analysing data collected from citizen science applications (e.g. iNaturalist), to identify data collected near or along transport routes that are at risk of enabling the transport of IAS, so as to enable rapid identification of IAS species outbreaks.*

Pollution: *Behind each pollution pathway, there is human or industrial activity. AI could be further applied to better understand these pollution pathways across air, water and soil. Applications include analysis of the activities which cause pollution such as untreated rural waste, pollutants from industrial, mining and agricultural activities, oil spills and toxic dumping. AI can also be applied to research into emerging pollutants such as microplastics and contaminants of emerging concern.*

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[26] Summary for policymakers of the methodological assessment of the diverse values and valuation of nature of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services | IPBES

Vision

A detailed understanding of the drivers of biodiversity loss is critical to conservation efforts. Without a clear analysis of the direct and indirect drivers, and the political economy incentive structures associated with biodiversity loss, there is a risk that any policy or action to halt and reverse biodiversity loss will be poorly targeted and ineffective. Whilst the direct drivers of biodiversity loss are reasonably well understood at a strategic level, there is a need to develop a much more granular understanding of the specific corporate, political economy drivers, and empower local communities to monitor their land and biodiversity assets.

AI offers an opportunity to create a radically more transparent and precise understanding of the drivers of biodiversity loss.

Whilst there are a range of existing data sources that can inform our understanding of the drivers of biodiversity loss, these are disparate, and manual analysis of these data sources is highly time- and resource-intensive. AI offers the ability to improve and automate this analysis, helping to identify patterns in the drivers by integrating a range of data sources, and thereby create a significant improvement in the transparency on the drivers of biodiversity loss at a granular level.

However, full transparency on these drivers cannot be achieved with existing open data streams. Ultimately governments will need to mandate data openness for supply chain data relating to international trade in high biodiversity risk sectors such as food, fashion, infrastructure and energy. Provided this data is made open in a machine-readable way, AI could then be harnessed to analyse this data to help connect areas where biodiversity loss is occurring (as identified through the monitoring efforts described in Section 4), with specific corporate activity data, enabling individual companies and financial institutions to be held accountable for the impact of their activities on biodiversity. This would, in turn, open up the potential for new biodiversity protection policies to be developed that draw on a more detailed understanding of the specific drivers of biodiversity loss, and are supported by AI-derived insight that enables enforcement.

Bottlenecks and challenges

Limited incentive for companies to open up their data to enable detailed monitoring of the drivers of biodiversity loss. *In the majority of countries around the world there are no incentives or requirements for companies in sectors with the greatest impacts and dependencies on biodiversity to share supply chain data. This can make it hard to gain a detailed understanding of the drivers of biodiversity loss in particular areas and to trace biodiversity loss risk across supply chains.*

Some biodiversity driver data is not openly available for political reasons. *Accessing financial data related to the underlying political and economic drivers of biodiversity loss may not always be possible, and some countries seek to halt international researchers and NGOs from accessing and publishing data related to the drivers of biodiversity loss in their jurisdictions.*

The cost and availability of real time satellite imaging data, together with the processing power required to analyse it, is a bottleneck for satellite monitoring of drivers. *Effective conservation requires ongoing monitoring of drivers. In many instances, this requires large amounts of satellite data. As biodiversity driver-monitoring initiatives scale they often find the cost of scaling access to high resolution satellite imagery to be prohibitive.*

Insufficient data collection, data standards and data sharing on biodiversity loss drivers: *For example, an analysis of the top challenges for the field of Invasive Alien Species in Europe found that the top threats included insufficient monitoring of IAS, a lack of standardisation in data management, and poor data sharing and communication across between countries. Initiatives such as [Biodiversity Information Standards]() (TDWG) are active in this area, aiming to foster international collaboration among the creators, managers and users of biodiversity information and to promote wider and more effective dissemination and sharing of knowledge.*

Limited awareness of AI solutions to monitor drivers of biodiversity loss. *While AI technologies and approaches are improving all the time, it is clear that there are already many useful applications of AI to understanding the drivers of biodiversity loss. Effort is now required to publicise and mainstream these tools and approaches across local communities, public and private sectors to increase capacity and understanding of the ways in which these drivers lead to biodiversity loss.*

Limited funding availability to maintain or scale tools to deliver ongoing monitoring of drivers. *Many of the tools and AI applications discussed above were developed by researchers and concerned parties such as environmental NGOs. Researchers and NGOs, especially in the less developed countries may lack resources and would benefit from funding from government and large corporations to support this type of work.*

AI is still in the pilot testing phase in terms of monitoring direct and indirect drivers and their relationships with biodiversity loss. *Many of the examples are scientific exercises rather than tried-*

and-tested approaches. The next step is for these pilot approaches to be scaled up and taken up by decision-makers globally.

AI derived insight on drivers is insufficient on its own: *AI is often used to 'sound the alarm' on illegal activities such as deforestation and illegal mining, however these initiatives need to be connected to advocacy and awareness raising to drive change. Additionally, local communities must have resources and readiness to take appropriate action when the alarm is raised.*

Drivers and indirect drivers can be complex, multi-dimensional issues. *For example, actors may be driven to illegal logging to improve challenging economic conditions, underscoring the need to consider the importance of a just transition that supports people to move to sustainable forms of development.*

Recommendations

- **Governments and businesses should adopt and adapt existing tools for monitoring the drivers of biodiversity loss.** *Available AI-driven tools for monitoring the drivers of biodiversity loss have not yet been adopted by decision-makers in government and the private sector. More work is required to determine how existing biodiversity driver monitoring tools can be tailored to the needs of decision makers.*

- **Governments should mandate supply chain data openness for high-risk drivers of biodiversity loss.** *The existing incentives for companies to report on biodiversity risk are not sufficient to encourage companies to share data on their supply chain biodiversity risks. Governments should mandate reporting of this data in a format that is machine readable so that data scientists can easily analyse and inter-link this data to understand and bring transparency to supply chain biodiversity risk.*

  Some governments are taking the lead here (e.g. EU and UK) however a large number of countries have no specific requirements for companies operating in their jurisdiction to report supply chain data for high biodiversity risk sectors. However, opening up data in this way raises issues of data governance, data sovereignty and data justice, and agreed principles should be followed.

- **AI-driven initiatives on the drivers of biodiversity loss should consider how to build public engagement and advocacy into their tools.** *Presenting information on the drivers of biodiversity loss is often insufficient to drive change by itself. It may be that the people who are best placed to address the drivers of biodiversity loss do not have the know-how to act on AI-generated insights. Initiatives should consider how to engage the public, for example by involving local NGOs and research groups, allowing for* *the inclusion of data from citizen science, and critically, facilitating a route for citizens to contact their political representatives about a particular biodiversity driver. For example [Surfers Against Sewage] have an app in the UK where they highlight waste water discharge by water companies into the sea, and make it easy for users to contact their local Member of Parliament (MP) about the issue.*

- **Governments, research communities, NGOs and citizen science initiatives need to build networks of sensors around key drivers of biodiversity loss.** *The more data that is available on the drivers of biodiversity loss, the easier it will be to understand them at a granular level, and the more accurate an AI system can be in identifying patterns. Networks of sensors monitoring everything from riverine water quality, to soil carbon content would help bring transparency to the economic drivers of biodiversity loss.*

- **Effort is needed to pool data on the drivers of biodiversity loss.** *Driver data is distributed across a number of different portals such as the [UN Biodiversity Lab] and [Nature.Map], but not all of these initiatives are AI-ready. Driver monitoring initiatives would benefit if there were a central data aggregator to enable greater linking of driver data. However, finding an organisation(s) with the appropriate credibility and remit is a challenge. For example, the Global Biodiversity Information Facility pools direct biodiversity observation data but has no plans to aggregate data related to the drivers of biodiversity loss.*

6. Using AI to support policy action on biodiversity

Context

We identify application domains where AI and ML can support policy design and public services by providing improved information streams for decision-making and support the decision-making process as such through policy impact assessments. We encourage policymakers to consider opportunities for working with ML experts and building ML capacity in relevant public sector bodies, in NGOs, and among local communities and local research groups that can be uplifted via the implementation of conservation practice. We further encourage public entities to release data that may be relevant to biodiversity management through public policies.

National and international biodiversity policy processes

For centuries national governments and international efforts have established observation networks to manage and monitor a diversity of natural resources. Planning and operational management of these natural resources have been viewed as an essential task of nation states securing their very existence and, at times, their expansion. Today, governments are responsible for reporting on the status and trends in biodiversity to achieve their own national mandates (e.g. national biodiversity plans, recovering species at risk, sustaining ecosystem services) and international obligations (e.g. Convention on Biological Diversity (CBD), Ramsar Convention, Convention on Migratory Species, etc.). The CBD Strategic Plan for Biodiversity 2011–2020, for instance, envisaged already that "by 2050, biodiversity is valued, conserved, restored and wisely used, maintaining ecosystem services, sustaining a healthy planet and delivering benefits essential for all people". Collectively, however, countries are lagging far behind the goals that they have established. For example, of the 20 Aichi Biodiversity Targets agreed by 196 nations for the period of 2011 to 2020, not a single one has been fully met6.

Consequently, new tools for protecting, conserving, and restoring biodiversity are greatly needed. There are several ongoing policy processes that are oriented and aimed to halt and reverse biodiversity loss. For example, political leaders participating in the United Nations Summit on Biodiversity in September 2020, representing 93 countries from all regions have committed to a series of ambitious goals to reverse biodiversity loss by 2030. Nations are now negotiating the next generation of the CBD's global goals, due for adoption at COP 15 in Montreal in 2022. This convene will help to shape and frame the biodiversity-related actions of governments and other actors for decades to come. Critical for the analytical support of policy processes to stabilise or reverse biodiversity loss are the following three fundamental issues: First, multiple goals are required reflecting nature's complexity, with different facets—genes, populations, species, deep evolutionary history, ecosystems, and their contributions to people—having markedly different geographic distributions and responses to human drivers. Second, interlinkages among these facets mean that goals must be defined and developed holistically rather than in isolation, with potential to advance multiple goals simultaneously and minimise trade-offs between them. Third, only the highest level of ambition in setting each goal, and implementing all goals in an integrated manner, will give a realistic chance of stopping—and beginning to reverse—biodiversity loss any time soon. Given these three fundamental issues and their associated complexity, AI approaches will be essential to supporting countries at all stages of the policy cycle (see section models and scenarios).

Policy setting for biodiversity by business

Under the UN CBD the Global Partnership for Business and Biodiversity which was established a decade ago a number of regional and sectoral business initiatives were launched and several commitments and pledges have been made by business organisations to take action to help reverse nature loss. Regional and national business commitments include the Brazilian Business Commitment on Biodiversity (Brazil), act4nature Portugal (Portugal), German Business for Biodiversity (Germany) and sectoral commitments are the Fashion Pact (Clothing & Textiles) and the Finance for Biodiversity Pledge (Finance). For example, in total 98 financial institutions representing 19 countries and over 13.9 trillion Euros in assets signed the Finance for Biodiversity Pledge in 2022. The Pledge was initiated by a group of 26 financial institutions calling on global leaders and committing to protect and restore biodiversity through their finance activities and investments and launched during the Nature for Life Hub on 25 September 2020 and the Biodiversity Summit of the United Nations General Assembly on 30 September 2020.

Pledge signatories call on global leaders and commit to protecting and restoring biodiversity through their finance activities and investments by:

1. *Collaborating and sharing knowledge*
2. *Engaging with companies*
3. *Assessing impact*
4. *Setting targets*
5. *Reporting publicly on the above before 2025*

In addition, there is the Task Force on Nature-Related Financial Disclosures, the Science Based Targets Initiative and the Taskforce on Nature Markets, noting that these initiatives are building the data infrastructure needed to embed nature into economic and financial decision making. Although many of these activities are in their start-up phase and only a limited number of businesses have set quantitative targets, it is clear that meeting these pledges will require considerable analytical support to enable business level planning and implementation of concrete policies and measures. AI-enabled data and services platforms will play a crucial role in supporting businesses to achieve their goals.

The policy process

AI is extremely well positioned as a technology to aid the biodiversity policy-making process from identifying the patterns of need to developing evidence-based programmes, forecasting outcomes and analysing effectiveness. All of these areas benefit from novel data collection and analytical methods including the subsequent modelling efforts that can be informed by AI. The risks of inappropriate use of such data or the outcomes of these modelling processes mean that responsible AI is even more important. Crucial areas include public policy as well as the principles of accountability, transparency, and fairness. The absence of such trust is the primary reason why AI has yet to be implemented at scale by governments in this area (Gilkins and Woolley, 2020). In charting progress in evidence-based policymaking, it is clear that data-driven approaches have matured over the last few decades and that mathematical models describing events or processes have largely become accepted for the purpose of modelling a city's climate prediction or forecasting the spread of a pandemic for policymaking. Further steps toward the integration of AI to support and extend such work is presently in its infancy. There is substantial effort internationally towards improving climate forecasting and linking climate models to land-based models to enable impact analyses. This is at the forefront of thinking behind the European Space Agency Digital Twin Earth Initiative which also links to the European Commission Destination Earth Programme. AI is explicitly part of these developments in recognition that the scale and complexity of data and challenges with interpretation are too great for standard mathematical and statistical approaches.

The potential role of AI in the policy cycle has been summarised in figure 7.1, where it can be a cutting-edge and advanced tool facilitating new ways for decision makers to access new information to inform the creation and implementation of effective policies. AI tools will never replace human policymaking, but they can be integrated into every step of the policymaking process from; 1) the **identification** *of the problem or issue from synthesis of large datasets, 2) the* **formulation** *of prospective solutions for that problem including forecasting and scenario planning, 3) the* **adoption** *of new insights deriving from that formulation to test for policy efficacy, 4) the* **implementation** *of the best practices and recommendations that emerge, and 5) the* **evaluation** *of the policy implementation with both the direct and indirect consequences that became evidential (Fig. 7.1).*

AI Has a Role at Evey Step of Policymaking

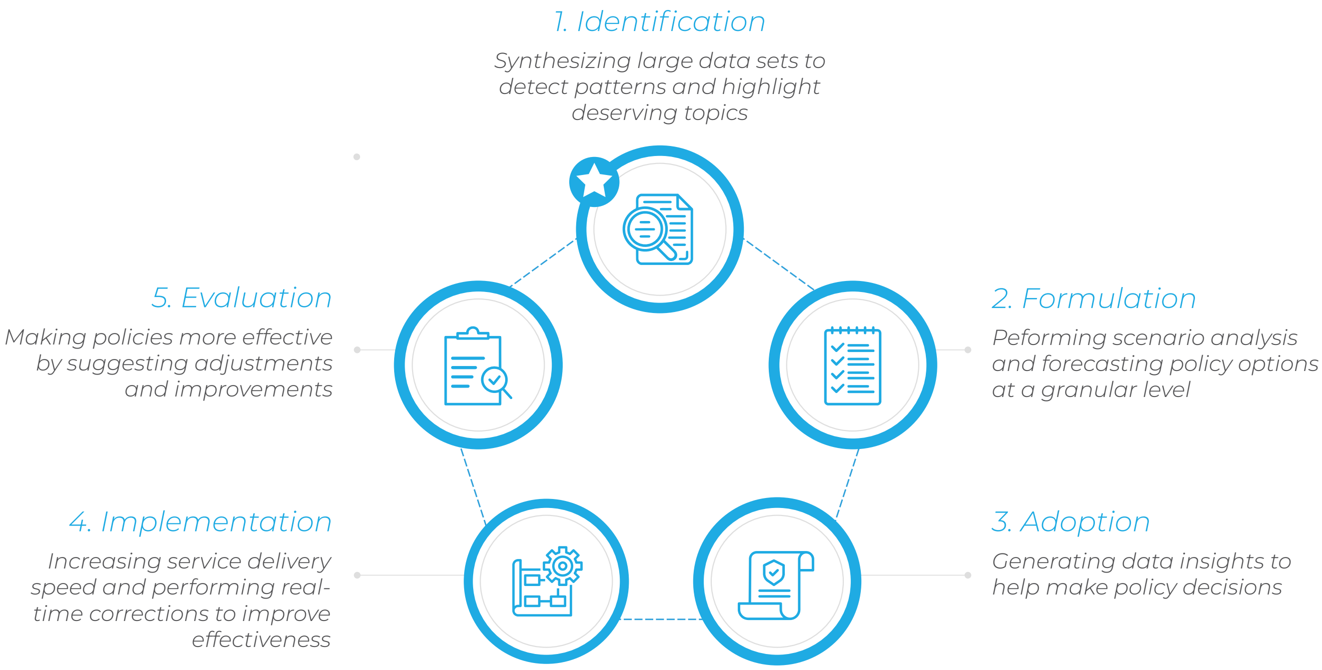


Figure 7.1: The role of AI in the policymaking cycle informing stages of identification, formulation, adoption, implementation and evaluation. In this way, AI can support every step in the policymaking process.

Source: Interviews and BCG experience

Conservation Area Prioritisation

Within the context of biodiversity recovery, AI can be effectively deployed to prioritise the spatial configuration of various conservation areas. The [CAPTAIN project](), offering conservation area priorisation through AI, provides a tangible example of the application of AI to policy interventions on protected area designation. It uses reinforcement learning to train AI models on the areas of the planet that could be prioritised for conservation using the best available data and resources. These models integrate basic species distribution data but can also handle complex multidimensional data including temporal trend analyses while considering predicted changes to land use and the climate. Experiments with simulated and empirical data have demonstrated that approaches such as this yield more reliable conservation solutions when compared to alternative state-of-the-art software for systematic conservation planning.

AI-Supported Collective Intelligence for Sustainability and Biodiversity Outcomes

AI can also be supportive of depicting various scenarios that could promote biodiversity recovery. For example, reinforcement learning, together with a set of tools to support collective decision-making processes, have been applied to global trade scenarios (focussed on beef and soybean trade *behaviour in 2019 integrating calculators of Argentina, Australia, Brazil, China and US; https://pure.iiasa.ac.at/id/eprint/17753/) to collectively address four global goals whilst adhering to national priorities and pathways and keeping global consistency. Here, AI must be applied to simultaneously consider various priorities when modelling various outcomes. In this example, the national targets included positive net forest cover change (>0 from 2030), biodiversity recovery (share of land supporting >50% by 2050), reduction in Greenhouse Gas Emissions (from agriculture <3.0Gt CO2 Eq., from land use change <0 by 2050), and an increase in Food security (Kcal feasible > MDER by 2050). The optimisation approach across country boundaries enabled by AI has significant potential for ongoing development of the international policies, and their targets, which are required for biodiversity net gain.*

Policy Enforcement: Current Application of AI

The enforcement of policies is one of the only areas where AI is currently incorporated into data-to-decision processes. The OceanMind and Global Fishing Watch examples in chapter 6 demonstrate a specific application area where enforcement and compliance to protect the world's oceans is enabled through AI, that spots specific patterns associated either with fishing or with being a container vessel which receives fish from individual fishing boats. Information on infringements related to Marine Protected Areas or territorial waters is passed to local enforcement agencies which will intercept the vessels and potentially prosecute. This is especially useful in remote areas where territorial waters are being breached.

Further opportunities

This section is organised such that the broadest opportunities are covered first, followed by some specific opportunities around particular policy activities and the associated AI applications.

Better policymaking for biodiversity through AI enabled models and scenarios

Models and scenario-planning built from AI hold tremendous potential for informing biodiversity policy processes. AI can deliver new insights for policy by: 1) supporting existing tools, 2) substituting existing tools, or 3) generating new application domains. Models can be used as digital twins to test a variety of policy responses to biodiversity decline and thereby contribute to good quality of life (human well-being) including enhanced delivery of ecosystem goods and services. In order to conduct in-silico policy experiments a large variety of variables are to be simulated, predicted or projected, by models of nature (biodiversity and ecosystem functioning) and nature's benefits. Figure 7.2 provides an overview of categories of variables that need to be considered to assess outcomes for nature or Nature's benefits. Many of these variables are, or could be, modelled by the use of AI.

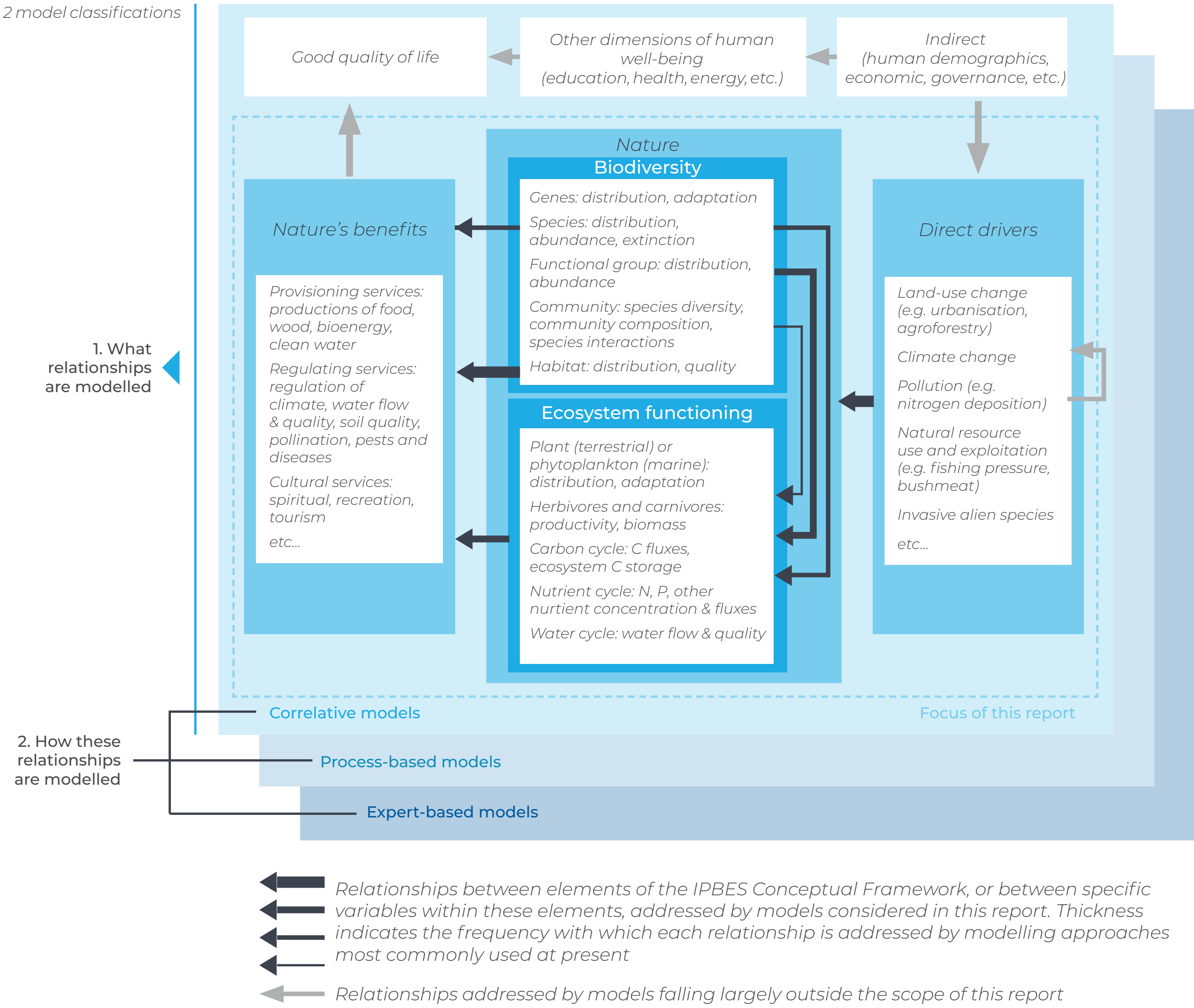


Figure 7.2: Major types of models of relevance to the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) activities, classified according to 'what relationships are modelled' (represented by the arrows linking elements of the IPBES Conceptual Framework, or variables within these elements) and 'how these relationships are modelled' (represented by the light-blue, green and pink-shaded panels). All of the relationships depicted on the light-blue-shaded 'correlative models' panel can also be modelled using 'process-based models' (green-shaded panel) or 'expert-based models' (pink-shaded panel).

Source: IPBES

Three broad approaches to modelling relationships between input and output variables are recognised and can be considered basic application domains for AI models: Correlative models, in which available empirical data are used to estimate values for parameters that do not have a predefined ecological meaning, and for which processes are implicit rather than explicit; Process-based models, in which relationships are described in terms of explicitly-stated processes or mechanisms based on established scientific understanding and model parameters therefore have a clear, predefined, ecological interpretation; Expert-based models, in which the experience of experts and stakeholders, including local and indigenous knowledge holders, is used to describe relationships and projections.

Models and scenarios serve different purposes along the policy cycle. Figure 7.1 depicts five different stages along the policy cycle. Identification, or agenda setting, uses exploratory scenarios with the purpose to define human development goals that respect Nature. One example of agenda setting modelling is around the bending the curve on biodiversity loss (LPR 2020; https://www.nature.com/articles/s41586-020-2705-y) which was conducted through a collaboration of four integrated assessment groups projecting land use changes based on scenarios of human development and nine biodiversity impact models (some of which used AI tools). Exploratory scenario modelling uses simulation models. Once targets are set target seeking scenarios become the method of choice. Target seeking involves optimisation techniques, for example in the minimisation of environmental impacts from dams (Flecker et al., 2022). The best known examples of target seeking scenarios relate to climate mitigation reaching 2C temperature change by 2100. Such target seeking scenarios use assumptions of broad policy tools such as a general carbon tax to compute shadow prices that drive the system towards the target. Policy implementation requires policy screening scenarios which use a very detailed model of policy design. Individual policy instruments (e.g. Brazilian forest code ruling that a certain percentage of the area of a farm needs to maintain forest cover or riparian areas need to be protected by buffer vegetation) are modelled individually and in combination to achieve practical policy goals of short to medium term. The assessment of the Brazilian Nationally Determined Contribution to the UNFCCC is a good example of detailed implementation policy assessment (Soterroni et al. 2019), which also led to a comprehensive biodiversity impact assessment (Brock et al. 2020). Models can use simulation and optimisation depending on the knowledge of behavioural rules of policy and economic agents. Policy reviews are used to identify the drivers explaining the policy gap.

Data and analytical infrastructure for policymaking

Policy developments supporting net biodiversity gain require data to be up-to-date, reliable, comparable among sites, relevant, and understandable. The work of the Intergovernmental Panel for Biodiversity and Ecosystem Services and recent assessments informing the formulation of international biodiversity targets have brought forward the need for a consolidated data and analytical

Systematic reviews and NLP: *Within the policymaking world, the use of systematic reviews of the literature has become commonplace in both health and environment decision support. These analyses frequently investigate a specific intervention to understand, from a range of literature sources, its efficacy. AI is particularly suited to analysis of these sources. As an example, even the selection of articles for review can be dramatically speeded up through AI:*

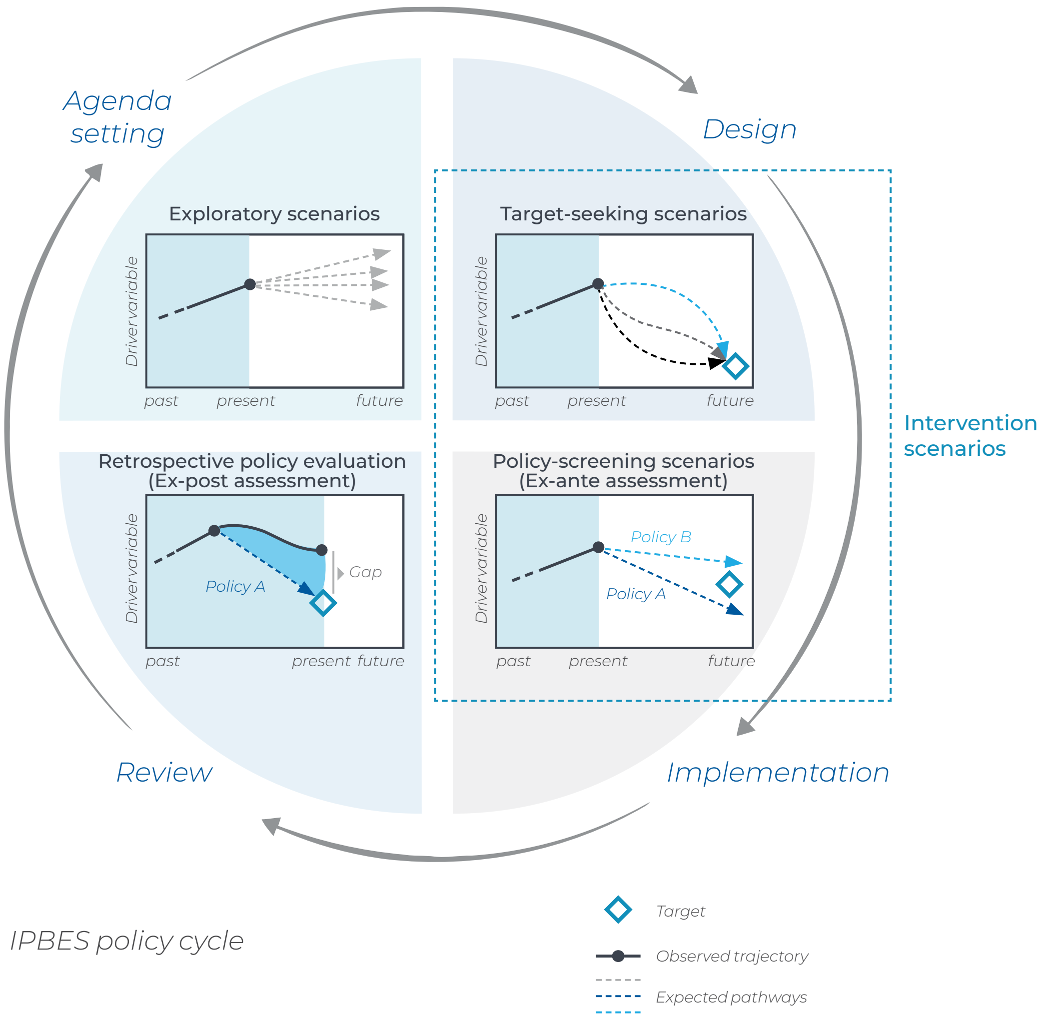
DistillerSR (https://www.evidencepartners.com/resources/guides-white-papers/the-case-for-artificial-intelligence-in-systematic-reviews). The grey diagonal line represents random order screening where relevant records are identified more or less evenly through the screening process. The green line represents screening using continuous AI reprioritisation. In this example, reviewers would have identified 100% of relevant records through screening only 18% of irrelevant records.

NLP specifically has significant potential to dramatically speed up the approach from years to days (see https://systematicreviewsjournal.biomedcentral.com/articles/10.1186/s13643-019-1074-9).

Ecosystem services and system modelling: *As the ecosystem services approach, incorporating diverse values of nature (IPBES Values Assessment 2022), is implemented by governments for a broad range of applications, the systems based approach will require AI to address its complexities and to enable a diverse community of stakeholders to simultaneously understand the implications for themselves with particular interventions and the potential of trade-offs to support actions (see https://www.sciencedirect.com/science/article/pii/S2212041617306423#!).*

Vision

The full adoption of AI together with system modelling and other computational techniques into all of the tools and systems supporting policymaking, provided that explainability, transparency and trust are enabled, will transform the information provided to decision-makers. There is the potential to tailor information to the precise requirements of each individual role and to display this in the most user-friendly format. Such a situation will yield clarity, has the potential to be rapid as new data or scenarios are incorporated, and may be able to see beyond the current complexities of datasets to understand the mechanisms underlying changes and to simulate and predict potential outcomes.



IPBES policy cycle

We recognise that interventions at all stages of the policy cycle will be needed if we are to reverse the decline of biodiversity. If each stakeholder knew their role and sphere of influence, collective intelligence approaches could be used to optimise policy outcomes whilst providing value and esteem to all stakeholders. This vision is required if we are to push our society to make crucial changes to our lifestyles and the management of our environment. Technological progress with AI tools and advances in monitoring systems and ubiquitous connectivity are enabling governments and citizens to play their part. Information and tools to visualise and understand it, will no longer be the limiting factor in the decades ahead. The onus will fall on the willingness of governments, corporates and individuals to change their behaviour to promote nature. In turn, this puts further emphasis on the vital role of policy, and its ongoing development in response to environmental changes, to maintain our trajectory for interventions towards a nature-positive future.

Bottlenecks and challenges

The principal bottleneck associated with developing nature-positive solutions is the willingness of governments, businesses and individuals to change their behaviour. Many of the dimensions herein are situated in the realm of politics and social processes,which are beyond the scope of this report. However, the primary role that AI could play within this context would be the enabling of novel information to be presented in a suitable form to inform the decisions of stakeholders. This could include all media opportunities from targeted social media campaigns to specific recommendations to politicians focussed around the interests of their electorate.

A second bottleneck is represented by the willingness and ability, or lack thereof, of policymakers to adopt new AI tools, finance their development as well as test, evaluate, and validate their outcomes in the crucible of challenging decision-making. Many biodiversity-related policy decisions will have multiple trade-offs and factors which are of high economic value and emotive to individual citizens. Even if an opportunity is fully explained, the absorptive capacity of policy making units in government bodies can frequently be limited, therefore further education and explanation is needed.

In some instances, the complexity of biodiverse systems is such that it is currently not possible to fully understand their functionality and the interplay between species and environments in coupled human and natural systems globally. These *dimensions present a data and modelling bottleneck which currently prevents communities selecting the optimal strategies for nature recovery.*

In terms of agenda setting, within the conservation community, biodiversity apex targets are often unclear ([Purvis 2020](#)), the methodological guidance to determine targets does not exist and there are no spatial maps within the National Biodiversity Strategies and Action Plans (NBSAPs). There are also bottlenecks associated with the lack of use of high resolution datasets, the non-analytical culture associated with planning and the lack of coordination nationally and internationally.

Within policy design, there is a strong emphasis on area-based conservation targets and policy inefficiency due to lack of geographic integration. There is also a lack of policy coherence and joint policy planning among ministries and across jurisdictional and (inter-)national scales.

Recommendations

- **Governmental-planning agencies** *should be using high resolution and high quality data to determine policy goals and incorporate AI-based optimisation techniques, linking to larger scale digital twins facilitating simulations of various scenarios for biodiversity, natural capital (e.g. climate change protection), and nature-based solutions. A federated infrastructure financed with support from agencies, and with public-private partnerships, through a combination of research and digital infrastructure bodies, is essential.*

- **Geographically-nested joint policy planning tools** *should be developed by agencies fostering novel collaborative partnerships with research organisations and industry, with AI-based platforms enabling joint policy optimisation. The generation of a business case for governments for the implementation of AI in biodiversity policymaking, identifying the cost savings that new technologies can offer together with advances in accuracy and the development of new capabilities.*

- **Establish a set of policy AI Labs around the globe** *acting as centres of excellence to bring policymakers and AI experts together, trialling policy scenarios and developing methodologies. These Labs will be spread around different geographies but will ensure that developing countries which may lack technical capability are supported through partnership arrangements with those having the capability. These labs could also offer policy fellowships for environmental and AI researchers to be placed within policymaking entities in government, inter-*

governmental organisations, NGOs or businesses to accelerate the uptake of integrative AI for biodiversity translational research tools and new methodologies.

- Development of a responsible AI for policymaking framework *featuring a set of tools to navigate the research-implementation gap and ensure that policies are formed with consideration of the direct and indirect consequences for global society as well as the local and rural communities living in biodiverse-rich regions. Creation of a set of standards and common APIs for AI and environmental monitoring, including biodiversity, with ETSI, leading to uptake of approaches within the tech, civil, and industrial sectors.*

7. Using AI to optimise action on biodiversity

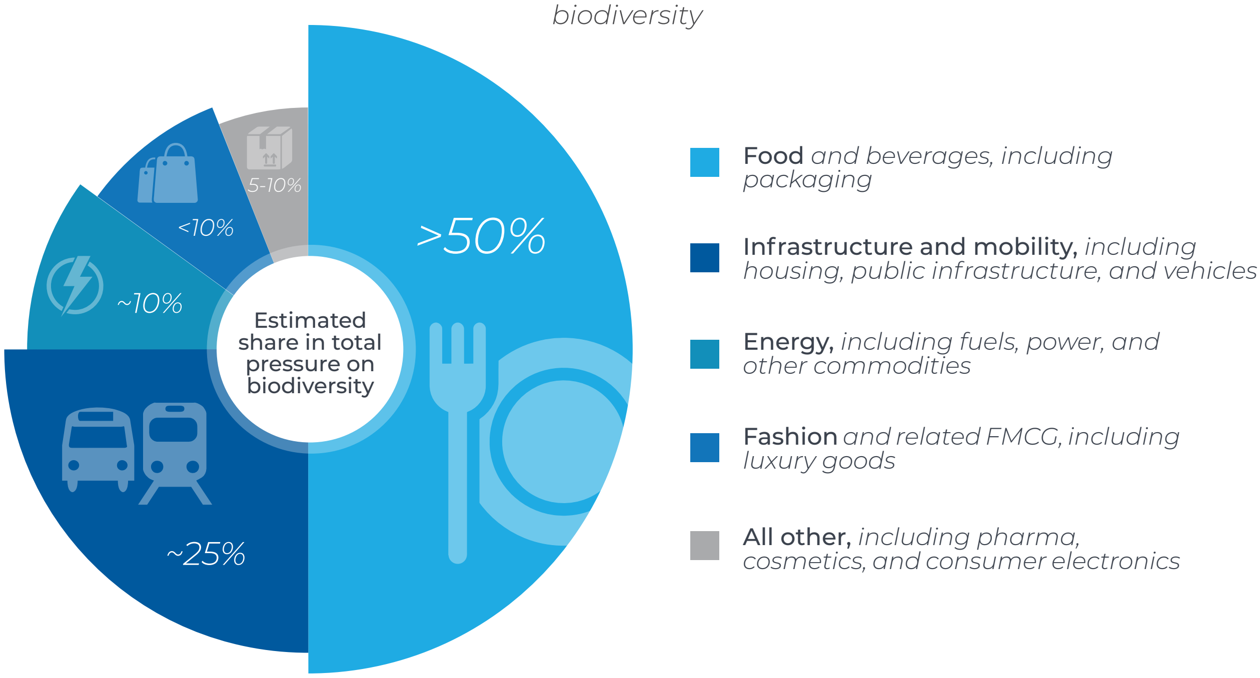
Context

Some of the most important opportunities to apply AI to support biodiversity conservation come in the direct implementation of new biodiversity-supporting approaches and systems in the private and public sectors. This section offers an analysis of where AI is currently, and could be, used to support biodiversity-positive systems and business models in both the private and public sectors.

Private Sector

Action on biodiversity is becoming an increasingly important focus for the private sector due to increasing public and political pressure. The transition to biodiversity positive business models also represents a significant business opportunity to forward-looking businesses. However, general understanding of and transparency on biodiversity loss is still nascent. A recent report[27] found that four major value chains – food & beverages, infrastructure & mobility, energy, and fashion – contribute to about 90% of pressure on biodiversity.

Figure 8.1: Four major value chains account for about 90% of pressure on biodiversity



Source: BCG

[27] *The Biodiversity Crisis is a Business Crisis | BCG*

Food

The food industry is the biggest contributor to the deterioration of natural ecosystems, accounting for more than half of human pressure on biodiversity. The conversion of natural ecosystems into cropland or pasture has been the principal cause of habitat loss, in turn reducing biodiversity. The 'cheaper food' paradigm, aimed at producing ever more food at ever lower cost has led to intensified agricultural production, which has degraded soils and ecosystems, and driven down the productive capacity of land. Current food production depends heavily on the use of inputs such as fertilizer, pesticides, energy and water, and on unsustainable practices such as monocropping and heavy tilling. This has reduced the variety of landscapes and habitats, threatening or destroying the breeding, feeding and nesting of birds, mammals, insects and microbial organisms, and crowding out many native plant species. To reverse the impact of food systems on biodiversity loss, a recent report by Chatham House and UNEP highlighted three priorities:

1. *Global dietary patterns need to move towards more plant-heavy diets to reduce the disproportionate impact of animal agriculture on biodiversity.*
2. *More land needs to be protected and set aside for nature to avoid the risk of conversion to agriculture and to enable us to conserve or restore whole ecosystems.*
3. *We need to farm in a more biodiversity-supporting way, limiting the use of inputs and replacing monoculture with polyculture farming practices.*

AI has the potential to support all three of these objectives, however the potential for AI to support and inform the setting aside of land as conservation areas is addressed in Section 6.

Moving to plant-heavy diets will require behaviour change, however food innovation and technology can make it easier for people to make this transition. Plant-based or lab-cultivated meat and dairy substitutes have the potential to shift the food industry away from a reliance on livestock, and thereby reduce its impact on biodiversity. For plant-based substitutes, identifying plants that have the potential to create meat and dairy substitutes requires teams to identify as many candidate plants as possible, analyse each plant down to the molecular level and predict how combinations of them will interact. The scale of data and complexity of the patterns means that AI offers the potential to accelerate progress. Examples of companies in this space include Eat Just, who are using AI to develop eggless egg and mayonnaise, and NotCo, who are focussed on meatless burgers and dairy-free milk. Another approach is to grow cultured meat and dairy substitutes in the lab. Animal Alternative Technologies, who are seeking to make cultivated meat indistinguishable from animal meat, *use AI to guide the growth of cultivated meat, and reduce time, costs, and risk in the development process. [Hoxton Farms] combines cell biology and machine learning to produce cell-cultured animal fat. [Imagindairy] is seeking to create lab-developed milk by drawing on the inherent milk recipes encoded in the genes of cows, and translating them into other organisms like yeast that could then generate milk proteins. They draw on machine learning to support modelling of the molecular evolution of proteins.*

AI is also being used to optimise traditional agricultural systems in ways that can support biodiversity conservation. To date AI has mainly been applied to support farm input efficiency by optimising the use of fertiliser, pesticides, and water. This can help reduce agricultural run-off, whilst reducing farm costs. Examples of companies in this space include [Trinity AgTech], who offer a farm management suite that includes AI-driven biodiversity analysis and optimisation. [Blue River Technology]'s See and Spray is a precision weed control solution that uses computer vision and machine learning to identify and target harmful weeds, reducing demand for pesticides. [Phytoform Labs] uses AI to precisely isolate the DNA sequences that can make plants more resistant to pests, thereby reducing the need for pesticides. AI enhanced weather forecasting can support more efficient water use. For example [XAG] claims that it's agricultural drones, and AI optimisation system allow farmers in China to use 30% less pesticide and 90% less water during crop protection[28].

Infrastructure

The infrastructure and mobility sector have a significant impact on biodiversity. Mining the raw materials required for infrastructure drives habitat conversion, and the extraction of mined materials often leads to soil, water and air pollution that can damage the integrity of ecosystems. The development of infrastructure then further drives land-use change, for example the construction of roads and railways can lead to both direct habitat loss due to the space required for them, as well as indirect habitat loss due to the subsequent development and resource exploitation that they enable. Applying AI to reduce the impact of infrastructure needs to start at the design phase. For example in designing vehicle material requirements, companies should seek to identify materials the mining of which would have a lower impact. AI is already being used to optimise battery design by companies such as [Aionics]. Further optimisation that considers the prevalence of materials in areas where they will not cause significant biodiversity loss would be a useful further step. [KoBold Metals], uses AI to improve predictions about where deposits of the materials required for battery metal deposits are located, thereby reducing the amount of ground that needs to be disturbed to find new ore bodies. More widely, mining sensors and cameras can be used to monitor mines and gather data, which is then analysed to better understand how waste can be reduced and how to be more energy efficient. Infrastructure with waste outputs can

[28] AgNews: XAG (2021)

use AI to help identify leaks that could cause pollution. For example in the water sector, Fido.Ai. is using AI to help water utilities find, assess and reduce leaks and become more efficient in managing their water networks.

Energy

The energy value chain accounts for around 10% of human pressure on biodiversity. This includes direct impacts from the extraction of fossil fuels such as coal, oil, and gas, including the impact caused by oil spills. The energy sector is also one of the most significant causes of climate change, which in turn is a driver of biodiversity. Addressing the climate crisis requires a rapid transition away from fossil fuels, which in turn will reduce the direct biodiversity impacts of the fossil fuel sector. However during the transition there is a need to mitigate the biodiversity impact of the sector. AI powered predictive maintenance, together with improved sensor technology can help identify oil rig parts that are faulty before their human operators notice, thereby reducing the risk of accidents, including oil spills. The US National Energy Technology Laboratory (NETL) has developed an Offshore Risk Modelling (ORM) suite that evaluates and reduces the risk of oil spill events. The suite can identify pressure during drilling activities and assess the integrity of offshore infrastructure to reduce the risk of equipment failure, and if spills do occur it can analyse data on ocean currents, emergency response availability and the behaviour of oil particles in the water to inform oil spill response teams. Another cause of oil spills is human error by tanker crews when transporting oil. AI navigational systems in ships can help prevent maritime crashes by providing enhanced information on navigational hazards.

The energy sector is one of the most significant causes of climate change, which in turn is a driver of biodiversity. The opportunities to deploy AI to help transition the energy sector away from fossil fuels and support climate action is covered by another GPAI report: Climate Change & AI: Recommendations for Government Action.

Fashion

The fashion industry accounts for about 10% of pressure on biodiversity. Similar to the food industry, the fashion value chain is dependent on the sourcing of raw materials through agriculture (e.g., cotton) and animal herding (e.g., wool, leather). The production of these commodities carries a significant biodiversity footprint. Growing cotton for example, one of the most important raw materials for fashion, is particularly insecticide and pesticide intensive. Although it grows on only 2.4 percent of global cropland, it accounts for 22.5 percent of the world's insecticide use[29]. The fashion sector also has an outsize impact on water pollution as approximately 25 percent of industrial water pollution comes from textile dyeing and treatment[30].

[29] Handle with Care: Understanding the hidden environmental costs of cotton," World Wildlife Magazine, Spring 2014, worldwildlife.org.

[30] Environmental impact of the textile and clothing industry, European Parliamentary Research Service, January 2019, europarl.europa.eu.

In addition to the ways AI can support a transition to regenerative agriculture which were addressed when discussing food, AI can also support circular economy business models for fashion. For example [Stuffstr]() buys unused clothing from consumers and partners with apparel retailers to recirculate the garments. The company uses AI to optimise price setting of the second hand items they buy and sell and to help classify all re-sale items. Customers are also increasingly purchasing clothing online, however due to the frequent need to return poorly fitting items this practice is causing significant wastage of garments and increases in e-commerce transport emissions. [MySize]() has developed virtual fitting room technology that uses AI and images that can be taken with a smartphone camera to help customers to purchase the correct sizes of clothing first time.

		Food & Beverages	Fashion	Energy	Infrastructure/ Mobility
Product Concept	*Use of All Assisted Design and Conceptualization*	*Medium*	*Medium*		*High*
Raw Material Production	*All for objective oriented smart sourcing (Deforestation focuse, Areas at risk focused, Type of Raw materials, Ingredients)* *All for crop diversity, crop rotation*	*High*	*Medium*		*Low*
Product Manufacturing	*All for sustainable manufacturing*	*Medium*	*Medium*	*Low*	*Medium*
Transportation Distribution	*All for sustainable logistics* *All for reverse logistics*	*Medium*	*Medium*	*Medium*	*Medium*
Retailing	*Personalized recommended engines for sustainable products/consumption*	*Medium*	*High*	*Low*	
Product in Use/ End of Life	*All based Waste recognition system*	*Low*	*Low*		*Low*

Fig 8.2: AI technology applicability in key sectors across the value chain steps with indicative impact

AI for biodiversity risk management

Companies and financial Institutions are increasingly interested in understanding their impact on biodiversity loss. This is driven by increasing consumer pressure and regulation. At the regulatory level, in 2021 France started requiring all financial institutions to disclose biodiversity and climate-related risks. In 2019 the EU started requiring companies to disclose activities that negatively affect biodiversity-sensitive sites. The Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standard (ESRS) will require companies with significant operations within the EU to disclose specific metrics on the impact their activities have on biodiversity and their dependencies on nature.

As a result, forward looking companies and financial institutions are now working to find data solutions to provide insight into the biodiversity impact at varying levels from a single commercial asset, a subsidiary, a parent company, an investment portfolio, or even a nation for sovereign debt insight. Due to the inherent spatial variation of biodiversity, a growing movement including the Taskforce on Nature-related Financial Disclosures (TNFD), has identified the value of a geospatial data-driven approach (WWF, World Bank, Global Canopy, 2022) and the World Economic Forum has recently published a report on the topic.

The approach takes asset data, the geolocated assets of a company, and applies observational data onto top of those assets to provide insight into aspects, such as water risk, land-cover change, deforestation, methane emissions and other variables. Due to the complexity of the data and patterns in it - AI will play a central role in this emerging field, for example in building and maintaining asset and supply chain datasets, supporting entity matching (assets to the correct parent company), data aggregation across supply chains, and data fusion across the diverse data points to better triangular and estimate the biodiversity impact of a given asset.

AI for land restoration and protected area management

There is increasing interest from public and private landowners to restore their land for nature. AI can support land managers to understand what opportunities for biodiversity restoration exist on their land, and if active restoration such as tree-planting is taking place, what species would be best given local conditions. Organisations such as Restor and Verna are using AI to support land owners and managers with land restoration.

In addition to the use of AI by private sector actors to reduce biodiversity loss, there are also instances where local and national governments can directly deploy AI, not for policy development, but for direct management of conservation areas and to support other effective area based conservation measures. For example, Protected Areas are defined as, 'a clearly defined geographical space, recognised, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values.' Today, there are over 260,000 protected areas[31] globally each with varying biodiversity value and integrity. In the context of increasing land use pressure from agriculture, urban expansion and infrastructure development, such areas, and others such as Key Biodiversity Areas, Indigenous lands, play an important role in conserving important ecosystems. Ensuring these areas are effectively managed and fairly governed has become a key component in safeguarding biodiversity.

Within conservation area management, AI has already been applied at differing scales: projects designed to support at the site-level to answer a specific use-case or need particular to the species

[31] https://www.protectedplanet.net/en

present or situation - to more multi-site level solutions, which can be applied across a state or region, to global scale, those which can be applied to all conservation areas globally.

For example, AI approaches have been used to help counter illegal wildlife trade (IWT) impacts. Both Protection Assistant for Wildlife Security (PAWS) and Spatial Monitoring and Reporting Tool (SMART), collate and digitise field data, wildlife observations, poaching, arrests and other events in real-time. Using ML these tools take the inputted data to predict poachers' future behaviour generates optimised patrol routes as output. For example, IWT developed the Connected Conservation Initiative working in Zambia's Lake Itezhi-Tezhi, which uses AI to detect boat traffic within forward-looking infrared (FLIR) thermal cameras data across 19km.

AI has also been applied to analyse audio data to identify wildlife risks. For example ZSL and Google, have applied ML to automatically classify gunshots in acoustic monitoring data collected in conservation areas in West Africa, and conservation NGO Rainforest Connection has worked to automatically classify soundscapes using AI which can detect and report illegal sounds, such as chainsaw noise from illegal logging.

Indigenous communities can play a pivotal role in biodiversity conservation as they own or occupy at least 22% of global land area which represents 80% of the world's biodiversity. For centuries, indigineous communities have had a close relationship with biodiversity and nature with well functioning internal structures that respect and steward natural resources. The role of indigenous communities in protecting biodiversity has been overlooked in the past but today there is realisation of this potential and there are efforts to partner with the communities in the fight against biodiversity loss while supporting their livelihood. AI can play a critical role in this effort by helping secure land rights, supporting and revitalising local languages and supporting monitoring activities. Traditional Indigenous knowledge is rich and important for biodiversity conservation. Language as a central feature of culture plays an important role both as a means of passing along this knowledge and for enabling indigenous communities to adopt new technologies that complement their traditional knowledge. AI can play a critical role in supporting translation for indigenous languages and developing smart systems that help with translation and documentation of indigenous knowledge. Combining modern science to traditional knowledge is an important step in ensuring that biodiversity conservation succeeds. For example, Te Reo Māori, the language of the Māori people of New Zealand was on the verge of collapse until a combination of legislation and AI technology revitalised it. Such interventions can be replicated in biodiverse regions of the world to promote biodiversity conservation efforts.

Further opportunities

Some of the examples of private sector action on biodiversity discussed above focus on deploying AI to increase system efficiency, which can both reduce biodiversity impact and generate cost savings. However, these efficiencies will only reduce pressure on nature if they lead to lower resource use. If the efficiency gains are used to produce more goods, there is likely no net benefit for biodiversity. As a result we need to see more AI applications that focus on supporting paradigm shifts towards alternative models that radically reduce pressure on biodiversity.

New fields such as plant based or lab-cultivated meat alternatives are growing rapidly, and there we expect to see a wide range of AI-driven applications emerging to create better alternatives to all the different current uses for livestock protein. In the traditional agriculture space there are a range of unexplored opportunities to apply AI to optimise regenerative agriculture techniques. In the fashion sector there are many more opportunities for AI to support circular economy business models and to optimise new paradigms such as waterless techniques for dying clothes to significantly reduce riverine water pollution.

One driver for all of these changes will come from enhanced transparency of corporate and financial institution biodiversity impact, which in turn, AI can enable. There are a range of opportunities to help companies and financial institutions to use AI to assess their baseline impact on biodiversity, to optimise their action on biodiversity, and to monitor the impact of corporate biodiversity policies. Data sharing initiatives will also be key to improving private sector disclosures and transparency. For example, the Australian AgriFood Data Exchange, provides an open data platform for organisations in the agrifood supply chain. The Exchange can help organisations to identify and anticipate biosecurity risks, benchmark performance to inform decision making, and bring traceability to the entire value chain. More data exchange platforms will be important to accelerating transparency and the shift to biodiversity-positive business models.

There are also opportunities to expand the application of AI to landscape restoration and protected area management by both private and public bodies. As the restoration movement continues to expand land managers there are opportunities to deploy AI to offer advice on restoration activity that can succeed in the context of climate change.

Vision

AI for biodiversity action in the private sector must evolve from isolated applications to more widespread and standardised approaches. We hope to see a Cambrian explosion of AI-enabled startups capitalising on the huge business opportunity to support paradigm shifts to biodiversity positive business models in the food, infrastructure, energy and fashion sectors. We expect that existing companies will also seek to deploy AI across their operations to support and enable paradigm shifts to biodiversity-positive business models. We hope that private sector transparency on nature-related risks will be mandatory in enough major trading blocs to enable global assessments of corporate supply chain biodiversity impact, creating further tail-winds for biodiversity-positive economic models. This vision will need to be driven by an increase in robust biodiversity policy and international targets to drive innovation.

Bottlenecks and challenges

Private sector

Insufficient biodiversity targets and strong biodiversity policy: *Without clear national and international policy signals the incentive for the private sector to allocate significant budget towards innovation in support of biodiversity, including AI applications, will be limited. The UN Convention on Biological Diversity has not yet succeeded in agreeing a global goal to halt and reverse biodiversity loss, and targets that were agreed, such as the UN Aichi targets for 2011 to 2020 have not been met. National level biodiversity policy is often insufficient to address biodiversity decline.*

Lack of clarity on the paradigm shifts required by the private sector to support biodiversity loss: *Each of the four sectors that have most impact on biodiversity: food, infrastructure, energy and fashion, will need to undergo paradigm shifts to transition to models that support biodiversity gain. At present there is limited consensus on what these transitions look like. This means insufficient resources are being deployed to support these paradigm shifts. This also makes it hard for data scientists and data engineers to know where they can have the most impact. Consensus around some of these shifts* *is increasing, for example in the food sector there is a recognised need for a shift towards plant-based diets and regenerative agriculture. However in other sectors there is less consensus on the paradigm shift required and how it can be achieved.*

Lack of standardised metrics for measuring corporate biodiversity impact: *The Dasgupta Review on the Economics of Biodiversity highlighted that standardised, credible, decision-useful data is required to underpin global standards that enable companies and financial institutions to report and act on nature-related risks and opportunities.*[32] *Developing simple, science-based metrics that adequately describe biodiversity impacts and dependencies is essential for meaningful private sector action. These metrics must be sufficiently robust to inform private sector decision-making. The TNFD Framework will make strides in this area.*

Challenge in integrating multiple data streams, models and scenarios: *The TNFD acknowledges that combining company data (e.g. asset type, location, production volumes) with data on the condition of local ecosystems is currently challenging and complex. Analysts may need to integrate multiple data sources and use models or proxies where data is unavailable. However, these types of analysis are vital to enable private sector action on biodiversity.*

Lack of open data to support sectoral paradigm shifts: *Open corporate biodiversity data can contribute to a broader understanding of their impacts on biodiversity, and provide insight about how best to achieve paradigm shifts to biodiversity positive business models. Open source sharing of private sector data can enable the combination and linking of multiple sources of biodiversity-related data.*

Lack of clarity regarding how to respect community data rights: *Using AI to support management of protected areas can entail data collection in areas where local communities and indigenous people live. There is no clear consensus regarding the balance between managing local data rights and gathering data for biodiversity conservation. This issue is addressed further in Section 8.*

Poor data management from protected area managers limits data that can be drawn on for AI applications. *Often data from conservation areas is not aggregated or even digitalised. Where it is digitised it may only live on a laptop, and end up getting lost. Such data can also legally be challenging to share internationally and can be sensitive (eg anti-poaching patrol routes). Finding ways to improve the aggregation of data at scale and enable ways of sharing sensitive data will enable learning between conservation areas, and for more to be gained from this data.*

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[32] 220321-TNFD-Data-discussion-paper-FINAL.pdf

Recommendations

Private sector

- **Governments and multilateral development banks should provide public funding for AI proof-of-concept application development to support paradigm shifts in key sectors (food, infrastructure, energy, fashion).** *In recognition of the insufficient incentive for the private sector to make high-risk investments in biodiversity-positive models, there is a need for public funding to address this gap. This should come in the form of grant based funding for early stage AI applications that seek to support paradigm shifts in the food, infrastructure, energy or fashion sectors. There is a particular need to support such applications in the Global South. Existing international funding bodies such as the multilateral development banks, international funds such as the Global Environment Facility and UN organisations such as UNEP and UNDP, should increase support for such applications.*

- **Companies within the four key value chains should coordinate to identify in more detail where AI can support biodiversity positive paradigm shifts.** *There is a need for sectoral working groups to coordinate analysis of where AI solutions could accelerate the transition to biodiversity positive business models and to identify what tools and resources would support the application of AI in these sectors. This could usefully be led by a reputable international organisation such as the World Economic Forum.*

- **There is a need to develop standardised metrics for measuring corporate biodiversity impact, and to support action to reduce biodiversity loss.**

Conservation Areas

- **Data Management and AI Opportunities for Conservation Areas events and courses should be offered to protected area managers.** *Protected area managers could benefit from meeting to discuss how they could use AI to support management of their land, and to discuss best practice for data management. The links developed from such events could enable the sharing of data and models to help disseminate effective uses of AI for conservation areas.*

8. Common Bottlenecks, Challenges and Recommendations

There are a range of issues holding back greater adoption of AI for biodiversity challenges that are common across all the potential AI applications to biodiversity challenges. These include the need to build stronger capacity and awareness on AI for biodiversity, the need to improve data and digital infrastructure, and the need for more targeted funding.

Data availability, openness and digital infrastructure

AI depends on large volumes of data, from which it can learn about its environment, the variables that might influence performance against the project objective, and their relationship to each other. Data inputs to an AI system need to be determined carefully. In some instances, this data might be historic time-series data, in others the data might be captured by sensors during the process of the AI making changes in the action space, which can help the AI to learn and improve as it goes.

Data usage rights and privacy

Biodiversity hotspots are commonly found in the Global South, and many have communities of indigenous people living within them. In seeking to collect data on such biodiversity hotspots, there is a risk that the data collected in these areas could be deemed to be undermining local communities' data rights. This in turn could undermine trust and cooperation between local communities and those seeking to protect biodiversity. The question of how the biodiversity community can collect and share data, whilst avoiding any perceived undermining of local communities' rights is central to supporting the application of AI to biodiversity challenges. If such issues are not considered and discussed with local communities carefully from the outset there is a risk that AI-for-biodiversity initiatives could be perceived as exploitative. There is currently no clear consensus about how best to recognise community data rights.

To fully understand an ecosystem, the direct and indirect drivers of biodiversity loss, and how to design solutions to address biodiversity loss can entail the collection of a range of data types including species observation data, driver monitoring data through to socioeconomic and well-being data. Many of these data types can either intentionally, or accidentally capture personal data, creating a need to carefully consider privacy concerns.

Data collection, discovery and access

As set out in Section 4 the amount of data relevant for biodiversity conservation is growing with large quantities of data being collected through a range of sensors ranging from satellites, to drones to camera *traps and smartphones. Biodiversity data is collected by academics, NGOs, citizen science initiatives, governments and the private sector. Whilst much of this data is dispersed around the world, to aggregate biodiversity data and improve access to it, the Global Biodiversity Information Facility (GBIF), was set up. GBIF is an international network and data provider funded by the world's governments and aimed at providing anyone, anywhere, open access to wide-ranging biodiversity data. The GBIF fulfils an important role in pooling open biodiversity data, addressing data gaps, and improving data quality. As set out in Section 4 there are areas where GBIF has comparatively less data, for example, there is less biodiversity data for the Global South than for the Global North and certain ecosystems are less well monitored, such as microorganisms and the deep oceans. The GBIF is active in seeking to address these gaps, but there is a need for greater financial provision to be made to support data collection in areas where there is less.*

The existence of, and access to, biodiversity data is the first step, however a related challenge is the ease with which data scientists can find and access data on key sectors that are driving biodiversity loss, such as the agriculture, transport and infrastructure, energy and fashion sectors. Monitoring such drivers goes beyond GBIFs remit. There is a need for a full assessment on the existing data required on the drivers of biodiversity loss, and where key gaps in the data exist to support effective action on its conservation. Section 5 notes the importance of governments supporting mandatory openness for trade data related to sectors that are critical drivers of biodiversity loss.

A wider challenge is that data on biodiversity and its drivers is highly context and location specific, and is highly specific to the land on which it is found. This makes it hard for AI systems to develop recommendations or solutions that work across a range of locations.

Data capture hardware

There are many different types of hardware that enable the capture of biodiversity data. Much of this professional hardware is becoming increasingly affordable and accessible, which should help democratise access to biodiversity data. Initiatives like the Arduino platform, a microcontroller device constructed to make interactive prototypes for a low cost, offers a low cost and modifiable alternative to data loggers and sensors. Even the smartphones of amateur naturalists can serve as affordable pieces of data capture equipment. It is important that raw data from any source can be easily cleaned and integrated into existing data resources.

Data quality, standards and licences

Even where data exists, and is accessible and discoverable, there are often challenges with the quality and standardisation of biodiversity-related data. To be usable by AI systems data needs to be machine readable, and often needs to be accurately labelled. At present there is a need for extensive data cleaning and labelling of biodiversity data. To facilitate the more efficient use of AI, there is a need for clear standards for biodiversity data collection to limit the amount of data wrangling required by data scientists and engineers. Biodiversity datasets are often not published under a specific *licence, creating risks for users. GBIF is already addressing some of these issues, deploying data using the Darwin Core Standard (DwC), however there is a need to build on their work to develop standards for data related to the drivers of biodiversity loss.*

Linking different data types

Many current use cases of AI for biodiversity use a limited number of data types. For example there are a wide range of applications that use satellite data, or camera trap data. However there are far fewer examples of applications that integrate a range of data sources. However in seeking to build a much clearer and more granular understanding of the drivers of biodiversity loss, there is a need to integrate and link a range of data types, for example to link satellite data on deforestation loss, with land ownership data of the farmers who take over that land to grow crops, and financial, supply chain and trade data to connect those agricultural products with companies selling them to consumers. This type of analysis requires a much deeper level of data integration and linking than is currently used. As such there is a need to develop ways of making it easier for data scientists and engineers to integrate and link a range of data types.

Recommendations

- **All biodiversity initiatives that use AI should prioritise outreach to local communities and seek to deploy privacy enhancing technologies to protect data privacy where appropriate.** *Ensuring dialogue with local communities on biodiversity data collection is a consideration that should be a key part of a responsible AI governance process for any organisation seeking to use AI for biodiversity challenges.*

- **A small group of high-ambition countries should establish an international data task-force on the drivers of biodiversity loss.** *This should seek to establish what data is needed to fully understand and address the drivers of biodiversity, what data currently exists and is accessible, what data standards and licences exist and whether they are adequate, what incentives there are for data sharing, and to propose methods to incentivize greater data collection and sharing where needed.*

- **A new initiative is needed that aggregates data on the drivers of biodiversity loss.** *The Global Biodiversity Information Facility pools direct biodiversity observation data but has no plans to aggregate data related to the drivers of biodiversity loss. Individual driver monitoring initiatives would benefit if there were a central data aggregator to enable greater linking of driver data.*

Awareness and capacity

As the nexus of AI and biodiversity has only emerged recently, many organisations working on biodiversity conservation lack access to the necessary skills and capacity on AI. This includes governments (local and national), private sector companies, NGOs and universities. There is therefore a need to build these skills and knowledge within relevant organisations.

AI awareness building in executives and senior management working on biodiversity

An immediate bottleneck to the application of AI is that executives and senior managers are rarely aware of the opportunities to apply AI to biodiversity challenges, and so do not allocate funding to explore its potential and to develop AI projects.

To address this, there is a need for training courses for leaders in NGOs, private sector, and governments covering the opportunities that AI offers, the types of conservation challenge it may be able to support and its potential risks. Such courses do not currently exist, but could usefully be developed through collaborations between AI experts and biodiversity experts from a range of organisations.

Data science for biodiversity capacity

In addition to the lack of awareness about the opportunities to apply AI to biodiversity challenges there is a need to build data science and data engineering capacity for biodiversity challenges. The successful application of AI in any field requires data scientists to have in-depth domain knowledge. At present there is a lack of data scientists working on biodiversity, and specifically, lack of data scientists who have in-depth knowledge of biodiversity and the specific sectors that are relevant to its loss and conservation.

There are two potential routes to addressing this lack of domain-specific data science capacity. The first option involves training data scientists on biodiversity and the second is to train quantitative ecologists in data science. Both options should be explored and will require bespoke training to be developed. Teams that successfully deploy AI to support conservation efforts will likely have team members with a conservation, ecology and data science background.

Biodiversity focussed organisations should consider developing bespoke training for data scientists on biodiversity, its drivers, the sectors that are most relevant to its loss, the dynamics within these sectors and the data and digital infrastructure that are currently used to assess biodiversity loss and manage its conservation. This training does not exist at present but could usefully be developed by conservation organisations in collaboration with the private sector and researchers.

At the same time there is a need to develop bespoke training for quantitative ecologists to develop data science knowledge and skills. Many quantitative ecologists have been *using advanced statistical analysis methodologies for many years and developing data science skills would enable them to build on their existing knowledge and skill base.*

Whilst on-the-job training for data scientists and ecologists is critical to building data science domain expertise on biodiversity, there is also a need to consider how to build a consistent pipeline of data science talent focussed on the application of AI for biodiversity challenges. Biodiversity-focussed organisations should consider partnering with universities to support the development of specific AI for biodiversity masters courses, PhDs and professorships focussed on the intersection of AI and biodiversity.

Knowledge transfer and community capacity for AI

There is a risk that organisations in the Global North develop AI solutions to biodiversity challenges in the Global South without sufficient input from institutions and communities in the Global South. To address this risk, organisations in the Global North seeking to support AI for biodiversity projects in the Global South should consider developing collaborations with local universities and communities to support the development of local capacity, to ensure that solutions are offered that are fully cognisant of the local context.

Communities living in the Global South, for example indigenous communities, are very aware of the threats to ecosystems in their area. Data scientists need to engage local communities, to support a bi-directional transfer of knowledge, where the data scientists can learn more about the local environment and context, and the local communities can learn more about how to use AI tools to support them to manage and protect their land.

Breaking community silos

The biodiversity and AI communities are diverse in their incentives and interests. However, the links between these communities are not as strong as they need to be. To successfully support the application of AI for biodiversity there is a need to build stronger bridges between existing biodiversity-related initiatives and the AI community.

Recommendations

- All biodiversity initiatives that use AI should prioritise outreach to local communities and seek to deploy privacy enhancing technologies to protect data privacy where appropriate. *Ensuring dialogue with local communities on biodiversity data collection is a consideration that should be a key part of a responsible AI governance process for any organisation seeking to use AI for biodiversity challenges.*

- **A small group of high-ambition countries should establish an international data task-force on the drivers of biodiversity loss.** *This should seek to establish what data is needed to fully understand and address the drivers of biodiversity, what data currently exists and is accessible, what data standards and licences exist and whether they are adequate, what incentives there are for data sharing, and to propose methods to incentivize greater data collection and sharing where needed.*
- **A new initiative is needed that aggregates data on the drivers of biodiversity loss.** *The Global Biodiversity Information Facility pools direct biodiversity observation data but has no plans to aggregate data related to the drivers of biodiversity loss. Individual driver monitoring initiatives would benefit if there were a central data aggregator to enable greater linking of driver data.*

Funding and investment

Funding & investment is required both to support specific applications of AI for biodiversity challenges, and to support the development of the wider infrastructure and tools required to facilitate AI's application to conservation. However, sourcing funding & investment is a challenge, particularly when seeking to apply AI to biodiversity challenges, as its full potential is not yet widely recognised. There is a wider challenge that the benefits that biodiversity offers humanity is not recognised in our economic decision making and as such the incentives for economic actors to ensure corporate activities are biodiversity friendly are not sufficient to drive large scale finance to the sector.

Available funds and grants

Conservation applications that use AI acquire funding from a range of sources, including philanthropic foundations, NGOs, large tech companies, donor country aid agencies, development banks, international environmental funds and government departments.

Philanthropic foundations have played a key role in supporting early stage initiatives to gain traction. Examples of philanthropic foundations that that have supported the application of AI to biodiversity challenges include: Flora Family Foundation, Gordon and Betty Moore Foundation, Bloomberg Philanthropies, Oak Foundation, MacArthur Foundation, The David and Lucile Packard Foundation, The Pew Charitable Trusts, Walmart Foundation and the Walton Family Foundation. The majority of these foundations are based in the USA.

NGOs play a key role in building and supporting innovative tech initiatives in support of conservation. Sometimes these are developed *in-house by NGOs, and sometimes initiatives are spun off. Active NGOs seeking to support the application of AI for conservation include WWF, Conservation International, WRI, & Wildlife Conservation Society.*

Large tech companies are playing an increasingly significant role in supporting new initiatives that seek to apply AI to biodiversity challenges. This support comes in the form of both funding and technical support. Microsoft's AI for Earth Innovation grant program funded several AI projects for biodiversity between 2017 and 2022, but the program's five year cycle has now ended. Google's AI for Social Good program provides funding and support to AI and data analytics projects that address societal challenges.

Philanthropic foundations, NGOs and tech companies tend to provide initial funding to enable AI-for-biodiversity projects to get off the ground, however there is often less funding available to scale such initiatives.

A range of governments, public funds and donor countries have supported more developed conservation initiatives seeking to apply AI. International funds such as the Global Environment Facility, various development banks and donor aid agencies have provided some AI-for-biodiversity projects with support.

Funding challenges

Funding sources are predominantly located in the Global North, creating a risk that there is a structural imbalance with less support for initiatives in the Global South. This creates a significant risk that funds will be used to support data scientists in the Global North to develop projects that seek to support biodiversity conservation in the Global South, where they do not have an understanding of the local context.

Whilst philanthropic funding is the most common source of funding for AI for biodiversity projects, such funds do not tend to allow unsolicited applications for funding, thereby limiting access to those with networks surrounding the fund. Open funding opportunities are sparse.

Most funding is also targeted at the development of new technologies and the establishment of exciting new startup initiatives. There is very little funding available for the scaling-up of AI for biodiversity projects.

Most initiatives assessed in this report seek grant funding. Large scale public funds, such as the GEF, and the international development banks have the finance to enable initiatives to scale up using public funding, however these organisations are at an early stage in building their understanding and support for AI initiatives.

As biodiversity becomes more salient to citizens, politicians and companies, it is likely that the market for AI initiatives offering biodiversity services to private companies will increase, enabling financial scalability. However at present most biodiversity initiatives cannot promise sufficient revenue to attract investment.

Recommendations

- Philanthropic foundations should consider a more open funding model that actively encourages applications from the Global South.
- Large public funds, and development banks should take a more active role in offering growth funding to enable AI-for-biodiversity initiatives to scale.
- AI for biodiversity projects should actively investigate where they can offer services to the private sector to reduce biodiversity to enable more sustainable income streams. *This might involve providing services for companies to meet their ESG targets, or by creating solutions to ensure a company's operations have a net-positive biodiversity impact.*

9. Sector-wide AI for biodiversity Roadmap

This section is an assimilation of recommendations from across the report. We have maintained these within the report so that it is possible to trace back recommendations at the end of the report to those within the sections of it. The cornerstone investments are highlighted in light grey as these are the enabling capabilities that need to be built globally.

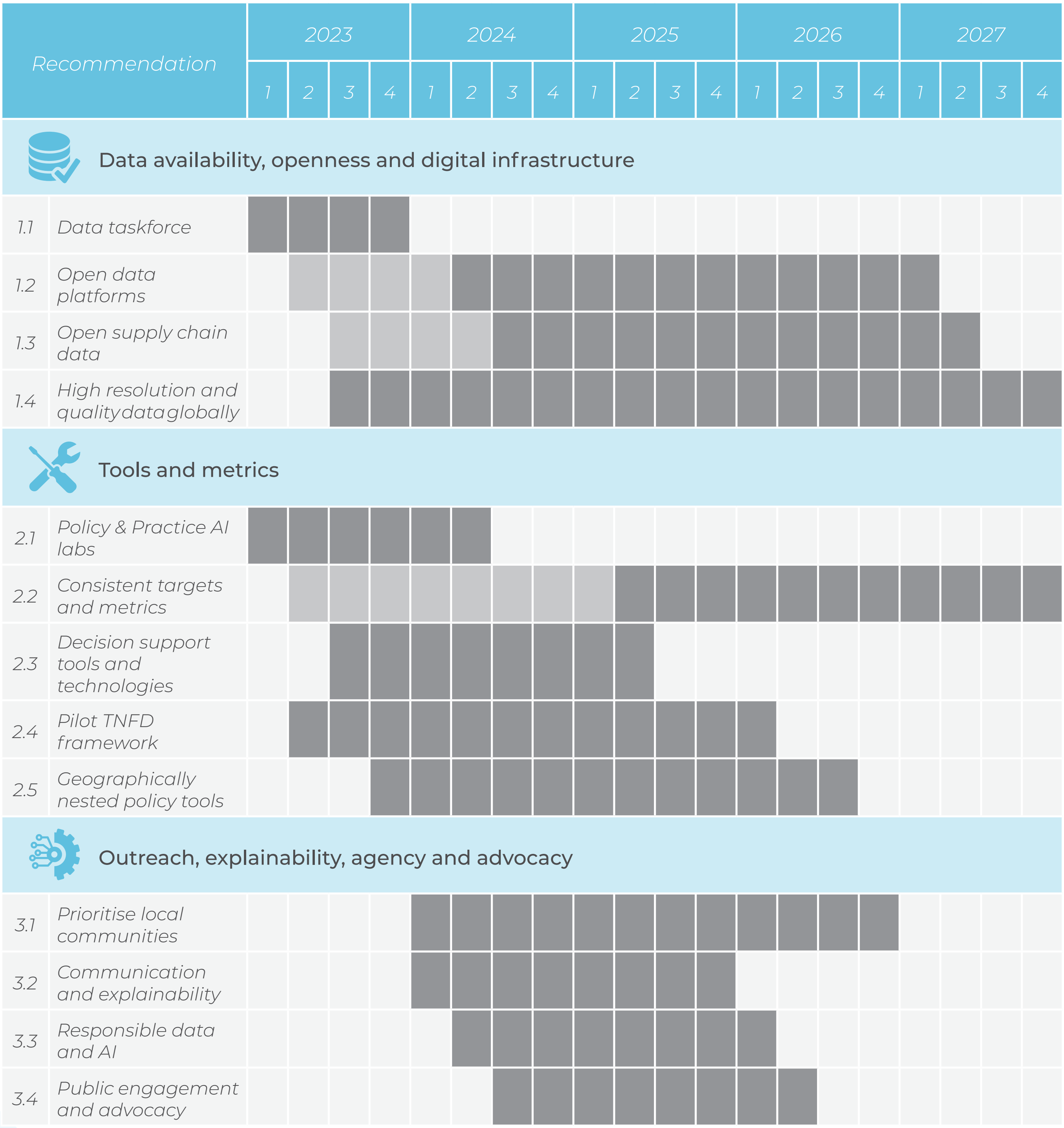
#	Recommendation	Description	Lead org(s)?	Start	Timing	Resource
	1. Data availability, openness and digital infrastructure					
1.1	Establish an international data taskforce on drivers of biodiversity loss	An international data taskforce is required that addresses the drivers of biodiversity loss, enabling the open data, aggregation and sourcing of new data detailed in the 3 recommendations below	Governments	Q1 2023	1 year set-up; ongoing	$
1.2	Fund open platforms that aggregate biodiversity relevant data and models	Open platforms will enable aggregation of datasets and sharing of data to understand risks, including supply chains, for companies and governments. Interoperability between platforms will support solutions drawing on global data and implementable at scale	Government funding	Q2 2023	1 year scoping; 3-year initiative	$$
1.3	Mandate supply chain data openness and support platforms for high-risk drivers of biodiversity loss	Require an openness of data on supply chains where high-risk drivers of biodiversity loss are present, with machine readable datasets	Government policy;	Q3 2023	1 year scoping; 3 year initiative	$
1.4	Increase use of high resolution and high quality data, including near-real-time monitoring, especially in geographies with current limited availability	An initiative to drive the acquisition and use of high resolution / high quality and near-real-time data, incorporating sensors around specific drivers. Drawing on federated infrastructure. End-users in government and industry working together with those developing and operating monitoring systems, with an emphasis on under-represented areas of the world.	Governments and industry	Q3 2023	5-year initial	$$$

#	Recommendation	Description	Lead org(s)?	Start	Timing	Resource
2. Tools and metrics						
2.1	*Establish a network of policy and practice AI labs globally*	*Centres of excellence for policymakers, practitioners and AI experts, trialling policy scenarios and developing methodologies, including policy AI fellowships and supporting the 3 recommendations below*	*Government policy, innovation and research agencies*	*Q1 2023*	*18 months*	*$$*
2.2	*Support establishment of globally, nationally and place-based consistent targets and metrics*	*Identify where AI can support target and metric setting through the adaptation of tools for monitoring drivers of biodiversity loss*	*Governments working with businesses and NGOs*	*Q2 2023*	*2 year*	*$$*
2.3	*Develop tools and technologies for decision support*	*Identifying entry points and using AI to support the development of tools and technologies that are cost effective support decision-making*	*Governments and businesses*	*Q3 2023*	*2 year*	*$$*
2.4	*Supporting the piloting of the TNFD framework with industry stakeholders*	*What role can AI play to support Support the development of simple, science-based metrics that adequately describe biodiversity impacts and dependencies to enable private sector decision-making, building on the TNFD*	*Businesses*	*Q2 2023*	*3 year project initially*	*$*
2.5	*Develop geographically nested joint policy planning tools*	*Support what's currently being conducted by nation states or think tanks Enabling joint policy optimisation with agencies and research organisations and industry, working across geographies, identifying cost savings for new technologies and advances in accuracy. AI for data generation and coordinative functions and optimization*	*Government planning bodies*	*Q4 2023*	*3 year project*	*$$*

#	Recommendation	Description	Lead org(s)?	Start	Timing	Resource
3. Outreach, explainability, agency and advocacy - enabled by the policy and practice AI labs						
3.1	*Prioritise outreach to local communities and seek to deploy privacy enhancing technologies to protect data privacy*	*Ensure dialogue with local communities on biodiversity data collection as part of responsible AI governance. Provide technologies and approaches to protect local communities from exploitation of their data and biodiversity, creating agency through proactive engagement with citizens and institutions which only AI can achieve*	*Governments, tech companies*	*Q1 2023*	*3 year development and roll-out*	*$$*
3.2	*Focus on communication and explainability of biodiversity data products*	*Increasing conservation impact through communication and driving adoption of solutions, incorporating transparent communication on uncertainties during monitoring and modelling.*	*Government, NGOs and industry*	*Q1 2024*	*2 year initial programme; ongoing*	*$*
3.3	*Ensure biodiversity monitoring follows FAIR and CARE principles and AI is applied in a responsible manner*	*Biodiversity monitoring data should be findable, accessible, interoperable and reusable. Data collection should provide benefits to researchers, policy-makers and indigenous communities and local people. AI applied to this data should be implemented responsibly so as not to increase inequalities and injustice.*	*Governments working with ETSI and responsible AI community*	*Q2 2024*	*2 year project*	*$*
3.4	*Build public engagement and advocacy into AI-driven initiatives on the drivers of biodiversity loss*	*Inclusion of the public, allowing for data from citizen science and facilitating a route for citizens to contact their political representatives about a particular biodiversity driver.*	*Governments, NGOs and industry*	*Q3 2024*	*2 year project*	*$$*
4. Capacity building - through the network of policy and practice AI labs						
4.1	*Develop AI for biodiversity training and specialist talent development*	*For biodiversity leaders on opportunities with AI and courses on biodiversity, AI and current digital approaches for data scientists and ecologists. Academic training from Masters to Professors with an emphasis on knowledge transfer between Global North and South*	*Government innovation and research funding agencies*	*Q1 2024*	*5 year programme*	*$$$*

#	Recommendation	Description	Lead org(s)?	Start	Timing	Resource
4.2	*Hold regular events to bring together the conservation and AI communities*	*Breaking down community silos through in-person events and networking, sharing perspectives and social interactions, leading to joint initiative creation*	*Biodiversity and AI communities associated with Universities - seed funded by government*	*Q1 2024*	*3 year*	*$*
5. Funding and investment						
5.1	*Development of tools to support funding and financing of projects*	*AI-enabled development of common tools to support funders, including AI as a unique enabler through a coordinative role*	*Governments and multilateral development banks*	*Q1 2023*	*2 year*	*$$*
5.2	*Ensure specific funding support for the Global South to develop solutions and grow capacity*	*Targeted funding for Global South organisations to work in partnership across the globe to develop solutions that will be effective to their geography and communities, including metrics to assess performance against targets.*	*Governments and multilateral development banks*	*Q3 2024*	*3 year initial*	*$*
5.3	*Public-private funding for AI and biodiversity*	*Support for public-private initiative funding through e.g. nature positive finance tools*	*Governments and multilateral development banks*	*Q1 2024*	*3 year*	*$$$*
5.4	*Proof of concept funding for AI and biodiversity*	*Funding for Proof of Concept in key sectors (including food, infrastructure, energy, fashion) with companies identifying AI opportunities for paradigm shifts in behaviour*	*Governments*	*Q3 2023*	*3 year*	*$$*
5.5	*Funding for scale-up and sustainability of AI and biodiversity solutions*	*Funding for scale-up of solutions, to enable growth of AI initiatives and businesses, including improved financial models to support viability and sustainability of solutions*	*Governments and businesses*	*Q2 2024*	*5 year*	*$$$*

GANTT Chart reflecting timetabling of implementation of recommendations.
Light grey shading represents scoping studies or other preparatory work.
Darker grey represents the main programme of activities in each case.



Recommendation		2023				2024				2025				2026				2027			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Capacity building																					
4.1	*AI for biodiversity training and talent*					■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
4.2	*Community building*					■	■	■	■	■	■	■	■	■	■	■	■				
Funding and investment																					
5.1	*Tools to support financing*	■	■	■	■	■	■	■	■												
5.2	*Ensure funding for Global South*							■	■	■	■	■	■	■	■	■	■	■	■		
5.3	*Public-private funding*					■	■	■	■	■	■	■	■	■	■	■	■				
5.4	*Proof of Concept funding*			■	■	■	■	■	■	■	■	■	■	■	■						
5.5	*Scale-up and sustainable solutions*						■	■	■	■	■	■	■	■	■	■	■	■	■	■	■