Ecological Informatics 89 (2025) 103157

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Automated near real-time monitoring in ecology: Status quo and ways forward

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ARTICLE INFO

Keywords:
Automation
Adaptive decision making
Digital twin
Evidence-based conservation
Workflow
Iterative

ABSTRACT

In the current epoch of rapid biodiversity decline, monitoring of ecosystems and the species which inhabit them has become increasingly important. A near real-time approach to ecological monitoring facilitates decision making and timely interventions within rapidly changing systems. Despite fast-paced technological advancements making the automated workflows required for near real-time ecological monitoring possible, their use is highly limited and there is yet to be a review of the current capacity for their creation. This paper summarises the current methods and technologies which could be used to create such workflows and the considerations for establishing them in decision-making systems. We identify key barriers to the adoption of a NRT approach across geographies and different fields of study in ecology. We also highlight the need to work collaboratively with technologists and stakeholders to establish efficient and long-lasting NRT workflows which can inform evidence-based decision making.

1. Introduction

Rapid ecosystem change is prevalent across the globe causing large-scale biodiversity loss and a deterioration in ecosystem services (Cardinale et al., 2012; Dobson et al., 2021; Hooper et al., 2012). In order to identify and subsequently mitigate or even prevent harmful change, ecosystems must be monitored. Such monitoring in practice comes in many different forms extending from citizen science observations (Adler et al., 2020; Brown and Williams, 2019) to networks of sensors (Gallacher et al., 2021; Porter et al., 2005), collecting a myriad of data. Advances in technology in recent decades have widened our capacity to monitor ecological change (Lahoz-Monfort and Magrath, 2021), vastly increasing the amount of digital ecological data available (Kays et al., 2020). Alongside this, increasing automation within the processes of collecting, processing, analysing and sharing data have made near real-time ecological monitoring workflows, which produce information from the data gathered, possible (e.g. Besson et al., 2022; Sethi et al., 2018).

Being able to monitor ecological change in near real-time facilitates early identification of undesired trends and the subsequent implementation of timely interventions (Lindenmayer et al., 2012; Maxwell et al., 2015; Wall et al., 2014). When real-time monitoring is discussed, thoughts often jump to the very high frequency monitoring in domains such as engineering where, for example, power grid operations require monitoring down to the millisecond (Haoming et al., 2019; Tomsovic et al., 2005). For ecological systems, this is simply not a universally pragmatic goal. Instead, we use the term near real-time (NRT) to describe the alternative goal of being able to monitor at a high enough frequency to capture meaningful change in the system being monitored. This working definition acknowledges both the differences in requirements for monitoring different ecological systems and issues, and the shared need to have up-to-date information available in order to make timely interventions. This approach can be highly informative for systems and issues which can develop or emerge quickly such as wildlife poaching (de Knegt et al., 2021; Wall et al., 2024), illegal harvesting (Andreadis et al., 2021), human-wildlife conflict (Wall et al., 2014), disease outbreaks (Kamoroff et al., 2022), wildfires(Zhang et al., 2023) and seasonal migration (De Koning, 2025).

The recognition of the benefits of working in NRT is reflected in the growing body of research dedicated to such methods. Currently, much of the literature relevant to this topic describes methods or technologies which facilitate a certain stage in a NRT ecological monitoring

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https://doi.org/10.1016/j.ecoinf.2025.103157
Received 19 April 2024; Received in revised form 16 April 2025; Accepted 17 April 2025
Available online 18 April 2025
1574-9541/

workflow, such as automated data processing (e.g. Bothmann et al., 2023; Pérez-Granados, 2023) or a new sensor for automated data collection (e.g. Barros et al., 2024; Lamont et al., 2022). A linked field is that of Big Data in ecology which has led to the emergence of iEcology, the generation of insights using these diverse online data sources, and the development of automated data analysis (Jarić et al., 2020). There are some studies which link this all together to create prototype NRT ecological monitoring workflows (e.g. Randon et al., 2022; Skov et al., 2021; Wall et al., 2014; Wang et al., 2022) but few of these are reported as established in ongoing monitoring routines (e.g. Brunoldi et al., 2016; De Koning, 2025; Sanguineti et al., 2021).

There is scattered literature available which provide syntheses or suggest new terminology to describe identified paradigms in NRT and automated ecological monitoring. Working in NRT is perhaps most well established in animal tracking which has given rise to the paradigm of the Internet of Animals (IoA), systems of on-animal devices where live data is analysed in NRT and integrated with other datasets (Kays and Wikelski, 2023). Besson et al. (2022) goes beyond this to discuss the broader application of methods and technologies for automated ecological monitoring but remains focused on sensor-based data collection and data analysis by AI. Perhaps the most comprehensive paradigm to date is the digital twin, a newly emerging term in the field of ecology but one well established in engineering and manufacturing (Enders and Hoßbach, 2019; Singh et al., 2022). Digital twins are defined as iterative models linked to their physical counterpart with real-time data (de Koning et al., 2023). In addition, concepts of real-world feedback informed by digital twins are also often central to their definition meaning they are often developed and used to tackle specific problems, such as those listed in this introduction (Khan et al., 2024a).

Despite the overlap in the concepts discussed, there appears to be a compartmentalisation of academic discourse on this subject. This paper seeks to bring these concepts together and identify minimum viable solutions for NRT ecological monitoring to lower the threshold for adoption of this approach. We identify key technologies and methodologies at each stage of a NRT ecological monitoring workflow alongside discussing potential barriers to their use. In addition, we consider difficulties in establishing a long-lasting and effective NRT ecological monitoring systems. We aim to provide an overview of the current field of NRT monitoring in ecology in order to facilitate the continued development in this field to tackle the pressing issues we face in the Anthropocene.

2. Data collection

Facilitated by the use of sensor technologies and citizen science, ecological data is being collected at an unprecedented rate (Kays et al., 2020). At the time of writing, the Global Biodiversity Information Facility (GBIF) alone contains over 3 billion occurrence records with an exponential increase in records since its establishment in 2001 (Global Biodiversity Information Facility, 2025). Of this data, those which are 'born digital' (digital records at the point of observation) are important for NRT monitoring as automation requires digital data (de Koning et al., 2023; Kays et al., 2020). As with all ecological monitoring, the type of data and the manner in which it is collected dictates the conclusions that can be drawn from it, therefore it is important to consider appropriate variables for the objective and establish standard data collection protocols to reduce bias (Elphick, 2008; Kelling et al., 2019; Oliveira et al., 2024). Furthermore, for this data to be integrated into NRT monitoring, it must be captured at a high enough frequency and transferred with a short enough lag time from the device used to record it to qualify for NRT. Transferring the data is important because in almost all cases, multiple devices or personnel are collecting data in the field and therefore this data needs to be collated at a central computer for processing and analysis.

2.1. Sensor devices

Perhaps the most obvious approach to generating such digital data is through the use of monitoring technology such as camera traps, passive acoustic sensors, environmental sensors, GPS collars, on-animal devices, unmanned aerial vehicles (UAVs) and satellite remote sensing. The rapid pace of data collection from these devices has quickly caught up with data volumes from museum specimens and citizen observations (Kays et al., 2020). There is a vast array of devices available for monitoring all aspects of ecological data which are comprehensively detailed in Lahoz-Monfort and Magrath (2021). However, in addition to the standard requirements one may have when selecting a device, such as relevance of the data to the intended goal and budget constraints, there are additional requirements to facilitate NRT monitoring: high frequency collection and automated data transfer.

To address the first of these requirements, the most suitable devices are those with the capacity to autonomously collect data (Besson et al., 2022). Many of the devices mentioned in Lahoz-Monfort and Magrath (2021), such as in-situ sensors and on-animal devices, have the capacity to be set up to autonomously collect data. Some devices are continuously active but capture data only when triggered by some stimulus in the environment such as motion, heat, sound or vibration to conserve energy (Lahoz-Monfort and Magrath, 2021). Others adopt a simpler method by collecting data at pre-defined intervals, as is often the case with GPS devices and satellite remote sensing. However, continuous monitoring alone does not constitute NRT monitoring. In order to facilitate automated data transfer, wireless data transmission capabilities (e.g. via satellite, cellular or low-power wide-area networks) are often essential. Like with data collection, data transfer can be triggered (in this case by the data collection itself) or also set at intervals. Outside of satellite remote sensing, wireless data transfer is perhaps most well-established in animal tracking technologies, largely driven by the logistical challenge of retrieving the sensors from the animal which leads to large-scale data loss (Kays et al., 2015). However, it is also increasingly integrated into in-situ devices, such as camera traps, to negate the need for laborious and costly data retrieval (Glover-Kapfer et al., 2019).

Currently there are an array of different devices being tested or deployed as part of NRT ecological monitoring workflows. Passive acoustic sensors are increasingly being tested for NRT data collection since they are a comparatively affordable devices, with upfront costs of around USD $50 per unit for the AudioMoth, which are easily set up to automatically collect and transfer data, although there are substantial bottlenecks at the data processing stage which we discuss later (Barber-Meyer et al., 2020; Gibb et al., 2019; Hill et al., 2018; Sethi et al., 2020). Despite these difficulties, early warning systems informed by NRT acoustic data have already been successfully established within the ARION (Brunoldi et al., 2016) and WHALESAFE (Sanguineti et al., 2021) projects to prevent collisions of dolphins and sperm whales with approaching vessels. Geofencing and other techniques using movement data from on-animal telemetry devices have been tested for alerting relevant personnel to imminent conflict events with elephants (Wall et al., 2014) and lions (Weise et al., 2019). The generation of similar alerts using camera trap imagery for elephants has also been successfully piloted (Whytock et al., 2023).

While these studies show that NRT ecological monitoring is possible with these devices, there are still a number of significant barriers to their widespread use. Firstly, wireless data transmission often relies upon cellular network access which is less available in remote and rural areas, particularly in Africa (International Telecommunication Union, 2024). Investments in increasing global internet connectivity are likely to continue in the future (United Nations, 2024) but, until these advancements are usable in the field, this can prevent implementation in rural areas in low-income countries (International Telecommunication Union, 2024). There are potential options for establishing satellite communication, the hardware for which costs in the range of a few hundred to over a thousand USD in addition to a monthly data plan

(Starlink, 2025). However, devices are still required to be connected to the satellite dish or modem in order to be able to transmit data which presents logistical issues for many studies which utilise multiple devices spread out over large areas. One potential solution is the use of radio frequencies to enable short-to-medium range communication between devices, such as via LoRa or Sigfox, as typically used in wireless sensor networks (WSNs) enabling data transfer to a central base station which has satellite communication capabilities (Boulmaiz et al., 2020; Porter et al., 2005). An example of such technology is Instant Detect 2.0,[1] a satellite-enabled camera trap system, created by the Zoological Society of London.

WSNs are also optimised for low-power use which is an issue for many sensor devices, especially those which monitor continuously and wirelessly transmit data, with a higher frequency of transmission requiring more power (Besson et al., 2022; Porter et al., 2005). Developments in power management techniques and the addition of solar panels or other renewable energies to remote sensor installations have greatly increased the frequency of data transfer possible in the field (Barros et al., 2024; Park et al., 2019). The emergence of edge computing (discussed further in Data Processing), processing raw data locally on devices before transmission (Cao et al., 2020), has increased storage and battery efficiency, thus extending the lifetime of the device (Miquel et al., 2023).

While there are many solutions created to combat the myriad of obstacles one may encounter when setting up NRT data collection and transmission in the field, they often come with high upfront and running costs. The upfront cost of commercially available devices are already a substantial barrier (Glover-Kapfer et al., 2019) and adding data transfer capabilities, edge computing or solar panels only increases that expense. For example commercially available GPS collars with data transfer capabilities cost thousands of dollars where VHF collars are often in the hundreds. Furthermore, the key distributers of these devices are based in North America and Europe leading to varying availability and often higher prices outside these regions. There are a number of DIY solutions developed to reduce these high up-front costs, mostly for telemetry devices, but these do not yet include NRT data transfer capabilities (e.g. Cain and Cross, 2018; Foley and Sillero-Zubiri, 2020; Quaglietta et al., 2012). The existing biases in allocation of funding worldwide for biodiversity monitoring are well known and as such, the resources to implement these device-based data collection systems are currently concentrated in North America and Europe (Adamo et al., 2022).

2.2. Digital data collection platforms

While monitoring using sensor devices is often first thought of when discussing digital data, observations made by humans still make up a significant quantity of the ecological data being collected, 87 % of GBIF occurrence data (Global Biodiversity Information Facility, 2025). Much of this is now driven by citizen science data collection which is increasingly used in ecological studies as a way of generating large quantities of data at reduced costs (Chandler et al., 2017; Loos et al., 2015; Schmeller et al., 2017). Previous discussions on NRT data collection focus on the use of devices as discussed above (Besson et al., 2022; Wall et al., 2014) However, considering the existing reliance on human observations for ecological monitoring, facilitating their inclusion into NRT ecological monitoring workflows could serve to lower the threshold for adopting a NRT approach.

The most widely used approach to facilitate this is the use of a digital data collection platform (DDCP), which is often in the form of a mobile application used for data entry. Using such a method produces 'born digital' data and therefore the rest of the workflow can be automated from the point of data entry. There are many versions tailored for both professional and citizen science data collection including ObsIdentify,[2] ObsMapp,[3] eBird,[4] EarthRanger,[5] Cluey,[6] iNaturalist[7] and many more. While there are existing DDCPs which may fit the needs of a NRT monitoring project, many are built on various open-source frameworks, such as the Open Data Kit, which can also be used to design a custom DDCP (Bokonda et al., 2020). DDCPs have already been established successfully in NRT ecological monitoring systems. The NRT data collected by field personnel via the EarthRanger Mobile app has been used in protected areas across Africa to inform responses to poaching, reduce human-wildlife conflict and monitor key animal populations (Wall et al., 2024). In Europe, citizen science data entered into Waarneming.nl via the ObsIdentify app is used to inform the Crane Radar, a digital twin which tracks *Grus grus* migration over Northwestern Europe (De Koning, 2025).

While DDCPs have the capacity to be integrated into a NRT monitoring system, there are a number of factors which need to be considered for their success. While most DDCPs are built with offline functionality, the device used to record the data will still need to have internet connection (e.g. via Wi-Fi or cellular network) in order to transfer the data to be processed and analysed alongside the rest of the data collected by people using other devices. Similar to the discussion on wireless data transfer with data collection devices, a lack of internet connection when working in remote areas prevents data transfer (International Telecommunication Union, 2024). However, unlike with in-situ devices, human data recorders are, in most cases, expected to return to areas with internet connection meaning that, instead of preventing data transfer, it imposes a lag time instead. How long this lag time is depends on the study, casual citizen scientists for example are expected to only spend relatively small amounts of time in remote areas (Mair and Ruete, 2016) whereas researchers may not have access to stable internet for much longer periods of time if working in remote areas.

The question of data collection frequency can also be a complex issue to address with DDCPs. The frequency of data collection is highly variable across citizen science and professional-led projects but there are some instances where it is sufficient to provide daily updates for NRT monitoring. In terms of professionals, field rangers or equivalent personnel who are regularly in the field throughout the year are most suitable for providing data for NRT monitoring. For citizen science, the motivation of the individual for contributing data highly influences how and when they make observations (Larson et al., 2020). There are distinct differences between unstructured (requiring little training and mostly opportunistic contributions), semi-structured (providing minimal guidelines and the possibility to collect additional data with each observation) and structured (requiring trained volunteers and protocol dictating sampling space and time) citizen science projects. Dedicated citizen scientists following a structured protocol are therefore the most likely of these groups to provide consistent data. However, the largest DDCPs for citizen science use are unstructured or semi-structured. Opportunistic records lead to temporal biases towards daylight hours, weekends (Courter et al., 2013) and under favourable weather conditions (Rosário Inês et al., 2024). There is also increased motivation to record interesting events such as breeding and migration which leads to certain species experiencing peaks in data collection (Marchante et al., 2024; Sullivan et al., 2014). In addition, taxonomic biases towards charismatic and more easily identifiable species also impose more general limits in terms of the volume of data available for different species (Callaghan et al., 2021; Troudet et al., 2017; Ward, 2014). Despite the irregularity of contributions by individuals for unstructured or semi-

1 https://instantdetect.co.uk/

2 https://waarneming.nl/apps/obsidentify/
3 https://observation.org/apps/obsmapp/
4 https://ebird.org/home
5 https://www.earthranger.com/
6 https://sensingclues.org/cluey
7 https://www.inaturalist.org/

structured citizen science projects, a steady influx of data can still be achieved with a large enough user base.

However, while these factors do not prevent these opportunistic observations from being used in a NRT ecological monitoring workflow, they contribute to the widespread discourse on the quality of such data (Brown and Williams, 2019; Johnston et al., 2023; Tulloch et al., 2013). Reliable data quality is important for NRT monitoring as it is difficult to enforce checks in an automated system (De Koning, 2025). Opportunistic observations could have potential for some relatively simple analyses (Brown and Williams, 2019; Capinha et al., 2024; Hochmair et al., 2020) but the reliability of the data increases with volunteer skill (Brown and Williams, 2019), the introduction of sampling protocol (Lewandowski and Specht, 2015) and mechanisms to verify observations (Ackland et al., 2024; Falk et al., 2019). Community-based checking of observations, such as that used by iNaturalist, can serve to improve the error rate in unstructured/semi-structured citizen science observations (White et al., 2023). However ensuring a workable time delay before an observation is validated for NRT use is highly dependent upon an experienced and invested community of "identifiers" (Campbell et al., 2023) and errors are still prevalent in difficult to identify taxa (McMullin and Allen, 2022). While investing in training and structuring citizen scientists is shown to increase data quality, there is a trade-off to be considered with the cost of such endeavours which span from tens of thousands to hundreds of thousands of dollars to implement (Tulloch et al., 2013). While not widely available and with a bias towards birds, an effective way of reducing this cost is to utilise existing skilled groups which produce reliable data voluntarily as was done in the creation of the Crane Radar (De Koning, 2025).

Despite DDCPs being a relatively low-technology solution compared to the use of sensor devices, there is still a requirement to have access to a mobile phone, or equivalent device, with the capacity to host DDCPs. Over half of the global population owns a smartphone (Richter, 2023) but the affordability of smartphones varies dramatically, even across low-income countries from 4 % to over 600 % of monthly average income (Alliance for Affordable Internet, 2020). In addition to this, establishing DDCPs in Africa and Asia is further complicated due to a deficit in citizen science data (Pocock et al., 2018) and more issues with internet connectivity (Alper and Miktus, 2019; The World Bank, 2024). Finally, while DDCP interfaces are generally designed to be user friendly, digital literacy is not universal (International Telecommunication Union, 2024). Considering these challenges, it is clear that DDCP-based data collection success is still biased towards high-income countries which have higher internet and smart phone accessibility and a larger citizen science user base.

2.3. Genetic data

In addition to data from sensor devices and human observation, collection of genetic samples in the field is also common in ecology. Of the genetic sampling techniques currently employed in ecological monitoring, environmental DNA (eDNA) is perhaps the most promising and relevant for working in NRT. eDNA is DNA shed by organisms as they interact with their environment which can be extracted from samples of water, soil or air to identify the species present (Ficetola et al., 2008; Lynggaard et al., 2022; Roh et al., 2006). eDNA has become popular in ecological monitoring due to its non-invasive methods and increasing cost-efficiency compared to other monitoring methods (Beng and Corlett, 2020; Evans et al., 2017; Leempoel et al., 2020). Potential applications for NRT ecological monitoring include the detection and tracking of invasive species and pathogens (Bass et al., 2023; Spitzen Van Der Sluijs et al., 2020; Thomas et al., 2020). However, the requirement for laboratory processing of these samples to extract useable data imposes a delay of days to weeks. Furthermore, the sustained frequency of samples required for NRT monitoring is not pragmatic in the vast majority of cases, considering the cost incurred by resources and expert time to process each sample (Goldberg et al., 2016).

At the cutting edge of eDNA research, pioneering tools to enable in-situ rapid DNA extraction and quantitative polymerase chain reaction (qPCR) to identify single species of importance are being developed and tested (Doi et al., 2021; Hansen et al., 2020; Kamoroff et al., 2022; Sepulveda et al., 2018; Thomas et al., 2020). These can be split into portable systems designed to be manually operated in the field (e.g. Thomas et al., 2020) and autonomous robotic samplers for remote use (Hansen et al., 2020). Similar hand-held devices have also been developed for more versatile genetic detection from eDNA, tissue or other biological matrices such as the Nucleic Acid Barcode Identification Tool (Holmes et al., 2024) and the Biomeme platforms (Biomeme, 2025). To facilitate data transfer to the rest of the NRT workflow, autonomous systems would need to be equipped with wireless data transfer capabilities while manually operated systems could use the same or simply require manual entry of results into a DDCP. While these developments are promising, their novelty means that they are very rarely used in practice and therefore have not reached the maturity level where they can be considered for NRT ecological monitoring.

3. Data processing

After it is collected, data needs to be processed which encompasses a myriad of techniques to prepare data for analysis including checking data quality, data transformation, annotation, data integration and preparing metadata. Appropriate processing is key to effectively utilising secondary data to enhance analysis and modelling without additional expenditure of time and resources on data collection (Marques et al., 2024; Pernat et al., 2024). For example, there are a myriad of processing methods described in the literature to foster increased use of widely available citizen science datasets by addressing bias and evaluating data quality (Bird et al., 2014; Capinha et al., 2024; Clare et al., 2019; Steen et al., 2021). In order to aid with standardisation and efficiency, many data processing software packages have been created, often tailored to address data from a specific collection method. There are many examples from the field of movement ecology as devices, such as those which use GPS, often include error which need to be accounted for (Fleming et al., 2020; Gupte et al., 2022; Joo et al., 2020). Given that the incoming data is of a standard format and type, such as those which may come from a sensor device or application programming interface (API) from a DDCP, scripts for automated data processing can be easily written, especially where pre-existing software packages are available.

However, the methods so far discussed cover processing relatively simple data and there is an increasing volume of more complex data which require human intelligence to process, such as photo and audio files. This has led to the development of artificial intelligence (AI) solutions to automate tedious and high volume data processing tasks which require human intelligence to interpret. The umbrella term AI applies to a growing group of techniques which includes machine learning, deep learning and neural networks. There has been significant investment in AI for ecological data processing such as classifying species and individuals from images, identifying species from audio recordings and habitat classification of spectral imagery (Chalmers et al., 2021; Ghaffarian et al., 2021; Vélez et al., 2023). This has in turn led to their increasing availability as more AI algorithms are made open access and developed for a wider variety of uses and ecosystems. Some examples include Agouti[8] and Wildlife Insights[9] for camera trap image classification and BirdNET for species identification from birdsong (Pérez-Granados, 2023).

AI is not only used for cloud processing, but also for on-device processing as a powerful form of edge computing. Edge computing is a new paradigm in computing where calculations are performed at the edge of

[8] https://agouti.eu/

[9] https://www.wildlifeinsights.org/

the network, thereby bypassing the need for such calculations to be performed by traditional cloud computing (Cao et al., 2020). In ecology, this often entails the integration of computing hardware, such as a Rasberry Pi, into monitoring devices which pre-process the data captured by the device before, for those with wireless connectivity, transferring the pre-processed data. If a workable trade-off between efficient computation and accuracy of the AI algorithm can be found, using edge computing to pre-process data can significantly reduce the energy consumption of data collection devices, thereby extending their lifetime (Huang et al., 2023; Miquel et al., 2023; Tulasi et al., 2023). Edge computing also reduces the operation costs and lag within the system introduced by transferring large quantities of raw data (Gallacher et al., 2021; Zualkernan et al., 2022). Examples of prototype camera traps using AI and edge computing have been tested in Australia for determining deer population density (Arshad et al., 2020) and in California for monitoring mountain lions and bobcats (Tulasi et al., 2023).

Despite the open availability of AI for ecological data processing, it is important to note that many are simply not yet developed for every specialist task they may be required to perform. For example, while passive acoustic sensors are relatively inexpensive when it comes to data collection, the use of AI for processing acoustic monitoring data is still very new and, as such, currently only limited datasets have been used to train algorithms (Sharma et al., 2023). Likewise, although AI is more widely used for species identification from camera trap imagery, accuracy is reduced when classifying species at new locations and identification is biased towards species with the highest volume of data over rarer or cryptic species (Schneider et al., 2020; Vélez et al., 2023). For training all forms of AI, reliance on the availability of training datasets proliferates existing biases in ecological data which often favour North America, Europe and Australia (Glover-Kapfer et al., 2019; Hoefer et al., 2023; Hughes et al., 2021; Vélez et al., 2023). As such, improving AI performance and accessibility beyond current applications is a considerable challenge requiring the availability of appropriate datasets, which require both significant funding and human resources to attain, and the ability to retrain the AI using them, which is often outside the skills of ecologists (Ellwood et al., 2020; Hahn et al., 2022; Hampton et al., 2013; Schneider et al., 2020). This requirement for the perfect training data set also means that many AI systems have high error rates in classification which need to be accounted for in analysis and when evaluating uncertainty (Rowland et al., 2021; Spence et al., 2025).

Combining AI and citizen science could be an especially powerful method of automating data processing (Willi et al., 2019; Torney et al., 2019; Palmer et al., 2021 in application to image classification) in terms of providing optimal speed, accuracy and cost-efficiency (McClure et al., 2020). Citizen science alone has been successfully used to process ecological data using platforms such as Zooniverse[10] for much the same reasons as AI, to reduce professional time spent on processing large volumes of photo or audio data. Most of these platforms are not set up to handle live data streams with a few exceptions such as the Instant Wild[11] app created by the Zoological Society of London which allows citizen scientists to process camera trap data in NRT. However, in order to acquire sustainably quick responses by citizen scientists such a project requires a devoted or numerous group (Maund et al., 2020). Therefore, sole reliance on citizen scientists for data processing efforts can easily lead to a breakdown of the NRT monitoring system without sustained engagement of citizen scientists which is difficult to achieve. While most of these platforms do not function in a real time manner (Zooniverse, 2024), use of citizen scientists for AI training does not require them to be (Willi et al., 2019). The only issue to overcome with this method is to impose a method to check for error from citizen science generated data so it is not proliferated in the AI (Baker et al., 2021). Taking random samples or having a community flagging system, similar to those described previously for DDCPs, to identify potential misidentifications which are then sent for approval by the professionals could be introduced to attempt to regulate and monitor error (Baker et al., 2021).

4. Data analysis

At this stage, the data is ready to be interpreted which requires analysis and/or modelling techniques to extract usable information for decision-makers. The current typical workflow for researchers and data analysts in ecology is to only perform analysis/modelling once the data for the whole project has been gathered or a periodic report is required. Selecting the appropriate model or analysis is dependent on the data available, the ultimate goal and underlying assumptions (Tredennick et al., 2021). There are a wide variety of pre-existing tools available to aid with analysis, such as R packages (e.g. Bachl et al., 2019; Pavoine, 2020; Vilela and Villalobos, 2015) and workbenches, which are also often connected to data repositories (e.g. Abarenkov et al., 2010; de Souza Muñoz et al., 2011; Kölzsch et al., 2022; Vogt et al., 2022). In addition to this, the open source code of many models are available on sites like GitHub,[12] although published papers which share model code still only constitute less than 20 % of all papers using models in ecology and evolution (Maitner et al., 2024). However, with a few notable exceptions at the cutting-edge of the field, analysis and modelling are not automated or conducted in NRT.

Much of the development in NRT analysis and modelling has been in the field of animal movement. This is reflected in the emergence of the concept of the Internet of Animals (IoA), systems of on-animal devices where live data is analysed in NRT and integrated with other datasets (Kays and Wikelski, 2023). Alert systems informed by analysis of NRT movement data from GPS tracking devices, the most simple of which being geofencing, are perhaps the most well-known NRT ecological monitoring workflows (Wall et al., 2014; Weise et al., 2019). Furthermore, one of the few workbenches designed for standardised analysis explicitly in NRT is MoveApps which can utilise live animal movement data hosted by MoveBank (Kölzsch et al., 2022). To the best of the authors' knowledge the only other workbenches available for NRT analysis are those provided by EarthRanger and Sensing Clues Foundation[13] and of these workbenches, only EarthRanger is open source (Wall et al., 2024).

An important alteration when switching from traditional analysis workflows to a NRT approach is to work iteratively. This lends itself to a Bayesian framework wherein prior knowledge is combined with new data to continuously update models, predictions and hypotheses (posterior) which can then be plugged back into the system as the new prior to be combined with the next set of data as it is collected (Dietze et al., 2018). Beyond enabling new observations to iteratively update model output, this approach has several distinct benefits for NRT ecological monitoring. Firstly, Bayesian methods enable the integration of expert knowledge as an informative prior which can enable predictions to be made even when data is limited, with the addition of new observations working to refine the model(Dietze et al., 2018; Morgan, 2014). Complimentary to this, Bayesian methods also enable the explicit quantification and presentation of uncertainty within the model output which can be used to aid decision-makers in interpreting this information (Dietze et al., 2018; White et al., 2019). Through enabling probabilistic model forecasts, Bayesian methods are powerful tools for enabling adaptive decision-making, especially in systems with high uncertainty (Dietze et al., 2018).

Pertinent to this discussion on Bayesian methods for NRT ecological monitoring are a number of new paradigms including digital twins, digital shadows and iterative near-term forecasting. Digital twins can be

[10] https://www.zooniverse.org/
[11] https://www.zsl.org/what-we-do/projects/instant-wild
[12] https://github.com/
[13] https://www.sensingclues.org/

defined as iterative models linked to their physical counterpart with real-time data which inform real-world feedback (de Koning et al., 2023). Without this real-world feedback, such as sending patrol teams to deter elephants from crop raiding, such a model would be termed a digital shadow (Kritzinger et al., 2018). This distinction is key when discussing NRT ecological monitoring as we argue that the development of such workflows should be targeted towards aiding decision-makers with real issues in the field (digital twins) rather than simply to gain a better understanding of the system (digital shadows). Linked to digital twins is the paradigm of iterative near-term forecasting, predictions on timescales of days to years rather than decades, which are increasingly relevant for decision-making due to the fast pace of ecological change in the Anthropocene (Henden et al., 2020; Lewis et al., 2022). While not all iterative near-term forecasting workflows provide data on timescales suitable for NRT ecological monitoring nor are they automated by definition, those which do facilitate sustainable production of daily to monthly forecasts to inform adaptive decision making (Dietze et al., 2018; Lewis et al., 2022).

It is important to note that NRT models and analyses themselves are not exclusively found within the research domains discussed. There are a significant number of papers describing NRT analysis and modelling methods which do not use the terms 'digital twin', 'digital shadow', 'near-term forecasting' or 'Internet of Animals' (e.g. Hobday and Hartmann, 2006; Jonsen et al., 2020; Randon et al., 2022; Skov et al., 2016). Furthermore, we argue that both iterative near-term forecasting (when automated and NRT) and IoA systems can be seen as either digital twins or digital shadows, depending on whether the information they produce are used to inform interventions in the field. Therefore, the introduction of the concept 'digital twin' to ecology serves to gather existing models and analyses across different study areas which fit this standard under a common term and to use this grouping to both highlight their specific merits for ecological monitoring and promote further development and standardisation in the field. As such, the term digital twin also aligns closely with the goals and processes described in a NRT ecological monitoring workflow, making the progress in digital twinning pertinent to this discussion.

Digital twins have been developed extensively in industry, aerospace and other fields (Enders and Hoßbach, 2019; Singh et al., 2022). However, the application of digital twins to ecological monitoring is still an emerging field and as such, standards are yet to be established and the limitations are still being explored. Consequently, most operational systems which could be classified as digital twins are relatively simple, often involving the identification of a species of concern in a designated area with a subsequent alert system, such as the AI system used in Tamil Nadu to identify elephants near train tracks and alert transport personnel (Kumar et al., 2020; Thomas, 2024; Wall et al., 2014). However, the real potential of digital twins, and what the field is working towards, is the integration of NRT data with models and more complex analyses for nowcasting, forecasting and scenario analysis. To the best of the authors' knowledge, at the time of writing there are only two ecological digital twins with this more complex analysis and predictive capacity which are also at the stage of being run on a server and regularly used: the Crane Radar (De Koning, 2025) and the Human-Bear Conflict Radar (Davison and Reijneker, 2025). However, there are numerous further projects currently developing digital twins in ecology and biodiversity monitoring including BioDT,[14] LTER LIFE[15]and Nature FIRST[16] which are exploring digital twin application to a wide variety of systems (e.g. Afsar et al., 2024; Ingenloff et al., 2024; Khan et al., 2024b).

A key consideration with conducting analysis/modelling (and processing) in NRT is the computational intensity and associated run time. The computation time for the processing and analysis/modelling must be shorter than the desired update interval to ensure NRT information availability to decision-makers. This computation time is dependent on the efficiency and complexity of the calculations, the volume of data and the computational power available (Schadt et al., 2010; Visser et al., 2015). Computation time for NRT approaches is reduced compared to traditional methods since data is dealt with at smaller volumes but use of computationally intensive methods, such as AI or agent-based modelling, or peaks in data input may still lead to computation overload (De Koning, 2025; Schadt et al., 2010). A further potential bottleneck in the development of digital twins is matching existing models, or sufficient system knowledge to create a model, with the available NRT data. Therefore, many of the complications in establishing NRT data collection and processing discussed so far in this paper are also highly relevant for digital twins and addressing them will contribute substantially to their development (Trantas et al., 2023). In-turn, digital twins can serve to reduce the required frequency for data collection via nowcasting, lowering the threshold for NRT monitoring requirements at the data collection and processing stages. The Crane Radar uses NRT data from citizen science observations on Waarneming.nl and wind forecasts (De Koning, 2025). As discussed previously, citizen science observations are not continuous and there can be delays in posting observations which the Crane Radar uses nowcasting to fill in and ensure a continuous NRT prediction of crane location (De Koning, 2025).

5. Data and information sharing

It could be argued that NRT ecological monitoring systems can be built and function well in a closed system, with no sharing functionality beyond that required for internal use within an organisation. Indeed, there are some instances where it is not appropriate to share data, such as in the case of sensitive species information which could lead to increased poaching (Frank et al., 2015; Sarkar and Chapman, 2021), or when there are further intricacies with data ownership, such as concerns surrounding Indigenous data sovereignty (Carroll et al., 2020). However, we argue that, as far as ethical, legal and data sensitivity concerns allow (e.g. Pritchard et al., 2022; Tulloch et al., 2018), sharing data, information and code should be pursued for NRT ecological monitoring workflows to accelerate development. Operation in separate silos without such sharing leads to wasted resources replicating data or processes already produced elsewhere which is a detriment to ecological monitoring as a whole (Wilkinson et al., 2016).

NRT ecological monitoring systems need, at minimum, to have the capacity to share the information produced in NRT with relevant decision-makers and other end users. One example of how this can be achieved is through text alerts to rangers to notify them of impending human-wildlife conflict events (Wall et al., 2014). A popular method of communicating this information is through online interfaces where end users can visualise the information and potentially even interact with it (Davison and Reijneker, 2025; De Koning, 2025; Sethi et al., 2020). This can be made open access (De Koning, 2025; Sethi et al., 2020) or under password protection for sensitive information (Davison and Reijneker, 2025). While these tools are perhaps most effective at communicating more complicated information, developing them requires technical skills most ecologists are not trained in (Beardsley et al., 2018) and raise further issues of ongoing maintenance which we discuss further in the implementation section.

In addition to sharing information produced by the NRT ecological monitoring workflow, there are also benefits to sharing the input NRT data and the underlying code itself. Outside of concerns over replicability and transparency (Culina et al., 2020; Fernández-Juricic, 2021; Kambouris et al., 2024), sharing code is important in order to provide building blocks for others who wish to establish NRT monitoring workflows and prevent time being wasted "re-inventing the wheel" (Gomes et al., 2022). Likewise sharing NRT data increases the available resources for those establishing new NRT monitoring systems, thereby

[14] https://biodt.eu/
[15] https://lter-life.nl/
[16] https://www.naturefirst.info/

lowering the threshold for their creation and expanding analysis possibilities (Wilkinson et al., 2016). When looking at platforms for code sharing, GitHub is the most well-established and also offers tools for version control and collaborative development, all essential components for accelerating NRT workflow development but the platform remains under-utilised by ecological researchers (Braga et al., 2023). Current options for data (or information) sharing include a number of comprehensive databases and research infrastructures designed to assemble and integrate knowledge on biodiversity occurrences, ecological interactions, taxonomies, ecosystem functions, and the impacts of people on nature, such as GBIF, DISSCO,[17] eLTER,[18] ITIS[19] and LifeWatch.[20] There are also repositories aimed at specialist subjects which welcome submissions from individuals without requiring such formal membership such as GenBank,[21] MoveBank,[22] and the Knowledge Network for Biocomplexity.[23] All of these platforms host a wide variety of data sets, with varying levels of access, from all the data collection methods discussed previously and at varying levels of processing and analysis. There are also storage functionalities integrated into DDCPs and some citizen science data processing platforms but access ranges from open to closed. With the exception of data from DDCPs, there are very few online repositories which host live data streams, where the data is uploaded in NRT as it is collected. Most exceptions to this are in the field of animal tracking where handling NRT data is more common. For example, MoveBank has the capacity to store animal tag data in NRT with the potential to share with the public using the Animal Tracker app (Kays et al., 2022) but the majority of data published on the repository is still from completed projects and are not open access, instead requiring permission from the data owners (Movebank, 2024).

Application programming interfaces (APIs) have been essential in facilitating automated data transfer but in order to use them, APIs need to be accessible and well documented. When accessing data, APIs may not be available for example if the data is sensitive, or may require an account to gain access. Where APIs are freely available, they may not be well documented which hinders their use, especially by those who are not technical experts. Good practice for APIs can be seen in various remote sensing and weather sources (Copernicus, 2024) as well as, for example, eBird and BOLD[24] where the APIs are freely accessible and well-documented. Increased demand for and investment in available and well-documented APIs in the future will increase the amount of data which can be integrated into NRT monitoring workflows. These requirements should also be considered when sharing the information or data produced by a NRT ecological monitoring system through APIs in order to enhance usability.

Despite a widespread appreciation of the benefits to science of sharing data and code alongside a willingness to do so, many still do not share (Culina et al., 2020; Gomes et al., 2022; Hampton et al., 2013; Mills et al., 2015; Tenopir et al., 2020). Code sharing in ecology continues to lag behind data sharing with only 27 % of publications sharing code compared to 79 % which shared data in a study focused on ecology journals which encouraged or mandated sharing (Culina et al., 2020; Public Library of Science, 2024). The reasons for this are multivariate and include resource issues such as a perceived lack of tools available to researchers to make good data management choices (Tenopir et al., 2020), issues of funding (Mills et al., 2015), perceived lack of time (Gomes et al., 2022) and technical and knowledge barriers to adopting new tools such as GitHub (Braga et al., 2023). In addition, researchers may have concerns over their data or code being misused or even "stolen" (Gewin, 2016). These concerns are made all the more salient in the current scientific landscape where publication metrics are closely tied to career opportunities and the threat posed by those with the resources to swiftly exploit open-source data, thereby "stealing" future publications, act as disincentives for researchers to share their hard-earned data (Gomes et al., 2022). Even if researchers do choose to share, for NRT data requirements, there is also the issue of when they choose to share. Researchers tend to only want to share their data when their research is published (Huang et al., 2012) and sharing of data in NRT is not contemplated by the majority (Hampton et al., 2015). Embargo lengths vary, often being capped at one to two years, but this is still of a sufficient length to render the data unusable for NRT monitoring (Michener, 2015).

Nevertheless, funders and journal publishers are increasingly pushing for and in some cases requiring FAIR and open data practices and there is a slow increase in the percentage of publications with accompanying data and/or code (Cannon et al., 2022; European Commission, 2024; Public Library of Science, 2024). While there is still some investment needed to address deficiencies in the digital infrastructure, fostering increased sharing of data in NRT and the code for NRT ecological workflows is also largely dependent on ethical and social considerations. More widespread adherence, especially by data users, to ethical guidelines for data reuse, increased incentives for data sharing and further training and discourse could serve to address many of the misgivings currently held by researchers (Duke and Porter, 2013; Gomes et al., 2022).

6. Implementation

While NRT ecological monitoring systems can be established solely to improve scientific understanding of a certain process or species, the main focus of this paper is the applied use of such a system for local and protected area management. Some suggested issues which could be aided by the use of NRT monitoring include wildlife poaching, illegal harvesting, human-wildlife conflict, disease outbreaks, wildfires and seasonal migration. Therefore, in addition to the specific technology and methodologies required to create a NRT ecological monitoring workflow, there are further considerations integral to applying this system for long-term success. These include ensuring long-term NRT data provision, effective maintenance of the system for continued function, considerations of ethics and sustainability and establishment in local decision-making and governance. Such a discussion is essential as, while there are NRT ecological monitoring systems in the current literature which would be classified as digital twins (Brunoldi et al., 2016; De Koning, 2025; Ovaskainen et al., 2024; Sanguineti et al., 2021), the majority would more aptly be described as digital shadows (Besson et al., 2022; Bjerge et al., 2022; Skov et al., 2021; Zheng et al., 2018). This disparity is indicative of the inherent challenges in establishing such a system effectively and the importance of the following discussion.

6.1. Data collection longevity

One key element for the continued function of the NRT monitoring workflow is to ensure sustainable provision of NRT data at the collection stage. Without data consistently being entered into the system, the NRT information for decision-makers will stop being produced or become unreliable. Therefore, establishing data collection methods in the field which ensure longevity of data provision to the rest of the NRT monitoring workflow is essential for long-term use. While NRT ecological monitoring workflows can be built from scratch, a more cost-effective and pragmatic approach is to adapt established monitoring practice to a NRT approach. However, in the field of ecology in general, long-term monitoring projects are few in number compared to the volume of short-term projects due to the various complications of sustaining research for

[17] https://www.dissco.eu/
[18] https://elter-ri.eu/
[19] https://itis.gov/
[20] https://maps.elie.ucl.ac.be/lifewatch/geoviewer.html
[21] https://www.ncbi.nlm.nih.gov/genbank/
[22] https://www.movebank.org/cms/movebank-main
[23] https://knb.ecoinformatics.org/
[24] https://v3.boldsystems.org/

more than a few years (Haase et al., 2018; Lindenmayer et al., 2012, 2022; Nielsen et al., 2009). For many projects, there is a struggle to sustain funding over multiple years since the return on investment is not always evident to funders (Lindenmayer et al., 2012; Waldron et al., 2017). There are also added uncertainties in long-term monitoring projects run by professionals due to project member turnover. In the case of citizen science projects, there is also a crucial need to ensure citizen engagement persists for the longevity of the project (Lotfian et al., 2022).

When collecting data with sensor devices, the lifespan of the selected device often influences the duration of a project, especially for on-animal devices with some devices lasting an animal's lifetime powered by solar panels but others becoming damaged or lost in a matter of months (Hussey et al., 2015; Kays et al., 2015). For in-situ devices, wear and tear from the local environment should also be taken into account as very high humidities, temperature extremes and wildlife interference can damage and dramatically reduce device performance, sometimes rendering them inoperable (Wearn and Glover-Kapfer, 2017). As such, person-hours are required to maintain the devices through replacing batteries, old, stolen, damaged and lost devices to avoid gaps in data provision (Glover-Kapfer et al., 2019; Muhametsafina et al., 2014). While some of the new technologies mentioned in the data collection section such as edge computing, wireless sensor networks and IoT could all aid in improving longevity of device functioning in ideal conditions, they are still susceptible to theft, damage and loss. There are many papers available discussing potential solutions to these outstanding issues such as elevating or concealing camera traps to reduce theft (Jacobs and Ausband, 2018; Meek et al., 2019) but devices are expected to be lost in the duration of most studies which needs to be factored into the assigned budget, especially when using more expensive devices.

6.2. Software maintenance

Software for all manner of purposes must be subject to some level of maintenance in order to maintain function (Chapin et al., 2001). A robust and sustainable software architecture is required in the initial development stage in order to foster efficient and effective maintenance and increase the longevity of the system (Cerf, 2017; Venters et al., 2014; Venters et al., 2018). There are several different types of maintenance which must be considered over the lifetime of the NRT monitoring system: corrective maintenance to fix bugs and defects; preventive maintenance to anticipate and fix potential issues; adaptive maintenance to handle any changes in the source data or software required to run the workflow; and performative maintenance to ensure efficiency and optimal user experience.

The need for effective maintenance can be illustrated using the work described in Sethi et al. (2020) establishing the SAFE Acoustics monitoring network in Borneo. This project deployed passive acoustic sensors as part of a NRT ecological monitoring workflow which was fully open source with a public-facing website (http://acoustics.safeproject.net/). However, just four years on at the time of writing, this website is broken and no longer produces the output described in Sethi et al. (2020). While this could also be due to cessation of data collection from the ending of the project, it illustrates that, without ongoing care and attention, investment in such NRT monitoring systems can easily be rendered obsolete.

However, the time and expertise required for such maintenance of a NRT monitoring system is a significant bottleneck for its implementation and longevity. The maintenance of these workflows is highly likely to take significantly more time than their initial development which means significant additional costs (Garcia et al., 2013; Rehman et al., 2018). Furthermore, there is a pervasive lack of technological and big data skills within the field of ecology (Ellwood et al., 2020; Hahn et al., 2022; Hampton et al., 2013) meaning that the majority of researchers who may use such a workflow and those who rely on the output information would not have the skills to alter and maintain the code themselves. Therefore, in order to both create and, crucially, to maintain the operational integrity of NRT monitoring systems, there is either a requirement to train ecologists in those skills or to foster partnerships, which can be difficult to maintain effectively, with technologists (Ellwood et al., 2020; Hahn et al., 2022; Pettorelli et al., 2014).

6.3. Data storage and computation

In order to facilitate a NRT workflow, there is an ongoing requirement for data storage and sufficient computational power to support NRT calculations. The use of cloud-based HPC for analysis and modelling incurs costs for computation, ranging from a few cents up to a few USD per hour, but also for cloud storage and data retrieval which are charged at a few cents per GB per month or per transfer respectively (Google, 2025; Amazon Web Services, 2025). For NRT monitoring using audio and photo files which can easily reach the tens if not hundreds of GB per month, these can add up to significant ongoing costs. Adopting edge computing can be a highly efficient way of reducing the volume of data handled (Miquel et al., 2023). For example, when looking at the data collected on Wildlife Insights, simply removing camera trap images with no subject at the point of collection would reduce the volume of data transferred and processed in the cloud by around 2/3 (Wildlife Insights, 2025). Making use of secondary data from repositories with available APIs such as MoveBank and eBird reduces the need to find storage solutions for raw data which can be easily accessed in the NRT workflow. Ensuring that the workflow efficiency is maximised using techniques such as parallelisation, vectorising operations and selecting algorithms with lower computational complexity are also important for reducing the computational costs incurred. However, as mentioned with maintaining NRT workflows, such skills are often outside those of ecologists, requiring partnerships with technologists to establish the most cost-effective methods (Ellwood et al., 2020; Farrell and Carey, 2018; Venters et al., 2018).

6.4. Sustainability and ethics

Key considerations when adopting a new monitoring approach include sustainability and ethical concerns. The production of relevant devices and technologies, computation and storage of data all consume energy and resources which contributes to climate change and other anthropogenic issues causes by over-consumption of resources (Fuchs, 2008). There are further ethical concerns surrounding data collection such as privacy issues (Sandbrook et al., 2021; Simlai and Sandbrook, 2021) and increased disturbance to wildlife (Vas et al., 2015). While these issues are not exclusive to NRT ecological monitoring, the adoption of this approach may be labelled as synonymous with an advocation for a widespread increase in the use of sensor devices and an increase in the intensity of data collection. However, we argue that established ecological monitoring practices should be integrated into NRT workflows in order to minimise requirements for further devices and bring greater value to data already being collected in the field. Furthermore, the emphasis on supporting real-world decision-making using NRT ecological monitoring also directs resources to tackling pertinent issues (Martínez-Harms et al., 2024).

6.5. Management systems

As previously discussed, the focus for NRT ecological monitoring should be centred on informing the management of rapidly developing systems (de Koning et al., 2023; Khan et al., 2024b; Trantas et al., 2023). As such, there are two key considerations for ensuring the information produced can inform real-world decisions: the value of the information and the capacity for response. The requirement for large scale coordination at the regional and national level and the inherently slow movement of legislation means that the capacity for response to NRT information is higher at the local level (Westgate et al., 2013). Responses at the local level include the initiation of direct interventions by personnel in the field, as is often seen when NRT monitoring informs issues of human-wildlife conflict (Wall et al., 2014; Weise et al., 2019), or the enabling of adaptive management (Dietze et al., 2018; Westgate et al., 2013). The capacity for response is also dictated by the motivation to invest in such responses which varies with the national and local sociopolitical climate and the overall resources available within that country (Mascia and Mills, 2018; Radeloff et al., 2013).

In order for the information produced by NRT ecological monitoring to aid in decision-making, it must be tailored to the needs of the decision-maker, trusted and fully understood. To meet these needs, workflows should be designed, implemented and iteratively developed through a co-production process rather than commonly adopted top-down approaches (Dietze et al., 2018). Co-production methods are increasingly employed in conservation to closely and deliberately engage important stakeholders, such as Indigenous peoples, local experts and local governance, with the goal of harnessing local knowledge, producing equitable solutions and ultimately fostering increased transparency and trust (Martínez-Harms et al., 2024). Use of co-production from the beginning of a project can also help to determine the suitability of NRT ecological monitoring workflow for a specific instance and whether the need is great enough to justify the cost (Beier et al., 2017). Furthermore, centring local communities and Indigenous peoples to ensure positive social impact and local support for conservation interventions is shown to increase the likelihood of their long term success (Bennett et al., 2019; Dawson et al., 2021). Despite the need for a co-production approach being broadly accepted in the digital twin literature, there is currently no literature available detailing its application in NRT ecological monitoring workflows (Bauer et al., 2021; Blair, 2021; de Koning et al., 2023; Dietze et al., 2018).

7. Conclusion

NRT ecological monitoring has the potential to be a powerful tool for decision-makers to identify undesired trends in rapidly changing systems early, enabling the implementation of timely interventions. While NRT ecological monitoring is possible and there are scattered instances of successful establishment in the field, widespread adoption is currently substantially limited. Within the current work on NRT ecological monitoring, focus has largely been on the themes of animal movement and human-wildlife conflict. Geographically, the potential for NRT ecological monitoring is concentrated in high-income countries, especially those in North America and Europe. These areas have widespread and stable connection to cellular networks, access to funding, well established citizen science groups and crucially have been the testing grounds for most of the technologies discussed in this paper. However, even within these countries, the requirement for strong interdisciplinary partnerships between ecologists and technologists to establish a NRT workflow is an ongoing challenge. Expanding the accessibility of NRT ecological monitoring is hindered by the concentration of ecological research focus and resources in high-income countries and wider issues of access to technology which make even the lower technology solutions discussed difficult to implement. Emphasis on integrating existing monitoring practices into a NRT workflow and increased sharing of code and live data streams will make NRT ecological monitoring easier to adopt and engaging in co-production will help direct where such an approach is needed.

CRediT authorship contribution statement

Anna Marie Davison: Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Koen de Koning:** Writing – review & editing, Supervision, Conceptualization. **Franziska Taubert:** Writing – review & editing. **Jan-Kees Schakel:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank Prof. Rob Alkemade and Prof. Ioannis Athanasiadis for their valuable feedback and helpful suggestions on an earlier draft of this paper. We would also like to thank the reviewers for their insightful contributions to this paper.

This study received funding from the European Union's Horizon Europe Research and Innovation Programme under grant agreement No 101060954 (NATURE-FIRST, https://doi.org/10.3030/101060954). Views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.

Data availability

No data was used for the research described in the article.

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