Closing Biodiversity Knowledge Gaps with Digital Agriculture

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Open Research statement

No data were collected for this study.

Keywords

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ABSTRACT

The global expansion and intensification of food production threaten biodiversity, vital for ecosystem services and food security. The Kunming-Montreal Global Biodiversity Framework (GBF) advocates drastic changes in agricultural management, yet translating recommendations into local action is challenging. Deciding on which, when, and how to implement sustainable agricultural management practices requires systematic reference data on biodiversity-management-yield interactions, but such data is currently lacking. Here, we discuss how Digital Agriculture can help tackle this gap. Although it uses technologies also applied in biodiversity monitoring, it is currently treated separately, leading to a duplication of effort and costs. Digital Agriculture offers the means to monitor biodiversity in food production systems, linking it directly to land management practices, and directly benefiting multiple stakeholders. This integration of monitoring efforts has the potential to increase the effectiveness of the GBF in achieving a sustainable agriculture transition.

IN A NUTSHELL

- Global food production expansion threatens biodiversity and food security.
- The Kunming-Montreal Global Biodiversity Framework calls for significant changes in agricultural management practices
- We lack systematic data on biodiversity-management-yield interactions
- Digital Agriculture offers an avenue for integrating biodiversity monitoring in food production systems, potentially enhancing the effectiveness of sustainable agriculture practices

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INTRODUCTION

The global expansion and intensification of food production systems has resulted in dramatic losses of biodiversity (IPBES, 2019). As the human population continues to grow, so does the demand for food (van Dijk et al., 2021), leading to a continued expansion of farmland areas that threatens thousands of species with extinction (IPBES, 2019). Many of these species benefit food security and resilience (IPBES, 2016), including through pollination (IPBES, 2016) maintenance of soil fertility (Fonte et al., 2023), and pest control (Lindell et al., 2018).

Changes to food production practices are needed to reduce their impacts on biodiversity (Delabre et al., 2021). The Kunming-Montreal Global Biodiversity Framework (GBF, CBD, 2022) recognizes this urgency, and advocates for sustainable land use to conserve biodiversity and nature's contribution to people. For farmland biodiversity, this is to be achieved through Target 10 in particular, which promotes the integration of biodiversity-provided services in food production (e.g., through sustainable intensification, (CBD, 2022). Nevertheless, despite evidence indicating that these practices can promote biodiversity gains without compromising food production (MacLaren et al., 2022), it has been argued that transition periods of lower productivity are likely (Kovács-Hostyánszki et al., 2017), creating possible food security challenges. Therefore, translating GBF recommendations into optimal management strategies that can achieve local benefits remains a challenge.

Systematic, long-term monitoring capabilities are necessary to provide reliable and scalable recommendations on when, where, and which agricultural management practices to implement to best promote biodiversity and its services (Toivonen et al., 2015). This is critical as ecological benefits may be slow, uncertain or scale and context dependent (Burian et al., 2024). As a support for long-term, systematic monitoring, the biodiversity community has largely reached consensus on key variables for measuring and monitoring biodiversity, referred to as Essential Biodiversity Variables (EBVs, Pereira et al., 2013). Recently, a similar set of Essential Ecosystem Service Variables (EESVs, Balvanera et al., 2022) was proposed. Changes in these variables can be contextualised in connection with ground-level biodiversity data, which are quickly evolving in both frequency and quality with the support of automated techniques (Besson et al., 2022). Nonetheless, understanding biodiversity-yield interactions requires reference data on crop conditions and management practices at the time the species was observed. Combining these data at the field and farm-level is critical for deriving reliable policy recommendations.

Yet, biodiversity studies often lack such detailed reference data. Instead, state-of-the-art literature relies on coarser agricultural statistics as proxies (e.g., at sub-national scales, Beckmann et al., 2019) which are typically incomplete, lacking temporal detail, or of uncertain quality (Kebede et al., 2024). In addition, despite technological advancements in biodiversity monitoring, data on farmland biodiversity is often scarce. These data limitations lead to thematically focused research (e.g., selected taxonomic groups such as birds, Scholefield et al., 2011, or simulation studies, Burian et al., 2024) and to custom choices of methods to analyse them (Gonzalez et al., 2023). Therefore, we cannot confidently generalise evidence research on the causes of biodiversity change (Gonzalez et al., 2023), such as on which agricultural management practices help increase or diminish biodiversity.

To better understand biodiversity-yield interactions, we must involve farmers (Hölting et al., 2022). They are ultimately responsible for implementing agri-environmental measures (e.g., in the EU Common Agricultural Policy, Pe'er et al., 2022), and control access to the lands where data is needed. To achieve this, various participatory strategies have been proposed (Hölting et al., 2022), some connecting networks of stakeholders, data, tools, and biodiversity monitoring programs (Kühl et al., 2020). However, we argue that current participatory strategies are insufficient, and agree with Pe'er et al. (2022), in that support for biodiversity monitoring and reporting must be made explicit. Because biodiversity monitoring constitutes an additional, challenging, and time-consuming task, we cannot expect farmers to perform it without legislative enforcement and financial support. Without such mechanisms, farmers may naturally see biodiversity monitoring as a secondary concern compared to other priorities (e.g., income and life quality, (Maas et al., 2021)). In addition, farmers may even view some aspects of biodiversity as pests (e.g., small mammals), and thus not share the urgency of implementing conservation measures (Maas et al., 2021).

Without the support of farmers, however, the sampling of farmland may become unrepresentative at the landscape-scale due to limited access to lands (Steinke et al., 2017). To obtain systematic and concurrent data on both biodiversity and food production, we must ensure the participation of farmers without imposing additional challenges on them. We propose this can be achieved through technologies used to optimise food production (hereafter 'Digital Agriculture', **Fig. 1**). Whereas Digital Agriculture helps farmers optimise food production, it may also provide highly valuable, but currently overlooked, biodiversity data streams (specifically relating to observations of non-agricultural species and, potentially, their traits, **Fig. 2**). Our work sheds light on an immediate and overlooked opportunity to obtain biodiversity data paired with data on food production and land management. We aim to stimulate technical advances that reduce redundancy and costs in environmental monitoring, while accelerating benefits for nature and people.

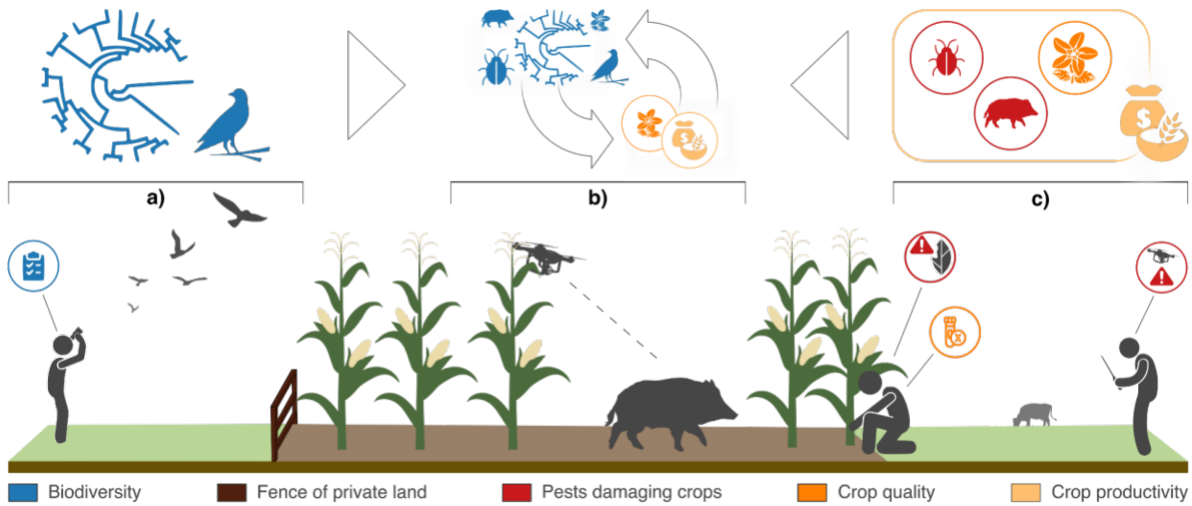

Figure 1. Unaccounted biodiversity in food production systems. a) A surveyor of biodiversity is located outside private farmland, but can record overpassing birds or other species detectable from the distance. Such information can enter public or private databases and then contributes to knowledge and monitoring of local biodiversity (shown in blue). The observation of areas within the farmland is, however, restricted (e.g. due to fencing or dense crop cultivation). **b)** Within the maize plantation, a wild pig is spotted by a drone. The drone was deployed by a land manager (**c,** on the right) with the intention of surveying crop conditions and detecting potential pests (in red). Simultaneously, another land manager collects data on pests in the cultivated crops (e.g. bugs, in red) and on crop conditions (in orange) to make management decisions. As shown at the top of panel **c**), information on pests and crop conditions informs on crop productivity (in yellow). Combining the biodiversity information and data given in **a)** with the pest and crop condition data given in **c**) provides a more complete picture of biodiversity and how biodiversity responds to (and affects) crop productivity (shown above **b**).

Parallels of Digital Agriculture and automated biodiversity monitoring

Digital Agriculture and automated biodiversity monitoring share many similar technologies. At the landscape level, drones are used to detect, locate, and count pests such as insects (Stumph et al., 2019), rodents (Keshet et al., 2022) or wild pigs (Friesenhahn et al., 2023). They are also used to detect plant diseases (Abbas et al., 2023) and to monitor cattle in large pasture areas (Soares et al., 2021). Similarly, drones are used in biodiversity surveys to detect wildlife more efficiently compared to human observations (Hodgson et al., 2018). At the ground level, passive acoustic sensors can measure crop height (Sharma et al., 2016) and are used to detect soniferous species such as birds (Fischer et al., 2023). On the other hand, active acoustic sensors can provide information on crop health (Colaço et al., 2018) and physiological traits that distinguish non-crop plant species (Rostami and Nansen, 2022). Most recently, robots equipped with artificial intelligence showed promise for extracting environmental DNA (eDNA) to detect microbes and insects harmful to crops (Kestel et al., 2022), and to survey different animal species, including insects, mammals, birds, and amphibians (Aucone et al., 2023). Robots are also increasingly used to assist in farmland management, such as weed removal (Zingsheim and Döring, 2024), and in biodiversity surveys across habitats inaccessible to humans (Angelini et al., 2023) such as potentially large farmlands. All of these technologies can be integrated with satellite remote sensing to monitor biodiversity change (Vihervaara et al., 2017) or long-term trends in food production (Basso and Antle, 2020).

Digital Agriculture: a hidden source of biodiversity data

Although Digital Agriculture and biodiversity monitoring have obvious parallels, they are treated as separate branches of environmental monitoring in research, university education and practice. This results in duplication of efforts and costs. Combining these branches would offer a low-cost pathway to improve biodiversity monitoring in food producing systems. More importantly, it would offer critical and novel insights into biodiversity-yield interactions that are only enabled through systematic and long-term data streams obtainable through Digital Agriculture (**Fig. 2**).

As an immediate benefit, this integration process can improve the coverage of biodiversity monitoring within food producing systems. For instance, applying biodiversity monitoring methods (e.g., image interpretation) to data obtained for the initial purpose of monitoring food production (e.g., drone imagery) could generate new data on species traits and occurrences otherwise missed (**Fig. 1**). These data could be directly linked to concurrent biophysical measurements of crop conditions, providing unique insights on species-specific functional responses in habitat selection. Conversely, failure to detect a species on farmland despite its presence in the regional species pool can provide valuable data on habitat preferences and dislikes. This will significantly advance our understanding of species-specific habitat and resource selection in agricultural landscapes (e.g., habitat vs. matrix, Fahrig, 2001), or even challenge our initial perceptions. In fact, evidence shows that some species can adapt to man-made habitats (Gruber et al., 2019), and that others thought displaced by cropland expansion can be 'rediscovered' with the support of farmers (Jess, 2023).

As a long-term benefit, time-series data on biodiversity and crop conditions obtained through systematic and periodic sampling would support robust causal analyses. This would enable us to generate reliable information on which management practices enhance or decrease biodiversity (Basile et al., 2021), and which ecosystem functions and ecosystem services are created or compromised (Magnano et al., 2023). Ultimately, as Digital Agriculture becomes a more common practice, reproducible landscape-level experiments become possible, enabling comprehensive analyses of cross-scale biodiversity-yield relationships, including detecting intensification traps (Burian et al., 2024), to directly support conservation and other forms of land management.

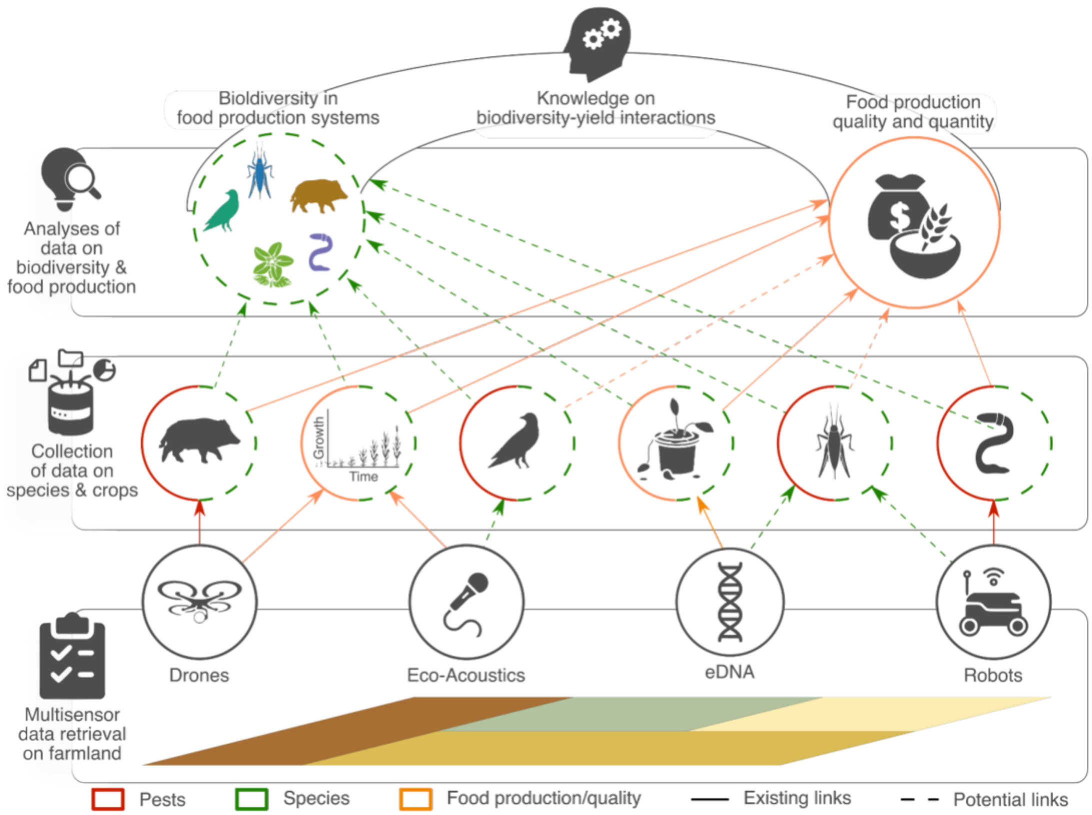

Figure 2. Sensing biodiversity through Digital Agriculture. A cropland area (where colours distinguish fields with different crops) is observed using different sensing technologies (indicated in the circles above the fields). These technologies provide several pieces of information, such as on pests, plant growth and conditions. All of the existing information links (shown with full lines) feed into food production and quality information systems (in orange). We here propose new information links (shown with dashed lines) that can feed monitoring systems for both biodiversity (in green) and food production and quality. Here, 'biodiversity' refers specifically to species observations and, potentially, species traits. For instance, whereas drones and robots inform on the presence of pests so that farmers can make management decisions, this information can additionally be used to distinguish different species for biodiversity information. Similarly, ecoacoustics and eDNA used to monitor crop growth and health can simultaneously be used to acquire information on roaming species not captured directly through image recognition. All of this information can be fed into biodiversity monitoring workflows that can distinguish and catalogue species occurrences and assess species traits. In addition, information on biodiversity can be combined with that on food production and quality to acquire new knowledge on species habitat preferences. This can help us establish causal links between biodiversity and food production and quality that inform on the provision of ecosystem services by particular species, and which can then feed the mapping of these services and subsequent policymaking, monitoring, and conservation.

Digital agriculture as a vehicle towards more confident policy recommendations

The value of Digital Agriculture technologies for biodiversity monitoring does not invalidate other sources of data, such as citizen science (Billaud et al., 2021) and taxonomic specialists (European Commission et al., 2022). Yet, with urban populations projected to increase by 13% by 2050 at the cost of those in rural areas (Heilig, 2019), citizen science, at least, is likely to be displaced away from food production systems. It is vital to ensure that policy recommendations, such as those on biodiversity-friendly agricultural management practices (GBF, target 10), are not skewed by sampling biases. Whereas site selection biases distort our perceptions of biodiversity change (Mentges et al., 2021), systematic monitoring capabilities can inform confident detections of biodiversity changes and their causes, which serves as a basis for confident policymaking (Gonzalez et al., 2023).

However, most countries still lack biodiversity monitoring programs (Kühl et al., 2020). Their implementation demands an annual investment of millions of US dollars (Juffe-Bignoli et al., 2016), clashing with global inequalities in economic power (World Bank, 2022). In some countries, biodiversity monitoring may, by necessity, even be considered a lower priority compared to other development issues, such as food security. In those countries, Digital Agriculture, which can already support several GBF targets by improving production efficiency, reducing waste, and optimising pest management (targets 7, 10, and 16, respectively), offers an avenue for joint biodiversity and food security monitoring without duplicating financial or organisational efforts.

Due to the existence of economic incentives for improving food production, biodiversity monitoring can capitalise on an industry worth US$6.2 trillion (FAO, 2023). In fact, in some regions, most investments in agriculture are already aimed at digital innovation, targeting both industrial and smallholder farming (e.g., as documented in the global south, Prasad et al., 2023). For instance, the UN-led *50 by 2030* initiative plans to invest US$500 million to digitise food production in multiple countries by 2030 (Zezza et al., 2022). Simultaneously, the UN-funded Consultative Group on International Agricultural Research (CGIAR) is advancing generalised principles and tools for sharing and distributing big, farm-level data (Basel et al., 2023). Through such initiatives, and combined with legislation prompting the sharing of new data streams – potentially at the level of individual farms – Digital Agriculture can help balance the costs of biodiversity monitoring in food production systems. This will enable more confident assessments of biodiversity-yield interactions, and of their contributions to people.

Benefiting farmers on the short-term for long-term biodiversity and sustainability returns

Capitalising on investments in Digital Agriculture for biodiversity monitoring demands cooperation between farmers, biodiversity experts and decision-makers. However, we must transcend current participatory strategies. Rather than involving farmers in biodiversity monitoring, which adds to the challenges of farming itself, collaborations could, for instance, coordinate smart solutions to deploy sensing technologies in ways that maximise returns for all stakeholders involved. For example, drones used to assess crop growth could also be employed to monitor green infrastructure in farmland without translating in an additional task for farmers. Similarly, automated deployments of acoustic sensors would enable the detection of pests, which benefits farmer's directly, while enabling recording and distinguishing various species (e.g. bats, insects, birds). In addition, cooperation could be extended to other disciplines. For instance, the involvement of engineers can support the adoption of new sensing technologies, such as robots (e.g. Pringle et al., 2023). Similarly, experts from other disciplines, such as agronomy and computer vision, could help calibrate sensing routines to increase knowledge benefits for scientists and farmers alike while reducing monitoring costs.

Such measures can help bridge the divide that many farmers feel between society's expectation to conserve nature and the desire to achieve production needs. Simultaneously, they would enable farmers and other stakeholders to jointly build knowledge about biodiversity-yield interactions, and on the effectiveness of management practices in promoting biodiversity and subsequent ecosystem services. Evidence suggests that such joint knowledge increases the likelihood that farmers will adopt recommended changes to management practices (Bartkowski et al., 2023). We emphasise that Digital Agriculture should not be regarded as a direct substitute for traditional biodiversity monitoring, and the expertise of taxonomic specialists remains indispensable. In fact, if not properly designed, monitoring through Digital Agriculture may even shift current biases in biodiversity data. However, combining traditional monitoring with joint on-farm learning involving scientists and farmers would bring us closer to a sustainable agriculture transition.

CONCLUSION

The adoption of the GBF sets an ambitious agenda to mitigate biodiversity losses, and emphasises the critical role of sustainable agriculture to achieve it. However, the decision on which sustainable practices to implement is hindered by uncertainties surrounding expected trade-offs between biodiversity and yield. Reducing uncertainties requires paired and systematic data on food production and biodiversity, which is either rare or non-existent. To tackle this gap, Digital Agriculture offers a cost-efficient solution. Because it employs some of the same technologies used to monitor biodiversity, the data it generates to monitor food production can, in principle, also provide concurrent and systematic data on non-agricultural species found in farmland. Most importantly, this would be achieved without creating additional tasks for farmers, and support the co-design of nature-based solutions sensitive to the needs and challenges of both farming and farmland biodiversity conservation.

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AUTHOR CONTRIBUTIONS

RR and AC designed the study. RR led the writing with contributions from MV, EP, MP, PV, CM, AE, DR, and AC. RR designed the figures.

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest.

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