Closing Farmland Biodiversity Knowledge Gaps with Digital Agriculture

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ABSTRACT

Digital agriculture and biodiversity monitoring share many data collection technologies and analytical methods, yet remain siloed. We propose a pathway to harness Digital Agriculture data streams for dynamic, near-real-time assessments of biodiversity-yield interactions aligned with policy-relevant indicators. Bridging these fields, enabled by advances in science and policy, can enhance farmland biodiversity monitoring and accelerate the urgently needed transition to sustainable agriculture, securing nature's contributions to people.

INTRODUCTION

Both agriculture and biodiversity science are undergoing rapid digital transformations. Research fields that were once constrained by sparse, irregular, or coarse-resolution data are now becoming increasingly data-rich. In agriculture, the widespread adoption of automated sensors for precision farming (hereafter 'Digital Agriculture'), including cameras[1,2], drones[3,4], and genetic sampling[5,6], enables continuous, high-resolution monitoring data[7,8]. These data are used to maximize yields, reduce waste, and increase the resilience and sustainability of farming systems[9]. Simultaneously, biodiversity monitoring is being revolutionized by the same sensing technologies[2,10,11], enabling unprecedented species- and community-level biodiversity assessments[12,13].

This convergence in technologies creates a unique opportunity: the potential to align agricultural and ecological monitoring infrastructures, methods, and objectives. Through Digital Agriculture, sensors established for digital farm management could also generate primary biodiversity data required for biodiversity monitoring and policy-relevant reporting[14,15]. In fact, both applications may even use the same methods to generate insights from generated data streams (e.g., same image segmentation algorithms[16,17]), increasing the potential for interoperability. Notably, primary biodiversity data are already generated through Digital Agriculture (**Fig. 1**), but collected for purposes other than biodiversity monitoring (e.g. pest control[1,3,18], soil management[19–21], phenotyping[22–24]). In some cases, primary biodiversity data may even be collected unintentionally and treated as 'noise' (e.g., ground nests[123] and molehills in drone imagery[26]).

A growing body of literature recognizes the importance of Digital Agriculture for biodiversity. For instance, farm-management data has been proposed as a tool for conservation by identifying low-productivity zones for conservation strips[8], or monitoring habitat quality[12]. At the policy-science interface, the Food and Agriculture Organization (FAO) supports these approaches through its 2022–2031 strategic plan, which encourages the application of digital technologies to optimize the use of natural resources, reduce environmental impacts, and promote biodiversity-friendly farming methods[27]. This aligns with the Global Biodiversity Framework (GBF) targets, particularly those related to sustainable land management (Target 10), reduced food waste (Target 16), and lower agricultural pollution (Target 7). However, despite overlapping objectives, biodiversity monitoring initiatives largely operate independently of the rapidly evolving digital agriculture sector. This disconnect limits the integration of high-resolution, real-time agricultural and biodiversity data, potentially missing valuable opportunities for more precise and responsive conservation planning.

Indeed, such data integration is rare among state-of-the-art agroecological monitoring schemes (**Fig. 2**). Although meta-analysis studies aimed at linking measured yield and biodiversity at the same locations[28,29], many biodiversity studies continue to rely on (sub)national agricultural statistics to assess biodiversity-yield interactions[30,31]. These statistics exhibit spatial gaps, temporal inconsistencies, and uncertain quality[32], or lack ecologically meaningful thematic and spatial detail[33]. Similarly, biodiversity data frequently originates from short-term or taxonomically narrow monitoring efforts[34–36]. Without systematic and temporally aligned data, data biases shape perceived biodiversity changes[37,38].

Through Digital Agriculture, agricultural landscapes, which now comprise nearly half of the world’s habitable land[39], could become living laboratories. Data streams on crop productivity, if repurposed for biodiversity monitoring, would offer direct evidence on biodiversity–yield interactions, which may be temporally and spatially dynamic[40] and dependent on local environmental and socio-economic contexts[34] (**Fig. 2**). Together with state-of-the-art sampling designs[37], Digital Agriculture could thus help build scalable causal inference frameworks needed for policy-relevant biodiversity change reporting[41] and evidence-based land management[42,43]. Crucially, integrating biodiversity monitoring into Digital Agriculture needs not to come at the expense of crop productivity. Instead, it can enable agricultural innovation while advancing sustainable development – particularly when co-designed across science, policy, and practice.

In this paper, we discuss how Digital Agriculture enables generating data on species occurrences and traits of ‘associated agrobiodiversity’[44]. This subset of biodiversity refers to wild species co-occurring in agricultural landscapes, which may account for large shares of known species pools (e.g., 51% of all vascular plants, earthworms, spiders, and wild bees in Europe[45]), and species affected by – and adapting to – agriculture-related habitat transformations[46,47]. This paper is organized in two major sections. First, we discuss how biodiversity monitoring is, in principle, already feasible through common applications in Digital Agriculture. Second, we propose pathways for operationalizing the use of Digital Agriculture for monitoring biodiversity, including through changes in participation strategies and monitoring cultures, and by capitalizing on established and foreseen funding schemes.

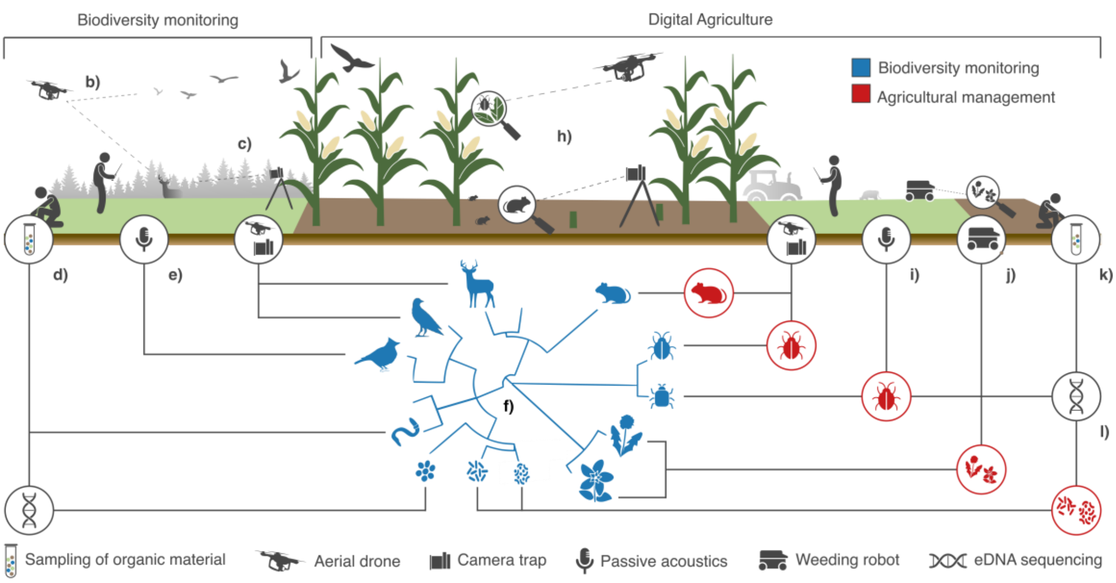

Figure 1. Uncovering biodiversity data through Digital Agriculture. a) Biodiversity monitoring is supported by various technologies, including drones (**b**), camera traps (**c**), eDNA (**d**), and passive acoustic monitoring (**e**). These technologies record species occurrences, enabling subsequent assessments of species and community compositions (in blue; **f**). Digital Agriculture (**g**) uses the same technologies in routine farm management practices (shown in red). Drones and camera traps (**h**), sometimes combined with passive acoustic monitoring (**i**), monitor pest occurrences and damages. Simultaneously, weeding robots facilitate the removal of weeds (**j**) that compete with crops for nutrients. Soil sampling (**k**), often used to control for nutrient availability, may also support the extraction of eDNA to control for harmful pathogens (**l**). Because biodiversity monitoring (**a**) shares technology requirements with Digital Agriculture (**g**), data from the latter, if made accessible to biodiversity monitoring experts, could enhance species and community composition assessments (in blue; **f**).

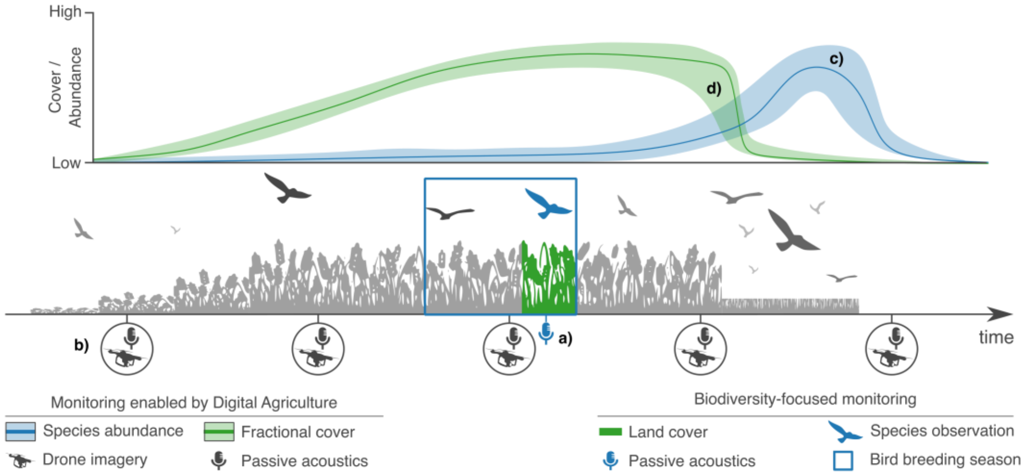

Figure 2. Potential for farm-level causal inference. a) In a biodiversity-focused survey, species observations (bird icon, in blue) are detected with passive acoustic monitoring. The timing of the survey is aligned with the breeding season of the target species (blue outline). Species detections are paired with categorical information on land cover (in dark green), a common practice in state-of-the-art agroecological research. **b)** Passive acoustic sensors are used to detect crop-damaging birds, while drones are used to quantify crop growth, damages, and health. If repurposed for biodiversity monitoring, data streams generated for pest and crop monitoring could be used to generate, for instance, time-series on bird richness (**c)** based on bird occurrences outside the breeding season (bird icons, in black). Being derived with data used for Digital Agriculture, biodiversity metrics (such as richness) would be directly paired with metrics informing on crop growth (e.g., vegetation cover fractions, **d**). Metrics generated with repeated and automated measurements could be accompanied by their respective, time-specific uncertainty (shaded ribbons in **c-d**). With concurrent, multi-temporal metrics on biodiversity and crop growth, the presence and magnitude of causal effects can be formally measured.

1. OPPORTUNITIES FOR MONITORING BIODIVERSITY THROUGH DIGITAL AGRICULTURE

In this section, we discuss overlaps between Digital Agriculture and automated biodiversity monitoring, specifically in terms of data requirements and methods. For this, we focus on three common applications of Digital Agriculture that routinely produce data required for biodiversity monitoring: the management of pests and weeds (**1.1**), the monitoring of soil nutrients and pathogens (**1.2**), and the phenotyping of domesticated plants (**1.3**). We link the data streams generated by these applications to primary biodiversity data on species occurrences and traits, and map them to Essential Biodiversity Variables (EBVs; **Fig. 3**). These variables, long endorsed by the biodiversity research community[48–50], now serve as headline indicators in the GBF (indicator 21.1; ref.[51]). As such, they are essential for policy-relevant monitoring of agroecosystems.

1.1. MANAGEMENT OF PESTS AND WEEDS

Globally, pests and associated crop diseases cause an estimated 20–40% loss in food production each year, amounting to approximately US$220 billion in damages[52]. The most damaging pests include invasive mammals, insects, and birds[53,54]. Weeds further contribute to crop losses[55] by competing with crops for water, nutrients and space, providing habitat for insect pests, and potentially harbouring harmful pathogens[56].

Monitoring and managing pests and weeds are common applications of Digital Agriculture. Spatial information on these factors helps optimize the use of pesticides[3], weed removal efforts[57], and the deployment of deterrents (e.g., playback of calls from competing species[18,58]. Drones and camera traps are routinely used to detect visible crop damage caused by insects[1,3], rodents[59] and larger mammals[60]. Drone imagery also enables weed mapping[16,57] and quantification of yield loss[60]. When visual detection is not feasible, insect traps are commonly used, informing on the presence, field-level abundance, and seasonal occurrence (or *phenology*) of insect pests[61]. Passive acoustic sensors, used to monitor insect pests[62], can also detect bird pests[18].

In fact, biodiversity scientists often rely on the same data and technologies used in Digital Agriculture. Drones have long supported species surveys[11], enhancing estimates of species richness and abundances (e.g., as demonstrated for birds[63], or the monitoring of endangered and elusive species (e.g., mammals[64]). Similarly, camera traps are commonly used to detect various taxa[2,65] – although rarely in agricultural lands[66] – as are camera-equipped insect traps[67] and passive acoustic sensors[68]. The generated imagery and audio recordings are increasingly used to train species identification models[69–72].

By leveraging Digital Agriculture for biodiversity monitoring, several Essential Biodiversity Variables can be enriched (EBVs; **Fig. 3**). These data are required to map species distributions[73] and abundances[74], and to subsequently infer the diversity of community level compositions[75] and interactions[76]. Image-based surveys could further capture species-specific traits, such as body mass[77] and landscape-level movements (e.g., using camera trap networks to detect individuals of a focal species[78]). Similarly, audio data could enable characterizing species movements within agricultural fields through acoustic localization[79]. These data provide a scalable basis for monitoring biodiversity within managed landscapes – data that is often missing from conventional biodiversity datasets.

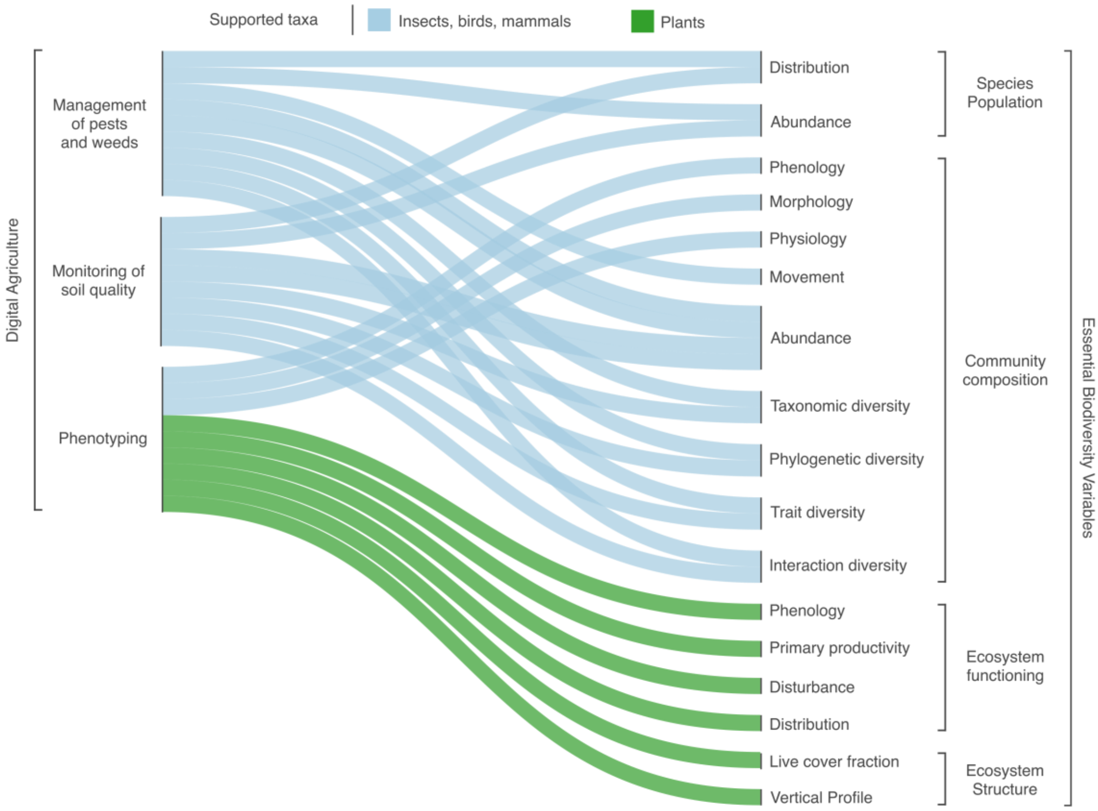

Figure 3. Potential synergies between Digital Agriculture and EBVs. On the left, the different applications of Digital Agriculture highlighted in this paper, namely pest and weed control, soil monitoring, and phenotyping. On the right, Essential Biodiversity Variables (EBVs) per thematic group. Lines link each Digital Agriculture application with one or multiple EBVs.

1.2. MONITORING OF SOIL NUTRIENTS AND PATHOGENS

Poor soil conditions are a critical constraint on food production globally. The United Nations estimates that up to 40% of the world's land is degraded, affecting close to 3.2 billion people[80]. Soil salinity alone, which hinders crop productivity[81], has led to reductions in agricultural yields of up to 70% in the affected areas[82]. The global costs of land degradation are substantial, US$ 878 billion per year, with regard to agricultural productivity, nature contributions to people, and other related sectors[80].

Regular assessments of soil condition and soil health are thus essential for optimizing crop productivity, making it a key application of Digital Agriculture. Soil sampling at the field-level shows variations in mineral compositions[83], nutrient contents[84,85], and functionality[19]. In some cases, the presence of earthworms is recorded as a proxy for soil quality[86]. More recently, the use of Environmental DNA (eDNA), has gained popularity in the monitoring of agricultural soils. Thanks to advanced genetic testing, which has become increasingly affordable and efficient[21], farmers may now tackle root-level microbial communities that hinder plant growth[5,21,84]. The derived data is then used to tailor soil management strategies, including targeted uses of fertilizers[20] and pesticides[87], and dynamic adjustments of crop rotation schedules[88].

Soil biodiversity, however, remains vastly underrepresented in global biodiversity databases[89]. Integrating soil eDNA analyses from agricultural surveys into biodiversity monitoring could substantially improve the representation of soil-dwelling taxa and microbial communities. eDNA has been shown effective in describing soil biodiversity in agroecosystems[10], including with regard to more elusive species[90]. If data from agricultural soil surveys, including eDNA, are stored in accessible formats (e.g., through whole-genome sequencing), and if these data become accessible to biodiversity scientists (e.g., using standardized metadata for eDNA[91]) they could directly feed biodiversity surveys.

Generate data streams can directly inform several EBVs (**Fig. 3**). Species occurrences inferred from eDNA are required to map species distributions and phenology, estimate species occurrences, and infer community-level compositions and interactions. Moreover, eDNA enables unique assessments of within-species variations in physiology[92] and traits[93], and community-level variations in phylogenetic diversity[94]. This would significantly expand the taxonomic and functional scope of biodiversity monitoring in agricultural systems.

1.3. PHENOTYPING OF DOMESTICATED SPECIES

Over the past three decades, approximately $3.8 trillion in crop and livestock production has been lost due to disasters[95]. These events have contributed to increased food prices, a trend expected to continue under climate change[96].

To increase the resilience of crops to extreme events, crop phenotyping has become a key application of Digital Agriculture[24]. This application, which implies measuring and describing the structural, physiological, and biochemical characteristics (traits) of individual plants or stands, plays a critical role in the selection of productive, disease and drought-resistant, and nutrient-efficient genotypes[24]. Some systems may monitor changing traits throughout the lifecycle of planted crops, helping optimize their management (e.g., through targeted irrigation[97], fertilizer use[23]) to maximize food production and quality[4].

Crop phenotyping is typically pursued with drone-, airborne-, and satellite-based sensors. For instance, hyperspectral imagery is used to measure carbon concentrations[98], whereas Light Detection and Ranging (LiDAR) help assess the vertical structure of plant stands to detect growth deficiencies[99]. Importantly, these technologies are not exclusive to agriculture: similar remote sensing methods are widely used in biodiversity surveys[100,101]. In fact, biodiversity experts already use phenotyping techniques to monitor agrobiodiversity[102], and broader vegetated ecosystems[103,104]. This is required to measure several EBVs (**Fig. 3**), including those on species-level morphological and physiological traits (e.g., height, nutrient content) and ecosystem function and structure (e.g., vertical profile, live cover fraction, primary productivity). Furthermore, multi-temporal phenotyping of crops, while informing on crop health, could also provide insights on disturbance regimes and land-use intensity (e.g., based on the timing of planting and harvesting, or the frequency of irrigation and fertilizer use).

2. ENABLING BIODIVERSITY MONITORING THROUGH DIGITAL AGRICULTURE

In many regions, comprehensive biodiversity monitoring programs remain underdeveloped or underfunded[105]. Maintaining such programmes incurs millions of US$ in annual costs[106,107], which may be feasible for higher-income countries[106]. However, persisting economic inequalities among countries[108] impair monitoring capabilities. In contrast, investments in Digital Agriculture are accelerating.

As of January 2025, the Food and Agriculture Organization (FAO) records 449 ongoing, public or private initiatives advancing the use of digital agriculture in all continents[109], ~89% of which are applied to farm-level management, from smallholder to large farms (**Fig. 4a**). While ~90% of all initiatives concentrate in Europe and Asia (**Fig. 4a**), this is likely to change in the future. In the Global South, most private investments in agriculture are already directed at digital innovation[110], and national governments – across all income levels – are increasing their support for digitization efforts[111,112]. In fact, every country hosts Digital Agriculture initiatives and, in all countries, >50% of those initiatives are directed at farm-level management, which includes, for instance, the deployment of drones, or the use of Big Data and Artificial Intelligence[109] (**Fig. 4b**).

As the digitalization of agriculture progresses, Digital Agriculture could help balance the organizational and financial burdens associated with biodiversity monitoring in farmland. However, enabling this requires new participatory strategies (particularly for farmers), changes in monitoring culture, and the mobilization of existing funding schemes to integrate monitoring capabilities.

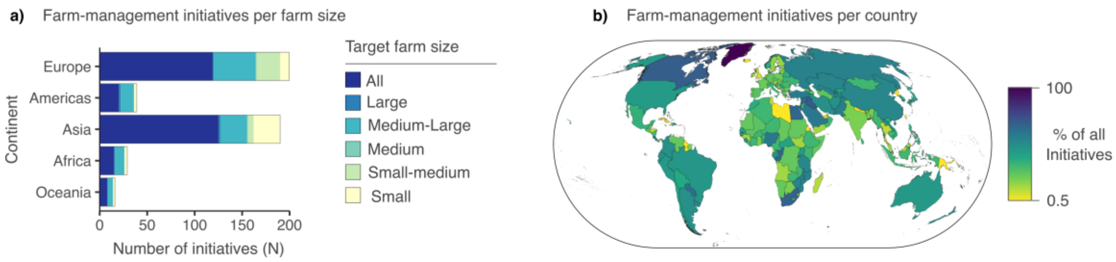

Figure 4. Global initiatives advancing Digital Agriculture. a) For each continent, the number of ongoing Digital Agriculture initiatives recorded by the FAO[109] that target farm-level management. Colours distinguish initiatives based on the farm size they target, namely small, medium, or large. Size categories are distinguished by FAO's Agritech Observatory[109]. "Small" distinguishes features and characteristics associated to "smallholder" farms, such as limited access to resources, finance, and technology. "Medium" describes highly active and specialized farms and agricultural holdings. "Large" refers to industrial farming. **b**) In each country, the proportion of all ongoing Digital Agriculture initiatives targeting farm-level management.

2.1. New participatory strategies involving farmers are needed

Farmers are ultimately responsible for implementing agri-environmental measures[113]. They also control access to the lands where biodiversity data must be collected to evaluate the effectiveness of those measures. Without their support, farmland biodiversity monitoring may become biased or unrepresentative[114], potentially misleading biodiversity change assessments.

A range of participatory strategies have been proposed[115], some connecting networks of stakeholders (including farmers), data, tools, and biodiversity monitoring programs[105] (**Fig. 5a-e)**. Modern participatory strategies aim to incorporate not only ecological objectives, but also cultural, labour, and societal considerations in how monitoring is structured and implemented[105] (**Fig. 5a-b**). However, we suggest current participatory strategies often place a significant burden on farmers. While they involve farmers in collecting – and sometimes analyzing – biodiversity data, and in informing policymaking (**Fig. 5c-e**), this can create an additional, challenging, and time-consuming task, adding to the challenges of farming itself. Simultaneously, despite the vast literature on the biodiversity benefits of agroecological measures, the benefits for farmers remain uncertain, and scale and context dependent[34]. As a result, generic policy recommendations or incentive schemes may fall short, and may inadvertently feed negative human responses to biodiversity conservation[116].

We propose a more balanced approach: involving farmers in biodiversity monitoring by offering them direct, actionable insights about the condition of their land, derived from biodiversity data (**Fig. 5g**). Digital Agriculture, in particular, would offer simultaneous data streams needed for biodiversity monitoring while supporting everyday agricultural land management. This would enhance, rather than replace, current monitoring and reporting systems. In this process, targeted, long-term biodiversity gains would be achieved through dynamic adjustments to farm management practices – especially if supported by continuous causal inference.

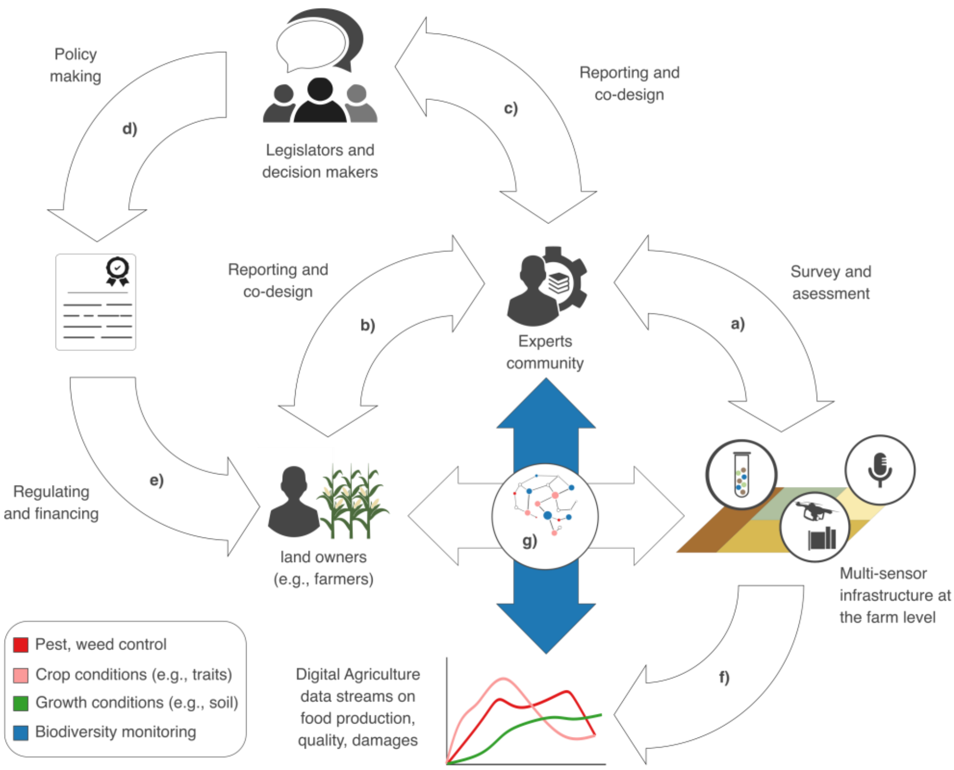

Figure 5. Farmer participation strategy. In current participatory strategies, **e**xpert communities conduct research on interactions between biodiversity and field management practices (**a**), and may involve farmers in monitoring activities and data analyses (**b**). Resulting literature fuels science-based reporting **(c)**. Policymakers use these reports as a basis for legislation (**d**) aimed at regulating and funding field-level management practices aimed at biodiversity gains (**e**). In this process, farmers profit from biodiversity monitoring only indirectly. Yet, they are exposed to the uncertainties of biodiversity gains, and of their influence on food production. Biodiversity monitoring, if established through Digital Agriculture, could directly provide insights on common management challenges (**f**). Resulting Digital Agriculture data streams would then offer insights on trade-offs between food production and biodiversity (**g**).

2.2. JOINT MONITORING CAN EASE THE ADOPTION OF DIGITAL AGRICULTURE

Industrial-scale farming systems are already adopting Digital Agriculture technologies[117]. Similarly, as the Digital Agriculture market grows, digitalization becomes financially accessible (e.g., as exemplified by the drone market[118]), including to smallholder and family farms, who are increasingly willing to adopt new technologies[119–121].

Yet, challenges remain for the latter, particularly in establishing the required infrastructure and in processing generated data streams[122]. However, we suggest such challenges may be effectively tackled in cooperation with biodiversity experts. As biodiversity monitoring becomes increasingly automated[13], biodiversity experts are increasing their technological fluency[12], including in those technologies enabling Digital Agriculture. In collaboration with farmers, biodiversity experts could help establish farm-level systems enabling the monitoring of both crop production and biodiversity. In addition, experts from other fields, such as robotics, could help enhance already existing farm-level management tools, such as weeding robots[123]. Support would be given through the calibration of image-recognition software to distinguish species occurrences and traits from ‘noise’ in acquired data (e.g., ground nests[25], molehills[26]). Importantly, such developments would not demand extensive science exploration, as literature already evidences the applicability of robots in automated biodiversity monitoring[124].

Expert support in digitizing farm-level monitoring may bridge the divide many farmers feel between political nature conservation targets and production needs. In fact, such initiatives would be of political relevance, aligning with international biodiversity conservation and monitoring targets. For instance, the Global Biodiversity Framework (GBF), by which 196 countries must abide, calls for capacity-building, technology transfer, and cooperation in biodiversity monitoring (Target 20)[125], which Digital Agriculture would directly support within agroecosystems. Ongoing policy-relevant such as FAO’s AGRI-NBSAPs, which helps signatory countries of the GBF develop capacity in monitoring agroecosystems[126], could also help enable biodiversity monitoring through Digital Agriculture. In fact, this would be in line with FAO’s long-term strategy, which is promoting the digitalization of agriculture.

2.3. JOINT MONITORING INITIATIVES CAN BUILD ON ONGOING INFRASTRUCTURE DEVELOPMENTS

Currently, over 70% of open data on agriculture originates primarily from satellite-based remote sensing applications[127]. This reflects persistent challenges in sharing farm-level data, often relating to their sheer volume and incompatibility, or to the absence of adequate digital platforms for open-access data sharing[122].

Ongoing initiatives are addressing these barriers. At the global level, the UN-funded Consultative Group on International Agricultural Research (CGIAR) is advancing common principles and tools for sharing and distributing big, farm-level data[128]. At the national level, publicly-funded expert groups aim to make farm-level data Findable, Accessible, Interoperable, and Reusable (FAIR), including that produced by national authorities (e.g., FAIRagro in Germany[129]). Simultaneously, multinational data harmonization projects are underway[130,131], and new data storage formats – some inspired by the compact structure of

DNA[132] – may ease future data storage constraints. Although these developments remain in pilot stages, we must actively plan for them. As they are realized, Digital Agriculture data could readily become available to ecologists, who can direct subsequent analyses to appropriate biodiversity platforms (e.g., GBIF), and use them in policy-relevant reporting.

2.4. FUNDING PROGRAMMES ARE ALREADY IN PLACE, BUT REQUIRE DIRECTION

Integrating Digital Agriculture and biodiversity monitoring demands funding mechanisms, but not new funding streams. We suggest that multi-billion-dollar funding programmes aimed at Digital Agriculture could already support integration without harming their primary goals. For instance, in low- and lower-income countries, the UN-led *50 by 2030* program will invest US$500 million by 2030 to digitize agriculture production[133]. Similarly, in high- and higher-income countries of Europe, the European Agricultural Fund for Rural Development (EAFRD) is dedicating €8 billion to transform rural communities through digitalization, a key goal of the European Green Deal[134]. This would conceptually include Digital Agriculture and associated biodiversity monitoring. Subsequent development projects could capitalize on well-documented experiences regarding multi-sensor monitoring of agriculture[8] and biodiversity[13]. Projects focused on research and innovation could also build on existing networks of research farms[135].

Conversely, funding mechanisms aimed primarily at biodiversity conservation could also enable Digital Agriculture. For instance, to promote and scale biodiversity-friendly land management practices, the GBF plans an annual global investment of at least US$500 billion (Target 18). Currently, acknowledged applications of these funds include, e.g., conservation easements and subsidies. However, we suggest that promoting Digital Agriculture is an equally suitable application of the allocated funds.

CONCLUSIONS

Biodiversity conservation efforts are gaining momentum through international policy such as the GBF or the EU Nature restoration Law. Many targets outlined in the GBF depend on the sustainable development of farm management[51], which in turn requires concerted monitoring efforts to track biodiversity trends. Digital Agriculture offers a promising, cost-effective avenue to bridge agricultural and biodiversity monitoring. In fact, it employs some of the same technologies and methods used to monitor biodiversity, making derived data – which already captures species occurrences and traits – usable for concurrent biodiversity monitoring. Most importantly, this would be achieved without placing additional burdens on farmers, with direct benefits for them. Yet, the monitoring of agriculture and biodiversity remain disconnected in research and practice. Explicit integration is required to minimize monitoring costs and calibrate pathways towards a more sustainable future.

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AUTHOR CONTRIBUTIONS

RR and AFC designed the study. RR led the conceptualization and writing in collaboration with AFC, with additional contributions from MB, MV, EP, MP, PV, CM, AE, and DR. RR designed the figures.

COMPETING INTERESTS STATEMENT

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

The source data of Figures 3 and 4 are provided with the paper

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