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PERSPECTIVE

Shedding light on pollination deficits: Cueing into plant spectral reflectance signatures to monitor pollination delivery across landscapes

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Abstract

1. Pollination underlies plant yield, health and reproductive success in agricultural and natural systems worldwide. It is therefore concerning that declining animal pollinator populations compounded by growing demands for food are leading to rising pollination deficits, with globally significant economic and environmental implications.
2. Despite this urgent issue, accurate and scalable tools to quantify and track pollination across useful spatiotemporal scales are lacking. Here, we propose to shed new light on pollination deficits, looking to remote sensing platforms as a transformative mapping and monitoring tool and a solution for pollinator conservation and crop management.
3. Providing a synthesis of our current understanding of pollination-triggered floral senescence and underlying ultrastructural and metabolic changes, we propose how spectral reflectance technologies could be applied to accurately detect pollination events in real-time and at the landscape scale.
4. *Synthesis and applications*: We highlight where research efforts can be targeted to produce scalable methods for identifying field-relevant bioindicators of pollination. We provide guidance on how spectral imaging accompanied by machine learning and coupled with autonomous operation technologies will enable applications to detect pollination delivery across complex landscapes. Ultimately, such an ecological application will transform our quantitative understanding of pollination services and, by directly linking plant yields and health, will reveal pollination deficits at high resolution to help mitigate risks to food security and ecosystem functioning.

KEYWORDS
crop, pollen limitation, remote sensing, spectral imaging

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Pollination is a vital biological process determining plant reproduction, genetic health and fitness, which fundamentally contributes to the productivity and stability of ecosystems worldwide (Ollerton, 2020). Subsequent development of seeds and fruits is not only important for wild plant reproduction and dispersal, but also underpins the yield and sustainability of most agricultural crops (Bishop et al., 2022; Rodger et al., 2021). High pollination rates are critical to feeding the global human population by meeting demands for: (i) food security, (ii) access to micronutrients, (ii) biofuels and animal feed, and (iv) medicinal and culturally valuable products (Camina et al., 2023; Eilers et al., 2011; Garibaldi et al., 2022; Kemmerling et al., 2021; van der Sluijs et al., 2016). Ensuring sufficient rates of pollination is thus essential to meeting sustainable developmental goals (Potts et al., 2016). Pollination deficits arise where demand for pollination outstrips supply (Box 1), with ineffective pollination placing a ceiling on yield potential or reproductive success of plant individuals (Aizen et al., 2019). Spatiotemporal patterns of pollination are uneven across landscapes, and thus, the ability to pinpoint where and when pollination deficits occur is critical to understanding how to harness biotic and abiotic pollination vectors to optimise farming efficiency (Woodcock et al., 2019). However, substantial gaps remain in our understanding of the spatiotemporal distribution of pollination service delivery. Furthermore, we have poor capabilities to accurately quantify the relationship between ecosystem function, pollinator population health, and plant productivity across agricultural and natural landscapes (Bishop et al., 2022; Garibaldi et al., 2022; Gill et al., 2016).

In this perspective, we first identify the knowledge gaps constraining our ability to develop strategies to bolster pollination and outline why issues with monitoring pollination delivery are rarely prioritised in a farmer's crop monitoring regime. Second, we provide a perspective on where research can be prioritised to improve landscape-scale pollination monitoring for the identification and mitigation of pollination deficits. Specifically, we focus on using spectral reflectance technologies to eavesdrop on the metabolic changes occurring in plant tissues following a pollination event.

1 | UNEVEN POLLINATION SERVICE DELIVERY LEADS TO SPATIOTEMPORALLY VARIABLE DEFICITS

Pollination deficits are widely considered to be common across plant taxa, whether via animal or wind pollination (Aguilar et al., 2006; Allen-Perkins et al., 2022; Burd, 1994; Hegland et al., 2008). Yet, true pollination service delivery is often unknown or contested due to difficulties in separating pollination effects from other confounding variables affecting plant yield and reproductive success (Adamidis et al., 2019), and challenges to monitoring pollination delivery in real-time (Garibaldi et al., 2020). We therefore propose three knowledge needs that must be addressed to improve our ability to understand and manage emergent pollination deficits.

BOX 1 What determines a pollination deficit and what are the consequences?

Pollination is the delivery of pollen from the male sexual organ (anther) to the female (stigma) culminating in embryo development and subsequently seed and fruit formation. To promote outbreeding and overcome the challenges of sessility, most flowering plants depend upon biotic or abiotic vectors—animals and/or wind—to transfer pollen. Vector-driven processes are however susceptible to stochastic and environmental influences, which can impact the efficiency of pollen transfer (Burd, 1994; Gardner et al., 2021). Consequently, when insufficient pollen is received by the flower, fertilisation is suboptimal and pollination deficits arise (Wilcock & Neiland, 2002). Some plant species or cultivars with reduced pollination dependency can compensate for low pollinator availability through autonogamy, or resource optimisation, which can mask pollination effects (Bos et al., 2007; Garratt et al., 2018; Lindström et al., 2015). However, for most pollinator-dependent angiosperms, pollination deficits result in reduced seed production and consequently yields and crop quality (Chakrabarti et al., 2011; Garratt et al., 2018; Olhnuud et al., 2022; Shen et al., 2018). In many natural plant populations, suboptimal pollination is associated with reduced outcrossing, and thus reduced seed and offspring quality, and reduced dispersal (Hesse & Pannell, 2011; Rodger et al., 2021). The accumulating effects of pollination deficits over time can lead to maladaptive traits and reduced competitive ability (Bittencourt & Sebbenn, 2008). Moreover, ineffective pollination commonly confers a direct fitness cost to plants, as resources invested into reproductive structures are rarely optimally remobilised (Wilcock & Neiland, 2002).

1.1 | Determine pollen dispersal dynamics to quantify spatiotemporal variation in pollination delivery

Animal-mediated pollination is determined by the spatiotemporal diversity and dynamics of pollinator populations (Bishop et al., 2022; Chakraborty et al., 2021; Gardner et al., 2021). At the local level, pollinator abundance can differ even within fields, determined by functionally varying foraging and dispersal capabilities, availability of preferred nesting habitats, field size and degree of connectivity across the patchwork of agricultural and natural land (Beyer et al., 2021; Bottero et al., 2023). At the regional level, habitat loss, pollution and emergent diseases are leading to pollinator losses (Bennett et al., 2020; Gill et al., 2016; Outhwaite et al., 2022), and phenological asynchronies driven by climate change are further jeopardising effective pollination services as peak bloom times of plants respond differently to pollinator emergence or peak flight

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activity (Duchenne et al., 2019). Yet, the direct impacts on pollination deficits at local to global scales remain unclear (Bennett et al., 2020; Rodger et al., 2021). In wind-pollinated plants, plant density, prevailing wind direction, pollen characteristics and weather conditions can all determine reproductive success, highlighting the importance of field design and topography in maximising fitness and crop yield (Hoyle & Cresswell, 2007; Kling & Ackerly, 2020; Labouche et al., 2017; Lukac et al., 2012). In sparsely distributed plant communities in natural landscapes, the reproductive success of composite species is also likely at risk from habitat fragmentation (Aguilar et al., 2006). Furthermore, yields in calorically vital crops such as rice and maize have been impacted by high temperatures which are expected to escalate with climate change (Matsui et al., 2020; Zhao et al., 2017). However, it remains challenging to monitor these effects in real-time, and pollination deficits in many wind-pollinated plants are likely going unnoticed.

1.2 | Gather more high-resolution data to shed light on pollination deficits

Landscape managers and farmers may collect pollinator-focused data, but current methods to measure pollination service delivery are often not fit for purpose (Garibaldi et al., 2020). The degree of petal drop may be surveyed, which indicates the end of a crop's flowering phase, and which may inform prediction of harvest time, but provides limited insight to the farmer on crop pollination delivery. To forecast pollination deficits in flowering crops, land managers are advised to infer pollination status using field-based active observations of pollinator visitations (e.g. PoMS; Carvell et al., 2016), and lethal trapping of pollinators for identification (Freitas et al., 2016; Vaissière et al., 2010). However, such surveys require heavy time investment and can be biased depending upon the landscape composition, pollinator community and methodology (Hutchinson et al., 2022; Webber et al., 2020). Current assessments of pollination status are typically conducted over coarse spatial and temporal scales, providing limited insight into pollination dynamics over one or multiple crop fields. It is therefore difficult to discern where and when pollination has occurred with appropriate accuracy, especially as pollinator visitation does not necessarily confer effective pollination service delivery (Senapathi et al., 2021). There is therefore a distinct need to develop direct monitoring methodologies for pollination service delivery in real-time and at the landscape scale.

1.3 | Improve the evidence base for targeting and monitoring pollination deficits

In highly pollinator-dependent systems, a lack of wild pollinators has seen farmers supplement with managed colonies (i.e. honeybees), or in extreme cases by hand pollinating (Osterman et al., 2021; Toledo-Hernández et al., 2020). This drives an economy for managed pollinators, which incur a significant expense to farmers, compounded by a lack of empirical tools to optimally target pollinator supplementation. Alternatively, farmers can invest in wild pollinator conservation on their land, yet there is currently little guidance for farmers on how to execute conservation strategies, such as how to optimise spatial configuration of new pollinator-friendly habitats and best align them with crop phenology (Gill et al., 2016; Lowe et al., 2021; Steele et al., 2019). Pollination deficits in wind-pollinated crops are traditionally mitigated in small-scale systems through mechanical pollination (Wurz et al., 2021), using drones to potentially scale this approach (Jiang et al., 2021; Li et al., 2017). To further maximise pollen dissemination efficiency, targeted breeding may prioritise phenotypic features including inflorescence architecture, for example filament length (Friedman & Barrett, 2009), and farmers may customise field design under their specific topographic and climate conditions (Xi et al., 2023). However, in most systems pollination is not prioritised in growing strategies, particularly as metrics for pollination service delivery do not extend to wind-pollinated plants, and monitoring pollination events remains a challenge.

2 | DETECTING POST-POLLINATION ACCELERATED FLORAL SENESCENCE AS A POLLINATION BIOINDICATOR

Given the data needs described above, there is a clear motivation for developing effective toolkits to provide rapid, real-time quantitative insights into plant–pollination status, and by coupling these datasets with detailed yield and pollen exclusion experiments, pollination deficits may ultimately be calculated (Garratt et al., 2021). A toolkit must be developed to quantify pollination status over useful spatiotemporal scales by harnessing current knowledge, not only on the ecology of plant–pollinator interactions but also crucially the plant's cellular responses to pollination. Apart from delayed responses, such as petal drop in flowering plants, there is currently a lack of definitive bioindicators to allow a pollinated plant to be objectively discerned from an unpollinated one in the field (Galbraith et al., 2015). Bioindicators should be linked to a real-time change in the molecular condition of a tissue, with the bioindicator itself either being detected through a diagnostic tissue sampling tool (e.g. crop disease lateral flow kits) and/or phenotypic change. We propose that cueing into plant senescence pathways could reveal a reliable set of candidate pollination bioindicators.

Floral senescence is a sequential and directional pattern of programmed cell death, occurring across all angiosperms once the stigma is no longer receptive (Rogers, 2006). Pollination is known to trigger accelerated senescence in individual flowers, and this is marked by a significant shift in metabolism and gene regulation (Borghi & Fernie, 2020; Tan et al., 2018; van Doorn & Woltering, 2008). A compatible pollen–stigma interaction triggers a cascade of regulatory activities in the flower, as it allocates resources to facilitate successful fertilisation. A suite of senescence-associated genes are rapidly upregulated, including those encoding cysteine proteases which play important regulatory roles in leaves

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(e.g. SAG12; James et al., 2018) and petals (Battelli et al., 2014). Pathways related to sugar metabolism and transport are upregulated during senescence as nutrients are relocated to the fertilised ovule (Ma et al., 2018). The action of pathways mediating catabolism and proteolysis eventually culminate in visible physiological changes such as wilting (symptomatic of a loss of turgor pressure) followed by programmed cell death (van Doorn & Woltering, 2008) leading to phenotypic changes such as petal wilt, and ultimately petal drop. Whilst these eventual phenotypes can be distinguishable under the naked eye, they do not occur immediately at the onset of a pollination event. The metabolic processes to initiate these downstream symptoms, however, begin to occur almost immediately upon receipt of pollen, in a repeatable and sequential manner, and are likely to be conserved across plant taxa (Weiss, 1995). Thus, bioindicators cueing into plant senescence pathways have the potential to be applied at fine timescales to reveal pollination status prior to petal drop. This would not only increase the accuracy and timeliness of detecting pollination deficits across heterogeneous landscapes but also provide an insight into the spatiotemporal dynamics of pollination delivery in the context of floral turnover.

Progress has been made towards quantifying pollination events through molecular characterisation (Evans & Kitson, 2020). At the individual scale, RNA sequencing has allowed the identification of parent cultivars from the rapid upregulation of cultivar-specific genes post-pollination (Lobaton et al., 2021), whilst eDNA sequencing and metabarcoding have revealed plant–pollinator networks across agricultural and natural landscapes (Gresty et al., 2018; Pornon et al., 2016). However, scalability remains a challenge as sampling representative tissues can be labour and time intensive whilst potentially overlooking spatiotemporal variation (Webber et al., 2020). The availability of pollination biomarkers is thus stalling the development of tools to reveal pollination deficits at the landscape scale and over full flowering phenology.

2.1 | Spectral reflectance signatures as a potential diagnostic tool for pollination

Imaging and spectral reflectance technologies represent an emerging solution to upscaling the use of pollination biomarkers. Spectral imaging has been shown in many controlled environments and field applications to reveal changes in plant tissue ultrastructure or metabolism in a non-destructive and high-throughput manner (Sarić et al., 2022). Hyperspectral imaging or spectroscopy is the measure of intensity of light reflectance at wavelengths across the spectrum (often from ultraviolet [UV] to near-infrared [NIR]). The optical properties of plant tissue determine the extent to which light across the spectrum is absorbed, reflected and scattered at each cell layer to produce a unique spectral signature (Figure 1; Karabourniotis et al., 2021). Reflectance signatures represent adaptive traits, which (i) in leaves are important for resisting UV damage whilst maximising absorption of photosynthetically active radiation, and (ii) in petal tissue underly important visual cues which, whilst invisible to the human eye, may signal attractiveness to insects (van der Kooi et al., 2019). Floral features have

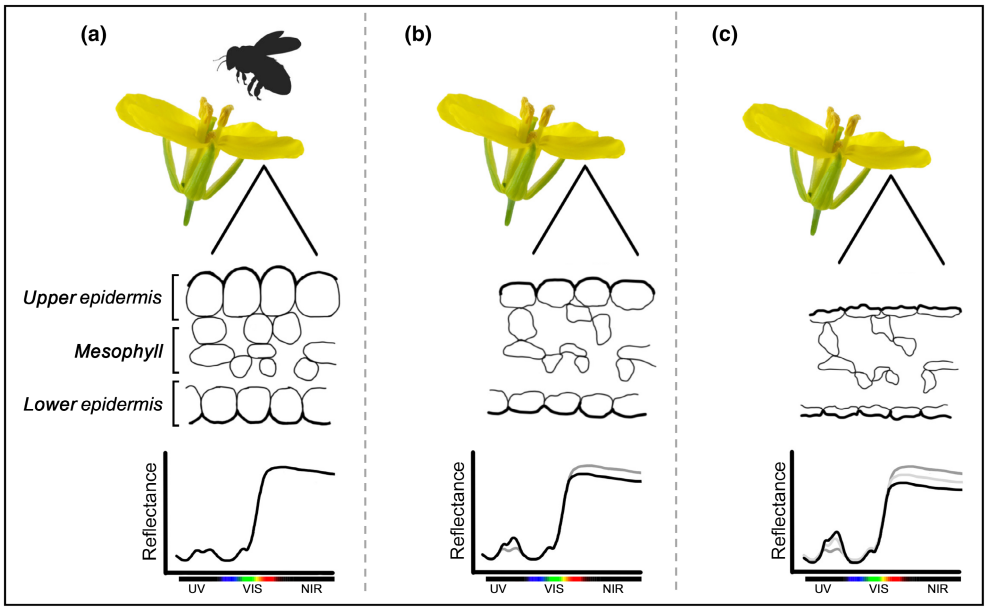

FIGURE 1 Spectral reflectance could shed light on floral pollination status. In this pollinator-dependent crop, oilseed rape (top), it may be difficult to distinguish a flower before pollination (a), from a flower at certain timepoints after pollination under the naked eye (b, c), prior to petal drop. However, pollination triggers a series of metabolic and ultrastructural changes within the floral tissue over time (middle). Theoretical spectral reflectance profiles (bottom) may reveal these previously hidden cell-level changes, as degradation of UV-absorbing pigments could result in an increase in reflectance of UV-dominant frequencies, and loss of cell turgidity and mesophyll density cause a relative decline in NIR-dominant frequencies.

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indeed been characterised using spectral reflectance and imaging (Gonzales et al., 2022). At the landscape level, reflectance profiles have been defined for estimating flower cover as a proxy for pollinator abundance and diversity (Ariza et al., 2022; Feilhauer et al., 2016; Gonzales et al., 2022; Torresani et al., 2023; Wilcock & Neiland, 2002), yet these studies do not attempt to directly measure pollination events. At closer range, imaging has facilitated detection and quantification of floral canopies in many crops and natural ecosystems (Arje et al., 2019; Guo et al., 2015; John et al., 2024; Yang et al., 2022; Zhang et al., 2021, 2022), and floral spectral reflectance profiles have also been characterised (Armold et al., 2010; Zheng et al., 2022). Moreover, there is a lack of research exploring the relationship between plant spectral reflectance and pollination, which is striking considering its relevance to insect-plant interactions (van der Kooi et al., 2019).

At high spatial resolution, hyperspectral or multispectral imaging can reveal ultrastructural features of plant tissues such as cell size, leaf thickness, mesophyll density, plastid frequency and pigment composition (Karabourniotis et al., 2021). Such features have informed development of spectral bioindicators to predict agriculturally important plant conditions, such as presymptomatic infection, drought, nitrogen and carbohydrate content (Grzybowski et al., 2021; Li et al., 2020; Mertens et al., 2021; Zhao et al., 2016). When plants are under stress, certain physiological characteristics underlying spectral signatures in leaves appear analogous to those exhibited in petals during pollination-triggered senescence (Figure 1). Soon after the onset of floral senescence petal cell, water content is reduced and epidermal cell integrity lost (Smith et al., 1992), in a manner qualitatively comparable to that in a drought-stressed leaf (Junttila et al., 2022). Floral palisade cells become disorganised with increased air space, plastids are degraded, pigment synthesis is downregulated and pigments dissipate (Jhanji et al., 2023; Nabipour Sanjbod et al., 2022; van Doorn et al., 2003), which represents a similar response to heat-stressed and senescing leaves (Castro & Sanchez-Azofeifa, 2008). Previous characterisation of spectral reflectance in petal tissue during senescence shows a decline in reflectance intensity across the whole spectrum over time, particularly in the blue-visible region (Steidle Neto et al., 2009), which accords with some spectral reflectance signatures associated with traits of leaf stress. The common ultrastructural features between stressed leaf tissue and senescing petals, and the systematic nutrient remobilisation and programmed cell death pathways triggered by pollination provide a good rationale to expect that spectral imaging could reveal floral responses to pollination. Moreover, whilst these features are invisible to the human eye, changes associated with shifts in the UV and visible light wavelengths may be obvious to insect vision, possibly representing honest signalling in some species (Papiorek et al., 2013; van der Kooi et al., 2019). Despite an abundance of research applying spectral reflectance and imaging to floral phenotypes, to our knowledge application of these technologies to directly measure pollination syndromes is yet to be properly explored.

2.2 | From experimental spectral reflectance signatures to field-applicable technologies

With a view to applying experimental spectral reflectance signatures to field-applicable technologies, accurate and reliable biomarkers need to be developed from the laboratory and translated to the field. A pipeline to developing such an agricultural technology begins with identifying the need for innovation and initiating proof-of-concept research. The first phases of research should explore the potential of hyperspectral reflectance to predict pollination status at close range and under controlled environments, to explore the feasibility of a spectral reflectance solution with limited noise (Figure 2). Controlled environment spectral phenotyping offers the possibility of a degree of automation to increase throughput (Humplík et al., 2015). Imaging under controlled environments also mitigates the need for complex segmentation or feature selection problems introduced by environmental factors. Although hyperspectral datasets can be large and noisy, these challenges are frequently overcome using machine learning tools, which have facilitated applications of hyperspectral imaging as powerful predictors for complex problems (Ge et al., 2019; Sousa & Small, 2023).

Given the diversity of spectral reflectance profiles across floral taxa, significant exploration will be required to determine both the species- and tissue specificity of floral pollination signals. This will ultimately determine the phenotype and growth habit of the crop types to which a pollination monitoring technology can be practically applied. The nature of mass-flowering crops such as oilseed rape, almond, legumes and orchard fruits represent obvious candidates for application of a pollination monitoring technology, with their conspicuous canopy of flowers visible for aerial imaging. However, other less densely grown crop and non-crop taxa would also be eligible, for example using a hand-held device, which would be a valuable tool for assessing pollination in high-value crops and ecologically relevant plants alike. The breadth of potential applications of this technology will be dependent on the establishment of robust bioindicators, which are highly associated with the post-pollination response. Existing studies of floral reflectance profiles provide a valuable reference from which to base exploratory studies and will inform the identification of pollination-associated spectral signatures across taxa (Armold et al., 2010).

To reduce the computational demands of hyperspectral reflectance profiles, single or combinations of wavelengths which are highly associated with the parameter of interest can be identified using dimensionality reduction or feature extraction. The resulting multispectral reflectance bioindicators or indices generate much smaller datasets and can be robust to noise introduced in the field by variations in illumination quality, measurement aspect and environmental features which can impact classification accuracy (Holmes et al., 2020). Achieving good prediction accuracy under noisy environments is likely to be particularly relevant to developing pollination biomarkers in a field context, given the expected subtlety of the signal. Multispectral indices measured using small,

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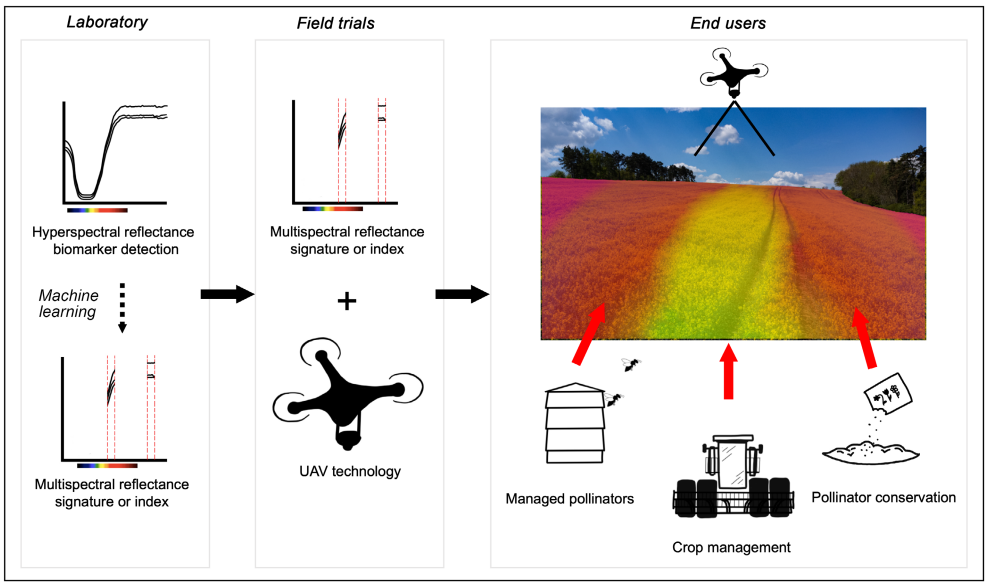

FIGURE 2 Proposed workflow for developing a field-applicable pollination monitoring tool. Hyperspectral reflectance under controlled conditions offers a valuable tool to explore the spectral characteristics of a tissue, and through dimensionality reduction and/or classification algorithms, can be used to identify multispectral bands. Multispectral bands or indices offer improved classification ability and reduced computational demands, making them valuable for field applications. When combined with UAV (unmanned aerial vehicle) technology, and machine learning classification tools, established spectral signatures represent a powerful real-time sensor technology. Such an accessible tool arms the end user with knowledge of the pollination service delivery to their crop, shedding light on otherwise hidden pollination deficits and empowering them to make informed decisions to optimise crop pollination. This may include introduction of managed pollinators, improved crop management (such as harvest time prediction) or wild pollinator conservation efforts.

low-cost sensors can offer superior performance and ease of interpretation and are therefore ideal for agricultural applications (Figure 2; Mahlein et al., 2013; Mantripragada et al., 2022). Such an approach has been successful in developing Normalised Difference Vegetation Index (NDVI) and other related multispectral vegetation indices which utilise combinations of narrow frequency bands (Huang et al., 2021). NDVI is widely employed as an indicator of chlorophyll and nitrogen content at the individual plant scale, and as a predictor of crop canopy development, yield and land use at the landscape to global scale (Huang et al., 2021; Zang et al., 2020). Similar to applications of NDVI for yield prediction, field experiments will be required to associate established pollination biomarkers with yield under optimal pollination to ultimately calculate pollination deficits in the field.

Powerful data analysis and statistical tools are required to process large spectral reflectance datasets at each stage of research and development to overcome the challenges of high dimensionality, redundancy and noise. Machine learning continues to be important for detecting even subtle signals in complex spectral datasets and has been employed in the prediction of plant traits (Omia et al., 2023). Supervised and unsupervised machine learning approaches have demonstrated high classification performance, with support vector machines, random forest, decision tree, K-means clustering and regression approaches frequently successfully applied in experimental field applications (Omia et al., 2023; Sarić et al., 2022; Yang et al., 2023). Furthermore, deep learning models such as neural networks have proven particularly effective for spectral image analysis, with the rise of pre-trained algorithms for transfer learning (e.g. ResNet, DenseNet; Huang et al., 2017) improving performance and accessibility to users working with limited training datasets (Paoletti et al., 2019). To maximise model performance, it is essential to mitigate often high signal-to-noise ratio and minimise overfitting by pre-processing the data (Holmes et al., 2020; Philpot et al., 2021). This may include calibration, normalisation, smoothing, dimensionality reduction and feature extraction. The combination of pre-processing methodology and classification model is generally selected on a case-by-case basis, informed by data type, a priori knowledge, signal subtlety, experimental design and other factors.

When integrated with unmanned aerial vehicle (UAV) engineering and computing capabilities, robust spectral bioindicators and machine learning can underly effective monitoring tools for the user on the ground, with a handful of plant phenotyping hardware and software applications based on machine learning and artificial intelligence already available to consumers. These tools are placing spectral technologies in the hands of end-users, offering data collection in real-time and at spatial scales ranging from hand-held sensors (Röckel et al., 2022; Siddiqua et al., 2022), to those mounted on fixed sensor platforms and unmanned aerial vehicles (UAVs; Raptis et al., 2023; Sishodia et al., 2020; Willcox et al., 2018). These technologies are increasingly employed on farms at all scales, where data is important for daily farm operations such as monitoring crop health status (Thompson et al., 2021). Furthermore, classification algorithms and computer vision systems combined with GPS are now allowing UAVs to be guided to the required data collection site

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to carry out spectral surveys and return to docking sites without human intervention (Yao et al., 2024). At even higher spatial resolution, satellites offer a wealth of spectral and image data on a global scale. These delivery solutions facilitate the spatial and temporal resolution needs demanded by environmental and agricultural monitoring and presents the opportunity to directly monitor pollination service delivery (Figure 2; Gonzales et al., 2022; Willcox et al., 2018). Understanding the potential of these technological advances will be essential for facilitating quantification of pollination events from the field to the global scale, and mapping pollination dynamics across the world's changing terrestrial ecosystems.

Our proposed technology to gather real-time high-resolution data on pollination delivery has the potential to transform the identification and mitigation of pollination deficits in crop and non-crop plants across landscapes. However, whilst data monitoring solutions are increasingly adopted on farms, there remain a number of barriers to their uptake and exploitation. Cost of initial investment, installation and maintenance of hardware and software, and limitations posed by education are frequently cited as key determinants of engaging with data on farms (Kumari et al., 2018; Thompson et al., 2021). The value to a farmer of adopting a pollination monitoring technology may therefore be maximised by its integration into existing infrastructure, which may be achieved most simply by embedding pollination-status prediction into existing user-friendly software tools associated with multispectral sensor-equipped UAV hardware. The second level of facilitation will be through financing access and training for users of the technology, which may be achieved through current government funding packages, or through partnerships with technology providers. A significant collaborative drive from government and industry will be essential to promote integration of new technologies throughout the agriculture sector (Department for Environment Food & Rural Affairs [DEFRA], 2022). Connectivity to internet infrastructure will likely be a significant roadblock, however, given the irregularity of access over rural areas (Idoje et al., 2021). This may necessitate development of index-based pollination-status predictors which minimises the size of the data captured to allow integrated rather than cloud-based data processing. It is essential that in the development of a spectral reflectance technology for pollination monitoring, the needs of users are considered directly, in terms of data collection and interpretation, and in implementing land management strategies to mitigate pollination deficits. We therefore propose a holistic approach which integrates expertise across disciplines and sectors, from land management, farming, conservation, engineering and policy.

3 | SYNTHESIS AND APPLICATION

The development of a toolkit to directly quantify pollination dynamics in wind and insect-pollinated plants would provide a novel insight into where pollination deficits lie, and be transformative for proactive and responsive land and pollinator management. Effective monitoring of pollination deficits and quantification of the yield consequences would not only strengthen the incentive to manage pollination as an agricultural input but also provide direct feedback of the efficacy of interventions whilst and contributing to evidence-based policymaking. Whilst spectral reflectance has been successfully applied as a bioindicator of plant stress, considering the parallels between plant stress and pollination-triggered senescence syndromes, we propose applying spectral reflectance to develop bioindicators of pollination, which represents a promising area for research. Spectral imaging performed by robotics for autonomous operation and remote sensing along with integrated artificial intelligence will enable tracking of pollination in real-time. With such technologies becoming increasingly advanced and accessible to farmers and conservationists, this will revolutionise crop agriculture and semi-natural habitat management. This paper calls for further work to identify field-relevant bioindicators of pollination, whilst considering farmer and industry insights to mobilise novel datasets for developing innovative pollination monitoring technologies.

AUTHOR CONTRIBUTIONS

Richard J. Gill conceived the initial idea. Catherine Parry and Richard J. Gill significantly expanded on the concepts, with help from Colin Turnbull and Laura M. C. Barter. Catherine Parry primarily conducted the literature review and wrote the first draft. Catherine Parry and Richard J. Gill finalised the writing of the paper, with additional inputs from Colin Turnbull and Laura Barter.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable as no new data were generated.

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