Advancing biodiversity monitoring in agricultural landscapes

This briefing is about an overview of innovations in biodiversity monitoring in agricultural landscapes, and some advantages and limitations of developments. Rapid progress is generating much larger biodiversity data sets, with higher frequency, scope, and detail than just a few years ago.

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What techniques measure biodiversity in agricultural landscapes?

Remote sensing and LiDAR allow continuous and repeatable monitoring that provides efficient and cost-effective monitoring. Unmanned aerial vehicles or drones can carry monitoring technology – but are limited by cost, skills, and access.

DNA-based monitoring – eDNA and metabarcoding is widely used for measuring species presence but limited by availability of reference DNA databases.

Automated robotics, sensors, image and sound recognition real-time species identification from images or sound with machine learning algorithms - un-skilled labour or volunteers can do fieldwork.

Citizen science and scorecard include farmer-led using simple scorecards, indicators, increase understanding and motivate improvement.

Key messages

- Technologies are available but some need improvements and validation of reliability before committing to monitoring programmes
- Technologies supplement rather than replace in situ observations and taxonomic expertise.
- Automatic recognition systems need training and verification against datasets – and expert taxonomy checks and auditing – to avoid locking in taxonomic errors
- **Equality of access issues**: governments, agencies, and individuals vary greatly in their ability to access and pay. For the public sector, there is the challenge of paying the costs on a long-term basis.
- More work is needed to encourage biodiversity **data sharing and interoperability**.

POLICY AND MONITORING BIODIVERSITY IN AGRICULTURAL LANDSCAPES

Monitoring and detection of protected species and overall biodiversity on agricultural land is a necessity to conserve and restore biodiversity in sustainable agriculture. Agriculture is highly dependent on biodiversity services and natural resources in the agricultural landscape. Understanding the impact of land use shifts, land management, pollution, and climate change requires monitoring of species and habitats. Monitoring at a higher spatial scale and over time allows the evaluation of status and trends.

Technologies, methods, and data manipulation software are rapidly developing and becoming affordable and practical to use. Their use promises to better inform policy decisions on land use, landscape features, and species conservation efforts in agriculture.

Biodiversity monitoring on agricultural land is required under EU laws and policies:

- The EU Birds and Habitats Directives require monitoring and reporting of the species and habitats under the scope of the directives, including semi-natural grasslands, forests, and wetlands.

- The EU Nature Restoration Law requires monitoring and reporting of the common farm-land bird index, the grassland butterflies index, and pollinator populations (EP 2024).
- The Common Agricultural Policy (CAP) monitoring framework uses the common farmland bird index as a measure of impact on biodiversity.
- the Invasive Alien Species Regulation, the Pollinators Initiative, and the proposed Soil Monitoring Law require reporting of species occurrences.

In this briefing, we give an overview of recent innovations in biodiversity monitoring in agricultural landscapes, and some advantages and limitations of the developments.

MONITORING METHODS

Introduction to methods

Biodiversity monitoring technologies and methods are being rapidly developed. Some are in the research phase, some are being used in pilots, and some are already used in agricultural landscapes. The technology development is matched with developments in the automation of large data management.

Remote sensing techniques can be divided into active (with emission) and passive (detection only) sensing and can be applied across the spectrum (visible, infrared and microwave).

Light detection and ranging (LiDAR) can be used with satellite data but also works airborne using an Unmanned Aerial Vehicle or drone. Unmanned Aerial Vehicles (UAVs) - drones - can be equipped with various monitoring technologies and employed in many environments (VASILONI et al, 2023).

DNA-based methods such as metabarcoding and environmental eDNA are used for assessments of species distribution, size of populations, and genetic diversity, from water, air or soil samples without disturbing the occurring species (Duley et al, 2023).

Sensors, robotics and machine learning are being rapidly advanced and piloted to use image or sound recognition to identify species in the field. Their advantage is that they do not disturb or damage the species.

Sound recognition or bioacoustics are sound signals from living organisms can be used to study and track animals, for ex-ample, bats, birds or bees, either with static sensors or with drones (Mutanu et al, 2022).

Image recognition (wildlife camera traps) is used to detect, identify and count larger animals in local settings.

Citizen science methods (scorecards and indicator transects) are simple low-cost methods that farmers can use either alone or with advisors in the field to measure the biodiversity impact of their management.

Remote sensing

Remote sensing refers to the use of a geospatial (or airborne) technology to extract information about the environment without physical contact from a large distance by measuring reflected or emitted electromagnetic radiation, on a recurrent basis.

Passive sensors include multispectral sensors and imaging spectrometers and measure patterns of ecosystem function, composition, vegetation phenology and disturbance regimes (Kerry et al, 2022).

Active sensors include radar and Light Detection and Ranging (LiDAR), and can measure patterns of ecosystem structure, like tree height (Reddy, 2021). RADAR systems have been used in ecological research for decades, but improved classification algorithms and technical advances as well as data-sharing have greatly broadened the range of applications (Bauer, Tielens and Haest, 2024). Light detection and ranging (LiDAR) is a widely recognized technology, especially the airborne laser scanner (ALS), which focuses on the emission and receipt of laser pulses. LiDAR produces a 3D point cloud of the structure of terrain and the vegetation above it (Melin, Shapiro and Glover-Kapfer, 2017).

Unmanned Aerial Vehicles (UAVs) provide in-situ sensing imagery, which can complement satellite-based observations.

Scope of application: remote sensing (Lidar and RADAR) of biodiversity can be used for habitat mapping including species area curve and habitat heterogeneity, species mapping/distribution, plant functional diversity/traits, spectral diversity including vegetation indices and spectral species, state of threats, land uses and conversions. The scale at which remote sensing-based studies measure attributes of vegetation varies with the sensor being used (from 5m for over 100m resolution). They can estimate biomass, monitor crop plant health and stress, detect pest or pathogen infestations, monitor soil fertility and target patches of high weed or invasive plant pressure, map flower resources from flower strips or set aside areas (Librán-Embid et al, 2020).

Users and usability: High expertise is required to interpret data (lower for UAVs). UAVs are being used by various private and public groups, including NGOs, state organizations, researchers and practitioners.

Availability and cost: Remote sensing technologies have reached a high degree of development, with recent developments in a variety of applications in ecology and conservation. UAVs have also developed drastically over the last 10 years, with progressive development of types and applications, as well as decreases in costs, but are not at the stage of being widely and systematically used for monitoring in agricultural landscapes (Librán-Embid et al, 2020). The cost of collection for LiDAR data is high (although costs decrease per unit area as total surveyed area increases).

Advantages: Remote sensing technologies (excluding UAVs) allow extensive spatial coverage. RADAR and Lidar allow visualizations of spatial-temporal changes and development of biotic and abiotic threats to species (”threat maps”).

Remote sensing technologies provide opportunity to improve and automate data collection. They are cost-effective in areas where traditional methods are expensive (e.g. monitoring of nocturnal species), work at various scales (up to 1500 ha) and in remote areas.

UAVs have become affordable and cost-efficient. They allow quick mapping of a targeted area with increased temporal and spatial resolution in comparison to satellite imagery (especially at small scale).

Limitations: One of the challenges associated with remote sensing data are the sparce temporal revisits of the satellites. Remote sensing data is technically complex to process, analyse and interpret. The use of UAVs in the field requires training and skill and is subject to regulations and restrictions to protect privacy and ensure safety.

DNA-BASED METHODS - E-DNA

Using drones for monitoring pollinator diversity in the Showcase Horizon project

Project: SHOWCASing synergies between agriculture, biodiversity and Ecosystem services to help farmers capitalising on native biodiversity (Horizon project, 2020-2025). Showcase is reviewing and testing the effectiveness of economic and societal incentives to implement biodiversity management in farming operations and examine farmer and public acceptance, including the testing of new monitoring methods.

Monitoring methods: The project has been testing novel approaches for surveying flowers as a proxy for bee pollinators using drone images (Torresani et al, 2023). The study surveyed bees and flowering plants in 30 grasslands in the Netherlands using pictures taken with unmanned aerial vehicles (UAVs), to be compared with traditional monitoring methods on the same survey sites. Different machine-learning methods were used to assess remote-sensing images. Authors found a high correlation between the estimates of flower cover and bee abundance and diversity from these different methods of data collection.

Anticipated results: the project will operationalise the approach and examine its reproducibility, further refine the methodology for using drones (determining what height is the most efficient to monitor flowers in grasslands) and standardise the method to obtain imagery from large areas and translate them automatically in flower cover data.

Source: project website https://showcase-project.eu/

Projects using similar monitoring methods: UAVs, in combination with remote sensing technology (Sentinel-2) have been used by Pla et al (2019) to provide information required for farmers to receive compensation from crop losses in the Ebro Delta, in Spain. UAVs allowed estimation of damages in rice crops at 10cm pixel definition.

Environmental DNA (E-DNA) is a novel technology using genetic material (skin cells, scales, hair, faeces, etc.) shed by animals in their environment to monitor species diversity (WWF 2022). Genetic material is extracted from a sample of soil, water, air, or snow, for example from soil particulate matter, or pollen sampling in the air (WWF 2022).

The DNA fragments are amplified and sequenced in the lab using molecular techniques to detect species presence or absence, each sample containing the genetic information of dozens to hundreds of animals (Sahu et al, 2023). Individual species can be singled out and monitored with this technology (WWF 2022). DNA metabarcoding allows the mapping out of multiple taxa within the same DNA sample with a high taxonomic resolution (Nørgaard et al, 2021).

Scope of application: E-DNA is useful for monitoring species distribution across taxa groups (Dornelas et al, 2023) and identifying species (Nørgaard et al, 2021). It is a potent tool in freshwater and marine eco-systems for identifying amphibians, aquatic invertebrates and macrofauna without using damaging sampling methods such as trawls or tissue biopsies (Dornelas et al, 2023; Sahu et al, 2023). E-DNA can be sampled in inhospitable environments, like the deep sea of the Arctic.

Users and usability: Molecular biology expertise is needed to perform and interpret results. With the right sampling kit, sampling can be conducted with limited expertise (Sahu et al, 2023).

Availability: E-DNA is a relatively mature technology compared to other novel monitoring techniques (Dornelas et al, 2023). It already has commercial uses, with companies like Oxford Nanopore and NatureMetrics (Dornelas et al, 2023; NatureMetrics 2024).

Policy relevance: used for water quality monitoring (Water Framework Directive), soil quality monitoring (CAP, Soil Monitoring Law), monitoring of invasive alien species (IAS regulation), and other environmental legislation requirements.

Advantages: E-DNA is a relevant tool to study species distribution and monitor tar-get species, even at low abundance. It is a non-invasive method for identifying amphibians and fish in aquatic ecosystems. E-DNA is fast to implement and reduces processing labour, chiefly for taxonomic error and resolution (Dornelas et al, 2023; Sahu et al, 2023).

Limitations: Comprehensive reference databases are a missing piece for data analysis. E-DNA monitoring is not yet able to measure species or community abundance, and genetic diversity, because research is still underway on the subject (Dornelas et al, 2023).

Novel E-DNA techniques in the European Joint Programme on Agricultural Soil Management (EJP Soil)

Project: Towards climate-smart sustainable management of agricultural soils (Horizon 2020, 2020-2025). The project includes a network of 'biopoints' from samples of the 2022 LUCAS survey, from which soil life is mapped via eDNA. The genetic diversity of the most important groups (Bacteria, Archaea, Fungi and invertebrates) is compared with newly developed national protocols. The aim is to evaluate the sampling and molecular protocols used for the 2018 and 2022 LUCAS Soil biodiversity component.

Results: This 'benchmarking' will help draw up a standard protocol for eDNA barcoding of the soil biome. Genetics can be used to develop indicators for each land use type (e.g. grassland, cropland), specific soil functions (e.g. organic matter and nutrient turnovers, water infiltration) or soil threats (e.g. soil contamination, salinisation, compaction). The presence of organisms of interest from a functional point of view (e.g. plant symbionts and pathogens, decomposers, bioremediators) will be evaluated.

Source: project website https://ejpsoil.eu/

Projects using similar monitoring methods: BIOSCAN Europe, NatureMetrics, GINAMO

AI-BASED ANALYSIS-METHODS

With recent technological advances in relations to computer power and deep learning, machines have become significantly more intelligent and reliable than ever. Deep learning allows an automated capability for machines to recognise, classify, and detect images, sounds, and behaviour of animals, plants, and even humans (Kerry et al, 2022).

Availability: in development, near maturity, with large potential for improvements and further deployment.

Advantages: automated imaging and species recognition can massively increase spatial sampling effort. No disturbances to wildlife or sensitive habitats. Less tedious method than with traditional taxonomic expertise methods.

AI based methods can assist citizen science monitoring efforts for studies based on camera traps when there are not enough volunteers to process images (Willi et al, 2019).

Limitations: Comprehensive centralised reference databases are a missing piece for data analysis and powering automation and interpretation potential (Dornelas et al, 2023).

The deployment of capable computers or capture devices to perform intensive computing in remote areas is challenging.

IMAGE RECOGNITION

Camera traps have a long history and have been used in ecology and conservation for over a hundred years. The development of computer power has allowed the collection and analysis of large quantities of images. The recent development of computer vision-based species identification tools has enabled the automation of the analysis of large volumes of evidence from the field (Elvekjaer et al, 2024). The ubiquity of smartphones with high-quality cameras and internet access has led to the development of smartphone apps that identify species in the field.

Scope of application: Image recognition can be used to measure species richness, track the presence of specific species (for example invasive alien species), monitor pollinator-plant interactions, and much more.

Cost and availability: A high level of expertise is needed to develop the application, but there are already several free or low-cost identification apps for smartphones. Cameras with image recognition are commercially available at a range of prices.

The Danish start-up FaunaPhotonics uses sensors to monitor the wing flutter pattern of in-sects visiting crops. A machine-learning algorithm associates the flutter with the insects' species, which is then reported to the farmer. This method allows the collection of data on insect abundance, activity, diversity and biomass.

Advantages: Opportunity to develop large-scale biodiversity monitoring schemes. Processing large amounts of data, avoiding surveyor bias, and reducing labour costs in the context of a reduction in taxonomic expertise availability. Image recognition solves the issue of the limited spatial/temporal cover of traditional surveying methods. It offers the opportunity to upscale citizen monitoring projects, which generate large quantities of data.

The possibility to analyse large data quantities allows the extension of the temporal and spatial monitoring scale (with revisits during the growing season) (Elvekjaer et al, 2024).

Limitations: Image recognition tools re-quire to have a precise and representative training dataset. Images collected by un-trained users, for example in citizen science initiatives, suffer from a high variability in data quality.

Policy relevance: Smartphone image recognition apps are already being used for policy, for example evidence related to agri-environmental measures in the CAP framework. For example, farmers in Ger-many can use a plant species identification app to prove the occurrences of indicator plant species to receive payments for maintaining biodiverse grasslands (Elvekjaer et al, 2024; Mäder et al, 2021). The technology offers the opportunity to upscale pollinator monitoring efforts.

Use of image recognition approaches in the Mambo Horizon project

Project: Modern Approaches to the Monitoring of Biodiversity (Mambo) (Horizon project, 2022-2026). The project is developing novel monitoring methods for biodiversity, including image and sound recognition-based artificial intelligence approaches, high spatial resolution remote sensing (drone imagery, airborne LiDAR) coupled with deep learning and automated identification tools based on multimedia content. MAMBO aims to increase knowledge and advance tools for monitoring species and their habitats more comprehensively. The project also intends to build a new global community of practice for the development and application of the monitoring technologies.

Results: The project developed an open machine learning challenge dataset comprising 5 million plant species observations distributed across Europe and covering most of its flora, high-resolution rasters, land cover, elevation, and coarse-resolution data. The aim is to evaluate the models' ability to predict the species composition in 22,000 small plots based on standardized surveys.

Image recognition-based AI approaches using camera trap images (Bjerge et al, 2023a). This study used a dataset consisting of 29,960 annotated insects (including bees, hoverflies, butterflies and beetles taxa) across more than two million images. Authors used the dataset to train and compare the performance of deep learning algorithms (called "You Only Look Once - YOLO"). The highest performing models were able to detect and classify small insects in complex scenes with "unprecedented accuracy".

Evaluation of AI models for the identification and prediction of birds, plants, snakes and fungi using LifeCLEF virtual lab (Joly et al, 2023). Several methods for image identification were tested.

- Convolutional neural networks, which use three-dimensional data for image classification and object recognition, were found to be the most powerful method for image and sound processing.
- Automated global plant species identification based on deep learning using participatory sciences data (Bonnet et al, 2023).
- Hierarchical classification of insects with deep learning: A method for automated classification of live insects with camera-based systems (Bjerge et al, 2023b). The dataset comprised 41,731 images of insects, combining images from time-lapse monitoring of floral scenes with images from the Global Biodiversity Information Facility (GBIF). The algorithm correctly classified new insect species at higher taxonomic ranks, while classification was uncertain at lower taxonomic ranks. Moreover, automated Anomaly detection could effectively flag novel taxa that were visually distinct from species in the training data.

Sources: Project webpage on cordis: https://cordis.europa.eu/project/id/101090273and project website: https://www.mambo-project.eu/library?type=3&search=

Projects using similar monitoring methods:

Automated insects monitoring in the UK: The UK Centre for Ecology and Hydrology developed an automated insects monitoring device that captures images of moths and classify them to species using existing workflows (like the AMI system Data Companion). The monitoring device consists of UV and white lights to attract moths. In the future, the pilot aims to integrate audible and ultrasound recording to increase the taxonomic coverage of the trap to include birds, bats, and orthoptera. The pilot is expected to be deployed in UK farms as part of the Agzero+, a five-year research programme supporting UK's transition towards sustainable agriculture.:

Woodnet aims to develop innovative tools for connectivity analysis in various landscapes, including forest, shrubland, and agricultural landscapes, focusing on semi-natural elements like forests and hedgerows.

Diopsis is a network of automated camera traps paired with AI species identification in the Netherlands.

SOUND RECOGNITION (ACOUSTIC MONITORING)

Acoustic monitoring technologies are based on measuring and distinguishing the sounds that animals produce for communication and navigation, from birds and bats to invertebrates (Browning et al, 2017).

Scope of application: Sensors can be placed in the field to get information on species distributions, behaviour and population, to build up a picture of communities of vocalising animals in a survey area, and to understand the relationship between animals and their acoustic environment (the 'soundscape') (Browning et al, 2017). Its popularity within ecological and conservation research has increased, with the development of various applications.

Cost and availability: The technology has rapidly developed over the last few years with advances in consumer technology (like smartphones) allowing drastic cost reduction. In parallel, developments in machine learning and computer vision allow automatic extraction of useful ecological information from many hours of sound recordings (Browning et al, 2017). Acoustic sensors are already being marketed by SMEs and used by private businesses, such as farming businesses, as well as in conservation research.

Policy relevance: Acoustic monitoring de-vices are already being used by private businesses to measure their environmental impact and improve their management. They are also being used to monitor bird and bat populations, two groups that are good indicators of the biodiversity value of farmland.

Agrisound start-up – AI acoustic insects monitoring devices. Companies in the food industry, including Tesco, M&S and Innocent, are using the AI acoustic monitoring technology with their farmer producers to collect data that to collect data on in-field targeted interventions and to inform their environmental reporting. Examples are the monitoring of pollinator visits to fruit crops and remote beehive management.

Advantages: Sound recording devices can be deployed in the observation terrain for an extended period, either delivering data directly if the sensor is directly connected, or storing data for periodic collection, with-out causing disturbance to wildlife.

Limitations: Acoustic index values must be calibrated against ecological community data collected by other means, such as traditional ecological survey data, so the method cannot be used on its own. The acoustic indices of many habitat and taxonomic groups are still poorly understood, and some acoustic indices are still sensitive to background noise (although recent AI developments are providing solutions to this challenge). Obtaining a degree of standardisation between studies to ensure comparability and repeatability is challenging (there are many methods to process data from monitoring).

Using passive acoustic monitoring in the BIOMON Horizon project

Project: Using passive acoustic monitoring methods to survey bird communities in biodiverse agricultural farmlands in the EU (Horizon project, 2022-2024). The project is developing passive acoustic monitoring approaches through machine learning techniques to survey bird communities in agricultural farmlands across Europe. PAM allows monitoring in places that are difficult to access and facilitates the targeting of nocturnal, rare or hard to detect species.

Results: One of the research outcomes was the comparison of acoustic indices in measuring bird species richness in biodiverse sites in Cyprus, China, and Australia (Mammides et al, 2024). The use of indices addresses the challenge associated with species' overlapping vocalisations. Acoustic indices are mathematical equations designed to summarise the temporal and/or spectral distribution of acoustic energy and offer proxies for species richness and composition.

The project also investigated the potential for extended use of Large Language Models (LLMs, such as Gemini and ChatGPt) to integrate multidisciplinary expertise in research projects (Mammides and Papadopoulos, 2024).

Source: https://cordis.europa.eu/project/id/101090273

Projects using similar monitoring methods:

The project Bioacoustic AI 'machine listening' for wildlife monitoring (2023-2027) is building up on the BIOMON project and investigating artificial intelligence enhanced acoustic tools for wildlife monitoring. The project is establishing a network of professionals

(BioacAI) to develop new AI methods for acoustic wildlife monitoring, using devices from leading European bioacoustics companies, in active wildlife monitoring deployments.

Acoustic monitoring of pollinators on solar farms: Led by the renewable energy company Low Carbon in partnership with Lancaster University and the UKRI Engineering and Physical Sciences Research Council. The study investigates how microclimatic variations within solar farms impact bees, hoverflies, and other invertebrates.

CITIZEN SCIENCE – SCORECARDS AND INDICATOR TRANSECTS

Farmers and their advisors use simple scoring systems or indicator transects in the field to monitor biodiversity - a form of citizen science.

Scope of application: Maintaining biodiversity of certain habitats in agricultural land – mainly grazing land or meadows. The ecological integrity of the field or patch is assessed, based on the presence of indicator species and/or indicators of positive or negative management.

Availability and cost: Methods are provided to both farmers and advisors or data collectors at no cost by the agricultural payment agency. The farmer or the farmer and advisor together fill out a form providing information and submit it to the agency. The assessment methods are simple so that farmers can readily learn and do the checking within a few hours. The method is available on paper, as an Excel file, or as a phone application. In some cases, the farmer submits the data directly, in others the farm advisor does it.

Policy relevance: Payments to farmers under the Common Agricultural Policy are increasingly using a result-based set-up, where the payment is conditional to the achievement of a precise environmental result. These types of payment schemes are in place in Ireland, France, Germany, and other countries. In Germany, a national eco-scheme and regional agri-environment schemes offer payments for hay meadows based on maintaining a minimum presence of indicator plant species in the meadow, measured by the farmer every summer using an indicator sheet on a transect. The ACRES scorecard system has been established as the method for payment of the Irish Collective Agri-environment programme (ACRES) in the Irish CAP strategic plan 2023-2027. Farmers receive payments by results based on the scoring of their field (positive and negative indicators, and assessment of threats and pressures).

Advantages: Very simple to use and understand and enables farmers to engage in biodiversity monitoring and preservation. The methods increase farmers' understanding and motivation. The scoring method enables farmers to see where they can improve their score in the next season or to verify if their management of the fields is maintaining their biodiversity value.

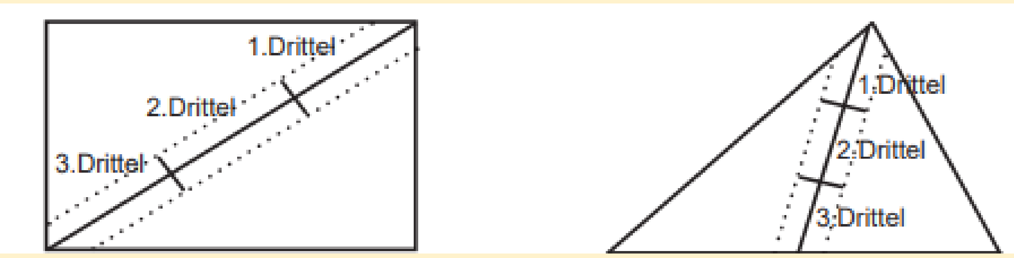
Limitations: The schemes do not generate biodiversity data that can be directly fed into wider biodiversity monitoring programmes, as not all farmers enter their fields into such schemes, but the results can be used to track trends over time on the agricultural areas that are under the schemes. Species-rich grassland agri-environment scheme in Germany

Policy measure: Species-rich grassland (Artenreiches Dauergrünland) - Baden-Württemberg -Eco-Scheme 5 and FAKT II programme implementation.

Description: This agri-environment scheme in Southwest Germany pays farmers managing species-rich grassland (both meadows and pastures) containing at least 4 or 6 key plant species. The 30 key species farmers must look out for are listed in a regional catalogue for Baden-Württemberg, with pictures to make recognition easier. The catalogue of indicators includes highly visible genera flowering reliably in spring, while grassed were excluded from the catalogue. Farmers also must record when they mow, pasture or fertilise their land, but there are no obligations concerning the practices themselves. Farmers are paid €230 per hectare for the field parcels in which 4 indicator species are found in each of the transect thirds and €260 per hectare for fields with 6 indicator species.

Monitoring methods: farmers walk through a diagonal transect across their field during the flowering season (usually between mid-May and mid-June) and must observe at least 4 or 6 species from the catalogue in each third of the transect. The catalogue is built to be user-friendly, so that species can easily be recognized, and their presence registered by ticking off a box in the list.

Diagram of the walk patterns



Example of the form farmers must fill out

Muster# für die Dokumentation der gefundenen Kennarten

Kennarten und Kennartengruppen / Drittel	Beispiel 33/1 Heuwiese 3.6.2023 1.	2.	3.	1.	2.	3.
Augentrost-Arten (1) Wiesen- u. Steifer A.*						
Baldrian-Arten (2) Kleiner u. Arznei Baldrian						
Bärwurz (3)						
Gewöhnliches Zittergras (4)		X	X			
Kohl-Kratzdistel (5)						
Margerite-Arten* (6)		X	X			
Blutwurz (7)						
Echtes Labkraut (8)						
Flügelginster (9)						
Gelbblütige Kleearten (10) Gewöhnl. u. Sumpf-Hornklee, Hopfenklee, Gewöhnl. Wundklee, Gewöhnl. Hufeisenklee		X				
Wiesenbocksbart-Arten* (11)		X	X			
Klappertopf-Arten (12) Zottiger, Kleiner u. Schmalblättriger K.	X	X	X			
Kleine Habichtskräuter (13) Kleines u. Öhrchen-H.						
Milch- und Ferkelkräuter (14) Steifhaariges u. Herbst-M., Gewöhnl. F.						
Pippau-Arten (15) Grüner, Sumpf-, Wiesen- u. Weichhaariger P.	X					
Schlüsselblumen (16) Große u. Arznei-S.						
Sumpfdotterblume (17)						
Bach-Nelkenwurz (18)						
Flockenblumen (19) Berg-, Perücken-, Wiesen- u. Schwarze F.	X		X			
Futter-Esparsette (20)						
Kartäuser-Nelke (21)						
Lichtnelken (22) Tag- u. Kuckucks-L.		X				
Rotklee (23)	X	X	X			
Storchschnabel-Arten (24) Wiesen-, Wald-, Sumpf- u. Blut-S.						
Tauben-Skabiose, Acker-Witwenblume (25)			X			
Thymian-Arten (26) Arznei- u. Sand-T.						
Wiesen-Knöterich (27)						
Wiesenknopf-Arten (28) Kleiner u. Großer W.	X					
Glockenblumen (29) Knäuel-, Rapunzel-, Wiesen- u. Rundblättrige G.	X					
Kreuzblumen (30) Sumpf-, Gewöhnl. u. Schopfige K.						
Sumpf-Vergissmeinnicht (31)						
Teufelskrallen (32) Schwarze, Ährige u. Kugel-T.						
Wiesen-Salbei (33)		X				
Summe der Kennarten	**6**	**8**	**7**			

* Umfasst eine Artengruppe (nach Buttler et al. 1998: Florenliste von Baden-Württemberg. Reihe Naturschutz-Praxis – Artenschutz, Band 1, Hrsg. Landesanstalt für Umweltschutz Baden Württemberg, Karlsruhe. 486 S.)

 # Eine Excel-Vorlage der Tabelle zur Dokumentation ist im Infodienst und unter www.lazbw.de verfügbar.

Project results: This scheme exists since 2000. Around 4 800 farmers are today enrolled in the scheme, with grassland fields covering 44 000 ha of grassland, which amount to 10% of all grassland in the Land. A wider uptake of the scheme is challenged by the rise of energy crops in the region, which is incompatible with extensive grassland management.

Sources:

Result based payment network's overview of the project

Agricultural Centre Bader-Württemberg guidance

IEEP's review of the scheme

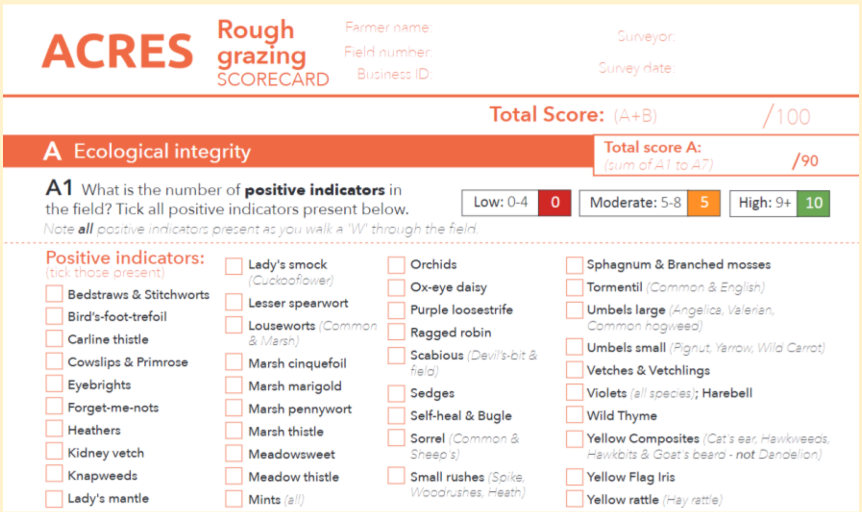
Irish ACRES Scorecard System

Scheme: Agri-Climate Rural Environment Scheme, CAP Strategic Plan, 2023-2027. The ACRES agri-environment scheme relies on a scoring system undertaken by advisors visiting farms and scoring together with the farmer. Farmers receive payments on a 5-year contract based their parcels' score, according to positive and negative indicators for ten ecosystem types (including grassland, peatland, scrub/woodland, rough grazing, coastal grassland, etc). A user-friendly booklet details indicators for each ecosystem type (Talmhaiochta, 2024). Mobile apps and training courses are available for farmers to get familiar with the system.

Monitoring method: Scorecards and field visit. A desk study takes place before the visit to the farm, which plans the walking route for the field's scoring in advance and checks that appropriate equipment for the scoring is available. The desk study is associated with a pre-scoring discussion with the individual farmers. Field scoring is undertaken in spring/summer months and are submitted via online form (AgriSnap). Farmers receive feedback on the scoring after the visit, as well as management and potential non-productive investments recommendations. The AgriSnap precision photo app for smartphones allows farmers or their advisor to send land parcel geotagged pictures and information to the department to validate scheme payments. A geotagged photograph is one that contains the Global Positioning System (GPS) location co-ordinates of the position of where the photo was captured.

The scoring is based on an ecological integrity assessment and an assessment of threats and future prospects. Positive and negative indicators are selected and assessed, and the aggregation determines the field's scoring, in association with other parameters (like vegetation structure). Positive indicators are aggregated following a simple method, based on the number of positive indicators per walking steps.

Example of the scorecard


ACRES Rough grazing SCORECARD

Farmer name:
Field number:
Business ID:
Surveyor:
Survey date:

Total Score: (A+B) /100

A Ecological integrity

Total score A: (sum of A1 to A7) /90

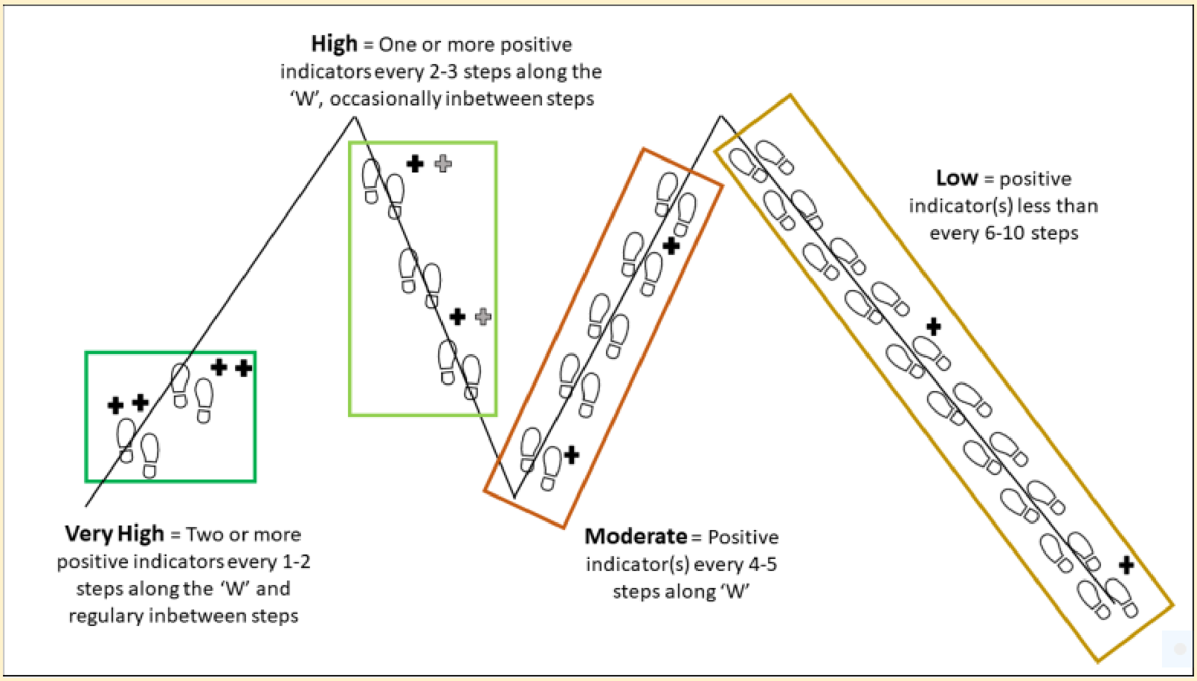
A1 What is the number of **positive indicators** in the field? Tick all positive indicators present below.
Note **all** positive indicators present as you walk a 'W' through the field.

Low: 0-4	0	Moderate: 5-8	5	High: 9+	10

Positive indicators: (tick those present)

- Bedstraws & Stitchworts
- Bird's-foot-trefoil
- Carline thistle
- Cowslips & Primrose
- Eyebrights
- Forget-me-nots
- Heathers
- Kidney vetch
- Knapweeds
- Lady's mantle
- Lady's smock (Cuckooflower)
- Lesser spearwort
- Louseworts (Common & Marsh)
- Marsh cinquefoil
- Marsh marigold
- Marsh pennywort
- Marsh thistle
- Meadowsweet
- Meadow thistle
- Mints (all)
- Orchids
- Ox-eye daisy
- Purple loosestrife
- Ragged robin
- Scabious (Devil's-bit & field)
- Sedges
- Self-heal & Bugle
- Sorrel (Common & Sheep's)
- Small rushes (Spike, Woodrushes, Heath)
- Sphagnum & Branched mosses
- Tormentil (Common & English)
- Umbels large (Angelica, Valerian, Common hogweed)
- Umbels small (Pignut, Yarrow, Wild Carrot)
- Vetches & Vetchlings
- Violets (all species); Harebell
- Wild Thyme
- Yellow Composites (Cat's ear, Hawkweeds, Hawkbits & Goat's beard - not Dandelion)
- Yellow Flag Iris
- Yellow rattle (Hay rattle)

The method for walking the parcel being scored



Accessibility and cost: The method is free for farmers. The development of the AgriSnap application cost €300 000.

Sources:

ACRES handbook (Talmhaiochta, 2024)

Agriland.ie (25 March 2024) DAFM spends €300,000 developing AgriSnap app.

KEY MESSAGES

Developments in biodiversity monitoring technologies and methods are rapidly advancing and generating much larger biodiversity data sets, with higher frequency, scope, and detail than was possible just a few years ago.

Advantages

Using automated technologies avoids surveyor bias, reducing labour costs and providing a partial solution to the decline in taxonomic expertise availability. These technologies are opening up opportunities to develop large-scale biodiversity monitoring schemes that can process large amounts of data over greatly extended temporal and spatial monitoring scales – day and night, throughout the growing season, and in remote or inaccessible places such as tree canopies.

- **Remote sensing imaging techniques** allow continuous and repeatable monitoring that already provides efficient and cost-effective means to determine plant and ecosystem diversity or ecological structures over large areas (Wang and Gamon, 2019).
- **DNA-based monitoring – eDNA and metabarcoding** – is already widely used for measuring water quality, looking for the presence of invasive alien species, and more.
- Automation through **robotics** offers quick species identification from **images or sound** recordings with the help of machine learning algorithms. Their use can reduce the need for extra time and resources as unskilled labour or volunteers can do the fieldwork. Image recognition solves the issue of the limited spatial and temporal cover of traditional surveying methods. It offers the opportunity to up-scale citizen monitoring projects, which generate large quantities of data.
- **Citizen science** approaches with farmers, using simple scorecards, indicators, and field transect or scanning methods, increase the understanding and engagement of farmers with managing their land for biodiversity (Ruck et al, 2024).

Limitations and challenges

A recent expert review of advances in biodiversity monitoring technologies (Dornelas et al, 2023) identified the advantages and disadvantages of progress so far. Some technologies are not ready to be deployed yet and more developments are needed before committing to the new methodology (i.e. some methods lack enough validation of their ability to reliably target taxa groups and habitats). The experts point to the need for more validation studies and the need for long term funding for biodiversity monitoring.

- **Species identification** remains a large hurdle for automation even if data are available to 'train' the system. This is a limitation to using such methods for rare species monitoring, given that there is much less data available for reference and training.

- Automation could **unintentionally "lock in" previous biases and errors in taxonomy**, and any automation system should have an auditing mechanism with expert supervision to avoid this.

- **Need for in situ observations and taxonomic experts**: There is a consensus among experts that these technologies should supplement rather than replace in situ observations for both scientific and social reasons.

- **Hidden costs**: Deploying a network of automated monitoring devices still requires infrastructure for maintenance and experts to verify the results, so the real costs are sometimes underestimated.

- **Equality of access issues**: governments, conservation agencies, and individuals vary greatly in their ability to access and pay for these technologies. For the public sector, there is the challenge of paying the costs on a long-term basis.

- To encourage biodiversity **data sharing and interoperability**, biodiversity monitoring schemes are being connected in the Biodiversa+ project BioDash, whilst the EuropaBON project developed a standardisation framework for reporting (Breeze et al, 2023; Naeslund et al, 2023).

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