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Research Article

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Posted Date: October 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11217861/v1

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Additional Declarations: No competing interests reported.

Monitoring habitat conservation status and assessing biodiversity: The Dehesa case

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Abstract

Monitoring heterogeneous agroforestry systems requires an integrated framework capable of producing comparable indicators across space and time, with statistical measures of uncertainty. We propose an operational and reproducible framework for designing environmental monitoring and estimating changes in the conservation status of extensive High Nature Value agroforestry systems, as exemplified by the Mediterranean Dehesa. Probability samples of farms, pixels, quadrats, trees, and fauna detections are integrated with auxiliary information from Sentinel-2 imagery and airborne light detection and ranging (LiDAR) through design-based and model-assisted statistical estimators. A permanent-panel design supports direct estimation of temporal change while accounting for covariance between monitoring occasions. The framework covers tree demographic structure, grassland productivity and nutritional quality, shrub cover, carbon stocks and removals, flora composition and diversity, and bird-community diversity. Linear, binary logistic, and multinomial logistic models are used according to the nature of the indicators, while probability-sampling foundations are retained for inference. Six numerical examples illustrate implementation in a 15.52-ha Dehesa study area and link the statistical formulations to documented datasets and reproducible R workflows. By combining probabilistic field observations with spatially exhaustive Earth observation data, the framework can improve monitoring efficiency and precision without replacing design-based measures of uncertainty. The approach provides a coherent basis for repeated conservation assessment, biodiversity monitoring, and carbon-farming monitoring, reporting, and verification, and is transferable to other heterogeneous agroforestry landscapes.

Keywords: probability sampling; model-assisted estimation; Earth observation; temporal change; ecological indicators; carbon farming.

Introduction

Mediterranean silvopastoral systems such as the Dehesa represent multifunctional landscapes resulting from centuries of interaction between human management and Mediterranean oak woodlands (Díaz et al., 1997; Parsons, 1962). The coexistence of scattered trees, grasslands, and shrub communities creates a structurally heterogeneous ecosystem that supports high biodiversity and provides multiple ecosystem services, including livestock production, carbon storage, soil protection, and cultural values (European Commission, 2013; Rodríguez-Rojo et al., 2022).

As one of the most representative High Nature Value farming systems in Europe, the Dehesa is recognized under Annex I of the European Union (EU) Habitats Directive (Council of the European Communities, 1992) as a habitat of Community interest whose conservation status requires periodic assessment and reporting. Despite its ecological and socioeconomic importance, inadequate tree regeneration, tree decline, land-use change, and climate-related pressures may compromise the system's long-term sustainability (Díaz et al., 1997; Rodríguez-Rojo et al., 2022). These challenges increase the need for statistically robust monitoring frameworks supporting conservation assessment, biodiversity monitoring, and emerging carbon farming initiatives (European Commission, 2026; European Parliament & Council of the European Union, 2024).

Against this legal background, the methodological problem addressed in this study is how to design statistically robust monitoring schemes capable of producing comparable indicators with quantified uncertainty across space and time. The proposed framework is intended to avoid two potential limitations: ground-based estimates that are not formally extrapolated to the whole habitat and wall-to-wall remote-sensing estimates whose sampling and model uncertainty is not explicitly quantified. The present work therefore develops an integrated framework for environmental monitoring and assessment tailored to heterogeneous landscapes such as the Dehesa, with a particular focus on change estimation.

The framework combines probabilistic ground surveys with auxiliary information derived from multispectral satellite imagery and airborne LiDAR data. Combining ground surveys and remote-sensing data has a long tradition in environmental and agricultural statistics, particularly for improving estimation efficiency while maintaining statistical rigor (Ambrosio Flores & Iglesias Martínez, 2000). Remote-sensing data are incorporated through model-assisted estimators designed to improve the cost-efficiency of ground surveys while preserving design-based inference (Särndal et al., 1992). Our focus is explicitly operational: we aim to estimate ecological indicators describing habitat structure, vegetation productivity, biodiversity, and carbon removal, together with measures of uncertainty derived from the sampling design and the assisting models. Particular emphasis is placed on consistent estimation of habitat dynamics over time within a unified monitoring framework.

While the methodology is illustrated through a Dehesa case study—representative of an extensive agroecosystem distributed across large areas of Spain and Portugal—the proposed approach is inherently generic and can be readily extended to other Mediterranean ecosystems and, more broadly, to habitats subject to periodic reporting under international conservation agreements. The framework is also directly relevant to emerging systems for monitoring carbon removal and carbon farming, where statistically coherent approaches to measurement, reporting, and verification (MRV) are increasingly required in climate-policy contexts.

The paper is organized at four complementary levels. The main text presents the operational monitoring framework and the proposed estimators, while Supplementary Material (Online Resource 1) provides the complete statistical derivations, including variance–covariance structures and variance estimators for temporal change. Numerical Examples (Online Resource 2) are provided for selected monitoring components under realistic Dehesa conditions. Each Numerical Example is linked to the README of its corresponding repository module, which provides access to the associated datasets and fully reproducible scripts.

The methodological framework covers the sampling designs and estimators used to monitor the tree, shrubland, and grassland component**s** of Dehesa systems, together with carbon removal and carbon farming indicators. Biodiversity assessment is subsequently addressed for vegetation and low-mobility fauna, whereas highly mobile fauna is considered separately, with particular emphasis on line-intersect-sampling. The Conclusions discuss the broader relevance of the proposed approach for operational habitat monitoring, conservation assessment, biodiversity monitoring, and carbon-oriented environmental policies.

Surveys for monitoring conservation status

Habitat conservation status is assessed through structural and functional indicators describing key habitat attributes over time, across spatial domains, and under different management regimes (Council of the European Communities, 1992; European Commission, 2013). In Dehesa systems, these indicators include tree density, age structure, and productivity; shrub cover; pasture composition and biomass; carbon removal and carbon farming variables; and metrics of faunal biodiversity.

In this study, each indicator is treated as a survey variable defined on spatial sampling units and observed at successive monitoring occasions. Habitat-level indicators are expressed as aggregates of these variables, including totals, means, proportions, and ratios, and are estimated from probabilistic samples of spatial units under a design-based inferential framework.

Probabilistic sampling requires the specification of one or more sampling frames. In this study, we consider the two main types of frames commonly used in environmental applications: area frames and list frames. Area frames are constructed from maps, aerial imagery, or satellite data, whereas list frames are derived from administrative or farm censuses. The corresponding sampling units therefore differ according to frame structure, consisting of polygons or points in area frames and farms in list frames (Ambrosio et al., 2023).

The sampling design may involve multiple stages, with different frames and probabilistic selection schemes applied at each stage. For area-based habitat and vegetation indicators, sampling over time follows a strict panel design in which the same sampling units are revisited at each monitoring occasion. Highly mobile fauna constitutes an exception, with independent samples selected by line-intersect sampling (LIS) at successive occasions. Consequently, the resulting designs are generally complex rather than simple random samples (Fuller, 2009).

For illustrative purposes, we consider a three-stage sampling design combining both list and area frames. A first-stage sample of Dehesa farms is selected from a list frame, while a second-stage sample of pixels is selected within the selected farms using an area frame derived from satellite imagery and stratified according to tree density using LiDAR-derived information. The third-stage sample depends on the ecological component being assessed. For the tree layer, the observational units consist of the tree clusters associated with the selected pixels. For the herbaceous and shrub layers, and for faunal taxa with limited mobility, samples of quadrats within the selected pixels are considered. For certain fauna taxa, particularly birds, whose individuals are highly mobile or cryptic and for which no well-defined sampling frame is available, LIS is employed.

Sampling schemes are designed, and estimators are selected, so that the resulting estimators are unbiased, or approximately unbiased, for the habitat aggregates of interest while achieving acceptable precision at operational survey costs. In addition to strictly design-based estimators relying exclusively on field observations, we consider model-assisted estimators that combine field data with auxiliary Earth observation (EO) information (Firth & Bennett, 1998; Särndal et al., 1992).

Auxiliary information includes vegetation indices derived from multispectral satellite imagery together with LiDAR-based variables such as tree height, crown structure, and shrub cover. Continuous survey variables are linked to auxiliary data through linear models, whereas categorical variables are treated using logistic formulations (McCulloch & Searle, 2001). In all cases, the model acts solely as an assisting tool, while statistical inference remains design-based and continues to depend on the probabilistic sampling design rather than on model validity. The integration of Earth observation data into probabilistic survey designs has become an active area of research in agricultural and environmental statistics (Ambrosio et al., 2023). Efficiency gains from model-assisted estimators depend primarily on the strength of the relationship between auxiliary EO variables and field observations (Särndal et al., 1992).

Once fitted, the model can be used to predict the survey variable from the auxiliary variables in spatial units not included in the sample. In principle, these auxiliary variables could be computed wall-to-wall over the entire habitat, allowing predictions to be obtained for every spatial unit and aggregated to derive the indicator of interest. However, such an approach is both costly and unnecessary.

The adopted sampling design is intended to provide a more cost-efficient alternative while preserving design-based inference. Auxiliary variables are computed only for the pixels within the farms selected at the first stage. They are then used to derive farm-level estimates of the indicator of interest. These estimates are subsequently expanded to the habitat level using the corresponding first-stage inclusion probabilities, and the sampling variance of the indicator of interest is estimated to obtain the required measures of uncertainty at the habitat level.

Estimation of change under a strict panel design

The primary objective of the proposed monitoring framework is to estimate temporal change in habitat indicators. For area-based habitat and vegetation components, the same farms, pixels, trees, and quadrats are revisited at each monitoring occasion under a strict panel design. Such designs are generally more efficient for change estimation than repeated independent samples because they allow covariance between occasion-specific estimators to be incorporated (Fuller, 1999). Highly mobile fauna is treated separately using independent LIS samples at each occasion.

Let $t = 1, \dots, T$ denote the monitoring occasions, where $t = 1$corresponds to the beginning of the monitoring period and $t = T$ to the final occasion. For each indicator monitored under the strict panel design, habitat-level estimates are obtained from the probabilistic multistage sampling design described above, using either direct design-based estimators or model-assisted estimators, depending on the availability of auxiliary EO information. Because the same sampling units are repeatedly observed, the estimators obtained at different occasions are generally correlated. Their joint uncertainty therefore depends not only on the sampling variance at each occasion but also on the covariance induced by repeated observation of the same units.

Although intermediate estimates may be produced when auxiliary EO information is available, intensive ground surveys are generally restricted to the initial and final occasions of the monitoring cycle for reasons of operational feasibility and cost efficiency. The strict panel design nevertheless ensures that repeated observations of the same sampling units support statistically coherent estimation of temporal change and its associated uncertainty.

The primary indicator of conservation dynamics considered in this study is the net change over the monitoring cycle, defined as $\Delta Y = Y_T - Y_1$ with estimator $\widehat{\Delta Y} = \hat{Y}_T - \hat{Y}_1$. A key advantage of the strict panel design is that the sampling variance of the change estimator explicitly incorporates the covariance between occasion-specific estimators: $\mathrm{Var}(\widehat{\Delta Y}) = \mathrm{V}(\hat{Y}_T) + \mathrm{V}(\hat{Y}_1) - 2\,\mathrm{Cov}(\hat{Y}_1, \hat{Y}_T)$. Unlike approaches based on independent cross-sectional samples, this framework accounts for the covariance structure induced by repeated observations. When the covariance between occasion-specific estimators is positive, as is commonly expected under a strict panel design, this generally results in a smaller variance for the estimated change. The same formulation applies to both direct design-based and model-assisted estimators. A compact matrix formulation of the panel estimators and their variance–covariance structure is provided in the Supplementary Material (Online Resource 1).

Tree conservation status

Trees (*Quercus* spp.) constitute the structural backbone of Dehesa ecosystems and are therefore a central element in conservation-status assessments. Monitoring tree condition requires indicators that quantify density, regeneration, demographic structure, and functional performance. These indicators are estimated in a design-based framework using probabilistic samples of trees to collect information on regeneration status and structural tree attributes. For illustrative purposes, we consider the three-stage sampling design described in Supplementary Material (Online Resource 1), in which the third-stage inclusion probability equals 1; that is, all trees associated with each selected second-stage pixel are included in the sample.

Earth observation (EO) auxiliary variables—such as tree height and crown area derived from LiDAR data—are incorporated through model-assisted estimators (Bhebhe et al., 2025; Lefsky et al., 2002). These estimators can improve the cost-efficiency of ground surveys while preserving design-based inference, making them suitable for estimating tree indicators at each monitoring occasion. Full statistical derivations and sampling-variance expressions are provided in the Supplementary Material (Online Resource 1).

Age structure

Tree regeneration is one of the primary indicators of Dehesa conservation status. A balanced demographic structure—characterized by sufficient recruitment of young individuals—is critical for long-term ecological stability (Pulido et al., 2001). The proportion of young trees relative to the total tree population can be estimated using design-based estimators relying exclusively on field observations. For the numerical illustration, field verification identifies effective trees among LiDAR candidates at t1, whereas DBH and young status (DBH < 15 cm) are simulated for the sampled effective trees, as are the t6 tree observations. Occasion-specific estimators of the total number and proportion of young trees are computed from the inclusion probabilities of the probabilistic sampling design (Section 3.1 of the Supplementary Material).

These design-based estimators are unbiased under the specified sampling design but may have limited precision when sample sizes are small. Model-assisted estimators combining ground observations with EO auxiliary variables are therefore considered as a means of potentially improving precision (Section 3.2 of the Supplementary Material). Two logistic models use LiDAR-derived predictors—such as crown area and tree height—to estimate whether a candidate is an effective tree and whether it is an effective young tree. The ratio of the corresponding model-assisted totals estimates the young-tree proportion, with potential precision gains depending on the predictive strength of the auxiliary variables (Section 3.2.2 of the Supplementary Material). This approach capitalizes on extensive spatial coverage by EO data while preserving design-based inference.

For the numerical illustration, the following operational conservation-status classification is adopted at the habitat level: (i) favorable when young trees account for at least 50% of the tree population; (ii) unfavorable–inadequate when they account for at least 10% but less than 50%; and (iii) unfavorable–bad when they account for less than 10%. These thresholds are illustrative decision rules rather than a generally prescribed legal classification.

Numerical illustration

The estimation of tree age structure is illustrated using data from a 15.52-ha Dehesa study area. Numerical Example 1 in Online Resource 2 demonstrates the calculation of design-based and model-assisted estimators of the total number and proportion of young trees under a strict panel design in which the same sampling units are repeatedly observed, using Sentinel-2 imagery, LiDAR-derived structural attributes, field verification of t1 tree candidates, and simulated young status and t6 tree observations. The associated datasets, scripts, intermediate products, and numerical outputs are available in the corresponding repository module, whose README documents the complete reproducible workflow.

Grassland conservation status

Herbaceous vegetation is a fundamental structural and functional component of Dehesa ecosystems, providing the primary forage base for livestock, sustaining soil ecological processes, and contributing to overall habitat quality. Monitoring its conservation status requires indicators that capture productivity, nutritional quality, and functional traits. Given the high spatial and temporal variability of Mediterranean grasslands, probabilistic survey designs combined with auxiliary Earth observation (EO) data provide a robust and operationally feasible approach. In particular, the use of a strict panel of pixels and quadrats revisited at each monitoring occasion allows the explicit estimation of temporal covariance terms and can improve the efficiency of change estimators.

For illustrative purposes, the three-stage sampling described in Section 2 of the Supplementary Material is adopted. The first and second stages are common to all habitat layers considered in this study. For

grassland monitoring, a third-stage sample of quadrats is selected within each sampled pixel, and pasture is harvested and analyzed within those quadrats to obtain the data required for estimating indicators of productivity, nutritional quality, and functional traits at each monitoring occasion, as well as their change throughout the monitoring cycle.

Productivity, nutritional quality, and functional traits

Pasture productivity—the amount of dry matter (DM) accumulated per unit area—is a central indicator of grassland condition and grazing capacity. Nutritional quality is characterized by parameters such as crude protein (CP), whereas fuel moisture content (FMC) and canopy water content (CWC) describe vegetation water status and further characterize the functional condition of the herbaceous layer. Functional traits, including leaf water content (LWC), specific leaf area (SLA), leaf dry matter content (LDMC), chlorophyll content (Cab), and leaf area index (LAI), provide additional insights into vegetation functioning.

These parameters can be modelled as functions of EO predictors, primarily multispectral vegetation indices, such as the normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), and normalized burn ratio (NBR), or, when available, hyperspectral metrics (Rouse et al., 1974; Serrano et al., 2023, 2024). Linear models are used to relate ground-measured parameters in quadrats to vegetation indices at the pixel level. These models capture broad spatial gradients, while explicit sampling-variance estimators ensure that uncertainty can be quantified under the probabilistic multistage panel design (Wolter, 2007).

Because the same pixels and quadrats are revisited at each monitoring occasion, occasion-specific estimators of productivity, nutritional quality, and functional traits can be derived within the general model-assisted framework introduced in Section 3.2 of the Supplementary Material. Ground observations are combined with EO auxiliary variables to improve estimator precision while preserving design-based inference. The net change over the monitoring period is estimated as the difference between the habitat-level estimators at the initial and final monitoring occasions, following the adopted strict panel formulation.

Details on model specification, estimation, and variance calculation are provided in Section 3.2.1 of the Supplementary Material.

Numerical illustration

A Sentinel-2-based area frame and simulated ground data are used under the strict panel design. Vegetation indices (NDVI, NDMI, and NBR) are computed for successive monitoring occasions, represented here by wet and dry seasonal observations that illustrate the strong seasonality characteristic of Mediterranean grasslands (Drusch et al., 2012; Serrano et al., 2022, 2023, 2024). A stratified random sample of pixels is selected, and within each sampled pixel, the same quadrats are revisited to obtain ground measurements of DM and CP.

Linear model parameters are estimated using weighted estimators that account for the inclusion probabilities of the multistage sampling design. Occasion-specific model-assisted estimators of habitat-level DM and CP are then computed for each monitoring occasion using ground observations and EO auxiliary variables within the adopted probabilistic panel framework.

The net change over the monitoring period is estimated as the difference between the estimators at the initial and final occasions ($t = 1$ and $t = T$), following the strict panel formulation adopted in this study. Corresponding sampling-variance estimators explicitly incorporate the covariance between the occasion-specific estimators arising from the repeated observation of the same pixels and quadrats, yielding design-

based measures of uncertainty for both occasion-specific levels and temporal change. The example illustrates the potential efficiency gains from incorporating EO auxiliary variables into model-assisted estimators, with confidence intervals derived from the corresponding design-based variance estimators.

The complete implementation and results are presented in Numerical Example 2. The associated datasets, scripts, intermediate products, and numerical outputs are available in the corresponding repository module, whose README documents the complete reproducible workflow.

Shrubland conservation status

Shrubland constitutes a key structural and functional component of Dehesa ecosystems. Shrub patches contribute to biodiversity conservation, soil protection, nutrient cycling, and carbon storage, while also increasing habitat heterogeneity across the landscape (Rodríguez-Rojo et al., 2022). Consequently, conservation-oriented management generally seeks to maintain a balanced shrub structure through selective clearing and natural regeneration processes rather than complete removal. Monitoring shrubland conservation status therefore requires indicators capable of quantifying shrub cover, structural heterogeneity, and temporal changes associated with management interventions and subsequent regeneration dynamics.

In the proposed monitoring framework, shrub cover and structural attributes are assessed using a probabilistic multistage sampling design consistent with the approach applied to trees and grasslands. Earth observation data, particularly airborne LiDAR, provide structural information that can be combined with field observations through model-assisted methods, potentially improving precision while preserving design-based inference (Estornell et al., 2012; Rodríguez Dorribo et al., 2025). Shrub cover and related structural metrics are estimated at each monitoring occasion using the corresponding inclusion probabilities and EO-assisted procedures. Temporal changes in shrub cover and structure are then quantified as differences between estimates obtained for the initial and final monitoring occasions. The corresponding variance estimators are described in detail in Section 3.2.1 of the Supplementary Material.

Shrub cover

Shrub cover is a widely used indicator of habitat condition because of its close relationship with microhabitat availability, soil protection, and faunal diversity.

LiDAR-derived canopy height models allow consistent detection of shrub layers and estimation of shrub height and biomass (Estornell et al., 2012; Rodríguez Dorribo et al., 2025). In Numerical Example 3, operational height thresholds of 0.3–1.5 m for low shrubs and 0.3–2.5 m for low and medium shrubs distinguish shrubs from herbaceous vegetation and tree canopies, supporting shrub-cover mapping at pixel, quadrat, or subpixel scales within monitored farms.

Repeated observation of the same spatial units over time enables direct estimation of temporal changes in shrub cover and related structural attributes. Ground observations are combined with LiDAR-derived auxiliary variables through model-assisted procedures that can improve estimation precision while preserving design-based inference.

The same model-assisted estimation framework used for grassland productivity is adopted for the shrub layer, based on a linear assisting model. Detailed statistical formulations, including joint variance–covariance expressions and derivations, are provided in Section 3.2.1 of the Supplementary Material.

Numerical illustration

Numerical Example 3 uses the Sentinel-2-based area frame and a LiDAR-derived canopy height model (CHM) processed for the same study area considered in the previous sections. The example focuses on pixels without trees in order to avoid canopy interference and maintain a consistent definition of the shrub layer throughout the monitoring period. LiDAR data are used to derive shrub occupancy at 1- m spatial resolution, whereas high-resolution orthophotography from the Spanish National Aerial Orthophotography Plan provides reference information on green vegetation cover for the sampled spatial units.

A simple linear model relates green cover interpreted from orthophotography at the quadrat level to LiDAR-derived shrub occupancy, with model parameters estimated using inclusion-probability weights from the three-stage sampling design. Habitat-level shrub-cover estimates are then obtained through model-assisted procedures, and temporal change is quantified as the difference between the estimates for the initial and final monitoring occasions. The corresponding sampling-variance estimators provide measures of uncertainty for both occasion-specific shrub-cover estimates and temporal change.

The example illustrates the integration of LiDAR-derived auxiliary variables within a model-assisted framework for shrub-cover monitoring under a probabilistic sampling design. The complete implementation and results are presented in Numerical Example 3. The associated datasets, scripts, intermediate products, and numerical outputs are available in the corresponding repository module, whose README documents the complete reproducible workflow.

Carbon removals and carbon farming

Land-use dynamics and vegetation transitions can be represented through spatially explicit longitudinal models that account for heterogeneity and spatiotemporal dependence (Ambrosio Flores et al., 2008). In Dehesa systems, such transitions involve changes in the structure and composition of the tree, shrub, and herbaceous layers and, consequently, in the carbon stocks represented by these vegetation components. In the proposed framework, carbon-stock change is therefore treated as an indicator of ecosystem condition and as a variable relevant to environmental policy. The European Union Carbon Removals and Carbon Farming (CRCF) Regulation (EU) 2024/3012 establishes a voluntary certification framework for permanent carbon removals, carbon farming, and carbon storage in products (European Parliament & Council of the European Union, 2024). The delegated methodology adopted by the European Commission covers agricultural and agroforestry activities on mineral soils and specifies the eligible practices and quantification requirements (European Commission, 2026).

For Dehesa landowners, voluntary CRCF certification may create opportunities for additional income by enabling quantified and independently certified net carbon removal or net soil emission reduction benefits to be represented by certification units. The economic value of these units will nevertheless depend on demand and on contractual arrangements outside the certification framework, because CRCF certification itself does not guarantee either a market or a particular level of remuneration (European Parliament & Council of the European Union, 2024).

Participation in CRCF certification entails monitoring, reporting, verification, and liability requirements during the activity and monitoring periods established by the applicable methodology. Operators seeking certification must quantify the net carbon removal or net soil emission reduction benefits relative to the applicable baseline, demonstrate additionality, and monitor stored carbon and any reversals in accordance with the certification methodology (European Commission, 2026; European Parliament & Council of the European Union, 2024). Consequently, the CRCF framework increases the need for statistically robust

MRV systems capable of estimating carbon-stock changes and their uncertainty and of documenting storage duration and reversal risks in heterogeneous agroforestry systems such as Dehesa systems.

Aboveground biomass (AGB) is estimated using model-assisted approaches under a probabilistic sampling design, combining field observations—such as tree DBH, herbaceous dry matter, and shrub cover—with auxiliary information derived from EO data, including vegetation indices for herbaceous biomass. Biomass carbon is calculated using the IPCC default carbon fraction of 0.47 and converted to CO_2 equivalent using the molecular-weight ratio 44/12 (Intergovernmental Panel on Climate Change [IPCC], 2006).

At each monitoring occasion, design-based estimators provide estimates of carbon stocks and their sampling uncertainty. When the same probability sample is observed repeatedly, estimation of carbon-stock change should incorporate the covariance between the occasion-specific estimators, because the estimators are not independent (Fuller, 1999; Särndal et al., 1992). This longitudinal perspective is particularly relevant to CRCF applications, which require stored carbon and any reversals to be monitored during the applicable monitoring period (European Commission, 2026; European Parliament & Council of the European Union, 2024). Repeated observation of the same sampling units under a strict panel design therefore supports the estimation of carbon trajectories and their uncertainty while preserving design-based inference.

For persistent biomass pools, carbon-stock change over the monitoring cycle is represented as a sequence of stock changes between consecutive monitoring occasions. Cumulative carbon-stock change is defined as $S_{1:T} = \sum_{t=2}^{T}(C_t - C_{t-1}) = C_T - C_1$, with estimator $\hat{S}_{1:T} = \sum_{t=2}^{T}\left(\hat{C}_t - \hat{C}_{t-1}\right) = \hat{C}_T - \hat{C}_1$. Although cumulative carbon-stock change is algebraically determined by the difference between the final and initial stocks, retaining the occasion-specific increments makes the temporal trajectory explicit and allows temporary losses, partial reversals, and subsequent recovery to be identified. This representation can therefore accommodate carbon-stock changes associated with climatic variability, disturbance, and management interventions such as pruning or shrub clearing.

A key distinction is required between vegetation layers and carbon pools. For either the tree or shrub layer, C_t represents a living-biomass carbon stock at monitoring occasion t. Cumulative stock change over the monitoring cycle is therefore algebraically equivalent to $S_{1:T} = C_T - C_1$, with estimator $\hat{S}_{1:T} = \hat{C}_T - \hat{C}_1$. Nevertheless, retaining the sequence of occasion-specific changes allows disturbance, recovery, and reversal dynamics to be described. In contrast, aboveground herbaceous biomass is a transient pool subject to grazing, senescence, and decomposition. Its carbon content may be reported at each monitoring occasion as an indicator of annual biomass-carbon production, but it should not be accumulated across years as carbon sequestration. For grassland-management activities, net carbon removal should instead be quantified through changes in eligible carbon pools, particularly soil organic carbon, relative to the applicable baseline (European Commission, 2026).

More generally, the proposed framework combines probabilistic panel sampling, EO auxiliary information, model-assisted estimation, temporal covariance, and explicit uncertainty estimation to monitor carbon stock change in Mediterranean silvopastoral landscapes. These elements provide a methodological basis for addressing the quantification and monitoring requirements of carbon farming MRV. However, the framework should not be interpreted as a complete CRCF certification methodology, because operational certification also requires application-specific baselines, additionality assessment, accounting for associated greenhouse gas emissions, storage and liability provisions, and independent verification under the applicable methodology (European Commission, 2026; European Parliament & Council of the European Union, 2024).

Trees

In Dehesa systems, destructive biomass sampling is unsuitable for routine monitoring; tree biomass must therefore be estimated from non-destructive dendrometric measurements using previously calibrated

allometric equations. Under the measurement-based approach established by the applicable CRCF methodology (European Commission, 2026), changes in living-biomass carbon are quantified from repeated field measurements combined with documented allometric relationships. For *Quercus ilex*, diameter alone is a strong predictor of individual-tree aboveground biomass, while the inclusion of tree height and crown projection radius can improve prediction (Canadell et al., 1988; Ruiz-Peinado et al., 2012). In the proposed framework, height and crown metrics are derived from LiDAR data, whereas operational monitoring would measure DBH for a probability sample of trees and use it to fit an assisting model relating DBH to LiDAR-derived variables (Bhebhe et al., 2025). In Numerical Example 4, DBH is simulated for the sampled effective trees verified in the field at t1. Because the selected tree allometric equation predicts AGB only, belowground biomass is estimated using an adopted root-to-shoot ratio of 0.40, consistent with the mean value of 0.41 reported for single-stemmed *Quercus ilex* trees in a Mediterranean forest (Canadell & Rodà, 1991). Accordingly, estimated total living tree biomass is estimated as 1.40 x AGB.

Several complementary biomass-modelling approaches are available for Mediterranean hardwood species in Spain. Species-specific equations based on tree-level dendrometric variables have been developed for *Quercus ilex* and *Quercus suber* (Canadell et al., 1988; Ruiz-Peinado et al., 2012). For young *Q. ilex* plantations, Juan-Ovejero et al. (2023) related destructively measured aboveground biomass to remotely sensed height, crown area, and biovolume. At the stand level, Calama et al. (2024) developed biomass models for young afforestations with native species, including *Q. ilex* and *Q. suber*, based on plantation age, stand density, and site index. These studies provide complementary support for combining field measurements collected under probability sampling with remotely sensed auxiliary information in carbon-monitoring applications.

Within the proposed model-assisted procedure, DBH predictions derived from LiDAR variables are used as inputs to an appropriate species-specific allometric equation for holm oak (e.g., Canadell et al., 1988; Ruiz-Peinado et al., 2012) to generate population-level predictions of aboveground biomass. Sample responses provide the residual correction required for design-consistent estimation; in Numerical Example 4, these responses use simulated DBH for field-verified effective trees at t1. Aboveground biomass is subsequently expanded to total living biomass and converted to carbon using the factors specified above. Changes in living tree carbon stock are estimated between consecutive monitoring occasions, thereby preserving the temporal trajectory of growth, pruning, loss, and recovery.

Grassland

The herbaceous layer follows an annual production–consumption cycle in which aboveground biomass is produced and subsequently removed through grazing, senescence, and decomposition. Dry matter (DM) is estimated at each monitoring occasion using the model-assisted framework described above, combining repeated observations of the same pixels and quadrats with auxiliary variables such as NDVI. The carbon temporarily contained in standing herbaceous biomass is estimated as $\hat{C}_t^H = f_C \widehat{DM}_t = 0.47\ \widehat{DM}_t$, where $f_C = 0.47$ is the adopted biomass carbon fraction (Intergovernmental Panel on Climate Change [IPCC], 2006). This quantity is interpreted as a transient biomass-carbon indicator rather than as a persistent carbon stock or carbon removal. Differences between occasion-specific estimates describe interannual variation in herbaceous biomass carbon, but values from successive years are not accumulated as carbon sequestration. Under the applicable CRCF methodology for agriculture and agroforestry on mineral soils, carbon removals attributable to improved grassland management would instead be quantified primarily through changes in organic carbon soil relative to the baseline, after accounting for the associated greenhouse gas emissions (European Commission, 2026).

Shrubs

Shrub cover and height can be characterized using LiDAR-derived structural metrics, which may be incorporated into assisting biomass models calibrated with field measurements (Estornell et al., 2012). Under the strict panel design, the same spatial units selected by probability sampling are observed at each

monitoring occasion, allowing changes in shrub living-biomass carbon stocks and the covariance between occasion-specific estimators to be estimated. Because shrubs constitute a persistent carbon pool, changes between consecutive monitoring occasions can represent both abrupt losses caused by management interventions, such as clearing, and subsequent regrowth. In Numerical Example 4, however, the relationship between shrub cover and biomass is an explicitly calibrated synthetic proxy because empirical calibration data are unavailable. The resulting shrub-carbon estimates are therefore illustrative and cannot support carbon crediting.

Integrated interpretation

An integrated carbon assessment of Dehesa systems must distinguish persistent carbon stocks in living woody biomass from transient annual flows of herbaceous biomass carbon. Accordingly, cumulative woody-stock change over the monitoring cycle is calculated by adding successive changes in tree and shrub carbon stocks. The shrub component is expressed on an area-equivalent basis for the entire farm before integration with tree carbon stock. Herbaceous biomass carbon is reported separately at each monitoring occasion and is not included in cumulative woody-stock change. This separation reflects the contrasting temporal behaviour of persistent and transient biomass pools and allows management interventions, climatic variability, losses, and recovery to be represented explicitly. The six-year illustration and the corresponding variance-estimation procedures are presented in Numerical Example 4.

Numerical illustration

A reproducible illustration of the carbon-accounting component of the proposed MRV framework is provided in Numerical Example 4. The example integrates the outputs for the three main vegetation layers of the Dehesa system—trees, grassland, and shrubs—within a common probabilistic panel framework combining model-assisted estimation, Earth observation auxiliary variables, and design-based variance estimation. Repeated observations of the same spatial sample allow the covariance between occasion-specific estimators to be incorporated into uncertainty estimation for changes in persistent woody carbon stocks. Annual herbaceous biomass-carbon flows are estimated within the same sampling framework but are reported separately and do not contribute to cumulative woody-stock change.

The numerical example considers a six-year monitoring cycle represented by a predefined sequence of dry (D) and wet (W) conditions. Tree carbon is treated as a persistent woody stock estimated using species-specific allometric equations applied to DBH predictions derived from LiDAR variables, with design-based residual correction based on simulated DBH for field-verified effective trees in the t1 probability sample and simulated tree responses at t6. Grassland biomass carbon is reported as a sequence of annual flows derived from repeated NDVI-assisted dry-matter estimation under the D–W–D–D–W–D sequence. Shrub carbon is represented as a persistent stock using estimated shrub cover and a synthetic relationship between shrub cover and biomass. Because this relationship has not been empirically calibrated for the study area, the shrub-carbon results are illustrative.

The results illustrate the contrasting temporal behaviour of the ecosystem components. Trees and shrubs are treated as persistent living-biomass carbon stocks, whereas annual grassland biomass carbon is reported separately as a transient flow and is not accumulated as carbon removal. The example estimates changes in the total living woody biomass carbon stock of the monitored Dehesa, including pre-existing trees and shrub vegetation, and is therefore relevant to ecosystem monitoring. However, these estimates should not be interpreted as carbon removals eligible for CRCF certification. Under the currently adopted eligibility rules, growth in the carbon stock of vegetation already present before submission of the activity plan is excluded from the temporary net carbon removal benefit. Only biomass carbon attributable to planting, seeding, or measures promoting natural regeneration implemented as part of the certified activity may be eligible, subject to the applicable baseline, additionality, uncertainty, associated emissions, and monitoring requirements (European Commission, 2026).

The associated datasets, scripts, intermediate products, and numerical outputs are available in the corresponding repository module, whose README documents the complete reproducible workflow.

Surveys for assessing biodiversity

In this section, biodiversity is represented by measurable attributes of species composition and diversity estimated from repeated probability samples. Rather than examining the ecological mechanisms underlying biodiversity change, we illustrate how species probabilities and diversity indices, together with their temporal changes, can be estimated under the proposed sampling framework. Earth observation auxiliary data may be incorporated through model-assisted procedures to potentially improve estimation precision.

Species richness and relative abundance are key dimensions of biodiversity and habitat conservation assessment (Hill, 1973; Magurran, 2004; Rodríguez-Rojo et al., 2022). We represent community composition through the probability distribution of observations across species or predefined ecological groups. The general framework can be applied to different vegetation layers and faunal groups, whereas the numerical illustrations focus specifically on the composition of herbaceous functional groups and bird assemblages.

Measures

Let K denote the number of possible species or predefined ecological groups considered for a given community, and let $\boldsymbol{\mu} = (\mu_1, \dots, \mu_k, \dots, \mu_K)$ denote the corresponding composition vector, where μ_k is the probability that an observation—such as a vegetation contact or faunal detection—is classified in category k, and $\sum_{k=1}^{K} \mu_k = 1$. When the categories correspond to species, richness is the number of species with $\mu_k > 0$, while evenness describes how uniformly observations are distributed among the species present (Magurran, 2004). When categories represent broader ecological groups, as in Numerical Example 5, $\boldsymbol{\mu}$ describes group composition rather than species richness.

The Shannon index summarizes community composition through the entropy function $H = -\sum_{k=1}^{K} \mu_k \ln(\mu_k)$, with $0 \ln(0)$ defined as zero (De'ath, 2012; Magurran, 2004; Shannon, 1948a, 1948b). Over K possible categories, H ranges from zero, when all observations belong to a single category, to $\ln(K)$, when observations are equally distributed among all categories. When the categories correspond to species, the index reflects both richness and evenness; when broader ecological groups are used, it describes the diversity of their compositional distribution.

Shannon entropy is not expressed on an effective-number scale, which can limit its direct ecological interpretation. Hill numbers complement it by expressing diversity as the effective number of equally represented species or categories and by allowing sensitivity to rare and dominant community components to vary with the order q (Hill, 1973). In particular, diversity of order $q = 1$, is the exponential of Shannon entropy; diversity of order $q = 0$ equals the number of represented species or categories; and diversity of order $q = 2$ places greater emphasis on richness and dominant categories, respectively. Hill-number indices are derived from the same estimated composition vectors used for Shannon diversity, with uncertainty requiring appropriate propagation through the corresponding nonlinear transformations.

In practice, the composition vector $\boldsymbol{\mu}$ is unknown and must be estimated from probability-sample observations, using sampling weights and, where appropriate, EO-derived auxiliary variables. Biodiversity can then be evaluated at complementary spatial scales. Shannon alpha diversity, H_α, is the appropriately weighted mean of local diversity across sampling units; gamma diversity, H_γ, is the Shannon entropy of the habitat-level composition vector; and additive beta diversity is defined as $H_\beta = H_\gamma - H_\alpha$, representing the compositional differentiation among sampling units (De'ath, 2012; Lande, 1996; Magurran, 2004). When

the categories are ecological groups rather than species, these measures describe diversity and heterogeneity in group composition.

Because these indices are nonlinear functions of the design-based estimators of composition probabilities, they can be estimated by substitution at each monitoring occasion and used to assess temporal changes in biodiversity. The Shannon indices $H_{\alpha,t}$, $H_{\beta,t}$, and $H_{\gamma,t}$, together with the corresponding Hill-number diversity indices, are computed at the initial and final monitoring occasions ($t = 1$ and $t = T$), and their changes are evaluated using the longitudinal variance structure appropriate to the corresponding sampling design. For area-based samples under a strict panel design, repeated observation of the same panel units permits estimation of the covariance between occasion-specific estimators, which must be incorporate into the variance estimator for biodiversity change under longitudinal monitoring (Fuller, 1999).

Multinomial logit model

For pixel p in farm i, community composition is represented by the probability vector $\boldsymbol{\mu}_{ip} = \left(\mu_{ip1}, \dots, \mu_{ipk}, \dots, \mu_{ipK}\right)^T$, where $\mu_{ipk}$is the probability that an observation is classified as species or ecological group k , and $\sum_{k=1}^{K} \mu_{ipk} = 1$. A multinomial logit model relates $K - 1$ category logits to the EO auxiliary-variable vector $\boldsymbol{x}_{ip}$, with one category serving as the reference. Sampling weights derived from the probability design are incorporated into model fitting. As with the linear and binomial-logit models used for the preceding indicators, the multinomial model acts as an assisting relationship: EO variables may improve estimation precision, but the fitted relationships are not interpreted as evidence of ecological causality (Firth & Bennett, 1998; Särndal et al., 1992).

Ground observations, sampling weights, and EO auxiliary variables are combined to obtain occasion-specific pixel-level estimates $\widehat{\boldsymbol{\mu}}_{ip}$. These estimates are used to derive local and habitat-level Shannon and Hill-number diversity measures. Temporal change and its uncertainty are evaluated using the strict-panel variance-covariance structure for area-based samples and the independent-occasion variance structure for LIS samples based on independently placed transects. Complete model specifications and variance–covariance expressions are provided in Section 3.2.3 of the Supplementary Material.

Biodiversity monitoring for vegetation and low-mobility fauna

The area-based probability-sampling framework applies most directly to biodiversity observations that can be assigned to fixed spatial sampling units, such as pixels, quadrats, or microhabitats. It can be used for vegetation and may be extended to low-mobility fauna when the target population, inclusion probabilities, and detection protocol can be defined in relation to those spatial units.

For biodiversity components satisfying these conditions, observations can be collected within the same area-based probability-sampling framework used for vegetation monitoring. The same spatial units are revisited under the strict panel design, although the organisms observed within them need not be the same at each occasion. Occasion-specific composition and diversity indicators are estimated from the resulting observations, and the estimated covariance between occasion-specific estimators is incorporated into the variance estimator of temporal change.

EO-derived spectral indices, structural metrics, and habitat descriptors may be incorporated as predictors in the multinomial assisting model. Their potential to improve estimation precision depends on their empirical association with observed composition and should be evaluated for each application. The resulting occasion-specific composition estimates are used to calculate the Shannon and Hill-number diversity measures described above.

Numerical illustration

Numerical Example 5 applies the multinomial framework to herbaceous functional-group composition in the same 15.52-ha Dehesa study area used in the preceding examples. The strict panel comprises 30 pixels—5 in the tree stratum and 25 in the no-tree stratum—with four permanent quadrats per pixel. At each monitoring occasion, 50 simulated point-intercept contacts are generated in every quadrat and classified as grasses, legumes, or others. Wet-season NDVI derived from Sentinel-2 imagery is used as auxiliary information in the estimation of functional-group composition across the monitored area.

The example illustrates how fixed-area point-intercept observations, probability-sampling weights, and Sentinel-2 auxiliary information can be combined to estimate functional-group composition and its temporal change. Shannon and Hill-number measures derived from the three functional-group probabilities describe diversity in group composition rather than species diversity. Because the illustration includes only one farm, the first-stage between-farm variance component cannot be estimated; consequently, the reported uncertainty reflects only the within-farm sampling stages and does not support population-level inference across farms. The complete implementation and results are presented in Numerical Example 5. The associated datasets, scripts, intermediate products, and numerical outputs are available in the corresponding repository module, whose README documents the reproducible workflow.

Biodiversity monitoring for highly mobile fauna

The EU Birds Directive establishes conservation and reporting obligations for wild bird populations. Under its current Article 12 reporting framework, Member States are required to report every six years on the implementation and main impacts of the measures adopted under the Directive, including information on the status and trends of wild bird species (European Commission, 2023; European Parliament & Council of the European Union, 2009, 2019). This requirement creates a need for repeatable and statistically based monitoring information. Highly mobile or difficult-to-detect fauna pose particular sampling challenges because individuals cannot generally be assigned permanently to fixed spatial units and their probability of detection may vary among observations. Wildlife surveys commonly address these problems through line-transect distance sampling, in which detection probability is modelled as a function of perpendicular distance and, potentially, additional covariates (Buckland et al., 2001; Thomas et al., 2010).

The present study does not develop distance-sampling detection models. Instead, it considers a deliberately simplified extension to mobile fauna of the classical line-intersect sampling (LIS) result derived for fixed spatial objects (de Vries, 1986, pp. 247–248; Gregoire & Valentine, 2003; Kaiser, 1983; Thompson, 2012). Its purpose is to illustrate how detections with geometrically defined inclusion probabilities can be incorporated into the general probability-sampling and model-assisted monitoring framework. Temporal change is estimated as the difference between occasion-specific estimates obtained from independent LIS samples at the initial and final monitoring occasions.

Line-intersect sampling (LIS)

Line-intersect sampling (LIS) selects spatial objects according to whether they are intersected by randomly located transect lines, with inclusion probabilities determined by the geometry of the objects and the sampling lines (de Vries, 1986; Gregoire & Valentine, 2003; Kaiser, 1983; Thompson, 2012). Here, this result is adapted only to an idealized encounter process in which each bird remains at a fixed location until the observer reaches its associated circular flushing zone. This construction is intentionally simpler than line-transect distance sampling and is not proposed as a replacement for detection-function modelling.

Unlike vegetation monitoring, where pixels or quadrats provide natural area-based sampling units, highly mobile fauna often lack a stable spatial partition compatible with repeated surveys. In the simplified formulation used here, LIS bases inclusion probabilities on encounter geometry rather than on fixed

observational plots. At each monitoring occasion, bird locations immediately before the survey are treated as fixed for design-based inference, and transect placement is selected independently of those locations.

LIS detection geometry and inclusion probabilities

Consider farm i, of area A_i, and a straight transect segment of length L whose location and orientation are selected at random. Immediately before surveying, bird j occupies a fixed location and has an associated circular flushing zone of radius r_{ij}. In the numerical illustration, individual flushing radii are generated from species-specific distributions and may therefore vary among individuals of the same species. The bird is included when the observer advancing along the transect intersects its flushing circle, causing it to flush. The observer records the species and estimates the distance between the observer's position at flushing and the bird's pre-flushing location; under the assumed geometry, this distance equals r_{ij}.

Applying the endpoint convention specified by de Vries (1986, pp. 247–248), the set of transect placements that includes bird j in farm i has area $2r_{ij}L$. Therefore, conditional on farm i having been included in the first-stage sample, the second-stage inclusion probability of bird j is $\pi_{j|i}^{(2)} = \frac{2r_{ij}L}{A_i}$, provided that $2r_{ij}L \leq A_i$. If m farms are selected at the first stage with inclusion probabilities proportional to their areas, so that $\pi_i^{(1)} = \frac{mA_i}{A}$, where $A = \sum_i A_i$ is the total area of the farm population, the overall inclusion probability of bird j in farm i is $\pi_{ij} = \pi_i^{(1)}\pi_{j|i}^{(2)} = \frac{2mr_{ij}L}{A}$. Thus, birds with larger flushing distances have higher inclusion probabilities. Inverse-probability estimators can consequently be constructed for total abundance and species-specific totals, with species proportions obtained from the corresponding ratio estimators. This result requires birds to remain at their initial locations until flushing, transects to be located independently of bird positions, every valid intersection to result in detection, and individuals not to be counted more than once.

Integration of LIS with the monitoring framework

Although its sampling geometry differs from the area-based framework, this simplified LIS design can be incorporated into the same general probability-sampling approach, as described in Section 3.2.3 of the Supplementary Material. A probabilistic sample of farms is selected at the first stage, while independent random transect samples are selected within farms at each monitoring occasion. The de Vries endpoint convention excludes the specified single intersections generated by a segment endpoint, thereby preserving the inclusion area $2r_{ij}L$ rather than adding a circular endpoint term.

Boundary effects must be handled separately from the endpoint convention. In the simplified implementation, a minus-sampling rule is assumed: birds whose circular flushing zones intersect the farm boundary are excluded from both the eligible population and the sample, so inference applies to the corresponding interior population. When LIS observations are combined with EO covariates—such as shrub cover, canopy structure, or NDVI within detection zones— model-assisted estimators may improve precision while retaining design-based inference. Because LIS samples are independent between occasions, the variance of change is estimated as the sum of the occasion-specific variances. The operational performance of this simplified extension, including the assumed flushing and detection process, requires empirical validation, as discussed under Limitations of the study.

Model-assisted estimation of biodiversity

Model-assisted estimation provides a principled way to integrate Earth observation information with fauna detections obtained through the simplified LIS design, subject to the sampling and detection assumptions described above (Firth & Bennett, 1998; Särndal et al., 1992; Thompson, 2012). The objective is to potentially improve the precision of estimates of biodiversity indicators, including composition

probabilities, Shannon diversity measures, and related Hill-number indices, while retaining design-based inference.

Under the simplified LIS formulation, faunal detections depend on encounter geometry and species-specific flushing behaviour, resulting in unequal inclusion probabilities and potentially sparse samples for some species. EO predictors—including NDVI, shrub cover, canopy structure, and LiDAR-derived habitat metrics—may characterize environmental gradients associated with species occurrence and relative abundance. When incorporated into the multinomial logit framework introduced in Section 3.2.3 of the Supplementary Material, these predictors may improve the precision of biodiversity estimates while maintaining design-based inference; the magnitude of any precision gain remains to be established empirically.

Model-assisted species probability estimation

Let y_{ijpkt} be the species indicator for individual j detected in farm i via LIS at monitoring occasion t, and let $\mathbf{x}_{ipt}$ be the EO predictors summarized for pixel p to which the detection location is assigned. The multinomial logit model introduced in Section 3.2.3 of the Supplementary Material provides occasion-specific species-probability estimates $\hat{\mu}_{ipkt}$, representing model-assisted predictions of relative species abundance at the pixel scale for each monitoring occasion.

Once $\hat{\mu}_{ipkt}$ is obtained, biodiversity indicators follow directly, including pixel-level Shannon indices H_{ipt} together with habitat-level α, γ, and β diversity measures. Related Hill-number diversity indices can be derived from the same estimated species probabilities, providing complementary measures of effective diversity and alternative sensitivities to rare and dominant species. These biodiversity indicators can then be used to estimate temporal changes between the initial and final monitoring occasions, within the repeated-survey framework adopted in this study.

Numerical illustration

The proposed framework uses strict panels for area-based habitat and vegetation indicators, allowing temporal covariance to be incorporated into uncertainty estimation for change. For highly mobile fauna, it instead uses independent LIS samples at successive monitoring occasions. Numerical Example 6 shows computationally how detections generated under the simplified de Vries geometry and EO-derived habitat covariates can be combined within a design-based repeated-survey framework. It should be interpreted as a methodological demonstration rather than as an empirical validation of the assumed flushing process, the precision gains, or comparative performance against line-transect distance sampling. The corresponding repository README documents the datasets, scripts, intermediate products, numerical outputs, and reproducible workflow.

Limitations of the study

The proposed framework draws on established probability-sampling, model-assisted estimation, and repeated-survey methods (Firth & Bennett, 1998; Fuller, 1999; Särndal et al., 1992). Evidence from agricultural and environmental applications supports the use of EO auxiliary data to improve the efficiency of estimators based on ground observations collected from area samples (Ambrosio et al., 2023; Ambrosio Flores & Iglesias Martínez, 2000). Nevertheless, the numerical examples use data from a single 15.52-ha Dehesa study area, where field verification established effective-tree status at t1, while sampled-tree DBH and young status, t6 tree observations, and other illustrative responses were simulated. Consequently, the reported precision gains and ecological changes should not be generalized without further evaluation at independent sites using operational field data.

A further limitation concerns highly mobile fauna. The proposed LIS extension relies on an idealized flushing-circle representation, fixed bird locations until flushing, certain detection at a valid intersection, the de Vries endpoint convention, and explicit boundary treatment. These assumptions are more restrictive than those accommodated by line-transect distance-sampling methods (Buckland et al., 2001; Thomas et al., 2010). Conditional on the stated sampling geometry, combining LIS with model-assisted estimation using pixel-level EO covariates remains design consistent. What remains to be assessed empirically is the adequacy of the assumed encounter process and the extent to which EO assistance improves precision relative to survey cost. Numerical Example 6 therefore demonstrates computational feasibility but does not establish robustness to animal movement, imperfect detection, or departures from the assumed flushing geometry. Future research should evaluate performance through replicated field surveys, comparison with distance-sampling detection models, and sensitivity analyses across habitats and monitoring occasions.

Conclusions

The framework developed in this study provides a unified probability-sampling approach for monitoring indicators relevant to habitat conservation status and ecosystem functioning in heterogeneous agroecosystems such as the Dehesa. By combining probabilistic multistage sampling with model-assisted estimators based on Earth observation (EO) data, it enables design-based inference for a broad set of ecological indicators, including vegetation structure, grassland condition, shrub dynamics, biodiversity, and carbon stocks and removals, thereby supporting carbon-farming monitoring applications.

A central contribution of the proposed approach is the integration of repeated surveys through a strict panel framework for area-based habitat and vegetation indicators, while monitoring of highly mobile fauna is illustrated using independent LIS samples at successive occasions. For area-based indicators, this longitudinal structure can improve the precision of change estimates when occasion-specific estimators are positively correlated, because their covariance is incorporated into the variance estimator for change. This structure provides a basis for long-term environmental monitoring and conservation assessment.

The study also demonstrates how biodiversity monitoring can be coherently integrated within the same probabilistic inferential framework across different ecological components. Area-based sampling using pixels, quadrats, or microhabitats provides a suitable basis for vegetation and may be extended to low-mobility fauna when the target population, inclusion probabilities, and detection protocol can be defined in relation to fixed spatial units. The deliberately simplified LIS extension illustrates a probability-sampling approach for highly mobile fauna under explicitly stated encounter assumptions.

The integration of ground observations with Sentinel-2, LiDAR, and other EO-derived predictors can support implementation of the proposed framework. These auxiliary variables may characterize spatial gradients in vegetation structure and habitat composition and, when incorporated through model-assisted estimators, may improve estimation precision while preserving design-based inference under the probability-sampling design. This combined EO–survey strategy may be particularly useful in large-scale monitoring contexts in which exhaustive field observation is not operationally feasible.

The proposed methodology is relevant to developing MRV systems associated with climate and biodiversity policy frameworks, including carbon-removal and carbon-farming certification, habitat conservation assessment, and biodiversity reporting under European Union regulations. By providing design-based estimators of both indicator levels and temporal changes, together with explicit uncertainty quantification, the framework can contribute to greater transparency, comparability, and reproducibility in ecosystem monitoring systems.

More broadly, the study contributes to bridging statistical survey theory, Earth observation, and policy-oriented environmental monitoring. The proposed framework may support applications beyond Dehesa

ecosystems, including other agroecosystems and semi-natural landscapes where integrated monitoring of biodiversity, ecosystem functioning, and carbon dynamics is required, subject to adaptation and independent validation.

Finally, the combination of probability sampling, model-assisted estimation using EO covariates, repeated-survey inference, and reproducible computational workflows provides a coherent methodological basis for environmental monitoring systems in which multiple ecological indicators are assessed and their uncertainty is explicitly quantified over time.

Data availability

During peer review, the complete repository supporting the numerical illustrations is available to editors and reviewers through a private, read-only Zenodo link. The shared record is an unpublished, version-controlled draft. A DOI-tagged public release will be deposited upon acceptance.

Statements and declarations

Ethical responsibilities. The author has read, understood, and has complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

Funding: The author received no specific funding for this work.

Competing interests. The author has no relevant financial or non-financial interests to disclose.

Author contributions. The author conceived and designed the study, developed the methodology, performed the analyses, prepared the data and code, and wrote and approved the manuscript.

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