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Report on the improvement of ecological effectiveness of collaborative schemes through multiscale spatiotemporal modeling of biodiversity indicators and their relations with environmental and anthropic drivers

Deliverable 2.7 (D14) v2.1

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SHOWCASE

SHOWCASing synergies between agriculture, biodiversity and Ecosystem services to help farmers capitalising on native biodiversity

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Review of contents

To ensure the quality and consistency of this deliverable, we implemented an internal review and validation process. The deliverable was drafted by the work task leader (CNR). All SHOWCASE EBA partners having carried out the field surveys and biodiversity indicator data collection, reviewed the draft D2.7 document and had the chance to make amendments and comments, which were then integrated by the task leader. A further quality check has been provided by the WP2 leader. Finally, the draft version was submitted to the project coordinator, for final review and validation.

Acknowledgments

We thank all SHOWCASE EBA partners for their support in carrying out Task 2.7 and delivering the biodiversity indicator data necessary to perform the spatiotemporal modelling and all the analyses reported in this Deliverable.
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Moreover, we thank all partners for reviewing the Deliverable and supporting us with comments and amendments. Finally, we thank all farmers and external experts for providing time and information and supporting the data collection process.

Summary

The report presents the results of project Task 2.7 tackling the spatiotemporal modelling and the upscaling from the field to the landscape scale of five SHOWCASE core biodiversity indicators: wild bee abundance and species richness, spider abundance and species richness, and vascular plant species richness. The indicators have been modelled in five case study areas (CSAs) encompassing the SHOWCASE EBAs in Hungary (Kiskunság), Spain (Guadalquivida), Portugal (Alentejo), the Netherlands (Zuid Limburg) and Switzerland (Solothurn).

After a brief introduction in **Chapter 1** of the state of the art and the goals of Task 2.7, **Chapter 2** of the Deliverable describes the methodology adopted to model the impacts of the implementation of biodiversity friendly farm management, as implemented by project partners in the SHOWCASE EBA fields. For all the EBAs with available data for the two years of surveys, a set of common predictors were associated with field data, providing a harmonized set of covariates to be used for the spatiotemporal modelling. The set of covariates encompasses terrain attributes, landscape structure descriptors, indices from remote sensing describing vegetation and soil status, and variables describing the implementation of the biodiversity friendly management practices. All the predictor data used are extracted from free data sources resorting as much as possible to EU official data sets. To fulfill the goal of upscaling field results, two different data driven approaches were tested: machine learning algorithms, in particular Random Forest (RF), and multiple linear regressions (MLR). Based on a set of error indices, the most accurate model was selected for each indicator in each CSA. The use of the measured and modelled biodiversity indicators as proxies of ecosystem services provision in the five EBAs is also discussed. Data driven model results for pollinator abundance were compared with the outcomes of the mechanistic model of Lonsdorf et al (2009), and selected ecosystem services were identified based on biodiversity indicator data as foreseen in the description of Task 2.7.

Chapter 3 of the Deliverable reports the results of the spatiotemporal modelling in each CSA for the five selected indicators, expressed as 0-1 interval normalized scores. In all cases MLRs outperformed RFs in terms of accuracy and agreement with observed data. A sixth composite indicator was calculated by summing and normalizing the five considered indicators. Raster maps at 10m resolution are presented for each indicator, for the two rounds of sampling of the two years under two different management scenarios: control and intervention. A total of 240 indicator maps were produced and analyzed. These maps provide a spatially explicit and time dynamic assessment of the potential impact of the implementation of biodiversity friendly management practices at landscape scale.

Chapter 4 of the Deliverable focuses on the comparison of the mechanistic and data driven model results for pollinator occurrence in the five selected EBAs, focusing on the impacts of the different drivers in the two approaches and on the resulting spatial patterns.

Chapter 5 closes the Deliverable by first comparing the biodiversity indicators modelling results across the five CSAs, as well as the related ecosystem services estimates and maps, and then summarizing the key findings of Task 2.7, providing an outlook on their further use for scientific analyses within SHOWCASE.

List of abbreviations

AE Absolute Error
API Application Programming Interface
BI Bare Index
BioDiv Biodiversity Indicator
CICES Common International Classification of Ecosystem Services
CLC CORINE Land Cover
CSA(s) Case Study Area(s)
DEM Digital Elevation Model
EBA Experimental Biodiversity Area
EEA European Environmental Agency
EU European Union
ES Ecosystem Services
GEE Google Earth Engine
GIS Geographic Information System
IoA Index of Agreement
IR Infra-Red
LUCAS Land Use / Cover Area frame statistical Survey
LULC Land Use/Land Cover
ME Mean Error
ML Machine learning
MLR Multiple Linear Regression
MSR Mean Square Residual
NDBSI Normalized Difference Bare Soil Index
NDSI Normalized Difference Soil Index
NDVI Normalized Difference Vegetation Index
NDWI Normalized Difference Water Index
NIR Near Infra-Red
NPP Net Primary Production
OSM Open Street Map
PlaR Plant species Richness (Indicator)
RF Random Forest
RMSE Rooted Mean Square Error
R^2 R squared
RS Remote Sensing
RSI Remote Sensing Index/Indices
SASI Soil Adjusted Salinity Index
SoSa Soil Salinity

SoSI Soil Salinity Index

SpA Spider Abundance (Indicator)

SpR Spider species Richness (Indicator)

SWF Small Woody Features

SWIR Short Wave Infra-Red

TWI Topographic Wetness Index

WBA Wild Bee Abundance (Indicator)

WBR Wild Bee species Richness (Indicator)

1 Introduction

Within the overall objective of SHOWCASE, i.e. to make biodiversity an integral part of European farming by identifying effective incentives to invest in biodiversity in diverse socioecological contexts, Task 2.7 contributes to an improved understanding of the spatial and temporal interrelations and mechanisms between the location and time of implementing biodiversity management and its effects on biodiversity indicators based on spatially explicit data. The underlying assumption is that the adoption of incentives that successfully modify farm management and enhance biodiversity results in land use/land cover changes that positively affect biodiversity indicators at different scales with an impact on the supply of biodiversity-based ecosystem services. Task 2.7 aimed to calibrate spatially explicit predictive models with classical statistical approaches (e.g. multiple linear regressions) and machine learning techniques (e.g. random forests) for mapping biodiversity indicators under two different management scenarios (i.e. implementation vs. control). To this goal, normalized biodiversity indicators derived from the biodiversity data collected in a group of selected EBAs under the two different management scenarios were used as inputs along with a uniform set of environmental covariates over a given spatial domain.

These sets of predictors for each EBA were entirely derived from freely available web resources and were integrated with Copernicus-Sentinel 2 remote sensing indices (RSI) retrieved via Google Earth Engine (GEE). Remote sensing (RS) represents a precious source of data which are spatially explicit, cost-effective, rapidly assessed, available for almost any area around the globe, multi-temporal and at a spatial resolution which is feasible for most ecosystem services (ES) assessment applications. The number of RS applications to ES assessment and mapping has increased significantly in the last decade and has addressed mostly provisioning services, such as timber and food production, and regulatory services, including air quality, climate regulation, extreme events prevention and control, waste treatment, erosion control, biodiversity, and soil fertility (Anayu et al., 2012). A systematic review of literature on RS of ES is provided by de Araujo Barbosa et al. (2015) who concluded that data and products provided by RS alone do not have the capabilities to effectively assess and map the full range of ES, and therefore there is the need for an integrated approach through the fusion of remotely sensed data with information from other sources (del Río-Mena et al., 2023; Awada et al., 2022; del Río-Mena et al., 2020; Thomas et al., 2020; Zhang, 2010; Zhu et al., 2018).

The use of RS products in monitoring, assessing, and mapping biodiversity is becoming increasingly popular due to its efficiency and high automatism (Luque et al., 2018; Wang and Gamon, 2019) and to the possibility to collect data and information over large areas and at a great frequency. Recent advancements in RS and Earth observation offer accessible and promising possibilities for large-scale biodiversity monitoring (Petrou et al.,2015), and provide extensive coverage, allowing for biodiversity upscaling from field to landscape and regional scales (Gamon et al., 2020). Examples range from mapping epiphytic plant communities (Palmroos et al., 2023) to bees and pollination related services (Galbraith et al., 2015), from mapping floral resources for pollinators (Gonzales, 2022) and pollination types (Feilhauer et al., 2016), to direct and indirect detection of insects (Rhodes at al., 2022; Wang et al., 2023).

Data and products provided by RS for ES assessment and mapping include, among many others, land cover maps for ecosystem extent, indicators of ecosystem conditions, phenology, NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), Leaf Area Index, NPP (Net Primary Production), terrain attributes such as slope, aspect and elevation, damage impacts and ecosystem structure (LiDAR, SAR). These data and products provide spatially explicit and, in the case of RSI, time-variant information that can be successfully used as a proxy to assess and map biodiversity indicators and their variation over time.

In general, the assessment of ES indicators via RSI is an indirect process. This means that the remotely sensed information is used as a proxy for some kind of variable (e.g., biomass provision) which in turn is used as a proxy for the actual ES (e.g., habitat for biodiversity). According to literature, two different approaches are commonly used to estimate in bio-physical units the variables which underpin the provision of a given ES. The first category directly uses the remotely sensed spectral signature or derived composite indexes and includes statistical regressions and/or radiative transfer models. The second approach uses RS data to generate land use/land cover classifications which are then linked to ES supply and used as input for physically based models of ES assessment.

This report builds on the contents of previous deliverable reports released by SHOWCASE partners, D1.3 (Overview of selected SHOWCASE biodiversity indicators, Séchaud et al., 2021), D1.2 (Experimental framework and standardized protocols for EBAs described in first version of a living document, Bretagnolle et al., 2021b), and D1.4 (Validated methods for testing reliability of landscape metrics-based biodiversity indicators, Torresani et al., 2023).

2. Upscaling biodiversity indicators from plot to landscape scale: predictors and methodological approach

2.1. Input data and target variables

Among the various types of possible farmland biodiversity indicators, whose use depends on the scale considered, the specific context, and the expected application (Herzog and Franklin, 2016), all EBA project partners made a selection based on the following criteria: 1) scientific support, 2) relevance at the European scale, 3) ease of data collection, 4) cost-effectiveness, 5) ecological meaning and 6) relevance for stakeholders. A further distinction has been made between core indicators, i.e., those common to all EBAs, and optional indicators specific for each EBAs. The selection of biodiversity indicators to model and map focused on the following five core indicators:

- Wild bees: abundance (WBA) and species richness (WBR)
- Spiders: abundance (SpA) and species richness (SpR)
- Vascular plants: species richness (PlaR).

Wild bees are essential pollinators of farmland ecosystems, and their recent decline has attracted public attention and raised awareness of the link between biodiversity and ES (Matias et al., 2017). The factors behind their decline are multiple and complex, but habitat destruction, pesticide application and the loss of floral resources (and year-long availability) have been shown to be important (Drossart and Gérard, 2020; Goulson et al. 2015).

Spiders are a large group of predator species, with several of them preying on agricultural pest insects and thus reducing crop damages (Birkhofer et al., 2018; Riggi et al. 2024). Spiders are sensitive to farming practices, and to vegetation composition and structure, therefore being good indicators of management at field level (Rusch et al., 2014).

Farmland vascular plants are the primary producers at the basis of the food chain, being thus essential to the maintenance and stability of higher trophic levels. Vascular plant diversity or richness is particularly sensitive to field management (Moreira et al, 2023), but also to the presence of pollinators or seed dispersers. Therefore, vascular plants are strong indicators of total biodiversity across environmental gradients and broad taxonomic realms (Brunbjerg et al., 2018), and they are widely studied and well documented.

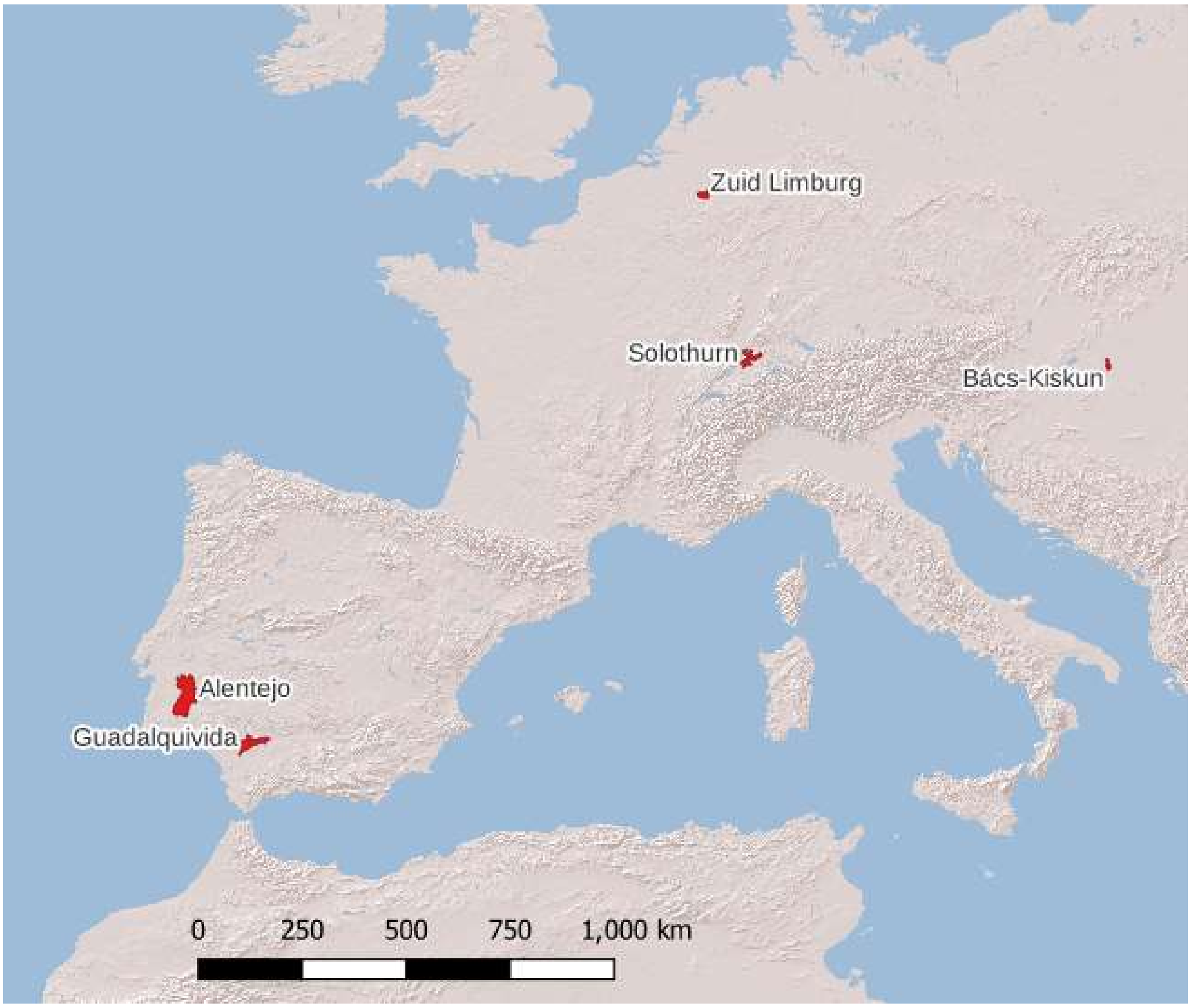

Figure 1: Case study areas for upscaling EBA biodiversity core indicators: Hungary (small part of the Bács-Kiskun county), Portugal (Evora in Alentejo Central, and Beja in Baixo Alentejo), Spain (Guadalquavida), Switzerland (Solothurn), and the Netherlands (Zuid-Limburg).

The five biodiversity core indicators have been modeled and upscaled from the field to the landscape scale in five EBAs (Figure 1). All the EBAs with field data for the two years 2022 and 2023 were considered, with the addition of the 2022 data from the Swiss EBA whose numerosity and timely availability allowed for the analysis to be carried out in time to meet the deadline of the present deliverable.

As the EBAs have been described in detail in a previous project deliverable report (Bretagnolle et al., 2021a), only the information necessary for the biophysical contextualization of the spatiotemporal dynamics of biodiversity indictors will be provided in this report. General information about the CSAs where the selected EBAs are located is provided in Table 1.

Table 1: Scale of assessment, target area and land use in the five selected SHOWCASE EBAs.

EBA	Target area	Extent of spatial assessment (and resolution)	Elevation range (m a.s.l.)	Target land use
HU	Bács-Kiskun	200.2 km^2 (10 m)	89-105	Arable land
ES	Guadalquivida	433.2 km^2 (10 m)	2-347	Permanent crops (stone fruit orchards)
PT	Municipalities of Evora, Portel, Cuba, Vidigueira and Beja	567.9 km^2 (10 m)	34-420	Permanent crops (olive orchards)
NL	Zuid-Limburg	170.0 km^2 (10 m)	5-317	Arable land
CH	Solothurn	196.6 km^2 (10 m)	321-796	Arable land

The modeling approach tested the predictive accuracy of two distinct statistical methods: a “classical” approach based on multiple linear regressions (MLR), and a machine learning (ML) technique, i.e. Random Forest (RF) (Jordan and Mitchel, 2015; Uddin et al, 2019). Such ML techniques have been recently used to map different environmental variables including plant and animal biodiversity (Cabezas et al., 2016; Melin et al., 2019; Zhao et al., 2022). In both cases, the same set of predictors were used in all CSAs. This required the creation of a stack of raster maps of the predictors for each CSA; to this end, all rasters were harmonized in terms of extent and reference systems. This was the same for all CSAs, i.e., the coordinate reference system ETRS89-LAEA Europe, also known in the EPSG Geodetic Parameter Dataset under the identifier: EPSG:3035, which represents the EEA and LUCAS reference grid.

In all CSAs, the raster stack of predictors for biodiversity indicators included the same set of 27 variables, belonging to four different groups:

1. Landscape elements: proximity to roads and proximity to Small Woody Features (SWF, Copernicus land Monitoring Services, CLMS 2018)
2. Terrain descriptors: elevation, aspect, slope, and their derivatives (8 variables)
3. Spectral signatures and RSI from Copernicus Sentinel 2 (14 variables)
4. Biodiversity management (3 variables)

The following table lists the predictors used for MLR calibration and RF implementation and their sources.

Table 2: List of predictors for upscaling SHOWCASE core biodiversity indicators.

Group	Predictor	Unit	Source	Resolution
1	Road proximity[a]	m	GIS calculation	10 m
1	SWF proximity[b]	m	GIS calculation	10 m
2	Elevation	m a.s.l.	Copernicus DEM	30 m
2	Aspect	degree from North	GIS calculation	30 m
2	Slope	%	GIS calculation	30 m
2	Catchment slope	%	GIS calculation	30 m
2	Catchment area	m^2	GIS calculation	30 m
2	Mod. Catchment area	m^2	GIS calculation	30 m
2	Topographic. wetness Index	m/rad	GIS calculation	30 m
2	Valley depth	m	GIS calculation	30 m
3	BI, bare Index	-	Sentinel 2, GEE	20 m
3	Blue (B2, 490 nm)	-	Sentinel 2, GEE	10 m
3	Green (B3, 560 nm)	-	Sentinel 2, GEE	10 m
3	IR, infra-red (B8, 842 nm)	-	Sentinel 2, GEE	20 m
3	NDBSI, Norm. Diff. Bare Soil Index	-	Sentinel 2, GEE	10 m
3	NDSI, Normalized Diff. Soil Index	-	Sentinel 2, GEE	10 m
3	NDVI, Norm. Diff. Vegetation Index	-	Sentinel 2, GEE	10 m
3	NIR, Near Infra-Red (B8A, 865 nm)	-	Sentinel 2, GEE	10 m
3	Red (B4, 665 nm)	-	Sentinel 2, GEE	10 m
3	SoSa, Soil Salinity	-	Sentinel 2, GEE	10 m
3	SoSI1, Soil Salinity Index1	-	Sentinel 2, GEE	10 m
3	SoSI2, Soil Salinity Index2	-	Sentinel 2, GEE	10 m
3	SoSI3, Soil Salinity Index3	-	Sentinel 2, GEE	10 m
3	SWIR Short Wave IR (B11,1610 nm)	-	Sentinel 2, GEE	20 m
4	Biodiversity Intervention	Dummy 0,1	EBA partners	-
4	Year of intervention	Dummy 0,1	EBA partners	-
4	Round	Dummy 0,1	EBA partners	-

[a] Source of vector data: Open Street Map. © OpenStreetMap contributors. Available under the Open Database License from: openstreetmap.org.
[b] Source of raster data (res. 5 m): https://land.copernicus.eu/en/products/high-resolution-layer-small-woody-features/small-woody-features-2018. https://doi.org/10.2909/a8e683b1-2f96-45c8-827f-580a79413018

Road proximity effects on forests and farmland biodiversity are well documented in the literature (Marcantonio et al., 2013; Fahrig et al. 2015; Bennet, 2017) due to their edge effects resulting in changes in the biotic and abiotic conditions, such as species composition, temperature, moisture, light availability, and wind speed (Delgado et al., 2007; Flory and Clay, 2009; Watkins et al., 2003). In agricultural landscapes where most of the native vegetation has been removed for cultivation, semi-natural road edges are considered valuable reservoirs of biological diversity because they may maintain several native plant communities (Delgado et al., 2007; Reed et al., 1996). To account for the influence of road networks on biodiversity indicators, a 10m resolution raster of the proximity to roads was created for each CSA (Figure 2) from the vector layers available from OpenStreetMap (OSM, 2021) and using GDAL (Rouault et al., 2024) raster analysis tools implemented in QGIS v3.22.11 (QGIS.org, 2022).

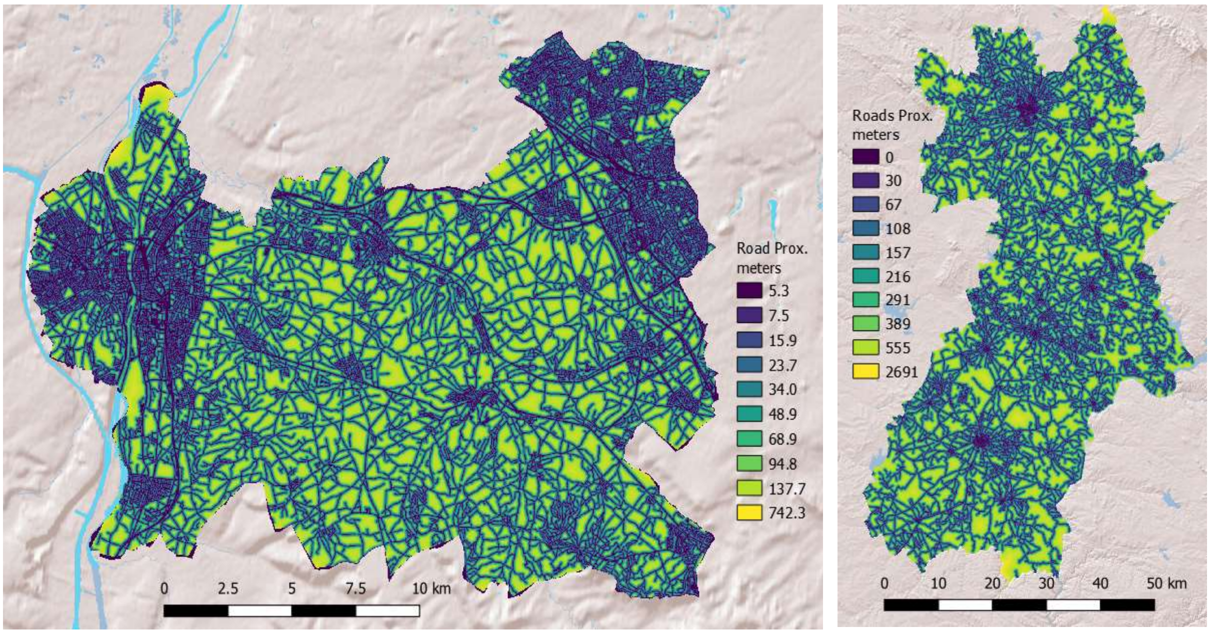

Figure 2: Examples of road proximity raster maps (resolution 10m) for the Dutch (left) and the Portuguese CSA.

To account for the effects on biodiversity abundance and richness due to the presence of landscape elements such as hedgerows, woodlots, isolated trees, and tree lines in the agrarian landscape, the 2018 5m resolution raster provided by EEA for the whole of Europe (Copernicus Land Monitoring Services, 2018) provided the basis to derive 10m resolution proximity maps in each CSA (Figure 3). These agricultural landscape features enhance the natural capital and support biodiversity, providing ES such as soil protection and pollination (Aviron et al., 2023; Czúcz et al., 2022; England et al., 2020).

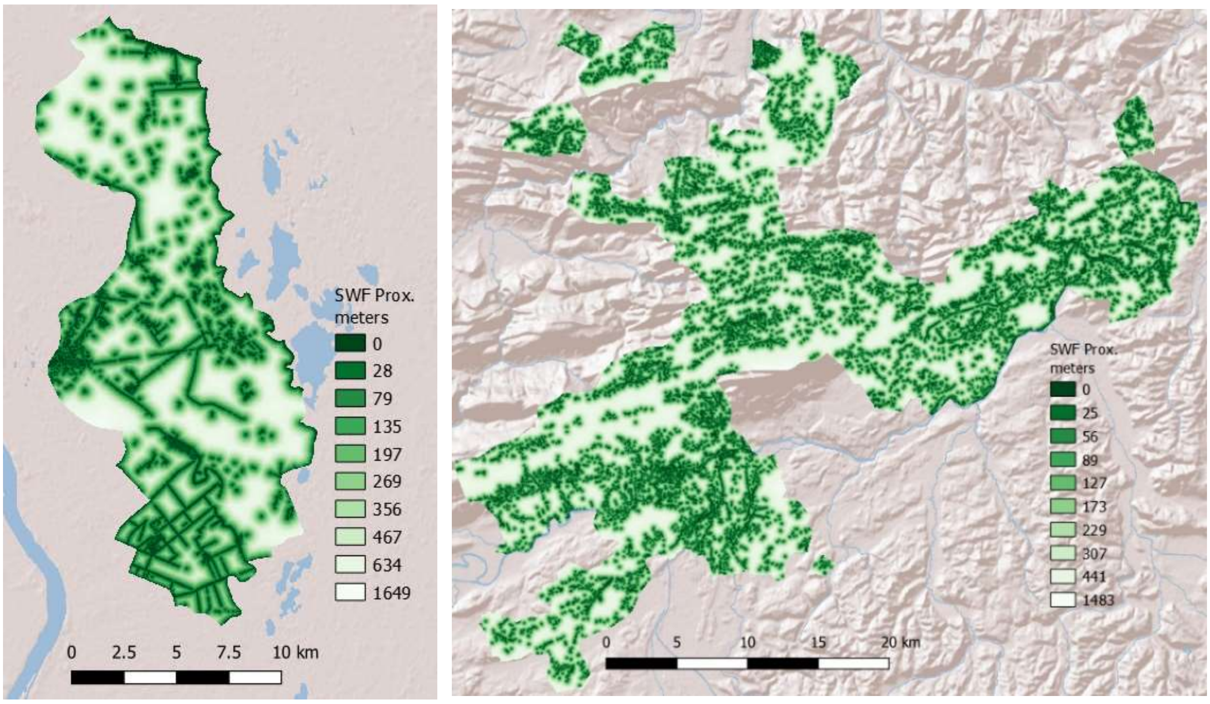

Figure 3: Examples of SWF proximity raster maps (resolution 10m) for the Hungarian (left) and the Swiss CSA.

The effects of local topography on biodiversity indicators were considered by including in the stack of predictors a set of eight terrain attributes derived from the Copernicus 30m resolution digital elevation model (DEM, Copernicus 2018) available for all CSAs (Figure 4). Topography is an important non-zonal factor affecting biotic and abiotic factors, with effects on vegetation patterns and characteristics (Yang and Da, 2006), species distribution (Cantón, 2004), and pollinator species richness (Le Clec'h et al., 2019), due to variations in natural illumination, temperature, moisture, and soil properties (Bennie et al., 2008, Carletti et al., 2008; Gong et al., 2008). The predictors derived from the DEM include aspect, slope, catchment slope, catchment area, modified catchment area, topographic wetness index, and valley depth (Boehner, and Selige, 2006), and were computed resorting to SAGA-GIS tools implemented in QGIS (Conrad et al., 2015).

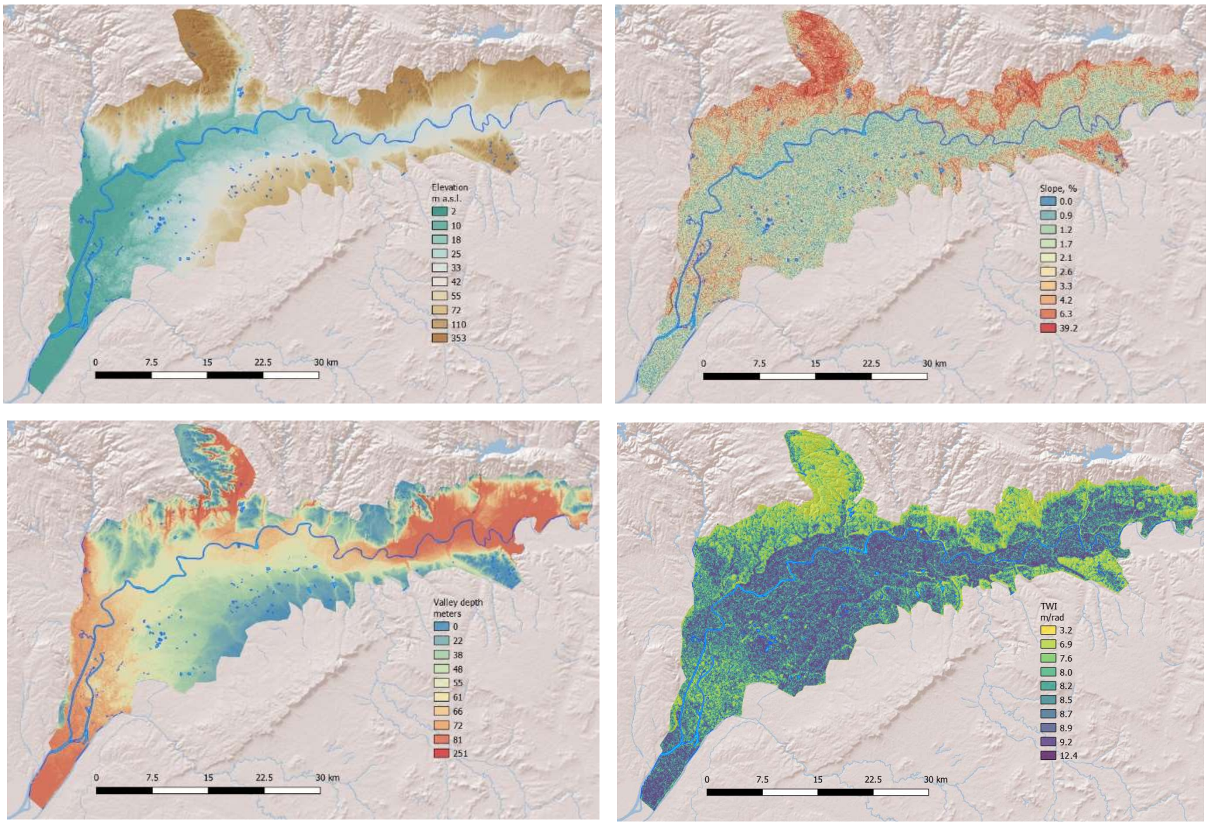

Figure 4: Examples of DEM derivates raster maps (resolution 30m) for the Spanish CSA: top-left elevation, top-right slope, bottom-left valley depth, and bottom-right topographic wetness index.

The third group of predictors is represented by time-dependent RS data. Using GEE (Gorelick et al, 2017) JavaScript API, available at the URL https://code.earthengine.google.com/, the vector layer with the boundary of each CSA was imported as an ESRI format shape file (EPSG 4326). As field surveys in each EBA occurred twice per year, a four-week time frame was set for each round of sampling to extract the required spectral bands. These were further used to calculate soil and vegetation RSI, such as the NDVI (Figure 5). For each band, it was possible to specify not only the time frame of interest and the % of cloud cover tolerance but also the statistics relevant to the goal of the assessment (e.g. median value, mean value, maximum). To upscale the SHOWCASE biodiversity core indicators, raster maps of monthly median values of RS images were extracted for each CSA, considering the time frame set by the two rounds of sampling and setting the cloud pixel percentage <10%. The following spectral bands were extracted for each sampling round each year (four weeks median value): **B2** (blue, central wavelength 490 nm), **B3** (green, central wavelength 560 nm), **B4** (red, central wavelength 665 nm), **B8** (IR, central wavelength 842 nm), **B8A** (IRn, central wavelength 865 nm) and **B11** (SWIR, central wavelength 1610 nm). The first four have a 10m spatial resolution, while the last two have a 20m spatial resolution. The above listed bands were used within the GEE JavaScript to calculate the following RSIs (Figure 3): **NDVI**, **NDBSI** (Normalized Difference Bare Soil Index), **NDSI** (Normalized Difference Soil Index), **BI** (Bare Index), **SoSI1** (Soil Salinity Index 1), **SoSI2** (Soil Salinity Index 2), **SoSI3** (Soil Salinity Index 3), and **SOSA** (SOil Salinity).

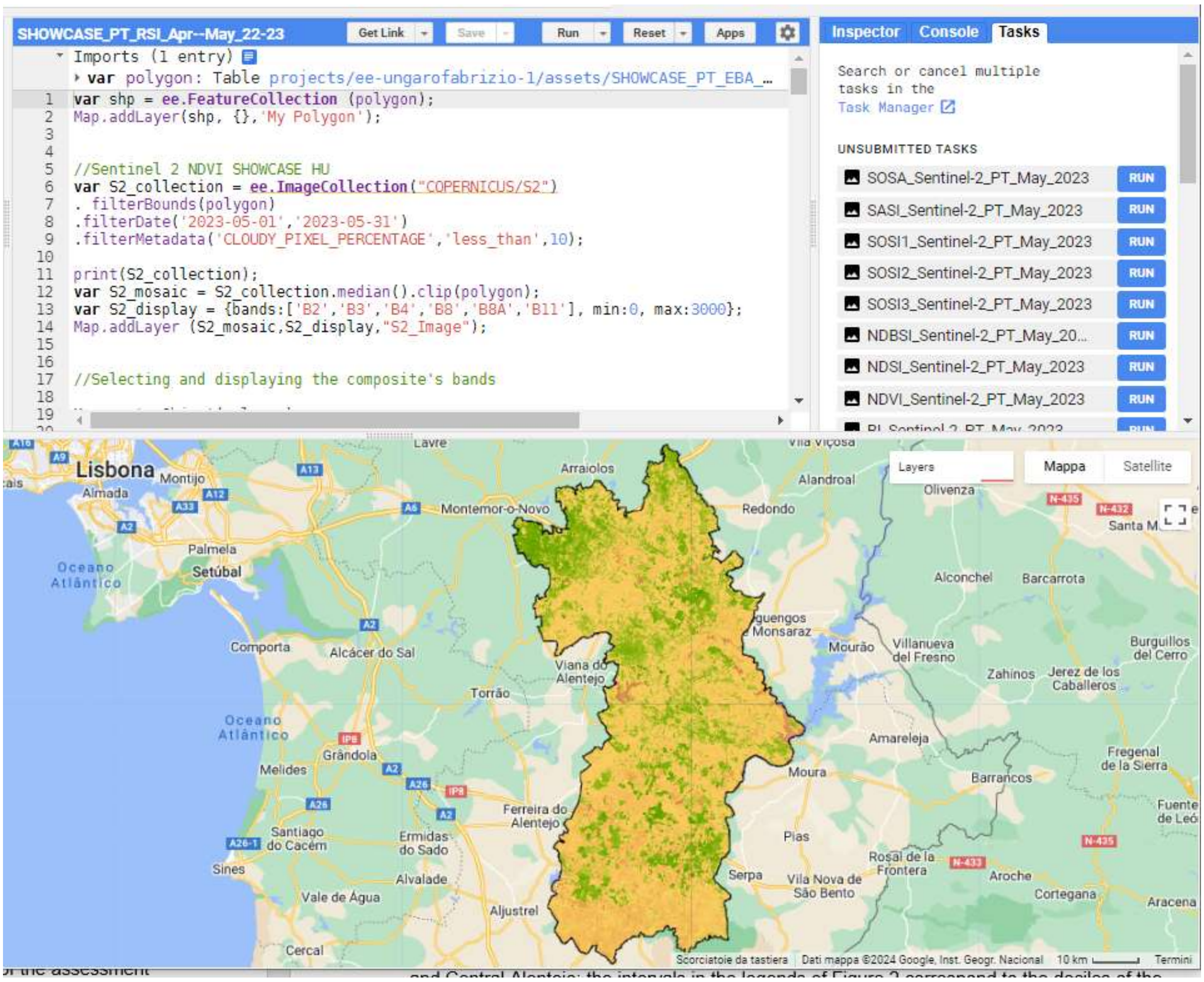

Figure 5. GEE JavaScript console: example of RSIs computation for May 2023 in the Portuguese EBA of Alentejo.

Examples of vegetation (NDVI) and soil (NDBSI) RSI are displayed in Figure 6 for the Portuguese and the Hungarian CSAs.

The last group of predictors is represented by 0-1 dummy coded variables to account i) for the effect of biodiversity management on the measured indicators, i.e. control vs. intervention providing in this way two different biodiversity management scenarios to compare, ii) for the sampling round (i.e., seasonal variability), and iii) for annual variability. In this way it is possible to assess not only the effect of treatment over the considered spatial domain, but also to explicitly account for variation over time and possibly forecast future trends by using the time variant RSI.

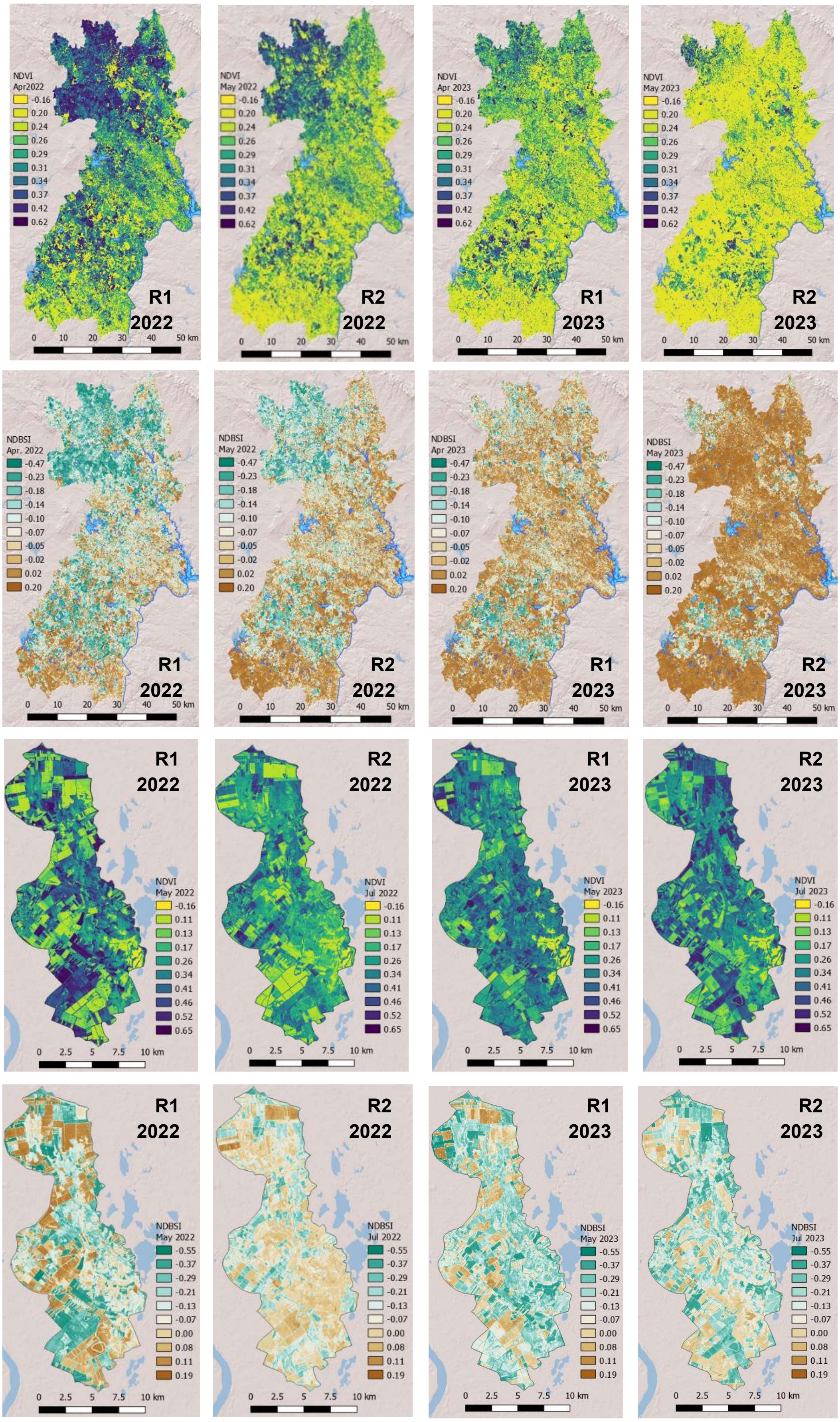

Figure 6. NDVI (1st and 3rd row) and NDBSI (2nd and 4th row) maps for round 1 and 2 in years 2022 and 2023 in the Portuguese (upper two rows) and Hungarian (bottom two rows) CSAs.

Before the spatial joining with the predictors, the experimental field data from each EBA were transformed into 0-1 indicator data resorting to an interval normalization (or min-max scaling) which returns data within a 0 to 1 interval (Wu et al., 2013):

$$Ind_i = (x_i\text{-}max) / (max\text{-}min) \qquad \text{Eq. (1)}$$

where Ind_i is the normalized [0-1] value of the abundance or richness indicator, x_i is the actual value (i.e. the individuals or the species count in any specific field), max and min are the maximum and the minimum respectively of each variable observed in the dataset. The formula in Eq. (1) gives high priority (i.e. values close to 1) to higher values of the considered indicator; the lowest value, 0, does not necessarily indicate that no individuals or species were observed, but that it is the lowest in the considered area at the time of samples collection. This data transformation was preferred to standardization as it preserves the original distribution of the data and retains the linear relationship between original and transformed values (Cabello-Solorzano et al, 2023). Also, constraining data within a 0-1 interval allows for immediate comparisons among indicators across scenarios, locations and different moments in time.

Figure 7 illustrates the flowchart of the mapping approach followed in Task 2.7, from raster data acquisition to the generation of upscaled maps of standardized biodiversity indicators.

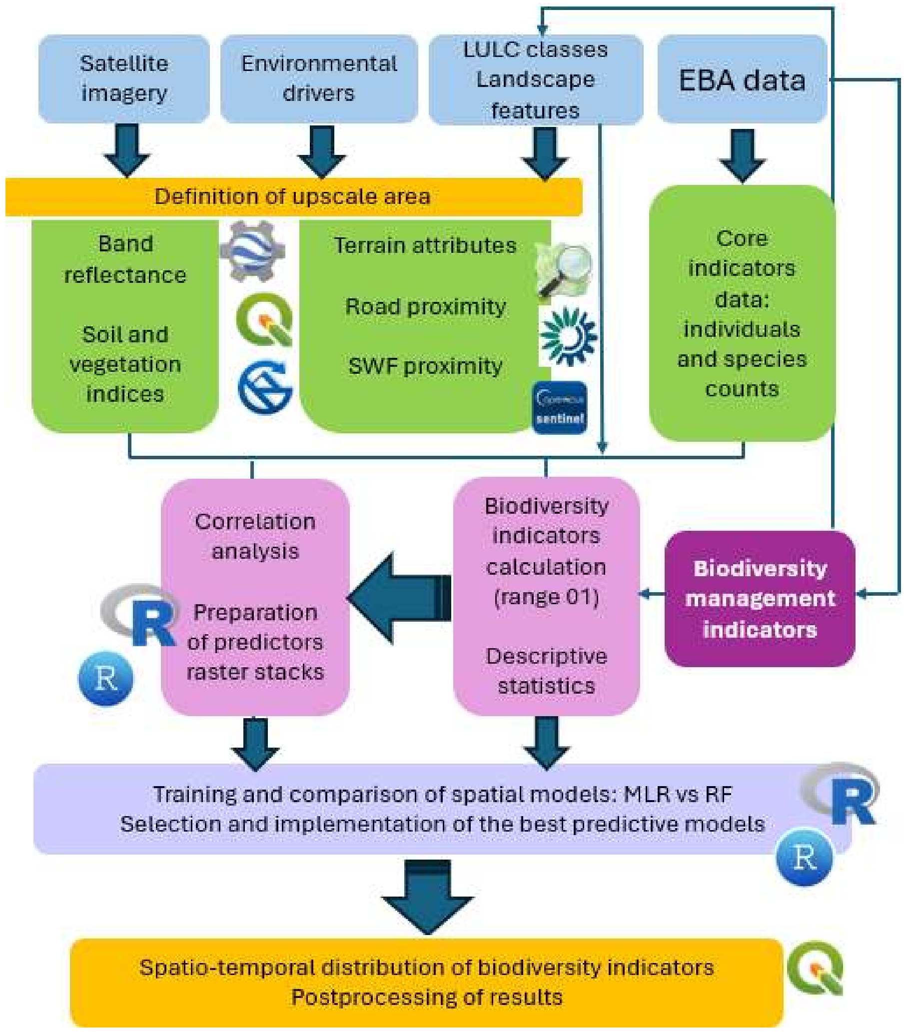

Figure 7. Flowchart illustrating the steps of biodiversity indicators assessment and mapping resorting to Remote Sensing Indices and time-invariant covariates.

2.2 Comparing model performance: MLR vs. RF

In each EBA two statistical methods were tested to identify which could better provide spatial estimates of the SHOWCASE core biodiversity indicators at the landscape scale. Multiple linear regressions (MLR) were calibrated resorting to a sequential replacement approach. This consists of iteratively adding and removing predictors in the model to identify a subset of predictors resulting in the best performing model, i.e. a model with the lowest prediction errors. There are three possible strategies of stepwise regression (James et al. 2013; Bruce et al, 2020):

1. *Forward selection*, which starts with an intercept but no predictors in the model, iteratively adds the most contributive predictors, and stops when the improvement is no longer statistically significant.
2. *Backward selection* (or backward elimination), which starts with all predictors in the model (full model), iteratively removes the least contributive predictors, and stops when you have a model where all predictors are statistically significant.
3. *Stepwise selection* (or sequential replacement), which is a combination of forward and backward selections. It starts with no predictors, then sequentially adds the most contributive predictors (like forward selection). After adding each new variable, it removes any variables that no longer provide an improvement in the model fit (like backward selection).

The third strategy was adopted and the underlying assumptions of MLR were checked by inspection of bivariate scatterplots of the variables of interest and by checking the normality of regression residuals.

Random forests were implemented in R v.4.3.2 (R Core Team, 2013) using Rstudio 2023.06.0 (RStudio Team, 2020) and the package '`randomForest`' version 4.7-1.1 (Liaw and Wiener 2002). Each forest ensemble was composed of 500 regression trees, and for each ensemble an extractor function for variable importance measures was applied based on the total decrease in node impurities from splitting on the variable, averaged over all trees. This allowed us to assess and plot the predictive power of each variable.

Calibration errors for MLR and RF were assessed by calculating the values of mean error (ME), absolute error (AE), rooted mean squared error (RMSE), index of agreement (IoA) and R^2. The IoA (Willmot, 1981) is a standardized measure of the degree of model prediction error which varies between 0 and 1, and is calculated as follows:

$$IoA = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \qquad \text{Eq. (2)}$$

where O_i is the observation value and P_i is the predicted value and $\bar{O}$ is the average observation values. The index of agreement represents the ratio of the mean square error and the potential error. The agreement value of 1 indicates a perfect match, and 0 indicates no agreement at all. The index of agreement can detect additive and proportional differences in the observed and simulated means and variances; however, IoA is overly sensitive to extreme values due to the squared differences.

2.3. Application of mechanistic models for pollinator abundance

A plethora of models is available to relate environmental conditions to biodiversity levels. However, there are trade-offs between their complexity, the information required to parameterize them, and the kind of outputs they can provide. Task 2.7 compared two conceptually different modelling approaches: (i) data-driven models i.e. statistical approaches calibrated on the biodiversity indicator data from 5 EBAs and (ii) the mechanistic model of Lonsdorf et al. (2009) as implemented in Zulian et al. (2013) to estimate pollinator abundance using the *k.explorer* interface (IMP, 2023). The model output is a dimensionless score with values ranging from 0 to 1, describing the expected relative pollinator abundance to a given location across the landscape. The model relies on the assessment of nesting and foraging suitability of the landscape for pollinators, calculated using expert assessment and available land cover maps, expressed in the form of lookup tables that link land cover types with the availability of floral and nesting resources. From the combination of nesting and foraging suitability a habitat suitability map for relative pollinator abundance at the landscape scale is derived. This is in turn corrected by an estimation of insect activity based on average temperature and solar radiation, which when below a certain threshold affect pollinator abundance outside the nesting sites (Figure 8).

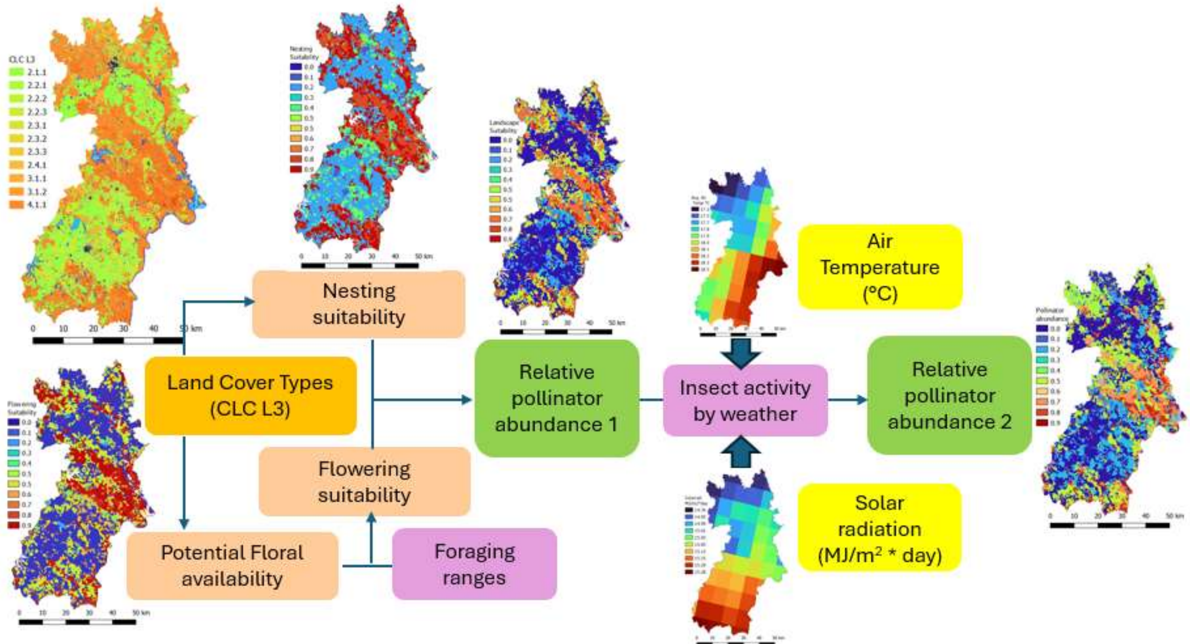

Figure 8. Flowchart outlining the structure of the pollination model which results in the calculation of the relative pollinator abundance for the Alentejo CSA (Portugal).

The climatic data used for the assessment were derived from WorldClim v2.1, with a 30s resolution (Fick et al., 2017) The land cover dataset plays a major role in determining model outcomes. Table 3 presents an example of land cover ranking table where each land cover type has a score from 0 to 1, according to its potential to provide floral and nesting resources. The last available vector layer version of the CORINE Land Cover (2018) was used. This model and its modifications have already been used to infer spatially explicit current (Koh et al., 2016; Zhao et al., 2019) and future trends in pollinators/pollination (Chaplin-Kramer et al., 2019) and to estimate pollinator natural capital (Ricketts and Lonsdorf, 2013).

The pollinator abundance estimated with the mechanistic model in each CSA was eventually compared for the target land use with that resulting from the application of the data-driven models calibrated with the observations of pollinator abundance from each EBA for the control sites. The relative differences were then assessed over the target land use in the whole area and mapped to highlight the magnitude and sign of the differences between the two approaches in a spatially explicit context.

Table 3: Examples of Floral Availability (FA) and Nesting Suitability (NS) scores for the CORINE Land Cover (CLC) types. HNV_F+/HNV_N+: high natural value farmland (additional scores). From: Zulian et al., 2013

CLC code	Description		FA	HNV_F+	NS	HNV_N+
111	Continuous urban fabric		0.05	0	0.1	0
112	Discontinuous urban fabric		0.3	0	0.3	0
121	Industrial or commercial units		0.05	0	0.1	0
122	Road and rail networks and associated land		0.25	0	0.3	0
123	Port areas		0	0	0.3	0
124	Airports		0.1	0	0.3	0
131	Mineral extraction sites		0.05	0	0.3	0
132	Dump sites		0	0	0.05	0
133	Construction sites		0	0	0.1	0
141	Green urban areas		0.25	0	0.3	0
142	Sport and leisure facilities		0.05	0	0.3	0
211	Non-irrigated arable land*		0.2	0	0.2	0
212	Permanently irrigated land*		0.05	0	0.2	0
213	Rice fields		0.05	0	0.2	0
221	Vineyards		0.6	0.2	0.4	0.1
222	Fruit trees and berry plantations		0.9	0	0.4	0.1
223	Olive groves**	intensive	0.2	0.2	0.4	0.1
		extensive	0.6	0.2	0.6	0.1
231	Pastures		0.2	0.2	0.3	0.2
241	Annual crops associated with permanent crops		0.5	0.2	0.4	0.1
242	Complex cultivation patterns		0.4	0.2	0.4	0.1
243	Land principally occupied by agriculture, with significant areas of natural vegetation		0.75	0.05	0.7	0.1
244	Agro-forestry areas***		0.5	0.4	1	0
311	Broad-leaved forest***		0.9	0	0.8	0
312	Coniferous forest***		0.3	0	0.8	0
313	Mixed forest***		0.6	0	0.8	0
321	Natural grasslands		1	0	0.8	0
322	Moors and heathland		1	0	0.9	0
323	Sclerophyllous vegetation		0.75	0	0.9	0
324	Transitional woodland-shrub		0.85	0	1	0
331	Beaches, dunes, sands		0.1	0	0.3	0
332	Bare rocks		0	0	0	0
333	Sparsely vegetated areas		0.35	0	0.7	0
334	Burnt areas		0.2	0	0.3	0
335	Glaciers and perpetual snow		0	0	0	0
411	Inland marshes		0.75	0	0.3	0
412	Peat bogs		0.5	0	0.3	0
421	Salt marshes		0.55	0	0.3	0
422	Salines		0	0	0	0
423	Intertidal flats		0	0	0	0

2.4. Biodiversity indicators as proxy for ecosystem services assessment and mapping

As foreseen in the GA, Task 2.7 investigated the scale dependency of spatial patterns and temporal dynamics of the selected biodiversity indicators and their relations with environmental and anthropic drivers. The biodiversity indicators selected provide the basis to assess ecosystem services provision under the two different management scenarios, i.e. control and intervention, at landscape scale. The five available biodiversity indicators stemming from the EBAs field surveys, were then used as proxies for specific ecosystem services allowing the estimation and mapping of their potential supply.

In the following paragraphs a brief literature review is provided to highlight the use of biodiversity indicators as proxy of ecosystem service provision.

Using **pollinators abundance** as a proxy for pollination ecosystem service provision is a common approach in ecological studies. Garibaldi et al. (2013) examined the relationship between pollinator abundance (including wild bees and honeybees) and crop pollination services. It was found that higher pollinator abundance, particularly of wild bees, was strongly correlated with increased fruit set in crops, demonstrating its use as a proxy for pollination service provision. The role of pollinator abundance in ensuring pollination services for global food production was highlighted by Klein et al. (2007) who used pollinator abundance data to estimate pollination service provision across different landscapes and crops in intensively managed agricultural systems. In heterogeneous landscapes with diverse habitats, Ricketts et al. (2008) synthesizing the results of 23 studies found that pollinator abundance was a reliable indicator of pollination service provision, and in their review paper Potts et al. (2016) highlighted that pollinator abundance was a critical indicator for evaluating the health of pollination ecosystems and their services. Ollerton et al. (2014) remarked that declines in pollinator abundance were directly linked to reduced pollination services, emphasizing the importance of monitoring pollinator populations, particularly in the context of climate change and habitat loss. The global meta-analysis by Dainese et al. (2019) used pollinator abundance as a proxy to quantify the contribution of biodiversity to crop pollination services across diverse agricultural systems, highlighting its robustness as strong proxy of pollination services.

Pollinators species richness is also commonly used as a proxy for pollination service provision, often alongside or in combination with pollinator abundance. While abundance measures the number of individual pollinators, species richness reflects the diversity of pollinator species present in an ecosystem. Both metrics are important because they capture different aspects of pollinator communities that contribute to pollination services. Garibaldi et al. (2011) found that higher pollinator species richness was associated with more stable and efficient pollination services, particularly in agricultural landscapes and that species richness was a better predictor of pollination stability than pollinator abundance alone, as diverse pollinator communities provided functional redundancy. Similarly, Fründ et al. (2013) highlighted that pollinator species richness enhanced pollination services through functional complementarity, where different species contributed unique pollination behaviors, showing that species richness was a key driver of pollination efficiency, as diverse communities filled more ecological niches. used historical data to show that declines in pollinator species richness were associated with reduced pollination services in natural and agricultural ecosystems. In a study using historical data, Bartomeus et al. (2013) found that species richness was a reliable indicator of pollination service provision over time and that declines in pollinator species richness were associated with reduced pollination services in natural and agricultural ecosystems. The relevance of pollinator species richness at regional scales was pointed out by Winfree et al. (2018), showing that diverse pollinator communities provided more consistent pollination services across different locations and times and that species richness was critical for maintaining pollination services in spatially and temporally variable environments. In the already cited global meta-analysis, Dainese et al, (2019) remarked that species richness was a critical factor in ensuring effective pollination services across diverse agricultural systems, adding that higher pollinator species richness significantly increased crop yield and quality, independent of pollinator abundance. All these studies highlighted how the relevance of species richness in the provision of pollination services derives from different factors:

i) functional complementarity: different pollinator species often have unique behaviors (e.g., flower preferences, foraging times, or pollination techniques) that collectively enhance pollination efficiency;

ii) resilience: diverse pollinator communities are more resilient to environmental changes, ensuring stable pollination services even if some species decline; and

iii) niche partitioning: species richness allows for better utilization of available floral resources, reducing competition and increasing overall pollination success.

In general, then, it can be concluded that pollinator abundance is often used to measure the quantity of pollinators, which is important for high-density flower visitation, while species richness captures the diversity of pollinators, which is crucial for ensuring pollination across different plant species, times, and environmental conditions. Both metrics are complementary and were often used together to provide a more comprehensive understanding of pollination service provision.

Spiders are important natural enemies of pests in agricultural and natural ecosystems (Reichert and Lockley, 1984), and their **abundance** and species **richness** have been often used as proxies for pest control regulating ecosystem services. Snyder and Wise (2001) examined the role of spider abundance and diversity in controlling herbivorous pests in agricultural fields. They found that higher spider abundance reduced pest populations, while species richness enhanced the stability of pest control over time, showing that both spider abundance and species richness were important for effective pest control, with species richness providing functional redundancy and resilience. Schmidt et al. (2003) investigated the role of spider abundance and diversity in controlling pest populations in cereal crops, where both metrics were positively correlated with reduced pest damage and increased crop yield, concluding that spider abundance and species richness were complementary proxies for pest control services. In assessing the importance of spider abundance and species richness in controlling pest populations across different agroecosystems in Europe and the US, Nyffeler and Sunderland (2003) concluded that diverse spider communities were more effective at pest suppression than single-species dominance as they jointly enhanced the stability and effectiveness of pest control services. The influence of local management and landscape complexity on spider abundance and species richness was investigated by Saqib et al. (2020), who found that complex landscapes supported higher spider diversity, which in turn enhanced pest suppression.

As for pollinators, both spider abundance and species richness are widely used as proxies for pest control services in agroecosystems: while abundance provides a direct measure of predation pressure, species richness enhances the stability, efficiency, and resilience of pest control. Studies often recommend promoting both metrics through habitat management (e.g., maintaining semi-natural habitats, reducing pesticide use) to optimize pest control services.

The fifth and last biodiversity core indicator surveyed in the SHOWCASE EBAs and addressed in this Deliverable report is **vascular plants species richness**. This indicator has often been used as a proxy for the supply of various ecosystem services, as plant diversity plays a critical role in maintaining several ecosystem functions. Here follow some examples from the scientific literature where vascular plant species richness has been used to represent ecosystem service supply. For example, Hector et al. (1999) simulated the impact of loss of plant diversity on primary productivity (provisioning service) by synthesizing grassland communities with different numbers of plant species. Results differed in detail at the eight European sites tested, but there was an overall log-linear reduction of average aboveground biomass with loss of species. In their synthesis paper Hooper et al. (2005) emphasized the importance of vascular plant species richness for ecosystem services such as primary production, decomposition, and nutrient cycling, with higher plant species richness enhancing the efficiency and stability of ecosystem services provision. From the meta-analysis of experimental works (N = 466) spanning 50 provided by Balvanera et al. (2006), it resulted that vascular plants species richness was positively correlated with ecosystem services such as biomass production, soil fertility, and pest regulation, making it a robust proxy for ecosystem services supply across a wide range of ecosystems. Díaz et al. (2007) investigated the role of plant diversity in maintaining ecosystem multifunctionality, focusing on regulating services such as pollination support, soil fertility, and water regulation, and emphasizing the role of plant diversity in maintaining ecosystem multifunctionality in natural and semi-natural environments. Plant functional composition proved also to be a key driver of soil-based ecosystem services, as highlighted by Fornara and Tilman (2008) who found that diverse plant communities enhanced soil carbon storage and nitrogen availability, representing then a proxy for carbon sequestration and soil nutrient cycling services, with higher plant diversity leading to greater soil carbon and nitrogen accumulation in agriculturally degraded soils. Focusing on grasslands and other herbaceous ecosystems, Zavaleta et al. (2010) and Lavorel et al. (2011) demonstrated that vascular plant species richness was essential for maintaining multiple ecosystem services, including forage production, soil fertility, water regulation and carbon storage. Both works emphasized that higher plant diversity supports greater functional diversity, which underpins ecosystem service provision.

Vascular plants species richness underpins then the supply of different categories of ecosystem services, including both provisioning and regulating services. The former encompass biomass production, forage provision, and genetic material, while the latter include nutrient cycling and regulation of soil quality, regulation of water quality, and soil erosion control. Furthermore, plant diversity provides habitat for other organisms, supporting biodiversity and associated services like pollination and pest control. Habitat provisioning, and the biodiversity within, is considered a type of "supporting" ecosystem service (Maes, 2012; Bastian, 2013), but this category is not explicitly considered in all ecosystem services classification scheme, the most notable example being provided by the Common International Classification of Ecosystem Services (CICES, Haines-Young and Potschin, 2018), whose hierarchically structured classification is one of the most used in the scientific literature. In the

CICES framework, supporting services or ecological functions are considered as the underpinning structures and processes that ultimately give rise to ecosystem services. A classification of these supporting services is not covered in CICES which seeks to identify the final services that link to the goods and benefits that are valued by people.

According to the CICES scheme version 5.1, currently under revision, the biodiversity indicators derived from the SHOWCASE EBAs survey can provide proxies for the following ecosystem services:

i) Wild bees' abundance and species richness indicators: proxies for **pollination** (regulation and maintenance - biotic ecosystem service, CICES v5.1 code 2.2.2.1);
ii) Spiders' abundance and species richness indicators: proxies for **pest control** (regulation and maintenance - biotic ecosystem service, CICES v5.1 code 2.2.3.1);
iii) Vascular plants species richness indicator: in this case as none of the possible ecosystem services (three provisioning services and seven regulation and maintenance according to the CICES classification) linked to plant species richness has been monitored in the SHOWCASE EBAs fields, it is considered more appropriate within the SHOWCASE project framework to use this indicator as a proxy for the supporting ecosystem service of **habitat provision for biodiversity**.

The spatiotemporal modelling and mapping of the five core biodiversity indicators provided then straightforward all the information and outputs necessary to assess and map the related ecosystem services: pollination and pest control regulation services are complementary depicted by the spatiotemporal joint mapping of abundance and species richness of wild bees and spiders respectively, both indicators being combined in a single 0-1 normalized indicator of ES provision, i.e. the two indicators are summed and then normalized, while indicator maps of vascular plants species richness provide the spatiotemporal modelling outputs for the supporting ecosystem service of habitat provision for biodiversity.

3. Upscaling biodiversity indicators from plot to landscape scale: results for five SHOWCASE EBAs

This section of the report illustrates the results of the spatiotemporal modelling of biodiversity indicator data for the five selected SHWOCASE core indicators in five EBAs: Hungary, Spain, Portugal, the Netherlands and Switzerland. All the data at the base of the analysis and modelling were provided by the SHOWCASE EBA partners and have been collected between 2022 and 2023 following the SHOWCASE biodiversity survey protocol (Bretagnolle et al., 2021b). In the case of the Dutch EBA, data were available also for 2021, while of the Swiss EBA data were available only for 2022. Data were provided in the form of excel files with a standardized format used in all EBAs (Figure 9). For all data points coordinates were provided in the EPSG 4326 reference system (WGS84).

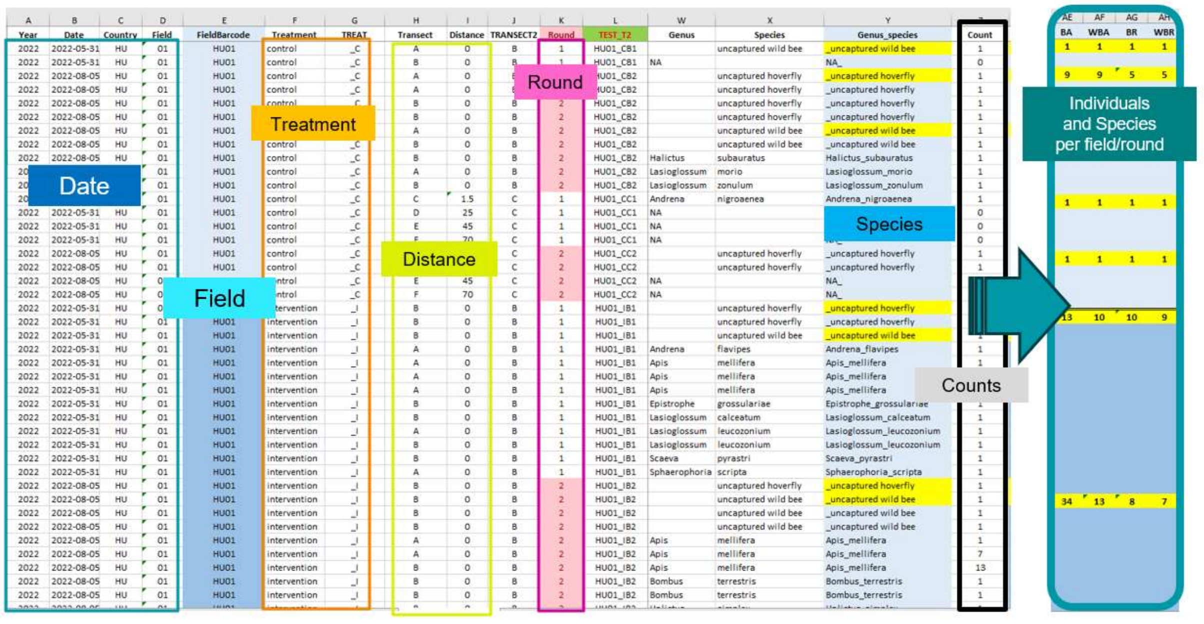

Figure 9. Example of standard excel data sheet for field observations with individual and species counts.

The data collected by EBA partners were first processed to calculate the sums of individuals and the number of species recorded in each field (control and intervention) in each EBA for every round of sampling and for the two years. The detailed description of the intervention in each EBA is given by Bretagnolle et al. (2021a). In the case of arable land (i.e. HU, NL and CH EBAs), to account for margin effects and for the presence of the floral strips at the verge of the intervention fields on biodiversity indicators, the observations from each field/round were divided into two groups, the first next to the field verge and the second referred to the center of the field. In the case of permanent crops (ES and PT EBAs) this division was not applicable as the interventions (i.e. flower strips) are localized in between the orchard rows.

The data (individuals sums and number of species) were then 0-1 normalized and joined with the set of predictors described in the previous section based on their coordinates to be analyzed for the spatiotemporal modelling.

The following sub-sections present the main results for upscaling the field scale observations in each EBA to the landscape scale in the corresponding CSA.

3.1 Hungarian EBA

The Hungarian CSA encompassing the EBA fields is in Central Hungary, in the Kiskunság area, in the Hungarian part of the Danube-Tisza valley (Figure 10). The area has an extent of ca. 20,000 ha with an elevation ranging from 89 to 105 m a.s.l., and stretches for ca. 30 km in the North-South direction, parallel to the course of the Danube River to the west, and is bordered to the east by the 35,722 ha Natura 2000 area of the Saline lakes of Kiskunság and the Turján region of Őrjeg (*Kiskunsági szikes tavak és az őrjegi turjánvidék*, HUKN10002) which occupies ca. 4596 ha of the south-eastern part of the CSA.

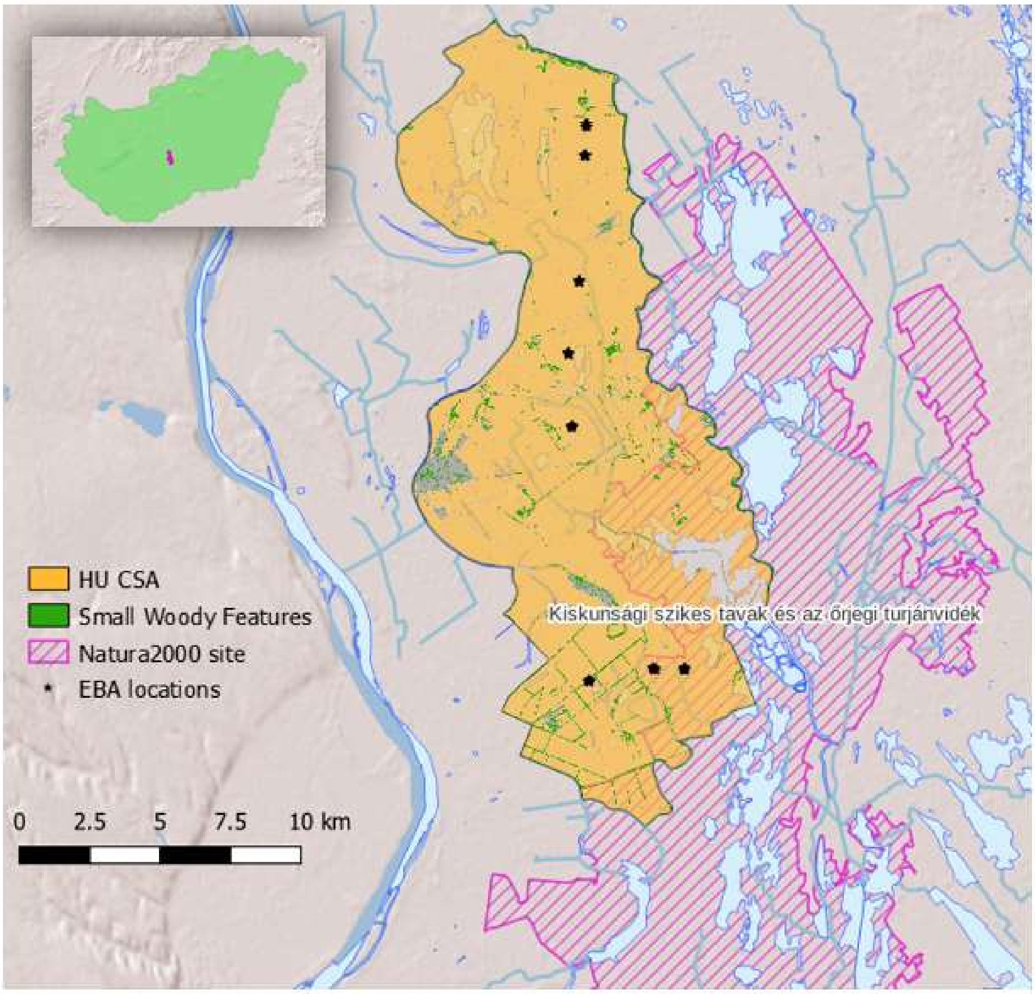

Figure 10. Geographical location of the Hungarian CSA.

The Natura 2000 site includes four shallow open water sodic-alkaline pans, three major sodic-alkaline reedbeds and an associated mosaic of saline marshes, meadows, aquaculture ponds and irrigated land. It is the largest and most important area of saline lakes and flats between the Danube and Tisza rivers in the Great Hungarian Plain. The Site supports notable species of breeding, migrating, wintering and resident birds, including the great bustard (*Otis tarda*), pied avocet (*Recurvirostra avosetta*), Eurasian bittern (*Botaurus stellaris*) and red-breasted goose (*Branta ruficollis*). It hosts several noteworthy plant species and communities endemic to the Pannonic biogeographic region, including *Aster tripolium* ssp. *pannonicus*. The lakes play an important role in the retention and storage of water and the regulation of the groundwater level in the surrounding area. Currently the Site is mainly used as extensive grassland, and for reed harvesting and other agricultural activities. According to CORINE Land Cover (2018), agricultural land occupies 85.5% of the CSA, with 81% of non-irrigated agricultural land (13861 ha), 15.0% of extensive grassland (2993 ha), 0.51% of areas with complex cultivation patterns (102 ha), and 0.73% of areas principally occupied by agriculture, with significant areas of natural vegetation (147 ha).

Following the SHOWCASE sampling protocol, the core indicator data were collected in two rounds (May and July) in 2022 and 2023 from eight control fields and eight intervention fields. Plant richness was sampled only once every year (in late spring-early summer). The descriptive statistics of the five biodiversity indicators for the two years are summarized in Table 4 for individual and species counts and their 0-1 normalized indicators.

Table 4: Descriptive statistics of the five SHOWCASE core indicators

Core Indicators	Valid N	Mean	Std.Dev.	Std. Err.	Min	Median	Max
Counts							
WBA	128	4.8	5.5	0.5	0.0	3.0	34.0
WBR	128	2.4	2.4	0.2	0.0	1.5	12.0
SpA	128	8.5	11.8	1.0	0.0	4.0	81.0
SpR	128	1.6	2.6	0.2	0.0	1.0	19.0
PlaR	64	15.6	11.8	1.5	0.0	12.5	46.0
Indicator (0-1)							
Ind WBA	128	0.200	0.223	0.020	0.000	0.118	1.000
Ind WBR	128	0.284	0.274	0.024	0.000	0.191	1.000
Ind SpA	128	0.171	0.221	0.020	0.000	0.092	1.000
Ind SpR	128	0.242	0.337	0.030	0.000	0.108	1.000
Ind PlaR	64	0.338	0.271	0.034	0.000	0.263	1.000

Table 5 summarizes the descriptive statistics of the five normalized indicators for control and intervention; statistically significant differences ($p < 0.05$) in indicator mean values were detected for WBA, WBR, and PlaR indicators, but not for SpA and SpR, which showed higher mean values observed for the control fields and lower for the intervention fields. Likewise, in terms of location along the transect, mean indicator values were significantly higher at the field margins than in the field center for WBA (0.282 vs. 0.117), WBR (0.414 vs.0.155) and PlaR (0.530 vs. 0.147) but not for spiders, although both mean SpA and SpR indicators were higher at the field margins (0.194 and 0.272) than in the field center (0.148 and 0.210). The same responses were observed in both control and intervention fields with significantly higher mean indicator values for WBA, WBR and PlaR at the field margins. Mean indicator values for the second sampling round were higher in the control fields for WBA, WBR and SpR, while in the intervention fields the increase was observed only for WBR and SpR. Wild bee abundance appears constant in the two years of observation, while there was an increase in wild bee richness in the second year, and this was observed in both control and intervention fields. In 2023 spider abundance increased in both control and intervention fields with respect to 2022, while the number of species dropped in the control fields while remaining constant in the intervention fields. In the two years, the number of vascular plants species remained constant in the control fields, while in the intervention fields there was a clear increase in 2023, although not statistically significant.

Table 6 summarized the MLR coefficients for the normalized biodiversity indicators. Given the geomorphology of the plain, regressors based on terrain attributes were not used, as a much more detailed DEM with a higher resolution (<1 m) would have been necessary to properly account for the influence of topography on biodiversity indicators.

Table 5: Descriptive statistics of the five SHOWCASE core indicators in the control and intervention fields of the Hungarian EBA

Indicator	Treatment	Means	N	Std.Dev.	Std.Err.	Min	Median	Max
Ind WBA	*Control*	0.153	64	0.188	0.023	0.000	0.088	1.000
	Intervention	0.246	64	0.245	0.031	0.000	0.172	1.000
	All Groups	0.200	128	0.223	0.020	0.000	0.118	1.000
Ind WBR	*Control*	0.206	64	0.234	0.029	0.000	0.143	1.000
	Intervention	0.362	64	0.290	0.036	0.000	0.364	1.000
	All Groups	0.284	128	0.274	0.024	0.000	0.191	1.000
Ind SpA	*Control*	0.198	64	0.253	0.032	0.000	0.097	1.000
	Intervention	0.143	64	0.181	0.023	0.000	0.080	1.000
	All Groups	0.171	128	0.221	0.020	0.000	0.092	1.000
Ind SpR	*Control*	0.270	64	0.352	0.044	0.000	0.111	1.000
	Intervention	0.213	64	0.321	0.040	0.000	0.105	1.000
	All Groups	0.242	128	0.337	0.030	0.000	0.108	1.000
Ind PlaR	*Control*	0.233	32	0.130	0.023	0.000	0.232	0.450
	Intervention	0.443	32	0.332	0.059	0.000	0.400	1.000
	All Groups	0.338	64	0.271	0.034	0.000	0.263	1.000

Table 6: Coefficients of the MLR calibrated for the normalized biodiversity indicators; significant coefficients in red (p <0.05) and blue (p<0.10)

Predictor	WBA	WBR	SpA	SpR	PlaR
Intercept	-5.76193	-0.41323	0.78523	0.69980	-0.10635
Dummy Treat	0.10016	0.17230	-0.00307	-0.05351	0.22816
Dummy Round		0.08937	0.04676	0.28064	
Dummy Year		0.10831	0.03423	-0.04742	0.06028
Road prox		-0.00033	-0.00011	-0.00032	-0.00008
SWF prox	-0.00012	-0.00009	0.00013	0.00014	-0.00001
BI	-7.66281			18.47382	
blue	-0.00208	-0.00059		0.00050	
green	0.00418			0.00023	
IR	-0.00142		0.00027	0.00049	-0.00134
Irn				-0.00194	
NDBSI	4.58230	-3.06751	-1.95857	-1.15849	6.46509
NDSI	1.22442	4.50094	2.99775	-10.68093	1.84071
NDVI	6.79444		-3.33803	11.37421	10.39707
red	0.00584		-0.00031		
SOSA		0.00048			0.00215
SOSI2	-0.00064	0.00022	0.00014	-0.00171	-0.00096
SOSI3	-0.00009				
SWIR			-0.00021	0.00019	-0.00108

Adopting the same set of predictors, random forests were calibrated for each indicator, providing an assessment of the relevance of each predictor expressed in terms of node purity, i.e. the capacity of each predictor to split the regression tree with an increase in homogeneity in the data partitions (Table 7). The contribution of each predictor is graphically represented in Figure 11, with order of relevance increasing along the Y axis.

Table 7: Relevance of RF predictors for the five biodiversity indicators in term of node purity; colors highlight the most relevant predictors (orange > brown >light brown)

Predictor	WBA Indicator		WBA Indicator		SpA Indicator		SpR Indicator		PlaR Indicator	
	NodePurity	Rel.%	NodePurity	Rel.%	NodePurity	Rel.%	NodePurity	Rel.%	NodePurity	Rel.%
dummy treat	0.063	1.58%	0.293	4.39%	0.025	0.72%	0.121	1.13%	0.286	8.44%
dummy year	0.041	1.03%	0.054	0.81%	0.026	0.77%	0.240	2.24%	0.019	0.55%
dummy round	0.032	0.81%	0.089	1.34%	0.048	1.40%	0.509	4.74%	0.000	0.00%
swf_prox	0.267	6.74%	0.429	6.43%	0.141	4.11%	0.734	6.84%	0.267	7.88%
road_prox	0.251	6.32%	0.838	12.54%	0.206	6.01%	0.525	4.90%	0.366	10.83%
bi	0.188	4.74%	0.280	4.19%	0.162	4.73%	0.442	4.12%	0.202	5.98%
blue	0.227	5.72%	0.373	5.59%	0.152	4.44%	0.752	7.01%	0.143	4.24%
green	0.258	6.49%	0.335	5.02%	0.179	5.24%	0.808	7.53%	0.173	5.11%
ir	0.215	5.41%	0.359	5.38%	0.230	6.73%	0.524	4.89%	0.165	4.88%
irn	0.274	6.90%	0.449	6.73%	0.239	6.98%	0.511	4.76%	0.174	5.15%
ndbsi	0.206	5.20%	0.377	5.64%	0.192	5.61%	0.440	4.10%	0.295	8.72%
ndsi	0.193	4.85%	0.338	5.05%	0.145	4.24%	0.672	6.26%	0.189	5.59%
ndvi	0.243	6.13%	0.343	5.14%	0.318	9.29%	0.607	5.66%	0.207	6.13%
red	0.210	5.28%	0.320	4.79%	0.235	6.86%	0.722	6.73%	0.171	5.05%
sosa	0.265	6.67%	0.286	4.28%	0.260	7.61%	0.699	6.51%	0.120	3.54%
sosi1	0.256	6.44%	0.346	5.17%	0.214	6.26%	0.710	6.62%	0.124	3.65%
sosi2	0.315	7.94%	0.437	6.54%	0.264	7.71%	0.504	4.70%	0.162	4.79%
sosi3	0.231	5.83%	0.374	5.60%	0.207	6.06%	0.700	6.53%	0.126	3.74%
swir	0.234	5.91%	0.358	5.36%	0.178	5.21%	0.507	4.73%	0.195	5.75%

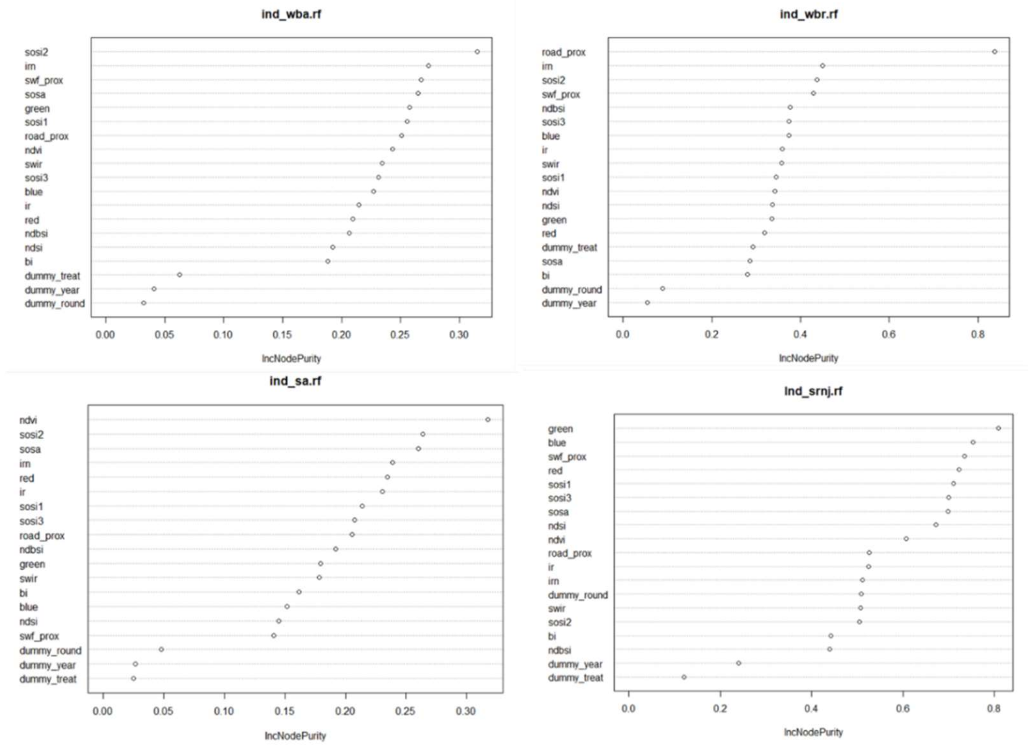

Figure 11. RF variable contribution plots for WBA (top left), WBR (top left), SpA (bottom left) and SpR (Bottom right) indicators.

It is worth noting that some predictors are relevant in both approaches, e.g. proximity to the field margins or to small woody features and RS soil salinity indicators, while the dummy coded management predictors were the least powerful in the RF approach, being instead highly significant in the MLR approach. The only notable exception is given by the PlaR indicator whose treatment dummy variable ranked third in terms of predictive power in the RF approach and was also highly significant in the MLR approach.

Table 8: Calibration error indices for the MLR and RF predictive models for the five biodiversity indicators

Error	*WBA Indicator*		*WBR Indicator*		*SpA indicator*		*SpR Indicator*		*PlaR Indicator*	
indices	RF	MLR	RF	MLR	RF	MLR	RF	MLR	RF	MLR
ME	-0.025	-0.001	0.002	-0.003	0.052	0.000	-0.034	-0.005	-0.116	-0.008
MSR	0.050	0.013	0.070	0.038	0.053	0.009	0.136	0.038	0.055	0.050
RMSE	0.252	0.116	0.277	0.195	0.258	0.093	0.311	0.194	0.267	0.223
R2	0.085	0.392	0.078	0.406	0.266	0.306	0.077	0.570	0.282	0.463
IoA	0.111	0.711	0.284	0.671	0.279	0.638	0.504	0.834	0.154	0.763

Table 8 summarizes the calibration error for the predictive models built with the MLR and the RF approach; from the values in the table, it appears clearly that in this case, and for all indicators, MLR models outperform RF with systematically lower ME, MSR, RMSE and higher values of IoA and R^2 (Figure 12).

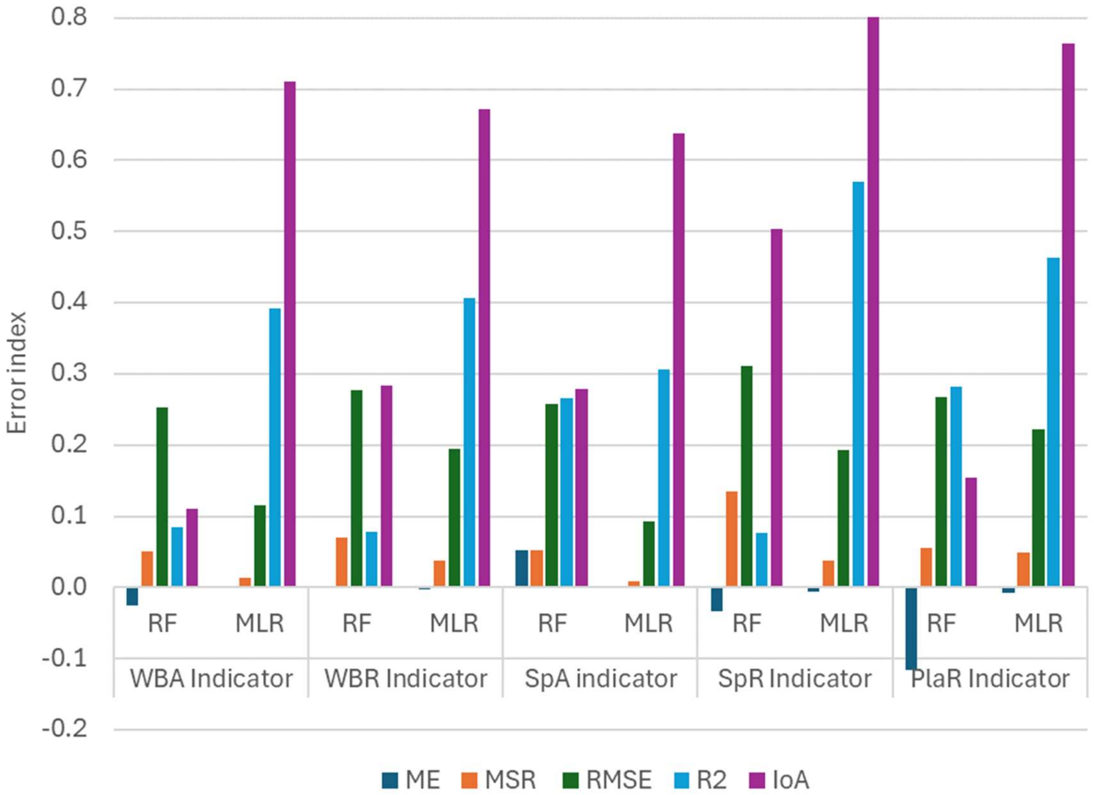

Figure 12: Calibration error indices for the MLR and RF predictive models for the five biodiversity indicators

The MLR models were then used to assess and map the five biodiversity indicators over the entire agricultural land area and raster statistics were calculated for each map to assess the average relative changes with respect to the baseline situation (year 1, control) and for each round the relative change due to the treatment implementation over the whole area. Although not realistic, this assessment provides a quantitative, spatially explicit and time dynamic evaluation of the potential impact of the biodiversity management practice implemented in the EBA. Figure 13 illustrates the spatial distribution of the WBA indicator for control and intervention scenarios during the two rounds in the two years. Table 9 reports the raster statistics for each map and summarizes the relative changes with respect to the baseline and to the control of each round.

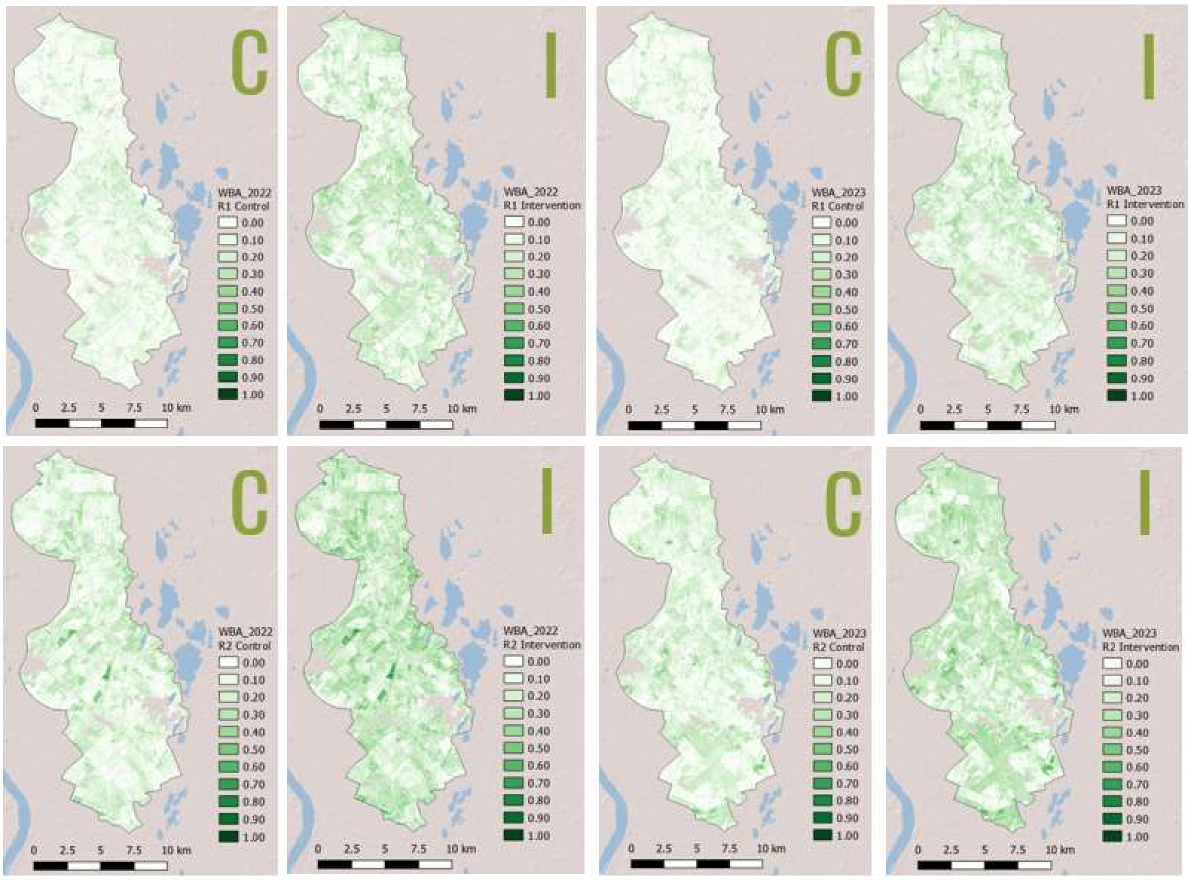

Figure 13: Predicted WBA indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 9: WBA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	WBA mean	median	stdev	min	max	Rel change baseline	Rel Change T
WBA 2022 r1 treatiszero	0.079	0.053	0.086	0.000	0.891	-	
WBA 2022 r1 treatisone	0.151	0.153	0.116	0.000	0.991	0.92	0.92
WBA 2022 r2 treatiszero	0.137	0.125	0.109	0.000	0.825	0.73	
WBA 2022 r2 treatisone	0.228	0.225	0.123	0.000	0.925	1.89	0.67
WBA 2023 r1 treatiszero	0.068	0.034	0.079	0.000	0.683	-0.14	
WBA 2023 r1 treatisone	0.143	0.134	0.105	0.000	0.783	0.81	1.11
WBA 2023 r2 treatiszero	0.127	0.127	0.105	0.000	0.670	0.62	
WBA 2023 r2 treatisone	0.211	0.227	0.128	0.000	0.770	1.69	0.66
Average changes						0.93	0.84

Figure 14 illustrates the spatial distribution of the WBR indicator for control and intervention scenarios during the two rounds in the two years. Table 10 reports the raster statistics for each map and summarizes the relative changes with respect to the baseline and to the control of each round.

Table 10: WBR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	WBR mean	median	stdev	min	max	Rel change baseline	Rel Change T
WBR 2022 r1 treatiszero	0.074	0.029	0.091	0.000	0.693	-	
WBR 2022 r1 treatisone	0.201	0.201	0.138	0.000	0.866	1.73	1.73
WBR 2022 r2 treatiszero	0.169	0.162	0.126	0.000	0.848	1.30	
WBR 2022 r2 treatisone	0.332	0.334	0.142	0.000	1.000	3.51	0.96
WBR 2023 r1 treatiszero	0.094	0.070	0.098	0.000	0.685	0.28	
WBR 2023 r1 treatisone	0.239	0.242	0.133	0.000	0.857	2.25	1.54
WBR 2023 r2 treatiszero	0.234	0.247	0.132	0.000	0.780	2.18	
WBR 2023 r2 treatisone	0.400	0.419	0.146	0.000	0.952	4.44	0.71
Average changes						2.24	1.23

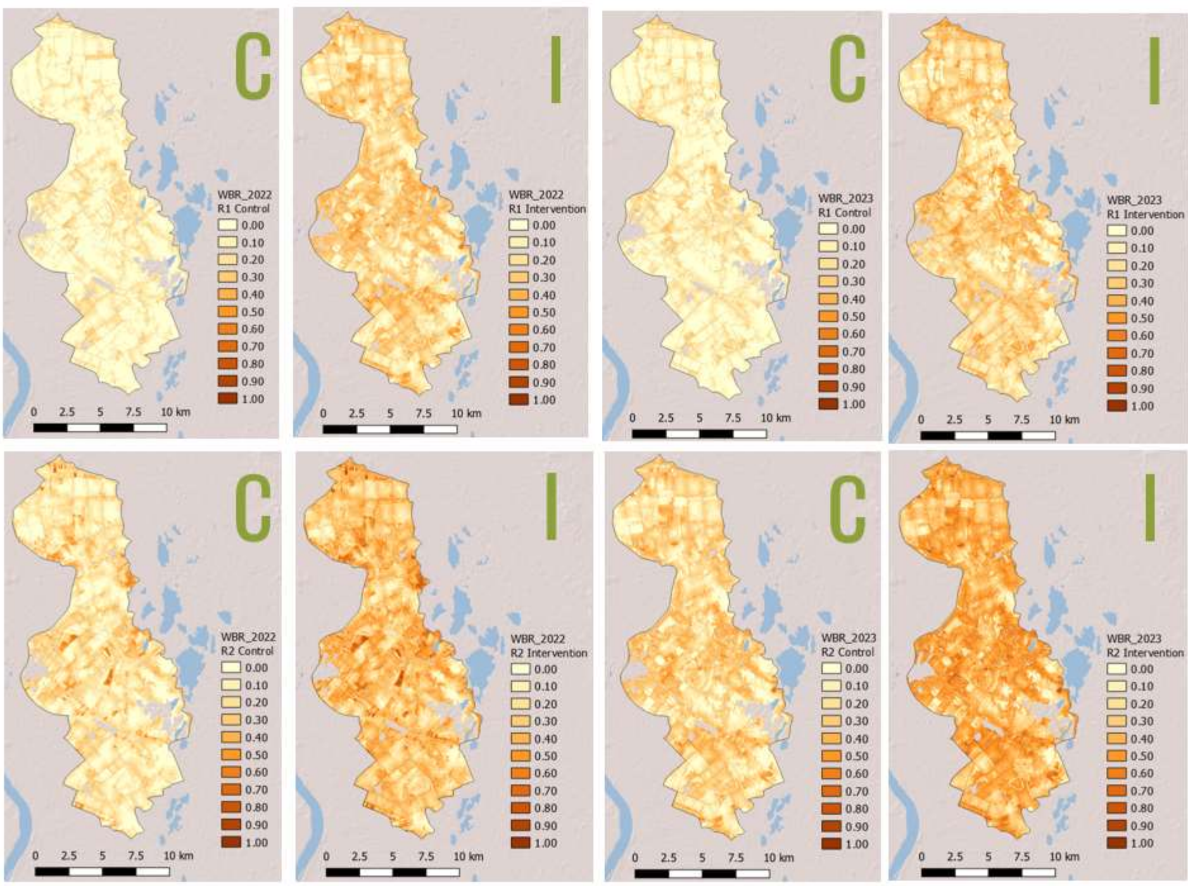

Figure 14: Predicted WBR indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

For both bee indicators the treatment results in positive changes in all sampling rounds with an average increase of 84 and 123% over the control for WBA and WBR respectively. Also, the trend with respect to the baseline is consistently positive, except for the first round of the second year where it resulted in a -14% average decrease of the WBA indicator.

For spider indicators, figures 15 and 16 illustrate the spatial distribution of the normalized SpA and SpR indicators respectively, for control and intervention scenarios during the two rounds in the two years. Table 11 and 12 report the raster statistics for each map and summarize the relative changes with respect to the baseline and to the control of each round.

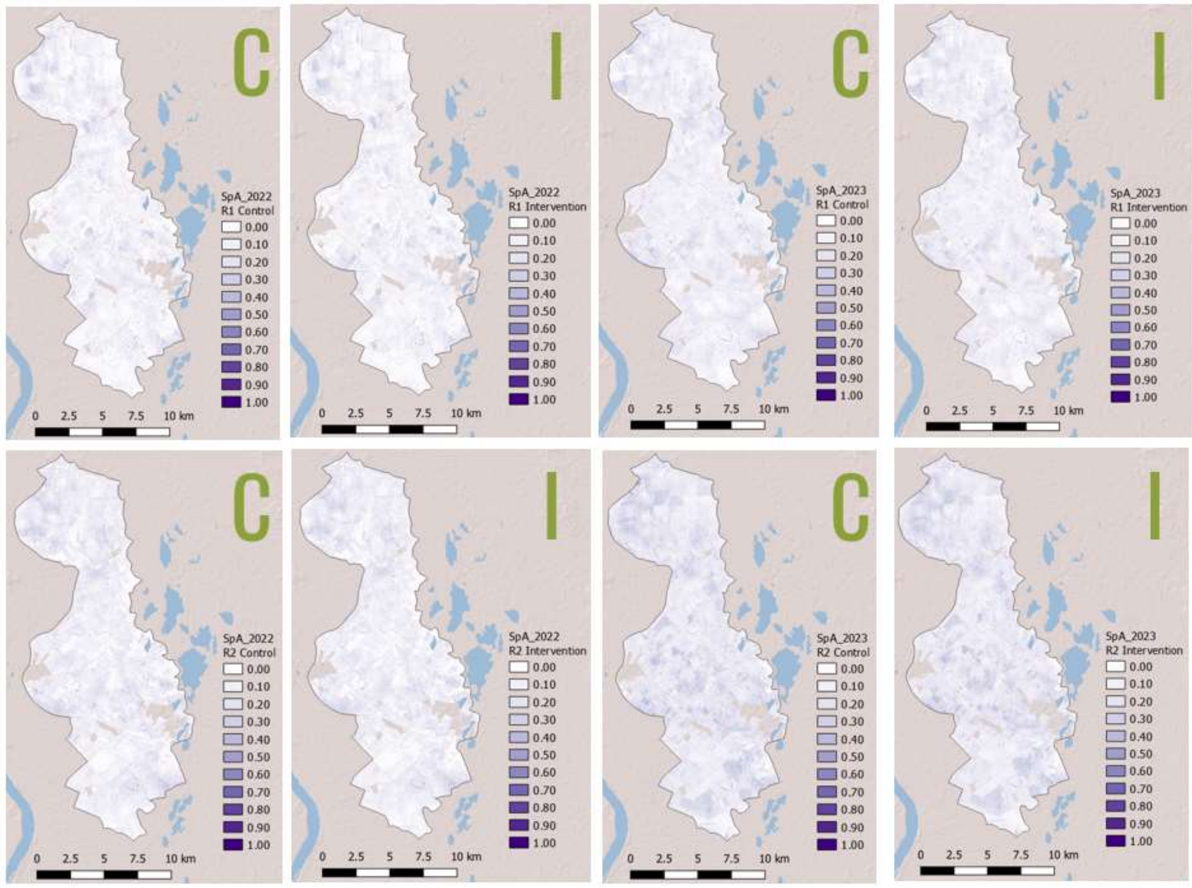

Figure 15: Predicted SpA indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 11: SpA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	SpA mean	median	stdev	min	max	Rel change baseline	Rel Change T
SpA 2022 r1 treatiszero	0.088	0.081	0.066	0.000	0.753	-	
SpA 2022 r1 treatisone	0.086	0.077	0.066	0.000	0.750	-0.03	-0.031
SpA 2022 r2 treatiszero	0.117	0.119	0.068	0.000	0.720	0.33	
SpA 2022 r2 treatisone	0.115	0.116	0.067	0.000	0.717	0.30	-0.024
SpA 2023 r1 treatiszero	0.118	0.113	0.062	0.000	0.701	0.34	
SpA 2023 r1 treatisone	0.115	0.110	0.062	0.000	0.698	0.30	-0.025
SpA 2023 r2 treatiszero	0.173	0.162	0.068	0.000	0.750	0.95	
SpA 2023 r2 treatisone	0.170	0.159	0.068	0.000	0.747	0.92	-0.018
Average changes						0.44	-0.025

Differently from the wild bee indicators, those for spiders were characterized by systematically negative changes with respect to control within the same round, but the overall trend with respect to the baseline was positive for SpA for the second round of 2022 and for the first and the second rounds in 2023. In the case of the SpR indicator the trend was positive only for the second round in both 2022 and 2023.

Table 12: SpA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	SpR mean	median	stdev	min	max	Rel change baseline	Rel Change T
SpR 2022 r1 treatiszero	0.150	0.131	0.132	0.000	1.000	-	
SpR 2022 r1 treatisone	0.110	0.077	0.119	0.000	1.000	-0.27	-0.27
SpR 2022 r2 treatiszero	0.560	0.516	0.232	0.000	1.000	2.73	
SpR 2022 r2 treatisone	0.511	0.463	0.238	0.000	1.000	2.40	-0.09
SpR 2023 r1 treatiszero	0.062	0.023	0.086	0.000	1.000	-0.59	
SpR 2023 r1 treatisone	0.036	0.000	0.070	0.000	1.000	-0.76	-0.42
SpR 2023 r2 treatiszero	0.360	0.321	0.201	0.000	1.000	1.39	
SpR 2023 r2 treatisone	0.308	0.268	0.201	0.000	1.000	1.05	-0.14
Average changes						0.85	-0.23

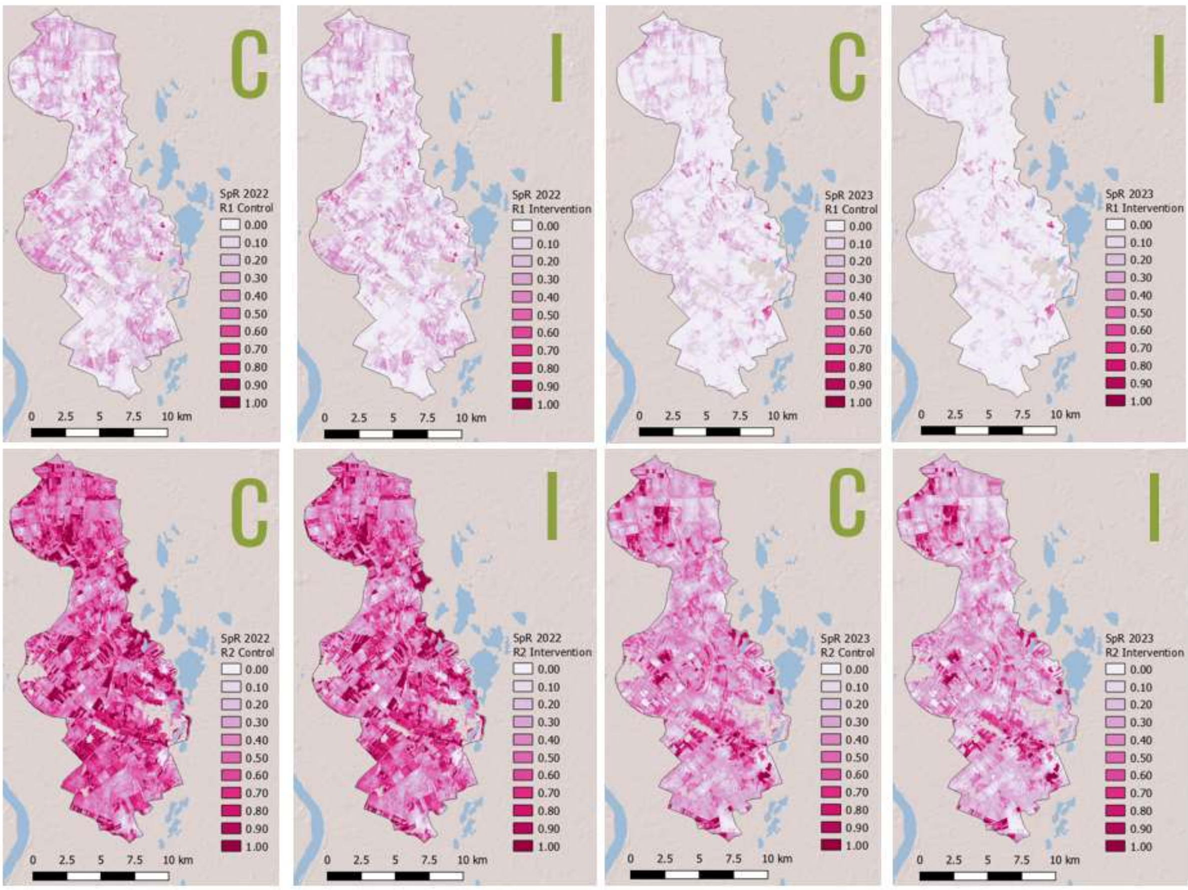

Figure 16: Predicted SpR indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

The spatiotemporal trend of the PlaR indicator is summarized in Table 13 and illustrated in Figure 17. The average changes with respect to the baseline and the average increase in the intervention fields with respect to the control ones during each round were almost equal, with 103 and 105% changes, respectively. Except for an average -5% decrease in the first round of 2023, the trend was always positive.

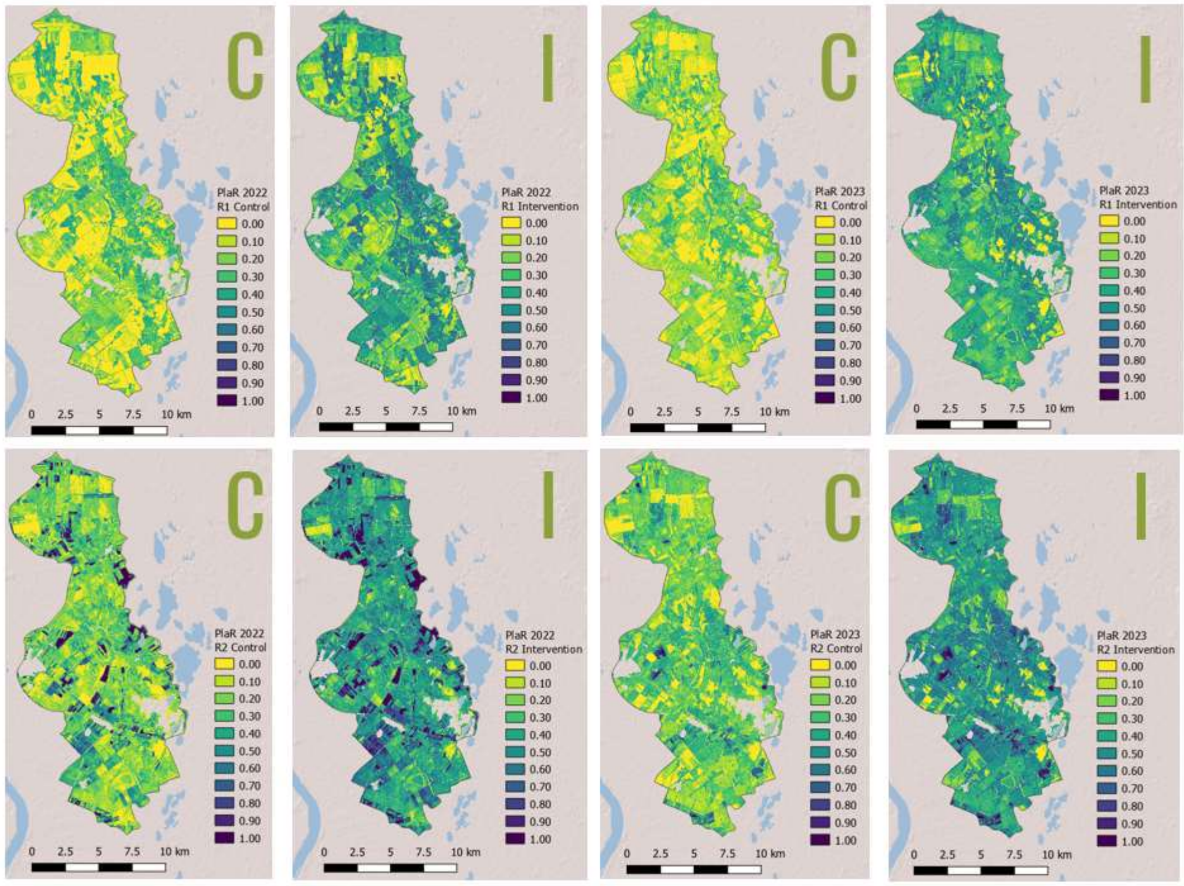

Figure 17: Predicted PlaR indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 13: PlaR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	PlaR mean	median	stdev	min	max	Rel change baseline	Rel Change T
PlaR 2022 r1 treatiszero	0.164	0.145	0.154	0.000	1.000	-	
PlaR 2022 r1 treatisone	0.359	0.373	0.197	0.000	1.000	1.19	1.19
PlaR 2022 r2 treatiszero	0.270	0.227	0.223	0.000	1.000	0.65	
PlaR 2022 r2 treatisone	0.481	0.455	0.210	0.000	1.000	1.93	0.78
PlaR 2023 r1 treatiszero	0.155	0.143	0.127	0.000	1.000	-0.05	
PlaR 2023 r1 treatisone	0.363	0.371	0.160	0.000	1.000	1.21	1.34
PlaR 2023 r2 treatiszero	0.245	0.249	0.159	0.000	1.000	0.49	
PlaR 2023 r2 treatisone	0.460	0.477	0.178	0.000	1.000	1.81	0.88
Average changes						1.03	1.05

To provide a composite indicator describing the overall biodiversity and its spatiotemporal dynamics over the CSA, the estimates of the five core indicators for each round were summed, and the sum 0-1 normalized. Results are shown in Figure 18, and the raster statistics are summarized in Table 14 along with the relative changes with respect to the baseline and for each round with respect to the control.

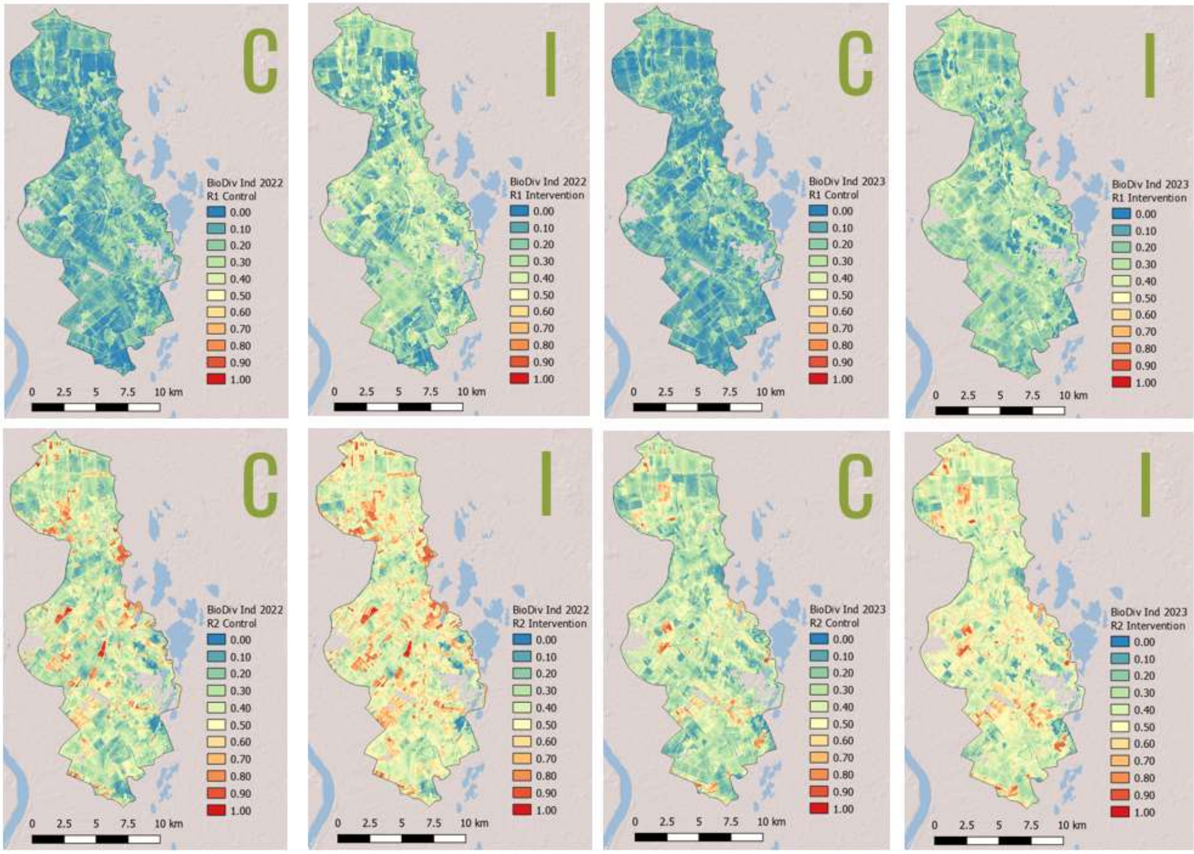

Figure 18: Predicted BioDiv indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 14: BioDiv indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	BioDiv mean	median	stdev	min	max	Rel change baseline	Rel Change T
BioDiv 2022 r1 treatiszero	0.151	0.136	0.096	0.000	1.000	-	
BioDiv 2022 r1 treatisone	0.254	0.258	0.127	0.000	1.000	0.68	0.68
BioDiv 2022 r2 treatiszero	0.377	0.347	0.177	0.000	1.000	1.49	
BioDiv 2022 r2 treatisone	0.463	0.443	0.172	0.000	1.000	2.06	0.23
BioDiv 2023 r1 treatiszero	0.148	0.130	0.094	0.000	1.000	-0.02	
BioDiv 2023 r1 treatisone	0.247	0.244	0.106	0.000	1.000	0.63	0.67
BioDiv 2023 r2 treatiszero	0.339	0.332	0.148	0.000	1.000	1.24	
BioDiv 2023 r2 treatisone	0.422	0.423	0.148	0.000	1.000	1.79	0.24
Average changes						1.12	0.45

The overall average biodiversity increase resulting from the implementation of the biodiversity friendly management practice was equal to 45%, with marked increase above 60% observed for the first rounds, while in the second rounds the difference between control and intervention were below 25% in both years. The overall trend with respect to the baseline was constantly positive, apart from the first round in 2023 which saw a -2% decrease. The overall joint trend of all the six indicators, with their synergies and trade-offs, is visually summarized in the radar graph depicted in Figure 19. The indicators values shown in the figure are averaged over the two rounds of each year

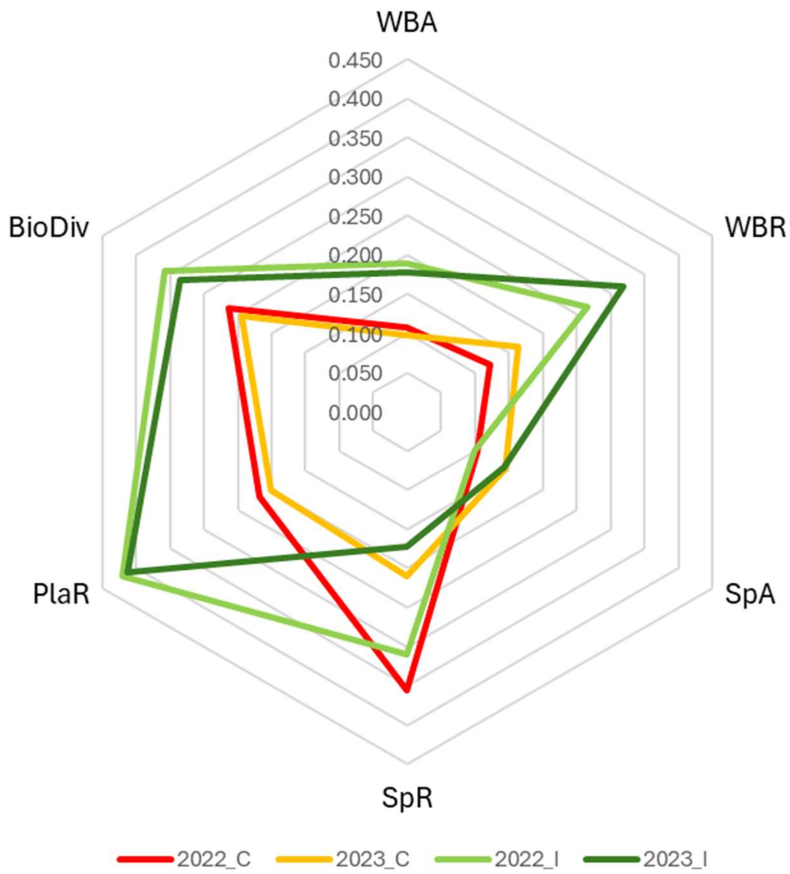

Figure 19: Radar graph of the round-averaged indicators for the control and the intervention in the two years of observation.

3.2 Spanish EBA

The Spanish CSA encompassing the SHOWCASE EBA fields is in Andalusia (Guadalquivida Community), in the alluvial plain on the Guadalquivir River and surrounding hills which border the plain to the North and to the South of the riverbed. The area has an extension of 433.2 km^2, with an elevation ranging from 2 to 347 m a.s.l. and stretches for ca. 90 km in the NE-SW direction from the municipality of Palma del Rio to south of Sevilla. The area is highly anthropized and characterized by intensive agricultural land use with fruit orchards and vegetable farms. In the last decade there has been a strong land cover transition towards citrus orchards which with 22,787 ha represent ca. 52% of the fruit orchard area (Junta de Andalucía, 2023) and 23% of the whole CSA. Other fruit orchards cover an area of 11,214 ha, with a share of 26% of the permanent crop area and 11% of the whole area. Olive orchards are present on 9,267 ha, representing 21% of the permanent crop area and 9% of the whole area, while vineyards occupy less than 50 ha, i.e. 0.1% of the permanent crop area and 0.05% of the whole area. In total the area of permanent crops exceeds 43,315 ha, which represents the target area for upscaling the core biodiversity indicators. Few seminatural elements are in the agricultural fields, and tree elements are mostly present along the river streams.

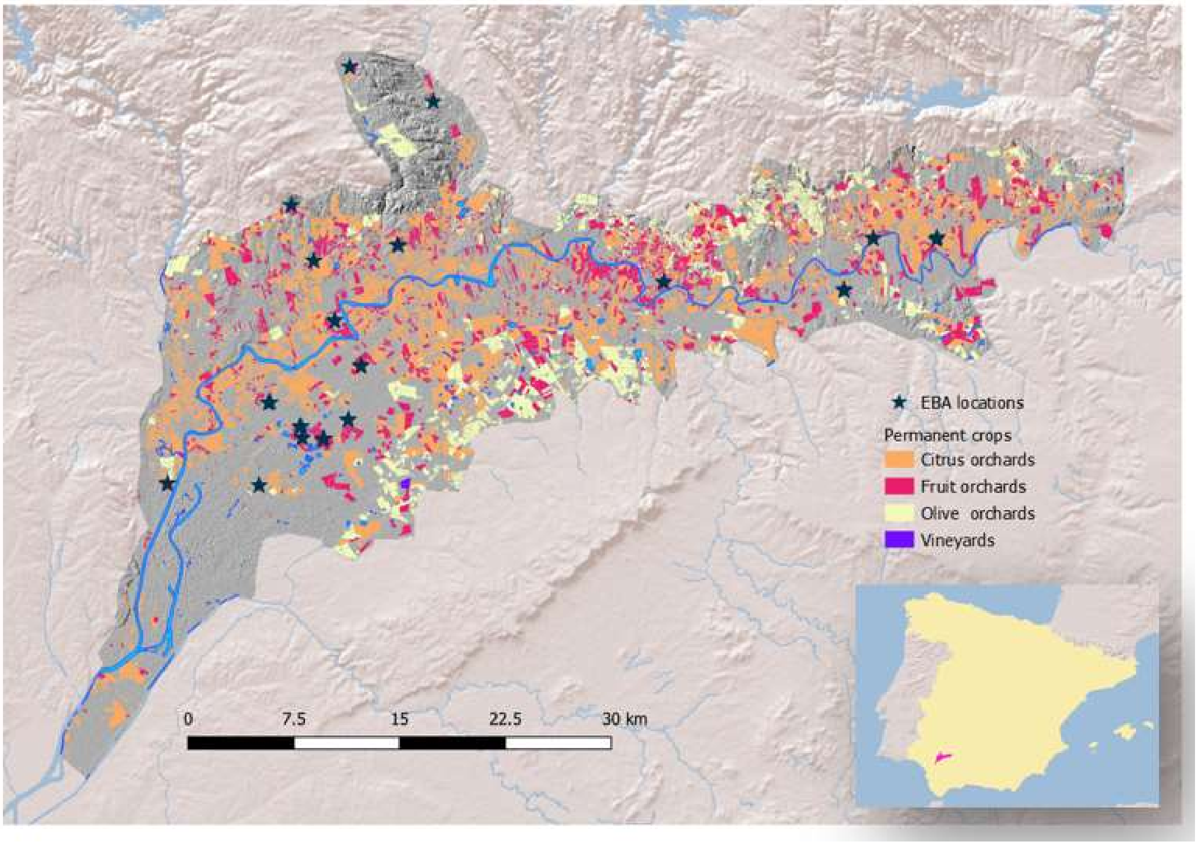

Figure 20. Geographical location of the Spanish CSA.

Following the SHOWCASE sampling protocol, the core indicator data were collected in two rounds (March and April) in 2022 and 2023 from eighteen control fields and eighteen intervention fields. Plant richness was sampled only once every year, in April 2022 (second round) and in March 2023 (first round). The descriptive statistics of the five biodiversity indicators are summarized in Table 15 for individual and species counts and their 0-1 normalized indicators. Table 16 reports the descriptive statistics of the five indicators for control and intervention fields for the two years of observations.

Table 15: Descriptive statistics of the five SHOWCASE core indicators in the Spanish EBA

Core Indicators	Valid N	Mean	Std.Dev.	Std. Err.	Min	Median	Max
Counts							
WBA	128	37.2	54.6	4.8	0	20.5	443
WBR	128	7.0	5.4	0.5	0	7	23
SpA	128	5.3	8.4	0.7	0	2.5	44
SpR	128	1.8	2.4	0.2	0	1	13
PlaR	64	12.2	5.6	0.7	0	11.5	26
Indicator (0-1)							
Ind WBA	128	0.189	0.245	0.022	0.000	0.102	1.000
Ind WBR	128	0.382	0.304	0.027	0.000	0.341	1.000
Ind SpA	128	0.257	0.306	0.027	0.000	0.114	1.000
Ind SpR	128	0.237	0.282	0.025	0.000	0.154	1.000
Ind PlaR	64	0.489	0.256	0.032	0.000	0.458	1.000

Table 16: Descriptive statistics of the five SHOWCASE core indicators in the control and intervention fields of the Spanish EBA

Indicator	Treatment	Means	N	Std. Dev.	Std. Err.	Min	Median	Max
Ind WBA	*Control*	0.070	64	0.136	0.017	0.000	0.034	0.959
	Intervention	0.308	64	0.271	0.034	0.000	0.213	1.000
	All Groups	0.189	128	0.245	0.022	0.000	0.102	1.000
Ind WBR	*Control*	0.196	64	0.225	0.028	0.000	0.167	0.882
	Intervention	0.568	64	0.256	0.032	0.000	0.588	1.000
	All Groups	0.382	128	0.304	0.027	0.000	0.341	1.000
Ind SpA	*Control*	0.210	64	0.290	0.036	0.000	0.067	1.000
	Intervention	0.305	64	0.316	0.040	0.000	0.200	1.000
	All Groups	0.257	128	0.306	0.027	0.000	0.114	1.000
Ind SpR	*Control*	0.198	66	0.286	0.035	0.000	0.000	1.000
	Intervention	0.276	66	0.276	0.034	0.000	0.200	1.000
	All Groups	0.237	132	0.282	0.025	0.000	0.154	1.000
Ind PlaR	*Control*	0.399	32	0.282	0.050	0.000	0.388	0.950
	Intervention	0.579	32	0.191	0.034	0.300	0.571	1.000
	All Groups	0.489	64	0.256	0.032	0.000	0.458	1.000

Statistically significant differences ($p < 0.05$) in indicator mean values were detected for WBA, WBR and PlaR indicators, but not for SpA and SpR indicators, even though the mean values observed for the control fields were lower than those observed for the intervention fields. Mean indicator values for the second sampling round were somewhat lower than in the first round in both control and intervention fields for WBA, WBR SpA and PlaR, while in the intervention fields a non-significant increase was observed only for SpR. Over the two years of observations, the mean values of the indicators showed an increase which was always more evident in the intervention fields, but this was statistically significant only for WBA in the intervention fields.

As similar trends in terms of responses to biodiversity management intervention and temporal dynamics were observed for the indicators of the Portuguese EBA and given the strong similarities of the agricultural systems considered in the two EBAs, i.e. intensive fruit orchards in Andalucia and intensive olive orchards in Alentejo, and the lack of statistically significant differences in the mean indicators values from the two data sets in terms of responses to management, rounds and year of sampling, a single dataset was used to calibrate more robust spatiotemporal models for upscaling effects from the field to landscape scale. These analyses are potentially generalizable to similar perennial systems in the south Iberian peninsula. The descriptive statistics for the ES-PT joint dataset are reported in Tables 17 and 18.

Table 17: Descriptive statistics of the five SHOWCASE core indicators for the ES-PT combined dataset

Core Indicators	Valid N	Mean	Std.Dev.	Std. Err.	Min	Median	Max
Counts							
WBA	168	33.1	49.5	3.8	0	17	443
WBR	168	7.6	6.4	0.5	0	7	42
SpA	191	11.5	19.6	1.4	0	5	170
SpR	191	2.2	2.8	0.2	0	1	15
PlaR	127	20.8	10.5	0.9	1	20	43
Indicator (0-1)							
Ind WBA	168	0.195	0.251	0.019	0.000	0.100	1.000
Ind WBR	168	0.362	0.298	0.023	0.000	0.294	1.000
Ind SpA	191	0.262	0.292	0.021	0.000	0.136	1.000
Ind SpR	191	0.265	0.288	0.021	0.000	0.200	1.000
Ind PlaR	127	0.524	0.261	0.023	0.000	0.500	1.000

Table 18: Descriptive statistics of the five SHOWCASE core indicators in the control and intervention fields of the Spanish and Portuguese EBAs

Indicator	Treatment	Means	N	Std. Dev.	Std. Err.	Min	Median	Max
Ind WBA	*Control*	0.065	84	0.120	0.013	0.000	0.039	0.959
	Intervention	0.325	84	0.280	0.031	0.000	0.232	1.000
	All Groups	0.195	168	0.251	0.019	0.000	0.100	1.000
Ind WBR	*Control*	0.179	84	0.204	0.022	0.000	0.143	0.882
	Intervention	0.544	84	0.264	0.029	0.000	0.568	1.000
	All Groups	0.362	168	0.298	0.023	0.000	0.294	1.000
Ind SpA	*Control*	0.203	96	0.258	0.026	0.000	0.088	1.000
	Intervention	0.322	95	0.313	0.032	0.000	0.222	1.000
	All Groups	0.262	191	0.292	0.021	0.000	0.136	1.000
Ind SpR	*Control*	0.221	98	0.289	0.029	0.000	0.101	1.000
	Intervention	0.311	97	0.281	0.029	0.000	0.250	1.000
	All Groups	0.265	195	0.288	0.021	0.000	0.200	1.000
Ind PlaR	*Control*	0.440	64	0.267	0.033	0.000	0.450	0.950
	Intervention	0.610	63	0.227	0.029	0.050	0.625	1.000
	All Groups	0.524	127	0.261	0.023	0.000	0.500	1.000

In the joint dataset for all indicators, mean SpA and SpR for the intervention fields were significantly higher ($p < 0.05$) than the means observed for the control fields.

The assessment of the relevance of each single predictor from the RF is presented in Table 19 and in Figures 21 and 22.

Table 19: Relevance of RF predictors for the five biodiversity indicators in term of node purity; colors highlight the most relevant predictors (orange > brown >light brown)

Predictors	WBA Indicator		WBR Indicator		SpA Indicator		SpR Indicator		PlaR Indicator	
	NodePurity	Rel. %	NodePurity	Rel. %	NodePurity	Rel. %	NodePurity	Rel. %	NodePurity	Rel. %
dummy_treat	0.099	1.44%	0.130	1.26%	0.078	0.69%	0.077	0.80%	0.053	0.95%
dummy_year	0.149	2.17%	0.071	0.69%	0.131	1.17%	0.078	0.82%	0.128	2.31%
dummy_round	0.022	0.32%	0.065	0.63%	0.123	1.09%	0.088	0.92%		
swf_prox	0.247	3.62%	0.358	3.47%	0.490	4.36%	0.358	3.73%	0.172	3.11%
road_prox	0.318	4.65%	0.309	3.00%	0.370	3.29%	0.340	3.53%	0.205	3.70%
aspect	0.316	4.62%	0.479	4.65%	0.405	3.60%	0.368	3.82%	0.238	4.30%
elevation	0.231	3.38%	0.293	2.85%	0.484	4.30%	0.342	3.55%	0.382	6.89%
slope	0.206	3.01%	0.373	3.63%	0.613	5.44%	0.324	3.37%	0.138	2.49%
catchslope	0.219	3.20%	0.356	3.46%	0.294	2.61%	0.218	2.27%	0.189	3.41%
catcharea	0.254	3.71%	0.578	5.62%	0.520	4.62%	0.499	5.19%	0.248	4.47%
modcatchar	0.229	3.34%	0.517	5.02%	0.471	4.18%	0.316	3.29%	0.256	4.61%
twi	0.264	3.86%	0.505	4.91%	0.388	3.45%	0.305	3.17%	0.446	8.05%
valleydept	0.219	3.20%	0.305	2.97%	0.512	4.55%	0.497	5.17%	0.250	4.50%
bi	0.441	6.44%	0.516	5.02%	0.492	4.37%	0.352	3.66%	0.193	3.48%
blue	0.220	3.21%	0.358	3.48%	0.546	4.85%	0.518	5.39%	0.202	3.65%
green	0.222	3.24%	0.397	3.85%	0.401	3.56%	0.390	4.05%	0.237	4.28%
ir	0.293	4.28%	0.408	3.97%	0.511	4.54%	0.339	3.53%	0.238	4.28%
irn	0.286	4.17%	0.430	4.17%	0.448	3.98%	0.327	3.40%	0.268	4.84%
ndbsi	0.438	6.40%	0.479	4.65%	0.398	3.53%	0.384	4.00%	0.205	3.69%
ndsi	0.306	4.47%	0.454	4.42%	0.440	3.91%	0.389	4.04%	0.237	4.28%
ndvi	0.316	4.61%	0.447	4.34%	0.550	4.89%	0.339	3.53%	0.237	4.27%
red	0.244	3.57%	0.391	3.80%	0.437	3.88%	0.482	5.02%	0.148	2.66%
sosa	0.268	3.91%	0.435	4.23%	0.417	3.70%	0.505	5.25%	0.150	2.70%
sosi1	0.261	3.81%	0.360	3.50%	0.385	3.42%	0.425	4.42%	0.157	2.83%
sosi2	0.264	3.85%	0.461	4.48%	0.520	4.62%	0.345	3.59%	0.204	3.67%
sosi3	0.234	3.42%	0.419	4.07%	0.390	3.47%	0.507	5.27%	0.174	3.15%
swir	0.280	4.09%	0.398	3.87%	0.443	3.94%	0.502	5.22%	0.191	3.44%

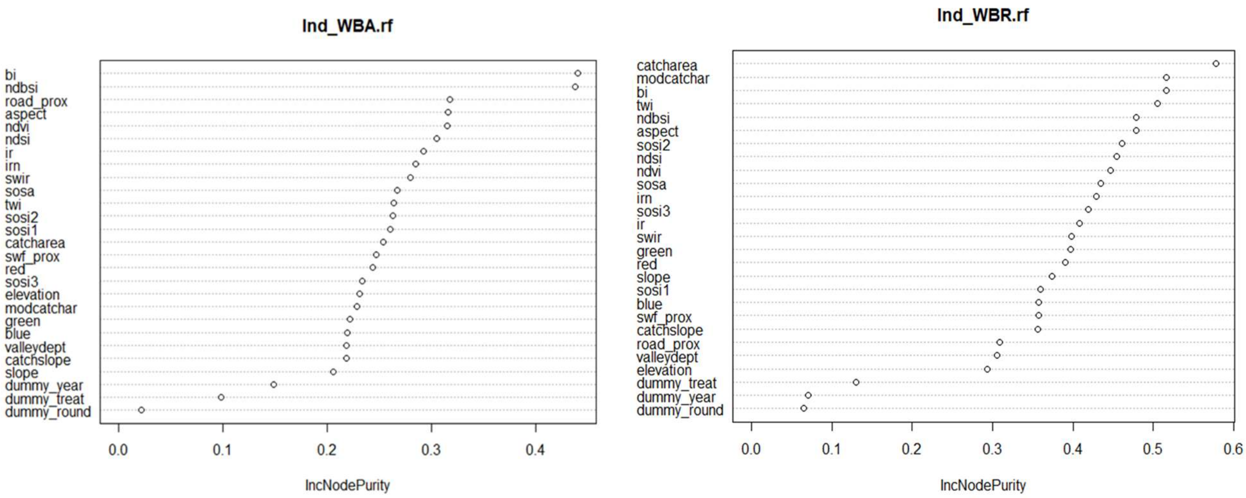

Figure 21. RF variable contribution plots for WBA (left) and, WBR (right) indicators for the Spanish and Portuguese EBA's.

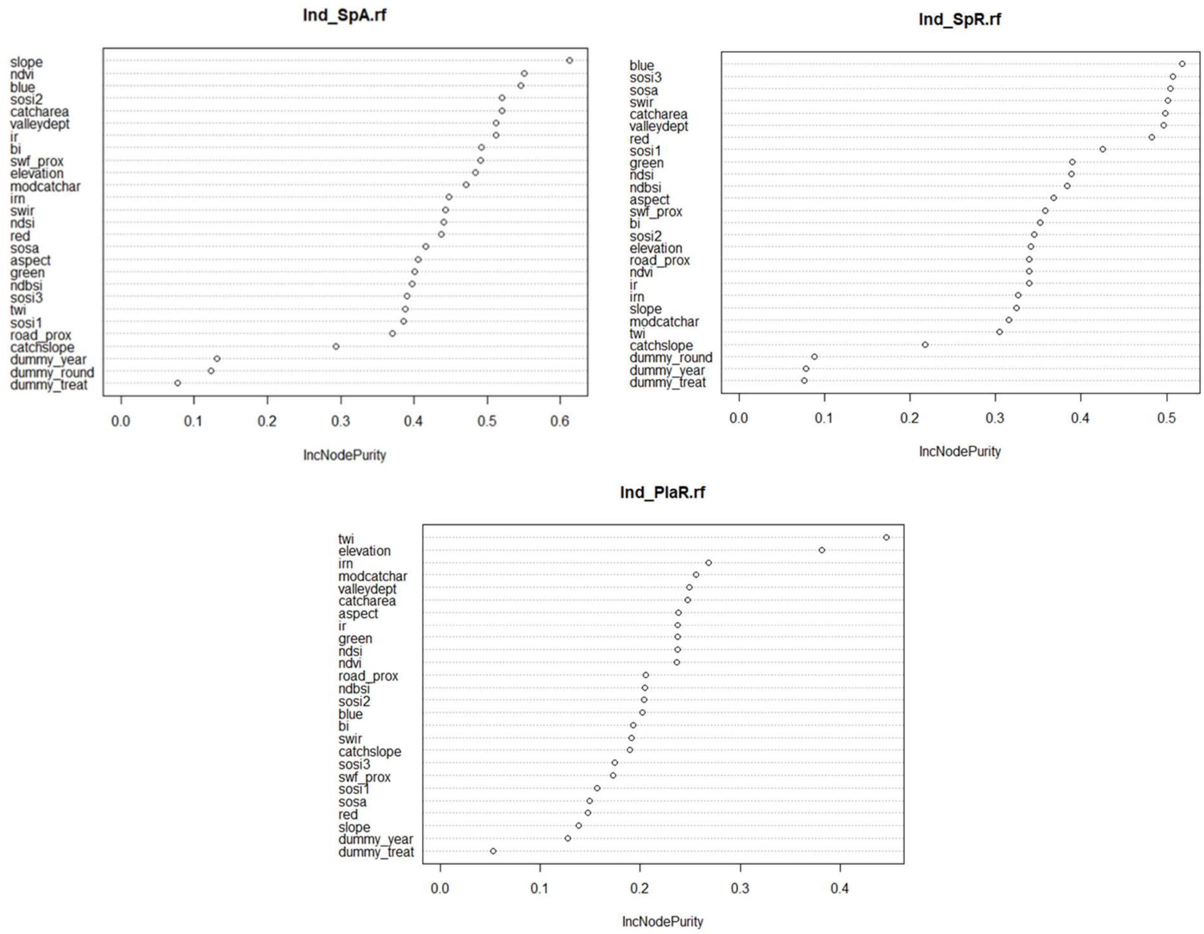

Figure 22. RF variable contribution plots for SpA (top left), SpR (top right) and PlaR (bottom center) indicators for the Spanish and Portuguese EBA's.

Contrarily to what was suggested by field observations, treatment dummy variables appeared not to be relevant contributors to the RF predictions for all the indicators, differently from terrain attributes and RSI which, in different combinations for the selected indicators, played a major role. For example, topographic wetness index and elevation were the most relevant predictors for PlaR followed by reflectance in the near-infrared band. The distance from the road network was a major determinant of WBA, while in the case of SpA, the distance from small woody features had medium predictive power. Bare soil-related RSI (e.g., BI and NDBSI) had strongly predicted both WBA and WBR, while vegetation index (NDVI) affected WBR, WBA and SpA with increasing predictive power.

The MLR coefficients for the normalized biodiversity indicators are summarized in Table 20, and from their statistical significance, it appears that treatment (dummy variable) is a statistically significant predictor for WBA, WBR and PlaR and that the stepwise combined approach included it also for SpA and SpR. Overall, there is a good agreement in terms of the predictors identified via stepwise MLR and the relevance of predictors as assessed via the RF algorithms. Nevertheless, for all indicators, the performance evaluated in terms of error indices (Table 21) highlights that MLR returns smaller calibration errors and provide higher agreement indices between observed and estimated indicator values (Figure 23). Only for the PlaR indicator the differences in the error indices are closer and of the same order of magnitude, but in this case, MLRs perform better than RF.

Table 20: Coefficients of the MLRs calibrated for the normalized biodiversity indicators; significant coefficients in red (p <0.05) and blue (p>0.10)

Predictor	WBA	WBR	SpA	SpR	PlaR
Intercept	1.953610	0.967043	1.724635	0.324924	-0.047122
Dummy Treat	0.139537	0.322600	-0.026903	0.014897	0.093101
Dummy Round	-0.088980	-0.352393	-0.092180	-0.101861	
Dummy Year	0.175778	-0.056377	0.178538		0.228596
Roads prox		-0.000388	-0.000249		-0.000177
SWF prox			0.000145		
Aspect	-0.000255			-0.000613	
Elevation		-0.000599	-0.000421		0.001589
Catch. Area			0.000004	0.000006	
CatchSlope		3.094585	-1.720080		
Mod. Catch. Area	0.000001	0.000001	0.000003		
TWI		0.083604	-0.179431		
Valley Depth	-0.000907	-0.001066	0.001642	0.001966	0.001427
BI		-6.709545	-3.000944	-0.836076	
blue	-0.001305				
green		-0.003600			
IR		0.000025			0.000290
IRn		0.000513			-0.000215
NDBSI	-0.885838				
NDSI		3.019846			
NDVI			-1.129670		
red				-0.000058	
SOSA		0.002370			
SOSI2	0.000044	0.000941			
SOSI3	0.000010				

Table 21: Calibration error indices for MLR and RF predictive model for the five biodiversity indicators

Error	*WBA Indicator*		*WBR Indicator*		*SpA indicator*		*SpR Indicator*		*PlaR Indicator*	
indices	RF	MLR	RF	MLR	RF	MLR	RF	MLR	RF	MLR
ME	-0.01	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.00	0.01	0.00
AE	0.18	0.10	0.24	0.15	0.24	0.12	0.24	0.13	0.18	0.14
SE	0.25	0.02	0.29	0.19	0.30	0.15	0.29	0.16	0.23	0.17
R2	0.03	0.49	0.07	0.52	0.02	0.51	0.03	0.45	0.19	0.43
MSR	0.06	0.02	0.08	0.04	0.09	0.02	0.08	0.03	0.05	0.03
IoA	0.19	0.78	0.27	0.81	0.16	0.79	0.07	0.77	0.48	0.75

The MLR models were then used to assess and map the five biodiversity indicators over the entire agricultural land area occupied by permanent crops in the Spanish and Portuguese CSAs. Based on the resulting raster maps (resolution 10 m), raster statistics were calculated for each map to assess the average relative changes with respect to the baseline situation (year 1, control) and for each round the relative changes from the treatment implementation over the whole target area to quantify the potential impact of the biodiversity management practice implemented in the EBA.

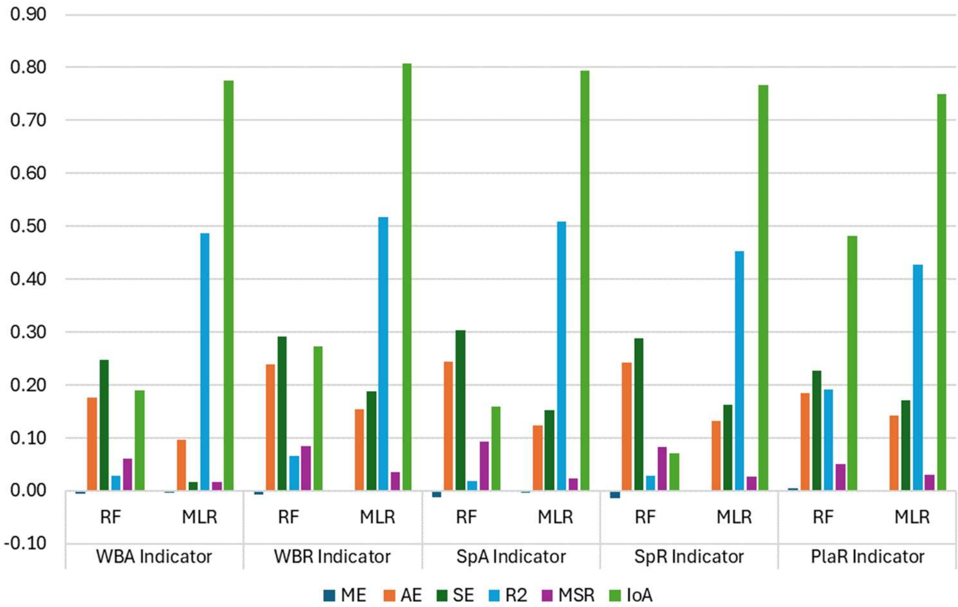

Figure 23: Calibration error indices for MLR and RF predictive model for the five biodiversity indicators

Table 22 reports the descriptive statistics of the WBA indicator estimates over the whole target area (43,315 ha). The results highlight a positive trend with respect to the 2022 baseline (control), with only the control at round 2 showing a -42% reduction in the average indicator value, very likely due to the hotter and dryer climate conditions. The increase due to the intervention with respect to the control was particularly evident in the first year, where values for the control were particularly low, with increases above 100 and 200% in the first and the second round respectively, while in the second year they ranged between 42 and 25%. This is probably due to the persisting drought conditions also in 2023. The maps underpinning the statistics presented in the table are shown in Figure 24.

Table 22: WBA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
WBA 2022 r1 treatiszero	0.089	0.084	0.072	0.000	1.000	-	
WBA 2022 r1 treatisone	0.221	0.224	0.085	0.000	1.000	1.47	1.47
WBA 2022 r2 treatiszero	0.052	0.038	0.055	0.000	0.977	-0.42	
WBA 2022 r2 treatisone	0.175	0.178	0.076	0.000	1.000	0.96	2.37
WBA 2023 r1 treatiszero	0.291	0.294	0.080	0.000	1.000	2.25	
WBA 2023 r1 treatisone	0.413	0.416	0.077	0.000	0.959	3.62	0.42
WBA 2023 r2 treatiszero	0.219	0.221	0.076	0.000	1.000	1.45	
WBA 2023 r2 treatisone	0.274	0.276	0.059	0.000	0.765	2.06	0.25
Average changes						1.63	1.13

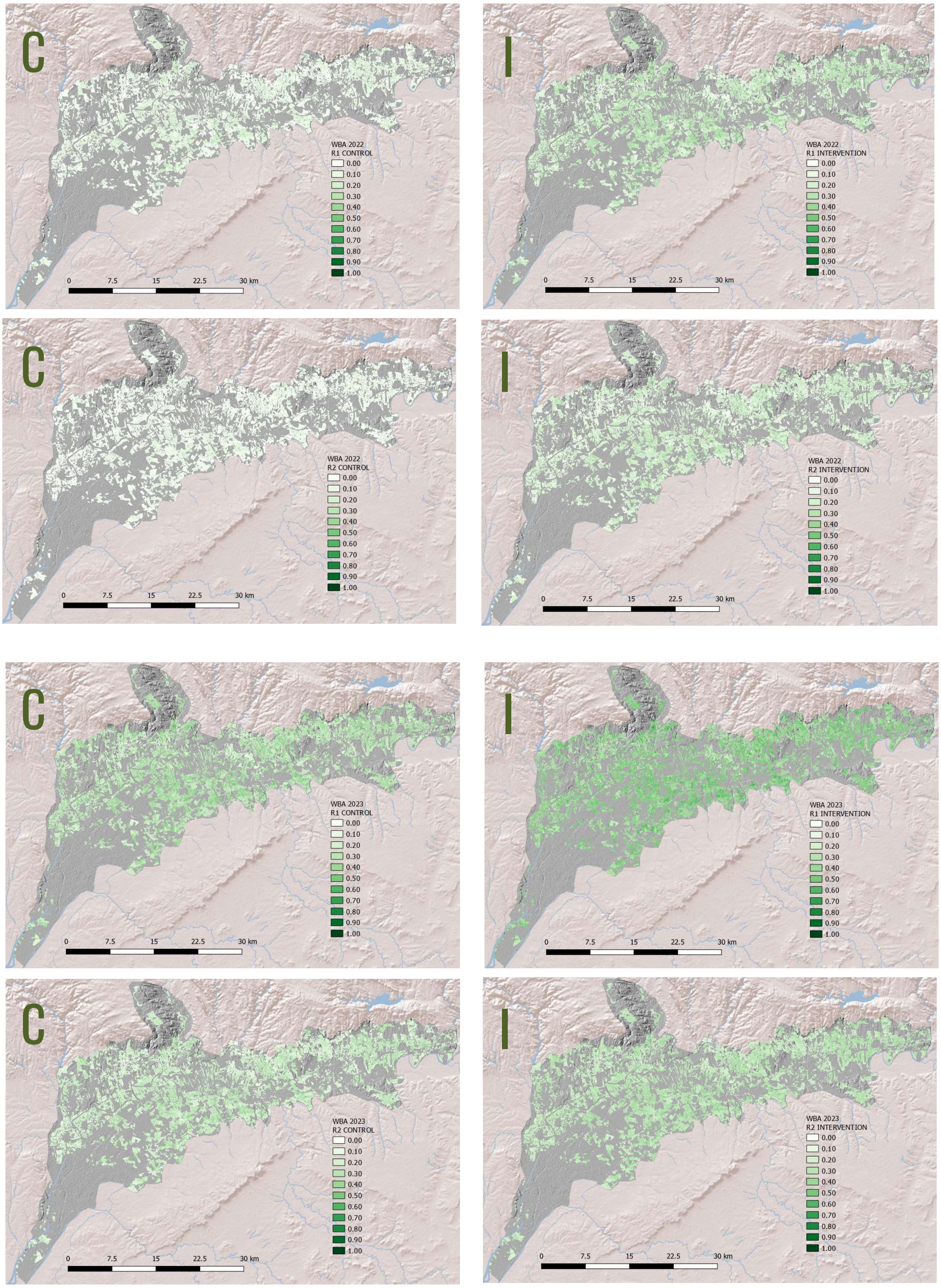

Figure 24: Predicted WBA indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

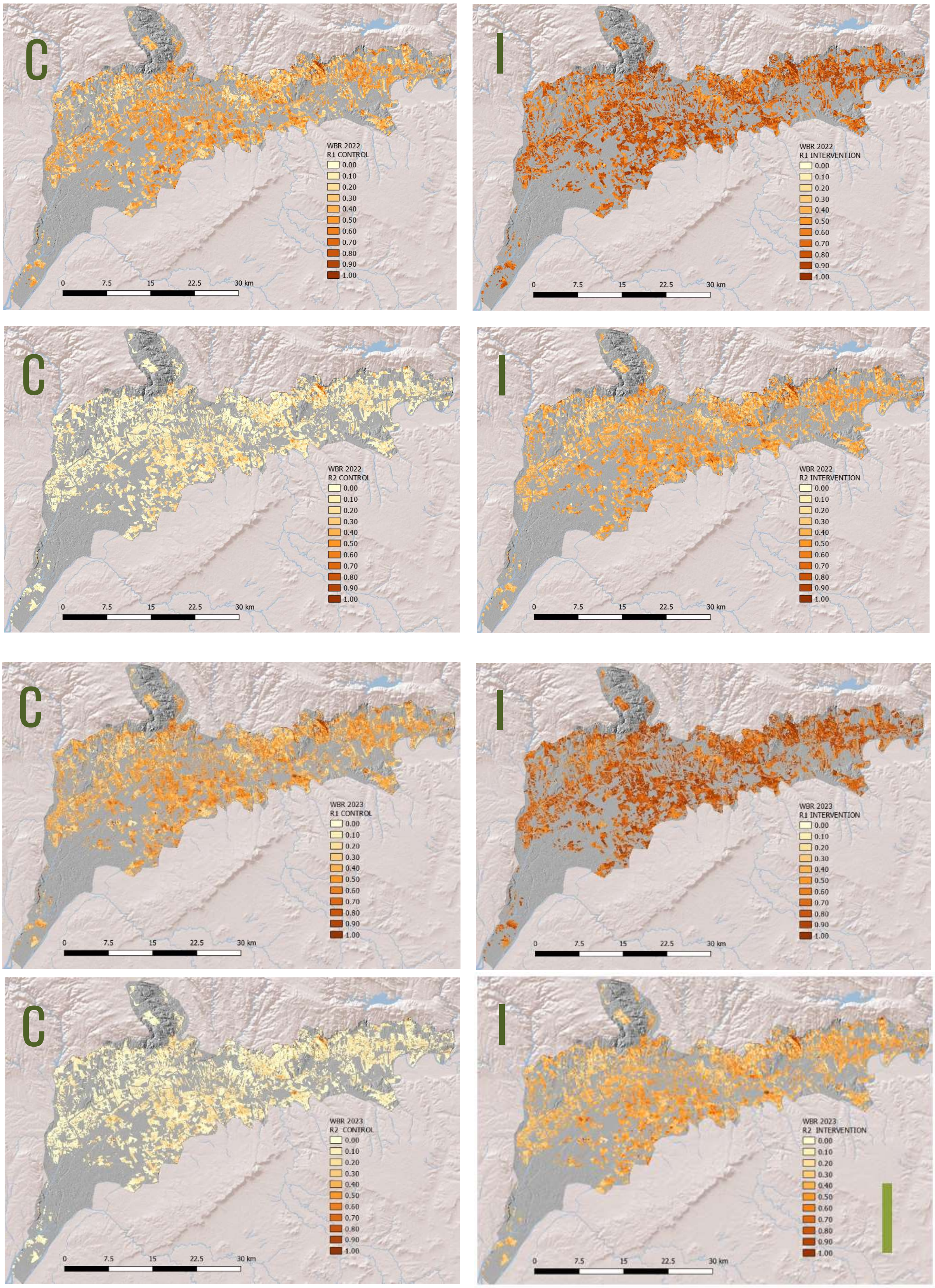

Figure 25: Predicted WBR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

Table 23: WBR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
WBR 2022 r1 treatiszero	0.411	0.411	0.159	0.000	1.000	-	
WBR 2022 r1 treatisone	0.729	0.734	0.151	0.000	1.000	0.78	0.78
WBR 2022 r2 treatiszero	0.120	0.101	0.120	0.000	1.000	-0.71	
WBR 2022 r2 treatisone	0.425	0.423	0.139	0.000	1.000	0.03	2.55
WBR 2023 r1 treatiszero	0.434	0.432	0.151	0.000	1.000	0.06	
WBR 2023 r1 treatisone	0.751	0.755	0.141	0.000	1.000	0.83	0.73
WBR 2023 r2 treatiszero	0.107	0.081	0.120	0.000	1.000	-0.74	
WBR 2023 r2 treatisone	0.408	0.404	0.141	0.000	1.000	-0.01	2.81
Average changes						0.03	1.72

The maps in Figure 25 illustrate the results of the spatiotemporal modelling of the WBR indicator for the permanent crops in the Spanish CSA, and Table 23 presents a synthesis of the descriptive statistics of the indicator estimates for the whole target area. The results highlight a lack of a regular trend with respect to the 2022 baseline (control), with the control at round 2 showing a -71 and -74% reduction in the average indicator value in 2022 and 2023 respectively. A negative trend with respect to the baseline value was also observed for round 2 in the intervention fields, but in this case the reduction was only -1%. The increase due to the intervention with respect to the control was evident in both years with very similar values in both rounds of the two years of observations, but the relative increases observed in the second rounds were about four times higher than those observed in the first rounds.

Table 24 reports the descriptive statistics of the SpA indicator estimates over the whole target area. The results highlight a consistently negative trend with respect to the 2022 baseline (control), with a stronger decrease in the indicator mean value in the second round of 2023 (-89%). The decrease in spider abundance due to the intervention with respect to the control was evident in the first year, with decreases equal to -10 and -13% in the first and the second round respectively, while in the second year a +8% increase was observed in the first round, followed by a -3% decrease in the second. The maps underlying the descriptive statistics presented in Table 24 are shown in Figure 26.

Table 24: SpA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
SpA_2022_r1_treatiszero	0.229	0.217	0.169	0.000	1.000	-	
SpA_2022_r1_treatisone	0.206	0.190	0.164	0.000	1.000	-0.10	-0.10
SpA_2022_r2_treatiszero	0.148	0.123	0.142	0.000	1.000	-0.36	
SpA_2022_r2_treatisone	0.128	0.096	0.135	0.000	1.000	-0.44	-0.13
SpA_2023_r1_treatiszero	0.190	0.191	0.087	0.000	0.494	-0.17	
SpA_2023_r1_treatisone	0.206	0.206	0.101	0.000	0.574	-0.10	0.08
SpA_2023_r2_treatiszero	0.026	0.026	0.017	0.000	0.104	-0.89	
SpA_2023_r2_treatisone	0.025	0.025	0.018	0.000	0.112	-0.89	-0.03
Average changes						-0.42	-0.05

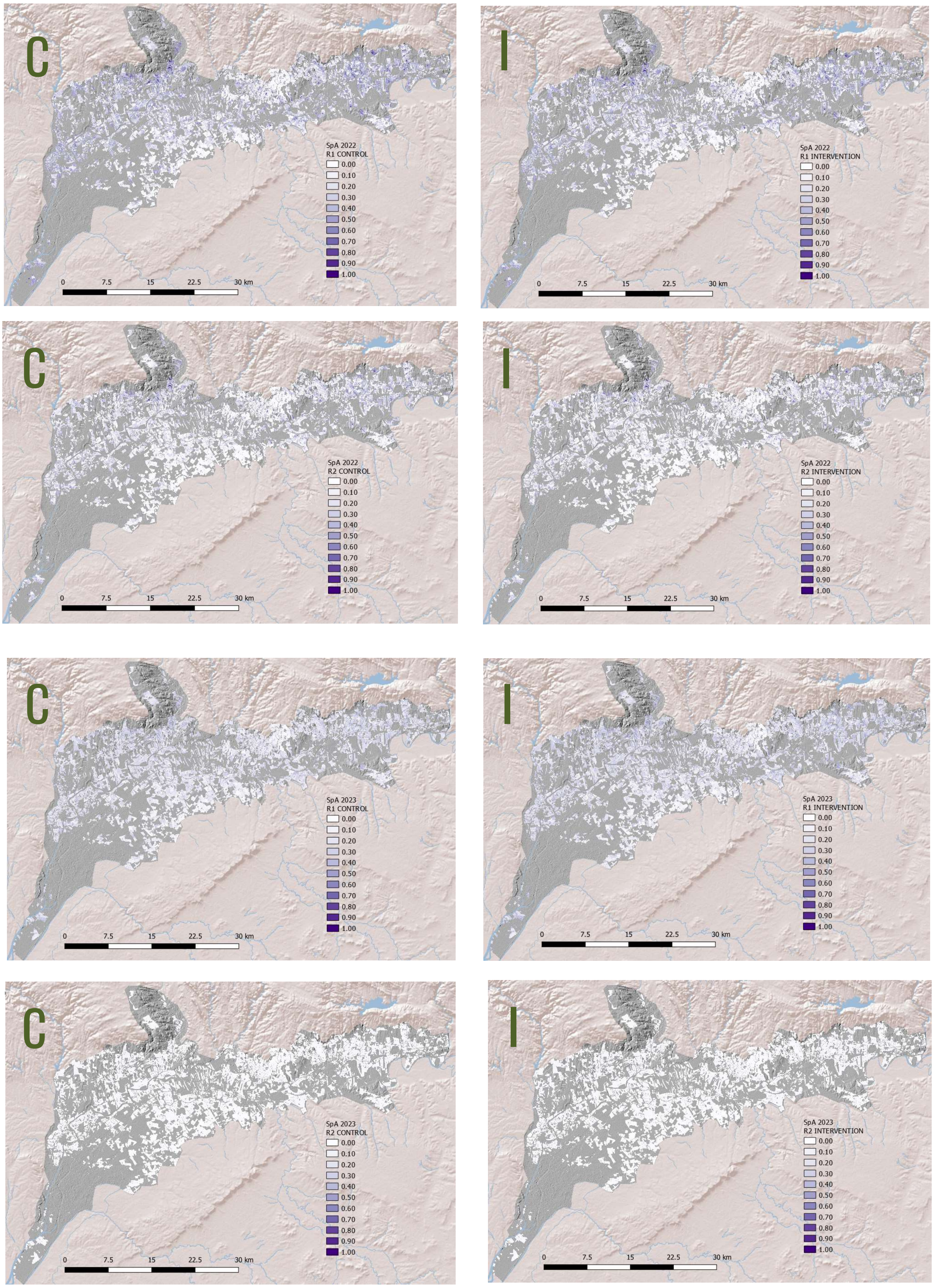

Figure 26: Predicted SpA indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

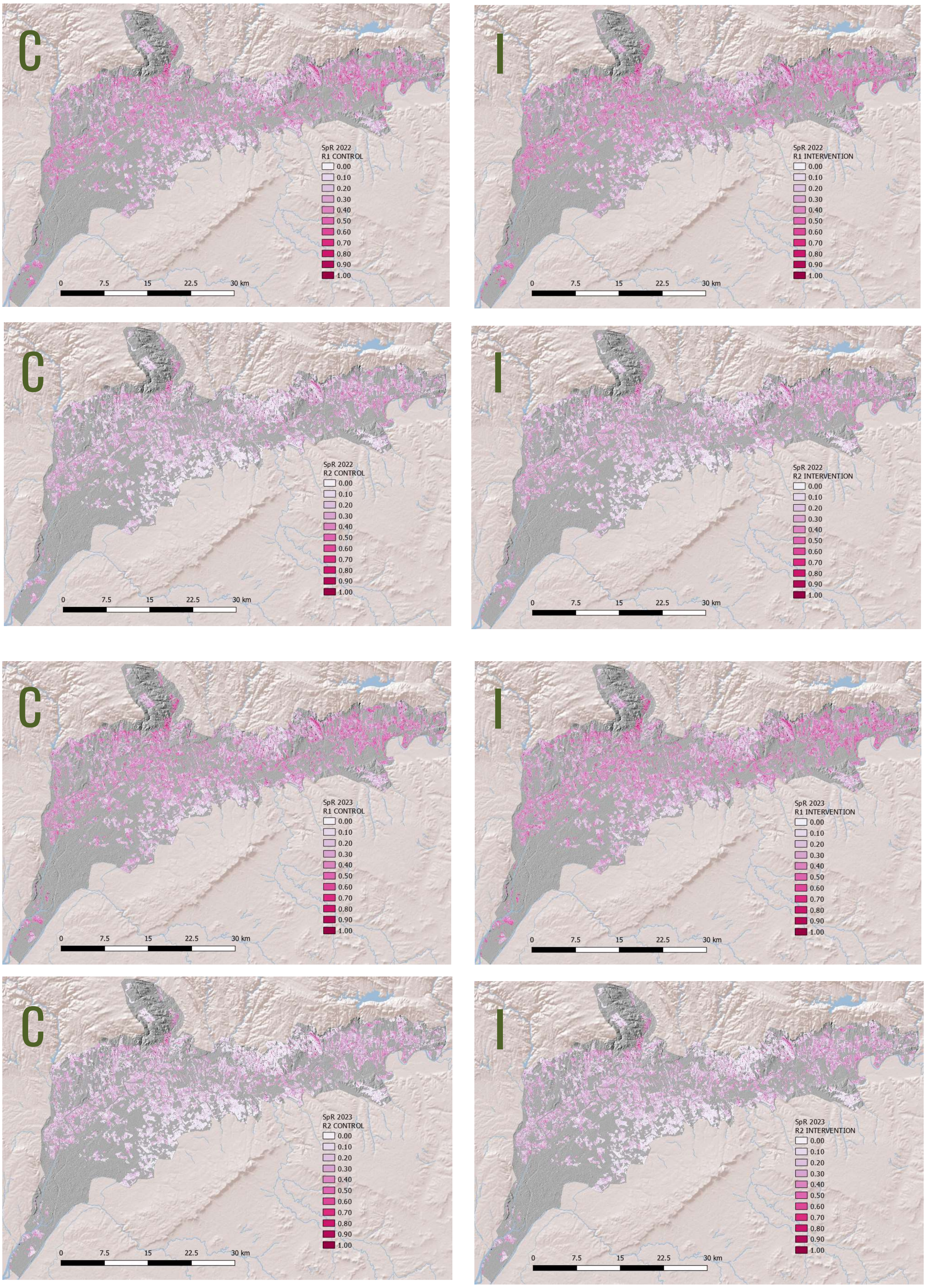

Figure 27: Predicted SpR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

The eight maps in Figure 27 depict the outcomes of the spatiotemporal modelling of the SpR indicator for the permanent crops in the Spanish CSA, and Table 25 synthesizes the descriptive statistics of the indicator estimates for the whole target area. The results highlight in both years a reduction with respect to the baseline in the second rounds for both control and intervention fields, which was slightly more evident in 2023. The relative change due to the intervention with respect to the control was always positive in both years with very similar values in both rounds and in the two years of observations, and equal to 5% for the first rounds and between 7 and 8% for the second.

Table 25: SpR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
SpR_2022_r1_treatiszero	0.277	0.272	0.137	0.000	1.000	-	
SpR_2022_r1_treatisone	0.292	0.287	0.137	0.000	1.000	0.05	0.05
SpR_2022_r2_treatiszero	0.188	0.181	0.129	0.000	1.000	-0.32	
SpR_2022_r2_treatisone	0.202	0.196	0.130	0.000	1.000	-0.27	0.07
SpR_2023_r1_treatiszero	0.282	0.278	0.133	0.000	1.000	0.02	
SpR_2023_r1_treatisone	0.297	0.293	0.133	0.000	1.000	0.07	0.05
SpR_2023_r2_treatiszero	0.165	0.155	0.126	0.000	1.000	-0.41	
SpR_2023_r2_treatisone	0.178	0.170	0.128	0.000	1.000	-0.36	0.08
Average changes						-0.17	0.07

The results for PlaR indicators are summarized in terms of descriptive statistics for the raster maps in Table 26. The implementation of biodiversity management results in an increase of the average value of the indicator at each round of the two years of observations, with an increase of ca. 30% for the two rounds in 2022, and a smaller increase of 17% for the two rounds of 2023. The overall trend with respect to the baseline was always positive, with the major gains detected in the intervention fields in the second year. The eight raster maps at 10 m resolution underpinning the figures reported in Table 26 are shown in Figure 28.

Table 26: PlaR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
PlaR_2022_r1_treatiszero	0.300	0.284	0.068	0.000	0.837	-	
PlaR _2022_r1_treatisone	0.393	0.377	0.068	0.012	0.930	0.31	0.31
PlaR _2022_r2_treatiszero	0.333	0.317	0.068	0.000	0.866	0.11	
PlaR _2022_r2_treatisone	0.426	0.410	0.068	0.006	0.959	0.42	0.28
PlaR _2023_r1_treatiszero	0.546	0.531	0.069	0.000	1.000	0.82	
PlaR _2023_r1_treatisone	0.639	0.624	0.069	0.081	1.000	1.13	0.17
PlaR _2023_r2_treatiszero	0.562	0.547	0.068	0.038	1.000	0.87	
PlaR _2023_r2_treatisone	0.655	0.640	0.068	0.132	1.000	1.18	0.17
Average changes						0.69	0.23

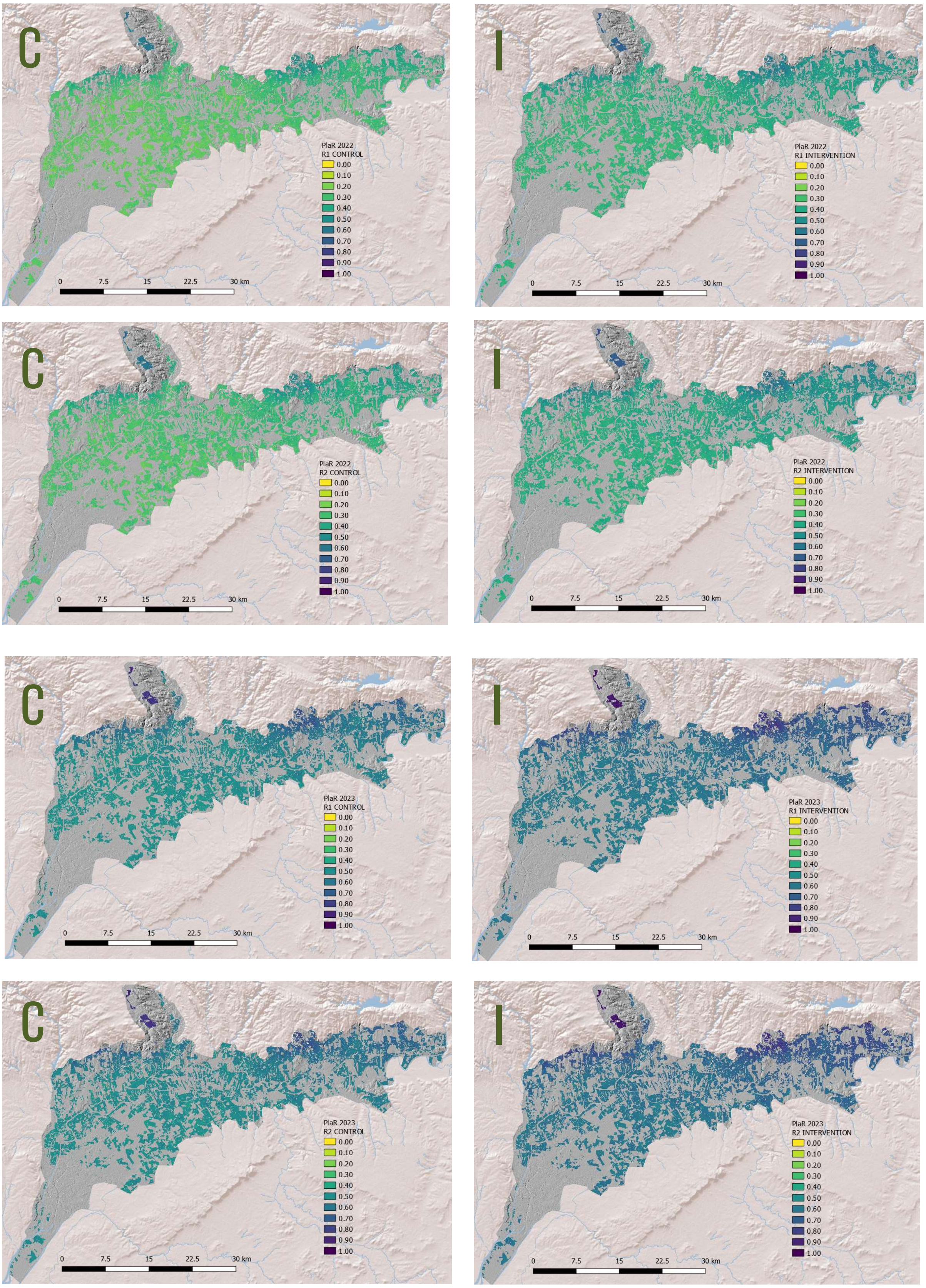

Figure 28: Predicted PlaR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

From the sum of the five biodiversity indicators for each round of sampling and for the two years of field observations, combined biodiversity indices were calculated, 0-1 normalized and mapped, as shown in Figure 29. The rasters were used as the basis to calculate zonal statistics for the target land use area, which are presented in Table 27.

Table 27: BioDiv indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
BioDiv_2022_r1_treatiszero	0.310	0.300	0.111	0.000	1.000	-	
BioDiv_2022_r1_treatisone	0.406	0.398	0.108	0.000	1.000	**0.31**	**0.31**
BioDiv_2022_r2_treatiszero	0.212	0.198	0.089	0.000	1.000	**-0.31**	
BioDiv_2022_r2_treatisone	0.290	0.281	0.093	0.000	1.000	**-0.06**	**0.36**
BioDiv_2023_r1_treatiszero	0.354	0.349	0.103	0.000	1.000	**0.14**	
BioDiv_2023_r1_treatisone	0.474	0.469	0.104	0.000	1.000	**0.53**	**0.34**
BioDiv_2023_r2_treatiszero	0.246	0.236	0.089	0.000	1.000	**-0.21**	
BioDiv_2023_r2_treatisone	0.334	0.327	0.093	0.000	1.000	**0.08**	**0.36**
Average changes						**0.07**	**0.34**

The overall average biodiversity gain resulting from the implementation of the biodiversity friendly management practice was equal to 34%, with a fairly constant increase in the two rounds of the two years between 31 and 36%. The overall trend with respect to the baseline was characterized by a marked decrease in the control fields in the second round in both years, equal to -31 and -21% in 2022 and 2023 respectively. The changes in the intervention fields with respect to the baseline were positive and remarkable for the first round, while for the second the change was negative in 2022 with a -6% decrease and slightly positive in 2023 with an 8% increase.

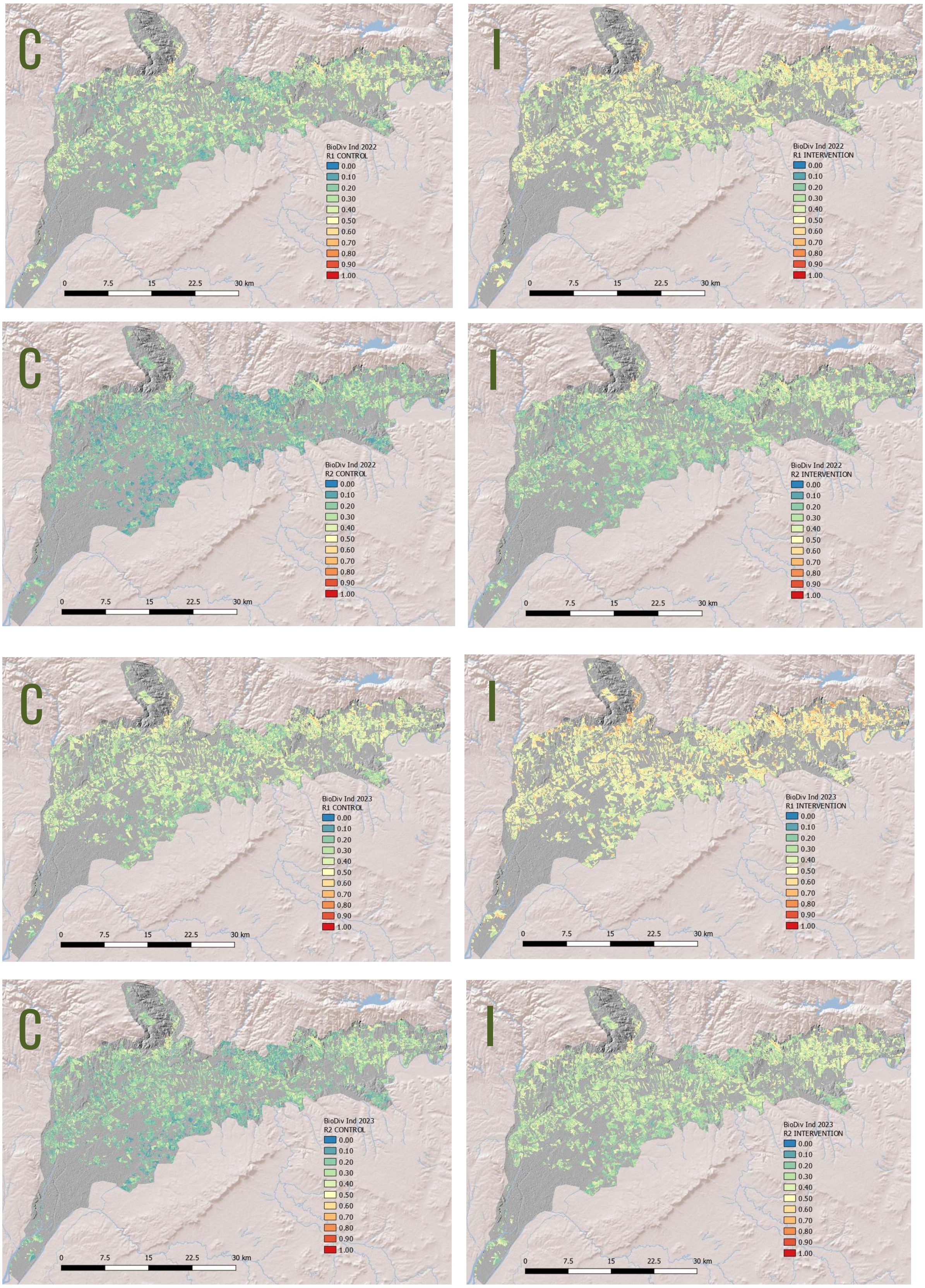

Figure 29: Predicted BioDiv indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

The overall joint trend of all the six indicators, with their synergies and trade-offs, is visually summarized in the radar graph depicted in Figure 31. The indicators values shown in the Figure are averaged over the two rounds of each year.

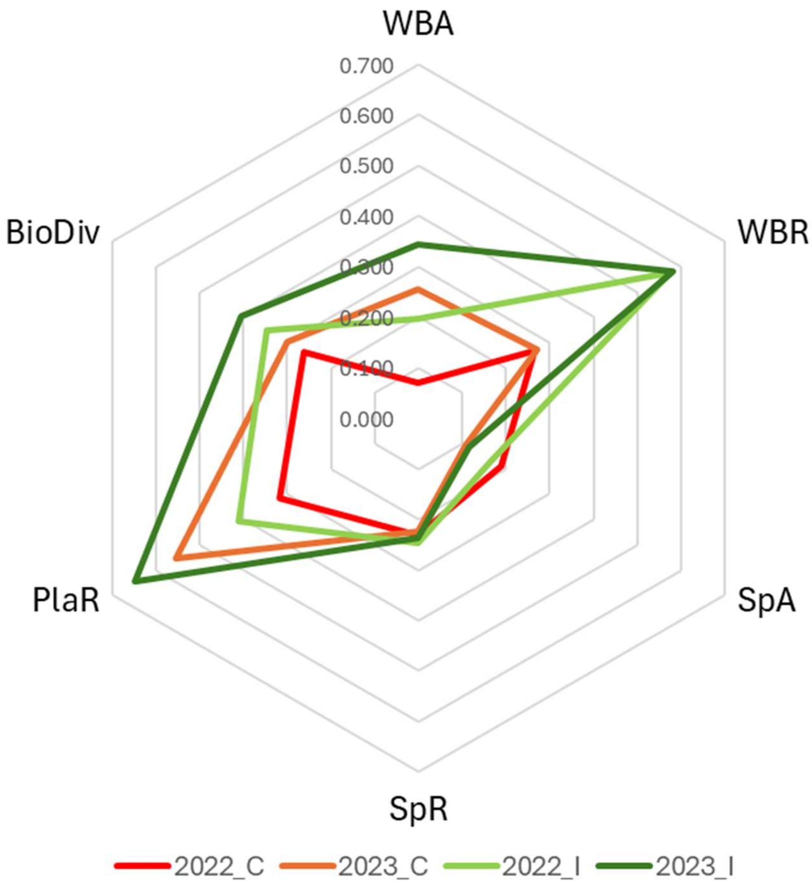

Figure 31: Radar graph of the round-averaged indicators for the control and the intervention in the two years of observation.

3.3 Portuguese EBA

The CSA encompassing the Portuguese EBA fields comprises five municipalities in southern Portugal in the Alentejo Central (Evora and Portel) and Baixo Alentejo (Beja, Cuba and Vidigueira) provinces. The areas of the five municipalities sum up to a total of ca 3,500 km2, 11.9% of which are occupied by permanent tree orchards for a total of 56,785 ha. Of this, a share of 74.5% is occupied by olive groves (42,295 ha), 14.3% by vineyards (8,111 ha), and 11.2% by fruit orchards (6,379 ha). The area has an elevation ranging between 34 and 420 m, with a gentle hilly morphology and uniform peneplains, and with few reliefs that generally follow the Hercynian Orogeny geologic main direction NW-SE. The area is characterized by the presence of natural and semi-natural vegetation in the form of extensive savanna-like forests mainly composed of cork (*Quercus suber* L.) and holm-oak (*Q. rotundifolia* L.) trees in varying densities, the characteristic Portuguese *montado*, which is considered a High Nature Value Farming System according to EEA. Within the CSA there are three Natura 2000 sites plus parts of four additional Natura 2000 sites at the NW and S borders of the area, for a total of 46,078.5 ha.

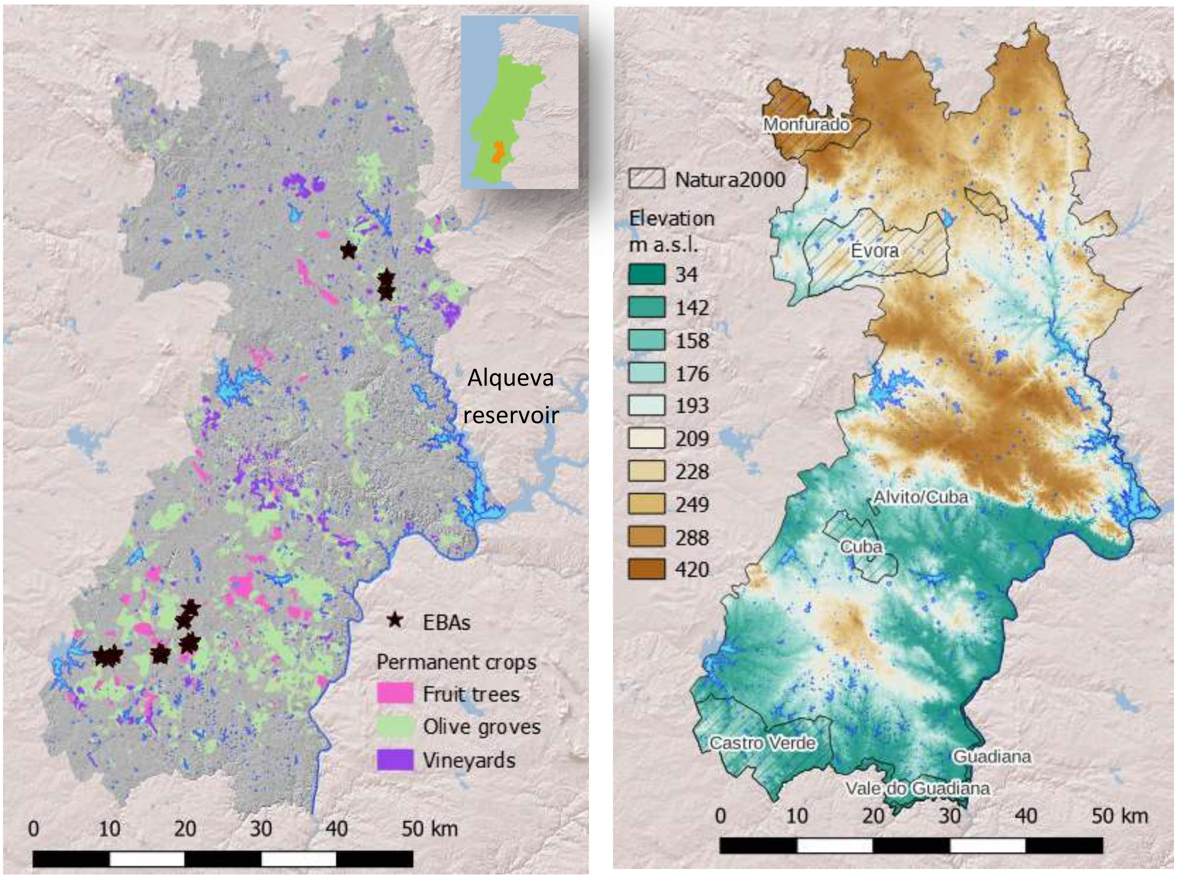

Figure 32. Geographical location and elevation of the Portuguese CSA with the locations of seven Natura2000 sites.

The proximity of the Alqueva reservoir to the east (surface area of 250 km2, capacity of 4,150 million m3) affects the microclimate of the area and provides a great source of water to regional agriculture, with 53.26% of olive groves benefitting from irrigation infrastructures, and the remaining 46.74% being rainfed (Rodríguez-Cohard et al. 2019; Fraga et al. 2020). To respond to market needs and societal demand, olive groves are undergoing a gradual intensification process to maximize their yields. Olive intensification is directly associated with an increase in tree density (Pastor et al. 2007) with highly intensive orchards having up to 2000 trees ha^{-1} and intensive groves 200 - 800 trees ha^{-1}. These together account for ca. 64% of the olive-growing area in Alentejo and are responsible for 75% of olive production (INE 2022a). Intensive groves have highly negative environmental impacts, mostly related to the fact that in most of them the herbaceous under-cover is entirely removed, resulting in a high risk of soil erosion and biodiversity loss, but also due to the high concentration of nitrates, phosphates, and potassium (Caraveli 2000; de Graaf et al. 2010; Guzman et al., 2022; Rodríguez Sousa et al., 2022).

Following the SHOWCASE sampling protocol, the core indicators data were collected in two rounds (April and May) in 2022 and 2023 from twelve control fields and twelve intervention fields. Plant richness was sampled twice a year and in April 2023 (first round). The descriptive statistics of the five biodiversity indicators are summarized in Table 28 for individual and species counts and their 0-1 normalized indicators. Table 29 reports the descriptive statistics of the five indicators for the control and intervention fields for two years of observations.

Table 28: Descriptive statistics of the five SHOWCASE core indicators

Core Indicators	Valid N	Mean	Std.Dev.	Std. Err.	Min	Median	Max
Counts	40	20.1	23.5	3.7	0	9.5	103
WBA	40	9.5	8.6	1.4	0	6	42
WBR	63	24.2	28.1	3.5	0	15	170
SpA	63	3.2	3.3	0.4	0	2	15
SpR	63	29.5	6.4	0.8	7	29	43
PlaR							
Indicator (0-1)	40	0.214	0.274	0.043	0.000	0.089	1.000
Ind WBA	40	0.295	0.270	0.043	0.000	0.190	1.000
Ind WBR	63	0.273	0.262	0.033	0.000	0.189	1.000
Ind SpA	63	0.325	0.293	0.037	0.000	0.250	1.000
Ind SpR	63	0.560	0.264	0.033	0.000	0.600	1.000
Ind PlaR	40	20.1	23.5	3.7	0	9.5	103

Statistically significant differences ($p < 0.05$) in indicator mean values were detected for WBA, WBR, SpA, and PlaR indicators, but not for the SpR indicator, even though the mean values observed for the control fields were slightly lower than those observed for the intervention fields. Mean indicator values for the second sampling round are somewhat lower than in the first round in both control and intervention fields for WBR, SpA, SpR, and PlaR, while in the intervention fields a non-significant increase is observed only for WBA. For the second year of observations, biodiversity indicator data from the Portuguese EBA are available at the moment of writing this report only for spiders. The mean values of both SpA and SpR indicators show a moderate increase in the second year of observations which is more evident in the intervention fields for the SpA indicator.

Table 29: Descriptive statistics of the five SHOWCASE core indicators in the control and intervention fields of the Portuguese EBA

Indicator	Treatment	Means	N	Std. Dev.	Std. Err.	Min	Median	Max
Ind WBA	Control	0.051	20	0.042	0.009	0.000	0.044	0.173
	Intervention	0.378	20	0.311	0.069	0.029	0.276	1.000
	All Groups	0.214	40	0.274	0.043	0.000	0.089	1.000
Ind WBR	Control	0.123	20	0.094	0.021	0.000	0.134	0.286
	Intervention	0.467	20	0.280	0.063	0.095	0.428	1.000
	All Groups	0.295	40	0.270	0.043	0.000	0.190	1.000
Ind SpA	Control	0.189	32	0.179	0.032	0.000	0.132	0.718
	Intervention	0.359	31	0.307	0.055	0.000	0.296	1.000
	All Groups	0.273	63	0.262	0.033	0.000	0.189	1.000
Ind SpR	Control	0.268	32	0.295	0.052	0.000	0.214	1.000
	Intervention	0.385	31	0.284	0.051	0.000	0.286	1.000
	All Groups	0.325	63	0.293	0.037	0.000	0.250	1.000
Ind PlaR	Control	0.481	32	0.248	0.044	0.000	0.500	0.933
	Intervention	0.643	31	0.259	0.047	0.050	0.722	1.000
	All Groups	0.560	63	0.264	0.033	0.000	0.600	1.000

As the same trends in terms of responses to biodiversity management intervention and temporal dynamics were observed for the indicators of the Spanish EBA, and given the strong similarities of the agricultural systems considered in the two EBAs, i.e. intensive fruit orchards in Andalucia and intensive olive orchards in Alentejo, it was decided to use a single data set to calibrate more robust spatiotemporal models for upscaling evidences from the field to landscape scale, potentially applicable to same permanent systems in the south Iberian peninsula. The descriptive statistics for the ES-PT joint dataset (see section 3.2) are reported in Table 17, and the results of model calibration for both RF and MLR models are presented in the previous subsection 3.2 on the Spanish EBA.

Table 30: WBA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
WBA 2022 r1 treatiszero	0.076	0.061	0.074	0.000	0.726	-	
WBA 2022 r1 treatisone	0.201	0.200	0.093	0.000	0.865	**1.66**	**1.66**
WBA 2022 r2 treatiszero	0.016	0.000	0.036	0.000	0.468	**-0.78**	
WBA 2022 r2 treatisone	0.095	0.086	0.079	0.000	0.607	**0.25**	**4.80**
WBA 2023 r1 treatiszero	0.222	0.219	0.096	0.000	0.822	**1.93**	
WBA 2023 r1 treatisone	0.362	0.359	0.097	0.000	0.962	**3.77**	**0.63**
WBA 2023 r2 treatiszero	0.239	0.227	0.131	0.000	1.000	**2.15**	
WBA 2023 r2 treatisone	0.377	0.366	0.134	0.000	1.000	**3.97**	**0.58**
Average changes						**1.85**	**1.91**

Table 30 summarizes the raster statistics for the WBA indicator estimates over the whole target area (56,780 ha). The results highlight a positive trend with respect to the 2022 baseline (control), with only the control fields at round 2 showing a -78% reduction in the average indicator value. The relative increase due to the intervention with respect to the control was particularly evident in the first year, where values for the control fields were particularly low, with increase above 160 and ca. 480% in the first and the second round respectively, while in the second year they ranged between 63 and 58%. The maps underpinning the statistics presented in the table are shown in Figure 33.

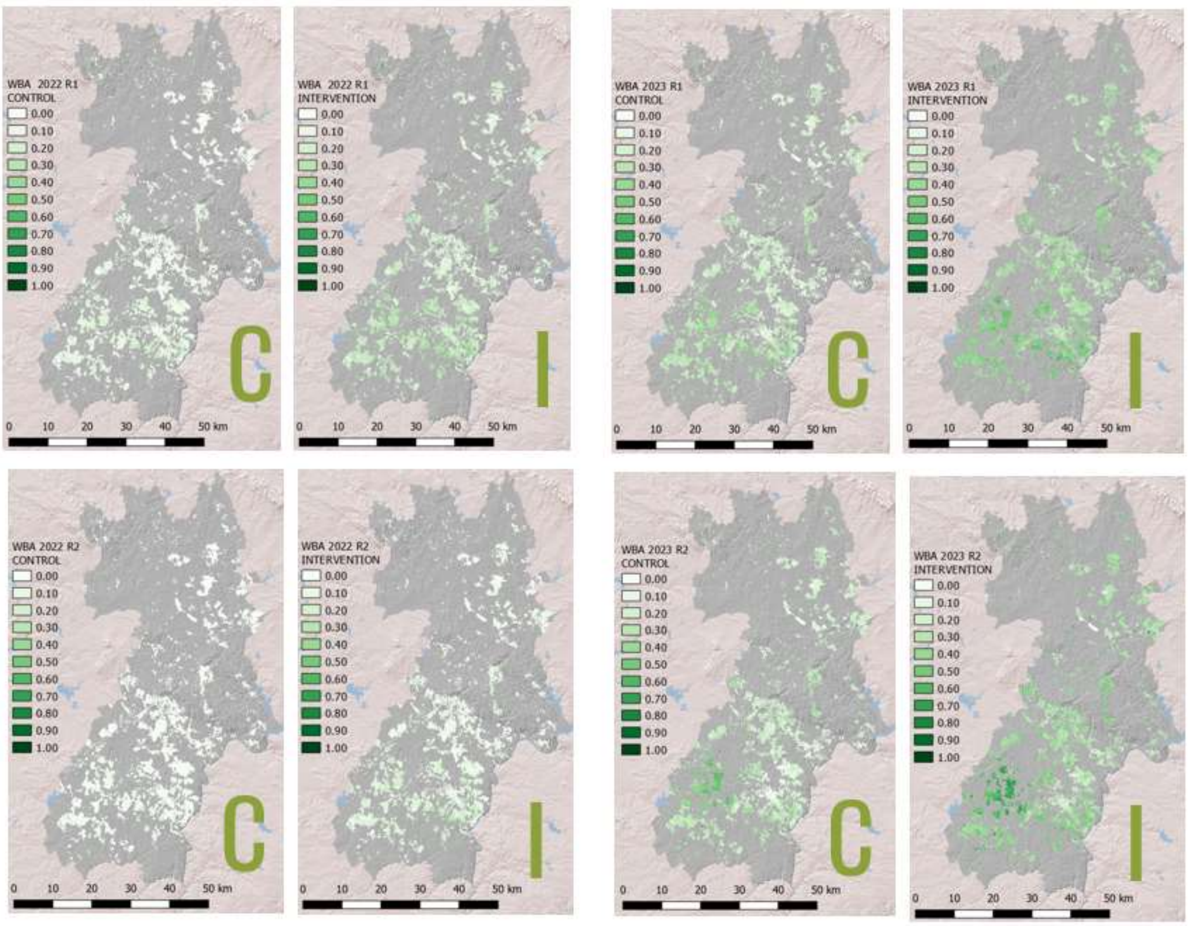

Figure 33: Predicted WBA indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Figure 34 illustrates the spatial distribution of the WBR indicator for control and intervention scenarios during the two rounds in the two years. Table 31 reports the raster statistics for each map and summarizes the relative changes with respect to the baseline and to the control of each round.

Table 31: WBR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	WBR mean	median	stdev	min	max	Rel change baseline	Rel Change T
WBR 2022 r1 treatiszero	0.258	0.246	0.176	0.000	1.000	-	
WBR 2022 r1 treatisone	0.570	0.568	0.185	0.000	1.000	1.21	1.21
WBR 2022 r2 treatiszero	0.023	0.000	0.072	0.000	1.000	-0.91	
WBR 2022 r2 treatisone	0.187	0.166	0.162	0.000	1.000	-0.27	7.27
WBR 2023 r1 treatiszero	0.190	0.169	0.162	0.000	1.000	-0.26	
WBR 2023 r1 treatisone	0.496	0.492	0.184	0.000	1.000	0.92	1.60
WBR 2023 r2 treatiszero	0.337	0.305	0.264	0.000	1.000	0.31	
WBR 2023 r2 treatisone	0.619	0.627	0.261	0.000	1.000	1.41	0.84
Average changes						0.34	2.73

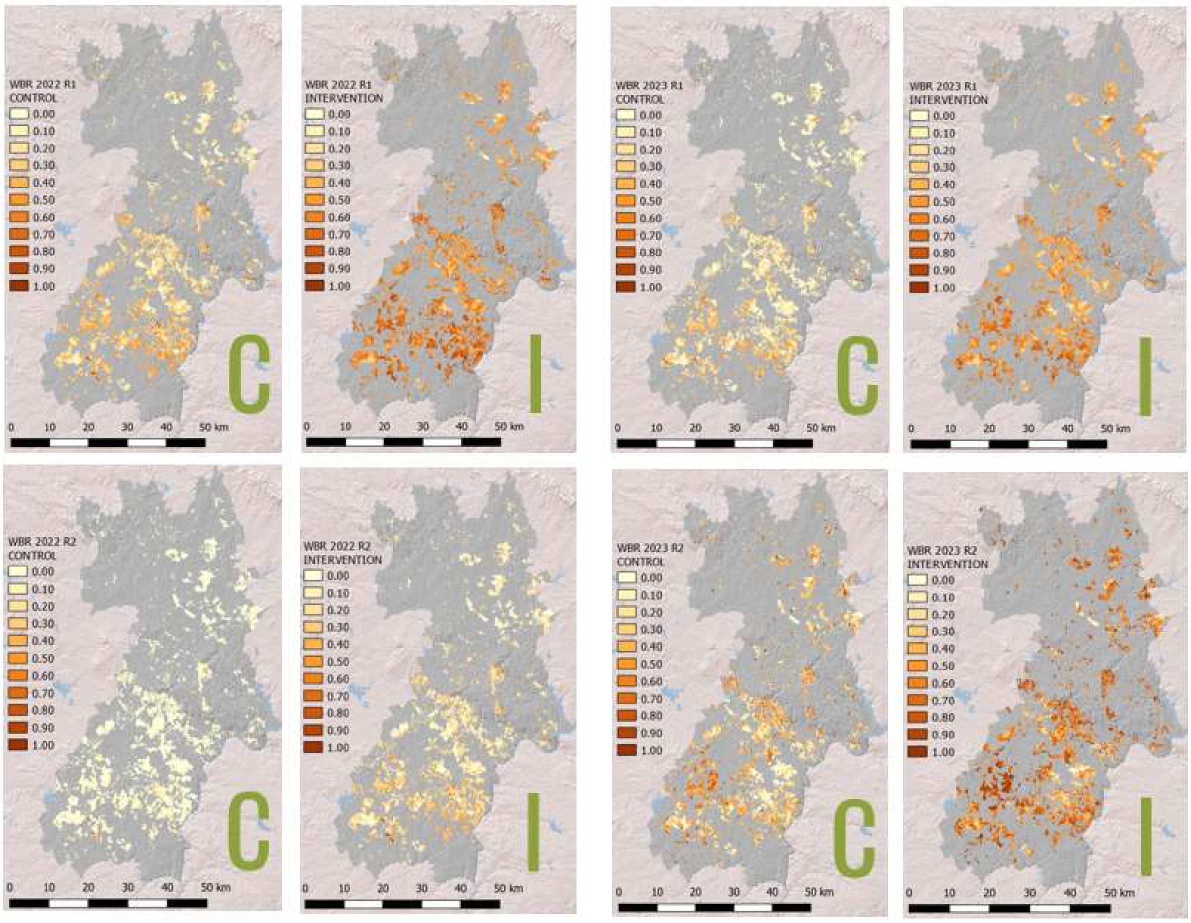

Figure 34: Predicted WBR indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

The relative increase due to the intervention with respect to the control was particularly evident in the first year, in which values for the control fields were low in the first round and extremely low in the second, resulting in an increase above 120 and 720% in the first and the second round respectively. In the second year the increases were equal to 160 and 84% for the first and the second rounds, respectively. With respect to the baseline, the changes were negative in both control (-91%) and intervention (-27%) fields in the second round of the first year, and in the control fields of the first round in 2023 (-26%).

Differently from the wild bee indicators, the intervention fields were characterized by systematically negative changes with respect to control within the same round. The decrease was slightly higher in the second rounds of both years, with -16 and -15 % decreases respectively in 2022 and 2023, while the corresponding figures for the first rounds are equal to -11 and -12%. Similarly, the overall average trend with respect to the baseline was negative for SpA for the second round of 2022 and 2023, with increases equal to +26 and 10% for the first round of 2023 for the control and intervention treatment, respectively. Figure 35 illustrates the spatial distribution maps of the SpA indicator for control and intervention scenarios during the two rounds in the two years.

Table 32: SpA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	SpA mean	median	stdev	min	max	Rel change baseline	Rel Change T
SpA 2022 r1 treatiszero	0.218	0.218	0.154	0.000	1.000	-	
SpA 2022 r1 treatisone	0.195	0.191	0.148	0.000	1.000	-0.11	-0.11
SpA 2022 r2 treatiszero	0.109	0.080	0.115	0.000	0.902	-0.50	
SpA 2022 r2 treatisone	0.091	0.053	0.107	0.000	0.875	-0.58	-0.16
SpA 2023 r1 treatiszero	0.275	0.277	0.141	0.000	0.847	0.26	
SpA 2023 r1 treatisone	0.241	0.242	0.133	0.000	0.807	0.10	-0.12
SpA 2023 r2 treatiszero	0.173	0.163	0.131	0.000	0.848	-0.21	
SpA 2023 r2 treatisone	0.146	0.134	0.120	0.000	0.807	-0.33	-0.15
Average changes						-0.19	-0.14

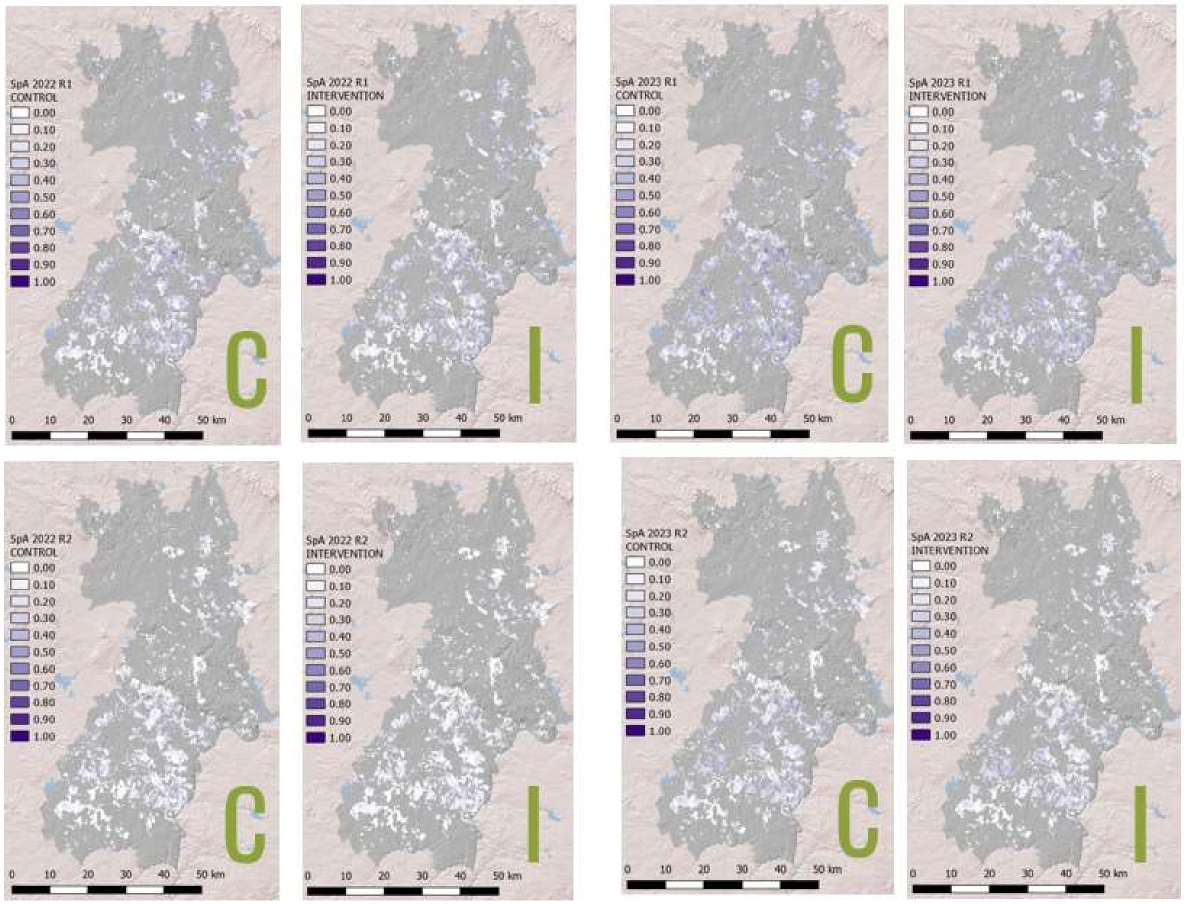

Figure 35: Predicted SpA indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

In the case of the SpR indicators, the relative changes with respect to the control were always positive and were very similar between rounds and years, ranging from 4 to 7%. The changes with respect to the 2022 control reference baseline were negative for the second round of 2022 and for the two rounds in 2023. The magnitude of relative decrease was greater in the second rounds of both years, with control fields characterized by a slightly higher decrease with respect to the intervention fields. On average an overall decrease of -25% in the indicator values was observed for the whole target area.

Table 33: SpR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
SpR_2022_r1_treatiszero	0.348	0.349	0.137	0.000	1.000	-	
SpR_2022_r1_treatisone	0.363	0.363	0.137	0.000	1.000	**0.04**	**0.04**
SpR_2022_r2_treatiszero	0.217	0.215	0.128	0.000	1.000	**-0.38**	
SpR_2022_r2_treatisone	0.232	0.230	0.130	0.000	1.000	**-0.33**	**0.07**
SpR_2023_r1_treatiszero	0.311	0.310	0.132	0.000	1.000	**-0.11**	
SpR_2023_r1_treatisone	0.325	0.325	0.132	0.000	1.000	**-0.07**	**0.05**
SpR_2023_r2_treatiszero	0.183	0.177	0.124	0.000	1.000	**-0.48**	
SpR_2023_r2_treatisone	0.196	0.192	0.126	0.000	1.000	**-0.44**	**0.07**
Average changes						**-0.25**	**0.06**

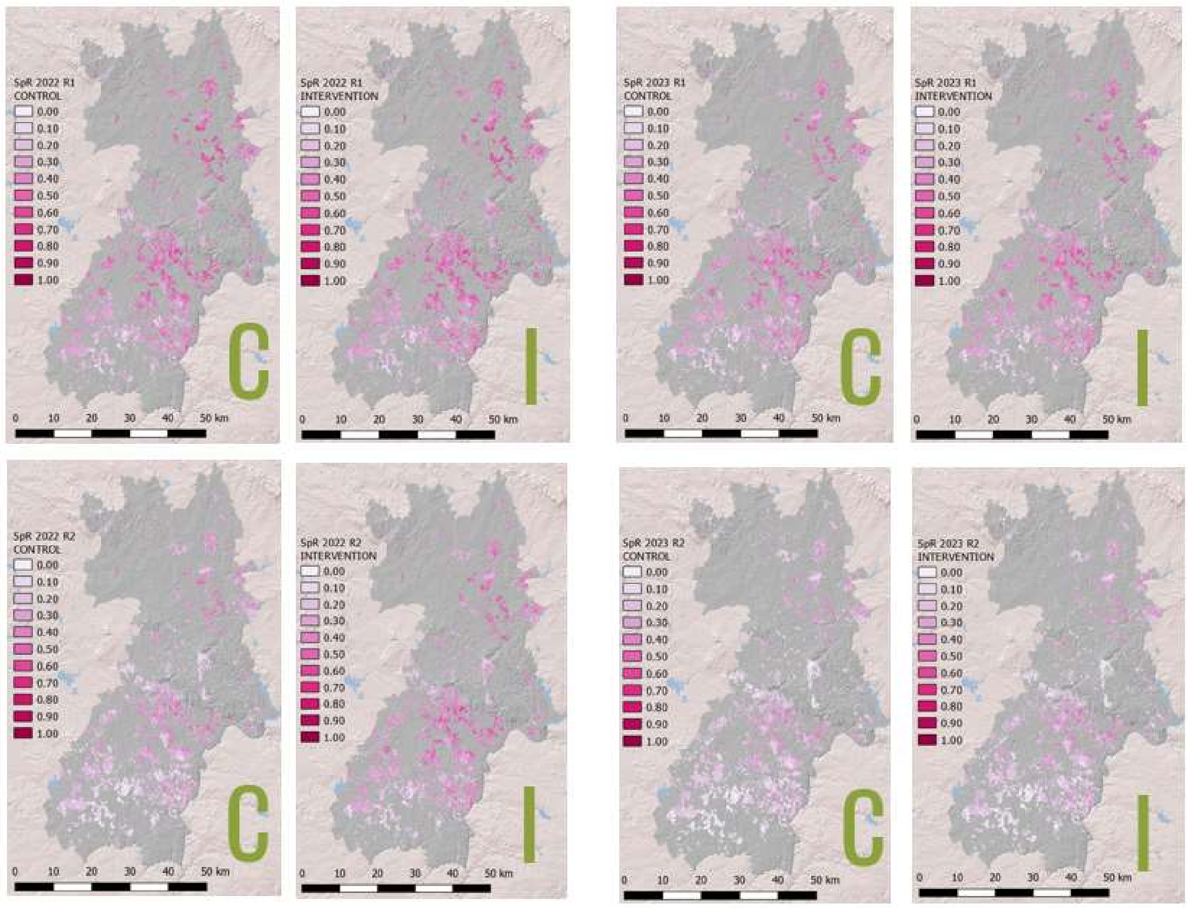

Figure 36: Predicted SpR indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Figure 36 illustrates the estimated spatial distribution of the SpR indicator values for the whole target area in the two rounds for the two years of observations.

The eight raster maps at 10m resolution showing the spatial distribution of the PlaR indicator are portrayed in Figure 37. The raster statistics summarised in Table 34 highlight a moderate increase in the intervention fields with respect to the control ones, which was very similar in the two rounds of the two years of observations, equal to 17% % in 2022 and to ca. 12% in

2023. The relative changes with respect to the baseline were always positive, and while in the first year they were only observed for the intervention fields, in the second year increases above 40% were observed also for the control fields.

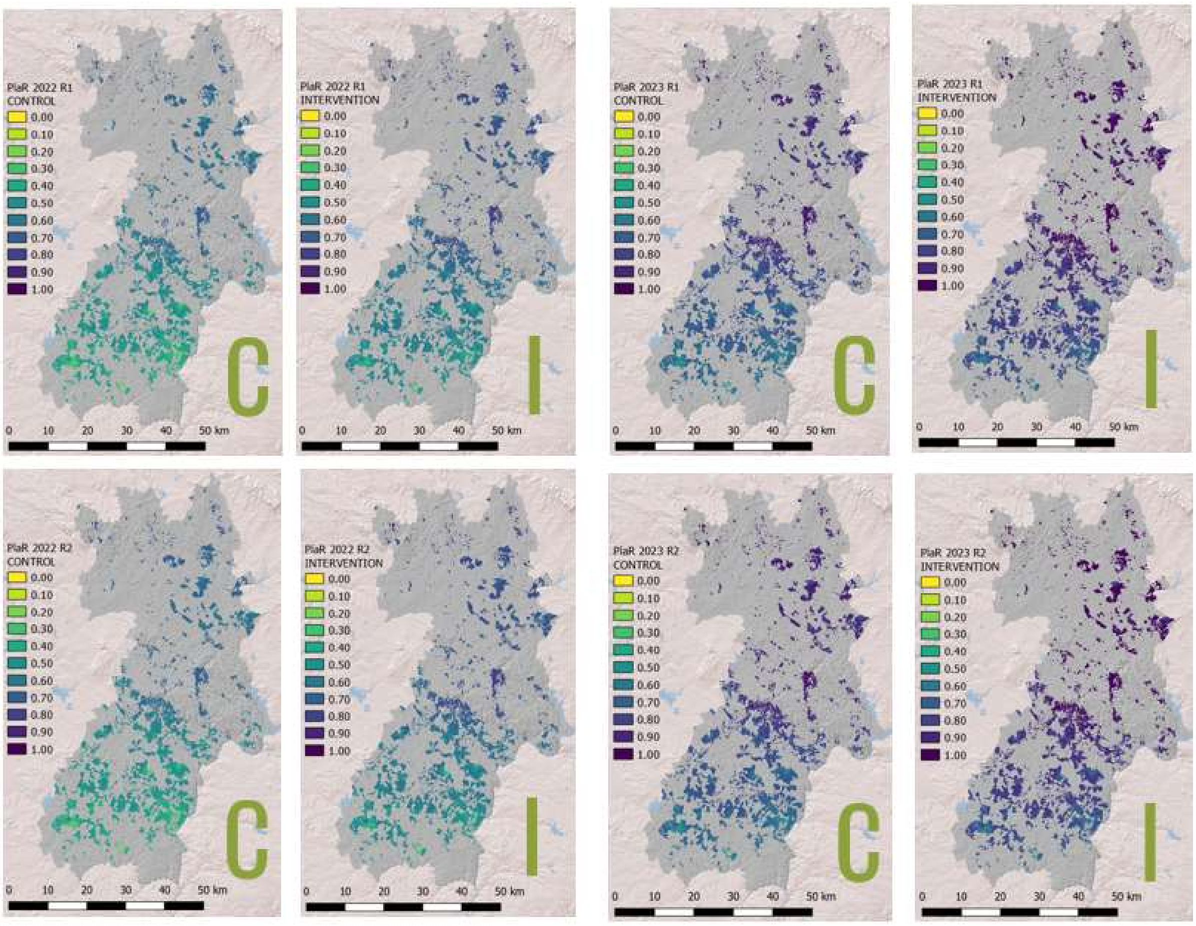

Figure 37: Predicted PlaR indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 34: PlaR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
PlaR_2022_r1_treatiszero	0.540	0.533	0.109	0.040	1.000	-	
PlaR_2022_r1_treatisone	0.633	0.626	0.109	0.133	1.000	**0.17**	**0.17**
PlaR_2022_r2_treatiszero	0.544	0.537	0.110	0.023	1.000	**0.01**	
PlaR_2022_r2_treatisone	0.637	0.630	0.110	0.116	1.000	**0.18**	**0.17**
PlaR_2023_r1_treatiszero	0.763	0.757	0.105	0.247	1.000	**0.41**	
PlaR_2023_r1_treatisone	0.853	0.850	0.100	0.340	1.000	**0.58**	**0.12**
PlaR_2023_r2_treatiszero	0.775	0.768	0.107	0.257	1.000	**0.44**	
PlaR_2023_r2_treatisone	0.863	0.861	0.100	0.350	1.000	**0.60**	**0.11**
Average changes						**0.34**	**0.14**

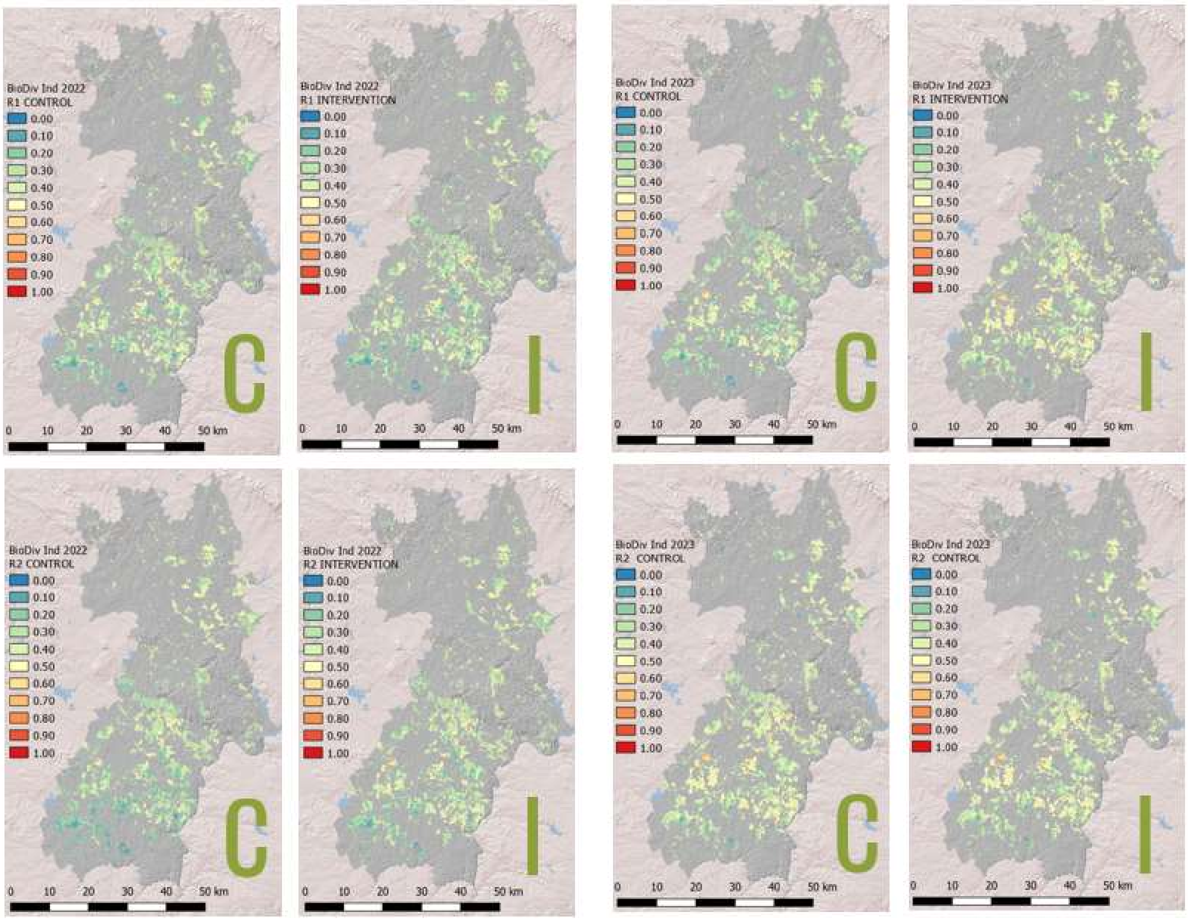

Figure 38: Predicted BioDiv indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Figure 38 shows the eight raster maps obtained by summing the five biodiversity indicators for each round of sampling and for the two years of field observations and normalizing the sum to have all estimated indicator values ranging from 0 to 1. The rasters were then used as the basis to calculate the zonal statistics for the target land use area, which are presented in Table 35.

Table 35: BioDiv indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
BioDiv_2022_r1_treatiszero	0.337	0.333	0.120	0.000	1.000	-	
BioDiv_2022_r1_treatisone	0.397	0.395	0.114	0.000	1.000	**0.18**	**0.18**
BioDiv_2022_r2_treatiszero	0.322	0.315	0.122	0.000	1.000	**-0.04**	
BioDiv_2022_r2_treatisone	0.352	0.341	0.127	0.000	1.000	**0.04**	**0.09**
BioDiv_2023_r1_treatiszero	0.333	0.327	0.112	0.000	1.000	**-0.01**	
BioDiv_2023_r1_treatisone	0.396	0.394	0.111	0.000	1.000	**0.17**	**0.19**
BioDiv_2023_r2_treatiszero	0.368	0.358	0.140	0.000	1.000	**0.09**	
BioDiv_2023_r2_treatisone	0.445	0.446	0.133	0.000	1.000	**0.32**	**0.21**
Average changes						**0.11**	**0.17**

The overall average biodiversity gain resulting from the implementation of the biodiversity-friendly management practice was equal to 17%, with an almost equal increase in the first rounds of the two years between 18 and 19%. The increases during the second rounds of the two years were however quite distinct, with a relative increase of ca 9% in 2022 and greater than 20% in 2023. The overall trend in relation to the baseline was characterized by a slight decrease in the control fields in the second round of 2022 and in the first round of 2023, equal to -4 and -1% in 2022 and 2023, respectively. The changes in the intervention fields with respect to the baseline were positive and very similar for the first rounds (18% in 2022, 17% in 2023), while for the second the change was modest in 2022 with a 4% increase but much higher in 2023 with a 32% increase.

All the evidence for the six indicators considered are summarized in the radar graph shown in Figure 39, where the synergies and trade-offs between indicators can also be visually appreciated along with the overall effect due to the biodiversity management implementation.

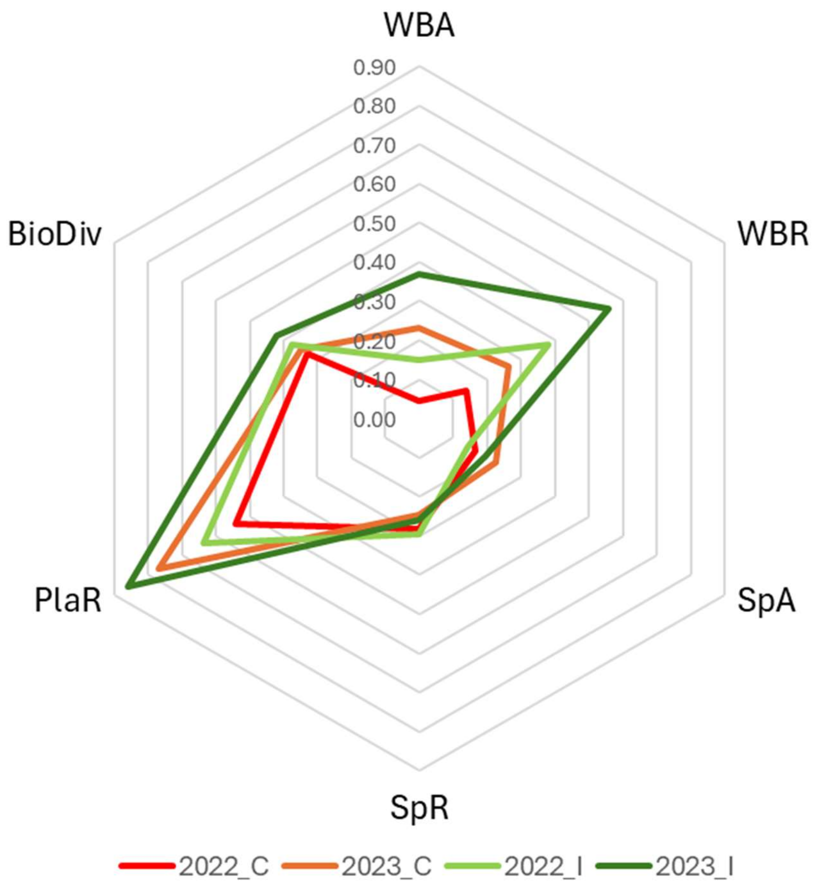

Figure 39: Radar graph of the round-averaged indicators for the control and the intervention in the two years of observation.

3.4 Dutch EBA

The Dutch CSA is located at the southernmost tip of the Netherlands in the region of Zuid-Limburg, the very south of the province of Limburg (Figure 40). South Limburg is characterized by a varied relief, intensive agricultural lands and nature reserves in the middle of highly urbanized areas, such as Maastricht in the northwest, and Heerlen in the northeast of the CSA. The area is 368.5 km^2 and is located on a plateau of loess soils in which several small rivers have eroded a range of valleys into the limestone substrate. The elevation ranges from 5 to 322 m a.s.l. (average 80 m a.s.l.). Intensive arable farming and orchards dominate the plateau and dairy farming dominates the valleys. Pastures are mostly intensive with mowing, grazing and fertilization. Annual crops are mainly grains (wheat, barley), potatoes, corn and sugar beet. Orchards are predominantly apples and pears, with a growing section of vineyards. A significant proportion of the valleys furthermore consists of Natura 2000 areas as the slopes, in particular, support species-rich calcareous grasslands. The Natura 2000 sites sum up to 4073 ha, i.e. 11.1% of the total area.

Farming in the area consists of a mix of dairy, orchard and arable farming, which are all very intensively managed. The target area for the upscaling of the field-based biodiversity indicators is represented by arable lands, which cover ca 17,000 ha, i.e. 46.5% of the whole area (Figure 40).

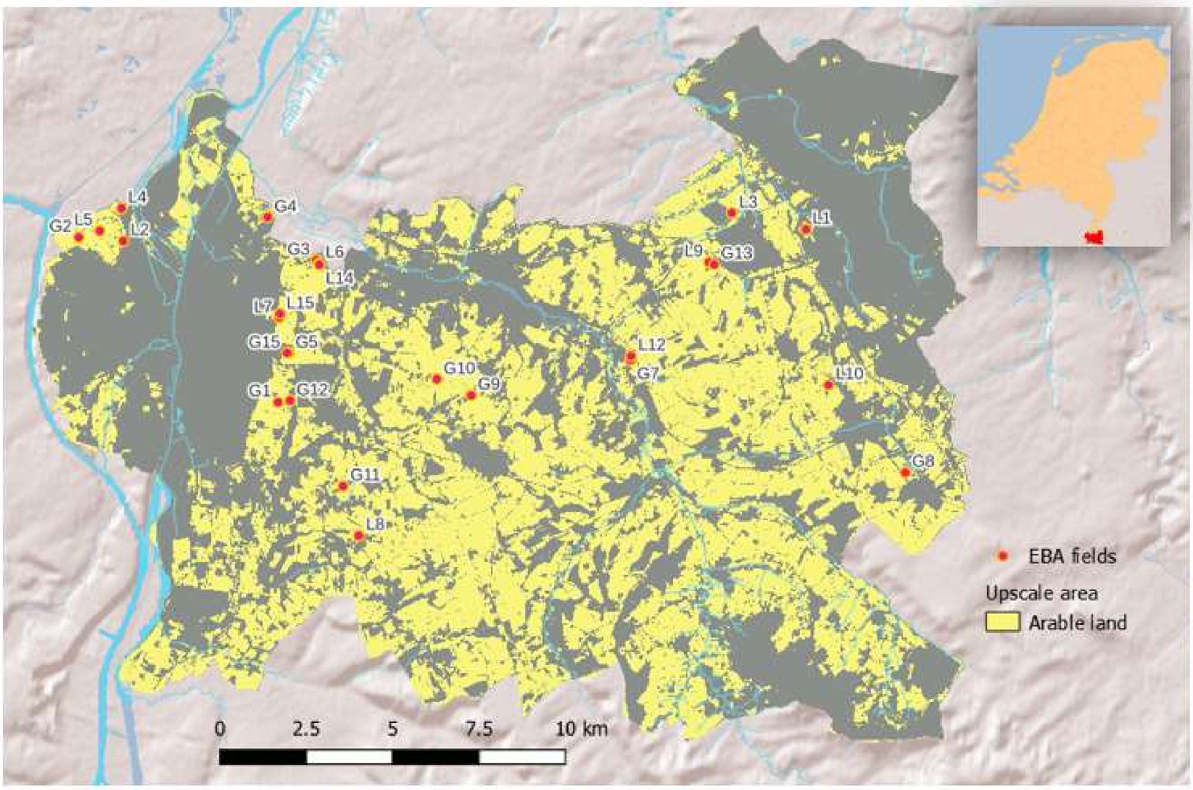

Figure 40. Geographical location of the Dutch CSA.

The Dutch EBA focused on two different interventions in separate studies: (i) lupin (*Lupinus albus* L. and *Lupinus angustifolius* L.) cultivation in arable fields (farmers financially supported to grow lupin) and (ii) (combinations of) hedges and semi-natural grasslands next to winter wheat. The biodiversity indicators data provided by the Dutch EBA partners for the spatiotemporal modeling and upscaling refers to the lupin experiment (in-field intervention). The available data were collected in two rounds in May and June 2021, in May and June 2022, and in May and July 2023. Not all the five biodiversity core indicators were collected at every round and in every year: spider indicators data are available for the two rounds of 2022, plants indicator data are available for the second rounds of 2021 and 2022, and wild bee indicators data are available for the two rounds of 2021, 2022 and 2023. The number and location of fields changed in the three years: in 2021 3 intervention and 3 control fields were sampled; in 2022 7 control and 7 intervention fields, and in 2023 3 control and 3 intervention fields.

The descriptive statistics of the five biodiversity indicators are summarized in Table 36 for individual and species counts and their 0-1 normalized indicators.

Table 36: Descriptive statistics of the five SHOWCASE core indicators

Core Indicators	Valid N	Mean	Std.Dev.	Std. Err.	Min	Median	Max
Counts							
WBA	58	17	23	3	0	5.5	86
WBR	58	3	3	0	0	2	10
SpA	46	22	24	4	0	14	97
SpR	46	4	3	0	0	3	14
PlaR	39	8	4	1	1	8	22
Indicator (0-1)							
Ind WBA	58	0.265	0.324	0.043	0.00	0.087	1.00
Ind WBR	58	0.262	0.283	0.037	0.00	0.200	1.00
Ind SpA	46	0.246	0.271	0.040	0.00	0.162	1.00
Ind SpR	46	0.330	0.270	0.040	0.00	0.268	1.00
Ind PlaR	39	0.493	0.270	0.043	0.00	0.429	1.00

Table 37 summarizes the descriptive statistics of the five normalized indicators for control and intervention; statistically significant differences ($p < 0.05$) in indicator mean values were detected for WBA and WBR indicators, with lower mean values observed for the control fields (0.052) and significantly higher for the intervention fields (0.479). In the case of PlaR indicator the mean value of the intervention field was higher (0.536) than that of the control fields (0.453), while for the spider indicators the mean values for the intervention and control fields were almost identical for both SpA (0.236 for control vs. 0.258 for intervention) and SpR (0.329 for control vs. 0.333 for intervention).

In terms of location along the transects in the fields, given the in-field intervention with lupin the mean indicator values are higher in the field center than at the field margins for WBA (0.256 vs. 0.186), PlaR (0.670 vs. 0.288), SpA (0.294 vs. 0.178) and SpR (0.352 vs. 0.297), but not for WBR (0.226 vs. 0.356). Difference in indicator mean values in the two locations are statistically significant ($p<0.05$) for WBA and PlaR. When considering the effects of the biodiversity management intervention and location, the same trend was observed for SpA, SpR and PlaR, with higher indicator mean values in the field center for both control and intervention fields, and with statistically significant differences ($p<0.05$) in the case of PlaR mean values at both locations. In the case of wild bee indicators, lower values of abundance and richness were observed in the center for the control fields, while for the intervention fields WBA is significantly higher at the field center, and WBR has very similar mean values in both locations.

Table 37: Descriptive statistics of the five SHOWCASE core indicators in the control and intervention fields of the Dutch EBA

Indicator	Treatment	Means	N	Std.Dev.	Std.Err.	Min	Median	Max
Ind WBA	*Control*	0.052	29	0.123	0.023	0.000	0.000	0.500
	Intervention	0.479	29	0.323	0.060	0.000	0.432	1.000
	All Groups	0.265	58	0.324	0.043	0.000	0.087	1.000
Ind WBR	*Control*	0.104	29	0.219	0.041	0.000	0.000	1.000
	Intervention	0.421	29	0.250	0.046	0.000	0.400	1.000
	All Groups	0.262	58	0.283	0.037	0.000	0.200	1.000
Ind SpA	*Control*	0.236	25	0.303	0.061	0.000	0.106	1.000
	Intervention	0.258	21	0.234	0.051	0.000	0.180	0.851
	All Groups	0.246	46	0.271	0.040	0.000	0.162	1.000
Ind SpR	*Control*	0.329	25	0.298	0.060	0.000	0.286	1.000
	Intervention	0.330	21	0.241	0.052	0.000	0.250	0.875
	All Groups	0.330	46	0.270	0.040	0.000	0.268	1.000
Ind PlaR	*Control*	0.453	20	0.272	0.061	0.000	0.417	1.000
	Intervention	0.536	19	0.269	0.062	0.000	0.583	1.000
	All Groups	0.493	39	0.270	0.043	0.000	0.429	1.000

Although not statistically significant, the mean indicator values for the second round are consistently higher for both control and intervention fields for all the four biodiversity indicators with two sampling rounds. Wild bee abundance and richness indicators increased between 2021 and 2022, and in 2023 remained constant in the intervention fields, while in the control fields WBA slightly decreased and WBR increased, although not significantly in both cases. In the two years 2021 and 2022, the vascular plant species indicator PlaR remained constant in the control fields, while in the intervention fields there was a clear increase in 2022, although not statistically significant.

The calibration of the predictive models and the assessment of estimation errors for both MLR and RF models were performed over the Dutch EBA dataset adopting the same set of predictors, which included also the terrain morphological attributes. Table 38 summarizes the MLR coefficients for the normalized biodiversity indicators to upscale field observations to the target land use over the entire CSA. The treatment dummy predictors are statistically significant only for the wild bee indicators, while the effect of seasonality (i.e. sampling round) was significant for both wild bee and spider indicators. The landscape structure variables expressed in terms of distance from the road network and from small woody features were significant predictors for almost all indicators.

Adopting the same set of predictors for each indicator, RF models were calibrated for each indicator, providing also an assessment of the relevance of each predictor, expressed in term of node purity, and of its relative values (Table 39). The contribution of each predictor is graphically represented in Figure 41 for the five biodiversity indicators, with order of relevance increasing along the Y axis. Distance from the road network ranked among the most relevant predictors for WBA, SpR and PlaR, while distance from small woody features was moderately relevant only for WBR. Elevation played a major role for both spider indicators, while slope was relevant for the PlaR indicator. Among the RSI, reflectance in the infra-red and in the near infrared bands along with those in blue and the green bands ranked among the most relevant for nearly all indicators.

Table 38: Coefficients of the MLR calibrated for the normalized biodiversity indicators; significant coefficients in red ($p < 0.05$) and blue ($p > 0.10$)

Predictors	WBA	WBR	SpA	SpR	PlaR
Intercept	-0.072897	0.051816	0.368848	-0.107650	-0.575951
Dummy Treat	0.109077	0.141194	0.011112	0.083860	0.045729
Dummy Round	-0.112772	-0.153117	0.161375	0.173590	
Dummy Year 1		-0.086327			
Road prox	0.000693			-0.000148	0.003122
SWF prox		-0.000299	-0.000771		-0.000368
Aspect					0.000917
CatchArea		0.00000034	-0.000003		
CatchSlope			-4.845689	-1.988216	
Elevation			-0.002039	-0.000943	
TWI			-0.031668	0.046178	
IR	0.000021	0.000050	-0.000096	0.000013	
Irn			0.000203		0.000111
NDVI				0.211364	0.498197
SOSA	0.000046				
SOSI2	-0.000038			-0.000026	

Table 39: Relevance of RF predictors for the five biodiversity indicators in term of node purity; colors highlight the most relevant predictors (orange > brown >light brown)

Predictors	WBA Indicator		WBR Indicator		SpA Indicator		SpR Indicator		PlaR Indicator	
	Node purity	Rel. %	Node purity	Rel. %	Node purity	Rel. %	Node purity	Rel. %	Node purity	Rel. %
dummy_treat	0.482	3.75%	0.695	3.69%	0.009	0.30%	0.011	0.36%	0.009	0.38%
dummy_location	0.197	1.54%	0.097	0.52%						
dummy_y1	0.043	0.33%	0.113	0.60%						
dummy_y2	0.093	0.72%	0.105	0.56%						
dummy_r1	0.294	2.29%	0.241	1.28%	0.041	1.40%	0.033	1.11%		
dummy_r2	0.162	1.26%	0.149	0.79%						
swf_prox	0.387	3.02%	0.751	3.99%	0.055	1.89%	0.082	2.77%	0.082	3.29%
road_prox	0.622	4.85%	0.473	2.51%	0.078	2.67%	0.143	4.86%	0.266	10.71%
aspect	0.416	3.24%	0.898	4.77%	0.049	1.66%	0.052	1.77%	0.075	3.02%
elevation	0.492	3.83%	0.690	3.67%	0.185	6.30%	0.189	6.39%	0.082	3.28%
slope	0.500	3.90%	0.647	3.44%	0.262	8.93%	0.136	4.61%	0.128	5.14%
catchslope	0.413	3.22%	0.748	3.97%	0.167	5.72%	0.201	6.82%	0.074	2.95%
catcharea	0.532	4.14%	0.662	3.52%	0.070	2.39%	0.085	2.87%	0.078	3.12%
modcatchar	0.501	3.90%	0.711	3.78%	0.081	2.77%	0.096	3.27%	0.082	3.30%
twi	0.373	2.91%	0.615	3.27%	0.113	3.86%	0.216	7.30%	0.089	3.57%
valleydepth	0.472	3.68%	0.794	4.22%	0.141	4.80%	0.103	3.49%	0.074	2.99%
swir	0.428	3.34%	0.728	3.87%	0.054	1.83%	0.103	3.48%	0.090	3.63%
sosi3	0.522	4.07%	0.712	3.78%	0.120	4.11%	0.120	4.08%	0.074	2.99%
sosi2	0.488	3.80%	0.708	3.76%	0.098	3.36%	0.097	3.28%	0.127	5.12%
sosi1	0.512	3.99%	0.735	3.91%	0.135	4.60%	0.113	3.82%	0.064	2.56%
sosa	0.446	3.48%	0.715	3.80%	0.136	4.65%	0.102	3.45%	0.057	2.28%
red	0.547	4.27%	0.750	3.98%	0.103	3.51%	0.118	3.99%	0.075	3.00%
ndvi	0.491	3.82%	0.736	3.91%	0.135	4.60%	0.109	3.69%	0.119	4.77%
ndsi	0.393	3.06%	0.773	4.11%	0.048	1.64%	0.123	4.16%	0.086	3.45%
ndbsi	0.445	3.47%	0.646	3.43%	0.120	4.08%	0.118	3.99%	0.098	3.96%
irn	0.553	4.31%	0.829	4.41%	0.155	5.29%	0.095	3.20%	0.182	7.32%
ir	0.461	3.59%	0.748	3.97%	0.184	6.28%	0.098	3.33%	0.149	6.01%
green	0.562	4.38%	0.771	4.10%	0.100	3.43%	0.108	3.65%	0.062	2.49%
blue	0.573	4.46%	0.866	4.60%	0.170	5.79%	0.154	5.23%	0.078	3.14%
bi	0.435	3.39%	0.714	3.79%	0.121	4.14%	0.149	5.04%	0.188	7.55%

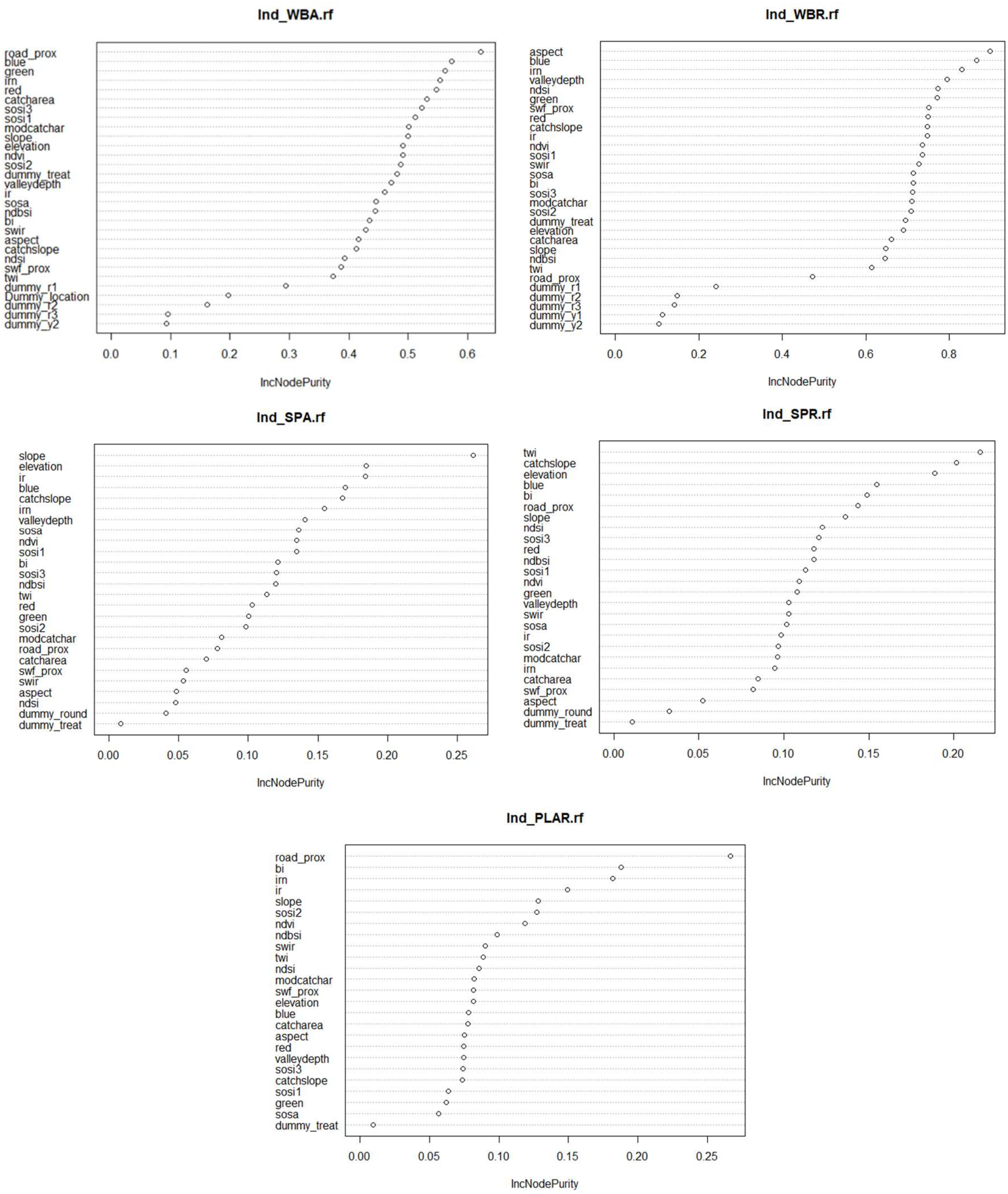

Figure 41. RF variable contribution plots for WBA (top left), WBR (top right) for SpA (middle left), SpR (middle right) and PlaR (bottom center) indicators.

The RF predictors ranking suggests that the dummy variables used to include the implementation of biodiversity management as a possible covariate for upscaling field results to the landscape scale, as well the impact of seasonality, are not relevant in the process of training the regression trees of the RF.

The calibration error indices and the statistical measures of agreement between observed and estimated indicator values are reported in Table 40, and graphically depicted in figure 42.

Table 40: Calibration error indices for MLR and RF predictive model for the five biodiversity indicators

Error indices	*WBA Indicator*		*WBR Indicator*		*SpA indicator*		*SpR Indicator*		*PlaR Indicator*	
	MLR	RF	MLR	RF	MLR	RF	MLR	RF	MLR	RF
ME	-0.002	-0.010	0.000	-0.004	-0.004	-0.007	0.000	-0.009	0.000	-0.003
AE	0.074	0.154	0.127	0.211	0.081	0.174	0.152	0.227	0.139	0.215
MSE	0.009	0.047	0.023	0.069	0.012	0.059	0.035	0.077	0.033	0.067
RMSE	0.092	0.217	0.151	0.262	0.108	0.243	0.188	0.278	0.182	0.259
IoA	0.780	0.287	0.754	0.229	0.927	0.533	0.694	0.138	0.821	0.301
R2	0.487	0.079	0.411	0.052	0.769	0.191	0.361	0.011	0.534	0.070

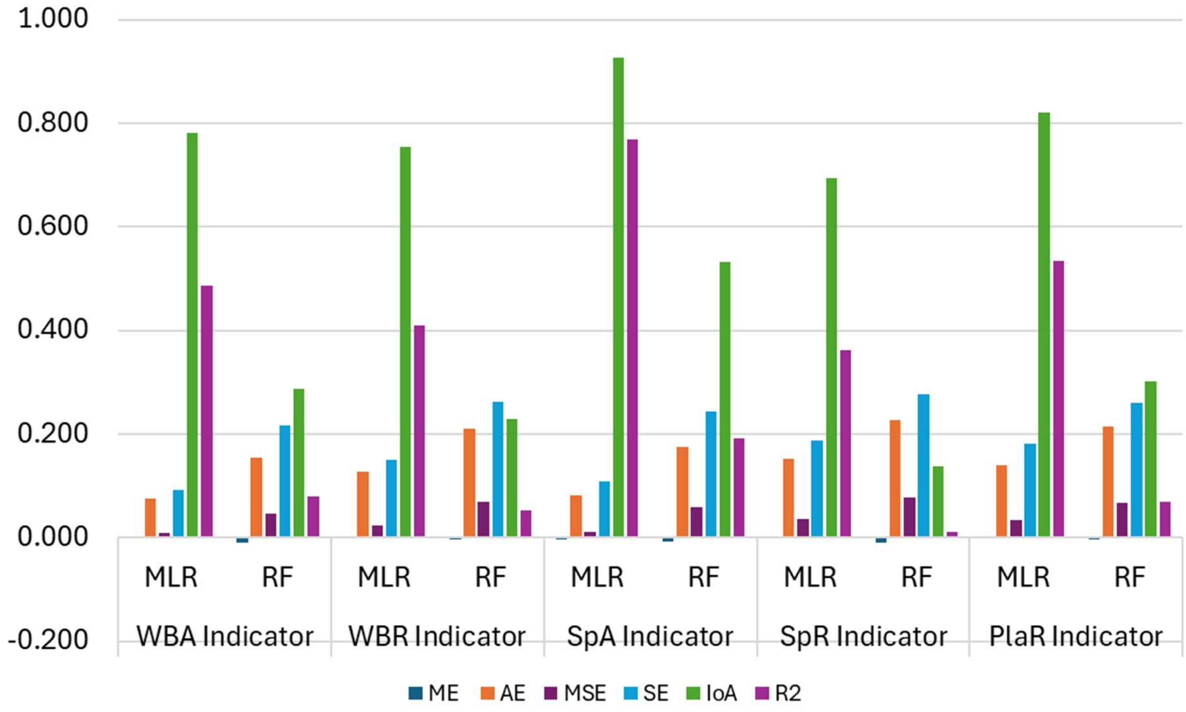

Figure 42: Calibration error indices for MLR and RF predictive model for the five biodiversity indicators in the Dutch EBA

Again, as already observed in the other EBAs considered so far, the results suggest that MLR models better describe the relationships between the target data and the predictor variables compared to RF models.

The MLR models were used to assess and map the five biodiversity indicators over the entire agricultural land area and raster statistics were calculated for each map to assess the average relative changes with respect to the baseline situation (year 1, control), and for each round the relative change due to the treatment implementation over the whole area. Although not realistic, this assessment provides a quantitative, spatial explicit and time dynamic evaluation of the potential impact of the biodiversity management practice implemented in the Dutch EBA.

The spatiotemporal dynamics of the WBA indicator in response to environmental and anthropic drivers are presented in Figure 43; only results for 2022 and 2023 are shown.

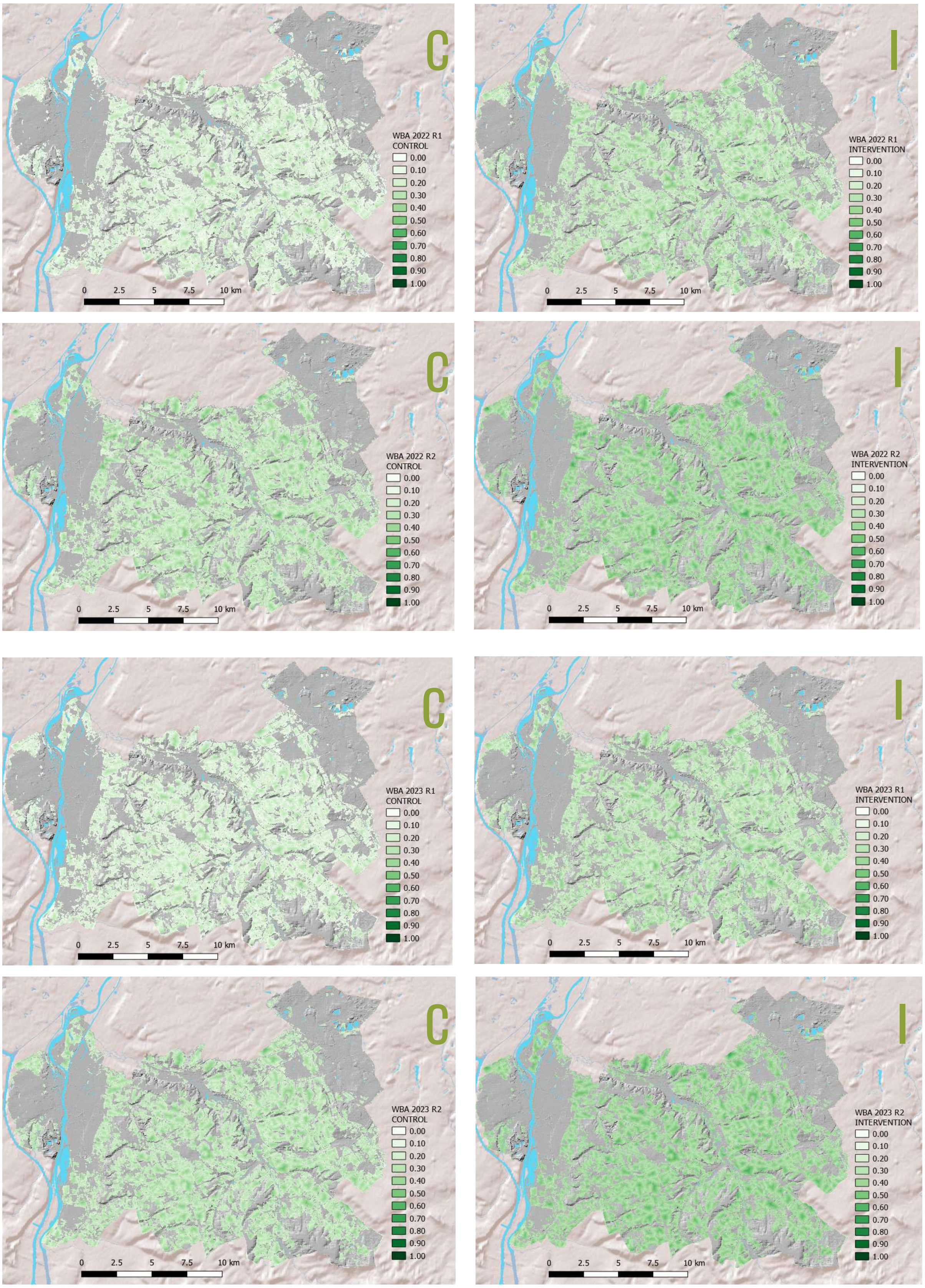

Figure 43: Predicted WBA indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

Table 41 reports the descriptive statistics of the WBA indicator estimates over the whole target area (ca. 17,000 ha). Results highlight a positive trend with respect to the 2022 baseline (control), with an increase greater than 100% in the intervention fields during round 2. The increase due to the intervention with respect to the control was slightly more evident in the first year, in which values for the control were somewhat lower, with increases equal to 70 and 43% in the first and the second round, respectively, while in the second year they were 65 and 41%. The resulting average increase due to the intervention in the whole area was 55%.

Table 41: WBA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
WBA 2022 r1 treatiszero	0.156	0.151	0.058	0.000	0.668	-	
WBA 2022 r1 treatisone	0.265	0.260	0.059	0.000	0.777	**0.70**	**0.70**
WBA 2022 r2 treatiszero	0.255	0.248	0.059	0.000	0.544	**0.63**	
WBA 2022 r2 treatisone	0.364	0.357	0.059	0.099	0.653	**1.33**	**0.43**
WBA 2023 r1 treatiszero	0.167	0.160	0.057	0.000	0.652	**0.07**	
WBA 2023 r1 treatisone	0.276	0.270	0.058	0.000	0.761	**0.77**	**0.65**
WBA 2023 r2 treatiszero	0.268	0.262	0.056	0.000	0.773	**0.72**	
WBA 2023 r2 treatisone	0.377	0.371	0.056	0.105	0.882	**1.42**	**0.41**
Average changes						**0.80**	**0.55**

Table 42 reports the descriptive statistics of the WBR indicator estimates over the whole target area (ca. 17,000 ha) for the two rounds in the two years 2022 and 2023. The results show a positive trend with respect to the 2022 baseline (control), with strong increase in the second rounds of both 2022 and 2023 in the intervention fields. The increase due to the intervention with respect to the control was more evident in the first rounds, in which values for the control are close to 0.1, with increases equal to 146 and 135% in the first and the second year, respectively, while in the second rounds they were equal to 58% in both years. The resulting average increase due to the intervention in the whole area was 99%. The spatiotemporal dynamics of the WBA indicator in response to environmental and anthropic drivers are presented in Figure 44.

Table 42: WBR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
WBR_2022_r1_treatiszero	0.096	0.096	0.053	0.000	1.000	-	
WBR_2022_r1_treatisone	0.237	0.238	0.054	0.000	1.000	**1.46**	**1.46**
WBR_2022_r2_treatiszero	0.245	0.246	0.046	0.000	1.000	**1.54**	
WBR_2022_r2_treatisone	0.387	0.388	0.046	0.077	1.000	**3.01**	**0.58**
WBR_2023_r1_treatiszero	0.104	0.103	0.056	0.000	1.000	**0.08**	
WBR_2023_r1_treatisone	0.245	0.245	0.057	0.000	1.000	**1.54**	**1.35**
WBR_2023_r2_treatiszero	0.244	0.246	0.048	0.000	1.000	**1.53**	
WBR_2023_r2_treatisone	0.385	0.387	0.048	0.081	1.000	**2.99**	**0.58**
Average changes						**1.74**	**0.99**

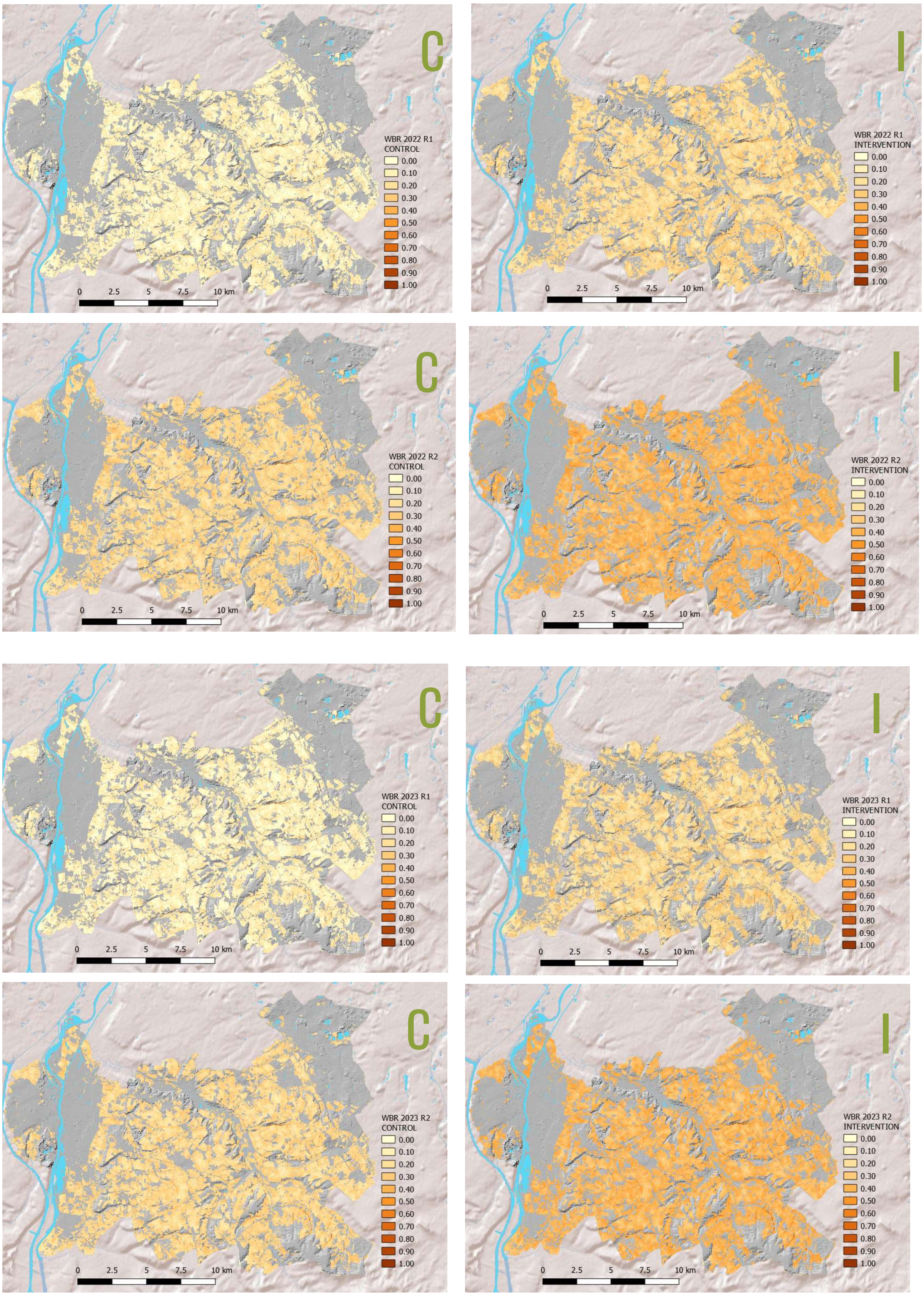

Figure 44: Predicted WBR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

Table 43 reports the descriptive statistics of the SpA indicator estimates over the whole target area. The results highlight a consistently positive trend with respect to the 2022 baseline (control), with stronger increases in the indicator mean value in the second rounds of 2022 and 2023 for both control and intervention fields, highlighting the relevance of seasonality. The increase in spider abundance due to the intervention with respect to the control was quite modest in all rounds of both years, being within 4 and 7%, with an average gain of 5%. The maps underlying the descriptive statistics presented in Table 43 are shown in Figure 45.

Table 43: SpA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
SpA_2022_r1_treatiszero	0.099	0.042	0.124	0.000	0.841	-	
SpA_2022_r1_treatisone	0.105	0.053	0.128	0.000	0.853	**0.07**	**0.07**
SpA_2022_r2_treatiszero	0.204	0.190	0.166	0.000	1.000	**1.07**	
SpA_2022_r2_treatisone	0.213	0.201	0.169	0.000	1.000	**1.16**	**0.04**
SpA_2023_r1_treatiszero	0.104	0.042	0.133	0.000	0.721	**0.05**	
SpA_2023_r1_treatisone	0.110	0.053	0.136	0.000	0.732	**0.12**	**0.06**
SpA_2023_r2_treatiszero	0.210	0.195	0.169	0.000	0.858	**1.12**	
SpA_2023_r2_treatisone	0.219	0.206	0.171	0.000	0.869	**1.22**	**0.04**
Average changes						**0.69**	**0.05**

The descriptive statistics presented in Table 44 refer to the SpR spatiotemporal estimates over the whole target area. The mean indicator values over the area were fairly constant for the same treatment and round in the two years of observations, with increases over the 2022 baseline being of the same order of magnitude, i.e. ca 35% in the intervention fields at the first rounds, ca. 72% for the control fields at the second rounds, and >100% for the intervention fields at the second rounds. Similarly, the relative changes observed in the intervention fields with respect to the control fields were almost equal in the two years, with increases of ca. 30% and 20%, respectively, for the first and the second rounds, for an average gain in SpR of 27%. The maps used to assess the figures in Table 44 are depicted in Figure 46.

Table 44: SpR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
SpR_2022_r1_treatiszero	0.242	0.240	0.132	0.000	0.724	-	
SpR_2022_r1_treatisone	0.323	0.324	0.138	0.000	0.808	**0.33**	**0.33**
SpR_2022_r2_treatiszero	0.422	0.428	0.143	0.000	0.930	**0.74**	
SpR_2022_r2_treatisone	0.505	0.512	0.146	0.000	1.014	**1.09**	**0.20**
SpR_2023_r1_treatiszero	0.248	0.245	0.137	0.000	0.765	**0.03**	
SpR_2023_r1_treatisone	0.329	0.329	0.143	0.000	0.848	**0.36**	**0.33**
SpR_2023_r2_treatiszero	0.410	0.414	0.143	0.000	0.896	**0.70**	
SpR_2023_r2_treatisone	0.493	0.498	0.147	0.000	0.980	**1.04**	**0.20**
Average changes						**0.61**	**0.27**

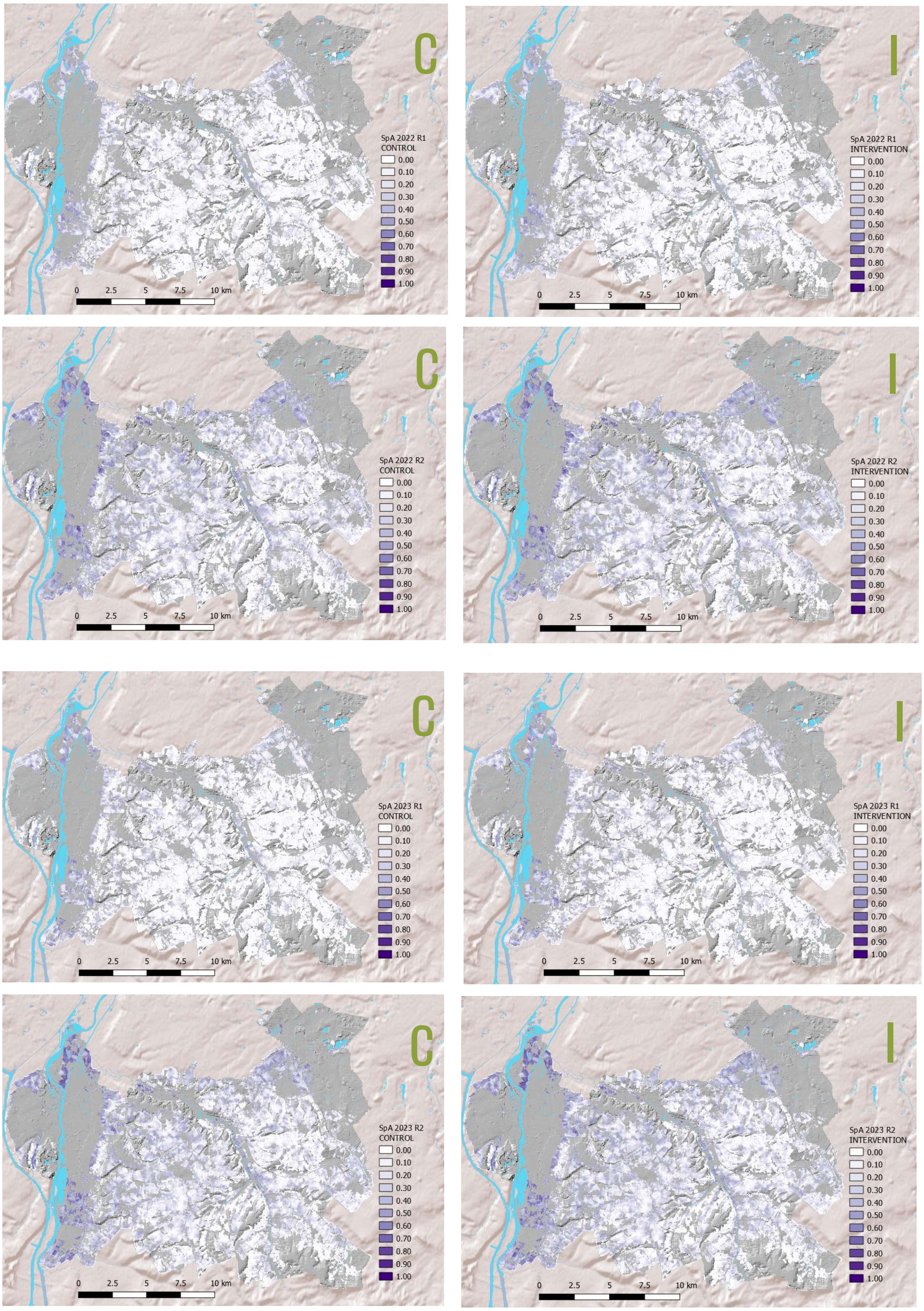

Figure 45: Predicted SpA indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

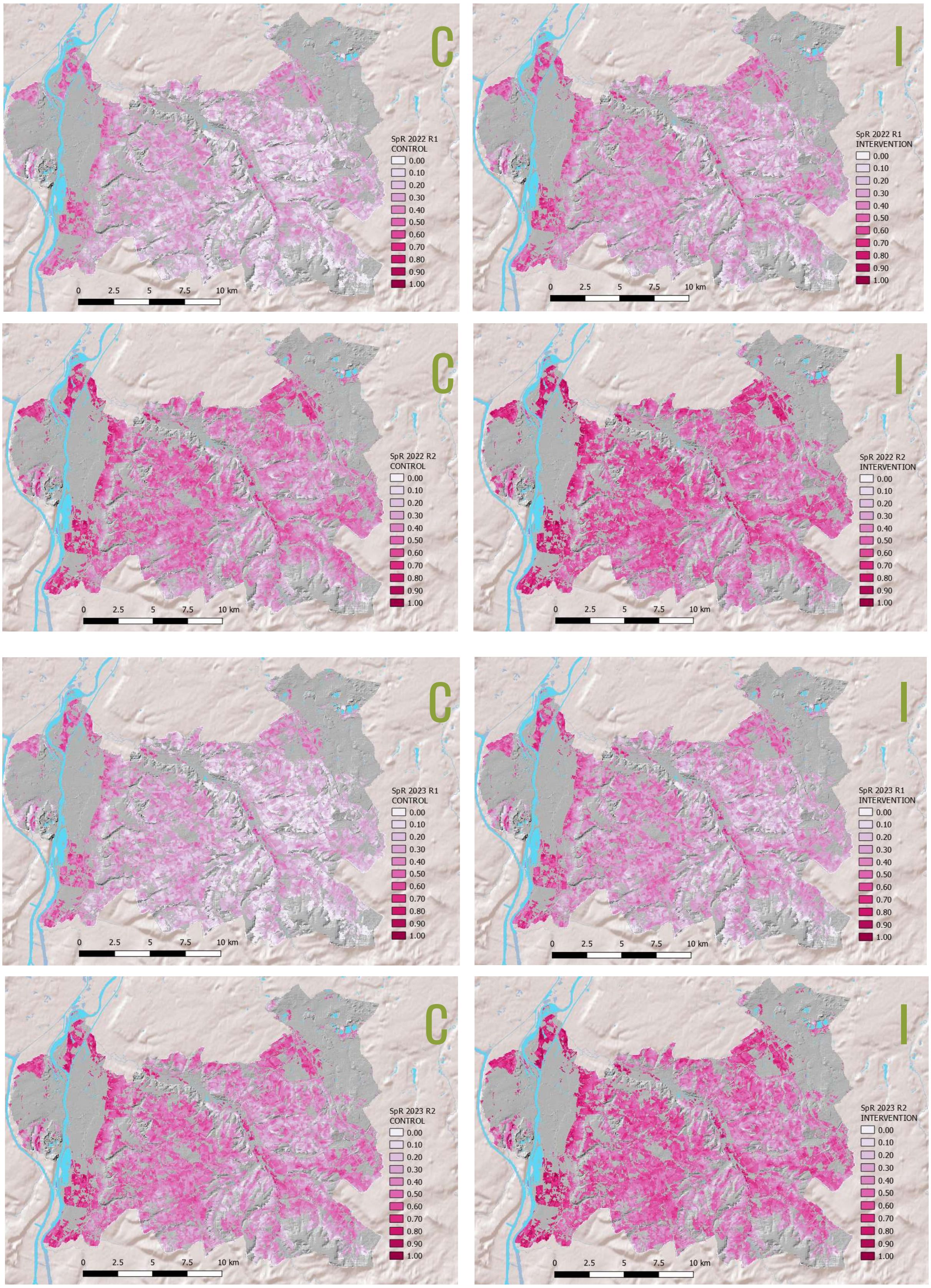

Figure 46: Predicted SpR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

Table 45: PlaR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
PlaR_2022_r1_treatiszero	0.538	0.536	0.254	0.000	1.000	-	
PlaR_2022_r1_treatisone	0.580	0.582	0.250	0.000	1.000	**0.08**	**0.079**
PlaR_2022_r2_treatiszero	0.555	0.541	0.236	0.000	1.000	**0.03**	
PlaR_2022_r2_treatisone	0.598	0.586	0.231	0.000	1.000	**0.11**	**0.077**
PlaR_2023_r1_treatiszero	0.553	0.548	0.256	0.000	1.000	**0.03**	
PlaR_2023_r1_treatisone	0.595	0.594	0.251	0.000	1.000	**0.11**	**0.076**
PlaR_2023_r2_treatiszero	0.529	0.519	0.244	0.000	1.000	**-0.02**	
PlaR_2023_r2_treatisone	0.572	0.565	0.240	0.000	1.000	**0.06**	**0.081**
Average changes						**0.06**	**0.078**

In the case of the PlaR indicator, the average gain in plant richness due to the in-field intervention to support biodiversity was consistent in the two rounds of the two years, being equal to ca. 8%, as shown in Table 45. The relative changes with respect to the 2022 control baseline were always positive except for the 2023 second round for the control, which showed a relative -2% decrease. The greatest changes were observed in the intervention fields at the second round in 2022 and at the first round of 2023, with a gain of 11% in both cases. The maps showing the spatiotemporal dynamics of the indicator are shown in Figure 47.

The final composite indicator describing the overall biodiversity indicator and its spatiotemporal dynamics over the Dutch CSA, have been calculated summing the estimates of the five core indicators for each round, and the sum eventually 0-1 normalized. The resulting maps are shown in Figure 48 and the raster statistics summarized in Table 46 along with the relative changes with respect to the baseline and for each round with respect to the control.

Table 46: BioDiv indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
BioDiv_2022_r1_treatiszero	0.427	0.421	0.170	0.000	1.000	-	
BioDiv_2022_r1_treatisone	0.511	0.507	0.153	0.000	1.000	**0.20**	**0.20**
BioDiv_2022_r2_treatiszero	0.513	0.508	0.146	0.000	1.000	**0.20**	
BioDiv_2022_r2_treatisone	0.535	0.531	0.142	0.000	1.000	**0.25**	**0.04**
BioDiv_2023_r1_treatiszero	0.411	0.401	0.166	0.000	1.000	**-0.04**	
BioDiv_2023_r1_treatisone	0.480	0.472	0.150	0.000	1.000	**0.12**	**0.17**
BioDiv_2023_r2_treatiszero	0.485	0.482	0.143	0.000	1.000	**0.14**	
BioDiv_2023_r2_treatisone	0.507	0.505	0.140	0.000	1.000	**0.19**	**0.05**
Average changes						**0.15**	**0.11**

On average the gain in biodiversity was more evident for the first rounds, with a relative increase of almost 20%, while for the second it is ca 5%, with an overall mean value of 11%. The trend with respect to the 2022 control baseline was always positive, except for the control fields in the first round of 2023 for which a mean decrease of -4% was estimated. The greatest gain was during the second round of 2022 with an increase of 25%, while the corresponding figure for 2023 was 19%.

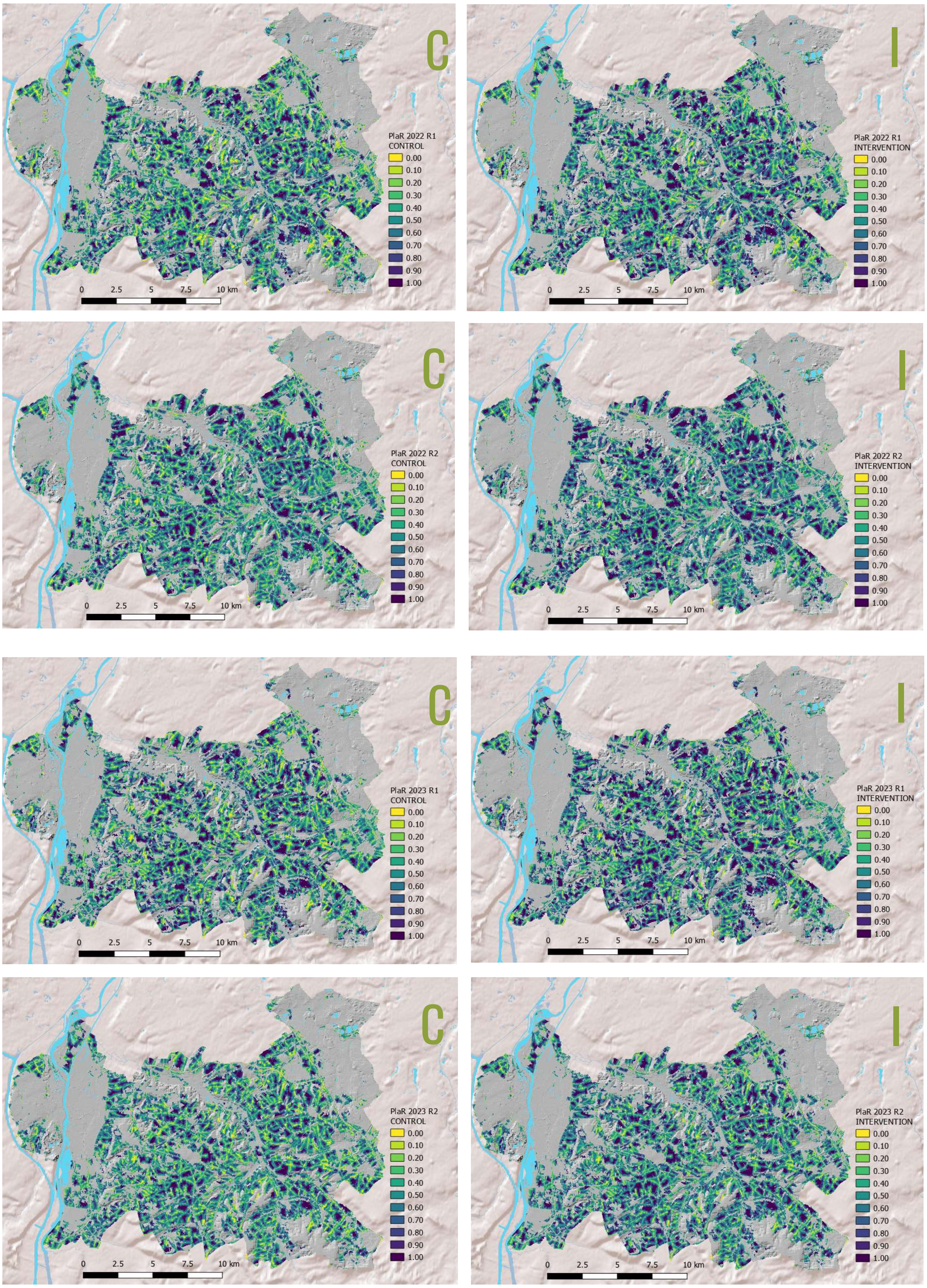

Figure 47: Predicted PlaR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

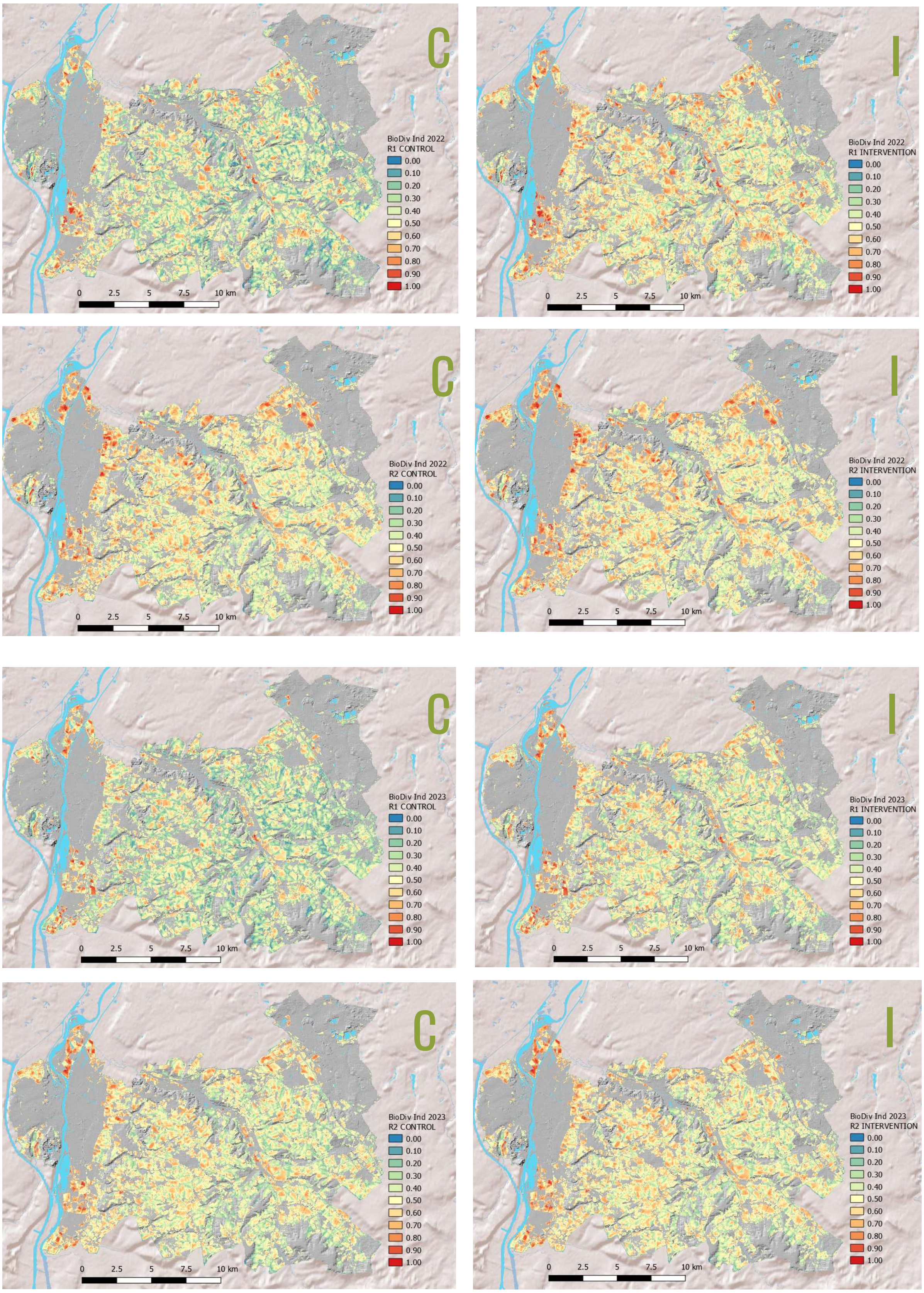

Figure 48: Predicted BioDiv indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

The overall joint trend of all the six indicators, with their synergies and trade-offs, is visually summarized in the radar graph depicted in Figure 49. The indicator values shown in the figure are averaged over the two rounds of each year.

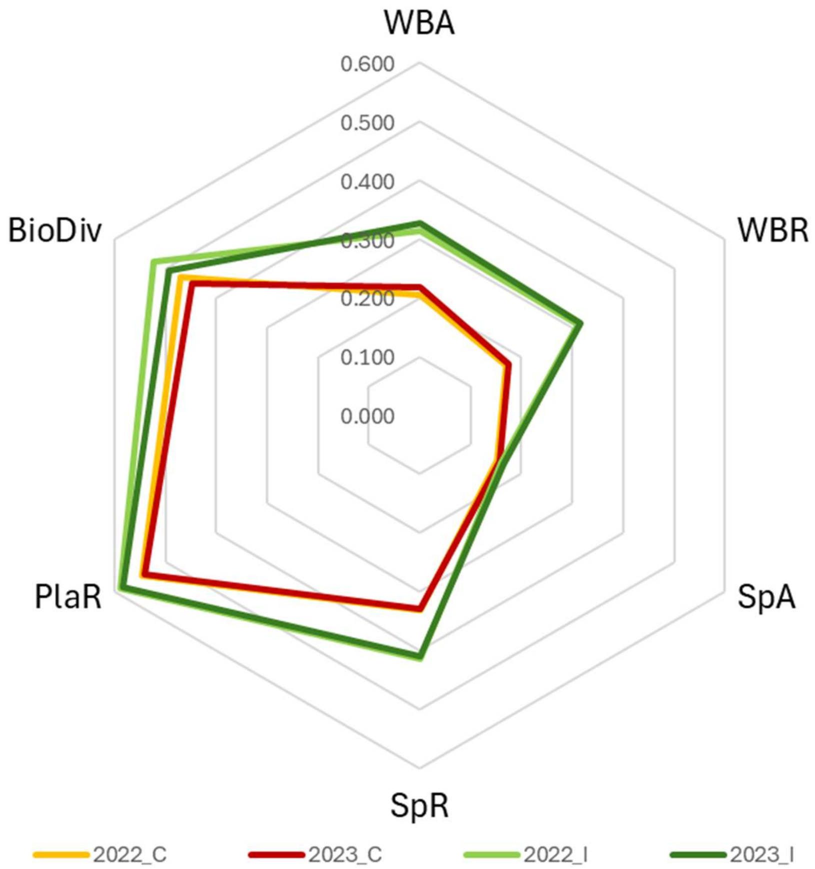

Figure 49: Radar graph of the round-averaged indicators for the control and the intervention in the two years of observation.

3.5 Swiss EBA

The Swiss EBA fields are in the canton of Solothurn in northern Switzerland and the target area for the upscaling of biodiversity indicators at landscape scale is the agricultural land (19,662 ha) representing ca. 25% of the total area of the canton. The area presents a wide range of elevations from the alluvial plain of the Aare River (277 m a.s.l) to the foothills of the Jura massif (1,445 m a.s.l). Agricultural land use is characterized by small-scale and diversified farming systems. The average farm size in the canton of Solothurn is 23 ha and the average parcel size is 0.9 ha, resulting in a heterogeneous pattern of croplands and grasslands. The predominant agricultural land use is permanent grasslands which covers around 165 km^2, i.e., 67% of the agricultural area in 2015, while rotational grasslands and arable land cover 14% and 32% of the cantonal area, respectively (FSO, 2015). The agricultural landscape is characterized by the presence of semi-natural elements, such as hedgerows, traditional orchards and sown wildflower strips. Agricultural production fields are interspersed with woodlots.

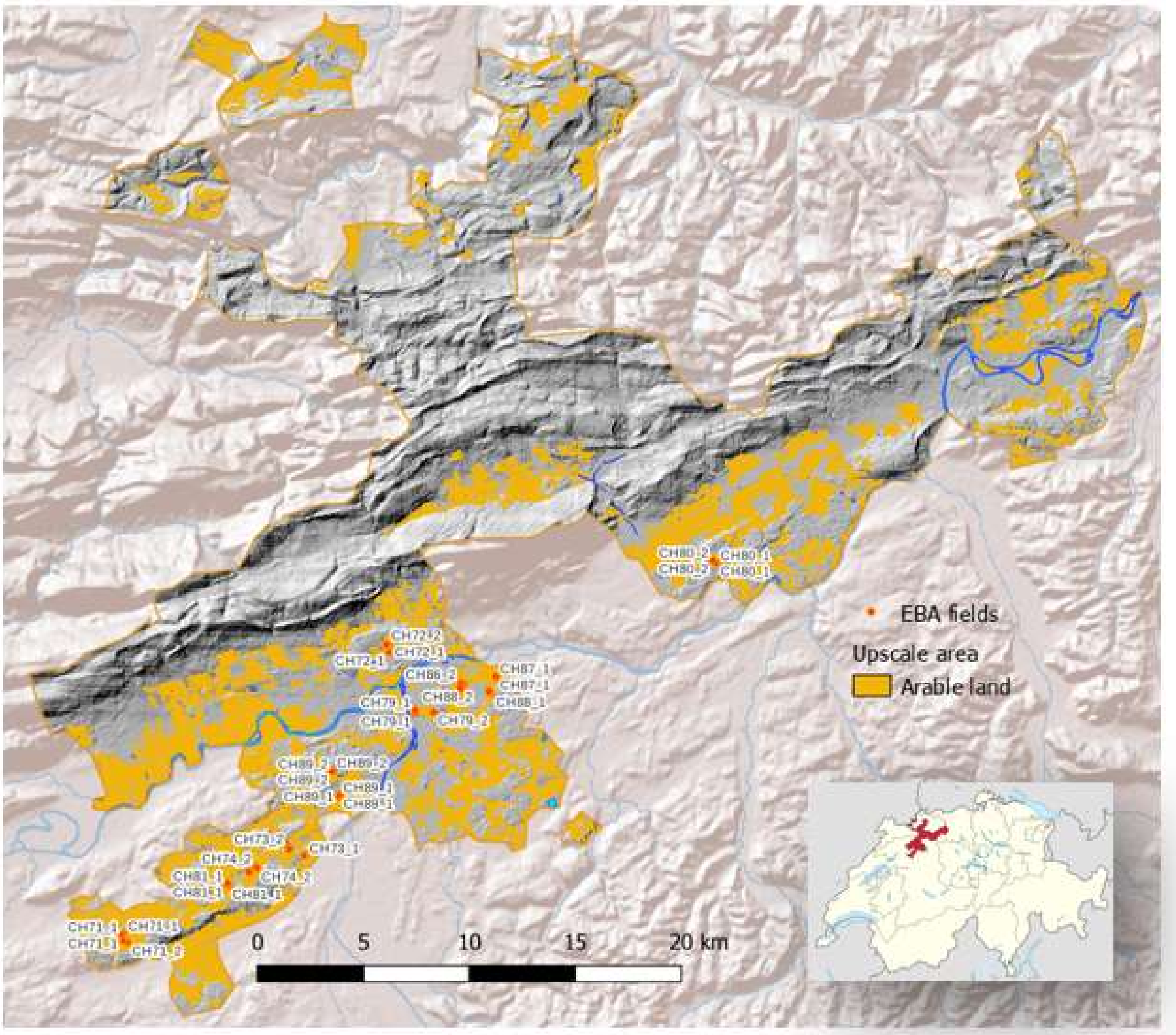

Figure 50. Geographical location of the Swiss CSA.

Following the SHOWCASE sampling protocol, the core indicator data were collected in two rounds (April and July) in 2022 and 2023 from eleven control fields with flower strips, and eleven intervention fields. Plant richness was sampled only once every year (first round). The descriptive statistics of the five biodiversity indicators are summarized in Table 47 for individual and species counts and their 0-1 normalized indicators for 2022, as the species identification for 2023 is still on-going at the time of writing this report.

Table 47: Descriptive statistics of the five SHOWCASE core indicators

Core Indicators	Valid N	Mean	Std.Dev.	Std. Err.	Min	Median	Max
Counts							
WBA	84	2.3	5.1	0.6	0	0	24
WBR	83	0.6	1.0	0.1	0	0	4
SpA	74	16.8	21.1	2.5	0	8	123
SpR	73	3.8	3.1	0.4	0	3	12
PlaR	45	12.6	7.3	1.1	2	11	33
Indicator (0-1)							
Ind WBA	84	0.106	0.230	0.025	0	0.000	1
Ind WBR	83	0.196	0.317	0.035	0	0.000	1
Ind SpA	74	0.186	0.195	0.023	0	0.159	1
Ind SpR	74	0.346	0.272	0.032	0	0.333	1
Ind PlaR	45	0.341	0.235	0.035	0	0.290	1

Table 48 summarizes the descriptive statistics of the five normalized indicators for the control and intervention fields; statistically significant differences ($p< 0.05$) in indicator mean values were detected for WBA, WBR and PlaR indicators, with higher mean values observed for the intervention fields and lower for the control fields. As for the spider indicators, SpA was slightly higher in the control fields, while the opposite was observed for SpR. Likewise, in term of location along the transect, mean indicator values were significantly higher at the field margins than in the field center for WBA (0.197 vs. 0.007), WBR (0.324 vs.0.051) and PlaR (0.456 vs. 0.231) but not for spiders, with both mean SpA and SpR indicators higher at the field center (0.155 and 0.219) than at the field margins (0.289 and 0.405). Similar responses were observed in both control and intervention fields with significantly higher mean indicator values for WBA, WBR and PlaR at the field margins detected in the intervention fields but not in the control ones; nevertheless, indicator values were always higher at the field margins. In the case of PlaR indicator, the differences in mean values were significant also in the control fields.

The mean sampling round values for the bee indicators were consistent in the control fields for both WBA and WBR, while in the intervention fields the mean values observed during the second round were somewhat lower in the case of WBA (0.207 and 0.180 respectively) and remarkably lower in the case of WBR (0.375 and 0.227 respectively). In the case of the spider indicators, a clear increase was observed for both indicators in the control sites, which was particularly evident for SpR (0.248 and 0.396 respectively at round 1 and 2), while at the intervention sites values remained almost constant over the season.

Table 48: Descriptive statistics of the five SHOWCASE core indicators in the control and intervention fields of the Hungarian EBA

Indicator	Treatment	Means	N	Std.Dev.	Std.Err.	Min	Median	Max
Ind WBA	*Control*	0.015	41	0.039	0.006	0.00	0.000	0.21
	Intervention	0.193	43	0.296	0.045	0.00	0.000	1.00
	All Groups	0.106	84	0.230	0.025	0.00	0.000	1.00
Ind WBR	*Control*	0.091	41	0.215	0.034	0.00	0.000	1.00
	Intervention	0.298	42	0.367	0.057	0.00	0.000	1.00
	All Groups	0.196	83	0.317	0.035	0.00	0.000	1.00
Ind SpA	*Control*	0.191	37	0.209	0.034	0.00	0.130	1.00
	Intervention	0.181	37	0.183	0.030	0.00	0.171	1.00
	All Groups	0.186	74	0.195	0.023	0.00	0.159	1.00
Ind SpR	*Control*	0.328	37	0.282	0.046	0.00	0.250	1.00
	Intervention	0.363	37	0.265	0.044	0.00	0.333	1.00
	All Groups	0.346	74	0.272	0.032	0.00	0.333	1.00
Ind PlaR	*Control*	0.270	22	0.211	0.045	0.00	0.242	0.71
	Intervention	0.410	23	0.241	0.050	0.00	0.355	1.00
	All Groups	0.341	45	0.235	0.035	0.00	0.290	1.00

The relevance of each single predictor in the RF models is presented in Table 49 and Figure 51.

Table 49: Relevance of RF predictors for the five biodiversity indicators in term of node purity; colors highlight the most relevant predictors (orange > brown >light brown)

Predictors	WBA Indicator		WBR Indicator		SpA Indicator		SpR Indicator		PlaR Indicator	
	IncNodePurity	Rel. %	IncNodePurity	Rel. %	IncNodePurity	Rel. %	IncNodePurity	Rel. %	IncNodePurity	Rel. %
dummy_treat	0.149	3.74%	0.149	1.98%	0.009	0.37%	0.023	0.47%	0.036	1.63%
dummy_round	0.011	0.28%	0.028	0.38%	0.011	0.45%	0.012	0.24%	0.015	0.70%
swf_prox	0.170	4.26%	0.501	6.65%	0.082	3.29%	0.312	6.35%	0.093	4.21%
road_prox	0.266	6.69%	0.270	3.59%	0.041	1.66%	0.102	2.08%	0.146	6.62%
aspect	0.269	6.76%	0.511	6.78%	0.084	3.37%	0.182	3.70%	0.076	3.42%
elevation	0.082	2.06%	0.191	2.53%	0.127	5.09%	0.207	4.21%	0.069	3.11%
slope	0.089	2.24%	0.213	2.82%	0.222	8.90%	0.388	7.89%	0.072	3.28%
catchslope	0.091	2.28%	0.146	1.93%	0.170	6.80%	0.245	4.99%	0.078	3.54%
catcharea	0.356	8.94%	0.223	2.96%	0.119	4.76%	0.210	4.26%	0.052	2.36%
modcatchar	0.445	11.19%	0.436	5.79%	0.039	1.56%	0.113	2.31%	0.133	6.01%
twi	0.398	10.00%	0.244	3.23%	0.145	5.80%	0.194	3.95%	0.079	3.59%
valleydept	0.191	4.79%	0.417	5.53%	0.073	2.92%	0.167	3.40%	0.068	3.09%
swir	0.085	2.13%	0.206	2.73%	0.059	2.34%	0.107	2.17%	0.095	4.30%
sosi3	0.076	1.91%	0.261	3.46%	0.078	3.11%	0.222	4.51%	0.072	3.27%
sosi2	0.088	2.20%	0.339	4.50%	0.135	5.42%	0.258	5.25%	0.157	7.11%
sosi1	0.078	1.97%	0.255	3.38%	0.073	2.92%	0.216	4.40%	0.079	3.60%
sosa	0.078	1.96%	0.254	3.37%	0.067	2.69%	0.195	3.96%	0.071	3.20%
red	0.094	2.37%	0.284	3.77%	0.076	3.05%	0.306	6.23%	0.083	3.76%
ndvi	0.110	2.77%	0.417	5.54%	0.151	6.05%	0.272	5.53%	0.066	2.98%
ndsi	0.151	3.80%	0.236	3.13%	0.054	2.15%	0.131	2.67%	0.073	3.31%
ndbsi	0.077	1.93%	0.272	3.61%	0.111	4.42%	0.174	3.53%	0.092	4.16%
irn	0.080	2.00%	0.521	6.91%	0.148	5.91%	0.204	4.14%	0.158	7.16%
ir	0.097	2.44%	0.352	4.67%	0.202	8.10%	0.182	3.71%	0.114	5.17%
green	0.173	4.35%	0.253	3.36%	0.052	2.08%	0.146	2.97%	0.063	2.85%
blue	0.186	4.68%	0.232	3.08%	0.059	2.34%	0.194	3.95%	0.100	4.55%
bi	0.090	2.26%	0.327	4.34%	0.111	4.43%	0.154	3.13%	0.066	3.01%

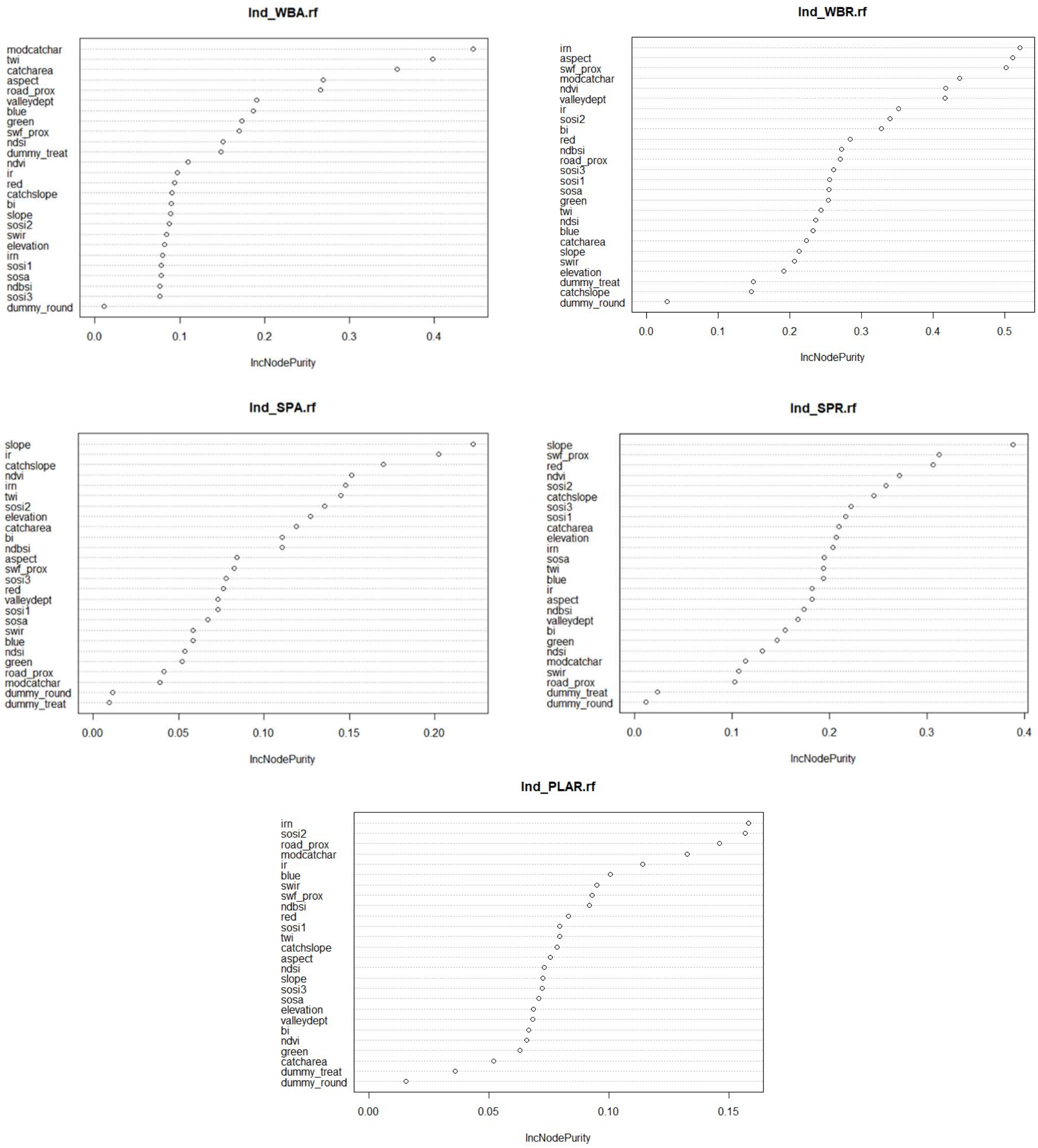

Figure 51. RF variable contribution plots for WBA (top left), WBR (top right) for SpA (middle left), SpR (middle right) and PlaR (bottom center) indicators.

In terms of RF predictor relevance, terrain attributes had a relevant impact on all indicators, in particular aspect, slope and catchment slope, TWI and valley depth. As observed in all the other EBA indicators datasets, the dummy variables accounting for treatment and seasonality ranked very low in their relevance as predictors. Remote sensing indices and spectral bands reflectance played a very minor role for bee indicators, while in the case of spiders and vascular plants they were relevant predictors, particularly SoSI2, red, NDVI, IRn and IR.

Table 50 summarizes the results of the MLR model calibration, reporting the coefficient of the regressions for the spatiotemporal prediction of the five biodiversity indicators. The dummy variable indicating the effect of treatment was statistically significant ($p<0.05$) for all indicators except for SpA, while effect of seasonality was negative and significant for WBR and positive, although statistically not significant, for SpA and PlaR. The effects of the distance to the road network (and to the field margins as well) was significant and negative for WBA, WBR and PlaR, and positive for SpR (i.e. more species richness in the center of the fields). Among the terrain derived predictors, aspect was relevant to all indicators and statistically significant for all excepted SpR. In addition, slope, catchment slope and TWI were selected as predictors by the stepwise procedure for nearly all indicators. Among the RSI, the reflectance in the near infrared was positively and significantly correlated with WBA and WBR, while SpA responded significantly to the reflectance in the infrared band. Both SpA and SpR were negatively and significantly correlated with NDVI.

Table 50: Coefficients of the MLR calibrated for the normalized biodiversity indicators; significant coefficients in red (p <0.05) and blue (p>0.10)

Predictors	WBA	WBR	SpA	SpR	PlaR
Intercept	0.91752	-1.12491	4.00139	-0.63858	-1.37192
Dummy treat	0.14139	0.18810	-0.04494	0.09048	0.23449
Dummy round		-0.09612	0.04654		0.25425
road prox	-0.00169	-0.00245		0.00198	-0.00248
swf prox		0.00035	-0.00028	-0.00073	
aspect	0.00073	0.00074	0.00049	0.00036	-0.00100
catcharea			0.00001	0.00001	-0.00001
catchslope	-2.34530	-0.86062		-2.70298	7.12782
elevation	-0.00048				
modcatchar			-0.00001		
slope			0.02781	0.06639	-0.02991
twi	-0.15845		0.11403	0.05555	0.20659
valley depth			-0.00032		
green			-0.00059		
IR			0.00113		
IRn	0.00027	0.00040			
NDBSI			-0.40685		
NDSI					0.15577
NDVI			-11.61398	-1.03900	-0.37497
red			-0.00206		
SOSI2	0.00025	0.00024		-0.00029	-0.00004

The results of the comparison of the predictive performance of the two approaches is summarized in Table 51 and graphically shown in Figure 52. Again, as observed in all of the other EBAs, MLR outperform RF in terms of lower calibration errors and higher values for indices of agreement between observed and estimated data. The only exception was observed for the WBA indicator: in this case the value of R^2 was higher for the RF estimates (0.592) than for the MLR ones (0.565) and the ME was lower for the RF than for the MLR, with all the other error indices and the IoA lower and higher, respectively, for MLR than for RF. It is worth noting that the value of IoA was negative in the case of RF prediction for the PlaR indicator, indicating a negative relationship between observed and predicted indicator values.

Table 51: Calibration error indices for MLR and RF predictive model for the five biodiversity indicators

Error indices	*WBA Indicator* RF	MLR	*WBR Indicator* RF	MLR	*SpA indicator* RF	MLR	*SpR Indicator* RF	MLR	*PlaR Indicator* RF	MLR
ME	-0.006	-0.019	-0.007	-0.019	-0.003	-0.001	0.000	0.000	0.006	0.000
AE	0.116	0.096	0.208	0.128	0.118	0.091	0.184	0.114	0.209	0.144
RMSE	0.170	0.155	0.271	0.176	0.184	0.131	0.241	0.145	0.253	0.175
R2	0.592	0.565	0.278	0.641	0.113	0.543	0.208	0.692	0.060	0.435
MSR	0.029	0.024	0.073	0.031	0.034	0.017	0.058	0.021	0.064	0.030
IoA	0.684	0.803	0.522	0.853	0.400	0.825	0.524	0.900	-0.258	0.755

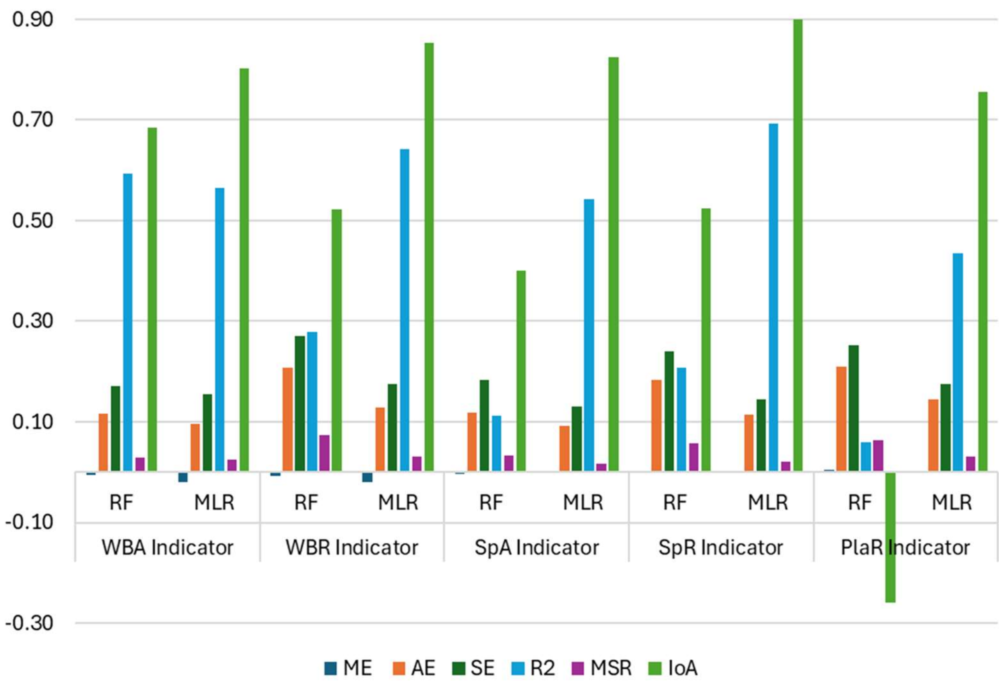

Figure 52: Calibration error indices for MLR and RF predictive model for the five biodiversity indicators in the Swiss EBA

Table 52: WBA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
WBA 2022 r1 treatiszero	0.050	0.000	0.075	0.000	1.000	-	
WBA 2022 r1 treatisone	0.139	0.129	0.120	0.000	1.000	1.80	1.80
WBA 2022 r2 treatiszero	0.049	0.000	0.075	0.000	1.000	-0.01	
WBA 2022 r2 treatisone	0.137	0.124	0.121	0.000	1.000	1.75	1.79
WBA 2023 r1 treatiszero	0.091	0.000	0.157	0.000	1.000	0.84	
WBA 2023 r1 treatisone	0.167	0.097	0.201	0.000	1.000	2.37	0.83
WBA 2023 r2 treatiszero	0.051	0.000	0.077	0.000	0.485	0.03	
WBA 2023 r2 treatisone	0.141	0.130	0.122	0.000	0.626	1.85	1.76
Average changes						1.23	1.54

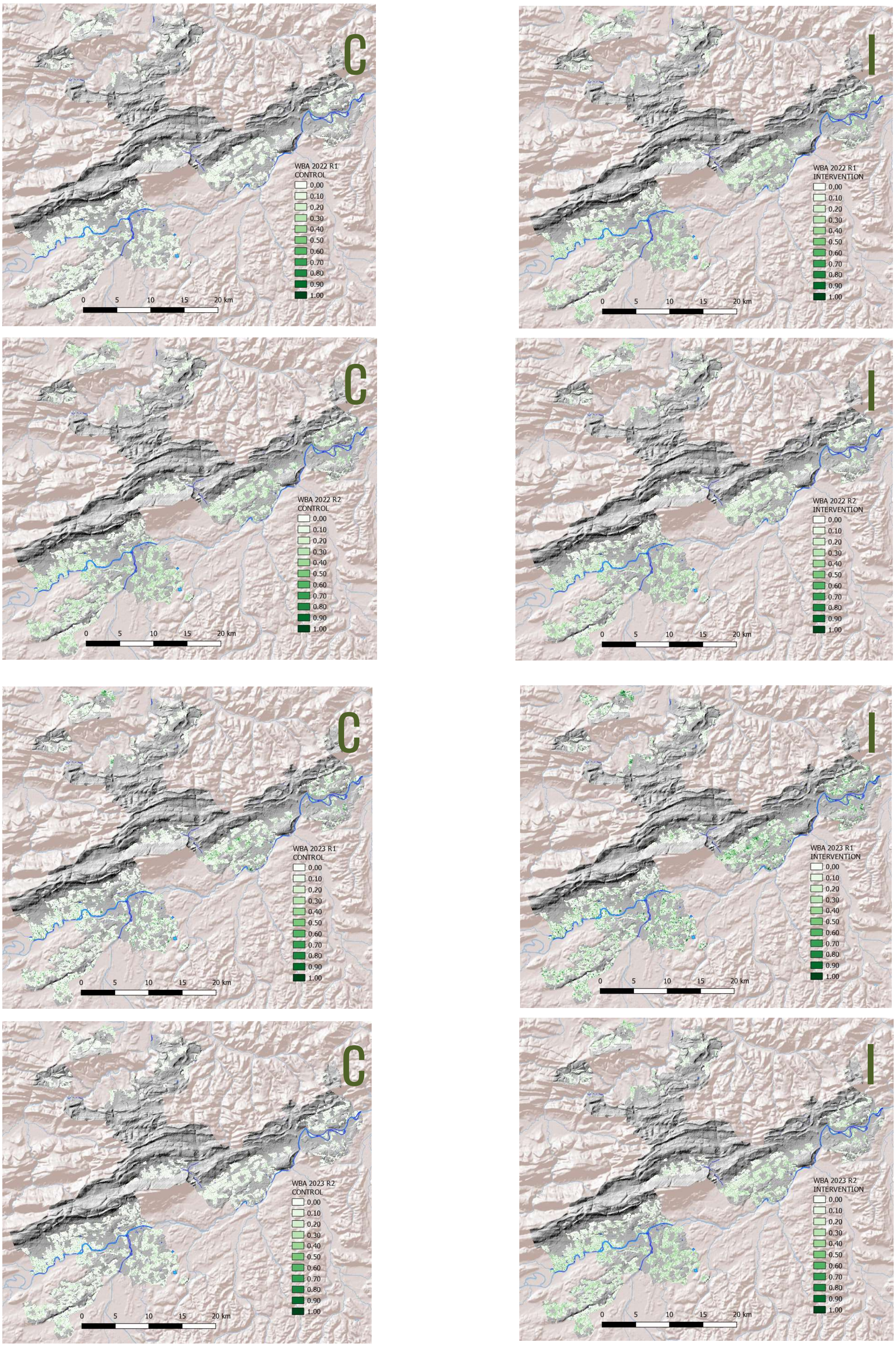

Figure 53: Predicted WBA indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

Table 52 summarizes the raster statistics for the WBA indicator estimates over the whole target area (16,662 ha). The results highlight that in 2022 the increase in the indicator value due to the intervention was almost equal in both rounds, i.e. ca. 180%, while in 2023 the increase in the second round was more than double with respect to the first one. The average gain due to the intervention was >150%. The sign of the trend with respect to the baseline was always positive, except for the control fields in the second round of 2022, with a decrease of -1%; the corresponding figure in 2023 was a small increase of 3%. The raster maps depicting the WBA indicator spatiotemporal variability are presented in figure 53.

Table 53: WBR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
WBA 2022 r1 treatiszero	0.185	0.167	0.158	0.000	1.000	-	
WBA 2022 r1 treatisone	0.352	0.355	0.187	0.000	1.000	**0.91**	**0.91**
WBA 2022 r2 treatiszero	0.100	0.047	0.125	0.000	0.784	**-0.46**	
WBA 2022 r2 treatisone	0.243	0.235	0.171	0.000	0.972	**0.31**	**1.43**
WBA 2023 r1 treatiszero	0.215	0.137	0.244	0.000	1.000	**0.16**	
WBA 2023 r1 treatisone	0.355	0.325	0.281	0.000	1.000	**0.92**	**0.65**
WBA 2023 r2 treatiszero	0.111	0.072	0.121	0.000	0.710	**-0.40**	
WBA 2023 r2 treatisone	0.264	0.260	0.162	0.000	0.898	**0.43**	**1.38**
Average changes						**0.27**	**1.09**

The raster statistics for the WBR indicator are summarized in Table 53. The gain in terms of average increase of the indicator was similar in the two years and more evident in the second rounds with values around 140%, while for the first rounds the increase was equal to 90% in 2020 and 65% in 2023. With respect to the control baseline of the first round in 2022, the average gain was ca. 30%, with a decrease in the average indicator values observed in the control fields at the second round in both years, equal to -46 and -40% in 2022 and 2023, respectively. The spatiotemporal dynamics of the WBR indicator is illustrated in Figure 54, which shows the predicted indicator maps for the two rounds in the two years for control and treatment management scenarios.

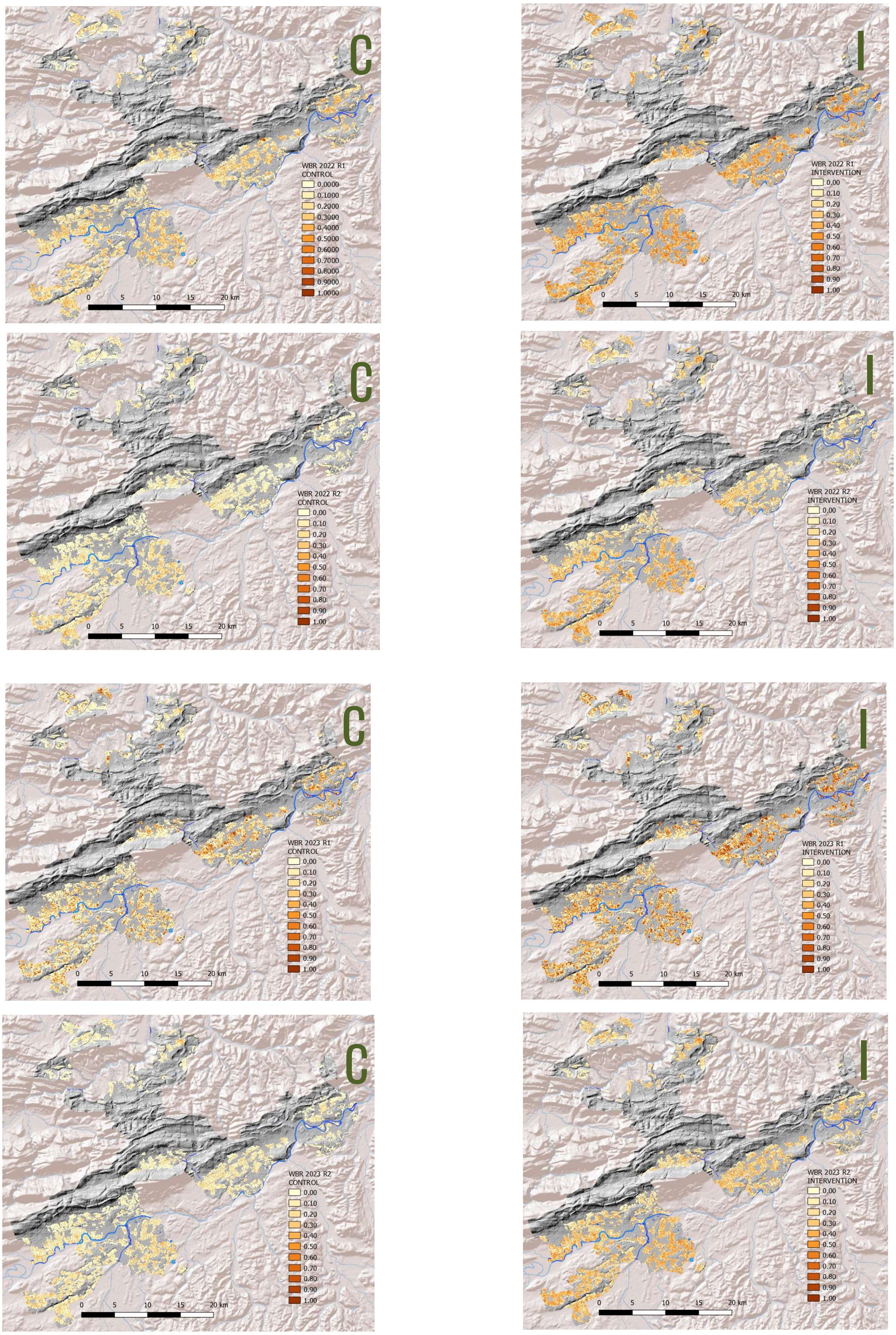

Figure 54: Predicted WBR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

The raster statistics for the spider indicators are summarized in Tables 54 and 55 for the abundance and the richness indicators, respectively.

Table 54: SpA indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
SpA_2022_r1_treatiszero	0.235	0.193	0.208	0.000	1.000	-	
SpA_2022_r1_treatisone	0.197	0.148	0.202	0.000	1.000	-0.16	-0.16
SpA_2022_r2_treatiszero	0.242	0.216	0.184	0.000	1.000	0.03	
SpA_2022_r2_treatisone	0.202	0.171	0.177	0.000	1.000	-0.14	-0.16
SpA_2023_r1_treatiszero	0.286	0.230	0.252	0.000	1.000	0.22	
SpA_2023_r1_treatisone	0.249	0.185	0.247	0.000	1.000	0.06	-0.13
SpA_2023_r2_treatiszero	0.230	0.213	0.171	0.000	1.000	-0.02	
SpA_2023_r2_treatisone	0.191	0.168	0.164	0.000	1.000	-0.19	-0.17
Average changes						-0.03	-0.15

As for the SpA indicator, the results highlight a negative impact of the intervention in all rounds and years, with a fairly constant decrease of the mean indicator value of -15%. With respect to the baseline, a 3% increase was observed in the control fields at the second round of 2022, while in 2023 positive gains were estimated for the first round in both control and intervention fields, with average increases equal to 22 and 6%, respectively. The raster maps underpinning the statistics in Table 54 are shown in Figure 55.

The impacts of the intervention and of the spatiotemporal dynamics were quite different for the SpR indicator. In this case we estimated an average increase of 28% in the mean value of the indicator in the intervention fields, with constant gains over rounds and years, as observed in the case of the abundance indicator. Likewise, the trend with respect to the baseline was always positive, excepted for the first round of the second year in the control fields where a -1% average decrease was predicted. The increase in the intervention fields was more evident in the second round of the second year, with a 45% average gain, while it was equal to or <30% in all other cases. During the second round of the second year, a 15% increase was estimated for the control fields as well. Figure 56 portrays the eight maps of the SpR indicator for the control and the intervention scenarios in the two rounds of 2022 and 2023.

Table 55: SpR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
SpR_2022_r1_treatiszero	0.276	0.245	0.226	0.000	1.000	-	
SpR_2022_r1_treatisone	0.355	0.336	0.234	0.000	1.000	0.29	0.29
SpR_2022_r2_treatiszero	0.279	0.250	0.220	0.000	1.000	0.01	
SpR_2022_r2_treatisone	0.359	0.341	0.227	0.000	1.000	0.30	0.29
SpR_2023_r1_treatiszero	0.274	0.236	0.242	0.000	1.000	-0.01	
SpR_2023_r1_treatisone	0.351	0.327	0.251	0.000	1.000	0.27	0.28
SpR_2023_r2_treatiszero	0.316	0.294	0.223	0.000	1.000	0.15	
SpR_2023_r2_treatisone	0.398	0.385	0.227	0.000	1.000	0.45	0.26
Average changes						0.21	0.28

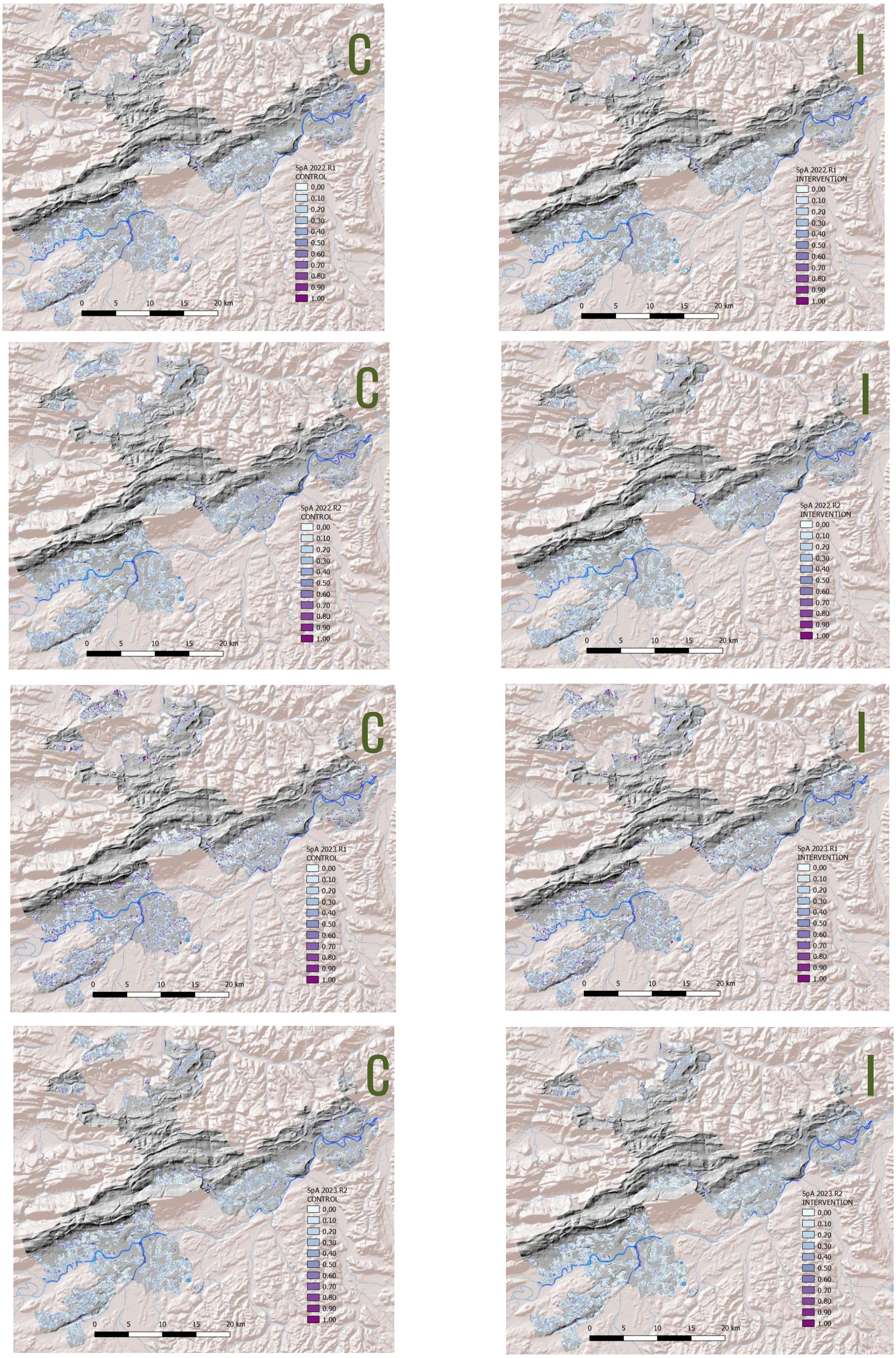

Figure 55: Predicted SpA indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention.

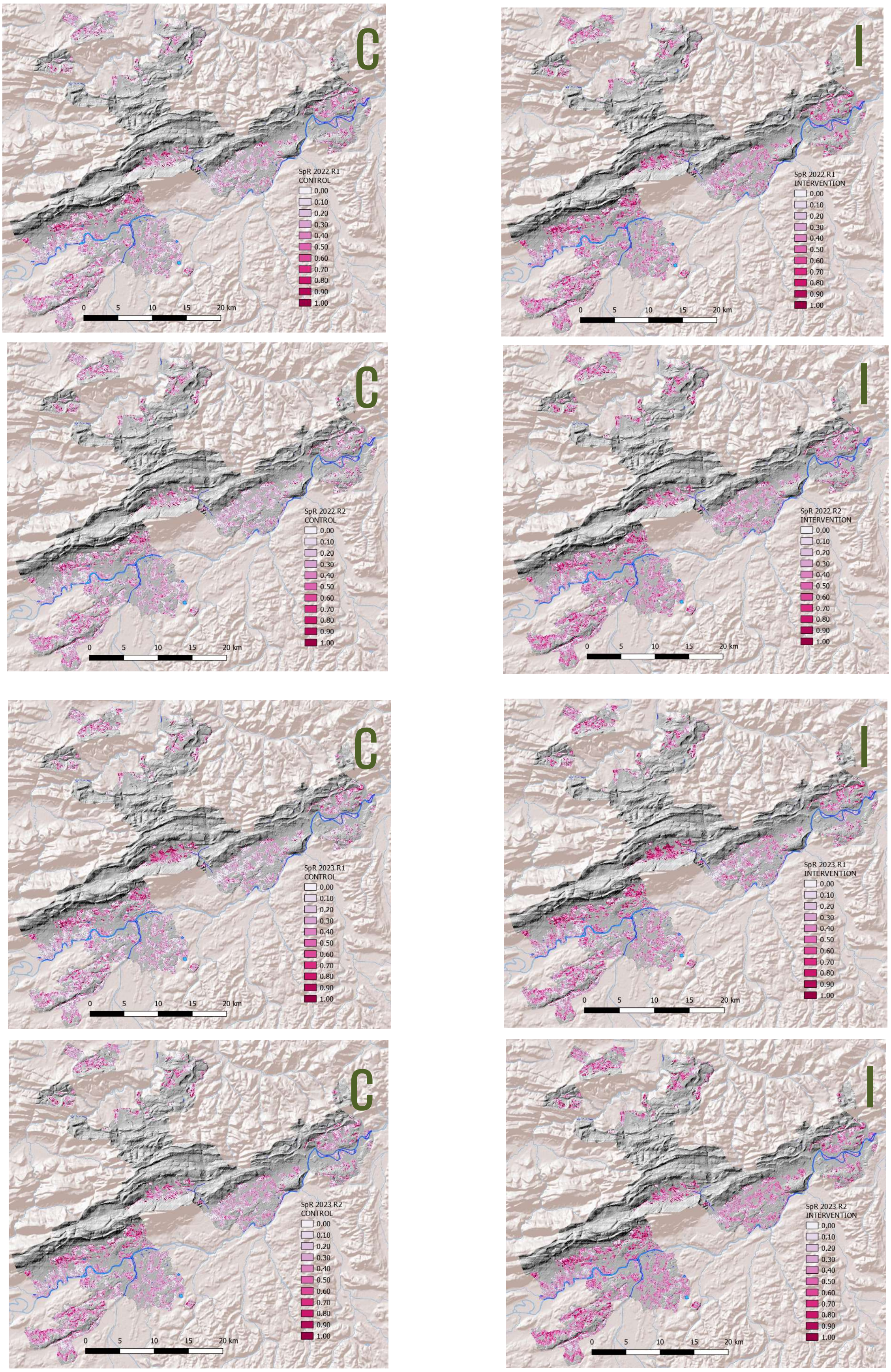

Figure 56: Predicted SpR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention

The descriptive statistics for the plant richness indicator PlaR are summarized in Table 56. The average increases in the indicator mean values were very similar in the two years, and in the first rounds these were almost double with respect to the second, with gains of ca. 60% and 34% respectively for the first and the second rounds. The average increase in the PlaR indicator resulting from the intervention was equal to 47%. Apart from the first round of 2023 in the control fields, which exhibited a decrease equal to -2%, the changes with respect to the baseline were always positive and nearly equal in the two years: for the intervention at rounds 1, ca. 60%, for the control at rounds 2, ca. 60%, and for the intervention at rounds 2, >125%. The raster maps underlying the zonal statistics presented in the table are shown in Figure 56.

Table 56: PlaR indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
PlaR_2022_r1_treatiszero	0.330	0.256	0.298	0.000	1.000	-	
PlaR_2022_r1_treatisone	0.528	0.491	0.271	0.000	1.000	**0.60**	**0.60**
PlaR_2022_r2_treatiszero	0.555	0.523	0.266	0.000	1.000	**0.68**	
PlaR_2022_r2_treatisone	0.746	0.757	0.216	0.000	1.000	**1.26**	**0.34**
PlaR_2023_r1_treatiszero	0.323	0.246	0.300	0.000	1.000	**-0.02**	
PlaR_2023_r1_treatisone	0.520	0.480	0.274	0.000	1.000	**0.57**	**0.61**
PlaR_2023_r2_treatiszero	0.564	0.532	0.264	0.000	1.000	**0.71**	
PlaR_2023_r2_treatisone	0.753	0.767	0.213	0.000	1.000	**1.28**	**0.34**
Average changes						**0.72**	**0.47**

From the sum of the five biodiversity indicators for each round of sampling and for the two years considered, the combined biodiversity indices were calculated, 0-1 normalized and mapped, as shown in Figure 58. The rasters were used as the basis to calculate zonal statistics for the target land use area, which are presented in Table 57.

Table 57: BioDiv indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Mean	Median	Std. Dev.	Min.	Max.	Rel change baseline	Rel Change T
BioDiv_2022_r1_treatiszero	0.330	0.311	0.135	0.000	1.000	-	
BioDiv_2022_r1_treatisone	0.409	0.394	0.126	0.000	1.000	**0.24**	**0.24**
BioDiv_2022_r2_treatiszero	0.339	0.316	0.131	0.000	1.000	**0.03**	
BioDiv_2022_r2_treatisone	0.364	0.353	0.127	0.000	1.000	**0.10**	**0.08**
BioDiv_2023_r1_treatiszero	0.321	0.303	0.147	0.000	1.000	**-0.03**	
BioDiv_2023_r1_treatisone	0.359	0.348	0.143	0.000	1.000	**0.09**	**0.12**
BioDiv_2023_r2_treatiszero	0.378	0.354	0.126	0.000	1.000	**0.15**	
BioDiv_2023_r2_treatisone	0.435	0.425	0.125	0.000	1.000	**0.32**	**0.15**
Average changes						**0.13**	**0.15**

The overall average biodiversity gain resulting from the implementation of the biodiversity friendly management practice was equal to 15%, with similar values in the two rounds of 2023, while in 2022 the gain for the first round (24%) was three times as much that of the second round (8%).

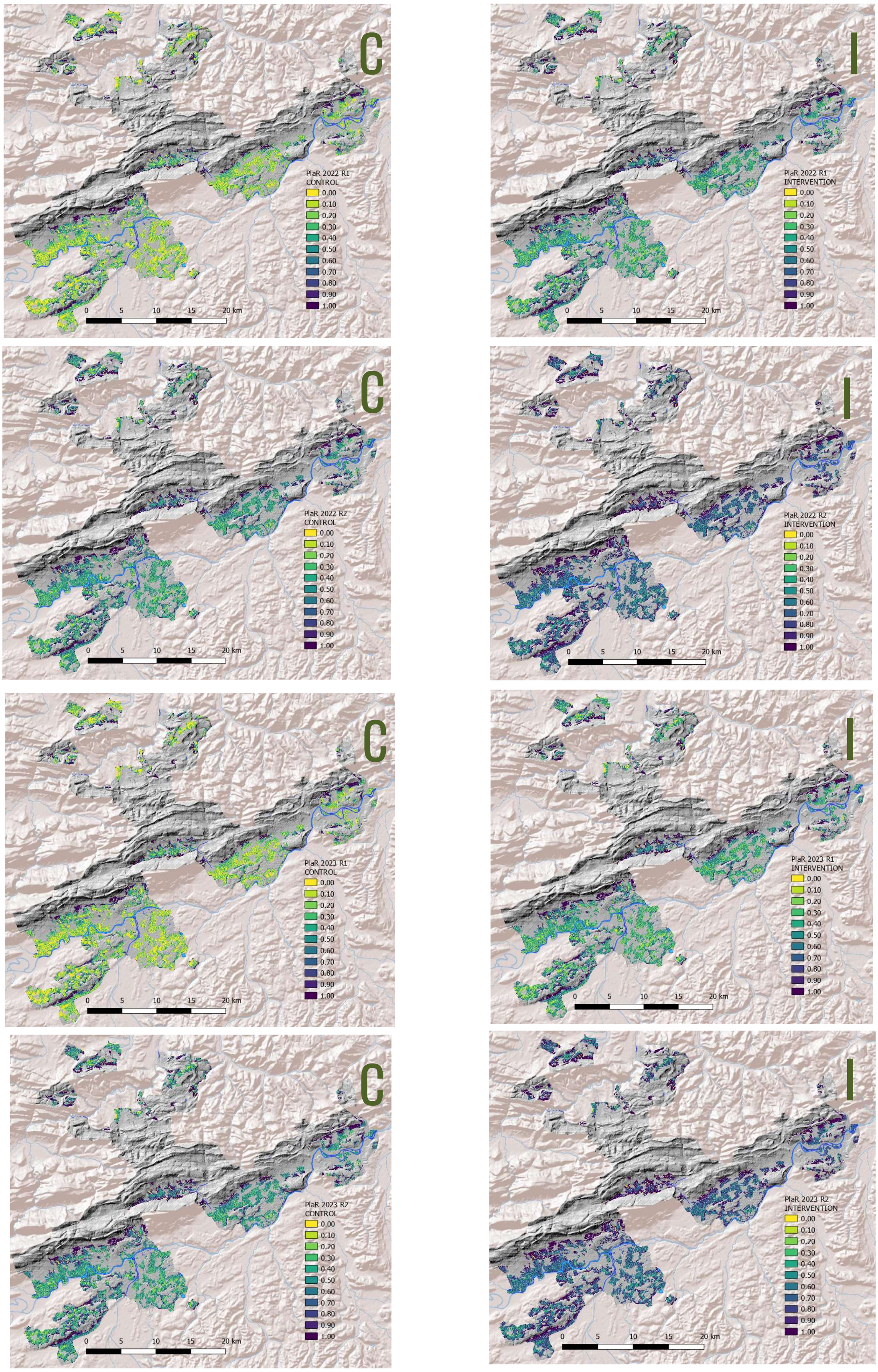

Figure 57: Predicted PlaR indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention

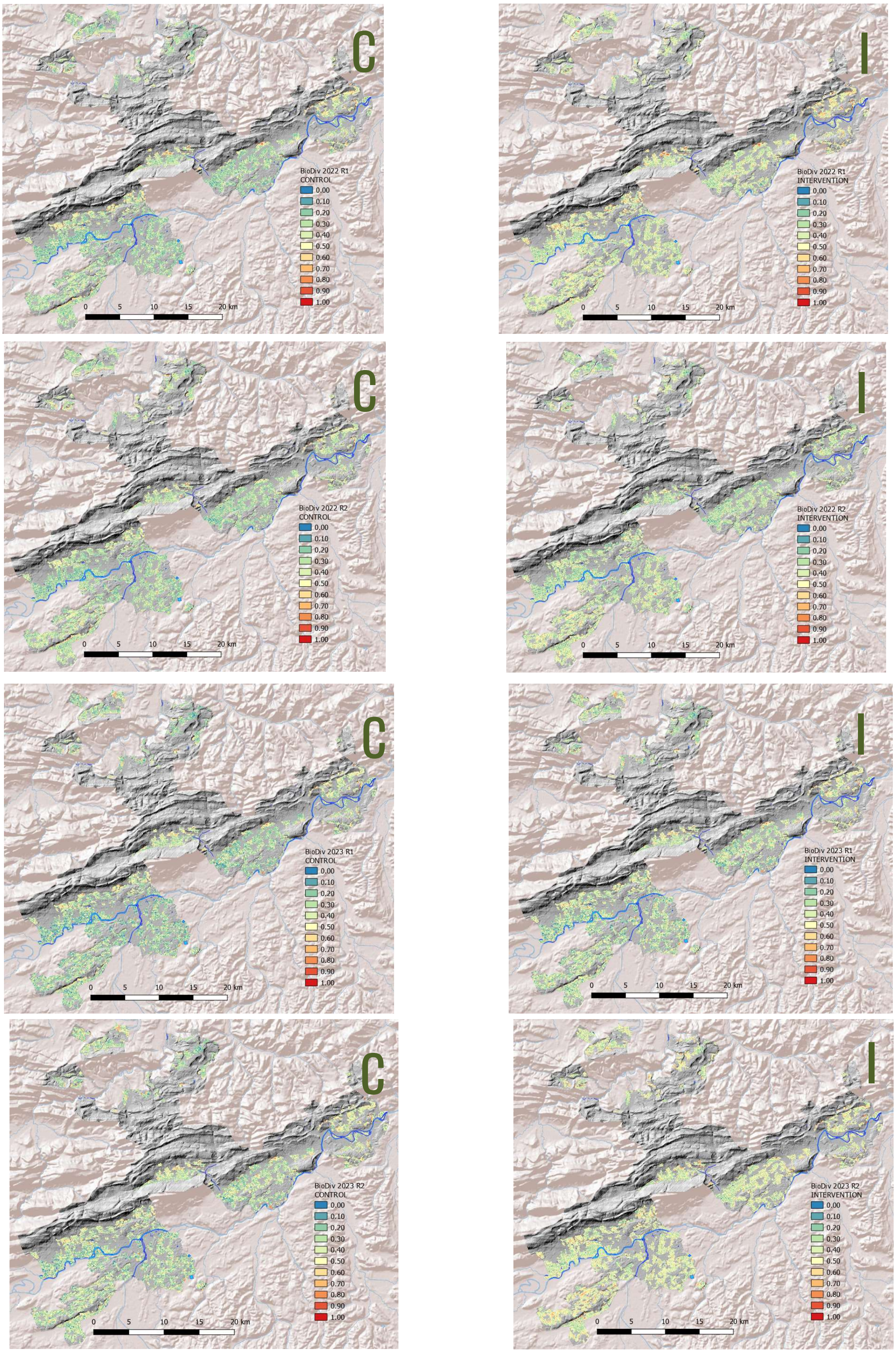

Figure 58: BioDiv indicator maps (res. 10 m) for round 1 (first row) and round 2 (second row) in 2022, and for round 1 (third row) and round 2 (forth row) in 2023; C: Control, I: Intervention

The overall trend of the BioDiv composite indicator with respect to the baseline is characterized by positive values except for a -3% decrease estimated for the control scenario in the first round of 2023. For the intervention scenario, the highest increase was observed in the second round of 2023 with a gain above 30%, while for the control scenario there was a 15% increase for the same round of the second year. The overall annual trends of the six upscaled indicators, averaged over the rounds of each year, are shown in Figure 59.

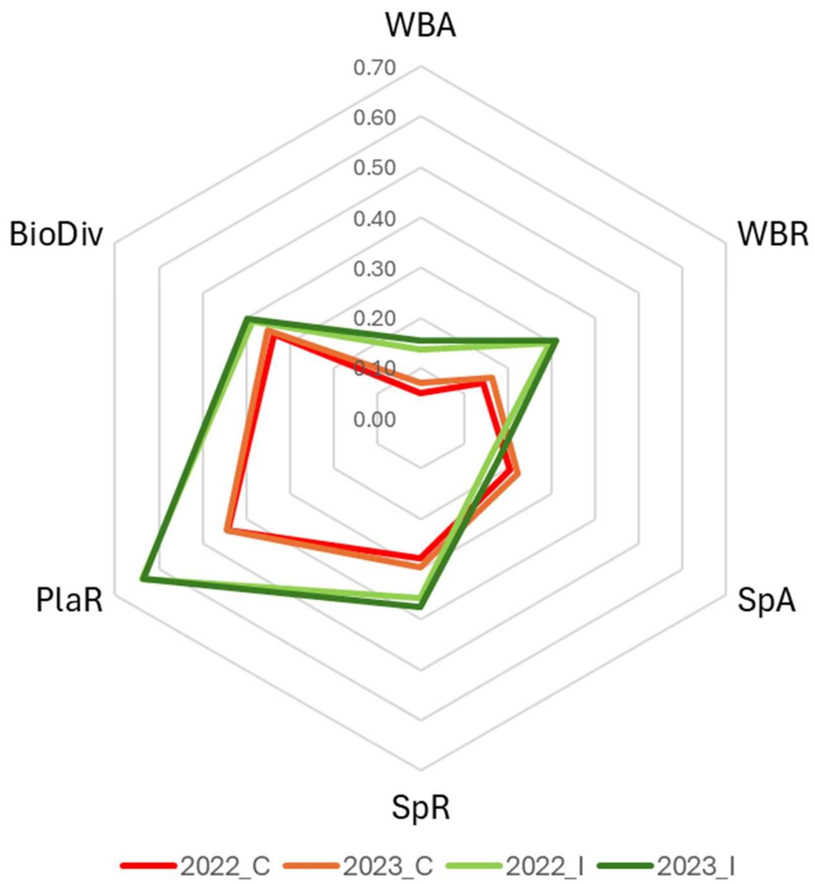

Figure 59: Radar graph of the estimates of the round-averaged indicators for the control and the intervention in the two years of observation.

4. Comparing mechanistic and data driven model results for pollinator occurrence in five EBAs

The mechanistic model of Lonsdorf et al. (2009) as implemented in Zulian et al. (2013) was applied in the five selected upscale CSAs encompassing the SHOWCASE EBAs to estimate pollinator abundance. The model provided as output a spatially explicit dimensionless score with values ranging from 0 to 1, describing the expected relative pollinator abundance to a given location across the landscape, i.e. the pollinator abundance for each pixel. This allowed the comparison with the WBA indicator inferred for the same CSAs via MLRs. Results are summarized in Table 58, where the model results are compared with the data driven approach results for the control scenarios. Descriptive statistics are also provided for the estimated WBA indicator means over the two rounds of the two years, and these figures for the five CSAs are compared with the mean scores and visually displayed in Figure 60.

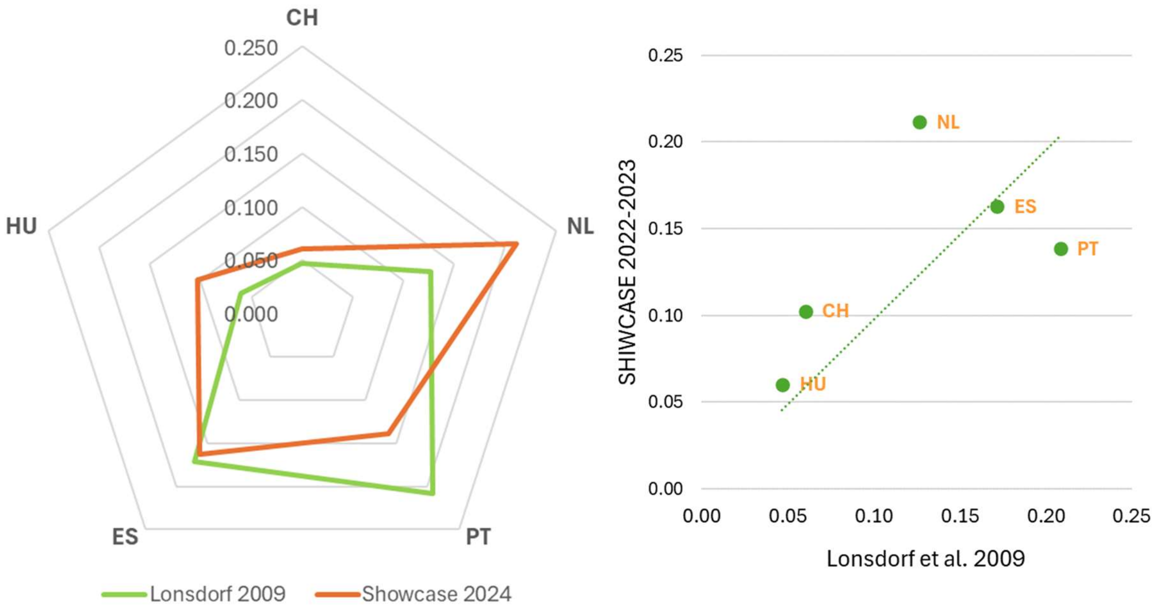

Figure 60: Radar graph and scatterplot comparing the WBA indicator estimates of the mechanistic model of Lonsdorf et al. (2009) with the data driven models calibrate for each EBAs.

In average terms, i.e. considering the mean value WBA indicators for the two rounds of the two years, the estimates over the whole area are almost equal for the Spanish CSA, with an average difference in the score values equal to 0.009 and a relative difference with respect to the mechanistic model score of 5.2%, i.e. a slight overestimation. In all the other CSAs the difference is greater, with a 33.6% overestimation in the Portuguese CSA and a 67.1% underestimation in the Dutch CSA. In the Hungarian, and to a less extent in the Swiss CSA, the mechanistic model again returns pollinator abundance scores smaller than the average ones estimated via the data driven approach under the control scenario.

Table 58: WBA indicator values and pollinator abundance estimated with the mechanistic model

EBA Country	Year	Round	Mean	Median	Std. Dev.	Min.	Max.	Mean Diff	Rel. Diff.
CH Solothurn									
Lonsdorf 2009			**0.047**	**0.047**	**0.125**	**0.005**	**0.829**		
	2022	1	0.050	0.000	0.075	0.000	1.000	-0.003	-6.1%
	2022	2	0.049	0.000	0.075	0.000	1.000	-0.002	-4.8%
	2023	1	0.091	0.000	0.157	0.000	1.000	-0.045	-95.8%
	2023	2	0.051	0.000	0.077	0.000	0.485	-0.004	-9.6%
Mean control			**0.060**	**0.000**	**0.096**	**0.000**	**0.871**	-0.014	-29.1%
NL Zuid Limburg									
Lonsdorf 2009			**0.127**	**0.153**	**0.104**	**0.005**	**0.787**		
	2022	1	0.156	0.151	0.058	0.000	0.668	-0.030	-23.3%
	2022	2	0.255	0.248	0.059	0.000	0.544	-0.208	-101.2%
	2023	1	0.167	0.160	0.057	0.000	0.652	-0.120	-31.8%
	2023	2	0.268	0.262	0.056	0.000	0.773	-0.222	-111.9%
Mean control			**0.211**	**0.206**	**0.058**	**0.000**	**0.659**	-0.165	-67.1%
PT Alentejo									
Lonsdorf 2009			**0.208**	**0.230**	**0.130**	**0.005**	**0.891**		
	2022	1	0.076	0.061	0.074	0.000	0.726	0.133	63.6%
	2022	2	0.016	0.000	0.036	0.000	0.468	0.192	92.1%
	2023	1	0.222	0.219	0.096	0.000	0.822	-0.014	-6.6%
	2023	2	0.239	0.227	0.131	0.000	1.000	-0.031	-14.8%
Mean control			**0.138**	**0.127**	**0.084**	**0.000**	**0.754**	0.070	33.6%
ES Guadalquivida									
Lonsdorf 2009			**0.172**	**0.237**	**0.118**	**0.005**	**0.899**		
	2022	1	0.089	0.084	0.072	0.000	1.000	0.082	47.9%
	2022	2	0.052	0.038	0.055	0.000	0.977	0.120	69.7%
	2023	1	0.291	0.294	0.080	0.000	1.000	-0.119	-69.4%
	2023	2	0.219	0.221	0.076	0.000	1.000	-0.047	-27.3%
Mean control			**0.163**	**0.159**	**0.071**	**0.000**	**0.994**	0.009	5.2%
HU Kiskunság									
Lonsdorf 2009			**0.060**	**0.010**	**0.156**	**0.005**	**0.822**		
	2022	1	0.079	0.053	0.086	0.000	0.891	-0.019	-30.7%
	2022	2	0.137	0.125	0.109	0.000	0.825	-0.076	-126.8%
	2023	1	0.068	0.034	0.079	0.000	0.683	-0.007	-12.1%
	2023	2	0.127	0.127	0.105	0.000	0.670	-0.067	-111.5%
Mean control			**0.103**	**0.085**	**0.095**	**0.000**	**0.767**	-0.042	-70.3%

As both models provide spatially explicit outputs, it is interesting not only considering the mean estimated values over the entire CSAs but also the difference in the spatial patterns of the estimated pollinator abundance. Figure 60 shows the estimated pollinator abundance with the two approaches; to highlight the differences in the spatial distributions the raster maps are displayed using a first legend with equal intervals and a second one based on the deciles of the estimated distribution. In addition, a map displaying the relative differences between the two results is provided, to highlights the occurrence of positive and negative differences with respect to the mechanistic model.

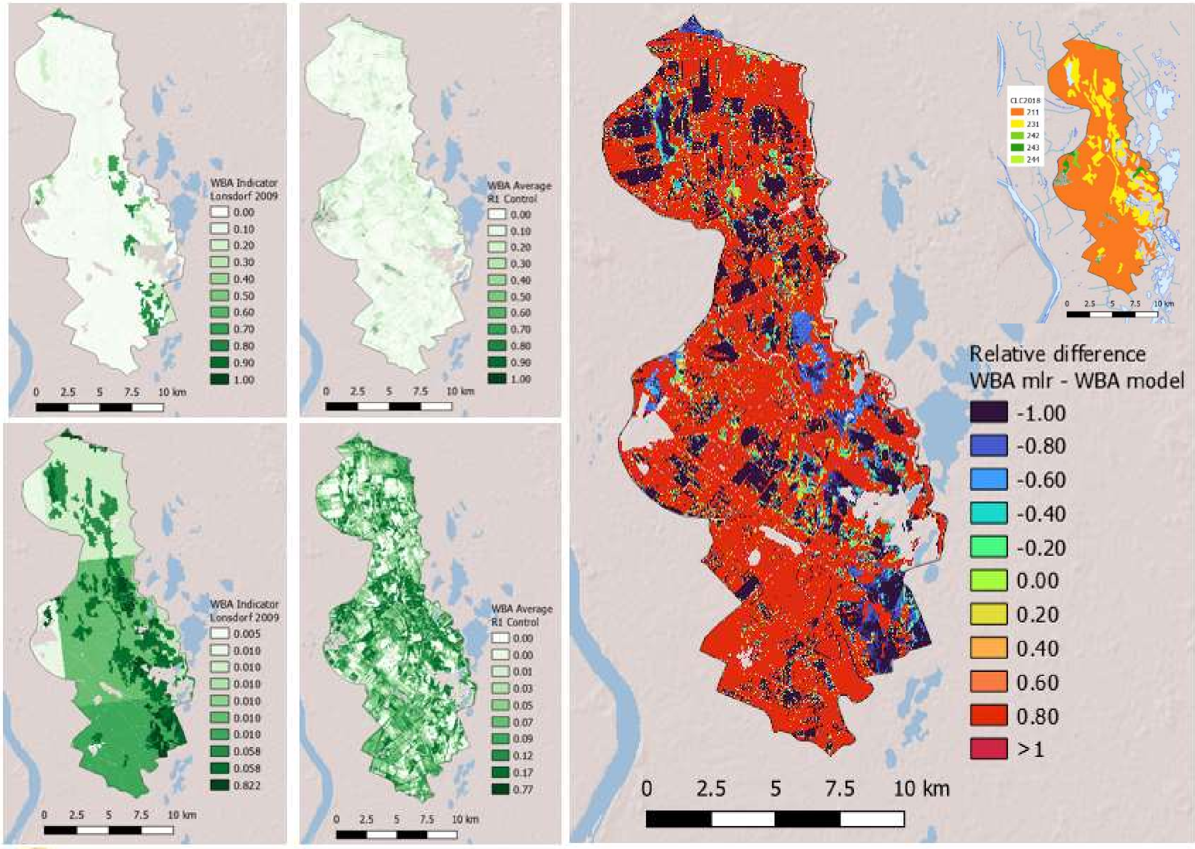

Figure 61: Comparison of estimated pollinator abundance in the Hungarian CSA: mechanistic model outputs (left), data driven output s(center) and relative differences with respect to the averaged outputs of the data driven model for the control scenario (right).

As can be seen in Figure 61, the relative differences were positive in most of the non-irrigated arable land use (81% of the area) with a systematic underestimation of pollinator abundance by the mechanistic model (average score 0.018) with respect to the data driven one (average score for the control scenario equal to 0.066). In the area under pasture (17.5% of the area) again the mechanistic model provided estimates which were significantly lower (average 0.068) than those estimated with the data driven model (average 0.104) and the same was observed for the area with complex cultivation patterns, representing ca. 0.6% of the area: here the mechanistic model returned an average score equal to 0.120, while the data driven estimates for the controls were equal to 0.163. Only for the land principally occupied by agriculture with significant areas of natural vegetation (ca. 0.9% of the total area), the mechanistic model provided higher pollinator abundance estimates, with an average score equal to 0.444 against the 0.144 provided by the data driven model. Results, and differences, are strongly determined by the scores that the model adopts for the different CLC classes to estimate nesting and flowering suitability for the pollinators. Furthermore, there was also an effect of the coarser resolution of the climate variables in determining pollinator activity, as it is evident from the raster map displaying the deciles of the estimated distribution of pollinator abundance with the mechanistic model (Figure 60, bottom left), with increasing values from north to south.

Figure 62 shows the relative differences between the two approaches for the target land use (i.e., permanent fruit orchards) for the Spanish CSAs; the figure displays the pollinator abundance map resulting from the two approaches.

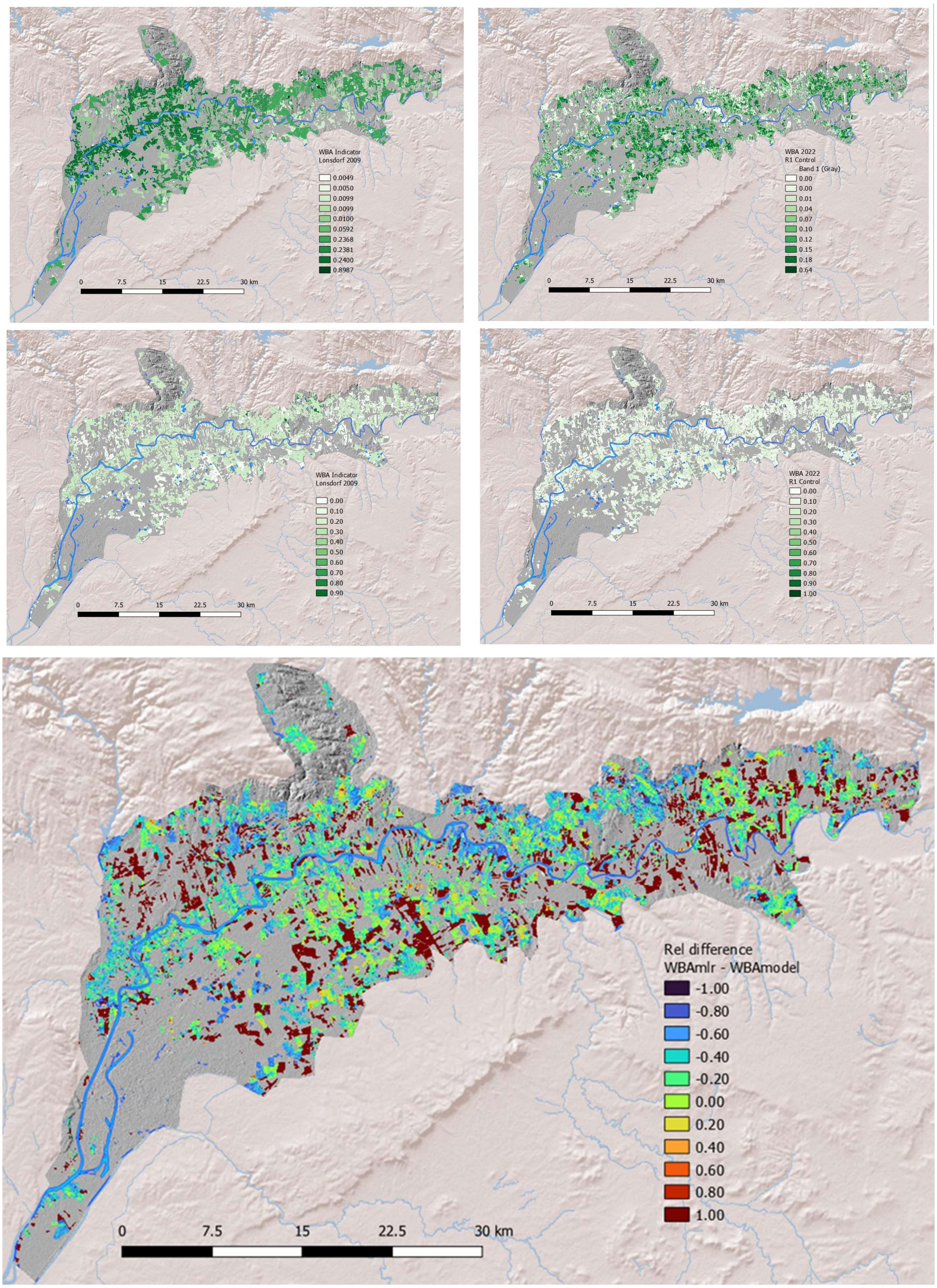

Figure 62: Comparison of estimated pollinator abundance in the Spanish CSA: mechanistic model outputs (top left), data driven outputs (top right) and relative differences with respect to the averaged outputs of the data driven model for the control scenario (bottom).

The mechanistic model returned overall higher values for the target area (0.172) when compared to the control MLR estimates for 2022 (0.089), but lower than that of 2023 (0.291).

When averaging all the control fields across all years and rounds (0.163), the two estimates were very similar, but the spatial patterns were quite different. According to the mechanistic model, higher pollinator abundance occurred north of the river stream, in the western part of the area, while according to the MLR predictions higher abundance was estimated south of the river in the central part of the CSA, where higher discrepancies between the predictions of the two models were observed.

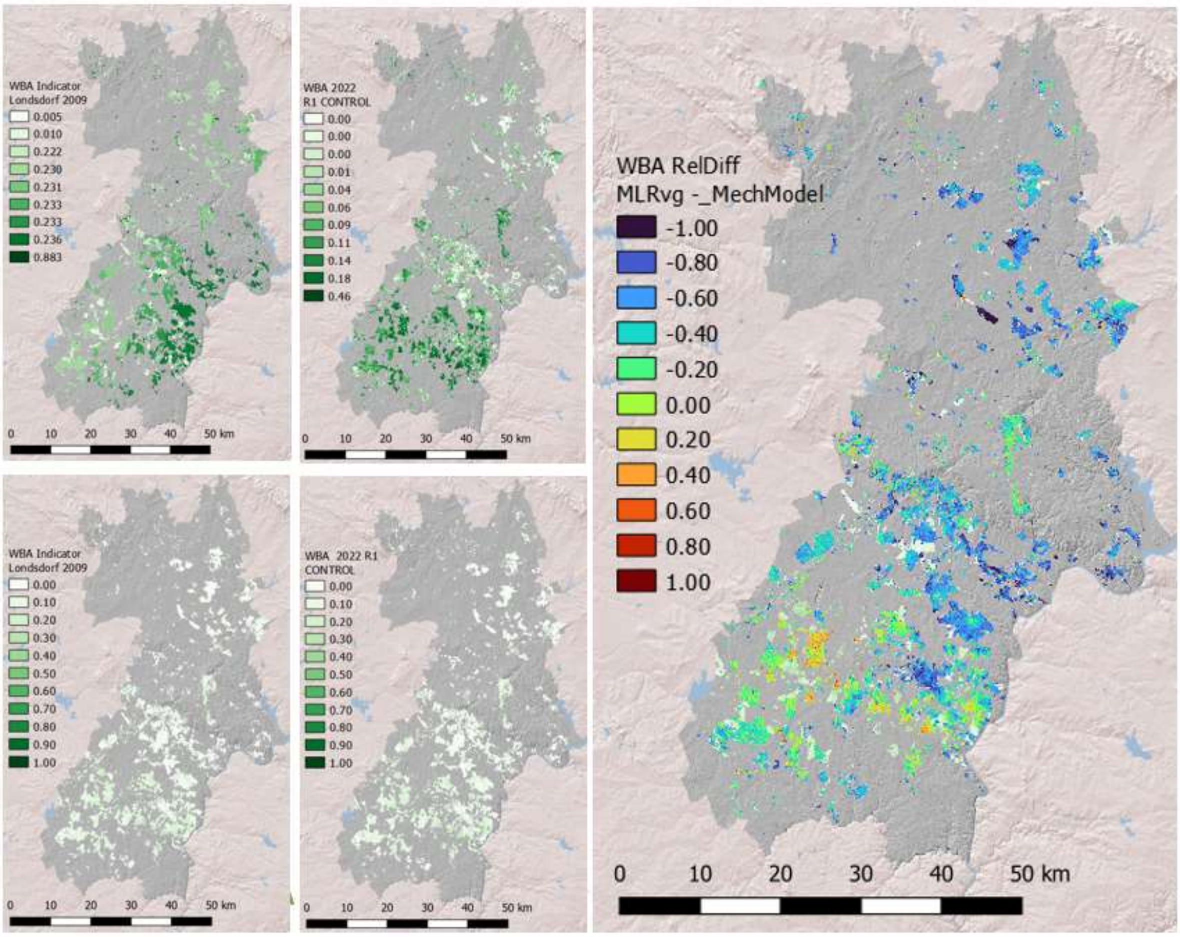

Figure 63: Comparison of estimated pollinator abundance in the Portuguese CSA: mechanistic model outputs (left), data driven outputs (center) and relative differences with respect to the averaged outputs of the data driven model for the control scenario (right).

In the Portuguese CSA, the mechanistic model provided higher estimates (0.208) with respect to the averaged outputs for the control scenarios predicted with the data driven approach (0.138). This is in great part due to the very low values estimated for the two rounds of 2022 (average 0.042) which were characterized by an extremely severe drought, the effects of which cannot be considered by the mechanistic model. This explanation could be supported by the fact that in 2023 average MLR estimates were very close to the predictions of the mechanistic model (0.231). Furthermore, from Figure 63 a north-south gradient in relative difference in model results appears very clearly, with the data driven model providing results well below those of the mechanistic approach in the north and in the center of the CSA, while positive differences are evident in the south-western part. Targeting only one land use class (i.e. permanent orchard) and considering that the CSAs spans over more than 100 km from north to south, it is likely that a key role is played by the climatic drivers used in the mechanistic model to consider the effect of weather on pollinator activity.

Results for the Dutch CSA are illustrated in Figure 64, which shows the output raster maps using a common legend with equal intervals and a legend with the deciles of the estimated distributions, and the relative differences between the two results.

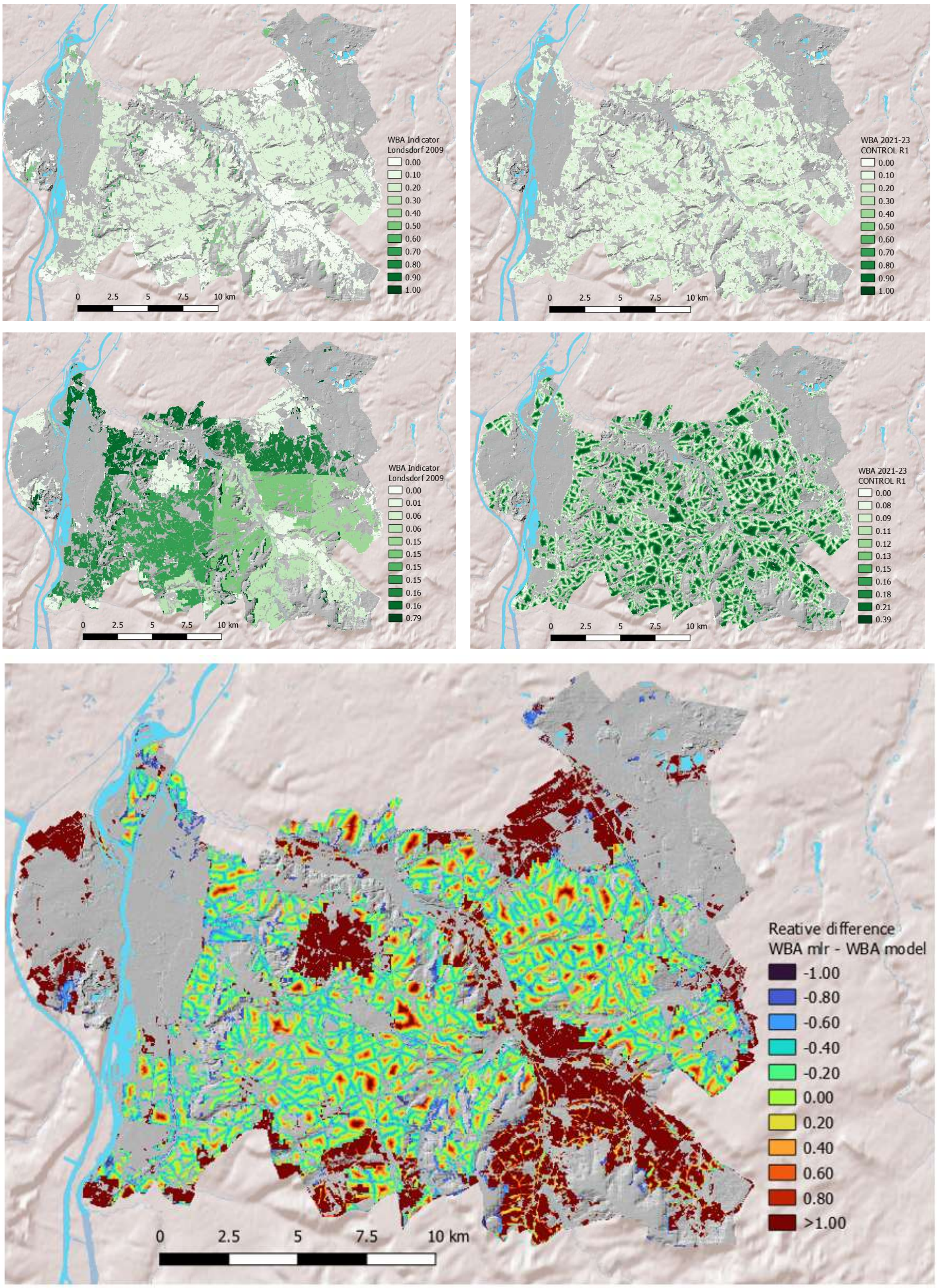

Figure 64: Comparison of estimated pollinator abundance in the Dutch CSA: mechanistic model outputs (top left), data driven outputs (top right) and relative differences with respect to the averaged outputs of the data driven model for the control scenario (bottom).

In this case results of the two approaches were similar when considering only the first rounds of data driven outputs for the control scenarios, which returned an average pollinator abundance equal to 0.16, which is close to the score of 0.13 provided by the mechanistic model. The spatial pattern of the relative differences between the two results displays two distinct features: large continuous areas where the MLR estimates were more than double those provided by the mechanistic model and smaller patches with a “bull’s eye” pattern particularly evident at the center of the large agricultural fields. The former pattern is likely to be due to the combined effects of average temperature and solar radiation, which the mechanistic model uses to account for the effect of weather on pollinator activity. The latter pattern is likely due to the MLR model which includes the distance from the road network as significant predictor of pollinator abundance, which in the case of the in-field intervention in the Dutch EBA fields, increases with increasing distance from the margin of the fields, being particularly evident in the case of large fields.

For the Swiss CSA, Table 58 shows that the results provided by the two models are similar in both rounds of 2022, being equal to 0.047 for the mechanistic model and 0.050 and 0.049 for the MLR model for the first and the second round, respectively. In 2023 the estimates of the data driven approach were higher for the first round (0.091), but again quite close to those of the mechanistic model in the second (0.051).

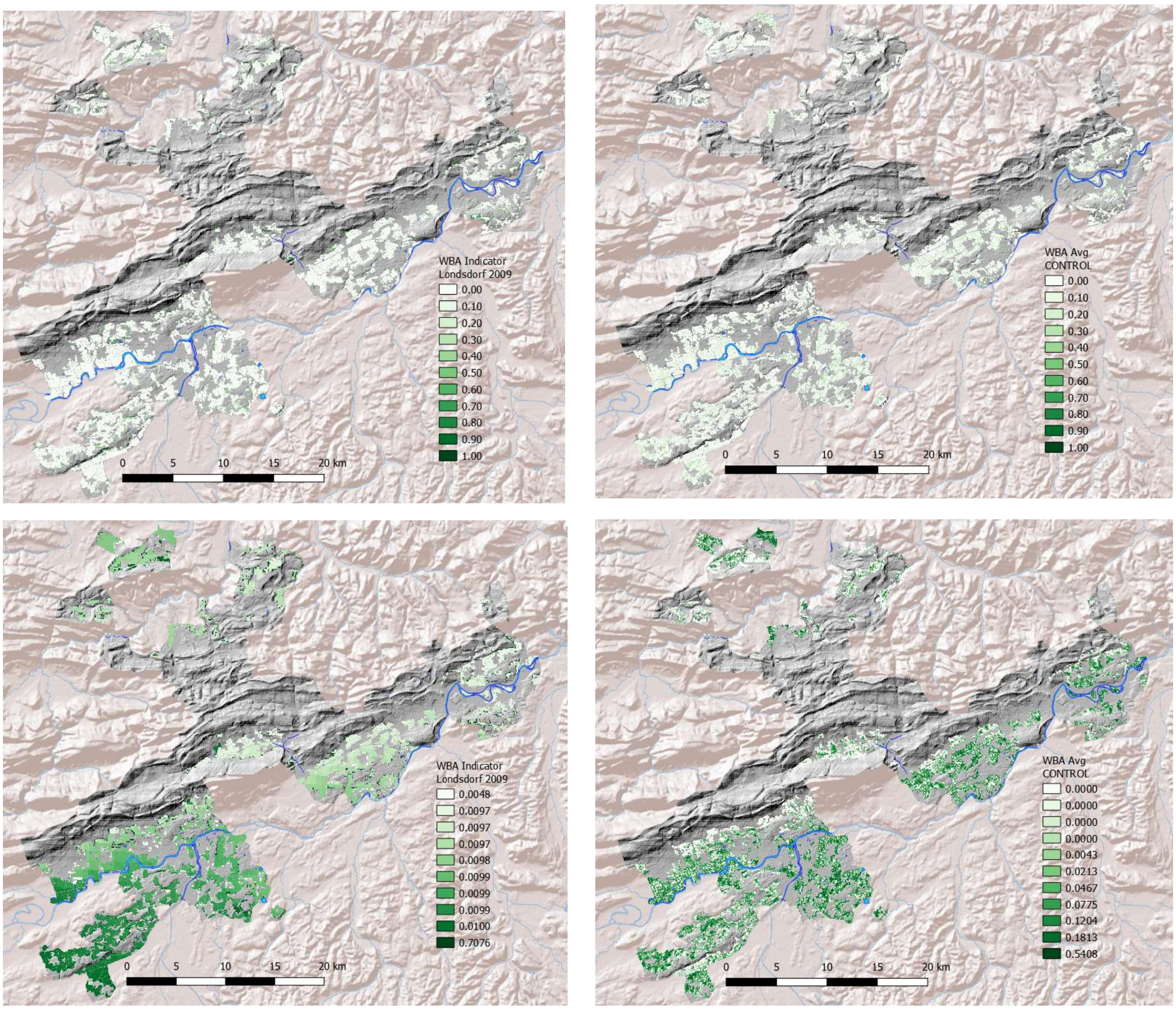

Figure 65: Comparison of estimated pollinator abundance in the Swiss CSA: mechanistic model outputs (left), data driven outputs (right).

In the maps shown in Figure 65 the differences between the two results appear to be difficult to detect using the same regular interval scale, being in both cases characterized by low occurrence values almost everywhere in the CSA. When using the deciles of the estimated abundance distribution, the differences in the spatial patterns were more evident, and in the case of the mechanistic model there was a dominant regional trend with decreasing values from the south-west to the north-east of the area, while in the case of the data driven approach the overall spatial trend was determined by the role played by elevation and terrain slope. Similar results have been found by Le Clec'h et al. (2019) who calibrated a data driven model to estimate pollinator abundance in the grasslands of the same CSA using MLR. The distribution of the relative differences between the data driven results and those of the mechanistic model with respect to the latter are shown in Figure 66.

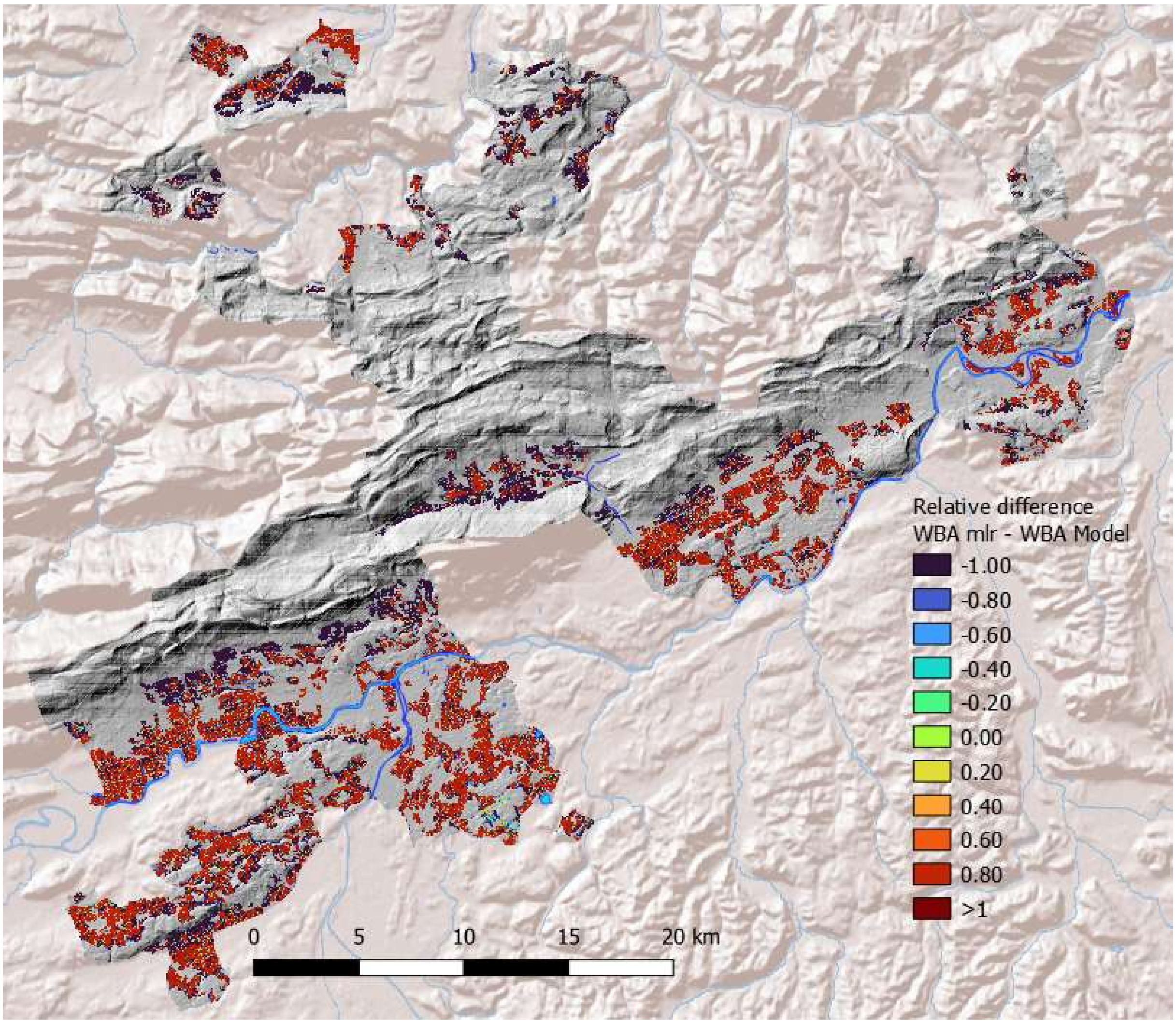

Figure 66: Comparison of estimated pollinator abundance in the Swiss CSA: relative differences between the data driven results and those of the mechanistic model with respect to the latter.

5. Discussion

The results presented in this Deliverable report provide an improved understanding of the potential impacts at the regional scale of the implementation of biodiversity management at the field scale. The MLR predictive models calibrated on field data delivered spatially explicit and time dynamic assessments of biodiversity indicators, highlighting the role played by the different drivers, and allowed for an assessment of the potential biodiversity gains resulting from the interventions in the specific context of each EBA.

5.1. Biodiversity indicators: comparing the five EBAs responses to biodiversity management

Using 0-1 interval normalised indicators allowed trends to be easily detected over time and space, the assessment of relative differences with respect to a baseline or a reference state, represented by the upscaling results for the control scenarios, and the comparison of results averaged over large areas among different CSAs. The following figures show the round averaged values and the relative differences of the indicators under the two biodiversity management scenarios in the five CSAs considered for the analysis. Average indicator values and their relative changes are summarized in Table 59.

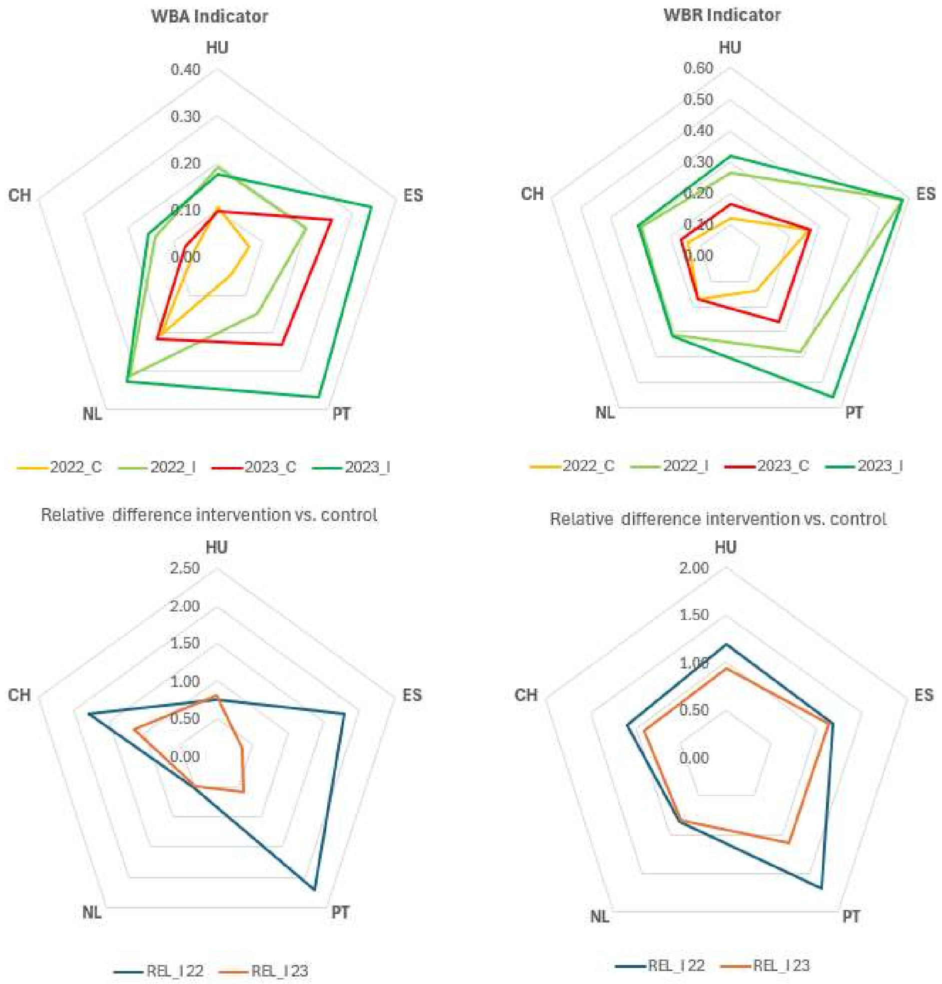

Figure 67: Average values in WBA and WBR indicators in the five EBAs in 2022 and 2023 and yearly relative differences (RI) due to the biodiversity management intervention

Table 59: Average biodiversity indicators in the five EBAs in 2022 and 2023 and relative differences due to the implementation of biodiversity management.

Indicator	Country	2022_C	2022_I	2023_C	2023_I	REL_I 2022	REL_I 2023
WBA	HU	0.11	0.19	0.10	0.18	76%	82%
	ES	0.07	0.20	0.25	0.34	180%	35%
	PT	0.05	0.15	0.23	0.37	221%	60%
	NL	0.21	0.31	0.22	0.33	53%	50%
	CH	0.05	0.14	0.07	0.15	179%	116%
WBR	HU	0.12	0.27	0.16	0.32	119%	95%
	ES	0.27	0.58	0.27	0.58	118%	114%
	PT	0.14	0.38	0.26	0.56	170%	112%
	NL	0.17	0.31	0.17	0.31	82%	81%
	CH	0.14	0.30	0.16	0.31	109%	90%
SpA	HU	0.10	0.10	0.15	0.14	-3%	-2%
	ES	0.19	0.17	0.11	0.12	-11%	7%
	PT	0.16	0.14	0.22	0.19	-12%	-14%
	NL	0.15	0.16	0.16	0.16	5%	5%
	CH	0.20	0.16	0.22	0.18	-22%	-20%
SpR	HU	0.35	0.31	0.21	0.17	-13%	-18%
	ES	0.23	0.25	0.22	0.24	6%	6%
	PT	0.28	0.30	0.25	0.26	5%	6%
	NL	0.33	0.41	0.33	0.41	25%	25%
	CH	0.28	0.36	0.30	0.37	29%	27%
PlaR	HU	0.22	0.42	0.20	0.41	93%	106%
	ES	0.32	0.41	0.55	0.65	29%	17%
	PT	0.54	0.63	0.77	0.86	17%	12%
	NL	0.55	0.59	0.54	0.58	8%	8%
	CH	0.44	0.64	0.44	0.64	44%	44%
BioDiv	HU	0.26	0.36	0.24	0.33	36%	37%
	ES	0.26	0.35	0.30	0.40	33%	35%
	PT	0.33	0.37	0.35	0.42	14%	20%
	NL	0.47	0.52	0.45	0.49	11%	10%
	CH	0.33	0.39	0.35	0.40	16%	14%

From the results in the table and trends shown in Figure 67, in the first year the highest relative increase in WBA mean indicator values were detected in the permanent orchards of Portugal and Spain, whose indicator values for the control baseline in 2022 are the lowest among the five EBAs. It is worth noting that the values for the intervention scenario in 2022 for these two CSAs were even lower than those for the control scenario in 2023. The figures were indeed quite similar in the Swiss CSA, with a very low WBA indicator value in the control of 2022 and a strong increase due to the intervention. In 2023, the relative increases estimated for the Portuguese and Spanish EBAs are much lower, as there was a general increase of the WBA indicator in both the control and intervention. The highest relative increase was observed in the Swiss EBA, for which the value of the WBA indicator for the control was only slightly higher than in the previous year. Relative changes in the Netherlands were constant in the two years, while in the Hungarian EBA there was an increase in 2023 with respect to 2022. For the WBR indicator, the relative increases were quite similar for the two years in all CSAs, with slightly higher values in 2022 in all cases. Again, higher relative increases were estimated for the permanent orchard of Andalucia and Alentejo, and lower ones for the in-field intervention in the arable fields of Zuid Limburg. The bee indicators are by far those most impacted by the implementation of the biodiversity friendly management.

The results for the two spider indicators in the five CSAs are shown in Figure 68. In the case of the SpA indicator, the changes due to the intervention were negative in almost all CSAs, with similar values in the two years, except for the increases in Guadalquivida in 2023, and in Zuid Limburg in 2022 and in 2023. The relative decreases were stronger in Solothurn.

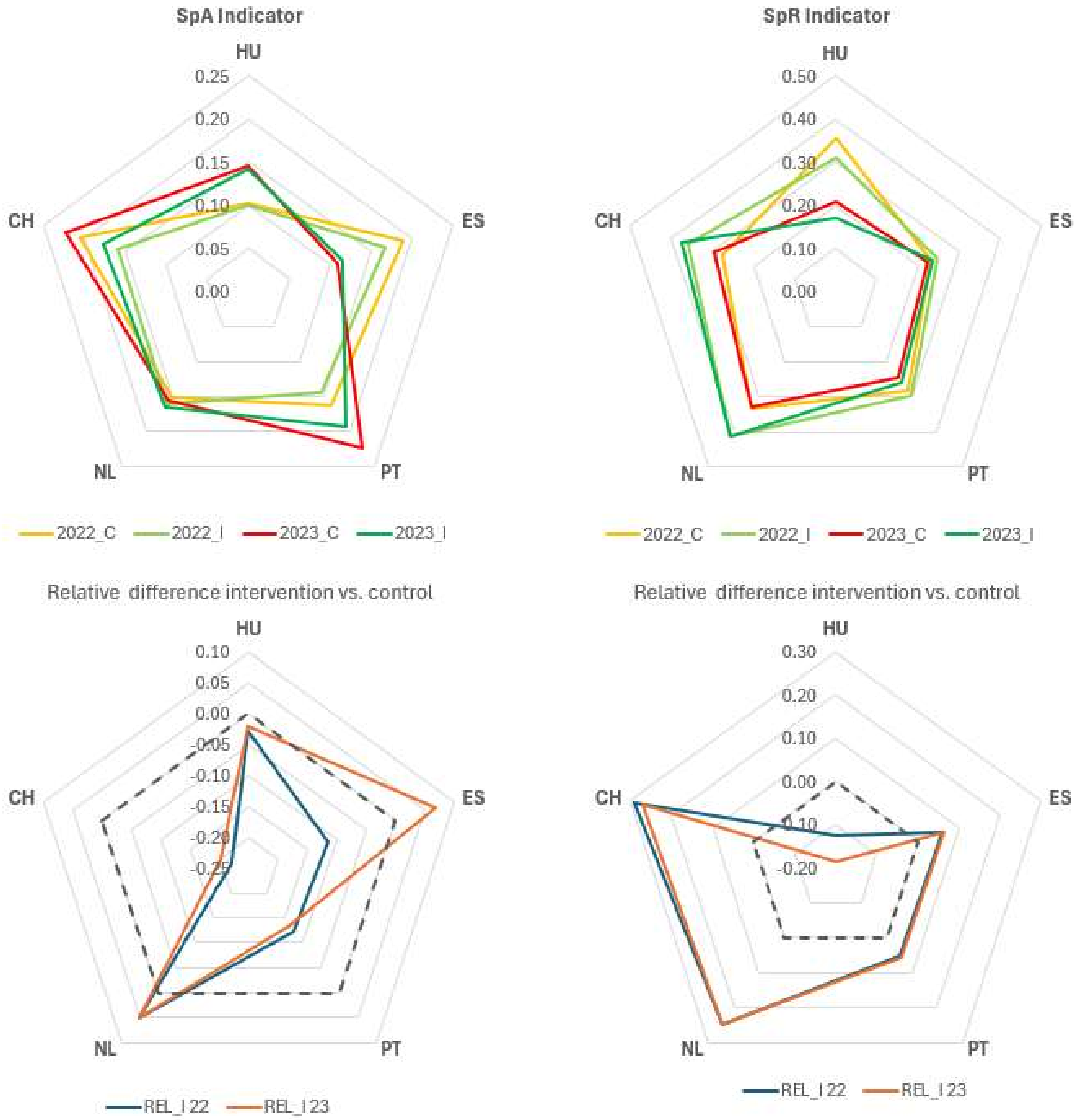

Figure 68: Average values in SpA and SpR indicators in the five EBAs in 2022 and 2023 and yearly relative differences (RI) due to the biodiversity management intervention

Differently from SpA, the relative changes in SpR due to the intervention were positive in all CSAs but Kiskunság, with very similar values in the two years. The highest relative increases were observed in the Swiss and in the Dutch CSAs.

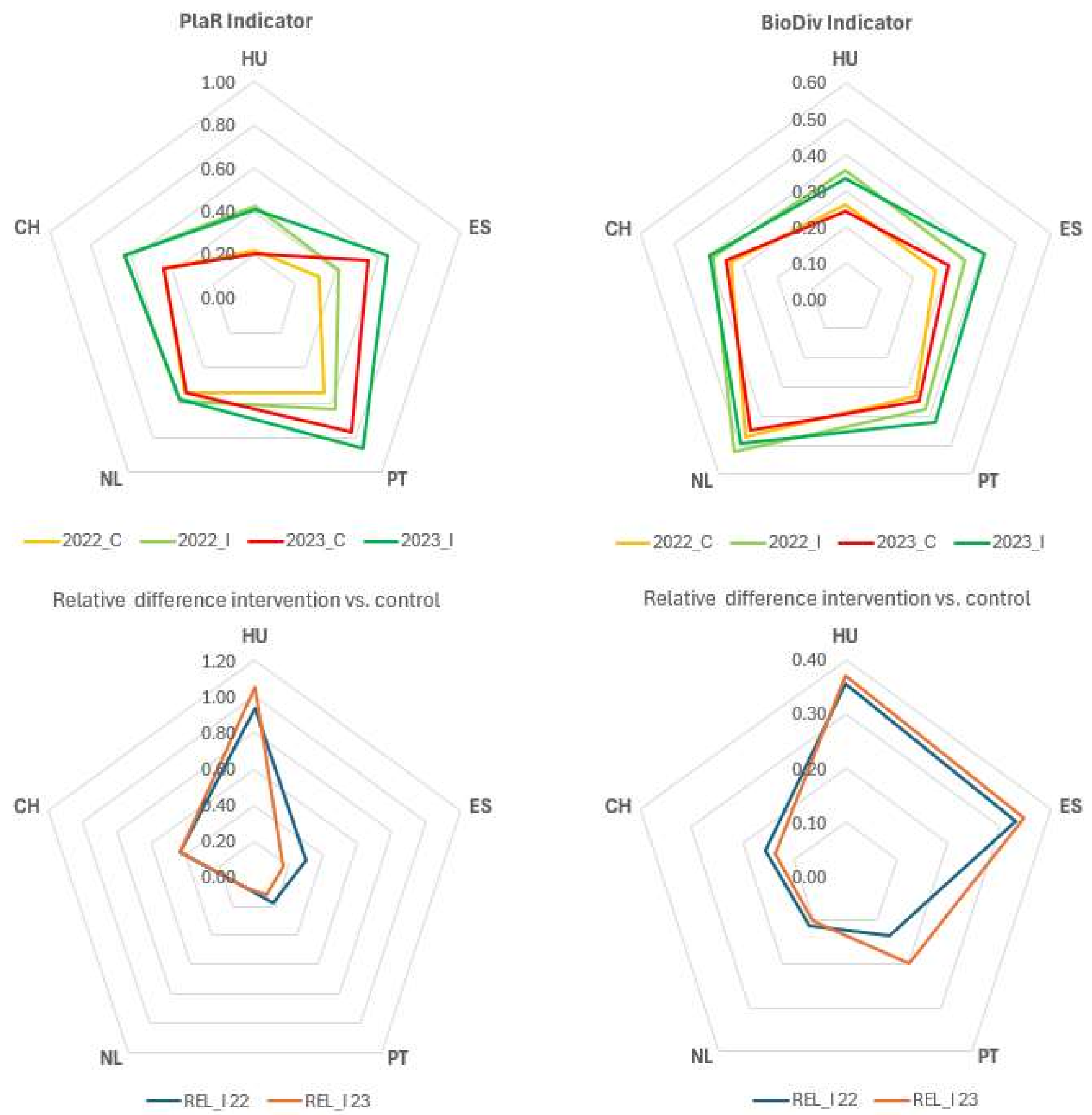

Figure 69: Average values in PlaR and BioDiv indicators in the five EBAs in 2022 and 2023 and yearly relative differences (RI) due to the biodiversity management intervention

The increase in vascular plant richness following the intervention is rather consistent in the two years; the highest increase was estimated for the Hungarian CSA and the lowest for the Dutch one (Figure 69). In the permanent orchards of the Portuguese and Spanish CSAs the values of the indicator for the control scenario in 2023 had average values higher than the intervention values in 2022, similarly to what was observed for the WBA indicator in the two sites.

The composite indicator BioDiv provides a synthesis of the overall effect of the intervention on all the considered biodiversity indicators, expressing the overall gain in biodiversity deriving from the adoption of management practices which promote farmland biodiversity. This was higher in areas with lower indicator scores for the control scenarios such as Kiskunság in Hungary and Guadalquivida in Spain with relative increase between 33 and 37%, while it was lower where the control indicators have high scores, as in Zuid Limburg characterized by a relative increase of ca. 10% in both years. This could be due to the farms in the Dutch EBA being organic and the ones in the Spanish EBA being extremely intensive

A synthetic representation of the overall biodiversity status in each CSA is shown by the stacked columns chart depicted in Figure 70, where each bar presents the contribution of each indicator to the overall biodiversity status in the two years of observations in the five EBAs under the two scenarios (i.e., control and intervention).

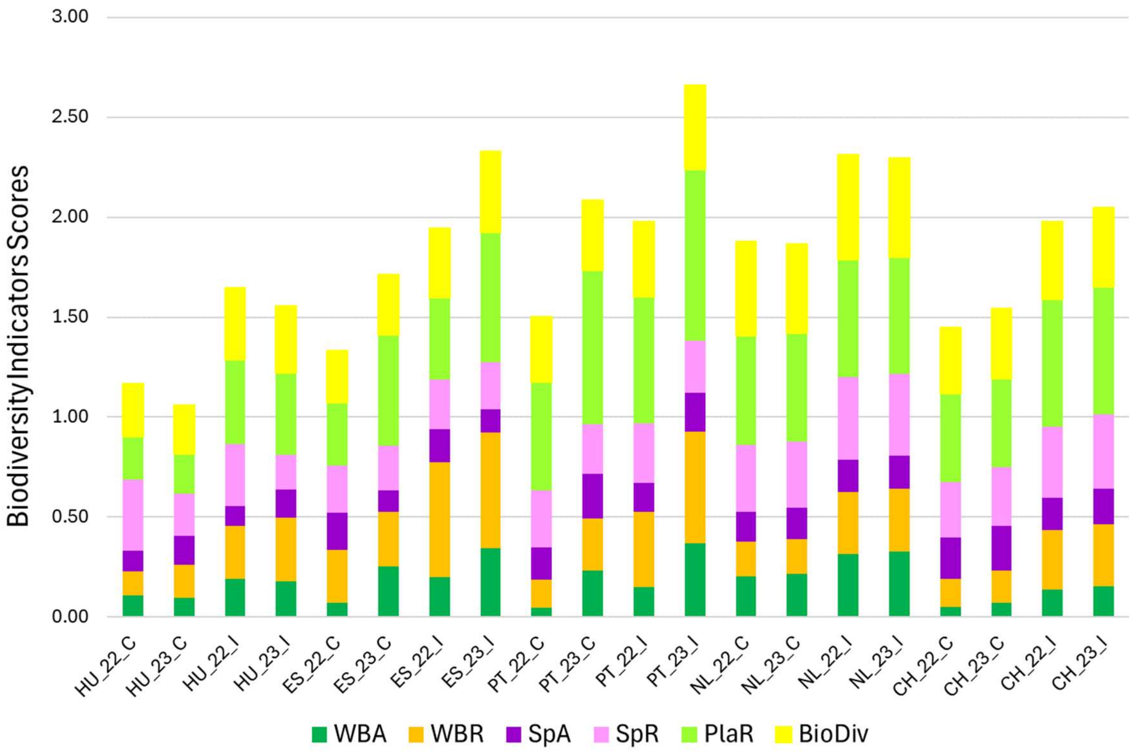

Figure 70: Overall biodiversity status in each CSA as contributed by the six biodiversity indicators under the two management scenarios (control and intervention) in 2022 and 2023

5.2. Biodiversity indicators: comparing data driven predictive models

The identification of the best approach to model the spatiotemporal variability of the biodiversity indicators based on EBAs data was based on the comparison of error and agreement indices for the predictions of a machine learning approach and of a more classical regression-based approach. As discussed in the second chapter of the report, RF and stepwise MLR were tested in all CSAs and on all indicators, and MLR systematically outperformed RF in terms of reduced calibration errors and increased agreement between observed and predicted values. Although there is a vast amount of literature reporting the superiority of machine learning algorithms and in particular RF over MLR, there are several cases that report the opposite. There are indeed specific scenarios where RF underperforms compared to MLR:

1. Limited Data Availability: in scenarios where there is limited data availability, MLR may outperform RF due to its ability to handle small datasets effectively (Adewale et al., 2024; Maia et al., 2021). When the number of features is extremely large compared to the number of

samples and the percentage of truly informative features is very small, the performance of traditional RF declines significantly (Gosh and Cabrera, 2022).

2. Linear Relationships: when the relationships between predictors and the target variable are predominantly linear, MLR may outperform RF, as it is well suited for capturing linear relationships (Zanella et al., 2017; Jenkins et al., 2018).

3. Interpretability: in cases where interpretability is crucial, MLR may be preferred over RF, as it provides easily interpretable coefficients for each predictor (Borup et al., 2023).

4. Overfitting Concerns: RF may underperform when there are concerns about overfitting, especially if the model is not validated on holdout data to ensure it is not over-fitted to the learning set (Adewale et al., 2024).

5. Bounded Outcome Variables: for bounded outcome variables restricted to the unit interval, classical modeling approaches based on mean squared error loss, such as RF, may suffer due to not accounting for heteroscedasticity in the data (Maia et al., 2021).

Data availability, strong linear relationships, and bounded outcome variables are all factors that might have played a role in the poor predictive performance of RF when applied to the SHOWCASE EBAs data. As for point 3, interpretability is indeed a desirable outcome provided by MLR as it might provide some insights useful to disentangle the complex relationships between anthropic pressures, landscape attributes, habitat features and biodiversity.

5.3. Biodiversity indicators: assessing the impact of drivers

The **impact of environmental and anthropic drivers** differed in the five EBAs considered in this report, but the identification of a subset of predictors resulting in the best performing models allows the assessment of which are variables are the most frequently chosen in the twenty MLR models that were calibrated.

The predictors describing **landscape features**, i.e. the distance from the road network and from small woody features, were selected in 70 and 60% of the MLR models, respectively, being statistically significant in 86 and 42% of the cases, respectively, where they were used as predictors. In all cases, pollinators and plant indicators increased closer to SWF and along field margins, and in particular wild bees' and plants' species richness declined with distance from field margins, confirming that diverse and structured agricultural landscapes with small cultivation units would favour farmland biodiversity. Based on the value of the standardised regression coefficients, though, the explanatory power of these predictors on average accounted for 4 to 13% of the observed variability, with a minimum in the case of the spider indicators (ca. 2%) and a maximum for plant species richness indicator (30%).

The effects of **terrain attributes** as drivers of biodiversity indicators were strongly linked to the geomorphological settings of each CSA. Among the terrain attributes, aspect, catchment slope and topographic wetness index were all considered in 40% of the regression models, being statistically significant in 88, 63, and 50% of the models, respectively, where they are used as predictors. As for aspects, significant responses of different signs were observed for pollinators in the Spanish and Portuguese EBAs as compared to the Swiss one: lower values for pollinators abundance in the SE-S-SW facing slopes in Guadalquivida and Alentejo, and higher values of both abundance and species richness in the SE-S-SW facing slopes in Solothurn. Such contrasting responses are likely to be due to the very different climatic conditions which characterised the two years of observations, with a strong and prolonged drought in the Iberian Peninsula. The topographic wetness index was significantly and positively correlated with the three species' richness indicators, while catchment slope had a different impact on the different indicators: positive on pollinators' and plants' ones, and negative on spiders' ones. Considering the value of the standardised regression coefficients, the explanatory power of the above mentioned three terrain attributes on average accounted for a share of the observed variability between 4 and 29% , with an average of 10% for aspect and TWI and 14% for catchment slope.

Among the **remote sensing indices** derived from Sentinel-2 data via GEE, 65% of the models included the soil index **SOSI2** (Douaoui and Lepinard, 2010, Yahiaoui et al., 2015) as predictor, 55% selected the reflectance in the **IRn band** (Sentinel-2 B8) and 50% the vegetation index **NDVI** (Rouse et al., 1974), highlighting the role played by bare soil conditions, soil moisture and vegetation cover status on the selected biodiversity indicators. Furthermore, ten additional indices among those listed in Table 2 were selected as predictors by the stepwise procedure. This confirms, as already observed by Torresani et al. (2023) in SHOWCASE D1.4, the relevance of vegetation and soil indices from Sentinel-2 data in describing the conditions that shape pollinator and predator communities at the regional scale. Additional value of RSI as predictors lies in their availability along the time continuum, which provides time variant predictors that can successfully catch and predict seasonal and yearly changes in the status of soil and vegetation affecting biodiversity and ecological processes. The results presented in this report refer to the two sampling seasons of 2022 and 2023, using RSI for the same seasons and years as predictors, but it would be possible to apply the models to back-cast and forecast in different seasons and years even in absence of additional ground data. Additionally, it would be possible to include additional data from new field surveys in the EBAs to the current datasets to improve the existing models.

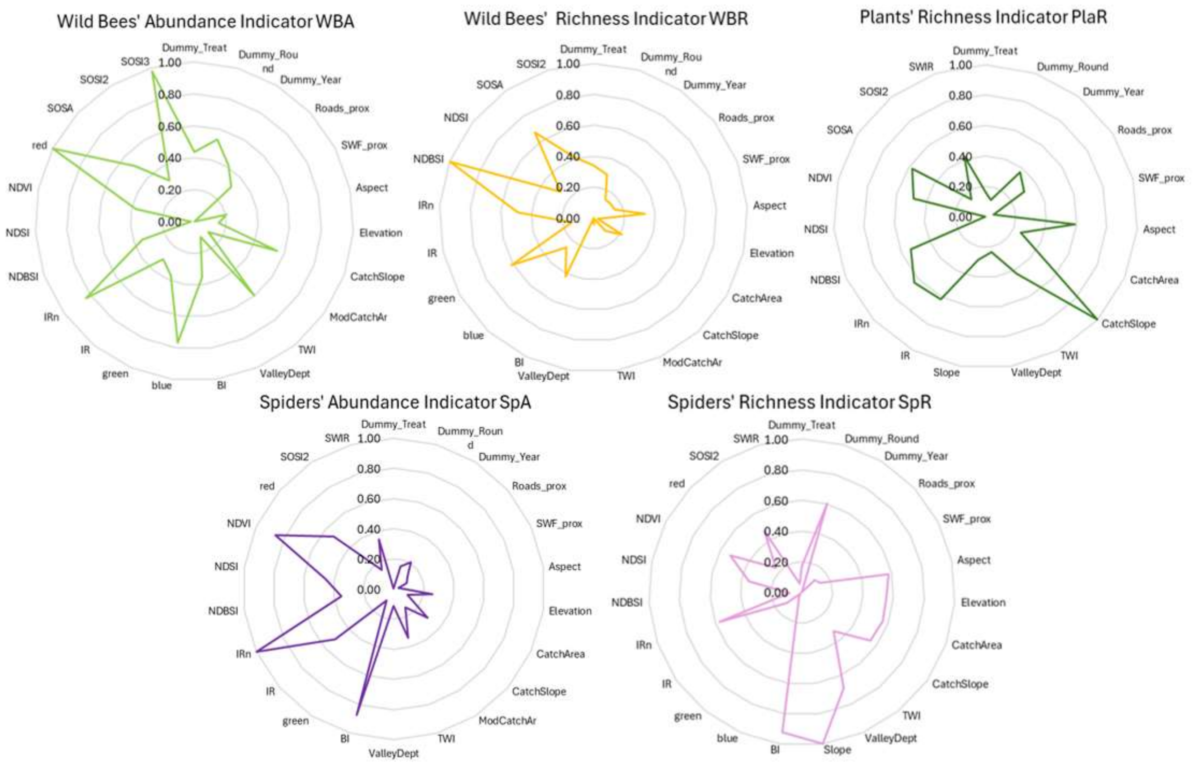

Figure 71: Average values of the standardized MLR correlation coefficients normalized scores (0-1) for the biodiversity indicators predictors for the five EBAs in 2022 and 2023.

To visualize the relevance of the different drivers, Figure 71 depicts the average values of the standardized MLR correlation coefficients normalized scores for the biodiversity indicators predictors over the five EBAs in 2022 and 2023. On a normalized 0 to 1 scale, considering all the five biodiversity indicators and the occurrence of each predictor in all the MLR models calibrated for the five EBAs, the average scores for the four groups of biodiversity drivers (cf. Table 2) would be equal to **0.26** for the biodiversity management, **0.15** for the landscape features, **0.31** for the terrain attributes and **0.40** for the remote sensing indicators (soil and vegetation health and moisture conditions). Seasonal and interannual variability scored **0.44** and **0.27**, respectively. A synthetic representation of the overall contribution of each predictor to each biodiversity indicators in the five EBAs is shown by the stacked columns chart depicted in Figure 72, where each bar presents the contribution of each predictor to the estimation of each single indicator in all EBAs in the two years of observations.

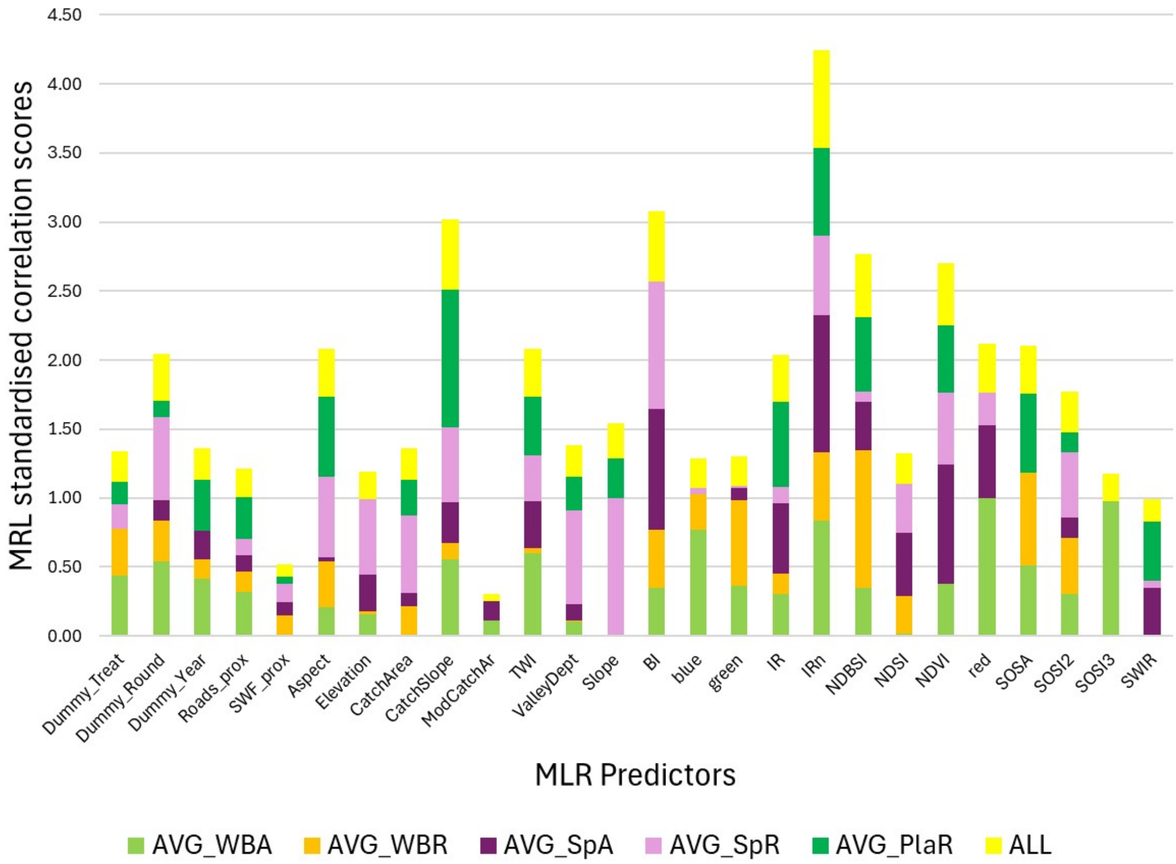

Figure 72: Overall average contributions in all EBAs of MLR predictors to each biodiversity indicator expressed in terms of MLR standardized correlations scores.

When considering separately the different biodiversity indicators surveyed in the five EBAs, the relevance of the different groups of predictors highlights very clearly that the impacts of the considered drivers changes noticeably, as can be seen in figure 73 which illustrates such differences in terms of normalised scores of the standardised MLR coefficients for bees, spiders and vascular plants indicators.

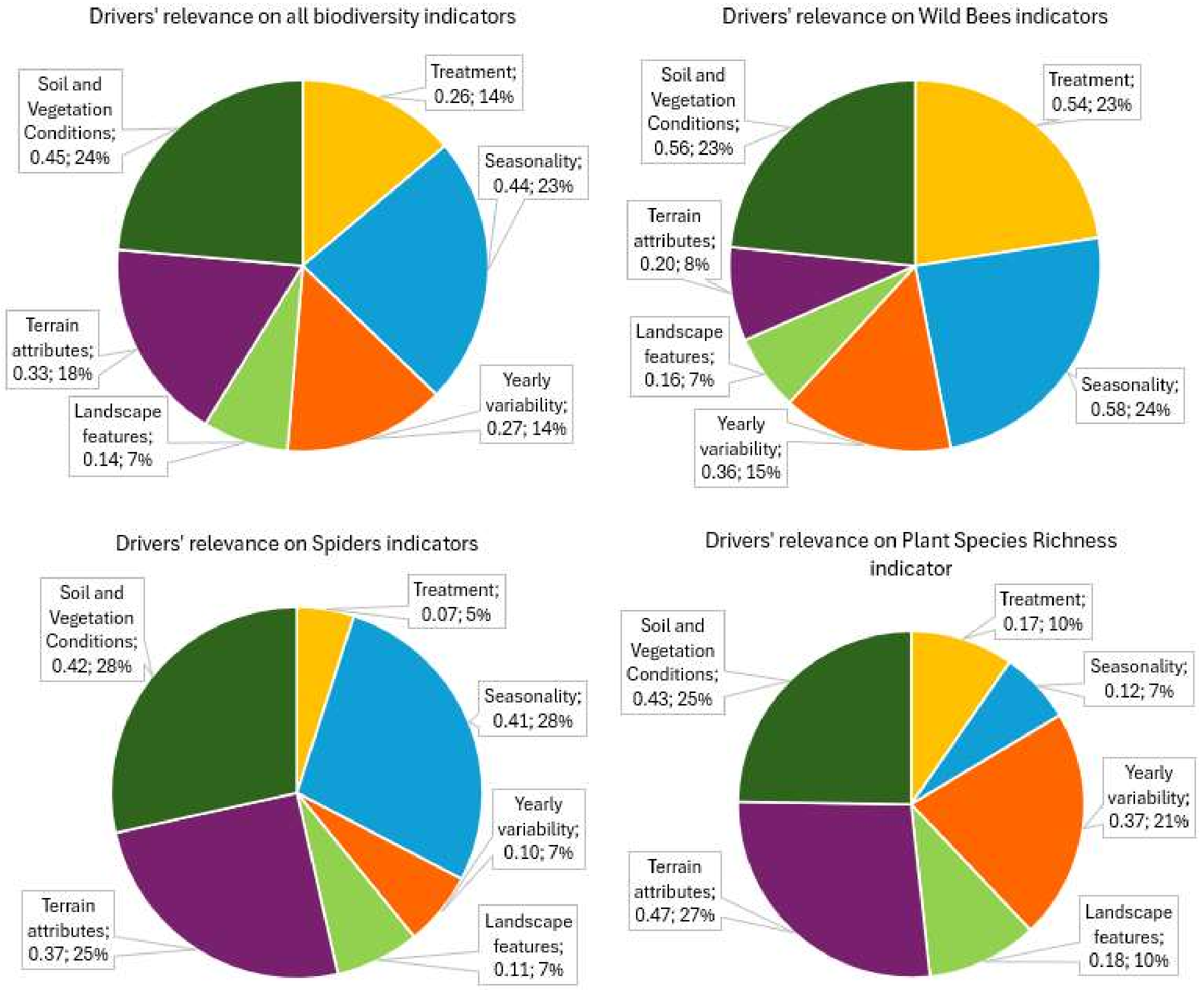

Figure 73. Pie charts showing EBAs averaged contribution of MLR predictors to wild bees (top right), spiders (bottom left) and vascular plants (bottom right) indicators expressed in terms of MLR standardized correlations scores. The overall scores are also shows (top right)

The highest overall score is observed for Soil and Vegetation Conditions (0.45) as assessed by the RSIs, indicating that these factors strongly influence all three biodiversity groups collectively. On the other side, the lowest overall score is associated to Landscape Features (0.14), suggesting that this factor has the minor influence across the three groups in the five EBAs. The bees indicators exhibit the strongest impact due to seasonality (0.58) and to Soil and Vegetation Conditions (0.56), indicating that these factors are particularly important for bee biodiversity. The lowest score for bees is with Landscape Features (0.16), suggesting that distance from roads and green infrastructures have a minor impact on bee populations. Spiders' indicators showed the strongest impact due to Seasonality (0.41) and Soil and Vegetation Conditions (0.42), similarly to bees, but the score values are slightly lower. The weakest impact on spiders indicators is that of biodiversity management treatment (0.07), which is notably low, indicating that flower strips have almost no influence on spider biodiversity indicator. Vascular plants showed the strongest scores for Terrain Attributes (0.47) and Soil and Vegetation Conditions (0.43), suggesting that these factors are critical for plant species richness. The lowest score for plants is for Seasonality (0.12), indicating that seasonal variability had little impact on plant biodiversity, as contrasted by yearly variation that resulted to play a much significant role. Soil and Vegetation Conditions consistently showed high scores across all groups (bees: 0.56, spiders: 0.42, plants: 0.43), making them the most influential factors for biodiversity overall. Seasonality is highly important for bees (0.58) and moderately important for spiders (0.41), but it has little effect on plants species diversity (0.12). Biodiversity management interventions are most relevant for bees (0.54) but have almost no impact on spiders (0.07) and only a moderate effect on vascular plants species richness (0.17). Terrain Attributes are particularly important for vascular plants diversity (0.47) and spiders (0.37), but less so for bees (0.20). Landscape Features have the lowest influence across all groups, with the highest correlation being only 0.18 (vascular plants species richness).

5.4. Biodiversity indicators: comparing modelling approaches for pollinators

The comparison between the predictions of the data driven model and those resulting from the application of the parametric model of Lonsdorf et al. (2009), as implemented in Zulian et al. (2013), has highlighted the role played by the several assumptions underlying the model. The parametric models offer spatially explicit predictions, but the resulting patterns depend on the thematic and spatial resolution of the drivers considered, in this case the land use/land cover class (thematic and spatial resolution) and the climatic data (spatial resolution). Both can be improved in terms of resolution, and finer-scale input raster can be used as in Häussler et al. (2017), but still they would only provide an average static assessment over the land use classes of a given site and for the reference time frame defined by the climatic variables. In their recent review on pollination supply models, A. Giménez-García et al. (2023) have proposed possible alternatives to overcome such limitations depending on local data and expert knowledge availability, which would allow the creation of locally specific tables to apply to the framework of the Lonsdorf modelling approach. If this is not possible, mechanistic models are better tailored to provide useful information over large regions rather than at local scales (Image et al., 2022). The outcomes of the two approaches can be compared, as shown in this report, in terms of average scores and value patterns and trends over a given area but comparing their performances in statistical terms is not feasible as the MLR models are expressions of the calibration data used to train them, and therefore the estimated values necessarily better replicate the observed ones when compared with the mechanistic model.

5.5. Biodiversity indicators as proxies for ecosystem services provision

Using the five biodiversity indicators as proxies for ecosystem services in the five EBAs, two regulating and one supporting service were assessed accordingly, namely pollination, pest control and habitat provision. Pollination and pest control regulating services were derived from the combination of the abundance and species richness indicators for wild bees and spiders respectively, resulting in additional 80 spatiotemporal mapping outputs. Habitat provision for biodiversity on the other side relied on vascular plants species richness as a proxy; in doing so no new spatiotemporal maps were estimated as these are coincident with those of the single indicator produced for the two rounds of the two years of observations in each EBA. The spatiotemporal maps of the pollination and pest control ecosystem services are presented in Appendix A along with the raster statistics for each CSA. The spatially averaged ecosystem services indicators values, as derived from postprocessing the raster maps, and their relative changes are summarized in Table 60 for the two rounds of sampling in the two years of EBAs survey; the box and whiskers plot in Figure 74 shows the average ecosystem services scores by case study area and treatment.

Table 60: Average ecosystem services indicators in the five EBAs in the two sampling rounds of 2022 and 2023 and relative differences due to the implementation of biodiversity management.

Ecosystem Service	Country	Round	2022_C	2022_I	2023_C	2023_I	REL_I 2022	REL_I 2023
Pollination	**HU**	**1**	0.128	0.241	0.136	0.261	88.2%	92.0%
	HU	**2**	0.231	0.350	0.281	0.392	51.7%	39.5%
	ES	**1**	0.304	0.533	0.388	0.594	75.0%	53.0%
	ES	**2**	0.107	0.345	0.180	0.396	221.4%	119.3%
	PT	**1**	0.232	0.481	0.264	0.501	107.1%	89.4%
	PT	**2**	0.029	0.191	0.288	0.498	554.9%	73.1%
	NL	**1**	0.141	0.373	0.232	0.403	163.6%	73.7%
	NL	**2**	0.406	0.451	0.402	0.444	10.9%	10.5%
	CH	**1**	0.117	0.246	0.153	0.261	109.5%	70.6%
	CH	**2**	0.112	0.229	0.141	0.274	104.2%	94.0%
Pest Control	**HU**	**1**	0.214	0.176	0.155	0.130	-17.8%	-15.9%
	HU	**2**	0.548	0.521	0.407	0.377	-5.0%	-7.3%
	ES	**1**	0.253	0.249	0.316	0.319	-1.7%	1.0%
	ES	**2**	0.168	0.165	0.173	0.183	-1.8%	5.8%
	PT	**1**	0.283	0.279	0.317	0.313	-1.4%	-1.1%
	PT	**2**	0.172	0.172	0.192	0.190	0.4%	-1.5%
	NL	**1**	0.267	0.312	0.246	0.288	17.0%	17.2%
	NL	**2**	0.383	0.415	0.391	0.424	8.4%	8.4%
	CH	**1**	0.255	0.276	0.280	0.300	8.2%	7.1%
	CH	**2**	0.260	0.281	0.273	0.295	7.9%	7.9%
Habitat provision	**HU**	**1**	0.164	0.359	0.155	0.363	119.0%	133.6%
	HU	**2**	0.270	0.481	0.245	0.460	77.8%	88.0%
	ES	**1**	0.300	0.393	0.546	0.639	31.0%	17.0%
	ES	**2**	0.333	0.426	0.562	0.655	28.0%	16.6%
	PT	**1**	0.540	0.633	0.763	0.853	17.2%	11.8%
	PT	**2**	0.544	0.637	0.775	0.863	17.1%	11.4%
	NL	**1**	0.538	0.580	0.553	0.595	7.8%	7.6%
	NL	**2**	0.555	0.598	0.529	0.572	7.7%	8.1%
	CH	**1**	0.330	0.528	0.323	0.520	60.0%	61.0%
	CH	**2**	0.555	0.746	0.564	0.753	34.4%	33.5%

Generally intervention maps show higher average scores for Pollination (+110% on average) and Habitat (+41% on average) compared to control across all countries and years. This would suggest that the interventions have the potential to effectively enhance these ecosystem services at landscape scale. Pest Control scores, though, show less consistent improvement (less than 2% on average) with interventions and, in some cases, the control scenario perform similarly, as in the Spanish and Portuguese CSAs, or slightly better, as in the Hungarian CSA.

In terms of yearly variability, in both scenarios indicator scores for Pollination and Habitat generally increase from 2022 to 2023 in 90% and 75% of the cases respectively, suggesting a possible cumulative positive effect of the interventions over time and/or more favourable climatic conditions. Increases in Pest Control are observed in the Portuguese, Spanish and Swiss CSAs, where for both scenarios average indicator scores were higher in 2023 with respect to 2022.

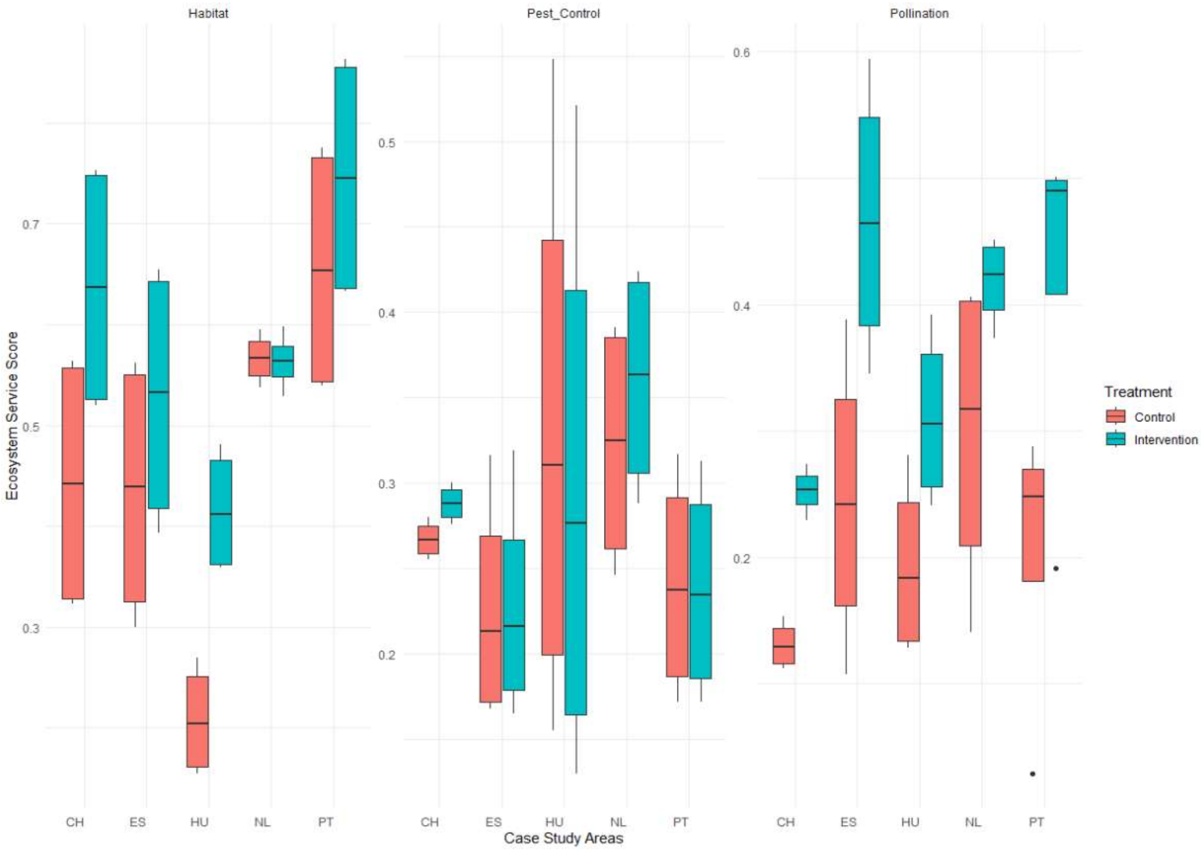

Figure 74. Average ecosystem services scores by CSA and treatment.

As for seasonality, in the Dutch and Hungarian CSAs there is a general increase from round 1 to round 2 for all indicators, while in the Portugues and Spanish ones Pollination and Pest Control decrease significantly from round 1 to round 2, while Habitat provision increases. Similarly in the Swiss CSA Habitat provision increased significantly from round 1 to round 2.

The round averaged indicator scores of the three ecosystem services and the relative differences of the indicator scores under the two biodiversity management scenarios in the five CSAs considered for the analysis are summarized in Figure 75.

In the **Hungarian CSA**, the pollination regulating service (HU) scores significantly higher for the intervention scenario across both years and rounds. For example, in 2022 Round 2, intervention scores (0.350) are significantly higher (+52%) than control scores (0.231). On the other hand, the Pest Control regulating service often score higher in the control than in the intervention scenario (e.g., 2022 Round 1: Control 0.214 vs. Intervention 0.176), suggesting that flower strips may not have the potential to significantly enhance pest control in this region. Intervention show a strong positive impact on Habitat provision, with scores more than doubling (+134%) in some cases (e.g., 2022 Round 1: Control 0.164 vs. Intervention 0.359).

In the **Spanish** and **Portugues CSAs** the average trends in potential ecosystem service supply resulting from the upscaling process are very similar for the three considered ecosystem services. Spain (ES). Under the intervention scenarios, Pollination service significantly results in higher potential scores, especially in round 2 of 2022, with relative increases of 221 (Control 0.107 vs. Intervention 0.345) and 555% (Control 0.03 vs. Intervention 0.191) in Guadalquivida and Alentejo respectively. In both CSAs, average the scores for Pest Control are nearly identical between control and intervention plots, indicating minimal impact from the interventions. In the Spanish CSA, the increase in Habitat Provision linked to the intervention is about 10% higher than that observed in the Portuguese CSA (23% vs. 14% over two rounds of the two years); in both cases though the relative increase due to the intervention is more evident in the first year, with very similar values for both rounds.

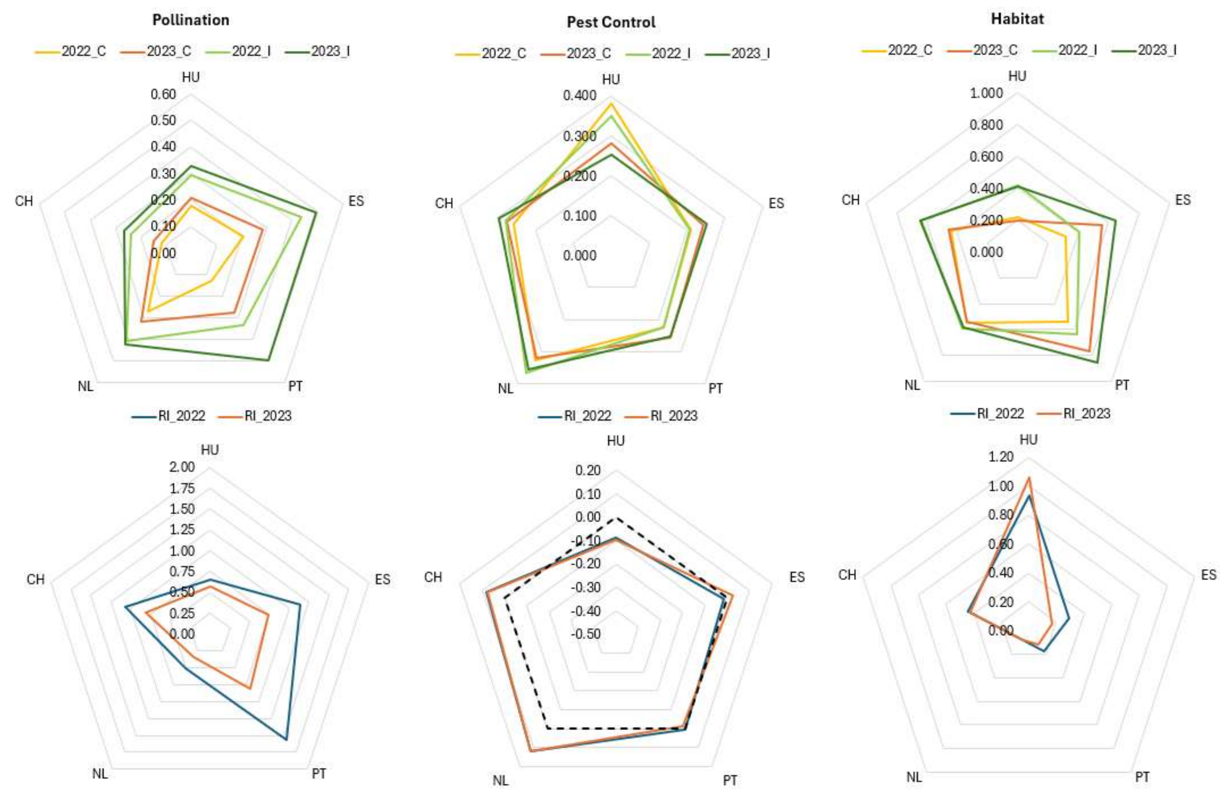

Figure 75. Average ecosystem services scores indicators in the five EBAs for the two scenarios in 2022 and 2023 and yearly relative differences (RI) due to the biodiversity management intervention (C: Control; I : Intervention)

In the **Dutch CSA** the average gain in potential Pollination service supply over the two rounds of the years of observation was ca. 65%, with the largest relative increase (+165%) in 2022 Round 1 (Control 0.141 vs. Intervention 0.373). As for Pest Control, results for the intervention scenario slightly outperform control, but the differences are small (average relative increase ca 13%). Slightly lower and very similar over the two rounds of the two years of observations is the average relative increase observed under the intervention scenarios for the Habitat Provisioning service, ranging from 7 to 8%.

In the **Swiss CSA** Pollination services show consistent improvements under the intervention scenario, with the largest relative increase over the control scenario (+110%) in 2022 round 1

(Control 0.117 vs. Intervention 0.246). Average scores for the Pest Control regulating service are similar between control and intervention scenario, with minor improvements in the latter (ca 8%). As for the Habitat provisioning service, the interventions scenario has a strong positive impact, with the largest relative increase (+61%) observed in 2023 Round 1 (Control 0.32 vs. Intervention 0.52).

6 Conclusions and outlook

The outcomes of the spatiotemporal modelling of the biodiversity indicators collected in the five EBAs considered by T2.7 allowed for assessing the potential gains in biodiversity stemming from the implementation of biodiversity management practices at field level and to upscale them at landscape level under different environmental and farming conditions. It was made evident that the five biodiversity indicators respond differently to the implementation of the interventions: results highlighted that the biodiversity management interventions are highly effective at promoting wild bees abundance and diversity, and vascular plant species diversity, enhancing then pollination regulating services and habitat provision service, but they have in all cases limited impact on spiders communities, and then on pest control regulating service.

As expected, the impact of interventions varies by CSA, very likely due to co-occurring differences in environmental conditions, crop types, management practices, and local biodiversity. The most profound impacts are observed in the most intensive agricultural systems, i.e., the intensive orchards of stone fruits in Andalucia and of olive trees in Alentejo, while the occurrence of organic farms and of more extensive agricultural farming systems result in moderate improvement of biodiversity indicators and related ecosystem services, as in the Dutch and the Hungarian CSAs.

Results highlighted also a marked seasonality effect on biodiversity indicators and on the related ecosystem services, with opposite trends depending on the regional climate patterns: in the EBAs of central continental Europe, biodiversity indicators and ecosystem services scores increase in late spring (round 2), while the opposite is observed in the EBAs of the southern Iberian Peninsula, where biodiversity scores and ecosystem services were always higher in early spring (round 1), highlighting the importance of timing for monitoring and intervention effectiveness. Furthermore the severe drought conditions observed in 2022 were coupled with a greater impact of the intervention with respect to the control compared to 2023, suggesting that such interventions could also play a role in mitigating the stress induced by the increased occurrence of extreme events which is a distinctive feature of the current climate crisis.

The predictive models presented in this report are entirely data-driven and, as such, they are assumptions-free, differently from mechanist models. As the data collected at field level in the field EBAs were processed separately for each EBA, the calibrated models stemming from such data are necessarily local specific. The estimated biodiversity increase depends then entirely on the observed data at local field scale and on the strength of their relationships with the set of predictor covariates used for the upscaling at landscape scale. The robustness of the models and the reliability of the estimates are moderate to good, depending on the accuracy of the spatial regression calibrated on available observations on the different EBAs.

As for the possible applications of the predictive models, each of them was calibrated on a set of local observations and predictors and, as such, should be used locally at field and/or at landscape scale to assess the potential gains or loss in term of biodiversity indicators under a business as usual scenario or under a scenario which foresees the implementation of biodiversity-friendly management options such as those implemented in the SHOWCASE EBAs. The approach has the potential to provide predictions for specific reference periods, either in the future and in the past, given the availability of time variant predictors from remote sensing. Furthermore, the mapping outputs have the potential to improve the implementation of biodiversity management strategies through enhanced spatial targeting, as they provide spatially explicit information about the location of hot and cold spots for biodiversity across a region.

The methodological approach though can be tailored to any case study area and to any scale provided adequate input data (observed biodiversity indicators) and predictors (spatial covariates) are available. As such, the approach could be implemented across EU, but if the goal would be to provide estimates at continental scale the calibration data set should be representative of the variability encountered at field scale over the agricultural lands across the whole EU, which is not the case for the SHOWCASE EBAs. Another data limitation for modelling applications stems from the fact that in the SHOWCASE EBAs only two scenarios were confronted, i.e. the control (or business as usual) and the intervention, making it not possible to detect non-linear behaviour or saturation effects in response to the treatment neither at field nor at landscape scale.

The results of Task 2.7 illustrated in this Deliverable can be linked to T2.3 to provide additional arguments to raise and reinforce biodiversity awareness among different types of farmers that are adopting biodiversity-enhancing management practices. In this respect T2.7 outcomes can elucidate biodiversity patterns beyond the farm level in a broader context at a landscape or regional level, besides providing insights into the potential biodiversity gain resulting from biodiversity-enhancing management practices in the specific context of each CSA.

Likewise, T2.7 outcomes are currently contributing to the integration of the spatial modelling with the economic analysis of Task 2.8 to elucidate the impact and the interconnection of incentive design on biodiversity management efficiency at landscape scale. More in detail, the cost analysis integration with the biodiversity drivers and gains at landscape scale is being carried out in the intensive stone-fruit orchards of the Guadalquivir River Valley, Andalucía, Spain. Building upon T2.7 outcomes for the Spanish CSA, the joint approach developed with T2.8 aims to the integration of an economic analysis, incorporating a cost-opportunity estimation framework to assess how different incentive structures influence farmer participation and conservation effectiveness. The allocation of the biodiversity management intervention changes when economic feasibility is introduced, as cost-related constraints impact where farmers are likely to adopt biodiversity-friendly practices. Farm management data, including production and additional costs, have been upscaled to the landscape scale highlighting their relationships with biodiversity indicators for pollinators and vascular plants. Preliminary findings indicate that the additional costs of implementing flower strips far exceed the payments provided under current flat-rate AES, making such interventions economically unfeasible under existing subsidy structures.

Finally, the outcomes of Task 2.7 can also contribute to elucidating spatial biodiversity patterns and temporal dynamics at the level of individual EBAs in the framework of the ongoing discussions with each multi-actor community and serve as a basis for further improvements of the biodiversity innovations as foreseen in Task 3.2, as well as effectively contribute to providing communication and policy recommendation material for WP4.

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Appendix. A Spatiotemporal maps of regulating ecosystem services in the five CSAs

A.1. Hungarian Case Study Area

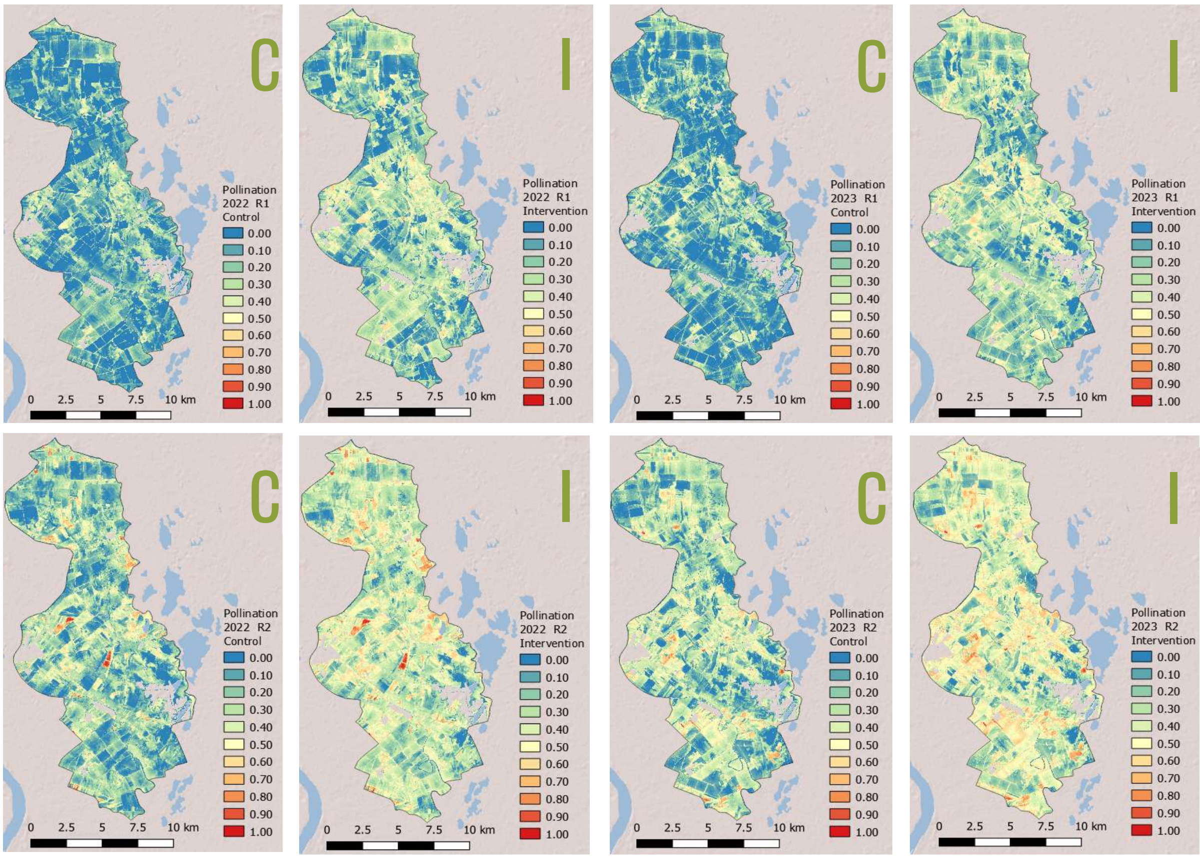

Figure 1.A: Predicted Pollination indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 1.A: Pollination indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Poll mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pollination 2022 r1 control	0.128	0.094	0.133	0.000	1.000	-	
Pollination 2022 r1 intervention	0.241	0.248	0.160	0.000	1.000	**0.88**	**0.88**
Pollination 2022 r2 control	0.231	0.215	0.168	0.000	1.000	**0.80**	
Pollination 2022 r2 intervention	0.350	0.349	0.157	0.000	1.000	**1.73**	**0.52**
Pollination 2023 r1 control	0.136	0.091	0.140	0.000	1.000	**0.06**	
Pollination 2023 r1 intervention	0.261	0.255	0.154	0.000	1.000	**1.04**	**0.92**
Pollination 2023 r2 control	0.281	0.293	0.173	0.000	1.000	**1.19**	
Pollination 2023 r2 intervention	0.392	0.417	0.166	0.000	1.000	**2.06**	**0.40**
Average changes						**1.11**	**0.68**

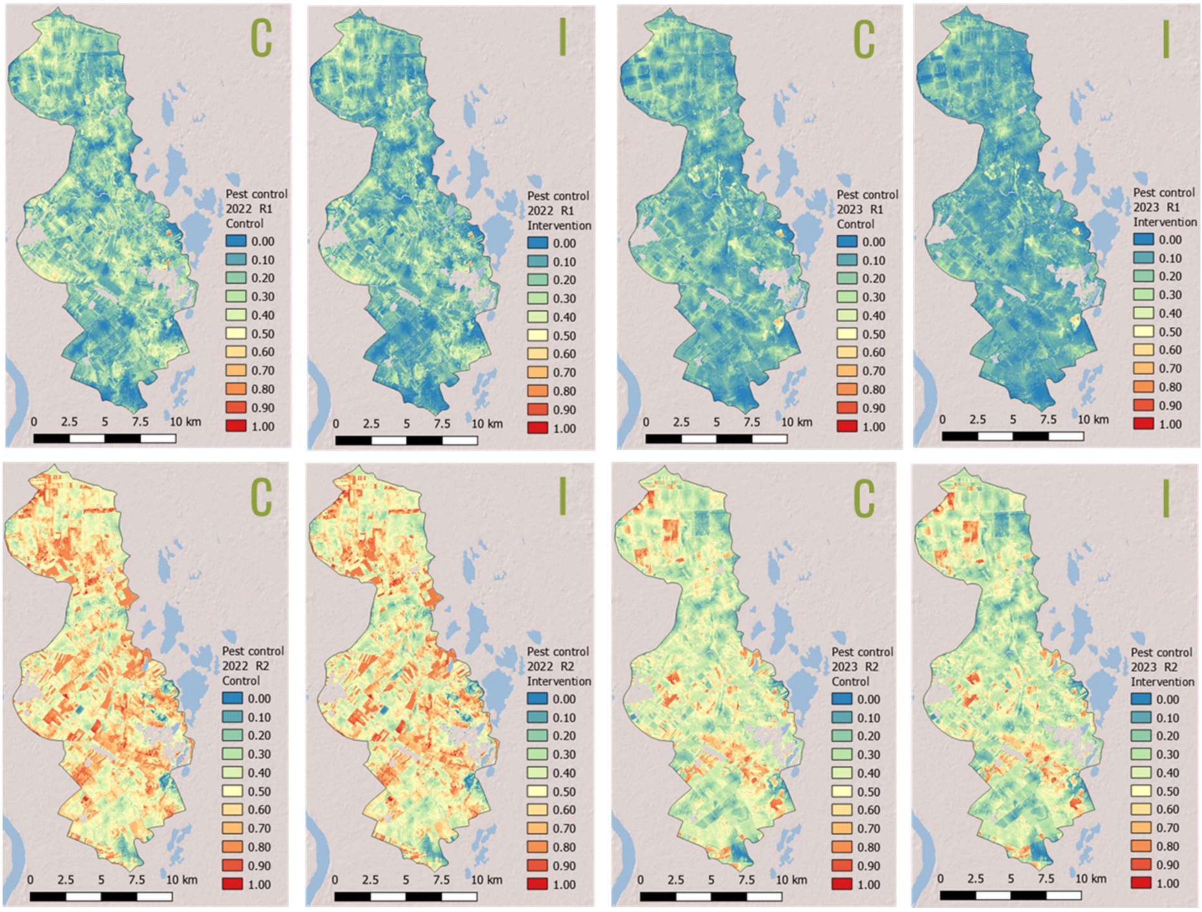

Figure 2.A: Predicted Pest Control indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 2.A: Pest Control indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Pest Ctrl mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pest Control 2022 r1 control	0.214	0.200	0.121	0.000	1.000	-	
Pest Control 2022 r1 interventior	0.176	0.159	0.112	0.000	1.000	-0.18	-0.18
Pest Control 2022 r2 control	0.548	0.531	0.175	0.000	1.000	1.56	
Pest Control 2022 r2 interventior	0.521	0.499	0.184	0.000	1.000	1.44	-0.05
Pest Control 2023 r1 control	0.155	0.140	0.089	0.000	1.000	-0.28	
Pest Control 2023 r1 interventior	0.130	0.116	0.078	0.000	1.000	-0.39	-0.16
Pest Control 2023 r2 control	0.407	0.386	0.159	0.000	1.000	0.90	
Pest Control 2023 r2 interventior	0.377	0.354	0.164	0.000	1.000	0.76	-0.07
Average changes						0.55	-0.12

Table 3.A: Habitat Provision indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Habitat mean	median	stdev	min	max	Rel change baseline	Rel Change T
Habitat 2022 r1 control	0.164	0.145	0.154	0.000	1.000	-	
Habitat 2022 r1 intervention	0.359	0.373	0.197	0.000	1.000	1.19	1.19
Habitat 2022 r2 control	0.270	0.227	0.223	0.000	1.000	0.65	
Habitat 2022 r2 intervention	0.481	0.455	0.210	0.000	1.000	1.93	0.78
Habitat 2023 r1 control	0.155	0.143	0.127	0.000	1.000	-0.05	
Habitat 2023 r1 intervention	0.363	0.371	0.160	0.000	1.000	1.21	1.34
Habitat 2023 r2 control	0.245	0.249	0.159	0.000	1.000	0.49	
Habitat 2023 r2 intervention	0.460	0.477	0.178	0.000	1.000	1.81	0.88
Average changes						1.03	1.05

Table 4.A: Summary raster statistics and relative changes in estimated ES scores due to intervention with respect to the control in the two years of observations in the Hungarian CSA.

Average	Poll mean	median	stdev	min	max	Avg. Rel Incr.
C2022	0.179	0.158	0.127	0.000	1.000	
C2023	0.208	0.198	0.137	0.000	1.000	
C	0.194	0.178	0.116	0.000	1.000	
I2022	0.296	0.295	0.135	0.000	1.000	0.648
I2023	0.326	0.333	0.142	0.000	1.000	0.567
I	0.311	0.309	0.123	0.000	1.000	0.605

Average	Pest Ctrl mean	median	stdev	min	max	Avg. Rel Incr.
C2022	0.381	0.381	0.118	0.000	1.000	
C2023	0.281	0.269	0.104	0.000	1.000	
C	0.331	0.330	0.098	0.000	1.000	
I2022	0.348	0.344	0.118	0.000	1.000	-0.086
I2023	0.254	0.241	0.102	0.000	1.000	-0.097
I	0.301	0.299	0.096	0.000	1.000	-0.090

Average	Habitat mean	median	stdev	min	max	Avg. Rel Incr.
C2022	0.217	0.192	0.152	0.000	1.000	
C2023	0.200	0.186	0.118	0.000	1.000	
C	0.209	0.197	0.113	0.000	1.000	
I2022	0.420	0.417	0.168	0.000	1.000	0.934
I2023	0.412	0.413	0.142	0.000	1.000	1.057
I	0.416	0.416	0.132	0.000	1.000	0.993

A.2. Spanish Case Study Area

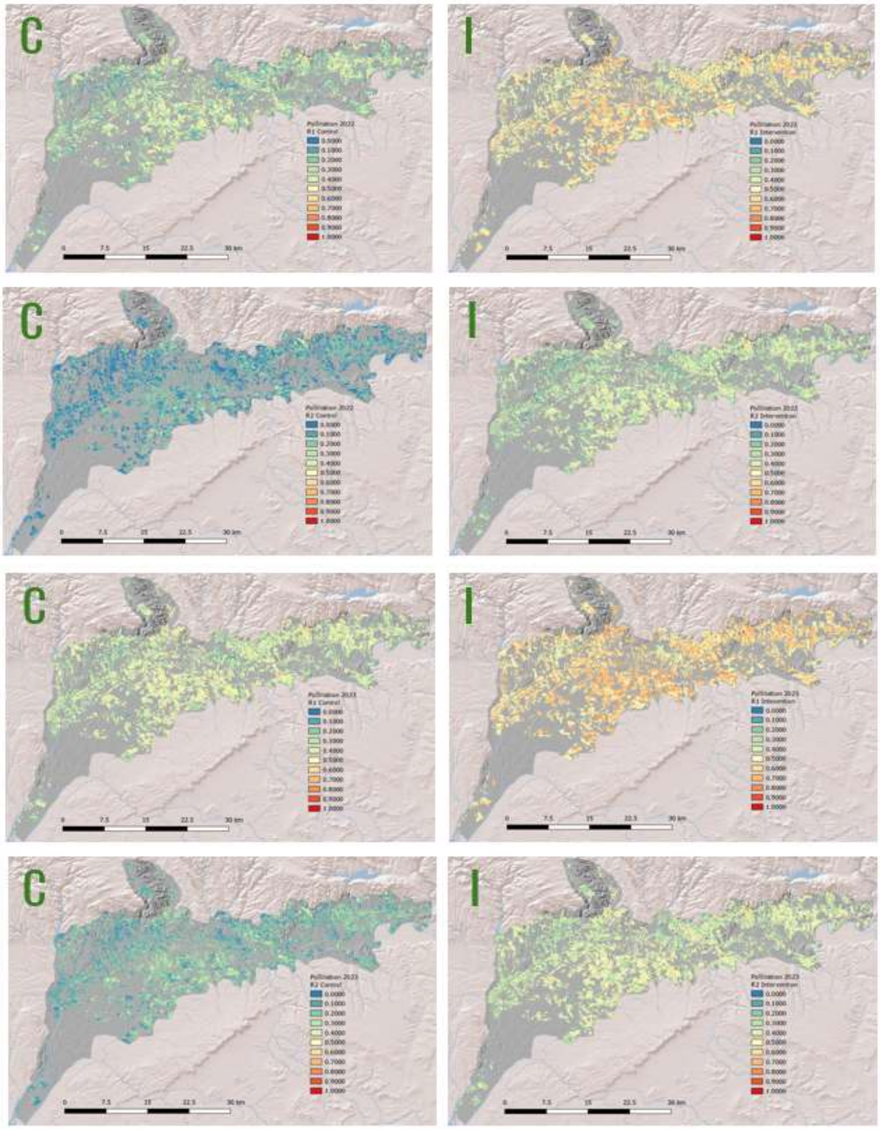

Figure 3.A: Predicted Pollination indicator maps (res. 10 m) for round 1 (1st and 3rd row) and round 2 (2nd and 4th row) for 2022 (1st and 2nd row) and 2023 (3rd and 4th row); C: Control, I: Intervention.

Table 5.A: Pollination indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Poll mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pollination 2022 r1 control	0.304	0.303	0.133	0.000	1.000	-	
Pollination 2022 r1 intervention	0.533	0.539	0.126	0.000	1.000	0.75	0.75
Pollination 2022 r2 control	0.107	0.091	0.099	0.000	1.000	-0.65	
Pollination 2022 r2 intervention	0.345	0.347	0.114	0.000	1.000	0.13	2.21
Pollination 2023 r1 control	0.388	0.390	0.117	0.000	1.000	0.28	
Pollination 2023 r1 intervention	0.594	0.598	0.106	0.000	1.000	0.95	0.53
Pollination 2023 r2 control	0.180	0.169	0.097	0.000	1.000	-0.41	
Pollination 2023 r2 intervention	0.396	0.395	0.108	0.000	1.000	0.30	1.19
Average changes						0.19	1.17

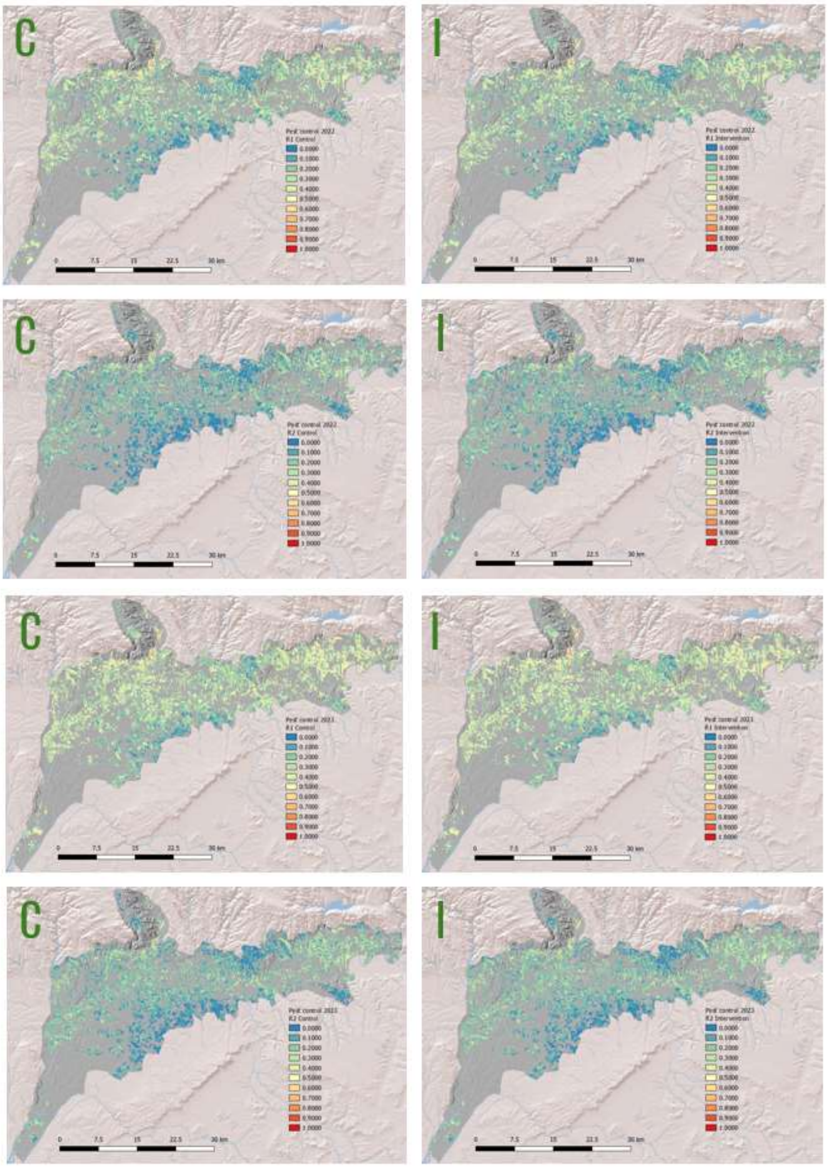

Figure 4.A: Predicted Pest Control indicator maps (res. 10 m) for round 1 (1st and 3rd row) and round 2 (2nd and 4th row) for 2022 (1st and 2nd row) and 2023 (3rd and 4th row); C: Control, I: Intervention.

Table 6.A: Pest Control indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Pest Ctrl mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pest Control 2022 r1 control	0.253	0.244	0.144	0.000	1.000	-	
Pest Control 2022 r1 intervention	0.249	0.238	0.141	0.000	1.000	-0.02	-0.02
Pest Control 2022 r2 control	0.168	0.151	0.126	0.000	1.000	-0.34	
Pest Control 2022 r2 intervention	0.165	0.146	0.123	0.000	1.000	-0.35	-0.02
Pest Control 2023 r1 control	0.316	0.313	0.138	0.000	1.000	0.25	
Pest Control 2023 r1 intervention	0.319	0.317	0.139	0.000	1.000	0.26	0.01
Pest Control 2023 r2 control	0.173	0.163	0.126	0.000	1.000	-0.32	
Pest Control 2023 r2 intervention	0.183	0.174	0.127	0.000	1.000	-0.28	0.06
Average changes						-0.11	0.01

Table 7.A: Habitat provision indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Habitat mean	median	stdev	min	max	Rel change baseline	Rel Change T
Habitat 2022 r1 control	0.300	0.284	0.068	0.000	0.837	-	
Habitat 2022 r1 intervention	0.393	0.377	0.068	0.012	0.930	0.31	0.31
Habitat 2022 r2 control	0.333	0.317	0.068	0.000	0.866	0.11	
Habitat 2022 r2 intervention	0.426	0.410	0.068	0.006	0.959	0.42	0.28
Habitat 2023 r1 control	0.546	0.531	0.069	0.000	1.000	0.82	
Habitat 2023 r1 intervention	0.639	0.624	0.069	0.081	1.000	1.13	0.17
Habitat 2023 r2 control	0.562	0.547	0.068	0.038	1.000	0.87	
Habitat 2023 r2 intervention	0.655	0.640	0.068	0.132	1.000	1.18	0.17
Average changes						0.69	0.23

Table 8.A: Summary raster statistics and relative changes in estimated ES scores due to intervention with respect to the control in the two years of observations in the Spanish CSA.

Average	Poll mean	median	stdev	min	max	Avg. Rel Incr.
C2022	0.206	0.196	0.110	0.000	1.000	
C2023	0.284	0.280	0.101	0.000	1.000	
C	0.245	0.238	0.101	0.000	1.000	
I2022	0.439	0.441	0.114	0.000	1.000	1.131
I2023	0.495	0.497	0.101	0.000	1.000	0.740
I	0.467	0.468	0.103	0.000	1.000	0.904

Average	Pest Ctrl mean	median	stdev	min	max	Avg. Rel Incr.
C2022	0.210	0.198	0.131	0.000	1.000	
C2023	0.244	0.238	0.128	0.000	1.000	
C	0.227	0.218	0.126	0.000	1.000	
I2022	0.207	0.192	0.129	0.000	1.000	-0.017
I2023	0.251	0.245	0.129	0.000	1.000	0.027
I	0.229	0.219	0.125	0.000	1.000	0.007

Average	Habitat mean	median	stdev	min	max	Avg. Rel Incr.
C2022	0.317	0.300	0.066	0.000	0.841	
C2023	0.554	0.538	0.067	0.025	1.000	
C	0.435	0.418	0.066	0.086	0.921	
I2022	0.410	0.393	0.066	0.048	0.935	0.294
I2023	0.647	0.631	0.067	0.118	1.000	0.168
I	0.528	0.511	0.066	0.159	0.967	0.214

A.3. Portuguese Case Study Area

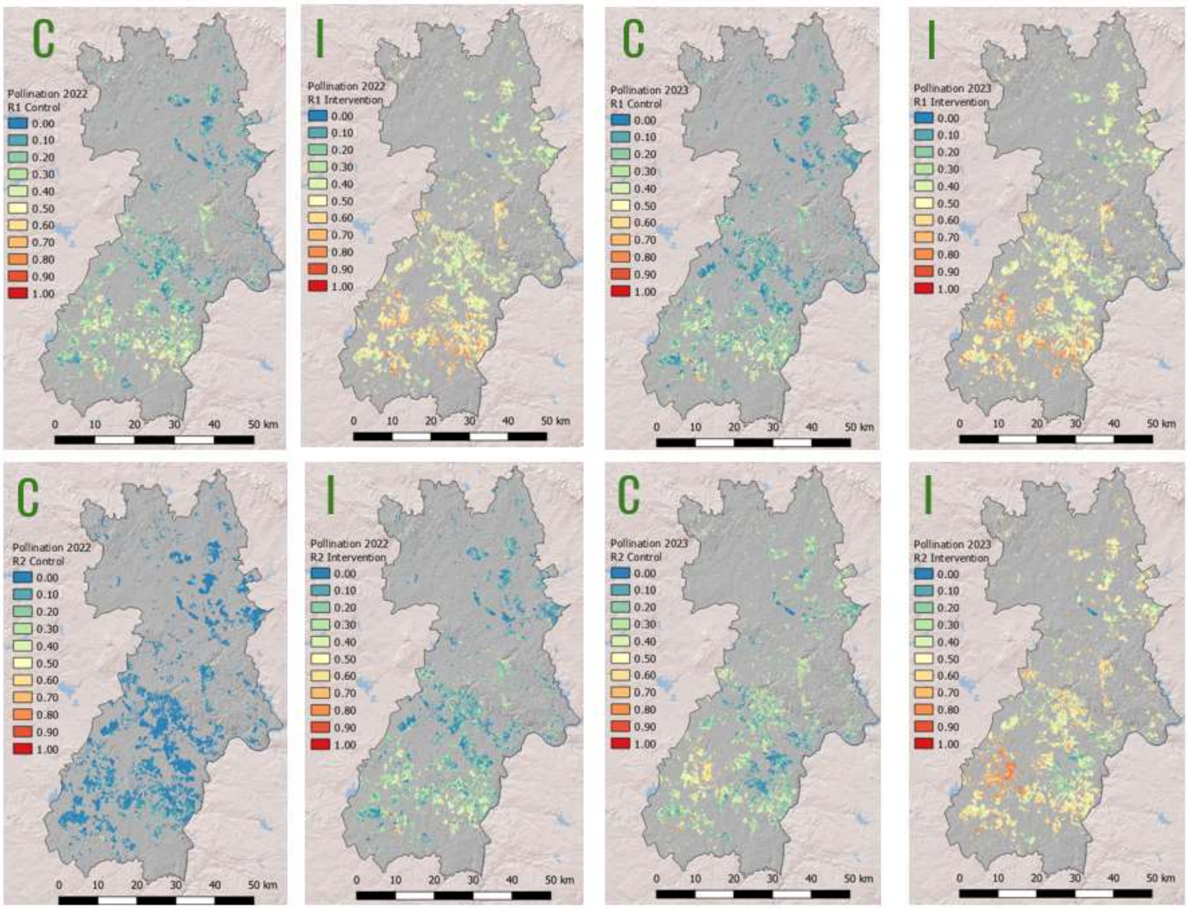

Figure 5.A: Predicted Pollination indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 9.A: Pollination indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Poll mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pollination 2022 r1 control	0.232	0.216	0.159	0.000	1.000	-	
Pollination 2022 r1 intervention	0.481	0.479	0.158	0.000	1.000	1.07	1.07
Pollination 2022 r2 control	0.029	0.000	0.070	0.000	1.000	-0.87	
Pollination 2022 r2 intervention	0.191	0.171	0.147	0.000	1.000	-0.18	5.55
Pollination 2023 r1 control	0.264	0.248	0.150	0.000	1.000	0.14	
Pollination 2023 r1 intervention	0.501	0.496	0.150	0.000	1.000	1.15	0.89
Pollination 2023 r2 control	0.288	0.267	0.181	0.000	1.000	0.24	
Pollination 2023 r2 intervention	0.498	0.498	0.181	0.000	1.000	1.14	0.73
Average changes						0.38	2.06

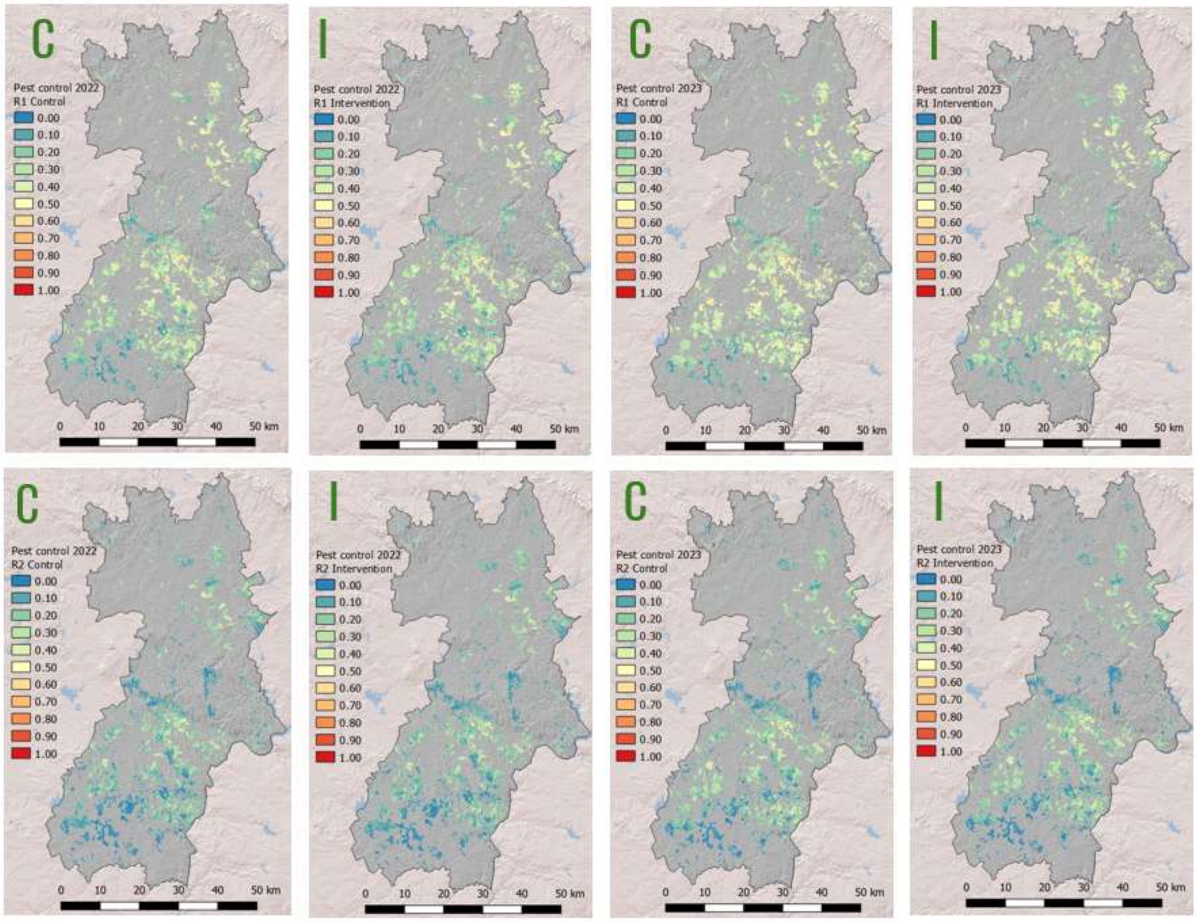

Figure 6.A: Predicted Pest Control indicator maps (res. 10 m) for round 1 (top row) and round 2 (bottom row) for 2022 (left) and 2023 (right); C: Control, I: Intervention.

Table 10.A: Pest Control indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Pest Ctrl mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pest Control 2022 r1 control	0.283	0.285	0.132	0.000	1.000	-	
Pest Control 2022 r1 intervention	0.279	0.279	0.130	0.000	1.000	-0.01	-0.01
Pest Control 2022 r2 control	0.172	0.161	0.113	0.000	1.000	-0.39	
Pest Control 2022 r2 intervention	0.172	0.160	0.111	0.000	1.000	-0.39	0.00
Pest Control 2023 r1 control	0.317	0.320	0.133	0.000	1.000	0.12	
Pest Control 2023 r1 intervention	0.313	0.316	0.132	0.000	1.000	0.11	-0.01
Pest Control 2023 r2 control	0.192	0.188	0.122	0.000	1.000	-0.32	
Pest Control 2023 r2 intervention	0.190	0.185	0.121	0.000	1.000	-0.33	-0.01
Average changes						**-0.17**	**-0.01**

Table 11.A: Habitat Provision indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Habitat mean	median	stdev	min	max	Rel change baseline	Rel Change T
Habitat 2022 r1 control	0.540	0.533	0.109	0.040	1.000	-	
Habitat 2022 r1 intervention	0.633	0.626	0.109	0.133	1.000	0.17	0.17
Habitat 2022 r2 control	0.544	0.537	0.110	0.023	1.000	0.01	
Habitat 2022 r2 intervention	0.637	0.630	0.110	0.116	1.000	0.18	0.17
Habitat 2023 r1 control	0.763	0.757	0.105	0.247	1.000	0.41	
Habitat 2023 r1 intervention	0.853	0.850	0.100	0.340	1.000	0.58	0.12
Habitat 2023 r2 control	0.775	0.768	0.107	0.257	1.000	0.44	
Habitat 2023 r2 intervention	0.863	0.861	0.100	0.350	1.000	0.60	0.11
Average changes	0.578					0.34	0.14

Table 12.A: Summary raster statistics and relative changes in estimated ES scores due to intervention with respect to the control in the two years of observations in the Portuguese CSA.

Average	Poll mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.131	0.111	0.106	0.000	1.000	
C2023	0.276	0.262	0.146	0.000	1.000	
C	0.203	0.187	0.114	0.000	1.000	
I2022	0.336	0.323	0.145	0.000	1.000	1.570
I2023	0.499	0.500	0.148	0.000	1.000	0.809
I	0.418	0.411	0.134	0.000	1.000	1.054

Average	Pest Ctrl mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.225	0.220	0.118	0.000	1.000	
C2023	0.255	0.254	0.125	0.000	1.000	
C	0.240	0.238	0.117	0.000	1.000	
I2022	0.226	0.220	0.117	0.000	1.000	0.002
I2023	0.251	0.250	0.124	0.000	1.000	-0.013
I	0.251	0.250	0.124	0.000	1.000	0.048

Average	Habitat mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.542	0.535	0.109	0.036	1.000	
C2023	0.769	0.763	0.106	0.261	1.000	
C	0.655	0.649	0.106	0.173	1.000	
I2022	0.635	0.628	0.109	0.129	1.000	0.172
I2023	0.858	0.856	0.100	0.354	1.000	0.116
I	0.747	0.742	0.103	0.266	1.000	0.139

A.5. Dutch Case Study Area

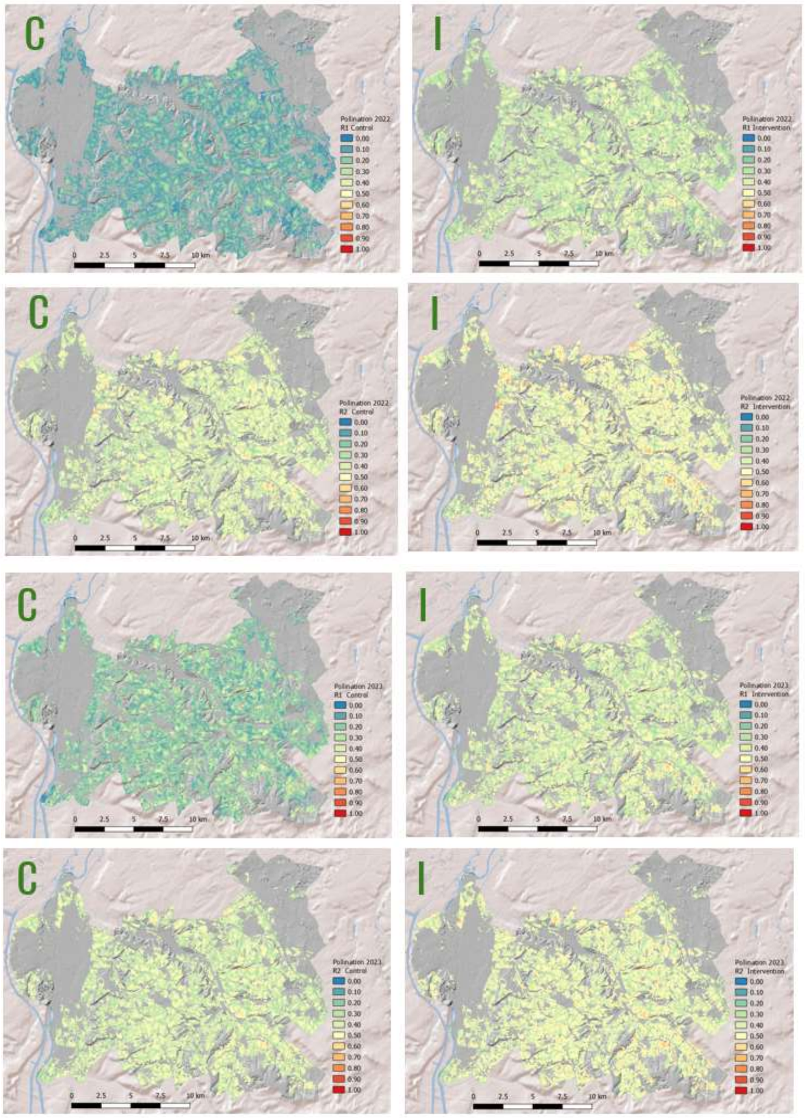

Figure 7.A: Predicted Pollination indicator maps (res. 10 m) for round 1 (1st and 3rd row) and round 2 (2nd and 4th row) for 2022 (1st and 2nd row) and 2023 (3rd and 4th row); C: Control, I: Intervention.

Table 13.A: Pollination indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Poll mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pollination 2022 r1 control	0.141	0.136	0.056	0.000	1.000	-	
Pollination 2022 r1 intervention	0.373	0.370	0.066	0.000	1.000	**1.64**	**1.64**
Pollination 2022 r2 control	0.406	0.404	0.068	0.000	1.000	**1.87**	
Pollination 2022 r2 intervention	0.451	0.448	0.075	0.000	1.000	**2.19**	**0.11**
Pollination 2023 r1 control	0.232	0.225	0.078	0.000	1.000	**0.64**	
Pollination 2023 r1 intervention	0.403	0.397	0.073	0.000	1.000	**1.85**	**0.74**
Pollination 2023 r2 control	0.402	0.401	0.064	0.000	1.000	**1.84**	
Pollination 2023 r2 intervention	0.444	0.443	0.071	0.000	1.000	**2.14**	**0.10**
Average changes						**1.74**	**0.65**

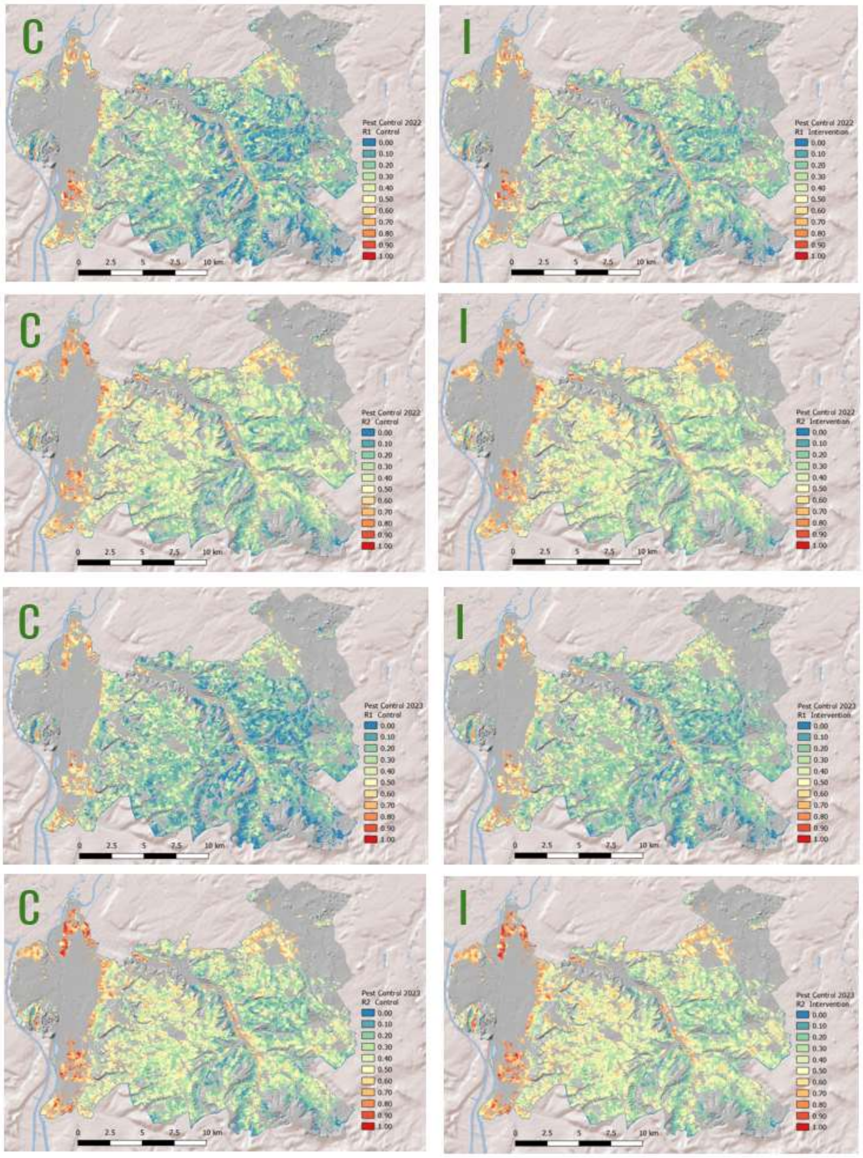

Figure 8.A: Predicted Pest Control indicator maps (res. 10 m) for round 1 (1st and 3rd row) and round 2 (2nd and 4th row) for 2022 (1st and 2nd row) and 2023 (3rd and 4th row); C: Control, I: Intervention.

Table 14.A: Pollination indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Pest Ctrl mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pest Control 2022 r1 control	0.267	0.229	0.189	0.000	1.000	-	
Pest Control 2022 r1 intervention	0.312	0.280	0.182	0.000	1.000	0.17	0.17
Pest Control 2022 r2 control	0.383	0.374	0.179	0.000	1.000	0.43	
Pest Control 2022 r2 intervention	0.415	0.408	0.172	0.000	1.000	0.55	0.08
Pest Control 2023 r1 control	0.246	0.206	0.178	0.000	1.000	-0.08	
Pest Control 2023 r1 intervention	0.288	0.254	0.172	0.000	1.000	0.08	0.17
Pest Control 2023 r2 control	0.391	0.380	0.187	0.000	1.000	0.46	
Pest Control 2023 r2 intervention	0.424	0.415	0.179	0.000	1.000	0.59	0.08
Average changes						0.32	0.13

Table 15.A: Habitat Provision indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Habitat mean	median	stdev	min	max	Rel change baseline	Rel Change T
Habitat 2022 r1 control	0.538	0.536	0.254	0.000	1.000	-	
Habitat 2022 r1 intervention	0.580	0.582	0.250	0.000	1.000	0.08	0.08
Habitat 2022 r2 control	0.555	0.541	0.236	0.000	1.000	0.03	
Habitat 2022 r2 intervention	0.598	0.586	0.231	0.000	1.000	0.11	0.08
Habitat 2023 r1 control	0.553	0.548	0.256	0.000	1.000	0.03	
Habitat 2023 r1 intervention	0.595	0.594	0.251	0.000	1.000	0.11	0.08
Habitat 2023 r2 control	0.529	0.519	0.244	0.000	1.000	-0.02	
Habitat 2023 r2 intervention	0.572	0.565	0.240	0.000	1.000	0.06	0.08
Average changes						0.06	0.08

Table 16.A: Summary raster statistics and relative changes in estimated ES scores due to intervention with respect to the control in the two years of observations in the Dutch CSA.

Average	Poll mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.274	0.271	0.055	0.000	1.000	
C2023	0.317	0.316	0.067	0.000	1.000	
C	0.295	0.293	0.056	0.000	1.000	
I2022	0.412	0.411	0.062	0.000	1.000	0.503
I2023	0.424	0.424	0.068	0.000	1.000	0.336
I	0.418	0.417	0.059	0.000	1.000	0.413

Average	Pest Ctrl mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.325	0.303	0.177	0.000	0.975	
C2023	0.318	0.294	0.179	0.000	1.000	
C	0.322	0.302	0.172	0.000	0.971	
I2022	0.364	0.346	0.171	0.000	0.977	0.119
I2023	0.356	0.335	0.173	0.000	1.000	0.118
I	0.360	0.343	0.166	0.000	0.973	0.118

Average	Habitat mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.546	0.538	0.231	0.000	1.000	
C2023	0.541	0.536	0.244	0.000	1.000	
C	0.544	0.535	0.223	0.000	1.000	
I2022	0.589	0.583	0.227	0.000	1.000	0.0778
I2023	0.583	0.582	0.240	0.000	1.000	0.0784
I	0.586	0.580	0.218	0.000	1.000	0.0781

A.6. Swiss Case Study Area

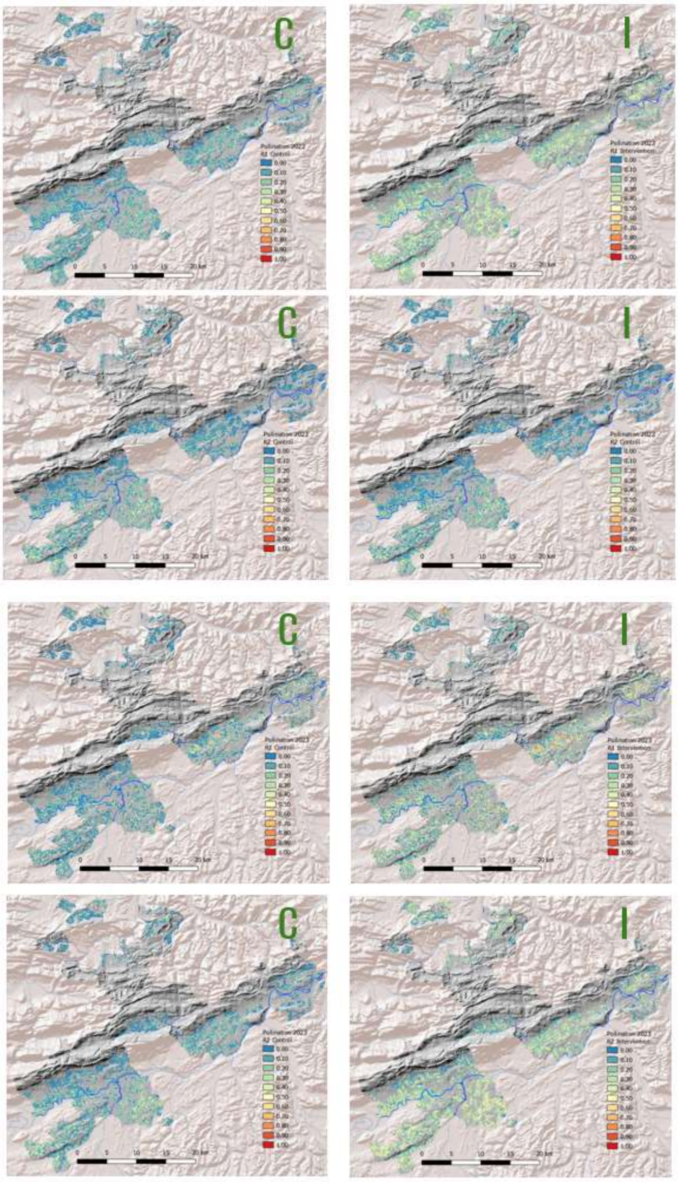

Figure 9.A: Predicted Pollination indicator maps (res. 10 m) for round 1 (1st and 3rd row) and round 2 (2nd and 4th row) for 2022 (1st and 2nd row) and 2023 (3rd and 4th row); C: Control, I: Intervention.

Table 17.A: Pollination indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Poll mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pollination 2022 r1 control	0.117	0.100	0.104	0.000	1.000	-	
Pollination 2022 r1 intervention	0.246	0.243	0.139	0.000	1.000	1.09	1.09
Pollination 2022 r2 control	0.112	0.059	0.136	0.000	1.000	-0.05	
Pollination 2022 r2 intervention	0.229	0.218	0.161	0.000	1.000	0.95	1.04
Pollination 2023 r1 control	0.153	0.080	0.192	0.000	1.000	0.31	
Pollination 2023 r1 intervention	0.261	0.215	0.232	0.000	1.000	1.23	0.71
Pollination 2023 r2 control	0.141	0.090	0.156	0.000	1.000	0.21	
Pollination 2023 r2 intervention	0.274	0.265	0.175	0.000	1.000	1.34	0.94
Average changes						0.73	0.95

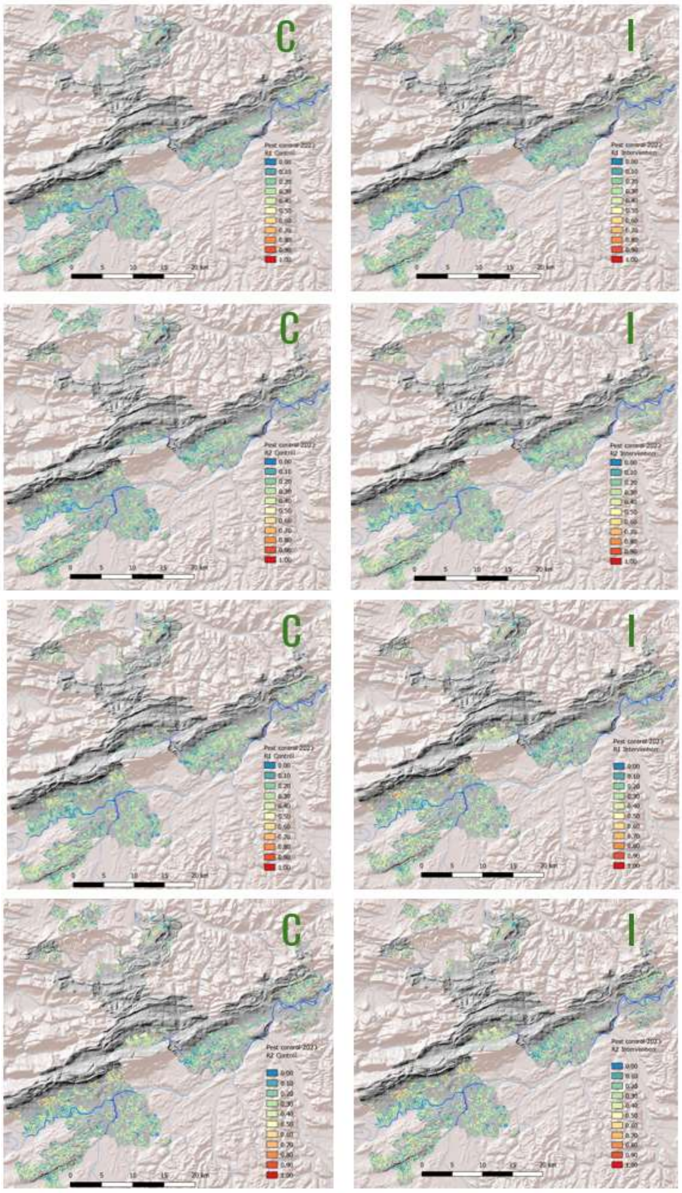

Figure 10.A: Predicted Pest Control indicator maps (res. 10 m) for round 1 (1st and 3rd row) and round 2 (2nd and 4th row) for 2022 (1st and 2nd row) and 2023 (3rd and 4th row); C: Control, I: Intervention.

Table 18.A: Pest Control indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Pest Ctrl mean	median	stdev	min	max	Rel change baseline	Rel Change T
Pest Control 2022 r1 control	0.255	0.227	0.182	0.000	1.000	-	
Pest Control 2022 r1 intervention	0.276	0.250	0.182	0.000	1.000	0.08	0.08
Pest Control 2022 r2 control	0.260	0.237	0.170	0.000	1.000	0.02	
Pest Control 2022 r2 intervention	0.281	0.261	0.171	0.000	1.000	0.10	0.08
Pest Control 2023 r1 control	0.280	0.250	0.198	0.000	1.000	0.10	
Pest Control 2023 r1 intervention	0.300	0.273	0.199	0.000	1.000	0.18	0.07
Pest Control 2023 r2 control	0.273	0.253	0.169	0.000	1.000	0.07	
Pest Control 2023 r2 intervention	0.295	0.277	0.168	0.000	1.000	0.16	0.08
Average changes						0.10	0.08

Table 19.A: Habitat Provision indicator raster statistics and relative changes with respect to the baseline and to the control of each round.

Indicator year r treat	Habitat mean	median	stdev	min	max	Rel change baseline	Rel Change T
Habitat 2022 r1 control	0.330	0.256	0.298	0.000	1.000	-	
Habitat 2022 r1 intervention	0.528	0.491	0.271	0.000	1.000	0.60	0.60
Habitat 2022 r2 control	0.555	0.523	0.266	0.000	1.000	0.68	
Habitat 2022 r2 intervention	0.746	0.757	0.216	0.000	1.000	1.26	0.34
Habitat 2023 r1 control	0.323	0.246	0.300	0.000	1.000	-0.02	
Habitat 2023 r1 intervention	0.520	0.480	0.274	0.000	1.000	0.58	0.61
Habitat 2023 r2 control	0.564	0.532	0.264	0.000	1.000	0.71	
Habitat 2023 r2 intervention	0.753	0.767	0.213	0.000	1.000	1.28	0.34
Average changes						0.73	0.47

Table 20.A: Summary raster statistics and relative changes in estimated ES scores due to intervention with respect to the control in the two years of observations in the Swiss CSA.

Average	Poll mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.115	0.069	0.109	0.000	0.791	
C2023	0.147	0.110	0.142	0.000	0.925	
C	0.131	0.103	0.118	0.000	0.772	
I2022	0.237	0.232	0.139	0.000	0.877	1.066
I2023	0.266	0.249	0.170	0.000	0.956	0.818
I	0.252	0.244	0.148	0.000	0.856	0.927

Average	Pest Ctrl mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.258	0.303	0.177	0.000	0.975	
C2023	0.277	0.294	0.179	0.000	1.000	
C	0.267	0.302	0.172	0.000	0.971	
I2022	0.278	0.346	0.171	0.000	0.977	0.081
I2023	0.297	0.335	0.173	0.000	1.000	0.075
I	0.288	0.343	0.166	0.000	0.973	0.078

Average	Habitat mean	median	stdev	min	max	Avg. Rel. Incr.
C2022	0.443	0.389	0.278	0.000	1.000	
C2023	0.453	0.389	0.280	0.000	1.000	
C	0.452	0.389	0.278	0.000	1.000	
I2022	0.637	0.624	0.240	0.000	1.000	0.4391
I2023	0.645	0.623	0.240	0.000	1.000	0.4251
I	0.637	0.623	0.239	0.000	1.000	0.4075