Complementary biodiversity metrics are essential to adequately evaluate no net loss – Supplementary Materials

1. Supplementary Material 1 – Further definitions and technical methodological details

1.1. Metric definitions

1.1.1. Mean Species Abundance (MSA)

Mean Species Abundance (MSA) is an assemblage-level measure of local biodiversity intactness, defined by (Alkemade et al., 2009) as:

$$MSA = \frac{1}{N_r}\sum_{s=1}^{N_r} \min\left(\frac{AB_{s,d}}{AB_{s,r}}, 1\right) \qquad \textbf{\textit{Eq S. 1}}$$

where N_r is the number of the original species s present in the reference ecosystem; $AB_{s,d}$ the abundance of the original species s in the disturbed ecosystem; and $AB_{s,r}$ the abundance of the original species s in the reference (undisturbed) ecosystem. $AB_{s,d}$ and $AB_{s,r}$ are defined relatively to equal surfaces.

In practice, MSA is not available at a global level using the theoretical definition provided by (Alkemade et al., 2009); this would require sampling every single ecosystem with its set of endemic species, which is unfeasible. The GLOBIO model has thus been developed. It relies on meta-analyses to determine pressure-impact relationships, quantifying how certain pressures driving biodiversity loss (land-use, climate change, etc.) impact the MSA value of a given ecosystem (Alkemade et al., 2009). This model, combined with global data on the intensity of these drivers, can then be applied at a global scale, to obtain global MSA values per grid cell. The equation below highlights how MSA is thus calculated in practice (Alkemade et al., 2009; Schipper et al., 2020):

$$MSA_{i,S} = \prod_x MSA_{i,S,x} \qquad \textbf{\textit{Eq S. 2}}$$

where $MSA_{i,S}$ is the MSA for species group S in grid cell i; and $MSA_{i,S,x}$ the MSA for pressure x on species group S in grid cell i.

This calculation is valid under two assumptions. First, the different pressures' effects are assumed independent from the others. This assumption is not always followed in practice; for certain pressure combinations, one pressure is considered to dominate over the other(s). Second, the meta-analyses used to construct the pressure-impact relationships are assumed to randomly and representatively sample the species communities. Alternatively, in version 4 of the GLOBIO model, if the land-use pressure is expected to be the greatest driver of impact, then the overall MSA is equal to MSA_{LU}. (Schipper et al., 2020)

The species groups and pressures covered depend on the version of the model being used. The study presented here uses MSA values provided by GLOBIO 4, covering climate change, land-use, roads, atmospheric nitrogen deposition and hunting pressures, and mammals, birds and plants for the species groups (Schipper et al., 2020). Aggregation over all species groups is performed by taking the mean of the MSA values over all species groups.

1.1.2. Land-cover change Impacts on Future Extinctions (LIFE)

Land-cover change Impacts on Future Extinctions (LIFE) scores are determined through calculation of changes in species persistence defined as a function of the species Area of Habitat

(AOH). Further details on species persistence (P) are presented here. For a given species it is defined according to (Durán et al., 2020) as:

$$P_s = (E_s)^z \qquad \textbf{\textit{Eq S. 3}}$$

where P_s is the persistence score for species s; E_s is the proportion of species s AOH that remains; and z is an extinction coefficient (between 0 and 1).

A change in persistence ΔP_s for species s between times T_1 and T_2 is calculated in the following way (Durán et al., 2020):

$$\Delta P_s = (E_{s,T_2})^z - \left(E_{s,T_1}\right)^z \qquad \textbf{\textit{Eq S. 4}}$$

where E_{s,t_1} (resp. E_{s,t_2}) is the proportion of species s area of habitat (AOH) that remains at T_1 (resp. T_2).

Considering potential differences in breeding and non-breeding grounds for migratory species P_s is calculated as:

$$P_s = {P_{s,br}}^{0.5} \cdot {P_{s,nbr}}^{0.5} \qquad \textbf{\textit{Eq S. 5}}$$

where P_s is the persistence score for species s; and $P_{s,br}$ (respectively $P_{s,nbr}$) is the persistence of species s in its breeding (respectively non-breeding) range.

1.1.3. Species threat abatement and restoration metric (STAR)

Species Threat Abatement and Restoration (STAR) scores (Mair et al., 2021) are based on local species-threats interaction. The threat abatement score is defined as $Q_{i,s}W_sC_{s,t}$ where $Q_{s,\mathrm{i}}$ is the current AOH of each species s in cell i (% of global current AOH for s); W_s is the IUCN Red List Category weight of species s (Least Concern = 0, Near threatened = 1, Vulnerable = 2, Endangered = 3, Critically Endangered = 4 (Butchart et al., 2007, 2004)); and $C_{s,t}$ is the relative contribution of threat t to species s extinction risk.

The score for a given threat t in cell i is obtained by summing the effect of this threat on all local species as follows:

$$T_{i,t} = \sum_s^{N_s} Q_{i,s}W_sC_{s,t} \qquad \textbf{\textit{Eq S. 6}}$$

where $T_{i,t}$ is the STAR$_\mathrm{T}$ score in cell i and for threat t; N_s is the total number of species s in cell i.

Likewise, a restoration score can be computed for any threat t and cell i as follows:

$$R_{i,t} = \sum_s^{N_s} H_{i,s}W_sC_{s,t}M_{i,s} \qquad \textbf{\textit{Eq S. 7}}$$

where $R_{i,t}$ is the STAR$_\mathrm{R}$ score in cell i and for threat t; N_s is the total number of species s in cell i; $H_{i,s}$ is the extent of restorable AOH of each species s in cell i (% of global current AOH for s); W_s is the IUCN Red List Category weight of species s (Least Concern = 0, Near threatened = 1, Vulnerable = 2, Endangered = 3, Critically Endangered = 4 (Butchart et al., 2007, 2004)); $C_{s,t}$ is the relative contribution of threat t to species s extinction risk; and $M_{i,s}$ is a recovery time discount factor.

While these definitions provide the calculation methodology for an aggregated score over all species for a given threat, the authors specify that the metric can also be defined at the species level (Mair et al., 2021). Summing over all threats t for a given species s in cell i, this could be expressed for the $STAR_T$ score as:

$$T_{i,s} = \sum_t Q_{i,s} W_s C_{s,t}$$

From which we can deduce:

$$T_{i,s} = Q_{i,s} W_s \qquad \textbf{\textit{Eq S. 8}}$$

where $T_{i,s}$ is the $STAR_T$ score for species s in cell i; $Q_{i,s}$ is the current AOH of species s in cell i (% of global current AOH for s); and W_s is the IUCN Red List Category weight of species s.

Per species, the global $STAR_T$ score (summed across locations and threats) is thus: 0 for Least Concern species, 100 for Near threatened, 200 for Vulnerable, 300 for Endangered, 400 for Critically Endangered (Mair et al., 2021).

For the $STAR_R$ score, the species level metric can be derived as:

$$R_{i,s} = \sum_t H_{i,s} W_s C_{s,t} M_{i,s}$$

From which we can deduce:

$$R_{i,s} = H_{i,s} W_s M_{i,s} \qquad \textbf{\textit{Eq S. 9}}$$

where $R_{i,s}$ is the $STAR_R$ score for species s in cell i; $H_{i,s}$ is the extent of restorable AOH of each species s in cell i (% of global current AOH for s).

The scores can further be summed across species to provide an overall score per cell (aggregated over threats and species), T_i and R_i (Mair et al., 2021).

The threats covered are those from the IUCN Red List, excluding those that were present in the past but unlikely to reoccur, as well as those that are not expected to cause populations to decline (Mair et al., 2021). The taxonomic groups covered are birds, mammals and amphibians from version 2019-3 of the IUCN Red List, including those species classified as Near threatened and threatened and excluding those marked as Data Deficient (Mair et al., 2021).

1.2. Further technical details on the simulation methodology

Each optimisation problem is set up using the *prioritizr* package (v8.0.3)(Hanson et al., 2023), based on a minimum set objective, targets based on the absolute magnitude of the loss, and proportional decisions (allowing partial selection of planning units). The problems are solved using the Gurobi solver (Gurobi Optimization, LLC, 2023) with a gap of 0, and forcing the solver to attempt to find a solution irrespective of pre-checks. The Gurobi solver rounds to 0 values that are smaller than 10^{-6}; a temporary multiplication factor is therefore applied to features and targets when losses are smaller than 10^{-6}, to ensure they are not rounded.

The packages used throughout the simulation are: *dplyr* (v1.1.4)(Wickham et al., 2023a), *exactextractr* (v0.10.0)(Daniel Baston, 2023), *ggplot2* (v3.5.0)(Wickham, 2016), *gurobi* (v11.0-1)(Gurobi Optimization, LLC, 2024), *magrittr* (v2.0.3)(Bache and Wickham, 2022), *plyr* (v1.8.9)(Wickham, 2011), *prioritizr* (v8.0.3)(Hanson et al., 2023), *scales* (v1.2.1)(Wickham et al., 2023b), *sf* (v1.0-16)(Pebesma, 2018; Pebesma and Bivand, 2023), *terra* (v1.7-74)(Hijmans, 2024), *tibble* (v.3.2.1)(Müller and Wickham, 2023), *tidyr* (v1.3.1)(Wickham et al., 2024).

1.3. IUCN threats/threat categories considered to relate to land-cover only

Rationale for inclusion is indicated in italics below the threat/threat category, based on threat descriptions provided in (IUCN, 2022).

1 Residential & commercial development

Development here is assumed to mostly transform land-cover; restoring land would remove the developments and therefore the threat.

2.1 Annual & perennial non-timber crops

2.2 Wood & pulp plantations

2.3 Livestock farming & ranching

These three categories appear to cover the conversion of land (not pollution of the land through these uses, which is covered in other threats).

3.1 Oil & gas drilling

3.2 Mining & quarrying

The main threat from these categories is assumed to be changes in land-cover.

5.3 Logging & wood harvesting

The main threat from this category is assumed to be changes in land-cover.

7.3 Other ecosystem modifications

According to the description of this threat, this is assumed to mainly relate to land-cover changes.

9.3 Agricultural & forestry effluents

If the agricultural or forestry land is restored to natural habitat, it can be assumed that the threat from effluents of agricultural/forestry activities on the site of these activities will also disappear, as the activity causing them will no longer occur.

1.4. Comparison of underlying data and scope for MSA, LIFE and STAR values used in this study

Table S 1. Comparison of the data for land-use change and AOH used to compute the metrics, as well as the taxa covered, and other elements on their scope.

	Land-use change (LUC)	**Current AOH**	**Original AOH**	**Taxa**	**Granularity - non LUC**
MSA (Schipper et al., 2020)	For urban and cropland: ESA climate change initiative land-cover map for 2015 (ESA CCI, 2017) For pasture and forestry land: downscaling country-level areas reported by the FAO (FAO, 2018)			birds, mammals, terrestrial plants	Pressures (climate change, roads, atmospheric nitrogen deposition, hunting) mapped at various granularities, modelled effects on assemblages through meta-analyses
LIFE (Eyres et al., 2024)		Map of estimated distribution of habitats (Jung et al., 2020): IUCN level 1 map for natural habitat, IUCN level 2 map for artificial habitat. This layer is originally based on (Buchhorn et al., 2020) which has 23 classes.	Map of potential natural vegetation (Jung, 2020), at IUCN level 1	amphibians, birds, mammals, reptiles	Populations at level of range maps - not site-specific Only LUC, no other threats considered Binary AOH/non-AOH - not considering intensity of management for artificial habitats
STAR (Mair et al., 2021)		Reclassification of ESA climate change initiative land-cover map for 2015 (ESA CCI, 2017) into 10 land-cover classes, matched to IUCN Red List assessment habitat classes	Backcasting using ESA climate change initiative land-cover map for 1992	amphibians, birds, mammals – globally threatened and near-threatened species	Expert mapping ranges (with errors) IUCN threats at level of range maps - not site-specific Populations at level of range maps - not site-specific Binary AOH/non-AOH - not considering intensity of management for artificial habitats

2. Supplementary Material 2 – Supplementary results

2.1. Sensitivity analysis on the number of losses per batch

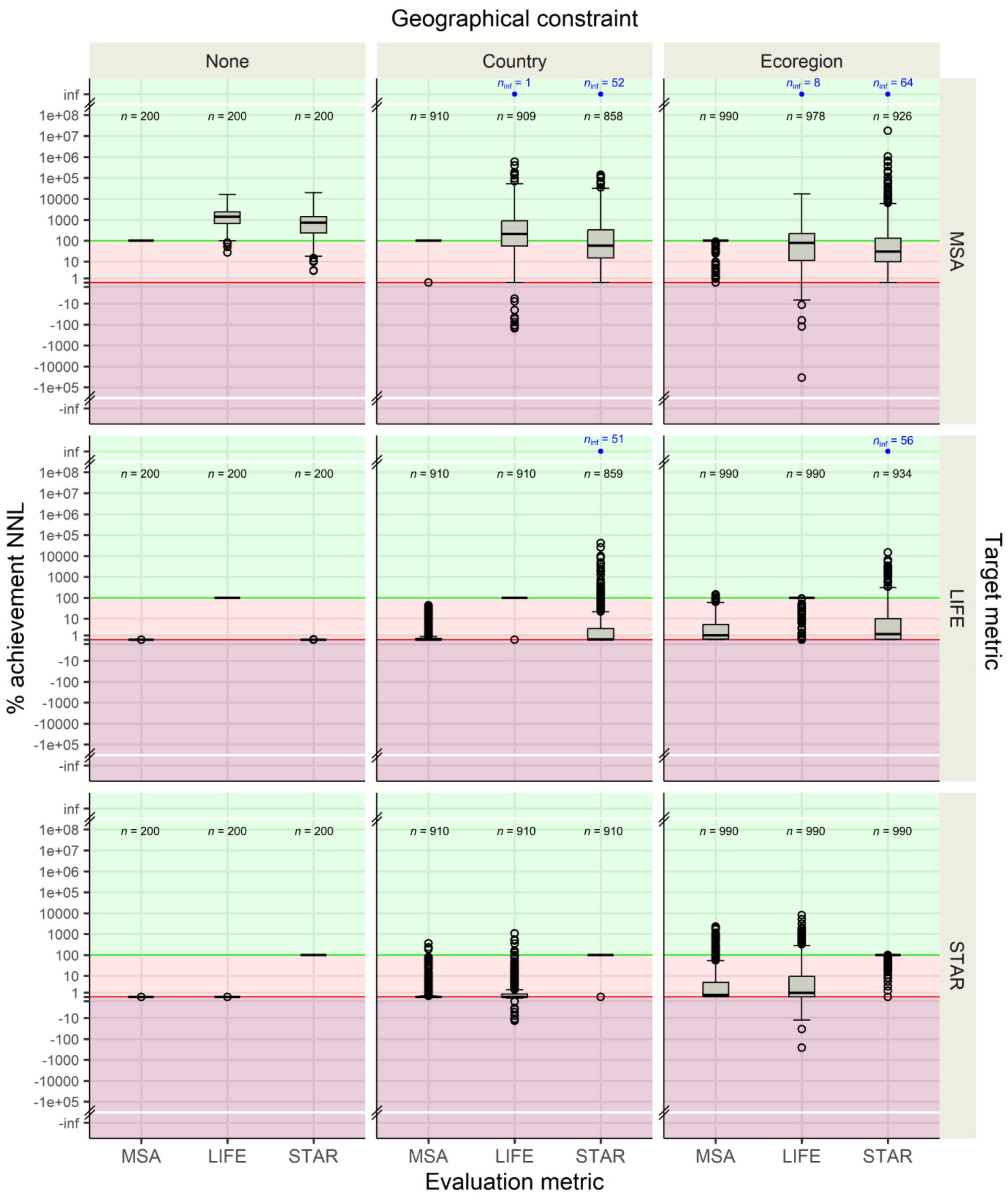

Figure S 1. Percentage achievement of NNL expressed per evaluation metric, depending on the target metric and geographical constraint, for 200 batches of 5 losses. See Main Text for detailed legend.

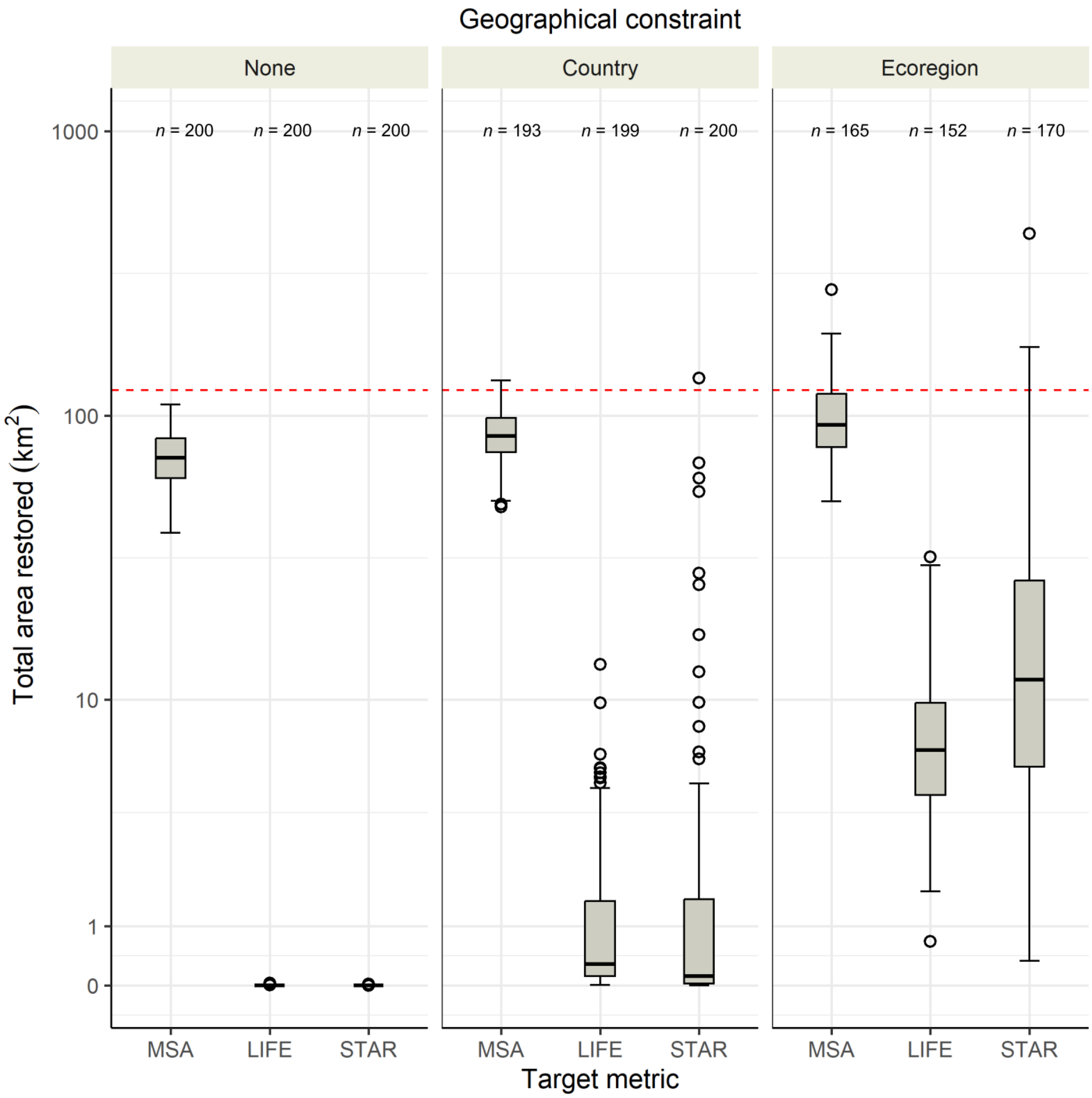

Figure S 2. Total area restored per batch, target metric and geographical constraint, for 200 batches of 5 losses, in the cases where NNL is consistently 100 % achieved within the batch (with the relevant grouping from the constraint). See Main Text for detailed legend.

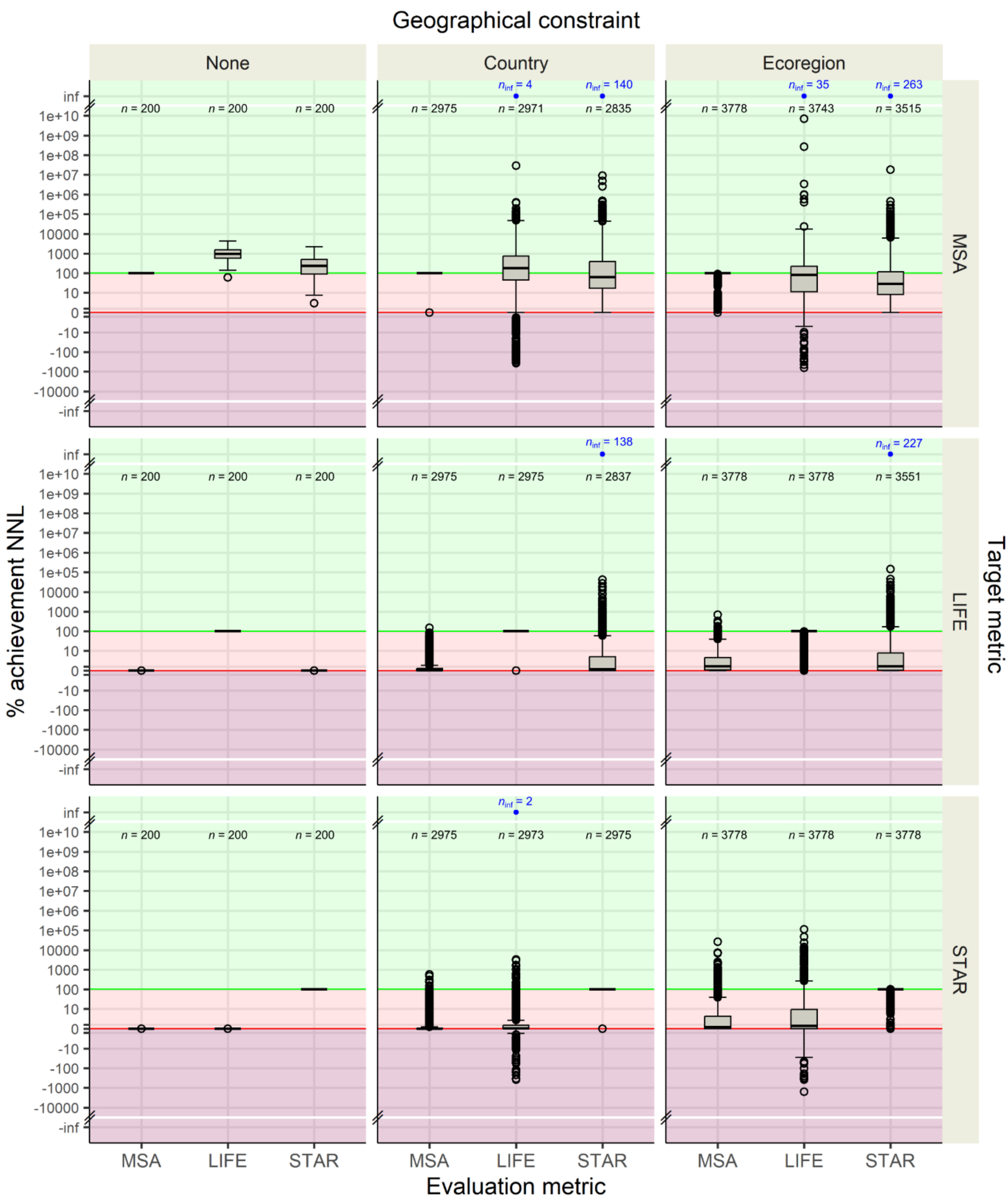

Figure S 3. Percentage achievement of NNL expressed per evaluation metric, depending on the target metric and geographical constraint, for 200 batches of 20 losses. See Main Text for detailed legend.

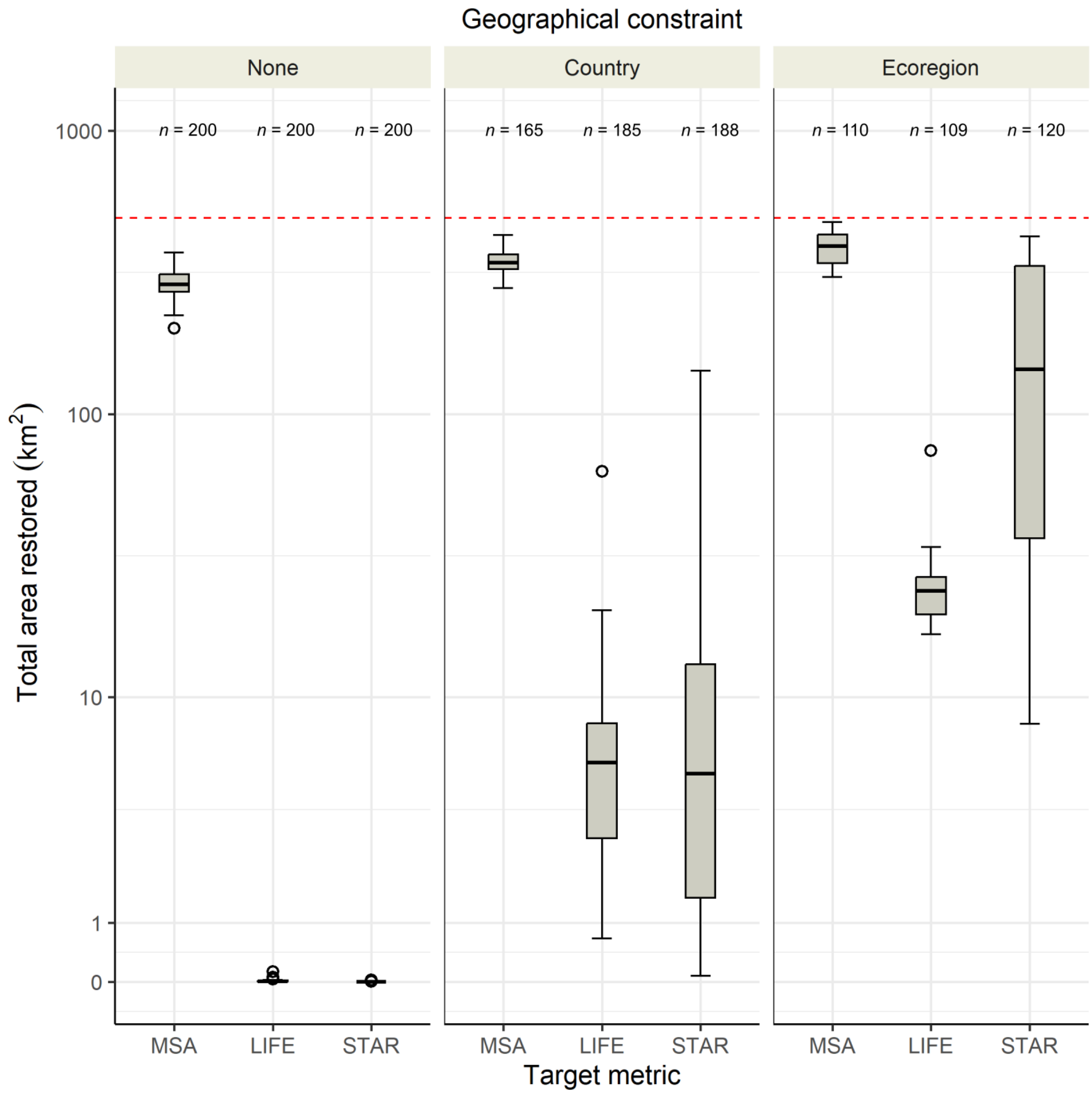

Figure S 4. Total area restored per batch, target metric and geographical constraint, for 200 batches of 20 losses, in the cases where NNL is consistently 100 % achieved within the batch (with the relevant grouping from the constraint). See Main Text for detailed legend.

2.2. Sensitivity analysis on the number of batches

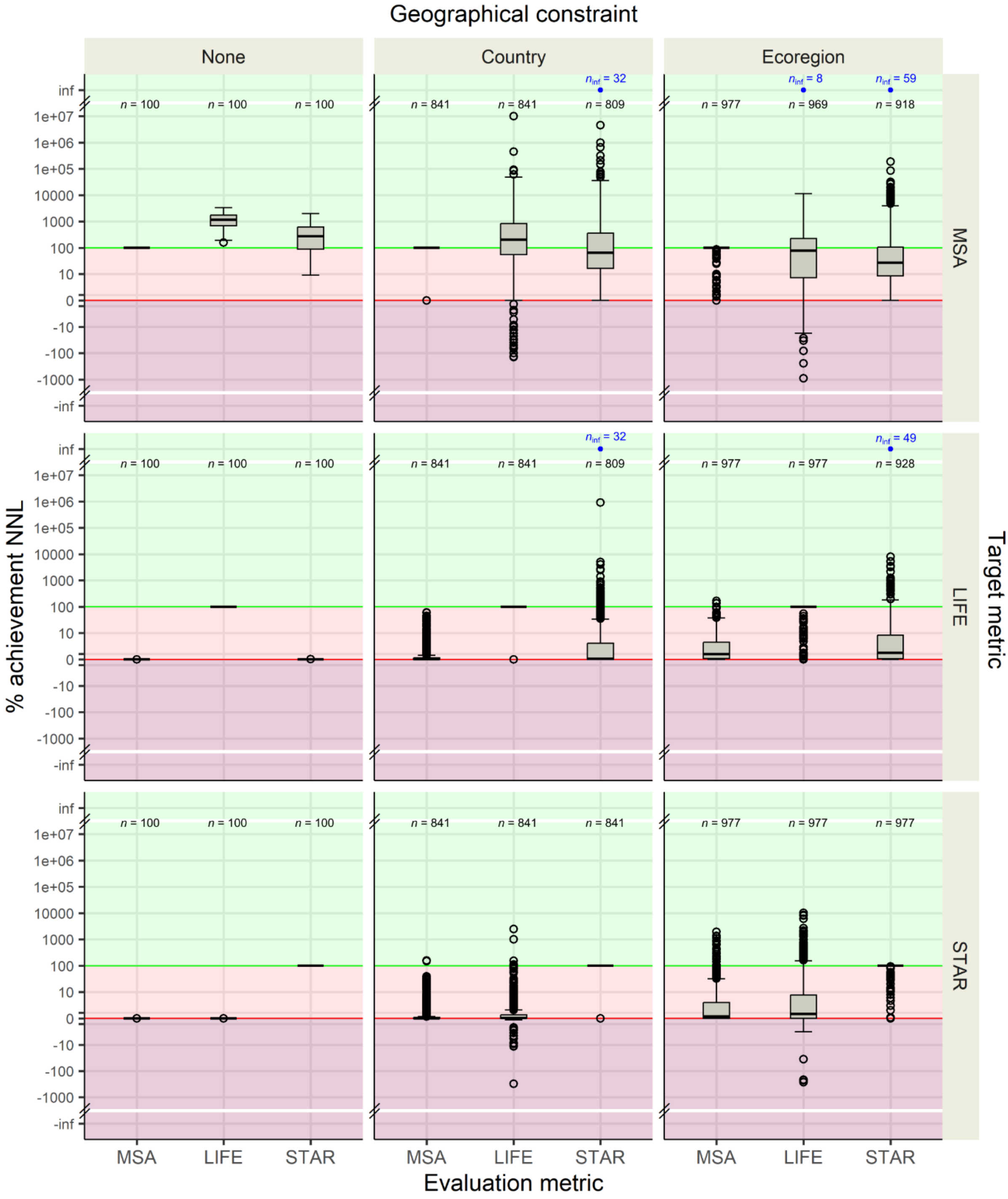

Figure S 5. Percentage achievement of NNL expressed per evaluation metric, depending on the target metric and geographical constraint, for 100 batches of 10 losses. See Main Text for detailed legend.

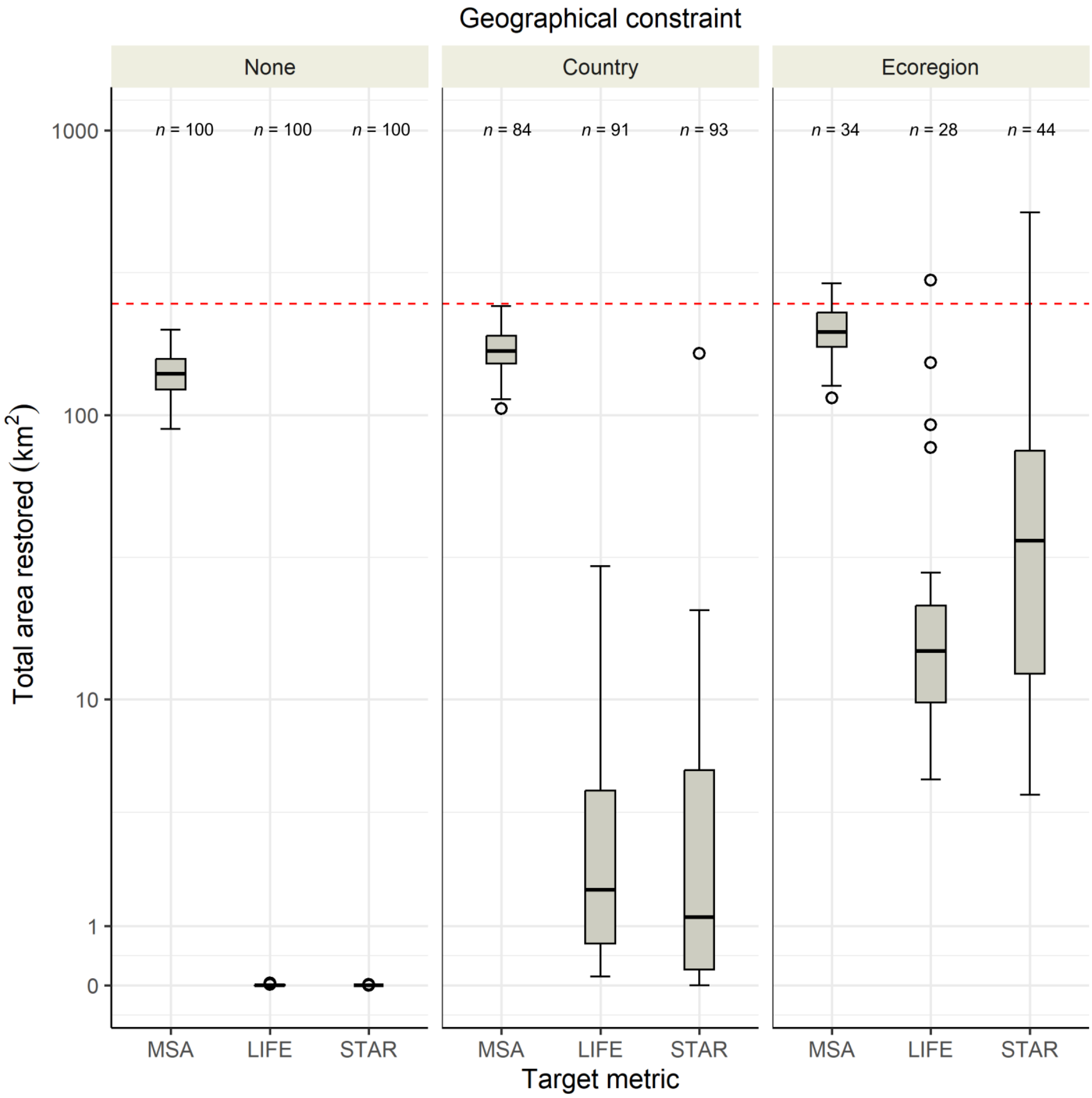

Figure S 6. Total area restored per batch, target metric and geographical constraint, for 100 batches of 10 losses, in the cases where NNL is consistently 100 % achieved within the batch (with the relevant grouping from the constraint). See Main Text for detailed legend.

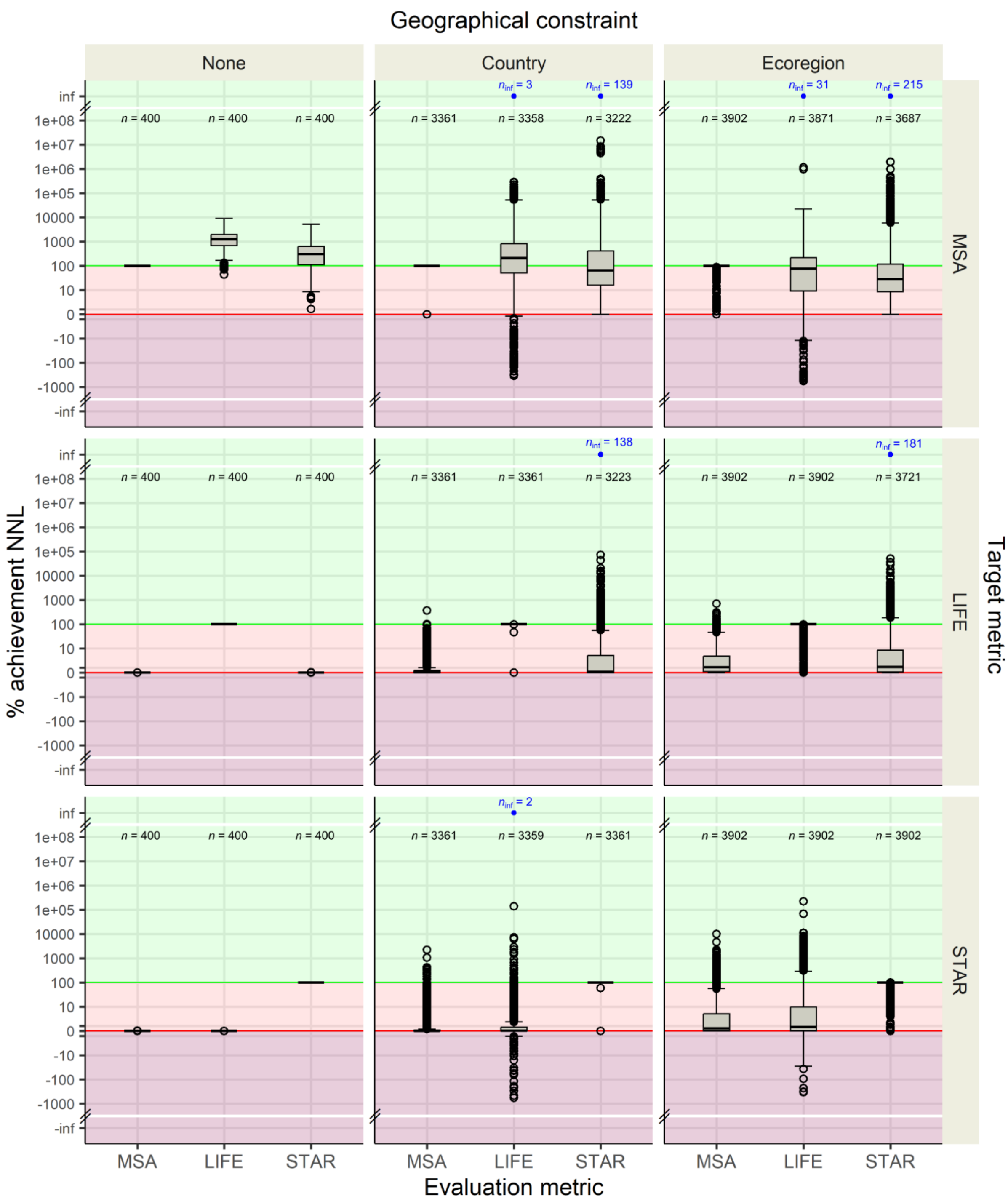

Figure S 7. Percentage achievement of NNL expressed per evaluation metric, depending on the target metric and geographical constraint, for 400 batches of 10 losses. See Main Text for detailed legend.

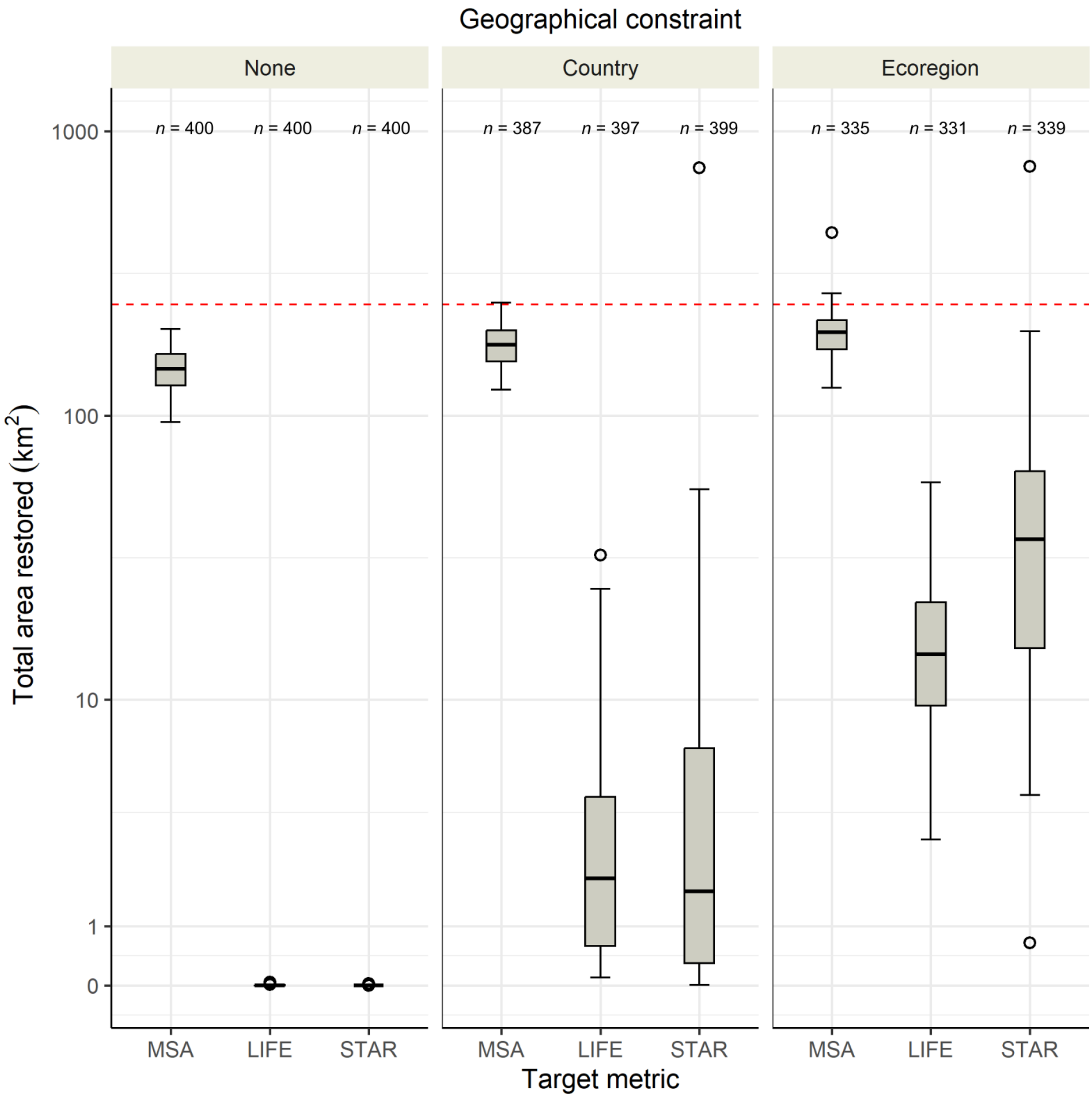

Figure S 8. Total area restored per batch, target metric and geographical constraint, for 400 batches of 10 losses, in the cases where NNL is consistently 100 % achieved within the batch (with the relevant grouping from the constraint). See Main Text for detailed legend.

2.3. Countries and ecoregions where NNL is not achieved

Table S 2. List of countries and ecoregions for which there is 0 % achievement of NNL for the target metric in Error! Reference source not found.**.**

	Geographical constraint	
	Country	Ecoregion
Common across metrics	Greenland (Den.)	Arctic coastal tundra; Arctic foothills tundra; Brooks-British Range tundra; Canadian High Arctic tundra; Canadian Low Arctic tundra; Canadian Middle Arctic Tundra; Davis Highlands tundra; Eastern Canadian Shield taiga; Northern Canadian Shield taiga; Northwest Territories taiga; Russian Arctic desert; Torngat Mountain tundra
Unique to LIFE – situations where there is insufficient potential gain		Alaska Peninsula montane taiga; Beringia lowland tundra; Central Ranges xeric scrub; Cherskii-Kolyma mountain tundra; Chukchi Peninsula tundra; Gibson desert; Northeast Siberian coastal tundra; Northern Pacific Alaskan coastal forests; Ogilvie-MacKenzie alpine tundra; Pacific Coastal Mountain icefields and tundra; Yamal-Gydan tundra

Table S 3. List of countries and ecoregions for which there is strictly between 0 and 100 % achievement of NNL for the target metric in Figure 2.

	Geographical constraint	
	Country	Ecoregion
Common across metrics		Carnarvon xeric shrublands; East Arabian fog shrublands and sand desert; Great Sandy-Tanami desert; Kola Peninsula tundra; Muskwa-Slave Lake taiga; Southern Hudson Bay taiga; Taimyr-Central Siberian tundra; Tibesti-Jebel Uweinat montane xeric woodlands
Common to MSA and LIFE		Alaska-St. Elias Range tundra; Northwest Russian-Novaya Zemlya tundra; West Saharan montane xeric woodlands
Common to MSA and STAR	São Tomé and Príncipe	Alaska Peninsula montane taiga; Beringia lowland tundra; Central Ranges xeric scrub; Chukchi Peninsula tundra; Gibson desert; Mentawai Islands rain forests; Midwest Canadian Shield forests; Northeast Siberian coastal tundra; Northern Pacific Alaskan coastal forests; Ogilvie-MacKenzie alpine tundra; Pacific Coastal Mountain icefields and tundra; São Tomé, Príncipe, and Annobón forests; Yamal-Gydan tundra
Common to LIFE and STAR		Carpentaria tropical savanna; Mitchell Grass Downs; Western Australian Mulga shrublands
Unique to MSA	Bahamas, The	Atacama desert; Cherskii-Kolyma mountain tundra; Solimões-Japurá moist forests
Unique to LIFE		Interior Alaska-Yukon lowland taiga; Kamchatka tundra; Khangai Mountains alpine meadow; Northeast Siberian taiga; Pilbara shrublands; Russian Bering tundra; Trans-Baikal Bald Mountain tundra
Unique to STAR		Canterbury-Otago tussock grasslands; Kimberly tropical savanna; New Zealand South Island montane grasslands; Simpson desert; Southern Andean steppe; Victoria Plains tropical savanna; Watson Highlands taiga; West Sahara desert

3. Supplementary Material 3 – Supporting information for the discussion of the results

3.1. Distribution of potential gain values across metrics

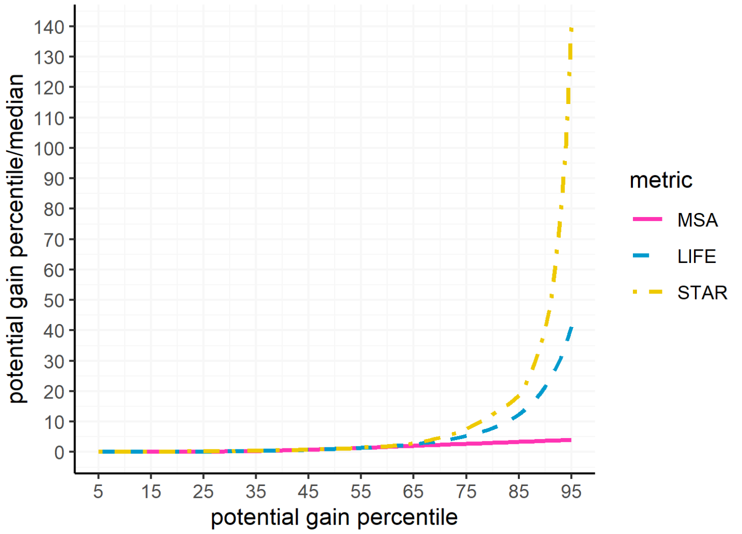

Figure S 9. Distribution of potential gain percentiles (5th to 95th) compared to the median, for the three target metrics, for all cells where the restorable proportion of the cell is >0.

3.2. Number of high potential gain (>85th percentile) cells in each country and ecoregion

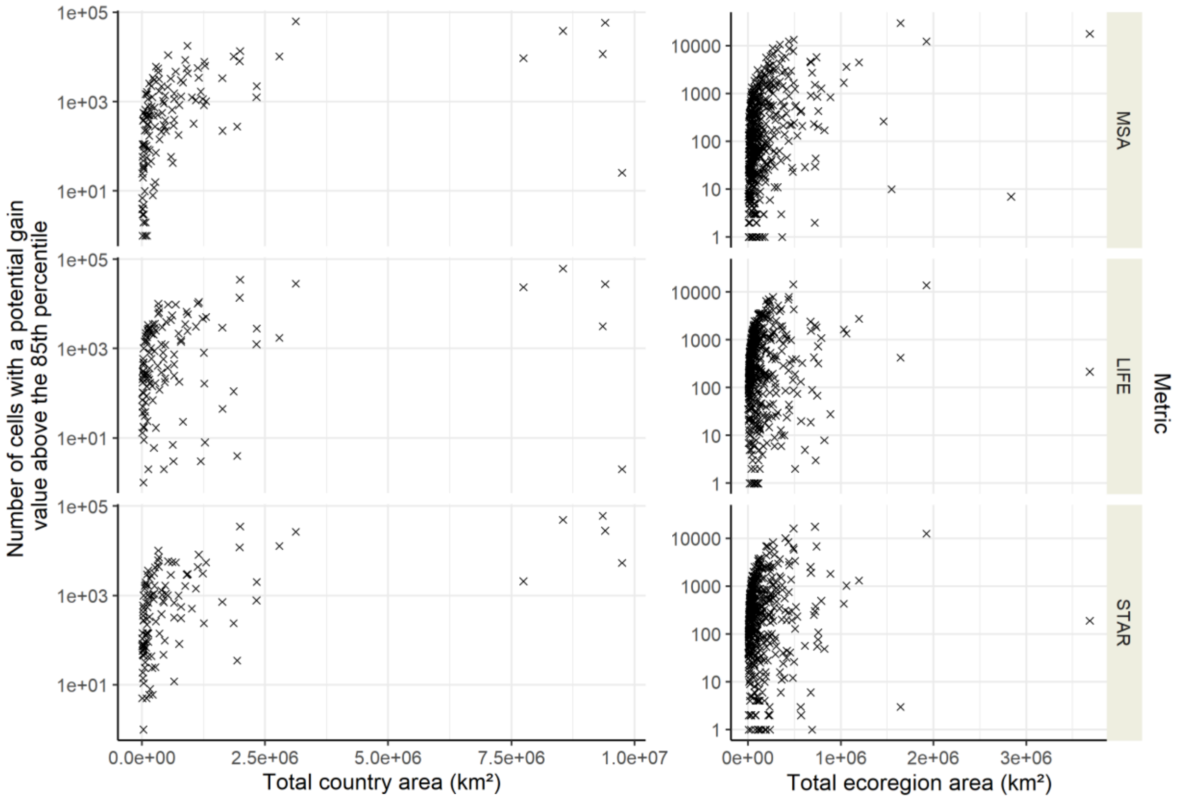

Figure S 10. Number of cells with a potential gain value above the 85th percentile per metric, in each country and ecoregion, as a function of the total country (left) or ecoregion (right) area. The minimum, maximum and median areas for countries (respectively ecoregions) are: 24.6 km², 1.67×10^7 km² and 7.38×10^4 km² (respectively 24.6 km², 3.91×10^6 km² and 6.69×10^4 km²). These are calculated based on the rasterised country and ecoregion maps (where each cell is attributed to a unique country and ecoregion); they are therefore an approximation.

3.3. Main limitations of MSA, LIFE and STAR

All three metrics inherit to a degree the limitations of the underlying spatial data they require, such as habitat or land-cover maps; these are not detailed here. MSA as calculated using the GLOBIO model is based on primary empirical data of species assemblages in disturbed and corresponding reference conditions, which are used to derive relationships between pressures and biodiversity outcomes (Alkemade et al., 2009; Hawkins et al., 2023; Schipper et al., 2020). It also currently only accounts for a subset of pressures biodiversity undergoes, ignoring potentially synergistic effects (Hawkins et al., 2023; Schipper et al., 2020). Regarding LIFE scores, the exact shape of the curve relating species persistence to AOH loss (captured by the value of the exponent) remains unknown, and is likely different for each species. Eyres et al. provide a sensitivity analysis exploring the effect on global LIFE scores of using exponent values other than 0.25 (Eyres et al., 2024). Other such studies would be welcome. Furthermore, the LIFE framework accounts for habitat presence and absence, not its quality, which can be affected by fragmentation, connectivity, man-made disturbances, and other threats such as invasive species, harbouring the need for future work. Regarding STAR, threat data is unevenly complete, and information on the spatial distribution of the threats is also lacking (Mair et al., 2021). Global scores also do not currently account for different stages of species' life cycles (breeding/non-breeding).

4. Supplementary Material 4 – Literature cited in the Supplementary Materials

Alkemade, R., van Oorschot, M., Miles, L., Nellemann, C., Bakkenes, M., ten Brink, B., 2009. GLOBIO3: A Framework to Investigate Options for Reducing Global Terrestrial Biodiversity Loss. Ecosystems 12, 374–390. https://doi.org/10.1007/s10021-009-9229-5

Bache, S.M., Wickham, H., 2022. magrittr: A Forward-Pipe Operator for R.

Buchhorn, M., Lesiv, M., Tsendbazar, N.-E., Herold, M., Bertels, L., Smets, B., 2020. Copernicus Global Land Cover Layers—Collection 2. Remote Sensing 12, 1044. https://doi.org/10.3390/rs12061044

Butchart, S.H.M., Resit Akçakaya, H., Chanson, J., Baillie, J.E.M., Collen, B., Quader, S., Turner, W.R., Amin, R., Stuart, S.N., Hilton-Taylor, C., 2007. Improvements to the Red List Index. PLoS ONE 2, e140. https://doi.org/10.1371/journal.pone.0000140

Butchart, S.H.M., Stattersfield, A.J., Bennun, L.A., Shutes, S.M., Akçakaya, H.R., Baillie, J.E.M., Stuart, S.N., Hilton-Taylor, C., Mace, G.M., 2004. Measuring Global Trends in the Status of Biodiversity: Red List Indices for Birds. PLoS Biol 2, e383. https://doi.org/10.1371/journal.pbio.0020383

Daniel Baston, 2023. exactextractr: Fast Extraction from Raster Datasets using Polygons.

Durán, A.P., Green, J.M.H., West, C.D., Visconti, P., Burgess, N.D., Virah-Sawmy, M., Balmford, A., 2020. A practical approach to measuring the biodiversity impacts of land conversion. Methods Ecol Evol 11, 910–921. https://doi.org/10.1111/2041-210X.13427

ESA CCI, 2017. Land Cover CCI Product, User Guide Version 2.0.

Eyres, A., Ball, T., Dales, M., Swinfield, T., Arnell, A., Baisero, D., Durán, A.P., Green, J., Green, R.E., Madhavapeddy, A., Balmford, A., 2024. LIFE: A metric for quantitatively mapping the impact of land-cover change on global extinctions. https://doi.org/10.33774/coe-2023-gpn4p-v4

FAO, 2018. FAOSTAT Land domain.

Gurobi Optimization, LLC, 2024. gurobi: Gurobi Optimizer 11.0 interface.

Gurobi Optimization, LLC, 2023. Gurobi Optimizer Reference Manual.

Hanson, J.O., Schuster, R., Morrell, N., Strimas-Mackey, M., Edwards, B.P.M., Watts, M.E., Arcese, P., Bennett, J., Possingham, H.P., 2023. prioritizr: Systematic Conservation Prioritization in R.

Hawkins, F., Beatty, C.R., Brooks, T.M., Church, R., Elliott, W., Kiss, E., Macfarlane, N.B.W., Pugliesi, J., Schipper, A.M., Walsh, M., 2023. Bottom-up global biodiversity metrics needed for businesses to assess and manage their impact. Conservation Biology e14183. https://doi.org/10.1111/cobi.14183

Hijmans, R.J., 2024. terra: Spatial Data Analysis.

IUCN, 2022. Unified Classification of Direct Threats.

Jung, M., 2020. A layer of global potential habitats. https://doi.org/10.5281/ZENODO.4038749

Jung, M., Dahal, P.R., Butchart, S.H.M., Donald, P.F., De Lamo, X., Lesiv, M., Kapos, V., Rondinini, C., Visconti, P., 2020. A global map of terrestrial habitat types. Sci Data 7, 256. https://doi.org/10.1038/s41597-020-00599-8

Mair, L., Bennun, L.A., Brooks, T.M., Butchart, S.H.M., Bolam, F.C., Burgess, N.D., Ekstrom, J.M.M., Milner-Gulland, E.J., Hoffmann, M., Ma, K., Macfarlane, N.B.W., Raimondo, D.C., Rodrigues, A.S.L., Shen, X., Strassburg, B.B.N., Beatty, C.R., Gómez-Creutzberg, C., Iribarrem, A., Irmadhiany, M., Lacerda, E., Mattos, B.C., Parakkasi, K., Tognelli, M.F., Bennett, E.L., Bryan, C., Carbone, G., Chaudhary, A., Eiselin, M., da Fonseca, G.A.B., Galt, R., Geschke, A., Glew, L., Goedicke, R., Green, J.M.H., Gregory, R.D., Hill, S.L.L., Hole, D.G., Hughes, J., Hutton, J., Keijzer, M.P.W., Navarro, L.M., Nic Lughadha, E., Plumptre, A.J., Puydarrieux, P., Possingham, H.P., Rankovic, A., Regan, E.C., Rondinini, C., Schneck, J.D., Siikamäki, J., Sendashonga, C., Seutin, G., Sinclair, S., Skowno, A.L., Soto-Navarro, C.A., Stuart, S.N., Temple, H.J., Vallier, A., Verones, F., Viana, L.R., Watson, J., Bezeng, S., Böhm, M., Burfield, I.J., Clausnitzer, V., Clubbe, C., Cox, N.A., Freyhof, J., Gerber, L.R., Hilton-Taylor, C., Jenkins, R., Joolia, A., Joppa, L.N., Koh, L.P., Lacher, T.E., Langhammer, P.F., Long, B., Mallon, D., Pacifici, M., Polidoro, B.A., Pollock, C.M., Rivers, M.C., Roach, N.S., Rodríguez, J.P., Smart, J., Young, B.E., Hawkins, F., McGowan, P.J.K., 2021. A metric for spatially explicit contributions to science-based species targets. Nat Ecol Evol 5, 836–844. https://doi.org/10.1038/s41559-021-01432-0

Müller, K., Wickham, H., 2023. tibble: Simple Data Frames.

Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. The R Journal 10, 439. https://doi.org/10.32614/RJ-2018-009

Pebesma, E., Bivand, R., 2023. Spatial Data Science: With Applications in R, 1st ed. Chapman and Hall/CRC, New York. https://doi.org/10.1201/9780429459016

Schipper, A.M., Hilbers, J.P., Meijer, J.R., Antão, L.H., Benítez-López, A., Jonge, M.M.J., Leemans, L.H., Scheper, E., Alkemade, R., Doelman, J.C., Mylius, S., Stehfest, E., Vuuren, D.P., Zeist, W., Huijbregts, M.A.J., 2020. Projecting terrestrial biodiversity intactness with GLOBIO 4. Glob Change Biol 26, 760–771. https://doi.org/10.1111/gcb.14848

Wickham, H., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York.

Wickham, H., 2011. The Split-Apply-Combine Strategy for Data Analysis. Journal of Statistical Software 40, 1–29.

Wickham, H., François, R., Henry, L., Müller, K., Vaughan, D., 2023a. dplyr: A Grammar of Data Manipulation.

Wickham, H., Pedersen, T.L., Seidel, Dana, 2023b. scales: Scale Functions for Visualization.

Wickham, H., Vaughan, D., Girlich, M., 2024. tidyr: Tidy Messy Data.