EUROPEAN PARTNERSHIP

Remote sensing applications for biodiversity monitoring: Scales, transparency and drones

Outcomes from the BioMonWeek 2026 workshop on remote sensing applications

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1. Plan and support research and innovation on biodiversity through a shared strategy, annual joint calls for research projects and capacity building activities
2. Set up a network of harmonised schemes to improve monitoring of biodiversity and ecosystem services across Europe
3. Contribute to high-end knowledge for deploying Nature-based Solutions and valuation of biodiversity in the private sector
4. Ensure efficient science-based support for policy-making and implementation in Europe
5. Strengthen the relevance and impact of pan-European research on biodiversity in a global context.

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Executive Summary

This report summarises the BioMonWeek 2026 interactive workshop on "*Remote sensing applications for biodiversity monitoring*" that are representative, scalable and useful for policy across regions and countries. The workshop combined expert inputs, live participant polling, and "fireside chat" discussions to identify design trade-offs, practical bottlenecks and real-world experiences. Three messages recurred throughout: (i) predictive modelling depends on evaluation of predictive performance and model uncertainty, i.e. model outcomes should not be taken at face value, (ii) remote sensing offers good opportunity to improve biodiversity monitoring but lack of standards is a major constraint on integration and sustainability in the long run; and (iii) policy usefulness requires an explicit pathway from observations, model validation, including uncertainty, comparability and a clear link to policy.

The participants represented multiple countries and biogeographic regions and brought research, monitoring and data management perspectives. Polling outcomes and "fireside chat" discussions highlighted that predictive accuracy is highly dependent on the scale at which a model is developed and applied. Mismatches between the scale of model development and the scale of application can substantially reduce performance and confidence in results.

Using concrete examples from national monitoring programmes in Sweden and Finland, the workshop illustrated both the opportunities and limitations of remote sensing for biodiversity monitoring and policy use. The report concludes with key discussion points and recommendations for future actions in the use of remote-sensing for biodiversity monitoring, including activities to improve validation practices, harmonisation of drone usage, and the development of policy-relevant monitoring pathways.

1. Background: Remote sensing applications and monitoring design challenges

Effective biodiversity monitoring is essential for informing environmental policy, supporting international reporting commitments, and guiding conservation and restoration efforts. At European and global levels, policymakers increasingly require monitoring systems that are scalable, comparable across regions, and capable of detecting change over time [1]. Despite this need, biodiversity monitoring remains fragmented, with substantial variation in methods, indicators, governance structures, and data availability across countries [2, 3].

Remote sensing has emerged as a critical tool for addressing some of these gaps. Satellite, airborne, and drone-based observations provide spatially consistent, repeatable data that complement field-based monitoring [4, 5, 6, 7]. When integrated with in-situ data (i.e. rubber boot collected data), remote sensing supports model-based indicators that enable large-scale assessments of habitat extent, condition, and change, helping to bridge spatial and temporal gaps in monitoring coverage [8, 9]. At the same time, predictive performance depends strongly on data quality, validation, and modelling choices, making transparency around uncertainty and fit-for-purpose use essential particularly in policy contexts.

However, the use of remote sensing and predictive modelling also raises important policy-relevant considerations. Model outputs depend strongly on data quality, validation strategies, and modelling choices, and their suitability varies across different use cases. While such models can be valuable for exploratory analyses, trend monitoring, and large-scale reporting, they may be less appropriate for fine-scale management decisions or regulatory applications if limitations and uncertainty are not clearly communicated [10, 11, 12].

Beyond technical issues, biodiversity monitoring design involves key governance challenges, including coordination across organisational levels, harmonisation of data outputs, and translation of monitoring results into formats usable by decision-makers. Addressing these issues requires transparent workflows, shared understanding of uncertainty, and closer dialogue between scientists, monitoring practitioners, and policymakers to ensure that remote-sensing-based approaches effectively support evidence-based policy [13, 14]. To foster this dialogue, an interactive workshop on "*Remote sensing applications for biodiversity monitoring*" was held at the European conference for biodiversity monitoring BioMonWeek 2026, which is summarised in this report.

2. Workshop overview and outcomes

The workshop "*Remote sensing application for biodiversity monitoring*" that was held at the European conference for biodiversity monitoring BioMonWeek 2026 in Montpellier aimed to explore how remote sensing and predictive modelling can support biodiversity monitoring. Particular focus was given to model performance, validation, scale, and fitness for policy-relevant use cases. A key objective was to foster open discussion on both the potential and limitations of current approaches, including the responsible use of model-based indicators and "imperfect" models in monitoring and decision-making contexts.

The workshop combined three thematic presentations with interactive Mentimeter polls and a fireside chat discussion. This format encouraged exchange across technical, operational, and policy perspectives, and facilitated discussion on challenges related to prediction accuracy, data quality, sampling design, and the integration of satellite and drone data across spatial scales.

Though a relatively small number of participants (ca. 13), the participants came from a broad mix of countries and organisations. Participants included researchers, monitoring practitioners from research institutes and national agencies (Figure 1), spanning multiple European biogeographic regions (Figure 2a), bringing expertise in field-based monitoring, remote sensing, modelling, and biodiversity assessment with a wide background in remote sensing applications (Figure 2b). This diversity supported balanced discussions on methodological advances, operational feasibility, and policy implications.

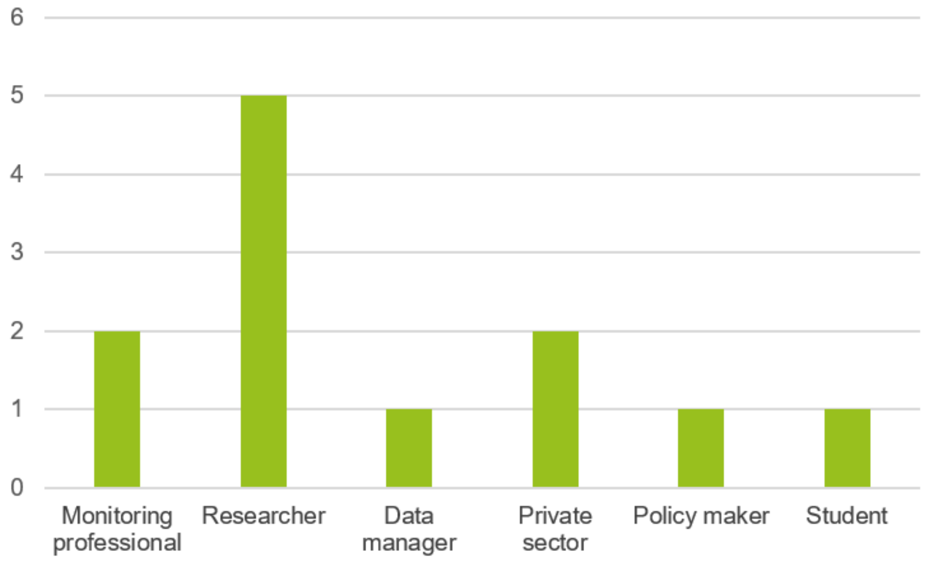


Figure 1. Participant professional backgrounds, multiple choice. Source: BioMonWeek 2026 workshop (*Mentimeter)* [16].

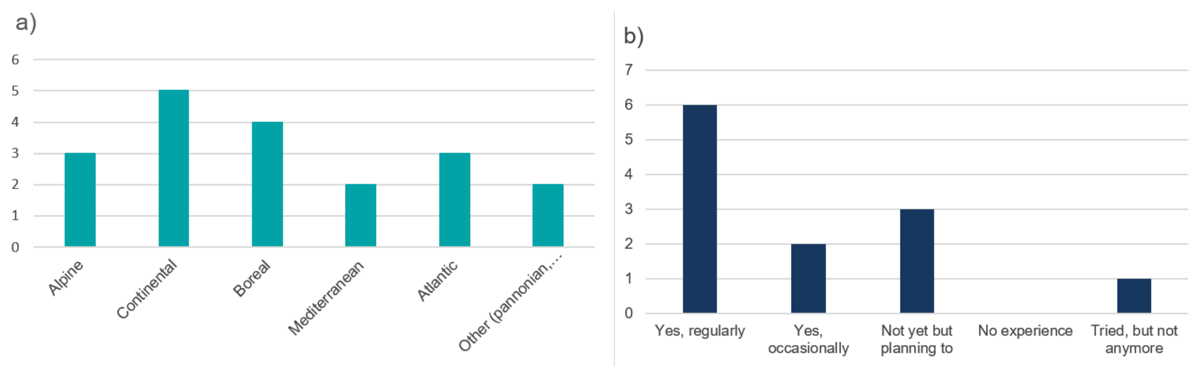


Figure 2 . (a) The distribution of biogeographic regions among the participants and (b) participants experience using remote sensing approaches. Source: BioMonWeek 2026 workshop (*Mentimeter) [16].*

2.1. Predictive model: performance evaluation is essential

A central point of the first presentation (Appendix 1) was that predictive models based on remote sensing are widely used and increasingly influential, but their performance varies strongly depending on scale, data availability, and modelling choices. Weak model performance, particularly when not transparently reported, limits the suitability of model outputs for policy use. This is especially problematic for fine-scale decision-making, where inaccurate, poorly validated models, or models designed for a larger scale may lead to misleading conclusions [10,12]. A recurring concern was the lack of methodological transparency in many modelling studies, which makes it difficult for non-experts, including policymakers, to assess the reliability and appropriate use of model outputs.

A key message was that structured cross-validation approaches are essential, as they can explicitly simulate interpolation and extrapolation scenarios and provide more realistic estimates of predictive performance. The presentation also emphasized that not all model structures are equally suited for predictive purposes; models developed for explanatory analysis often perform poorly when used for prediction, underscoring the need to clearly distinguish between explanatory and predictive objectives.

The presentation further pointed out that data gaps and heterogeneity across datasets remain major challenges for biodiversity modelling. Incomplete coverage, varying data quality, and inconsistencies between datasets,including so-called “meta-datasets” (i.e. the description of the data and/or model) limit both model reliability and transferability. Addressing these issues will require more organised and standardised data collection frameworks that are fit for the question and scale addressed. For optimal performance of model outputs, designing models thus includes designing data collection. Particularly if model-based approaches are to be used for monitoring biodiversity metrics for policy use at various national, European, or global scales. Overall, this presentation underlined that improving predictive performance is not only a technical exercise, but also a prerequisite for responsible and transparent use of models in policy-relevant biodiversity monitoring.

2.2. Upscaling habitat monitoring: opportunities & challenges

The second presentation (Appendix 2) addressed the challenge of upscaling field-based habitat inventories to wall-to-wall habitat maps using remote sensing. It highlighted the increasing availability of Earth observation data, including high-resolution aerial imagery, airborne LiDAR, and multiple satellite sensors, which together offer strong potential for large-scale biodiversity monitoring, which was exemplified with experiences from Finland, where large scale monitoring is not established yet.

Machine-learning and deep-learning approaches were presented as effective tools for integrating heterogeneous field observations with multi-dimensional remote-sensing data [10]. However, their performance depends heavily on access to large and representative training datasets. In this context, drones were highlighted as a valuable option for complementing traditional field data. High-resolution drone data could be used to up-scale the limited field data which would enable larger training sets for the large-scale remote sensing methodsIdeally the drone data would be collected in close temporal alignment with field surveys.

From a policy-relevant perspective, the main limitations identified were not only the availability of training data or practical technical solutions, but also the lack of clear and harmonised protocols for connecting the sampling design, data, and modelling workflows. Without such frameworks, there is a risk that modelled habitat type maps and quality attributes lack consistency and reliability across regions and scales. The presentation emphasised that verification against field data remains essential to ensure data quality and suitability for use in monitoring and decision-making contexts.

2.3. From remote sensing outputs to policy-relevant indicators

The presentation focused on the challenge of linking spatial scales in vegetation monitoring by combining satellite and drone data to improve monitoring performance (Appendix 3). In current field-sampling programmes, species and vegetation data are collected in plots ranging from 0.25 to 1 000 m², which can limit the ability to capture spatial heterogeneity and broader vegetation structure.

The presentation demonstrated how Sentinel-2 data are increasingly used in monitoring frameworks, particularly for large-scale and repeated observations, but noted that additional spatial detail is often needed to support calibration and interpretation. In this context, drones were highlighted as an effective tool to enhance sampling by extending spatial coverage around field plots and providing very high-resolution information on vegetation structure.

Examples from coastal dune systems and the alpine regions showed how drone imagery enables highly detailed segmentation of functional plant groups, such as dwarf shrubs, creating “near-ground truth” datasets to work as labelling of coarse resolution data. Such data can improve understanding of fine-scale dynamics and provide valuable reference information for larger-scale assessments [15].

From a policy-relevant perspective, the presentation emphasised that drone data can play a key role in providing high-quality ground-truth and calibration data for satellite-based vegetation models, as well as for drone-based deep-learning approaches. Designing for and strengthening the connection between plot-based observations, drone surveys, and satellite monitoring was identified as essential for improving consistency, representativeness, and confidence in multi-scale monitoring outputs used for policy relevant indicators and decision-making.

2.4. Fireside chat discussion: key challenges & lessons learned

The fireside chat discussion focused on challenges related to prediction accuracy, model validation, data scale, and the combined use of drone and satellite imagery in ecological modelling. Building on the Mentimeter responses and presentations, the discussion highlighted several interlinked issues that affect the credibility and policy relevance of model-based biodiversity indicators.

A central theme was prediction accuracy and model validation. Participants stressed that the scale at which models are validated must match the scale at which results are applied. Many models are trained and validated using local or plot-level data, yet their outputs are later interpreted at national or European scales. This scale mismatch introduces uncertainty that is rarely communicated clearly. It was also noted that models cannot be expected to achieve unrealistic levels of accuracy when human observers themselves cannot reliably distinguish certain ecological features. Reported near-perfect model performance was therefore viewed with caution, often indicating potential overfitting, which remains under-reported and insufficiently scrutinised in scientific publications.

Closely related was the issue of data quality and sampling bias. Participants emphasised that a model is only as reliable as the data used to train it. Field data often reflect accessibility rather than ecological representativeness, for example, sampling locations near roads might introduce systematic bias. The importance of truly independent training and validation datasets was repeatedly highlighted, along with the sober recognition that completely unbiased validation is often not realistic. Participants also acknowledged that complete spatial coverage is rarely feasible or even necessary if sampling is well designed.

Spatial modelling and scale emerged as another key challenge. There is a strong need for modelling at finer spatial scales (e.g. within valleys or specific habitat types), yet results are frequently aggregated or extrapolated far beyond their original scope, significantly lowering model predictive power and accuracy. Policy-makers typically see only final products and may not be fully aware of underlying data sources, assumptions, or limitations, reinforcing the need for transparency.

The discussion also addressed the role of drones and remote sensing. Drone-based data are still less explored than satellite data but offer significant potential, particularly for high-resolution mapping, training data collection, and calibration of coarser resolution data , such as satellite and aerial imagery. Comparing drones and satellites directly was considered unhelpful, as they serve fundamentally different purposes. Participants noted emerging tools such as PlantNet for species identification and discussed the potential of multispectral drones for species distribution modelling, while stressing the need for standards and validation.

Finally, temporal factors were highlighted. Seasonal timing and time of day strongly influence remote-sensing outputs, however these factors are often not or under-accounted for in modelling workflows. Species-level identification, including tree species, remains challenging across biomes, though techniques such as class weighting in deep-learning models were noted as promising ways to address class imbalance.

Overall, the fireside chat discussion emphasized that improving biodiversity modelling is not only a technical challenge, but also a matter of scale awareness, transparency, validation, and communication, particularly when models are used to inform monitoring and policy decisions.

3. Discussion and future recommendations

The workshop discussions highlighted that advances in remote sensing and modelling have outpaced the development of shared standards, validation practices, and guidance on fitness-for-purpose use, particularly in policy-relevant biodiversity monitoring. While predictive models and Earth observation data offer strong potential to address spatial and temporal gaps in monitoring, their reliability remains highly dependent on data quality, model design, and scale alignment.

A recurring concern was prediction accuracy and overfitting. Participants noted that unrealistic model performance often reflects overfitting rather than ecological reality, however overfitting is rarely documented or systematically assessed. Future modelling efforts should adopt structured cross-validation strategies, clearly separate training and validation data, and explicitly report limitations and uncertainty. Distinguishing between explanatory and predictive modelling objectives should become standard practice, especially when outputs are intended for policy use.

The discussions also highlighted persistent scale mismatches, where locally collected field or drone data are used to inform regional or continental models. Validation and application scales must be aligned, and modelling approaches should be designed with explicit consideration of representativeness across scales.

Regarding drones, participants recognised their growing role in high-resolution monitoring and calibration of satellite-based models but highlighted the absence of standards for drone data collection, including sensor choice, flight design, temporal alignment with field surveys, and processing workflows. Developing harmonised drone standards, this should be ideally coordinated across initiatives, which was identified as a priority to ensure consistency and reproducibility.

Overall, future monitoring frameworks should prioritise transparent workflows, harmonised and standardised data collection, and closer collaboration between field ecologists, remote sensing specialists, and policymakers. Strengthening these elements will be essential for ensuring that model-based indicators are credible, interpretable, and suitable for decision making.

3.1. Recommended next steps

Based on the workshop discussions and participant feedback, several next steps can be identified to strengthen the use of remote sensing and modelling in biodiversity monitoring:

1) **Strengthen validation and reporting practices**

   Validation emerged as a critical bottleneck. Future efforts should prioritise structured validation strategies that match the scale of application, ensure clear separation of training and validation data, and explicitly assess risks of overfitting. Scientific journals, projects, and monitoring programmes should encourage transparent reporting of uncertainty, limitations, and model robustness.

2) **Clarify fit-for-purpose modelling approaches**

   Modelling approaches should be selected based on intended use cases (e.g. exploratory analysis, trend monitoring, policy reporting), with a clear distinction between explanatory and predictive models. Unrealistic model performance expectations should be avoided, we should recognize that models cannot exceed the reliability of the underlying data.

3) **Develop harmonised standards for drone data collection**

   While drones offer strong potential for high-resolution monitoring and calibration of satellite-based models, there is a clear need for defined standards including sensor selection, flight design, temporal alignment with field sampling, and processing workflows. Coordination of emerging initiatives in this area should be supported.

4) **Improve integration across scales and data sources**

   Monitoring frameworks should better link plot-based field data, drone imagery, and satellite observations, ensuring representativeness across scales and reducing biases related to sampling design and accessibility.

5) **Enhance communication with policy users**

   Clearer communication of data sources, assumptions, and limitations is needed so that policymakers can interpret results appropriately and use outputs with confidence.

3.2. Topics suggested for future workshops

Finishing the workshop, participants were asked to rank their interest in continuing discussions topics. They prioritised remote sensing and modelling and validation (Figure 3) as key areas for further exchange. In addition, participants expressed a strong interest in more open and in-depth discussion on topics that revolve around using drones and translation from research to policy. This feedback indicates a clear demand for deeper, more focused workshops, particularly on validation, methodological standards, and the science-policy interface.

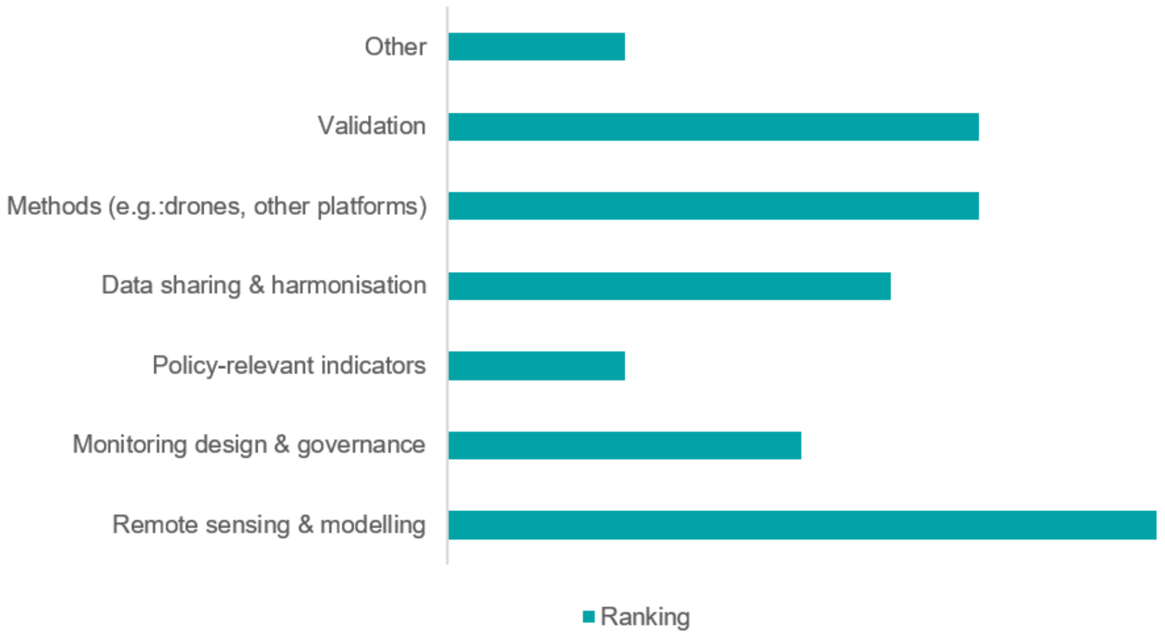


Figure 3. Topics prioritised by participants for future remote sensing workshops Source: BioMonWeek 2026 workshop (Mentimeter) [16]

3.3. Main take-home messages

The key messages participants took from the workshop were that modelling is challenging but holds promise, provided limitations are acknowledged; measurement noise and uncertainty must be accounted for; independent validation remains insufficient; and human expertise is still essential in biodiversity monitoring. Overall, the workshop highlighted cautious optimism: progress is possible, but only through transparency, standardisation, and collaboration.

4. References

[1] Moersberger, H., Valdez, J., Martin, J. G. C., Junker, J., Georgieva, I., Bauer, S., Beja, P., Breeze, T. D., Fernandez, M., Fernández, N., Brotons, L., Jandt, U., Bruelheide, H., Kissling, W. D., Langer, C., Liquete, C., Lumbierres, M., Solheim, A. L., Maes, J., … Bonn, A. (2024). Biodiversity monitoring in Europe: user and policy needs. *Conservation Letters*, 17, e13038. URL: https://doi.org/10.1111/conl.13038

[2] EuropaBON (2023). The future of biodiversity monitoring in Europe: Increasing the policy impact and effectiveness of biodiversity monitoring in Europe: current state and gaps. IIASA Policy Brief #37. URL: https://iiasa.ac.at/sites/default/files/2023-03/PB37_Biodiversity_WEBnew.pdf

[3] Santana, J. et al. (2025). Large biodiversity monitoring gaps remain across Europe. *Conservation Letters*. URL: https://conbio.onlinelibrary.wiley.com/doi/pdf/10.1111/conl.13134

[4] Pettorelli, N. et al. (2014) Satellite remote sensing for applied ecologists: opportunities and challenges. *Journal of Applied Ecology*, 51, 839–848. URL: https://doi.org/10.1111/1365-2664.12261

[5] Luque, S; Pettorelli, N; Vihervaara, P; Wegmann, M; (2018) Improving biodiversity monitoring using satellite remote sensing to provide solutions towards the 2020 conservation targets. *Methods in Ecology and Evolution*, 9 (8) pp. 1784-1786. 10.URL: https://besjournals.onlinelibrary.wiley.com/doi/10.1111/2041-210X.13057

[6] Reddy, C.S. Remote sensing of biodiversity: what to measure and monitor from space to species?. Biodivers Conserv 30, 2617–2631 (2021). https://doi.org/10.1007/s10531-021-02216-5

[7] Nature (2026). Building the backbone for Europe's biodiversity monitoring. *Nature* (Roadmap article). https://www.nature.com/articles/s44358-026-00140-6

[8] Platel, A; Sandino, J; Shaw, J; Bollard, B; Gonzalez, F; (2025) Advancing Sparse Vegetation Monitoring in the Arctic and Antarctic: A Review of Satellite and UAV Remote Sensing, Machine Learning, and Sensor Fusion. *Remote Sensing*, 17 (9) p. 1513. URL: https://www.mdpi.com/2072-4292/17/9/1513

[9] Spake, R., O'Dea, R.E., Nakagawa, S. et al. Improving quantitative synthesis to achieve generality in ecology. *Nat Ecol Evol* 6, 1818–1828 (2022). https://doi.org/10.1038/s41559-022-01891-z

[10] Andermann, T., Häggmark, J., Olsson, P., Högström, A., 2024. Deep learning segmentation model produces accurate biodiversity predictions at 10 m spatial resolution. https://doi.org/10.21203/rs.3.rs-4734879/v1

[11] Gamon, J. A., Wang, R., Gholizadeh, H., Zutta, B., Townsend, P. A., & Cavender-Bares, J. (2020). Consideration of scale in remote sensing of biodiversity. *Remote sensing of plant biodiversity*, 425-447. Available at: https://link.springer.com/chapter/10.1007/978-3-030-33157-3_16

[12] Koldasbayeva, D., Tregubova, P., Gasanov, M. et al. Challenges in data-driven geospatial modeling for environmental research and practice. *Nat Commun* 15, 10700 (2024). https://doi.org/10.1038/s41467-024-55240-8

[13] Lipsanen, A. et al. (2026). Strategic Biodiversity Monitoring Governance Document (Phase III): Recommendations towards harmonised biodiversity monitoring on transnational and national scales across Europe. Biodiversa+ report. https://www.biodiversa.eu/wp-content/uploads/2026/04/D2.21_Strategic-biodiversity-monitoring-governance-Phase-III-report.pdf

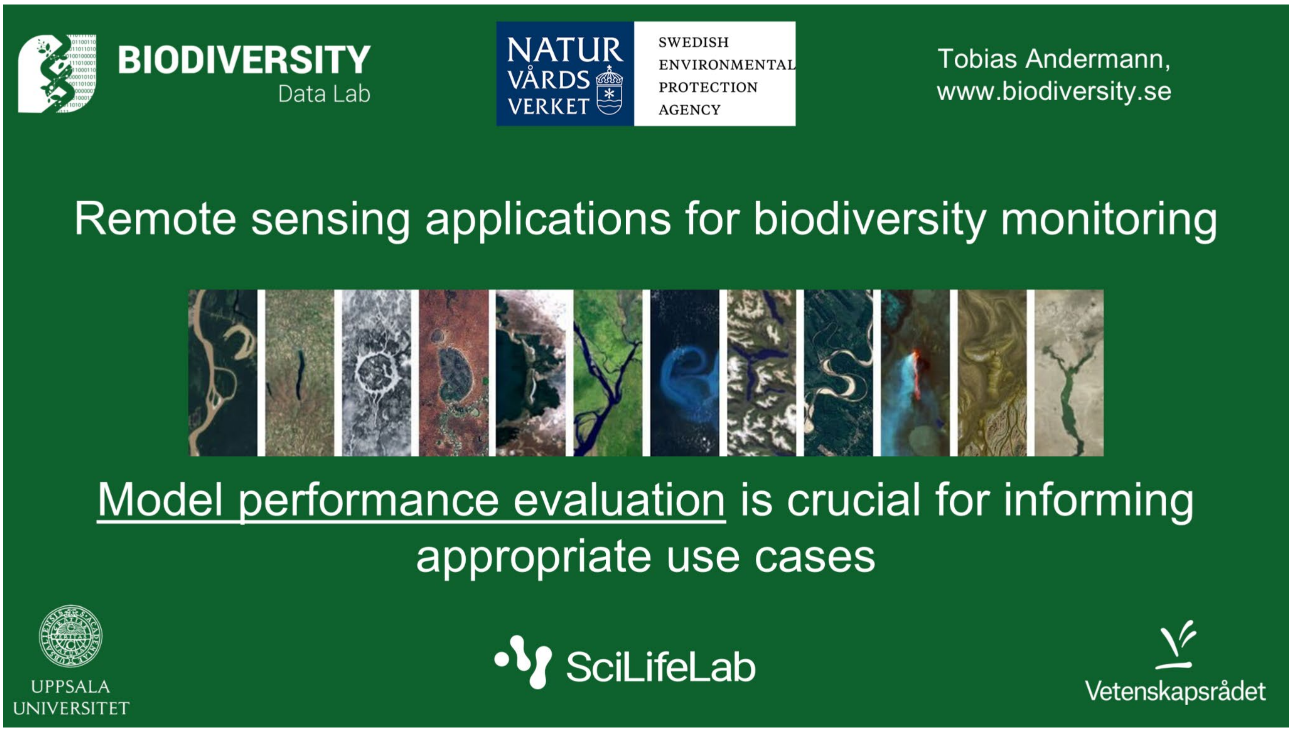
[14] Silva del Pozo, M., Body, G., Rerig, G., Basille, M. (2023). Guide on harmonising biodiversity monitoring protocols across scales. Biodiversa+ report. https://www.biodiversa.eu/wp-content/uploads/2023/10/Biodiversa_Harmonising-monitoring-protocols.pdf

[15] Cronvall, E., Adler, S., Sandström, P., Skarin, A. Quantifying winter forage resources for reindeer: Developing a method to estimate ground lichen cover and biomass at a local scale. *Trees, Forests and People* 19, 100768 (2025). https://doi.org/10.1016/j.tfp.2024.100768

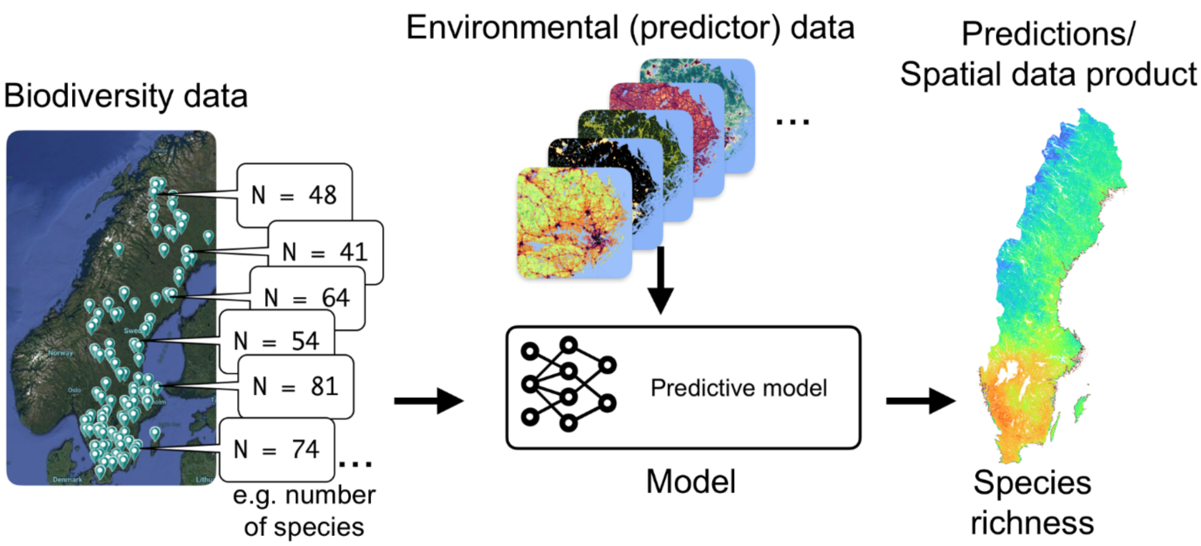
[16] Workshop organisers (2026). Participant responses and Mentimeter outputs from BioMonWeek 2026 workshop 'Remote sensing applications for biodiversity monitoring: Scales, transparency and drones'

Appendix 1: Model performance evaluation is crucial for informing appropriate use cases

Presentation by Tobias Andermann, BioMonWeek 2026 workshop "Remote sensing applications for biodiversity monitoring"



How to build a predictive biodiversity model



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Any model can produce a map, but to what degree can we trust it?

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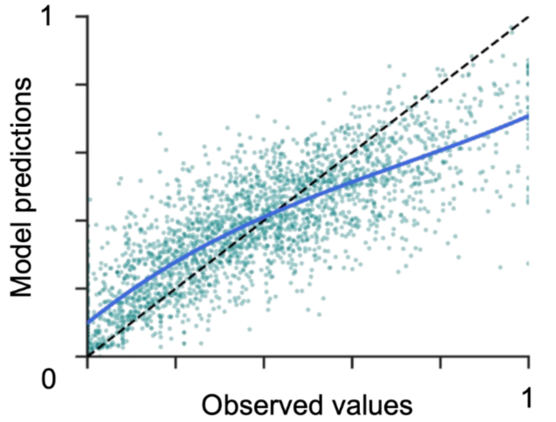
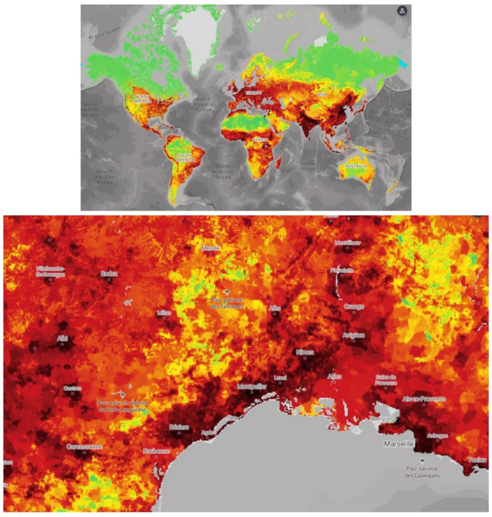
Predictive performance metrics

- Pearson correlation coefficient (**r**)
  - Linear association between predicted and observed values
- Spearman rank correlation (**ρ**)
  - Rank-based
- Mean Absolute Error (**MAE**)
  - Absolute differences
- Mean Absolute Percentage Error (**MAPE**)
  - Relative differences

Should be based on **<u>independent</u>** test data



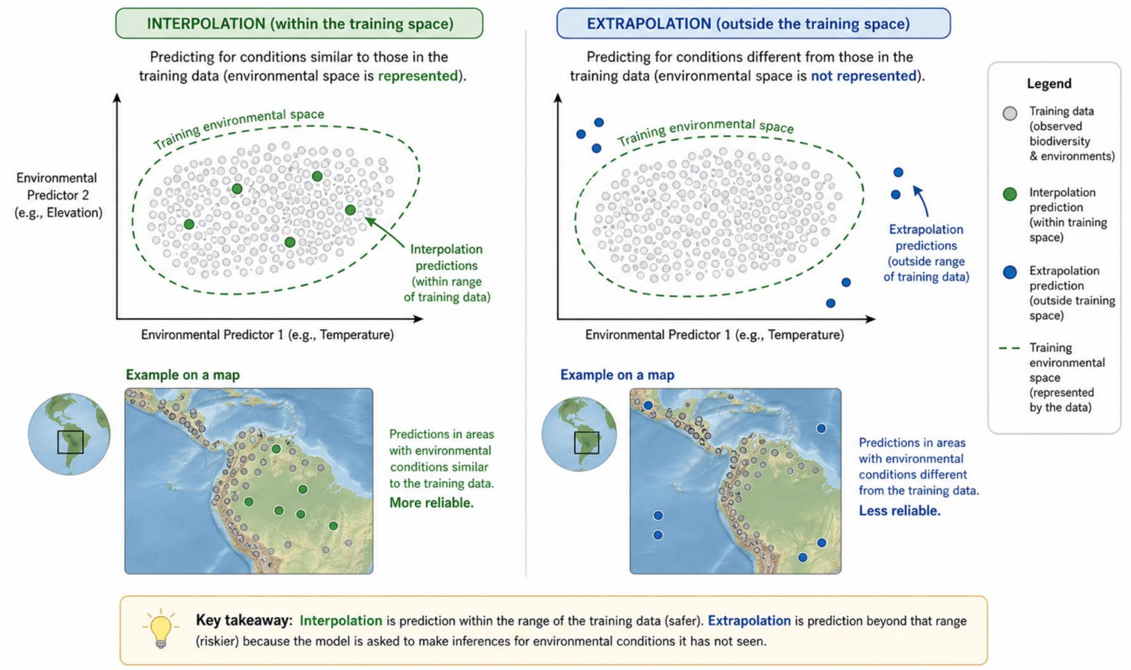
Predictive performance evaluation is essential when using model for predictions



The **Biodiversity Intactness Index (BII)**, predicted globally at 1km resolution (Newbold et al., 2015, ***Nature***)

- Model has not been tested for predictive performance, but is often used to produce spatially explicit maps
  - Recommended as model-based indicator for reporting/monitoring by CBD and IPBES

PREDICTS: Training data, 817 studies comprising 35,736 sampling sites in 101 countries (meta-database)



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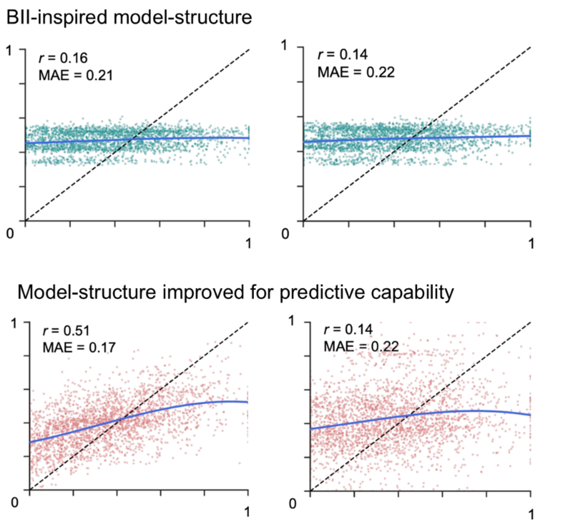
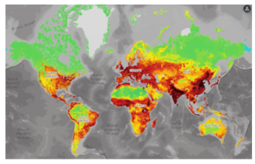
Models need to be fit for purpose



Nyström et al. 2025, preprint, https://doi.org/10.32942/X2507T



Biodiversity Intactness Index (BII)

- Structured cross-validation approaches can simulate interpolation/extrapolation
- Not every model structure is optimal for predictive tasks (explanatory vs. predictive)
- Data gaps and heterogeneity of datasets remains challenge for modeling (metadatasets)
- We need more organized and standardized data collection to model most biodiversity metrics globally

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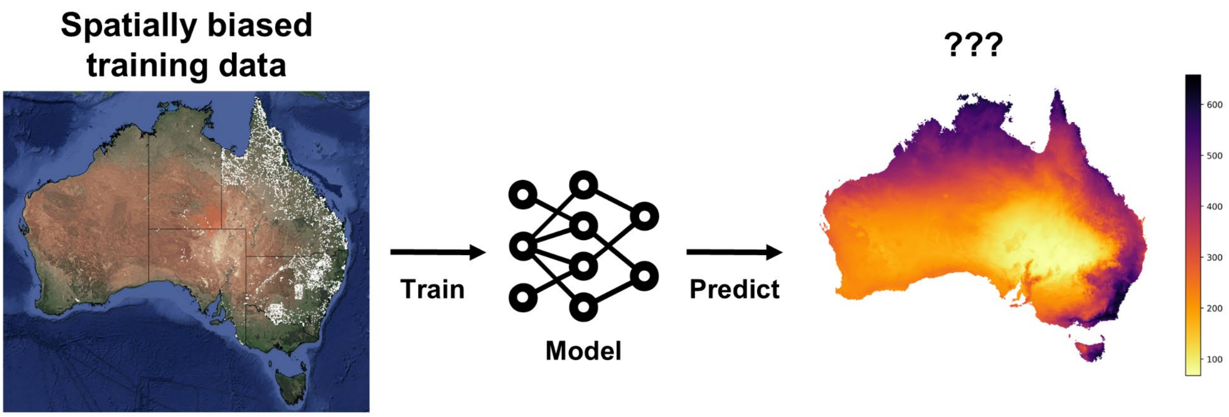
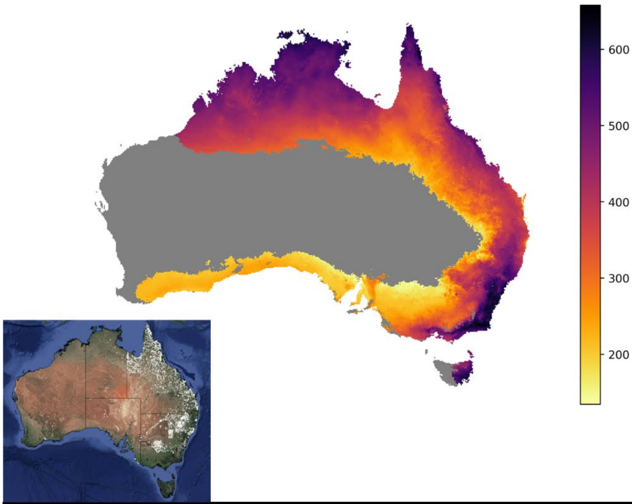
Where can we trust the model to make predictions?

Predicting species richness of vascular plants

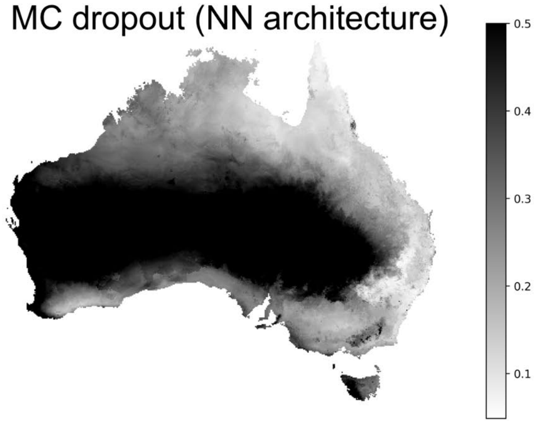


Andermann et al., 2022, https://doi.org/10.3389/fpls.2022.839407

Predicting species richness of vascular plants



Uncertainty determined with
MC dropout (NN architecture)



Andermann et al., 2022, https://doi.org/10.3389/fpls.2022.839407

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What are we able to model?
Classification of ecosystem integrity/naturalness

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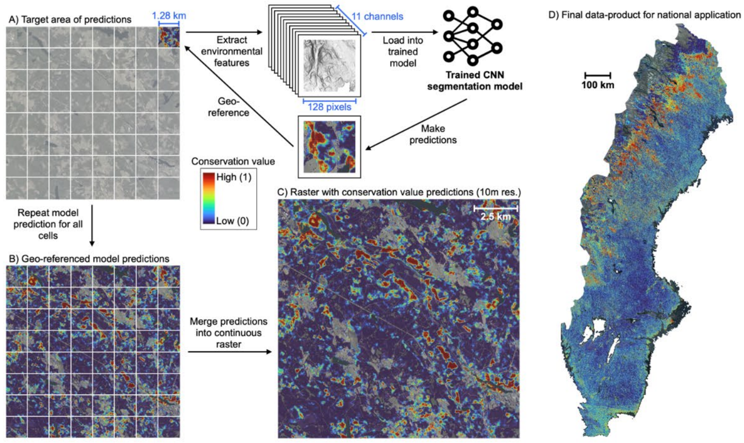
National/regional scale models

Training data:

Low conservation value forests (forestry registry):
- forest parcels that have been clearcut within last 80 years
- ~ 593,000 annotated polygons in Sweden

High conservation value forests (manual inventories):
- high naturalness (according to Swedish Forest Agency)
- ~67,000 annotated polygons in Sweden

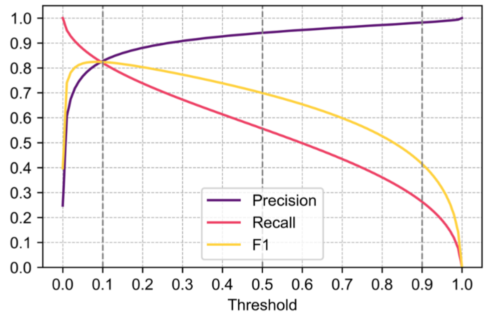
Mapping high-conservation-value forests

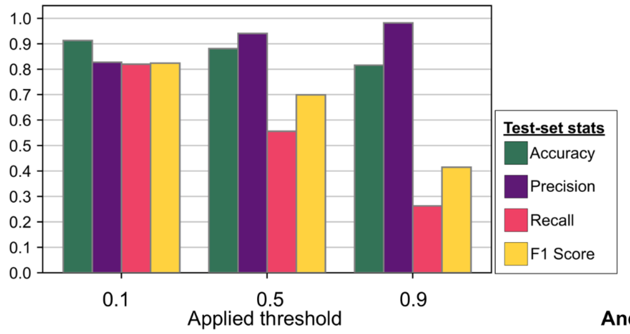


Andermann et al., preprint, https://doi.org/10.21203/rs.3.rs-4734879/v1

Model performance

- **Precision:** Proportion of pixels inferred as target class, which are correctly predicted
- **Recall:** Proportion of existing target class pixels that were correctly identified





$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

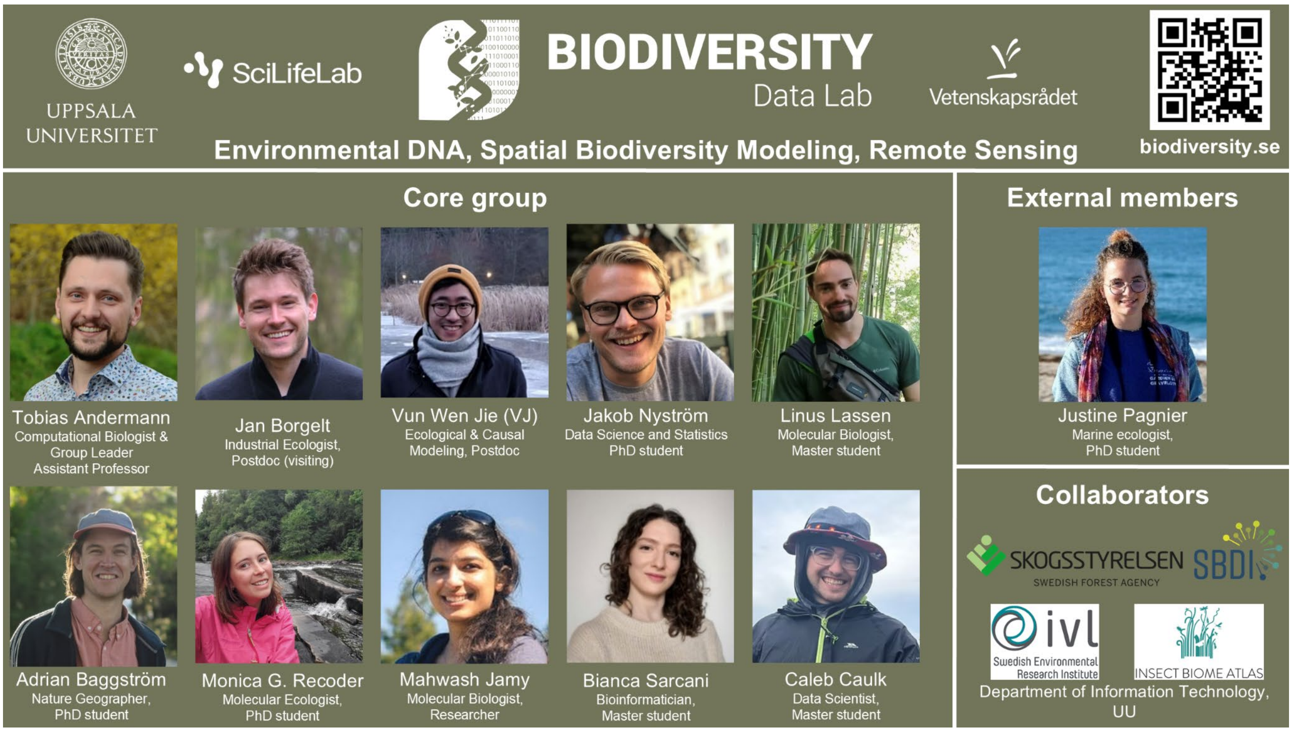
$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Andermann et al., preprint, https://doi.org/10.21203/rs.3.rs-4734879/v1

Discussion topics

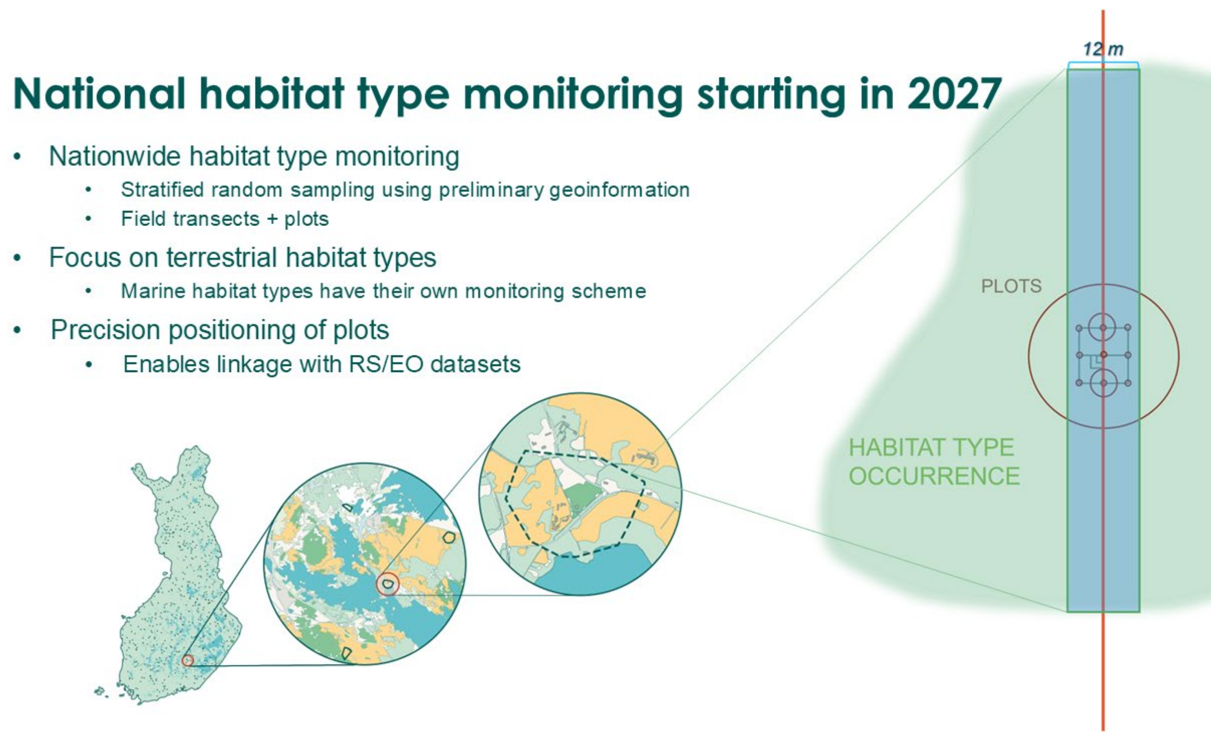
- How to strike a good compromise between recognizing limitations and promoting use cases?
  - What is good enough?
- Are we ready to use model-based indicators for biodiversity monitoring?
- Which biodiversity metrics are most important for global monitoring?
  - Ecosystem integrity?
  - Species composition/richness?

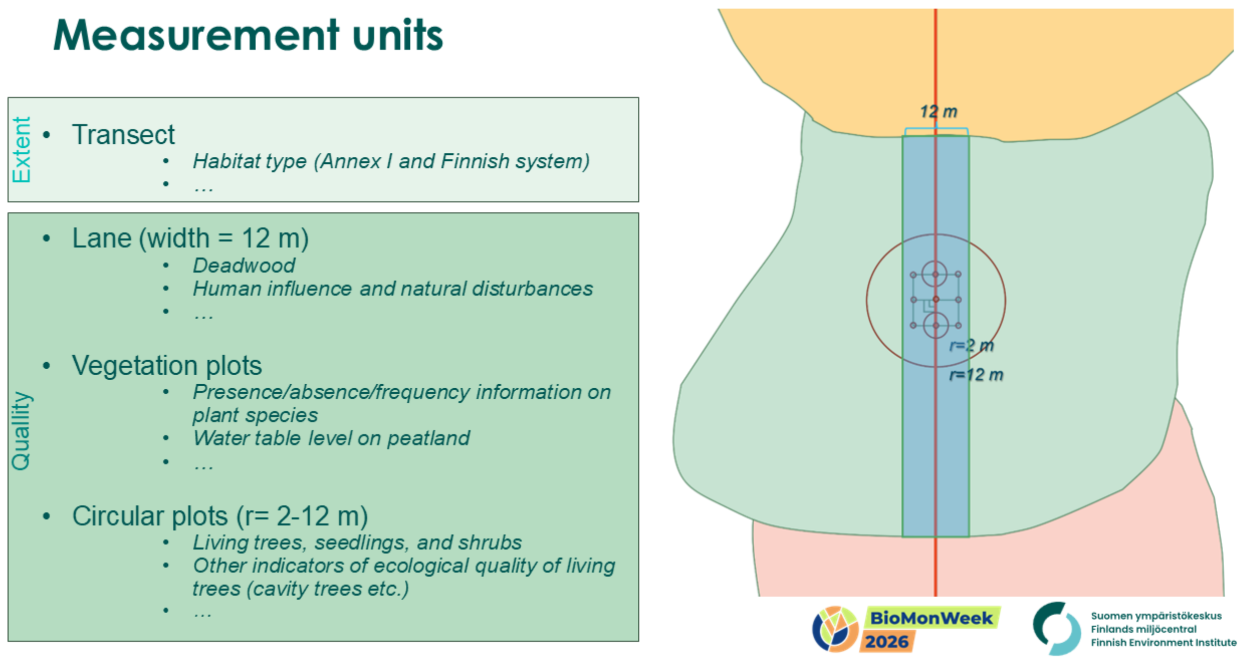
Tobias Andermann, PhD | Assistant professor, Uppsala University | SciLifeLab and Wallenberg DDLS fellow | www.biodiversity.se 14



Appendix 2: From habitat type field inventory to a wall-to-wall habitat type map?

Presentation by Topi Tanhuanpää, BioMonWeek 2026 workshop “Remote sensing applications for biodiversity monitoring”

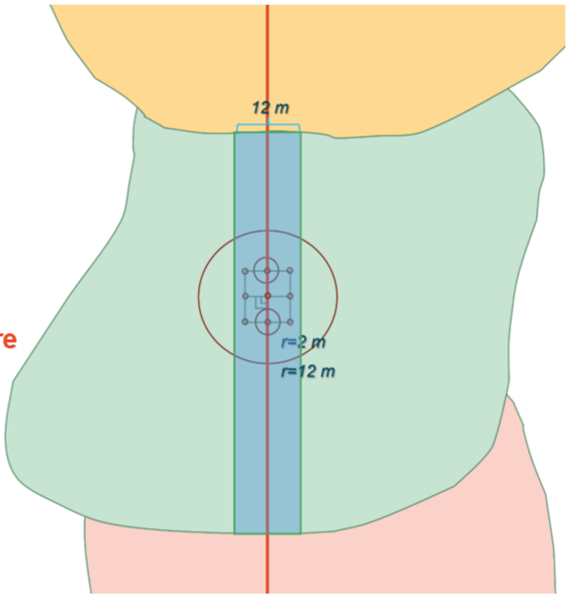

National habitat type monitoring starting in 2027
• Nationwide habitat type monitoring
• Stratified random sampling using preliminary geoinformation
• Field transects + plots
• Focus on terrestrial habitat types
• Marine habitat types have their own monitoring scheme
• Precision positioning of plots
• Enables linkage with RS/EO datasets
12 m
PLOTS
HABITAT TYPE
OCCURRENCE


Measurement units
Extent
• Transect
• Habitat type (Annex I and Finnish system)
• …
Quality
• Lane (width = 12 m)
• Deadwood
• Human influence and natural disturbances
• …
• Vegetation plots
• Presence/absence/frequency information on plant species
• Water table level on peatland
• …
• Circular plots (r= 2-12 m)
• Living trees, seedlings, and shrubs
• Other indicators of ecological quality of living trees (cavity trees etc.)
• …
12 m
r=2 m
r=12 m
BioMonWeek
2026
Suomen ympäristökeskus
Finlands miljöcentral
Finnish Environment Institute

Estimates for habitat types

- The system enables estimates of habitat type coverage and quality **at the national level**

But how to estimate where the habitat patches are and what is the ecological condition?



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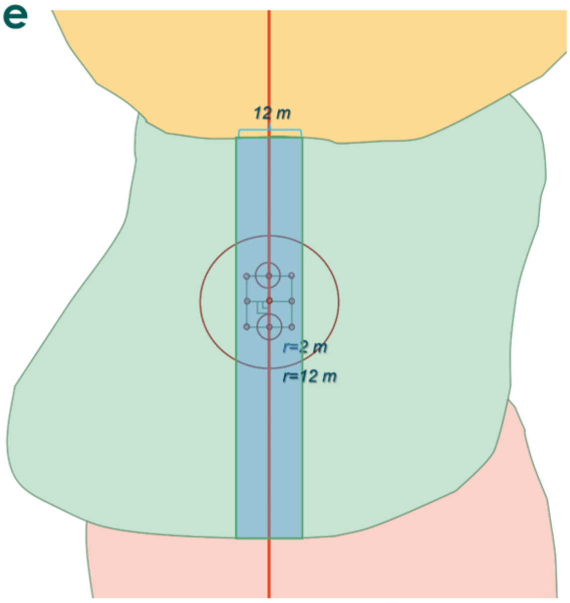
A simple plan for upscaling the data

- Plenty of RS/EO-datasets available
  - Aerial images (GSD 0.25 m)
  - Airborne LiDAR (20 points/m^2)
  - Different satellite sensors
- Machine and deep learning methods
  - Efficient in combining diverse field data with multidimensional RS data
  - Crave loads of training data
  - Need to be verified with field data to ensure the quality

But is the field data enough for all this? Probably not.



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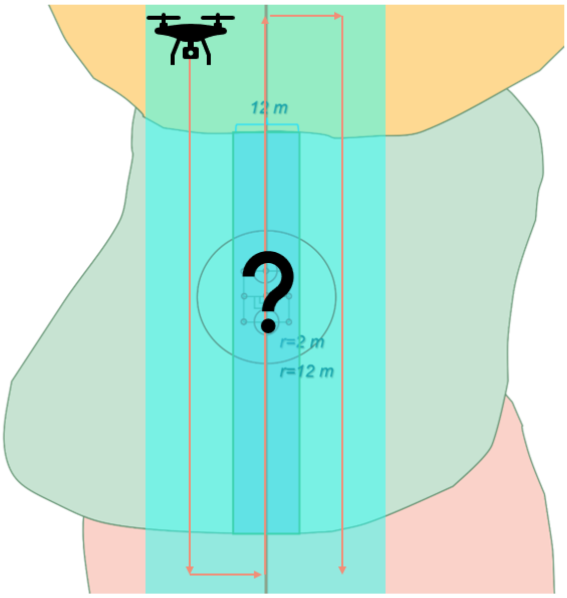
How about first upscaling the field data?

- Using drones for capturing training data from wider areas
  - Multiple sensor options
  - Very high spatial resolution
  - Ideally would be collected simultaneously with the field data

- **But how to do this meanigfully and efficiently?**
  - **Sensors**
  - **Flight patterns and automatization**
  - **Data procressing**
  - **What else?**



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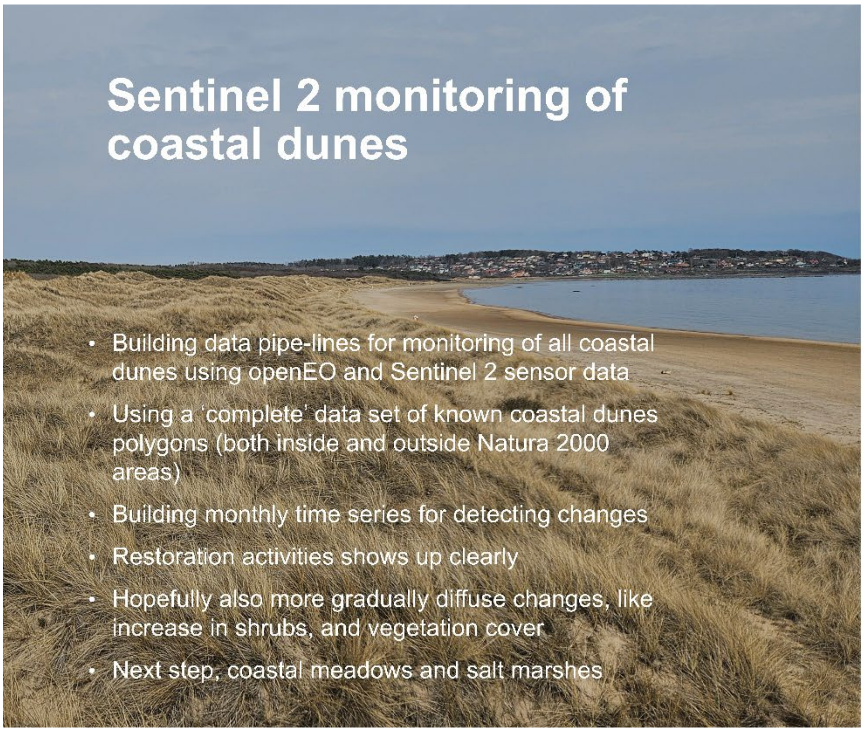
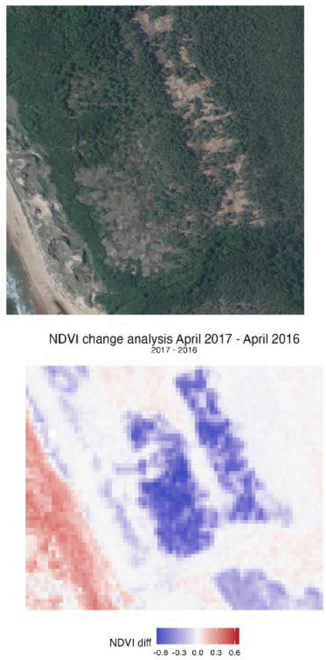
Appendix 3: Linking spatial scales: Boosting vegetation monitoring performance with drone- and satellite data

Presentation by Hans Gardfjell & Arvid Sjöberg, BioMonWeek 2026 workshop "Remote sensing applications for biodiversity monitoring"

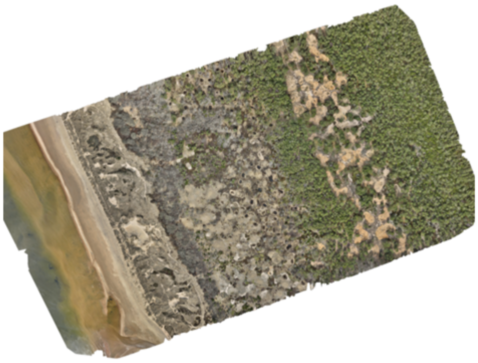

SLU
NATUR VÅRDS VERKET
biodiversa+
Swedish seashore inventory
• Started as a LIFE+ Nature project in 2012
• Coastline 45 000 km, shore area 600 km²
• Surveys 10 coastal Annex I habitats plus 7 coastal dune habitats
• Uses a hierarchical, balanced two-stage sampling design
1. Remote sense line-intersect sampling using photogrammetry and aerial images
2. Field inventory in a stratified selection of field transects


Sentinel 2 monitoring of coastal dunes
• Building data pipe-lines for monitoring of all coastal dunes using openEO and Sentinel 2 sensor data
• Using a 'complete' data set of known coastal dunes polygons (both inside and outside Natura 2000 areas)
• Building monthly time series for detecting changes
• Restoration activities shows up clearly
• Hopefully also more gradually diffuse changes, like increase in shrubs, and vegetation cover
• Next step, coastal meadows and salt marshes


NDVI change analysis April 2017 - April 2016
2017 - 2016
NDVI diff
-0.6 -0.3 0.0 0.3 0.6

Drones improving spatial resolution

- In our field sampling programs, species and vegetation data are collected in sampling plots of the sizes from 0.25 – 1000 m^2
- A larger spatial coverage could improve the understanding of the vegetation structure and we are currently starting to build a collection of drone imagery from coastal dunes.
- Drone images from different years allows for detailed change analysis of shrubs, dwarf-shrubs, and other functional plant groups
- Better ground truth calibration data for satellite sensor-based vegetation models

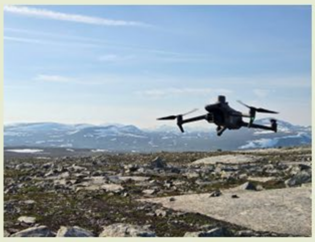


ELEVATE

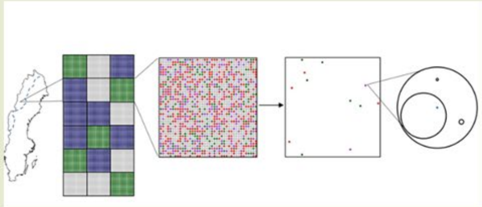
Implementing new technologies into the Swedish alpine vegetation monitoring program NILS

Focusing on drones/UAS and deep neural networks

Project financed by Naturvårdsverket (Swedish EPA)



Images by NILS Alpine Inventory

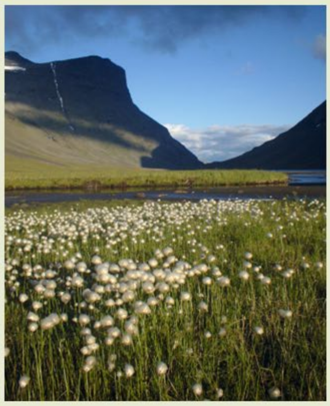


NILS Alpine Inventory

Two stage inventory design:

1. Model based identification of interesting habitats
2. Field inventory by personnel

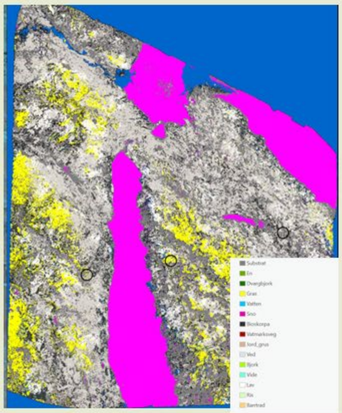
The design is tested and reliable, however limited in spatial resolution.
Drones since 2021: ca 200 flights.



Images by Adler *et al.* (2020) & NILS Alpine Inventory, respectively.

Drones and deep neural networks

1. Compiling orthomosaics from drone images
2. Annotating class training polygons (15 classes)
3. DNN training and inference pipeline
4. Highly detailed segmented vegetation map

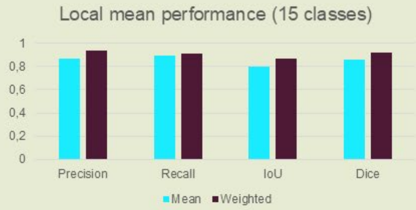


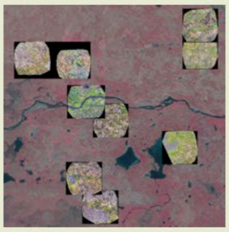
Drones and deep neural networks

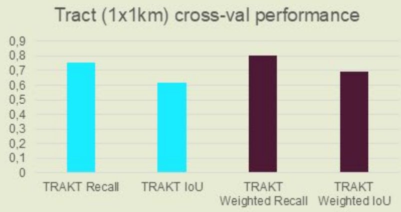
High metric scores on local data.

Lower on “regional” data.

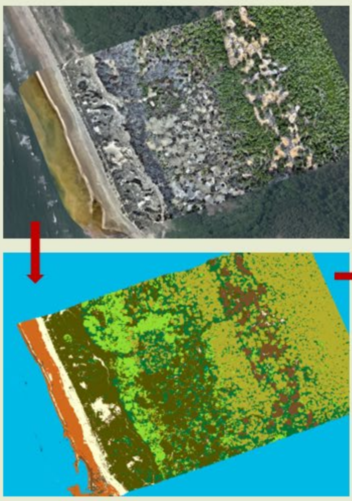
Transferability of models is a weak-point

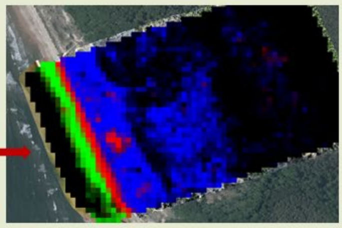




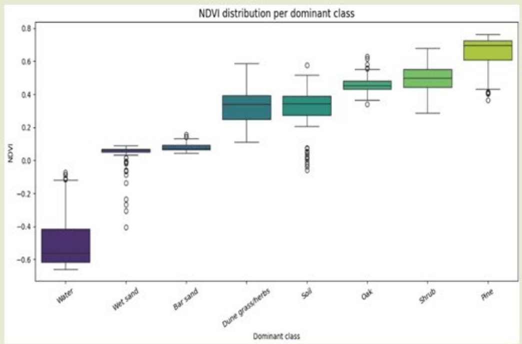


Segmenting dune vegetation: A mini-case study

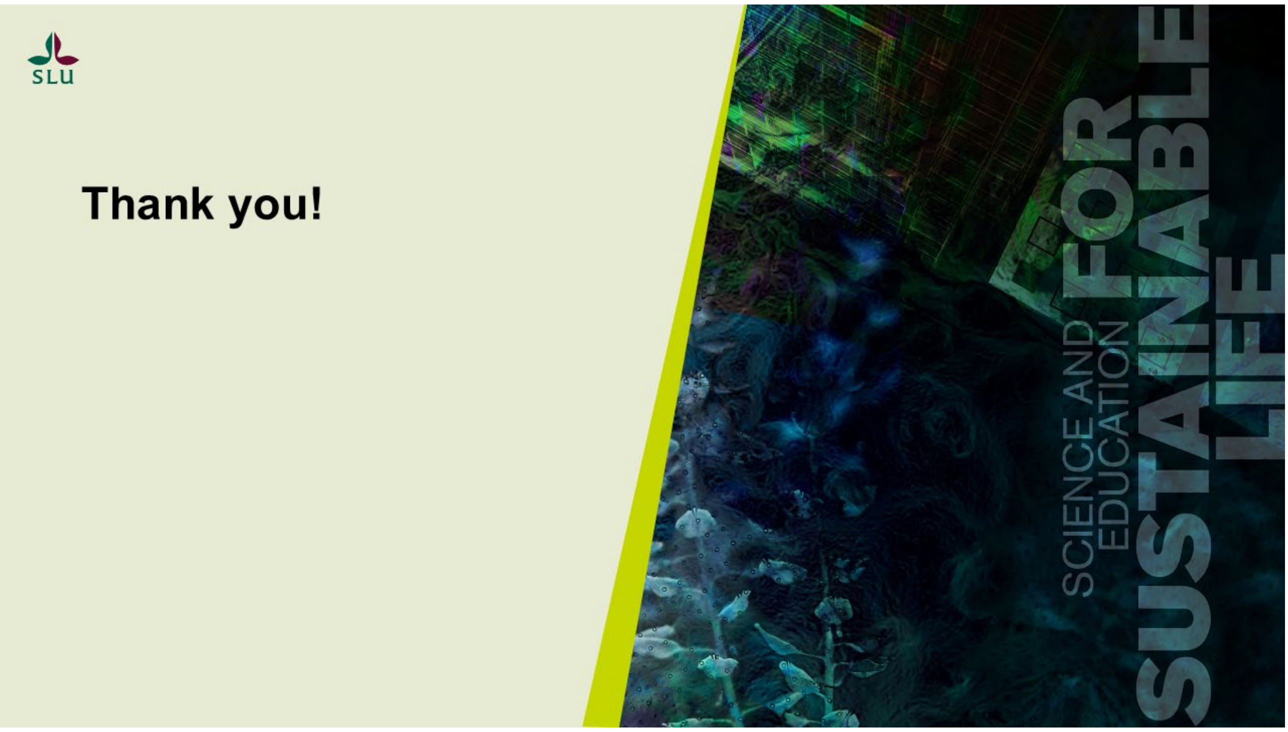




Class fractions within S2 pixels (10x10m NDVI)



Using drone segmentation models we can differentiate dune vegetation using Sentinel-2 NDVI data.


SLU
Thank you!
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