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# Unlocking ground-based imagery for habitat mapping

N. Morueta-Holme [1,*,@], L.L. Iversen [2,@] D. Corcoran [3,4,@] C. Rahbek [1,5,6,7,@] and S. Normand [3,4,8,@]

**Fine-grained environmental data across large extents are needed to resolve the processes that impact species communities from local to global scales. Ground-based images (GBIs) have the potential to capture habitat complexity at biologically relevant spatial and temporal resolutions. Moving beyond existing applications of GBIs for species identification and monitoring ecological change from repeat photography, we describe promising approaches to habitat mapping, leveraging multimodal data and computer vision. We illustrate empirically how GBIs can be applied to predict distributions of species at fine scales along Street View routes, or to automatically classify and quantify habitat features. Further, we outline future research avenues using GBIs that can bring a leap forward in analyses for ecology and conservation with this underused resource.**

## Highlights

The urgency of the biodiversity crisis calls for high-quality habitat data now.

Ground-based images (GBIs) represent one of the least-utilized fine-grain data sources with a worldwide coverage and low acquisition cost.

The integration of GBIs with other data sources and computer vision can provide objective approaches to improve species–habitat models.

We need to understand how GBIs complement existing remote sensing resources, and develop standardized descriptive statistics characterizing the composition and complexity of GBIs.

## An emerging approach for habitat mapping and biodiversity research

In a rapidly changing world, it is more important than ever to understand the processes driving biodiversity dynamics. Fine-grained data on habitats and environmental factors across large extents are a core piece of the puzzle towards a fuller understanding of the processes determining species community changes across spatial and temporal scales [1,2]. Such data can serve to monitor species' responses to human-induced environmental change, test the predictive ability of standing ecological theories, and evaluate effects of conservation actions.

Airborne **remote sensing** (see Glossary) from satellites, airplanes, and drones is quickly improving and providing some of these needed data products [3,4]. However, the lack of public imagery of <10 m pixel resolution with global coverage restricts the quantification of local and short-term processes that affect species communities across scales [1]. Further, the orthogonal nature of much airborne remote sensing data and the ground-truthing needed when appending biological information introduce limitations. For example, understoreys in dense forests, regions with prevalent cloud cover, mountain gorges, and vertical **habitats** like cliffs remain largely hidden to airplane and satellite remote sensing, especially for spectral sensors [5–7]. *In situ* habitat data can help validate and complement remote sensing [8], but new field collections are costly and skewed towards regions with more resources: temperate North America and Europe. Closing data gaps in regions with limited resources will require novel approaches to automate data collection and leverage existing but underused datasets to fill in missing information.

**GBIs** are a promising complement to airborne remote sensing for mapping habitat characteristics at the fine scales needed. The GBIs that are useful for habitat mapping capture the local habitat in a photo with spatial coordinates and a time stamp, providing a stepping-stone between large-scale remote sensing data and individual organisms. The availability of such images has exploded in the past decades with the expansion of Street View, social media, photo deposits such as Flickr, camera trap databases, and digitized archives of historical landscape photos [9–11]. Google Street

[1]Center for Macroecology, Evolution and Climate, Globe Institute, University of Copenhagen, Copenhagen, Denmark
[2]Department of Biology, McGill University, Montréal, Québec, H3A 1B1, Canada
[3]Section for Ecoinformatics & Biodiversity, Department of Biology, Aarhus University, Aarhus, Denmark
[4]Center for Sustainable Landscapes under Global Change, Department of Biology, Aarhus University, Aarhus, Denmark
[5]Center for Global Mountain Biodiversity, Globe Institute, University of Copenhagen, Copenhagen, Denmark
[6]Institute of Ecology, Peking University, Beijing, China
[7]Danish Institute for Advanced Study, University of Southern Denmark, Odense, Denmark
[8]Center for Landscape Research in Sustainable Agricultural Futures, Department of Biology, Aarhus University, Aarhus, Denmark

View alone provided panoramic and 360° images along 16 million kilometers in 2019, corresponding to 25% of global roads [9]. Combined with citizen science approaches to data collection and deep learning algorithms for automating data extraction, standardization, and synthesis, these datasets open the gates for achieving unprecedented coverage of key ecological parameters such as land cover, vegetation type, structure, biomass, habitat complexity, and species identity.

The recent review of existing applications of repeat GBIs and public archives [12] evidences the emerging interest in boosting this underused data source. Depauw *et al.* [12] showcased how temporal changes in species occurrences and landscape features can be quantified from images alone. Here, we focus on the extraction of information from **multimodal** approaches, combining multiple images and ancillary data. We provide an overview of existing usages of GBIs for habitat mapping, and propose new multimodal and **computer vision** applications within ecology research. We then outline ways forward for unlocking the full potential of these data sources for further understanding species–environment relations.

## The problem of habitat mapping

Accurate quantification and representation of wildlife habitats is key for understanding species–environment relationships. Habitat mapping seeks to represent and predict biological patterns based on environmental gradients [13]. Reliable maps are essential to implement conservation efforts, yet inconsistencies in the accuracy and precision of current maps require urgent development in this area [1,14].

Approaches to mapping focus on classification and/or quality assessment. Terrestrial landscapes are typically classified into vegetation types based on phytosociology (i.e., the composition and cover of plant communities), or, increasingly, into habitat types based on biotope concepts that account for geographic, abiotic, and biotic features [15]. Such classifications are the foundation for policies and monitoring schemes like the European Union (EU) Habitats Directive. However, inconsistent interpretations of how to classify habitats across jurisdictions, and even across individual experts, introduces high uncertainty when identifying endangered ecological communities and comparing habitats across regions [16,17].

Similar issues affect the quantification of habitat quality. Ecologists have long proposed that structurally complex habitats enhance species richness [18,19]. Hence, many indices of structural complexity (e.g., fractal dimension, rugosity, foliage height diversity) have been developed to estimate habitat quality and diversity in the field as a surrogate for richness or for capturing the habitat features important to specific species [20]. However, complexity measures are often ambiguous for interpretation, hindering consistent application [21].

There is a need for comparable and repeatable measures to quantify, classify, and map ecological complexity of habitats. As the focus of conservation changes towards supporting ecosystem dynamics and processes instead of static baseline conditions, this need is only increasing [14,22]. So could GBIs be part of the solution? Could we classify the habitat and quantify its quality for a species simply based on a photo?

## Existing usages of GBIs for habitat mapping

GBIs have mostly been used to identify species or specific landscape features directly visible from the image (cf. [12]), yet the idea of assessing habitat characteristics and quality from GBIs is not new. In the 1950s, Evans and Coombe [23] used analog hemispheric photographs to estimate light conditions in woodlands. Later, Alados *et al.* [24] applied metrics of fractal geometry and structural heterogeneity to study plant responses to grazing based on photos. Such uses of

*Correspondence:
morueta-holme@sund.ku.dk
(N. Morueta-Holme).
@Twitter/X: @NMoruetaHolme
(N. Morueta-Holme), @lifeinmud
(L.L. Iversen), @DerekCorcoranB
(D. Corcoran), @Carsten_Rahbek
(C. Rahbek), @SigneNormand
(S. Normand).

GBIs can reduce time-consuming field measurements of structural features, and can enable analyses of the study objects based on photographic records [25,26].

Descriptive statistics developed for image analysis are a step towards objective metrics of complexity. The texture of images contains latent information on the structural and spatial arrangement of objects captured. Applications of texture analysis of GBIs [e.g., with the **mean information gain (MIG) index**] include capturing old-growth forest structure [27], correlates of functional composition of riparian plants [28], and associations between vegetation complexity and bat occurrences [29]. However, most recent developments of image complexity metrics stem from marine and remote sensing research: for example, from studies of species–habitat relationships in coral reefs [30,31].

So far, quantitative analyses for habitat characterization in ecology have relied on 'semi-manual' approaches, only partly aided by computing tools. Two exceptions are the use of computer vision on Street View imagery to map breeding habitats for dengue mosquitoes (*Aedes* sp.) [32] and to predict indicator species richness from image classifications [33]. Fine-grained habitat mapping and characterization across large extents will require a certain level of automation. In the following sections, we discuss the most promising avenues of multimodal approaches to analyze GBIs, and how advances in computer vision from other research fields can be extended to habitat mapping.

## Habitat characterization with multimodal approaches

The adage of 'a picture is worth a thousand words' reflects the fact that images contain a lot of information which can be difficult to extract. A powerful way to translate the information to quantifiable components is to combine individual or sets of GBIs with other data types (Figure 1).

One challenge arises when converting 3D landscapes into 2D images: distortion of distances and areas. However, **monoplotting** and **simultaneous localization and mapping (SLAM)** techniques can combine individual GBIs with 3D data such as high-resolution digital elevation models (DEMs) or light detection and ranging (LiDAR) point clouds. This involves merging spectral and structural information, allowing the quantification of habitat area or vegetation structure on the georectified images [34–36]. Complementing GBIs with airborne remote sensing or 360° images can provide context to mitigate issues with concealed landscape regions, preventing misinterpretations such as confusing a nearby hedgerow with a forest.

Multiple images of the same landscape scene also offer interesting possibilities. Sets of images along a spatial gradient – such as those captured by Street View-style photography or stereo-photography – can serve to measure objects with **photogrammetry**, as done for complex morphological traits such as deer antlers [37] and canopy height from aerial stereo-images [38]. Extended to GBIs, photogrammetry could help estimate the height, biomass, and structure of individual tree crowns or smaller plants, and provide insights into the structural variation of forest patches along environmental gradients [12,39].

Similarly, images repeated along temporal gradients can help us to understand habitat change dynamics [40]. Repeat photography of archive imagery often offers higher temporal depth and resolution than airborne remote sensing, especially useful in places with fast vegetation dynamics or with complex topography [12,41]. If compiled across large extents representing orthogonal gradients of environmental change, such approaches could help attribute the importance of drivers like land use versus climate change. A digital archive such as the Mountain Legacy Project in the Canadian Rocky Mountains provides >120 000 historical photos and 8000 repeats, enabling the mapping and analysis of a century of tree-line changes and their drivers [42].

## Glossary

**Computer vision:** discipline within artificial intelligence (AI) that focuses on methods to automate the processing, analysis, and interpretation of information from digital images.
**Ground-based images (GBIs):** landscape scene captured in a photograph with a spatial and temporal reference.
**Habitat:** the group of physical and chemical parameters forming spatial gradients across a landscape.
**Mean information gain (MIG) index:** information theoretic measure of structural complexity in spatial data used to quantify habitat complexity in images of natural scenes. Values range from 0 for images with pixels distributed randomly to 1 for images of a single solid color. Intermediate values are associated with spatially heterogeneous data.
**Monoplotting:** a technique for relating individual, oblique ground-based or aerial photographs to a digital elevation model of the corresponding landscape. The technique allows one to georeference the photograph with corrections for tilt and relief.
**Multimodal:** refers to an approach using data spanning multiple types and contexts, such as GBIs, species occurrences, text labels, remote sensing images, climate data, etc. Multimodal machine learning approaches enable the construction of more robust models for prediction and classification by fusing various data forms, in some ways mimicking human intelligence.
**Ontology:** a set of concepts and categories in a subject area used to represent their properties and relations. For habitat mapping, an ontology helps standardize habitat descriptors, including physical properties and environmental processes.
**Photogrammetry:** the science of collecting and measuring objects from images, including tools like Structure from Motion that applies triangulation to estimate and quantify 3D structures from overlapping 2D image sets.
**Remote sensing:** process of acquiring information about areas from a distance. In this paper, we use the expression 'airborne remote sensing' for data acquired from a drone, aircraft, or satellite.
**Simultaneous localization and mapping (SLAM):** the process of simultaneously estimating camera pose and 3D structure of a scene. Visual SLAM uses images in the process, and

Multimodal analyses at the scale of features or pixels on images add to existing metrics of image complexity. Further development of such descriptive statistics will ultimately help in the investigation of relationships between habitat diversity and biodiversity, with more detailed metrics of habitat complexity that are repeatable across ecosystems.

can be indirect (relying on feature matching from multiple images), direct (relying directly on pixel-level data without feature extraction), or hybrid (combining the two techniques).

## 'Habitat recognition' and habitat suitability models

Alongside the development of objective metrics for habitat descriptors, computer vision offers opportunities for automatic habitat classification and assessment of habitat quality for biodiversity. Advances in GBI analysis within socioeconomic and human health research are particularly relevant. Computer vision perception tasks have been successful in classifying neighborhoods as 'safe' or 'unsafe', predicting housing prices, and monitoring socioeconomic developments [43]. Similarly, the interest in associations between greenspace and human health in cities has spurred research using automated segmentation and classification to quantify greenspace from Street View products across large extents [9]. Despite the similarity of the problems, such approaches remain largely unexplored for GBI-based habitat mapping (but see [33]).

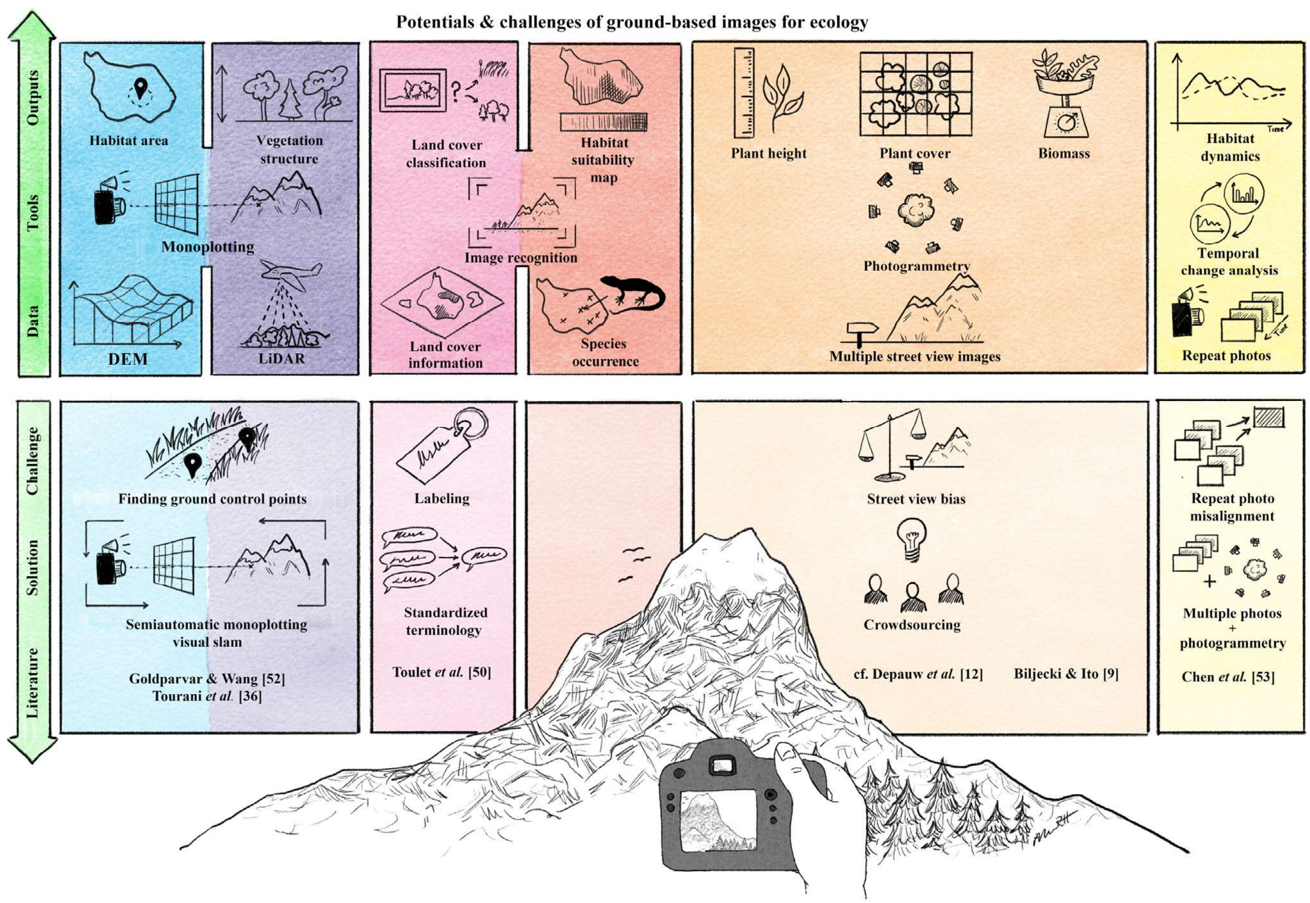


Figure 1. Multimodal characterization and mapping of habitats with ground-based images (GBIs) of a landscape. Upper part shows opportunities of habitat characterization with GBIs, with example outputs derived from combining GBIs with other datasets applying integrative tools. Lower part shows the weaknesses of GBI approaches, illustrating main current challenges and possible solutions with examples for inspiration in the published literature (see also Box 3). The challenges highlighted can be relevant for more than one application. Abbreviation: DEM, digital elevation model. See also [9,12,36,50,52,53].

Image recognition algorithms can automatically classify images if trained with large sets of GBIs labeled with land cover or land use information (Box 1). Existing images can be labeled manually, as done for species on camera trap datasets or remote sensing images, and could be crowd-sourced [44,45]. Alternatively, georeferenced GBIs can be enriched with other datasets by spatial overlay. The Eurostat Land Use/Cover Area frame Survey (LUCAS) inventory program provides >5.4 million labeled GBIs across the EU. The images have been used mainly for ground-truthing maps derived from remote sensing [46], but with just a small subset, we show good results in automatic habitat classification (Box 1).

Very-high-resolution habitat models of species can also be created by labeling georeferenced GBIs with occurrence data. With this approach, studies have linked human health to exposure to greenspaces with Street View imagery, which reflect what humans experience on the ground better than satellite imagery [47,48]. As we show in Box 2, this whole-image classification

## Box 1. Automating habitat classifications from European land use monitoring images

As part of the EU-wide Land Use/Cover Area frame Survey (LUCAS), Eurostat has collected and labeled GBIs every 3 years since the early 2000s. The program was developed for mapping and monitoring land use and land cover changes across the EU. Surveyors captured sets of five images (one of the point, and one for each cardinal direction) in a ~240 000 stratified sample points within a 2-km regular grid across the EU territory. In 2020, the database included >5.4 million geolocated photos with labels for up to 106 variables following a standardized, hierarchical nomenclature [54].

The labeled LUCAS images and metadata represent a first step towards providing a high-quality image recognition dataset for automatic classification of new ground-based imaging and reduce manual labeling, akin to existing image recognition of, for example, species, objects, and perceived neighborhood safety [43–45]. Besides the potential extension to GBIs from sources other than LUCAS, such automated classifications could accelerate ground-truthing for, for example, land cover maps from airborne remote sensing. As an initial test (Figure I), we used a convolutional neural network (CNN) model to automatically classify a balanced subset of 1093 LUCAS images from Denmark into four habitats (croplands, grassland, artificial land use, and woody vegetation), achieving an overall accuracy of 0.734 and a κ value of 0.650. Automatic classification could be improved by increasing the number of training images, balancing the classes further, or exploring the use of majority voting with the LUCAS dataset. Classification probabilities output by the model could be used as input in species distribution models as proportion data.

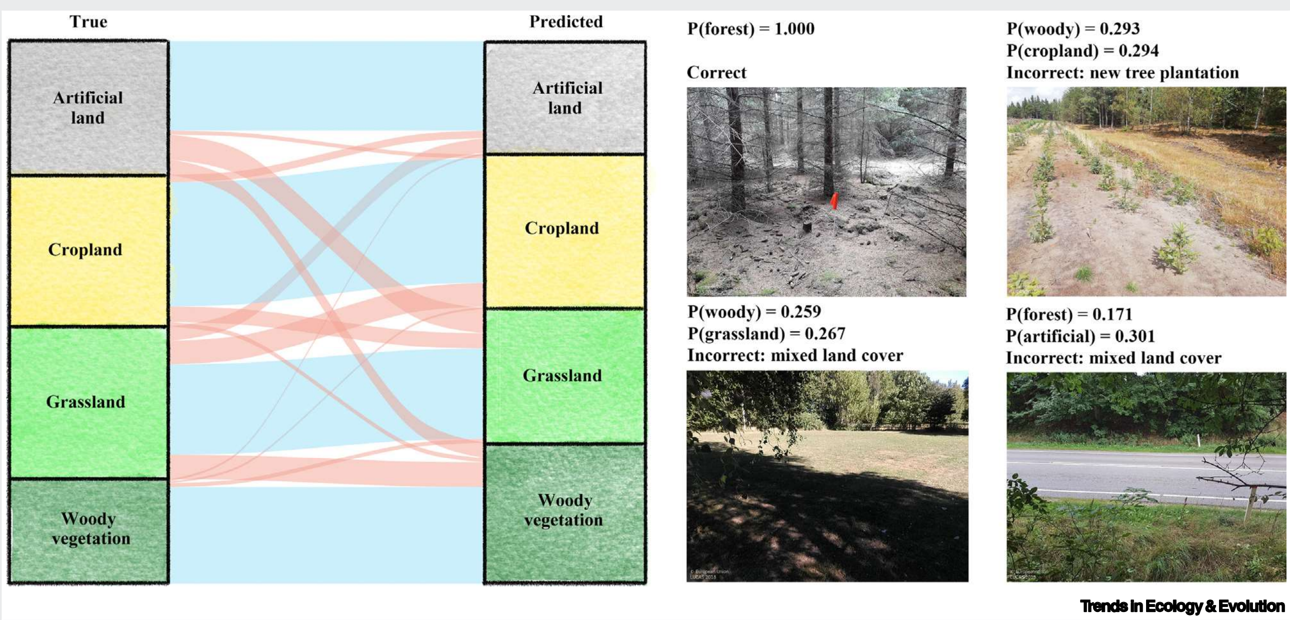


Figure I. Image classification success for four land-cover classes and examples of misclassifications. (A) Sankey chart of relative distribution of images with predicted land-cover classifications consistent (blue) or inconsistent (red) with 'true' class as defined by surveyors on site. (B) Example images show that misclassifications – in this case for true class forest – likely arise due to the landscape context used by surveyors in the field and the difficulty of classifying transition vegetation and mixed land-cover habitats.

approach is also promising for species sensitive to fine-scale habitat structures and undergo a majority of their life cycle within a relatively small territory.

As for multimodal GBI approaches, we see several research and conservation avenues that could benefit from the computer vision approaches outlined. Carefully tuned habitat models could be applied to other GBI sources (public image archives, entire Street View networks) to identify suitable locations for species of interest. Such models can also help monitor changes in habitat quality over time with repeated imagery. Further, GBI-based model predictions could serve as input to climate envelope models or hierarchical models to study questions on the relative importance of broad versus local-scale environments for species distributions. The ability of GBI-based approaches to provide new insights into biodiversity–environment relationships and/or improve local scale predictions of species distributions remains an open question, but our study cases show promising results (Figure 1 and Boxes 1 and 2).

## Challenges and the way forward

The promising opportunities have a 'dark underbelly' of methodological and conceptual challenges that must be surmounted to unlock the full potential of GBIs for habitat mapping (Figure 1 and Box 3). High predictive performance of computer vision algorithms requires large amounts of data, which in turn sets high demands to label standardization, matching of labels and images, and representativeness of geospatial data.

A standardized labeling system for characterizing habitats and their complexity customized for biodiversity research has been missing (but see [14]). There is a need for an **ontology** for knowledge-driven approaches to GBIs, whether for manual labeling by researchers, crowd-sourced identification of habitat features, or automatic habitat classification. Such an ontology, together with well-curated image datasets – just as for remote sensing [49] – will ensure repeatability across observers and geographical regions, help describe images in a standardized way, and improve the accuracy of computer vision classifications and support their ecological interpretation. Such datasets have enabled the transfer of tools across disciplines, but are still missing for habitat mapping. In the meantime, semi-supervised labeling [50] using, for example, LUCAS, or enriching GBIs with other spatial datasets (intactness index, ecosystem functional type, or IUCN habitat maps [14,51]), may be a next-best choice.

Ensuring spatial alignment across multimodal data is also essential. For instance, monoplotting techniques require the identification of ground control points on the GBIs and an elevation model. Control points must further be temporally stable for rephotography. Emerging advances in computer vision allow for (semi-)automated identification of ground control points (for the subset of GBIs containing features such as boulders, mountain tops, or buildings), increasing the prospects for upscaling monoplotting to large areas (cf. [31,52]). Similarly, advances in SLAM and computational rephotography of buildings and humans can use photogrammetry and feature-matching to help relocate the vantage point and match the historical image during GBI recapture or post-processing of image sets [36,40,53].

### Box 2. Tracking habitat suitability from landscape images

Using repeat Google Street View images, we can predict regional changes in roadside habitat suitability for the threatened sand lizard (*Lacerta agilis*) in Denmark. We used the pre-parameterized Xception convolutional neural network model architecture in TensorFlow [55] to estimate the probability of sand lizard presence from a landscape image. The image classification is thus purely data driven and is most suited as a predictive model and for generating hypotheses on potential drivers of habitat suitability and temporal changes. Ecological interpretation could be aided by the application of habitat characterization approaches (see Figure I). Understanding the true value of species detection via ground-based imaging will require studies exploring how these images capture complementary and overlapping information compared to existing remote sensing methods.

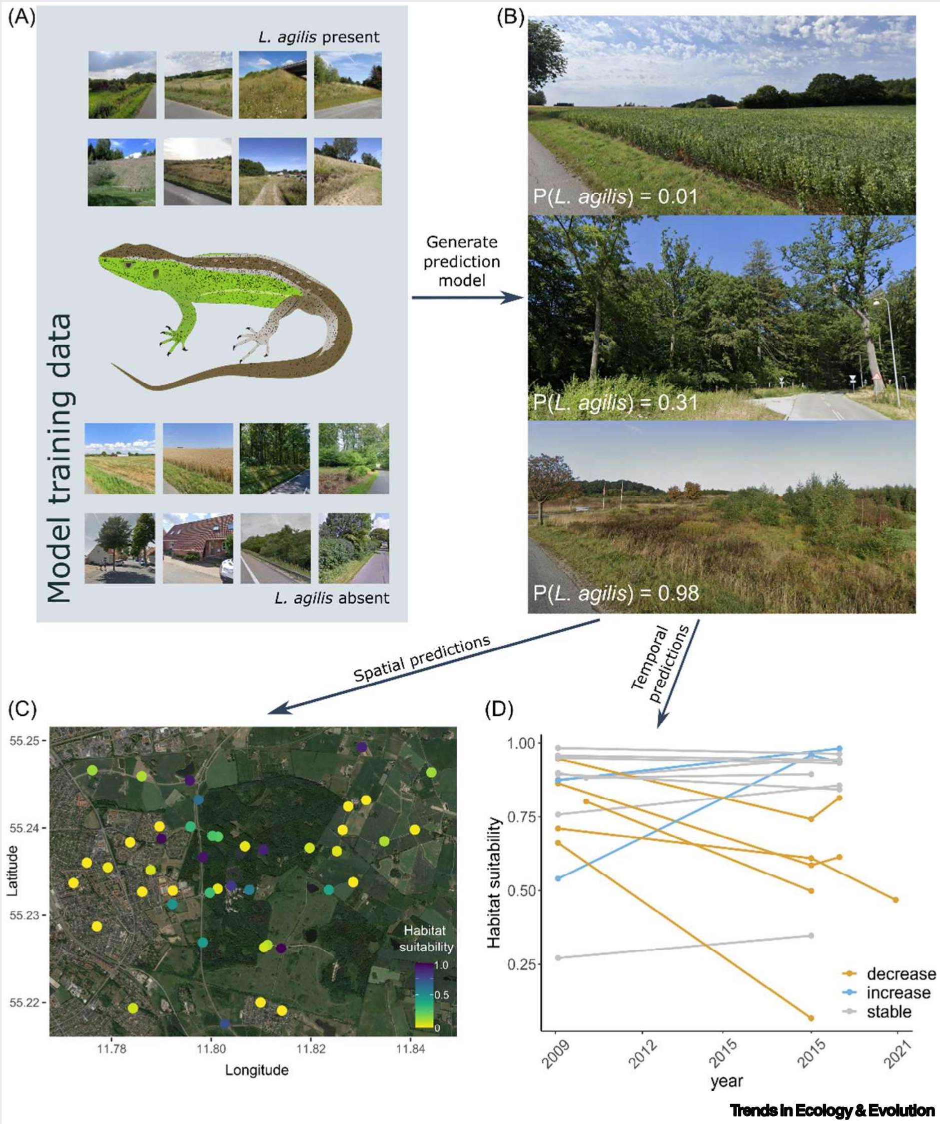


Figure I. Schematic of the procedure for estimating the probability of the presence of the sand lizard (*Lacerta agilis*) from ground-based images (GBIs). (A) Example GBIs spatially overlaid with known absences and presences of *L. agilis* that we used in model training. (B) Three examples of estimated probabilities, spanning from low to high probability of lizard presence. For new images with no pre-existing information on species presence, the estimated probability reflects how suitable a habitat is for sand lizards: in this case expressed as P(*L. agilis*). (C) Georeferenced landscape images (here provided by Google Street View) can give an overview of potentially suitable habitats without any prior fieldwork or knowledge of species distribution. (D) Based on repeated landscape images across time (from Google Street View) changes in habitat suitability can be estimated. The panel shows changes across a 12-year period for 15 known sand lizard populations. Trends indicate changes in suitability >0.10.

Finally, applications using GBIs from Street View imagery face the problem of geographical biases. Google Street View products, for instance, are heavily biased towards cities and roads of western countries. Such biases may lead to unintended errors in predictions of deep learning algorithms. Models trained in western countries could fail to identify habitats for a species in countries with low image coverage: for example, if models only recognize landscapes with specific cultural branding

### Box 3. How far are we from upscaling ground-based imaging for habitat mapping?

Using GBIs for habitat mapping in ecology presents unique technical challenges to ensure image quality and accuracy of spatial referencing. Ethical aspects also require consideration in responsible data handling.

(i) Standardizing image quality from disparate sources of GBIs – with, for example, blurriness, lens distortion, and changing light conditions – is a significant challenge. Initial applications of GBIs for habitat mapping can use standardized sources like Land Use/Cover Area frame Survey (LUCAS). When expanding to crowd-sourced datasets of more mixed quality, existing evaluation methods such as signal-to-noise ratios and human or deep-learning assessments can score quality [56]. Typically, standard quality is achieved simply excluding poor images (sometimes 99% of images for high quality demands [42]). Progress in image enhancement techniques (such as super-resolution) deserves more exploration in research [57,58].

(ii) Spatial referencing is a necessary yet challenging step after standardizing quality of GBI for accurate quantification of habitat features on the image. Spatial referencing and alignment of with additional images or other sources such as digital elevation models (DEMs) can be done with monoplotting tools but require ground-control points and manual input, which limits upscaling to larger sets of images [34,41,42]. Applications of semi-supervised identification of ground-control points and image segmentation have succeeded in quantifying flooding from challenging images, although with modest accuracy [52,59]. Similar approaches have achieved mean error in height estimation down to 0.218 m from GBIs for urban features the size of a small tree [60]. The approach is scalable, but requires visible objects of known height (a door in this example), which limits applications in habitat quantification. Visual positioning systems (VPSd) and simultaneous localization and mapping (SLAM) are already used in urban analytics and robotics to estimate camera position and extract features from GBIs stemming from different camera types [36,61]. Together with tools such as SegmentAnything for feature extraction [62], such computational advances are promising for more accurate spatial referencing of natural scenes without ground control points. Research in their applicability within habitat mapping and rephotography, and further development of tools for propagating uncertainties in estimates of spatial features [39] will be essential to upscale the use of GBIs in ecology. Following frameworks that translate existing geographical information standards to GBIs [63] can ensure accuracy assessments and management of uncertainty and support adequate method selection for ecological applications.

(iii) Ethics and privacy are important to consider when working with GBIs, regardless of data source (social media, crowdsourcing, or the public domain) [12,64]. Solutions to protect privacy include anonymizing GBIs prior to analysis and publication (e.g., blurring human faces as done in public Street View imagery). Responsible data-sharing should be ensured through early adoption of best practices and recommendations from related big data fields [12,64].

as suitable. Yet, with over six billion subscriptions worldwide[i], smartphones are now 'a technology of the many' and more accessible than, for example, drones. Together with the increased availability of 360° cameras that can be handheld or mounted on backpacks, imagery is increasingly collected beyond western countries and off the main roads [9]. Such bottom-up approaches to Street View imagery collection on open access platforms (e.g., Mapillary) offer the most promise to overcome these spatial biases, and grows the importance of citizen involvement in biodiversity monitoring.

## Concluding remarks: GBIs and computer vision – paradigm shift in ecological analysis or distracting hype?

The rapid developments in air- and space-borne remote sensing products beg the question: why should we bother to use GBIs? We do not expect GBIs alone to be a golden solution to species and habitat mapping. However, the high resolution, easy-to-replicate nature, and horizontal landscape position – providing a complementing vantage point to other data sources – make GBIs a powerful tool in multimodal approaches and computer vision applications. Utilizing the full potential of GBIs will rely on progress in the data acquisition pipeline, robustness in object detection and classification algorithms, and ecologists' ability to use the specific strengths of this type of data (see Outstanding questions). The potential return on investment is large: a leap forward in understanding of species–environment relationships across spatial scales, improving monitoring of species community trajectories, measuring the effects of conservation management actions, and ultimately contributing to the alleviation of the biodiversity crisis.

### Outstanding questions

Can GBI-based models provide new insights into species–environment relationships over time and space?

How much can the integration of high-resolution GBIs increase the predictability of species occurrence and richness models (from local to global scales)? We need empirical evidence that this approach is worth the effort of heavy computation and complex analytical frameworks.

Can we develop standardized methods for quantifying and understanding habitat change dynamics?

To what degree do GBIs capture complementary and overlapping information from airborne remote sensing products?

What are the most useful metrics for characterizing habitats from images across habitat types, and how can we integrate them into a standardized ontology for labeling?

Do GBIs from 360° cameras offer significant information advances over 'standard' GBIs (e.g., from phone cameras)?

Can we develop easy-to-use pipelines and guides for ecologists to process GBIs and integrate them with remote sensing, or analyze before/after GBI images from different sources?

How much can advances in GBI-based research contribute to the democratization of biodiversity monitoring across the globe in terms of species and habitat data collection, labeling, and education through citizen science?

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## Author contributions

N.M-H. proposed the initial idea and led manuscript writing together with L.I.I.; L.I.I. and D.C. led the analyses, and all authors refined and further developed the original idea and participated in writing.

## Declaration of interests

No interests are declared.

## Resources

[i]www.ericsson.com/49d3a0/assets/local/reports-papers/mobility-report/documents/2022/ericsson-mobility-report-june-2022.pdf

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