

# The responsible use of global remote-sensing datasets

Matthew E. Fagan, Naomi B. Schwartz & Ruth S. DeFries



In this age of abundant remote-sensing data, global datasets are increasingly relied upon to analyse the planet at unprecedented scale and resolution. We offer three considerations on uncertainties and potential misapplications of global datasets, to ensure results appropriate for decision making.

The use of remote-sensing data to map Earth's land surface dates back to balloon surveying more than a century ago. Decades later, the advent of remote-sensing data from satellites designed for civilian applications created many new opportunities. The first application of satellite data to map global land cover was explicitly for the purpose of incorporating land cover in climate models from the Advanced Very High Resolution Radiometer, a sensor designed for meteorological applications<sup>1</sup>. At present, many research fields rely on satellite data with increasingly higher spatial and temporal resolution, for applications that range from local-scale humanitarian assistance to global-scale planetary health<sup>2</sup>. In ecological and environmental science, global datasets derived from satellite data have been used in thousands of studies (for example, the Hansen et al.<sup>3</sup> forest cover product, which has around 13,000 citations). Such applications have real-world consequences for human lives and allocation of resources, and so it is imperative that they are developed with rigour and care.

The scientific community is responsible for ensuring that global datasets are appropriate for the intended applications and that users are aware of uncertainties and potential misapplications. Scientists who create these datasets must move past their novelty, and grapple with the elephant in the room: recognizing how global remote-sensing data can be used inappropriately for science and decisions that affect the public. Here, we identify three common challenges to effective use of global data: what we map (for example, blind spots that affect data availability); how we map (for example, predictions across local extents); and where we make inferences (for example, the limitations of resolution) (Fig. 1). We highlight examples in our areas of speciality, from the literature on global land cover and terrestrial carbon, and propose potential solutions to these challenges. Although these examples are specific to terrestrial systems, we believe the issues they raise apply to most global remote-sensing datasets. We call for global products that appropriately contextualize and communicate their limitations.

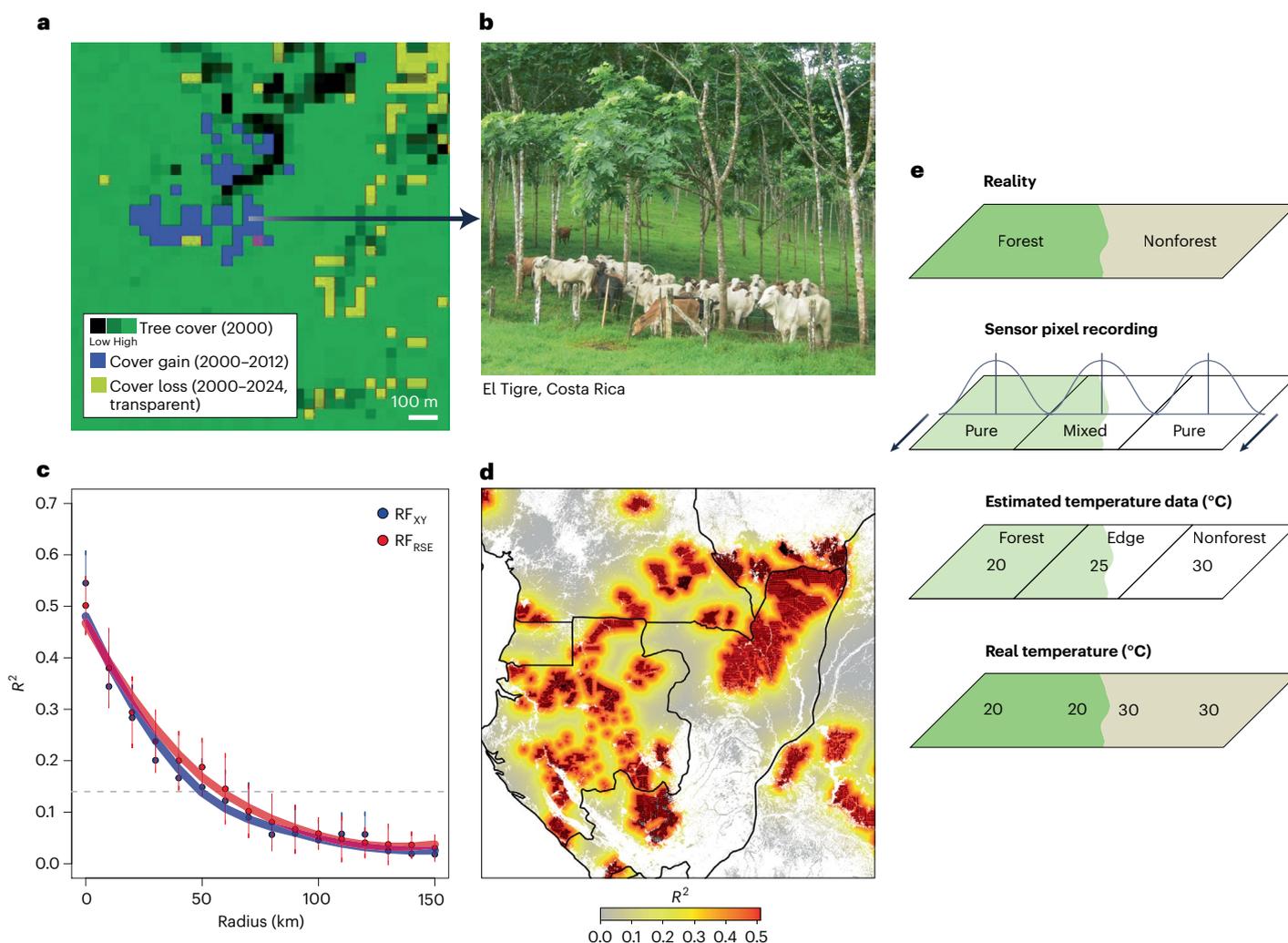
## What to map?

With advances in remote-sensing technology and methods, scientists are able to detect far more nuance and detail than ever before. However, certain phenomena remain undetected in global datasets,

which can generate biases. These gaps emerge for two key reasons. First, data creators make choices about what phenomena they set out to map. These choices are influenced by personal and societal ideas about what phenomena are important. For example, although drylands cover 40% of the Earth's land surface and contain about 25% of the human population, a disproportionate share of global remote-sensing data products focus on closed-canopy forests<sup>4</sup> (which cover similar proportions of the land surface<sup>3</sup> and human population). Second, there are fundamental limits to what satellites can observe from above. Satellites can image forest canopies, but not understories or deep-belowground features. They have a direct view only of human activities that visibly alter the Earth's surface at relatively large scales. As a result, certain phenomena remain particularly challenging to map at the global level, which can generate biases in outcomes from analyses of these large datasets.

For example, consider global conservation and restoration prioritization maps, which are generated by incorporating multiple global-scale datasets to identify areas that minimize costs of conservation and restoration while maximizing certain ecological or social benefits. Costs are often estimated as the economic value of current land uses, calculated from land cover maps, global commodity prices and estimated crop yields (for example, ref. 5). Yet many non-agricultural land uses and traditional livelihood activities are at best only partially represented in global land-cover datasets. Among these are pastoral activities and non-timber forest product harvests, which do not substantially alter the land surface and are not easily detectable by satellite – and because their contributions to global markets are often negligible, they are not included in macroeconomic datasets either<sup>6</sup>. Notably, Indigenous and resource-poor local people are more likely to depend on these livelihood activities. Such omissions create blind spots – both in what we cannot see, and in what we do not look for – and they disproportionately affect marginalized communities. As highlighted by frameworks such as the CARE (collective benefit, authority to control, responsibility and ethics) principles for Indigenous data governance, what is mapped determines whose relationships to land are rendered visible. Decisions that do not consider these blind spots may potentially lead to unjust outcomes – for example, the designation of protected areas in which harvesting or hunting are not allowed, but where these activities are important to local livelihoods.

Not all ecosystems and human activities that matter for scientific analysis or decision-making can be detected, and not everything that is detected matters. Blind spots encompass both 'known unknowns' (issues of which data-creators are aware) and 'unknown unknowns', giving users false confidence in scientific predictions. For an informed usage of global data, it is critical to keep in mind both the fundamental physical limits of remote sensing (and their effect on what phenomena are and are not mapped) and the sociocultural biases that influence what phenomena receive the most attention and knowledge from the remote-sensing community.



**Fig. 1 | What to map, how to map and where to infer. a, b,** What: a blind spot. A global forest map (a; data from ref. 3) shows forest recovery, but intense pastoral land use (b) continues under the canopy. **c, d,** How: the graph and map highlight the poor transferability of forest training data for biomass prediction in central Africa, showing declines in model fit (c) with distance from the dark-red training

data (d). **e,** Where: coarse-resolution mixed pixels can misestimate temperature (or biomass and other properties) at forest edges. Map data ©2025 Google (a). Panels c, d adapted from ref. 9, CC-BY 4.0 (<http://creativecommons.org/licenses/by/4.0/>). Panel e adapted from [https://commons.wikimedia.org/wiki/File:Mixed\\_pixel.svg](https://commons.wikimedia.org/wiki/File:Mixed_pixel.svg), CC-BY 3.0 (<https://creativecommons.org/licenses/by/3.0/>).

## How to map?

All global data products derived from remote sensing are modelled estimates with associated uncertainty, be they process models (for example, global climate models) or statistical learning models (for example, land cover predictions). Quantifying and reporting uncertainty in these predictions is considered an essential best practice (for example, ref. 7), and yet the habit of using these estimates as inputs into further analyses is so ingrained that users refer to them as datasets (global rainfall datasets and global land cover datasets), while potential errors (that is, biases, and known and unknown uncertainties) are often not incorporated in the resulting analyses. Such conflation has probably become more widespread owing to the popularity of statistical (or ‘machine’) learning applications in ecological and environmental studies. Relying on remote-sensing data, statistical learning models use known locations (labelled or measured ‘training data’) to predict

unknown locations. The accuracy of a global model depends on the spread, density, variability and accuracy of its training data. Statistical models generally perform the least well outside the domain of their input data: this is known as the problem of ‘transferability’<sup>8</sup>.

Transferability challenges affect the reliability of global datasets. The location and density of the training data are typically not published, and spatial uncertainty in model predictions is not consistently quantified and/or provided to users. Thus, spatial biases in global datasets are often unknown. Although these shortfalls are understandable (global training data take a great deal of effort to amass, and quantifying spatial uncertainty can be cost- and time-prohibitive for global datasets), they often result in users not knowing where a model is failing to predict well. The main goal of a global dataset is to be reliable and used by other scientists, which makes it imperative to support users with information about uncertainties.

## BOX 1

### Recommendations for global datasets

To strengthen transparency and usability, we recommend dataset producers:

- (1) Maintain living, citation-ready 'known issues' changelog databases (using drug side-effect databases as inspiration);
- (2) Maintain community organizations that support standardized issue reporting;
- (3) Encourage journals and repositories to adopt 'post-publication notes' for geospatial datasets;
- (4) Generate spatially explicit error maps to complement error matrices; and
- (5) Bundle uncertainty layers with all dataset downloads.

For dataset users, we encourage:

- (1) Careful assessment of local predictions;
- (2) Sensitivity analyses using multiple independent global datasets; and
- (3) Conservative analysis across dataset resolutions.

Together, these steps would foster accountability and reproducibility.

Another problem deriving from transferability is that models can have high global accuracy and quantified spatial uncertainty, and yet be inaccurate and unexpectedly uncertain at local extents due to transferability<sup>9,10</sup>. Global estimates of accuracy and uncertainty are often based on sampling and/or internal model variability, and therefore prone to miss local variability. For example, Hansen et al.<sup>3</sup> estimated the accuracy of their global forest change model at the biome scale, with 1,500 samples. Predicting tree cover change from this dataset in individual regions or countries without local quality assessments can lead to erroneous conclusions.

Users should check how accurate a dataset is estimated to be, and its known limitations. Published critiques of global datasets will not be collected in one location: there are no databases that list documented errors in global data products (analogous to pharmaceutical drug side-effect databases), but there should be. Users should always do a 'reality check' and spend time inspecting global datasets in local areas with which they are familiar, to learn firsthand where they might be inaccurate. Individual products can be assessed and modified (for example, using in situ calibration data), but studies should also use multiple sources where possible, as they can correct for each other and/or provide a range of estimates (for example, ref. 11). However, as data independence is critical, multiple lines of evidence that are derived from the same satellite sensors may be redundant or misleading.

#### Where to make inferences?

Although many global land-cover datasets now exist at fine scales of 10 to 30 m or less, there are numerous global datasets that remain available only at markedly coarser scales, from 100–500 m (for example, carbon) to 1+ kilometres (for example, surface temperature). It is common practice for researchers to combine remote-sensing data from coarse and fine scales to make predictions at the finest scale

(that is, 10 or 30 m). The resulting resolution is unclear, driven by the resolution of the most important model predictors. However, this practice is acceptable in theory, as long as the producers account for coarse-scale errors and quantify accuracy at spacings smaller than the coarse-scale inputs (for example, ref. 12).

Greater challenges arise when researchers attempt to make fine-scale conclusions on the basis of coarse-scale datasets, or of correlations between fine-scale and coarse-scale datasets. Coarse pixels are made up of many smaller fine pixels, and often mixtures of different land uses, creating 'mixed pixels'. They can be a poor tool to elucidate fine-scale processes.

Take forest and non-forest edges. Global land-cover datasets allow the calculation of forest landscape fragmentation at fine resolution. But processes of interest at forest edges, such as biomass, temperature and productivity, are usually measured using coarser-resolution products. This disconnect between the fine scale of forest fragmentation and the coarse scale of the variable of interest has led to a variety of potentially spurious conclusions. For example, a recent study used coarse-scale biomass and tree cover products to argue that forest biomass declined near tropical forest edges<sup>13</sup>. However, the coarse-scale tree cover product had a 60% tree cover threshold, which means that many forest 'edge' pixels were mixed, including large areas of non-forest. The coarse-scale biomass estimates over those 'edge' pixels are necessarily lower, because mixtures of forest and non-forest have lower overall biomass than pure forest pixels. This mixed-pixel problem potentially affects several papers that use fine-scale data to predict coarse-scale properties such as biomass (for example, ref. 14).

Several regional and global studies of forest edges have appropriately used only data at fine-to-moderate resolution, revealing notable variation in edge structure and function (for example, ref. 15). We recommend that global studies of fine-scale processes should be conservative about using coarse-scale predictors, discarding or accounting for known mixed pixels wherever possible. Whenever possible, matching the scale of the response variable with the resolution of the predictor is optimal.

#### Towards responsible use of remotely sensed data

The field of global data products is young – only decades old. As it matures, best practices and metadata have to mature as well. The scientific community must continue to push for global dataset producers to carefully report accuracy and spatial uncertainty in their predictions. But we must also support users with best practices: evaluating local performance, being careful with resolution and mixed pixels, and understanding the limits of a global overhead perspective. In an ideal world, every global dataset would come with thoughtful guidance on limitations and blind spots, quantified spatial error and training data locations, and an open-source collation of known errors and critical publications (Box 1). Until datasets meet these standards, we encourage users to carefully and critically assess the global products they select, and to be cautious when using them. As scientists increasingly have access to satellite data and computing power to produce global datasets, so must they grow their ability to provide actionable insights from the data.

Matthew E. Fagan<sup>1</sup>✉, Naomi B. Schwartz<sup>2</sup> & Ruth S. DeFries<sup>3,4</sup>

<sup>1</sup>Department of Geography and Environmental Systems, University of Maryland Baltimore County, Baltimore, MD, USA. <sup>2</sup>Department of Geography, University of British Columbia, Vancouver, British Columbia, Canada. <sup>3</sup>Department of Ecology, Evolution,

---

# Comment

and Environmental Biology, Columbia University, New York, NY, USA.

<sup>4</sup>Climate School, Columbia University, New York, NY, USA.

✉ e-mail: [mfagan@umbc.edu](mailto:mfagan@umbc.edu)

Published online: 10 December 2025

## References

1. DeFries, R. S. & Townshend, J. R. *Int. J. Remote Sens.* **15**, 3567–3586 (1994).
2. Lautenbacher, C. C. *Space Policy* **22**, 8–11 (2006).
3. Hansen, M. C. et al. *Science* **342**, 850–853 (2013).
4. Fagan, M. E. *Glob. Change Biol.* **26**, 4679–4690 (2020).
5. Strassburg, B. B. N. et al. *Nature* **586**, 724–729 (2020).
6. Pritchard, R., Sauls, L. A., Oldekop, J. A., Kiwango, W. A. & Brockington, D. *Conserv. Biol.* **36**, e13919 (2022).
7. Olofsson, P. et al. *Remote Sens. Environ.* **148**, 42–57 (2014).
8. Meyer, H. & Pebesma, E. *Nat. Commun.* **13**, 2208 (2022).
9. Ploton, P. et al. *Nat. Commun.* **11**, 4540 (2020).
10. Pletcher, E., Smith-Tripp, S., Evans, D. & Schwartz, N. B. *Int. J. Remote Sens.* **45**, 492–507 (2024).
11. Fesenmyer, K. A. et al. *Nat. Commun.* **16**, 4572 (2025).
12. Williams, B. A. et al. *Nature* **636**, 131–137 (2024).
13. Chaplin-Kramer, R. et al. *Nat. Commun.* **6**, 10158 (2015).
14. Zhao, Z. et al. *Nat. Geosci.* **14**, 479–483 (2021).
15. Bourgoin, C. et al. *Nature* **631**, 570–576 (2024).

## Competing interests

The authors declare no competing interests.

## Additional information

**Peer review information** *Nature Ecology & Evolution* thanks He Yin and Edward Mitchard for their contribution to the peer review of this work.