



SUSTAINABLE
FOREST
TRANSITIONS



Global forest dataset incongruence creates high uncertainties for conservation, climate, and development policy

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We quantify the spatial agreement among 10 global forest datasets commonly used to measure forest cover at global levels. We find only 26% spatial agreement among these datasets. This low level of agreement leads to up to tenfold differences in estimates for carbon accounting, forest–poverty mapping, and biodiversity habitat.

We provide guidance for data choices based on data user needs.

The problem

Satellite-derived global forest datasets (GFDs) have become a dominant source of information for large-scale forest monitoring.

GFDs vary in spatial resolution, forest definitions, detection algorithms, and temporal span and consistency.

The practical implications of GFD differences for quantitative social and environmental policy questions remain undertested.

Research approach

We show how the conclusions decision-makers and researchers could draw about the status and changes in the world's forests may be heavily influenced by their choice of GFD.

We do so by, first, quantifying spatial congruence (i.e., area of agreement in forest classification) between the eight most used GFDs that measure forest cover at single points in time (static maps).

Then, we overlay two global change products and the eight static maps to assess how GFD choice influences estimates in three illustrative case studies: Kenya's forest carbon; forest-poverty mapping in India; and habitats for the white-cheeked spider monkey (*A. marginatus*) in Brazil.

Static forest cover data

1. Copernicus Global Land Cover (CGLC)
2. Global Land Analysis and Discovery - Global Land Cover and Land Use Change (GLAD-LCLUC)
3. European Space Agency - WorldCover (ESA-WC)

4. European Space Agency - Climate Change Service Land Cover (ESA-C3S-LC)
5. Environmental Services Research Institute Land Cover (ESRI-LC)
6. Japan Aerospace Exploration Agency Forest/Non Forest (JAXA-FNF)
7. Moderate Resolution Imaging Spectroradiometer, Land Cover Type - Annual International Geosphere - Biosphere Programme Classification System (MODIS-IGBP)
8. Moderate Resolution Imaging Spectroradiometer, Land Cover Type - Food and Agriculture Organization of the United Nations Land Cover Classification System (MODIS-FAO)

Forest cover change data

9. Vancutsem et al.¹ Tropical Moist Forest Cover Change (Vancutsem-TMFCC)
10. Hansen et al.² Global Forest Cover (Hansen-GFC)



References: ¹Vancutsem et al. 2021. Sci Adv; ²Hansen et al. 2013. Science.

Results

Of the total area classified as forest by at least one dataset (6.8 billion hectares), only 26% was classified as forest by all eight static datasets (Figure 1). Spatial agreement was relatively high in tropical moist broadleaf forests (50%) and much lower in tropical dry broadleaf forests (12%).

Forest biomass carbon in Kenya. Forest classification differences produced wide variation in estimates of 2010 forest biomass carbon (2–37%) and its spatial distribution across Kenya.

Forest proximate people living in poverty in India. Estimates of the number of people living in and around forests that are poor varied up to tenfold among the forest datasets. For 2016, estimates varied from 23.1 million people (MODIS-IGBP) to 252.1 million people (ESA-WC).

Biodiversity habitat mapping in Brazil. Across the six years (2016–2021) studied for the white-cheeked spider monkey (*A. marginatus*), the two forest cover change datasets (Hansen-GFC and Vancutsem-TMFCC) exhibited 37% overlap in the area classified as deforested (although it was nearly 50% in the single year 2021).

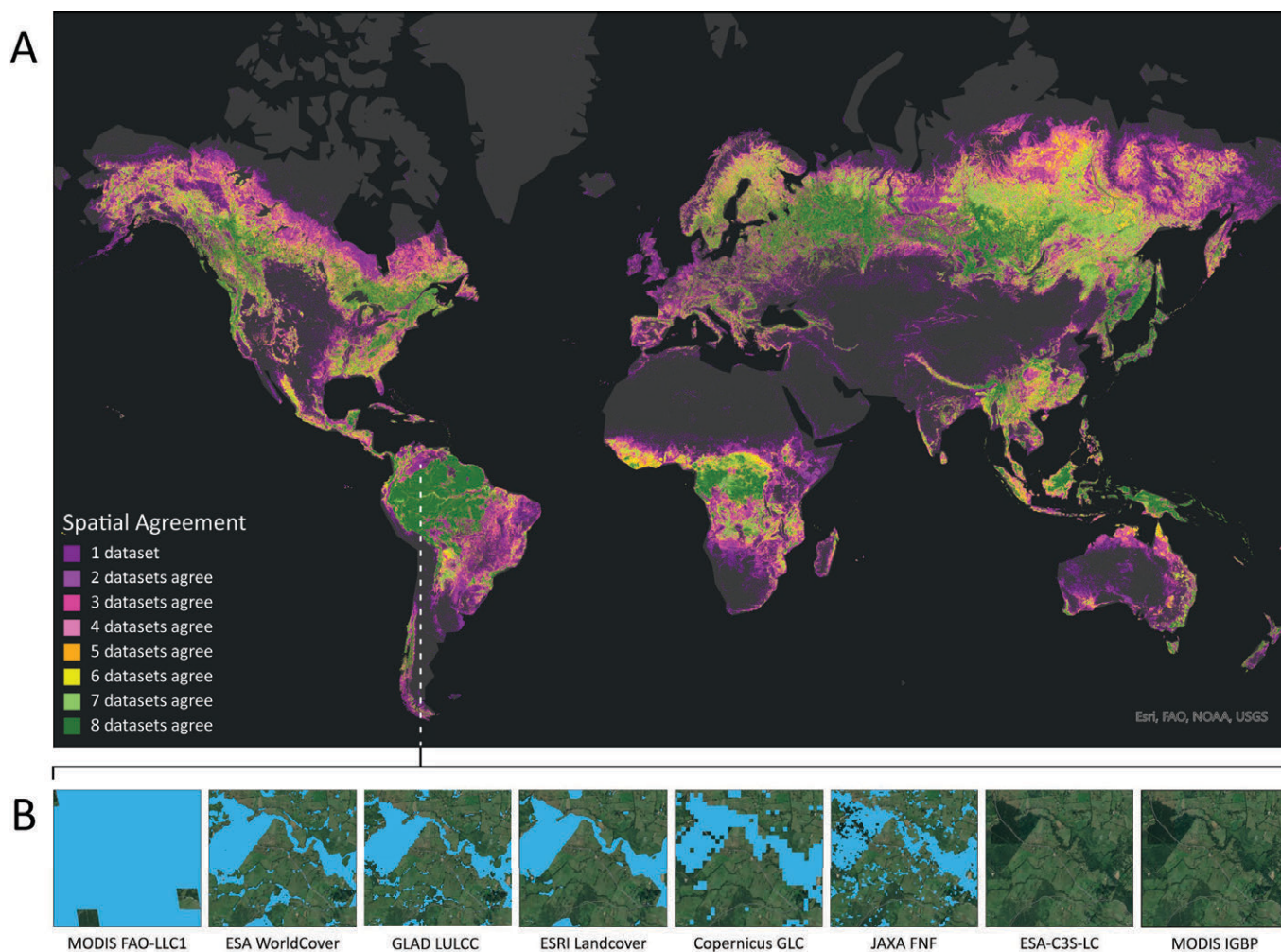
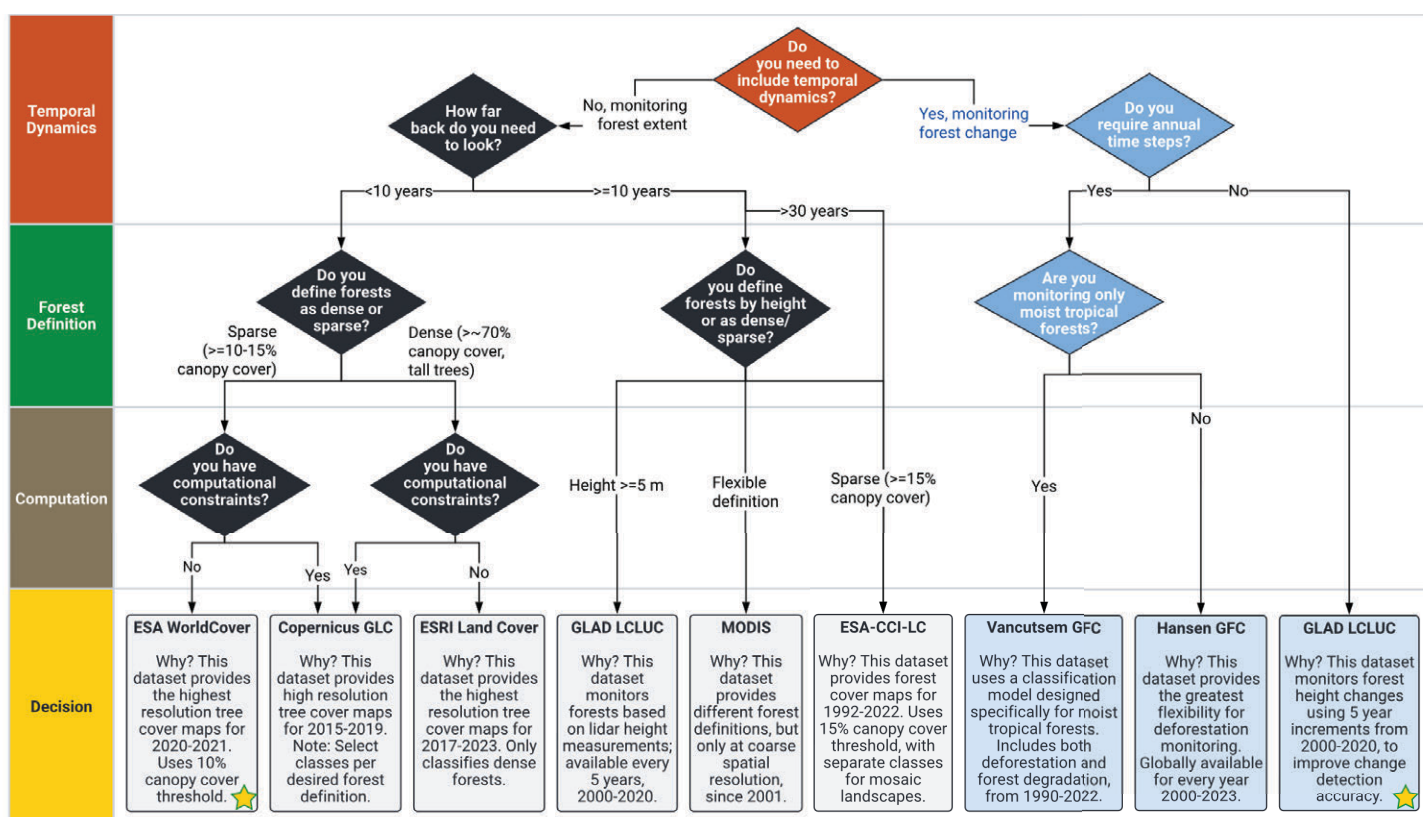


Figure 1: Spatial congruence of eight forest cover datasets. (A) Spatial agreement of forest cover classifications between eight land cover datasets. Full agreement between all eight datasets corresponds to a value of eight (dark green), and no agreement between the datasets corresponds to a value of 1 (dark purple). (B) Illustrative case study of a random area (approximately 16 km²) selected in the country of Colombia showing how the eight different datasets captured forests and trees differently for the same area. Blue areas are where the datasets classified land cover as forested.

Recommendations

Our analyses lead to three recommendations:

1. When selecting a GFD for a particular purpose, carefully review parameters and methodologies used to produce datasets through our decision tree in Figure 2.
2. Include sensitivity and uncertainty analyses as a part of studies employing GFDs. For example, by testing how results vary when using alternative datasets that are justifiable to use for the given problem.
3. Increased standardization and harmonization of land cover datasets and GFDs through strategic data governance. Governing bodies, major space agencies, and international earth observation initiatives could collaboratively generate standardization protocols for forest monitoring. For example, for reporting both fractional cover (e.g., tree canopy cover percentages) and uncertainty maps.



★ Recommended as best available, if it meets user's end needs, including regional accuracy.

Note: Users may need to pre-process datasets to remove tree cover that does not meet forest definition (e.g., using a minimum forest area).

Figure 2: Decision tree to guide dataset selection for different applications.

Decision-tree branches include (1) temporal dynamics (whether the user aims to monitor forest cover or forest cover change), (2) forest definition (whether the user defines forests by height, dense canopy cover, or sparse canopy cover, or [for forest cover change] whether the user is only monitoring moist tropical forests), and (3) computational constraints (whether the user has the computational capacity to run their analysis with very high-resolution data). Stars indicate the datasets recommended by the authors based on our review, if they meet the user's needs. Note, this decision tree does not account for regional differences in classification accuracy, which are influenced by factors such as training data, modeling approach, and algorithm performance. Where possible, users should consult independent validation studies to assess which dataset is most appropriate for the specific application. Black/grey boxes (left) indicate choices for static forest cover data, and blue boxes (right) indicate choices for forest cover change data. **4**

About the authors



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About Sustainable Forest Transitions

Sustainable Forest Transitions examines how drivers of reforestation can benefit the environment and local communities, while improving the design and evaluation of forest-sector interventions. The project was selected by the European Research Council (ERC) and funded by UK Research and Innovation (UKRI) under grant number EP/X023222/1.

About the FLARE Network

The Forest and Livelihoods: Assessment, Research and Engagement Network seeks to advance knowledge at the intersection of forests and livelihoods and facilitate its application to policy and practice. FLARE is a vibrant international community of scholars, students, and professionals from a range of environmental and social NGOs, development agencies, donors, and research organizations. The FLARE Network is funded by the Ford Foundation under grant number 151716.

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