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

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Summary

Forests are central to climate, biodiversity, and development goals, but effective monitoring and evaluation of their contributions depends on reliable data. Satellite-derived global forest cover and change datasets (GFDs) are widely used to address this need. However, differences in resolution, forest definition, and methodology challenge their use in research and policy. Yet how GFD differences affect key forest-related estimates remains poorly understood. Here, we quantify global area-based spatial congruence among ten GFDs and test their influence on three national policy-relevant estimates: carbon accounting, forest-poverty mapping, and biodiversity habitat. We find only 26% spatial congruence among GFDs at native resolution. This low congruence translates to an order-of-magnitude difference in national case study indicator estimates. We demonstrate that GFD selection fundamentally shapes monitoring and evaluation outcomes, particularly in biomes with fragmented or sparse tree cover. We provide a decision-support framework to guide GFD selection according to different forest-related science and policy applications.

Keywords: forest policy, sustainable development, conservation, climate change, poverty, remote sensing

Introduction

Forests are critical ecosystems that provide multiple services essential to achieving global sustainability goals. They are key to climate change mitigation both through carbon uptake (sequestering roughly 15.6 billion metric tons of CO_2 each year) and reduced emissions through avoided deforestation (since deforestation, fire, and disturbance release roughly 8.1 billion metric tons of CO_2 each year)[1]. Forests are essential for biodiversity, providing habitat for the majority

of terrestrial species, including roughly 80% of amphibian species, 75% of bird species, and 68% of mammal species – along with housing approximately 60,000 different tree species[2]. Beyond these critical ecological functions, forests directly support the livelihoods and resilience of over 1.6 billion people worldwide, many of whom are among the global poor[3]. These central roles in climate, biodiversity, and livelihoods mean that forest ecosystems are fundamental to major international policies and finance mechanisms, including the Paris Agreement, the Kunming-Montreal Global Biodiversity Framework, and many United Nations 2030 Sustainable Development Goals (SDGs)[2,4,5]. Consequently, national governments, non-governmental organizations, and private sector investors actively rely on accurate, timely data on the extent of forest conservation, deforestation, and reforestation to track progress, allocate resources, enforce regulations, and inform more just and effective sustainability policy.

Satellite-derived global forest datasets (GFDs) have become a dominant source of information for large-scale forest monitoring, often replacing costly and time-consuming ground-based inventories. The rapid rise in GFDs generated with increasingly advanced remote sensing and machine learning techniques, together with high-performance, cloud-based geospatial platforms, offers unparalleled access to high-resolution, globally available data. This unprecedented access has led to wide adoption of GFDs by researchers, policymakers, and practitioners for a range of uses. For example, numerous empirical studies have quantified how forest conservation policies reduce deforestation (e.g. Börner et al. [6]), support local livelihoods (e.g., Ordóñez et al. [7]), and generate climate-relevant carbon offsets when properly designed (e.g., West et al. [8]).GFDs are especially important for applications in countries where there is a lack of high-quality, recently updated, national or regional land cover datasets. Relatively few countries or regions have publicly available datasets that could be used as alternatives, with

notable exceptions including Brazil[9], North America[10,11], Europe[12,13], and China[14,15]. In many cases, however, regional or national data may not be readily available or may have different limitations than the GFD (e.g., different classification errors or not available annually).

Despite their widespread use, GFDs are not interchangeable: they vary significantly in spatial resolution, forest definition, classification methodology, model training procedures, and temporal consistency and span. Prior work has demonstrated several conceptual and technical variations in global land cover and forest cover datasets[16-20], even as these same products have underpinned high-impact evaluations of conservation programs[6,21] and econometric studies linking land-cover change to economic outcomes[22,23]. These variations – for example, a dataset classifying forest as pixels with 30% tree canopy cover versus 10% tree canopy cover – have been shown to change the estimated extent of forests from 35% to 22% of the world's land area [17]. These differences ultimately dictate which forests are counted, and how they are represented in climate finance, measurements of forest-based livelihoods, and tracking progress towards biodiversity conservation goals. However, the practical implications of GFD discrepancies for quantitative social and environmental policy questions remain undertested.

The uncertainty arising from this data incongruence presents a challenge to evidence-based conservation and development action. Although recent studies have quantified the classification accuracy of several recent, high-resolution GFDs (e.g., Xu et al. [24]), the extent of spatial disagreement among them and other widely used GFDs, both in terms of mapped forest extent and location, has not been systematically characterized. The choice of GFD can determine whether a region is prioritized for climate and biodiversity financing, or whether people's forest-related livelihoods are captured by governing bodies. These challenges are particularly noticeable in biomes with sparse or fragmented tree cover, where forest extent is highly sensitive

to forest class definitions. Here, we quantify how GFD choice propagates uncertainty into real-world assessments.

We shed light on how the conclusions decision makers and researchers 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 assessing whether and how different GFDs affect estimates of forest extent. We quantify 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 (see Methods and Table S1 for details). Then, by overlaying two global change products and the eight static maps in three illustrative case-studies (Kenya's forest carbon, forest-poverty mapping in India, biodiversity habitat in Brazil), we show how choice of GFD can alter downstream estimates by up to an order of magnitude. We compare datasets based on their published forest class definitions, which differ substantially in biophysical thresholds and classification logic and do not reflect a standard forest land use definition (e.g., FAO [25]). Most global forest datasets apply a biophysical definition of forest, typically based on minimum tree canopy cover, tree height, and/or vegetation type thresholds. We use the term "forest cover" when referring to forest land cover classes in GFD products[17].

Our aim is to quantify spatial congruence across available GFDs and to provide illustrative examples of how differences in forest representation, under each dataset's own published methodology and forest definition, affect downstream sustainability-relevant analyses. While sample-based area estimation is the recommended standard for unbiased national estimates[26,27], our comparative approach provides a complementary perspective relevant to many researchers and practitioners who use GFD products directly in ecological, social, or policy studies.

Results

Spatial agreement of forest cover data

The eight forest cover datasets exhibited low overall agreement (Figs. 1 and 2). Of the total (or union) of the area classified as forest by at least one dataset (6.8 billion ha), only 26% was classified as forest by all eight datasets. Systematic pairwise comparison of each of the eight datasets revealed that some datasets agreed strongly with one another while others overestimated or underestimated forest extent relative to others (Figs. 2 and S3). CGLC had the highest pairwise agreement with the other datasets, while MODIS-IGBP, followed by ESA-C3S, had the lowest pairwise agreement with the others. Withholding MODIS-IGBP, the spatial congruence was still only 35% among the other seven datasets (Table S2). When we included savanna classes for the MODIS-IGBP dataset (Fig. S1), agreement among the eight GFD increased to 35%, suggesting that savannas and savanna-forest transitions were sometimes classified as forest due to the characteristically sparse tree canopy cover commonly found in these ecosystems.

Differences in classification were most apparent at finer-grained spatial scales. Some datasets classified large swaths of fragmented tree cover and mosaic landscapes as entirely forested. Some datasets captured smaller forested patches and linear tree features, whereas others missed these (Fig. 1b). Based on visual inspection across multiple global locations, ESA-WC and GLAD-LCLUC appeared comparatively better at capturing small patches and linear features. While Figure 1b provides one illustrative example, this is a qualitative observation and does not represent a formal or systematic evaluation. Additionally, we show that, as expected, areas with lower tree canopy cover have much lower spatial congruence than areas with high levels of tree

canopy cover (Fig. S2, Table S3). We would not expect to have full agreement for low tree cover due to differences in forest definition among the datasets: only five of the eight would capture sparse canopy cover forests, so Fig. S2 and Table S3 should be interpreted accordingly.

To reduce the effects of differing native resolutions across datasets, we aggregated all GFDs to a common 500-meter resolution (see Methods for the normalization approach). This harmonized-resolution analysis (normalized to 500-meter resolution, Table S4) differs from that in Figure S2 and Table S3, which rely instead on each dataset's original resolution and native forest class definitions. Harmonizing the datasets by spatial resolution increased the global congruence only slightly: from 26% to 27% (Table S4, lines 1 and 4). When both normalizing and removing the MODIS dataset with a conflicting forest definition, spatial congruence increased to 45% and 30% for the sparse 10% cover threshold and dense 60% threshold, respectively (Table S4; from 35% and 27% without normalization, respectively, Table S2). Although standardizing resolution increased technical agreement to 45%, a majority of the world's forest area remains subject to incongruent forest data. We further grouped datasets by their forest definition (sparse vs. dense) and recalculated congruence. After normalizing all datasets to a 500-m resolution (10% cover threshold) and using only the six datasets with sparse forest classes, average spatial congruence increased to 47% (from 27%, Table S4: lines 1-3). With a 60% threshold and using only the four datasets with dense forest classes, congruence increased to 42% (Table S4: lines 4-6). These findings illustrate that spatial resolution normalization contributes to improved spatial congruence but explains only part of the spatial disagreement. These patterns also suggest that definitional alignment improves consistency more than resolution normalization alone. Differences in classification methodology, including the choice of algorithm, training data, and the spectral and spatial properties of the input imagery,

are also known to affect land cover product accuracy and likely contribute to observed discrepancies in forest representation across GFDs [24,28].

Spatial agreement by biome

Spatial agreement on forested areas varied greatly by biome (Fig. 3, Table S5). We found relatively high spatial agreement for the 'tropical and subtropical moist broadleaf forests' biome, with 50% of forested area in complete agreement across the eight datasets. In comparison, there was relatively low spatial agreement for the 'tropical and subtropical dry broadleaf forests' biome, with only 12% of forested area in complete agreement (Fig. 3). We found that the 'temperate broadleaf and mixed forests,' 'temperate conifer forests,' and 'boreal forests or taiga' biomes had moderate spatial agreement across the eight datasets, with 33%, 32%, and 23% of area, respectively. The 'tropical and subtropical coniferous forests' biome also had low spatial agreement, with 14% of forested area in full agreement. Because of this variance, the total estimated forested land area for each of the 14 biomes varied substantially between GFDs (Table S6).

Explaining incongruence across global forest cover datasets

Four main differences explained the (in)congruence between the eight GFDs: (1) spatial resolution, (2) forest definition, (3) classification methodology, and (4) temporal consistency and span.

(1) Spatial resolution (defined as the pixel size for classifying land cover) affects estimates because it determines the detail at which land cover patterns can be detected. For example, higher spatial resolution maps could detect distinct forest and agriculture

patches in mosaic landscapes. Datasets such as CGLC and JAXA-FNF offer intermediate spatial resolution, losing some of the potential detail of higher resolution data but requiring fewer computational resources to store and process than the higher resolution datasets.

(2) Forest definition (defined as the tree canopy cover density and/or height used to define forest land cover classes) affects estimates because it determines which trees are captured in forest estimates. For example, a 10% canopy cover minimum would include sparse savannas whereas a 70% canopy cover minimum would only capture dense forests. ESRI-LC has the most conservative definition of forests (dense clusters of trees), whereas most of the other datasets use a tree canopy cover of 10-15% as the lower cutoff for defining forests. MODIS-IGBP has a conservative definition of forests but also includes savanna classes that capture regions with lower-density tree canopy cover.

(3) Classification methodology (defined as the underlying imagery sources and algorithm used to assign land cover labels to pixels) affects estimates because it determines the accuracy of the resulting land cover map. Choices about the sensor, the machine learning algorithm (e.g., random forest, deep learning, decision tree), the class labels used, the quantity and accuracy of the training data[29,30], and whether the algorithm is regionally specific (e.g., if different classification algorithms are created for different biomes) all have important implications for land cover maps. Imagery techniques included optical, Synthetic Aperture RADAR (SAR) and light detection and ranging (lidar). For example, ESA-WC and JAXA-FNF incorporate SAR/lidar data along with optical data (e.g., Sentinel-1 and ALOS PALSAR-2, respectively), whereas most of the other GFD use only optical data (CGLC, ESRI-LC, C3S-LC, and MODIS). GLAD-LCLUC is based on

optical Landsat imagery but uses lidar data from GEDI for calibration, enhancing the model's ability to characterize forest structure. Radar imagery allows estimation of vegetation structure and canopy height, especially in regions with frequent cloud cover, while optical imagery is used to measure and classify tree canopy cover and vegetation type. Each type of sensor has strengths and limitations that can influence the resulting dataset's global and regional uncertainty.

(4) Temporal consistency (defined as the ability to detect inter-annual changes in forest cover) and temporal span (defined as the available years of data) affect time series analyses. Temporal consistency determines how well the GFD track forest cover loss and gain over time. The data processing methods used to create temporally compatible data affect the uncertainty in detected changes.

Across datasets, tradeoffs exist between spatial resolution and temporal span since higher spatial resolutions have only become possible with more recent satellite imagery technology. Longer-term GFD typically had much lower spatial resolution. The ESA-WC and ESRI-LC datasets had the highest spatial resolution (10-meters). However, they were only available for the years 2020-2021 and 2017-2023, respectively. By contrast, ESA-C3S and MODIS Land Cover had the longest temporal coverage (1992-2022 and 2001-2021, respectively), but they had the coarsest spatial resolution (300-meters and 500-meters). GLAD-LCLUC forest extent data were only available for the years 2000 and 2020, but they also provided estimates of total forest cover gain, loss, and disturbance over that period. The two forest cover change datasets (Hansen-GFC and Vancutsem-TMFCC) were both 30-m spatial resolution and multi-decadal.

Quantifying the influence of global forest cover dataset selection on sustainability measures

231 Our global analyses reveal several sources of variation between eight different GFDs,
232 which collectively combine to generate low, and biome-specific, levels of agreement between
233 datasets. Here, we test the practical implications of this (dis)agreement between GFDs on three
234 different case-studies. We selected case study countries across three different continents to
235 demonstrate the differences in GFDs and the implications for countries where there is a
236 concentration of forest-related research[31,32]. These case studies reveal order-of-magnitude
237 differences in estimates (e.g., a reporting range of between 23.1 million to 252.1 million people
238 living in poverty near forests in India).
239
240 *Above- and below-ground carbon density in forested areas in Kenya*
241 Many authors have used GFDs to estimate carbon storage to identify the effect of climate
242 change policies or conservation (e.g.,[33,34]). We used the case of Kenya to illustrate how forest
243 dataset selection affects estimates of biomass carbon storage attributed to forests, employing a
244 widely-used above- and below-ground biomass carbon dataset (Fig. S4)[35]. We selected Kenya
245 due to relatively low spatial GFD agreement (Figs. 1 and S5), the diversity of biomes, and
246 widespread low-density forest systems, allowing us to test the differences between GFD in
247 mapping forest carbon.
248 We overlaid the GFD and biomass carbon data[35] to assess relative estimates of carbon in
249 areas classified as forest. We emphasize that this analysis is illustrative and not meant to provide
250 a new estimate of forest biomass carbon. We also note that there is high uncertainty in the
251 carbon density data layer[36], which we did not study here.
252 Differences in forest classification had two important implications for estimates of total
253 biomass carbon stored in Kenya's forested areas. First, these differences led to wide variation in

the *amount* of carbon, with estimates ranging from 2% (MODIS-IGBP) to 37% (JAXA-FNF) of Kenya's total biomass carbon stored in forests (Table S7). Second, these differences led to variation in the estimated distribution of *where* carbon is stored in forested lands (Fig. 4 and S6). While two datasets may have similar total forest carbon estimates, they were not necessarily distributed equally across space. For example, CGLC and ESRI-LC have similar estimates of total forest carbon in Kenya, but where it is located is dramatically different (Table S7, Fig. S6).

Forest-proximate people in poverty in India

Identifying people affected by forest policy decisions is critical for meeting sustainable development goals[37,38]. We mapped forest-proximate people living in poverty in India, which is the most populated country in the world, where many people rely on forests for their livelihoods[39]. Forest-proximate people in poverty is used as an indicator of forest dependency, where we defined forest proximity as rural populations living in or within 1 km of a forested area, with poverty status determined using gridded wealth indices calibrated to national poverty rates (Methods). The country has a long history of forest conservation, management, and restoration efforts that are intimately linked with local communities[40].

We found that our national estimates of the number of forest-proximate people living in poverty varied by an order of magnitude among the forest datasets (Table S8). For 2016, estimates varied from 23.1m people (MODIS-IGBP) to 252.1m people (ESA-WC), holding all other variables constant. In contrast to the Kenya case study, the spatial distribution of *where* forest-proximate people were living in poverty was similar when comparing two datasets with similar magnitudes of forest area, such as ESRI-LC and CGLC (Fig. 5) but still drastically different across all eight datasets (Fig. S7). This case study does not imply that one dataset is

277 more accurate or appropriate than the other; rather, it demonstrates how the choice of forest
278 definition and classification system can have large effects on estimates and distribution of forest-
279 proximate populations.
280
281 *Forest habitat for endangered species in Brazil*
282 Forest extent is often used as a proxy for species habitat[41,42]. We examined how
283 differences in GFD selection may affect biodiversity analyses. We selected Brazil as a case study
284 given its global importance for biodiversity and its well-studied forest cover change dynamics.
285 The white-cheeked spider monkey (*Ateles marginatus*) is an endangered, forest-dwelling species
286 found in the Brazil (in the states of Mato Grosso and Pará). We estimated the forested habitat
287 available within the IUCN defined species range (Table S9) and estimated forest cover change
288 within the region for the period 2016-2021 (Table S10).
289 When considering forest cover *change*, the two forest change datasets (Hansen-GFC and
290 Vancutsem-TMFCC performed dramatically differently, with less than 50% spatial congruence
291 between them (Table S10). Across the six years studied for *A. marginatus*, the two forest cover
292 change- datasets overall exhibited moderate overlap in the area classified as being deforested in
293 each year by both datasets (37% agreement for the period 2016-2021, though this was nearly
294 50% in the single year 2021) (Figs. 6 and S8, Table S10). Importantly, Vancutsem-TMFCC only
295 applies to tropical moist forests, so while the dataset is available across the topical band, it does
296 not capture other forest types.
297

Discussion

We provide systematic evidence that GFD selection can introduce order-of-magnitude uncertainty into monitoring global sustainability challenges. Our results reveal extensive differences in what is classified as "forest" across eight widely used global forest cover datasets (GFDs) and show how dataset choice affects related social and environmental analyses in key sustainability domains. These discrepancies may shape how governments, NGOs, and researchers measure progress toward global climate, biodiversity and development goals. These findings illustrate that millions of people could be overlooked or mistargeted when allocating funding towards forest-based adaptation and livelihood goals and that billions of trees may be overlooked when quantifying the roles of forests and trees towards climate and biodiversity goals. Our findings suggest a need for researchers and decisionmakers who use GFDs to carefully consider the appropriateness of which dataset they select for a given application and/or to use several different GFDs to generate a range of estimates for any given analysis. Based on our review of currently available datasets, we generated a decision tree to help guide user's dataset selection based on the parameters of their application (Fig. 7).

The ten GFDs varied in their spatial resolution, forest definition, classification methodology, and temporal consistency and span. These factors mean that some of these datasets may be less suitable (or indeed, unsuitable) for assessing forest cover and change in some biomes or for some land use types (e.g., fragmented forests or tropical dry forests). Datasets with a higher spatial resolution, such as ESA-WC and GLAD-LCLUC, are more likely to capture smaller features, land cover heterogeneity, and landscape fragmentation. Venter et al. [43] similarly found that ESA-WC was well-suited to detect smaller areas of trees outside of forests, including hedgerows[43]. However, since some datasets capture tree extent at such a fine spatial resolution,

pre-processing steps may be necessary to remove classified tree cover that does not fit the user's desired definition of forests. Reporting often relies on clear definitions of forests, but we show that small definitional differences can translate into large discrepancies in reporting.

The 'best fit' dataset for a given application will depend on desired spatial resolution, forest definition, temporal consistency, temporal span, and biome and may change as new datasets and classification algorithms become available. For example, Newton *et al.* [38] estimated the number and spatial distribution of forest-proximate people using CGLC data for the primary analyses since it was the best available data at the time of analysis in 2021 (and an improvement on their earlier analysis)[3,38]. However, as of 2023, ESA-WC and ESRI-LC were available at much higher spatial resolution than CGLC and could now be used to generate improved estimates. Additionally, alternative data products, such as burned area and active fire datasets, have been proposed as potentially useful datasets for tracking forest loss, particularly for regions with deforestation driven by shifting cultivation[44]. Methods have also been proposed to harmonize multiple land cover datasets of different sources and resolutions to improve the accuracy of classification[45-47]. Such harmonized datasets could be valuable for standardizing monitoring and reporting of climate, biodiversity, and development targets.

Our analyses are consonant with recent studies that have also highlighted issues with consistency and accuracy of alternative land cover datasets[17,18,24,48,49] and the importance of harmonizing forest definitions[50,51]. We advance previous work by explicitly exploring the implications of forest dataset selection for social-ecological analyses. For example, Sexton *et al.* [17] explored the effects of different forest definitions using eight forest cover datasets from around the year 2000 but did not assess how such differences may influence sustainability-related indicators or downstream applications. Our analysis, based on more recent datasets, found

similar incongruence among datasets, despite notable improvements in underlying data and processing methods. To illustrate the consequences of these discrepancies, we presented three case studies across different domains: carbon accounting, forest-poverty relationships, and biodiversity habitat. While these examples are not intended to be globally representative, they highlight the types of variability and interpretive challenges that may arise depending on which GFD is selected. Considering the differences that we found in GFD, specific datasets may have been used by researchers in contexts where an alternative dataset might have provided very different insights, and/or where considerable care is needed in interpreting the analyses. While we are not the first to call for such care in using land cover and change datasets (e.g., [43,52]), our work provides quantitative examples of how such care is warranted through our case studies. Our aim is to underscore the importance of dataset selection in sustainability applications, not to generalize specific findings across all landscapes.

Our analyses lead to three major recommendations. First, we suggest that researchers (and other users of these datasets) carefully review the dataset parameters and the methodology used to produce the datasets when selecting a GFD for a particular purpose[53]. We provide initial guidance through our decision tree (Fig. 7), which organizes datasets by their spatial resolution, temporal span, and forest definition. However, the optimal GFD is highly dependent on the analytical goal and computational capacity. For instance, moderate resolution datasets (e.g., CGLC) may be sufficient and more computationally efficient for global environmental (e.g., forest habitat estimation) or social (e.g., forest-proximate people estimation) analyses, as CGLC (100-meter resolution) performed similarly to the higher resolution datasets like ESA-WC and ESRI-LC (10-meter resolution) in our case studies. While spectral range and resolution are important, the classification quality is also strongly influenced by how time-series imagery and

phenological dynamics (e.g., seasonal greenness or land surface phenology) are incorporated into the model. Products that leverage these temporal signals, particularly through multi-season compositing or phenology-informed classifiers, often demonstrate improved accuracy and ecological relevance[54]. National and subnational analyses (e.g., for carbon accounting or species distribution modeling) will generally benefit from higher spatial resolution and time-series-informed forest and tree cover data. Even then, these still need to be used with caution. ESA-WC and ESRI-LC datasets are the highest resolution land cover classification data currently available, but they have important differences in forest definition. We also found that some biomes had more disagreement than others, and caution is especially needed for the tropical and subtropical dry forests biome. Additionally, we note the challenges when interfacing between datasets, such as between the GFDs and the carbon biomass dataset. The underlying spatial resolution and forest definitions of the GFD continue to have big implications when aggregating to a normalized resolution, especially for datasets that do not provide information on the estimated percent tree canopy cover per pixel. For example, it is hard to know what percent of the 300-m biomass carbon pixels is truly covered by trees when normalizing by spatial resolution.

Second, we suggest that researchers include sensitivity and uncertainty analyses as a part of studies employing GFD[38,55]. As illustrated by our case studies, different datasets may generate estimates that can vary by over an order of magnitude. Beyond scrutinizing GFD options and choosing the best available data for their primary analyses, we recommend that researchers test how results vary when using alternative datasets, particularly those with comparable spatial resolution, temporal span, and forest definitions. This approach allows uncertainty to be attributed more directly to classification methodology (e.g., model accuracy, training data) rather

than definitional differences alone. Where available, regional or national datasets with different modeling approaches but similar forest definitions can further support sensitivity analyses. However, in many regions such alternatives may not exist. Even in those cases, using multiple global products can still provide a sense of the range of plausible estimates, rather than a single value. To help enable more robust uncertainty analyses, we also recommend that dataset producers provide error bounds or a classification probability maps to indicate pixel-level confidence. Among the ten datasets included in this paper, only CGLC and the MODIS land cover products included such uncertainty indicators.

Third, despite improvements in GFD quality, we recommend increased standardization and harmonization of land cover datasets and GFDs through strategic data governance. Given the order-of-magnitude uncertainty introduced by GFD choice, governing bodies (e.g., the UN FAO, UNFCCC, major space agencies, and international earth observation initiatives) could collaboratively generate standardization protocols for forest monitoring. New protocols for reporting both fractional cover (e.g., tree canopy cover percentages) and uncertainty maps are urgently needed. Until GFD producers and key policy data users commit to improved standardization, a fundamental technical choice made in a laboratory will continue to dictate resource allocations and undermine the global community's ability to credibly track progress towards climate and development goals. Given the current lack of data harmonization, we suggest that, where possible, assessments of forest-related policies should use consistent data sources over the analysis period[23]. To achieve consistency, researchers can (1) use the same GFD used in the initial policy design, (2) re-generate the baseline assessment using the newly available GFD, or (3) use different datasets for the baseline and endline analysis but assess the resulting potential bias in the estimates and explicitly document the discrepancies. Differences in

forest definition and classification methods between datasets, and within the same dataset over time, can lead to biases in impact estimates if the dataset is inconsistent. Additionally, we suggest using care when using forest cover change data. We found that forest cover change datasets (Hansen-GFC and Vancutsem-TMFCC) had considerable disagreement. Accuracy of change detection maps can be affected by the data collection methods, including factors such as seasonality, topography, and shadow presence.

One limitation of our approach is driven by the temporal inconsistency across the eight forest cover datasets. CGLC currently was only available through 2019 while ESA-WC was only available for 2020-2021. Additionally, there may be some within-year variability of when the land cover maps were generated based on when the satellite imagery was collected during the year. This likely contributed to some of the differences within our analyses, especially when considering forest cover change. The within-year variability and imagery collection date(s) may be important considerations for research use, where data sources need to be properly harmonized. For the forest cover change comparison, there were important differences in how the Hansen-GFC and Vancutsem-TMFCC datasets tracked change over time. The Hansen-GFC data only records the first year that a pixel is deforested, after which it is removed from future loss classification. Vancutsem-TMFCC, on the other hand, classifies pixels as stable, degraded, deforested, or gain for each year of the dataset, so a pixel can fluctuate through deforestation and regrowth cycles.

New datasets continue to be released, creating new possibilities for research using and assessing global forest and tree cover datasets. Some of these new datasets are at unprecedented spatial resolution (e.g., Tolan et al. [56]), which will further enhance understanding of forest and

435 tree cover dynamics. Future research will need to incorporate these and other new datasets to
436 provide updated guidance on forest cover dataset selection.
437 Additionally, new assessments of accuracy are needed to improve the ability of
438 researchers to use forest cover data appropriately. Validation assessments that are independent
439 (i.e., conducted by a third party, not by dataset developers), based on a common validation
440 dataset designed to be adaptable to different forest definitions, would create a consistent metric
441 with which to compare datasets (e.g., lidar datasets could provide a useful ground truth metric).
442 Biome-specific accuracy assessments would allow researchers to decide which dataset would
443 perform best for an analysis or case study region. Some independent accuracy assessments have
444 been conducted using global ground truth data for some groupings of these datasets[24,43,57]. For
445 example, both Xu *et al.* [24] and Venter *et al.* [43] recently compared ESRI-LC, ESA-WC, and
446 Google's Dynamic World (which is a near-real-time, user-generated, 10-m land cover
447 algorithm). While we did not perform accuracy assessments or make use of the uncertainty data
448 associated with several of our included datasets, we echo prior recommendations to carefully
449 evaluate forest cover data in selecting for an application and to conduct accuracy
450 assessments[26,43].
451 High quality, regularly updated information on forest cover and forest cover change is
452 critical to inform a wide range of social and environmental sustainability science and policy
453 analyses. Our quantitative comparison of ten widely used public, global forest cover datasets
454 highlights the challenges in accurately mapping forests and forest cover change. Our assessment
455 illustrates how a user's choice of GFD can affect climate, poverty, and biodiversity analyses
456 leading to over an order-of-magnitude difference that can undermine policies aimed to address
457 global agendas. Forests are at the forefront of several key climate and biodiversity agendas,

458 including those of the UNFCCC, the Science Based Targets Network, and the European Union's
459 Regulation on Deforestation-free Products. Our paper provides insights as to how researchers,
460 policymakers, investors, and forest managers who support or monitor actions to achieve these
461 targets might select appropriate GFD depending on their specific sustainability question of
462 interest.
463
464 **Methods**
465 *Data collection: land cover and forest cover datasets*
466 We identified and compiled globally available datasets to estimate forest cover and forest
467 cover change. We reviewed the properties of each dataset and compared the strengths and
468 weaknesses of each based on published documentation and peer-reviewed analyses. Our review
469 included land/forest cover datasets that: (1) defined at least one forest or tree cover class, (2)
470 included recent years (at least one year between 2018 and 2023), (3) were available globally, and
471 (4) which are publicly available and accessible.
472 The eight land/forest cover datasets we identified were: (1) Copernicus Global Land
473 Cover (CGLC)[58], (2) GLAD Global Land Cover and Land Use Change (GLAD-LCLUC)[59], (3)
474 ESA WorldCover (ESA-WC)[60,61], (4) ESA Copernicus Climate Change Service Land Cover
475 (ESA-C3S-LC)[62,63], (5) ESRI Land Cover (ESRI-LC)[64], (6) JAXA Forest/Non- Forest (JAXA-
476 FNF)[65], (7) MODIS Land Cover Type – Annual International Geosphere-Biosphere Programme
477 (IGBP) Classification System (MODIS-IGBP)[66], and (8) MODIS Land Cover Type – FAO-Land
478 Cover Classification System (MODIS-FAO)[66]. The two forest cover change-specific datasets
479 that we identified were: (1) Vancutsem Tropical Moist Forest Cover Change (Vancutsem-
480 TMFCC)[67], and (2) Hansen Global Forest Change (Hansen-GFC)[68]. Importantly, Vancutsem-

TMFCC applies only to tropical moist forests and does not capture change in other forest types, even within its tropical band coverage. Analysts should take care not to extrapolate its classifications to areas outside its intended biome scope.

We present a limited review of 16 other datasets that did not meet our inclusion criteria to provide the reader with historical context and reference material for alternative data sources. These additional resources include GlobeLand30 land cover, Terra MODIS Vegetation Continuous Fields, NASA's GEDI Forest Canopy Height, and the Spatial Database of Planted Trees datasets, as well as 12 historically relevant land/forest cover datasets (Table S1, Supplemental Document S1).

Data analysis

We used four approaches to assess agreement between forest cover datasets and to evaluate the implications of the differences among the datasets for social and environmental analyses. First, we mapped the spatial agreement across the eight datasets, quantified pairwise agreement between each dataset, and estimated agreement for each of 14 biomes. Next, we carried out three case study analyses from different world regions to highlight the extent and significance of disagreement among datasets on estimates of (1) above- and below-ground carbon density on forested lands in Kenya, (2) forest-proximate people in poverty for India, and (3) forest habitat for an IUCN red-listed forest-dependent species, the white-cheeked spider monkey, in Brazil.

To evaluate spatial agreement between GFDs, we used two complementary methods (Fig. S9):

(1) Native-resolution overlay: We overlaid each dataset at its original spatial resolution (e.g., comparing a 500-m dataset directly with a 30-m one), identifying pixels where both datasets classified an area as forest. While this reflects how users might combine off-the-shelf products, it introduces some scale mismatches.

(2) Harmonized-resolution comparison: To address these scale mismatches, we also conducted a separate analysis in which all datasets were aggregated to a common 500-meter grid. Fine-resolution datasets were upscaled by calculating the proportion of forest pixels within each coarse 500-m cell from each product's native forest class definition. We then applied consistent forest thresholds or 10% and 60% forest-class coverage to derive binary forest/non-forest maps at 500-m. MODIS datasets were excluded from the alternate threshold analyses when their forest definition did not align with the cutoff.

For our analyses, we compared the datasets at their original resolutions and at a normalized spatial resolution (500-m). To harmonize spatial resolution across products, we aggregated each GFD to 500-meter resolution by calculating the percentage of each 500-m cell covered by pixels classified as forest according to the dataset's native classification. We then applied uniform forest cover thresholds (10% and 60%) based on the percent of pixels within the 500-m grid that fell into the original forest class(es) to classify the 500-m cells as forested or non-forested. This approach preserves the underlying forest definition of each dataset. No statistical bias correction or regression alignment was performed, as datasets do not measure equivalent biophysical quantities. This process should not be interpreted as statistical normalization of bias across datasets; no regression or calibration was applied, and each product's native classification logic was preserved.

We conducted all of our geospatial analyses in Google Earth Engine (GEE)[69]. We generated the maps in ArcGIS Pro using the exported GeoTIFF files from GEE. The global figures are presented at 1000-m spatial resolution, but higher resolution maps are available through GEE (see code availability). The biomass carbon maps published in this paper are presented at 1000-m resolution, the forest-proximate people maps are presented at 100-m resolution, and the forest cover change maps are presented at 30-m resolution. We retained the original spatial resolution for each dataset to maintain the distinct features for each and show how these different data products differ. As a result, a 500-meter forest pixel from one dataset would contain 2,500 10-meter forest and non-forest pixels from another dataset, and the spatial agreement estimate is the area where the datasets agree using the variation down to the 10-meter pixel scale (see Fig. S9 for illustration). For the spatial agreement analysis, we used the full datasets (using all forest or tree cover classes). We used only two of the eight land cover classification systems available for MODIS Land Cover: MODIS-IGBP and MODIS FAO-LLC1 (MODIS-FAO). We found that MODIS IGBP, UMD, and LAI had very high similarity and that MODIS FAO-LLC1, FAO-LLC2, APFT, and BCG have very high similarity (Fig. S10).

Spatial agreement analysis

We compared the spatial agreement between the eight selected datasets. We overlaid the maps in GEE to determine areas with high and low agreement of forest classification. We tabulated the pairwise agreement between each global dataset to identify the proportion of pixels that each pair of datasets agreed was classified as forest cover. We defined pairwise agreement in two ways:

$$Pairwise\ Agreement_1 = \frac{Number\ of\ pixels\ both\ i\ and\ j\ define\ as\ forest}{Number\ of\ forest\ pixels\ in\ i + Number\ of\ forest\ pixels\ in\ j}$$ (Equation 1)

The definition in Equation 1 indicates the proportion of agreement across the entire area defined as forests by either dataset "i" or dataset "j." The resulting matrix is symmetrical across the diagonal. High agreement using this definition means that both datasets defined forest pixels similarly.

$$Pairwise\ Agreement_2 = \frac{Number\ of\ pixels\ both\ i\ and\ j\ define\ as\ forest}{Number\ of\ forest\ pixels\ in\ i}$$ (Equation 2)

The definition in Equation 2 indicates the proportion of agreement across the area defined as forests by only dataset "i." The resulting matrix is asymmetrical across the diagonal. High agreement using this definition means that dataset "j" captured at least most of the pixels that dataset "i" captured. If in this case, looking across the diagonal there is low agreement, this indicates that dataset "j" defined more pixels as forest than dataset "i."

Additionally, we tabulated the area defined as forests by each of 14 biomes. The biomes are defined by the RESOLVE ecoregions 2017 dataset[70]. We identified datasets for each biome that included significantly more or less forest area based on standard deviation. This allowed us to describe which biomes had high agreement across the datasets, and how the datasets captured forest cover for each biome differently.

We do not perform sample-based estimation or formal accuracy assessment. All area and congruence estimates are based on pixel-level comparisons across products using each dataset's published classification and forest definitions, following a typical user's experience of applying these products in analyses. This analysis should not be interpreted as statistically representative of forest extent or change.

Estimating above- and below-ground carbon density in forested areas in Kenya

To examine the implications of GFD selection on overlaid carbon biomass estimates, we intersected eight forest datasets for 2019–2020 with the 2010 Global Aboveground and Belowground Biomass Carbon Density map[35]. We chose Kenya for its ecological diversity, policy relevance, and previously observed low GFD congruence. Kenya's forests are important for livelihoods through timber production, firewood, and non-timber forest products as well as carbon storage[71]. Kenya has relatively low forest cover with historically high deforestation rates, but the national government has committed to conserving and restoring its forests through efforts including the African Forest Landscape Restoration Initiative[72].

The biomass carbon data layer was already conditioned on 2010 tree canopy and land cover inputs and therefore partially reflects forest extent. Rather than re-estimating carbon storage for 2020, our goal was to demonstrate how alternative GFDs intersect differently with a fixed carbon layer, simulating a typical user overlay analysis. Since we held the carbon density map constant for our analyses of different GFDs, we considered only relative estimates of biomass carbon rather than generating actual estimates of biomass carbon stored in forests, which would have changed over the decade between 2010 to 2020. Because carbon values were held constant across all GFDs, the results reflect only the effect of forest extent classification differences. We did not attempt to correct for temporal mismatch, biomass uncertainty, or resolution inconsistencies (the biomass carbon dataset is at 300 m resolution). As such, this case study should be interpreted as a demonstration of how GFD choice can influence apparent spatial and quantitative outcomes in carbon accounting, not a formal carbon assessment. Accurate estimation of forest biomass carbon requires harmonizing the scales of the biomass carbon dataset, the ground-truth data used for validation, and the forest extent dataset[73]. We recognize

592 that this is not a perfect measure of present-day biomass carbon density, but it was sufficient to
593 provide an illustrative analysis to describe the potential impacts of dataset selection on carbon
594 storage estimates in forested areas.
595
596 *Forest-proximate people living in poverty in India*
597 To understand the implications of divergent GFDs for social-economic analysis, we
598 estimated the number of rural forest-proximate people living in poverty in India in the year 2016
599 using each of the eight forest cover datasets (in each case using the closest available year of
600 forest cover data to 2016). For this case study analysis, we transformed the datasets that had a
601 "tree cover" class instead of a forest class (i.e., ESRI-LC and ESA-WC) to use a conservative
602 sparse forest definition of areas of at least 0.5-ha, based on the FAO's minimum area to define
603 forests. To set the minimum forest size, we removed any tree cover patches that were smaller
604 than 0.5 ha based on square kernel connectedness.
605 We used the methodology developed in Newton *et al.* [38] to map the number of forest-
606 proximate people using WorldPop population data (100-m resolution) and each of the forest
607 cover datasets. We defined forest proximity as rural populations living in a forested area or
608 within 1 km of a forest in rural areas, as in Newton *et al.* [38]. To incorporate the poverty data
609 layer, we used the gridded Relative Wealth Index (RWI) published by Chi et al. [74]. The RWI is
610 an asset-based wealth index taken from the Demographic and Health Survey (DHS) Program
611 survey. Chi *et al.* [74] used machine learning to bring in many other spatial data sources to estimate
612 RWI for the entire country. These estimated RWI data are available nationally in India at a 2.4
613 km spatial resolution. We selected an RWI value such that the number of people in poverty
614 below the RWI threshold matched the national, published multidimensional poverty rate of

615 24.85% for the year of analysis[75]. The RWI threshold that satisfied this criterion was -0.20. This
616 case study is not intended to validate one dataset over another, but rather to assess how
617 differences in forest definitions influence socio-economic indicators when overlaid with
618 population and poverty data.
619
620 *Estimating habitat availability and change for two endangered species in Brazil*
621 We estimated the forested habitat availability for a forest-dwelling, IUCN red-listed
622 endangered species, the white-cheeked spider monkey (*Ateles marginatus*). According to the
623 IUCN Red List species assessment, the primary threat to the white-cheeked spider monkey,
624 extant to Mato Grosso and Pará in Brazil, is the loss of its forest habitat from deforestation due to
625 expanding soy bean farming, cattle ranching, and urbanization[76].
626 To examine the implications of forest dataset selection on habitat availability and
627 deforestation threat for these species, we overlaid each of the forest cover datasets on the species
628 range polygon shapefile[77,78] and calculated the area of forest cover defined by each dataset within
629 this polygon. We then used forest cover change datasets for the years 2016-2021 to estimate
630 forest loss within the habitat region. We did not set a constraint on when IUCN conducted the
631 last assessment of the species since we held the species range constant. This may not be a perfect
632 measure of the present-day species range, but it is sufficient to provide an illustrative analysis to
633 describe the estimates of forested habitat areas.
634 For forest cover change estimation, we used the two land cover change datasets (Hansen-
635 GFC and Vancutsem-TMFCC) as the primary focus of the analysis. We do not report results
636 using the panel of the annual land cover datasets (taking the difference between the raster maps
637 across years) since this approach does not use rigorous change detection algorithms and can lead

to false positive or negative changes. For the Hansen-GFC dataset, we isolated loss data for each year. For the Vancutsem-TMFCC dataset, we followed the methods presented by European Commission (2021) to create maps for forest cover loss (deforestation only and deforestation plus degradation) and gain for each year[79].

Resource availability

Lead contact

Further information and requests for resources should be directed to Sarah Castle (castle3@wisc.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

Data: All datasets used in this study were derived from published sources cited in the Methods section. The following datasets are available through the Google Earth Engine (GEE) Data Catalog (Accessed: 15 December 2023):

- Copernicus Global Land Cover (CGLC) (https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_Landcover_100m_Proba-V-C3_Global)
- ESA WorldCover (ESA-WC) (https://developers.google.com/earth-engine/datasets/catalog/ESA_WorldCover_v100 and https://developers.google.com/earth-engine/datasets/catalog/ESA_WorldCover_v200)
- JAXA Forest/Non- Forest (JAXA-FNF) (https://developers.google.com/earth-engine/datasets/catalog/JAXA_ALOS_PALSAR_YEARLY_FNF4)

- MODIS Land Cover Type (MODIS-LC) (https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MCD12Q1)
- Hansen Global Forest Change (Hansen-GFC) (https://developers.google.com/earth-engine/datasets/catalog/UMD_hansen_global_forest_change_2022_v1_10)
- WorldPop for administrative boundaries and gridded population density data (https://developers.google.com/earth-engine/datasets/catalog/WorldPop_GP_100m_pop).
- RESOLVE Ecoregions 2017 for biome limits (https://developers.google.com/earth-engine/datasets/catalog/RESOLVE_ECOREGIONS_2017)

ESA Copernicus Climate Change Service Land Cover (ESA-C3S-LC) was available for download from https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover (Accessed: 15 December 2023). ESRI Land Cover (ESRI-LC) was available on GEE using the code available from https://gee-community-catalog.org/projects/S2TSLULC/ (Accessed: 15 December 2023). GLAD Global Land Cover and Land Use Change (GLAD-LCLUC) was available on GEE using the code available from https://glad.umd.edu/dataset/GLCLUC2020 (Accessed: 15 December 2023). Vancutsem Tropical Moist Forest Cover Change (Vancutsem-TMFCC) was available on GEE using the code available from https://forobs.jrc.ec.europa.eu/TMF (Accessed: 15 December 2023).

The Spawn *et al.* [35] aboveground and belowground biomass carbon density data is available to download from https://daac.ornl.gov/VEGETATION/guides/Global_Maps_C_Density_2010.html (Accessed: 15 December 2023). The species habitat ranges were obtained for the IUCN Red List database (available for download from: https://www.iucnredlist.org with valid request; Accessed: 15

December 2023). Gridded relative wealth index data from Chi *et al.* [74] were downloaded from https://data.humdata.org/dataset/relative-wealth-index (Accessed: 15 December 2023).

High resolution images for figures 1, 4, 5, and 6 are available on figshare dx.doi.org/10.6084/m9.figshare.24898275.

Code: The Google Earth Engine codes for data processing and analyses are openly available through GitHub at: https://github.com/saraheb3/forestdatasets/. Datasets without sharing restrictions (e.g., those available in the Google Earth Engine data catalog) are directly accessible in the published code. Datasets with sharing restrictions (e.g., IUCN red list species habitat layers) are not shared as assets, but users may download the latest IUCN red list species habitat layers and import them into the code to run their own analyses.

Supplemental information

Document S1: Supplemental documentation of key aspects of the global forest (land) cover and change datasets.

Figures S1-S10. Tables S1-S10. Supplemental references.

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Author contributions

Conceptualization: S.E.C, P.N., J.A.O., and D.C.M.; Methodology: S.E.C, P.N., J.A.O., K.B., and D.C.M.; Formal Analysis: S.E.C.; Writing – Original Draft: S.E.C.; Writing – Review & Editing: S.E.C, P.N., J.A.O., K.B., and D.C.M.; Visualization: S.E.C. and J.A.O.; Supervision: D.C.M.; Funding Acquisition: S.E.C, J.A.O., and D.C.M.

Declaration of interests

The authors declare no competing interests.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Microsoft Copilot with a detailed set of prompts to generate the initial draft of the graphical abstract, and we sparingly used Gemini to edit language for clarity and conciseness during the manuscript review process. The original submission was written with no use of AI. After using this tool, the authors carefully reviewed and edited the content and takes full responsibility for the content of the publication.

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Figures legends and figures

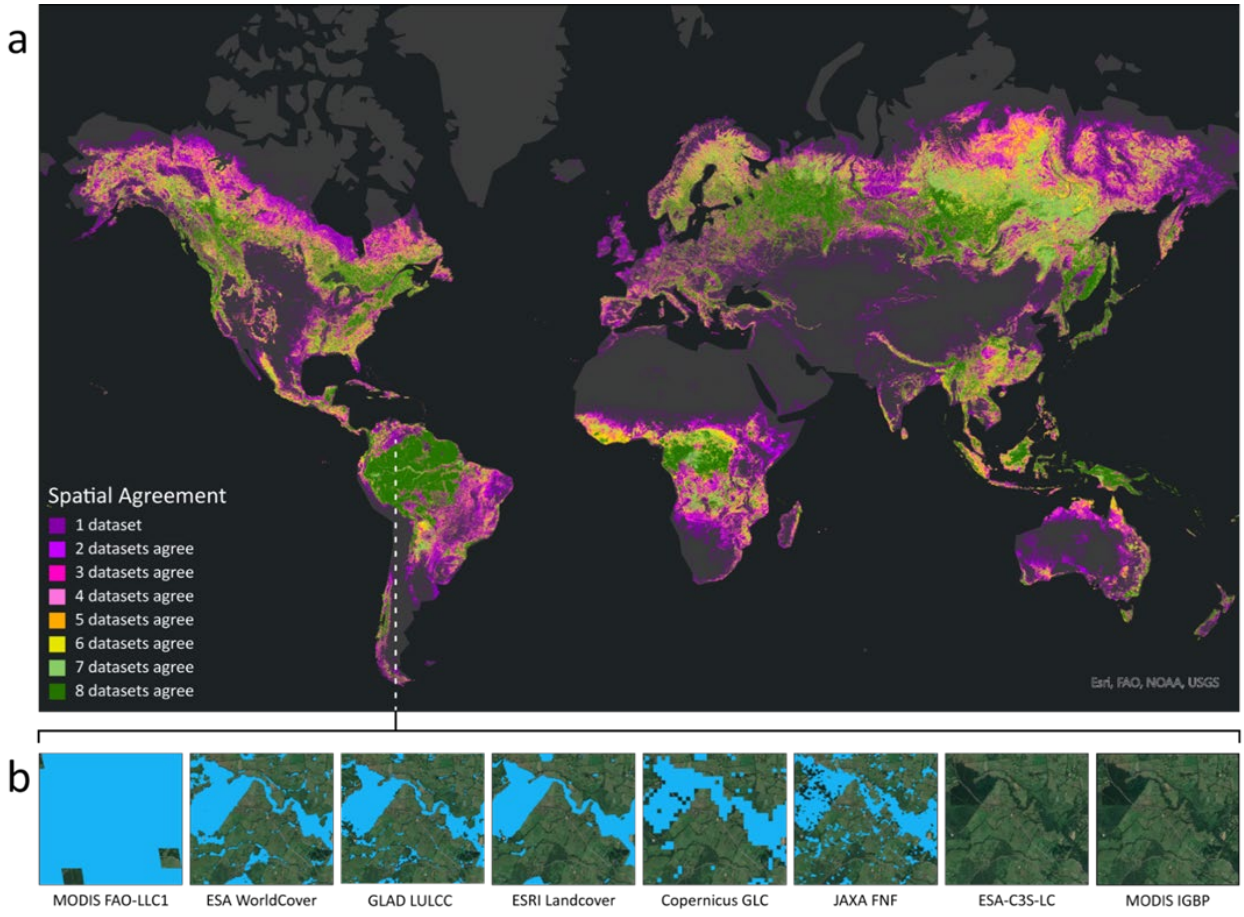
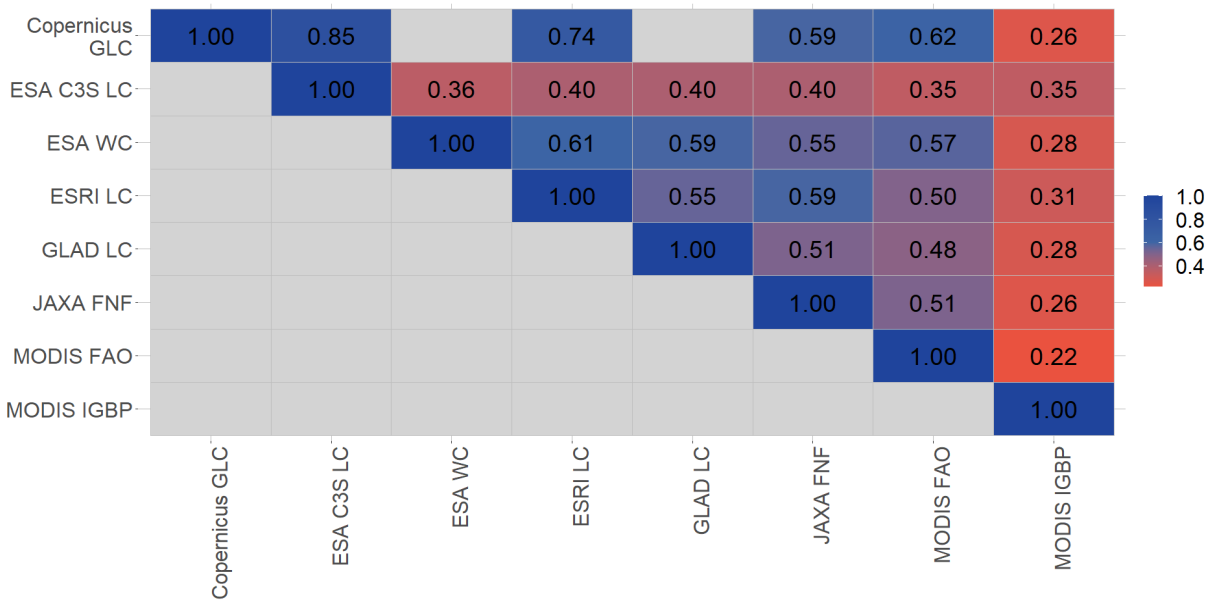


Fig. 1. (a) Spatial agreement of forest cover classifications between eight land cover datasets. Spatial agreement is defined as the number of datasets that define a pixel as forest, between 1 and 8. Full agreement between all eight datasets corresponds to a value of eight (dark green), and no agreement between the datasets corresponds to a value of 1 (dark purple). No color (gray) indicates that none of the datasets classified the area as forest. All data are from the year 2019 except for ESA-WC and GLAD-LCLUC, which are from 2020. (b) Illustrative case study of a random area (approximately 16 km^2) 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.



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980 **Fig. 2.** Pairwise agreement between each dataset. CGLC for 2019 is compared to 2019 data for
981 the other datasets, where available (not available for ESA-WC or GLAD-LCLUC). All other
982 comparisons are for 2020. Pairwise agreement is defined as the area of intersection where both
983 datasets agree is forest ($F1 \cap F2$) divided by the total forest area defined by the union of both
984 datasets ($F1 \cup F2$). Blue indicates high overall spatial agreement between two datasets; red
985 indicates low overall spatial agreement between two datasets. Pairwise agreement using forest
986 areas for each individual dataset (showing which forest cover datasets relatively over/under-
987 estimate forest cover compared to each other) is presented in Table S1.

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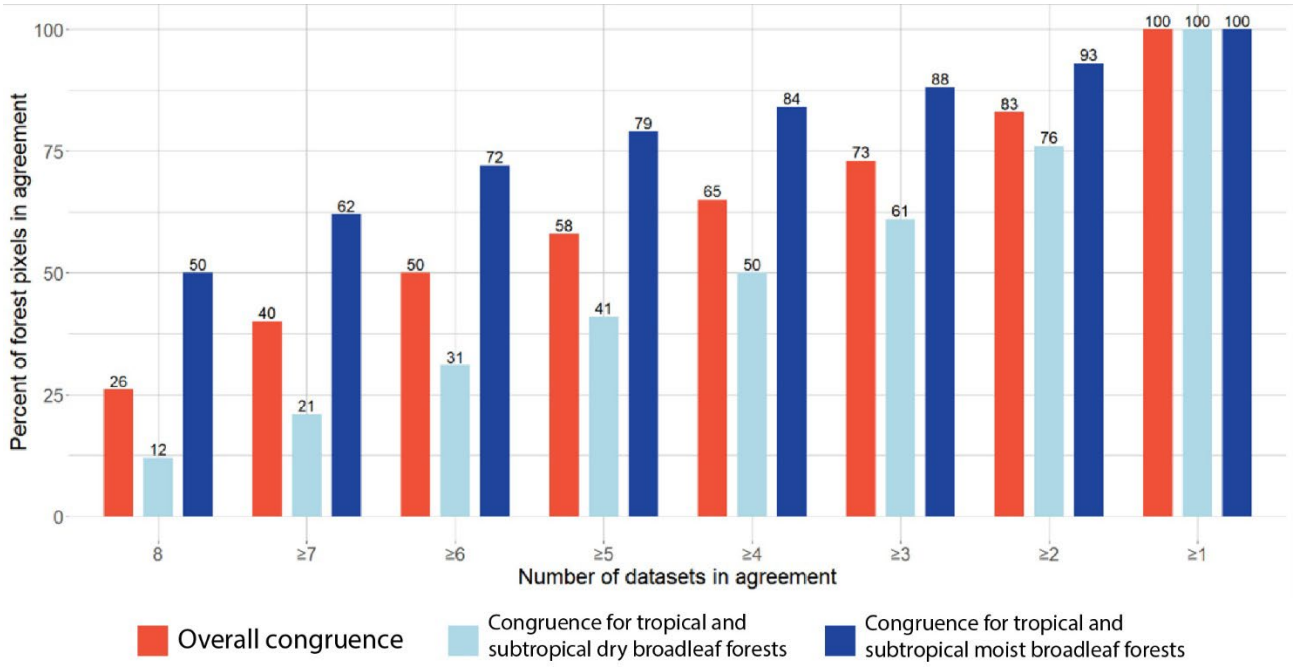

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990 **Fig. 3.** Cumulative histogram showing the percent of forest pixels in agreement between the
991 eight datasets globally (leftmost bars, in red) and for two forest biomes, tropical and subtropical
992 dry broadleaf forests (center bars, in light blue), and tropical and subtropical moist broadleaf
993 forests (rightmost bars, in dark blue).
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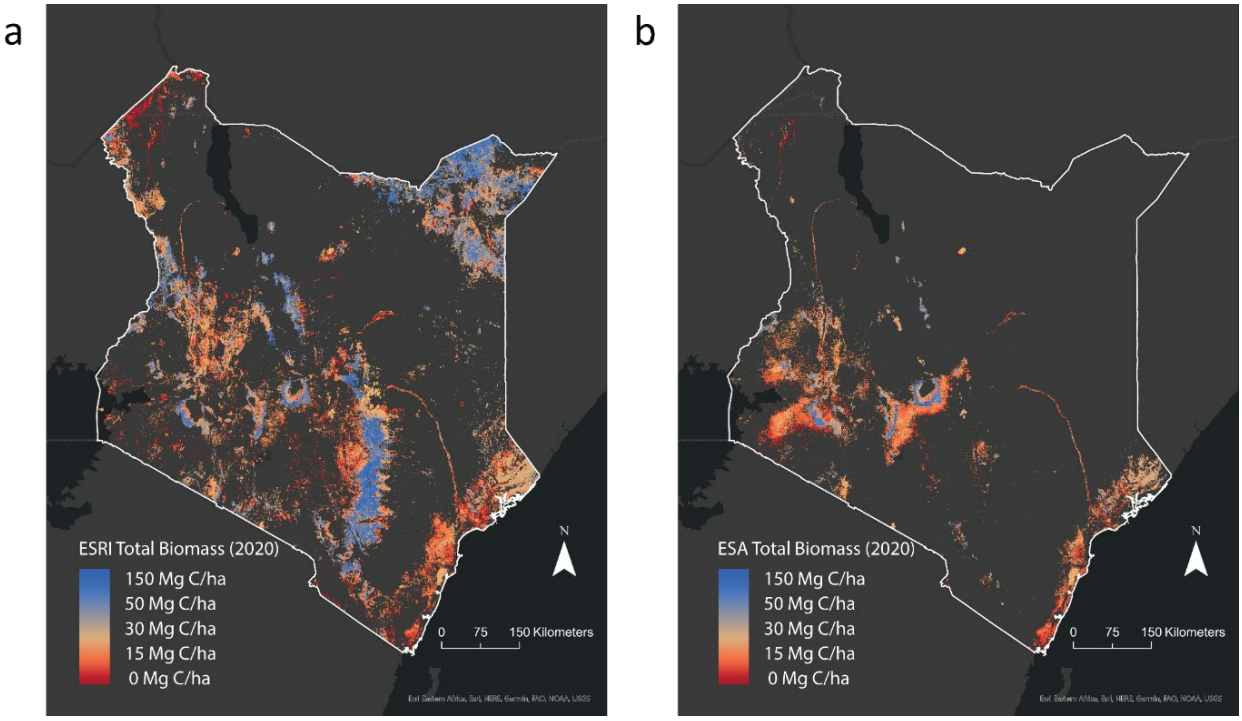

Fig. 4. Estimates of the amount and distribution of forest above- and below-ground carbon biomass in Kenya using two 2020 land/forest cover datasets, (a) ESRI Land Cover, where 26% of total national biomass is located in areas classified as forest; and (b) ESA WorldCover, where 6% of total national biomass is located in areas classified as forest. Total biomass carbon estimates were generated from the Spawn *et al.* [35] dataset for the year 2010 and held constant (see Fig. S4 for above-ground and below-ground layers and Fig. S5 for results for all eight GFDs). These maps include the disputed Ilemi Triangle, using the administrative boundaries defined by WorldPop. Note: Carbon density is based on 2010 forest extent and was not updated for 2020. This analysis is illustrative only and intended to show how different GFDs intersect with a fixed carbon map, not to estimate present-day carbon stocks.

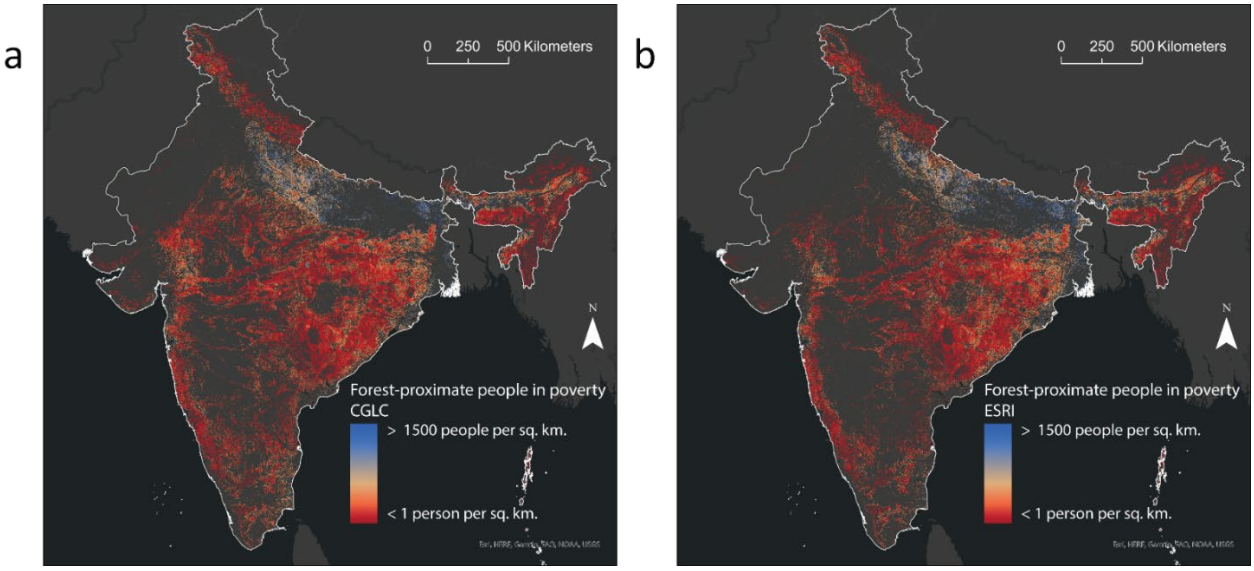

Fig. 5. Estimates of the number of forest-proximate people living in poverty in India in 2016 following the methodology in Newton *et al.* [38]. We defined forest proximity as people living in or within 1 km of forests, and we defined poverty using the gridded Relative Wealth Index (RWI) published by Chi *et al.* [74]. People living in poverty and in proximity of forests are shown using two different forest cover datasets: (a) Copernicus Global Land Cover (left) and (b) ESA-C3S Land Cover (right). We used country boundaries using the administrative boundaries defined by WorldPop; however, there are several disputed boundaries of India, including the Kashmir region (Aksai Chin and Demchok) as well as Arunachal Pradesh.

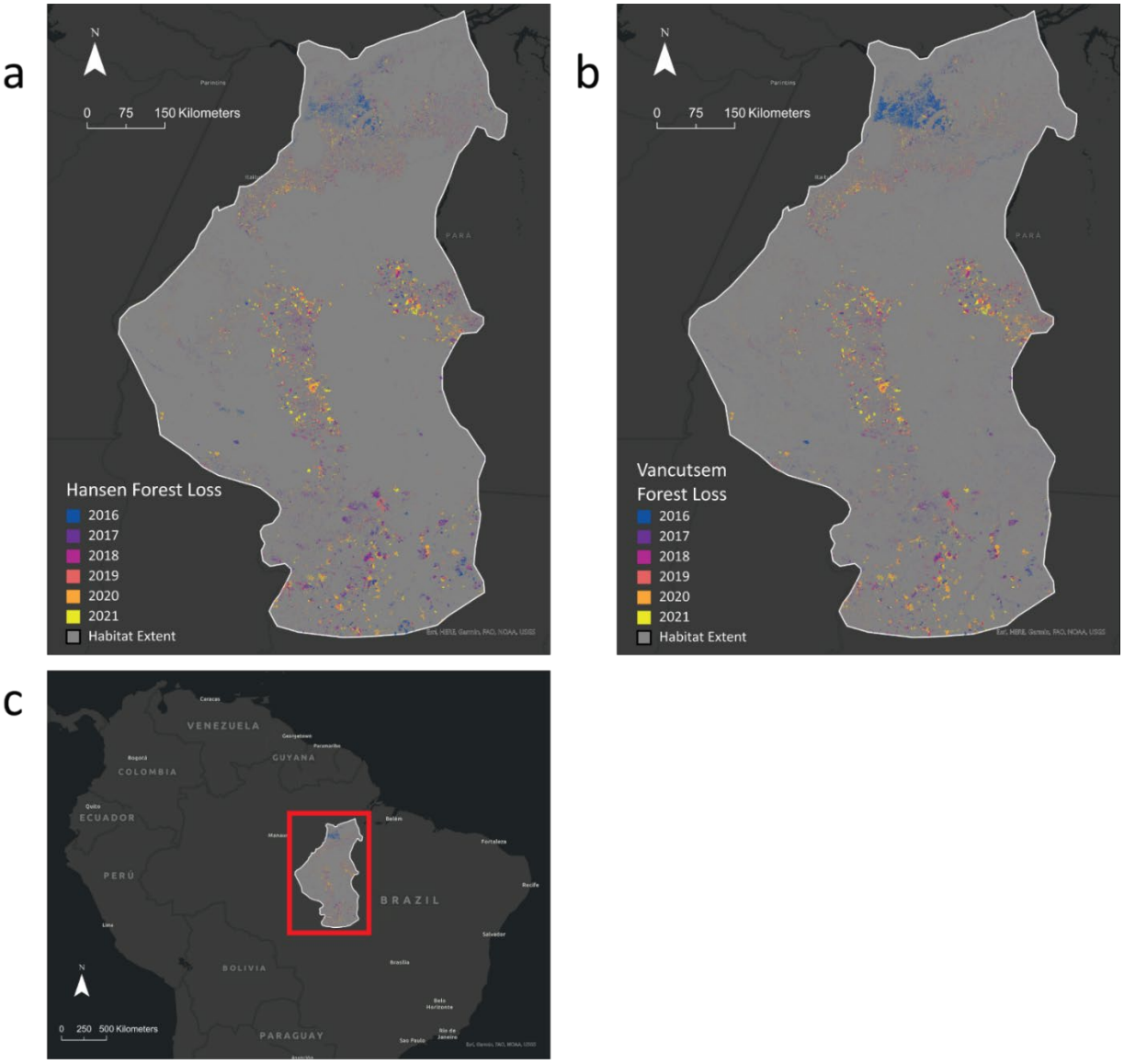

Fig. 6. Forest cover loss by year between 2016-2021 for (a) Hansen-GFC and (b) Vancutsem-TMFCC for the white-cheeked spider monkey's (*Ateles marginatus*) species range. Panel (c) shows the region where the white-cheeked spider monkey habitat is located. The Vancutsem-TMFCC map includes both forest loss and forest degradation. The map for Vancutsem-TMFCC loss data (excluding degraded forest areas) is provided in the supplemental information (Fig. S8). Forest gain is not shown in these maps since the Hansen-GFC dataset did not provide annual forest gain data.

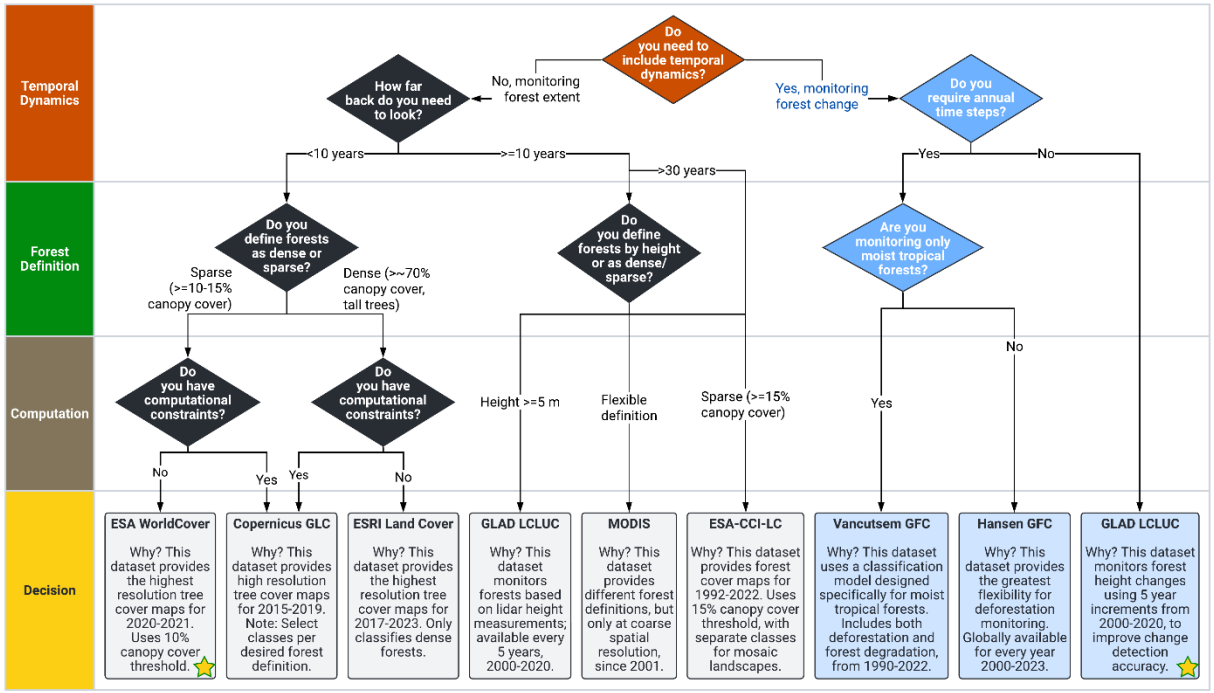

Fig. 7. Decision tree to help guide dataset selection for different applications. Decision tree branches include (1) temporal dynamics: whether the user aims to monitor forest cover or forest cover change; (2) forest definition: whether the user defines forests by height, dense canopy cover, or sparse 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. The stars indicate the datasets recommended as best available by the authors based on our review, if they meet the user's needs. We note that 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, and varies by world region. Where possible, users should consult independent validation studies (e.g.,[24,28,43,57,80]) to assess which dataset is most appropriate for their specific application.