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Spatiotemporal inconsistencies in Landsat satellite observations bias environmental-change analyses and monitoring

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ABSTRACT

Satellite remote sensing is vital for research, monitoring, and policy addressing environmental-change and sustainability issues from climate and ecosystem changes to food and water security. Here, Landsat satellite data play a crucial role, thanks to their unique global, long-term, and high-resolution coverage. Yet, spatial and temporal data gaps in the Landsat archive may propagate into derived remote-sensing products and thereby threaten the validity of downstream applications, especially when data users have limited training in remote sensing. To improve awareness of these issues, we here demonstrate that global, historical Landsat data provide a spatially and temporally highly uneven, frequently interrupted, and seasonally incomplete coverage. Using a causal-discovery framework, we moreover show that these inconsistencies are inherited in several state-of-the-art, global time-series products, causing pervasive biases in perceptions of changes in tropical moist forests, arable lands, and seasonal water resources (significant biassing effects detected in 84.6-93.6% of our country-specific tests, depending on land-change facet). These biases can impair reliable analyses and monitoring of diverse environmental changes and human development issues targeted by international policy frameworks including the Kunming-Montréal Global Biodiversity Framework, the Paris Agreement, and the Sustainable Development Goals. We discuss avenues towards better uncertainty reporting and bias control in satellite-based monitoring and related applications, highlighting needed contributions from both product developers and users.

Keywords: earth observations, causal inference, change assessments, national indicators

Highlights

1) Coverage of historical Landsat satellite data is spatiotemporally uneven
2) Global time-series of forest, arable-land and water inherit signals of these inconsistencies
3) The inherited inconsistencies cause widespread bias in perceived land changes
4) These biases variously affect the reliability of environmental-change research and monitoring
5) Developers and users of remote-sensing data both have a part in minimising biases

1. INTRODUCTION

Land-surface changes are key elements of global environmental change and central to sustainable-development challenges ranging from climate and biodiversity protection to water and nutrition security (IPBES, 2019; IPCC et al., 2019; Rounsevell et al., 2012; UNCCD, 2017; Verburg et al., 2015). Reliable data that capture land changes globally over several decades, yet at high spatial and temporal detail, are a critical resource for diverse application domains from basic environmental-change research (Dietze et al., 2018; Hertel et al., 2019; Runge et al., 2019) to policy-making and associated monitoring (Anthony Lehmann and Giuliani, 2020; Nakalembe et al., 2021). For example, such data vitally support global policy agendas like the Global Biodiversity Framework, the Paris Agreement, or the UN Sustainable Development Goals (SDGs) by facilitating regular monitoring and progress reporting and periodic recalibration (Xu et al., 2020) and by helping secure practical commitments through identification of national and sectoral responsibilities (Perino et al., 2022).

Satellite remote sensing supports diverse environmental-change analyses and allows monitoring many policy indicators at multiple spatial and temporal scales (Anderson et al., 2017) and, with the support of open-data policies of key satellite archives (Wulder and Coops, 2014), (geo)computational advances (Cracknell, 2018), and investments in technical capacity-building (Mora and Wijaya, 2012), has become a primary tool for countries to inform the sustainable management of their natural resources and to meet their international reporting obligations (Anderson et al., 2017).

In particular, the Landsat program (Zhu et al., 2019) fulfils a vital role for continuous land-surface monitoring due to its unique combination of long historical coverage (**Fig. 1a**) and relatively high spatial and temporal image resolution (global and at 30-m since 1984, typically every 16-days). Due to the longevity of the program, Landsat data are key to evaluating long-term environmental changes against historical baselines (ESA, 2020), or in response to human interventions (Schmidt-Traub et al., 2017). Moreover, Landsat data support forward-looking policy support by enabling credible future scenario projections to anticipate emerging development issues and calibrate political action (Gregory et al., 2012). Correspondingly, Landsat data have become an integral part of a growing number of mapping applications supporting environmental-change research and monitoring (e.g., Pekel et al., 2016; Potapov et al., 2022; Vancutsem et al., 2021). Yet, the Landsat archive has extensive gaps due to historical data losses (Wulder et al., 2016, **Fig. 1b**), and available data face spatial and temporal inconsistencies due to, for instance, cloud cover (Ju and Roy, 2008) or data degradation (Wulder et al., 2016).

Remote sensing experts are generally aware of such issues. In fact, remote sensing literature discusses how data volumes and intra-annual temporal coverages affect the robustness of spectral metrics (Frantz et al., 2023) that ultimately inform remote sensing products, and how stringent quality controls impact data volumes (Zhang et al., 2022). Furthermore, extensive literature provides technical recommendations on how to tackle inconsistent data coverages. This includes seasonal and epoch-based compositing (Hansen et al., 2013; Potapov et al., 2022), filling of data gaps by harmonising multiple sensors (Claverie et al., 2018), or detecting changes continuously to tackle interruptions in data coverage (Vancutsem et al., 2021; Zhu and

Woodcock, 2014). Many resulting products are then validated using strict protocols (e.g., through sample-based assessments of accuracy, area, and uncertainty).

However, although existing literature and protocols address various limitations in satellite data, they cannot completely prevent their propagation into derived data products. In fact, many applications remain sensitive to satellite data availability. For instance, they may respond negatively to the lack of observations over specific dates (e.g., when monitoring deforestation, Sales et al., 2022, or land uses, Fan et al., 2022; Prishchepov et al., 2012), or require observations spread consistently throughout a year (e.g., when mapping phenology, Mas and Soares de Araújo, 2021, e.g., to monitor vegetation responses to climate change, Ma et al., 2022). Moreover, remote sensing data products ultimately reach broad user communities that include resource managers, policy-makers, and scientists of different disciplines, many of whom have limited or no training in remote sensing. These communities are unlikely to engage with the existing, mostly technical literature on data limitations that is targeted at remote sensing experts. In fact, a recent survey suggests that users are largely unfamiliar with the limitations of Landsat-based data products (Molder et al., 2022).

To improve the use of remote sensing data products in downstream applications, there is a need for studies that sensitise users and non-expert developers about their inescapable uncertainties. This will ultimately improve the transparency of science communication, limiting the risk of data misuses, and combating distrust in scientific data caused by misunderstandings of uncertainties (Gustafson and Rice, 2020).

Here, we take needed steps to bridge between data users and producers. First, we demonstrate the magnitude of spatial and temporal variations of data limitations in the global, historical Landsat archive since 1984, when the world first received a near-global, 30-metre-resolution, Landsat data coverage, which paved the way to a multitude of scientific advances in satellite remote sensing. To this end, we map different facets of between- and within-year data coverage by daytime Landsat observations. Second, we use a causal inference framework to demonstrate how spatial and temporal variations in observation frequencies affect our perception of changes in the extents of tropical moist forests (**Fig. 1d**), arable lands (**Fig. 1e**), and seasonal surface water (**Fig. 1f**), as mapped by state-of-the-art products that are extensively used in environmental-change analyses and monitoring. Finally, we provide recommendations on how to improve the reporting of data limitations, and how to best account for them in future developments and applications of remote-sensing data products.

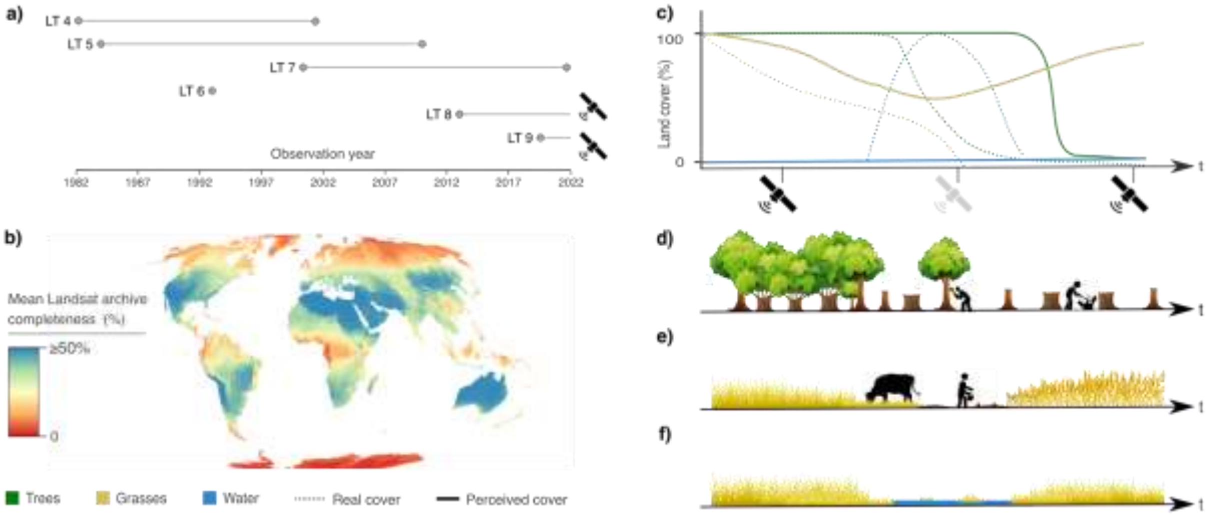

Figure 1. Temporal gaps in satellite observations and their conceptual link to biased perceptions of land changes. a) Five operational Landsat (LT) satellite missions provided a seemingly uninterrupted global coverage for 1984-2022 (grey lines; satellite icons indicate active missions). **b**) However, the Landsat archive provides much less continuous data. **c)** Data gaps influence our perception of change trajectories. Dashed lines depict true trajectories, and continuous lines show trajectories measured with satellite data. In the x-axis, satellite observations (black satellite icons) are temporarily interrupted (grey satellite icon). During the observation period, the y-axis measures changes in percentages of trees (in green, **d**), grasses (in yellow, **e-f**), and surface water (in blue, **f**). Note, no solid water line is shown due to the absence of satellite data. **d)** Data gaps hide the start of logging, leading new satellite observations to perceive abrupt changes. **e)** Grassland losses due to grazing precede the planting of wheat, but data gaps during this transition makes these indistinguishable, leads us to perceive grassland losses followed by grassland gains. **f)** Similarly to **d)**, data gaps hide temporal variation in the proportions of (savanna) grasses that are seasonally covered by water.

2. METHODS

2.1. Quantification of satellite data limitations

Estimating the archive's data coverage. We described the Landsat archive in terms of its historical data coverage between 1984 and 2023 (Fig. 1a). To this end, we accessed Landsat imagery from the level 2 of Collection 2, including data from tiers 1 and 2 from Google Earth Engine, using Python's GEE API (Gorelick et al., 2017). Using these data, we evaluated the frequency and recurrence of satellite observations enabled by Landsat, both in space and time, and quantified and mapped variations in data-coverage to highlight inconsistencies that are expected to affect the accurate mapping of land-surface features and their changes.

We highlight the existence of data gaps through a metric on the overall annual 'completeness' of the Landsat archive (Fig. 1b). This corresponds to the per-pixel average number of unique observation dates (i.e., discounting observations masked by the presence of cloud cover or cloud shadows) divided by the idealised expectation of one image taken every 16 days per active sensor (i.e., the typical Landsat recurrence). We quantified the expected number of images for each descending tile drawn in the World Reference System 2 (USGS, 1998), which is used by the data providers to split and georeference raw imagery. Then, we rasterized the tiles into regular raster grids with a resolution of 10-km at the equator, and combined them to obtain a global grid.

In addition, we explored variations in temporal completeness of Landsat data coverage. To evaluate global, spatiotemporal variation, we analysed the availability of seasonally complete Landsat-data varies across years and geopolitical regions distinguished by the United Nations

Statistical Division. For this, we quantified the proportions of all 30-m pixels within larger, 10-km pixels for which Landsat data exist in every month of a given focal year (Fig. 2a). Additionally, we analysed the annual continuous seasonal coverage, by counting the unique months in a given year for which each 30-m pixel has usable Landsat data. To explore spatial variation in this metric, we mapped its multi-year average (Fig. 2c-d, Fig. S3) and its multi-year standard deviation (Fig. S1c-d, Fig. S4) at 10-km resolution.

Third, we explored breaks in the continuity of Landsat data coverage by mapping the number of years without any Landsat observations since 1984 (Fig. 2b), and the length of interruptions following the first acquisition year (Fig. S5). As with the continuous seasonal coverage metric, we explored global variation in coverage continuity by first quantifying the respective metrics for each 30-m pixel and then mapping their average values at 10-km resolution.

When calculating each of our different data-coverage metrics, we considered 'usable pixels' as those not covered by either clouds or cloud shadows, as indicated in the 'QA_PIXEL' band, while treating any masked pixels as 0s.

2.2. Analyses of effects of satellite data limitations on perceived land changes

General design of case studies. We analysed biassing effects of spatiotemporal variation in Landsat data coverage on perceptions of different land changes in three case studies (detailed separately below). We chose three complementary land-change facets (i.e., changes in extents of, respectively, tropical moist forests, arable lands, and seasonal surface water) that are all central to different environmental and sustainability issues and the focus of extensive satellite-informed research, management, policy and monitoring. We focused on changes as indicated in three global, state-of-the-art Landsat-based time-series products developed to support change analyses and monitoring for the respective land-cover classes, each of which is widely used in different research fields and applications (e.g., triple-digit annual citations). Specifically, we focused on changes as perceived when comparing proportional coverage of a given larger area by pixels with a given land-cover label between time steps, as is common practice in different communities using remote-sensing-based data products.

For each case study, we hypothesised that perceptions of the respective land change are biased by variation in a specific metric of satellite-data coverage, reasoned to likely affect the accurate and consistent mapping of the respective land-cover variable or its change. We formally tested for such data bias by identifying causal signatures of the respective data limitation in the respective land change (detailed in next section). Failing to find causal signatures of inconsistencies in the observation process in the perceived land-change trajectory would lead us to reject the respective hypothesis. The rationale for these tests is that a perceived land change is (by definition) biased if the presence of systematic data error (i.e., non-random spatial/temporal variation in data coverage) alters the specific nature of the change (e.g., its magnitude, timing, or direction).

We focused these formal tests on effects detectable across representative samples from country-level 'populations' of pixels. We used this spatial scale of analysis because it is the most relevant for monitoring and progress-reporting towards international policy goals (i.e., via national indicators (UNFCCC, 2015) and because investments national institutions are often best placed to make investments in better environmental-change research and monitoring capacities (e.g., through project budgets that accommodate for the time needed for more rigorous data scrutiny). We ran our causal inference workflow for the time periods covered by each of the used Landsat-based dataset. In addition, we ran a second set of analyses focusing on years from 2000 onwards, which is the baseline year typically chosen to monitor SDGs with satellite remote sensing (ESA, 2020). We performed this second set of analyses to explore in how far conclusions regarding biassing effects of Landsat data limitations would qualitatively differ when only considering a period that, due to generally richer Landsat data coverage (first fully-global data coverage achieved in 2000), might be expected to be less prone to systematic misclassifications.

We note that whereas monitoring and reporting by countries with very limited own monitoring capacities commonly relies on global time-series products like those analysed here, higher-capacity countries often use nationally focused products that may have higher regional accuracies (e.g., benefitting from denser and more representative in-situ data; Han et al., 2017; Nesha et al., 2021). Insofar that the latter products also build on the Landsat archive, however, they are equally exposed to its regional inconsistencies. Moreso, even higher-capacity countries variously combine their national data with regional to global thematic products to achieve the needed thematic detail in their national maps and monitoring products (e.g., Vačkář et al., 2018; Van Deventer, 2021).

Causal analysis approach. We tested for causal effects using Convergent Cross Mapping (CCM, Clark et al., 2015; Sugihara et al., 2012), a technique that relies on state-space reconstruction to identify causal links between two temporal variables. We chose this approach as it can accurately detect causality even if causal links are weak or nonlinear. CCM builds on the logic that if a putative causal driver X (e.g., temporal variation in Landsat data coverage) and a putative causal outcome variable Y (e.g., a perceived land-change trajectory) are part of the same dynamic system and X causally influences Y, the historical states of Y will contain information about X (i.e., X will have transferred information onto Y), allowing the reconstruction of past and present states of X based on lagged time-series values of Y. By reconstructing X's state space from Y in a process called 'cross-mapping', CCM assesses the extent to which Y can predict X. The prediction accuracy is measured as the Pearson's correlation coefficient (ρ, 'rho') between the observed values of X and the values predicted via state-space reconstruction from Y (i.e., the amount of information transfer). To identify the causal relationship, CCM then tests whether ρ increases with increasing time-series length (i.e., whether observed X and reconstructed X 'converge'). This way of identifying causality builds on the tenet that, if X truly causally influences Y, the accuracy of predicting X should improve as more of Y's time series is used for cross-mapping due to the better representation of the underlying dynamics of the system. The formal evidence for the existence of a causal effect is provided by the statistical significance of the observed convergence pattern, based on a nonparametric-bootstrapping comparison of the observed ρ values from cross mapping to expected ρ values under the null hypothesis of no causality.

Note that whereas a significant increase of ρ with time-series length provides formal evidence for the existence of a causal relationship, the magnitude of ρ itself is only a measure of information transfer between variables X and Y, and as such cannot be interpreted as a measure of effect size. This is because some unknown portion of the transferred information might be due to synchrony of X and Y by a common driver (leading to a higher ρ). Whereas common drivers of improvements in Landsat-data coverage and increases in areas affected by land-changes may be hard to conceive, we cannot rule out this possibility. Similarly, noise can affect the precision of state-space reconstruction (leading to a lower ρ). Therefore, we provide ρ values in supplementary tables 2, 4, and 6 simply as an indication of how well information on Y can predict X.

CCM simultaneously considers all inter-annual changes along the respective time-series (i.e., including gross losses and gains), and may thus find sufficient signals of causal effects even if there are no long-term, net changes or if causal effects only exist during temporal subsets of the entire time-series. However, the relatively short lengths of the time-series considered in our case studies (depending on the data product, 5-30 time-steps) could impair the effectiveness of classical CCM (Sugihara et al., 2012). To tackle this issue, we used a spatial extension of the CCM method that was shown to be robust to short time-series with as little as 5-20 steps (Clark et al., 2015). The method uses dewdrop regression to combine information from multiple time-series of the same system (here, the same country). We implemented this spatially extended CCM method using the multispatialCCM R package (Clark et al., 2015).

Because CCM exploits variations in two time-series, we did not apply it at Landsat's native 30-m resolution, where the vast majority of pixels does not experience any changes (Pontius et al., 2004), but instead performed our CCM analyses using 10-km pixel aggregates. In each 10-km pixel, we quantified each target variable as annual aggregated areas (accounting for latitudinal variations in area using the Haversine method; Sinnott, 1984), and pixel-level averages of the number of unique observation dates obtained recorded by Landsat sensors (see subsection Data on Landsat data coverage).

Excepting case study 2 (see its sub-section below for explanation), we specifically tested for causal effects of year-to-year anomalies (i.e., of positive/negative outliers from a multi-year moving average) in a relevant Landsat data-coverage metric on anomalies in the respective inferred land change. To this end, we calculated the differences between the annual values of each of these variables and their respective trendlines, which we derived with Locally Weighted Scatterplot Smoothing (LOWESS, Seabold and Perktold, 2010), using a span of 0.4.

Case study 1: Timing of tropical deforestation. We analysed data on the first year of deforestation between 1990 and 2021 from the Tropical Moist Forest dataset (TMF, Vancutsem et al., 2021). For an initial exploration of possible data biases, we compared the directions of deforestation trends reported by national statistics (FAO, 2020) with the directions of country-level aggregate forest changes mapped by the TMF during the statistics' respective reporting periods (noting that due to conceptual differences in forest definitions, these sources are not fully comparable). Then, to formally test for the presence of biases in the perceived forest changes, we used CCM (*see previous section*) to detect causal links between year-to-year anomalies in TMF-inferred deforestation rates and anomalies in the number of unique dates with usable Landsat pixels (i.e., without clouds, cloud shadows). Here, we hypothesised that improvements in the per-pixel average number of unique observation dates contributed to causing perceptions of disproportionately high deforestation rates due to the backlog of one or more data-limited year(s) during which the detection of deforestation was not feasible or incomplete. The choice of this data coverage metric is in alignment with the methodology behind the TMF, which detects forest changes dynamically between continuously acquired and overlapping satellite observations. We focused these analyses on 10-km pixels showing forest-cover changes over the respective focal period, and applied them to 110 tropical moist forest countries.

Case study 2: Arable-land expansion. We analysed a dataset mapping Global Arable-Land Extents for four-year epochs between 2000 and 2019 at a 30-m resolution (GALE; Potapov et al., 2022). We first explored the potential existence of data biases by evaluating whether the GALE-inferred gains/losses contradicted the directions of arable-land changes inferred from national statistics (FAO, 2023). For this, we conceptually aligned the FAO-reported arable-land areas to the GALE by subtracting areas of temporary pastures and meadows (following the recommendation by FAO data experts for making these specific datasets comparable; Tubiello et al., 2023). We then aggregated the annual FAO values to per-epoch maximum areas per country. We chose maxima because the GALE product maps any arable land within a given epoch, making it sensitive to maximum extents. To confirm the presence of data bias, we again used CCM, applied to 10-km pixels experiencing both gains in arable-land extents, and improvements in Landsat data coverage, in the 129 countries where GALE-inferred gains contradict FAO-inferred losses (i.e., the dominant form of disagreements; **Fig. 3c**). Here, we hypothesised that an increased number of observation dates enables a more accurate detection of characteristic seasonal management interventions on arable lands such as planting and harvesting, and subsequently thus a more reliable distinction of arable lands from other land-cover/use types. Note that because the GALE dataset is produced across epochs, we recalculated our Landsat data coverage metric over those same epochs.

Case study 3: Seasonal surface-water gains. We analysed changes in seasonal surface water based on the Global Surface Water dataset (GSW, Pekel et al., 2016). This dataset maps surface water annually between 1984 and 2023 at a 30-m resolution. We first explored the possible existence of data biases by assessing the plausibility of long-term trends in seasonal surface-water amid in-situ evidence. For this, we compared GSW-inferred trends to river-discharge values measured at gauge stations (WMO, 2022). Because upstream surface water limits discharge (Duan et al., 2018), long-term changes in discharge should be correlated with upstream surface-water changes.

To enable this comparison, we took several steps to align both data sources. First, because the GSW maps seasonal water annually, we summarised the gauge station data to the same temporal resolution. For each station and year, we then estimated the annual range of discharge values. Larger ranges reflect either dry periods or periods of flooding, in both of which the GSW is expected to map seasonal water. Second, we estimated upstream seasonal-surface-water extents. For this, for each station and year, we used data on the river-flow connectivity between hydrological (sub-)basins (Lehner et al., 2008) to trace the upstream path most likely followed by water accumulated along a river. Here, we excluded gauge stations situated downstream of dams (using data by Mulligan et al., 2020). We did so to avoid misinterpreting any true disconnects between discharge and surface-water levels that may be caused by dams disrupting natural water flows. Additionally, at each gauge station, we did not compare discharge measurements against upstream seasonal-surface-water extents in years when the latter was estimated from groups of pixels containing missing values. Missing values appear in the GSW when water detection was avoided due to insufficient satellite observations. Upstream water extents represented by such pixels are likely to depict artificial and positive long-term trends due to gradual improvements in satellite data coverage and frequency, preventing an objective comparison with local discharge measurements.

These pre-processing steps preserved 3,917 stations. Then, we focused on the 4194 stations with a minimum of 8 data years (**Fig. S8a**) to enable subsequent smoothing. For each station, we smoothed their respective discharge and upstream surface-water time-series using LOWESS, and identified cases where both surface water and discharge experienced significant change trends using Mann-Kendall tests (Kendall, 1938; $p < 0.05$). We restricted our comparison of the directions between discharge and surface-water trends to the 1,413 stations, where both trends were significant (**Fig. S8b**).

Following the described analyses, we then used CCM to formally test whether changes in seasonal completeness of Landsat data (approximated by the frequency of months with satellite observations) indeed bias perceptions of changes in seasonal surface-water extents. We hypothesised this to be true based on the premise that having satellite observations during more months of a given year makes detecting any short-lived seasonal water occurrences more likely. Note that our use of the number of months as our seasonal data-coverage metric is in alignment with the methodology behind the GSW, which first classified water on a monthly basis to then distinguish seasonal from permanent water occurrences. Again, we applied the CCM analysis separately for each of 196 countries experiencing water gains, here focussing on 10-km pixels with seasonal surface water at any point during the observation period.

Sample selection. In each case study, for each country, we randomly selected samples to be used in the CCM analysis. We determined the number of samples separately for each country using Yamane's formula for finite populations (Yamane, 1967). The formula is given estimated as $N/(1 + N * e^2)$, where N is the number of pixels from which to sample, and e is a margin of error of 0.05.

When selecting samples, we limited our pool of candidates to those 10-km pixels where there were positive, long-term trends in the target variable and in data coverage. To detect long-term trends, we applied the Mann-Kendall test (Kendall, 1938) as implemented in the R package *Kendall* (McLeod, 2022). A significant long-term trend was indicated by a p-value < 0.05. Finally, we selected samples using the function *mvrnorm* of the R *MASS* (Venables and Ripley, 2002). This function enables the random selection of samples representative of a multivariate distribution. The multivariate distribution used for sampling was defined by the absolute change in the target variable, and by the standard deviation of the data coverage.

The number of samples extracted varied per target variable (**Supplementary Fig.6**). We obtained 19,077 samples for tropical deforestation (16,597 for the 2000-2020 period), 45806 for arable-land, and 24,522 for Global surface water (6,885 for the 2000-2020 period).

3. RESULTS AND DISCUSSION

3.1. Spatial and temporal variations in data quality and coverage

An uneven history of satellite observations. Between 1984 and 2023, the Landsat archive gathered 17,553,123 daytime images (average of 15.6 observations /km2, standard deviation

(SD) of ±15.8; see **Fig. S1a in *Supplementary Material***). This means that, on average, we have a deficit of 209.7 observations per km2 (SD: ±510.9), the equivalent of 9.1 years of data (SD: ±22.2 years), assuming these data were obtained every 16-days by a single satellite sensor. This deficit is caused by cloud coverage, cloud shadows, sensor degradation, and other issues (Fig. S1b, *see **Methods***).

The global coverage of Landsat data evolved gradually (**Fig. 2**, **Fig. S3**) through a growing network of receiving stations established in all continents except Antarctica (**Fig. S2a**). Whereas the archive covered 85.8% of the global land surface by the end of the 1980s (mean of 11.6 observations per Landsat pixel, SD: ±7.6) a 25% increase since 1984, this coverage increased nearly five-fold by the end of the 2010s (mean of 48.32 observations per pixel, SD: ±18.6) **Fig. S3**). However, improvements were not uniform. Many countries lacked (or still lack) the infrastructure and know-how to continuously collect and preserve data from overpassing satellites (Wulder et al., 2016, **Fig. S2b**), or to directly profit from centralised (but incomplete) online archives (SCU, 2022). As a result, many world regions, particularly at low and very high latitudes, have lagged behind in establishing coherent monitoring capabilities (**Fig. 2a**).

Despite gradual improvements, changes in satellite technologies caused several abrupt changes in data coverage. Since the launch of Landsat 7 in 1999, Landsat on-board data storages reduced the reliance on global networks of receiving stations for preserving data prior to their archiving (Wulder et al., 2016). Combined with improvements in data transmission and warehousing, this rapidly expanded the Landsat archive. Since 2003, however, mechanical issues in Landsat 7 degraded as much as 25% of pixels per image (USGS, 2004). When Landsat 5 ended in 2010, available images were thus of poor quality. When Landsat 8 was launched in 2013, in turn, data coverage improved dramatically. The average proportion of countries' lands recorded monthly by a Landsat sensor (i.e., 1-2 images every 16-days; Fig. 2a) increased from 14.7% before 2013 (SD: ±25.2%) to 49.4% thereafter (SD: ±36.9%). Yet, the interoperability between Landsat 8 and earlier missions was hindered by differences in spectral information (Roy et al., 2016), a challenge not typically addressed by state-of-the-art remote sensing products.

Data coverage varies in space and time. With the exception of much of North America, nearly all lands have full-year interruptions in data coverage (**Fig. 2b**). Of these lands, 31.4% have ≥1-year interruptions after their first observation year, including most islands and most of Africa (**Fig. S5a**). Oftentimes these interruptions persisted for several years, leaving various Central African regions without usable images during >10 consecutive years (**Fig. S5b**). When data are available, their frequency varies (**Fig. 2c-d**).

Much of the world has a large number of Landsat images (**Fig. S1a**). This is the metric commonly reported in publications on new Landsat-based time-series products (e.g., Pekel et al., 2016; Potapov et al., 2022; Vancutsem et al., 2021). Yet, only a relatively small, and non-random, subset of those images provide a dense temporal coverage. Consistently high coverage only exists for dryland regions (**Fig. 1b**). In contrast, in most equatorial forest regions of the world, less than half of existing images are usable due to persistent cloud cover (Ju and Roy, 2008; **Fig. S1b**). In addition, in areas such as the Sahel belt and Central Asia, annual averages in observation frequencies (Fig. 1c) are exceeded by their fluctuations (**Fig. S1c**). Similarly, in those regions, seasonal data coverages are highly incomplete, often with less than three data months in a given year (Fig. 1d), and with fluctuations of a similar magnitude between years (**Fig. S1d**).

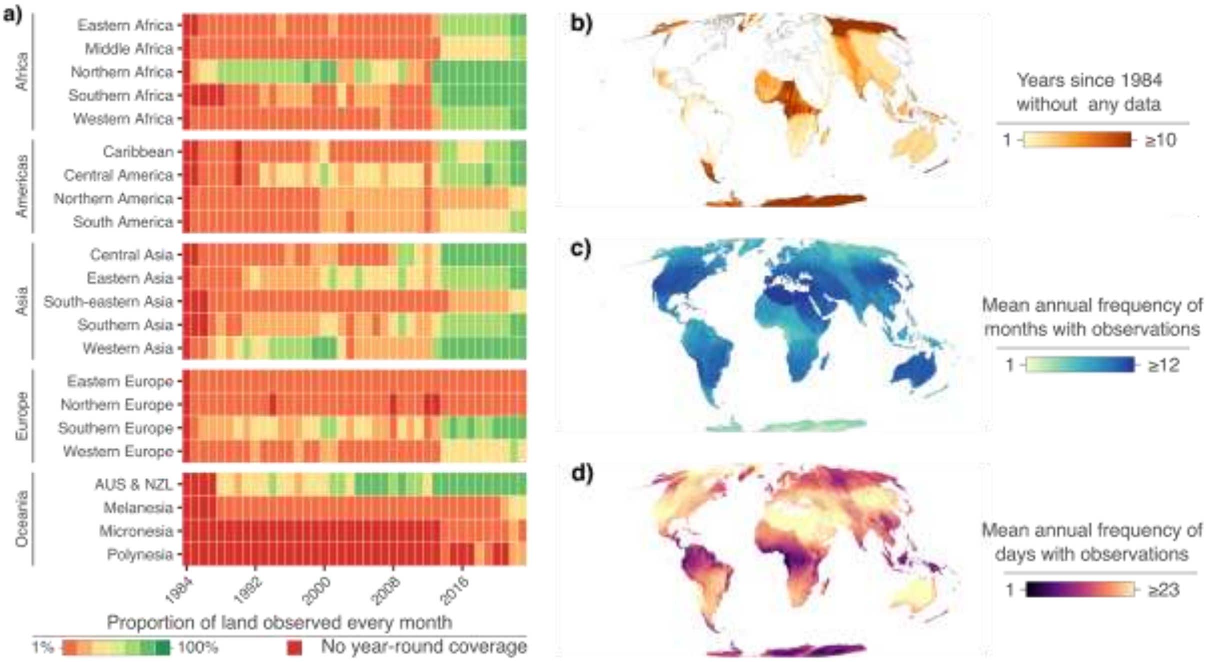

Figure 2. Spatiotemporal variation in Landsat satellite data coverage and quality. a) Year-to-year and regional variation in proportions of land areas observed during every month of the year, highlighting both interruptions and gradual improvements and a sharp increase in coverage in 2013, after the launch of Landsat 8. **b**) Accumulated ≥1-year data gaps. **c)** Global variation in average annual number of months with observation. d) Global variation in average annual numbers of observation dates.

3.2. Data limitations bias perceptions of key land changes targeted by policy and monitoring

The highlighted temporal and spatial inconsistencies in Landsat data may extend into derived time-series products of vegetation, land use, and other land-surface features. If insufficiently addressed, this may cause non-random errors (i.e., biases) in change signals derived from these products at different scales, and thus potentially bias downstream applications sensitive to such biases, such as assessments and monitoring of land changes, analyses of their causes and consequences, or training and calibration of predictive models. As the following three case studies demonstrate, Landsat data limitations indeed variously distort perceptions of prominent environmental-change issues globally and in nearly all countries, casting doubts on the reliability of reported global patterns and the comparability of national changes monitored under major international policy frameworks.

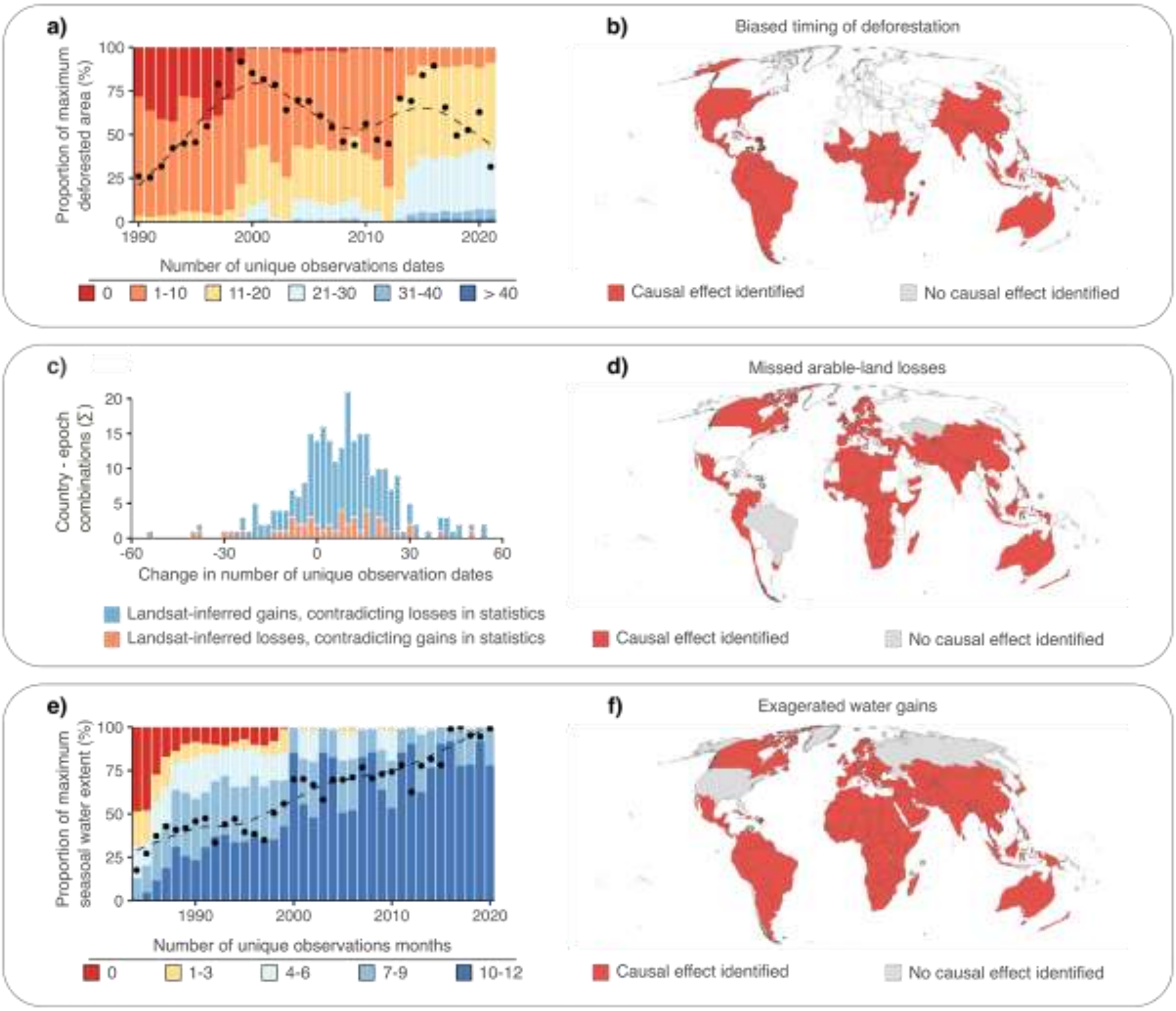

Figure 3. Effects of satellite data limitations on perceived land changes. a) Points: annual lost tropical moist forest areas normalised by the maximum extent, revealing positive/negative outliers relative to smoothed trend (LOWESS with 0.4 span; dashed line). Colours indicate percentages of forest extent observed with different maximum annual data qualities. **b**) Countries where temporal inconsistencies in Landsat-data coverage evidently bias perceived timings of tropical-moist-forest losses (evidence found in all relevant countries, shown in red; white countries do not have tropical moist forest). Evidence of biassing effects is from country-specific tests using spatial convergent cross-mapping (CCM; Clark et al., 2015). CCM is a causal-discovery method that attempts to reconstruct the state-space trajectory of a putative driver variable (here: anomalies in annual frequencies of Landsat-observation dates) from the time-lagged time-series values of a putative outcome variable (here: anomalies in annual deforestation extents) and then identifies a causal effect based on a significant improvement in the accuracy of the state-space reconstruction with increasing time-series length (see ***Methods*** for details). **c**) Frequency of disagreements in the direction of Landsat-inferred arable-land losses/gains between mapped 4-year epochs and changes derived from official statistics, distributed along a gradient of changes in frequencies of Landsat observation dates between epochs. Country-level contributions to the histograms are weighted by an indicator of the quality of national statistical data(World Bank, 2021). **d**) as in **b)**, but showing countries with (red) and without (grey) evidence for biassing causal effects of improvements in Landsat observation-date frequencies on Landsat-inferred gains in arable lands that contradict statistics-inferred losses. **e**) as in **a)**, with points indicating the annual global extent of seasonally inundated areas, normalised by the maximum extent, and colours indicating percentages of the maximum extent observed with different levels of seasonal Landsat-data completeness. **f**) as in **b)**, but for effects of anomalies in seasonal data completeness on anomalies in changes in seasonal surface-water areas. Details on country- and variable-specific test results and numbers of samples used per country are in the supplements (Fig. S6; Supplementary tabl**es 2, 4, and 6**). In b), d), and f), points indicate distinguish the outcome of causal analyses for small countries that would otherwise be imperceptible.

Case study 1: Varying observation frequencies bias perceived timings of deforestation events. Tropical moist forests are vital carbon and biodiversity stores and provide billions of people with income, food, and medicine. Yet, these forests accounted for >90% of global deforestation since 2000 (FAO, 2020). Changes in tropical moist forest extents are thus a major concern of international policies including the Global Biodiversity Framework, the Glasgow Leaders' Declaration on Forests and Land Use, the EU Regulation on Deforestation-Free Products, and the 2030 Agenda for Sustainable Development (among others). Correspondingly, the recently published Landsat-based Tropical Moist Forest product (TMF, Vancutsem et al., 2021) is poised to play a prominent role in global monitoring.

The TMF tackles gaps in Landsat data by handling temporal data for each pixel independently. Forest cover and change are classified continuously. Then, by assuming change is absent if not observable, a seemingly annual time-series is generated. Yet, given that data coverages vary in time and space, the true timing of forest-change events is oftentimes uncertain. Accordingly, change magnitudes can be overestimated following data gap years, or in years when high observation frequencies are needed to track progressive change events such as creeping deforestation.

We examined the TMF and, indeed, found indications of such biases. We registered unusually extensive deforestation rates during two periods since 1990, both marked by rapid improvements in the Landsat archive (**Fig 3a**). From 1999 to 2000, right after the launch of Landsat 7, we noted a 65.2% increase in deforestation, more than twice the maximum year-over-year increase (31.9%) between 1990 and 1999. Similarly, the 2012-2013 deforestation increase of 60.5% coincides with higher image frequencies following the launch of Landsat 8. This is nearly twice the recorded maximum between 2001 and 2012 (30.8%) when Landsat 7 was the main source data, despite its continued degradation since 2003. Where data was absent or potentially unusable for ≥1-year, we found higher deforestation immediately following such gaps (**Fig. 3a**; *see **Methods***). Overall, we found that 10.85% of global deforestation events captured over the 1990-2021 period followed periods with no data, and are thus potentially allocated to the wrong years (Fig. S5a). However, this percentage can be much higher regionally (e.g., 19.7% in North America) and during the particularly data-limited 1990s (e.g., 36.9% in Western Africa).

To confirm whether temporal inconsistencies in data coverage biased our perception of the timing of deforestation, we used a formal causal analysis technique developed for detecting causal relationships between two time-series called Convergent Cross Mapping (CCM, Sugihara et al., 2012; Clark et al., 2015; *see **Methods***). This technique allowed us to identify cases where perceived changes are biased because some components of those changes (e.g., their magnitudes or directions) are in part caused by variation in the observation process (i.e., in data coverage). Based on these analyses, we found that deforestation anomalies can be partially attributed to anomalies in the number of unique observation dates in all tropical-moist-forest countries (**Fig. 3b; Supplementary table 1**; *see **Methods***). .

Such distorted perceptions of deforestation years may bias timing-sensitive applications, including the modelling of carbon emissions (IPCC et al., 2019) and extinction debts (Figueiredo et al., 2019), or attributions of forest changes to socio-political conditions (Nackoney et al., 2014). For example, deforestation inside the Luo Scientific Reserve (Democratic Republic of Congo), that reportedly happened during the first Congo war (1996-1997) due to human displacement (Nackoney et al., 2014), would be falsely attributed to processes in the immediate post-war period when Landsat data were again available following a multi-year data gap **(Fig. S7b**).

These biases may also cast unfair perceptions of progress in curbing deforestation. For example, twelve countries indicated by the TMF as having increasing deforestation rates around the Landsat 8 launch reported decreasing trends relative to the previous reporting period (Keenan et al., 2015), although we stress that due to conceptual differences, these changes are not directly comparable (Chazdon et al., 2016). These include countries experiencing forest transitions and/or that are recognized for their long-term progress in forest restoration (e.g., Cuba, Goulart et al., 2018).

Case study 2: Increasing data frequencies miss regional arable-land losses. Accurate data on extents of arable lands and their changes are essential for monitoring agricultural lands under sustainable use (SDG indicator 2.4.1), the productivity of agricultural systems (e.g., indicator 2.1.4 of the Comprehensive African Agriculture Development Programme), and the development of rural economies (e.g., the World Bank's World Development Indicator set 3.1), as well as for detecting and evaluating changes in the status of natural ecosystems (e.g., the Global Biodiversity Framework's headline indicator A2).

Mapping arable land requires a dense time-series. This enables detecting changes driven by planting and harvesting, which help improve mapping accuracies (Fan et al., 2022), but which may be overlooked due to temporal inconsistencies in the Landsat archive. To tackle this issue, a recently developed data product maps Global Arable-Land Extents in four-year epochs (here referred to as 'GALE', Potapov et al., 2022), by exploiting all Landsat-based satellite observations in an entire epoch to more accurately characterise crop phenology. Although this prevents shorter-term change assessments, it is a necessary compromise. Yet, this approach is not immune to year-to-year improvements in data frequencies (**Fig. S3**). These improvements increase the detectability of key intra-annual changes related to land management, and may thus lead to overestimations of arable-land gains.

We first examined the GALE for indications of potential change biases. To this end, we compared national aggregates of the GALE with corresponding FAO statistics on arable-lands. We adjusted the latter following expert recommendations to conceptually match these data with the GALE (Tubiello et al., 2023). We identified 129 suspicious-looking countries and dependent territories where mapped gains contrasted with reported losses (**Fig. S8, Supplementary Table 3**). This relates to arable-land expansions in >12 billion 30-m pixels, more than the combined number of arable-land pixels of all Amazonian countries in 2019 (FAO, 2023, **Fig. S7c**). Disagreements with reported losses peaked between the 2008-2011 and 2012-2015 epochs (36.0% of cases). The first peak coincides with the discontinuation of Landsat 5 in 2010, when parallelly captured Landsat 7 images were heavily degraded, causing an abrupt decrease in data frequencies. The second peak coincides with the launch of Landsat 8 in 2013, which led to a massive increase in data frequencies and moreover marked a shift in sensing technologies. Compared to previous sensors, Landsat 8 provides data for different spectral ranges (Roy et al., 2016). We found no indication that the GALE is corrected for these issues.

Naturally, cases of GALE-FAO disagreements alone do not provide evidence of biases in GALE-inferred change perceptions, as they might equally reflect known errors in FAO data (See et al., 2015). To identify those cases where changes are demonstrably caused by the GALE's underlying observation process, we again used CCM (*see* ***Methods***). Focusing on the

129 countries with positive disagreements (i.e., where the GALE mapped gains instead of losses in one or more epochs), our analyses confirmed that in 90.7% of those countries, changes in observation frequencies contribute to causing perceived arable-land changes (Fig. 3d; Supplementary table **4**). These include several top food-producing countries that together accounted for 93.3% of the global cereal production in 2021 (World Bank, 2023), including several that are well-known for their large arable-land losses (e.g., China, Bangladesh, Canada). They also include 28 of the top-30 most food-insecure countries (e.g., Sierra Leone, Afghanistan), where misinterpreting losses of arable lands as gains could misinform policy-makers on emerging crises (Fig. 3d).

Overestimated arable-land gains can also lead to unfair evaluations of progress towards more sustainable food production by exaggerating conflicts of food security with ecosystem protection and climate-change mitigation. For example, two recent studies using GALE data (Meng et al., 2023; Wang et al., 2023) reported extensive cropland expansion into global protected areas that massively accelerated between the mid-2000s and mid-2010s. The above-described data biases surrounding the 2013 launch of Landsat 8 (**Fig. 2a**, **Fig. 3c**), however, likely render these assessments unreliable. This is illustrated in India, where sudden changes in Landsat data apparently led the GALE to misinterpret wetland pixels as arable-lands, leading to the false mapping of agricultural conversion of an entire Ramsar wetland of >3,000 ha (**Fig. S7d**).

Case study 3: Improving seasonal data completeness exaggerates water gains. Freshwater ecosystems are indispensable for human life and prosperity, climate regulation, and biodiversity persistence. Various international policies mandate monitoring their extent (e.g., UN Watercourse Convention, EU Water Framework Directive, 2030 Agenda for Sustainable Development). For example, SDG indicator 6.6.1 tracks changes in surface-water bodies such as lakes, rivers, and reservoirs, for which the Landsat-based Global Surface Water product (GSW, Pekel et al., 2016) provides critical input. In particular, the GSW's ability to depict seasonal water occurrences is crucial for sustainability questions. In many dryland regions, seasonal water bodies lasting only a few months per year support food and water security for people and livestock (Michalak et al., 2023). Additionally, even outside drylands, seasonal flooding of riverplains affects nutrient inputs in, and leaching from, major agricultural regions (Talbot et al., 2018).

The GSW classifies water occurrences monthly. Then, it distinguishes seasonal from permanent water annually based on interruptions in monthly classified water observations. The authors of the GSW accounted for temporal inconsistencies in the Landsat archive by only classifying pixels in years with ≥10 observations. This reduces some bias without precluding global mapping. However, the nearly 5-fold increase in seasonal water mapped by the GSW between 1984 and 2020, with positive trends over 90.1% of the maximum seasonal-water extent, cannot be disconnected from data improvements. Specifically, because the GSW maps water if as little as 43.5% of the expected annual number of satellite observations are available, seasonally biased distributions of those images could miss seasonal water occurrences, or misclassify seasonal for permanent water (if only covering dry or wet seasons, respectively). Therefore, improvements in seasonal data completeness (i.e., number of months with usable data) could be falsely mapped as seasonal-water gains (Yamazaki and Trigg, 2016).

We found that, indeed, global seasonal surface-water gains strongly correlate with improvements in the number of Landsat observations (r^2=0.88; **Fig. 3e**) and are oftentimes unsupported by local discharge measurements (90.7% of gauge stations with significant long-term changes showed disagreements in change directions, **Fig. S9**; Supplementary table 5, see ***Methods***). Using CCM, we found formal evidence that changes in seasonal data completeness contributed to causing perceived changes in seasonal surface water in 87.8% of all countries and dependent territories (**Fig. 3f; Supplementary table 6; see Methods**). These include 28 of the top-30 countries with the highest levels of water stress (e.g., Syria, Sudan; World Bank, 2023), where mapping false seasonal-water gains and losses could potentially result in drastic mischaracterizations of water-related sustainability issues.

General conclusions from our case studies. Our main conclusion is that there are pervasive biases in perceptions of land changes inferred from state-of-the-art Landsat-derived time-series, which are inherited from temporal inconsistencies in the underlying Landsat satellite observations. This conclusion is based on our extensive testing for biassing causal effects using a causal-discovery framework (CCM), which showed significant evidence for causal effects in nearly all tested combinations of countries and land-change facets. Our tests of bias-causing effects focusing on years from 2000 onwards yielded qualitatively similar results (**Fig. S10**; **Supplementary tables 7-8**), demonstrating that this conclusion does not depend on including the particularly data-poor 1990s, but is valid also for the generally more data-rich post-2000 period.

We note that in all three cases discussed here, we cannot ascertain whether any specific pixel-level changes under suspicion are actually false, nor that any perceived changes exclusively, or even primarily, originate from data inconsistencies. However, our results show that year-to-year variations in data coverage contribute to causing perceived year-to-year land changes, and that we would not have perceived changes of the same nature and/or magnitude without changes in data coverage. Although we demonstrate these issues with a focus on Landsat data, they are expected to apply similarly to other satellite data archives used in global land-change monitoring (e.g., AVHRR, MODIS, Sentinel), given that those, too, are uneven in their data coverage (Dech et al., 2021; Justice et al., 2002; Sudmanns et al., 2020).The identified biases in land-change perceptions may contribute to distorted or unbalanced narratives about sustainability challenges. In the worst case, misperceptions of progress towards food- and water-security goals in lower-income countries, that in reality reflect improvements over initially more limited data, might hamper adequate international support and timely policy interventions. Risks of such misinterpretations seem particularly high when comparing progress against pre-2013 baselines, after which Landsat 8 offered substantially improved spatial and temporal data coverage.

3.3. Future needs: bias corrections, fair product validations, support to users, and a shared sense of responsibility

The data limitations we demonstrated are being acknowledged in the remote sensing community (Frantz et al., 2023; Lewińska et al., 2023; Zhang et al., 2022) and commonly discussed in published materials describing new data products. For example, the authors of the TMF discuss how observation frequencies affect the detection of deforestation, and those of the GSW discuss difficulties in detecting water due to varying data completeness. However these fundamental issues are typically discussed only swiftly and in general terms. Those discussions may resonate with remote sensing experts, who are closely familiar with them. By contrast, for many non-expert data users, the eye-popping advances achieved through legacy programs such as Landsat can lend any product derived with it an appearance of high quality, driving data choices and overconfident uses (Molder et al., 2022). Given the central role of satellite-based land-change observations in environmental and sustainability policy, monitoring, and related scientific fields, it is imperative that we take our collective management of data limitations to a whole new level. To this end, several steps can be taken by both expert and non-expert communities to improve the usability, interpretability, and sound application of remote-sensing-based data products, including more rigorous bias-controls by data developers, as well as support for (and commitment by) data users to detect and address uncertainties.

Improving the handling and reporting of data uncertainties and biases. Some of the data issues we described can be tackled by raising standards for correcting for satellite data limitations before developing products. For example, methods to correct for spectral differences between Landsat sensors – which likely explain some of the abrupt year-to-year changes in Landsat-based data products – are readily available (Che et al., 2021; Roy et al., 2016). Although some developers already use such methods (Gong et al., 2020; Senf and Seidl, 2021), this remains rare. Additionally, an increasing array of approaches can fill gaps in satellite archives (Asare et al., 2020; Yin et al., 2017), for instance, by fusing sparse Landsat data with coarser-resolution but less incomplete data from MODIS and AVHRR sensors to generate global, seamless data cubes (as showcased by Liu et al., 2021). Naturally, such methods carry their own uncertainties, and their effectiveness likely depends on the severity of satellite data limitations.

Additionally, we need higher standards for validating remote sensing data products. We recognize that the products analysed here were, in fact, extensively validated. In addition, the most recent ones follow current best practices in sample-based estimations of map accuracies and uncertainties (Olofsson et al., 2014). However, even current best practices do not account explicitly for gradients in satellite data coverage. This is problematic because data limitations can not only locally reduce the performance of classification algorithms, but also impede the accurate visual interpretation of images. Yet, global, multi-decadal products (including those analysed here) are typically validated against reference samples derived by visually interpreting Landsat images, especially for pre-2000 periods, where few alternative sources of validation data exist (Chazdon et al., 2016). As a result, the very pixels and years when classification algorithms are most likely to fail may either be systematically underrepresented by validation samples (as samples there are less likely accepted as 'validation-grade'), and/or their samples' labels may include more errors. This means that reported accuracy scores may not be generalizable to the complete maps, and may in the worst case exaggerate true accuracies, even if developers otherwise followed best practices regarding spatiotemporally and environmentally representative sampling.

To tackle such spatial and temporal biases when validating remote sensing data products, predictive models could be used to probabilistically estimate class-confusion probabilities beyond the validation samples. Such models could directly account for different sources of bias in relevant observation processes, for example, by incorporating covariates capturing the quality of the satellite data underpinning image-derived reference samples, factors limiting the collection of samples in the field (e.g., accessibility), and environmental factors linked to varying performance of classification algorithms (e.g., topography). As a result, the modelled, contiguous probability estimates would offer a more representative basis for calculating accuracy scores for any given region of interest than the raw validation samples. Remote sensing has a rich set of tools to minimise data biases as far as possible (e.g., gap filling, randomised sampling; Asare et al., 2020; Olofsson et al., 2014), but approaches to explicitly model and account for remaining biases remain rare (Stehman et al., 2018). In turn, other fields in which data are usually highly biased have developed long traditions of developing models to explicitly account for sampling biases (e.g., ecology, Chadwick et al., 2023; Chauvier et al., 2021; Fink et al., 2023, hydrology, Rasmussen et al., 2016). Integrating approaches from these fields (e.g., Vanselow et al., 2021) could substantially improve the robustness of accuracy reporting (Simmonds et al., 2022).

Beyond the immediate benefits through enabling more reliable accuracy assessments, the modelling of contiguous uncertainties can also help empower data users to better address remaining data limitations in their applications. This is especially so, if the contiguous uncertainties are provided in ways that enable efficient uptake in commonly used downstream analysis frameworks (e.g., via probabilistic sampling in Bayesian analyses, or via weighting of input data in Machine Learning). For example, mapping products showing per-pixel probability-mass functions of different classes would make it much easier for product users to derive unbiased area estimations over larger regions, compared to the classical way of mapping just the highest-probability class per pixel. Similarly, per-pixel probability-mass functions of alternative temporal class sequences could readily be propagated into change analyses and indicators (Kirchner et al., 2021; Rowland et al., 2021).

All these measures would imply more time needed for the development and quality-assurance of these products, and thus likely lead to fewer products entering the market following peer-review. This would be desirable from the perspective of data users, who are already overwhelmed by too many products to choose from, with little guidance on which ones to trust.

Helping users choose fit-for-purpose data products. To promote sensible uses of time-series products, we must acknowledge that many users have little to no training in remote sensing. Such users require support both in selecting the most adequate products and in understanding the implications of those products' uncertainties for their desired applications.

One way to provide such support could be through cloud-based tools that automatically identify candidate products for a given user-specified application and assess where within a specified region and period each product could plausibly support this application, given limitations in the products' underlying satellite data. To interpret the users' descriptions of their applications and translate those into targeted product queries, such tools could draw on Large Language Models (LLMs; as demonstrated by Li and Zhang, 2023). LLMs could be pre-trained on expert literature on both the data requirements of common application types (e.g., temporal consistency for change analyses) and on the satellite-data requirements for mapping different variables. For example, literature shows that mapping arable lands is best achieved with satellite observations made during periods of key management interventions such as sowing and harvesting (Fan et al., 2022; Prishchepov et al., 2012). Information on these periods obtained from regional crop calendars (Belén Franch and Whitcraft, 2022), and provenance metadata on the candidate products' satellite-data inputs (Fischer et al., 2023) could be integrated with customised satellite-data-coverage metrics (e.g., measuring the completeness of satellite observations over target dates) to perform data queries. Summaries of the test's results and rationales, the recommended product(s), and areas/periods where the application is likely to be unreliable could be communicated to users via automatically generated light-weight reports.

Data queries and reports will require metrics of data quality and availability that can effectively guide product selections while considering application-specific data requirements. While the data-coverage metrics analysed in this paper are broadly relevant for different applications in land-change monitoring, certain applications will require custom metrics. Existing literature on specialised remote sensing applications can provide guidance for constructing such metrics (e.g., Fan et al., 2022; Mas and Soares de Araújo, 2021; Prishchepov et al., 2012; Vaudour et al., 2019). For instance, in temperate regions, image composites centred around phenological peaks are relevant for forest monitoring, and data frequencies estimated within those temporal windows would be most informative (Lewińska et al., 2023). In other cases, further research into application-specific data requirements may still be needed before adequate metrics to measure data limitations can be conceived (e.g., for inconsistent data quality in mountain regions; Vanonckelen et al., 2014).

Towards responsible uses of data products. Clearly, there is a need, and opportunity, for better data products, data-quality information, and support tools. Ultimately, however, none of those can take away the responsibility of data users for ensuring that the used data products are fit-for-purpose for their specific applications, nor for evaluating the plausibility of their studies' original results. Oftentimes, steps as simple as skimming through contextually relevant literature or visually exploring historical high-resolution images (e.g., using Google Earth) can already reveal issues (e.g., as demonstrated in **Fig. S5**). Similarly, regional bar plots of annual areas often suffice to reveal suspicious-looking anomalous trends in time-series products that warrant further scrutiny.

Optimally, data users of remote sensing products would explore causal associations between target variables and satellite data-coverage metrics. Here, effect-size measures (e.g., combining CCM with S-Map, Deyle et al., 2016) may be used to evaluate whether the magnitudes of any identified biassing effects of data-quality limitations are tolerable, given the studies' specific goals and conclusions. Users interested in Landsat-based products may use data-coverage metrics such as ours in such analyses (*see* ***Data and code availability***).

4. CONCLUSIONS

While Landsat satellite data are vital for environmental-change and sustainability analyses and monitoring, their uneven spatial and temporal coverage extends into derived monitoring products. This leads to widespread biases in perceptions of changes in ecosystems, food, and water resources. Recognition of these data limitations and efforts to address them are needed by both data developers, data users, and developers of support tools. Whereas data developers are best positioned to attenuate the imprint of input-data limitations on their products and to improve transparency on remaining uncertainties, data users are ultimately responsible for choosing appropriate products and for assuring the soundness of any conclusions made through them. Shared ownership of the problem by different stakeholders seems essential for assuring robust environmental-change analyses, assessments, and monitoring in order to promote responsible policy decisions.

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AUTHOR CONTRIBUTIONS

RR and CM designed the study. RR developed the analysis with support from CM and CC. RR developed the data underlying the study and ran the analysis. RR and CM designed the figures. RR, CM, and CC interpreted the result and wrote the paper.

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