Limitations in the Landsat satellite archive bias SDG monitoring

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Highlights

1) Coverage and quality of historical Landsat satellite data are spatiotemporally uneven
2) Global time-series of forest, arable-land and water inherit signals of these limitations
3) The limitations cause bias in perceived land changes with sustainability implications
4) Biased change perceptions are more likely in lower-income countries
5) Developers and users of remote-sensing data both have a part in minimising biases

ABSTRACT

Satellite remote sensing is vital for monitoring, research, and policy addressing sustainability challenges 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, gaps and quality limitations in the Landsat data 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 are spatially and temporally uneven, frequently interrupted, and have seasonally incomplete coverage and quality. Using a causal-discovery framework, we moreover show that these limitations are inherited in several state-of-the-art, global time-series products, biassing perceptions of changes in forests, arable-lands, and water resources. These biases can impair reliable assessments of environmental and human development issues targeted by the Sustainable Development Goals (SDG) framework, and disproportionately affect lower-income countries. We provide global data-quality information to support the explicit consideration of potential biassing effects in future uses of remote-sensing products derived from Landsat data, and discuss avenues towards better uncertainty reporting and bias control in satellite-based sustainability monitoring and related applications.

Keywords: remote sensing, sustainability, post-2020, Landsat, SDG

1. INTRODUCTION

193 countries committed to 17 Sustainable Development Goals (SDGs, UN general Assembly, 2015) to comprehensively address the environmental and social impacts of economic development. Yet, nearing the target year 2030, we are still far from meeting these goals (Moyer and Hedden, 2020). Widespread and rapid land alterations (Winkler et al., 2021) cause biodiversity loss (IPBES, 2019), accelerate climate change and threaten regional food

and water security (UN DESA, 2022). The global 2030 SDG Agenda foresees regular progress monitoring and reporting as a basis for their periodic recalibration (Xu et al., 2020), and to identify national responsibilities for sustainability issues that help secure practical commitments (Perino et al., 2022).

Satellite remote sensing allows monitoring many SDG indicators at multiple spatial and temporal scales (Anderson et al., 2017) and, thanks to 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 meet their reporting obligations (Anderson et al., 2017, p. 20).

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 (30-m since 1982, typically every 16-days). Thanks to the program's longevity, 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 SDG 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 quality issues 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, Olofsson et al., 2014).

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 the launch of the first 30-metre-resolution sensor in 1982, which paved the way to a multitude of scientific advances in satellite remote sensing. To this end, we map the between- and within-year frequency, recurrence, and quality of daytime Landsat images. Second, we use a causal inference framework to demonstrate how spatial and temporal variations in these dimensions of quality affect our perception of changes in the extent of forests (**Fig. 1d**), arable lands (**Fig. 1e**), and seasonal surface water (**Fig. 1f**) mapped by state-of-the-art products relevant for SDG monitoring. Third, we evaluate whether data-quality-related biases in perceptions of change vary across countries with differing financial capabilities to sustain sophisticated national monitoring systems. Finally, we provide recommendations on how to improve the reporting of data limitations, and how to best include them in future remote sensing data products.

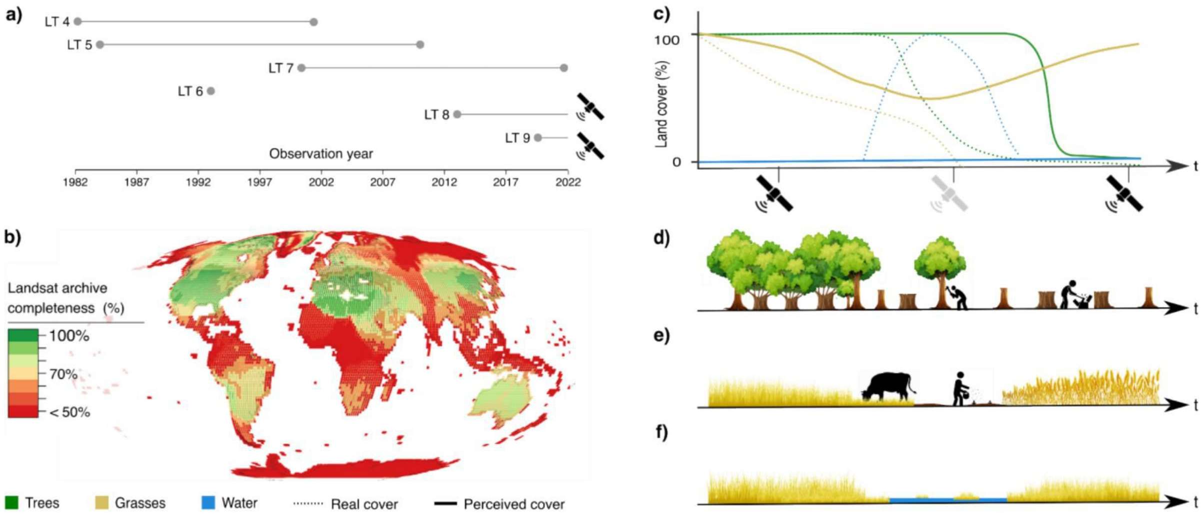

Figure 1. Temporal gaps in satellite observations and their conceptual link to biased perceptions of land changes. a) Five operational Landsat (LT) satellite missions provided a seemingly uninterrupted global coverage for 1982-2022 (grey lines; satellite icons indicate active missions). **b)** However, 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 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

We developed a suite of metrics on the annual and year-to-year frequency and recurrence of Landsat images, weighted by their respective quality. The quality of individual images directly reflects geometric and spectral issues (USGS, 1998) and cloud cover (Ju and Roy, 2008), and indirectly shadows and haze, which typically accompany clouds. We calculated our metrics for each year, and for each descending tile drawn in the World Reference System 2 (USGS, 1998). We then combined tile-level metrics by averaging them into global 1-km-resolution grid cells, while taking into account tile overlaps. We obtained the data feeding our metrics from the metadata provided with each Landsat acquisition (USGS, 2021). We used all metadata recorded between 1982 and 2022, but disregarded those relating to Landsat's Multispectral Scanner System imagery, which are not commonly used in remote sensing applications due to their lower spatial and spectral resolution compared to Landsat 4-9.

Image quality. We created a normalised metric between 0 (worst) and 1 (best) on the quality of each Landsat image j (QI). For a given year y and tile t, QI is given by $Q_{y,t,i} / 9 * (100-C_{y,t,i})$, where C is the cloud-cover percentage at the time of the image acquisition. Q is a qualitative metric between 0 and 9 that is used by the United States Geological Survey to grade the number of bad scans in an image (USGS, 1998).

Within-year variations in data quality. In each year, we used the estimated QI of each corresponding satellite image – but excluding those with QI=0, which implies the absence of any usable data – to calculate several within-year quality metrics. First, we summed the QI of all images, weighing annual image frequencies by the proportion of usable pixels (hereafter 'quality-weighted frequency'). Second, we counted the number of months with images to measure our ability to perceive within-year (e.g., seasonal) changes. Third, we estimated the maximum QI as a proxy for increases and decreases in visibility (e.g., due to cloud cover) relative to other years, which informs on our ability to perceive abrupt changes to the Earth's surface.

Estimating archive completeness. We quantified the 'completeness' of the Landsat archive as the proportion of usable images relative to an idealised expectation of one image taken every 16 days per active sensor (which is the typical recurrence). Here, the number of usable images corresponds to the sum of the annual quality-weighted frequencies. As a complement to this analysis, we counted the number of years without any satellite image data since 1982 to measure breaks in the continuity of Landsat.

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

Causal analysis approach. We tested for biassing effects of data-quality on perceptions of land-change in three case studies. We tested for causal effects using Convergent Cross Mapping (CCM, Clark et al., 2015; Sugihara et al., 2012), a technique that can identify causal links between two temporal variables, even if these are not separable or if links are weak or nonlinear. To achieve this, CCM first constructs co-called 'shadow manifolds' of the two variables, which summarise their past behaviour over time. CCM then establishes whether there is a causal relationship between the variables by finding corresponding points in the shadow manifolds of these variables (via "cross-mapping"), and testing whether the shadow manifolds 'converge', i.e., whether information from the causal variable has been embedded in the effect variable. The CCM outputs inform on the significance of the causal association, and on the ability of the causal variable to predict the outcome variable. The rationale for these tests is that a perceived land change is (by definition) biased if the presence of non-random data error (i.e., by spatial/temporal variation in our data-quality metrics) alters the specific nature of the change (e.g., its magnitude, timing, or direction).

In each study case, variables have varying and sometimes short time-series. We used an enhanced version of the original CCM method (Clark et al., 2015) that is robust to short time-series by applying dewdrop regression to combine information from multiple time-series. To this end, we ran the CCM analyses on a country-by-country basis, taking advantage of every relevant pixel within. We focused on causal effects detectable for these country-level aggregations, as this is the typical scale of SDG progress reporting (UNFCCC, 2015).

Case study 1: Timing of deforestation. We analysed data on the first year of deforestation between 1982 and 2021 from the Tropical Moist Forest dataset (Vancutsem et al., 2021). To align these data with our quality metrics, we aggregated them from their native 30-m resolution into a 1-km resolution by summing the corresponding pixel areas.

For an initial exploration of possible 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. 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 changes in TMF-inferred deforestation rates and year-to-year changes in the maximum annual QI. Here, we hypothesised that improvements in data quality caused disproportionately high deforestation rates shortly after extended temporal gaps due to the backlog over data-limited year(s) during which no deforestation could be detected. To estimate year-to-year-changes in deforestation and data quality, we calculated positive/negative outliers for each of these variables based on the differences between annual values and their respective trendlines derived with Locally Weighted Scatterplot Smoothing (LOWESS, Seabold and Perktold, 2010), using a span of 0.4. We focused on pixel time-series experiencing ≥1 forest-cover change and ≥1 year without data.

Case study 2: arable-land expansion. We analysed a global dataset mapping the extent of arable-land for four-year epochs between 2000 and 2019 (GLAD, (Potapov et al., 2022). To match these data to our quality metrics, we aggregated them from their native 30-m resolution to a 1-km resolution by the summing per-pixel areas.

To explore the potential existence of biases, we evaluated whether the GLAD-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 GLAD 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 GLAD 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. Here, we specifically evaluated whether the epoch-to-epoch time-series of GLAD-inferred arable-land gains that contradict FAO-inferred losses (i.e., the dominant form of disagreements; **Fig. 3c**) showed any causal signals of concurrent variations in quality-weighted Landsat image frequencies. For this, we recalculated the quality metrics per four-year epoch and aggregated them nationally, considering only pixels where the GLAD mapped arable-land at any point between 2000 and 2019. Specifically, we here focused on pixels with both GLAD-inferred arable-land gains and increases in quality-weighted Landsat image frequencies.

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). To assure the comparability of these data with our quality metrics, we aggregated the 30-m GSW to a 1-km resolution by summing per-pixel areas.

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 connectivity of river flows within 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. S7a**) 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. S7b**).

Additionally, we used CCM to formally test our hypothesis that changes in seasonal Landsat data completeness bias perceptions of changes in seasonal surface-water extents. Our hypothesis is based on the premise that observing a pixel during extended periods of time within a given year increases the likelihood of detecting any short-lived seasonal water occurrences. Specifically, we tested for effects of positive/negative outliers in annual numbers of months with usable Landsat data on positive/negative outliers in seasonal surface-water areas. We detected outliers based on differences between annual values and LOWESS trendlines. We applied the CCM analysis separately for each country, focussing on pixels with seasonal surface water at any point during the observation period.

Comparisons between lower- and higher-income countries. We tested for asymmetries in the prevalence of confirmed biases in perceptions of land changes between higher- and lower-income regions of the world, as distinguished by World Bank data (Solt, 2020). For simplicity, we aggregated countries classified as either 'low-income' or 'lower-middle-income' into a 'lower-income' group, and those classified as either 'upper-middle-income' or 'high-income' into a 'higher-income' group.

To test for differences in the prevalence of bias in perceived land changes between lower-income and higher-income groups, we applied the McNemar test (McNemar, 1947) to frequencies of countries with significant causal effects vs. no effects in either group. To account for spatial autocorrelation, we matched each higher-income country to its spatially closest neighbour in the lower-income group, with replacement. The income-group comparisons for arable-land and surface-water changes thus had a sample size of 133 (N=133/83 for higher/lower-income countries) and that for tropical-moist-forest changes a sample size of 41 (N=36/41 for higher/lower-income countries).

3. RESULTS AND DISCUSSION

3.1. Spatial and temporal variations in data quality and coverage

An uneven history of satellite observations. Between 1982 and 2022, the Landsat archive gathered 17,553,123 daytime images (average of 1,618 per 1-km pixel [±1,599], see **Fig. S1a in *Supplementary Material***). This means that 33.1% of images possible under a 16-day revisit frequency are missing (*see **Methods***). Moreover, the average 1-km pixel lost an additional 44.8% of observations (±17.6%, **Fig. S1b/d**) due to quality issues such as clouds, haze, cloud shadows, or sensor degradation. This leaves an average of 1,429 images per pixel (±887, **Fig. S1c**).

The global coverage of Landsat data evolved only gradually (**Fig. 2a**, **Fig. S3**) thanks to a network of receiving stations established in all continents except Antarctica (**Fig. S2a**). Whereas the archive grew by an average of 118,362 images per year during the 1980s (±67,104), this rate increased nearly five-fold by the 2010s (**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. S2a-b**), 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 (**Fig. 2a**). The average proportion of countries' lands with a 16-day coverage increased from 17.5% before 2013 (±30.8%) to 89.4% thereafter (±26.4%). 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 limitations vary in space and time. Except for much of North America, nearly all lands have full-year interruptions in data coverage (**Fig. 2b**). Of these lands, 36.2% have ≥1-year interruptions after their first observation year, including most islands and most of Africa (**Fig. S4a**). Often, these interruptions persisted for several years, leaving several Central African regions without usable images during >10 consecutive years (**Fig. S4b**). When data are available, their frequency and quality vary (**Fig. 2c-d**). Much of the world has a large number of *any* Landsat images (**Fig. S1a**), which 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 have high quality. Consistently high coverages of high-quality images only exist for dryland regions (**Fig. S1c**). 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 fluctuations in quality-weighted image frequencies exceed annual averages (**Fig. 2c-d**). Similarly, in those regions, seasonal data coverages are highly incomplete, often with less than three data months in a given year, and with fluctuations of a similar magnitude between years (**Fig. 2e-f**).

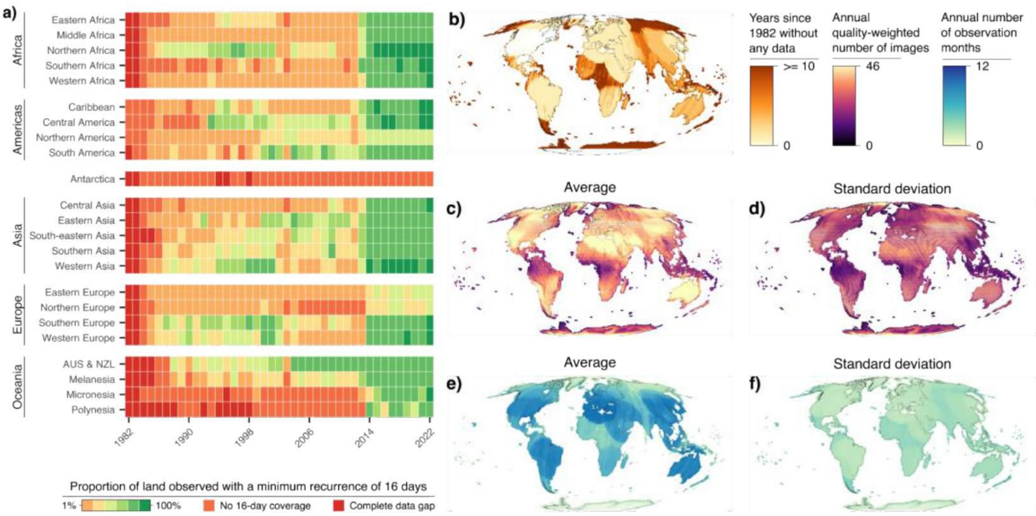

Figure 2. Spatiotemporal variation in Landsat satellite data coverage and quality. a) Year-to-year and regional variation in proportions of land areas observed during every month of the year, highlighting both interruptions and gradual improvements and a sharp increase in coverage in 2013, after the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

3.2. Data limitations bias perceived changes in SDG indicators

Temporal and spatial inconsistencies in Landsat data may, unless addressed, immediately affect the monitoring of any land-change-related SDG. Data unevenness in earlier decades, too, influences SDG monitoring, even if more indirectly. For example, in light of known data constraints (ESA, 2020), the SDG monitoring framework has chosen 2000 as the baseline year for measuring changes in extents of forests (indicator 15.1.1) and water-related ecosystems (indicator 6.6.1). Yet, changes in greenhouse gas emissions (indicator 13.2.2), which depend on both forest (Pearson et al., 2017) and wetland extents (Zhang et al., 2017), are generally evaluated against a 1990 baseline (UN DESA, 2022). Long-term, temporally consistent time-series products are thus needed, to not only meet the specific monitoring needs for individual SDG indicators, but also to assure that monitoring across SDGs is coherent, and that systemic interrelations between SDGs are adequately captured. However, as we demonstrate in the following three case studies, data limitations distort our perception of changes in several SDG indicators.

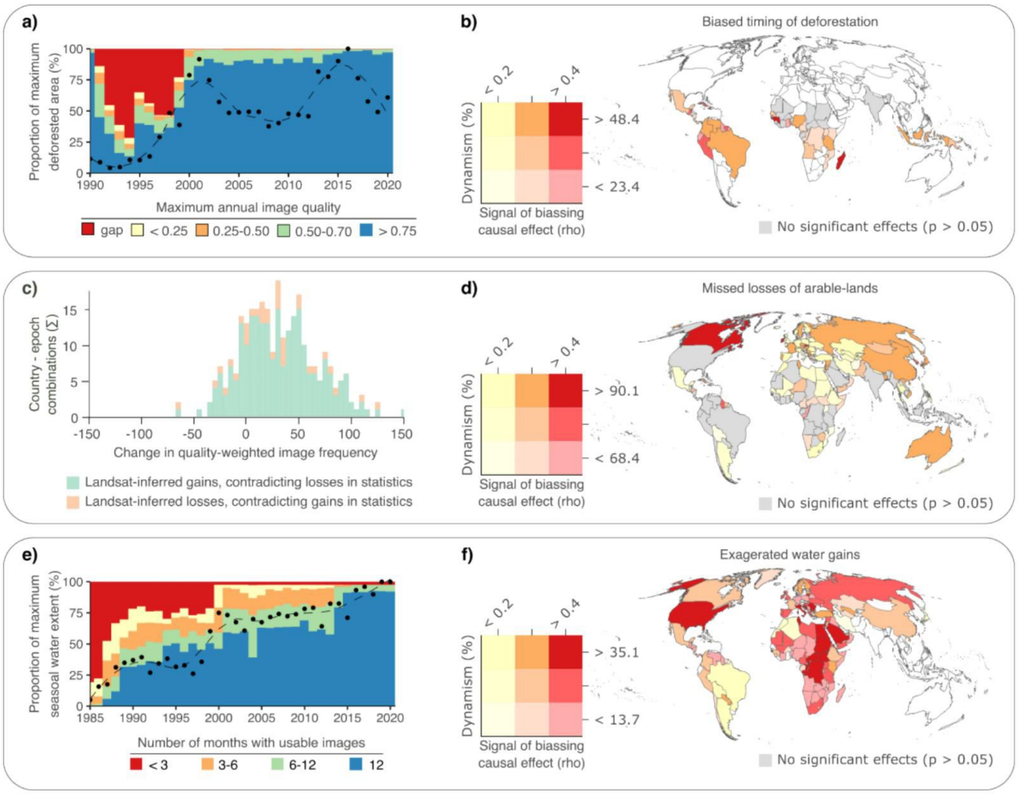

Figure 3. Effects of satellite data limitations on perceived land changes. a) Points: annual lost tropical moist forest areas normalised by the maximum extent, revealing positive/negative outliers relative to smoothed trend (LOWESS with 0.4 span; dashed line). Colours indicate percentages of forest extent observed with different maximum annual data qualities. **b**) Country-level differences in evidence of biassing causal effects (rho; x-axis), compared to proportions of the maximum forest extent experiencing changes (hereafter 'dynamism'; y-axis). **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 quality-weighted Landsat image frequencies between epochs. Country-level contributions to the histograms are weighted by information on national statistical reporting performances (World Bank, 2021). **d**) is similar to **b**), but measures effects of improvements in Landsat data quality on Landsat-inferred gains in arable-land that contradict statistics-inferred losses. **e**) Analogous to **a**), points indicate the annual and global seasonally inundated areas, normalised to maximum extent, and colours indicate percentages of the maximum extent observed with varying seasonal Landsat data completeness. **f**) is as **b**), but for effects of anomalies in completeness on anomalies in seasonal water areas.

Case study 1: Gaps in quality data bias perceived timings of deforestation events. Changes in forest areas are the focus of SDG indicator 15.1.1. Tropical moist forests, in particular, accounted for >90% of global deforestation since 2000 (FAO, 2020) and are vital carbon sinks (SDG 13) and biodiversity refuges (SDG 15) that provide billions of people with income, food, and medicine (SDGs 1, 2, and 3). Accordingly, the recently published Landsat-based Tropical Moist Forest product (TMF, Vancutsem et al., 2021) is poised to play a prominent role in global SDG 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 quality and coverage vary in time and space, the true timing of forest-change events is often uncertain. Accordingly, change magnitudes can be overestimated following data gap years, or in years when high image 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 of 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 58.4% of deforestation mapped since 1990 follow periods with no data, and are thus potentially allocated to wrong years (**Fig. S5a**; *see **Methods***).

To confirm whether data limitations influenced 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, Clark et al., 2015; Sugihara et al., 2012; *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 and/or quality).

Based on this analysis, we found that deforestation anomalies can be partially attributed to those in maximum annual image quality in 68.8% of tropical-moist-forest countries (**Fig. 3b**; *see **Methods***). The distorted perceptions of deforestation years may bias timing-sensitive applications related to SDGs, including 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. S5b)**.

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 frequencies of quality data miss regional arable-land losses. Accurate data on arable-land extents are essential for mapping agricultural lands under sustainable use (indicator 2.4.1), and are also closely linked to indicators on deforestation (15.2.1) and on losses of water-related ecosystems (6.6.1, UN DESA, 2022).

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 may be overlooked due to gaps in the Landsat archive. To tackle this issue, a recently developed global product (GLAD, Potapov et al., 2022) maps arable-land in four-year epochs, exploiting all images in an entire epoch to more accurately characterise crop phenology. Although this precludes shorter-term change assessments, it is a necessary compromise. Yet, this approach is not immune to year-to-year improvements in high-quality image 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 examined the GLAD for indications of change biases. To this end, we compared national aggregates of the GLAD against corresponding FAO statistics on arable-lands. We adjusted the latter following expert recommendations to conceptually match these data with the GLAD (Tubiello et al., 2023). We identified 123 suspicious-looking countries where mapped gains contrasted with reported losses (**Fig. S6**). This relates to arable-land expansions in >800 million 30-m pixels, more than the combined number of arable-land pixels of all Amazonian countries in 2021 (FAO, 2023, **Fig. S5c**).

Disagreements 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 GLAD is corrected for these issues.

Naturally, cases of GLAD-FAO disagreements alone do not provide evidence of biases in GLAD-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 GLAD's underlying observation process, we again used CCM (*see **Methods***). Focusing on countries with positive disagreements (i.e., where GLAD mapped gains instead of losses), our analysis confirmed that, for 48.4% of countries in this category, changes in quality-weighted image frequencies not only contribute to causing perceived arable-lands changes, but can also predict the temporal patterns of the latter (**Fig. 3d**). These include top food-producing countries that together accounted for 38.4% 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 food-insecure countries (e.g., Yemen, Zimbabwe), where misinterpreting losses of arable lands as gains could misinform policy-makers on emerging crises.

Overestimated arable-land gains can also lead to unfair evaluations of progress towards SDG target 2.4 (sustainable food production) by exaggerating conflicts of food security with ecosystem protection and climate-change mitigation. For example, two recent studies using GLAD 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, may render these assessments unreliable. This is illustrated in India, where sudden changes in Landsat data apparently led the GLAD to misinterpret wetland pixels as arable-lands, leading to the false mapping of agricultural conversion over an entire Ramsar wetland of >3,000 ha (**Fig. S5d**).

Case study 3: Improving seasonal data completeness exaggerates water gains. 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 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 river plains 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 the monthly occurrences. The authors of the GSW accounted for temporal inconsistencies in the Landsat archive by only classifying pixels 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 images 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 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 seasonal data completeness (r^2=0.80; **Fig. 3e**) and are often unsupported by local discharge measurements (90.7% of gauge stations with significant long-term changes showed disagreements, **Fig. S7**; see ***Methods***). Using CCM, we found that changes in seasonal data completeness contributed to causing perceived changes in seasonal surface water in 144 countries, with moderate to high predictive power (**Fig. 3f**). These countries include several with severe water stress (e.g., Yemen, Sudan, World Bank, 2023), where mapping false seasonal-water gains and losses could potentially result in drastic mischaracterizations of water-related sustainability issues.

In all the 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 limitations. However, our results show that year-to-year variations in data coverage and/or quality 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 quality. 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 and quality (Dech et al., 2021; Justice et al., 2002; Sudmanns et al., 2020).

3.3. Biases disproportionately affect lower-income countries

Monitoring data that are consistent (and thus comparable) in space and time are essential to support international SDG-related policymaking that is both equitable across boundaries (Xu et al., 2020) and fair in acknowledging the historical development of national issues (Coolsaet and Pitseys, 2015). Yet, our results call into question whether contemporary Landsat-based monitoring can really provide fair support, as biassing effects of data limitations are highly uneven across countries. Notably, countries with limited financial capacities to produce independent, higher-quality monitoring data that might counter perceptions based on global satellites are more strongly affected by biases in the latter. Specifically, we found that biassing effects on perceived arable-land and seasonal-water trends were significantly more frequent in lower-income than in higher-income countries (McNemar's tests, arable-land: 51.9% of lower-income vs. 46.1% of higher-income, $p<0.05$; water: 89.7% vs. 73.1%, $p<0.05$; note there was a near-significant difference in deforestation bias in the opposite direction among the respective income groupings of tropical-moist-forest countries; 51.9% vs. 46.1%, $p=0.07$; *details in **Methods***).

The geographical biases in land-change perceptions may contribute to distorted or unbalanced narratives about sustainability challenges between lower- and higher-income countries. 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.

3.4. Future needs: bias corrections, fair product validations, and support to users

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 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 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 quality and coverage. This is problematic because limitations in satellite images 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 (Olofsson et al., 2014).

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). 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 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 select 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. Such tools can simultaneously 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-quality metrics (e.g., measuring the quality of images 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-quality metrics analysed here 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., land-surface mapping 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. Often, 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-quality 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 driven by data-quality limitations are tolerable, given the studies' specific goals and conclusions. Users interested in Landsat-based products may integrate our quality metrics in such analyses. However, we caution that we designed our layers (*see* ***Data availability***) to measure broad-scale variations in data availability and quality. Those differences are captured effectively by focusing on the issues recorded during the sensing process. These reflect both constrained visibility (directly by clouds, and indirectly by cloud shadows and haze), technical sensing issues (related to atmospheric corrections, orthorectification, and sensor degradation), and data losses. Users interested in finer-scale inferences should instead compute our quality metrics using the available pixel-level metadata, and also incorporate the modelled, pixel-level information on clouds, cloud shadows, and atmospheric opacity that accompanies each Landsat acquisition. We caution, however, that the algorithms used to model the latter may not be universally reliable (Foga et al., 2017; Skakun et al., 2022).

4. CONCLUSIONS

While Landsat satellite data are vital for sustainability monitoring, their uneven coverage and quality extends into derived monitoring products. This can bias perceptions of changes in ecosystems, food, and water resources, particularly impacting less developed nations. Recognition of these limitations and efforts to address them are needed by both data developers, data users, and developers of support tools. Data developers are best positioned to attenuate the imprint of input data limitations on their products, and to improve transparency on remaining uncertainties. In turn, 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 is an essential step in assuring robust change assessments in order to promote responsible policy decisions.

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