The survivorship bias in remote sensing

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Abstract

Survivorship bias refers to the fact that conclusions are drawn from a non-representative sample limited to cases that have survived a selection process. This article shows that this bias affects scientific literature, which tends to select successful experiments and hide failures. Remote sensing, like other data-driven sciences, is affected by survivorship bias, making it difficult to have a clear idea of the data's and methods' actual potential and limitations. A typology of failure causes is proposed to encourage critical reading of the bibliography, and perspectives are outlined to overcome survivorship bias by improving practices within the academic and industrial remote sensing communities.

1. Introduction

Survivorship bias in remote sensing arises when analyses rely only on data that "survive" various selection, acquisition, or processing stages, such as clear-sky, noise-free, or high-quality imagery, while excluding incomplete, degraded, or missing observations. This selective reliance on idealized data acquisition and processing conditions distorts perceptions of environmental and geospatial phenomena, often exaggerating model performance (Carpenter and Lynch, 1999), obscuring uncertainty, and overrepresenting regions with favourable conditions. In Earth observation, studies frequently prioritize the most reliable or visually appealing satellite scenes, inadvertently neglecting areas where data quality is compromised, such as cloud-prone or data-scarce regions. Although these omissions are merely technical, their consequences are far-reaching: they skew environmental assessments, misrepresent trends in global change, and reinforce geographic and socio-technical inequities by favouring researchers who have the means to access advanced computing capabilities, pay for high quality data and fund more expensive field expeditions. Addressing survivorship bias is therefore essential to ensure that the conclusions drawn from remote sensing are actually based on the real potential and limitations of the data and algorithms, and accurately reflect the Earth's complexity rather than an idealized subset of it. This phenomenon mirrors a broader challenge in scientific research, namely, the culture of *positive publication bias*. Indeed, the famous injunction "*publish or perish*" pressures researchers to continually disseminate results, yet journals often favor studies reporting clear, successful outcomes, while negative or inconclusive findings are more likely to be rejected, so that they are systematically underrepresented (Fanelli, 2013; Fanelli et al., 2017). In other words, failures remain largely hidden. As a result, published successes may not always be reproducible, arising instead from chance, selective conditions, or the persistent efforts of researchers with much greater expertise than standard users. Just as positive publication bias shapes the scientific literature, survivorship bias in remote sensing filters which observations are considered "worthy," producing an incomplete picture of reality.

This paper provides a critical discussion of survivorship bias in remote sensing and data-driven sciences, moving beyond purely technical considerations to explore its ethical and epistemological implications. It highlights how selective visibility, whether in datasets, algorithmic outputs, or published research, can misrepresent the true performance of remote sensing methods and Geospatial Artificial Intelligence (GeoAI) models. By linking the roots of positive publication bias to the operational realities of Earth observation, this study establishes a framework for benchmarking, recognizing, classifying and mitigating survivorship bias. Specifically, it shows how survivorship bias behaves in the context of remote sensing, explores its consequences for methodological evaluation and environmental interpretation, and proposes pathways toward greater transparency, reproducibility and inclusivity. Ultimately, the paper advocates for a more responsible behaviour in the scientific ecosystem, one that values lessons from failures as much as from successes, and it lays the foundation for more equitable and trustworthy geospatial intelligence, ensuring that research reflects the full diversity and complexity of the Earth system and its interaction with society.

2. The positive publication bias in science

The well-known academic maxim *"publish or perish"* underscores the constant pressure on researchers to produce and disseminate scientific results. However, the publishing ecosystem often favors positive outcomes from successful studies, while studies reporting inconclusive or negative results are frequently overlooked. As Fanelli (2013) noted, despite broad recognition of this "positive publication bias", many researchers still practice self-censorship, choosing not to disclose unsuccessful experiments that could be interpreted as poor quality work. Consequently, published scientific literature often represents a partial reality based on a non-representative sample of scientific results, emphasizing methods that appear effective while ignoring those that failed. These omissions contribute to a distorted understanding of scientific progress and an overestimation of methodological reliability. Moreover, the consequences of this reliability imbalance extend beyond academic visibility. As Mlinarić et al. (2017) highlighted,

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publishing failures is not merely an act of transparency but a vital component of scientific advancement. Reporting failures prevents the unnecessary repetition of mistakes, saves time and resources, and provides a more nuanced understanding of methodological strengths and limitations. Moreover, some scientific breakthroughs emerged from unexpected or failed results. As an example, the Michelson-Morley experiment, originally intended to detect the ether wind, produced null results that later inspired Einstein’s theory of special relativity. Similarly, in the 17th century, as Jean Richer was measuring the parallax of Mars from Cayenne, he noticed by coincidence that the pendulum was swinging more slowly at the equator, and the publication of this unexpected difficulty helped Newton validate his theory of universal gravitation and demonstrate the Earth’s equatorial bulge. These historical cases illustrate how failures can act as catalysts for paradigm shifts when openly examined, contextualized and shared with the scientific community. Furthermore, publishing only successes creates a misleading narrative that inflates scientific confidence and conceals inherent uncertainties.

This phenomenon reflects the broader concept of survivorship bias, the tendency to draw conclusions from a non-representative subset of “survivors” who remain visible after a selective process. For instance, classic analogies assume that ancient buildings were more durable than modern ones simply because the surviving structures are still standing, overlooking the fact that countless others from the same era have long since perished, while a number of more recent ones could very well survive for a very long time. Similarly, in data-driven disciplines, survivorship bias manifests when researchers focus exclusively on clean, complete, or well-performing datasets while disregarding those marred by error, noise, or incompleteness. For instance, in a recent study that employed a Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM)-Markov hybrid model using large-scale satellite imagery for land-use classification (McRoberts et al., 2018) and future projections, the model failed to accurately capture real-world urban growth patterns. Despite the sophisticated design, the predicted results deviated from the observed trend of increasing urbanization, resulting in a clear mismatch between simulation and observation. Consequently, the researcher hesitated to publish the findings, fearing that a paper highlighting the model’s shortcomings might not be accepted. However, publicizing failures is important to such an extent that initiatives are emerging to raise awareness of them and even promote them (Mlinaric et al., 2017). Indeed, such cases are valuable to the scientific community, as they provide critical lessons about the limitations and opportunities of observation and modelling, and offer avenues for methodological improvement.

Remote sensing is also subject to the survivorship bias due to potential failures that are little known because they are rarely mentioned in literature. Thus, building on this understanding, it becomes clear that survivorship bias should be addressed in remote sensing as well, not simply about improving technical accuracy, but also about reshaping the scientific culture surrounding Earth observation. As this discipline becomes increasingly intertwined with GeoAI, machine learning, and automated data processing, the risks of amplifying hidden biases grow even greater. For example, recognizing and reporting methodological limitations, sensor-related errors, and model misclassifications should therefore be treated as essential components of scientific integrity rather than as shortcomings.

3. The case of remote sensing

3.1 A scientific field prone to survivor bias

While explicit discussions of survivorship bias are uncommon in the remote sensing literature, many studies can stimulate conceptual discussion by providing clear illustrations of this phenomenon, such as missing data, coverage bias, and limited transparency in data handling (Shen et al., 2015; Yousefi et al., 2024). For instance, McRoberts et al. (2018) investigated the influence of imperfect reference data on remote-sensing-based estimators of land-cover-class proportions. The bias occurs when analyses rely solely on “surviving” experiments, e.g., based on cloud-free, high-quality and temporally consistent data, while excluding data affected by sensor malfunctions or atmospheric interference. Such omissions may seem trivial, but they can profoundly distort spatial analyses, trend detection and environmental monitoring outcomes. For instance, using only clear-sky optical data inherently neglects tropical regions that are frequently cloud-covered, where it is easy to abandon an initially planned experiment due to a lack of acceptable quality data, leading to the underrepresentation of entire ecosystems and a reduced understanding of their functioning. In another study, an illustrative example of survivorship bias in remote sensing-driven analysis can be found in the “spatiotemporal assessment and projection of social vulnerability of cities in Iran” (Shirmohammadi et al., 2025). While the research effectively integrates 36 socioeconomic indicators and environmental risk factors using deep learning models such as LSTM, it highlights a broader challenge: the uneven availability and quality of spatial and socioeconomic data across regions. For example, many local data sets are incomplete, inconsistent or outdated, leading to reliance on standardized or interpolated data that may not capture on-the-ground realities. This selective use of accessible, high-quality data risks reinforcing survivorship bias, in which models appear robust during validation but overlook uncertainty in data-scarce areas. As a result, projections of vulnerability might overrepresent well-documented regions while underestimating risks in areas with limited data coverage or weaker reporting infrastructures. Similarly, when GeoAI or machine learning models are trained exclusively on high-quality imagery, they internalize a biased view of the Earth, one that reflects the best rather than the full picture. This overrepresentation of ideal data conditions creates an illusion of accuracy, overstating data adequacy and algorithmic robustness. The implications extend further into scientific reporting. Indeed, as in other research domains, studies that yield clear, quantifiable success in remote sensing, such as precise classifications or high validation metrics, are far more likely to be published than those reporting challenges or uncertainties. This selective reporting amplifies survivorship bias within the literature itself, shaping collective perceptions of methodological effectiveness and progress. Even the peer review principle does not prevent bias, as it seems that reviewers do not encourage authors to report failures, even though these are situations they are familiar with in practice. In any case, it is also well known that authors themselves do their utmost to present successful results and refrain from reporting their failures. It is therefore a shared responsibility. Consequently, the whole academic and industrial community risks becoming overconfident in its tools and datasets by underestimating the systemic limitations embedded in the data-acquisition and processing pipeline.

Furthermore, when defining and categorizing bias in remote sensing and GeoAI research, it is important to recognize that survivorship bias contains several interconnected aspects that define different forms of bias that shape how the results are ultimately reported in scientific publications. Beyond data and method choices (Chang et al., 2022; Fan et al., 2025; Okirya et al., 2025), publication practices themselves favor positive or successful outcomes over negative or inconclusive results. Understanding these interconnections is crucial for developing robust, transparent, and reproducible research workflows. To provide a structured perspective, we propose the following typology (Table 1), which categorizes the main manifestations of the survivorship bias and their potential impact on the research lifecycle, highlighting where survivorship bias emerges from different biases. These biases can be found in all data driven sciences, and typical examples in remote sensing are given here.

Bias type	Description	Example in remote sensing
Publication bias	Preference for positive results over negative or inconclusive outcomes.	Studies showing model success in flood detection or social vulnerability mapping are published, while failed detection studies are not.
Selection bias	Studies designed under ideal conditions, not reflective of real-world constraints.	Model training is based only on accessible urban areas with rich ground truth data.
Reproducibility bias	Overfitting and lack of replication or transparency in methods and datasets.	Algorithms cannot be independently validated due to proprietary data.
Operational bias	Logistical, environmental or computational constraints.	Unmanned Aerial Vehicle (UAV) missions are constrained by weather or regulations, resulting in incomplete mapping.
Human bias	Research carried out by highly qualified researchers.	Highly skilled users choose the best data and program their own data processing tools to increase the chances of success.
Financial bias	Research benefiting from significant funding.	Resources provide access to powerful instruments and computing resources, and fund more productive fieldwork.

Table 1. Proposed typology: main manifestations of survivorship bias in remote sensing research

To examine the causes of these biases in greater detail, a clear typology of failures is essential to guide responsible reporting and interpretation. Therefore, the next section presents examples of success and failure in remote sensing research.

3.2 Failures and successes in remote sensing

Remote sensing failures are due to a complex set of limitations that occur at different stages of the process. They may be related to unsuitable sensor (e.g., noise, distortion or unsuitable spectral range and resolution), unsuitable acquisition date (constrained by orbit or weather, and preventing the synchronization of data acquisition with the phenomenon being observed or with verification work in the field), variation of acquisition conditions in time series (e.g., viewing angle, sun elevation and weather), disturbing phenomena (e.g., atmosphere or vegetation-induced decorrelation in differential Interferometric Synthetic Aperture Radar (InSAR)) (Zebker and Villasenor, 1992), an inappropriate method of data processing or result validation (e.g., ignoring missing data or cloud-covered areas, overfitting in machine learning models, selective ground truthing, temporal bias in time-series analysis, ignoring uncertainty in algorithm outputs or selective performance metrics), among other causes.

Far from leading to isolated failures, some of these limitations or biased experimental conditions have affected entire user communities for a long time. For example, the success of differential radar interferometry following the launch of ERS-1 in the 1990s prompted geoscience researchers to abandon traditional topographic techniques for measuring Earth's crustal deformation in radar imagery to meet the demand for geological risk management for users in the field of civil security. However, the need for a pair of images with very close orbits limited feasibility demonstrations to highly improbable conditions (Raucoules et al., 2007). In this context, the publication of exceptionally accurate results created the illusion for some time that an ideal technique for ground monitoring had been found. In reality, it took another 20 years and the development of the permanent scatterer method to enable the development of operational solutions such as the European Ground Motion Service (EGMS). With regard to mapping the Earth's topography, it was only in the 2000s that the Shuttle Radar Topography Mission (SRTM) finally provided a global Digital Elevation Model (DEM) that had long been lacking in all regions without detailed mapping. In tropical forest regions, however, SRTM is a canopy surface model, but it is often used as if it were a terrain model, leading to significant errors in hydrological applications, as analyzed by Caldeira et al. (2024). In the optical domain, the atmosphere has always been a major obstacle. While atmospheric corrections improved radiometric quality in cloud-free regions, cloud cover was treated with a tolerance threshold in command or download platforms, and the ‘clouds’ or ‘shadows’ classes were accepted in land use land cover classification results, provided they affected only a small portion of the territory. When cloud removal algorithms were finally proposed to create cloud-free image syntheses from time series such as those from Sentinel-2 (Meraner et al., 2020; Singh et al., 2025), another source of failure emerged, as these methods require the assumption that the terrain has not changed between the different acquisition dates, which is quite unlikely, for example, in the highly dynamic landscapes of tropical regions.

A comprehensive typology of failure and success in remote sensing research is depicted in Table 2.

Category	Failure factors	Success factors
Sensor limitation	Low resolution, limited spectral coverage, cloud obstruction, incomplete temporal data	Well-calibrated multi-sensor fusion Pansharpening
Orbital constraint	Revisit period too long or acquisition date inappropriate	Selection of high temporal resolution systems
Data acquisition	Cloudy scene, insufficient data quality, variable conditions within time series	Robust atmospheric correction, rigorous data selection, BRDF-based modeling

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Field work constraints	Access difficulties, insufficient sampling, inappropriate location and date of data collection	Time and financial resources Local partnership for field data collection
Methodology and algorithms	Overfitting, unrealistic assumptions, neglecting uncertainty quantification.	Transparent modeling, cross-validation, explainable AI integration.
Operational challenges	Lack of ground truth, unrealistic study areas, limited computing power.	Real-world testing and access to validation datasets.

Table 2. Typology of failure and success in remote sensing research.

It is also worth mentioning that the common practice of research implementing remote sensing methods leads to an artificial increase in the chances of success, since the work is often organized in the form of pilot projects, carried out by highly qualified researchers in areas they are already familiar with and where they have previously carried out work, enabling them to know in advance the conditions for success, in short in much more favorable conditions than in real life, which questions their reproducibility.

3.3 Impact

The fact that literature is skewed by survivorship bias has unfortunate consequences for the remote sensing profession, both for the advance of science and for its operational applications. In academic settings, students and early-career researchers often rely on studies that highlight only successful applications of sensors, algorithms and geospatial datasets, as well as on consensual literature reviews, organizational reports or widely used software tools. This selective exposure can foster over-optimistic perceptions of remote sensing capabilities, masking the limitations and challenges that often arise in real-world applications. When failures, uncertainties, or low-quality results are underreported, learners may internalize a skewed understanding of the field, overestimating model performance or the reliability of data sources. They may also interpret their own failures as consequences of extreme bad luck or incompetence, which can undermine their professional ambition. This situation is exacerbated by the fact that doctoral theses are often structured as collections of articles accepted for publication, depriving doctoral students of the freedom to report their failures, study their causes, and discuss the reproducibility of their successes in their final thesis. Such trends illustrate how survivorship bias permeates not only research outcomes but also knowledge transfer, shaping expectations and decision-making in geospatial science and GeoAI. The above-mentioned phenomenon is closely tied to the issue of positive publication bias in remote sensing, as already observed in other scientific fields like hydrology (Yaswanth et al., 2023; Okirya et al., 2025), medicine (Vrudhula et al., 2024), among others.

In terms of transfer from research to commercial or operational applications, attempts to apply a new method to normal situations may fail for the same reason, in contrast to the successes reported in misleading literature. Indeed, a result obtained in a pilot project in a perfectly known area, achieved through the stubborn efforts of an overqualified researcher working 80 hours a week owing to the absolute need to publish something, cannot be easily reproduced by professionals seeking a method that can be applied anywhere in a normal professional context, i.e. by technicians working standard business hours. This difficulty can discourage the implementation of remote sensing methods. Moreover, it partly explains a well-known phenomenon in the field of innovation. Indeed, on a Technology Readiness Level (TRL) scale of 1 to 9, the lowest levels (concept definition and feasibility demonstration, which fall within the competence of academic research) do not easily progress to the higher levels expected by industry for investing in reliable and reproducible technology. This difficulty, known as the "valley of death", can be explained in part by survivorship bias, since reproducing successful published results in real-life situations may have limited success and lead to the abandonment of an idea that would only require adjustments and critical examination of possible causes of failure.

A similar impact, but with much greater financial consequences, can be seen in the case of the very costly design of space-based Earth observation systems. The instrumental and orbital characteristics of a future space mission are inspired, in variable proportions, by the capabilities of industry and the expectations of users, the former being much more clearly expressed than the latter because the user community is a poorly defined group that is not organized to be able to express a consensus requirement. In both cases, however, any innovation risks being neutralized by the supposed knowledge of what previous systems have achieved, as reported in the scientific literature. Space agencies, therefore, rely on biased information to justify the enormous investments required for the continued development of space-based Earth observation systems.

4. Perspectives to overcome the survivorship bias

Initiatives are emerging to make failures known and even promote them as relevant information and a source of insight (Shen et al., 2015; Fan et al., 2025, Mlinarić et al., 2017). Addressing publication bias in remote sensing requires a multi-level approach, ranging from actionable steps within professional societies like ISPRS to broader cultural shifts across the scientific community. To do so, the authors suggest as a foundational step establishing a clear identification and definition of the various types of bias embedded in the more general survivorship bias. These different types of bias, already listed in Table 1, can be commented as follows.

- Regarding the **publication bias**, that consists in the preferential publication of positive or successful results over negative or inconclusive ones, one must insist on submitting articles to publishers that do not hide failures, promote journals that accept such contributions, and encourage the writing of doctoral theses in the traditional form (where the author is free not to hide the difficulties faced along the way) rather than as a collection of articles.
- **Selection bias** arises when research conducted under idealized or non-representative conditions, rather than reflecting real-world variability: a method validated over a region that is too small and too well known should be extended to a larger region, which is easier to do nowadays thanks to the available data and computing capabilities.
- To avoid the **reproducibility bias** and make results easier to replicate, it is preferrable to choose data sources that can be found anywhere in the world, and processing tools that can be accessed free of charge or obtained easily.
- **Operational bias** can be reduced if published works clearly indicate, where applicable, that they required significant computational, human and financial resources, and, where possible, suggest ways to apply the same approach in less favorable conditions.
- To reduce **human bias**, the level of contribution of the human operator must be specified, and in particular, the requirements in terms of workload and technical skills required.

- **Financial bias** occurs when the cost of an experience that one wishes to replicate is underestimated. Although it is not particularly relevant to cite costs that may vary over time and between countries, it is necessary to mention whether the success of an experiment was made possible by significant financial support.

To avoid these multiple biases, a transparent publication of research results is necessary, in which the missing conditions are identified, i.e., the discrepancy between ideal conditions (an experiment conducted over a very well-known and accessible area by highly qualified and available researchers with significant financial resources) and real conditions. To do so, it is necessary to identify the causes for which these discrepancies happen. It is in this spirit that a standardized typology of failure causes has been suggested above (Table 2), which can serve as a basis for a more comprehensive analysis aimed at raising awareness among the remote sensing community. Indeed, a structured classification of failure types can help to clarify a complex situation where several types of limitations arise and interact.

In many projects involving remote sensing methods, the choice and quality of data are limited by constraints related to sensors and their orbits, observation dates and conditions are not always favorable, and the operational environment may limit fieldwork and data processing, all of which is further constrained by the technical skills of operators and insufficient financial resources. The accumulation of these causes of failure easily leads to unsatisfactory results that cannot be published.

In this context, the authors encourage a culture of negative or inconclusive results in remote sensing research, promoting transparency around unsuccessful experiments. To do so, the practical strategies include creating dedicated journal sections or conference tracks focused on “Lessons Learned” from failures, and highlighting studies that document challenges, uncertainties or non-reproducible outcomes as valuable contributions to the field. Furthermore, though some journals may not accept case studies, we urge leveraging case studies and expert insight as key players. For example, real-world examples where initially successful studies later proved non-reproducible can provide actionable lessons. The authors experienced that expert interviews and surveys can further illuminate common sources of bias, informing both methodological and reporting improvements. However, we can go beyond a qualitative consensus and artificial intelligence and bibliometric tools to uncover hidden patterns of survivorship bias in publications. This includes (a) systematic reviewing of remote sensing literature to quantify the prevalence of selective reporting; (b) topic modeling or sentiment analysis to identify trends favoring positive results; and (c) formation of working groups to gather examples of failure and non-reproducible successes through structured surveys. Finally, the authors suggest developing guidelines for unbiased publication to establish clear, enforceable guidelines for fair publication practices, endorsed by ISPRS and other scientific bodies that can help normalize transparency, improve reproducibility and set realistic expectations for remote sensing research.

By combining practical level actions with broader community-oriented initiatives, these measures can improve research behavior and transform the scientific ecosystem. This approach not only mitigates survivorship bias but also fosters more accurate, reliable and equitable geospatial science. Table 3 summarizes perspectives for addressing survivorship bias in the remote sensing literature, ranging from proactive practical ISPRS-level actions to broader scientific community initiatives.

Level	Action / Initiative	Description / Examples
Practical (ISPRS-level)	Define and categorize bias	Clarify types: publication, selection and reproducibility bias.
	Develop a typology of failures.	Classify methodological (overfitting, wrong assumptions), operational (sensor calibration, data mismatch), and application-level failures (replicability across regions/times).
	Promote a “negative results” culture.	Propose dedicated journal sections or conference tracks for lessons learned from failures.
Intermediate (Community-level)	Promote case studies and expert insights	Document non-reproducible studies, interviews and surveys to identify common sources of bias.
	Analyse literature by AI-driven methods	Use topic modeling, sentiment analysis, and bibliometric approaches to detect patterns of survivorship bias.
Ambitious (Scientific ecosystem-level)	Develop guidelines for unbiased publication	Establish transparent, ethical and reproducible reporting practices endorsed by ISPRS and scientific bodies.

Table 3. Summary of the perspectives for addressing publication and survivorship bias.

This concern must be addressed by recognized organizations such as the International Society for Photogrammetry and Remote Sensing (ISPRS). At the practical level, such organizations can lead efforts in a coordinated, multi-level strategy to define and categorize different forms of bias, develop standardized typologies of methodological, operational and application-level failures, and promote a research culture that values “negative results.” At the community level, collective learning can be advanced through case studies, expert surveys, and AI-driven literature analyses that reveal hidden patterns of bias across studies (Iyer et al., 2025). Finally, at the scientific ecosystem level, it is essential to develop and adopt global guidelines that encourage transparent, ethical and reproducible reporting practices, supported by major scientific societies and journals.

5. Conclusion

This study emphasizes that survivorship bias in remote sensing is a pervasive challenge, arising from selective reliance on high-quality, complete or easily accessible data while neglecting observations compromised by clouds, noise, temporal gaps, or processed under unfavourable conditions. Such selective visibility not only inflates perceived model accuracy but also obscures uncertainties and limits the reproducibility of scientific findings. Combined with positive publication bias in the broader scientific community, these tendencies distort both the methodological understanding and the operational applicability of remote sensing methods. The limitations highlighted in this paper and illustrated through a few examples include the difficulty of capturing truly representative datasets, the frequent underreporting of failed experiments and the tendency for research to be conducted under idealized conditions that are not easily transferable to real-world conditions. These constraints underscore the need for more transparent and inclusive reporting practices, especially in the context of GeoAI and remote sensing workflows. Looking ahead, overcoming survivorship bias in remote sensing will require multi-level strategies. At the professional society level, clear definitions of bias, standardized typologies of failures and dedicated venues for publishing negative results can establish foundational best practices. At the community level, leveraging case studies, expert surveys and AI-driven literature analysis can uncover patterns of non-reproducibility and identify common sources of methodological bias. At the broader scientific ecosystem level, developing guidelines for transparent, reproducible and ethical reporting, endorsed by organizations such as ISPRS, can promote cultural change across the field. Collectively, these initiatives aim to normalize reporting of challenges, ensure more realistic expectations for models and methods, and foster a more equitable, trustworthy, and scientifically rigorous approach to Earth observation and GeoAI research.

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