A community data commons for equitable Earth Science

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Key Points:

- Community-curated, analysis-ready data commons remove the last mile of Earth observation data preparation for resource-limited users
- A volunteer-built catalog now serves 4,400 datasets and millions of monthly requests spanning 228 countries and territories
- Durable governance, shared stewardship with Indigenous and local communities, and diversified support can secure these commons

Abstract

Earth observation has entered an era of extraordinary data abundance, yet the analysis-ready, well-documented, reproducible datasets that climate, water, agriculture, and disaster research actually require remain scarce. Every research group that repeats the same preprocessing pays a last-mile cost that falls hardest on the institutions and communities least able to afford it. Here we describe how a grassroots response to this gap, the Google Earth Engine (GEE) Community Catalog, has grown over six years of unfunded, volunteer operation into critical scientific infrastructure: 4,400 curated, cloud-ingested datasets totaling 585 TB across 16 thematic domains, serving nearly 4 million monthly data requests, with cumulative reach spanning 228 countries and territories and demand led by Brazil, the United States, and India. Drawing on this experience, we examine what a peer-produced data commons reveals about equity in global science, including the hosting of Indigenous territory data and datasets built by and for local communities, and about the sustainability paradox facing community infrastructure that the scientific enterprise depends upon but does not fund. We distill five transferable lessons for building community data commons: treat curation as scientific labor, design for findability first, build loops rather than pipelines, meet communities where they are and share stewardship, and plan succession from the start. As Earth observation confronts both accelerating environmental change and accelerating data growth, community data commons are not a convenience; they are essential infrastructure for equitable and anticipatory science.

Plain Language Summary

Satellites and sensors now produce more information about our planet than ever before, but most of it is not ready to use. Before scientists can study floods, droughts, or cities, they must spend weeks preprocessing data, and every group repeats this work separately. Researchers with limited funding, connectivity, and computational power are hit hardest. We describe a community data commons in the form of a free, volunteer-run catalog where people help curate datasets, document and make them available for everyone without any barriers. Over six years this catalog has grown to more than four thousand datasets and now serves millions of requests every month from nearly every country on Earth. The catalog hosts datasets from a wide range that affect governance and narratives around Indigenous territories and health facilities and those that are created by local communities. We draw five lessons from this experience for anyone building shared scientific resources, and we argue that science funders, agencies, and universities should support this kind of community infrastructure, because accessibility begins with findability and we are arguing for usability as part of the paradigm. It is truly one of the fastest ways to make Earth science both equitable, fair and accessible.

1. Introduction: The Usability Gap and the Last Mile of Earth Observation

Earth observation has never produced more data, and using that data has rarely felt harder. Petabyte-scale archives from public agencies and commercial constellations are distributed across incompatible portals, divergent metadata conventions, and platform-specific access layers, so that the decisive constraint on most analyses is no longer acquisition but preparation (Gomes et al., 2020; Sudmanns et al., 2020; Crowley et al., 2023). The opening of the Landsat archive demonstrated how removing barriers to access multiplies scientific and economic value (Zhu et al., 2019), and cloud platforms co-locating data with computation have removed the download bottleneck for many workflows (Gorelick et al., 2017; Abernathey et al., 2021; Tamiminia et al., 2020; Saah et al., 2023). Yet a critical gap persists between data that are technically open and data that are actually usable: analysis-ready (Dwyer et al., 2018), well documented, consistently preprocessed, and citable.

Every research group that independently repeats reprojection, cloud masking, mosaicking, and format conversion pays what we call the last mile of Earth observation, by analogy to the last mile of climate services that separates skillful forecasts from usable decision support (Baylis et al., 2025). The cost of this last mile is not evenly distributed. It falls hardest on students, on under-resourced institutions, on public agencies with constrained information-technology environments, and on researchers in regions where bandwidth and computing budgets are limiting, i.e., on precisely the people and places where Earth observation could matter most.

Field evidence further confirms that institutional participation is hindered not by a lack of interest, but by the structural realities of unreliable connectivity, sparse training, and resource constraints (Naji et al., 2026). The central challenge of data-intensive Earth science has therefore shifted from a crisis of access to a crisis of accessibility: the accumulated technical, temporal and knowledge cost of turning available data into usable information. That friction slows science and narrows participation.

The scientific costs also compound the equity costs. Silent methodological divergence among independently preprocessed versions of the same source data undermines comparability across studies, and the rapid adoption of machine learning has amplified the stakes: leakage, uncontrolled preprocessing choices, and irreproducible pipelines are now documented drivers of unreliable findings across computational science (Kapoor & Narayanan, 2023), while reproducibility and replicability remain persistent challenges for geospatial research specifically (Kedron et al., 2021; Peng, 2011; Baker, 2016).

Community standards for the geoscience paper of the future have long called for archived, citable data and workflows (Gil et al., 2016), and publishers and societies, including the American Geophysical Union (AGU), have moved to make FAIR data a norm of scholarly practice (Wilkinson et al., 2016; Stall et al., 2019). But findability, the first letter of FAIR, is where Earth observation loses the most value in practice: the greatest waste occurs before any analysis begins, when a researcher never discovers that the dataset they need already exists in usable form. Climate services research reached a parallel conclusion years ago, that better decisions require more than better data (Findlater et al., 2021). Hence, the central infrastructural dilemma posed in this commentary is straightforward: who assumes the responsibility of making

Earth observation data universally findable and usable, and through what mechanisms can such efforts be sustained?

2. A Community-Driven Response

Since 2020, a practical solution to this challenge has been steadily taking shape. The Google Earth Engine (GEE; Gorelick et al., 2017) Community Catalog (Roy et al., 2026) began as a single maintainer's curated list and has become, in six years of continuous, unfunded, volunteer operation, one of the most heavily used community data infrastructures in the geospatial sciences (Figure 1). Its model is peer production in the classic open-source sense (Benkler, 2006; Raymond, 2001): community members request or contribute datasets; maintainers and contributors develop open preprocessing scripts that transform source data into cloud-optimized, documented, analysis-ready assets; every asset carries license, citation, and provenance metadata.

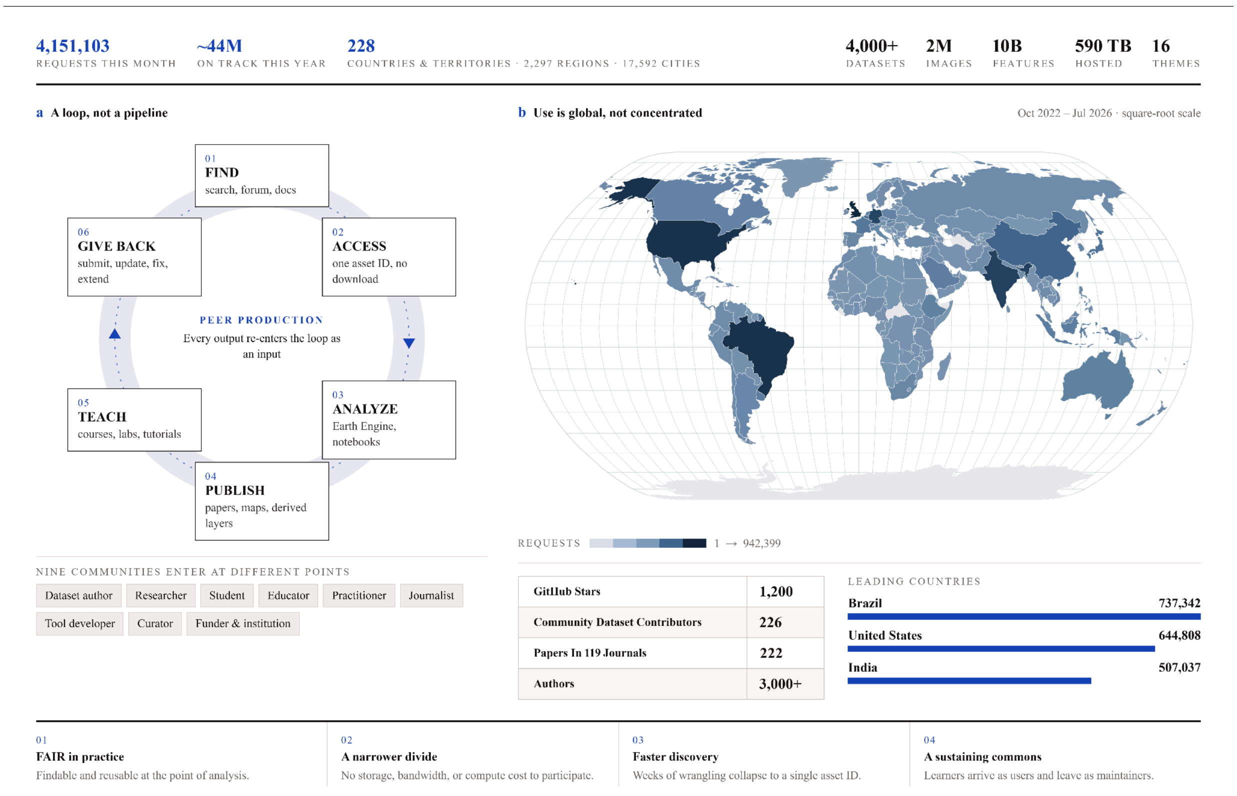

Figure 1. A community-curated data commons (Ostrom, 2015) and its global reach. **a.** Six activities form a closed loop; outputs of one journey re-enter as inputs to the next, which is what sustains an unfunded catalog. Nine communities of practice enter at different points. **b.** Requests

to the catalog documentation by country, October 2022 – July 2026, on a five-class square-root scale; grey indicates no requests. All requests are counted, measuring documentation reach rather than unique users. The headline monthly figure, catalog holdings, and statistics as of July 2026.

Operating as a closed loop rather than a linear pipeline (Figure 1a), the catalog engages nine distinct communities: dataset authors, researchers, students, educators, practitioners, journalists, software developers, curators, and funding agencies. Participants enter at various stages, and each output cycles back into the system as an input. Consequently, the individuals who initially require a dataset take on the responsibility of preparing it, thereby benefiting all subsequent users.

As of August 2026, the catalog hosts 4,400 curated, cloud-ingested assets totaling approximately 585 TB, spanning 789 image collections (~2 million individual images) and 3,139 feature collections (~10 billion individual features), organized across 16 thematic domains from hydrology (Ma et al., 2026) and agriculture (Kerner et al., 2024) to population (WorldPop, 2026), hazards (Svoboda et al., 2002), biodiversity (Hudson et al., 2017), and others. Its holdings are precisely the frequently requested, preprocessed research datasets that authoritative archives leave unserved: harmonized bathymetry for 1.4 million lakes (Khazaei et al., 2022), high-resolution global population distributions (WorldPop, 2026), weekly United States Drought Monitor updates ingested on operational cadence (Svoboda et al., 2002), community-mapped health facilities (Humanitarian Data Exchange, 2026), and the MapBiomas land-use collections produced by a Brazilian multi-institution collaborative network (Souza et al., 2020).

Institutional providers consisting of 33 organizations across seven countries and four multilateral bodies (Supplementary Table 1), including the United States Geological Survey, the United States Forest Service, Natural Resources Canada, the Swiss Federal Office of Topography, and the Food and Agriculture Organization of the United Nations, now use the catalog to disseminate their own open data (totalling 121 datasets as of August, 2026; Supplementary Table 1), and Google (2025) has recognized it as Earth Engine's first and largest Community Data Catalog. Demand is global and measurable (Figure 1b): the catalog served 4,151,103 data requests in a single recent month (25 June to 24 July 2026) and its cumulative reach since October 2022 spans 2297 regions, 17,592 cities, and 228 countries and territories, with Brazil the single largest source of demand ahead of the United States, and India third.

Moreover, the scientific impact of this curation is underscored by more than 200 peer-reviewed articles spanning upwards of 115 academic journals (Figure 2). These scholarly works, representing the efforts of over 3,000 authors, rely upon the commons for analysis-ready inputs, while a dedicated cohort of 226 community members has actively expanded the catalog through direct dataset contributions.

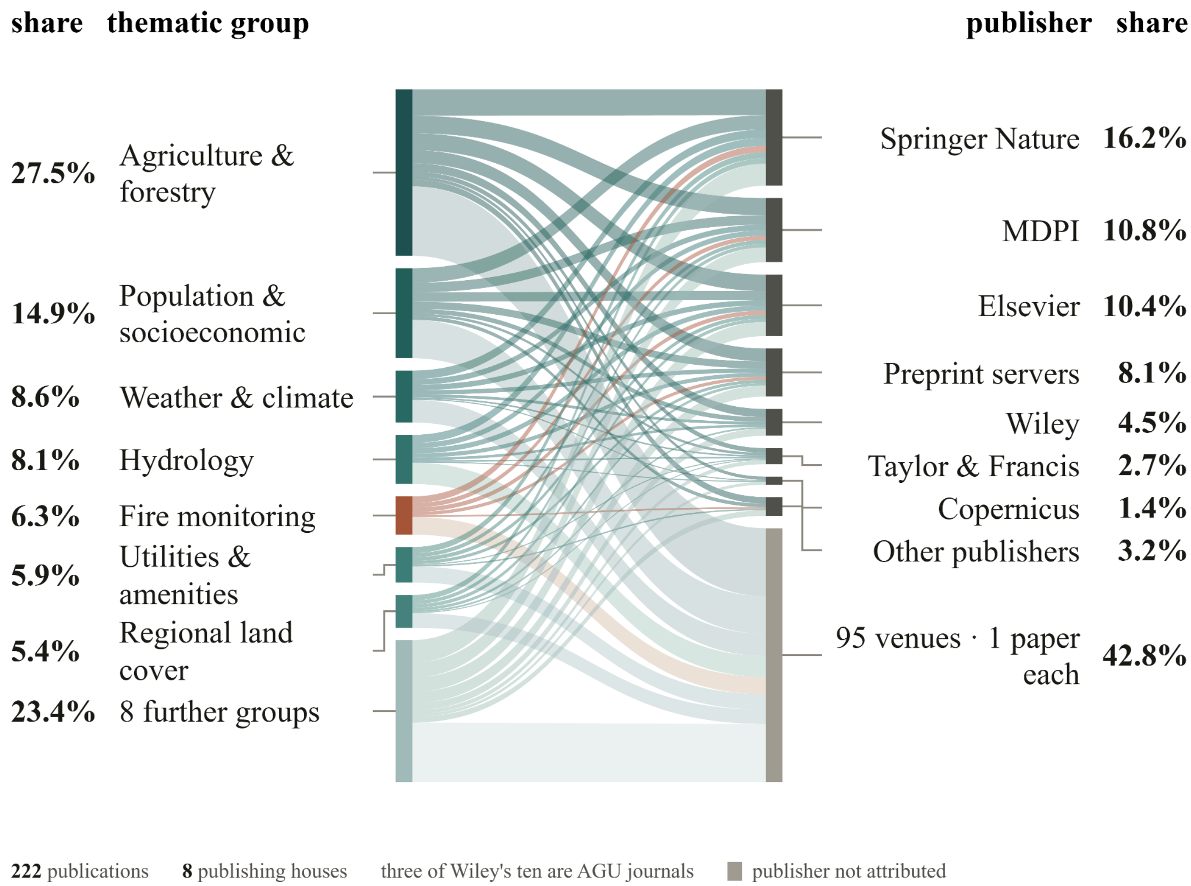

Figure 2. Scholarly impact and domain distribution of datasets in the Google Earth Engine Community Catalog. Here, we show the breakdown of peer-reviewed publications utilizing catalog holdings across major academic publishing houses, and the distribution of hosted assets across major thematic domains, including hydrology, agriculture, population, and climate.

Two design choices explain much of this reach. The first is that the commons (Ostrom,1990) publishes work, not just data: every asset arrives with executable code examples, per-dataset citation guidance, license terms, and provenance and data release notes are version-controlled in the open alongside the catalog, so a skeptical user can audit exactly how an analysis-ready asset has evolved. Releases archived with persistent digital object identifiers give every study a citable, immutable snapshot of the catalog state (Roy et al., 2026), addressing the versioning ambiguity that plagues living datasets. The second is that access is engineered to be nearly frictionless: a single asset identifier replaces weeks of acquisition and wrangling, no local download is required, and independent community integrations extend the same access into the tools people already use, most notably the Earth Engine Data Catalogs Plugin for QGIS (Wu, 2026) that surfaces the full catalog inside QGIS (2026). The fact that external developers chose to extend the commons independently without compensation or solicitation, demonstrates the very ecosystem impact detailed in this commentary: infrastructure truly matures when external, independent contributors actively expand upon it.

3. From Open Data to Equitable Science

The claim that data commons foster equity and reduce barriers is frequently made (Ostrom, 1990; Grossman, 2023); here, it is demonstrably realized. Broadened participation becomes directly measurable once the last mile of data preparation is eliminated. That Brazil, not the United States, is the largest cumulative source of demand (Figure 1b and Figure 3a), and that most requests originate outside the country whose satellites and cloud platforms dominate the underlying supply chain, is direct evidence that the barrier being removed was binding.

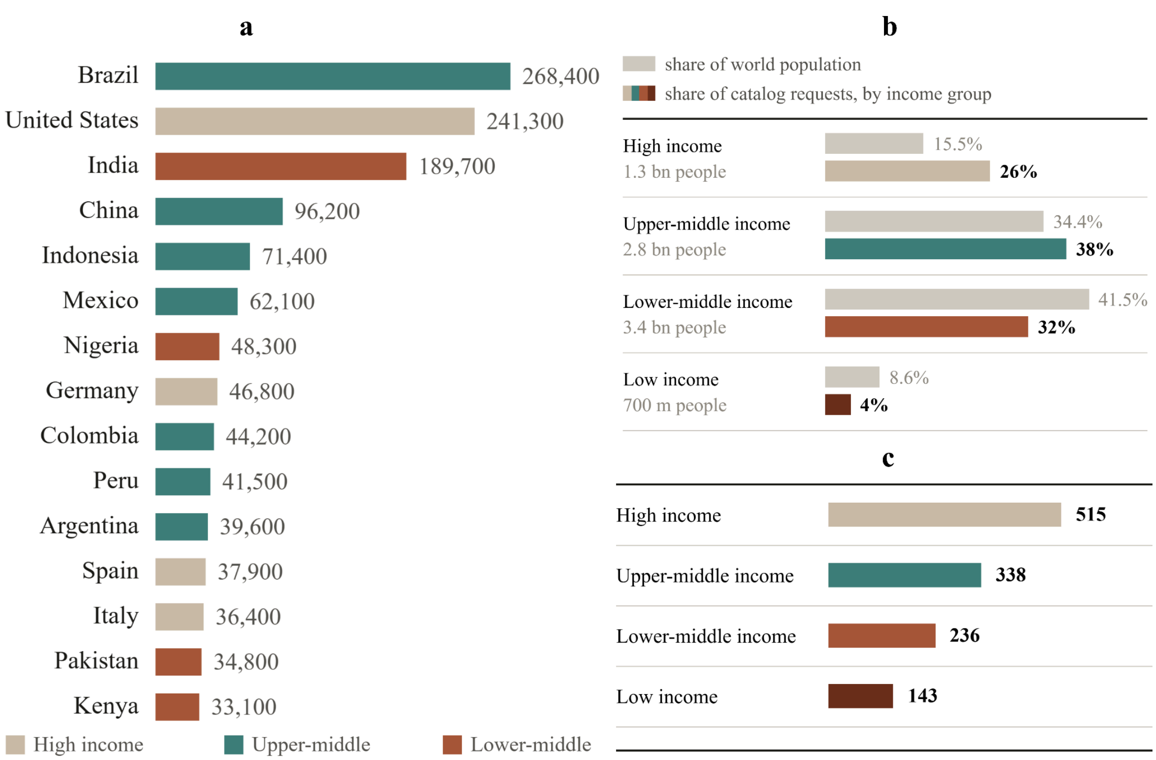

Figure 3. Global usage patterns and equity of demand. **a.** Top 15 national sources of demand (June 25 – July 24, 2026), colored by the World Bank (2026) income group. **b.** Catalog request volume relative to global population share by income group. **c.** Monthly requests per million inhabitants by income group, illustrating the reliance of middle-income regions on the community commons.

A comparative analysis of catalog request patterns and global population distribution (Figure 3b) indicates that middle-income demographics account for the substantial majority of overall catalog demand. Normalized per-capita metrics (Figure 3b) further show that the commons primarily benefits institutions where lacking analysis-ready data creates systemic exclusion (Naji et al., 2026), underscoring its role as an equity-advancing technology. A researcher with a laptop and a browser in the Global South can now run continental-scale analyses that a decade ago required institutional data engineering, because storage, bandwidth, and compute costs that would otherwise be borne by every user are absorbed once by the commons and its hosting platform.

The same logic serves under-resourced users inside wealthy countries: state and tribal agencies, community colleges, food banks and local governments navigating hazards, and educators who have folded the catalog into university courses and international training programs. This is what the FAIR principles look like in practice when they are implemented as working infrastructure rather than aspiration (Wilkinson et al., 2016), and it is why we argue that findability and analysis-readiness are equity technologies, not conveniences.

The commons also functions as teaching infrastructure, which compounds its equity effects across career stages. Because every dataset carries worked code examples and consistent documentation, instructors have folded the catalog into university courses and international training programs, and students meet real, current, analysis-ready data on day one instead of spending a semester's project on acquisition (Gandhi, 2026; Wu, 2025; Crowley et al., 2023). The stated mission of the project, to make data accessible, ties it to an analysis platform, and reduces the digital divide, is thus operationalized in three mutually reinforcing ways: cost (storage and preprocessing absorbed once by the commons), capability and compute (documentation and examples that lower the expertise threshold), and community (a forum and contribution pathway that turn isolated users into participants).

Findability completes the mechanism. Interdisciplinary users typically do not know which of thousands of datasets answers their question, and keyword search fails precisely those who lack domain vocabulary; a curated commons with consistent metadata, thematic organization, and semantic search converts discovery from an insider skill into a public good. Such operational details are intentionally commonplace. Given that the obstacles marginalizing many potential Earth observation practitioners are largely routine (Naji et al., 2026), it is the provision of accessible infrastructure, rather than specialized computational methods, that effectively dismantles these systemic barriers. Equity of access, however, is only half of the obligation. The other half concerns whose data the commons carries and on whose terms, and it is here that community data infrastructure must go beyond FAIR.

4. Indigenous Data, Local Communities, and Shared Stewardship

The catalog hosts the Native Land territories dataset (Native Land Digital, 2021), which maps Indigenous territories, treaties, and languages across the Americas, Australia, and increasingly the world. Its inclusion makes Indigenous geographies visible inside mainstream Earth observation workflows: analysts overlaying wildfire, drought, land-cover change, or infrastructure data on Indigenous territories can now do so directly, and land acknowledgement moves from ceremony toward analysis. The catalog propagates the data stewards' own framing faithfully, including the essential caveats that the maps do not represent legal boundaries and that definitive information belongs to the nations themselves. This matters because Indigenous peoples manage or hold tenure over roughly a quarter of the global land surface, lands that intersect disproportionately with the world's remaining intact ecosystems (Garnett et al., 2018), so Earth science that cannot see Indigenous geographies is Earth science that misses a quarter of its subject. The integration of these datasets into the community commons further secures their prominence, provides a durable archival framework, and explicitly credits the scientific labor of providers who collaborate with local communities to maintain these living assets.

Hosting such data also imposes duties that generic open-data principles do not capture. The Collective benefit, Authority to control, Responsibility, and Ethics (CARE) Principles for Indigenous Data Governance articulate what data commons owe the communities represented in their holdings, complementing rather than competing with FAIR (Carroll et al., 2020). For a community catalog, CARE implies concrete practices: carrying the stewards' licenses and caveats without dilution, deferring to source communities on representation and takedown, and treating Indigenous data sovereignty as a governance requirement rather than a metadata field.

The same ethic extends to local and community-generated data more broadly. The catalog's holdings include collaboratively produced national mapping (Souza et al., 2020), community-mapped health facilities, locally contributed datasets from the Congo Basin (Slagter et al., 2024) to the Indus Delta (Gilani et al., 2022), and operational layers (Supplementary Table 1), such as weekly drought conditions (Svoboda et al., 2002), that ranchers, county agencies, and food-security programs use in recurring seasonal decisions.

This is where community data commons connect to the co-production agenda in climate services: decision support becomes actionable when the people who make decisions shape the information they receive (Norstrom et al., 2020; Baylis et al., 2025; Lemos et al., 2014; Wilby & Lu, 2022), and a commons whose contribution loop is open to practitioners is co-production infrastructure by construction. In regions where climate services have long invested in making national data usable (Dinku et al., 2018; Hansen et al., 2019), a global commons does not replace local institutions; it lowers the cost of the data layer on which they build and the barrier of entry to get to these datasets.

Stewardship of this kind is operational, not rhetorical, and the Native Land entry illustrates the practices involved. The source dataset is deliberately in flux, updated continuously by its stewards through community input, so the catalog treats currency as part of fidelity, pointing users to the stewards' living platform rather than freezing a stale copy as authoritative. The documentation carries the stewards' pedagogy along with their polygons, including the role of land acknowledgement and the explicit instruction that definitive boundaries belong to the nations themselves. And the entry exists inside a governance conversation rather than outside one: as community data commons mature, decisions about representing contested geographies, honoring takedown requests, and distinguishing data about Indigenous peoples from data governed by them will need legitimate processes, not maintainer discretion. We do not claim the catalog has solved Indigenous data governance; we claim, more modestly, that a commons willing to carry these data must also be willing to carry these duties, and that CARE provides the vocabulary for doing so (Carroll et al., 2020). The reward for getting this right is substantial: local and Indigenous communities are not a peripheral audience for Earth observation but among its most consequential users, managing fire, water, wildlife, and land under accelerating change, often on recurring seasonal decision calendars where data timing matters as much as data quality (Baylis et al., 2025). A commons that serves weekly drought conditions to a ranching community, or land-cover change to a territorial government, on the platforms and bandwidths they actually have, is climate adaptation infrastructure in the most literal sense.

5. What the Commons Enables

The scientific return on curation is visible in what downstream researchers have built. Catalog-hosted data underpin global, national, and regional analyses of flood threat to cropland and food systems (Han et al., 2024; Kerner et al., 2024; Nabil et al., 2021; Mayer et al., 2021), characterizations of urban land and its climate consequences (Chakraborty et al., 2024; Chakraborty et al., 2025; Theobald et al., 2025), global critical infrastructure layers (Nirandjan et al., 2022), climate and land use projections (Abatzoglou et al., 2018; Qin et al., 2020; Sohl et al., 2018; Chen et al., 2020), and a broad hydrology and water-security literature. These primarily include evapotranspiration (Kim et al., 2026; Huerta et al., 2022), irrigation (Muturi et al., 2026; Nagaraj et al., 2021; Majumdar et al., 2024), and groundwater (Hasan et al., 2023; Ma et al., 2026) domains where analysis-ready inputs feed directly into operational water accounting (Volk et al., 2026; Melton et al., 2022). The anticipatory uses matter particularly for this journal's readership: weekly drought conditions, seasonal crop indicators, and hazard layers hosted in the commons are the raw material of early warning, and the global crop-monitoring community has shown how such inputs translate into pre-season and in-season forecasts that give food-security institutions time to act (Becker-Reshef et al., 2019; Anderson et al., 2024). Machine learning across the Earth sciences increases, rather than decreases, the value of this curation: data-driven Earth system science is bounded by the quality and consistency of its inputs (Reichstein et al., 2019; Majumdar et al., 2024), and transparent, versioned, uniformly preprocessed datasets are the substrate that makes learned models auditable at all (Zhou et al., 2022). None of these downstream results required the commons to exist; all of them were made faster, cheaper, and more reproducible because it did, and many of the smaller-team studies among the 200+ publications would likely not have been attempted without it.

The pattern these examples share is worth naming, because it is the argument for curation in miniature. Global surface water mapping demonstrated a decade ago what becomes possible when an authoritative, analysis-ready product is computed once and shared with everyone (Pekel et al., 2016): thousands of downstream studies, none of which had to repeat the underlying processing. A community commons generalizes that model from flagship products to the long tail of research data, the harmonized bathymetries, drought indices, population grids, crop masks, and regional mosaics that no single agency owns but nearly every applied study needs. The long tail is also where the commons serves anticipation most directly. Ingesting operational layers, most notably weekly drought conditions (Supplementary Table 1), on a predictable schedule enables early-warning workflows to rely on resilient identifiers instead of fragile and often manual scraping routines. Operational stakeholders require the very same guarantees that benefit researchers, including version control, documented provenance, and standardized preprocessing, before they will rely on a dataset for recurring decision-making. A parallel logic applies across the expanding GeoAI ecosystem (Lunga & Hänsch, 2026): developers depend on training inputs that are predictably structured and rigorously documented, and catalog-level standardization turns thousands of fragmented datasets into a dependable foundation for machine learning. Model builders need training data whose preprocessing is documented and consistent, and a commons that guarantees those properties at the catalog level converts thousands of heterogeneous sources into a coherent substrate for learning (Reichstein et al., 2019).

6. Fragilities: The Sustainability Paradox of Community Infrastructure

The qualities that make the commons agile are also its greatest vulnerabilities, and honesty about them is a precondition for fixing them. First, curation rests on a handful of maintainers: the bus factor, i.e., risk of key personnel loss, of the catalog is small, its institutional memory is concentrated, and volunteer labor, however sustained, is not a succession plan. This is the general condition of digital infrastructure, where indispensable open resources are maintained by unfunded individuals while the institutions that depend on them look away (Eghbal, 2020). Second, day-to-day access is tied to computing donated by a single company; the arrangement has been generous and stable, but a commons whose availability depends on any one platform's continued goodwill carries concentration risk that no amount of community goodwill offsets. Third, the commons is now a supply chain: data and preprocessing code consumed millions of times per month are a meaningful target for tampering and a meaningful source of silent error, so security, integrity verification, and provenance are no longer optional refinements but core obligations. Fourth, growth itself strains volunteer governance (Fia & van Maanen, 2025; Ostrom, 1990): decisions about what to ingest, how to represent contested or sensitive data, including Indigenous data, and when to deprecate assets require legitimacy that informal maintainership cannot indefinitely supply.

These fragilities are addressable, and the directions are known. Governance can be formalized without bureaucratizing the community: cross-sector steering, documented contribution and dispute processes, and a contributor ladder that converts users into committers that distribute both authority and knowledge. Platform concentration can be reduced by publishing catalog metadata in open, portable standards and mirroring priority assets to neutral storage, so the commons survives any single host. Institutional adopters, the agencies, universities, and international organizations that already rely on the catalog, can convert reliance into support: contributed curation effort, mirrored storage, letters and memoranda that make the dependence legible to funders, and direct sponsorship. Publishers and societies can help by treating dataset curation as citable scholarship, extending the FAIR-data norms they already enforce (Stall et al., 2019) to the infrastructure that makes compliance practical. And science funders can recognize a category that current portfolios mostly miss: modest, sustained operating support for community data infrastructure returns value across every program that consumes Earth observation, at a cost that is a rounding error against the missions that produce the data. The commons documented here has run unfunded for six years; that is a testament to its community and an indictment of the funding system around it.

Two technical directions deserve specific mention because they convert sustainability from aspiration into architecture. The first is open metadata standards. Publishing the complete catalog in the SpatioTemporal Asset Catalog specification (STAC Contributors, 2021) and in columnar GeoParquet form (Open Geospatial Consortium, 2023) makes the commons queryable by any client and portable to any host, while machine-learning-ready descriptors in the Croissant family (Akhtar et al., 2024) make the same holdings legible to modern training pipelines and dataset search engines. Standards are the exit rights of a data commons: they are what make platform concentration a preference rather than a dependency, and they are cheap to adopt relative to what they insure against. The second is verifiable integrity. Checksums recorded at acquisition and carried through every transformation, cryptographically signed releases, and public software bills of materials would let any consumer confirm that a served asset is bit-identical to the validated release and that the code that produced it is what the repository says it is. For infrastructure consumed millions of times per month, these are the data-supply-chain analogues of practices the software world has already adopted, and community commons should adopt them before an incident makes the case instead.

7. Five Lessons for Building Community Data Commons

Reflecting on six years of operation, and deliberately echoing the lesson-driven framing that climate services research has used to close its own last mile (Baylis et al., 2025), we offer five transferable lessons for communities, institutions, and funders contemplating data commons of their own.

Lesson 1: Treat curation as scientific labor. Preparing a dataset well, once, for everyone, is research infrastructure work with measurable downstream returns in publications, reproducibility, and participation. Credit it in authorship and citation, count it in careers, and fund it in budgets. A commons run on invisible labor will eventually run out of it.

Lesson 2: FAIR begins with findability, so design for discovery first. The largest losses occur before analysis starts, when usable data go unfound. Invest in rich, machine-actionable, standards-based metadata and in discovery interfaces that speak the language of scientific intent rather than dataset names; findability is the multiplier on every other investment in the stack.

Lesson 3: Build a loop, not a pipeline. A commons that separates producers from consumers inherits the maintenance burden forever. Design contribution pathways, recognition, and low-friction validation so that users become contributors; the peer-production loop is what lets the catalog track emerging needs without central planning, and it is the only growth model that scales with community rather than budget.

Lesson 4: Meet communities where they are, and share stewardship. Serve data on the platforms, bandwidths, and toolchains people actually have; propagate licenses and caveats faithfully; and where holdings represent Indigenous peoples and local communities, adopt CARE alongside FAIR, deferring to source communities on representation and control (Carroll et al., 2020). Equity of access without equity of governance is only half a commons.

Lesson 5: Plan succession from the start. Version and archive immutably, keep credentials and infrastructure in organizational rather than personal custody, document operations as if handing them over tomorrow, and build governance that can outlive founders, platforms, and funding cycles. The measure of a commons is not whether it works today but whether it is robust enough to lose any single person, institution, or host and continue.

8. Conclusions

In an era of accelerating climate change and compounding environmental threats, timely, accessible, and actionable data have never mattered more, and the gap between open data and usable data has never been more consequential. Community data commons close that gap in the only way that scales: by organizing the people who need the data into the community that maintains it. The catalog described here demonstrates that such commons can reach essentially every country on Earth, can carry Indigenous and community data with care, can underpin anticipatory science from drought and earthquake early warnings to flood risk.

Investing in, learning from, contributing to, and governing community-built commons well is among the highest-leverage actions available for rapid, collaborative, and equitable Earth science, and Earth's future will be anticipated best by the widest possible community of people equipped to see it coming. To researchers, we suggest a small act with large aggregate consequences: cite the data commons you use, in the reference list and not only the acknowledgments, so that curation accrues the scholarly credit that careers and funding decisions can see. To agencies and international organizations already disseminating data through community channels, we suggest converting quiet reliance into explicit partnership. To funders, we suggest that the marginal dollar spent sustaining shared data infrastructure may be the highest-return dollar in an Earth science portfolio. And to the communities, from graduate students to territorial governments, who have built and used this commons for six years, we offer the conclusion this experience compels: the commons works. It remains only for the institutions of science to decide that infrastructure this useful deserves to be more than a volunteer effort.

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Knoxville (Qiusheng Wu), University of Maryland (Catherine Nakalembe), University of Southampton (Andy Tatem), Arizona State University (Hannah Kerner), The University of Alabama in Huntsville (Emil Cherrington), Desert Research Institute (Eric Jensen, Justin Huntington, Peter ReVelle, Beatrice Gordon), and individual contributors (Zara Khan, Andrew Saah) who have substantially promoted the use of the community catalog. Additionally, we thank platforms and projects like the U.S. National Science Foundation (NSF) ACCESS program, which provides compute units on Jetstream 2, enabling rapid preprocessing of datasets as community requests are made. Finally, our deepest appreciation goes to all community catalog contributors, notably the authors who enabled open and FAIR science by making their data publicly accessible.

Conflict of Interest

The primary author is the founder and all co-authors serve as maintainers of the Google Earth Engine Community Catalog without receiving financial remuneration. The authors formally declare no competing financial or personal interests.

Data Availability Statement

This commentary did not create or generate any new datasets. The community catalog metadata, documentation, and code are openly available at https://gee-community-catalog.org and https://github.com/samapriya/awesome-gee-community-datasets, with versioned releases archived at https://doi.org/10.5281/zenodo.21876800 (Roy et al., 2026).

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Supplementary Information for "A community data commons for equitable Earth Science"

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Supplementary Table 1. Data providers by scope. Source organizations grouped by U.S. federal vs. international, ranked by dataset contribution.

ACRONYM	ORGANIZATION	AFFILIATION	DATASETS
UNITED STATES: FEDERAL · 16 ORGANIZATIONS			**79**
USGS	United States Geological Survey	Interior	**23**
NASA	National Aeronautics and Space Administration	Independent	**16**
NOAA	National Oceanic and Atmospheric Administration	Commerce	**15**
USFS	U.S. Forest Service	Agriculture	**6**
ORNL	Oak Ridge National Laboratory	Energy	**5**
NRCS	Natural Resources Conservation Service	Agriculture	**4**
Census	U.S. Census Bureau	Commerce	**1**
DHS	U.S. Department of Homeland Security	Homeland Security	**1**
DOS	U.S. Department of State	State	**1**
EPA	U.S. Environmental Protection Agency	Independent	**1**
ERS	Economic Research Service	Agriculture	**1**
FEMA	Federal Emergency Management Agency	Homeland Security	**1**
NASS	National Agricultural Statistics Service	Agriculture	**1**
USACE	U.S. Army Corps of Engineers	Defense	**1**
USDA	U.S. Department of Agriculture	Agriculture	**1**
USFWS	U.S. Fish and Wildlife Service	Interior	**1**
INTERNATIONAL AND NON-U.S. NATIONAL · 17 ORGANIZATIONS			**42**
ESA	European Space Agency	Europe (multinational)	**7**
Copernicus	Copernicus Programme, European Commission	Europe (EU)	**6**
ECCC	Environment and Climate Change Canada	Canada	**4**
FAO	Food and Agriculture Organization of the UN	United Nations	**3**
JRC	Joint Research Centre, European Commission	Europe (EU)	**3**
World Bank	World Bank Group	Global (multilateral)	**3**
AAFC	Agriculture and Agri-Food Canada	Canada	**2**
AIST	National Institute of Advanced Industrial Science and Technology	Japan	**2**
METI	Ministry of Economy, Trade and Industry	Japan	**2**

ACRONYM	ORGANIZATION	AFFILIATION	DATASETS
NRCan	Natural Resources Canada	Canada	**2**
swisstopo	Federal Office of Topography	Switzerland	**2**
GA	Geoscience Australia	Australia	**1**
IGN	Institut national de l'information géographique et forestière	France	**1**
JAXA	Japan Aerospace Exploration Agency	Japan	**1**
NLSI	National Land Survey of Iceland	Iceland	**1**
UNEP	United Nations Environment Programme	United Nations	**1**
UNOCHA	UN Office for the Coordination of Humanitarian Affairs	United Nations	**1**
TOTAL: 33 ORGANIZATIONS ACROSS 7 COUNTRIES AND 4 MULTILATERAL BODIES			**121**