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# To enhance sustainable development goal research, open up commercial satellite image archives

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**To adequately study smallholder farms, researchers need access to very high-resolution satellite data. This will provide critical tools, data, and scientific underpinning for the policies necessary to meet the targets defined under the SDGs. Image credit: Cristina Chiarella (photographer).**

Observing the Earth with satellites offers clear advantages when it comes to tracking the health of the planet—consistent measurements that can be translated into environmentally relevant estimates, such as carbon, crop productivity, or land use. The resulting information covers large regions, irrespective of administrative boundaries. These measurements also drastically reduce costs compared with on-the-ground data collection efforts. Earth observation (EO) data thereby efficiently deliver timely insights that can directly inform sustainability debates, including with regard to United Nations (UN) Sustainable Development Goals (SDGs). At the heart of these efforts are open data initiatives linked to the public release of medium- to high-resolution EO image archives, such as Landsat (from the US Geological Survey) or Copernicus data (from the European Space Agency [ESA]). A growing body of scientific literature attests to the important role of EO data in providing timely and accurate information that's directly relevant to the SDGs (1).

Unfortunately, the potential of EO data cannot be fully tapped everywhere, particularly not in regions hosting "smallholder" farms—meaning farms operating on less than 2 hectares of land. These farms are important cornerstones of global food production, delivering a third of the global food supply on only one-quarter of the gross agricultural area (2). Recent studies have reported stagnating or even declining productivity in smallholder systems (3), threatening food security in

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regions with rapidly growing populations—often those exposed to extreme events in a changing climate. More effective research efforts and sustainability interventions are therefore sorely needed. However, EO approaches in smallholder agricultural landscapes often require data at very high spatial resolution of 2 meters or higher. SDG research is hampered in smallholder landscapes because these data remain paywalled by commercial satellite operators.

We argue that mobilizing existing very-high-resolution (VHR) satellite data will improve the uptake of EO techniques for smallholder agricultural monitoring. The resulting insights, in turn, will help provide critical tools, data, and scientific underpinning for the policies necessary to meet the targets defined under the SDGs, 84% of which are currently off-track (4). SDG 2, which aims specifically to “end hunger, achieve food security and improved nutrition and promote sustainable agriculture,” shows stagnating or negative trajectories since 2015 across nearly all world regions.

As a group of scientists concerned with the sustainability of smallholder agriculture, we call for coordinated efforts to facilitate access to commercial EO image archives containing spatially comprehensive and repeated satellite image acquisitions at very high spatial resolution over low- and middle-income countries hosting most smallholder regions. This would greatly accelerate SDG monitoring and research, enabling progress toward reaching SDG 2 and ultimately mitigating hunger in smallholder-dominated systems.

## Earth Observation

International organizations have already recognized the potential of EO data for SDG monitoring. For example, the Group on Earth Observation, the Committee on Earth Observation Satellites, and the ESA confirmed that 34 SDG indicators related to 11 of the 17 SDGs can be either directly or indirectly informed with space-based EO data (5). For monitoring indicators related to the targets defined in SDG 2, EO delivers crucial data. In particular, EO can inform Target 2.3, which aims to double the productivity and incomes of small-scale food producers, and Target 2.4, which focuses on ensuring sustainable food production systems.

To be clear, EO is not a panacea for achieving the SDGs. That’s in part because of the requirements for infrastructure and technical expertise needed to process large volumes of EO data into actionable insights, conditions that continue to hamper the uptake of EO in many world regions (6).

Nevertheless, the capability of EO data for delivering policy-relevant information that is consistent across large areas and decadal time frames, irrespective of data-collection routines that vary country to country, has helped tackle key blind spots for multiple SDG indicators. Thus, we contend that commercial VHR image providers should grant access to researchers in order to improve these SDG monitoring schemes.

## Smallholder Regions

Not all regions benefit equally from EO-based SDG monitoring. EO methods that were developed for regions with large and homogeneous crop fields may fail in those areas dominated by smallholders. Smallholder farms often have very small fields (less than 0.1 hectare) that contain noncrop vegetation or multiple crops and undergo frequent fallow cycles. The characteristics of smallholder landscapes can compromise the usefulness of EO technologies when the phenomenon of interest is very small in relation to the spatial resolution of available EO data (7). For example, a field of 0.1 hectare in size covers roughly one 30 × 30-meter pixel in a Landsat image, and many fields are even smaller than that (Fig. 1). Such scale mismatches prohibit detailed analyses at the level of management units.

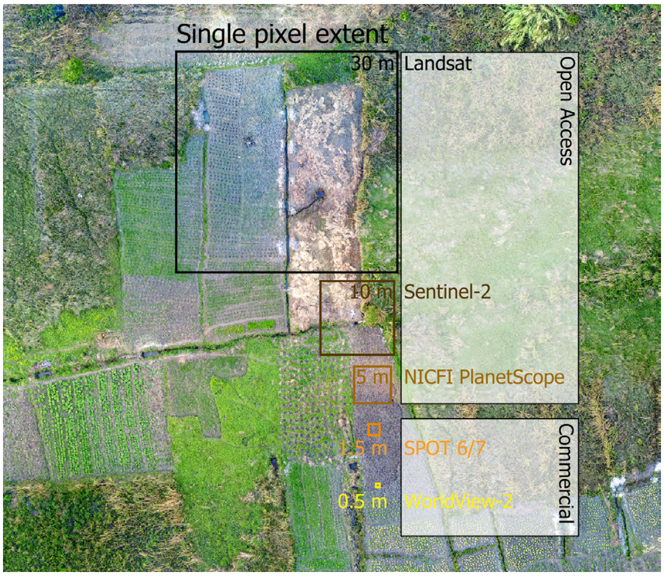


**Fig. 1. Smallholder farm in the North of Mozambique seen from above. The spatial resolution of openly accessible and commercial satellite systems relevant for SDG monitoring is shown here for comparison.**

As a result, our knowledge about even basic agricultural parameters, such as the distribution of cropland, remains comparatively limited in smallholder-dominated regions. Existing (typically global) cropland maps often do not accurately represent local or regional realities (8), disagree in space and over time (9), exclude shifting cultivation (10), or do not distinguish actively used from fallow cropland (11). These knowledge gaps are particularly concerning because smallholder farms are key contributors to global food production, farm biodiversity, and employment (2, 12). Simultaneously, recent evidence highlights stagnating or declining country-level productivity trends in African smallholder farming systems (3). (Ethiopia, Mali, and Tanzania have stagnating agricultural productivity; Malawi and Nigeria have declining productivity.)

There are two major bottlenecks that challenge the monitoring of smallholder agriculture. First, appropriate volumes of reference data are needed to train and evaluate machine learning models, and these are typically not available in smallholder contexts (13). Recently, researchers have mitigated the scarcity of reference data through advanced learning techniques. As an example, deep learning models can be transferred across regions, allowing researchers to use larger volumes of reference data where data are ubiquitous (e.g., Europe), and then adapting the model to their target region (e.g., sub-Saharan Africa) with smaller quantities of reference data (14, 15). While not fully mitigating the reference data bottleneck, these techniques allow researchers to use state-of-the-art deep learning models

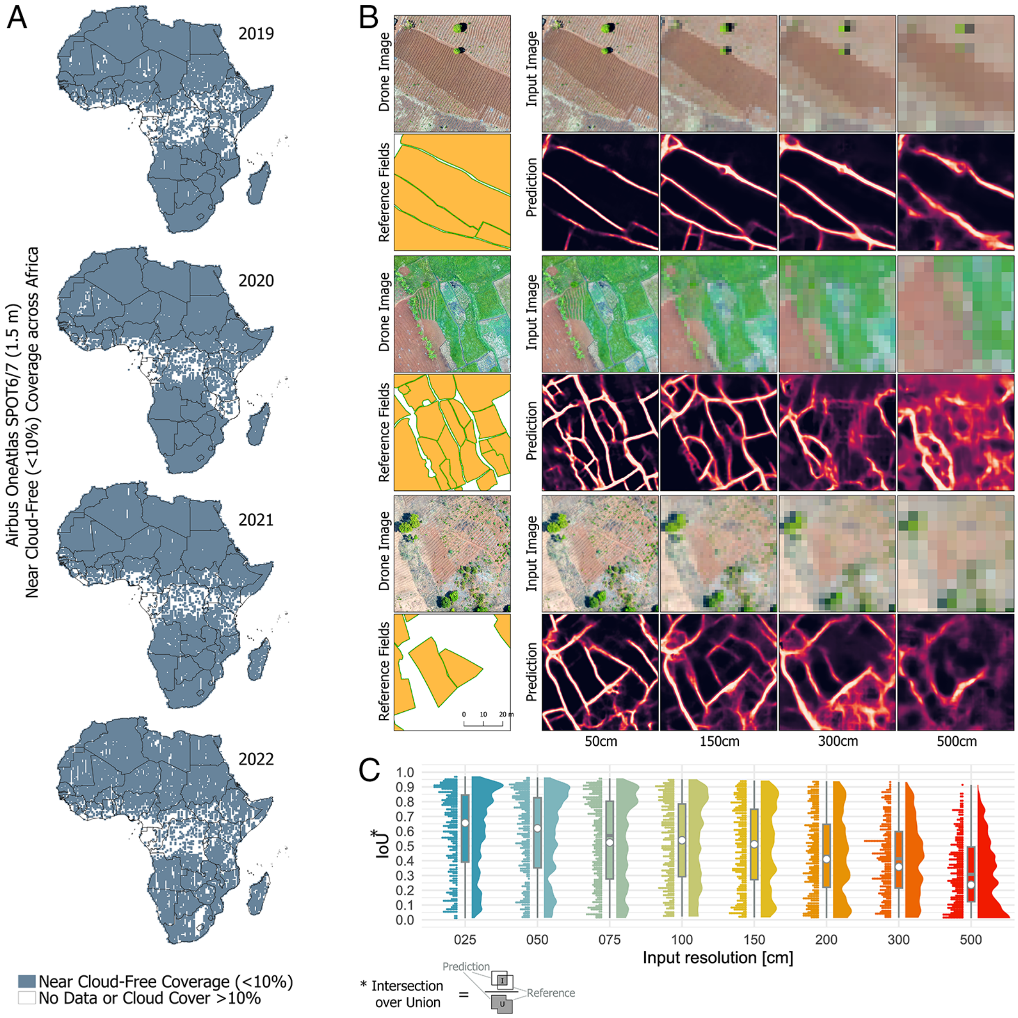


**Fig. 2.** **Maps of coverage of SPOT6/7 images with cloud cover below 10% for 2019–2022 across Africa were created using metadata from the OneAtlas Living Library accessed via Descartes Labs (© Airbus DS) (*A*). The results of our field delineation experiment in agricultural landscapes in the north of Mozambique are shown. We acquired drone images at <10-centimeter resolution during field work in 2021. Reference data on field delineations (*n* = 1,543) have been digitized on-screen from the imagery by two trained interpreters. Field boundaries were predicted using a set of deep learning models trained as described in refs. 15 and 17, using imagery in varying spatial resolution ranging from 25 centimeters to 5 meters (*B*). The overall model performance measured as IoU declined with increasingly coarse spatial resolution (*C*).**

to address sustainability questions in regions where reference data are scarce (16).

Second, timely VHR EO image data are currently not freely available over most regions. These data are vital to untangling the complexities of smallholder agricultural landscapes. VHR EO data are acquired and maintained by commercial image providers such as Maxar, Planet Labs, or Airbus and are typically marketed at high costs. Data from the SPOT6/7 satellites operated by Airbus, for instance, are delivered at a spatial resolution of up to 1.5 meters. These data offer cloud-free continental coverage for Africa at near-annual intervals since 2017 (Fig. 2*A*). Unlocking these archives would drastically enhance SDG monitoring in smallholder agriculture. Yet, the data are marketed for a price of around 2.00 € per square kilometer (https://up42.com/), translating into a conservative price estimate of 52,000 € for a one-time coverage of Rwanda (one of the smallest African countries) or 1.6 million € for Mozambique (one of the poorest African countries). Few institutions involved in sustainability research can afford such costs, and especially not at regular intervals required for monitoring. The high cost of VHR imagery therefore poses an accessibility constraint that remains a major impediment to unfolding the full potential of EO technologies (6, 13).

We argue that improved access to commercial VHR EO data will aid in delivering accurate, timely, spatially detailed, and thematically rich information on smallholder agriculture, which is needed to better understand and mitigate challenges such as productivity declines.

A few notable examples demonstrate the potential of VHR data for SDG-related interventions in smallholder contexts. Jain et al. (18), for example, showed that targeting fertilizer applications based on yield estimates from commercial VHR EO data (PlanetScope, SkySat) can efficiently double yields and improve nitrogen use efficiency at near constant costs. Timely VHR data are also a common source for collecting reference data in regions or situations where access to the ground is challenged or rapid information retrieval is crucial. In another case, access to commercial satellite data from Maxar (WorldView-2, WorldView-3, QuickBird) and Planet (PlanetScope, SkySat) allowed researchers of NASA's Food Security and Agriculture Program to produce rapid-response cropland maps for the food security relief efforts of the

Togolese government during the COVID-19 pandemic (19). The maps allowed the government to target and prioritize cash transfers and social protection campaigns, effectively protecting small-scale farmers from shocks triggered by the pandemic.

**The massive success of previous efforts to open access for satellite imagery, as exemplified by the Landsat, Copernicus, and NICFI programs, underscores the value of open EO image archives for driving innovation in sustainability research.**

## Field Delineation

The importance of matching image resolution and the complexity on the ground is particularly apparent when it comes to delineating individual crop fields. Detailed, accurate, and repeated field delineations are a prerequisite for assessing EO-based indicators linked to SDG 2.3 and 2.4 at the scale of individual fields. Field delineations in smallholder agriculture allow for precise monitoring of the extent of small-scale farming and facilitate downstream analyses on the types, productivity, and vigor of crops, or how land is managed, for individual units of production. Also, at aggregate (e.g., national) scale, such data can facilitate the assessment of disaster impacts, risk indicators, food security, rural livelihoods, or scale transitions in agriculture, which can manifest in changing field size. Consequently, the Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) listed field delineations as Essential Agricultural Variables with clear implications for the targets embedded in SDG 2 (Zero Hunger), as well as 1 (Ending Poverty), 12 (Responsible Consumption and Production), 13 (Climate Action), 15 (Life on Land), and 17 (Global Partnerships for the SDGs) (20).

We have shown in the smallholder landscapes in the north of Mozambique that accurate mapping of field boundaries—required to delineate fields—is only possible at spatial resolutions of less than 2 meters (Fig. 2*B*). We measured model performance as intersection over union (IoU), a metric of the amount of overlap between predicted and reference field areas. The spatial agreement was generally low, even at the highest spatial resolution, compared to world regions with more industrialized agriculture. Decreasing the spatial resolution from less than 1 meter to 5 meters substantially degraded model performance by more than 65% (Fig. 2*C*), most notably affecting small fields. This experiment supported findings in the scientific literature documenting that accurate field delineations in smallholder contexts can only be produced using commercial VHR satellite imagery, ideally with a spatial resolution of less than 2 meters when fields are small (15), pointing to the need for improved access to such EO data.

## Ensuring Access

Commercial providers allow use of their imagery through open data programs and offer their data for specific purposes, typically with quantitative, regional, or temporal restrictions. One example is the Maxar Open Data Program, which provides VHR imagery for disaster response. Another is an education and research program from the company Planet, which offers a limited monthly quota of imagery covering 3,000 square kilometers for download to university-affiliated students and researchers for general scientific inquiry. In some cases, public institutions such as ESA and NASA partner with commercial providers to enable the release of restricted amounts of data for methods development, as, for example, WorldStrat (21), or to grant quota for specific research projects (e.g., the NASA Commercial SmallSat Data Acquisition Program or ESA Third Party Mission projects).

However, these programs are subject to opaque review procedures, limited in data volume, and partly accessible only to researchers affiliated with a particular institution, funder, or country. Thus, while these initiatives do allow users to interact with commercial VHR imagery, the quantitative, temporal, and regional restrictions often render these programs ill-suited to tackle key sustainability questions. Plus, high VHR data costs and limits on access further widen the gap between scholars affiliated with institutions from low- and middle-income countries and those working in comparatively well-funded institutions in the Global North.

There are government-led initiatives that have shown promise. Norway's International Climate and Forest Initiative (NICFI) and partners addressed the scarcity of high-resolution satellite imagery suitable to track fine-grained processes in tropical forests through the NICFI Satellite Data Program. The first phase of the program, which ended in January 2025, opened monthly commercial image mosaics at 4.8-meter spatial resolution across the tropics for the purpose of halting or reducing tropical deforestation and forest degradation and for other sustainability-oriented uses. The success of this program can hardly be overstated. Within three years, more than 23,500 users from universities, nongovernmental organizations, governmental institutions, and international organizations across 158 countries have used the data for sustainability-centered research, as of 2023 (22). The data supported more than 100 peer-reviewed publications, e.g., on mapping the condition and changes in tropical forest ecosystems (23).

Beyond academia, nongovernmental organizations used NICFI data for mapping, monitoring, and reporting applications, to manage fire risks in protected areas, or to empower and defend the rights of Indigenous communities. Intergovernmental (e.g., the UN Food and Agriculture Organization and the UN Development Programme) and national institutions (of Brazil, Cameroon, Ethiopia, Ghana, Gabon, Panama, Tanzania, and Mozambique, among others) relied on the data for measurement, reporting, and verification in the context of UN Framework Convention on Climate Change initiatives to reduce emissions from deforestation and forest degradation (REDD+). NICFI data were also used for the design of land use policies or for improving traceability in global commodity supply chains.

The NICFI satellite data program thus undoubtedly demonstrated how publicly accessible high-resolution EO data can yield positive impacts for the protection of forest ecosystems across the tropics. Unfortunately, even the 4.8-meter resolution NICFI data were insufficient for core aspects of SDG monitoring in smallholder regions.

The massive success of previous efforts to open access for satellite imagery, as exemplified by the Landsat, Copernicus, and NICFI programs, underscores the value of open EO image archives for driving innovation in sustainability research. We see the potential of VHR EO data in the context of the SDGs and sustainability research at large as a strong incentive for public entities and commercial providers to join forces and improve access (similar to the NICFI Satellite Data Program), to make VHR EO data for smallholder regions a digital public good available for noncommercial, sustainability-oriented research.

Making VHR imagery available for noncommercial purposes may also be a win–win strategy from the point of view of EO data providers, as the enhanced visibility of the data products and the potential for a growing user base may stimulate novel tools and applications relevant to the private sector. Opening VHR EO data archives for scientific applications can advance the democratization of sustainability science, while at the same time driving progress toward the SDGs through better monitoring.

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