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Satellite Data in Agricultural and Environmental Economics: Theory and Practice

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ABSTRACT

Agricultural and environmental economists are in the fortunate position that a lot of what is happening on the ground is observable from space. Most agricultural production happens in the open and one can see from space when and where innovations are adopted, crop yields change, or forests are converted to pastures, to name just a few examples. However, converting remotely sensed images into measurements of a particular variable is not trivial, as there are more pitfalls and nuances than "meet the eye". Overall, however, research benefits tremendously from advances in available satellite data as well as complementary tools, such as cloud-based platforms, machine learning algorithms, and econometric approaches. Our goal here is to provide agricultural and environmental economists with an accessible introduction to working with satellite data, show-case applications, discuss pitfalls and available solutions, and emphasize the best practices. This is supported by extensive supporting information, where we describe how to create different variables, common workflows, and a discussion of required resources and skills. Last but not least, example data and reproducible codes are made available online.

JEL Classification: Q5, Q10, Q15, C31, R10

1 | Introduction

Satellite data have several features of interest to agricultural and environmental economists. It can provide measurements in high frequency and high resolution, over long periods of time and with a wide spatial scope. It is also often more objective and measurement is more methodologically unified than survey data, for example. At times, it provides the only cost-effective and reliable measurement available for specific locations (Burke et al. 2021; Donaldson and Storeygard 2016; Lobell et al. 2020). Other times, it is a crucial cross-check to verify other measurements, or it enables the modeling of new variables that may be required for other uses such as causal inference (Wuepper and Finger 2023).

Satellite data, however, cannot replace ground data, such as survey data, and it is commonly most useful in combination (Nakalembe and Kerner 2023; Kerner et al. 2024). Moreover, it comes with its own list of issues and pitfalls, such as new sources of measurement error (Jain 2020) and added uncertainty, for instance, when the satellite data are altered during the pre-processing stage using machine learning and other approaches. As such, understanding the potential and limitations of satellite data has become an important skill for agricultural and environmental economists, to effectively utilize this data source.

Many satellite measurements come in the form of spectral bands that can be combined to show ground features of interest such

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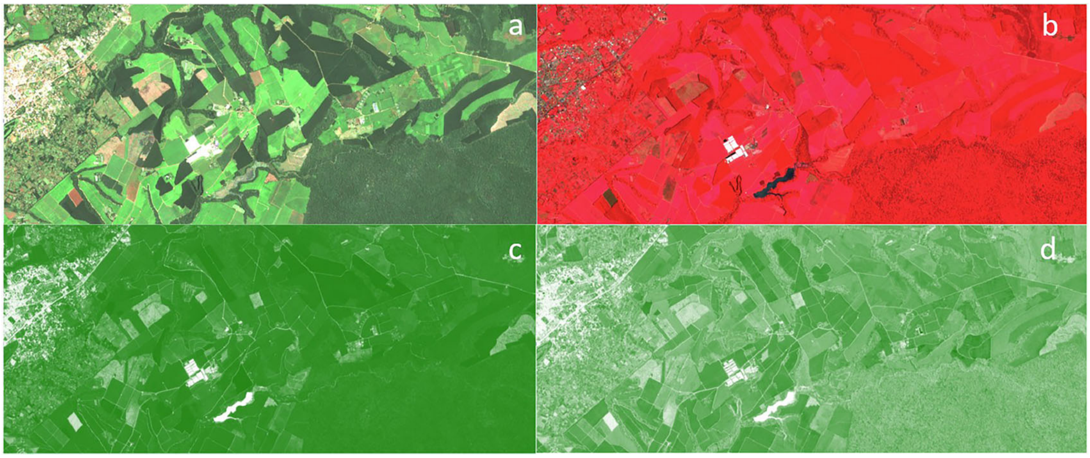


FIGURE 1 | Satellite view on cropland areas. (a) true color composite, (b) false color composite, (c) normalized difference vegetation index, (d) enhanced vegetation index. *Source:* Sentinel-2.

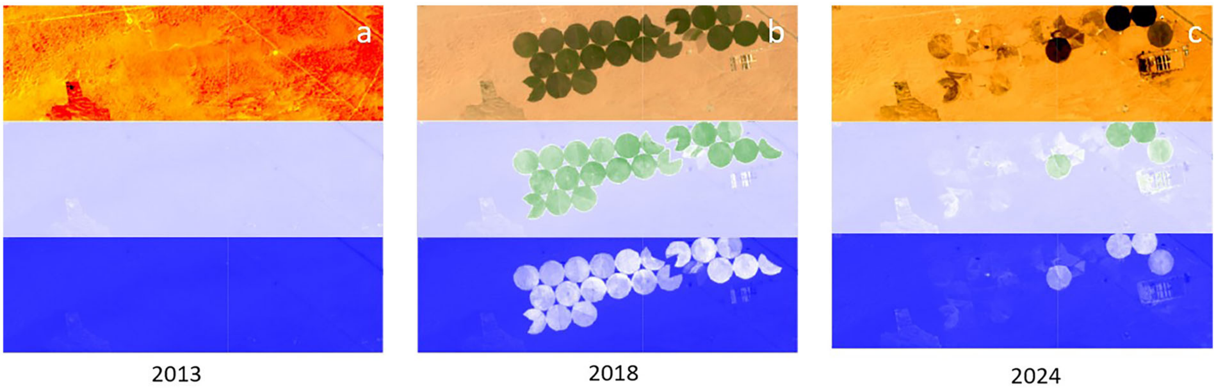


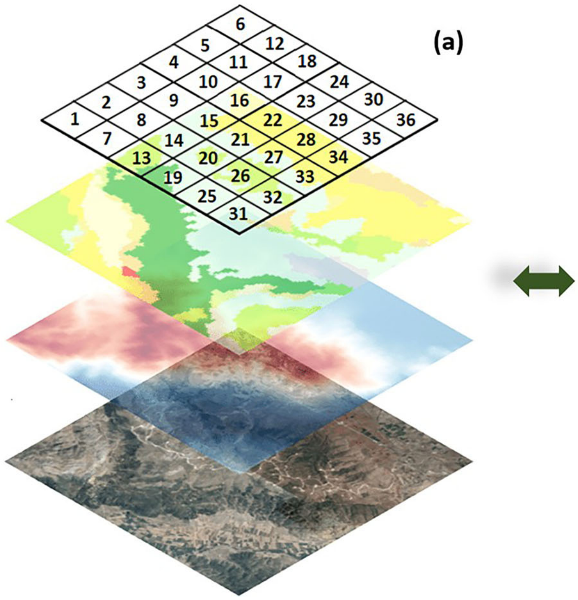
FIGURE 2 | Panel data. Among the advantages of satellite data is the general continuity with which units are observed. In this example, an agricultural project in Saudi Arabia has been created with a visible appearance of irrigated croplands between 2013 and 2018 and a subsequent disappearance between 2018 and 2024. For each period, shown on top is the true color composite, shown in the middle is the NDVI, and shown at the bottom is the EVI. *Source:* Landsat 8 data courtesy of the US Geological Survey.

as croplands from different regions or countries (Figure 1) or the same cropland at different time periods (Figure 2). These synoptic views of the ground features, croplands, could help better understand many crop attributes such as yield, drought periods, crop health, phenology stage, scale of farms, type of crops, and distance of farms to water bodies among others.

Oftentimes, these images need to be converted into tabular format for actual econometric analyses. This step is fundamentally straightforward, as there is a close correspondence between the two formats, and the same information can be stored alternatively in multiple layers or in a single table (Figure 3). The basic workflow for this is to stack the images showing all required variables on top of each other and overlay that with a layer of the relevant analytical unit (e.g., equal-sized grid-cells, or a map of administrative boundaries) with a similar coordinate reference system. Then, for each of these units, a statistic of the variables shown in the images can be calculated (such as, mean, minimum, maximum), and the output can be saved or exported in tabular format (Figure 3).

In contrast to, for example, survey data collection, satellite data can be "collected" relatively inexpensively and frequently. The advancements in satellite technology have significantly reduced the cost of acquiring high-resolution spatial data, up to ~3 m, (Figure 4). The economies of scale in satellite operations combined with the ability to cover large and remote areas efficiently make it highly cost-effective. Additionally, the continuous improvements in satellite sensors and data processing techniques have enhanced (and continues to enhance) the accuracy and usability of satellite-derived information, further increasing its value as a survey tool. Finally, and especially useful, satellite data can usually be spontaneously collected, in contrast to, for example, survey data, for which the data collection must be planned long in advance and once the data are collected, revisit can take years. With satellite data in contrast, a researcher might create a dataset and later realize that an important variable is missing, which can then be separately processed and added to the initial data. During peer-review, further data might be asked for (further outcome variables, for instance, or data on specific mechanisms). These too, can still be added at comparably low cost or effort.

A choice one has is what satellite platform to use. Important differences are especially the available spatial resolution and temporal frequency of measurement. It is thus an important



(b)

ID	Var_1	Var_2	Var_3
1	25	10	50
2	24	11	51
3	22	9	52
4	10	7	53
5	4	6	54
6	24	5	55
7	25	9	49
8	20	10	50
9	26	8	51
10	18	6	52
11	16	6	53
12	24	3	54

FIGURE 3 | Correspondence between Satellite Images and Data Tables. Each of the lower three images (layers) stores a variable. Overlaying them with a unique identifier such as a numbered grid-cell or a map of administrative boundaries (e.g., with country names) allows to compute spatial statistics (e.g., averages or standard deviations per grid-cell) which can then be displayed in a table, ready for research as economists are used to. *Source:* Authors, spatial layers from Vasiljević et al. (2020).

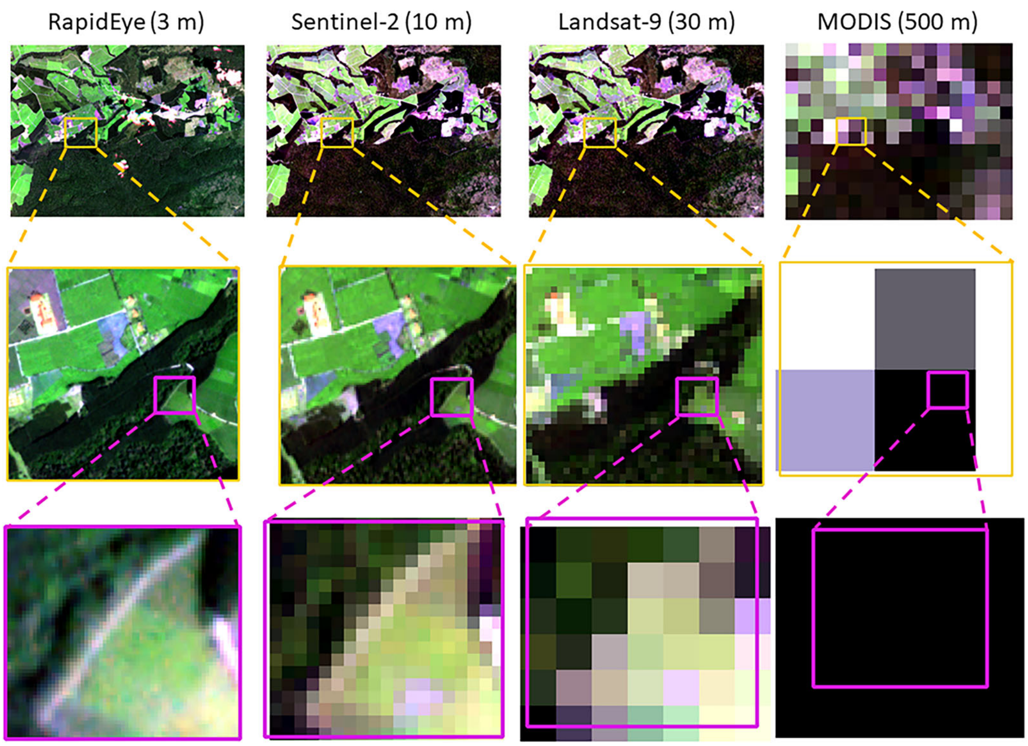


FIGURE 4 | Spatial resolution differences of satellite platforms. Here compared are Planet Lab's RapidEye, Sentinel-2, Landsat, and MODIS, zoomed in to different levels of detail. Shown are tea fields in Kericho, Kenya. *Source:* Authors, data from Planet Labs (2024). RapidEye imagery Planet Labs 2024; Sentinel-2 data Copernicus Sentinel, ESA 2024; Landsat-9 data courtesy of the US Geological Survey (USGS); MODIS data courtesy of NASA.

choice of which platform to use and there is often a trade-off between measurement resolution and frequency, and the research question often dictates a minimum required resolution or frequency, while computational power sets a maximum for the overall size of the dataset.

Figure 4 shows the difference in spatial resolution between four common satellite platforms, namely, the RapidEye of Planet Labs (2024) which provides a high level of detail, with a spatial resolution of only 3 m, and for comparison Sentinel-2 (10 m resolution), Landsat-9 (30 m), and Moderate Resolution Imaging

Spectroradiometer (MODIS) (500 m). Sometimes, it is sufficient for researchers to use coarser data, for example, at a resolution of 1 km or greater, which is usually done by aggregating up higher resolution data, for example, from MODIS. Other times, it is pivotal for the researchers to quantify very precisely what exactly happened when and where, and then every meter improvement in measurement resolution might help (e.g., to detect tea crop plots among small-scale tea farmers [<0.01 ha plots]).

The work with satellite data often involves machine learning, for example, to detect specific patterns in the data (classification), or to transform measurements into the actual variables of interest (prediction). Classification examples include the mapping of cropland dynamics over time, which requires to distinguish croplands from other land-covers (Potapov et al. 2022) and of deforestation and its drivers, which requires to identify forest loss and classify it according to its spatial shape as driven by different threats (Curtis et al. 2018). An example for prediction is the modeling of crop yields based on satellite estimates of biomass (Lobell et al. 2015).

A fundamental issue is how well the geospatial mapping (prediction) model that is calibrated with the available ground-truth (reference) sample, can be transferred beyond the training area or/and time periods. Briefly, this transferability across space (geographical regions) and time (e.g., years), also known as the "transfer learning" performance, is complicated by two types of shifts between the training and the application (extrapolation/generalization) domain (i.e., "domain shift") that are especially relevant for geospatial data such as satellite data (Kluger et al. 2021). The two shifts are shifts in the "labels" distribution (e.g., the proportion of crop types), and in the features/covariates used to predict the target variable of interest (e.g., the same crop types may exhibit different satellite-measured spectral-temporal signature due to variations in climate regimes, weather, or farm management practices). In turn, the model transferability, and thus the reliability of the mapping data products, is influenced by the model design (including data normalization procedures), evaluation objective, and the employed accuracy assessment procedure (Rolf 2023, 2024).

This paper contributes an accessible introduction to using satellite data for research in agricultural and environmental economics, complementing related introductions of Donaldson and Storeygard (2016), Jain (2020), and Burke et al. (2021). We particularly focus on agri-environmental applications such as studies involving crop yields, agricultural pollution, land degradation, and agricultural technology and innovation. Our main contribution is that we not only cover a large number of example studies showcasing what satellite data can be used for, and generally discuss common pitfalls and potential remedies, but in particular, in the supporting information we provide detailed technical explanations and instructions, and we provide practice data and code online. Thus, we go beyond providing a broad overview of the topic, giving researchers the knowledge and tools to incorporate satellite data in their research.

In the next section, we begin with the foundations of satellite measurements, including a selected overview on popular satellite platforms such as Sentinel and MODIS (Section 2). We then go through many examples of satellite data applications in agricultural and environmental economics, to showcase how researchers have recently used satellite data (Section 3). We then discuss potential pitfalls and remedies (Section 4) and conclude (Section 5). In the supporting information, we explain common workflows, how to actually construct various variables, and what skills and resources are typically required. On GitHub, we provide links to data and codes[1].

2 | Foundations

Here we look at selected satellite platforms with sensors at spectral and spatial resolutions that are relevant for agriculture. We pay specific attention to free and open-access data from both Sentinel and MODIS which everyone can access and use without proprietary constraints. We pay more attention to these because of their differences in spatial and temporal resolutions with Sentinel having higher spatial resolution but relatively lower temporal resolution while MODIS has higher temporal resolution but lower spatial resolution. There are also other distinct advantages and drawbacks of these and other platforms. Below, we discuss the Sentinel and Landsat platforms (Section 2.1), the MODIS platform (Section 2.2), further data (Section 2.3), what different satellites directly measure (signatures) (Section 2.4), and evolving advances in remote sensing for agriculture (Section 2.5).

2.1 | Sentinel and Landsat

Sentinel is a series of missions for earth observation that were developed by the European Space Agency (ESA) in a collaborative project with the European Commission as part of the European Union's Copernicus program (ESA 2024). It aims at providing timely and reliable information for monitoring and managing the environment, climate change, and civil security. There are already six Sentinel missions designed for specific use cases depending on the specifications of their sensors and orbital alignment. Here we briefly describe data from Sentinel-1 and Sentinel-2, as well as Landsat satellites, all of which are specifically designed for land monitoring purposes.

Sentinel-1: This is equipped with a C-band Synthetic Aperture Radar (SAR) instrument that enables it to monitor the earth surface irrespective of weather conditions since 2014. It can penetrate clouds, a major problem for optical sensors, and is thus primarily preferred in regions of high cloud cover, detecting land cover changes, ground motion, and emergency response strategies during natural disasters like floods (Kumar et al. 2022). Sentinel-1 has three spatial resolutions (10, 25, and 40 m). The scenes come pre-corrected for thermal noise, radiometric calibration, and terrain, normally achieved using the 30 m Shuttle Radar Topography Mission (SRTM 30) product.

Sentinel-2: This has a multispectral imaging instrument with the ability to capture very high resolution (10 m) optical imagery since 2017. It is specifically useful for monitoring agricultural lands, land cover, and other environmental changes. The revisit time for this satellite is 10 days while the whole constellation has a shorter revisit period of 5 days.

Landsat: Although the Sentinel missions started relatively recently (after 2013), *Landsat* missions provide high spatial resolution (30 m) data continuity spanning over half a century with Landsat 5 (March 1984 to May 2012), Landsat 7 (July 1999 to April 2022), Landsat 8 (April 2013 to present), and Landsat 9 (since October 2021). Landsat multispectral optical sensors (e.g., the Operational Land Imager instrument on board the Landsat 8 platform) are similar to the Multispectral Imager on board the Sentinel-2 (however, their combined use requires careful harmonization (Claverie et al. 2018)). Although Sentinel-2 samples the so-called "red edge" spectral region which is particularly useful for vegetation characterization, Landsat also carries a thermal infrared sensor that also aids in better detection of clouds and shadows (such as those provided in the standard quality assurance/control layer that accompanies the data products, e.g., the highest-calibrated Landsat Collection 2 Level 2 Science Products). Landsat data have been the workhorse for generating various types of land-based thematic information, such as land cover, land cover change, and vegetation condition (e.g., vegetation indices) (for a review of various essential and aspirational large-scale data products, see e.g., Radeloff et al. 2024). With two Landsat satellites in orbit most of the time, image acquisitions are provided every 8 days.

2.2 | MODIS

MODIS is a sensor aboard Terra and Aqua satellites designed for monitoring land and water, respectively (NASA 2024). The sensor was launched on Terra satellite in 1999 and on Aqua in 2002. The dual placement of the sensor allows for coverage across the diurnal cycle. There are about 40 data products that are generated by MODIS including land cover classification, net primary productivity (NPP), chlorophyll fluorescence, leaf area index, fire radiative power, and atmospheric aerosols among others. These can be useful to agriculture in various ways, for instance, photosynthetically active radiation and chlorophyll fluorescence products can inform the vigor of crops in the field. The temporal resolution of the sensor is 1–2 days and gathers images at 36 different spectral bands. The data gathered by the sensors are useful for global monitoring for changes across land water spaces. The images have a swath of about 2330 km cross track at 250 m (bands 1 and 2), 500 m (bands 3–7), and 1000 m (bands 8–36) spatial resolutions. Although the spatial resolutions are quite coarse, compared to Landsat or Sentinel, they are very useful for monitoring environmental changes at regional or global scales. These are especially useful where more frequent coverages are crucial such as changes in burnt area in case of wildfires. Generally, all the aspects of land that can be monitored by Sentinel can also be monitored by MODIS more frequently but at a coarser spatial resolution. Terra and Aqua satellites are on their way to retirement, and the subsequent data continuity is provided by the Visible Infrared Imaging Radiometer Suite (VIIRS) instruments aboard the Suomi National Polar-orbiting Partnership satellite (launched in 2011), NOAA-20 (launched in 2017) and NOAA-21 (launched in 2022)[2].

2.3 | Further Data

For some use cases, the "standard" data provided by Sentinel, Landsat, or MODIS is not sufficient, and for example, higher resolution, or a different type of measurement is required.

Planet Inc.'s PlanetScope constellation of nanosatellites, for example, first launched in 2013, provides very high spatial and temporal resolution data compared to Landsat and Sentinel, with 3-m resolution and daily revisit capability. Some of the data are freely available for research, for example, the pan-tropical monthly basemaps through Norway's International Climate & Forests Initiative (NICFI) program[3]. The German DLR Space Agency EnMAP (Environmental Mapping and Analysis Program) mission, launched in 2022, provides hyperspectral data (available by request[4]) with 242 spectral bands at 30-m resolution. The NASA Global Ecosystem Dynamics Investigation (GEDI) mission[5], launched in 2018 on board the International Space Station, which uses a (waveform) lidar sensor, and directly measures height and other vertical (three-dimensional) structural metrics with a 25-m footprint along the sampled ground transects. Although primarily designed for forest structure and biomass assessment, the GEDI data have also proven useful for crop type mapping based on crop height (Tommaso et al. 2021). NASA's Landsat Next, expected to launch in 2030–2031, will feature a resolution of 10–20 m and 26 spectral bands (superspectral)[6]. The ESA's FLuorescence EXplorer (FLEX), expected to be launched in 2025, will provide the most direct measurements of photosynthetic activity, at 300-m resolution.

2.4 | Remotely Sensed Signatures and Derived Indices

The primary satellite observable is referred to as the *spectral* signature, which is the reflectance of the earth surface in discrete wavelength bands (blue, green, red, near-infrared [NIR], shortwave-infrared [SWIR] domains) which conveys diagnostic information about the properties of earth's surface cover (Atzberger 2013; Weiss et al. 2019).

Mapping land cover, such as the extent of cropland, is based on differences in the remotely sensed *spectral* signatures between land cover types. The *temporal* signature captures different phenological characteristics, such as distinct intra-annual temporal developments associated, for example, with plant growth cycles.

Going beyond the qualitative spectral-temporal differences between land cover types (such as cropland vs. non-cropland, or different crop types, e.g.), and to a lesser extent, between crop types, some primary variables that can be physically retrieved from remotely sensed radiometric measurements include: (1) plant density, leaf area, green cover, leaf biochemical content, leaf orientation, canopy height, the fraction of absorbed photosynthetically active radiation, and albedo; (2) land surface temperature (vegetation/soil) and thus plant water in the emitted thermal domain; and (3) soil moisture and surface roughness in the microwave domain (Homolová et al. 2013; Weiss et al. 2019).

The satellite observable canopy optical reflectance (or radar backscattering) contains the compound (aggregate) effect of these leaf/canopy biophysical and biochemical properties, which influence is wavelength-dependent (their optical-reactivity, or absorption features, occur in certain wavelengths). In practical terms, then, whether for example, certain farming practices or outcomes can be detected by satellites depends on whether such practices present soil/plant diagnostic features that belong to the above state variables. Even if that is the case, the challenge is, however, to extract (isolate) from the remotely sensed signal, parts of the signal that uniquely express the variations in the state variable of interest. Spectrally, with broad waveband multispectral sensors in the current operational earth-observing satellites, measurement in a spectral channel (band) may contain absorption features of different leaf constituents (e.g., plant water, lignin, cellulose, and nitrogen-containing proteins in the shortwave infrared band) (Kokaly 2001). Spatially, the signal recorded for a given satellite image pixel contains contributions from the different surface materials (e.g., growing crops, soil, crop residues) that are present within that measurement footprint. Indeed, in the science of remote sensing, a variety of spectral vegetation indices (Main et al. 2011; Montero et al. 2023), or/and the combination of different sensors (optical, SAR, thermal) (Pinter et al. 2003), serve to maximize sensitivity of the remote sensing indicator/predictor to the cropping system variable of interest, whilst minimizing sensitivity to other sources of variations that contribute to the system's remotely sensed signal.

Vegetation indices are derived from combinations of two or more bands of the electromagnetic spectrum, for instance red, blue, green, and infra-red bands (see Figure 1 in the introduction). Using different combinations and calibrations, these signals can be converted to a range of different indices that can be used to measure a range of variables, such as crop yields, irrigation, forest degradation, and to delineate distinct features such as water bodies from cropland, among others.

One of the most widely utilized vegetation indices in agriculture is the Normalized Difference Vegetation Index (NDVI). NDVI quantifies the health of green vegetation in an area by measuring the difference between the NIR and red bands of the electromagnetic spectrum. It therefore serves as a reliable indicator of vegetation vigor, biomass production, and photosynthetic activity that could be difficult to detect from a single band. By analyzing NDVI values obtained from satellite imagery, farmers can assess the spatial variability of crop health within their fields, identify areas of stress or nutrient deficiency, and implement targeted interventions such as irrigation, fertilization, or pest control, among others.

In addition to NDVI, the Enhanced Vegetation Index (EVI) and Soil Adjusted Vegetation Index (SAVI) are indispensable alternatives in agricultural monitoring. EVI, for instance, minimizes atmospheric influences and background noise, thereby providing more accurate assessments of vegetation dynamics in areas prone to atmospheric interference or soil reflectance variations. Similarly, SAVI adjusts for soil brightness, making it particularly useful in arid or semi-arid regions where soil background can significantly affect vegetation indices' accuracy.

Different vegetation indices have been formulated for different applications. For modeling crop yields, for example, Burke and Lobell (2017) use the NDVI, the Green Chlorophyll Vegetation Index (GCVI), and the EVI.

The Land Surface Water Index along with NDVI and land surface temperature has been used to identify irrigated fields (Massari et al. 2021). The Normalized Difference Tillage Index has been used to differentiate crop residues from bare soil, and thus detect soil tillage practices (Zheng et al. 2014). Here, thanks to the ease for satellite data access and contemporary computing capability, researchers have the flexibility to compute different satellite indicators like vegetation indices if not readily available and test the different indices in their application.

2.5 | Evolving Advances in Remote Sensing

Improvements in artificial intelligence especially, in computer vision, are further advancing the limits of what we can achieve with remotely sensed data. Supervised machine learning techniques, for instance, rely on large amounts of training samples to calibrate models that can be used with some level of uncertainty to predict on unseen data. Although this has found important usage in still images like detecting objects in photographs, the same techniques have been used successfully with spatially explicit remotely sensed data. For instance, mapping the extent of cocoa plantations in Ghana and Ivory Coast (Kalischek et al. 2023), crop classification (Teixeira et al. 2023), oil palm in (Zortea et al. 2018; Dalagnol et al. 2022), and detection of forest degradation (Dalagnol et al. 2023) among many others. These techniques are cost effective and useful especially in areas where observation data are inadequate. For instance, the cocoa plantation mapping study by Kalischek et al. (2023), showed not only the extent of cocoa plantations in both countries, but also how much the plantations have contributed to forest loss.

Although these were national-level investigations, the advances can be upscaled to global-level investigations. For instance, they can help in detection of how much of the crop such as coffee or tea is coming from deforested land across the globe. Such findings fit well into the enactment of such policies as the European Union Deforestation Regulation when such crops as coffee farms are mapped globally. In addition, the techniques are going beyond the need for a lot of annotated data in building the predictive models toward reliance on foundational models to self-learn and map the features of interest. Such self-learning models have shown good results in agriculture too (Li et al. 2024; Sornapudi and Singh 2024). The future of leveraging AI and remote sensing data holds great potential for many agricultural challenges across the globe.

3 | Applications

In this section, we discuss research using satellite data to measure outcomes, treatments, for causal identification, to test assumptions, and for practical applications.

3.1 | Using Satellite Data to Measure Outcomes

Covered here are crop yields, cropland areas, rural poverty and development, land degradation and improvement, and agricultural pollution.

3.1.1 | Crop Yields

A variable of major research and policy relevance is crop yields. As an alternative to the use of satellite measurements, one can measure crop yields on the ground, ask farmers to report them, or use official statistics, such as those provided by the FAO (2024a). When relying on ground measurements or farmer reports, the data are usually patchy and commonly available for selected farms. Official statistics on the other hand, are only available at highly aggregated levels such as national. Satellite sensors provide data that are global but also comparably high resolution and high frequency, wall-to-wall crop yield measurements. This can be based on a vegetation index, such as the NDVI or the EVI (NASA LP DAAC 2024a), or a derived product, such as NPP (NASA LP DAAC 2024b), measured on global croplands, as for example, identified by Potapov et al. (2022). Such measurement is based on established correlations between biomass and crop yields. Analysis of the commonly reported results in percentage terms, for example, a policy is estimated to have increased crop yields by 10% (based on a 10% increase in satellite-measured biomass). More exact—but also more computationally and technically demanding—satellite observations can be combined with crop models, to produce actual field-scale yield estimates for different crops (Khaki et al. 2021). A particularly interesting approach is SCYM (which stands for "a scalable satellite-based crop yield mapper"), as developed by Lobell et al. (2015). This generic algorithm, implemented with Landsat data in Google Earth Engine, is based on two steps. First, regionally parameterized crop models are used to statistically predict yields from crop phenology and climate covariates. Second, to generate yield estimates for each pixel and crop, the models from step one are applied to satellite imagery and gridded climate datasets based on crop-type maps.

An illustrative application of this is Deines et al. (2019) who estimate the impact of conservation tillage on crop yields. A map of tillage practices is provided by Azzari et al. (2019), who use a random forest classifier trained on ground data from 5866 fields in the region. To quantify crop yields (maize and soy), the SCYM of Lobell et al. (2015) is used[7], and for inference, a causal forest algorithm is used. On average, they find a small positive effect.

An example for the approach based on measured biomass on cropland is the study of Wuepper, Wang et al. (2023), who rely on the EVI. They are interested in how crop yields change in response to countries' institutional changes and they measure crop yields globally as the annual maximum[8] of the EVI on 1 km^2 grid-cells identified as cropland over 20 years[9]. They find that 10% improved institutions lead to 2.2% higher crop yields globally.

Strobl and Strobl (2011) are interested in the impact of large dams in Africa, and they measure crop yield with the NPP on crop fields over time. NPP measures biomass production in terms of grams of carbon per m^2. This can be converted into kilocalories, and hence to nutritional value. They estimate that upstream dams have on average provided up to 12% of the daily minimum per capita kilocalorie demand in downstream communities and increased agricultural production by 1%.

Asher et al. (2023) estimate the long-run development impact of India's irrigation canals. Their measure of crop yield is again based on the EVI and they find a larger crop yield effect in the dry season (+7.1%) and a smaller effect in the rainy season (+1.7%). The main long-run effect is a population increase around irrigated villages, advancing structural change.

To estimate the effect of Russia's Ukraine invasion on agricultural production, Deininger et al. (2023) use 4 years of panel data based on satellite imagery and extensive ground truth data. Using machine learning techniques, they identify both location and extent of all conflict-related damages to crops and fields, and both extent of area grown with crops and, for cereals fields, peak NDVI as crop yield measure. As a final step, they convert NDVI into actual cereal yields, based on available statistical data, measured in tons per hectare.

3.1.2 | Cropland Area

Complementary to the measurement of crop yields on current cropland is the identification of cropland changes, that is, expansion and abandonment. In the study of Wuepper, Wang et al. (2023), the global land cover classifications from Friedl and Sulla-Menashe (2019) are used to estimate whether institutional changes lead to changes in the extent of countries' cropland area. The data provides 17 different land cover classes, which include different types of croplands, grasslands, and forests. Wuepper, Wang et al. (2023) find that countries' cropland area tends to expand in response to increased economic freedom, mostly at the expense of forests.

Olsen et al. (2021) focus specifically on the impact of conflict-driven cropland abandonment on food insecurity in South Sudan. They combine Sentinel-1, Sentinel-2, Landsat-8, and MODIS imagery, as well as a Copernicus land-cover product, and use a random forest algorithm to identify all abandoned croplands. They found that the conflict caused 16% of croplands to be abandoned between 2016 and 2018.

Finally, Sukhtankar (2016) is an example for another related outcome: Identifying the area planted with a specific crop (sugarcane). Sukhtankar (2016) empirically investigates whether privately owned sugar mills affect farmers' crop choices and welfare differently than cooperative-owned and public mills, using a Regression Discontinuity Design. The satellite imagery showing sugarcane production comes from the National Remote Sensing Centre of India. It is found that private ownership increases sugarcane production and farm incomes.

3.1.3 | Rural Poverty and Development

Huang et al. (2021) are interested in the impact of an anti-poverty program in Rural Kenya. To measure poverty, they combine satellite data with deep learning. What they catch are visible changes in housing quality that reflect improving household welfare. The alternative to their measurement approach would have been repeated in-person visits for interviews with a large number of people who can be difficult to reach. Huang et al. (2021) re-analyze a program for which such interviews exist too, and are able to show that they recover the same information. Whereas at the national level, night-lights data can already capture economic change, particularly in rural areas this does not work well, because there is often too little night light. Daytime imagery, however, shows what materials roofs are made of, and this in turn, is a more reliable proxy for economic change, as Huang et al. (2021) show. Using their approach, they find the same, positive treatment effect of the program as does the comparison evaluation based on extensive survey work—at a much lower cost.

Ratledge et al. (2022) develop this further and estimate the causal effect of electricity access on poverty in rural Uganda. They solve several issues, such as first, making sure that their modeling of the outcome (poverty) is independent from their treatment (electrification). Would they have used night-lights, for example, to predict poverty, they would have "built-in" their treatment effect into their outcome data. Second, they address the issue of attenuation bias that is often a feature of modelled data that contains less variance than actual outcome data.

Smith (2023) uses satellite data to study land values. Specifically, he is interested in the long-run effect of land concentration on the American frontier. To construct the land use values, he uses land use data from USDA (2024) and agricultural productivity data from FAO (2024b). He then finds that historic land concentration leads to an increased reliance on tenant farming, lower investments, and lower land values that persist today.

3.1.4 | Land Degradation and Improvement

Ali et al. (2020) use Landsat 7 imagery over Ethiopia to construct pixel-level annual and seasonal averages of NDVI, SAVI, and Land Surface Water Index (LSWI) to evaluate the performance of soil and water conservation measures. They find large treatment effects which they can also cross-verify with ground measures of river sediment loads.

Focusing on pastures in China, Hou et al. (2023) examine the effect of a land tenure reform on grassland quality, as measured by NDVI. According to their estimates, the combination of privatization of land use rights and security protection improved grassland conditions by 3%.

Another outcome of major policy relevance is land-cover changes and particularly forest changes (deforestation, forest degradation, forest restoration). Satellite data combined with machine learning provides globally consistent forest measurements in high resolution and a long period of time, allowing policy evaluations based on difference-in-differences, differences in discontinuities, and similar. An exemplary study that uses such data is that of Groom et al. (2022). They evaluate Indonesia's moratorium on forest concessions, using difference-in-differences with the forest change dataset provided by Hansen et al. (2013). They found a small, positive effect on forest cover and that the moratorium was quite cost-effective.

Wuepper et al. (2024) globally evaluate the effectiveness of all major public policies that countries implemented from 2001 to 2017. They use differences in discontinuities. They consider deforestation, forest degradation and improvement, and net primary production, at a spatial resolution of 1 km^2. Like Groom et al. (2022), they use the data of Hansen et al. (2013) to measure tree cover change, and changes in forest conditions are quantified with the EVI, which measures the health of forests based on their color (NASA LP DAAC 2024a), and NPP, which approximates how much carbon the vegetation accumulates (NASA LP DAAC 2024b). Wuepper et al. (2024) estimate that countries' public policies reduced global tree cover loss by 4 percentage points—but with large between-country differences, mostly explained by policy stringency and enforcement.

3.1.5 | Agricultural Pollution

Also, agricultural air and water pollution can be derived from satellite measurements, enabling research, for example, on potential policy levers to mitigate these issues. Agricultural air pollution, for example, is a major human health hazard. Nian (2023) uses high-resolution satellite data to measure agricultural fires at a resolution of 1 km^2 for all of China. The data are provided by China's Ministry of Ecology and Environment (MEE) which collects daily straw burning data from the MODIS of NASA's Satellites TERRA and AQUA. These satellites overpass China four times a day and a fire point is identified when a thermal anomaly is detected within a pixel using an algorithm that exploits the mid-infrared radiation from fires. Nian (2023) then estimates and compares the effectiveness of two different mitigation levers: economic incentives and regulation. He estimates that demand from new biomass power plants reduced agricultural fires by 30% but a ban around airports was ineffective.

Tang et al. (2023) are interested in the effect of intensive agriculture on water quality in China and exploit the fact that nutrient pollution in water creates algae blooms that are detectable on satellite imagery. The data on algae blooms is provided by Wang et al. (2023) who developed an algorithm to automatically detect algal blooms on MODIS Aqua images. Tang et al. (2023) find that a 1% increase in intensively farmed cropland leads to a 0.5 percent increase in the size of algae blooms and a 0.24% increase in their duration.

In India, Jack et al. (2022) use high-resolution satellite imagery from Planet Labs (2024) and Sentinel-2 to identify residue burning on crop fields. Combining these two different measures is helpful, as the Planet Labs (2024) data are measured more frequently (roughly every 2–3 days), so less likely to miss a burning event, whereas the Sentinel-2 data are collected less frequently (every week to 10 days) but provides mid-infrared measurements, which helps to separate burned and unburned plots. Jack et al. (2022) then combine monitoring data and spot checks to train a random forest model to categorize crop fields into burned and not burned. This is used in an analysis of a randomized control trial in which farmers are being paid not to burn their crop residues. To address liquidity constraints and farmer distrust, a portion of the money was paid unconditionally upfront. They find that this strategy reduces straw burning by 10 percentage points, in contrast to the standard contract, which has no effect.

3.2 | Using Satellite Data to Measure Explanatory Variables

Covered here are environmental conditions, agricultural pollution, and farming structures and practices.

3.2.1 | Environmental Conditions

Variables that have an especially long history of being measured with satellite data are measures of environmental conditions. For example, to correctly predict climate change impacts on global agricultural productivity, it is important to understand the impact of water supply on global crop yields and its relation to temperature stress. To answer this research question, Proctor et al. (2022) use satellite-measured soil moisture data measured by the ESA (Dorigo et al. 2017; Gruber et al. 2019). This data provides surface soil moisture measures up to a depth of approximately 5 cm at daily 0.25°×0.25° resolution. Other used data include crop yields from FAO (2024a) and temperature and rainfall data from NOAA (2024). In another study, Proctor et al. (2018) studied the potential effect of geoengineering on global crop yields, using natural volcanic eruptions as a natural experiment. Their main satellite data are measures of stratospheric aerosol optical depth and cloud fraction data (Sato et al. 1993; World Radiation Data Centre 2015).

Anderson et al. (2021) combine a range of satellite-measured variables such as soil moisture (from the Global Land Evaporation Amsterdam Model), precipitation (from the Climate Hazards group Infrared Precipitation with Stations), and the EVI (from the MODIS satellite MOD13A1 V6 product) with data on locusts, conflicts, and food insecurity. They then quantify the roles of conflict, drought, and locusts on food insecurity in Sub-Saharan Africa. One of their findings is that violent conflict exacerbated drought-related food insecurity.

Malacarne and Paul (2022) examine the impact of adopting improved management practices on food security and nutritional diversity in Tanzania and Mozambique—in general, and in the context of drought resilience. To measure household-specific drought conditions, they alternatively use cumulative rainfall from Funk et al. (2015) and the Global Vegetation Health Index (VHI) from NOAA (2018). With both they find that improved management practices lead to better nutritional outcomes, but much less so under drought conditions.

3.2.2 | Agricultural Pollution

He et al. (2020) use satellite data to detect agricultural straw burning in China (relying on the same data as Nian (2023), which we discuss above). He et al. (2020) are interested in the health impact of straw burning and find a considerable increase in deaths from cardiorespiratory diseases.

Another angle to the effect of air pollution is shown by Proctor (2021), who globally estimates the effect of changes in sunlight due to changes in clouds on crop productivity. He finds that average maize and soy yields have been reduced by 1% and 0.1% due to air pollution and could further decrease by 1.8% and 0.4% under further climate change. The main data source is the remotely sensed cloud data of Rossow et al. (2016).

In contrast, Taylor and Schlenker (2021) estimate how much CO_2 fertilization has contributed to USA agricultural productivity increases over time. The data comes from the NASA GES DISC (2024) repository—specifically, the CO_2 measurements from NASA's Orbiting Carbon Observatory-2 (OCO-2) satellite. For identification, they then exploit wind patterns, year-to-year anomalies from county-specific trends, and the spatial first-differences approach of Druckenmiller and Hsiang (2018).

Skidmore et al. (2023) estimate the effect of pesticide pollution on the incidence of childhood cancer in Brazil, focusing on the gradual spread of high-intensity soy production and exploiting that pesticide pollution always moves downstream and never upstream within a watershed. To do so, they use remotely sensed land cover maps from Mapbiomas (2023), which map soy, sugarcane, all other temporary crops, pasture, mining, and remaining natural vegetation, and they use remotely sensed watershed data from Instituto Brasileiro de Geografia e Estatística (2023). Skidmore et al. (2023) indeed find a robust connection between upstream agricultural intensification relying on toxic pesticides and downstream cancer incidences.

3.2.3 | Farming Structures and Practices

Ali et al. (2018) estimate the costs and benefits of land fragmentation in Rwanda and measure their treatment variable, land fragmentation, as least-cost walking distance between homestead and parcels, using the global topography layer provided by the ASTER Science Team (2018). They find that land fragmentation negatively affects yield but also reduces yield variability, so it is unclear whether reducing land fragmentation would actually be a real improvement for Rwanda's farmers.

Deines et al. (2023) use satellite data to estimate the effect of cover crop adoption on maize and soybean yields for over 90,000 fields in the USA between 2019 and 2020. Their identification of cover crop adoption is based on daily measures of the greenness of fields (using a fusion of Landsat and Modis data, with dynamic, phenology-based thresholds for the identification of cover cropping (Zhou et al. 2022). Using causal forests analysis, they estimate an average yield loss of 5.5% for maize and 3.5% for soy.

Chen et al. (2023) also estimate the impact of no-till adoption, but they focus on agricultural land values instead of yields. Their no-till adoption is measured by satellite too, but in a different way. Their measurement uses the percentage share of crop residues that high-resolution satellite imagery shows. This is used to classify cropland into categories such as no-till (more than 50% crop residues), or reduced tillage (less than 50% residues, but more than 15%), and so forth (Hagen et al. 2020). Chen et al. (2023) estimate that no-till adoption significantly increases land values in the US.

3.3 | Satellite Data for Causal Identification

Achieving causal identification is regularly among the main challenges in applied economics fields like agricultural and environmental economics (Henningsen et al. 2024). In many data sets, it is not obvious whether there exists a feasible source of exogenous variation to make an estimated relationship causal. Satellite data frequently provides such a source of exogenous variation. Other times, it assists to test the identifying assumptions.

3.3.1 | Instrumental Variables

Duflo and Pande (2007) study the agricultural impact of irrigation dams in India. Clearly, the mere correlation between the regional number of dams and agricultural productivity has no causal interpretation because regions with more dams differ from regions with fewer dams in many dimensions (e.g., agricultural potential). What is available for causal identification here is an instrumental variable: The natural suitability of a river for the construction of a dam. The river gradient can be too high or too low for dam construction, and this is orthogonal to the confounding factors one might worry about. This strategy of exploiting arguably random variation in geography and the natural environment as instrumental variables is popular. Macchiavello and Morjaria (2020) estimate the effect of competition among Rwandan coffee mills on the performance of relational contracts and exploit geographic variation in the regional suitability to build a coffee mill. Rubio-Ramos (2023) estimates the effect of violence on social capital in the context of fluctuating coca production in Colombia. Here, the instrumental variable is an interaction between coca-market shocks and a suitability score for coca production, based on ecological conditions to grow coca, derived from satellite measurements.

A related strategy exploits satellite-measured weather conditions to construct an instrumental variable. One example is the study of Crost and Felter (2019). They are interested in the effect of export crop revenue on inner-country conflict and they specifically focus on the case of banana exports in the Philippines. Here, insurgent groups use banana export revenues to finance their operations, but the issue is that the generated export revenues could potentially be endogenous, so they need exogenous shifts in banana prices. This is provided by random weather variations in Ecuador, the world's leading banana exporter. When growing conditions in Ecuador are bad, the global banana price goes up, increasing revenues in the Philippines.

Axbard (2016) studies the effect of fishermen's income on sea piracy. As an instrumental variable for fishermen's income, he uses satellite-measured, exogenous changes in environmental fishing conditions. Satellite data provides chlorophyll-a concentrations and sea surface temperatures of the ocean. The data comes from the NASA Modis Aqua satellite (Acker and Leptoukh 2007). The constructed instrumental variable then measures fishing conditions in each month.

3.3.2 | Regression Discontinuity Designs

Satellite-measured geographical and environmental variation is equally helpful to identify causality in the context of regression discontinuity designs[10]. An example is the study of Jones et al. (2022), in which they estimate the agricultural impacts of hillside irrigation systems in Rwanda. A naïve comparison of irrigated and non-irrigated farms and fields would be misleading, as there are other relevant differences. However, the studied irrigation systems use gravity to transport water to the fields, which can be exploited to set up a convincing regression discontinuity design, with the main irrigation channel marking the cutoff, and then there is a downhill side that has access to irrigation, and an uphill side that does not. The discontinuity that arises between these two sides identifies the causal impact of irrigation. They find a large profit boost but limited adoption because of binding local labor market constraints.

3.3.3 | Quasi-Random Exposure

The literature on agricultural pollution has the advantage that studies can exploit the directionality of the pollution, when the pollution is transported by wind or water currents. Sometimes, it can even be exploited that there are random deviations, for example, wind directions can abruptly change. A first example study is that of Ferguson and Govaerts (2024), who study the impact of adopting conservation agriculture in Mexico relying on various satellite data sources, measuring, among others, air quality, and random wind direction changes. The latter is their source of exogenous variation. They combine this with complementary data on the roll-out of relevant extension services, as well as agricultural profits, and infant deaths in down-wind locations. For their study, the important advantage of using satellite data is that they can rely on measurements from exactly the right locations (up-wind vs. down-wind) and timing (there is strong seasonality in agricultural burning). At the global level, Pullabhotla et al. (2023) estimate the burden of biomass fires on infant mortality, using georeferenced data on more than 2 million births matched to satellite-derived burned area exposure. Also in this study, the source of exogenous variation in exposure to agricultural air pollution is random wind direction changes. As demonstrated by Rangel and Vogl (2019) in Brazil, combining high-frequency changes in wind directions and fire locations is key in this literature, because agricultural activities, fires, and economic outcomes are so intertwined, that the pure panel variation in agricultural burnings alone is not sufficient to recover actual causal effects.

3.3.4 | Counterfactual Modeling

One can also explicitly model the counterfactual to an observed outcome for causal identification. For example, Wuepper et al. (2021) quantify global anthropogenic land degradation. Specifically, Wuepper et al. (2021) focus on four land degradation dimensions: soil erosion, deforestation, and both above and below-ground carbon. For each, they show two maps: One map of the current status, and one natural/historic benchmark. The difference between the two quantifies anthropogenic land degradation. To model the counterfactual scenario without anthropogenic land degradation, a key input is the global land cover mix without humans. This is provided by Bastin et al. (2019), who use satellite imagery from protected areas all around the world to train a random forest algorithm whose environmental characteristics are predictive of the natural vegetation seen in these protected areas. They then used this algorithm to "fill in the gaps" between the protected areas, to create a global land cover layer without humans.

3.4 | Cross Validations and Assumptions Testing

Another useful application of satellite data are cross-validations of variables and the creation of "placebo-variables" that can be used to falsify assumptions.

3.4.1 | Cross-Validation of Alternative Measurements

It is common to rely on farmer self-reported data in agricultural economics, for example, to measure field and farm sizes, crop yields, labor use, and so forth—even though it is well known that these self-reports are affected by all sorts of measurement errors, including systematic biases (Abay et al. 2019; Gourlay et al. 2019); and from other outcome variable we know too that available measures can be unreliable, e.g., we know that officially reported deforestation rates can be biased downward when illegal deforestation is purposefully hidden, especially when the government itself is involved (Balboni et al. 2021; Burgess et al. 2012), and democracies report more reliable economic performance measures than dictatorships, with the latter showing an upward bias (Martinez 2022).

Having an alternative, satellite-derived measure can be used to understand the reliability of the reported measure of a variable. In addition, this even allows to disentangle misreporting and misperception, which is useful because sometimes misperception affects behavior in a way that misreporting does not (Abay et al. 2021). Lobell et al. (2020) demonstrate how well crop yields can be captured using satellite data. Thus, when crop yields are an important variable in a study and they are measured not with full-plot crop cuts but, for example, based on farmer reports or sub-plot crop cuts, or any other imperfect crop yield measure, a comparison—and possibly combination or even exchange- of the measure with a satellite-derived measure can improve the reliability of the analysis.

3.4.2 | Testing Identifying Assumptions

As an example for a satellite data-enabled test of an identifying assumption, Wuepper et al. (2024) use a spatial difference-in-discontinuities design to estimate the global impact of public policies on forest conservation and they use satellite data to show that their identified discontinuities in forest conditions at the international border are not simply the result of discontinuities in forest potential. They use the data of Bastin et al. (2019), who in turn use photo-interpretations of high-resolution satellite imagery showing tree cover in protected areas, which are then used to train a machine learning algorithm to produce a global map of natural tree cover potential.

In their study on the effect of countries on the global rate of soil erosion, Wuepper et al. (2020) use a similar approach but model their counterfactual even more, going from natural tree cover globally to natural land cover more generally and converting this to a natural rate of soil erosion globally at a spatial resolution of 1 km^2. They show that globally, there would be no discontinuity in soil erosion at current international borders on average, so the actual discontinuity is caused by the countries.

Moreover, satellite measured exogenous, environmental variables can also directly be used in placebo tests without any additional modeling of a specific counterfactual. This is common practice especially in regression discontinuity designs (Wuepper and Finger 2023). For example, Burgess et al. (2018) exploit deforestation discontinuities at Brazil's borders to estimate the effect of Brazil's forest policies. To test whether Brazil's border actually presents an exogenous treatment variable, they estimate whether there are discontinuities in the slope of the land and the distance to urban areas, water, and roads. They find no discontinuities in these exogenous variables, so conclude that the forest discontinuities must be purely politically caused.

3.5 | Satellite Data for Non-Causal Research

Satellite data are not only used in research that aims to identify causal effects, but it is also being used in research investigating its practical usefulness for extension services, insurance products, and other financial and information services. Moreover, satellite data have opened up new possibilities for descriptive research, especially at larger scales.

3.5.1 | Insurance

Boucher et al. (2024) explore the impact of providing drought-tolerant seeds and satellite-based index insurance for farmers in Tanzania and Mozambique. They find that combining these two complementary technologies reduces a good share of farmers' drought risk exposure. Nevertheless, inducing sustained uptake proved to be a challenge, as a share of farmers who did not experience a drought early enough dis-adopted these technologies again.

Vroege et al. (2021) demonstrate how freely available satellite data can be used to design an index insurance that effectively mitigates farmers' financial drought risk exposure. Using data from eastern Germany they also show that their insurance product based on satellite data outperforms a competing product based on meteorological measurements at ground stations.

3.5.2 | Credit

Möllmann et al. (2020) investigate whether remotely sensed vegetation health indices can predict agricultural credit risk in Madagascar. They indeed find this to be the case, which indicates that it is possible to reduce the default risk to rural banks and thereby make them expand credit access.

3.5.3 | Extension Services

A first example is the study of Jain et al. (2019), who demonstrate how to utilize high-resolution satellite data (from SkySat and Planet Labs) to identify which fields would benefit the most from improving agricultural practices. They show that the impact of an agricultural innovation could be doubled by targeting the fields with the most potential instead of a uniform treatment.

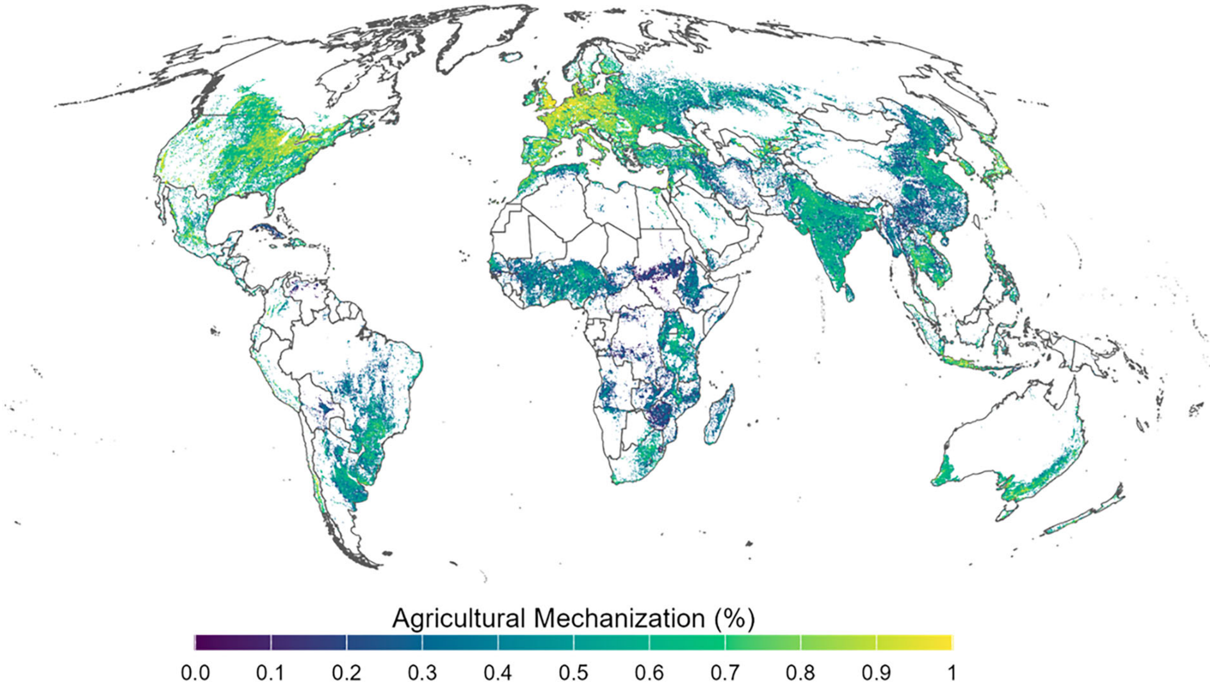


FIGURE 5 | Global Agricultural Mechanization, modelled using Satellite Data. For a long time, research and policymaking had to rely on outdated and mostly incomparable global data on agricultural mechanization rates of different countries and regions. Combining a range of data-sources and machine learning, it has become possible to create up-to-date, methodologically unified data that can be displayed in a table or a map. *Source:* Roman et al. (2024).

3.5.4 | Descriptive Research

Advances in the availability of satellite data and complementary machine learning tools are also reinvigorating and improving descriptive research. Often, this research is performed at large scales (even up to the global level) and the main product is a detailed map of a policy-relevant phenomenon, such as agricultural mechanization (Roman et al. 2024, Figure 5), human development (Sherman et al. 2023), or agricultural GDP (Ru et al. 2023).

4 | Pitfalls and Remedies

The main pitfalls we cover here are measurement error, missing accuracy assessments, and (currently) unobservable variables.

4.1 | Measurement Error

Measurement error in satellite-derived variables is ubiquitous (see Alix-Garcia and Millimet 2023; Proctor et al. 2023; Remelgado et al. 2024). Depending on whether the mis-measured variable is on the left or the right regression side and which kind of measurement error dominates (e.g., random or systematic, and if it is systematic, whether it is positive or negative), estimated effects might be exaggerated or attenuated (Proctor et al. 2023), and even coefficient sign flips are possible.

Classical measurement error is simply the result of imprecision, for example, caused by random clouds blocking the view of the satellite, or because the data has a lower resolution than the phenomenon under study. For example, a satellite measurement might have a resolution of 100 hectares (1 km^2) whereas the actual variation of interest happens on agricultural fields with an average size of 3 or 4 hectares.

Researchers are especially worried about systematic measurement error, that is, non-random measurement error. Systematic measurement error in satellite data can be caused by spatial and/or temporal inconsistencies in the data, which we separately discuss below, before turning to potential remedies.

Moreover, the more processed the initial satellite data, the higher is the risk that additional measurement errors have been introduced. First of all, predicted variables tend to vary less than the actual phenomenon they are supposed to reflect. This is because extreme values get systematically underestimated, causing mean reverting error (Proctor et al. 2023; Ratledge et al. 2022). Second, the predictor variable used to create a variable of interest might directly include or exclude the effect of interest. For example, nighttime lights are a popular predictor to produce high-resolution maps of economic development. However, in their study on the effect of rural electrification on economic development, Ratledge et al. (2022) cannot rely on nighttime lights to create their economic development variable, as nighttime-lights are basically an alternative measure for electricity access. The opposite mistake is being made when a variable is modeled in such a way that the effect of interest is explicitly excluded. This might happen in a study on the effect of sustainable farming practices on on-field biodiversity, if the available biodiversity measure is modelled biodiversity habitat quality, based on land cover types. If in this measure, biodiversity only varies between land-cover types and not within, no effect can be detected.

4.1.1 | Spatial Inconsistencies

An illustrative example for well-known spatial inconsistencies is the global forest loss data of Hansen et al. (2013). Besides all its strengths, the data also contains measurement error that systematically varies with topography, climate, cloud-cover, and type of deforestation (Alix-Garcia and Millimet 2023; Gordon et al. 2024; Pendrill et al. 2022). For example, in their evaluation of a forest conservation program in Mexico, Alix-Garcia and Millimet (2023) find that land owners' participation is correlated with terrain topography and cloud-cover which both affect the probability that forest loss is detected. Before the correction, this leads to a bias in estimated program effectiveness (see subsection 4.1.3 for their solution on how to fix this).

Spatial inconsistencies can also result from the spatial heterogeneity of the underlying processes on the ground being mapped, combined with the varying sensitivity of the calibrated algorithm or trained machine learning model used for detection. For example, improvements in the algorithms used in the Hansen et al. Global Forest Change (GFC) data products have enhanced the sensitivity of detection to smaller-scale tree cover loss. These improvements impact regions differently, such as increasing detection accuracy for smaller-scale deforestation in West and Central Africa and Southeast Asia, and selective logging in temperate forests of Europe and North America (Weisse and Potapov 2021). Similarly, spatial inconsistencies in cropland extent maps between large-scale industrial farming regions and smaller-scale smallholder farming areas are well-documented (Kerner et al. 2024). The map accuracy in different regions is also influenced by whether the calibration/training data adequately represent those regions (Meyer and Pebesma 2021, 2022; Rolf 2023). Finally, hybrid satellite-survey data products can exhibit spatial inconsistencies caused by varying spatial resolutions of the used survey data, that is, some data is more aggregated than others (Yu et al. 2020).

4.1.2 | Temporal Inconsistencies

Temporal inconsistencies can arise from technical changes in the satellite platform and sensors, from measurement interruptions, and from changes in the processing and interpretation algorithms applied to transform the raw satellite data into specific thematic information, and when data from different sensors is fused together.

In the first case, as a concrete example, while the subsequent Landsat missions have been designed with continuity in mind (similar spectral and spatial resolution), fusing data from the different Landsat satellites requires careful consideration. The scan line corrector failure in Landsat 7 has caused systematic missing data (22% data loss per scene) since May 2003. Before Landsat 7 (i.e., before 1999), the earlier Landsat missions did not have a systematic global data acquisition plan, hence resulting in very sparse data record before 2000. In 2012, the number of captured images was particularly low due to the decommissioning of Landsat 5 in 2011, and thus leaving only Landsat 7 acquiring images (typically two Landsat satellites are in operation at the same time) in the meantime before the launch of Landsat 8 in 2013. Differences in data density ultimately result in variations in the number and timing of clear-sky observations, introducing a source of variability in temporal composites (e.g., yearly means), or in the reconstruction of phenology and temporal dynamics of croplands.

In the second case, as developers of satellite data products improve their processing chain and interpretation algorithm (preprocessing e.g., cloud masking, or training data used in machine learning-based product, or expert rules integrating other satellite-based ancillary maps as they become available), temporal inconsistencies in the data products between subsequent updates (versions) can be expected. A notable example is the note for caution with regard to possible temporal inconsistencies in the GFC annual tree cover loss data products (Hansen et al. 2013)[11], which may have a better detection of small-scale tree cover loss after 2013 in some regions due to the improved data from Landsat 8, as well as enhanced detection particularly from 2015 onward due to improved algorithm (Breidenbach et al. 2022; Ceccherini et al. 2020, Ceccherini et al. 2021, Ceccherini et al. 2022; Palahí et al. 2021; Weisse and Potapov 2021).

In the third case, temporal inconsistency can also stem from the fusion of data from different satellite sensors. For example, while Landsat-8/9 and Sentinel-2 data have similar sensor spectral settings, their fusions require careful spatial (reconciling 10-20-m Sentinel-2 with 30-m Landsat-8/9 resolutions, image scenes co-registration) and spectral (bandpass adjustment) harmonization. Fortunately, end users can take advantage of the readily available Harmonized Landsat Sentinel-2 (HLS) data products (Claverie et al. 2018) which provide near-daily (2–3 days) observations at 30-m spatial resolution.

Beyond satellite-based data products, hybrid products (fusion of satellite, census, surveys, and models) are also often affected by temporal inconsistencies due to changes in input data used, that is, the underlying sub-national statistics, ancillary data (including satellite-based data such as cropland extent), or the downscaling/spatial allocation algorithm. For instance, the Spatial Production Allocation Model (SPAM) datasets—developed for the years 2000, 2005, 2010, 2017, and 2020 (corresponding to different release versions)—should not be directly compared across different years, as noted by the authors (Yu et al. 2020).

4.1.3 | Addressing Measurement Error Ex-Post and Ex-Ante

There are various ways to correct the different kinds of measurement error in different contexts: Analyses of binary outcomes such as pixel-level deforestation coded as yes or no are especially likely to be biased by systematic measurement error (because the measurement error is then always negatively correlated with the truth). If one has some knowledge about the source of the measurement error (e.g., it might be connected to topography or cloud cover), one can use the misclassification logit or scobit models proposed by Alix-Garcia and Millimet (2023). These model the measurement error as a function of the problematic covariates and off-the-shelf code is available for Stata[12]. An advantage of using either of these models to correct for measurement error is that the correction is ex-post, in the analysis stage, and does not require any change to the data itself. A limitation is that they only work for binary outcomes. Other approaches correct the measurement ex-ante, during the dataset construction, and they are more broadly applicable, as discussed below.

One example of an ex-ante correction measure is the augmented loss function of Ratledge et al. (2022), which is specifically set-up to correct for mean-reverting measurement error when modeling variables based on satellite data. Ratledge et al. (2022) add a penalty term to their loss function, which penalizes bias in each quintile of the distribution. Thus, instead of having a global loss function that prioritizes the mean of the distribution to minimize prediction error, this augmented loss function explicitly treats each part of the distribution as equally important. The code is available for R[13].

An especially general and versatile way to reduce bias from measurement error is multiple imputation (Proctor et al. 2023). This can be implemented with standard code in R, Stata, and Python[14]. The main requirement is that one has at least a small amount of ground truth data. As Proctor et al. (2023) demonstrate, not much of this calibration data is actually needed and it can come from locations somewhat far away. Fundamentally, the approach of Proctor et al. (2023) consists of two steps: First, the calibration data is used to estimate the structure of the measurement error present in the satellite data. Second, the estimated structure of the measurement error is used to correct parameter estimates and uncertainty measures in the subsequent regression analysis.

A final example of how one can mitigate measurement error-induced bias is the approach proposed by Gordon et al. (2024), based on adversarial debiasing. The original inspiration for adversarial debasing was the recognized problem outside of agricultural economics that machine learning predictions can be biased (e.g., discriminating against personal characteristics such as race or gender in a job or credit application). To solve this problem, adversarial debiasing was invented, which, like the approach of Proctor et al. (2023), consists of two steps: First, a standard prediction model attempts to minimize prediction error for the variable of interest (e.g., crop yield, soil erosion). However, non-standard, this first model has a loss function with a penalty that is informed by a second model. This second model—the adversary—is fed with the measurement errors from the first model and tries to predict the treatment status for each observation. The better the second model can predict each observation's treatment status, a larger penalty is added to the loss function of the first model. Thus, the approach of Gordon et al. (2024) aims to minimize prediction error while also uncorrelating errors from treatment status. An advantage of the adversarial debiasing approach—that it shares with the multiple imputation approach—is that there is no need to have any information about the source of the measurement bias. A drawback of the multiple imputation approach compared to the adversarial debiasing approach is that its effectiveness depends on the specified functional relationship between measurement error and the dependent and independent variables (essentially, non-calibration data is treated as missing at random, conditional on covariates). However, the adversarial debiasing approach is computationally quite demanding, must be specifically adapted for each individual variable, and there is not yet an off-the-shelf code available.

4.2 | Missing Accuracy Assessments

It is standard practice in geospatial publications to quantify the spatial accuracy of created maps. Why this is important is e.g., demonstrated by Estes et al. (2018) who show how the accuracy of cropland maps affects "downstream" errors in subsequent analyses, such as in the estimation of carbon stocks and crop yields. In contrast, quantifying the reliability of geospatial data is not common practice in applied economics. This is acceptable when this has previously been done, for example, for published datasets, there usually exist reliable accuracy assessments. An example is the extremely often used forest cover data of Hansen et al. (2013). This data has been used by economists more than 10.000 times by now and there is no need to replicate the initial accuracy assessment every time. However, when new maps/variables are being produced, validation and quantification of uncertainty are important. Especially the direct use of a vegetation index such as NDVI as a measure for for example, deforestation, or crop yield, or land cover change, without any validation makes it difficult to interpret subsequent analytical results.

For satellite-based, gridded datasets, the accuracy assessment can aim to summarize the accuracy (error) of the entire map into a single accuracy statistic (global accuracy, i.e., for the entire population of grid cells), or to provide a spatially explicit per grid cell information of error or uncertainty (local accuracy) (Meyer and Pebesma 2022). Although global accuracy indices, such as overall accuracy, user's accuracy, and producer's accuracy (Olofsson et al. 2014), provide useful summaries of the overall reliability of the mapping data products, they do not inform users about the reliability of the map in the local areas they may be interested in. In practice, geospatial data product providers employ various indicators to inform spatially explicit (per pixel) uncertainty of the model predictions, such as on ensemble-based prediction variance (e.g., Van Den Hoogen et al. 2019) and area of applicability (AOA) based on feature space similarity between training data locations and the model extrapolation areas (Meyer and Pebesma 2021, Ceccherini et al. 2022), among others (Singh et al. 2024).

In practice, map accuracy is computed either by using an existing dataset that is used for calibration and validation of the mapping model, or by collecting a new set of reference data not used in the model development. Strongly recommended is the latter (FAO 2016; Olofsson et al. 2014; Olofsson 2021) and the accuracy assessment sample should be a probability sample. This is especially feasible for target variables that can be reliably identified by visually interpreting satellite imagery. Crucially, the use of probability sample allows one to unbiasedly quantify the map accuracy and the error-adjusted areas of the mapped classes, along with the uncertainty (standard errors) of their estimates, based on sampling theory.

When collecting a new, probability sample of reference data is not feasible (and thus one should rely on existing reference data), the mapping model accuracy is typically estimated by randomly splitting the reference data into calibration (training) set and validation (test) set. Here, for the purpose of realistically assessing the map accuracy, the train-test reference data partitioning should resemble prediction situations that are encountered while predicting the whole geographic area of interest from the reference data. To achieve this, the splitting of the reference data can account for the geographic distances between the training and the test sample, known as spatial cross-validation (CV) procedure (Roberts et al. 2017; Ploton et al. 2020). Rolf (2023) suggests that the choice between spatial and non-spatial CV should be guided by the specific evaluation objective, and highlights the distinction between estimating map accuracy as a population parameter and assessing model's predictive performance under its anticipated operational conditions.

4.3 | Unobservables

An obvious weakness of satellite data is that many variables of interest to agricultural and environmental economists cannot be measured well—or at all—from space. This is yet another reason why satellite data is complementary to other data and is seldom sufficient as the sole data source for an analysis. For example, for many questions in agricultural and environmental economics, it is useful to be able to objectively measure what happens on the fields in a region. One might record with high spatial and temporal resolution when and how a field was prepared, how it was managed throughout the season, and what agricultural and environmental outcomes can be observed at different points in time. What is missing, however, is to which farm the field belongs.

Sometimes, fields are far away from the homestead and scattered widely, so one needs reliable information about the boundaries of each farm, if one wants to conduct a farm-level analysis. The farm-level is usually the most relevant unit to study farmers' decision-making, so this is common. Also, many variables that are relevant explanations for farmers' choices cannot be optimally measured. Preferences, behavioral biases, social interactions, culture, and personality are all important explanations for the behavior of farmers (Wuepper, Bukchin-Peles, et al. 2023) and none of these can yet be directly measured with satellite data.

Combining cadastral data, farmer surveys, ground truth data, and then remote sensing measures can provide the kind of rich analyses that build on all the individual data strengths while compensating for all the individual data weaknesses. In addition, creativity and advances in technologies and novel data availability will likely make some variables measurable with satellites in the future that will surprise us.

5 | Conclusion

Satellite data usually cannot be the only data-source but is immensely useful for many research endeavors when combined with other data (for ground truthing and to cover everything that cannot be seen on a satellite, such as the boundaries of individual farms, or farmer preferences, or property rights). Here, we have discussed many applications of satellite data and what to consider when working with it. Details on variable construction and workflows can be found in the supporting information. Practice code and data can be found online[15].

Our intention is to inspire and enable many more uses of satellite data in agricultural and environmental economics, as well as raise the average reliability of research in this domain. We acknowledge that remote sensing measurements, processing algorithms, and analytical models are advancing rapidly; and both space agencies and companies are frequently adding new measurements to the arsenal. We thus expect that this will enable a range of exciting new research applications, providing many new insights for research and policy.

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Endnotes

[1] https://github.com/land-economics-ilr-uni-bonn/sat-agri-econ

[2] https://www.earthdata.nasa.gov/news/blog/from-modis-viirs-continuing-legacy

[3] https://www.planet.com/nicfi/

[4] https://www.enmap.org/

[5] https://gedi.umd.edu/

[6] https://landsat.gsfc.nasa.gov/satellites/landsat-next/

[7] Based on previous mapping efforts by Jin et al. (2017) and Lobell and Azzari (2017)

[8] To measure crop yield, it is usually more reliable to use maximum values and not the mean, as the mean can be biased by the measured color of a field when there is no full crop cover (fallow period, color being dominated by color of soil and not of the crop after planting, residue burning turning fields dark, etc.). A drawback is that this does not capture the yield obtained from multiple harvests.

[9] At this scale, it is not currently feasible to produce precise crop yield estimates for each crop so instead, Wuepper, Wang et al. (2023) control for crop types in their regressions.

[10] See Wuepper and Finger (2023) for an in-depth discussion

[11] https://storage.googleapis.com/earthenginepartners-hansen/GFC-2023-v1.11/download.html

[12] https://people.smu.edu/dmillimet/stata-code/

[13] https://github.com/nwrat/RCQSB2022_public

[14] In Stata, one can use the mi commands, in R one can use the mice package, in Python one can use the IterativeImputer within the scikit-learn library.

[15] https://github.com/land-economics-ilr-uni-bonn/sat-agri-econ

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.