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Accelerated global cropland expansion and primary production increase in the 21st century.

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Spatiotemporally consistent data on global cropland extent is a key to tracking progress toward hunger eradication and sustainable food production^{1,2}. Here, we present an analysis of global cropland area and change for the first two decades of the 21st century derived from satellite data time-series. We estimate 2019 cropland area to be 1,244 Mha with a corresponding total annual net primary production (NPP) of 5.5 Pg C yr⁻¹. From 2003 to 2019, cropland area increased by 9% and crop NPP by 25%, primarily due to agricultural expansion in Africa and South America. Global cropland expansion accelerated over the past two decades, with a near doubling of the annual expansion rate, most notably in Africa. Half of the new cropland area (49%) replaced natural vegetation and tree cover, indicating a conflict with the sustainability goal of protecting terrestrial ecosystems. From 2003 to 2019 global population growth outpaced cropland area expansion, and per capita cropland area decreased by 10%. However, the per capita annual crop NPP increased by 3.5% as a result of intensified agricultural land use. The presented global high-resolution cropland map time-series supports monitoring of sustainable food production at the local, national, and international levels.

Global population growth and increasing standards of living inevitably cause the expansion and intensification of global agricultural land use to fulfill growing demands for food, biofuel, and other commodities^{3–5}. In turn, agriculture expansion and intensification threaten ecosystem functioning and lead to species extinction through habitat loss and fragmentation^{4,6,7}. The United Nations 2030 Sustainable Development Goals (SDGs) call for balancing increasing agricultural production with maintenance of ecosystem services⁸. Implementation of SDGs to improve food security, protect freshwater and terrestrial ecosystems, and mitigate climate change require national policies and international cooperation that are based on consistent, independent, and timely data on agriculture extent and productivity². Spatiotemporally consistent satellite observations provide the most accurate and cost-effective solution for global agricultural land use mapping and monitoring⁹. Satellite data have been shown to enable national and global agriculture mapping^{10–14}. However, no globally consistent cropland time-series data at locally relevant spatial resolutions exist to date.

Here, we present a global cropland extent and change dataset that can serve as a tool for monitoring national and global progress towards SDGs. We define cropland as land used for annual and perennial herbaceous crops for human consumption, forage (including hay), and biofuel. Perennial woody crops, pastures, and shifting cultivation are excluded from the definition. The fallow length is limited to four years for the cropland class. Our definition is consistent with the arable land category reported by the Food and Agriculture Organization of

the United Nations (FAO)¹⁵. We utilized the consistently processed Landsat satellite data archive¹⁶ from 2000 to 2019. The Landsat time-series data were transformed into multitemporal metrics that described land surface phenology. These metrics were used as independent variables for a machine learning classification to map global croplands extent. The classification models were locally calibrated using extensive training data collected by visual interpretation of freely available high spatial resolution remotely sensed data. We used a probability sample, stratified based on the cropland maps, to estimate cropland area and its associated uncertainty, and to analyze pathways of land use conversion. Sample reference data were collected through visual interpretation of Landsat and higher spatial resolution satellite images. Cropland maps were integrated with the Moderate Resolution Imaging Spectroradiometer-derived annual net primary production (NPP)¹⁷ as a proxy variable for analyzing crop productivity. The analysis was performed in four-year intervals (2000-2003, 2004-2007, 2008-2011, 2012-2015, and 2016-2019), with each epoch hereafter referred to by the last year of the interval.

Using probability sample data, we estimated the 2019 global cropland area to be 1244.2 ± 62.7 Mha (the uncertainty represents 95% confidence interval). Of the global cropland area, 55% is in Eurasia, 17% in Africa, 16% in North and Central America, 9% in South America, and 3% in Australia and New Zealand (Extended Data Table 1; see Extended Data Fig. 1 for region boundaries). During the first two decades of the 21st century, global cropland area increased by 101.9 ± 45.1 Mha, equivalent to 9% of the 2003 cropland area (Fig. 1). The largest cropland expansion was observed in Africa (by 53.2 ± 39.4 Mha, or 34%). South America had the largest relative cropland gain (by 37.1 ± 8.7 Mha, or 49%). Australia and New Zealand as well as Southwest Asia displayed moderate cropland expansion (below 10% of the 2003 area). North America, Europe, North and Southeast Asia featured small net cropland area change but pronounced gross cropland gain and loss, which balanced each other at the continental scale.

From 2003 to 2019, the global population increased by 21% from 6.4 to 7.7 billion¹⁸, outpacing cropland expansion. As a result, global per capita cropland area decreased by 10%, from 0.18 ha person⁻¹ in 2003 to 0.16 ha person⁻¹ in 2019. Increase in per capita cropland area was observed only in South America, while it decreased in all other continents (Fig. 2). The largest relative decrease of per capita cropland area was observed in Southwest Asia (by 19%). Southeast Asia had the smallest 2019 per capita cropland area (0.08 ha person⁻¹), while Australia and New Zealand had the largest per capita area (1.34 ha person⁻¹).

Of the total 2019 cropland area, 217.5 ± 37.7 Mha (17%) represent new cropland established since 2003. In South America and Africa, this proportion is the highest (39% and 34%, respectively). Half of the new croplands replaced natural woody and herbaceous vegetation (49% of gross cropland gain area, Extended Data Table 2). Of that total, 11% represent dryland conversion through irrigation, mostly found in Southwest and Southeast Asia and North America. The largest proportions of natural vegetation conversion to croplands (excluding dryland irrigation) were found in Africa (79% of all gross cropland gain area), Southeast Asia (61%), and South America (39%). The other half of cropland expansion (51%) was due to pasture conversion and recultivation of abandoned arable land. Nearly all cropland expansion in Australia, New Zealand, Europe, and Northern Asia was found within pastures and long fallows

(with no crop cultivation for more than 4 years). In North and South America cropland expansion through the conversion of pastures and long fallows was more common (75% and 61%, respectively) than through clearing of natural vegetation.

Abandonment or conversion to other land uses affected 10% of the 2003 cropland area (115.5 ± 24.1 Mha). Of that area, 52% was converted into pastures or abandoned (Extended Data Table 2); such conversions may be temporary and followed by crop recultivation years later. Industrial and residential construction and infrastructure development was the second largest driver of gross cropland loss, responsible for 16% of the total cropland area reduction. In Southeast Asia, 35% of cropland reduction was due to urban sprawl. A portion (13%) of 2003 cropland was converted to permanent woody crops or aquaculture, with the highest proportion of such transitions in Southeast Asia (28%). Flooding caused by surface water increase, water erosion, and reservoir construction affected cropland area on all continents (3% total reduction). The remaining 16% of cropland reduction represented tree plantations or restoration of natural vegetation after cropland abandonment.

A comparison of our 2003 and 2019 sample-based cropland area estimates with FAO 2003 and 2018 arable land area (Extended Data Fig. 2) shows sound agreements (R^2 of 0.94 and 0.98 for the year 2003 and 2019, respectively). Our sample-based cropland area estimate is smaller (by 16% and 11% for 2003 and 2019, respectively) compared to FAO arable land area. The FAO arable land change confirms our findings; both datasets demonstrate a net increase in global cropland area, with Africa and South America showing the largest net gains. The net loss of arable land area in North America, Europe, North and Southwest Asia reported by the FAO was not confirmed by our results.

The global Landsat-based cropland map time-series is complementary to the sample analysis in characterizing global area dynamics (Fig. 3). The sample analysis showed high accuracy of the global cropland maps with variability between regions and lower accuracies for change dynamics (Extended Data Table 3). The cropland map time-series allowed us to disaggregate change over time and conduct national-scale analyses.

Global cropland expansion accelerated over the past two decades, with a near doubling of the annual expansion rate from 5.1 to 9.0 Mha year⁻¹ (Extended Data Table 4). The change in annual cropland expansion rates highlights differences between cropland establishment in Africa and South America. In Africa, cropland expansion accelerated from 2004-2007 to 2016-2019 with a more than twofold increase in annual expansion rates. In contrast, cropland expansion in South America decelerated by 2019 with an annual expansion rate reduced almost by half compared to the 2004-2007 interval.

At the national level, the US had the largest cropland area by 2019 closely followed by India and China (Supplementary Information Table 4). The largest net cropland increases were found in Brazil (by 23.1 Mha, or 77% increase over year 2003 cropland area) and India (by 15.5 Mha, or 13%). The largest cropland area reductions were found in Russia (by 5.7 Mha, or 6% decrease over year 2003 cropland area) and Cuba (by 0.5 Mha, or 28%). Our satellite-based 2019 cropland

map area is comparable with the 2018 arable land extent reported by the FAO at the national scale (R^2 of 0.97, Extended Data Fig. 3).

The global MODIS-derived annual NPP within cropland area (Extended Data Fig. 4) increased by 25% between 2003 and 2019 (from 4.4 Pg C yr⁻¹ to 5.5 Pg C yr⁻¹, Fig. 1). South America had the highest NPP increase (by 0.38 Pg C yr⁻¹, or 88%) followed by Africa (by 0.29 Pg C yr⁻¹, or 50%) (Extended Data Table 5). The per capita annual crop NPP also increased globally by 3.5%, balancing the per capita cropland area reduction. Two processes contributed to the global crop NPP increase, namely the increase of cropland area and the increase in crop productivity per unit area. We found that the mean NPP per unit area within stable crops increased by 10%, from 402 g C m⁻² yr⁻¹ in 2003 to 442 g C m⁻² yr⁻¹ in 2019. The highest NPP increase within stable crops was found in South America (from 528 g C m⁻² yr⁻¹ in 2003 to 730 g C m⁻² yr⁻¹ in 2019, or by 25%). The NPP gain within stable croplands explains 34% of the total cropland NPP increase from 2003 to 2019.

The 2019 global cropland map (Fig. 3) shows that global crop distribution does not follow national boundaries, but rather reflects agricultural potential, population, and land use history. Major lowland regions of the world have been converted to homogeneous agricultural landscapes, including the Great Plains in North America, the Pampas in South America, the Pontic steppe in Europe, the North China and Manchurian Plains in East Asia, the Indo-Gangetic Plain in South Asia, parts of the Sahel region in Africa, and Southeast Australia (Extended Data Fig. 5). Cropland expansion in South America occurred synchronously in Brazil, Argentina, Paraguay, Bolivia, and Uruguay. A similar pattern of simultaneous cropland expansion was observed within Sahelian and Central African countries. In Southwest and Southeast Asia, cropland gain was mostly found in drylands, while tree plantations, orchards, aquaculture, and urban areas replaced former croplands in China and the Lower Mekong countries. In Russia, the massive cropland abandonment in the north¹⁹ was partly compensated by the recent cropland expansion in the southern steppe regions, primarily through fallow land recultivation. The cross-boundary distribution of major cropland areas and synchronous cropland dynamics illustrate the importance of international cooperation to ensure global progress towards SDGs.

Global cropland maps provide spatial context on national, cross-boundary, and local crop dynamics reflecting the history of land tenure, national policies, and abrupt events like natural and man-made disasters (Extended Data Fig. 6). In Eastern Europe, the Baltic states and Russia's Kaliningrad region featured cropland expansion through recultivation of long fallows abandoned after the breakdown of the USSR, while cropland area in neighboring Poland and Belarus was relatively stable. Cereal, forage, and hay production land of the northern Great Plains have different dynamics within Canada, where we observed land abandonment or conversion to permanent pastures, and the USA, where land management has been intensified. The irrigated croplands in Saudi Arabia declined following the depletion of groundwater resources and the implementation of state policies to discourage water-intensive crop production²⁰. The 30 m spatial resolution of the cropland maps supports the analysis of local dynamics factors, e.g., cropland abandonment after radioactive contamination following the 2011 nuclear disaster on the Fukushima Daiichi nuclear power plant in Japan.

Changes in total and per capita mapped cropland area from 2003 to 2019 demonstrate the variability of national responses to the need for increased food production to feed a growing population (Extended Data Fig. 7). For most countries with moderate cropland area gains, we observed small decreases in per capita cropland area, indicating increasing stress to existing agricultural systems. In many African nations (e.g., Cameroon, Chad, Tanzania, Uganda, among others) the relatively large cropland area increases compensated for population growth and resulted in small changes in per capita cropland area. In other countries, cropland increase was not adequate to follow population growth, causing a substantial decrease of cropland per capita (e.g., in Ethiopia, Nigeria, Pakistan, Senegal, Tajikistan). Per capita cropland area decreased nearly twofold in Niger, which experienced high population growth and slow cropland expansion. Per capita cropland area reduction can be an indicator of food insecurity in poor countries that rely on subsistence agriculture, while rich countries like Saudi Arabia can compensate for cropland area decline with food imports^{21,22}. Several African countries with rapid cropland increase (Angola, Cote d'Ivoire, Democratic Republic of the Congo, Mozambique, and Zambia) and South American countries with industrial export-oriented agricultural expansion (Brazil, Bolivia, Paraguay, and Uruguay) increased per capita cropland area. The Baltic states of Lithuania and Latvia had the largest increase of cropland per capita due to cropland gain through recultivation of agricultural lands abandoned in the 1990s coupled with a sharp population decline (more than 20% reduction since 2000). Despite their small size, these countries are among the top-15 global wheat exporters.

More than three quarters (77%) of the global population lives in regions with per capita cropland area and crop NPP below the year 2019 global average (Extended Data Fig. 8). The lowest per capita 2019 crop NPP was in Southwest Asia (40% of the global average), which decreased by 7% since 2003. Per capita cropland area in Southeast Asia in 2019 was half the global average. In contrast, per capita cropland areas and crop NPP in North America, Europe, and North Asia in 2019 were twice the global average. South America had nearly three-fold higher per capita crop NPP than the global average, and it increased by 59% since 2003. Although per capita cropland area and crop NPP decreased by more than 10% in Australia and New Zealand since 2003, the region still led the world in both measures in 2019. Regions with cropland area and crop NPP above the global average include the largest grain and soybean exporting countries (Australia, Argentina, Brazil, USA, Russia).

Regional accuracies (Extended Data Table 3) highlight the limitations of the Landsat-based cropland maps. North and South America, which are dominated by large-scale industrial farming have the highest accuracies. In Europe, Asia, and Africa, the global map underestimates cropland area due to spatial resolution limitations in mapping heterogeneous landscapes. Cropland maps in Australia and New Zealand overestimate cropland area due to the inclusion of intensively managed planted pastures which are not always separable from crops using Landsat data. Additionally, mapping change was shown to be more difficult with accuracies generally lower across all regions. A probability-based sample analysis is the recommended good practice approach²³ to estimating land cover and land use extent and change, including croplands. The global cropland map time-series enables a higher sampling efficiency through stratification at the sub-national, national, and global scales. The difference between our sample-based and map-

based cropland area estimates and the arable land area reported by the FAO is related to the definitional inconsistency. The FAO country reports may include unused arable land and other agricultural land uses^{9,15}, while our estimates represent the actively cultivated cropland area.

The annual MODIS NPP is the only publicly available globally consistent data that reflect recent changes in crop productivity. These data have been shown to underestimate NPP compared to processed-based model estimations, especially for irrigated crops²⁴. The difference in spatial resolution between Landsat-based cropland maps and MODIS-based NPP data may impede the analysis of crop productivity within heterogeneous landscapes. Our Landsat-based cropland extent time-series data can provide a useful input for improved NPP modeling at higher spatial resolution and with better precision.

High-resolution satellite-based synoptic data on cropland extent and change provide the basis for tracking progress toward sustainable food production at the local, national, and international levels and for applying crop condition monitoring to support decision-making²⁵. Cropland extent is a key variable required to estimate emissions from agriculture and is, therefore, a part of the Essential Climate Variables required for monitoring and modeling the Earth's climate²⁶. Locally relevant cropland map time-series enable the monitoring of land use conversion within high conservation value ecosystems and protected areas²⁷. The cropland extent map, integrated with other high spatial and temporal resolution data, such as forest change²⁸ and surface water extent²⁹ can provide a comprehensive overview of human-induced environmental change. The presented method is suitable for monitoring of global croplands and assessing the progress of individual countries towards sustainable food production.

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231 Fig. 1. Global cropland area (map-based and sample-based) and annual crop net primary
 232 production (NPP). Cropland area was mapped for each four-year interval. Sample analysis was
 233 performed only for the first and the last intervals. The MODIS-based annual NPP represents
 234 four-year average within the cropland map for the corresponding time interval. The error bars for
 235 sample-based crop area estimates represent 95% confidence interval while error bars for NPP
 236 represent one standard deviation of annual values within the time interval.

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240 Fig. 2. Total and per capita cropland area change, 2003-2019, per geographic region. The size of
 241 the bubbles reflects regional 2019 cropland area.

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245 Fig. 3. Global cropland extent and change, 2000-2019. The map shows proportion of stable
246 cropland, cropland expansion, and cropland reduction within $0.025^{\circ} \times 0.025^{\circ}$ grid cells. The
247 original cropland map time-series has a spatial resolution of 0.00025° per pixel, approximately
248 30 m at the Equator.

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Methods

Cropland Mapping Extent and Time Intervals

The global boundaries for the cropland mapping were informed by the USGS global cropland map¹¹. The cropland mapping extent was defined using the geographic 1°×1° degree grid. We included every 1°×1° grid cell that contains cropland area according to the USGS map. Small islands were excluded due to the absence of Landsat geometrically corrected data (Supplementary Information Fig. 1).

The cropland mapping was performed at four-year intervals (2000-2003, 2004-2007, 2008-2011, 2012-2015, and 2016-2019). Using a long interval (rather than a single year) increased the number of clear-sky satellite observations in the time-series, which improves representation of land surface phenology and the accuracy of cropland detection. For each four-year interval, we mapped an area as cropland if a growing crop was detected during any of these years. This way, we implemented the criterion of the maximum fallow length: if an area was not used as cropland for more than four years, it was not included in the cropland map for the corresponding time interval.

Source Landsat Data

We employed the global 16-day normalized surface reflectance Landsat Analysis Ready Data (Landsat ARD¹⁶) as input data for cropland mapping. The Landsat ARD were generated from the entire Landsat archive from 1997 to 2019. The Landsat top of atmosphere reflectance was normalized using globally consistent MODIS surface reflectance as a normalization target. Individual Landsat images were aggregated into 16-day composites by prioritizing clear-sky observations.

For each four-year interval, we created a single annualized gap-free 16-day observation time-series. For each 16-day interval, we selected the observation with the highest near-infrared reflectance value (to prioritize observations with the highest vegetation cover) from four years of Landsat data. Observations contaminated by haze, clouds, and cloud shadows, as indicated by the Landsat ARD quality layer, were removed from the analysis. If no clear-sky data were available for a 16-day interval, we filled the missing reflectance values using linear interpolation.

The 16-day time-series was transformed into a set of multitemporal reflectance metrics that provide consistent land surface phenology inputs for global cropland mapping. The multitemporal metrics methodology is provided in detail in ref¹⁶ and ref³⁰. The Landsat metrics set was augmented with elevation data³¹. This way, we created spatially consistent inputs for each of the four-year intervals. The complete list of input metrics is presented in Supplementary Information Table 1.

Global Cropland Mapping

Global cropland mapping included three stages that enabled extrapolation of visually delineated cropland training data to a temporally consistent global cropland map time-series using machine

learning. At all three stages, we employed bagged decision tree ensembles³² as a supervised classification algorithm that used class presence and absence data as the dependent variable and a set of multitemporal metrics as independent variables at a Landsat ARD pixel scale. The bagged decision tree results in a per-pixel cropland probability layer, which is thresholded at 0.5 to obtain a cropland map.

The first stage consisted of performing individual cropland classifications for a set of 924 Landsat ARD 1°×1° tiles for the 2016-2019 interval (Supplementary Information Fig. 1). The tiles were chosen to represent diverse global agriculture landscapes. Classification training data (cropland class presence and absence) were manually selected through visual interpretation of Landsat metric composites and high-resolution data from Google Earth. An individual supervised classification model (bagged decision trees) was calibrated and applied to each tile.

At the second stage, we used the 924 tiles that had been classified as crop/no-crop and the 2016-2019 metric set to train a series of regional cropland mapping models. The classification was iterated by adding training tiles and assessing the results until the resulting map was satisfactory. We then applied the regional models to each of the preceding four-year intervals, thus creating a preliminary time-series of global cropland maps.

At the third stage, we used the preliminary global cropland maps as training data to generate temporally consistent global cropland data. Because the regional models applied at the second stage were calibrated using 2016-2019 data alone, classification errors may arise due to Landsat data inconsistencies before 2016. The goal of this third stage was to create a robust spatiotemporally consistent set of locally calibrated cropland detection models. For each 1°×1° Landsat ARD tile (13,451 tiles total) we collected training data for each four-year interval from the preliminary cropland extent maps within a 3° radius of the target tile, with preference to select stable crop and no-crop pixels as training. Training data from all intervals were used to calibrate a single decision tree ensemble for each ARD tile. The per-tile models were then applied to each time interval, and the results were post-processed to remove single cropland class detections and omissions within time-series and eliminate cropland patches below 0.5 ha. Manual masks to remove map artifacts (e.g., crop overestimation over temperate wetlands and flooded grasslands) were applied in some regions to improve the map quality. The final global cropland map time-series are available at <https://glad.umd.edu/dataset/croplands/>.

Sample Analysis

The sample analysis had two objectives: to estimate cropland area and its associated uncertainty and to assess cropland map accuracy. The analysis was performed separately for each of the seven regions outlined in Extended Data Fig. 1, as well as globally. The regional boundaries were aligned with national boundaries to enable comparison with national data. Only land pixels were considered; pixels labeled as permanent water and snow/ice in the Landsat ARD data quality layer were excluded. In each region, we selected five strata based on the map time-series corresponding to stable croplands, cropland gain and loss, possible cropland omission area, and other lands (Supplementary Information Tables 2 and 3). The possible cropland omission stratum (stratum 4) includes areas where omission errors are probable, specifically, pixels that were not

mapped as cropland and either (a) were identified as crops by the USGS cropland map¹¹ or (b) had the decision tree-based cropland probability between 0.1 and 0.5. We randomly selected 100 sample units (Landsat data pixels) from each stratum (500 samples pixels per region, 3,500 in total).

Sample interpretation was performed visually using available remotely sensed data time-series, including Landsat ARD 16-day data, composites of selected multitemporal metrics, and high-resolution images provided by Google Earth (Supplementary Information Fig. 2). Each sample pixel was interpreted by two experts independently and the disagreements were discussed and resolved by the research team. The interpretation legend includes the 2003-2019 cropland dynamics categories and land use transition types. The sample reference data and interpretation results are available at <https://glad.umd.edu/dataset/croplands/>.

Area estimation

The sample-based area estimation was performed following^{33,34}. The 2003 and 2019 total cropland area, stable crops, gross cropland loss and gain, and net change were estimated within each region separately, and for the entire world using Eq. 1. The area and the total number of Landsat pixels for each region and each stratum are provided in Supplementary Information Table 3. For each of the 100 sample pixels sampled in each stratum, p_u was defined by class presence, e.g., for 2003 cropland, $p_u = 0$ (2003 cropland absence) or $p_u = 1$ (2003 cropland presence). The p_u was defined similarly for the 2019 cropland, stable crop, gross cropland loss and gain classes. For the net cropland area change, p_u had values 1 (cropland gain), -1 (cropland loss), and 0 (no change).

Eq. 1 $\hat{A} = \sum_{h=1}^H A_h \bar{p}_h$
 where $\hat{A}$ – estimated cropland/cropland change area;
 A_h – area of stratum h ;
 H – number of sampling strata;
 $\bar{p}_h = \frac{\sum_{u \in h} p_u}{n_h}$ – mean cropland/cropland change proportion of samples in stratum h ;
 n_h – sample size (number of sample pixels) in stratum h ;

The standard error of area was estimated from the variances of cropland (or cropland dynamics category) class values p_u for sample pixels in each stratum using Eq. 2. The 95% confidence interval was obtained by multiplying standard error by 1.96.

Eq. 2 $SE(\hat{A}) = \sqrt{\sum_{h=1}^H A_h^2 (1 - \frac{n_h}{N_h}) \frac{s_{ph}^2}{n_h}}$
 where $SE(\hat{A})$ – standard error of cropland/cropland change class area;
 $s_{ph}^2 = \frac{\sum_{u \in h} (p_u - \bar{p}_h)^2}{n_h - 1}$, sample variance for stratum h .

Proportion of land use trajectories

We analyzed the land-use trajectories of cropland loss and gain using reference sample data within cropland gain and loss strata only. Inclusion of sample pixels from other strata where cropland change was detected would have inflated the area of land use trajectories that these pixels represent (i.e., if a sample pixel from a stable cropland stratum was interpreted as cropland gain due to forest clearing, including the proportion of forest clearing from this large stratum will dominate the total regional estimate). The proportion of each land use trajectory (within cropland gain and loss separately) was estimated from the sample and reported as the percent of the total gain or loss along with its standard error (Extended Data Table 2). Combined ratio estimator for stratified random sampling³⁴ was employed to estimate the percentages (Eq. 3).

$$Eq. 3 \quad \hat{R} = \frac{\sum_{h=1}^H A_h \bar{y}_h}{\sum_{h=1}^H A_h \bar{x}_h} \times 100$$

where $\hat{R}$ – estimated class proportion expressed as percentage;

H – number of sampling strata;

A_h – area of stratum h ;

$\bar{y}_h = \frac{\sum_{u \in h} y_u}{n_h}$, the sample mean of the y_u values in stratum h where $y_u = 1$ if pixel u is classified as belonging to a specific transition in the reference sample interpretation, and $y_u = 0$ otherwise;

$\bar{x}_h = \frac{\sum_{u \in h} x_u}{n_h}$, the sample mean of the x_u values in stratum h , where $x_u = 1$ if pixel u is classified as any cropland loss/gain in the reference sample interpretation, and $x_u = 0$ otherwise.

The standard error of the estimated ratio of class proportion expressed as percentage was calculated using Eq. 4.

$$Eq. 4 \quad SE(\hat{R}) = \sqrt{\frac{1}{\hat{X}^2} \sum_{h=1}^H A_h^2 \left(1 - \frac{n_h}{N_h}\right) (s_{y_h}^2 + \hat{R}^2 s_{x_h}^2 - 2\hat{R} s_{xyh}) / n_h} \times 100$$

where $SE(\hat{R})$ – standard error of the estimated proportion expressed as percentage;

N_h – total number of pixels in stratum h ;

n_h – number of sample pixels in stratum h ;

$\hat{X} = \sum_{h=1}^H A_h \bar{x}_h$ – the estimated total area of cropland loss/gain expressed in area units;

$s_{y_h}^2$ and $s_{x_h}^2$ are the sample variances in stratum h and s_{xyh} is the sample covariance in stratum h estimated as follows:

$$s_{y_h}^2 = \sum_{u \in h} (y_u - \bar{y}_h)^2 / (n_h - 1)$$

$$s_{x_h}^2 = \sum_{u \in h} (x_u - \bar{x}_h)^2 / (n_h - 1)$$

$$s_{xyh} = \sum_{u \in h} (y_u - \bar{y}_h)(x_u - \bar{x}_h) / (n_h - 1)$$

Map accuracy

The map accuracy metrics include overall accuracy (the proportion of correctly mapped sample pixels), user's accuracy of the cropland class (which reflects the cropland class commission) and producer's accuracy of the cropland class (which reflects the cropland class omission)³³. All accuracy metrics and respective standard errors are presented as percentages (Extended Data Table 3).

To estimate overall accuracy, we defined $y_u = 1$ if pixel u is classified correctly and $y_u = 0$ if pixel u is classified incorrectly. The estimator for overall accuracy is then expressed by Eq. 5, and standard error for overall accuracy is computed using Eq. 6.

$$\text{Eq. 5} \quad \hat{O} = \frac{\sum_{h=1}^H N_h \bar{y}_h}{N} \times 100$$

where $\hat{O}$ – estimated overall accuracy, expressed as percentage;

H – number of sampling strata;

N_h – total number of pixels in stratum h ;

N – total number of pixels in the reporting region;

$\bar{y}_h = \sum_{u \in h} y_u / n_h$ is the sample mean of the y_u values in stratum h .

$$\text{Eq. 6} \quad SE(\hat{O}) = \sqrt{\frac{1}{N^2} \sum_{h=1}^H N_h^2 (1 - n_h/N_h) s_{y_h}^2 / n_h} \times 100$$

where $SE(\hat{O})$ – standard error of the overall accuracy, expressed as percentage;

n_h – number of sample pixels in stratum h ;

$s_{y_h}^2$ – the sample variance: $s_{y_h}^2 = \sum_{u \in h} (y_u - \bar{y}_h)^2 / (n_h - 1)$

For estimating user's accuracy of the croplands class, we define $y_u = 1$ if sample pixel u is correctly mapped as cropland otherwise $y_u = 0$, and define $x_u = 1$ if sample pixel u is mapped cropland, otherwise $x_u = 0$. For the producer's accuracy, define $y_u = 1$ if sample pixel u is correctly mapped as cropland, otherwise $y_u = 0$, and define $x_u = 1$ if sample pixel u was interpreted as cropland, otherwise $x_u = 0$. The estimator of user's accuracy and producer's accuracy is then expressed as a ratio estimator (Eq. 7) and their standard error calculated using Eq. 8, which are similar to Eq. 3 and 4, except that the strata are weighted by their total number of pixels (N_h) instead of the areas (A_h) for the purposes of map accuracy assessment (with pixel being the primary mapping unit).

$$\text{Eq. 7} \quad \hat{R} = \frac{\sum_{h=1}^H N_h \bar{y}_h}{\sum_{h=1}^H N_h \bar{x}_h} \times 100$$

where $\hat{R}$ – estimated user's/producer's accuracy, expressed as percentage.

Eq. 8

$$SE(\hat{R}) = \sqrt{\frac{1}{\hat{X}^2} \sum_{h=1}^H N_h^2 \left(1 - \frac{n_h}{N_h}\right) (s_{yh}^2 + \hat{R}^2 s_{xh}^2 - 2\hat{R}s_{xyh}) / n_h} \times 100$$

where $SE(\hat{R})$ – standard error of the estimated user's/producer's accuracy, expressed as percentage.

$$\hat{X} = \sum_{h=1}^H N_h \bar{x}_h$$

388

389 Crop Net Primary Production

390 The crop net primary production (NPP) was evaluated using the globally consistent Collection 6
 391 MODIS-based annual year-end gap-filled NPP product (MOD17A3HGF¹⁷). The product
 392 provides the sum of total daily NPP through the year at a 500 m spatial resolution (Kg C m⁻²
 393 year⁻¹). The annual NPP data were resampled to our Landsat ARD data grid and were overlaid
 394 with the corresponding four-year cropland maps to calculate total and per unit area NPP for each
 395 region and each year. We used average annual NPP for each four-year interval, except for the
 396 2000-2003 interval, where a three-year average was used instead to avoid using the year 2000
 397 when MODIS data were incomplete. The standard deviation of the annual estimates is provided
 398 along with the interval average as an uncertainty metric.

399 Per capita cropland area and crop NPP

400 We employed the 2019 Revision of World Population Prospects¹⁸ to calculate global, regional,
 401 and national population for years 2003 and 2019. Because the boundaries of analysis regions
 402 (Extended Data Fig. 1) are aligned with country boundaries, we were able to summarize the
 403 regional population totals from national data. The population data were related to our sample-
 404 based (for global and regional estimates) and map-based (for national estimates) cropland area to
 405 estimate per capita cropland area and change. Similarly, we related regional crop NPP to
 406 population data to estimate per capita crop NPP for 2003 and 2019.

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Data and Code Availability

All global cropland maps, cropland dynamic maps, and sample data available at <https://glad.umd.edu/dataset/croplands/>. The global Landsat ARD data, metric generation and image classification codes are available from <https://glad.umd.edu/ard>.

Author Contributions

P.P. designed the research and performed the global mapping; P.P., S.T., and A.T conducted the sample analysis; P.P., A.T., X.S., V.Z., A.P., and M.H. wrote the manuscript; V.Z., A.K., Q.S, and J.C. provided calibration data; A.P. designed data visualization.

Extended Data

Extended Data Fig. 1. Regions of analysis.

Extended Data Fig. 2. Comparison of FAO arable land area estimates with sample-based cropland area by region. Error bars represent the 95% confidence interval of the sample-based area estimates. Region abbreviations: AFR – Africa; SWA – Southwest Asia; ANZ – Australia and New Zealand; SEA – Southeast Asia; ENA – Europe and North Asia; NAM – North and Central America; SAM – South America.

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500 Extended Data Fig. 3. Per-country comparison between 2018 FAO arable land area and 2019
 501 map-based cropland area from this study.

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505 Extended Data Fig. 4. MODIS-derived annual NPP (from MOD17 product) within the mask of
506 cropland for the 2016-2019 interval. The NPP data represent the four-year average for the 2016-
507 2019 interval.

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511 Extended Data Fig. 5. 2019 cropland proportion within $0.025^{\circ} \times 0.025^{\circ}$ grid cells. The original
512 cropland map has a spatial resolution of $0.00025^{\circ} \times 0.00025^{\circ}$ per pixel, approximately 30 m at the
513 Equator.

Extended Data Fig. 6. Regional-to-local scale examples of cropland dynamics, 2000-2019. A – Cross-boundary cropland dynamics in Eastern Europe (center at 22.48° , 54.35°); B – Cropland dynamics on the border between Saskatchewan, Canada, and Montana, the USA (center at -106.08° , 48.99°); C – Decline of irrigated cropland area, Saudi Arabia (center at 43.58° , 27.14°); D – Cropland abandonment after 2011 nuclear disaster on Fukushima Daiichi nuclear power plant, Japan (zoom-in image center at 141.03° , 37.42°)

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528 Extended Data Fig. 8. Regional comparison of the values of natural logarithm of the ratio of
 529 regional (x) and global ($\bar{x}$) 2019 per capita sample-based cropland area, ha person⁻¹ (x axis); and
 530 values of natural logarithm of the ratio of regional (y) and global ($\bar{y}$) 2019 per capita crop NPP,
 531 kg C year⁻¹ person⁻¹ (y axis). The size of the bubbles reflects 2019 regional population.

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534 Extended Data Table 1. The regional and global map-based and sample-based cropland and
 535 cropland dynamics areas (Mha). Sample-based estimates include 95% confidence intervals in
 536 parenthesis.

		Cropland area 2000-2003	Cropland area 2016-2019	Net change 2003-2019	Gross gain 2003-2019	Gross loss 2003-2019
Africa	<i>map</i>	142.6	189.6	47.0	62.1	15.1
	<i>sample</i>	155.1 (39.8)	208.3 (47.4)	53.2 (39.4)	71.5 (33.9)	18.3 (19.4)
Southwest Asia	<i>map</i>	224.9	250.9	26.0	42.6	16.6
	<i>sample</i>	237.3 (20.6)	244.8 (21.4)	7.5 (11.7)	29.3 (7.1)	21.8 (9.1)
Australia and New Zealand	<i>map</i>	42.8	46.0	3.2	5.2	2.0
	<i>sample</i>	37.3 (2.7)	40.3 (3.5)	3.0 (2.2)	4.0 (2.1)	1.1 (0.2)
Southeast Asia	<i>map</i>	172.9	184.5	11.6	30.9	19.3
	<i>sample</i>	192.7 (20.9)	191.1 (21.8)	-1.6 (8.6)	23 (4.1)	24.6 (7.4)
Europe and North Asia	<i>map</i>	234.7	233.7	-1.1	29.5	30.5
	<i>sample</i>	252.3 (21.3)	253.2 (20.7)	0.9 (6.8)	25.3 (6.2)	24.4 (2.5)
North and Central America	<i>map</i>	196.9	201.5	4.6	21.3	16.7
	<i>sample</i>	192.1 (12.4)	193.9 (14.4)	1.8 (11.9)	20.8 (9.2)	19 (7.4)
South America	<i>map</i>	75.4	109.3	33.8	41.3	7.5
	<i>sample</i>	75.5 (6.6)	112.6 (10.3)	37.1 (8.7)	43.5 (8.6)	6.4 (1.5)
World	<i>map</i>	1090.3	1215.5	125.2	232.9	107.7
	<i>sample</i>	1142.3 (55.8)	1244.2 (62.7)	101.9 (45.1)	217.5 (37.7)	115.5 (24.1)

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540 Extended Data Table 2. Relative importance of different types of land use conversions for
 541 cropland establishment (gain) and abandonment (loss), estimated from sample reference data.
 542 The analysis was restricted to mapped cropland loss and gain areas. The values in the table
 543 represent percent of each conversion type from the total cropland loss or gain area in each region
 544 and globally (with standard error in parenthesis). Region abbreviations: AFR – Africa; SWA –
 545 Southwest Asia; ANZ – Australia and New Zealand; SEA – Southeast Asia; ENA – Europe and
 546 North Asia; NAM – North and Central America; SAM – South America.

		AFR	SWA	ANZ	SEA	ENA	NAM	SAM	World
Cropland gain	Replacing pastures and reclamation of abandoned agricultural lands	17 (12)	47 (12)	91 (13)	29 (11)	97 (14)	75 (13)	61 (12)	51 (5)
	Dryland irrigation	3 (13)	15 (12)	0 (0)	10 (12)	0 (0)	9 (12)	0 (0)	5 (5)
	Conversion of natural vegetation or tree plantations	79 (13)	37 (12)	9 (13)	61 (12)	3 (12)	16 (12)	39 (11)	43 (5)
Cropland loss	Cropland abandonment or conversion to pastures	42 (12)	57 (12)	65 (12)	9 (11)	78 (13)	48 (11)	63 (12)	52 (5)
	Conversion to other intensive agriculture	6 (14)	15 (12)	15 (13)	28 (11)	5 (11)	10 (11)	17 (11)	13 (5)
	Construction, infrastructure, and mining	17 (13)	10 (12)	6 (13)	35 (11)	10 (11)	17 (11)	8 (11)	16 (5)
	Flooded land (natural and water reservoirs)	6 (14)	3 (12)	2 (13)	6 (11)	1 (11)	2 (11)	5 (11)	3 (5)
	Restoration of natural vegetation, tree plantations	29 (13)	15 (11)	13 (13)	23 (11)	6 (11)	23 (11)	7 (11)	16 (5)

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550 Extended Data Table 3. Regional and global map accuracy metrics (expressed as percentage).

551 OA stands for overall accuracy, UA for user's accuracy, and PA for producer's accuracy.

552 Standard errors of accuracy metrics are shown in parenthesis.

		Cropland 2000-2003	Cropland 2016-2019	Stable cropland	Cropland gain	Cropland loss
Africa	OA	96.9 (0.7)	96.5 (0.8)	97.2 (0.6)	97.9 (0.6)	99.4 (0.3)
	UA	71.3 (4.1)	77.3 (3.2)	71.9 (4.6)	57 (5)	48 (5)
	PA	65.8 (8.3)	70.6 (7.9)	64.6 (8.2)	49.4 (12)	39.9 (21.5)
Southwest Asia	OA	96.2 (0.7)	96.2 (0.7)	95.7 (0.8)	98.6 (0.2)	98.9 (0.3)
	UA	90.1 (2.7)	87.5 (2.8)	86 (3.5)	59 (4.9)	66 (4.8)
	PA	85 (3.2)	89.2 (3.2)	82.5 (3.5)	85.9 (8.6)	52.1 (10.7)
Australia and New Zealand	OA	99.1 (0.2)	98.9 (0.2)	99.2 (0.2)	99.6 (0.1)	99.9 (0)
	UA	86 (3.2)	84.6 (3)	88.5 (3.3)	57 (5)	54 (5)
	PA	98.7 (0.4)	96.8 (2.5)	95.8 (1.6)	73.8 (19.1)	100 (0)
Southeast Asia	OA	97.3 (0.6)	96.6 (0.7)	96.7 (0.7)	99.3 (0.1)	99.2 (0.2)
	UA	92.8 (2.3)	86.5 (2.8)	87 (3.4)	69 (4.6)	78 (4.2)
	PA	83.8 (4.2)	84.1 (4.2)	80.1 (4.6)	92.4 (6.3)	60.6 (9.3)
Europe and North Asia	OA	96.8 (0.7)	96.8 (0.7)	96.1 (0.7)	99.2 (0.2)	99.6 (0.1)
	UA	93.1 (2.2)	93.6 (2)	92.7 (2.7)	71 (4.6)	79 (4.1)
	PA	86.4 (3.3)	86.1 (3.3)	79.3 (3.9)	83.1 (9.3)	98.8 (1.2)
North and Central America	OA	98.5 (0.5)	97.8 (0.5)	98.6 (0.4)	99 (0.3)	99.4 (0.3)
	UA	93.6 (2.2)	90.8 (2.3)	93 (2.6)	67 (4.7)	82 (3.9)
	PA	96.2 (2.2)	94.7 (2.6)	97 (1.7)	69.7 (14.9)	72.2 (14.1)
South America	OA	99.5 (0.2)	99.1 (0.3)	99.4 (0.2)	99.3 (0.3)	99.8 (0)
	UA	94.1 (2)	94.5 (1.6)	93.9 (2.4)	88 (3.3)	76 (4.3)
	PA	94.3 (3.5)	92 (3.9)	90.7 (4)	83.7 (7.9)	89.2 (9.6)
World	OA	97.5 (0.2)	97.2 (0.3)	97.3 (0.2)	98.9 (0.1)	99.4 (0.1)
	UA	90 (1.1)	88.5 (1)	88.3 (1.3)	67.4 (1.9)	73.3 (1.9)
	PA	86 (1.8)	86.4 (1.9)	82.9 (1.9)	73.3 (5.8)	70.3 (6.4)

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556 Extended Data Table 4. Map-based annual cropland area change (Mha year⁻¹).

	2004-2007	2008-2011	2012-2015	2016-2019
Africa	1.7	2.4	3.7	3.9
Southwest Asia	1.8	1.2	1.8	1.7
Australia and New Zealand	0.3	0.1	0.3	0.2
Southeast Asia	0.4	0.5	1.1	1.0
Europe and North Asia	-1.2	0.1	0.7	0.2
North and Central America	-0.5	0.1	1.0	0.6
South America	2.7	2.0	2.3	1.5
World	5.1	6.3	10.9	9.0

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560 Extended Data Table 5. Average annual net primary production (NPP) within cropland area, Pg
 561 C yr⁻¹. The average value is provided for each four-year interval within the corresponding
 562 cropland map. The year 2000 was excluded due to incomplete MODIS data, and the three-year
 563 average for 2001-2003 was provided instead. Standard deviations of annual values are shown in
 564 parenthesis (Pg C yr⁻¹).

	2001-2003	2004-2007	2008-2011	2012-2015	2016-2019
Africa	0.58 (0.02)	0.63 (0.01)	0.7 (0.02)	0.79 (0.02)	0.88 (0.03)
Southwest Asia	0.55 (0.03)	0.61 (0.02)	0.63 (0.05)	0.62 (0.05)	0.65 (0.03)
Australia and New Zealand	0.2 (0.02)	0.2 (0.02)	0.22 (0.02)	0.22 (0.01)	0.22 (0.03)
Southeast Asia	0.74 (0.04)	0.76 (0.01)	0.78 (0.02)	0.83 (0.02)	0.86 (0.03)
Europe and North Asia	1.08 (0.02)	1.11 (0.03)	1.09 (0.05)	1.1 (0.05)	1.14 (0.01)
North and Central America	0.83 (0.05)	0.91 (0.05)	0.92 (0.05)	0.92 (0.05)	0.97 (0.06)
South America	0.44 (0.03)	0.57 (0.01)	0.64 (0.04)	0.74 (0.02)	0.82 (0.02)
World	4.43 (0.15)	4.8 (0.08)	4.98 (0.07)	5.21 (0.14)	5.53 (0.01)

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Supplementary Information

Supplementary Information Fig. 1. Cropland mapping extent (a set of processed $1^{\circ} \times 1^{\circ}$ Landsat ARD tiles) and training tiles (which were separately classified to create a global training set).

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575 Supplementary Information Fig. 2. Online image interpretation interface. A – sample ID. B –
 576 link to Google Earth interface (provides sample outline). C – Landsat ARD 16-day clear-sky
 577 NDVI and shortwave infrared band (1.6 μm) normalized surface reflectance for the sample pixel.
 578 NDVI value (-1 to 1) scaled to the range 0-2, and reflectance (0 to 1) scaled to range 1-3. D –
 579 Landsat interquartile means for each time interval (2000-2003, 2004-2007, 2008-2011, 2012-
 580 2015, 2016-2019) using band combination SWIR (1.6 μm) / NIR / Red. E – Landsat maximum
 581 NDVI composite for each time interval using band combination NIR / SWIR (1.6 μm) / SWIR
 582 (2.2 μm). F – Landsat snow-free season amplitude using band combination NIR / SWIR (2.2
 583 μm) / NDVI. In each Landsat composite the selected sample pixel is outlined in red.

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587 Supplementary Information Table 1. Landsat multi-temporal metrics. Q1 and Q3 stand for 1st
 588 and 3rd quartiles; NDVI stands for the Normalized Difference Vegetation Index.

Metrics for individual spectral bands and indices		
<i>Annual 16-day observation data</i>		<i>Statistics extracted for each band (index) and recoded as metrics</i>
<u>Normalized surface reflectance:</u> Blue (482 nm); Green (561 nm); Red (654 nm); NIR (864 nm); SWIR1 (1609 nm); SWIR2 (2201 nm). <u>Normalized ratios:</u> NIR/Green; NIR/Red; NIR/SWIR1; NIR/SWIR2; SWIR1/SWIR2. <u>Other indices:</u> Spectral variability index; Tasseled Cap Greenness.		Minimum; Maximum; Median; Average; Average between min and Q1; Average between Q3 and max; Average between Q1 and Q3; Standard deviation; Total absolute difference (sum of absolute differences between 16-day interval values); Amplitude min to max; Amplitude Q1 to Q3; Amplitude median to max.
Metrics derived from 16-day observations ordered by a corresponding variable		
<i>Variable used for observation ordering</i>	<i>Annual 16-day observation data</i>	<i>Statistics extracted for each band (index) and recoded as metrics</i>
NIR/Red normalized ratio; NIR/SWIR2 normalized ratio; brightness temperature.	<u>Normalized surface reflectance:</u> Blue (482 nm); Green (561 nm); Red (654 nm); NIR (864 nm); SWIR1 (1609 nm); SWIR2 (2201 nm).	Minimum; Maximum; Average between min and Q1; Average between Q3 and max; Amplitude min to max; Amplitude Q1 to Q3.
NDVI-based phenology metrics		SRTM-based topography metrics
Start of season (SOS) NDVI value; End of season (EOS) NDVI value; SOS to maximum NDVI slope; Maximum to EOS NDVI slope; SOS to maximum NDVI amplitude; Maximum to EOS NDVI amplitude; SOS to EOS NDVI average; SOS to EOS NDVI total.		Elevation (meters).

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594 Supplementary Information Table 2. Strata definitions. For all strata, only land pixels were
595 considered; pixels labeled as permanent water and snow/ice in the Landsat ARD data quality
596 layer were excluded.

Stratum ID	Stratum definition
1	Cropland detected for both 2000-2003 and 2016-2019 intervals (stable cropland)
2	Cropland detected for 2016-2019 but not for 2000-2003 (cropland gain)
3	Cropland detected for 2000-2003 but not for 2016-2019 (cropland loss)
4	Possible cropland omission. Includes pixels that were not mapped as cropland and either (a) were identified as crops by the USGS cropland map or (b) had decision tree-based cropland likelihood between 0.1 and 0.5. for either time interval.
5	No cropland detected.

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599 Supplementary Information Table 3. Regional strata design for sample analysis. From each
600 stratum, we randomly sampled 100 Landsat data pixels. Region abbreviations (in square
601 brackets) used in sample interpretation interface
602 https://glad.geog.umd.edu/Potapov/Global_Crop/region_index.html.

Region	Stratum ID	Stratum area, Mha	N Landsat data pixels
Africa [AFR]	1	127.526	1734945656
	2	62.108	832287249
	3	15.089	205379304
	4	980.335	13144624830
	5	1778.860	24678278719
Southwest Asia [SWA]	1	208.332	3178440471
	2	42.586	658784671
	3	16.555	272983747
	4	327.859	5282381360
	5	904.372	14276931819
Australia and New Zealand [ANZ]	1	40.840	632262477
	2	5.178	80371180
	3	1.992	30780348
	4	106.495	1595940550
	5	639.163	9224591599
Southeast Asia [SEA]	1	153.584	2417025020
	2	30.896	480905111
	3	19.331	295816615
	4	360.637	5428379429
	5	1066.219	16822192585
Europe and North Asia [ENA]	1	204.192	4100803095
	2	29.461	610382468
	3	30.546	641970865
	4	328.740	6788487596
	5	837.569	19714599814
North and Central America [NAM]	1	180.202	3166064873
	2	21.335	367406884
	3	16.702	280651515
	4	326.299	5342386489
	5	783.962	13579648743
South America [SAM]	1	67.955	1006589638
	2	41.307	585378867
	3	7.472	109594042
	4	288.612	4019591418
	5	1325.860	18253454476

603

604 Supplementary Information Table 4. National cropland area (map-based estimates), ha×10³.

	2000-2003	2004-2007	2008-2011	2012-2015	2016-2019
Afghanistan	2084.9	2426.6	2704.1	2907.7	3165.7
Albania	300.3	270.0	260.7	255.0	243.5
Algeria	4999.4	5382.4	5578.9	5579.3	5635.6
Andorra	0.1	0.1	0.1	0.1	0.1
Angola	1131.6	1213.3	1424.3	2142.3	2994.9
Antigua and Barbuda	0.2	0.1	0.1	0.2	1.3
Argentina	37695.1	41071.4	43333.9	44310.8	43358.3
Armenia	301.8	282.9	289.2	326.4	365.5
Australia	42368.0	43412.6	43602.7	44706.0	45469.6
Austria	1303.6	1313.3	1318.7	1312.4	1264.8
Azerbaijan	1727.0	1652.9	1727.1	1928.6	2124.5
Bahamas	1.3	1.2	1.2	1.1	1.2
Bahrain	0.3	0.2	0.2	0.2	0.3
Bangladesh	6592.0	6638.9	6631.5	6669.5	6556.9
Barbados	3.9	3.2	3.3	5.7	8.0
Belarus	5150.2	5410.2	5677.1	5904.1	5673.7
Belgium	878.7	888.0	898.4	916.3	933.2
Belize	21.4	17.3	20.7	34.6	56.0
Benin	1851.1	1915.0	2101.5	2381.9	2698.1
Bhutan	9.9	9.9	10.7	11.1	12.6
Bolivia	1370.7	1630.6	1965.3	2305.4	2709.9
Bosnia and Herzegovina	200.3	202.7	221.0	235.1	237.9
Botswana	115.8	119.0	151.4	214.4	284.9
Brazil	30101.7	36350.9	40625.0	47535.0	53203.4
Brunei	0.0	0.0	0.0	0.2	0.3
Bulgaria	3443.5	3409.3	3507.4	3669.8	3706.5
Burkina Faso	2646.3	2967.1	3322.5	3709.7	4242.1
Burundi	285.5	293.5	315.7	349.6	409.2
Cambodia	4383.9	4644.6	4902.3	5518.7	5966.8
Cameroon	1254.4	1343.6	1456.3	1798.6	2090.7
Canada	36998.6	37005.2	36988.6	37613.1	38216.2
Cayman Islands	0.0	0.0	0.1	0.1	0.1
Central African Republic	63.9	56.2	76.7	147.6	256.0
Chad	3330.2	3774.2	4246.5	5090.9	5934.5
Chile	1070.6	1016.2	1063.7	1146.9	1202.1
China	117968.0	118426.7	119422.4	121364.1	123346.5
Colombia	545.0	501.0	542.5	654.4	902.2
Costa Rica	89.1	91.7	112.8	140.9	174.9
Cote d'Ivoire	691.3	680.0	800.4	1020.1	1361.2

Croatia	923.3	908.2	918.2	922.7	916.2
Cuba	1805.1	1494.6	1377.8	1328.8	1306.8
Cyprus	270.5	253.9	250.9	262.0	271.0
Czech Republic	2855.0	2800.3	2742.4	2712.4	2667.1
Democratic Republic of the Congo	1535.4	1600.7	1899.3	2650.6	3811.0
Denmark	2221.4	2242.6	2262.7	2275.3	2246.4
Dominican Republic	293.2	291.3	311.7	331.8	380.1
East Timor	45.8	46.5	49.0	50.9	54.3
Ecuador	293.4	285.6	309.8	346.4	397.8
Egypt	2913.4	3000.9	3100.4	3255.7	3451.3
El Salvador	72.3	65.7	67.1	74.1	78.2
Eritrea	266.0	261.6	270.7	276.8	287.1
Estonia	420.1	561.7	616.3	660.1	669.7
Ethiopia	14178.0	14091.4	14607.0	15444.9	16060.8
Fiji	28.6	29.3	32.1	35.2	38.2
Finland	1869.0	1926.8	1944.4	1968.8	1967.9
France	16827.0	17042.7	17153.8	17271.9	17482.2
French Guiana	5.1	4.8	3.5	1.9	1.1
Gabon	1.4	1.1	1.7	3.4	3.8
Gambia	247.5	252.2	257.9	271.1	282.5
Georgia	407.9	359.3	349.4	360.5	347.6
Germany	12023.5	12095.7	12289.9	12386.0	12289.4
Ghana	1948.9	2122.1	2304.6	2594.6	2995.1
Greece	2321.1	2202.7	2166.1	2110.7	2046.2
Guadeloupe	10.7	9.2	9.9	12.5	14.3
Guatemala	287.7	303.6	329.9	362.3	350.2
Guernsey	0.5	0.4	0.4	0.4	0.3
Guinea	147.8	153.1	176.4	241.7	333.1
Guinea-Bissau	34.1	36.0	39.7	46.4	60.1
Guyana	120.5	116.9	124.5	143.4	141.7
Haiti	72.9	65.6	70.5	77.0	86.8
Honduras	93.0	75.2	82.8	97.0	114.7
Hong Kong	0.1	0.0	0.0	0.0	0.1
Hungary	4681.5	4649.5	4634.1	4638.1	4568.7
Iceland	46.7	37.1	42.1	46.9	54.3
India	121370.8	126890.6	130182.1	134066.0	136899.1
Indonesia	6903.7	7146.4	7357.9	8020.5	8770.6
Iran	12179.4	13087.3	13254.3	13464.8	14081.8
Iraq	4713.3	4090.2	4051.7	5073.9	6296.5
Ireland	447.7	398.9	398.3	429.3	469.8
Isle of Man	7.8	7.1	7.3	6.9	7.5

Israel	438.6	425.8	425.0	430.1	426.4
Italy	7817.8	7693.5	7603.4	7617.4	7547.1
Jamaica	30.2	34.4	35.0	33.4	27.7
Japan	3100.6	3146.7	3154.1	3172.3	3187.0
Jersey	4.3	4.1	4.1	4.1	4.2
Jordan	241.2	231.9	231.9	244.2	259.1
Kazakhstan	20738.7	20745.9	21097.4	21644.2	22031.2
Kenya	4238.2	4497.3	4981.4	5433.1	5788.1
Kosovo	200.2	205.3	209.5	210.2	184.3
Kuwait	4.6	4.7	5.1	7.1	9.9
Kyrgyzstan	1173.3	1300.7	1361.2	1393.7	1419.3
Laos	966.3	1028.1	1111.8	1246.3	1360.5
Latvia	562.2	702.8	789.1	927.6	1017.2
Lebanon	108.7	101.8	102.9	104.8	109.1
Lesotho	211.6	210.4	213.9	228.2	246.2
Liberia	0.1	0.2	0.3	0.4	0.8
Libya	734.8	744.7	792.0	846.7	914.6
Liechtenstein	0.8	0.8	0.8	0.8	0.8
Lithuania	1182.7	1429.8	1586.5	1830.0	1966.0
Luxembourg	53.2	52.1	52.3	52.8	53.1
Macedonia	329.0	313.5	310.3	305.4	293.2
Madagascar	1252.5	1370.0	1463.5	1697.7	1972.3
Malawi	1721.9	1823.3	1937.6	2137.8	2319.7
Malaysia	306.3	301.1	296.9	298.8	307.4
Mali	4468.4	4871.3	5258.6	5675.9	6135.5
Malta	3.3	3.0	3.2	3.5	4.0
Martinique	0.8	1.2	1.5	2.3	3.4
Mauritania	23.0	17.7	22.8	35.9	50.9
Mexico	10035.8	10110.3	10500.1	10951.3	11168.6
Moldova	1873.0	1844.9	1832.1	1841.0	1853.7
Mongolia	380.9	374.3	409.5	455.5	561.1
Montenegro	16.5	15.8	15.5	14.3	12.5
Morocco	6259.4	6328.7	6435.5	6369.2	6311.3
Mozambique	1789.8	1970.3	2359.2	3069.3	3940.2
Myanmar	10551.8	10780.4	11009.7	11392.9	11739.0
Namibia	360.7	388.8	421.2	512.6	582.1
Nepal	1621.2	1671.3	1720.9	1763.3	1827.3
Netherlands	1016.5	996.0	987.8	985.5	982.7
New Caledonia	1.4	1.5	1.5	1.8	2.0
New Zealand	463.6	454.0	518.5	527.2	547.8
Nicaragua	160.3	165.4	193.6	223.0	241.7

Niger	7090.1	7453.4	7663.9	7817.6	8023.8
Nigeria	28379.6	29625.6	30780.1	32056.3	32967.3
North Korea	1727.2	1765.3	1804.8	1880.4	1929.6
Norway	419.4	420.2	424.0	431.4	440.4
Oman	16.8	14.4	16.5	23.1	30.7
Pakistan	16977.0	17831.4	18239.4	18554.7	18906.2
Palestine	75.4	69.3	67.8	70.0	75.3
Panama	34.6	29.2	45.4	80.0	121.3
Papua New Guinea	15.4	14.9	15.4	17.5	23.0
Paraguay	1518.1	1937.8	2206.1	2529.9	2814.7
Peru	745.8	794.5	853.0	950.8	1086.6
Philippines	3156.9	3223.6	3286.5	3486.4	3667.9
Poland	11619.9	11766.3	11742.2	11869.2	11948.8
Portugal	702.4	624.7	594.8	591.2	662.5
Puerto Rico	25.0	17.5	18.4	19.8	27.0
Qatar	2.8	2.9	3.8	4.9	6.7
Republic of Congo	55.7	66.6	83.7	115.3	170.7
Romania	7231.4	6955.7	7008.8	7418.1	7545.1
Russia	90919.6	85969.5	85186.5	85167.5	85260.0
Rwanda	768.0	784.1	813.0	854.2	912.0
Saint Kitts and Nevis	1.0	0.4	0.1	0.1	0.3
Saint Lucia	0.1	0.1	0.1	0.2	0.3
Saint Pierre and Miquelon	0.2	0.2	0.2	0.2	0.2
San Marino	1.2	1.1	1.1	1.1	1.1
Saudi Arabia	1346.5	1284.6	1198.4	1251.7	1298.0
Senegal	2936.2	3077.5	3189.6	3316.7	3410.0
Serbia	2398.3	2426.2	2439.4	2457.4	2445.7
Sierra Leone	18.1	22.1	25.2	29.0	32.2
Singapore	0.1	0.2	0.2	0.3	0.4
Slovakia	1419.6	1380.3	1358.0	1354.4	1342.4
Slovenia	134.4	144.7	148.8	150.7	143.2
Solomon Islands	0.0	0.0	0.0	0.1	0.1
Somalia	714.6	786.8	852.1	1032.6	1179.9
South Africa	7181.5	7040.8	6959.3	7297.3	7731.6
South Korea	1410.2	1349.8	1313.2	1268.8	1249.7
South Sudan	195.4	197.2	223.1	297.0	389.6
Spain	11586.1	11352.1	11208.7	11344.7	11406.3
Sri Lanka	762.0	788.2	830.9	917.4	997.3
Sudan	14587.1	15309.3	16081.3	17419.9	18694.0
Suriname	37.2	33.1	35.8	39.5	40.8
Swaziland	69.4	73.1	77.2	89.8	104.4

Sweden	1833.9	1842.7	1849.6	1889.0	1899.5
Switzerland	294.7	301.6	295.3	292.5	275.0
Syria	4402.6	4247.6	4131.2	4301.6	4560.6
Taiwan	340.0	321.4	316.4	323.2	329.9
Tajikistan	1054.4	1072.7	1086.0	1093.7	1131.6
Tanzania	9569.9	10276.4	11621.9	13700.2	15577.5
Thailand	16944.4	17363.8	17386.1	17550.8	17379.3
Togo	997.5	1018.0	1083.5	1186.6	1338.6
Trinidad and Tobago	3.4	3.7	3.9	3.6	3.3
Tunisia	1809.0	1856.0	1871.2	1892.9	1933.2
Turkey	17764.7	17988.5	18091.8	18171.3	18297.4
Turkmenistan	2015.6	2245.0	2366.0	2499.1	2618.0
Uganda	3306.1	3790.7	4309.0	5048.2	5788.4
Ukraine	31416.6	31236.3	31664.8	32368.9	32705.2
United Arab Emirates	35.3	7.9	6.6	8.5	10.7
United Kingdom	5739.1	5615.4	5689.4	5849.1	5991.7
United States	146839.8	145009.8	144912.5	147661.2	149131.5
Uruguay	1291.4	1695.4	2301.5	2635.5	2673.8
US Virgin Islands	0.0	0.1	0.1	0.1	0.3
Uzbekistan	5435.8	5579.3	5612.6	5672.0	5794.6
Vanuatu	0.0	0.0	0.0	0.1	0.1
Venezuela	628.3	622.6	662.2	702.7	724.7
Vietnam	5139.5	5072.9	5019.6	5062.7	5009.5
Western Sahara	0.0	0.1	0.1	0.2	0.2
Yemen	532.0	474.1	501.5	563.8	628.0
Zambia	1852.8	2077.1	2578.9	3296.1	4082.6
Zimbabwe	4365.8	4520.6	4762.8	5282.6	5823.5