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HarvestGRID: high-resolution harvested crop areas of the United States from 1981 to 2019

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Abstract

The United States is a major producer and exporter of agricultural goods, fulfilling global demands for food, fiber, and fuel while generating substantial economic benefits. Agriculture in the U.S. not only dominates land use but also ranks as the largest water-consuming sector. High-resolution cropland mapping and insights into cultivation trends are essential to enhance sustainable management of land and water resources. Existing data sources present a trade-off between temporal breadth and spatial resolution, leading to gaps in detailed geographic crop distribution. To bridge this gap, we adopted a data-fusion methodology that leverages the advantages of various data sources, including county-level data from the U.S. Department of Agriculture, along with several gridded land use datasets. This approach enabled us to create annual maps, termed HarvestGRID, of irrigated and harvested areas for 30 key crops across the U.S. from 1981 to 2019 at a resolution of 2.5 arc minutes. Over the past four decades, irrigated harvested area has remained relatively stable nationally; however, several western states exhibit a declining trend, while some eastern states show an upward trend. Notably, more than 50% of the irrigated land in the U.S. lies above three major aquifers: the High Plains, Central Valley, and Mississippi Embayment Aquifers. We assessed the accuracy of HarvestGRID by comparing it with other large-scale gridded cropland databases, identifying both consistencies and discrepancies across different years, regions, and crops. This dataset is pivotal for analyzing long-term cropland use patterns and supports the advancement of more sustainable agricultural practices.

1. Introduction

Agricultural practices have significantly reshaped the Earth's landscape. Globally, 15 million square kilometers of natural vegetation have been converted into croplands, and approximately 31.5 million square kilometers are used as pastureland [1]. While agriculture is vital for providing food, fiber, and fuel, it also uses a substantial portion of the planet's resources [2]. In the United States (U.S.), croplands and pastureland account for about 17% and 28% of the total land use, respectively [3]. The U.S. is the world's largest food exporter and among the largest food producers [4], generating nearly $400 billion annually in revenue [5].

While essential to society, agriculture is resource intensive, consuming more water than all other sectors combined [6], contributing almost 10% of total U.S. greenhouse gas emissions [7], and degrading the nation's ecosystems and waterways [8, 9]. At the same time, food production is threatened by climate change, water scarcity, and environmental degradation [10, 11]. To fully assess these risks and explore opportunities to make agriculture more sustainable and resilient, we must understand the spatial and temporal patterns of crop cultivation. Further, spatially-refined time-series data of croplands is crucial for assessing food security, water resource availability, and land management strategies [12].

Crop harvested areas are typically estimated through either farmer surveys or remote sensing, with each method presenting its own set of strengths and weaknesses. Survey-based estimates, while often more accurate at the specific spatial scale they are available, suffer a lack of spatial detail, the presence of missing records, and susceptibility to human errors. Moreover, conducting farmer surveys is often expensive and challenging to scale up. On the other hand, remote sensing offers a more cost-effective alternative, providing consistent, high-resolution data across extensive geographical areas. However, remotely-sensed harvested croplands can be inaccurate, particularly when differentiating between crops with similar spectral signatures [13]. To leverage the advantages of both methods, several studies [1, 14] have adopted a data-fusion approach. This technique utilizes survey data as a reliable 'ground truth' for an administrative unit, and then applies remote sensing data to achieve detailed spatial disaggregation within that administrative unit.

Significant advancements have been made in developing cropland datasets, each contributing uniquely to our understanding of agricultural patterns. Ramankutty *et al* [1] developed a dataset detailing global croplands at a 5-arc minute spatial resolution, integrating administrative level statistics with satellite-based land use data for the year 2000. While this dataset provides total harvested area per grid, it does not differentiate between crop types or between irrigated and rainfed agriculture. Building on this, Monfreda *et al* [15] differentiated between 175 crops and 11 major crop groups, also at 5-arc minutes, yet still did not distinguish irrigated and rainfed agriculture. This differentiation is crucial because crop productivity and water use differ significantly between rainfed and irrigated agriculture [16]. Portmann *et al* [12] further expanded on these efforts by offering datasets at 5 arc minutes that separated irrigated and rain-fed croplands for 26 crop classes at a monthly level for the year 2000. More recently, Grogan *et al* [14] provided irrigated and rainfed harvested areas for 26 crops at 5 arc minutes at the monthly level for the year 2015. Despite these advancements in providing monthly estimates, a limitation of these studies is their focus on single-year snapshots. This lack of consistent data covering extensive time periods limits the ability to analyze long-term trends.

Parallel to the advancements in global cropland data sets, remote sensing and survey instruments have been employed to identify croplands in the U.S. at unparalleled spatial resolution and detail. The Cropland Data Layer (CDL; [17]) provides a time-series of crop-specific harvested areas in the U.S. at 30 m grid pixels. The CDL uses satellite imagery and supervised image classification based on each crops' spectral signature to classify the crop grown in each 30 m pixel. Despite its high spatial resolution, the accuracy of this dataset is limited for less common crops [18], and it is not available nationally before 2008. In contrast, the U.S. Department of Agriculture (USDA) agricultural survey and census records provide less spatially detailed (county level) data, but these records, particularly during census years, are of higher quality and stretch back several decades (in some cases more than a century). While USDA survey and census records are available further back in time, there are gaps in the USDA survey records. For example, figure 1(a) shows USDA survey data reporting an unlikely sharp and sudden decrease to zero harvested corn area for the years 2010, 2011, 2013, 2014 and 2015 in Canyon County, Idaho. Although surrounding counties also showed similar reductions in corn production, state level values were consistent with previous years, suggesting missing records at the county level over actual reductions in crop acreage. Though these types of data gaps within USDA's survey data are not uncommon (see additional examples in figures 1(b)–(d)), the survey data is generally of high quality compared to other cropland data products.

The primary objective of this study is to create a spatially detailed and consistent harvested crop area dataset for the U.S. from 1981–2019, filling a critical data gap. We use a data-fusion approach, combining the high spatial resolution but shorter time-scale and less accurate CDL data with the low spatial resolution but longer time-scale and more accurate USDA survey data, to produce a gridded time-series of harvested area records. The 30 crops included in our data product account for approximately 98% of the total harvested area, and 94% of the irrigated cropland in the U.S. Through this research, we provide a novel data product called the Harvested Gridded Rainfed and Irrigated croplands Data, HarvestGRID [20], which consists of (i) total harvested crop area and (ii) irrigated harvested crop area for 30 major crops in the U.S. from 1981 to 2019 at a spatial resolution of 2.5 arc minutes. The total harvested area and irrigated harvested area provide crop-specific total harvested area and crop-specific irrigated harvested area for each grid cell. The difference between the total and irrigated area provides the rainfed area. A description of each data product is available in table 1.

The extensive time span of our dataset enables researchers to conduct in-depth analyses of long-term changes and trends in agriculture and serves as a consistent and easily usable input for national-scale modeling efforts. Our focus on the U.S. allows us to leverage the high-quality survey and census data provided by the USDA, which is available at more detailed administrative levels, like counties and states, compared to other countries that often report such data at the national level. Moreover, this research provides a reproducible workflow to create downscaled crop grids for any year and crop.

This paper is structured as follows. In section 1, we present background information, identify data gaps in the literature, and finally state our research objectives. In section 2, we describe methodological details and various data sources used in our study. We describe how we identified and rectified missing data in the USDA survey and census records to enhance the accuracy of our dataset. In this section, we also describe our

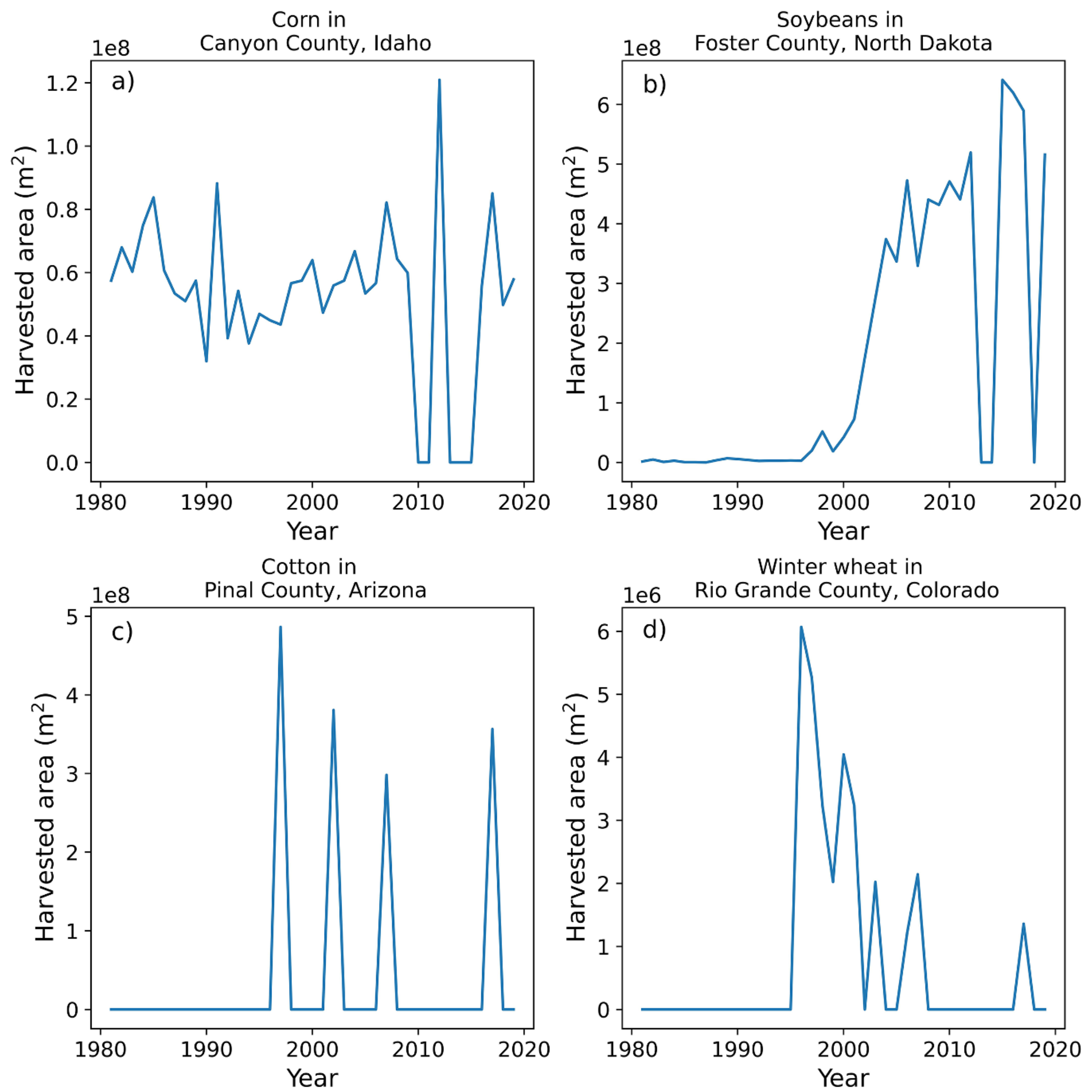

Figure 1. (a) Temporal anomalies (i.e. sudden and sharp changes) in crop harvested area across different counties: (a) Total harvested area for corn in Canyon County, Idaho; (b) Total harvested area for soybeans in Foster County, North Dakota; (c) Irrigated harvested area for cotton in Pinal County, Arizona; and (d) Total harvested area for winter wheat in Rio Grande County, Colorado reported by USDA [19]. State level records were consistent with previous years, suggesting missing records at the county level over actual reductions in crop acreage.

Table 1. Overview of HarvestGRID attributes. All data can be retrieved from the data repository Hydroshare [20]. The data is available as a NetCDF4 file for each crop. Each NetCDF4 crop file has two spatial coordinates (latitude, longitude), one temporal coordinate (Year), and four data variables as listed below.

Variable	Description
Total harvested area	The total annual harvested area (m^2) for a crop in each 2.5 arc minute grid cell from 1981-2019 for the CONUS.
Irrigated harvested area	The irrigated harvested area (m^2) for a crop in each 2.5 arc minute grid cell from 1981-2019 for the CONUS. The remaining total harvested area is rainfed.
Data methods (Total)	Method/data source used to obtain each total harvested area record.
Data methods (Irrigated)	Method/data source used to obtain each irrigated harvested area record.

data-fusion approach in detail. Section 3 details our data product and illustrates how irrigated and rainfed croplands have evolved over space and time in the U.S. Lastly, we discuss how our data can be used and some of the key assumptions and limitations of the data production in section 4.

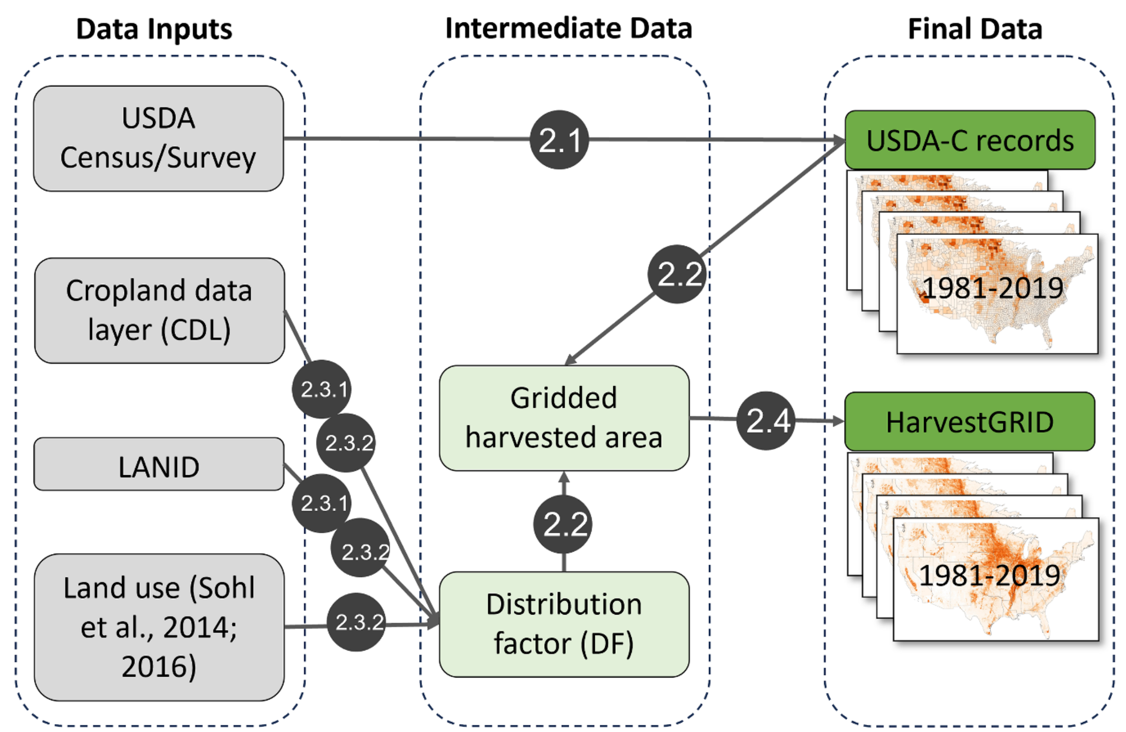

Figure 2. Schematic overview of the data and steps required to create our two data products, USDA-C and HarvestGRID, of harvested croplands in the United States. The numbers inside the dark circles on the arrows refer to subsections in the methods section where these procedures are detailed. In section 2.1, we process USDA census and survey records, and fill in missing values. In section 2.2, we use data fusion to disaggregate the corrected county-level records to grid level using distribution factors (DFs). These DFs, described in section 2.3, represent fraction of cropland within a county for a given year, crop, and irrigation status that is within each grid cell within the county. In section 2.4, we ensured that the total cropland allocated to any grid cell did not exceed the maximum allowable cropland area for that cell.

2. Materials and methods

We combined administrative level records from USDA with gridded land use data products to produce a gridded time-series of harvested area records. USDA provides a time-series of crop-specific annual total and irrigated harvested areas at the county and state level. Although these records lack spatial detail, they are useful in analyzing long-term trends because of their extensive historical coverage. However, as noted in section 1 and in figure 1, there are gaps in the USDA records. To address these data gaps, we implemented several steps described in section 2.1. We refer to these corrected USDA records as USDA-C throughout the paper. We note that USDA-C records largely follow USDA records, and deviate only when USDA records are missing or inconsistent. The resulting corrected dataset, i.e. USDA-C, provides a more complete representation of harvested areas. In section 2.2, we describe how we computed what fraction of cropland within a county for a given year, crop, and irrigation status is within each grid cell within the county. We call these fractions the distribution factor (DF). Finally, we applied our data-fusion approach, described in section 2.3, to disaggregate these corrected county-level records (i.e. USDA-C) into 2.5 arc minute grids using DFs. We refer to these disaggregated records as HarvestGRID throughout the paper. This data-fusion approach ensured that the distribution of crops within each county was consistent with the gridded data products, while the total harvested area for each crop within a county matched the USDA-C records. An overview of the methods is shown in figure 2.

2.1. Processing of USDA data

We obtained county and state level records of harvested areas for 30 crops from USDA, spanning from 1981 to 2019. Our exploratory data analysis of the USDA records revealed that (i) records of irrigated harvested areas were more frequently missing than those of total harvested areas; (ii) minor crops had a higher incidence of missing records compared to major crops; (iii) missing records were more common at the county level than at the state level; and (iv) survey years had more missing records than census years (typically years ending in 2 and 7). To address the missing records, we filled in data using several techniques described below. The processed USDA records, i.e. USDA-C, consists of data records derived from one of the following: (1) records directly obtained from USDA county-level records (56% of records and 83% of acreage); (2) estimates based on county-level USDA total harvested area and irrigation fraction (8% of records and 5% of acreage); (3) estimates derived from state-level USDA records and county fractions (15% of records and 10% of acreage), (4) values obtained through linear interpolation (10% of records and 1% of acreage), and 5) values extended by backfilling (11% of records and 1% of acreage). Table S1 provides a crop-specific breakdown of the number of records and acreage obtained from each of these methods. These methods were applied in a prioritized, hierarchical manner: first, county-level USDA data was used whenever available, followed by estimates based on county-level total harvested area and irrigation fractions. If those were unavailable, we used state-level data with county fractions. Linear interpolation and backfilling, which are less reliable, were employed only as a last resort, in that order, when no other methods could provide estimates of harvested area records. Each record in USDA-C is clearly labeled with the method used in its derivation. This labeling provides flexibility to the end-users to identify and filter records based on their origin.

We directly obtained records from USDA whenever data is available, ensuring that USDA-C records aligned perfectly with existing USDA records whenever possible. USDA-C deviates from USDA records when USDA records are missing, however. Approximately 90% of the total acreage (55% count of records) and 50% of irrigated acreage (58% count of records) directly corresponds with the original county-level USDA records. We note that we use more accurate USDA census records when available (typically every 5 years), and use survey records when census records are not available.

We utilized county-level total harvested area and irrigated fractions (IF) from the nearest year to estimate county-level irrigated records, where total harvested records are available, but irrigated records are missing. Irrigation fraction (IF) is defined as the ratio of crop-specific irrigated harvested area in a county to the total harvested area for the same crop in the same county as shown in equation (1). The irrigated fraction (IF) tells what fraction of cropland within a county for a given crop and year is irrigated. We obtained IF from remotely sensed data, i.e. from CDL and Landsat-based National Irrigation Dataset (LANID, [21]) for cases where IF from USDA records is not available. We used temporally averaged CDL and LANID data from 2008 to 2019 to obtain IF prior to 2008 for which either CDL data or both CDL and LANID data is unavailable. We estimated the missing irrigated harvested area by multiplying total harvested area and irrigation fraction from the nearest year as shown in equation (2),

$$\mathrm{IF}_{c,y}^{\mathrm{county}} = \frac{\mathrm{area}_{c,\mathrm{irrigated},y}^{\mathrm{county}}}{\mathrm{area}_{c,\mathrm{total},y}^{\mathrm{county}}} \tag{1}$$

$$\mathrm{area}_{c,\mathrm{irrigated},y}^{\mathrm{county}} = \mathrm{IF}_{c,\mathrm{nearestyear}}^{\mathrm{county}} \times \mathrm{area}_{c,\mathrm{total},y}^{\mathrm{county}} \tag{2}$$

where IF refers to irrigated fraction. Subscripts irrigated and total refer to the irrigated portion of the harvested area and the total harvested area, respectively. Subscripts c, y, and nearestyear refer to crop type, year, and nearest year with complete records, respectively.

We utilized state-level data USDA records and county fractions (CF) to estimate county level records where records are suppressed (i.e. records masked for privacy concerns due to limited responses) or where state level records are available, but county level records are partially or entirely missing. County fraction (CF) is defined as the ratio of harvested area in a county to the harvested area in the state as shown in equation (3). The county fraction (CF) tells what fraction of cropland within a state for a given crop, irrigation status, and year is within each county within that state. We obtained CF from the nearest year with complete records, i.e. all the counties growing the crop in question are reported that year within the state. The Cropland Data Layer is used to calculate CF if CF can not be calculated from USDA. We used temporally averaged CDL data from 2008–2019 to calculate CF prior to 2008 for which CDL data is unavailable. To estimate the suppressed or missing records, we employed a three-step process. First, we calculated the total harvested area for each state by aggregating all available county-level data. We then subtracted this sum from the corresponding state-level record to estimate the total suppressed or the total missing area. Finally, this difference was allocated across the suppressed counties or the missing counties within a state using a weighted county fraction as shown in equation (4),

$$\mathrm{CF}_{c,i,y}^{\mathrm{county}} = \frac{\mathrm{area}_{c,i,y}^{\mathrm{county}}}{\mathrm{area}_{c,i,y}^{\mathrm{state}}} \tag{3}$$

$$\mathrm{area}_{c,i,y}^{\mathrm{county,type}} = \frac{\mathrm{CF}_{c,i,\mathrm{nearestyear}}^{\mathrm{county}}}{\sum_{\mathrm{type}} \mathrm{CF}_{c,i,\mathrm{nearestyear}}^{\mathrm{county}}} \times \left(\mathrm{area}_{c,i,y}^{\mathrm{state}} - \sum_{\mathrm{county}} \mathrm{area}_{c,i,y}^{\mathrm{county}} \right) \tag{4}$$

where CF means county fraction. Superscript type and i refers to the type of record to be estimated, which can be either suppressed counties or missing counties and irrigation status (i.e. rainfed or irrigated).

We used linear interpolation and constant backfill to fill data gaps, particularly for minor crops, which do not have any records at the county level for a given year. For instance, the data for almonds is available for 1996, 1997, and 2002, and then consistently from 2008 onwards. This means that there are gaps in the records between 1997 and 2002, and again between 2002 and 2007. Methods described in the earlier section are inadequate to fill in such gaps. To address these gaps, we employed linear interpolation to estimate missing records based on existing data points. Furthermore, we used a constant backfill to extrapolate the records, for instance, for years prior to 1996 in the case of almonds. Constant backfill involves extending the latest available data point backwards to cover missing years. We concede that this is problematic especially when analyzing changes in crop acreage across the years. The alternative, however, is also misleading as it will show the crop is not being grown when it actually is being produced. We reiterate that the method used to estimate each record within USDA-C is clearly labeled, allowing end users to easily remove records if the assumptions to produce these records are not appropriate for the data user's particular purpose. Additionally, we note that only a small fraction (approximately 1 per cent each) of the total acreage is from linear interpolation or backfilling, which means that these estimation techniques have small impact on the overall data product.

2.1.1. Additional processing for alfalfa and other hay:

The USDA records sometimes distinguished between alfalfa and other hay, while in other instances it provided aggregated records as total hay. We disaggregated hay into alfalfa and other hay using the alfalfa fraction derived from the nearest year for which the alfalfa fraction data is available. The alfalfa fraction is defined as the ratio of total harvested area for alfalfa to total harvested area for hay as shown in equation (5). We obtained alfalfa harvested area for missing years by multiplying the alfalfa fraction from the nearest year with the total hay area as shown in equation (6). Harvested area for other hay was the difference between hay and alfalfa,

$$\text{alfalfaFrac}_{y}^{\text{county}} = \frac{\text{area}_{\text{alfalfa},y}^{\text{county}}}{\text{area}_{\text{hay},y}^{\text{county}}} \tag{5}$$

$$\text{area}_{\text{alfalfa},y}^{\text{county}} = \text{alfalfaFrac}_{\text{nearestyear}}^{\text{county}} \times \text{area}_{\text{hay},y}^{\text{county}} \tag{6}$$

where alfalfaFrac refers to the fraction of hay that is alfalfa.

2.2. Data fusion

We disaggregated USDA-C county-level records into 2.5 arc minute grids using the distribution factors (DF), described in detail in section 2.3. We reiterate that the DF represents the fraction of cropland within a county for a given year, crop, and irrigation status that is within each grid cell within the county. While it is possible to directly derive gridded harvested area by taking the product of CDL and LANID rasters, we opt to utilize USDA-C records at the county level and use DFs to disaggregate to the sub-county level for two reasons: (1) National coverage of CDL is not available prior to 2008, whereas USDA records are available for a longer period. The longer coverage from USDA (and therefore USDA-C) crop survey and census records allows consistency in our time-series, at least at the county level, over the entire period of analysis. (2) The creators of the CDL and LANID data products used the USDA census data [19] to validate their output; thus, we too use it as our reference benchmark. Time-series of crop-specific gridded values (2.5 arc minute) of harvested area were calculated by taking the product of DF and county level harvested area from USDA-C (area), as shown in equation (7),

$$\text{area}_{c,i,y}^{\text{grid}} = \text{DF}_{c,i,y}^{\text{grid}} \times \text{area}_{c,i,y}^{\text{USDA}-\text{C}}. \tag{7}$$

2.3. Distribution factor (DF)

We derived the distribution factor from two raster datasets: the Cropland Data Layer (CDL) and the Landsat-based National Irrigation Dataset (LANID) post-2008. The CDL provides annual crop-specific land cover information at 30 m resolution, while the LANID provides annual irrigation status information at the same resolution, using a supervised decision tree classification method. Since national coverage of CDL was not available prior to 2008, we further incorporated a time-series of agricultural land use data [22, 23] to obtain the distribution factors for the pre-2008 period. Although we followed different methodologies to compute DFs pre- and post-2008 due to data limitation, our dataset is always consistent with harvested area from USDA-C at the county level throughout our analysis period. We provide a more detailed description of the steps below.

2.3.1. Distribution factor post-2008

To obtain the distribution factor, we first performed a pixel-wise multiplication of CDL and LANID rasters to identify crop-specific irrigated harvested areas at a 30 meter resolution. The remaining CDL pixels that were not irrigated were assumed to be rainfed. We then aggregated these resultant 30 m resolution crop-specific harvested areas to 2.5 arc minute grid cells. We computed the crop-specific DF for each 2.5 arc minute grid cell in a county by dividing the aggregated crop-specific harvested area of a grid cell by the sum of all aggregated crop-specific harvested areas in a county using equation (8). This step allowed us to disaggregate USDA-C to a finer spatial scale while preserving crop area at the county level. For cases where USDA-C harvested area was available, but the intermediate gridded data product did not report harvested area for a specific crop for a county, we computed a non-crop-specific DF by dividing the total aggregated harvested area of a grid cell (i.e. sum of all crops and irrigation status in a year) by the sum of all aggregated harvested areas in a county using equation (9),

$$\mathrm{DF}_{c,i,y}^{\mathrm{grid}} = \frac{\mathrm{area}_{c,i,y}^{\mathrm{grid}}}{\sum^{\text{all grids in a county}} \mathrm{area}_{c,i,y}^{\mathrm{grid}}} \tag{8}$$

$$\mathrm{DF}_{c,i,y}^{\mathrm{grid}} = \frac{\sum_c \sum_i \mathrm{area}_{c,i,y}^{\mathrm{grid}}}{\sum^{\text{all grids in a county}} \sum_c \sum_i \mathrm{area}_{c,i,y}^{\mathrm{grid}}}. \tag{9}$$

2.3.2. Distribution factor pre-2008

The CDL does not provide national coverage prior to 2008; therefore, we utilized land use data, along with other data, to derive crop-specific gridded irrigated croplands. Specifically, we utilize modeled agricultural land use data for the years between 1981–1992 from Sohl *et al* [23], and land use data from Sohl *et al* [22] for the years between 1992–2005. For the years 2006 and 2007, we assumed that agricultural land use patterns were similar to those observed in 2005. The agricultural land use data that we used was available at 250 m resolution, which we aggregated to 2.5 arc minutes to match the resolution with the final data product. Since Sohl datasets are not crop-specific, we assigned crops to agricultural lands by assuming that a crop is historically (pre-2008) more likely to be grown on agricultural land if that same crop was observed to be grown on these lands more recently (post-2008). We do this by first calculating crop-specific average harvested area for each grid cell from 2008–2019 using equation (10),

$$\mathrm{AvgArea}_{c,i}^{\mathrm{grid}} = \frac{1}{12} \times \sum_{\mathrm{year}=2008}^{2019} \mathrm{area}_{c,i,y}^{\mathrm{grid}} \tag{10}$$

where AvgArea is the average crop-specific area for the twelve years between 2008 and 2019 within each 2.5 arc minute grid cell.

We then divide this temporally averaged crop area from CDL by the sum of the average area for all crops and all irrigation conditions from CDL and LANID. We then multiply this quotient by the aggregated agricultural land use area from Sohl *et al* [22, 23] for each grid as shown in equation (11). This gives us the harvested area, area, in each 2.5 arc minute grid cell by crop type and irrigation status for each year before 2008,

$$\mathrm{area}_{c,i,y}^{\mathrm{grid}} = \frac{\mathrm{AvgArea}_{c,i}^{\mathrm{grid}}}{\sum_c \sum_i \mathrm{AvgArea}_{c,i}^{\mathrm{grid}}} \times \mathrm{area}_{y}^{\mathrm{grid,Sohl}}. \tag{11}$$

Finally, we computed the crop-specific distribution factor, DF, for each grid cell in a county by dividing the crop-specific harvested area of a grid cell by the sum of all grid cells in a county containing the same crop using equation (12). This step allowed us to compute crop-specific DF pre-2008, which allows us to disaggregate USDA-C to 2.5 arc minute grids,

$$\mathrm{DF}_{c,i,y}^{\mathrm{grid}} = \frac{\mathrm{area}_{c,i,y}^{\mathrm{grid}}}{\sum^{\text{all grids in a county}} \mathrm{area}_{c,i,y}^{\mathrm{grid}}}. \tag{12}$$

2.4. Redistributing excess area

We ensured that the total cropland allocated to any grid cell did not exceed the maximum allowable cropland area for that cell. The total cropland for a grid is the sum of all crops for both irrigated and rainfed conditions as shown in equation (13). The maximum allowable cropland for a grid cell is the size of the grid cell minus the non-agricultural lands, such as urban lands, forests, water bodies, etc plus land area assigned as double cropping as described in equation (14). In the less than 1.5% of instances where the area of croplands exceeded the maximum allowable cropland area (MAA) within a grid cell (i.e. $Cropland_y^{grid} > MAA_y^{grid}$), we iteratively distributed the excess crop area to other grid cells within the county in the following order:

i) grid cells containing the crop of the same type and same irrigation status
ii) grid cells containing the crop of any irrigation status
iii) grid cells containing any crop
iv) grid cells containing shrubland, grassland, or fallowed croplands
v) grid cells containing double crops

$$\mathrm{Cropland}_y^{\mathrm{grid}} = \sum_c \sum_i \mathrm{area}_{c,i,y}^{\mathrm{grid}} \tag{13}$$

$$\mathrm{MAA}_y^{\mathrm{grid}} = \mathrm{GridSize} - \mathrm{NonAgLand}_y^{\mathrm{grid}} + \mathrm{DoubleCropping}_y^{\mathrm{grid}} \tag{14}$$

where Cropland is the area of all crops, MAA is the maximum allowable area, NonAgLand is the area of all non-agricultural lands (e.g. forests, urban lands, water bodies, etc), and *DoubleCropping* is the area of land assigned as double cropping in CDL.

When redistributing excess croplands from a grid cell, we assume that the ratio of crop-specific excess area and total excess area is equal to the ratio of crop-specific harvested area and total harvested area for the grid cell. That is, if 40% of the cropland in the grid cell is corn, we assume 40% of the excess area that needs to be reallocated to other grid cells is corn acreage.

3. Results

In this section, we present our findings on total and irrigated harvested area for 30 major crops in the U.S. at various spatial scales. We then compare our results with existing studies to evaluate the accuracy of our data product.

3.1. Harvested croplands in the U.S

Over the period of 1981–2019, the total annual average harvested area allocated to 30 major crops in the U.S. was 1269.4 square kilometers, of which about 195.11 square kilometers (15.35%) were irrigated as shown in table 2. Corn, soybeans, winter wheat, other hay, and alfalfa dominated crop production in the U.S. Collectively, these five crops accounted for almost 80% of the total harvested area, and approximately 65% of irrigated harvested area. Although rice was the 11th largest crop, accounting for less than 1% of total harvested area, it represented more than 6% of irrigated harvested area, good for 7th in irrigated area among all crops. Almost all (>99%) of the rice production was irrigated. Similarly, crops such as almonds (78.4%), potatoes (76.6%), walnuts (73.6%), tomatoes (67.8%), and grapes (62.1%) had high irrigated fractions.

Figure 3 illustrates the spatial distribution of average annual total harvested area (figure 3(a)) and average annual irrigated harvested area (figure 3(b)) for the 30 crops combined. Additionally, figures S1(a)–(z) [20] presents the spatial distribution for each crop individually. While crops are cultivated nationwide, notable concentrations of croplands occur in the Midwest and near major water bodies, such as the High Plains Aquifer, Central Valley Aquifer, Mississippi Embayment Aquifer, and major rivers. Specifically, croplands overlaying the Mississippi Embayment Aquifer, Central Valley Aquifer, and High Plains Aquifer account for approximately 14%, 10% and 30% of irrigated harvested area in the U.S., respectively. Areas overlying these three aquifers account for more than half of irrigated harvested area, although these areas represent less than 10% of U.S. land area. Certain crops show region specific cultivation. For instance, almost all of the almond production is in California. Similarly, the majority of cotton production is in southern states. Production of rice is mostly in California, along the border of Arkansas and Mississippi and southern regions of Louisiana and Texas.

Figure 4 shows a time-series of crop-specific annual irrigated harvested areas and total harvested areas from 1981–2019 in the U.S. Corn, soybean, and wheat, the three mostly widely grown crops, contributed to approximately 23.1%, 18.5%, and 22.5% of total harvested area, respectively, in 1981. The share of total harvested area dedicated to corn and soybeans increased to approximately 30.0% and 25.6%, respectively, by 2019, while wheat's share decreased to approximately 12.9%. We find a similar trend in irrigated harvested area; corn and soybeans show and increasing trend while wheat shows a decreasing trend. The increase in corn and soybean irrigated harvested areas can be attributed to expansion of irrigation in corn and soybean

Table 2. Average annual irrigated and total harvested area for 30 major crops in the U.S. from 1981 through 2019.

S.No.	Crop	Average (1981–2019) annual irrigated harvested area (km^2)	Average (1981–2019) annual total harvested area (km^2)	Irrigated fraction (%)
1	Alfalfa	25.57	91.35	28.0
2	Almonds	2.0	2.55	78.4
3	Apples	0.64	1.94	32.7
4	Barley	4.81	23.28	20.7
5	Beans	2.80	7.03	39.8
6	Canola	0.13	3.82	3.4
7	Corn	50.65	325.16	15.6
8	Cotton	18.12	45.48	39.9
9	Durum wheat	0.87	11.32	7.7
10	Grapes	2.51	4.04	62.1
11	Lentils	0.02	1.42	1.4
12	Millet	0.09	1.84	4.8
13	Oats	0.90	14.47	6.3
14	Oranges	1.46	2.8	52.1
15	Other hay	13.94	148.61	9.4
16	Peanuts	2.12	6.22	34.1
17	Peas	0.15	2.31	6.3
18	Pecans	0.27	2.03	13.3
19	Potatoes	3.95	5.15	76.6
20	Rice	11.95	11.99	99.6
21	Sorghum	5.50	37.52	14.7
22	Soybeans	23.18	282.50	8.2
23	Spring wheat	2.97	57.44	5.2
24	Sugarbeets	2.07	5.30	39.1
25	Sugarcane	1.82	3.50	52.2
26	Sunflower	0.78	10.25	7.6
27	Sweet corn	0.75	2.77	27.1
28	Tomatoes	1.12	1.65	67.8
29	Walnuts	0.75	1.02	73.6
30	Winter wheat	13.22	154.64	8.6
	Total	195.11	1269.40	15.4

producing areas in Arkansas, Mississippi, Missouri, Illinois, Indiana and other mid-western states. We find that irrigated wheat production has declined in almost all the states in the U.S. The fraction of irrigated soybeans more than doubled from 6.6% in 1981 to 15.6% in 2019. Irrigated harvested area has remained fairly constant at the national level as shown in figure 4(b). However, a closer look reveals that the irrigated area has changed at the state level; several western states exhibit a declining trend, while some eastern states show an upward trend.

Figure 5 shows a time-series of irrigated harvested areas for various states in the U.S. We see a sharp increase in irrigated area for Arkansas and Mississippi, almost doubling from 1981 to 2019. This increase in irrigated harvested area in Arkansas can be primarily attributed to the increase in soybeans, which increased by more than fourfold between 1981 and 2019. Similarly, the increase in irrigated harvested area in Mississippi can be attributed to the increase in soybeans, which increased by nearly 50% from 1981 to 2019. Similarly, we observe large percent changes in irrigated harvested areas in eastern states like Delaware, Maryland, and Michigan that had smaller irrigated harvested areas to begin with. These changes can be primarily attributed to changes in irrigated harvested areas for corn and soybeans. We observe minor reduction in both total and irrigated harvested areas for several western states like Washington, Oregon, California, Colorado, Idaho, and New Mexico, as shown in figures 5 and 6. Several states, like Arkansas, Louisiana, Mississippi, Wisconsin, Iowa, Delaware, and Maryland, show a downwards trend in total harvested areas but an upwards trend in irrigated harvested areas.

3.2. Comparsion with other cropland datasets

The county level harvested crop area dataset produced from this study (i.e. USDA-C) matches the USDA census and survey records and deviates only when USDA records are missing. Similarly, the gridded data product from this study (HarvestGRID) always aligns with the USDA-C (and mostly aligns with USDA) when aggregated to the county level. We note that harvested area records from USDA are considered to be of

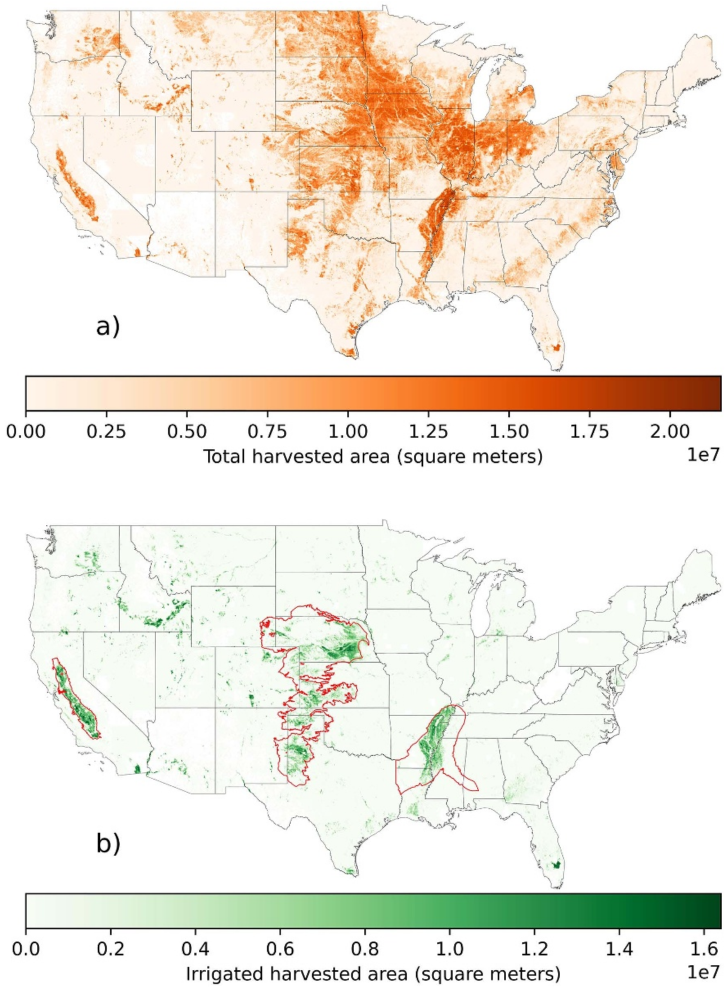

Figure 3. Spatial distribution of average annual (a) total harvested area (b) irrigated harvested area in m^2 per 2.5 arc minute grid cell, which is roughly 21 km^2. Boundaries of the Central Valley, High Plains, and Mississippi Embayment aquifers are shown in red in panel b.

high quality, and are widely used to create sub-county level estimates [1, 12] or to validate estimates derived from remote sensing [18, 21], despite the occasional missing data as noted previously.

We compared our datasets, USDA-C and HarvestGRID, with existing data products [12, 14, 24–27]. It is challenging to make direct comparisons because time-series of harvested area records are not readily available. Most data products are only available for specific years. For instance, MIRCA2000 [12] is available only for the year 2000 while GAEZ + 2015 (referred to as GAEZ2015 hereafter) [14] is only available for the year 2015. Spatial Production Allocation Model (SPAM) [24] provides crop-specific harvested area for 2000, 2005, 2010, and 2020. We compare our data product for the years 2000, 2005, and 2010 (referred to as SPAM hereafter), years that are common between both datasets. Additionally, these data products are available at coarser spatial scales than HarvestGRID; MIRCA2000, GAEZ2015, and SPAM are all available at 5 arc minutes. To facilitate a meaningful comparison with HarvestGRID, we upscaled our data product from a finer resolution of 2.5 arc minutes to match the 5 arc minutes of the existing datasets. Similarly, we aggregated the records from MIRCA2000, GAEZ2015, and SPAM to the county level to compare with USDA-C. Additionally, the number and type of crops reported in our study and previous studies do not match. We restricted our comparisons to those crop types that were available in both our current study and the referenced data products. Table S2 [20] shows the list of crops compared with our study.

We compared our total harvested area with existing studies at both the grid level and at the county level. We made crop-specific comparisons, and we compared total cropland, i.e. the sum of all crops common between the compared datasets. We compared only those grid cells for which both the current study and existing data product reported a non-zero value. Figure 7 shows a hexagonal binning plot comparing crop-specific harvested areas from the current study with the previous studies at the grid and county level. Figure S2 [20] shows similar comparisons for the total cropland. The hexagonal binning plot divides the two-dimensional space into hexagonal bins, and the color of the bin represents the density of data points in

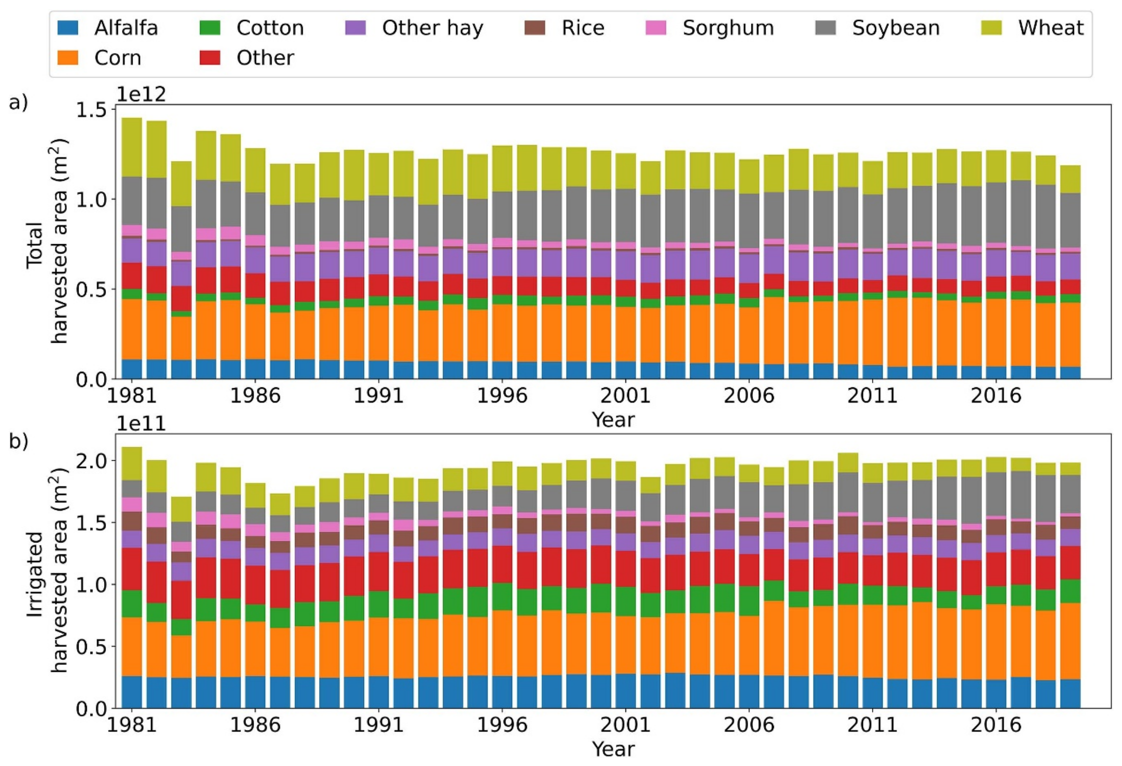

Figure 4. Time-series showing (a) annual total harvested area and (b) annual irrigated harvested area from 1981 to 2019.

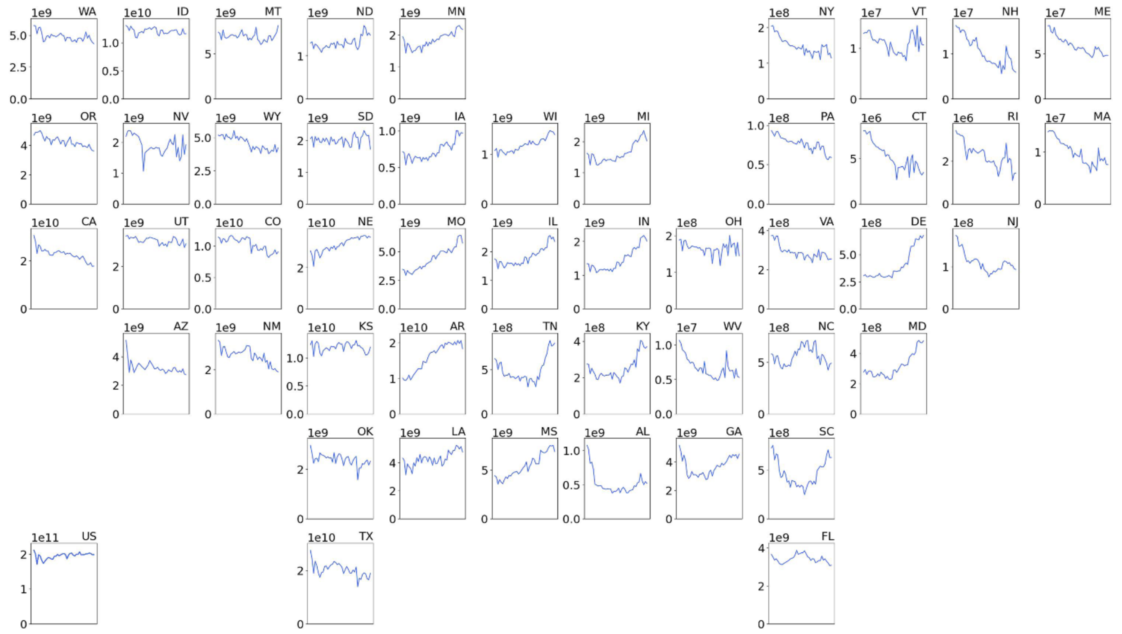

Figure 5. Time-series of irrigated harvested area for crops from 1981 to 2019 for each state in the contiguous U.S. The trend in total irrigated harvested area for the contiguous United States is shown in the bottom left corner.

that bin. Lower density of points is represented by the color blue, while higher density is represented by the color red. A higher density of points along the 1:1 line, indicated by the red line in the figure, means that the two datasets compared are generally in agreement.

Although we see higher density of points along the 1:1 line, there is a large spread (especially for smaller values). However, we find that our data product matches more closely with existing data products when compared at the county level. This suggests that there is high uncertainty at the grid level amongst all of the compared datasets, and precaution must be taken when making conclusions at the grid level. Similarly, when

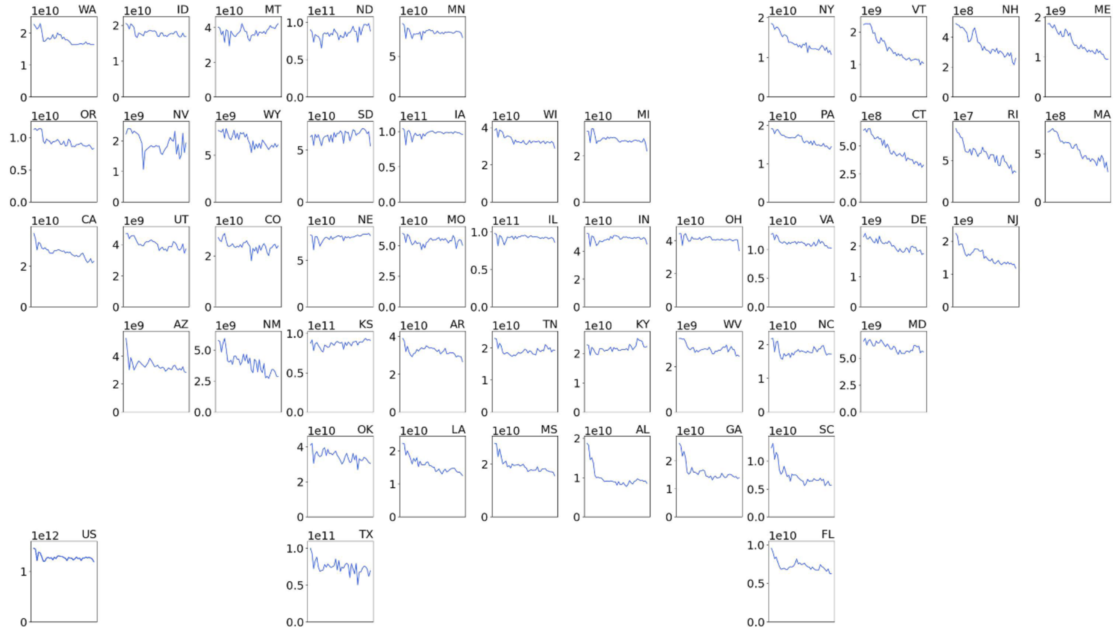

Figure 6. Time-series of total harvested area for crops from 1981 to 2019 for each state in the contiguous U.S. The trend in total harvested area for the contiguous United States is shown in the bottom left corner.

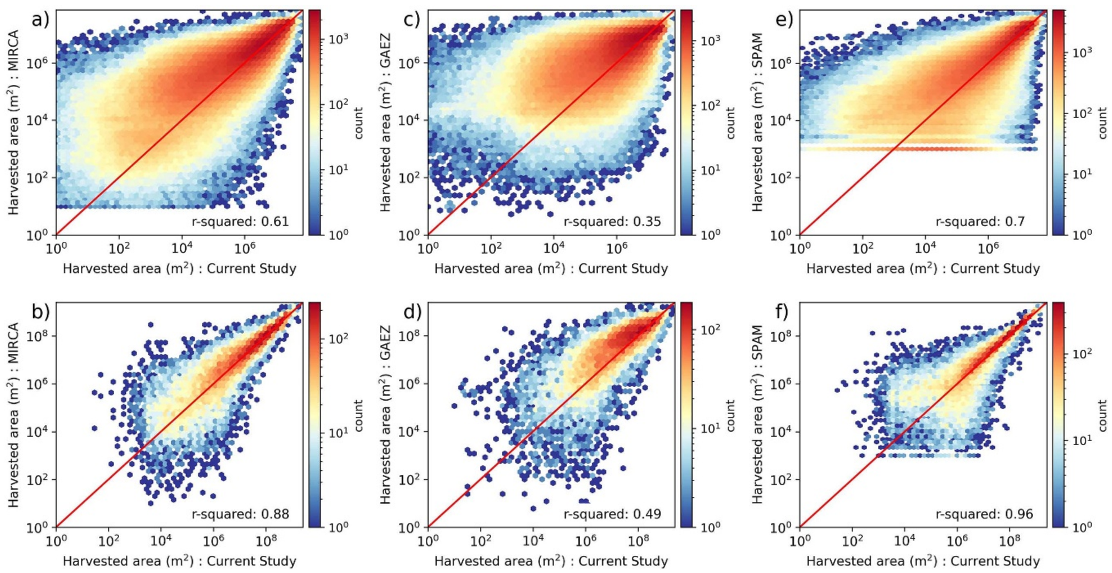

Figure 7. Crop-specific comparisons of harvested area from current study (x-axis) with previous studies (y-axis) at (a) grid level and (b) county level from MIRCA2000 [12], (c) grid level and (d) county level from GAEZ2015 [14], and (e) grid level and (f) county level from SPAM [24–27]. The red line represents the 1:1 line where the two data products are the same. The red color indicates higher density of points whereas the blue color represents a lower density of points.

comparing the data for total cropland, the alignment is much higher. The coefficient of determination is equal to 0.61 and 0.88 when crop-specific comparisons are made between the current dataset and MIRCA2000 at the grid and county level, respectively. The coefficient of determination increases to 0.65 and 0.93 for grid and county level, respectively, when compared for total cropland. The coefficient of determination is equal to 0.35 and 0.49 for crop-specific comparisons between the current dataset and GAEZ2015 for grid and county level, respectively. These coefficients of determination increase to 0.50 and 0.59 for grid and county level, respectively, when compared for total cropland. We find that our data matches more closely with SPAM; the coefficient of determination is equal to 0.7 and 0.96 when crop-specific comparisons are made between the current dataset and SPAM at the grid and county level, respectively. The coefficient of determination increases moderately to 0.73 and 0.96 for grid and county level, respectively, when compared for total cropland.

The observed discrepancies between our results and harvested areas reported in previous studies is likely due to methodological differences, as well as differences in input parameters. Furthermore, we use different land use and remotely sensed cropland datasets than previous studies to disaggregate county level statistics to the grid level, which can explain larger differences at the grid level compared to the county level.

4. Discussion and conclusion

We utilized a data fusion approach [1, 15], integrating administrative-level statistics with gridded land use data products, to produce a time-series of gridded harvested areas spanning 1981–2019. This data product represents a significant advancement over previous efforts, which primarily offered snapshots of harvested areas. The significance of our dataset lies in its potential applications, offering a valuable resource for understanding and analyzing trends in harvested areas over the past four decades. By tracking crop-specific harvested areas, we can estimate water usage for agriculture, as different crops have varying water needs [28, 29]. This information is valuable in identifying regions at risk of water stress and for assessing broader environmental impacts, such as changes in soil health [30]. Researchers and policymakers can leverage this information to inform decisions related to agriculture, land use planning, and resource management. Furthermore, HarvestGRID can serve as a nationally consistent gridded dataset for land surface, crop, and hydrologic models.

It is important to note that our dataset focusses on 30 major crops in the U.S., collectively representing about 98% of the total harvested area nationwide [19]. However, this representation may be less accurate at the county level, especially for areas where the cultivation of these 30 crops is less predominant. In such cases, our dataset may not fully capture the trends of crop production for those specific counties. For such instances, we recommend using alternative data sources [24, 31], to supplement records for missing crops.

While our dataset is useful, it is important to recognize and account for the inherent uncertainties associated with our data product. Notably, uncertainties from the input datasets used in our model are transferred to the final data product. The USDA employs sampling techniques to choose a subset of farmlands and utilizes standard questionnaires for data collection [32]. This method heavily depends on responses from farmers, making it susceptible to human errors. Moreover, crops with limited cultivation may not be adequately represented in the sample, leading to potentially larger errors. Despite our efforts to address inconsistencies in the USDA dataset, it is important to acknowledge that not all inconsistencies could be entirely eliminated and the degree of uncertainty could not be fully specified due to reporting limitations in the underlying input data. While less than two percent of the count of total harvested records are based on interpolation or backfilling, this percentage is much higher for minor crops. Several minor crops, such as almonds and sweet corn, do not have records for the earlier years of our study period, which required us to fill these gaps using linear interpolation and backfilling. We reiterate that we specify the method employed to derive each record in the USDA-C and HarvestGRID, enabling end users to filter out any records depending on their use-case.

Additionally, any uncertainties associated with the gridded data products used as input within our study are also present in our data product. Remotely sensed data products, relying on spectral signatures to distinguish crops, exhibit varying accuracy based on factors such as crop type, geographic location, and quality and quantity of satellite imagery available [33]. Furthermore, since crop-specific gridded data before 2008 were unavailable, we assumed that the distribution of crops prior to 2008 resembled the average crop distribution post-2008. While acknowledging that this assumption may affect the sub-county spatial accuracy of HarvestGRID, it is crucial to highlight that we have ensured the consistency of HarvestGRID at the county level by aligning it with the USDA-C data. It's also important to note that crop production is influenced by the complex decision-making processes of farmers [12], a variable that is challenging to accurately model in our and similar datasets.

The novel datasets generated from this research offer an unparalleled time-series of irrigated and total harvested area records for major crops in the U.S., spanning both county-level granularity (USDA-C) and a finer 2.5 arc minute grid resolution (HarvestGRID). These new data products will provide valuable information to researchers and policymakers for resource allocation, water management, and land use planning. Additionally, we show crop-specific temporal and spatial variations of harvested areas at multiple spatial scales. Moreover, through comparison with existing data products, we reveal substantial disparities, particularly at the grid level, underscoring the need for further research. This dataset provides valuable insights into harvested area trends over four decades, assisting researchers and policymakers understand how croplands have evolved over the last four decades in an unprecedented level of detail.

Data availability statement

The data produced from this study and the supplementary figures and tables are publicly available at Hydroshare [20]. The data and the supplementary information can be accessed through this URL: www.hydroshare.org/resource/6775800f22bd4be9b24e472038294fe7/.

Author contributions

L T M conceived the study and secured financial support to carry out the research. L T M and G L designed the study. G L led data collection, processing, and modeling efforts. G L and L T M analyzed the data. G L and L T M wrote and edited the manuscript. OpenAI's GPT-4 (9 Febuary 2024) was used to improve the readability of sections of the penultimate draft of this manuscript.

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Conflict of interest

The authors decalre no competing interests.

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