A review of global gridded cropping system data products

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Abstract
Agricultural monitoring, seasonal crop forecasting and climate change adaptation planning all require identifying where, when, how and which crops are grown. Global gridded cropping system data products offer useful information for these applications. However, not only the main sources of information (satellites, censuses, surveys and models) but also the spatial and temporal resolutions of these data products are quite distant from each other because of different user requirements. This is a barrier to strengthening collaborations among the research communities working to increase the capacity of societies to manage climate risks for global food systems, from extreme weather disasters to climate change. A first step is to improve cropping system data products so they can be used more seamlessly across various applications than they are currently. Toward this goal, this article reviews global gridded data products of crop variables (area, yield, cropping intensity, etc) using systematic literature survey, identifies their current limitations, and suggests directions for future research. We found that cropland or crop type mapping and yield or production estimation/prediction together accounted for half of the research objectives of the reviewed studies. Satellite-based data products are dominant at the finer resolution in space and time (<10 km and daily to annual), while model-based data products are found at the coarser resolutions (>55 km and ≥decadal). Census-based data products are seen at intermediate resolutions (10–55 km and annual to decadal). The suggested directions for future research include the hybridization of multiple sources of information, improvements to temporal coverage and resolution, the enrichment of management variables, the exploration of new sources of information, and comprehensiveness within a single data product.

Abbreviations

Abbreviation | Description
---|---
AVHRR | Advanced Very High Resolution Radiometer
ChinaCrop Phen1km | 1 km gridded annual crop phenology dataset for China
GAEZ | Global Agro-Ecological Zoning global dataset of historical yields of major crops
GFSAD1K | Global Food Security Support Analysis Data at 1 km
GGCM | Global Gridded Crop Model
GGCMI | Global Gridded Crop Model Inter-comparison
M3Crops | harvested area and yields of 175 crops
MIRCA | Monthly Irrigated and Rainfed Crop Areas around the year 2000
MODIS | Moderate Resolution Imaging Spectroradiometer
PCAM | Probabilistic Cropland Allocation Model
PSHW | potential sowing and harvesting windows of major crops
RiceAtlas | spatial database of global rice calendars and production
SAGE | crop calendar dataset developed at the Center for Sustainability and the Global Environment, University of Wisconsin-Madison
SPAM | Spatial Production Allocation Model
1. Introduction

Food supply disruptions, price rises and increases in food insecurity in 2020 under the ongoing pandemic represent risks for this interconnected world (World Bank 2020). Given the globalized food supply chain, extreme weather disasters under climate change would put additional pressure on our food system (Mbow et al 2019). To seamlessly address the risks emerging from extreme weather due to climate change, research communities working on agricultural monitoring, seasonal crop forecasting and climate change adaptation need to strengthen their mutual collaboration.

Global gridded cropping system data products serve as a basis to address questions regarding sustainable development in terms of food security, biodiversity conservation and climate mitigation—more specifically, questions related to the goals and targets in the 2030 Agenda for Sustainable Development (United Nations 2015). Global data products of cropland areas and their historical changes (Ramankutty and Foley 1999, Klein Goldewijk 2001) have widely been used since their release in the late 1990s and early 2000s. Then, crop-specific harvested area maps and yield datasets (Leff et al 2004, Monfreda et al 2008, You et al 2009) were released in the 2000s. Harvested area, yield and cropping intensity (number of harvests per year) are the components of production (Iizumi and Ramankutty 2015), and production is a linchpin in national food balance analyses. Compared to harvested areas, yields fluctuate year by year due to weather conditions and have also increased dramatically over the last century. Yield growth, rather than harvested area growth, has contributed predominantly to increased production over the last half century (Blomqvist et al 2020) and will remain important in the coming decades for feeding increasing populations while reducing pressure on the environment resulting from land-use changes. Reflecting this importance, two historical yield data products covering the last decades, one based on censuses (Ray et al 2012) and the other largely based on satellite data (Iizumi et al 2014), became available in the early 2010s.

Although satellite observations have formed key inputs for cropping system data products, the value of satellite data depends on crop variables and the application type. The cropping intensity (or crop calendar) can be analyzed using time series of satellite vegetation indices (e.g. Whitcraft et al 2015). However, crop modelers generally utilize census-based crop calendars as inputs (Elliott et al 2015). This difference in the selection of the source of information depends on the user requirements of each application type regarding the timeliness, availability of crop-specific information, spatial and temporal resolutions and accuracy of the data products.

Operational agricultural monitoring and forecasting have tight timelines of a few weeks to regularly release information for their users during the growing season. Project-based climate change risk assessments designed to inform national governments for adaptation planning span a few years. Assessments aiming to provide recommendations so that policymakers and other players can prepare interventions may fall in the middle of these two timelines, depending on the urgency of the necessary responses and their priority in the agenda (Mann et al 2019). Consequently, these application types and associated data products are rather independent of each other at present.

There are few review articles on global gridded cropping system data products compared to those on techniques specific to certain application types, such as satellite remote sensing for agricultural monitoring (Rembold et al 2013, Dong and Xiao 2016) and process-based crop modeling for climate change impact assessments (White et al 2011, Jones et al 2017). The literature that partly discusses gaps in existing data products is specific to different application types: agricultural monitoring (Atzberger 2013, Fritz et al 2019), seasonal crop forecasting (Delincé 2017, Iizumi and Kim 2019), food security assessments (Brown 2016) and land-use change models (Hertel et al 2019). For all of these application types, it is imperative to identify where, when, how and which crops are grown. Therefore, this article reviews global gridded cropping system data products across application types, identifies the current limitations, and discusses possible future improvements to these data products.

2. Methods

2.1. Systematic search

We conducted a systematic search for peer-reviewed articles, data papers and reviews published between 2000 and 2020 (as of 29 October) in ISI Web of Science v.5.35. We adopted a Boolean search key4 to filter nonagricultural studies from those focused on cropping system data products. This search identified 243 papers, which were successively screened based on their titles, keywords and abstracts, in accordance with the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) approach (Page et al 2021). One paper was likely a misregistered...
record in the database and had not yet been pub-
lished at the timing of our search. While global
data products were our primary interest, we did not
exclude local or regional data products. In addition
to the systematic search output, we also included 19
papers of importance from historical perspective that
were not included in the systematic search but were
identified by checking the title of the references of
recent papers. Eighteen papers were excluded since
dey did not present any analysis focusing on crop
(these papers only analyze vegetation indices without
distinction of cropland from other land cover and
land use), and therefore fell outside the scope of this
review. Twenty-two papers presenting crop-related
but non-spatial analysis were also excluded. As a res-
ult, 221 papers were used in our quantitative analysis
(figure 1). We further included what we consider key
papers to provide recent examples and a historical
perspective on the data product compilation or that
complement our discussion; these papers were col-
lected from outside the target period of the system-
atic search and were thus not used in the quantitative
analysis.

2.2. Quantitative analysis
We collected the spatial and temporal resolutions and
sources of information on the main crop variables
as well as the research objectives of the 221 studied
papers. The crop variables collected here include the
planted and harvested areas, yield, production, date
of phenological events, area under specific agronomic
practice, etc. Since production can be decomposed
into harvested area and yield, we counted both area
and yield variables when production was the target
crop variable of a paper. Even when a paper con-
sidered area and yield separately and did not explicit-
ly present production, we categorized it as a paper
analyzing production.

Four sources of information—satellite, census,
survey and model—were considered here. Censuses
include the statistics of crop variables for a given
administrative unit, whereas surveys are more
local information collected by field measurements
or household questionnaires. Many gridded data
products were, in reality, hybrids of multiple sources
of information (e.g. census and satellite). However,
the degree of hybridization ranged from simple to
complex and was difficult to evaluate objectively. For
this reason, we did not set up any ‘hybrid’ category
for the source of information. Instead, for instance,
we considered hybrid data products under both the
census and satellite categories.

Moreover, we noticed issues such as a single paper
containing multiple crop variables and data products.
We focused only on crop variables if multiple vari-
ables (yield, weather, soil and management) were
analyzed together. If multiple spatial resolutions of a
crop variable were studied, all resolution values were
collected. If yield was studied, the annual resolution
was assigned even if the crop models computed the
yield at a daily time step. Similarly, the assigned res-
olution was annual if satellite images obtained at a few
time points during the season were used to estimate
the crop acreage for a specific year.
Using the collected samples, we drew histograms of the research objective, spatial resolution, temporal resolution by the different sources of information. The effective sample sizes were 205, 205 and 197, respectively (supplementary data available online at stacks.iop.org/ERL/16/093005/mmedia). To this end, the research objective samples were categorized into (a) yield or production prediction/estimation; (b) cropland or crop type mapping; (c) crop calendar or crop phenology estimation; (d) agronomic management mapping; (e) assessment of damages from natural disasters, pest and disease outbreaks; and (f) others. These were the major research themes found in agricultural monitoring, seasonal crop forecasting and adaptation planning studies. If a paper had multiple objectives, the corresponding categories were all counted. The first category of the research objective (yield or production prediction/estimation) was further divided into production versus yield only and into seasonal estimations/predictions at the timing of preharvest and postharvest versus long-term projections at the decadal scale (e.g. climate change impacts). The second category of the research objective (cropland or crop type mapping) was separated into crop-specific analyses versus noncrop-specific analyses.

3. Results

In the following sections, we present an overview of the research objectives of the papers reviewed here and describe the spatial and temporal resolutions of the data products used therein. Satellite-based data products accounted for 42% of the effective samples, followed by model-based data products (29%) and census-based data products (20%). The representation of survey-based data products was as small as 9%. The high share of satellite-based data products was consistent with the result that 'specific crop is not identified' appeared most frequently, followed by major crops (wheat, maize, soybean and rice) as the crop or crop group studied in the reviewed papers (figure S1). Although we counted multiple times when a single paper deals with multiple research objectives, spatial resolutions or temporal resolutions, multiple counts accounted for only 12.2% (32 papers), 8.4% (22 papers) and 3.1% (8 papers) of the reviewed papers for research objective, spatial resolution and temporal resolution, respectively. Therefore, the risk that multiple counting inappropriately skewed the results in figure 2 and table S1 is small. Although not an exhaustive list, some key data products are highlighted in table 1 to give readers examples.

3.1. Research objectives

Cropland or crop type mapping (27%) and yield or production estimation/prediction (26%) accounted for a majority of the samples (figure 2), followed by crop calendar estimation (15%) and disaster damage assessment (12%). Relatively few studies (9%) aimed to assess management. Others (11%) included studies estimating greenhouse gases or pollutant emissions from croplands, risk assessments of human health or malnutrition, etc.

Satellite-based data products were widely used across many objective categories, particularly in crop calendar estimation and cropland and crop type mapping but were rarely used in management mapping (figure 2). Instead, model- or census-based data products were utilized for management mapping; this reflects the fact that satellite data are useful to characterize land cover (the physical land type) but find it challenging to map land use (how people are using the land). In yield or production estimation/prediction, model- and satellite-based data products all contributed to the research objective, with moderate variations in their shares. Survey-based data products (derived from household surveys) were predominantly used in disaster damage assessment.

Out of the 55 papers studying cropland or crop type mapping, 71% conducted crop-specific analyses (table 2). The remaining 29% studied noncrop-specific cropland areas and their changes. Census-, survey- and model-based data products were primarily used for crop-specific analyses and rarely for noncrop-specific analyses. In contrast, satellite-based data products were used for both crop-specific and noncrop-specific analyses. This again signifies the limitations of satellite data in identifying details beyond land cover and the additional value of census, survey- and model-based information for characterizing land use and management.

Over 60% of the 54 papers that aimed to predict/estimate yield or production dealt with only yield irrespective of the sources of information or timeframes (46% of estimation/prediction plus 17% of projection; table 2). Notably, a paper was coded as...
Table 1. Examples of gridded cropping system data products for the area, yield and crop calendar.

| Data product name (source)                  | Variable(s) and related notes                                                                 | Crop coverage | Temporal coverage and resolution | Spatial coverage and resolution | Reference                        |
|---------------------------------------------|---------------------------------------------------------------------------------------------|---------------|----------------------------------|--------------------------------|----------------------------------|
| M3Crops (census)                            | Area harvested and yield                                                                   | No distinction among seasons/systems | 175 crops | Circa 2000 (1997–2003 or 1990–1996) | Global; 0.083° (10 km; national or subnational) | Monfreda et al (2008) |
| MIRCA (census)                               | Area harvested and planting and harvesting months                                          | Rainfed and irrigated seasons/systems are distinguishable | 26 crops | Monthly, circa 2000 (1998–2002) | Global; 0.083° (10 km; national or subnational) | Portmann et al (2010) |
| SPAM (hybrid: census, satellite and model)  | Area harvested and yield                                                                   | Irrigated, rainfed high-input, rainfed low-input and rainfed-subsistence systems are distinguishable but no distinction among seasons | 42 crops | Circa 2010 (2009–2011). No time continuity is guaranteed with its predecessors SPAM 2000 (You et al 2014) and 2005 (Wood-Sichra et al 2016) | Global; 0.083° (10 km) | Yu et al (2020) |
| GAEZ (hybrid: census and model)             | Area harvested, yield and production; crop suitability and agro-ecological attainable yield | Rainfed and irrigated seasons/systems are distinguishable; crop suitability includes distinctions between single and multiple cropping | 23 crops | Circa 2010 (2009–2011) | Global; 0.083° (10 km) | Fischer et al (2021) |
| Ray2012 (census)                             | Area harvested and yield                                                                   | No distinction among seasons/systems | 4 crops (maize, rice, wheat and soybean) | 1961–2008 and annual. Three 5 yr averages, 1995 (1993–1997), 2000 (1998–2002), and 2005 (2003–2007), are publicly available | Global; 0.083° (10 km; national or subnational) | Ray et al (2012) |
| RiceAtlas (census)                           | Area harvested; production; and planting and harvesting dates                              | No distinction between rainfed and irrigated systems, but seasons are distinguishable | Rice | Circa 2010 (2010–2012) | Global; 2725 spatial units (national or subnational) | Laborte et al (2017) |
| PCAM (model)                                 | Likelihood of the existence of a harvested area                                             | No distinction among seasons/systems | 17 crops | 1961–2014; annual | Global; 0.5° (55 km) | Jackson et al (2019) |
| GFSAD1K (hybrid: satellite and census)       | Crop dominance and crop mask                                                              | Irrigated and rainfed systems are distinguishable, but no distinction exists between seasons | Aggregated (wheat, rice, maize, barley and soybean) | Circa 2010 (2007–2012) | Global; 0.0083° (1 km) | Thenkabail et al (2016) |

(Continued.)
| Data product name | Variable(s) and related notes | Crop coverage | Temporal coverage and resolution | Spatial coverage and resolution | Reference |
|-------------------|-------------------------------|---------------|----------------------------------|---------------------------------|------------|
| GDHY (hybrid: census, satellite and model) | Yield | No distinction between rainfed and irrigated systems, but seasons are distinguishable (major/second for maize and rice; winter/spring for wheat; and major only for soybean) | 4 crops | 1982–2016; seasonal | Global (some locations have no data); 0.5° (55 km) | Iizumi and Sakai (2020) |
| GGCMI phase 1 (model) | Yield (and other crop variables, such as days from planting to anthesis and maturity) | Irrigated and rainfed systems are distinguishable; only main season is available even when multiseason of a crop exist. | 19 crops | 1901–2012; annual | Global (all ice-free land surface irrespective of current cropland distribution); 0.5° (55 km) | Müller et al (2019) |
| SAGE (census) | Planting and harvesting dates | No distinction between rainfed and irrigated systems, but seasons are distinguishable | 19 crops | 1990s or early 2000s | Global (some locations have no data); 0.083° (10 km; national or subnational) | Sacks et al (2010) |
| PSHW (model) | Likelihood of occurrence of planting and harvesting | Rainfed and irrigated seasons/systems are distinguishable | 4 crops | Circa 2000 (1996–2005); daily | Global (all ice-free land surface irrespective of current cropland distribution); 0.5° (55 km) | Iizumi et al (2019) |
| ChinaCropPhen1km (hybrid: satellite and survey) | Dates of heading and maturity; green-up and emergence (wheat only); transplanting (rice only); and early vegetative stage V3 (maize only) | No distinction between rainfed and irrigated systems, but seasons are distinguishable (winter and spring wheat, spring and summer maize, and single and double rice) | 3 crops (rice, wheat and maize) | 2000–2015; daily | Mainland China; 0.0083° (1 km) | Luo et al (2020) |
Table 2. The research objective subcategories for yield or production estimate/prediction and cropland and crop type mapping.

| Research objective subcategories               | Share (%) |
|-----------------------------------------------|-----------|
|                                               | Satellite | Census | Survey | Model | Subtotal* |
| Yield or production estimation/prediction (n = 54) |           |        |        |       |           |
| Production estimation/prediction (n = 9)       | 6         | 11     | 0      | 0     | 17        |
| Production projection (n = 4)                  | 0         | 2      | 0      | 0     | 8         |
| Yield estimation/prediction (n = 26)           | 17        | 6      | 6      | 17    | 46        |
| Yield projection (n = 9)                       | 0         | 2      | 0      | 15    | 17        |
| Others (n = 6)                                 | 4         | 4      | 0      | 4     | 12        |
| Cropland or crop type mapping (n = 55)         |           |        |        |       |           |
| Crop-specific (n = 39)                         | 34        | 15     | 4      | 18    | 71        |
| Non-crop-specific (n = 16)                     | 22        | 2      | 0      | 5     | 29        |

*The sum of the values does not equal to 100 because of rounding.

'yield' only if it did not also present the harvested area; a paper presenting both the yield and harvested area fell into the 'production' category even if it did not explicitly describe production in the paper. Only 25% of the analyzed studies discussed production (17% of estimation/prediction studies plus 8% of projection studies). Others (12%) included, for instance, yield gap estimation. All four sources of information contributed to yield estimation/prediction, whereas model-based data products were predominantly used for long-term projection (specifically climate change impact assessments using process-based crop models). When projections were conducted based on census-based data products, simple linear extrapolations of past trends were used.

3.2. Spatial resolutions

The spatial resolutions of the data products mostly ranged from 0.03 km to 200 km, with a peak at 1–10 km (figure 3). The spatial resolution of the utilized data product was closely related to the source of information. Satellite-based data products were dominant for the relatively fine-resolution data products in the 1–10 km (mostly due to the use of AVHRR imageries), 0.25–1 km (MODIS), 0.03–0.25 km (Landsat) and <0.03 km (Sentinel-2) spatial resolutions. With fine resolutions <0.03 km, survey-based data products derived from field measurements were also found. In contrast, census-based data products were dominant at intermediate spatial resolutions of 10–55 km, driven by the M3Crops, MIRCA and SPAM (table 1). At the coarser resolutions of 55–200 km, model-based data products were predominantly driven by the GGCM outputs.

The satellite-based data products were characterized by their relatively fine spatial resolutions. The global 1 km crop mask map (GFSAD1K; table 1) is such an example (although GFSAD1K is coded as a hybrid data product, it is largely based on satellite data). Another example is the 500 m resolution average irrigated and rainfed areas for paddy and nonpaddy crops for the 2004–2006 period (Salmon et al 2015). Field sensing technology, which is used in precision agriculture, makes yield data available for a few hundred hectares of area at an extremely fine spatial resolution of a few meters (Robinson et al 2009). In many cases, the high spatial resolution of satellite-based data products was obtained in exchange for not distinguishing specific crop type (table 2; figure S1). Crop-specific analyses using satellite-based data products were feasible when accompanying crop-specific cropland map. The Cropland Data Layer products for the United States (Boryan et al 2011) and paddy rice area mapping (Oyoshi et al 2016) were examples of such crop-specific cropland map. Studies using model-based data products also used census-based data products to identify geographic harvested area distributions. Or studies using model-based data products performed for the entire ice-free land area (Müller et al 2019).

3.3. Temporal resolutions

The temporal resolution of the data products we reviewed fell within the range of daily resolutions to an average of a few decades (≥decadal), with a peak in the twice-a-month-to-annual range (figure 4). Satellite-based data products were dominant for relatively higher daily to-twice-a-month
and twice-a-month-to-annual resolutions, as satellite
vegetation indices (interpolated to daily time series)
are used to capture crop phenology characteristics
over a season. Census-based data products (represen-
ted by M3Crops, MIRCA and SPAM) dominated the
annual-to-multiyear and multiyear-to-decadal resol-
utions, as they represent averages over a few years
(table 1). Model-based data products (represented
by GGCM outputs) were dominant when assess-
ing yield impacts from weather extremes (annual-to-
multiyear timescales) and climate change (≥decadal).
The number of crops studied in a paper was espe-
cially high at the decadal-scale analysis since census-
based data products were used for such analysis in
conjunction with model-based data products (table
S1). However, at finer temporal resolutions where
satellite-based data products were dominant, only a
limited number of major crop types (wheat, maize,
soybean and rice) were selected as the target crops.

Neither satellite-, model- or census-based data
products provide complete information for analyz-
ing cropping intensity or multicropping patterns.
Satellite-based data products are powerful in detect-
ing the average annual number of vegetation activity
peaks over several years (that is, as an indicator of the
cropping intensity), but determining the crop type of
each peak without prior local knowledge is still chal-
lenging (Becker-Reshef et al 2018). SPAM uses crop-
ing intensities that are determined based on national
statistics and expert judgment as inputs in the spatial
disaggregation model (Yu et al 2020). The coarse tem-
poral resolution of census-based data products makes
deriving the annual number of harvests impossible.
Studies deriving the cropping intensity from census-
based data products adopt indirect indicators, such
as the sum of the harvested area of crops divided
by total cropland area (Ray and Foley 2013) or the
fraction of the year in which the cropland is covered
with crops (Siebert et al 2010). Although it does not
represent actual multicropping patterns, the global
map of dominant crop belts presented by Leff et al
(2004) contained information that could be useful
in inferring those patterns. To the best of our know-
ledge, Frolking et al (2002), (2006) presented pioneer-
ing work mapping the actual patterns and associated
cropping intensities in China and India. Waha et al
(2020) presented recent progress in mapping multi-
cropping patterns at the global scale.

4. Discussion

Having reviewed the existing global data products
of cropping systems, we next suggest directions for
future research to improve the utility of these data
products for various applications. These include
the hybridization of multiple sources of informa-
tion, improvements to temporal coverage and
resolution, the enrichment of management variables,
the exploration of new sources of information, and
comprehensiveness within a single data product.

These topics were derived from the following inter-
pretations of our analysis results. Among other
research objectives reviewed in this study, manage-
ment mapping and associated data products are most
under-studied. The difficulties of satellite remote
sensing in identifying cropland area under specific
crop type and management despite its high share in
the studies reviewed here emphasize the necessity of
hybridizing satellite data and other sources of informa-
tion. Therefore, the potential of models and sur-
veys that have hitherto been rarely used in hybridiza-
tion compared to censuses is worth discussing. The
limitation of satellite data also leads to the lack of
crop-specific data products at higher temporal resol-
utions hindering estimates of the impacts on season-
by-season production from extreme weather events.
Furthermore, the comprehensiveness of data product
needs to be improved so that one can analyze the risks
from extreme weather disasters to climate change
seamlessly.

4.1. Hybridization of multiple sources of
information

In hybridization, different sources of information
are combined using a theoretical model. Almost all
gridded data products are based on some sort of
hybridization. However, the degree of hybridization
has a wide spectrum. For instance, spatially disaggreg-
ating census data at an administrative unit level to
grid cells using satellite cropland maps is one example
of hybridization. However, M3Crops, using a simple
proportional allocation method with a small num-
ber of assumptions, is considered a census-based data
product rather than a hybrid data product (table 1).
In contrast, SPAM could be considered a hybrid data
product (table 1) because, in this product, many more assumptions based on economic theory and inputs (crop prices, market accessibility, land suitability, etc) are used together in an optimization framework to conduct spatial disaggregation.

Hybrid data products are expected to have more complete spatial and temporal coverages as well as more uniform representativeness in space and time than non-hybrid products due to their use of spatial data as inputs in theoretical models. While this is a reasonable expectation, substantial discrepancies exist among data products (Anderson et al. 2015, See et al. 2015, Adhikari and De Beurs 2016, Iizumi et al. 2018). Second, data products derived using complex hybridization methods are not necessarily more reliable than those based on simple methods, suggesting that this expectation has not been well founded, as explained using an example below.

A simple hybridization of censuses and satellite land cover maps was used to develop global cropland extent maps (Ramankutty and Foley 1998, Ramankutty et al. 2008, Lu et al. 2020). Then, crop-specific harvested area (and yield) maps were developed by disaggregating census data by proportionally allocating the data onto geospatial cropland maps (Leff et al. 2004, Monfreda et al. 2008). More complex hybridization methods have emerged, and some of these methods consider economic factors (You et al. 2014, Song et al. 2018, Joglekar et al. 2019, Yu et al. 2020). However, complex methods have not yet matured. As alerted by Yu et al. (2020), it is inappropriate to directly compare the harvested areas and yields of SPAM2010 with those of its predecessors SPAM2000 and SPAM2005 to analyze historical changes; the lack of temporal continuity in the major inputs to the spatial allocation model and the high sensitivity of the model to these inputs are the reasons for this deficiency.

Hybridization methods are promising for developing crop calendar products. Existing crop calendar data products are based on either census data or satellite data, and these two sources of information are quite distant from each other in terms of their data product compilation methods and user communities. SAGE and MIRCA (table 1) represent the former case. The latter case can be found in Kotsuki and Tanaka (2015) and Sakti and Takeuchi (2020); these data-sets were developed in hydrological modeling communities but have rarely been used for crop modeling because, in these products, crop types are not distinguishable. Although it is not a global data product, ChinaCropPhen1km (table 1) combined satellite leaf area index values, national cropland maps and crop phenology observations to derive the key phenological dates (heading, maturity, etc) of maize, rice and wheat over China on an annual basis from 2000 to 2015 at a 1 km resolution. ChinaCropPhen1km represents a notable improvement, offering a replicable method for developing global crop calendar data products.

4.2. Improvements to temporal coverage and resolution

Most existing data products are not time series but represent the average conditions at specific time points, such as in 2000, 2005 and 2010. This is a major limitation in characterizing annual variations and trends in yields, production totals, and other aspects of farming systems. Continuing efforts have been made to overcome this limitation for cropland maps (Ramankutty and Foley 1999, Klein Goldewijk et al. 2017). However, annual time-series crop-specific harvested area data products, such as Ray2012 and PCAM (table 1), are currently rare. Global annual land cover maps covering historical periods have only recently become available (Defourny et al. 2017, Winkler et al. 2021).

In addition to extending the temporal coverages of data products, there is also room to improve the temporal resolutions of existing data products. GDHY can distinguish seasonal yield; the yields of winter and spring wheat are separately available, for instance. Distinguishing among the different seasons of a given crop is important for precisely associating seasonal weather conditions with variations in yields. This importance is further emphasized by the fact that management practices differ by season. For example, monsoonal rainfall strongly affects rice cropping patterns in Asia; consequently, rainfed conditions dominate during the wet season, and irrigated conditions accompany the dry season. The average yields differ among the seasons as a result. Moreover, rice harvesting in the tropics occurs nearly every month due to multiple rice cropping and long planting windows per season. Data products comprising yields with resolutions of twice a month or monthly resolutions enable the dynamic patterns of multicropping to be captured and may be informative for agricultural monitoring and forecasting. Process-based models used for adaptation planning also gain value from such higher-temporal-resolution data products through the in-depth validation of models. This point is also applicable for harvested areas; RiceAtlas (table 1) represents an improvement in this direction.

4.3. Enriching management variables

Global gridded data products of some management variables have rapidly improved in recent years. Fertilizer use and irrigation are prime examples. Data products comprising nitrogen (N) and phosphorus (P) applications and manure production circa 2000 were developed by Potter et al. (2010). Then, N, P and potassium (K) application rates for specific crops became available in Mueller et al. (2012). Annual manure N production and application data products covering the period from 1860 to
2014 were developed afterwards (Zhang et al. 2017). Irrigation-related data products include the average yields in 2000 under irrigated and rainfed conditions (Siebert and Döll 2010), the annual irrigated land area from 1900 to 2005 (Siebert et al. 2015) and high-resolution (1 km) irrigated areas circa 2005 (the average of 1999–2012; Meier et al. 2018) in addition to MIRCA. These new data products enable simulations of the impacts of agricultural intensification on the Earth system (Lombardozzi et al. 2020) and identifications of rainfed cropland areas where sustainable irrigation expansion is possible (Rosa et al. 2020a, 2020b). The field farm sizes in approximately 2005 (Fritz et al. 2015) and pesticide use from 2015 to 2025 (Maggi et al. 2019) represent recently added variables.

However, much-needed management data products, including variables related to tillage practice, are still scarce. A lack of information on the varieties (or cultivars) adopted by producers persists, although data on the performance of varieties and producer adoption rates are occasionally found (DeBruin et al. 2017, Kobayashi et al. 2018, Nalley et al. 2018). This shortfall should be addressed in future research, given the claim that improved varieties explain one-fourth to half of the historical yield growth and the rest is attributed to improved management (the increased use of synthetic fertilizers, irrigation, chemicals and machinery, and improved input-use efficiency) (Herdt and Capule 1983, Jones 2013).

As noted earlier, it is imperative to identify where, when, how and what crops are grown. SPAM has added valuable information about who is growing crops. In SPAM, harvested areas and yields are separately available for four farming types: irrigated, rainfed high-input, rainfed low-input and rainfed subsistence farming. This is a remarkable improvement since the work of Dixon et al. (2001) and is expected to be useful when assessing the progress of the Sustainable Developmental Goal 2 (zero hunger), in which small-scale food producers are the target of policy.

Some further ideas for future management data product compilations are described herein. Replacing the market access information used in the development of SPAM with a more plausible data product (Verburg et al. 2011) or a global road and railway infrastructure data product (Koks et al. 2019) that can be used as a proxy of market access is worth considering. Hybridizing census-based estimates of small-scale farmers’ contributions to total production and crop diversity (Ricciardi et al. 2018) with satellite farm field size maps (Fritz et al. 2015) may provide further insights beyond the findings of recent efforts based on national-level data (Herrero et al. 2017, Mehrabi et al. 2021).

4.4. Exploiting new sources of information

The outputs of process-based crop models, both at the site and global scales, may play a role in future data product compilations, although caution is required for users to avoid circularity. If model outputs become data products, then those data products cannot be used for causal inference without much care as to whether the dependent crop variable and explanatory variables are truly independent of each other. GGCM historical simulations (Müller et al. 2019) are beginning to be used to investigate the relationships among climate, management and yield in the real world as a proxy of actual yields (Heino et al. 2020). However, crop models are primarily used for adaptation planning and have rarely been used for agricultural monitoring, seasonal crop forecasting or data product compilation, with some exceptions (for instance, crop models are intensively used for seasonal crop forecasting in Europe; van der Velde and Nisini 2019). Emerging research (Lobel et al. 2015, Jin et al. 2017, Deines et al. 2021) has combined site-level crop model simulations with satellite imagery and weather observations to estimate yields over multiple states of the United States at 30 m resolution without the need for model calibration. This approach is, in principle, applicable globally (Azzari et al. 2017) and may play a role in developing a very-fine-resolution yield data product.

While numerous studies have estimated crop phenology solely based on satellite data, crop phenology models, a key component of crop models, are accurate in estimating the dates of key phenological events when the planting date and daily temperature are given. As global daily meteorological data products are available (Skakun et al. 2017, Toreti et al. 2019), the key limitation is information on planting date. Therefore, combining model-based planting dates such as those in PSHW (table 1) with satellite data has the potential to improve crop calendar data products.

Dense crop observations are becoming increasingly available primarily through precision-agriculture applications (e.g. Robinson et al. 2009, Deines et al. 2021). Although it is not available everywhere, such information is valuable for developing new data products at unprecedentedly fine spatial resolutions if confidentiality can be ensured.

4.5. Comprehensiveness within a single data product

Finally, future data product compilations should consider the comprehensiveness within a single data product. Season-by-season harvested area and yield, in addition to cropping intensity, are required to compute production at an increased temporal resolution. Currently, most census-based data products record annual harvested areas that aggregate multiple seasons. These products are useful when computing production on an annual or multiyear average basis but are insufficient when analyzing production at monthly to seasonal resolutions in the face of extreme weather events. Production shocks have more direct
relevance for commodity markets and food insecurity than fluctuations of any single component of production. This can be understood if one imagines that an increase in area compensates for a decrease in yield, leading to unchanged production. Another example is that doubling the cropping intensity increases production without changing either the planted area or yield. Studies addressing some elements of these issues are beginning to emerge (Cohn et al 2016, Lesk et al 2016, Rezaei et al 2021). We therefore emphasize the importance of covering all production components with a single data product so that users can perform complete and consistent analyses. GAEZ provides complete information on area, yield and multi-cropping pattern. However, although GAEZ is useful when analyzing production impacts from changes in mean climate condition, further information about changes in area, yield and crop failure at time scales shorter than a month is required when analyzing production shocks from extreme weather events. RiceAtlas contains crop calendar, harvested area and production information for up to three seasons. Such data products are valuable for solving the ambiguity of current data products in studying multicropping, which is an important measure of agricultural intensification and adaptation (Waha et al 2020) and is currently understudied because of its elusive-ness and complexity (Bégué et al 2018). However, this advantage of RiceAtlas is traded off against the number of crop types covered since RiceAtlas only covers one single crop, while other data products containing both area and yield at annual resolution (M3Crops, SPAM and GAEZ) cover many more (23–175) crops or crop groups (table 1).

5. Conclusions

Many global gridded cropping system data products have become available during the last two decades. These products serve as a basis for many research and applications related to agricultural monitoring, seasonal crop forecasting and adaptation planning. The user requirements that need to be met depend on the application type, which determines the selection of the source of information. As a result, the spatial and temporal resolutions of the utilized cropping system data products vary by application type. However, in the face of increasing extreme weather disasters under climate change, these application types all must contribute to increasing the capability of societies to manage climate risks seamlessly in the globalized food system. Toward this goal, we emphasize the importance of improving global gridded cropping system data products so they become more commonly used across various application types than they are currently.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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