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Global cropping intensity gaps: Increasing food production without cropland expansion

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ABSTRACT

To feed the world's growing population, more food needs to be produced using currently available cropland. In addition to yield increase, increasing cropping intensity may provide another promising opportunity to boost global crop production. However, spatially explicit information on the cropping intensity gap (CIG) of current global croplands is lacking. Here, we developed the first spatially explicit approach to measure the global CIG, which represents the difference between the potential and actual cropping intensity. Results indicate that the global average CIG around the year 2010 was 0.48 and 0.17 for the temperature- and temperature/precipitation-limited scenarios, respectively. Surprisingly, global harvest areas can be expanded by another 7.36 million km^2 and 2.71 million km^2 (37.55% and 13.83% of current global cropland) under the two scenarios, respectively. This will largely compensate the future global cropland loss due to increasing urbanization and industrialization. Latin America has the largest potential to expand its harvest area by closing the CIGs, followed by Asia. Some countries in Africa have a large CIG, meaning that some additional harvests can potentially be achieved. Our analysis suggests that reducing the CIG would provide a potential strategy to increase global food production without cropland expansion, thus also helping achieve other Sustainable Development Goals such as biodiversity conservation and climate change mitigation.

1. Introduction

The Sustainable Development Goals of the United Nations adopted in 2015 articulate a road map to "the future we want" in terms of human welfare and environmental sustainability (Obersteiner et al., 2016; Gao and Bryan, 2017). One of these 17 ambitious goals is to end global starvation and achieve zero hunger by 2030. However, this goal faces great challenges as global demand for food production continues to increase due to global population growth, changes in diets, and biofuel consumption (Godfray et al., 2010; Kastner et al., 2012). Several estimations show that global agricultural production may need to grow by 70–110% to meet the increasing demands associated with human uses and livestock feed by 2050 (Alexandratos, 2009; Tilman et al., 2011). This requires searching for effective strategies to raise future food production (Erb et al., 2016).

Agricultural land expansion or extensification has made a great contribution to past increases in global food production (Macedo et al., 2012; Levers et al., 2016). However, further extensification of cropland in future, often through altering natural ecosystems through land clearing, seems to be unlikely because cultivation of this potentially available land is at odds with efforts toward biodiversity conservation, greenhouse gas emission mitigations, and the management of regional climate and hydrological changes, and would incur high costs associated with the provision of necessary infrastructure. Thus, the most likely scenario is that more food needs to be produced from the same amount of (or even less) land through the intensive use of cropland (Wu et al., 2014a,b). Agricultural intensification is normally achieved either by increasing the yield per unit area of individual crops or by increasing the number of crops sown on a particular area of land, or both (Gregory et al., 2002).

Numerous studies have revealed a large yield gap and proposed solutions for closing this gap by growing adoption/application of fertilizers, irrigation, mechanization, and improved seed varieties (Licker et al., 2010; Neumann et al., 2010; Mueller et al., 2012; Kravchenko et al., 2017). However, while acknowledging the great implications of crop yield growth for global food security, some scientists doubt its ability to meet increasing future food demand (Pugh et al., 2016). Although yields continue to increase in many areas, yields also either

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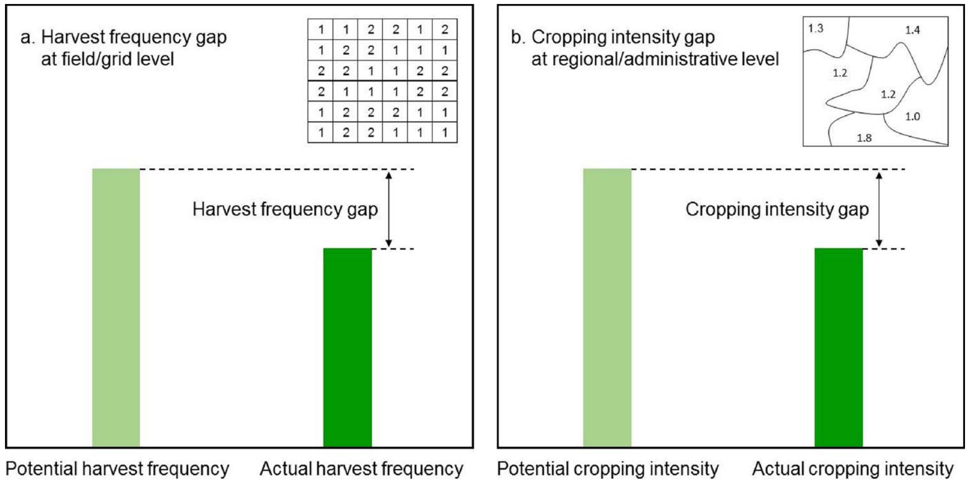

Fig. 1. Illustration of the concept of harvest frequency and cropping intensity gap.

never improve, stagnate, or collapse in other areas (accounting for about 25% of global croplands) (Ray et al., 2012; Grassini et al., 2013). Projections on future yields found that yield increase is obviously less than the expected annual growth rate required to double global production by 2050 (Ray et al., 2013). This could be the real future situation because it becomes more difficult to sustain further yield increases as farmers' yields approach the potential threshold. Furthermore, how best to close the yield gap largely depends on the capacity of local farmers to access and use seeds, water, nutrients, pest management, soils, and knowledge, all of which face considerable technical and/or market constraints, such as high input costs or low returns from increased production. Closing yield gaps is also associated with uncertain impacts on the environment and the potential for negative feedback effects that could undermine future food production (Foley et al., 2011).

More intensive use of existing croplands by increasing cropping intensity may provide a possible alternative for increasing global food production (Dias et al., 2016; Meng et al., 2017). An increase in cropping intensity by increasing the number of crops per cropping cycle or intercropping with other crops can increase the frequency of harvests each year, resulting in increased food supplies without additional cropland expansion (Mauser et al., 2015). Numerous studies have assessed cropping intensity potential using climatic indicators (IIASA/FAO, 2012; Liu et al., 2013a,b; Zhang et al., 2013; Yang et al., 2015) or to map the actual cropping intensity across space using multiscale remote sensing data or by integrating remote sensing and consensus data (Galford et al., 2008; Siebert et al., 2010; Biradar and Xiao, 2011; Jain et al., 2013; Langeveld et al., 2014; Zuo et al., 2014). These studies generally focusing on either actual or potential cropping intensity have helped to shed light on the status of cropping intensity and its contribution to global production growth, while the global-scale gap between actual and potential cropping intensity remains little explored. Ray and Foley (2013) analyzed the "harvest gap", that is, the gap between the maximum harvest frequency that is theoretically possible and the harvest frequency seen today. However, they computed the maximum harvest frequency using only a temperature variable and excluded the significant impacts of precipitation. Moreover, their study used FAO agricultural statistics to calculate actual harvest frequency, which was restricted to a country-level analysis, thereby ignoring the spatial heterogeneity, in particular in large countries such as China, India, and the United States. Furthermore, the FAO agricultural statistics were taken from different and inconsistent data sources. This may create some inconsistencies in the results and may introduce errors such as underestimation in some places and overestimation in others. Spatially explicit and accurate information on the cropping intensity gap (CIG) is thus critically needed as it can help to identify regions that can harvest their croplands more frequently and those that have the potential to increase harvest areas by a more intensive use of their standing croplands to achieve the Sustainable Development Goals (Yu et al., 2017).

The objective of this study is thus to propose a spatially explicit approach to exploring the global CIG in 2010. We used an adapted IIASA/FAO GAEZ approach to calculate potential harvest frequency (HF_p) and satellite observation data consistently to map actual harvest frequency (HF_a) at a grid level. The results of HF_p and HF_a were then aggregated to calculate the potential cropping intensity (CI_p) and the actual cropping intensity (CI_a), as well as the CIG for individual countries. Using this CIG, we finally identified regions where a large potential CIG exists, and evaluated the case for increasing cropping intensity to expand the harvest areas without cropland expansion.

2. Methods and materials

2.1. The CIG concept

CIG was introduced here to measure the amount of incremental cropping intensity that is possibly available if all croplands in a given region are fully intensively used. Intensive use of cropland is widespread across the world. Several concepts, e.g., harvest/cropping frequency, cropping intensity, multiple cropping index, exist as a proxy for cropland use intensity (Iizumi and Ramankutty, 2015; Stephan et al., 2016; Yu et al., 2018). Harvest/cropping frequency, normally expressed in integer numbers, measures the number of harvests of a particular plot or field in one specific year (Fig. 1a). Cropping intensity is essentially related to what other scientists have called "multiple cropping" and is defined as the ratio of the sum of the annual harvested area to total cropland for a given region or administrative unit. It is expressed as an average value in floating numbers, which is slightly different from harvest frequency (Fig. 1b). In the current study, the terminology of cropping intensity is preferable as the main objective is to understand the CIGs at regional to global scales, rather than field or plot level. The CIG can then be conceptualized as the difference between the potential cropping intensity (CI_p) and the actual cropping intensity (CI_a) in a given spatial unit. However, the potential harvest frequency (HF_p) and the actual harvest frequency (HF_a) for each grid cell of cropland need to be first determined.

2.2. Measuring potential harvest frequency

To estimate the regional CI_p, the HF_p for each grid of cropland was first determined. Theoretically, the success of a crop harvest for a plot or field of land is critically dependent on the crops in question and the

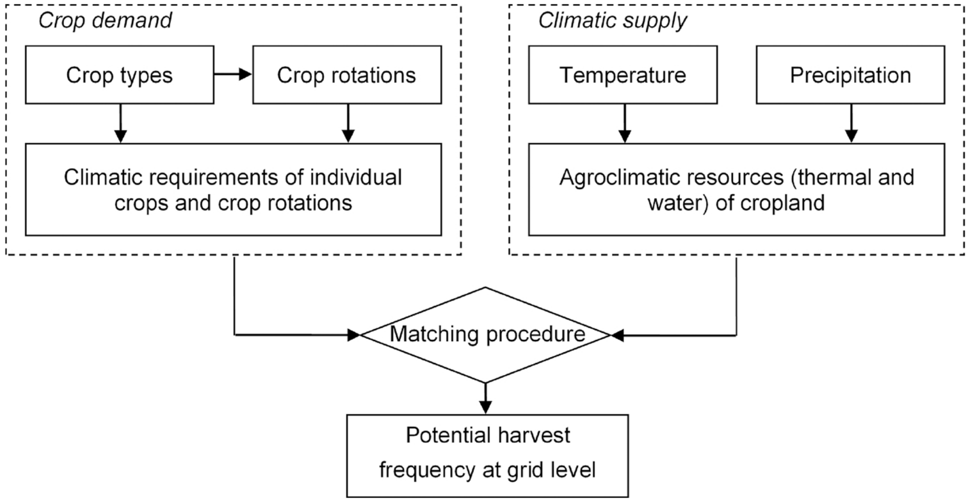

Fig. 2. A matching procedure for estimating potential harvest frequency.

climatic conditions, as each crop requires a specific type of growing season—warm temperatures for a sufficiently long time—for the successful completion of all stages in the life cycle for sequentially grown crops: germination, growth, floral initiation, grain filling, and maturity. With this assumption, we used an adapted GAEZ model in this study (IIASA/FAO, 2012; see Supplementary Methods of measuring cropping intensity gap). This model adopted a simple matching procedure to estimate the HF_p by comparing the individual crop demands with the surrounding climatic supply (Fig. 2).

On the demand side, we focused our analysis on four widespread crops (rice, wheat, maize, and soybean) (Table S1), and traditional sequential cropping practice across the world to estimate a more realistic HF_p. For the four crops considered, crop rotations or combinations can be very flexible. Here, we considered those widespread crop rotations across the globe to ensure that the algorithm uses typical cropping sequences in cultivation cycles. As a result, different harvest frequency and its crop rotations were finally determined, and the corresponding climatic requirements were calculated (Table 1). On the supply side, we used growing degree days (GDD) as a heat indicator and introduced precipitation as a water indicator and the climatic characteristics for each grid of cropland were calculated in a standard GIS software environment (ESRI ArcGIS 9.1) (Figs. S1 and S2). Soil and topography were assumed not to be the major limiting factors given the fact that these croplands are already under cultivation for different crops. Finally, the climatic requirements of individual crops and crop rotations were matched with the climatic supply. The C programming language was used to develop the matching program, allowing the model directly to access the multiple GIS grid format data and text format data. When both thermal and water supply characteristics in a grid cell matched well with those of crop requirements, the HF_p was considered possible for that grid cell.

Table 1
Different potential harvest frequency, crop rotations/combinations, and thermal and water requirements.

Potential harvest frequency (HF_p)	Crop rotations/ combinations	Annual GDD (°C)	Annual precipitation (mm)
No cropping	–	≤1600	≤300
Single cropping	winter wheat or spring wheat	≥1600	≥300
Double cropping	–	≥3600	≥600
	winter wheat/maize or soybean	≥4300	≥730
	winter wheat/rice	≥4700	≥1000
	maize/soybean	≥4800	≥710
	rice/rice	≥5100	≥1300
Triple cropping	rice/rice/rice	≥7000	≥1850

2.3. Measuring actual harvest frequency

We used time-series satellite data to derive HF_a (see Supplementary Methods of measuring cropping intensity gap), which corresponds with the general framework widely adopted by previous studies (Heller et al., 2012; Jain et al., 2013). It is recognized that time series of satellite signals measure well the seasonal variations in crop growth cycle. Each crop normally exhibits a behavior of an annual cycle, that is, it continuously grows from the stage of green-up to the stage of maturity and after that, it begins senescence until its harvest stage. Correspondingly, the time-series data of that crop follow an annual cycle of increase and decline: they increase quickly at the outset of the growing season, reach the maximum value at the mature stage, and then decline rapidly until reaching a very low level at its harvest. With this, the entire cycle of growing season has one maximum in time-series data, although it tends to vary across space and time. It is thus possible to detect HF_a or the numbers of crops grown each year using the time-series data.

It should be noted that mapping HF_a requires time-series data with good time resolution, over homogeneous areas that are cloud-free and not affected by atmospheric and geometric effects and variations in sensor characteristics. In this study, asymmetric Gaussian function fitting was first used to minimize the perturbations and reduce contamination in the time-series data (Jönsson and Eklundh, 2002). (Fig. S3). We then extracted the number of local maximums over the course of one growing year from the smoothed time-series data. A local maximum was defined as having a higher value than the three points before and three points after that point. The sensitivity of the asymmetric Gaussian function fitting method to small maximums in portions of the time series where the vegetation index range is low may slightly amplify small real peaks, thereby creating false peaks in the smoothed time series. We removed these false detections by preventing values of 0.4 normalized difference vegetation index (NDVI) or below from being detected as local maximums, following previous studies (Sakamoto et al., 2005; Galford et al., 2008) (Fig. 3). The amplitude of the second maximum in Fig. 3a is too small and is likely caused by the existence of weeds or other green cover. In such cases, although there are two local maximums, the HF_a is set to one, i.e., single cropping pattern. Compared with Fig. 3a, the amplitude of the second maximum in Fig. 3b is relatively large and exceeds a certain fraction of the amplitude of the first maximum; the number of annual seasons is thus set at two, which corresponds to two harvests.

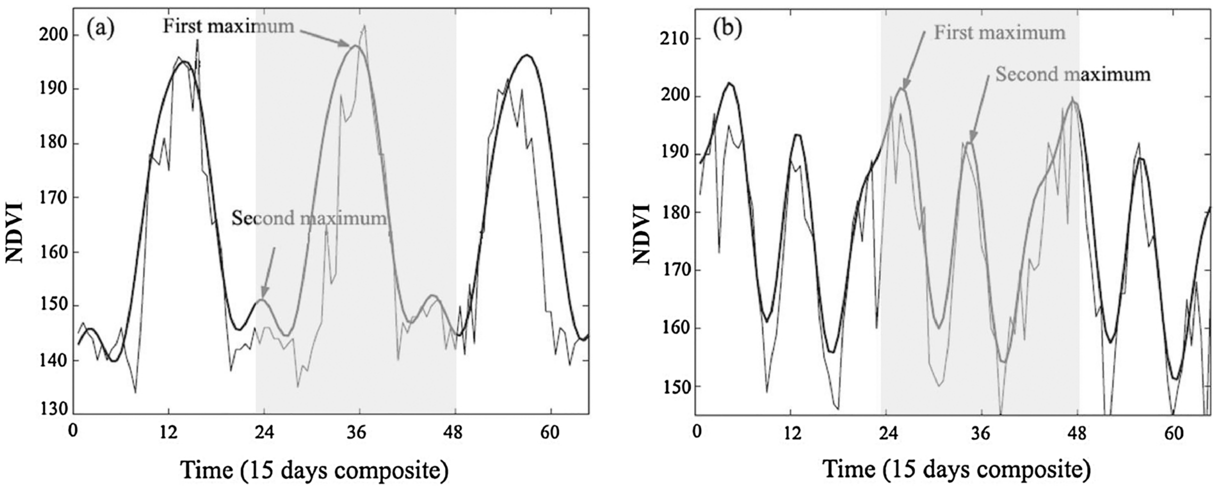

Fig. 3. Local maximums and actual harvest frequency detected from smoothed time-series data.

2.4. Assessment of CIG

The results of HF_p and HF_a in raster format were then aggregated to calculate the CI_p and CI_a for individual countries. We finally combined the CI_p and CI_a to compute the country-level CIG as well as harvest area gap, which indicates the extra harvest area that can be expanded by increasing cropping intensity without a need for cropland expansion:

$$CI_p = \frac{\sum HF_{pi}}{n}, \quad (1)$$

$$CI_a = \frac{\sum HF_{ai}}{n}, \quad (2)$$

$$CIG = CI_p - CI_a + e, \quad (3)$$

$$HAG = CIG \times CL, \quad (4)$$

where HF_{pi} and HF_{ai} indicate the potential and actual harvest frequency for cropland *grid* $i = 1,2,3\ldots n$, and n indicates the number of cropland grids within that country. CI_p is the maximum potential cropping intensity when all croplands are exploited as intensively as possible, CI_a is the actual cropping intensity achieved under current biophysical and socioeconomic constraints, and e is a term to correct those cases where $CI_a > CI_p$, which is possible due to greenhouse agriculture and data errors. In these cases, the negative CIG values are set to zero, meaning that there is no intensity gap left. HAG is the harvest area gap (or extra harvest area) for one country, while CL is the total cropland area for that country.

2.5. Data preparation

This study was carried out for the year 2010 with respect to the availability of used data, which can ensure a good consistency of input datasets. The HF_p of global croplands was estimated using the global climate dataset of the Climate Research Unit (CRU) of the University of East Anglia (Harris et al., 2014). This dataset represents the monthly mean climate conditions interpolated from observed station data for the period 1901–2015, and is provided in a grid format with a resolution of 0.5 ° latitude/longitude. The variables of interest used in this study are monthly temperature and precipitation.

To map the HF_a, global NDVI datasets for the period January 2009 to December 2011 at a spatial resolution of 8 km and 15-day interval were collected from the NASA third-generation Global Inventory Monitoring and Modeling System (GIMMS) derived from the NOAA-AVHRR series satellites. The GIMMS NDVI3g dataset has a similar spatial resolution to the CRU climate dataset and is widely used for global vegetation monitoring due to its long-term data archives. These NDVI3g datasets have been corrected to remove some nonvegetation effects caused by sensor degradation, clouds, and stratospheric aerosol loadings from volcanic eruptions. Detailed information on the processing and quality issues of the GIMMS dataset can be found in Tucker et al. (2005).

The MODIS global land cover dataset for 2010 was obtained from Boston University and was used to extract global cropland distribution (Friedl et al., 2010). Previous work showed that the global MODIS dataset had a better accuracy in cropland mapping than other global datasets (Wu et al., 2008, Lu et al., 2016). This dataset with the basic IGBP classification scheme contains 17 classes, including two classifications of cropland, i.e., "cropland" and "cropland/natural vegetation mosaic." To be consistent with the GIMMS NDVI3g dataset, we used the majority-rule approach to aggregate the 500 m MODIS data to the coarser spatial resolution. This approach searches for the land cover type with the highest frequency within the new coarser grid cell (Wu et al., 2008). In addition, the Global Hunger Index (GHI) (von Grebmer et al., 2013) was used here to investigate whether closing CIGs can play a potentially important role in increasing food production in those food-insecure countries.

3. Results

3.1. Potential cropping intensity

The HF_p for current global cropland was estimated from the potential crop rotations/combinations under current climatic conditions (Fig. S4) and mapped into three major types: no cropping, single cropping per year, and double cropping per year (including triple rice cropping due to its low percentage areas). Fig. 4 shows the distribution of HF_p under the temperature- and temperature/precipitation-limited scenarios. If temperature constraints alone were taken into account in the climatic model, all cropland in the southern hemisphere and most of the cropland in the northern hemisphere can be potentially used for double cropping, while cropland in high-latitude regions of the northern hemisphere is suitable only for single cropping (Fig. 4a). This is not surprising, as the boreal regions are normally too cold for cultivation; the temperate zones have sufficiently warm periods for many crops, while the tropics have adequately warm temperatures throughout the year. Globally, the aggregated areas of cropland potential for single and double cropping are 8.8 and 11.2 million km^2, respectively. However, when precipitation was included as another constraint factor in the climatic model (Fig. 4b), the total areas of global cropland potentially used for single and double cropping under the

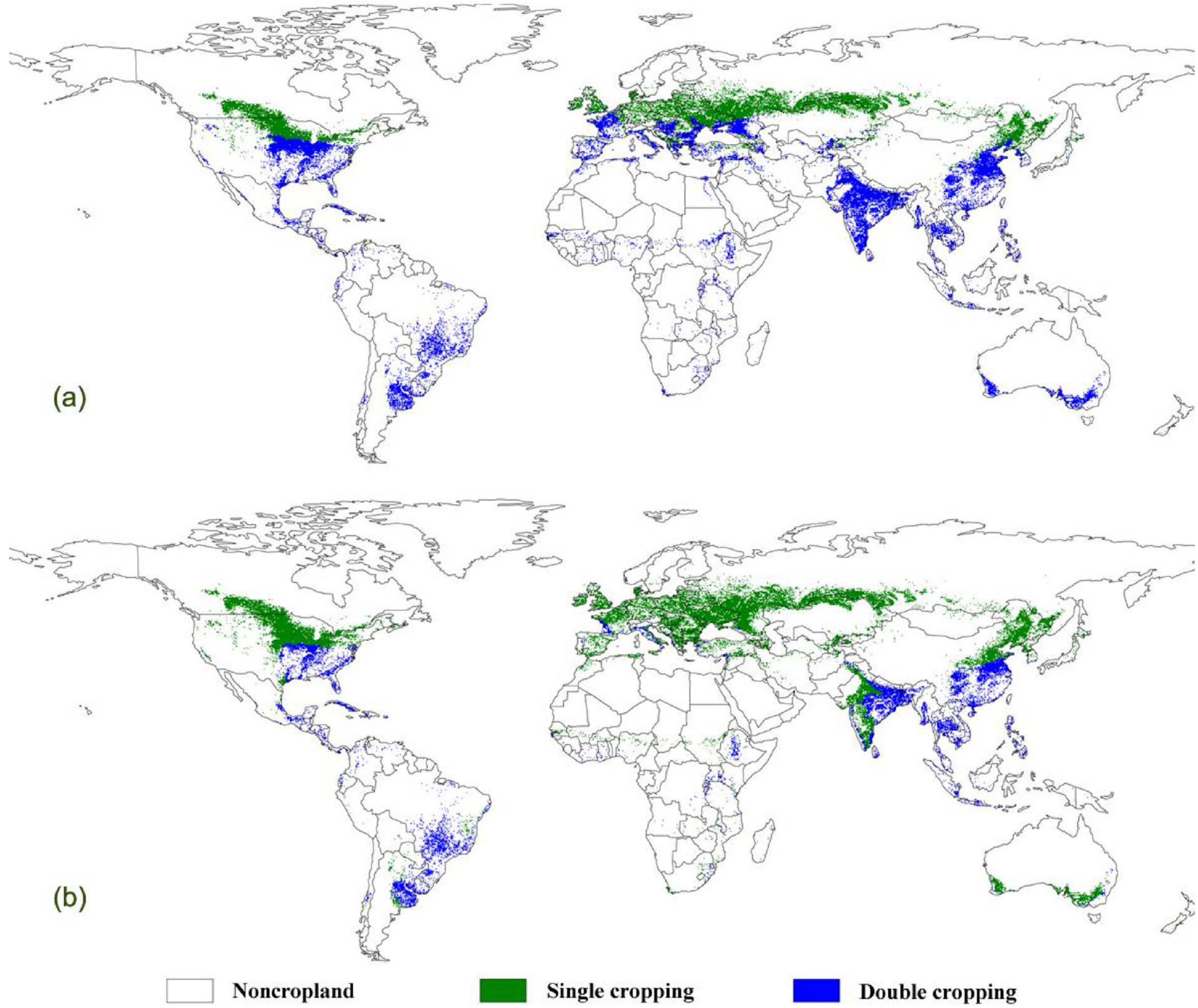

Fig. 4. Potential harvest frequency for current global croplands at grid level. (a) Under temperature constraint; (b) under both temperature and precipitation constraints.

contemporary climate were estimated to be 14.1 and 5.9 million km^2, respectively. Thus, the potential double cropping areas are significantly lower than those in Fig. 4a.

The CI_p between temperature- and temperature/precipitation-limited scenarios shows significant differences around the world. Under the temperature-limited scenario (Fig. 5a), the globally averaged maximum CI_p is ≈ 1.74 (Table 2). Most countries around the world except for those located in the northern high-latitude regions have a high CI_p. Under the temperature/precipitation-limited scenario (Fig. 5b), the globally averaged maximum CI_p is ≈ 1.42 and decreased by about 18.4% (Table 2). Latin America has the largest CI_p (1.89), followed by Africa (1.50), Asia (1.48), and Oceania (1.43). Europe (1.04) and North America (1.15) have a relatively low CI_p. The limited rainfall leads to a decrease of the CI_p of 24.8%, 19.8%, 23.9%, 5.5%, 12.6%, and 23.7% for Africa, Asia, Europe, Latin America, North America, and Oceania, respectively. This indicates that precipitation is of great importance when determining the potential cropping intensity for some regions (e.g., subtropical deserts of Africa, semiarid and arid regions of Asia and Australia) where there are sufficiently warm temperatures throughout the year, but a lack of precipitation. We also found that several countries globally—in Africa and Asia, and especially in Latin America—are able to harvest their standing cropland about twice every year.

3.2. Actual cropping intensity

The HF_a of current global cropland derived from GIMMS NDVI3g datasets is shown in Fig. 6. In general, single cropping occurs throughout all cultivated areas worldwide, but it is most common in middle- and high-latitude regions in the northern hemisphere. The regions that can produce two crops per year are geographically converged and located in countries in Asia and North America (such as China, India, and the USA), as well as in some regions of Europe and Australia. For the globe as a whole, the total areas aggregated from satellite observation for single and double cropping are 15.7 million km^2 and 4.6 million km^2, respectively.

Fig. 7 shows the calculated CI_a for individual countries. Globally, the average CI_a is ≈ 1.26 (Table 2). The highest values of CI_a are in Oceania (1.44), Asia (1.30), and Africa (1.29), and the lowest in North America (1.11). Latin America also has a high CI_a (1.27). In South and Southeast Asia, about one-third of the cropland is irrigated, which is one of the reasons why the average CI_a in Asia is considerably higher than in the other regions. China has a significantly high CI_a of 1.37, whereas India has a CI_a of 1.36. Several African countries along the equator, such as Kenya, Tanzania, Ethiopia, and the Congo, have a high CI_a. Ecuador and Colombia in South America also show a relatively high CI_a.

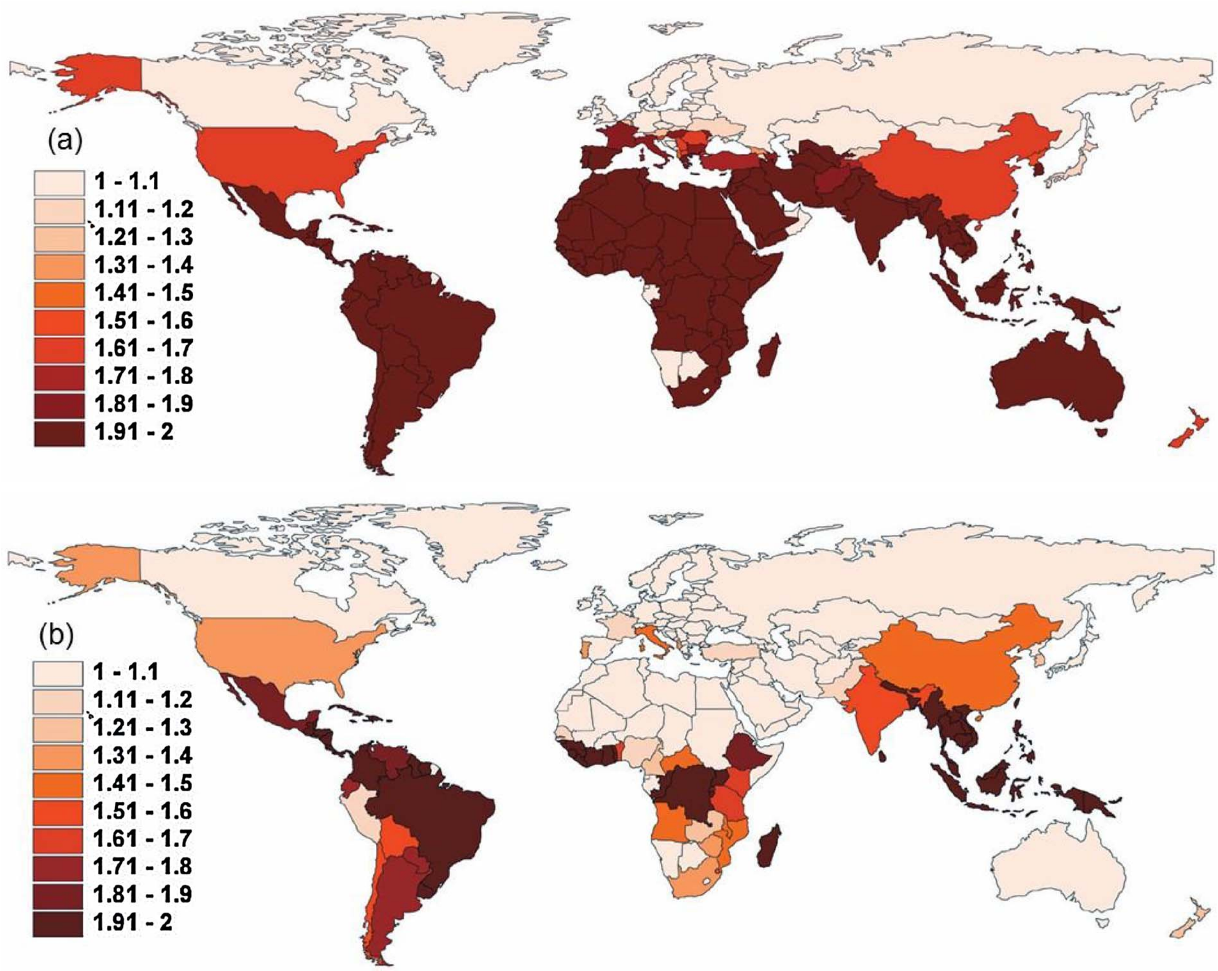

Fig. 5. Potential cropping intensity for individual countries. (a) Under temperature constraint; (b) under both temperature and precipitation constraints.

Table 2
Regional potential cropping intensity, actual cropping intensity, and cropping intensity gap.

Regions	CI_p-1	CI_p-2	CI_a	CIG-1	CIG-2
Africa	2.00	1.50	1.29	0.71	0.21
Asia	1.85	1.48	1.30	0.55	0.18
Europe	1.37	1.04	1.17	0.20	0.01
Latin America	2.00	1.89	1.27	0.72	0.61
North America	1.32	1.15	1.11	0.21	0.04
Oceania	1.88	1.43	1.44	0.44	0.01
Global	1.74	1.42	1.26	0.48	0.17

Note: CI_p-1 is the potential cropping intensity under temperature constraint; CI_p-2 is the potential cropping intensity under temperature and precipitation constraint, CI_a is the actual cropping intensity in this study, CIG-1 is the difference between CI_p-1 and CI_a, and CIG-2 is the difference between CI_p-2 and CI_a.

3.3. CIG

The global average CIG is 0.48 and 0.17 for the temperature- and temperature/precipitation-limited conditions, respectively (Fig. 8, Table 2). This difference is largely due to the considerable CI_p decrease caused by the precipitation constraint.

At the continental level, Latin America has the largest concentration of CIG under both scenarios, followed by Africa and Asia (Table 2). Thus, extra increases in harvest areas each year are theoretically possible in these regions through intensifying cropping systems alone. Europe and North America, however, have limited CIG, particularly under the temperature and precipitation constraints. Indeed, adoption rates of new agricultural technologies or management measures such as irrigation, pesticides, and fertilizers are very high in these developed regions, which may mitigate the limiting effect of climate and result in bringing more croplands into multiple cropping. Thus, these regions are harvesting their standing croplands more frequently or closer to the maximum CI_p.

Several countries across the globe have a significant CIG. Latin American countries such as Colombia, Chile, Argentina, Mexico, Uruguay, Venezuela, Guatemala, Brazil, and Panama have a CIG of more than 0.5, which suggests that another harvest every two years is theoretically possible, while the gaps in Cuba and Nicaragua are higher at around 0.9, which roughly means a possible extra harvest every year. Several important agricultural countries in South and Southeast Asia, such as Thailand, the Philippines, Malaysia, Indonesia, Vietnam, and Myanmar, also have a CIG of 0.5–0.9, suggesting that these countries have some potential to increase the annual food production per unit of cropland through land use intensification. In Africa, some countries, such as Ethiopia, the Congo, the Central African Republic, Tanzania, Zambia, Madagascar, and Guinea, have a large CIG, which means that some additional harvests can potentially be achieved.

3.4. Extra harvest areas by closing CIGs

The HAG gained under the assumption that the CIG is closed differs between regions (Fig. 9). Global harvest areas can be boosted by 7.36 million km^2 and 2.71 million km^2 (37.55% and 13.83% of current global cropland) under the temperature- and temperature/precipitation-limited scenarios, respectively, although extra harvests may not

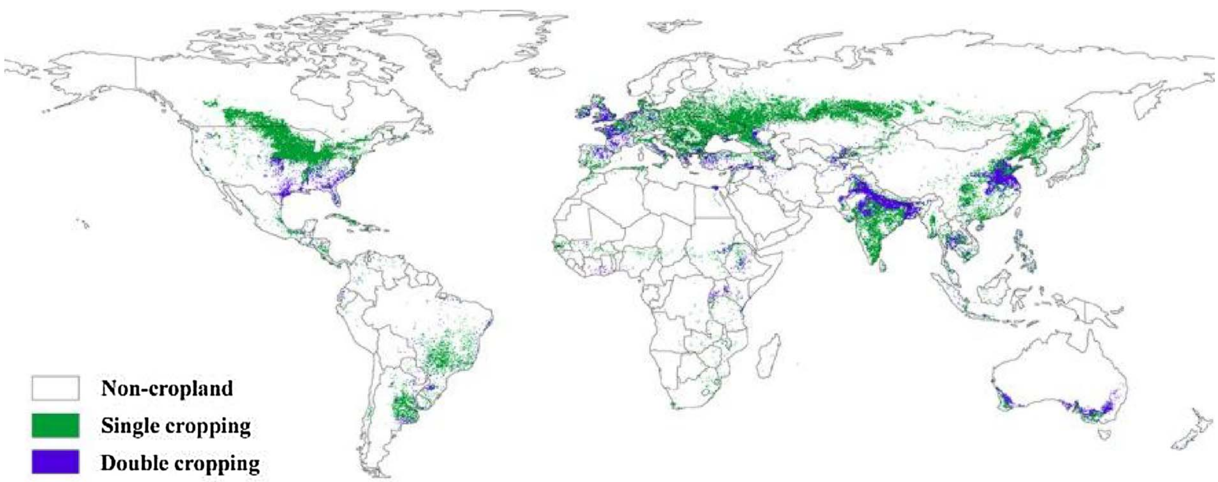

Fig. 6. Actual harvest frequency for current global croplands at grid level.

retain the same productivity because investments for a second crop may be less profitable at least in the short term. Latin America has the largest potential to achieve extra harvest area (more than 1.28 million km^2) by closing CIGs, followed by Asia (1.00 million km^2). Although Africa has a high CIG (Table 2), the absolute quantity of additional harvest area by closing the CIG is smaller than that of Latin America and Asia, largely due to its low percentage of cropland distribution. Europe and Oceania can barely gain any additional harvest area.

4. Discussion

4.1. Comparison with other studies

We first compared our CI_a in 2010 with those in 2000 estimated by Siebert et al. (2010) using the global MIRCA2000 dataset on monthly irrigated and rain-fed crop areas. It is believed that the temporal difference between these two studies has less impact on the comparison as the rates of change in the global average of cropping intensity for the period of 2000–2010 largely remain unchanged (Ray and Foley, 2013). Table 3 shows that, in general, the global average of CI_a between Siebert et al. and our study is slightly different: 1.13 versus 1.26, respectively. These two results are quite consistent in Asia, which has a high CI_a among the regions. The major difference occurs in Africa and America, for which there are two possible reasons. One is that the CI_a by Siebert et al. was based on the MIRCA2000 dataset on irrigated and rain-fed crop areas; this dataset has limited crop coverage of 26 crops and may not track some of the minor crops, which could lead to underestimating the total annual harvest areas when aggregating them to calculate CI_a. Instead, we used the satellite observation data to map the intensive use of cropland, which is widely recognized to be more objective than the statistics (Donaldson and Storeygard, 2016). The second reason is that our estimate based on GIMMS NDVI3g ignored the presence of fallowed cropland (which could be real in some regions in America and Africa although its areas are small). Each pixel of cropland was assigned to either a single cropping or double cropping category. This could cause an overestimation of annual harvest areas, thus resulting in a higher CI_a.

We further compared our CIG in 2010 with the average cropland harvest frequency gap for 2011 calculated by Ray and Foley (2013) (Table 3, Fig. S5). Our estimate of CIG tends to be smaller than that of Ray and Foley, in particular, under the temperature/precipitation-limited scenario. On the one hand, Ray and Foley did not consider precipitation as a limiting factor in mapping CI_p, which may cause a relatively high estimation of CI_p, as well as a higher CIG than our study in such regions as in Africa and mid-east Asia. Moreover, Ray and Foley estimated global HF_p using a simple rule, that is, if a cropland grid cell has a mean monthly minimum temperature $\geq 10\,°C$, the number of possible harvests in that grid cell was set at two. Instead, we used the GDD as a heat indicator, which is more restrictive than that used by Ray and Foley. They may thus have estimated a higher CI_p than our study in some regions such as the northern high-altitude regions. On the other hand, the CI_a estimated by Ray and Foley is much lower than those

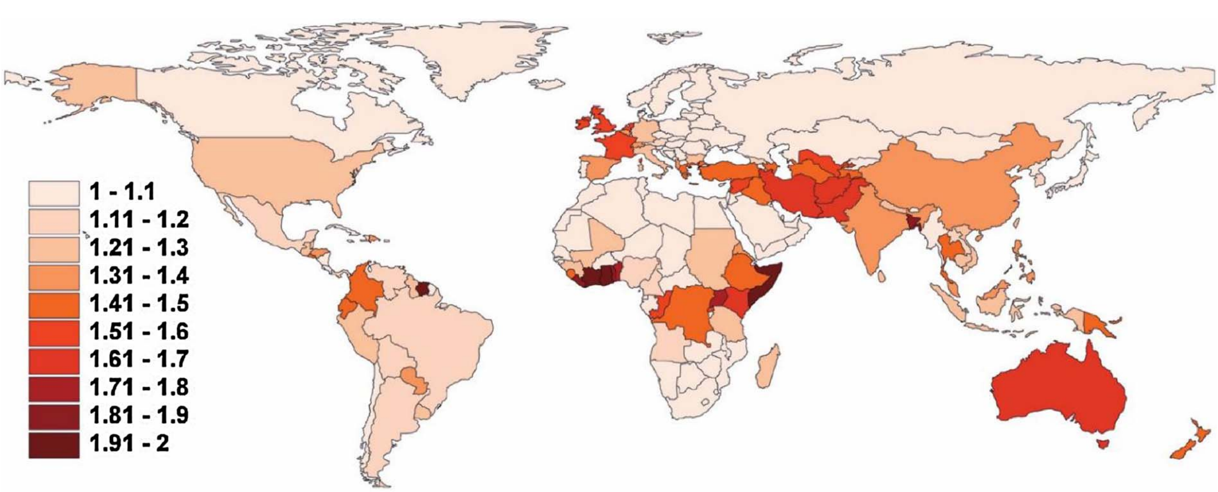

Fig. 7. Actual cropping intensity for individual countries.

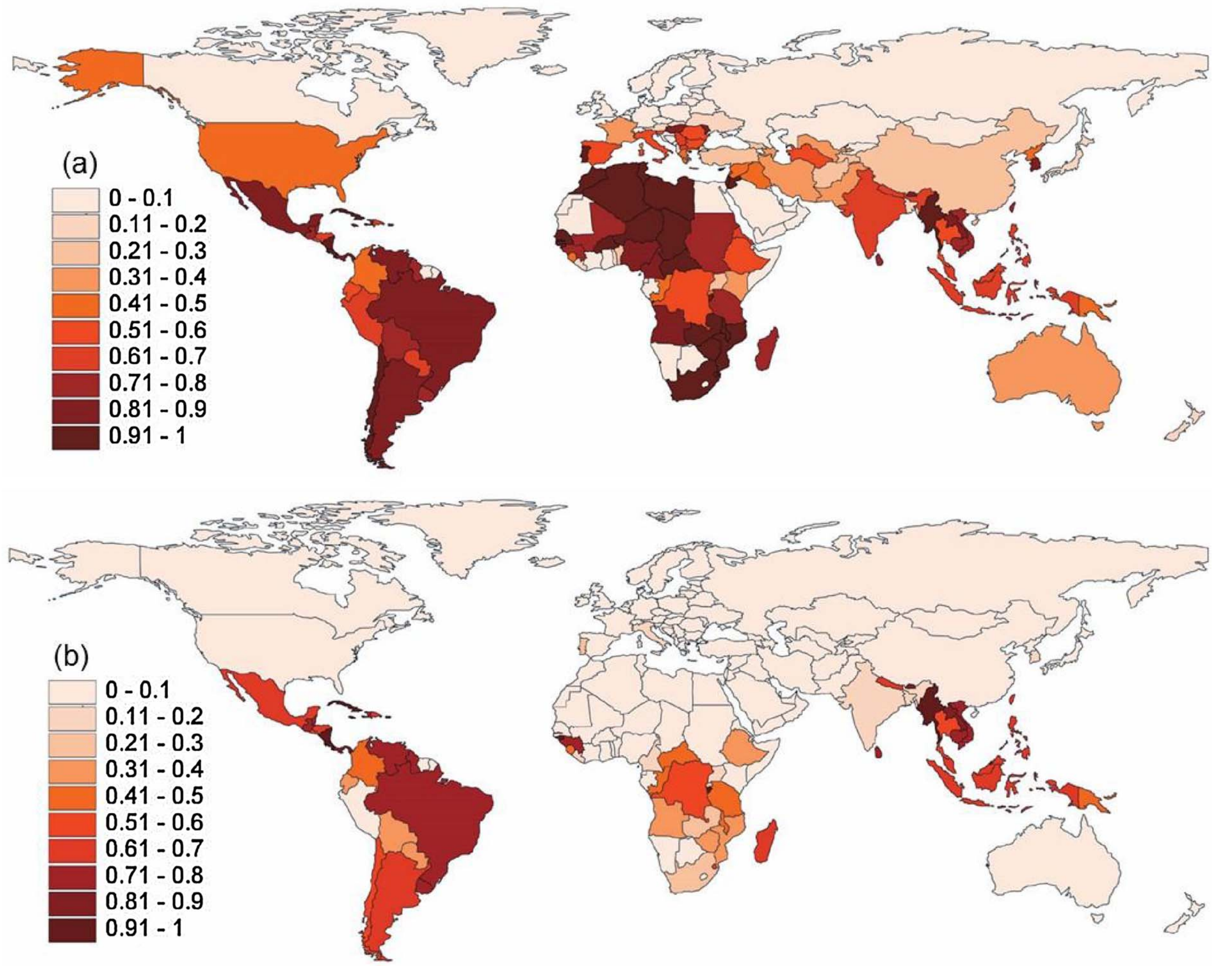

Fig. 8. Cropping intensity gap for individual countries. a) Under temperature constraint; b) under both temperature and precipitation constraints.

values reported in our study and by Siebert et al., largely due to errors or reporting issues of FAO statistics. It is clear that this underestimation provides a too optimistic map of CIG.

4.2. Implications of CIGs

To capture whether cropping intensity can potentially play an important role in increasing food production in those food-insecure countries, we compared the CIG map with the GHI in 2013. South Asia, Southeast Asia, and sub-Saharan Africa are the regions with high GHI

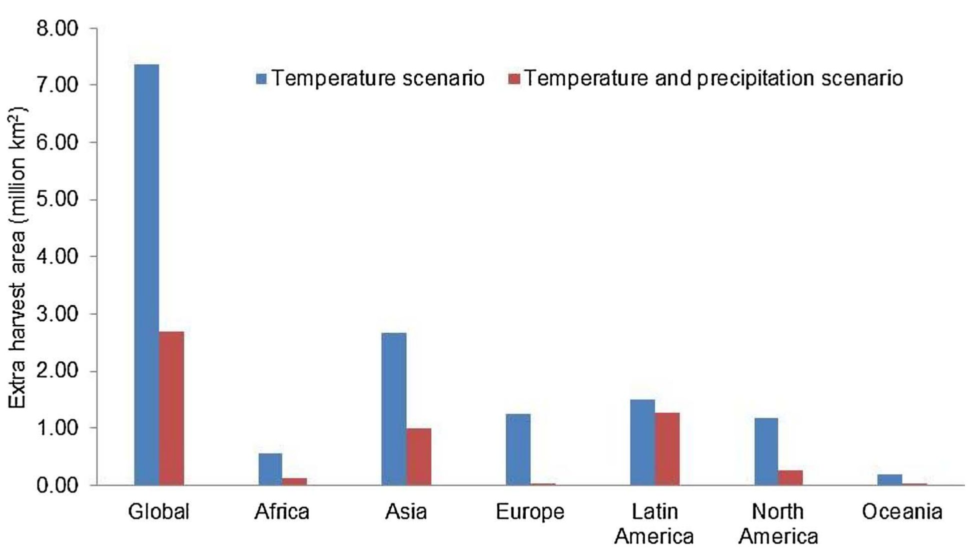

Fig. 9. Aggregated extra harvest areas gained by closing cropping intensity gap.

Table 3
Summary of the three comparative studies.

	CI_p			CI_a			CIG		
	Input data	Method	Global average	Input data	Method	Global average	Temporal coverage	Spatial details	Global average
Siebert et al.	–	–	–	MIRCA crop areas	Ratio of harvested crop areas to total cropland area	1.13	2000	About 10 km	–
Ray and Foley	Temperature	Threshold	1.45	FAO statistics	Ratio of harvested cropland to total cropland	0.84	2010	Country	0.61
This study	Temperature, precipitation	GAEZ	1.74, 1.42	Time-series NDVI	Peak-counting	1.26	2011	8 km, country	0.48, 0.17

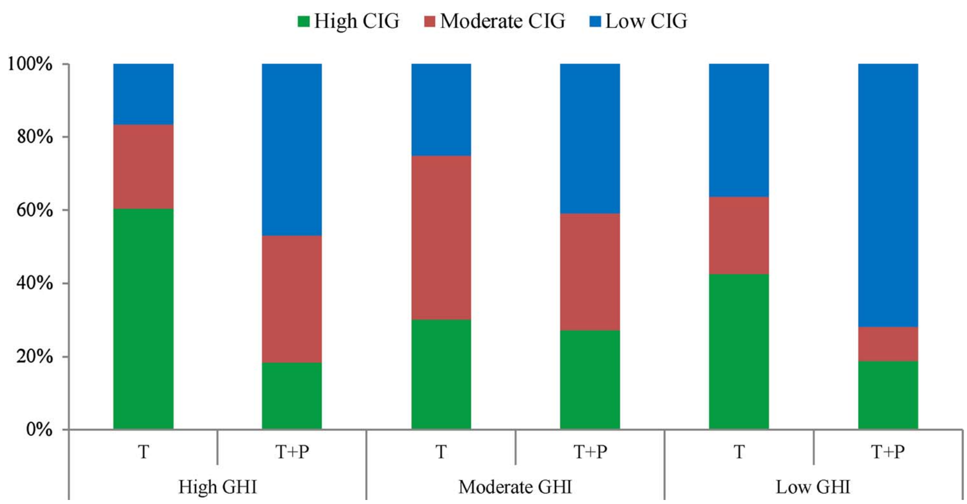

Fig. 10. Global hunger index (GHI) and cropping intensity gap (CIG) under temperature- (T) and temperature/precipitation-limited (T + P) scenarios.

scores, indicating country-specific shortcomings in ensuring food security. Fig. 10 shows the CIGs for high, medium, and low GHI regions under the temperature- and temperature/precipitation-limited scenarios. Importantly, these regions with a high or moderate GHI tend to have a high or moderate CIG in both scenarios. For example, more than 80% of high GHI countries have a high and moderate CIG under the temperature-limited scenario, meaning that reducing CIG would provide another opportunity to increase food production and help people escape extreme hunger in these countries. We also found that the CIG declines in high GHI regions, in particular, when precipitation is considered as another limiting factor. This suggests that water resources are determinant for intensive use of cropland and improving water management, and irrigation infrastructure may be one of the priority tasks in these regions to expand the harvest areas. It may be possible to increase harvest areas and production in countries with a large CIG through telecoupling processes (Liu et al., 2013a,b) such as transfers of technology (e.g., seeds) and knowledge from countries with a small CIG. Moreover, several countries with low GHI scores also have a large CIG, meaning that there is a reserve for these countries to increase food production further by narrowing these gaps.

5. Conclusions

It is critical for human society to increase food production to feed the increasing global population. Recent studies show that future urbanization and industrialization will result in a 1.8–2.4% loss of global croplands by 2030 and about 80% of global cropland loss will take place in Asia and Africa (Jiang et al., 2013; D'Amour et al., 2017). This will undoubtedly add pressure to potentially strained future food systems and threaten livelihoods in vulnerable regions. Our study demonstrates that agricultural intensification through increasing cropping intensity may provide a promising opportunity to increase global food production as it can expand extra harvest area without a need for cropland expansion. The global average CIG is 0.48 and 0.17 for the temperature- and temperature/precipitation-limited scenarios, respectively. We estimated that global harvest areas can be increased by another 7.36 million km^2 and 2.71 million km^2 under these two scenarios, which will largely offset the negative impacts of future urbanization on global cropland loss. Latin America has the largest potential to expand its harvest area by closing the CIG, followed by Asia. Some countries in Africa have a large CIG, meaning that some additional harvests can potentially be achieved. Thus, it is necessary to consider the role of cropping intensity when making policies related to food production, land use management, and planning.

Although reducing CIG would increase global food production and help people escape extreme hunger in food-insecure countries, it is not necessarily universally appropriate. Figs. 6 and 7 show that the CIG in some African and Asian countries is greatly reduced by precipitation, and water resources are thus one of the key limiting factors of CIG. Improving water management and irrigation infrastructure may benefit the intensive use of cropland in these regions. Moreover, increasing cropping intensity may reduce soil organic carbon, the diversity of soil microbiota and arthropods, thereby requiring other agricultural inputs such as irrigation and fertilizer, as well as an increase herbicide and pesticide application (Ray and Foley, 2013). All these factors together may lead to the long-term deterioration of soil, water resources, and the agricultural land base itself. Further, it is also limited by other socio-economic factors, such as investment cost and benefit, transportation networks, and farmer access to credit. Thus, closing the CIG involves evaluating its eco environmental effects and taking these trade-offs into consideration. Only if it is done sustainably is this an attractive strategy for enabling food production to meet rising food demands and increase households' profits or income.

There are some limitations to this study. It used a simplified approach and was based on some assumptions about CIGs. A number of factors, e.g., technological advancement, social preferences, and policy intervention, which may also have a strong influence on CIGs, were not taken into account in this study. Further study on potential harvest frequency should consider the effects of global climatic change and anthropogenic adaptation such as adoption of irrigation, which may mitigate the limiting effects of climatic background and bring more croplands into multiple cropping (Wu et al., 2014a,b). Moreover, when satellite images are used to map the actual harvest frequency, the spatial resolution and method for information extraction can also cause some bias in the outputs. The coarse GIMMS NDVI3g dataset used here can preserve a good pixel homogeneity and spectral discrimination in homogeneous regions with a large cropland coverage and large field sizes. However, in the heterogeneous or transitional zones, the "mixed pixel" problem is a considerable challenge for coarse-scale harvest frequency mapping efforts simply because the landscape heterogeneity is more detailed than the resolution of the satellite sensor (Wu et al., 2008). Thus, improving the capacity for discriminating actual cropping frequency from coarse resolution satellite data is of great importance for global CIG analysis. Furthermore, estimation of actual harvest frequency needs also to account for the pervasiveness of leaving cropland fallow. These improvements will help to represent better the current real situation of used croplands and their future intensive use to achieve the Sustainable Development Goals for human welfare.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.landusepol.2018.02.032.

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