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[a] Key Laboratory of Resources Remote Sensing & Digital Agriculture, Ministry of Agriculture, Beijing, China [b] Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing, China [c] Center for Spatial Information Science, University of Tokyo, Tokyo, Japan [d] International Food Policy Research Institute, Washington, DC, USA

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# Global-scale assessment of potential future risks of food insecurity

Wenbin Wu[a,b,c], Peng Yang[a,b], Huajun Tang[a,b,*], Liangzhi You[d], Qingbo Zhou[a,b], Zhongxin Chen[a,b] and Ryosuke Shibasaki[c]

[a]*Key Laboratory of Resources Remote Sensing & Digital Agriculture, Ministry of Agriculture, Beijing, China;* [b]*Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing, China;* [c]*Center for Spatial Information Science, University of Tokyo, Tokyo, Japan;* [d]*International Food Policy Research Institute, Washington, DC, USA*

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This paper presents an approach of combining biophysical, social, and economic factors for spatially explicit assessment of potential future risks of food insecurity at a global scale over the period of 2000–2020 under a certain scenario. In doing that, two indicators, namely per capita food availability and per capita Gross Domestic Product (GDP), were selected to cover the four dimensions of food security, with the former representing the status of food availability and stability, and the latter reflecting the situation of food accessibility and affordability. These two indicators were then linked to an integrated modeling framework. Under this framework, a GIS-based EPIC model was adopted to estimate the potential yields of different crop types under a given biophysical and agricultural management environment, a crop choice decision model was used to model the changes in crop areas through tracking the crop choice decisions, and the IFPSIM model was utilized to evaluate the crop price in the international market. Based on these two indicators, the potential risks of food insecurity were assessed with a spatial resolution of six arc-minutes. The results show that both changes in per capita food availability and changes in per capita GDP during 2000–2020 vary across regions worldwide. Some regions such as China, most eastern European countries, and most southern American countries where there is an increase in per capita food availability or an increase in the capacity to import food between 2000 and 2020 might be able to improve their food security situation. On the contrary, certain regions such as southern Asia and most African countries will likely remain hotspots of food insecurity in the future. In these regions, both the per capita food availability and the capacity of being able to import food will decrease between 2000 and 2020. Although most developed countries will also experience both a decrease in per capita food availability and a decrease in per capita GDP, these countries are likely to be food-secure due to their higher income and purchasing power.

**Keywords:** food insecurity; assessment; crop yield; crop area; per capita food availability; per capita GDP

## Introduction

Food security was defined by the United Nations Food and Agriculture Organization (UN/FAO) as a 'situation that exists when all people, at all times, have physical,

*Corresponding author. Email: hjtang@mail.caas.net.cn

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social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life' (FAO 2006, 17). The food security status of any group can be generically considered as the principle outcome of food systems, which includes a set of dynamic interactions between and within the biogeophysical and human environments, resulting in the production, processing, distribution, preparation, and consumption of food (Gregory, Ingram, and Brklacich 2005). With this, the three traditional components of food security are availability, access, and utilization. Food availability relates to the availability of sufficient food, i.e., to the overall ability of the agricultural system to meet food demand. Access to food refers to the ability of a unit of individuals to obtain access to acquire appropriate foods for a nutritious diet. Food utilization refers to individual or household capacity to consume and benefit from food (Ericksen 2008). More recently, as climate change issues have caught great attention from the world, food stability, which relates to individuals who are at high risk of temporarily or permanently losing their access to the resources needed to consume adequate food, is also considered one important component of food security (Schmidhuber and Tubiello 2007).

It is well-known that our current society is regarded as more civilized than any periods before in human history; however, there are still a number of people living in an insecure food situation. According to an FAO report, 2009 has been a devastating year for the world's hungry, marking a significant worsening of an already disappointing trend in global food security since 1996. FAO estimates that globally, approximately 1.02 billion people are undernourished worldwide in 2009 (FAO 2009). Many countries, in particular the developing countries, are fighting against the food crisis in pervasive ways. The eradication of poverty and hunger was also included as one of the United Nations' Millennium Development Goals adopted in 2000. One of the targets of the Goals is to halve the proportion of people who suffer from hunger between 1990 and 2015 (World Bank Group 2003). To achieve this food security goal, more and better-targeted investments, innovations, and policy actions are required to focus on human resources, agricultural research, rural infrastructure, water resources, and farm- and community-based agricultural and natural resources management (Rosegrant and Cline 2003). All these are usually based on a better understanding of the dynamics, risks, and forces that shape the factors affecting food security (Lobell et al. 2008). In this regard, food security assessment will be high on the policy agenda for most countries.

Food security status can be analyzed for any unit ranging from an individual, a region to a nation. Previous and ongoing studies on assessment of food security are normally conducted at a national level (Adejuwon 2006; Deng et al. 2006; Lobell et al. 2008). These national analyses of food security, however, have some limitations in its usefulness for policy-makers and pose new challenges for future hunger reduction, since they do not reflect the considerable variations in the food security situation of households within a particular country. The sub-national studies are also recognized to be necessary to quantify food security indicators (UN Millennium Project 2005). Thus, specific attention should be paid to a spatially explicit assessment on food security (Liu et al. 2008). Furthermore, while there have been considerable progresses in understanding the sensitivities of crop yields or productions to environment change, in particular, climate change (Rosenzweig and Parry 1994; Ewert et al. 2005; Fischer et al. 2005; Parry, Rosenzweig, and Livermore 2005; Battisti and Naylor 2009), these assessments of food security remain rather limited. Food security is concerned not only with food availability but also with access to and stability and utilization of food. Although increases in food production have resulted in successes in reducing the prevalence of hunger and improving nutrition worldwide, these successes are shadowed by serious concerns about other aspects of food systems that pose threats to social, economic, and environmental goals and hence undermine food security. Those studies, which focus only on crop production, provide only a partial assessment of food security (Gregory, Ingram, and Brklacich 2005; Brown and Funk 2008). Thus, a holistic approach for assessment of food security is needed to cover as many major components of food security as possible.

The objective of this study is to propose an approach for spatially explicit assessment of potential future risks of food insecurity at a global scale over a period of approximately 20 years, starting with the year 2000. The reason that we selected the future period of 2000–2020 for our analysis is mainly due to two reasons. First, this time period is most relevant to large agricultural investments, which typically take 15–30 years to realize full returns (Lobell et al. 2008). Second, a shorter period will lead to smaller changes in some factors, such as adaptation, diet patterns, etc.

## Methodology

### *General framework*

In this study, we combined the biophysical, social, and economic factors to assess potential future risks of food insecurity at a global scale, as shown in Figure 1. Population as a social factor can largely influence the total demand for food. Food production as a biophysical factor can directly influence the local food supply, while gross domestic product (GDP) as an economic factor can impact the purchasing power

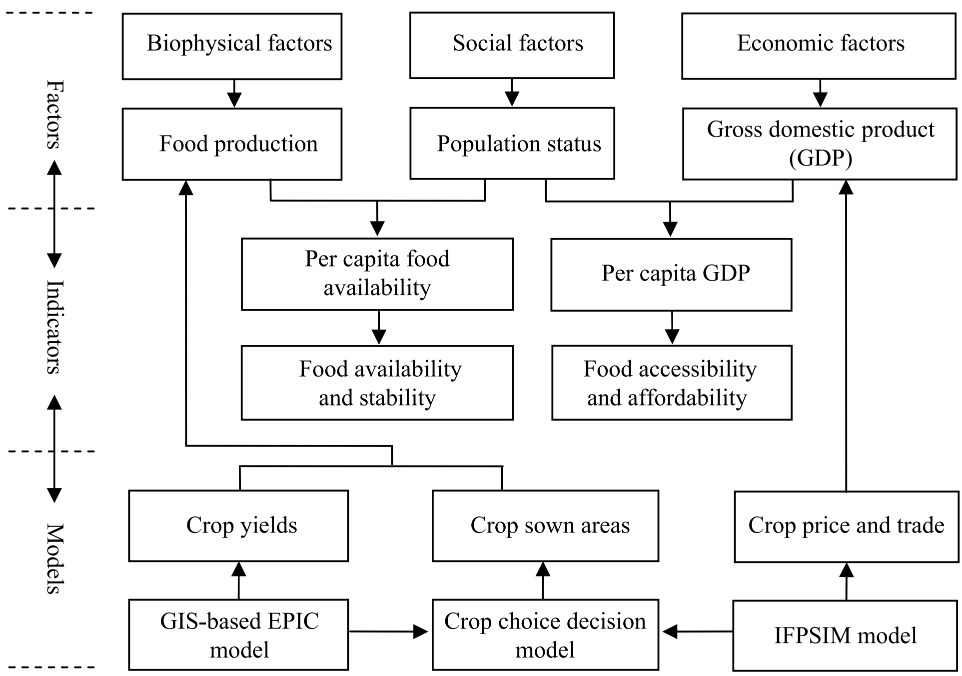


Figure 1. Framework for spatially explicit assessment of potential future risks of food insecurity.

of consumers. In general, a higher population growth requires an increasing amount of food supply, and may impose threat to local food security. Future food supply normally relies on domestic production when the purchasing power is not strong enough. Although some countries such as India can produce enough food to feed their entire population, there are still a large number of hungry populations because many people are very poor and cannot afford to purchase sufficient food from the market. On the other hand, when local food production cannot meet the growing demand for food in some countries such as Singapore, a high per capita GDP can allow their people to purchase needed food from the market, and thus remains food security. Low food production and poverty are thus two determining factors to starvation.

Based on these three factors, two indicators were selected to cover the four components of food security. One indicator denotes the per capita food availability and was used to represent the status of food availability and stability. The other indicator describes the per capita GDP and was used to reflect the situation of food accessibility and affordability. The per capita food availability was determined by total food production and population, while the per capita GDP were determined by total GDP and population. These two indicators were linked to an integrated modeling framework, which includes three main models and their relationships are shown in Figure 1. The total food production was defined by crop yields and crop areas. Of these, crop yields were analyzed with the GIS-based Environmental Policy Integrated Climate (EPIC) model, while crop areas were estimated with the crop choice decision model. The per capita GDP was analyzed with the International Food Policy and Agricultural Simulation (IFPSIM) model. The three models are described in more detail later.



### *GIS-based EPIC model*

A GIS-based EPIC model (Version 8120) was adopted here to estimate the potential yields of different crop types under a given biophysical and agricultural management environment (Wu et al. 2007). The EPIC model was initially developed by the United States Department of Agriculture, Agricultural Research Service in 1984 with the purpose of understanding the relationship between soil erosion and crop productivity. In EPIC, a general plant growth model with crop-specific parameters is used to simulate the growth of rice, wheat, maize, sorghum, and soybean, among others. The EPIC calculates daily potential biomass as a function of solar radiation, leaf area index (LAI), and a crop parameter for converting energy to biomass. The potential plant growth is driven by photosythentically active radiation. The amount of solar radiation captured by the crop is a function of LAI and the amount of solar radiation converted into plant biomass is a function of the crop-specific radiation-use efficiency. The daily potential biomass is decreased by stresses caused by water shortage, temperature extremes, nutrient insufficiency, and soil aeration inadequacy. The daily potential biomass is decreased in proportion to the severity of the most severe stress of the day. Crop yield is estimated by multiplying above-ground biomass at maturity by a water stress adjusted harvest index (Williams, Dyke, and Fuchs 1990).

The EPIC was originally a site-specific model, and uses a daily time increment to simulate weather, hydrology, soil erosion by wind and water, nutrient cycling, tillage, crop management and growth, and field scale costs and returns. It is thus not possible to use the original EPIC model directly for large-area applications. However, by integrating EPIC with GIS, the EPIC model gains the possibility of estimating crop yields from field level to small country or sub-regional scale (Priya and Shibasaki 2001). It treats each grid cell as a site and simulates the crop-related processes for each predefined grid cell with spatially distributed inputs. Subsequently, Tan and Shibasaki (2003) expanded this GIS-based EPIC model to a global level and applied it to detecting crop yields and predicting the effects of future global warming on the yields of major crops at a global level. In their research, the loose coupling approach was used to integrate GIS with the EPIC via data exchange using either ASCII or binary data format between these two packages.

### *Crop choice decision model*

The crop choice decision model was used to analyze the changes in crop areas by investigating changes in crop choice decisions among a variety of available alternatives. This crop choice decision model was developed by Wu et al. (2007) using the Random Utility Theory (RUT). The RUT is a well-established method for quantifying the preferences of individuals choosing an option from a finite set of potential alternatives. Here we only give a short description of the crop choice decision model; a complete description has been documented in Wu et al. (2007).

In this model, the term 'utility' was used to describe a mathematical function that expresses the preferences of discrete crop choices of land users in a utility maximizing framework. Using these relative crop utilities, farmers seek to maximize their income by allocating their lands to those crop cultivation activities that they perceive will provide the greatest return or that will carry the least risk. The allocation of land to specific crop types is then translated into the conversion of an area from one crop coverage to another. The utility ($U_i$) of each possible crop is assumed to comprise two parts:

$$U_i = V_i + \varepsilon_i \tag{1}$$

where $V_i$ is the systematic and observed component of the latent utility for crop $i$, and $\varepsilon_i$ is the random or 'unexplained' component.

Because of the random component, scientists can never expect to predict choices perfectly. This leads to the expression for the probability of choice. Assuming that the random error terms are distributed independently and identically and follow the Gumbel distribution, the probability that a crop, $i$, is chosen for cultivation can be estimated using the Multinomial Logit model (Seo and Mendelsohn 2008):

$$P_i = \frac{e^{V_i}}{\sum_{i-1}^{N} e^{V_i}} \tag{2}$$

where $i$ denotes the crop types used for analysis ($i$ = 1, 2, … $N$), $P_i$ is the probability for crop type $i$, and $V_i$ is the observed utility of crop type $i$, which can be stated as:

$$V_i = a_i + \sum_{j=1}^{M} b_j x_j \tag{3}$$

where $a_i$ is an alternative specific constant for crop type $i$, $j$ is the number of explanatory variables ($j$ = 1, 2, … $M$), $x$ is the explanatory variable, and $b_j$ is the coefficient to be estimated for the variable $x_j$ (Mcfadden 1973). In the construction of this model, four main variables, namely, crop yield, crop price, rural population density, and road accessibility, were selected as the explanatory variables for computation of crop utilities (Wu et al. 2007).

### *IFPSIM model*

The IFPSIM model was utilized to evaluate the price of crops in the international market. The IFPSIM is a multi-commodity, multi-regional, and multi-period world agricultural trade and policy simulation model developed and designed on the Ohga Model Building System (OMBS) (Ohga and Yanagishima 1996). It is a partial equilibrium and interactive model, allowing for the simultaneous determination of supply, demand, trade, stock levels, and prices for 14 commodities of the world. A complete description of the regions used in the model has been documented by Ohga and Gehlar (1993).

Food demand in each region is divided into three categories: demand for food for human consumption, for livestock and for the production of processed food, and it is described by individual income, population, and the consumer purchase price of the crop in question. Food supply in one region comprises the supply of crops and the supply of livestock products. The supply of crops is described by crop yields, sown areas and the producer price for each crop. The total food demand or supply in the world is determined from the summation of the demand or supply in each region. In the international market, crop price is determined by the level at which world supply is equal to world demand, where all variables are simultaneously determined, while world market clearing prices are derived by equating the sum of gross imports and the sum of gross exports (Ohga and Yanagishima 1996). One of the important features of the IFPSIM model is that it can deal with changes in demand and supply both inside and outside of one region. This is especially important in relation to trends in global trade. Thus, the crop price in one region estimated by the IFPSIM model reflects not only the demand (and supply) of the internal market, but also the demand (and supply) of the external market.

### *Assessment of potential risks of food insecurity*

Based on the crop yields simulated with the GIS-based EPIC model and the crop areas simulated with the crop choice decision model, the food production of each crop in a grid cell can be calculated. To assess the changes in total food production of all studied crops as a whole, we firstly summed up the food production from all four crops for 2000 and 2020, and computed the change ratio ($CR\_p$) values using the following Equation 4.

$$CR\_p = \frac{\sum_{i=1}^{4} Y_i^{2020} \times A_i^{2020}}{\sum_{i=1}^{4} Y_i^{2000} \times A_i^{2000}} \qquad (4)$$

where *CR_p* is change ratio of total food production; *Y* is crop yield for crop type *i*; *A* is crop areas for crop type *i*.

A *CR* value higher than one in a grid cell means total food production in that grid cell will increase in the future, while a *CR* value lower than one means the total food production will decrease. Yet, it should be noted that assessment of food security by thinking only the total food production and disregarding the population status remains limited. Even though the overall food production will not decrease for some regions, per capita food availability may decrease when considering future population growth. To understand whether the projected changes in total food production will influence the overall food availability, we calculated relative changes in per capita food availability (*CR_a*) for the same period using the following Equation 5.

$$CR\_a = \frac{\sum_{i=1}^{4} Y_i^{2020} \times A_i^{2020} \,/\, POP^{2020}}{\sum_{i=1}^{4} Y_i^{2000} \times A_i^{2000} \,/\, POP^{2000}} \tag{5}$$

where *CR_a* is change ratio of per capita food availability; *Y* is crop yield for crop type *i*; *A* is crop areas for crop type *i*; *POP* is total population.

As per capita GDP can strongly impact the purchasing power and determine whether a country or region is able to import more foods in the future, a separate analysis for changes in per capita GDP was then undertaken. In doing that, we first computed the overall global increase in per capita GDP between 2000 and 2020 as done in Liu et al. (2008). We then calculated the relative difference between the growth rate of per capita GDP in a grid cell with the global average per capita growth rate. In case the growth rate of per capita GDP in a grid cell is higher than the global average per capita growth rate during the period of 2000–2020, it was assumed that people in this grid may have more purchasing power and financial capacity to import food when the per capita food availability in this grid decreases in the future. The effect of the increasing purchasing power may compensate the decrease in per capita food availability in these areas. In case the growth rate of per capita GDP is lower than the global average growth rate, we assumed that less food per capita will be purchased in that grid cell.

Finally, we combined the changes in per capita food availability with the changes in per capita GDP to examine the future hotspots of potential food insecurity through identifying the areas with both decreased per capita food availability and a slower growth rate of per capita GDP than the global average growth rate in the future.

## Data sources

According to the FAO statistical database, the four crops of rice, maize, wheat, and soybean make up nearly 80% of the global cereal harvested area and 86% of global cereal production (FAO 2006). Only these four major crops were taken into account in this case study.

A very large amount of input data, including spatial and socio-economic data, was required in this study to run the models. Among them, the most important input data are climatic data, soil data, population data, and GDP data. Historical and future monthly data on maximum temperature, minimum temperature, and precipitation between 2000 and 2020 were obtained from the high resolution projections of MIROC (Model for Interdisciplinary Research on Climate) 3.2. The MIROC GCM were developed for the Fourth Assessment Report of Intergovernmental Panel on Climate Change (IPCC) by the Center for Climate System Research, University of Tokyo, the National Institute for Environmental Studies in Japan, and the Frontier Research Center for Global Change, Japan Agency for Marine-Earth Science and Technology (K-1 model developers 2004). In order to reduce the abnormal variations of climate change, 10-year average data were calculated for the year 2000 (1991–2000) and 2020 (2011–2020). Soil parameters of soil depth, texture, percent sand and silt, bulk density, pH, and organic carbon content were derived from the Global Soil Data Products (Scholes, Skole, and Ingram 1995). The population and GDP data were collected from the International Institute for Applied Systems Analysis (IIASA) (Grübler et al. 2007). The IIASA datasets were produced with a 30 arc-minute resolution for the period of 2000–2100. The projections of future population and GDP follow the qualitative scenario characteristics of the original IPCC Special Report on Emissions Scenarios (SRES). Since there is little difference between the different scenarios in terms of GDP and population development in the relatively short time span between 2000 and 2020, only the population and GDP data for the A1 scenario were used in this study. All other data used for model simulations have been described in detail in Wu et al. (2007).

Owing to a large degree of variation in data from sources with different spatial and temporal resolutions, it was necessary to perform a procedure of data reprocessing and standardization. To do this, all spatial data were converted into GIS grid data with a cell size of six minutes by six minutes in the ESRI ArcGIS 9.1 software environment, while the socio-economic data were processed and stored as text format data. Additionally, for all spatial data we excluded from the model estimation some geographical regions of the world (mainly those covered by ocean or permanent glaciers) in both Northern and Southern Polar Regions. The final test area covered the globe from longitude 180.0°W to 180.0°E and from latitude 84.0°N to 56.5°S.

## Results and analysis

### *Changes in crop yields*

Figure 2 presents the change ratio of crop yields for four crops during the period of 2000–2020. The results show that except for crop yields of these four crops in many regions remaining unchanged in the next 20 years, there are considerable changes in crop yields. According to our results, rice in some regions in northern India, northern China, and Japan may benefit more from global climate change, while yields of rice crop in south-eastern and southern Asia will decrease. Maize yields show an obvious decrease in some regions located in south-western and northern China, western Europe, northern Great Plains in the USA, and southern Brazil. In other regions, maize gains the increase in yields. Similar to maize, the yields of wheat will be dominantly reduced in 2020 compared to 2000, which is indicated by the change ratio being generally lower than 1 in most regions. Soybean may benefit from climate change in Argentina and northern China, but it may decrease in Brazil, southern China, and northern Great Plains in the USA.

As some inputs of GIS-base EPIC, such as soil data and agricultural management data, were assumed to be constant in the future simulation due to the difficulties of

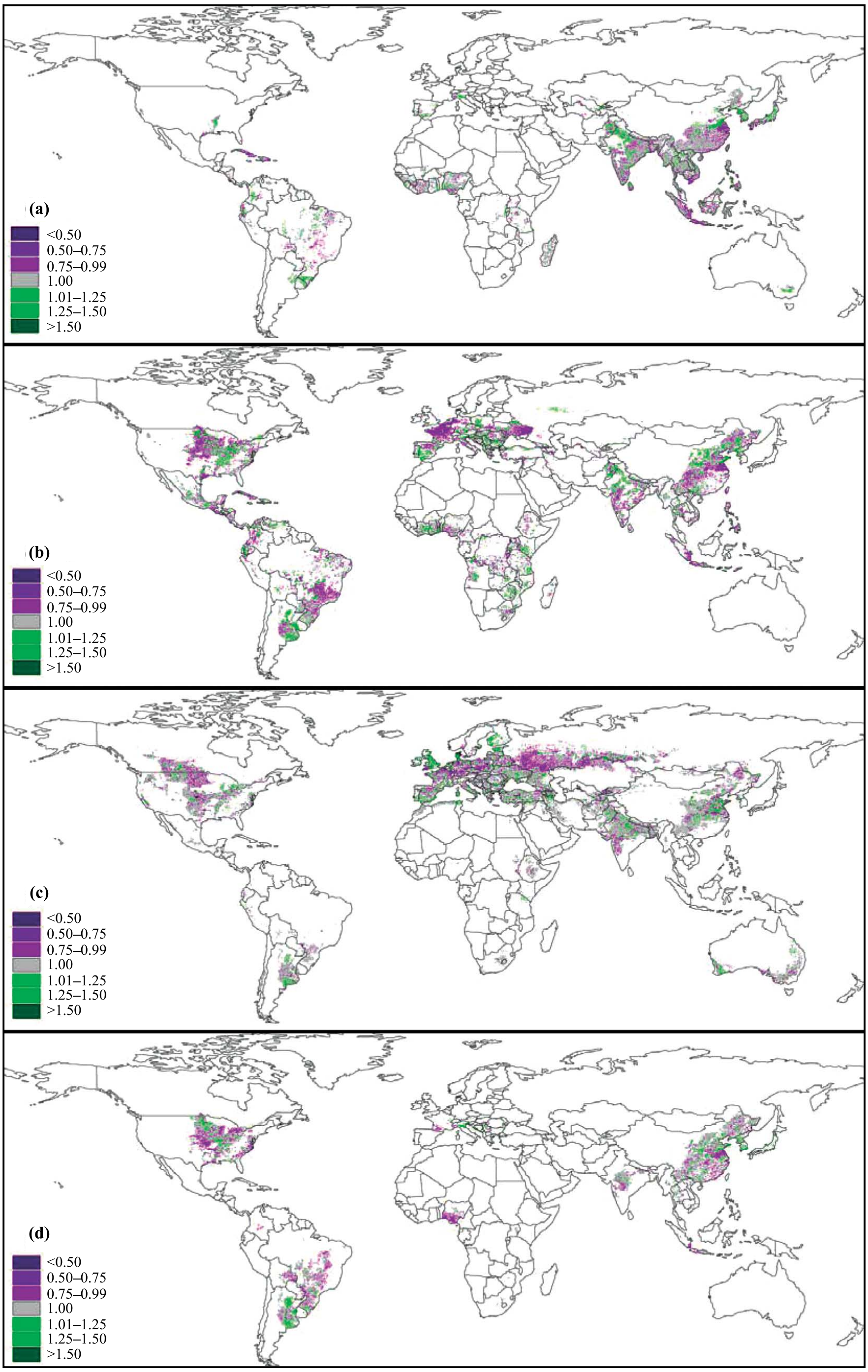


Figure 2. Changes in crop yields during 2000–2020 for (a) rice; (b) maize; (c) wheat; and (d) soybean. Note: the legend less than 1 means that crop yields will decrease between 2000 and 2020, more than 1 means that crop yields will increase between 2000 and 2020. For instance, the legend 0.5–0.75 means a reduction between 50% and 25%. See online version of this article for full-colour figures.

collecting these data for the future, the changes in crop yields can be explained by the future climate change. Different aspects of climate change, such as increased temperature and changed rainfall, all have different effects on crop yields. Their different effects on crop yields do not act independently, but all interact with each other. In general, higher temperatures tend to reduce grain yields because warmer temperatures reduce the length of the growing season so less radiation is intercepted, resulting in lower biomass production (Xiao et al. 2008). As for the four crops in this study, wheat has an optimal temperature of generally between 15°C and 20°C, and all rice, maize, and soybean have an optimal temperature of 25°C. At present, the annual average temperature in some regions (like tropical regions in Asia) may be already above the optimal temperature of a crop during the crop growing period. In the future, global warming will lead to higher temperatures, which are even further away from the optimal temperatures of that crop, leading to reduction of crop yield. In other regions (like northern China and northern Europe), the annual average temperature is currently lower than the optimal temperature of crops. Due to climate change, temperature will further increase until 2020. These temperatures are closer to the optimal temperature of a certain crop; as a result, there will be a general increase in the crop yields of that crop.

Changes in precipitation patterns can have both negative and positive effects on agricultural production. In general, in semi-arid and arid environments, higher precipitation will increase crop yields, whereas a decrease in rainfall will further limit plant production. However, in zones that already have a high rainfall, an increase in precipitation can also increase soil water logging and nutrient leaching, which can reduce crop growth and thus crop yields. In addition, the difference between C3 crops (rice) and C4 crops (maize) can also partly explain the different responses of rice and maize to future climate change.

### *Changes in crop areas*

The global geospatial distribution of sown areas for four crops in 2000 and 2020 is shown in Figure 3. For the globe as a whole, in general, rice, maize, and wheat crops generally showed a constant growth in global total sown areas during the period of 2000–2020, while soybean crop showed a slight decreasing trend during the simulation period. The global totals of sown areas were projected to increase from 151, 160, and 207 million hectares in 2000 to 204, 208, and 251 million hectares in 2020 for rice, maize, and wheat, respectively. By 2020, the total sown areas of soybean were projected to be about 86 million hectares, with a decrease of 2% with respect to 2000.

Figure 4 illustrates the simulated sown areas and their predicted changes for four major crops during the period 2000–2020 in six continental regions (Africa, Asia, Europe, Latin America, North America, and Oceania). Generally, changes in sown areas of individual crops vary across regions of the world. The sown areas of rice, maize, and wheat were predicted to increase at different rates from 2000 to 2020 in each of the continental areas. In particular, rice in Asia, maize in Africa and Latin America, and wheat in Asia and Europe showed a significant increasing trend over time. In Oceania, only wheat crop showed a substantial increase in sown areas while the other three crops displayed little or no changes. The changes in sown areas for soybean were uneven across the world. Sown areas of soybean in Africa, Asia, and North America declined, while the other regions showed a tendency to slightly increase the sown areas of soybean.

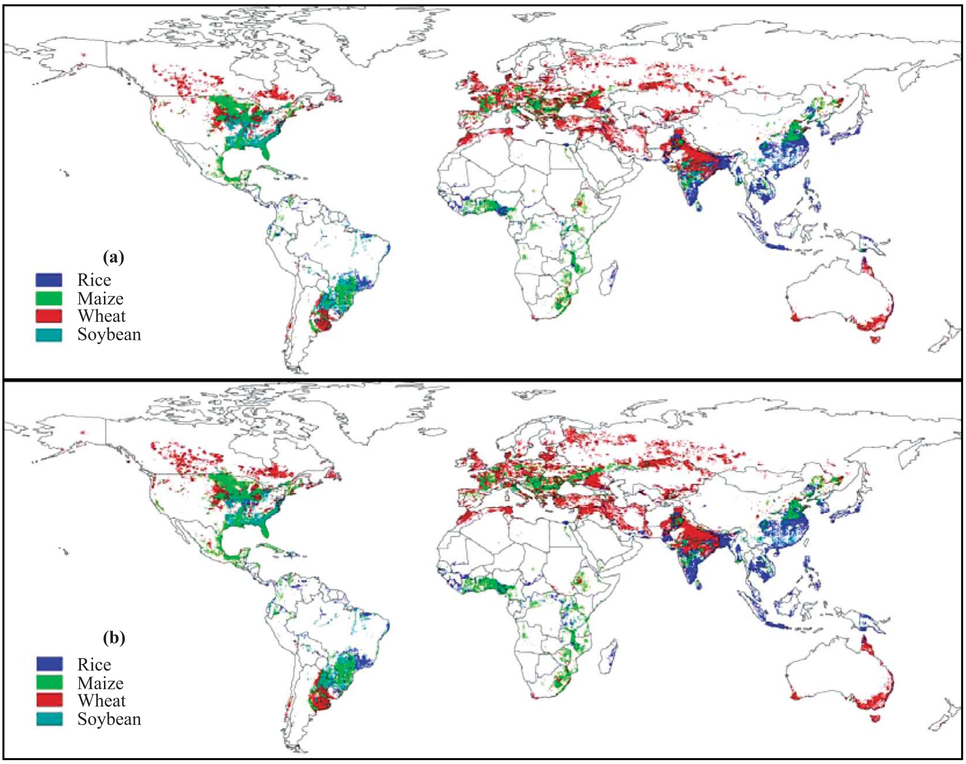


Figure 3. Global distribution of sown areas for major crops in (a) 2000 and (b) 2020. See online version of this article for full-colour figures.

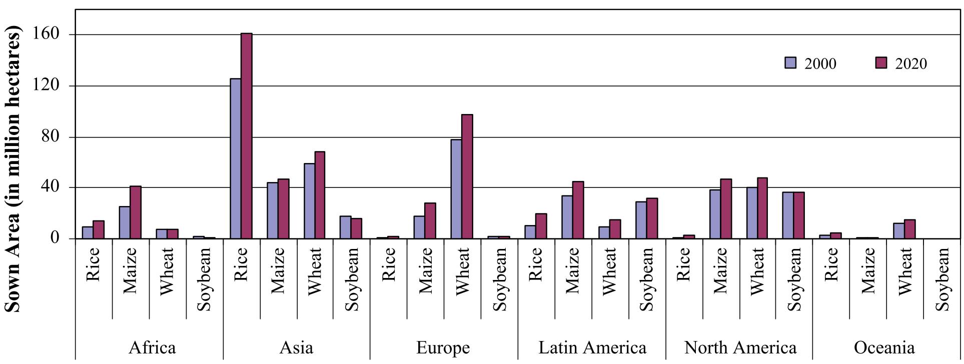


Figure 4. Changes in sown areas of major crops in different continents during 2000–2020.

### *Changes in total food production and per capita food availability*

Figure 5 shows the calculated change ratio of food production (*CR_p*) during the period of 2000–2020. It can be seen that in several regions such as southern China, southern and south-eastern Asia, western and eastern Europe, northern Great Plains in

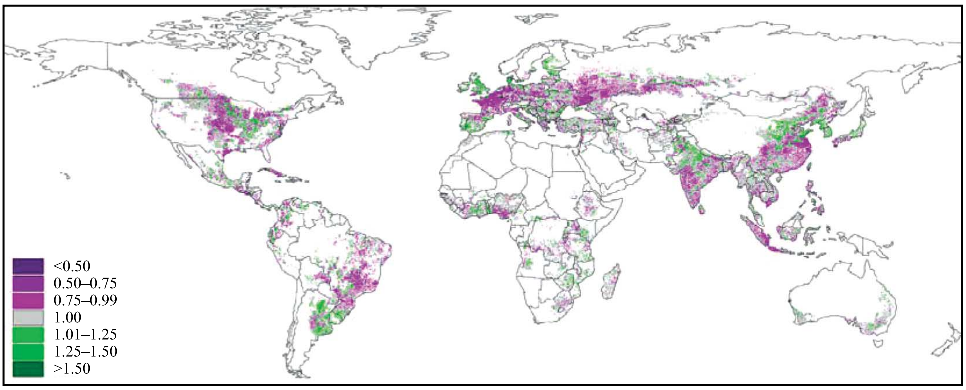


Figure 5. Changes in total food production during 2000–2020 (see Figure 2 for legend description). See online version of this article for full-colour figures.



the USA, Brazil, and some African countries, climate change will result in a reduction in total food production. Adaptation and mitigation measures should be taken soon to combat the adverse effect of climate change on crop production. In contrast, climate change will lead to an increase in total food production in some regions in northern China, northern India, northern Europe, central USA, Argentina, Australia, and some eastern African countries such as Kenya and Zimbabwe.

When considering the population growth, changes in per capita food availability between 2000 and 2020 may show different trends from what is shown in Figure 5. Figure 6 shows the calculated changes in per capita food availability (*CR_a*) between 2000 and 2020. Grid cells with an increase in per capita food availability are shown in green tones (figures can be viewed in colour online). A substantial increase in per capita food availability can be found in some parts located in north-eastern and south-western China, eastern and southern Europe, USA, and Brazil. Noticeable increase can also be found in some regions in south-eastern Asia, Argentina, south-eastern Africa, and Australia. Grid cells with decreased per capita food availability during 2000–2020 are displayed in magenta tones. These areas are located in northern and

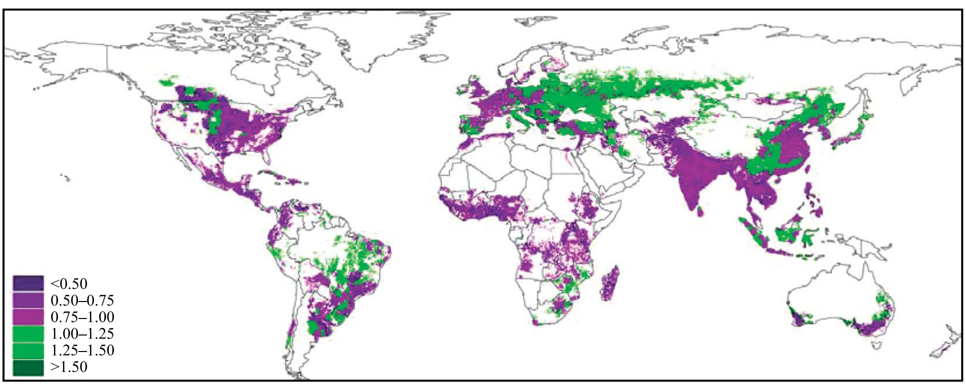


Figure 6. Changes in per capita food availability during 2000–2020 (see Figure 2 for legend description). See online version of this article for full-colour figures.

southern China, most southern and south-eastern Asian countries, western Europe, the USA, Brazil, Argentina, and most African countries.

### *Changes in per capita GDP*

It can be argued that the hotspots located in Figure 6 may change when there will be a substantial increase in purchasing power in 2020. Based on the growth rate of per capita GDP in grid cell and the global average growth rate between 2000 and 2020, the relative changes in per capita GDP with respect to the global average were calculated and shown in Figure 7. Not surprisingly, areas with the highest growth rate of GDP per capita during 2000–2020 are located in developing countries such as China, south-eastern Asian countries and Latin-American countries. Some south-eastern and northern African countries such as Botswana, Mozambique, Morocco, and Egypt also have a projected higher growth rate of GDP relative to the global average growth rate. These areas with a relative higher GDP growth are likely to have the capacity of being able to import food in the future. The increasing purchasing power in these areas may compensate the decrease in per capita food availability. The areas in particular located in southern Asian countries and most African countries are likely to experience a dramatic decrease in the capacity to import food on a per capita basis than currently as the growth rates of GDP in these areas are 35–50% lower than the world average growth rate between 2000 and 2020. The food supply in these regions will strongly rely on the local food production due to their low capability of purchasing food from outside. It can also be found that most developed countries have the lower growth rate of GDP per capita relative to global average. The lower growth rates of GDP per capita in these developed countries may also have some impacts on their food supply.

### *Potential risks of food insecurity*

Based on the changes in per capita food availability (shown in Figure 6) and the changes in per capita GDP (shown in Figure 7), it is possible to identify the future

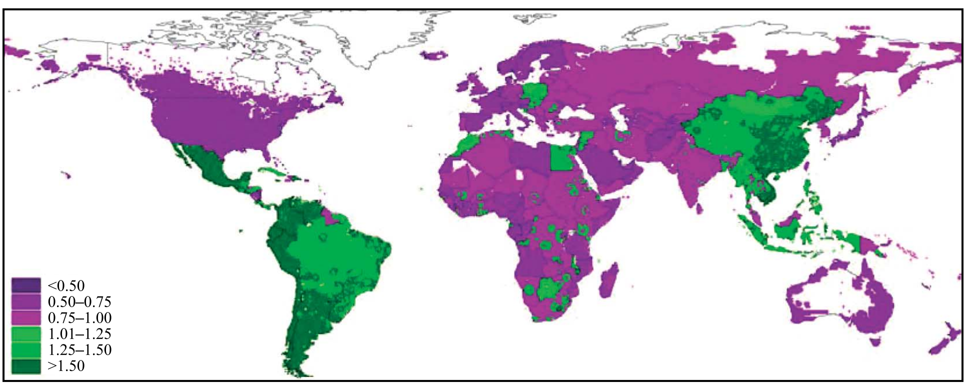


Figure 7. Changes in per capita GDP during 2000–2020. Note: the legend less than 1 means a lower growth rate of GDP than the world average growth rate between 2000 and 2020, and more than 1 indicates a higher growth rate of GDP than the world average growth rate between 2000 and 2020. For instance, the legend 1.25–1.5 means the growth rate of GDP is 25–50% higher than the world average growth rate. See online version of this article for full-colour figures.

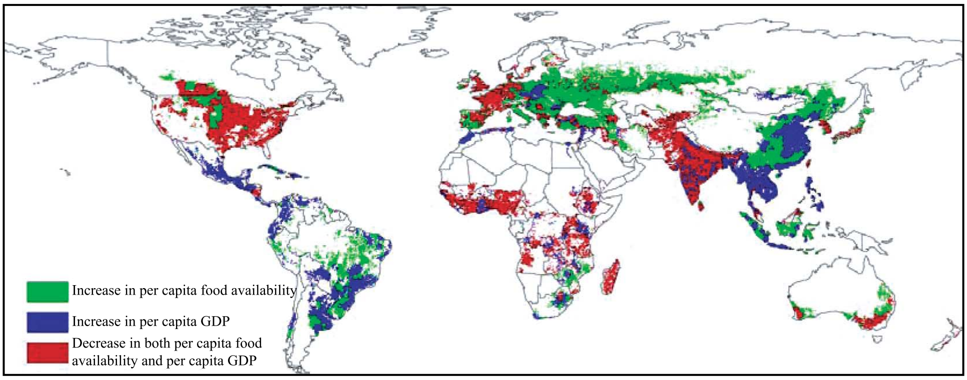


Figure 8. Potential risks of global food insecurity. See online version of this article for full-colour figures.



hotspots of food insecurity by identifying those grid cells where per capita food availability will decrease and the growth rate of per capita GDP will be below the world average during the period of 2000–2020. These results can be categorized into three classes, as shown in Figure 8. Both the classes shown in green tones and blue tones might be able to improve their food security situation due to either an increase in per capita food availability or an increase in the capacity to import food between 2000 and 2020. According to our results, China, most eastern European countries and most southern American countries are not likely to face severe food insecurity in the next 20 years. However, the grid cells in red tones located in southern Asia and most African countries will likely remain hotspots of food insecurity in the future. In these regions, both the per capita food availability and the capacity of being able to import food will decrease between 2000 and 2020, thus more efforts are needed to combat hunger in terms of future actions. It should be noted that although most developed countries such as western European countries, the USA, and Japan will also experience both a decrease in per capita food availability and a decrease in per capita GDP, these countries are likely to be food-secure as their populations rely less on subsistence agriculture and their higher capability of importing food due to stronger purchasing power and financial support, as well as the substantial adaptive capacity and proactive food management systems.

## Discussion

This paper presents an approach of combining together the biophysical, social, and economic factors for spatially explicit assessment of potential future risks of food insecurity at a global scale over the period of 2000–2020 under a certain scenario. Two indicators, i.e., per capita food availability and per capita GDP, were selected to cover the four dimensions of food security, with the former representing the status of food availability and stability, and the latter reflecting the situation of food accessibility and affordability. These two indicators were linked to an integrated modeling framework. Under this framework, the GIS-based EPIC model was adopted to estimate the potential yields of different crop types under a given biophysical and agricultural management environment, the crop choice decision model was used to model the changes in crop areas through tracking the crop choice decisions by using an optimization approach, and the IFPSIM model was utilized to evaluate the crop price in the international market. Based on these two indicators, the potential risks of food insecurity were assessed with a spatial resolution of six arc-minutes.

It is recognized that despite the importance of future security status for human-environment systems, our knowledge of them is usually precarious. Improved foresight of future food security can help to better inform policy decisions. Because the future has not happened, it provides no means for immediate verification. Uncertainties in social, political, and economic development both globally and regionally make it impossible to predict future food security conditions. Instead, it is possible to explore what might happen given certain assumptions about societal developments and environmental changes through the construction of scenarios. In this regard, the assessment results of food insecurity in this study do not constitute a 'prediction' of the future, but identify the potential risks of future food systems that will negatively affect a population or subpopulation, as well as the factors (such as crop areas, crop yields, food production and GDP) in food systems that contribute to the risks (Leikas et al. 2009). Whether these risks could be translated into the 'likelihood' of certain futures occurring remains controversial, but the hotspot regions of food insecurity in this study should gain more attention as there is a high potential risk of food security and hunger may occur there.

Just like all other scenario studies, this study has a number of limitations and uncertainties at both the technical and conceptual levels. While scenarios provide a methodology for exploring the consequences of uncertainty, it is important that users of scenarios are aware of the additional uncertainties that can be introduced by the scenario methodology itself (Rounsevell et al. 2006). We used the SRES socio-economic scenarios to drive the crop price models and the MIROC climate change scenarios to drive the crop yield model. All the future scenario interpretations, parameterization, and the downscaling from global to regional level were based on judgments that may be subjective, and thus have high uncertainty. When these future scenarios data were used as the input for model simulation, they might contain some uncertainties (Wu et al. 2008).

Second, three models on which future food insecurity assessment was conducted also contain uncertainties. When models were used to construct future scenarios, their input parameters were changed according to a set of rules that was designed to explore or depict these future scenarios. The inherent uncertainty of these parameter values can bring about some bias in the outputs from model simulations (Verburg, Veldkamp, and Rounsevell 2006). Any lack in the capacity of models to represent future processes is a source of uncertainty and should be minimized. Even when the causal relationship between the parameters and individual models was well constructed, potential future changes may not necessarily be described by the relationships derived from past and present observations, which limits their applicability for future predictions (Rounsevell et al. 2006).

Furthermore, the approach to identify hotspots of food insecurity contains certain subjective elements. The study only considered the four globally widespread crops and ignored other region-specific crop types. This could underestimate the food production for some regions. We also considered limited adaptive capacity such as the use of new crop varieties and crop management options. All these together could influence the results of assessment of potential risks of food insecurity to some extent.

## Conclusions

This study indicates that the future changes in climate have both negative and positive effects on crop yields for the four crops. There is a common trend for all major crops to increase or stabilize their areas as a response to different levels of socio-economic and biophysical changes although the change rates are different. The results also show that both changes in per capita food availability and changes in per capita GDP vary across regions worldwide. This could be likely to influence the future food security status during the period of 2000–2020, and this influence differs from region to region. Some regions such as China, most eastern European countries and most southern American countries where there is an increase in per capita food availability or an increase in the capacity to import food between 2000 and 2020 might be able to improve their food security situation. On the contrary, certain regions such as southern Asia and most African countries will likely remain hotspots of food insecurity in the future. In these regions, both the per capita food availability and the capacity of being able to import food will decrease between 2000 and 2020, thus more efforts are needed to combat hunger in terms of future actions, such as food aid and development programs. It should be noted that although most developed countries will also experience both a decrease in per capita food availability and a decrease in per capita GDP, these countries are likely to be food-secure due to their higher income and purchasing power.

The assessment results of food insecurity in this study are neither real predictions nor facts, but indicate some hotspot regions with a high potential risk of food insecurity in the future. These results can help explore what might happen given certain assumptions about societal development and environmental changes and provide valuable information for food risk management and policy-making to combat future hunger.



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