

# Penny wise, pound foolish: Substitution cost of cropland lost to urbanization

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## Article

**Keywords:** Urbanization, cropland, substitution cost

**Posted Date:** March 19th, 2021

**DOI:** <https://doi.org/10.21203/rs.3.rs-267714/v1>

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# Abstract

Urbanization has appropriated millions of hectares of cropland<sup>1</sup>, and this trend will persist as cities continue to expand<sup>2</sup>. Here we estimated the substitution cost by comparing the yield potential between the converted and newly cultivated land as determined by climate and soil properties. To do so, we used robust spatial upscaling techniques, well-validated crop simulation models, and soil, climate, and cropping system databases<sup>3-5</sup>, focusing on populous countries exhibiting high rates of land conversion. We found that productivity of new cropland is substantially lower than the land it replaces, which means that projection of food production potential must account for expected cropland loss to urbanization and the lower productivity of new land that replaces it. Policies that protect existing farmland from urbanization would relieve pressure on expansion of agriculture into natural ecosystems and reduce the associated greenhouse gas emissions and biodiversity loss.

## Main Text

Prior to the establishment of global supply chains and modern transport systems, most large cities were provisioned with food from surrounding farmland. For this reason, many of the world's major cities were established in locations with good soils and adequate rainfall or irrigation to ensure a dependable food supply<sup>6</sup>. Hence, as urban populations grow, surrounding croplands are converted to urban uses. With rapid urban growth rates of the past 30 years, global conversion of cropland near urban areas has been occurring at 1.2 million ha y<sup>-1</sup> (1). Continuing rapid urbanization<sup>7</sup> suggests that conversion of agricultural lands for urban uses will proceed rapidly into the foreseeable future. At the same time, land area devoted to production of staple food crops is expanding worldwide at a rapid rate<sup>8</sup>. Much of this expansion occurs far from cities and comes at the expense of rainforests, wetlands, and grasslands, which reduces biodiversity and water resources supported by these natural habitats<sup>9,10</sup>.

At issue is the degree to which the loss of existing farmland, and development of new cropland elsewhere, affects food production capacity and yield stability due to differences in soil and climate associated with this substitution. For example, if soil of new cropland holds less water or is located in a region with harsher climate than converted cropland, a decrease in yield potential and yield stability is likely to occur, or *vice versa*. Here we define yield potential as the yield obtained with good crop and soil management that minimizes losses from abiotic and biotic stresses<sup>11</sup>. Robust estimates of this "substitution cost" based on yield potential are needed to assess the impact of land conversion on current and future food production capacity, especially in relation to expected climate change scenarios and strategies for conservation of natural resources.

Despite their importance, robust estimates of substitution costs are lacking. For example, an econometric model used to evaluate future global food production potential assumes the substitution cost represents a fixed proportion (1.5x) of the converted land without justification for the proportion used<sup>12</sup>. Other studies estimate substitution cost as the ratio between current yields on cropland in urbanizing areas

*versus* yields on cropland distant from cities<sup>2</sup>, which often confounds the substitution cost with regional differences in sophistication of crop and soil management practices employed by farmers and their access to inputs and supporting services. Other estimates of substitution costs are generic and do not differentiate among major food crop species<sup>1,13</sup>. Estimating substitution costs specific for each major food crop is important because diets in developing countries are typically comprised of one or two major staple crops, which, in turn, have specific requirements in terms of the climate and soils to which they are best adapted. Finally, most previous studies are based on data organized within coarse gridded spatial frameworks that have been found unreliable for estimating crop production potential on existing cropland at sub-national spatial scales<sup>14</sup>. Approaches used to estimate substitution costs to evaluate future global food production capacity are summarized in **Supplementary Table 1**.

This study overcomes the limitations of past studies by utilizing robust spatial upscaling techniques, well-validated crop-specific simulation models, and soil, climate, and cropping system databases at finer spatial resolution, using primary data sources as much as possible, to estimate yield potential and yield stability of current and newly developed croplands<sup>3,4</sup>. To determine the crop production “cost” of this substitution, we compare yield potential and yield stability of cropland in regions with contracting or expanding production area in the first decade of the new millennium for rice in China (irrigated) and Indonesia (rainfed and irrigated), and rainfed maize in Nigeria. These countries and crops were selected because they: (1) have large populations and associated food demand, (2) are projected to undergo rapid land use change due to urbanization<sup>15</sup>, and (3) the evaluated crops represent major staples in national diets and account for a large proportion of total farmland in each country<sup>16</sup>. To avoid the confounding influence of differences in sophistication of crop and soil management and use of inputs on converted *versus* new cropland, we evaluate differences in yield potential instead of current average yields, as the former assumes use of best management practices in both expanding and contracting regions. Substitution costs estimated in this way are therefore dependent on differences in endowments of climate, soil, and access to irrigation. A spatial framework that delineates areas with similar crop production potential and yield stability based on climate was used to upscale substitution cost estimates from sub-national to national scale<sup>4,5</sup>.

## Results

Population growth and urbanization are key drivers of land use change worldwide. For example, in China, total production area of seven major staple food crops decreased substantially in regions surrounding the most rapidly growing cities during the 2000–2010 period (Fig. 1). In contrast, cropland expansion occurred in central and northeastern China where urban population growth was much slower.

One reason for differences in total grain production between cropland lost to urbanization and new cropland is cropping intensity (*i.e.* number of crops grown each year on the same piece of land). In China, irrigated rice area has been decreasing in regions surrounding mega-cities such as Shanghai (current population: 27 M<sup>7</sup>), Guangzhou (13 M), and Hangzhou (8 M) where warm climate and long growing

season allow production of two rice crops per year on the same field (called double cropping). Expansion of irrigated rice production occurred mostly in central and northeastern regions where only a single rice crop can be grown each year given a cooler climate and shorter frost-free period (Fig. 2a). National average yield potential of converted rice land was 15.2 t ha<sup>-1</sup> compared with 11.2 t ha<sup>-1</sup> for newly established rice land (Fig. 2b). While yield potential for a single crop is highest in central and northern provinces, total annual production potential per hectare is about 70% greater in south and southeast of China due to annual double cropping. Taking into account all areas undergoing cropland conversion or expansion, the area-weighted national substitution cost in China is 1.3 hectares (Table 1), which means that, on average at national scale, proportionally more cropland (1.3x) is required to replace the productive potential of one hectare of rice land lost to urbanization. Not accounting for differences in cropping intensity would lead to the (wrong) conclusion that new crop area in China has higher rice yield potential than crop area lost to urbanization. Yield stability on new and converted cropland, as quantified by the inter-annual coefficient of variation (CV), is similar in both cases because rice is produced with irrigation, which avoids yield losses from drought and greatly increases yield stability compared to rainfed crop production<sup>19</sup>.

Table 1

Substitution cost estimated by comparing the annual yield potential of new areas brought into crop production versus cropland converted to other uses during the 2000–2010 period. Crop intensity refers to the number of crops of rice (China and Indonesia) or maize (Nigeria) grown each year on the same piece of land. Yield stability is estimated by the inter-annual coefficient of variation in annual yield potential.

	China		Indonesia		Nigeria	
	Irrigated rice		Rice <sup>†</sup>		Rainfed maize	
	Converted	New	Converted	New	Converted	New
Average crop intensity (crops y <sup>-1</sup> )	1.7	1.2	1.7	1.4	1	1
Irrigation proportion (%)	100	100	94	20	nil	nil
Annual yield potential (t ha <sup>-1</sup> )	15.2	11.8	16.9	13.4	11.6	8.5
Substitution cost (ha)	1.3	-	1.3	-	1.4	-
Yield stability (CV in %)	8	8	4	3	27	51
<sup>†</sup> Includes irrigated and lowland rainfed rice.						

A similar situation occurs in Indonesia, where highly productive irrigated rice area in West and Central Java, the island with fastest population growth (+ 122 km<sup>-2</sup> y<sup>-1</sup>; in 2000-2010<sup>20</sup>), has been converted to other uses<sup>21</sup> while rice area expanded mostly into more marginal agricultural regions, with slower population growth, such as in South Sumatra (+ 14) and South Kalimantan (+ 17) (Fig. 2c). Total annual yield potential is about two-fold greater in irrigated double (or even triple) rice systems in West and

Central Java compared with those marginal regions, where single-crop tidal and flood-prone rice systems are dominant (Fig. 2d). In these harsher environments, rice is typically grown during the wet season and water supply depends exclusively on ocean tides and rainfall, which allows only one rice crop per year in most cases and reduces yield potential from exposure to both flooding and drought stress during the same growing season<sup>22</sup>. Considering all land conversion and expansion throughout the country, national average substitution cost for rice in Indonesia is 1.3 hectares (Table 1).

In Nigeria, the greatest reduction in rainfed maize area occurred in southern coastal regions with humid tropical climate around Port Harcourt (+ 0.7 M population increase, 2000–2010). Most new maize area came from northward expansion into the more sparsely populated Guinea Savanna region, which has lower annual rainfall and greater year-to-year variation in rainfall amounts (Fig. 2e). As a consequence, rainfed yield potential of new maize land is considerably lower and much less stable than the converted land it replaced, with a national average substitution cost of 1.4 hectares (Fig. 2f; Table 1). In contrast to Indonesia and China, farmers in most of Sub-Saharan Africa lack adequate access to inputs and extension services. As a result, the difference in potential productivity between new *versus* converted land reported here would not have been captured if the analysis was based on the very low current yields attained by maize farmers throughout the country ( $1.8 \text{ t ha}^{-1}$ ), which would lead to the conclusion that converted land has a substitution cost near unity (**Supplementary Table S2**).

Sub-national estimates of annual yield potential for new and converted cropland show enormous variation due to endowments of climate and soil. For example, across rice producing regions in China, total annual yield potential ranges from 10 to  $19 \text{ t ha}^{-1}$  in both new and converted croplands (Fig. 2). Similarly, wide ranges of annual production potential can be observed across rice and maize producing areas in Indonesia and Nigeria, respectively. Hence, national average substitution costs based on area-weighted estimates of annual yield potential, as given in Table 1, hide enormous variation in sub-national estimates of annual production potential (Fig. 2). As a result, using a fixed substitution cost to estimate the impact of land conversion on crop production at subnational levels can give misleading input to inform national agricultural and land-use policies, including prioritization of investments in agricultural research and development.

Accuracy of substitution cost estimates are highly sensitive to data quality, precision of cropland distribution maps, spatial scale at which the data are analyzed and aggregated, and reliability of crop yield potential simulations. We have confidence in the spatial framework used for upscaling results from sub-national to national scale because it has proven to be robust in estimating yield potential at sub-national to national scales for a number of crops and countries across a wide range of soils and climates<sup>5,14,23</sup>. Likewise, crop simulation models used to evaluate crop yield potential have been widely validated in China, Southeast Asia, and Sub-Saharan Africa<sup>14,24,25</sup>. While we attempted to use the best available sub-national data sources for cropland distribution, cropping systems, climate, and soil properties as described by Grassini et al.<sup>3</sup>, data quality is always a concern for long-term weather records and soil properties, which are input to the simulation models and, thus, may be a source of uncertainty<sup>26</sup>.

Similarly, crop models may not account for all possible factors limiting crop production. For example, currently available rice simulation models do not account for the negative effect of alternate cycles of drought and submergence, which are frequent in tidal and flood-prone systems of the new Indonesian rice areas but less common in regions with irrigated production<sup>19</sup>. Similarly, the best available rice models have limited ability to simulate the effects of cold sterility<sup>27</sup>, which may be important for estimating yield potential in high-latitude temperate environments as found in northeastern China where rice production area is expanding. In both cases, inclusion of these factors in simulating yield potential would tend to increase estimated substitution costs as found in this study.

## Discussion

Global land-use trends document that increases in crop production area now contribute more to global supply of staple food crops than the rise in crop yields, which reverses trends of previous decades when crop yield increases were more prominent<sup>8</sup>. Reliance on conversion of new land to meet increasing food demand is amplified by loss of existing farmland to urbanization. Hence, accurate estimation of the impact from these trends on food production capacity provides critical input to development of agricultural and land-use policies at national and global scales to achieve appropriate balance between food security and environmental goals. Using new methods to make such an assessment, as reported herein, with finer spatial resolution and more robust simulation of crop yields and yield stability than previously possible, we find that average national substitution costs range from 1.3 for rice in China and Indonesia to 1.4 for maize in Nigeria. Despite relatively little variation in these national averages, there was enormous variation in yield potential of both converted and new land at sub-national scales in all three countries. Hence, fixed ratios for estimating substitution costs, as employed in some studies<sup>12</sup>, should be used with caution as input to strategic national land-use plans. Similarly, use of current yields<sup>2</sup>, rather than yield potential, underestimates substitution costs by a large margin when average farm yields in both converted and new land are limited by lack of inputs and technologies to overcome nutrient deficiencies, weeds, and pests, which is the case for maize in Nigeria. In addition, year-to-year variation in Nigerian rainfed maize yield potential is two-fold larger on new rainfed maize land than on farmland lost to urbanization (Table 1), which means food production on new land is much less reliable than on converted land. Similar assessments are possible for other countries that have sub-national data on changes in population<sup>7</sup>, crop production area<sup>17</sup>, and crop production systems, soils, and climate<sup>26</sup>.

Conversion of cropland for urban use can be penny wise when substantial profits accrue from such land development. But these conversions can also be pound foolish for several reasons when new cropland has substantially lower yield potential, less yield stability, or both. First, a substitution cost greater than one increases pressure to further expand cropland area to meet food demand through conversion of rainforests and grasslands at the expense of biodiversity and other ecosystem services provided by natural habitat. Second, deforestation and conversion to agricultural land use accounts for 17% of global greenhouse-gas emissions contributing to climate forcing<sup>28</sup>. Third, in rainfed systems, reduced yield stability makes it riskier to invest in fertilizer and other inputs to raise yields in new production areas,

which in turn contributes to slower rates of increase in crop yields<sup>3,29</sup>. And fourth, while we assessed substitution costs based solely on differences in annual crop yield potential, the overall cost would be higher if one also considers the greater production costs (fertilizer, labor, transportation) and required investments in infrastructure (roads, canals, drainage systems) associated with establishing crop production in remote areas where expansion typically occurs. We conclude that in countries where land substitution costs are large, as found in this study, there is strong justification for land-use policies that seek to conserve prime farmland at the periphery of urban areas<sup>2</sup> supported by agricultural development and land-use policies that seek to accelerate yield gains on existing farmland through sustainable intensification while also ensuring conservation of natural ecosystems<sup>8,30</sup>. Continuing current land-use trajectories undermines progress towards the tripartite goals of food security, conservation of natural resources, and addressing the threat of climate change.

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## Declarations

### Acknowledgements

This research was funded jointly by the Office of Global Engagement at the Institute of Agriculture and Natural Resources (IANR) at the University of Nebraska-Lincoln (UNL) and UNL Daugherty Water for Food Global Institute. Research was also supported by Bill & Melinda Gates Foundation, the Indonesian Agency for Agricultural Research and Development (IAARD), the earmarked fund for the National Key Research and Development Program of China, and China Agriculture Research System. The authors thank the local agronomist and extension workers in China, Nigeria, and Indonesia who helped retrieve data needed for crop modeling, such as soil characteristics, crop sequence, cultivar selection, sowing dates, and plant density.

## Author Contributions

Research was conceived by J.F.A, P.G., and K.G.C. Conceptualization was elaborated by J.F.A, P.G., J.I.R.E, and K.G.C. Data acquisition and processing were performed by J.F.A, J.I.R.E, F.A, A.B, and N.D. Statistical analysis, and figures were prepared by J.F.A. The manuscript was written by J.F.A, P.G., and K.G.C., with input from all authors.

## Competing interest declaration

The authors declare no competing interests.

## Methods

### *Estimation of land productivity*

Our analysis of farmland substitution costs is based on comparison of annual crop yield potential of converted and new croplands rather than on differences in current farm yields of both land categories. As noted in the main text of our paper, the latter approach can mask differences in the inherent productive capacity of agricultural land, as determined by soil quality and climate, due to differences in sophistication of crop and soil management practices or access to inputs and markets, all of which can limit yields<sup>31</sup>. In many developing countries, and especially at the frontiers of current agricultural areas, farmers have limited access to inputs, equipment, supporting services and technologies. However, we also evaluated substitution costs based on current average yields and the results are presented in **Supplementary Table 2** although we believe these results are less useful. For example, substantial funding is allocated by government agencies and charitable foundations (e.g., Bill & Melinda Gates Foundation, CGIAR, USAID–Feed the Future Initiative) to improve farmer access to markets, technologies, and information in developing countries. Therefore, an analysis of land substitution costs to inform national policies concerning agricultural development and land use policies based on current yields would not only mask the potential cost of cropland substitution based on use of modern farming practices, but it would also quickly become outdated as farmers gain access to markets, technologies, and information.

Yield potential is the yield of a crop cultivar when grown with water and nutrients non-limiting and biotic stress effectively controlled<sup>11,32</sup>. Under these conditions, crop growth rate is determined by solar radiation, temperature, atmospheric CO<sub>2</sub>, and genetic traits that govern the length of growing period and light interception by the crop. For rainfed crops, rainfall amount and distribution and soil water holding capacity also impose an upper limit to crop productivity. Hence, yield potential is the most relevant parameter for estimating crop production potential of irrigated crop systems, while water-limited yield

potential is the appropriate benchmark for rainfed crops. Current yield is defined as the yield achieved in farmer's fields in recent years within a defined spatial unit.

We used crop models to estimate yield potential in each country. The main challenge to obtain accurate simulations using crop models is the availability of high-quality primary data for climate, soil, and crop management, which are the most sensitive parameters determining yield potential. Weather stations are sparse and soil and cropping system information is rarely adequate to estimate yield potential for many crop production areas in developing countries. To overcome that limitation, we used the Global Yield Gap Atlas<sup>26</sup> (GYGA) "bottom-up" spatial framework that identifies the minimum number of sites needed for robust estimation of yield potential at local, regional, and national scales<sup>4,5,23,33</sup>.

The GYGA framework delimits climate zones (CZ) based on spatial variation in three key variables influencing crop growth and yield: growing degree-days, temperature seasonality, and aridity index<sup>5</sup>. The framework evaluates all CZs that account for >5% of total national harvested area for each crop (either irrigated or rainfed water regime). Within each CZ, buffer zones of 100-km radius (called "sites" in main text) were created around existing weather stations where measured weather data are retrieved, with each buffer "clipped" by CZs borders. For each crop-water regime, buffers were selected sequentially starting from the buffer with largest crop harvested area, including only buffers that account for >1% of national crop harvested area and minimizing overlap (<20%) among adjacent buffers, until approximately half of the national harvested area is covered for the target crop. Crop area distribution maps of maize and rice around 2005 (average for 2004-2006), disaggregated by water regime, were retrieved from the International Food Policy Research Institute (IFPRI–MAPSPAM database)<sup>34</sup>. MAPSPAM provides 10 x 10 km grid-cell resolution maps of harvested area for each of the major food crops. In a few cases (14%) there were no weather stations in areas where new cropland was established. Additional buffers were created in selected producing regions without MAPSPAM data or where there were no weather stations. In the last case, we used secondary gridded weather data from the NASA-POWER database<sup>35</sup>. A total of 50, 55, and 16 buffers were created for irrigated rice in China, rainfed or irrigated rice in Indonesia, and rainfed maize in Nigeria, respectively. **Figure 2** only shows buffers with significant change in net area (greater than 15,000 or 10,000 hectares for rice and maize, respectively) in the 2000-2010 period.

Within each buffer, dominant soil types and crop management data were taken from the GYGA database to portray the dominant cropping system(s) used for simulation of annual yield potential. In summary, crop management, soil, and climate factors governing yield potential, as well as subnational data on current farm yields reported by government agencies were populated at the buffer level using observed data to the extent possible. Upscaled estimates of current yields and yield potential at CZ scales were based on aggregation of crop area-weighted values of all buffer zones within each CZ. A detailed description of the GYGA spatial upscaling methodology can be found elsewhere<sup>3,4,26</sup>.

### *Yield and substitution cost assessment*

Three countries undergoing rapid urbanization during the last few decades were selected as case studies<sup>36</sup>. Crop area distribution in 2000 (average for 1999-2001) and 2010 (2009-2011)<sup>17</sup> from MAPSAM was used to estimate net change in crop area for that 10-year period in each buffer and CZ, which in turn was used to identify areas of rapid crop expansion or contraction for maize (Nigeria) and rice (China, Indonesia). In the case of Nigeria, maize is grown under rainfed conditions, which means crop growth depends on stored soil water at sowing and in-season rainfall to meet its water requirements. In the case of rice, nearly all rice production in China occurs on irrigated land, while both irrigated and lowland rainfed rice are grown in Indonesia.

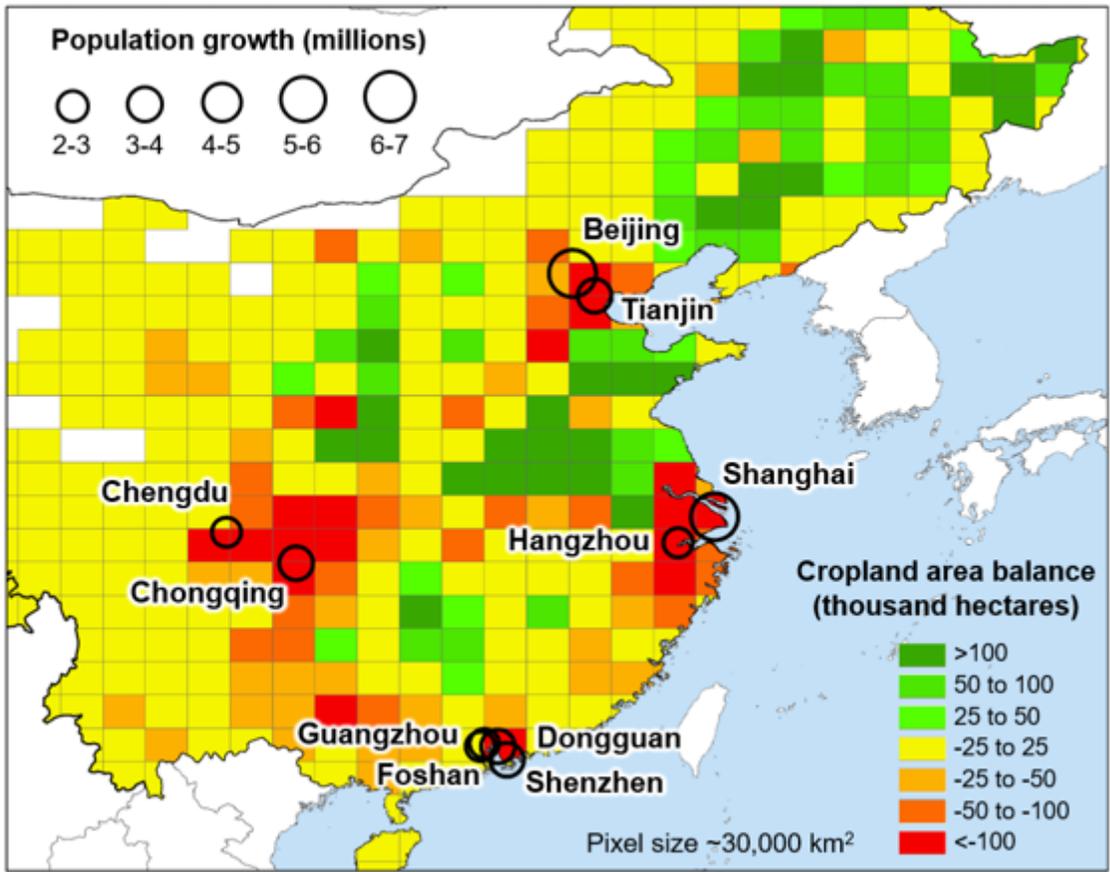
Locally calibrated crop models were employed to estimate yield potential of rice or maize in each buffer within each country<sup>14,24,25</sup>. We used Hybrid-Maize<sup>37</sup> for maize simulations in Nigeria and Oryza V3<sup>38</sup> for rice simulations in China and Indonesia. Ten or 15 years of weather data were employed for yield potential and water-limited yield potential, respectively, as per GYGA methodology<sup>26</sup>. Soil and crop management data, including cropping intensity within each buffer were collected with the assistance of local agronomists. Current yields were obtained from official statistics at the lowest administrative level at which they are available within each buffer, for the most recent five years. Using a longer time period would bias estimation of current yields due to influence of a technology trend<sup>39</sup>. Details on the methodology followed to estimate yield potential in each country and data sources can be found in **Supplementary Table S3** and elsewhere<sup>13,21,24</sup>.

Current yields and yield potential, as well as crop intensity and yield stability, in buffers experiencing large cropland substitution of rice or maize were compared with those at buffers where cropland is currently expanding (**Figure 2**). We estimated yields on an annual basis to account for the higher crop intensity in those regions where two or even three crops were produced each year on the same piece of land (rice in Indonesia and southern China). Then, for each country, we calculated the average annual yield (either current or potential) in CZs with expanded or contracted crop-specific area, weighted by the crop area net balance within each CZ (2000-2010). National average substitution costs were computed as the ratio between the weighted average yield in CZs with contracted area *versus* the weighted average yield in CZs with expanded crop area in the study period. For comparison, substitution costs were estimated separately based on either current yields (**Supplementary Table 2**) or potential yields as reported in **Table 1**. In this study, yields are reported at 15.5 and 14% seed moisture for maize and rice, respectively, which correspond to the commercial yield reporting standards for these crops.

## Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Figures



**Figure 1**

Changes in cropland area for seven major staple food crops (rice, maize, wheat, soybean, barley, sorghum, and cassava)<sup>17,18</sup> and change in population of major cities from 2000 to 2017. Labeled cities correspond to urban centers with population growth larger than 2 million inhabitants during that period. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

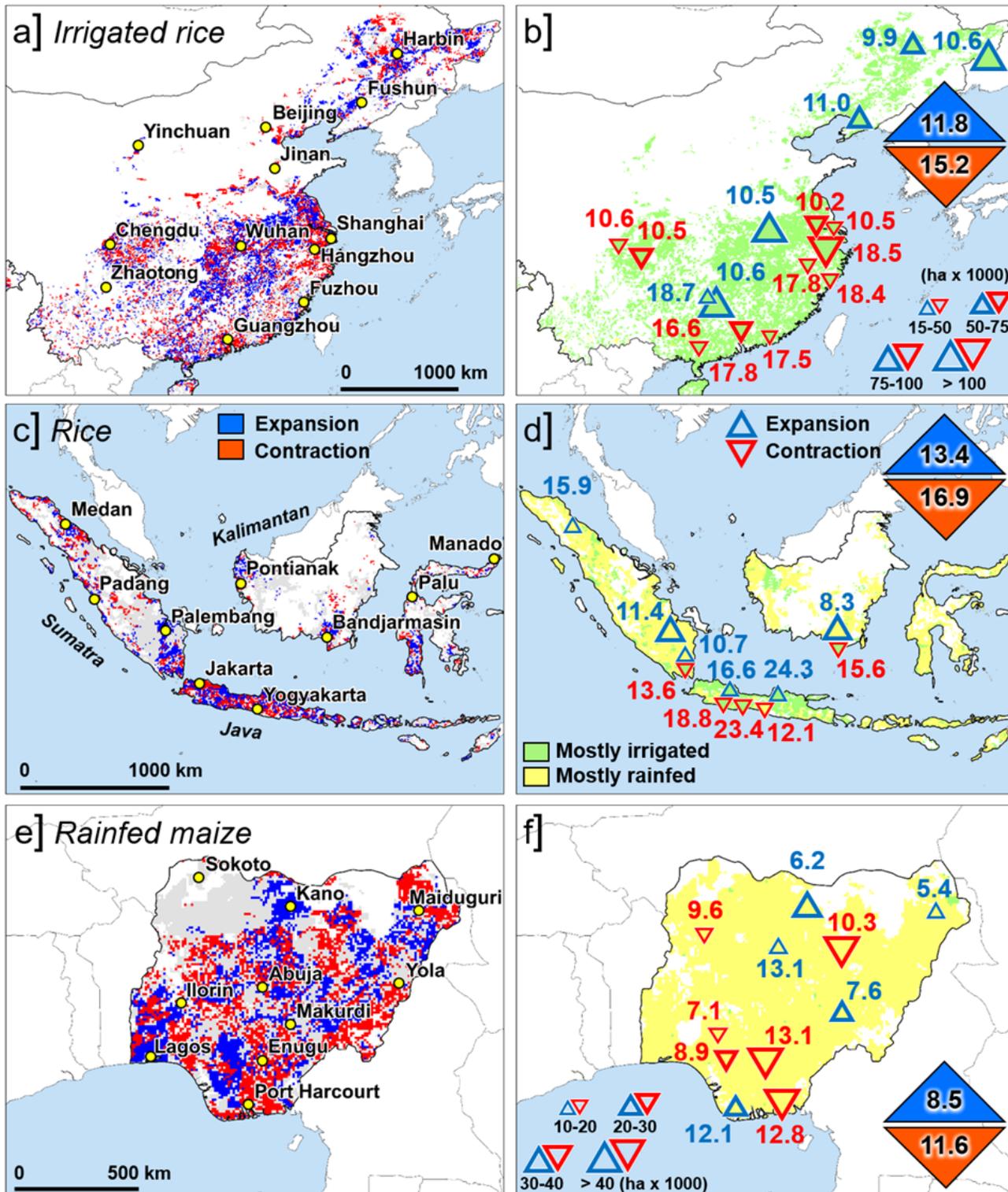


Figure 2

Left panels: net change in cropland area (2000-2010) in (a) China (irrigated rice), (c) Indonesia (rainfed and irrigated rice), and (e) Nigeria (rainfed maize)<sup>17,18</sup>. Colored areas are those with at least 50 hectares of cropland per pixel (each approximately 10000 ha). Regions where crop area is contracting are shown in red, while regions where crop area is expanding are shown in blue (>250 ha change per pixel in both cases). Right panels (b, d, f): annual yield potential (t ha<sup>-1</sup>) at sites with significant change in net area

balance (greater than 20,000 and 10,000 hectares for rice and maize in the period from 2000 to 2010, respectively; blue triangles: positive net change, red inverted triangles: negative net change). Yields at sites with no significant change in net area (smaller than 15,000 or 10,000 hectares for rice and maize, respectively) are not shown. Weighted national yield averages (insets in right panels) were calculated using GYGA aggregation procedures based on a climate zone spatial framework<sup>4</sup>. A number of administrative capitals are shown as a reference in left panels. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

## Supplementary Files

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