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Explaining the global spatial distribution of organic crop producers

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ABSTRACT

Organic farming has been proposed as a feasible way to reduce the environmental impacts of agriculture, provide better products to consumers, and improve farmers' income. How organic farmers are distributed worldwide, however, remains unknown. Using publicly accessible registries of organic crop farmers we mapped their distribution globally and related it to local socio-economic, climatic, and soil characteristics. We show that organic crop farmers are mostly present in areas with favorable socio-economic and climatic conditions, both globally but also within countries. Within developed countries, the locations of organic crop farmers often do not differ significantly from the locations of conventional crop farmers. In developing countries, there are, however, larger differences and organic crop farmers concentrate in the more accessible and developed regions. Our results suggest that crop farmers in poor areas may not have sufficient access to certification and markets. To promote the spread of organic farming, certification and other incentives could target farmers in areas with lower market access and higher levels of poverty which could improve value chains for organic products in these areas.

1. Introduction

Advancements in agriculture and cropland intensification have contributed to increases in food production crucial for ensuring global food security (Meyfroidt, 2018; Muller et al., 2017). At the same time, intensification through increased use of synthetic inputs has led to negative environmental and social consequences (Verburg et al., 2013). Different strategies have emerged to reduce the environmental impacts of agriculture, while at the same time supporting food security; organic agriculture is among the most promising (Reganold and Wachter, 2016; Seufert and Ramankutty, 2017).

Evidence suggests numerous environmental benefits of organic farming: reduced soil loss and increased organic matter, lower carbon emissions, and higher biodiversity values (Bengtsson et al., 2005; Blackman and Naranjo, 2012; Gomiero et al., 2011). Certified organic farming can lead to higher profits (Crowder and Reganold, 2015), improving the income of smallholder farmers (Ayuya et al., 2015; Barrett et al., 2001; Bolwig et al., 2009; DeFries et al., 2017). For certain crop types, organic farming can under the right conditions maintain yields or even improve the production efficiency (Seufert et al., 2012; Tzouvelekas et al., 2001). However, such benefits are contested (Hole et al., 2005), particularly when it comes to looking at environmental benefits per crop unit (Seufert and Ramankutty, 2017). Some studies warn that upscaling organic farming could lead to disruptions in food security and more widespread environmental degradation through displacement effects (Connor, 2008; Leifeld et al., 2013; Muller et al., 2017). In some cases, organic farming has been reported to cause increased poverty and inequality between rich and poor farmers (Beuchelt and Zeller, 2011; Getz and Shreck, 2006; Gómez Tovar et al., 2005).

Both the proponents and opponents of organic farming often fail to consider the spatial context in which organic farming is occurring (Seufert et al., 2012). Knowledge on the spatial distribution and the location characteristics influencing organic certification is limited to local- or country-scale examples. Proximity to markets in larger urban centers has been identified as an important spatial driver in several European examples (Frederiksen and Langer, 2004; Ilbery and Maye, 2010), as well as in Kenya (Ayuya et al., 2015), Korea (Choi, 2016) and the United States (Kniss et al., 2016; Kuo and Peters, 2017). In England, organic farmers tend to be located on good soils (Gabriel et al., 2009), whereas in Germany, they were preferentially located in areas with poorer soils and a higher share of natural areas (Auerswald et al., 2003; Schmidtner et al., 2012). Organic farmers in the United States are more likely found in areas with a more temperate climate and varied terrain (Kuo and Peters, 2017). However, depending on crop type, these patterns may deviate, as has been demonstrated for organic grape

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production in California (Kniss et al., 2016). Moreover, organic farmers are found to concentrate spatially due to strong influence of other farmers in their direct vicinity (Ilbery and Maye, 2010; Schmidtner et al., 2012; Wollni and Andersson, 2014). Overarching trends in these observations, or which factors affect the distribution of organic farmers on a global level, have not been investigated.

Understanding the global distribution and the local spatial context of organic farmers is important for numerous reasons. First, identifying the areas where organic farming is present today is crucial to support expansion of certified cropland in the future (Tayleur et al., 2018). Second, to improve access to organic certification, an understanding of its spatial distribution is needed (Tayleur et al., 2017). Moreover, to be fully aware of potential benefits and consequences of organic farming, we need to understand its intersections with local environments and cultures (Getz and Shreck, 2006). To support such analysis, our objective was to systematically map the locations of organic crop farmers worldwide based on publicly available data from national authorities and certifiers. We present and analyze, for the first time, the global spatial distribution of organic crop farming. The only similar mapping attempt so far focused on certified commodity crops in tropical countries and did not cover organic certification (Tayleur et al., 2018). Official statistics already give an overview of the distribution of organic farmers globally: the majority of organic crop farmers are smallholders in developing countries, but a considerable portion of organic cropland is located in developed countries (Europe, North America and Australia together represent 50% of organic areas although they only have 6.3% of all farmers) (Willer and Lernoud, 2018). We went beyond such aggregate statistics by studying the spatial distribution within countries and the influence of local socio-economic, climate, and soil and terrain characteristics on the spatial distribution of organic crop farmers.

2. Methods

2.1. Data collection

We collected data on certified organic crop farmers from publicly available datasets (full details on data collection in the Supplementary material). The locations were collected from national repositories on organic producers, or webpages and recent reports from major certifiers and official institutions (Tables S1 and S2). The IFOAM – Organics International definition of organic farming was followed when collecting producer's data to ensure consistency. Organic farming is defined as agricultural activities, with limited or forbidden use of synthetic inputs such as fertilizers and pesticides (IFOAM, 2017; Seufert et al., 2017). Some countries have different terms describing organic agriculture, such as biological (Italy, Spain, France), ecological (Central European countries), or both (Germany, Canada). Although these are different terms, the practices of production are falling under the IFOAM definition (Seufert et al., 2017). Only data on currently certified field operations and crop farmers with a physical address were included. Certificates that were surrendered, withdrawn, or under conversion were disregarded. Some registries provide information on the exact type of crops produced, while most only provide information on the type of organization (producer, handler, processer), or type of agricultural activity (e.g. plant production). We, therefore, did not differentiate between different crops produced by organic farmers. We excluded records on handlers and processers of organic products. Addresses of livestock farms often did not equal the location where land was managed under organic principles. Organic feed that was used in such farms was produced elsewhere. To avoid such inconsistencies between certificate location and operation address, livestock farms were excluded from our analysis (unless they also produced crops or animal feed themselves). Inclusion and exclusion criteria are discussed in more detail in the Supplementary Methods.

The addresses were geocoded using Google Maps (Google Maps, 2017) and mapcarta (Mapcarta, 2017). While most addresses allowed automatic geocoding, some farmers had to be identified manually. Some addresses were descriptive, or the place of the field operation was not immediately recognized by Google. Addresses in regions that do not use the Latin alphabet were also mostly not identified automatically. This was the case for several parts of the world – Middle East and North Africa, Former Soviet Union, and South-east Asia. Details on geocoding and manual identification of addresses, are provided in Supplementary Methods.

Geocoded addresses were allocated on a 1 km spatial grid, using an equal area projection in a geographic information system (ESRI, 2015). This way, the uncertainty related to the potential distance between the physical address of the crop farmer and the corresponding field operation was reduced. We excluded duplicate records where it was clear that the certificate presents the same farmer, which can hold multiple certificates for different crops. Such certificates were identified by the same farmer name, and same address. We included only one record from such duplicates.

2.2. Data analysis

We studied the potential effect of numerous socio-economic, climatic, soil and terrain variables on the spatial distribution of organic crop farmers. Depending on the characteristics of the available data, two different types of analysis were performed. In countries with representative data (i.e. all organic farmers were included in the dataset) binomial logistic regressions were performed using locations of organic crop farmers as presence and a similar sized (random) sample of all other arable lands as absence data. Logistic regression is a common approach when studying the spatial determinants of land use and land management (Neumann et al., 2011; van Asselen and Verburg, 2012; Van Dessel et al., 2011). We performed logistic regression using SPSS 24 (IBM Corp., 2016). In countries with unrepresentative data (i.e., the set of organic producers identified was not complete), we applied maximum entropy modeling that is appropriate to such data structures (Phillips et al., 2006; Wisz and Guisan, 2009). Data was considered as representative in countries where the numbers overlapped with reported statistics on organic producers (Willer and Lernoud, 2018). Also, data from countries where lower numbers of organic farmers were recorded but where the data was provided by official governmental institutions (e.g. government agencies responsible for organic farming, Table S1) were considered as representative – such countries were France and Italy.

Besides analyzing the spatial distributions within countries or regions (Supplementary material), we also performed global analyses. A logistic regression was conducted using data from all countries with representative data. To study potential variation in the spatial distribution of organic crop farmers in countries with different shares of organic farming, separate regressions were performed for groups of countries where organic farming is nationally significant, countries that are significant global producers, and countries where organic agriculture remains a niche activity. We hypothesized that within countries in different development stages and with different shares of organic farming the spatial determinants of organic agricultural may be structurally different. Countries were defined as nationally significant in case the national share of organic cropland covered > 2% of total cropland. Significant global producers were countries with > 1% of total global organic cropland. Other countries were defined as niche countries. The extent of our analyses and the defined global regions are described in Supplementary material (Figs. S1 and S2). For all criteria, the latest data from the IFOAM was used (Willer and Lernoud, 2018). We additionally studied the spatial distribution of cooperatives of organic producers. We performed the logistic regression for Peru (a country where such data was accessible), using locations of cooperatives (Fig. S3).

It was hypothesized that access to markets (both by exporting products and access to more wealthy consumers), and access to information and mechanisms related to organic certification were processes that influence the spatial allocation of organic crop farms. We therefore used data representing the distribution of population, agricultural activities, distance to markets and level of economic development. Population density and the density of rural population were expected to affect the distribution of organic crop farmers by representing potential consumers and agricultural activities at a location (Neumann et al., 2015). The market access index was used to study the accessibility to national and international markets, the effect of available capital to farmers, and role of road and transport infrastructure (Verburg et al., 2011). The market access index goes beyond only representing the distribution of population and cities as it accounts for the distance to major markets, but also the type of infrastructure, and terrain characteristics influencing the travel time (comparison with the distribution of population in the Supplementary Material Table S3 with detailed documentation in Verburg et al., 2011). This way it helps identifying areas where it is, among others, easier to access financial mechanisms, receive information on organic certification, buy agricultural inputs, and finally, making it less costly to transport products to markets. We used data on areas equipped with irrigation (Siebert et al., 2013; Siebert et al., 2005) as a proxy to study the effect of the level of agricultural mechanization and infrastructure (Kuemmerle et al., 2013). The global poverty map (Elvidge et al., 2009), and gridded GDP data (Nordhaus, 2006) were used to represent the influence of the level of development at a location (Kummu et al., 2018).

We hypothesized that bio-physical variables that limit or encourage agricultural activities and crop choices might influence the choice for engaging in organic farming. Temperature, precipitation, potential evapotranspiration (PET), and the aridity index (Hijmans et al., 2005) were selected as climatic variables as they determine potential vegetation growth and represent different aspects of cultivation suitability for different crop types (Licker et al., 2010; Panagos et al., 2015). To study the influence of terrain, we focused on altitude and slope that can pose constraints to agricultural activities (Havlík et al., 2011). We considered seven soil variables that describe different physical and chemical soil characteristics: shares of clay and sand, cation exchange capacity (CEC), soil pH, drainage and depth, and organic content (ISRIC, 2018; Stoorvogel et al., 2016). Soil variables define the suitability for crop production by characterizing soil structure, fertility, and ability to store water, while the different factors have different influences on different crop types (Gardner et al., 1999). All spatial data were projected to an equal area projection and converted to a 1 km spatial resolution. All explanatory factors are described in more detail in the supplementary material (Table S3).

Correlations between variables were calculated to be able to reduce multicollinearity for each country or region. Highly correlated variables (Pearson correlation coefficient > 0.8) were excluded. For the logistic regression, the data was standardized at the level of analysis (country, region, global).

Forward conditional regressions were conducted in countries with representative data using a balanced sample of presence (organic crop farmers) and absence points for each country or region. For absence points, we randomly selected a spatially balanced sample distributed on a cropland mask to reduce potential bias due to spatial autocorrelation. Such an approach has been demonstrated as optimal when sampling absence data (Hirzel and Guisan, 2002), particularly to reduce the uncertainty related to biased sampling, and sampling of locations, where organic crop farmers are unlikely to occur. Before sampling the absence data, we excluded the locations of organic crop farmers, to remove pseudo-absence data (Wisz and Guisan, 2009). We used the IIASA-IFPRI hybrid cropland map (Fritz et al., 2015) as a cropland mask for all countries and regions outside Europe. In Europe, the CORINE land cover map was used (EEA, 2015). In Belgium, Denmark and Slovenia, the data did not allow for differentiation between crop and livestock farmers. In these three countries we also considered pastures, together with the cropland mask. In Australia and Argentina, a few organic crop farmers were mapped outside the cropland mask (due to the uncertainties related to the cropland map). We added the areas where we mapped organic crop farmers to the cropland mask, to not exclude them from our analysis. To evaluate the predictive ability of our regression models, we calculated the Receiver Operating Characteristics (ROC) and the Area Under Curve (AUC) values (Supplementary material). The AUC was also interpreted as an indicator of the extent to which organic farmers differ from conventional farmers based on spatial location characteristics. Low AUC values indicate that differences in the spatial distribution of organic farmers, compared to conventional farmers, cannot be explained by the included spatial variables, indicating a probable low difference in the spatial location of conventional and organic farming. To study the robustness of our models, additional tests were performed. First, to check if our models performed better than a random model, we also calculated models using a randomly allocated presence data set (within the cropland area). Without exception, all test regressions had AUC values of around 0.5 while no model had an AUC higher than 0.53. Secondly, the regressions were performed using different random samples of absence points. Our regression results did not change significantly for different samples for most countries (the regressions consisted of the same variables with the overall relationships and their strengths remaining similar). In five countries, regressions with a different random sample had slightly different results (Supplementary material). Additionally, three countries had to be excluded (Armenia, Kazakhstan and Uruguay) as the regressions differed significantly with each different random absence sample. These countries all have only a few dozen organic farmer observations within relatively large total farming areas, explaining this sensitivity. Finally, we performed additional logistic regressions using spatial data that was aggregated to 10 km resolution for a number of larger countries (Argentina, Australia, Brazil, Canada and USA) to test sensitivity to location accuracy and data resolution (Supplementary material). We observed that the regressions differed particularly in terms of local soil characteristics (Argentina, Australia and Brazil), but also rural population (Argentina, Brazil and USA), market accessibility and irrigation (Australia, Brazil and USA). This may indicate that results are indeed sensitive to location inaccuracies in some contexts, and implies potential uncertainties of our results. At the same time, this can also describe the heterogeneity of the regional spatial distribution of organic crop farmers.

In countries and regions where our points presented only a portion of total producers (Table S1), we performed maximum entropy modeling using MaxEnt (Phillips et al., 2017, 2006). MaxEnt is suitable to study the factors influencing the spatial distribution in case of limited presence-only data, with high uncertainty on the exact location of absence-data (Elith et al., 2011; Fithian and Hastie, 2013). MaxEnt has a good predictive power particularly with small datasets (Wisz and Guisan, 2009), useful for countries and regions where we had limited data on organic farmers. Although mostly used in ecological studies to study species distribution, it has also been applied in studying agricultural management or cropland extent. Among others, it has been used to study the distribution of specific crops, potential shifts in their spatial extent due to climate change, and carbon sequestration potential of specific land management types (Duan and Zhou, 2013; Liu et al., 2015; Luedeling and Neufeldt, 2012; Machovina and Feeley, 2013). Similar to the logistic regression analysis, we limited the MaxEnt analysis to cropland areas only. Details of our MaxEnt application are described in the Supplementary material.

Farmers' decisions to adopt organic farming are heavily influenced by other farmers in their surroundings who converted to organic (Allaire et al., 2015a; Gabriel et al., 2009; Schmidtner et al., 2012; Wollni and Andersson, 2014). We therefore also looked at neighborhood effects by counting the number of occurrences of finding multiple organic crop farmers located within the same 1 km cell.

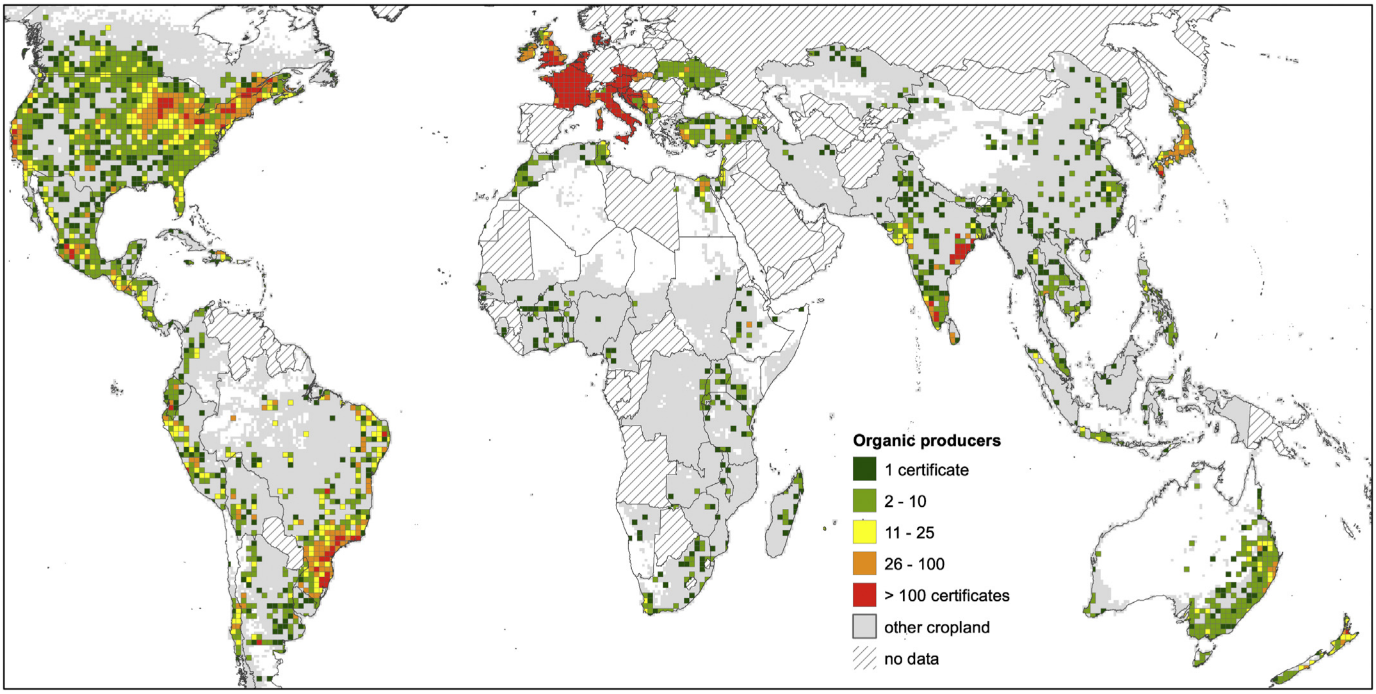

Fig. 1. Global spatial distribution of collected organic crop farmers' certificates. The map presents the total number of all collected data aggregated to 100 × 100 km spatial units (Eckert IV equal area projection). Countries with representative/unrepresentative data are defined in the Table S1. Cropland (Fritz et al., 2015) is marked with gray.

3. Results

3.1. First global map of organic crop farmers

We mapped 112,724 certified crop farmers in 150 countries around the world (Figs. 1 and 2). There is a higher density of organic crop farmers in high-income countries, particularly closer to larger cities (e.g. Fig. 2a, c–e). In high income countries, organic crop farmers are often found equally spread in high densities across the total cropland area within the individual countries (e.g. Fig. 2b). Two main exceptions to this pattern are found in Argentina and Australia, where, together, 1739 farmers are spread over > 9200 km^2 organic cropland (Willer and Lernoud, 2018). For comparison, over 3000 organic crop farmers in Slovenia cultivate an area that equals 0.8% of the organic cropland of Argentina and Australia combined (Willer and Lernoud, 2018).

Despite the large number of crop farmers mapped, our collection of certified farm locations includes only 5% of all global certified organic crop farmers. However, together the farmers included in our data cultivate 38% of the total global organic cropland. Cropland represents 36% of the total global organic area (Willer and Lernoud, 2018). We likely recorded considerably more crop farmers in countries where one certificate presents a cooperative or a similar collective association - a predominant way of organic production in numerous countries of Latin America, Africa and the former Soviet Union (Bravo-Monroy et al., 2016; Jena et al., 2012; Willer and Lernoud, 2018)ypo. Although membership data on individual cooperative certificates is not available, certifiers report that 711 cooperative certificates from Latin America correspond to 63,000 producers (whereas we treated them as 711 certificates) (BIOLATINA, 2018). Data on organic crop farmer distribution is representative for 42 countries, mostly in North America, Oceania, and considerable parts of Europe and South America (Tables S1, S4). However, data on organic crop farmers in important organic producing countries such as China, Germany, Spain, and Poland are missing. In Africa and Asia (together with the former USSR), we only cover 6 countries with representative data, and mapped 0.1 and 1% of all farmers respectively (Table S4).

3.2. Organic crop farmers are concentrated in areas with favorable socio-economic, climate and soil conditions

Globally, organic crop farmers are located in areas with more beneficial socio-economic, climatic and soil conditions (Table 1, Table S5). They can be found in more densely populated areas with better access to markets, and areas with lower poverty levels. Moreover, it is more likely that we find them in areas equipped with irrigation. They are often located in areas with more rainfall, higher temperatures and lower evapotranspiration. The influence of soil characteristics on the spatial distribution of organic crop farmers is less pronounced. Overall, they tend to be more frequently situated in areas with shallow, less drained soils, a higher pH, and higher organic matter and sand content (Table 1, Table S5). While they are more likely found at lower elevations, also a positive association was found with steeper slopes.

Small differences are found between countries with different shares of organic agriculture (Table 1, Table S5). In countries where organic farming has a high share, rural population and irrigation are not significant, and organic crop farmers are more likely to occur on soils with a lower organic content. In niche countries, where the share of organic farming is low, the occurrence of organic crop farmers is negatively correlated to rural population.

When looking at individual countries and regions, again, the positive effect of favorable socio-economic, climatic and soil characteristics on the distribution of organic crop farmers is observed (Tables 1 and 2, and Tables S6, S7 and S8). Particularly poverty has a negative effect on the likelihood that an organic crop farmer is present at a location, which we identified in 34 of the 42 countries and regions analyzed (Tables S6 and S8). However, there are also clear differences between countries. The negative influence of poverty is not limited to lower income countries – organic crop farmers are also negatively related to poverty in upper-middle- and high-income countries such as Argentina, Canada, Chile, China, and several members of the European Union. In Australia, Egypt, and the United States, organic crop farmers are even more likely to be found in areas with higher degrees of poverty/lower wealth (Table 1). In most European countries, rural population density

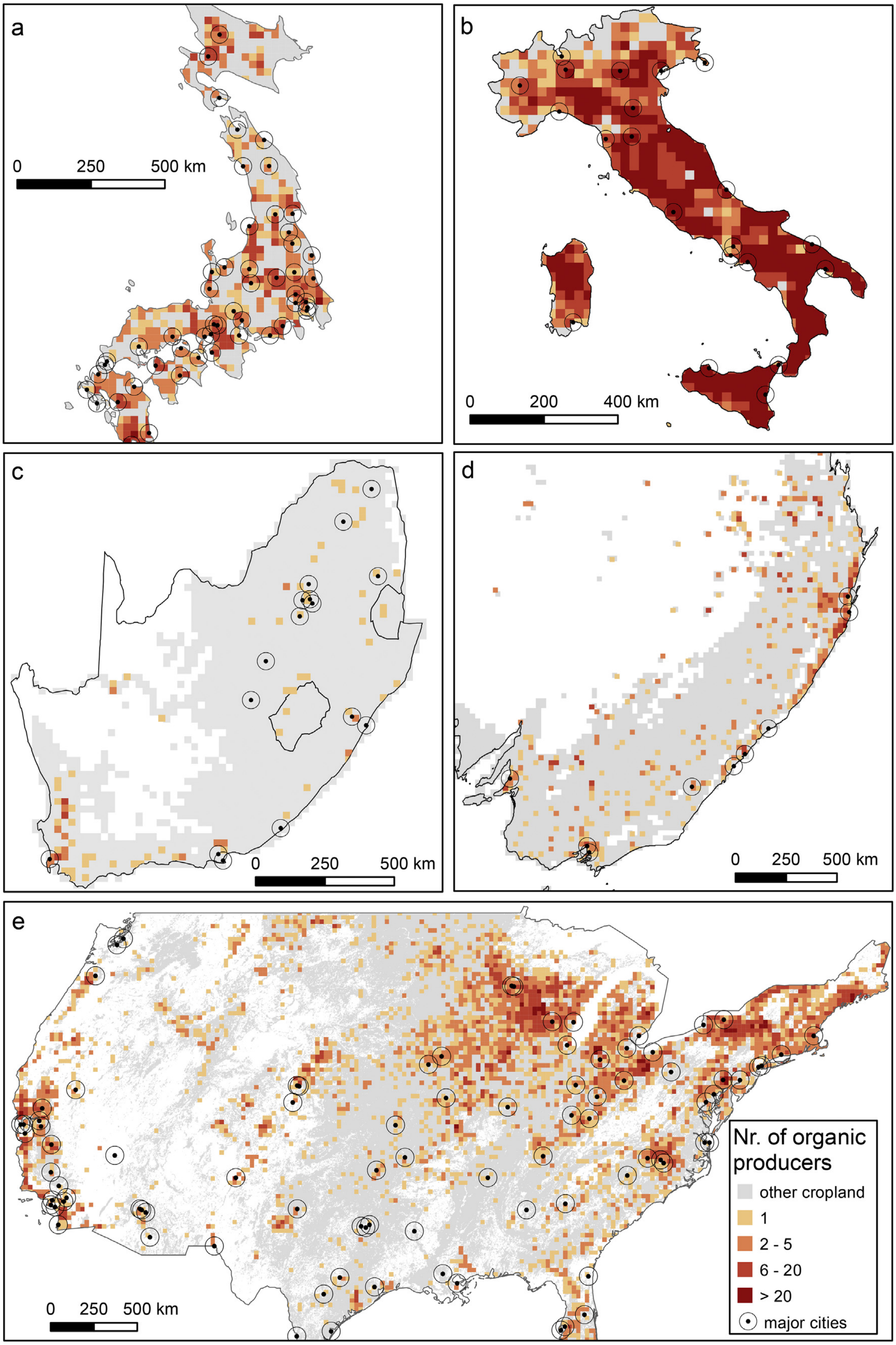

Fig. 2. Detailed distribution of organic crop farmers in a) Japan, b) Italy, c) South Africa, d) Eastern Australia, and e) United States of America. The map presents the total number of all collected data within a 25 × 25 km spatial unit (Eckert IV equal area projection). Data for all these countries is representative. The legend is valid for all figures. Major cities are settlements with over 200,000 inhabitants (Natural Earth, 2018).

Table 1

Summarized regression results for organic crop farmers globally and in selected countries with representative data. All regression coefficients are reported only for variables that have $p < .05$ significance (forward conditional regression), variables marked with * have $p < .01$ significance. Empty cells mean a variable is not significant for that country. AUC (area under curve) is a measure for the goodness of fit of the regression model. Complete regression results for all studied countries are provided in Tables S5, S6 and S7.

	Sample size	Population density	Rural population	Market access	Poverty	Irrigation	Soil drainage	Soil organic content	Soil pH	Slope	Altitude	Temperature	Precipitation	AUC
Argentina	556			0.66*	−1.79*	0.50*	−0.92*		0.44*		0.84*	−0.37*		0.97
Australia	1183	1.78*	0.11*		0.34*	−0.08*	−0.20*			0.34*		0.46*	0.30*	0.91
Austria	18,551	−0.13*	−0.03	−0.07*	−0.10*		0.18*		−0.12*				0.23*	0.63
Belgium	2015	−0.21*			−0.17*			−0.12*	−0.11				0.64*	0.74
Brazil	9004	0.92*	0.75*	0.17*	−0.33*	−0.09*			0.16*	0.12*		−0.23*	0.11*	0.94
Canada	2568	0.79*	0.25*	0.12	−0.35*					0.17*	−6.50*		0.71*	0.89
Egypt	289	0.07		1.12*	0.49	−1.16*				−0.85*		−1.50*	−10.48*	0.89
France	11,624	0.06*	−0.05*	0.04*	−0.27*	−0.05*		−0.07*	0.03	0.11*	0.11*	0.23*	0.07*	0.63
Italy	18,985	0.06*	−0.08*	−0.34*	−1.41*	−0.41*	0.04*	−0.44*	0.06*		0.28*	0.35*	−0.04*	0.80
Japan	1485			0.47*		0.35*				−0.82*	−0.21	0.49*		0.82
New Zealand	523	3.52*	0.25*		−0.22			0.21*		0.22	−1.43*	−0.67*	1.05*	0.87
India - Odisha	4275	0.24*	−0.38*		−0.32*	−0.21*	0.24*	−1.19*	−0.37*	0.13*		0.71*	0.68*	0.84
Peru - cooperatives	311			−0.26*	0.24*	0.15								0.71
Slovenia	3516					−0.13*	0.17*	0.07*	−0.13*		1.01*	0.53*		0.70
South Africa	119	3.0			−1.08*	0.28		0.52					−0.35	0.92
Ukraine	294	0.29*			−0.59*			0.24			−0.57*		0.80*	0.80
USA	11,457	0.23*		0.36*	0.00*	0.26*	−0.17*		−0.22*		−0.51*	−0.82*		0.78
Global - all	98,752	0.58*	0.09*	0.37*	−0.43*	0.18*	−0.04*	0.03*	0.04*	0.33*	−0.09*	1.00*	0.33*	0.88
Global - Nationally significant	71,692	0.24*		0.16*	−0.53*			−0.07*		0.33*	0.06*	0.38*	0.25*	0.85
Globally significant	22,945	0.57*	0.14*	0.29*		0.21*	−0.12*	0.03*	0.07*	0.22*	−0.29*	−0.9*	0.59*	0.83
Global - Niche	4115	0.23*	−0.07*	0.20*	−0.61*	0.18*		0.09*			−0.25*	1.13*	0.65*	0.90

Table 2

Summarized maximum entropy results for organic crop farmers in selected regions and countries with unrepresentative data. Values present the contribution of a variable to the spatial distribution of organic crop farmers in %, and the direction of the influence (+ − means that a variable is positive to a certain value and then negative). Empty cells present variables with a contribution below 1%. Variables with * contribute > 1% in additional runs without poverty. AUC (area under curve) is a measure of the goodness of fit of the maximum entropy model. Complete maximum entropy results for all studied countries are provided in Table S8.

	Sample size	Population density	Rural population	Market access	Poverty	Irrigation	Soil drainage	Organic content	Soil pH	Slope	Altitude	Temperature	Precipitation	AUC
Africa - East	185	44.5	1	1.2	−20.8	4			−2.5	−2.1	± 1.8		15.1	0.96
Africa - West	93	8.2	4.2	31.8	−6.8	−2.2	−1.8				9.3			0.96
Bolivia	216	4.8		6	−13.5				1.9	−4.9	3.3	4.8	−4.6	0.98
Central America	343	7.4	2.2	8.8	−25.8	−4.1	−2.9	1.8	± 1.2	14.8	7.3	6.9	2.6	0.92
China	269	1.7*	−1.6*	3.1*	−74.1	−2.5		1.4	−1.8		± 1.7	−5	2.2	0.9
Ecuador	392	3.3*	−1.8*	1.7	−72.4	3.1		2.7		−0.6*	3.2	3.7*	−2.8	0.96
India	1692			2.9	−41.6	−7.4		3.7	−1.1	−3.7	−2.7	5	7.4	0.86
Middle East and North Africa	224	2.5	−1.7	5.7	−28.6	−7.6	−2.3	1.3			−39.6	1.4	−1	0.95
Mexico	1698	1.1	1*		−78.3	4.3*		2.4	−1.7	1.6	± 2.9	−0.2*	1.1	0.9
Peru	766	−13.3	−5.6	7	−35.7	−4.3			± 2.4	−3.1	−3.7	20.1	−2.5	0.92
Southeast Asia - mainland	178	14.3		4.8	−22.2	± 6.1	3.1		−5.2	−5.9	17.9		−8.5	0.9
Southeast Asia - maritime	263	−5.2	3.4	20.3	−29	−2.8		−3.5	± 1.3	−3.1	17.5	2.5	−2.8	0.95
Turkey	418		± 3.4		−45			−2.7	−6.5	2.3	−4.1	20.2		0.92

does not play a significant role. Organic crop farmers are in Austria, Ireland, and Italy more likely found in areas less connected to markets (Table 1). In several of the studied countries and regions (19) organic crop farmers are negatively related to the extent of irrigation (Tables S6 and S8). This shows, that irrigation is not necessarily relevant to the occurrence of organic agriculture on a local scale, depending on regional agricultural contexts.

In nearly all analyzed countries and regions, organic crop farmers are positively related to precipitation and temperature (Tables 1, 2, and Tables S5, S6, S8). In a few countries, however, they tend to occur in drier areas. These are countries in north and south Africa, south-east Asia, Ecuador, Italy, Peru, and Brazil (Table 1, Tables S6 and S8). In countries spanning over different climatic regions such as Argentina, Brazil, China, Mexico and the United States, organic crop farmers are more likely found in more temperate areas with lower temperatures (Tables 1, 2).

There are fewer similarities among countries in terms of the effect of soil and terrain conditions, demonstrating that their role depends on the regional/local context (and potentially depends on different crop types specific for some regions). The effect of soils is more similar in South American countries, looking at the influence of clay, pH and soil depth (Tables 1, 2, Tables S4, S6). In Australia, Croatia, Italy, Turkey, the United States, the Indian state of Odisha, and countries in West Africa combinations of soil conditions indicate that organic farmers cultivate land less suitable for cropland activities (Tables 1,2 and Tables S6 and S8). In South and West Africa, mainland and maritime South-East Asia, France, Italy and Slovenia, and numerous South American countries, organic crop farmers are more likely found at higher altitudes. In Mexico and the rest of Central America, East Africa and China, they tend to occur in mid-altitudes (Table 2, Table S8). Organic crop farmers on steeper slopes are more likely found in developed countries, probably indicating a high share of permanent crops (e.g. vineyards and orchards) (Willer and Lernoud, 2018). Higher likelihood for organic crop farmers in areas with higher altitudes, steeper slopes and poorer soils can, however, also be explained by economic and agronomic obstacles in converting to organic farming on more suitable areas (e.g. profitability of conventional agriculture on fertile plains can present an obstacle to conversion).

In developed organic markets, we identified less evident influences of spatial characteristics on the spatial distribution of organic crop produces. This is demonstrated by their spatial pattern, weak regression coefficients and low AUCs (area under curve of the Receiver Operating Characteristic) (Table 1, Table S5). We observed this mostly in European countries: Austria, Czech Republic, France, Ireland, and particularly Denmark and the Netherlands (Table S6). Countries with the smallest differences in location between conventional and organic farming are also countries with the highest shares of organic farmers, as indicated by the negative relationship between the AUC and the share of organic farmers (Fig. S4).

In some countries we observed strong clustering of organic producers in specific locations, demonstrated by the ratio between the total number of organic crop farmers and the number of unique locations (Table S9). For example, around 9000 organic crop farmers in Brazil are located on 1250 unique locations. Countries with a considerable share of organic farmers that are characterized by a high share of unique locations are mostly European countries like Belgium, Czech Republic, Denmark, France and the Netherlands.

4. Discussion

4.1. What affects the spatial distribution of organic crop farmers?

The identified strong impact of poverty levels and access to market on location choices is similar to what has been observed for certified crops under other certification schemes (Tayleur et al., 2018). The influence of other variables, such as rural population, market access, GDP, and irrigation also suggest that organic crop farmers are more likely to be found in areas with better socio-economic conditions. This is supported by local studies, where particularly distance to markets and urban population have been identified to play a role in the conversion to organic farming, both for reaching affluent domestic markets as well as for better access to international markets (Allaire et al., 2015b; Giovannucci and Ponte, 2005; Karki et al., 2011; Koesling et al., 2008). In developing countries, organic farmers mostly produce commodity crops for export to more developed markets with only a minor portion being produced for domestic consumption (Willer and Lernoud, 2018). Being close to established supply chains of commodity crops (Ton, 2013) can, therefore, explain the identified positive effect of market accessibility. Furthermore, crop farmers who are better connected to markets are also more likely to receive more information on the benefits of organic farming, whereas farmers in remote areas are mostly influenced informally (Wollni and Andersson, 2014).

Additionally, our findings on how locations of organic crop farmers in developed organic markets are more similar to conventional farmers can be explained by specific regional and historic contexts. First, these highly developed organic markets are mostly smaller (European) countries, where consumers and export markets are close to producers – making it possible to sell products locally (e.g. Ilbery and Maye, 2010). These are countries with high levels of overall socio-economic development, with a relatively large consumer base (more wealthier consumers). Such countries also have a well-developed certification sector, good transport and institutional infrastructure. Finally, organic certification has been present for a while in developed organic markets such as the European Union, where regulation on organic production of agriculture already exists since 1991 (EC, 1991; Padel et al., 2009). In less developed organic markets (“niche” countries), organic certification is at a much earlier stage and may still be developing.

Organic farming affects the whole farming system and is not an adoption of a single technique – in developed countries, converting can mean a significant change to established farming practices, and can result in failure due to risks in the transition period (Kerselaers et al., 2007). Farmers in poor areas who cannot afford such experimentation could, therefore, be less likely to convert. Evidence from developing countries, however, also suggests that conversion to organic farming might be a smaller obstacle, as agriculture can be organic by default, but not yet certified (Ayuya et al., 2015; Bolwig et al., 2009). Conversion to organic farming in such conditions can be merely a continuation of existing cropland management, fertilization and pest control practices (Bolwig et al., 2009). Nevertheless, optimization of farm operations, implementation of biological plant protection and fertilization, with potential changes to crop types would be necessary to achieve a successful conversion to organic. This is especially the case when there is poor cropland management due to lower accessibility (or lack of finances) to agricultural inputs.

In this study, we focused on a set of socio-economic variables that can explain a considerable part of the spatial distribution of organic crop farmers. However, explaining the socio-economic processes that limit or drive conversion is complex. Organic farmers are a heterogeneous group with a variety of attitudes towards the choice of farming method, including changes to lifestyle and environmental values (Darnhofer et al., 2005; Malek et al., 2019; Tzouramani et al., 2014). Moreover, there are large differences in the spatial determinants for certification of different crop types (Tayleur et al., 2018). The data collected for this study did not allow distinguishing producers of different crop types. Other potential obstacles for certification we were unable to address are related to bureaucracy and the required financial resources, lower education and insufficient information, and organizational support (Barrett et al., 2001; Beltrán-Esteve et al., 2012; Boncinelli et al., 2017; Salazar, 2014; Veldstra et al., 2014).

4.2. The role of data and collective associations

Our inventory shows that significant efforts for improving the accessibility of data on organic farmers are necessary. Only then will it be possible to identify location characteristics that drive and limit certified organic farming in developing countries in more detail as well. To achieve this, certifiers and national institutions need to work together to establish common databases of publicly accessible information on organic certification. Due to unavailability and inaccessibility of data, we were so unable to map most farmers in Africa and Asia. Certifier reports, however, indicate that our collection of certificates includes considerably more organic crop farmers than the number of mapped certificates suggests. In some regions (e.g. India and Latin America) one certificate often presents a group association (e.g. cooperative). Exact numbers of farmers in such groups are often unknown. In Peru, 40% (311 certificates) of our records are cooperatives. Membership data are available for only 29 of these cooperative certificates, but these certificates cover 41,000 producers (42% of all organic farmers in Peru). These cooperatives also differ, to some extent, from individual organic crop farmers. They are more likely found in areas with higher poverty levels, and lower access to markets (Table 1). This suggests, that such institutional support, either from governments or collective associations can help with certification in areas with less favorable socio-economic conditions, that can otherwise be less likely to convert to organic. Other studies support our results and show that farmers in Latin America are more likely to adopt organic agriculture if they are part of a cooperative (Bravo-Monroy et al., 2016; Wollni and Brümmer, 2012). We can therefore assume, that we covered considerably more organic crop farmers in these Latin American countries than the numbers of mapped locations suggest. When assuming that our records cover all certificates for Central and Latin America, our dataset would include 346,000 additional crop farmers (Willer and Lernoud, 2018) and 12 more countries would have representative data.

5. Conclusion

Organic farming is promoted as a way to provide food in a more sustainable way, reducing the environmental impacts of agriculture. Our results indicate, that, particularly in countries where organic agriculture is less developed, organic crop farmers are present in areas with relatively favorable socio-economic conditions. To sustain trends of increases in organic production in these countries (Willer and Lernoud, 2018), efforts are needed to support access to certification for farmers in poorer regions and by providing better market access. In developing countries, organic certification often implies a continuation of existing cropland management (Ayuya et al., 2015; Bolwig et al., 2009). Therefore, it is mainly the certification and access to value chains to reach consumers that is hampering a further expansion of certified organic production. Targeting such areas with less-favorable socio-economic conditions can indeed pose a higher risk for establishing a steady and successful supply of organic products due to a potentially higher rate of certification failures and problems in establishing value chains. Nevertheless, this way organic farming can become a tool for improving famers' livelihoods while at the same time limiting the input of artificial fertilizers and pesticides. The process can, therefore, be seen as a component of sustainable intensification strategies.

The outcomes of this study can help with identifying areas with a high potential for organic crop production and potential increases in the number of organic producers in the future. Most importantly, our results are a step forward towards providing support for more efficient certification to farmers in economically less developed and poorly connected areas. To achieve this, certifiers, national institutions and collective associations, need to work together to improve access to certification, reduce its costs, and target areas where accessing markets is too difficult or costly by individual farmers.

Data availability statement

The datasets analyzed in this study are publicly available from the sources listed in the article or the Supplementary material. All data prepared in this paper on the approximate locations of organic farmers are available freely on https://dataverse.nl/dataverse/BETA (upon publication of the paper).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2019.102680.

References

Allaire, G., Poméon, T., Maigné, E., Cahuzac, E., Simioni, M., Desjeux, Y., 2015a. Territorial analysis of the diffusion of organic farming in France: between heterogeneity and spatial dependence. Ecol. Indic. 59, 70–81. https://doi.org/10.1016/j.ecolind.2015.03.009.
Allaire, G., Cahuzac, E., Maigné, E., Poméon, T., 2015b. Localisation de l'agriculture biologique et accès aux marches. Rev. D'Études En Agric. Environ. 96, 277–312. https://doi.org/10.4074/S1966960715012035.
van Asselen, S., Verburg, P.H., 2012. A land system representation for global assessments and land-use modeling. Glob. Chang. Biol. 18, 3125–3148. https://doi.org/10.1111/j.1365-2486.2012.02759.x.
Auerswald, K., Kainz, M., Fiener, P., 2003. Soil erosion potential of organic versus conventional farming evaluated by USLE modelling of cropping statistics for agricultural districts in Bavaria. Soil Use Manag. 19, 305–311. https://doi.org/10.1079/SUM2003212.
Ayuya, O.I., Gido, E.O., Bett, H.K., Lagat, J.K., Kahi, A.K., Bauer, S., 2015. Effect of certified organic production systems on poverty among smallholder farmers: empirical evidence from Kenya. World Dev. 67, 27–37. https://doi.org/10.1016/j.worlddev.2014.10.005.
Barrett, H.R., Browne, A.W., Harris, P.J.C., Cadoret, K., 2001. Smallholder farmers and organic certification: accessing the EU market from the developing world. Biol. Agric. Hortic. 19, 183–199. https://doi.org/10.1080/01448765.2001.9754920.
Beltrán-Esteve, M., Picazo-Tadeo, A.J., Reig-Martínez, E., 2012. What makes a citrus farmer go organic? Empirical evidence from Spanish citrus farming. Span. J. Agric. Res. 10, 901. https://doi.org/10.5424/sjar/2012104-2957.
Bengtsson, J., Ahnström, J., Weibull, A.-C., 2005. The effects of organic agriculture on biodiversity and abundance: a meta-analysis: organic agriculture, biodiversity and abundance. J. Appl. Ecol. 42, 261–269. https://doi.org/10.1111/j.1365-2664.2005.01005.x.
Beuchelt, T.D., Zeller, M., 2011. Profits and poverty: Certification's troubled link for Nicaragua's organic and fairtrade coffee producers. Ecol. Econ. 70, 1316–1324. https://doi.org/10.1016/j.ecolecon.2011.01.005.
BIOLATINA, 2018. Listas de Operadores Certificados. List of Certified Operators, Certified by BIOLATINA (in spanish) [WWW Document]. URL. http://www.biolatina.com/productoresc.html, Accessed date: 18 March 2018.
Blackman, A., Naranjo, M.A., 2012. Does eco-certification have environmental benefits? Organic coffee in Costa Rica. Ecol. Econ. 83, 58–66. https://doi.org/10.1016/j.ecolecon.2012.08.001.
Bolwig, S., Gibbon, P., Jones, S., 2009. The economics of smallholder organic contract farming in tropical Africa. World Dev. 37, 1094–1104. https://doi.org/10.1016/j.worlddev.2008.09.012.
Boncinelli, F., Riccioli, F., Casini, L., 2017. Spatial structure of organic viticulture: evidence from Chianti (Italy). New Medit Mediterr. J. Econ. Agric. Environ. 16, 55–63.
Bravo-Monroy, L., Potts, S.G., Tzanopoulos, J., 2016. Drivers influencing farmer decisions for adopting organic or conventional coffee management practices. Food Policy 58, 49–61. https://doi.org/10.1016/j.foodpol.2015.11.003.
Choi, H., 2016. A typology of agro-innovation adoptions: the case of organic farming in Korea. Reg. Environ. Chang. 16, 1847–1857. https://doi.org/10.1007/s10113-016-0932-4.
Connor, D.J., 2008. Organic agriculture cannot feed the world. Field Crop Res. 106, 187–190. https://doi.org/10.1016/j.fcr.2007.11.010.
Crowder, D.W., Reganold, J.P., 2015. Financial competitiveness of organic agriculture on a global scale. Proc. Natl. Acad. Sci. 112, 7611–7616. https://doi.org/10.1073/pnas.

1423674112.
Darnhofer, I., Schneeberger, W., Freyer, B., 2005. Converting or not converting to organic farming in Austria:farmer types and their rationale. Agric. Hum. Values 22, 39–52. https://doi.org/10.1007/s10460-004-7229-9.
DeFries, R.S., Fanzo, J., Mondal, P., Remans, R., Wood, S.A., 2017. Is voluntary certification of tropical agricultural commodities achieving sustainability goals for small-scale producers? A review of the evidence. Environ. Res. Lett. 12, 033001. https://doi.org/10.1088/1748-9326/aa625e.
Duan, J., Zhou, G., 2013. Dynamics of decadal changes in the distribution of double-cropping rice cultivation in China. Chin. Sci. Bull. 58, 1955–1963. https://doi.org/10.1007/s11434-012-5608-y.
Earth, Natural, 2018. Populated Places - Version 4.1.0 Free Vector and Raster Map Data at naturalearthdata.com. [WWW Document]. URL. https://www.naturalearthdata.com/downloads/10m-cultural-vectors/10m-populated-places/ (accessed 11.19.18).
EC, 1991. Council Regulation (EEC) No 2092/91 of 24 June 1991 on organic production of agricultural products and indications referring thereto on agricultural products and foodstuffs. Off. J. Eur. Communities L198 (1991), 1–15 ((22.7.91). European Council).
EEA, 2015. CORINE Land Cover 2006 — Copernicus Land Monitoring Services. [WWW Document]. URL. http://land.copernicus.eu/pan-european/high-resolution-layers/imperviousness/view (accessed 12.4.15).
Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E., Yates, C.J., 2011. A statistical explanation of MaxEnt for ecologists: statistical explanation of MaxEnt. Divers. Distrib. 17, 43–57. https://doi.org/10.1111/j.1472-4642.2010.00725.x.
Elvidge, C.D., Sutton, P.C., Ghosh, T., Tuttle, B.T., Baugh, K.E., Bhaduri, B., Bright, E., 2009. A global poverty map derived from satellite data. Comput. Geosci. 35, 1652–1660. https://doi.org/10.1016/j.cageo.2009.01.009.
ESRI, 2015. ArcGIS Desktop: Release 10.5. Environmental Systems Research Institute, Redlands, CA.
Fithian, W., Hastie, T., 2013. Finite-sample equivalence in statistical models for presence-only data. Ann. Appl. Stat. 7, 1917–1939. https://doi.org/10.1214/13-AOAS667.
Frederiksen, P., Langer, V., 2004. Localisation and concentration of organic farming in the 1990s - the Danish case. Tijdschr. Voor Econ. En Soc. Geogr. 95, 539–549. https://doi.org/10.1111/j.0040-747X.2004.00338.x.
Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., Havlik, P., Mosnier, A., Thornton, P., Wood-Sichra, U., Herrero, M., Becker-Reshef, I., Justice, C., Hansen, M., Gong, P., Abdel Aziz, S., Cipriani, A., Cumani, R., Cecchi, G., Conchedda, G., Ferreira, S., Gomez, A., Haffani, M., Kayitakire, F., Malanding, J., Mueller, R., Newby, T., Nonguierma, A., Olusegun, A., Ortner, S., Rajak, D.R., Rocha, J., Schepaschenko, D., Schepaschenko, M., Terekhov, A., Tiangwa, A., Vancutsem, C., Vintrou, E., Wenbin, W., van der Velde, M., Dunwoody, A., Kraxner, F., Obersteiner, M., 2015. Mapping global cropland and field size. Glob. Chang. Biol. 21, 1980–1992. https://doi.org/10.1111/gcb.12838.
Gabriel, D., Carver, S.J., Durham, H., Kunin, W.E., Palmer, R.C., Sait, S.M., Stagl, S., Benton, T.G., 2009. The spatial aggregation of organic farming in England and its underlying environmental correlates. J. Appl. Ecol. 46, 323–333. https://doi.org/10.1111/j.1365-2664.2009.01624.x.
Gardner, C.M.K., Laryea, K.B., Unger, P.W., 1999. Soil Physical Constraints to Plant Growth and Crop Production. Food and Agriculture Organization of the United Nations.
Getz, C., Shreck, A., 2006. What organic and fair trade labels do not tell us: towards a place-based understanding of certification. Int. J. Consum. Stud. 30, 490–501. https://doi.org/10.1111/j.1470-6431.2006.00533.x.
Giovannucci, D., Ponte, S., 2005. Standards as a new form of social contract? Sustainability initiatives in the coffee industry. Food Policy 30, 284–301. https://doi.org/10.1016/j.foodpol.2005.05.007.
Gómez Tovar, L., Martin, L., Gómez Cruz, M.A., Mutersbaugh, T., 2005. Certified organic agriculture in Mexico: market connections and certification practices in large and small producers. J. Rural. Stud. 21, 461–474. https://doi.org/10.1016/j.jrurstud.2005.10.002.
Gomiero, T., Pimentel, D., Paoletti, M.G., 2011. Environmental impact of different agricultural management practices: conventional vs. organic agriculture. Crit. Rev. Plant Sci. 30, 95–124. https://doi.org/10.1080/07352689.2011.554355.
Havlík, P., Schneider, U.A., Schmid, E., Böttcher, H., Fritz, S., Skalský, R., Aoki, K., Cara, S.D., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., Obersteiner, M., 2011. Global land-use implications of first and second generation biofuel targets. Energy Policy 39, 5690–5702. https://doi.org/10.1016/j.enpol.2010.03.030.
Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978. https://doi.org/10.1002/joc.1276.
Hirzel, A., Guisan, A., 2002. Which is the optimal sampling strategy for habitat suitability modelling. Ecol. Model. 157, 331–341. https://doi.org/10.1016/S0304-3800(02)00203-X.
Hole, D.G., Perkins, A.J., Wilson, J.D., Alexander, I.H., Grice, P.V., Evans, A.D., 2005. Does organic farming benefit biodiversity? Biol. Conserv. 122, 113–130. https://doi.org/10.1016/j.biocon.2004.07.018.
IBM Corp, 2016. IBM SPSS Statistics for Windows, Version 24.0. IBM Corp, Armonk, NY.
IFOAM, 2017. The IFOAM Norms for Organic Production and Processing. Edited Version of the IFOAM Norms 2014.
Ilbery, B., Maye, D., 2010. Clustering and the spatial distribution of organic farming in England and Wales. Area. https://doi.org/10.1111/j.1475-4762.2010.00953.x.
ISRIC, 2018. ISRIC SoilGrids1km visualisation and distribution website. WWW Document. In: SoilGrids1km, URL. http://soilgrids1km.isric.org/ (accessed 11.6.15).
Jena, P.R., Chichaibelu, B.B., Stellmacher, T., Grote, U., 2012. The impact of coffee certification on small-scale producers' livelihoods: a case study from the Jimma zone. Ethiopia 43, 429–440. https://doi.org/10.1111/j.1574-0862.2012.00594.x. P. R. Jena et al./Agricultural Economics 43 (2012) 427-438. Agric. Econ.
Karki, L., Schleenbecker, R., Hamm, U., 2011. Factors influencing a conversion to organic farming in Nepalese tea farms. J. Agric. Rural. Dev. Trop. Subtrop. 112, 113–123.
Kerselaers, E., De Cock, L., Lauwers, L., Van Huylenbroeck, G., 2007. Modelling farm-level economic potential for conversion to organic farming. Agric. Syst. 94, 671–682. https://doi.org/10.1016/j.agsy.2007.02.007.
Kniss, A.R., Savage, S.D., Jabbour, R., 2016. Commercial crop yields reveal strengths and weaknesses for organic agriculture in the United States. PLoS One 11, e0161673. https://doi.org/10.1371/journal.pone.0161673.
Koesling, M., Flaten, O., Lien, G., 2008. Factors influencing the conversion to organic farming in Norway. Int. J. Agric. Resour. Gov. Ecol. 7, 78. https://doi.org/10.1504/IJARGE.2008.016981.
Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P.H., Estel, S., Haberl, H., Hostert, P., Jepsen, M.R., Kastner, T., Levers, C., Lindner, M., Plutzar, C., Verkerk, P.J., van der Zanden, E.H., Reenberg, A., 2013. Challenges and opportunities in mapping land use intensity globally. Curr. Opin. Environ. Sustain. Hum. Settlements Indust. Syst. 5, 484–493. https://doi.org/10.1016/j.cosust.2013.06.002.
Kummu, M., Taka, M., Guillaume, J.H.A., 2018. Gridded global datasets for gross domestic product and human development index over 1990–2015. Sci. Data 5, 180004. https://doi.org/10.1038/sdata.2018.4.
Kuo, H.-J., Peters, D.J., 2017. The socioeconomic geography of organic agriculture in the United States. Agroecol. Sustain. Food Syst. 1–23. https://doi.org/10.1080/21683565.2017.1359808.
Leifeld, J., Angers, D.A., Chenu, C., Fuhrer, J., Kätterer, T., Powlson, D.S., 2013. Organic farming gives no climate change benefit through soil carbon sequestration. Proc. Natl. Acad. Sci. 110, E984. https://doi.org/10.1073/pnas.1220724110.
Licker, R., Johnston, M., Foley, J.A., Barford, C., Kucharik, C.J., Monfreda, C., Ramankutty, N., 2010. Mind the gap: how do climate and agricultural management explain the 'yield gap' of croplands around the world?: investigating drivers of global crop yield patterns. Glob. Ecol. Biogeogr. 19, 769–782. https://doi.org/10.1111/j.1466-8238.2010.00563.x.
Liu, Z., Yang, P., Tang, H., Wu, W., Zhang, L., Yu, Q., Li, Z., 2015. Shifts in the extent and location of rice cropping areas match the climate change pattern in China during 1980–2010. Reg. Environ. Chang. 15, 919–929. https://doi.org/10.1007/s10113-014-0677-x.
Luedeling, E., Neufeldt, H., 2012. Carbon sequestration potential of parkland agroforestry in the Sahel. Clim. Chang. 115, 443–461. https://doi.org/10.1007/s10584-012-0438-0.
Machovina, B., Feeley, K.J., 2013. Climate change driven shifts in the extent and location of areas suitable for export banana production. Ecol. Econ. 95, 83–95. https://doi.org/10.1016/j.ecolecon.2013.08.004.
Malek, Ž., Douw, B., van Vliet, J., van der Zanden, E., Verburg, P.H., 2019. Local land-use decision-making in a global context. Environ. Res. Lett. 14. https://doi.org/10.1088/1748-9326/ab309e.
Mapcarta, 2017. Mapcarta Locations. [WWW Document]. URL. http://mapcarta.com.
Google Maps, 2017. Google maps locations. [WWW Document]. URL. www.google.com/maps.
Meyfroidt, P., 2018. Trade-offs between environment and livelihoods: bridging the global land use and food security discussions. Glob. Food Secur. 16, 9–16. https://doi.org/10.1016/j.gfs.2017.08.001.
Muller, A., Schader, C., El-Hage Scialabba, N., Brüggemann, J., Isensee, A., Erb, K.-H., Smith, P., Klocke, P., Leiber, F., Stolze, M., Niggli, U., 2017. Strategies for feeding the world more sustainably with organic agriculture. Nat. Commun. 8. https://doi.org/10.1038/s41467-017-01410-w.
Neumann, K., Stehfest, E., Verburg, P.H., Siebert, S., Müller, C., Veldkamp, T., 2011. Exploring global irrigation patterns: a multilevel modelling approach. Agric. Syst. 104, 703–713. https://doi.org/10.1016/j.agsy.2011.08.004.
Neumann, K., Sietz, D., Hilderink, H., Janssen, P., Kok, M., van Dijk, H., 2015. Environmental drivers of human migration in drylands – a spatial picture. Appl. Geogr. 56, 116–126. https://doi.org/10.1016/j.apgeog.2014.11.021.
Nordhaus, W.D., 2006. Geography and macroeconomics: new data and new findings. Proc. Natl. Acad. Sci. 103, 3510–3517. https://doi.org/10.1073/pnas.0509842103.
Padel, S., Röcklinsberg, H., Schmid, O., 2009. The implementation of organic principles and values in the European regulation for organic food. Food Policy 34, 245–251. https://doi.org/10.1016/j.foodpol.2009.03.008.
Panagos, P., Borrelli, P., Meusburger, K., Alewell, C., Lugato, E., Montanarella, L., 2015. Estimating the soil erosion cover-management factor at the European scale. Land Use Policy 48, 38–50. https://doi.org/10.1016/j.landusepol.2015.05.021.
Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. 190, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026.
Phillips, S.J., Anderson, R.P., Dudík, M., Schapire, R.E., Blair, M.E., 2017. Opening the black box: an open-source release of Maxent. Ecography 40, 887–893. https://doi.org/10.1111/ecog.03049.
Reganold, J.P., Wachter, J.M., 2016. Organic agriculture in the twenty-first century. Nat. Plants 2, 15221. https://doi.org/10.1038/nplants.2015.221.
Salazar, R.C., 2014. Going organic in the Philippines: social and institutional features. Agroecol. Sustain. Food Syst. 38, 199–229. https://doi.org/10.1080/21683565.2013.833155.
Schmidtner, E., Lippert, C., Engler, B., Häring, A.M., Aurbacher, J., Dabbert, S., 2012. Spatial distribution of organic farming in Germany: does neighbourhood matter? Eur. Rev. Agric. Econ. 39, 661–683. https://doi.org/10.1093/erae/jbr047.
Seufert, V., Ramankutty, N., 2017. Many shades of gray—the context-dependent performance of organic agriculture. Sci. Adv. 3, e1602638. https://doi.org/10.1126/

sciadv.1602638.
Seufert, V., Ramankutty, N., Foley, J.A., 2012. Comparing the yields of organic and conventional agriculture. Nature 485, 229–232. https://doi.org/10.1038/nature11069.
Seufert, V., Ramankutty, N., Mayerhofer, T., 2017. What is this thing called organic? – how organic farming is codified in regulations. Food Policy 68, 10–20. https://doi.org/10.1016/j.foodpol.2016.12.009.
Siebert, S., Döll, P., Hoogeveen, J., Faures, J.-M., Frenken, K., Feick, S., 2005. Development and validation of the global map of irrigation areas. Hydrol. Earth Syst. Sci. 9, 535–547. https://doi.org/10.5194/hess-9-535-2005.
Siebert, S., Henrich, V., Frenken, K., Burke, J., 2013. Update of the Digital Global Map of Irrigation Areas to Version 5. Rheinische Friedrich-Wilhelms-Universität, Bonn, Germany and FAO, Rome, Italy. https://doi.org/10.13140/2.1.2660.6728. 170pp.
Stoorvogel, J.J., Bakkenes, M., Temme, A.J.A.M., Batjes, N.H., Ten Brink, B., 2016. S-world: a global soil map for environmental modelling: S-world: a global soil map for environmental modelling. Land Degrad. Dev. https://doi.org/10.1002/ldr.2656.
Tayleur, C., Balmford, A., Buchanan, G.M., Butchart, S.H.M., Ducharme, H., Green, R.E., Milder, J.C., Sanderson, F.J., Thomas, D.H.L., Vickery, J., Phalan, B., 2017. Global coverage of agricultural sustainability standards, and their role in conserving biodiversity: certification standards and biodiversity. Conserv. Lett. 10, 610–618. https://doi.org/10.1111/conl.12314.
Tayleur, C., Balmford, A., Buchanan, G.M., Butchart, S.H.M., Corlet Walker, C., Ducharme, H., Green, R.E., Milder, J.C., Sanderson, F.J., Thomas, D.H.L., Tracewski, L., Vickery, J., Phalan, B., 2018. Where are commodity crops certified, and what does it mean for conservation and poverty alleviation? Biol. Conserv. 217, 36–46. https://doi.org/10.1016/j.biocon.2017.09.024.
Ton, P., 2013. Productivity and Profitability of Organic Farming Systems in East Africa. IFOAM - International Federation of Organic Agriculture Movements, Bonn.
Tzouramani, I., Alexopoulos, G., Kostianis, G., Kazakopoulos, L., 2014. Exploring risk management strategies for organic farmers: a Greek case study. Renew. Agric. Food Syst. 29, 167–175. https://doi.org/10.1017/S1742170513000057.
Tzouvelekas, V., Pantzios, C.J., Fotopoulos, C., 2001. Technical efficiency of alternative farming systems: the case of Greek organic and conventional olive-growing farms. Food Policy 26, 549–569. https://doi.org/10.1016/S0306-9192(01)00007-0.
Van Dessel, W., Van Rompaey, A., Szilassi, P., 2011. Sensitivity analysis of logistic regression parameterization for land use and land cover probability estimation. Int. J. Geogr. Inf. Sci. 25, 489–508. https://doi.org/10.1080/13658810903194256.
Veldstra, M.D., Alexander, C.E., Marshall, M.I., 2014. To certify or not to certify? Separating the organic production and certification decisions. Food Policy 49, 429–436. https://doi.org/10.1016/j.foodpol.2014.05.010.
Verburg, P.H., Ellis, E.C., Letourneau, A., 2011. A global assessment of market accessibility and market influence for global environmental change studies. Environ. Res. Lett. 6, 034019. https://doi.org/10.1088/1748-9326/6/3/034019.
Verburg, P.H., Mertz, O., Erb, K.-H., Haberl, H., Wu, W., 2013. Land system change and food security: towards multi-scale land system solutions. Curr. Opin. Environ. Sustain. 5, 494–502. https://doi.org/10.1016/j.cosust.2013.07.003.
Willer, H., Lernoud, J., 2018. The World of Organic Agriculture. Statistics and Emerging Trends 2018. FiBL - Research Institute of Organic Agriculture. IFOAM - Organics International, Frick, Switzerland.
Wisz, M.S., Guisan, A., 2009. Do pseudo-absence selection strategies influence species distribution models and their predictions? An information-theoretic approach based on simulated data. BMC Ecol. 9, 8. https://doi.org/10.1186/1472-6785-9-8.
Wollni, M., Andersson, C., 2014. Spatial patterns of organic agriculture adoption: evidence from Honduras. Ecol. Econ. 97, 120–128. https://doi.org/10.1016/j.ecolecon.2013.11.010.
Wollni, M., Brümmer, B., 2012. Productive efficiency of specialty and conventional coffee farmers in Costa Rica: accounting for technological heterogeneity and self-selection. Food Policy 37, 67–76. https://doi.org/10.1016/j.foodpol.2011.11.004.