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How do countries specialize in food production? A complex-network analysis of the global agricultural product space

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How do countries specialize in food production? A complex-network analysis of the global agricultural product space

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Abstract

In the last years, there has been a growing interest in studying the global food system as a complex evolving network. Much of the literature has been focusing on the way countries are interconnected in the food system through international-trade linkages, and what consequences this may have in terms of food security and sustainability. Little attention has been instead devoted to understanding how countries, given their capabilities, specialize in agricultural production and to the determinants of country specialization patterns. In this paper, we start addressing this issue using FAO production data for the period 1993-2013. We characterize the food production space as a time-sequence of bipartite networks, connecting countries to the agricultural products they produce, and we identify properties and determinants underlying their evolution. We find that the agricultural product space is a very dense network, which however displays well-defined and stable communities of countries and products, despite the unprecedented pressure that food systems have been undergoing in recent years. We also find that the observed community structures are not only shaped by agro-ecological conditions but also by economic, socio-political, and technological factors. Finally, we discuss the implications that such findings may have on our understanding of the complex relationships involving country production capabilities, their specialization patterns, food security, and the nutrition content of the domestic part of their food supply.

Keywords: Food systems; Food production; Specialization; Bipartite networks; Community structure detection; Hypergeometric filtering.

1 Introduction

The concept of food system is increasingly recognized as central for developing policies achieving food security, improving nutrition, and moving towards more sustainable systems (Muller et al., 2017; Béné et al., 2019). Despite this, our understanding of the evolving food system is recent and incomplete (Puma, 2019).

Several features shaping current food systems have developed relatively quickly and are rapidly evolving, which makes more difficult to fully characterize them. Recent events and multiple factors have been placing unprecedented pressure on food systems: population growth (Godfray et al., 2010), dietary changes (Khoury et al., 2014; Finaret and Masters, 2019), rising food prices and agricultural production shocks (Headey, 2011; Tanaka and Hosoe, 2011; Sartori and Schiavo, 2015), over-exploitation of natural resources (Hazell and Wood, 2007; Hanjra and Qureshi, 2010; Cassidy et al., 2013), climate change (Schmidhuber and Tubiello, 2007; Battisti and Naylor, 2009; Gornall et al., 2010; Coumou and Rahmstorf, 2012), and increasing biofuels and biomass use (Woods et al., 2010; Tilman et al., 2011; Nonhebel and Kastner, 2011). Meeting an increasing and more sophisticated demand while moving towards more sustainable food systems has become a growing challenge at the international policy level.

The global food system is a complex, dynamic, and highly interconnected network of activities involving the production, processing, transport, and consumption of food. In addition, a high number of very heterogeneous stakeholders are involved in those activities. Multiple issues shape and affect food systems, including the governance of food production and trade, food supply and distribution, sustainability, food waste, biodiversity, and the impact of food on population health.

Therefore, recent efforts aiming to improve our understanding of food systems have focused on a systems approach, considering their multiple elements (Puma, 2019). Several researchers have made progress understanding key characteristics of global food trade and the consequences that this may have in terms of food security and sustainability (see, for example, Shutters and Muneepeerakul, 2012; Ercsey-Ravasz et al., 2012; Puma et al., 2015; Torreggiani et al., 2018). Much less studies have focused on food production using a complex-networks approach. Khoury et al. (2014) have shown that agricultural production has changed in composition in the last 60 years and that national food supplies have diversified in regard to contributing measured crop commodities. In addition, national food supplies have become increasingly similar in composition, based upon a suite of truly global crop plants. In response to the shift of agriculture toward specialization and mechanization, there has been a call for a transition toward a new model of agriculture, which incorporates practices enhancing biodiversity and environmental services, and takes into account the social implications of production practices, market dynamics, and product mixes (Bowman and Zilberman, 2013).

Despite the relevance of the production side of food systems, little attention has been devoted to understanding how countries, given their capabilities, specialize in food production, and what are the determinants of their specialization patterns. In this paper, we address this issue using FAO production data for the period 1993-2013. We characterize the food production space as a time-sequence of bipartite networks, connecting countries to the agricultural products they produce, and we identify properties and determinants underlying their evolution. We obtain the product-product and country-country projected networks based on node similarity to detect the structure of their communities. Using a hypergeometric filtering approach, we analyze the community structure of the bipartite networks, where communities are essentially clusters of links characterized by a higher 'within' connectivity, but a much sparser connectivity 'between' nodes belonging to different clusters.

We claim that understanding specialization patterns of countries in food production can provide relevant insights for the evaluation and policy design seeking to achieve food security, healthy diets, and more sustainable food systems. In the last decades, countries have been going through dietary transformations towards more diverse foods, different nutrient composition, sustainability, and a variety of credence attributes (see, for example, Finaret and Masters, 2019). Accordingly, agricultural production also did become more diversified but also more similar in composition (Khoury et al., 2014). Most countries now consume more homogeneous food in terms of their composition, despite not all countries have natural conditions to produce these general products. However, trade of agricultural products has been also increasing, shaping and, to a certain degree, homogenizing the variety of available food at the country level (Torreggiani et al., 2018).

In this context, we investigate whether countries have changed their food production systems and their specialization patterns. Our main contribution derives from the study of the food system as an evolving complex network. We present the first analysis of the evolution of the food product space (the network that links agricultural products according to the capabilities necessary for their production revealed by countries) and of the network of food producers countries (the network that links countries according to the similarity of their revealed capabilities to produce agricultural products), analyzing the emerging communities of products and countries, and studying their properties to understand how and why countries specialize in agricultural production given their capabilities. While most of the existing studies have focused on international trade data to describe the food system, we use agricultural production data. This allows us to provide a more accurate picture of agricultural capabilities and of the diversification patterns in production baskets.

Our research is guided by the following questions. How countries specialize in food production? Do they rely and take advantage of their natural conditions and other capabilities necessary for food production? Or, in addition to that, do they produce agricultural goods for which they do not have the "optimal" natural conditions but for which they have developed economic and technological capabilities? Are countries specialized in the production of related products or do they instead diversify their production baskets?

We use methodologies from network analysis and the theoretical background from recent research that has made a great advance in understanding how capabilities shape production of different types of products and how this, in turn, fosters economic development (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Caldarelli et al., 2012; Cristelli et al., 2013; Hausmann et al., 2014; Zaccaria et al., 2014; Cristelli et al., 2015). This literature has shown that what countries produce and how they use their production capabilities to diversify production are relevant aspects shaping their development processes. Different studies have proven that the "product space" conditions the development of countries because economies grow by upgrading the products they produce and export. In this view, technology, capital, institutions, and skills needed to make newer products are more easily adapted from some products than from others. More sophisticated products are located in a densely connected core whereas less sophisticated products occupy a less-connected periphery. Empirically, countries move through the product space by developing goods close to those they currently produce. Poorest countries tend to be located in the periphery, where moving toward new products is harder to achieve, which may help explaining why they find difficulties in developing.

Interestingly, several products in the periphery of the world product space are agricultural products. Therefore, this literature has not devoted great attention to them because they are not relevant to reach sectors in the core. However, agricultural production is certainly one of the main determinants of food supply at the country level. In addition, specialization patterns have implications for biodiversity, sustainability, and global food security. All this provides a strong motivation for applying such a methodology, for the first time, to study the food production system. In addition, this type of analysis have used trade data to study how countries specialize according to their capabilities. Instead, we use agricultural production data which avoids the possible bias that might derive from the fact that not all goods produced in the domestic market are necessarily exported.

Our analysis shows that the agricultural product space is very dense, meaning that many products are produced by a high number of countries. We observe that different products are jointly produced because they share the need of similar capabilities, including natural conditions, for their production. Interestingly, despite the high density of the network, it is possible to detect that these products cluster in well-defined communities.

In the same way, we find that the network of countries is very dense but characterized by a small number of communities, which means that, given their agricultural capabilities, it is possible to consistently classify countries by their specialization patterns.

Furthermore, we employ an econometric model to determine the probability that two countries belong to the same community. We show that countries within a community are not only characterized by similar endowments of natural resources, but also by other similar economic, political, social, and technological features.

We also observe that some countries are specialized in one specific community of similar products, while others have more diversified production baskets. In this sense, the networks provide a picture of the specialization patterns of countries according to their capabilities and can be helpful to better understand how the domestic part of countries food supplies differ in terms of food security, sustainability, and nutritional content.

Finally, we observe that both the agricultural product space and the network of agricultural countries are very stable over the period of twenty-one years, despite the unprecedented pressure and changes that the global food system has been undergoing in recent years.

The remaining of the paper is organized as follows. In Section 2, we describe the data and the methodology. In Section 3, we present the main results. In Section 4, we discuss the main findings and conclude.

2 Data and Methodology

To study how countries specialize in food production, we introduce the concept of world agricultural products network, which can be represented by a bipartite matrix where rows represent countries and columns are products.

Several contributions have been employing a similar approach to explore country product diversification (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Tacchella et al., 2012; Caldarelli et al., 2012; Zaccaria et al., 2014). These studies have shown that the possibilities of diversification into new products are strongly determined by the capabilities revealed in the products currently exported. Due to data limitations for world production, these studies have used trade data to measure and map capabilities, assuming that exports reflect production capabilities. This is, they assume that the presence or the absence of a product in a country's export basket reveals the production capabilities of that country. This can have a bias because exports might not necessarily capture all domestic capabilities.

Instead, we take advantage of the fact that FAO (2019) provides comparable data on world agricultural production. These data allow us to have a more precise definition of the agricultural capabilities of countries because products for domestic consumption that might be not exported are also considered, avoiding the possible bias that can result from using export data only.

Thus, although the set of capabilities necessary for production cannot be directly observed, the fact that different countries produce identical products may indicate that these countries share capabilities that are needed to produce these products. In the case of agriculture, production requires not only technology, capital, institutions, and skills, which are certainly difficult to be quantified, but it also depends on natural conditions necessary to produce agricultural products.

Identifying natural characteristics and capabilities is not an easy task. Indeed, natural, environmental, and climatic conditions can be very heterogeneous within countries allowing them to diversify their agricultural baskets. For example, it is unlikely that a country's natural resources endowment is evenly distributed throughout its territory. Thus, we need a measure of relatedness to quantify the presence of a set of diverse natural characteristics and capabilities that determine diversification patterns.

In the product-space literature (for example, in Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Tacchella et al., 2012; Zaccaria et al., 2014), a complex product in the space of the universe of products is one that is produced by only a few highly competitive countries. Similarly, a complex product in the case of the agricultural product space is a product that only a few countries can produce (i.e. non ubiquitous). Countries with high capabilities in agriculture are, therefore, those that can produce a wide set of products, but also that have capabilities to produce goods that only a few countries can produce.

2.1 Data and definitions

We build the world agricultural products network using data from FAO (2019) on food production at the country level for the period 1993-2013 for 169 countries that are detailed in Table SI.1 of the Supplementary Information.

In order to build the agricultural product space, we use production data of 219 different food products. For the purpose of our work, an agricultural or food product means any product or commodity, raw or processed, that is marketed for human consumption (excluding water, salt, and additives) or animal feed. Agricultural products are classified by FAO (2019) in four main groups: crops, crops processed, livestock primary, and livestock processed (see list of products in Table SI.2 of the Supplementary Information).[1] All data are in tonnes, but in order to have comparable and relevant measures for food supply, we also transform them to kilocalories, fat, and protein content, using the data provided by FAO (2001).

2.2 The world agricultural product space

As mentioned, the world agricultural products network can be represented by a bipartite matrix: rows represented by countries and columns by products. The entries of this matrix take the value of one when a country is considered a relevant producer of a given product. One possible way of detecting relevant producers is to look at the revealed comparative advantages (RCA) of countries (Balassa, 1965). Thus, we measure patterns of

[1] We excluded production of live animals because data are given in stocks of animal heads, which is not comparable with the rest of agricultural production. In addition, we excluded fibers for textiles and other products for non-food uses.

specialization by computing countries' RCA for each agricultural product.[2] This approach has been widely used to measure production capabilities (proxied with exports data) at the country level (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Zaccaria et al., 2014) and at the firm level (Bruno et al., 2018), and technological capabilities (Petralia et al., 2017).

Given that agricultural production is in tonnes, we weight production in order to build the indicator of RCA. We use the agricultural gross production value (GPV) from FAO (2019), which is built by multiplying gross production in physical terms by output prices at farm gate. The variable is in constant 2004-2006 million dollars.

The RCA indicator reads:

$$RCA_{ikt} = \frac{Q_{ikt}/\sum_j Q_{jkt}}{GPV_{it}/\sum_j GPV_{jt}} \tag{1}$$

where Q is production of product k, i is a country, t is a given year, and GPV is the agricultural gross production value. We adopt the convention that $RCA_{ikt} \geq 1$ reveals that country i is a relevant producer of product k at time t.

Consequently, the agricultural products bipartite matrix M contains elements that are defined as:

$$m_{ik} = \begin{cases} 0 \text{ if } RCA_{ik} < 1, \\ 1 \text{ if } RCA_{ik} \geq 1. \end{cases} \tag{2}$$

We study how the bipartite matrix M evolves over the period 1993-2013.

Product and country relatedness

We define the agricultural product space as a network-based representation of global agricultural production, where nodes represent agricultural products and ties among them indicate their degree of relatedness. The fact that different products are jointly produced by a set of countries allows us to entail that some capabilities are common for those countries and for a couple of products. Thus, relatedness between a pair of goods derives from the fact that these two goods are commonly produced together.

There are several possibilities to measure product relatedness or similarity (see, for example: Zhou et al., 2007; Hidalgo et al., 2007; Caldarelli et al., 2012; Zaccaria et al., 2014; Boschma et al., 2014). Our measure of relatedness is based on the Jaccard index:

$$P_{kk'} = \frac{V_{kk'}}{V_k + V_{k'} - V_{kk'}}, \tag{3}$$

where $V_{kk'} = \sum_i m_{ik} m_{ik'}$ is the number of co-occurrences in which two different countries

[2] This measure has been mostly employed for international trade. In the case of production, the measure also considers domestic consumption, giving also relevance to products that might be not relevant for international consumption.

produce products k and k', and $V_k = \sum_i m_{ik}$ is the total number of countries that produce k, and similarly for $V_{k'}$.[3] Products are coded using the FAO (2019) classification, which disaggregates agricultural production into 219 products (after excluding non-food products).

The matrix P can be seen as the network of world agricultural products or the agricultural product space, in which nodes are represented by products and links by the degree of relatedness between them, i.e. the elements $P_{kk'}$. Therefore, the coherence of a production basket is due to the relatedness strength within products, in the sense that there are certain technological, natural, and economic characteristics common to each one of the products.

Following the same strategy, we can obtain the network of countries producing agricultural goods where nodes are countries and ties represent the degree of similarity of countries' production baskets. Country relatedness is defined as:

$$C_{ii'} = \frac{\Lambda_{ii'}}{\Lambda_i + \Lambda_{i'} - \Lambda_{ii'}}, \tag{4}$$

where $\Lambda_{ii'} = \sum_k m_{ik} m_{i'k}$ is the number of products that are produced by countries i and i', $\Lambda_i = \sum_k m_{ik}$ is the total number of products produced by i, and similarly for $\Lambda_{i'}$.

Link-weight filtering

The networks of relatedness between products and between countries are highly dense, making it difficult to detect their structural and topological properties because many, possibly irrelevant, links are included. This is because most countries tend to produce a relatively wide variety of basic products, which consequently makes relatedness between any pair of products or countries to be greater than zero. To assess whether a link is statistically significant or not, we adopt a null model based on the hypergeometric filter (Tumminello et al., 2011; Iori and Mantegna, 2018).

More specifically, let NS_u and NS_v be the node strength of nodes u and v (either products or countries) and M the sum of node strengths for all the nodes (i.e. network volume), rounded to the nearest integer. We want to assess the statistical significance of any given link w_{uv} against the statistical benchmark defined by the hypergeometric distribution, i.e. the probability of observing w_{uv} under the null hypothesis of random co-occurrence –that is to say row entries are equally probable across column entries given their strength, and vice-versa (Feller, 1968).

Formally, the hypergeometric probability of observing a link w_{uv} in a network of volume

[3] The Jaccard index has been widely used as a similarity measure to detect co-occurrences of data, although there is still a debate concerning the most appropriate measure for their normalization (Boschma et al., 2014). For a discussion of alternative methods, see: Leydesdorff (2008) and Eck and Waltman (2009).

M and row/column sums equal to NS_u and NS_v reads:

$$H(w_{uv}|M, NS_u, NS_v) = \frac{\binom{NS_u}{w_{uv}}\binom{M-NS_u}{NS_v-w_{uv}}}{\binom{M}{NS_v}}. \tag{5}$$

The corresponding p-value can be written as:

$$p(w_{uv}) = 1 - \sum_{X=0}^{w_{uv}-1} H(X|M, NS_u, NS_v). \tag{6}$$

Note that the hypergeometric null hypothesis takes directly into account the heterogeneity of countries and products to the total intensity of their interactions with other countries or products.

For each pair of nodes u, v, we then separately evaluate the significance of its link weight w_{uv} according to whether the corresponding p-value is lower than a 1% threshold. Thus, non-significant links are removed, and significant ones are kept with their original weights.

Community structure detection

In order to detect communities in matrices P and C, we employ the Louvain algorithm, which is a method to detect communities from large networks (Blondel et al., 2008). The algorithm optimizes a function known as "modularity" over the possible divisions (or communities) of a network. Modularity aims to capture the degree to which a network can be partitioned in groups of nodes, with higher interaction within groups than between them. The algorithm incorporates a configuration model to build the probability of connection among nodes considering structural attributes of the network itself. The modularity function compares the within communities share of links in the observed network with the share of such links that would be expected on the basis of chance (given the configuration model).

Community attaching econometric model

The methodology used for community detection allows us to identify communities that, in the case of countries, emerge whenever a group of countries produce comparatively more similar products between them than with countries outside the community. In agriculture, similar natural conditions will probably determine to some extent the production baskets of the countries within each community. However, there may be a number of additional country characteristics shaping the formation of communities. In order to quantitatively explore what determines that any two countries belong to the same community and, therefore, the emergence of such communities, we run Logit regressions, as cross-sections for a selected number of years, to examine the probability of country co-occurrence in the same cluster as a function of a set of covariates aiming to capture country-pair similarity along geographical, technological, socio-political, and economic dimensions. We estimate the following model:

$$\text{Prob}\{y_{ij} = 1|\text{X}\} = \Lambda(\alpha + \beta\text{X}_{ij} + \lambda_i + \lambda_j), \tag{7}$$

where the dependent variable y_{ij} is a dummy that indicates whether a pair of countries i and j belong to the same community; α is a constant term; X is a vector of covariates including: the log of the geographical distance between a pair of countries; the log of the difference in countries' latitudes, as a proxy of the differences in climate and agro-ecological zones; a variable indicating whether two countries belong to the same geographical region; the log of the difference in the GDP per capita of a pair of countries; the difference in the level of an index of human capital of a pair of countries; the difference in the political systems of a pair of countries; and four additional variables related with agricultural inputs that, for a pair of countries, denote differences in: agricultural labor, agricultural machinery, fertilizers consumption, and irrigated land, all of them expressed over agricultural land and in logarithms. All variables considering differences are in absolute values. Finally, λ_i and λ_j are country fixed effects; and Λ is the logistic function. In Table SI.3 of the Supplementary Information, we describe the explanatory variables and their sources.

3 Results

3.1 The agricultural product space

We observe that the agricultural product space is very dense, meaning that many products are produced by a high number of countries. Figure 1 shows the network representation of matrix P, which formally is the projection of the bipartite matrix M in the agricultural product space using the Jaccard index, for the years 1993 and 2013.

The Jaccard index allows to measure the degree of relatedness between products in order to understand which products are more connected. Figure 1 shows the statistically significant links validated with the hypergeometric filter at the 1% level of significance, which allows us to detect that different products are jointly produced because they share the need of similar natural conditions and capabilities for their production.

Table 1 presents network statistics of the full network and the link filtered network of agricultural products every five years between 1993 and 2013, revealing a very stable network architecture.

A remarkable feature of these networks is that, even without filtering the links, they have three or four very well-defined communities, which are clearly observed after applying the hypergeometric filter. In fact, after validation, we always observe four communities,

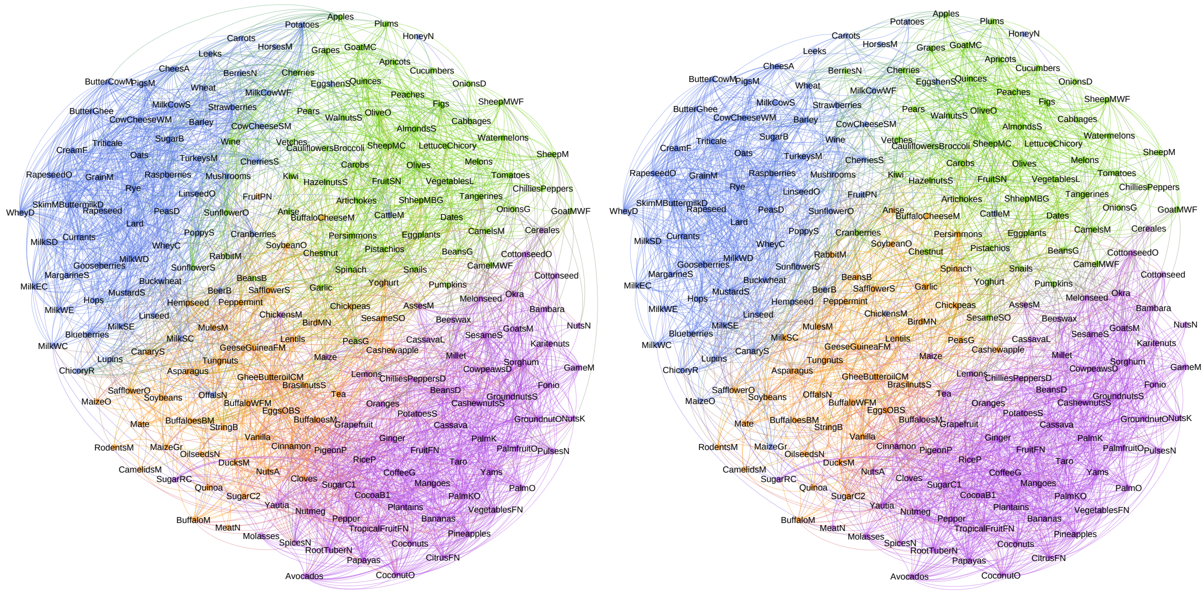

Figure 1: Agricultural product space. Product relatedness. Links are validated by the hypergeometric filter at the 1% level of significance. Colors represent different detected communities (Louvain algorithm) in the corresponding year: in blue "Crops and livestock", in green "Vegetables and fruits", in purple "Tropical fruits and crops", and in orange "Special livestock, oils and crops". Nodes' positions are fixed in order to facilitate the comparison between each year. Left: 1993. Right: 2013

Table 1: Network statistics of the agricultural product space for selected years

Year	1993	1998	2003	2008	2013
			Full Network		
Nodes	218	218	219	219	219
Density	0.76	0.76	0.77	0.77	0.77
Average link weight	0.25	0.25	0.25	0.25	0.24
Link weight skewness	1.18	1.12	1.17	1.18	1.12
Average node degree	163.95	165.43	167.38	167.80	168.69
Average node strength	19.48	19.95	20.05	19.90	19.73
Communities	4	3	3	4	4
Modularity	0.22	0.22	0.22	0.21	0.21
			Filtered Network*		
Density	0.13	0.13	0.13	0.13	0.12
Communities	4	4	4	4	4
Modularity	0.54	0.55	0.56	0.56	0.55

Notes: Link weight: ($P_{kk'} > 0$). Node degree: $ND_k = \sum_{k'} A_{kk'}$, with $A_{kk'} = 1$ if $P_{kk'} > 0$, and zero otherwise. Node strength: $NS_k = \sum_{k'} P_{kk'}$. *Links are validated by the hypergeometric filter at the 1% level of significance which remain intensively connected and concentrate a great extent of the total density: 76% in 1993 and 78% in 2013, considering inner links, i.e excluding link weights connecting nodes that belong to different communities. An evidence in favor of the latter is that the network's architecture reveals high modularity after links have been removed.

In brief, despite the high density of the network, we detect that agricultural products cluster in four well-defined communities, portrayed in different colors in Figure 1 and named for illustrative purposes as: "Crops and livestock" (in blue), "Vegetables and fruits" (in green), "Tropical fruits and crops" (in purple), and "Special livestock, oils and crops" (in orange).

These four communities connect highly related products. For example, mangoes, bananas, papayas, coconuts, plantains, avocados, and coffee, which are mostly tropical fruits and crops, appear embedded in a single community (in purple). In blue, we observe crops such as wheat and barley, as well as processed crops, and processed livestock products, such as butter and cheese. In the community in green, most products are vegetables, nuts, and fruits from Mediterranean or sub-tropical regions. Finally, in orange, some special meats and by-products from camelids, buffalos, and rodents, oil crops and oils such as linseeds, soybeans, and safflowers, as well as other specific products such as mate and quinoa, are clustered in one smaller community. This community mostly groups certain products with a low relevance in global food production: quinoa, Brazil nuts, safflower seeds and oil, mate, and camelids and rodents meat. Furthermore, it includes a few relevant products, in terms of global consumption, such as soybeans and soybeans oil. This forth community is smaller in size and less stable than the other three communities, which is observed in the fact that, although there is a group of products that appear regularly, it changes its composition more deeply in different years. Instead, the other communities maintain their main products during the whole period (see Figure SI.2 in the Supplementary Information).

We observe that the composition of the communities is relatively stable during the period of twenty-one years. Several of the products that change community do so in only one year and those that change more often are usually those that appear in the borders of the communities. Clearly, the changes in the communities of products can be explained by the changes in the production patterns of countries. Thus, it is interesting that the communities that are relatively more robust –"Tropical fruits and crops" and "Crops and livestock"– include products that might need more specific conditions, such as machinery for extensive production of crops, or tropical weather for some fruits. The community "Vegetables and fruits" includes products that might be produced in different environments, particularly some vegetables. Instead, the community "Special livestock, oils and crops" includes a group of products that require specific conditions, which are the more stable products within the community. In brief, we observe that products that share the need of similar capabilities group in communities within the network.

3.2 The network of countries

Next, we analyze how countries are related given their agricultural production baskets. Figure 2 shows the network representation of matrix C for 1993 and 2013.

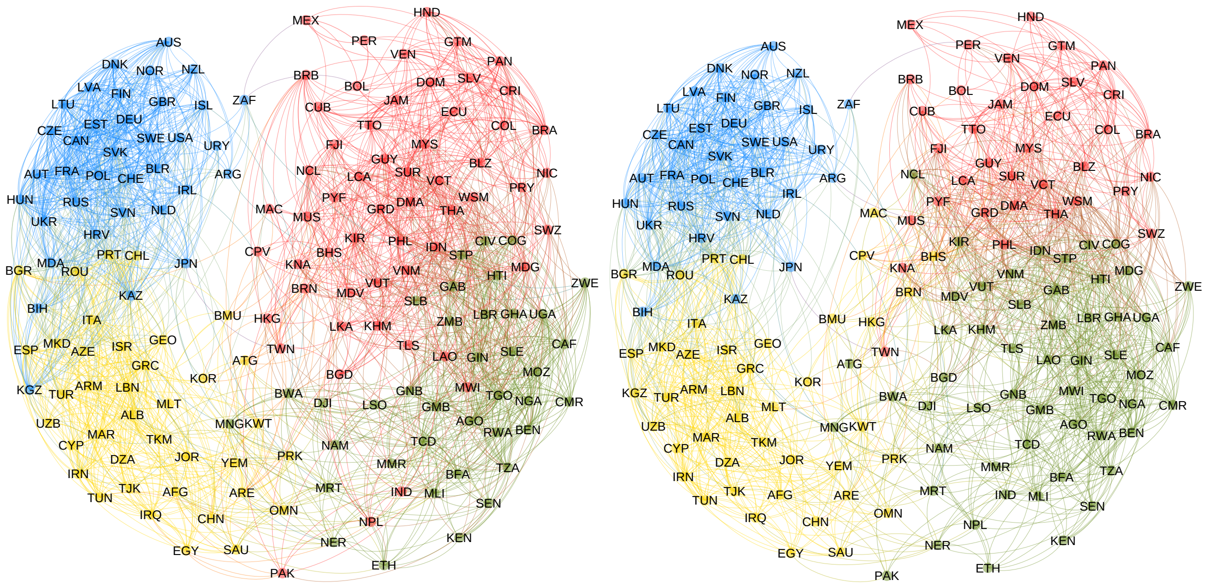

Figure 2: Network of countries relatedness. Links are validated by the hypergeometric filter at the 1% level of significance. Colors represent different detected communities (Louvain algorithm) in the corresponding year: in red "Tropical I", in green "Tropical II", in yellow "Subtropical", and in blue "Tempered". Nodes' positions are fixed in order to facilitate the comparison between each year. Left: 1993. Right: 2013. ISO codes are defined in Table SI.1 of the Supplementary Information

Table 2 presents statistics every five years for the full network and the link validated network of countries, which reveals a very stable network between 1993 and 2013. The network is highly connected with 169 countries (nodes). The average number of connections of a node is very high, 161.91 in 1993 and 164.78 in 2013, which implies that most countries are endowed with a set of common capabilities and/or natural resources that allows them to simultaneously produce different products. For example, all countries share capabilities to produce eggs, some types of meat and dairy products, and even some crops and fruits. However, despite the high node degree, we observe a relatively low level of cohesion. On the average, the node strength is 21.46 in 1993 and 22.68 in 2013, which derives from the fact that the average link weight distribution is strongly right-skewed (see Figure SI.1 in the Supplementary Information).

The network is fully-connected and it also reveals the presence of communities, where members seem to be related by their geographical closeness, understood as their environmental and agro-ecological characteristics, which determine their natural production capabilities. For the same reason, it is not surprising to note that there are no remarkable differences between the networks in 1993 and 2013. Like in the agricultural product space,

Table 2: Network statistics of countries' production similarities for selected years

Years	1993	1998	2003	2008	2013
			Full Network		
Nodes	169	169	169	169	169
Density	0.96	0.97	0.98	0.97	0.98
Average link weight	0.30	0.31	0.31	0.31	0.30
Link weight skewness	0.76	0.72	0.84	0.78	0.70
Average node degree	161.91	163.01	163.91	163.63	164.78
Average node strength	21.46	22.09	22.09	22.53	22.68
Communities	2	2	2	2	2
Modularity	0.21	0.21	0.21	0.20	0.20
			Filtered Network*		
Density	0.15	0.15	0.15	0.14	0.14
Communities	4	4	5	4	4
Modularity	0.56	0.56	0.56	0.55	0.57

Notes: Link weight: $(P_{kk'} > 0)$. Node degree: $ND_k = \sum_{k'} A_{kk'}$, with $A_{kk'} = 1$ if $P_{kk'} > 0$, and zero otherwise. Node strength: $NS_k = \sum_{k'} P_{kk'}$. *Links are validated by the hypergeometric filter at the 1% level of significance

the communities of countries are well-defined and relatively stable over the period (see Figure SI.2 in the Supplementary Information). Without filtering links, we detect two well-distinguished communities of great size in the network. After validating links, we typically detect four communities and modularity increases.[4] Inner links of these four communities add up to 78% in 1993 and 79% in 2013 of the total density.

Figure 3 shows the geographical distribution of countries that belong to the main four detected communities after filtering in 1993 and 2013.

These four communities of countries seem to be mainly clustered by geographical factors. For example, countries with tropical weather appear in two different communities. In green, the detected community mainly clusters economies from Africa and Asia, such as India, Tanzania, and Angola, which are located in the tropics. Another group of mostly tropical countries, like Colombia, Panama, and Jamaica, appear in a different community (in red). Countries from Mediterranean or warm subtropical regions are grouped in a community in yellow. In blue, most countries are those with tempered climate that mainly have extensive agricultural production systems, such as Australia, Argentina, Canada,

[4]In the years 1994, 2002 and 2003 we detect a fifth smaller community (between 11 and 20 countries), composed by a group of countries that detached from the communities "Subtropical" (in yellow), "Tropical I" (in red), and "Tropical II" (in green). In the years in which there are four communities, these countries usually appear as hubs in their borders, for example, Hong Kong (HKG), Antigua and Barbuda (ATG), Bermuda (BMU), and Djibouti (DJI).

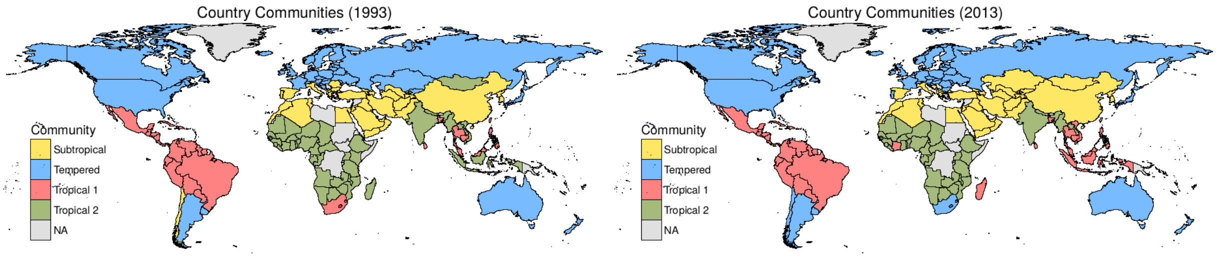

Figure 3: Geographical distribution of countries in each community. 1993 and 2013. Colors represent communities as in the networks of Figure 2

United States, and Eastern European countries. For illustrative purposes, we name these four communities as: “Tropical I” (in red), “Tropical II”‘(in green), “Subtropical” (in yellow), and “Tempered” (in blue).[5]

Interestingly, two of these communities mostly include more developed countries (blue and yellow), and the two other communities cluster mainly less developed or developing countries (red and green). This might indicate that not only geographical, climatic, and environmental conditions are relevant determinants of the communities but also other features (such as technological, economic, political, and institutional capabilities), which can be proxied by the development levels of countries.

In order to quantitatively explore what determines that any two countries belong to the same community, we run a Logit regression to examine the probability as a function of a set of covariates aiming to capture country-pair similarity along geographical, technological, socio-political, and economic dimensions. Table 3 shows the estimation results for the cross-sections 1993, 2003 and 2013, and Figure 4 shows the marginal effects of the covariates in the same years.

The estimated results are stable for the different cross-sections. The estimations indicate that all variables related with geographical conditions are relevant determinants of the probability that two countries belong to the same detected community; the geographical distance as well as the difference in latitudes between two countries both have a negative and statistically significant impact on the probability that two countries belong to the same community. Likewise, the variable that indicates if two countries belong to the same geographical region is positive and statistically significant. This implies that more similar natural conditions increase the probability that any two countries belong to the same community.

Furthermore, the variables related with economic, socio-political, and technological features of countries are also relevant variables affecting the probability that a pair of countries belong to the same community. Differences in GDP per capita and human capital

[5]These communities might include countries that could hardly be classified as having the type of climate indicated by the name of the community. However, we use these names as broad categories to identify the communities in the analysis.

Table 3: Determinants of community attaching. Logit estimations for 1993, 2003 and 2013

	Logit Estimations		
Variables	1993	2003	2013
Distance (ln)	-0.293***	-0.526***	-0.479***
	(0.079)	(0.081)	(0.075)
Diff. in latitudes (ln)	-0.632***	-0.542***	-0.577***
	(0.039)	(0.039)	(0.037)
Same region	1.498***	1.120***	1.022***
	(0.132)	(0.138)	(0.126)
Diff. in GDP pc (ln)	-0.603***	-1.148***	-0.543***
	(0.066)	(0.069)	(0.065)
Diff. in human capital	-1.105***	-0.799***	-0.876***
	(0.115)	(0.106)	(0.106)
Diff. in political systems	-0.399**	-0.179	-0.989***
	(0.157)	(0.190)	(0.200)
Diff. in agricultural labor (ln)	-0.627***	-0.536***	-0.605***
	(0.059)	(0.058)	(0.049)
Diff. in agricultural machinery (ln)	-0.288***	-0.234***	-0.011
	(0.044)	(0.043)	(0.037)
Diff. in fertilizers consumption (ln)	-0.081**	0.043	-0.163***
	(0.041)	(0.035)	(0.034)
Diff. in irrigated land (ln)	-0.720***	-0.332***	-0.500***
	(0.042)	(0.042)	(0.039)
Constant	5.710***	7.738***	7.115***
	(0.834)	(0.867)	(0.817)
Observations	7,352	7,405	7,599
Pseudo R^2	0.442	0.449	0.400

Notes: The dependent variable is a dummy indicating whether two countries belong to the same detected community. Robust standard errors are in parentheses. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.10$

of countries are both negative and statistically significant, which implies that countries with similar development levels are more likely to be in the same community. Likewise, differences in the political systems of countries are negative and significant determinants of the probability of belonging to the same community. In addition, the variables that aim to capture differences in labor, capital, land, and technological endowments of countries' agricultural systems, are also relevant determinants of the probability that two countries belong to the same community. This implies that the higher the differences in agricultural inputs, technology, and other related endowments of two countries, the lower the probability that they will be in the same community.

Overall, these results indicate that not only geographical conditions, but also other political, institutional, technological, and economic factors are important determinants of the co-presence of country pairs in the same community. And, therefore, this implies that specialization patterns of countries in agricultural production are related to a set of

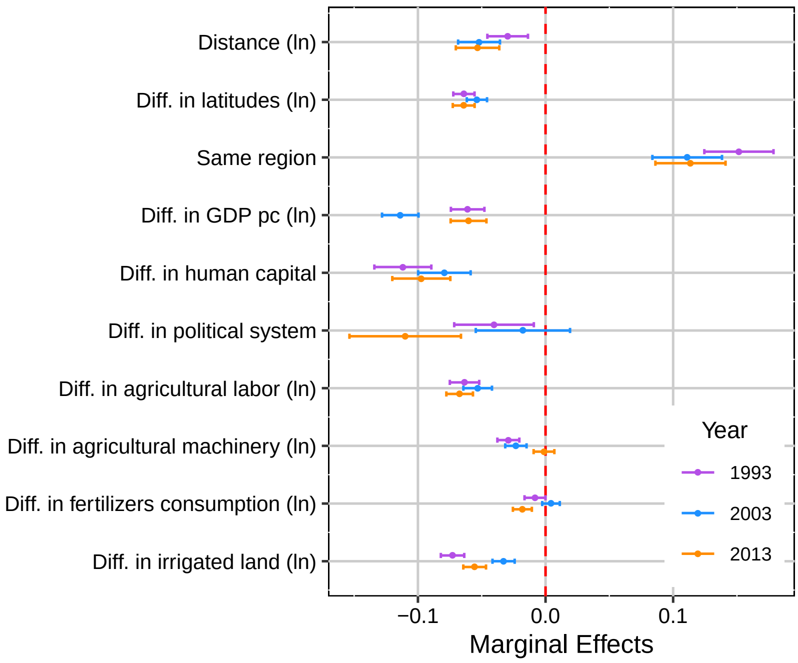

Figure 4: Estimated marginal effects of the covariates in Equation (7), computed by the delta method at averages for the cross-sections 1993, 2003 and 2013. Dots represent the point estimate of marginal effects and bars are 95% confidence intervals. x-axis: marginal effect of the covariate on the probability that two countries belong to the same community. y-axis: covariates used in the model

natural, socio-political, technological, and economic features of countries.

3.3 Specialization in food production

The networks of products and countries allows us to observe how products are related through the need of a set of common capabilities and how countries specialize in food production according to a set of capabilities that allows them to produce a basket of related products. The communities detected in the product space include products that are more similar between them than with products outside the community, in terms of required capabilities. Likewise, the communities in the network of countries include countries that share similar capabilities for agricultural production.

Overall, the network analysis allows us to evaluate how countries specialize in food production, which has implications for their food supplies, for developing more sustainable food systems, and for achieving food security. Next, we analyze the specialization patterns that characterize the communities in the networks.

The four detected communities in the product space are clearly different in their composition in terms of kilocalories, proteins, and fat content. The contribution of these communities to global food production for 1993 and 2013, measured in kilocalories, proteins, and fat content can be observed in Table 4.

Table 4: Production shares by community in total production, measured in kilocalories, proteins, and fat content. 1993 and 2013

Year	1993			
Community	Products	Kilocalories	Proteins	Fats
Crops and livestock	52	0.39	0.48	0.38
Tropical fruits and crops	60	0.37	0.26	0.36
Vegetables and fruits	68	0.04	0.03	0.07
Special livestock, oils and crops	38	0.19	0.23	0.18
Year	2013			
Community	Products	Kilocalories	Proteins	Fats
Crops and livestock	62	0.32	0.39	0.34
Tropical fruits and crops	67	0.57	0.38	0.46
Vegetables and fruits	57	0.05	0.02	0.10
Special livestock, oils and crops	33	0.07	0.21	0.10

An interesting thing to notice is that a community might be highly diversified in the number of products but at the same time contribute relatively low to food production, in all the measures considered. The community "Crops and livestock" includes 52 and 62 different products (in 1993 and 2013) and has a share of 39% and 32% in kilocalories, of 48% and 39% in proteins, and of 38% and 34% in fats. The community of "Tropical fruits and crops" groups 60 products in 1993 and 67 products in 2013, and contributes with 37% and 57% of total kilocalories, 26% and 38% of proteins, and 36% and 46% of fats, in 1993 and 2013, respectively. The community "Vegetables and fruits" includes 68 products in 1993 and 57 products in 2013. It contributes with only 4% and 5% of total kilocalories, 3% and 2% of proteins, and 7% and 10% of fats, in 1993 and 2013, respectively. Finally, the smaller community of "Special livestock, oils and crops", includes 38 products in 1993 and 33 products in 2013, contributing with 19% and 7% of total kilocalories, 23% and 21% of proteins, and 18% and 10% of fats, in 1993 and 2013.

It is important to note that the differences in the contributions to total food production using the alternative measures are related with the composition of the communities in terms of products' characteristics. Not surprisingly, the community "Vegetables and fruits" has a lower contribution in all the measures considered compared to communities that include meat, dairy products, or oil crops. Although we can observe changes in the shares, overall, the communities are relatively stable in terms of quantity of products and contribution to food production, considering that we are comparing a period of twenty-one years.

The geographical distributions of agricultural production of these communities can be observed in Figure 5, where each map shows the production shares of countries' total production –in kilocalories– in each of the four detected communities of products for 1993 and 2013.[6]

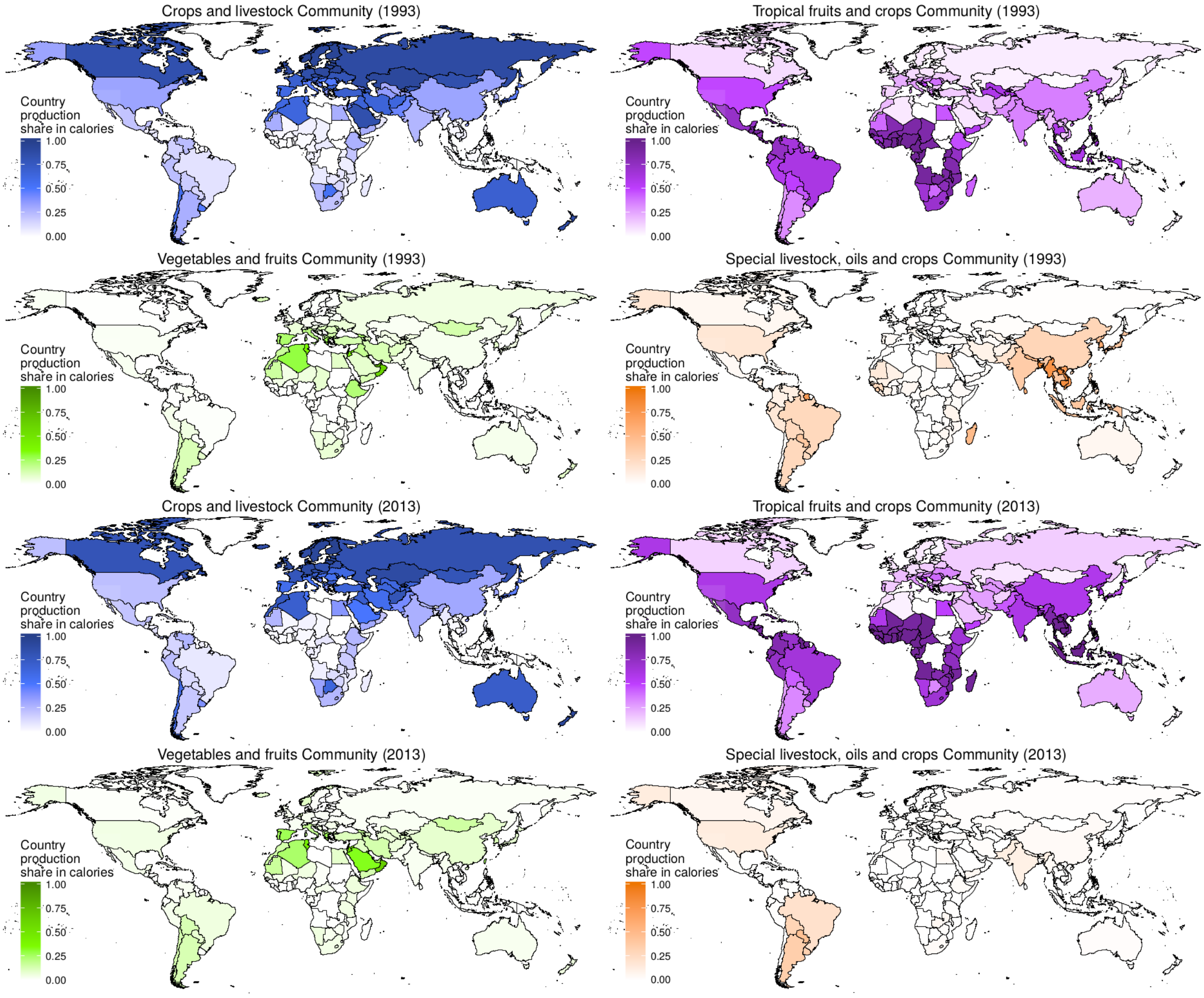

Figure 5: Countries' production shares in kilocalories in each community. 1993 and 2013. Colors represent communities as in the networks of Figure 1. Color intensity represents the share of a country's total production in the production of the community

Typically, most countries have higher shares in one specific community, i.e. they specialize in the production of closely related products within a community of products. Several countries concentrate almost all their production in one single community, in particular, in "Tropical fruits and crops" or in "Crops and livestock". For example, Malaysia and Ghana with 99%, and Indonesia and Swaziland with 98%, of their total production in the community of "Tropical fruits and crops" (in purple). Also, we observe countries with highly concentrated production shares in the community "Crops and livestock" (in green), such as Estonia with all its production in this community, Latvia and Ireland, with 99% of their total production in that community, and Finland, with 98%. In contrast, other countries appear to have more diversified production baskets, distributing

[6]The geographical distribution of food production measured in proteins and fats can be seen in Figures SI.3 and SI.4 of the Supplementary Information.

their production in products that belong to different communities, for example, Italy, Greece, Spain, and to a lesser extent, Argentina, and the United States.

We can also look at the contribution of the four detected communities of countries to world food production. This contribution can be observed in Table 5 for 1993 and 2013, measured in kilocalories, proteins, and fat content. We observe that production is more evenly distributed across the communities of countries, compared to what we observe in the communities of products.

Table 5: Production shares by community in total production, measured in kilocalories, proteins, and fat content. 1993 and 2013

Year		1993			
		Share			
Community	Countries	Population	Kilocalories	Proteins	Fats
Tempered	35	0.19	0.39	0.47	0.39
Subtropical	38	0.36	0.28	0.28	0.24
Tropical I	51	0.14	0.14	0.11	0.18
Tropical II	45	0.31	0.19	0.15	0.19
Year		2013			
		Share			
Community	Countries	Population	Kilocalories	Proteins	Fats
Tempered	37	0.18	0.34	0.43	0.32
Subtropical	37	0.34	0.25	0.25	0.21
Tropical I	58	0.19	0.25	0.17	0.36
Tropical II	37	0.29	0.16	0.15	0.12

However, the "Tempered" community clearly produces a higher share of food in all kilocalories, proteins, and fats. This community is followed by the "Subtropical", with some exceptions, depending on the year and measure considered. The "Tropical I" and "Tropical II" communities have lower shares of food production in most of the cases.

It is also interesting to note that the share of kilocalories, proteins, and fats produced by each community not necessarily correlates with the share of global population of each community. The "Tempered" community is the more unbalanced because, despite it has the lowest share in total population, it produces the highest shares in all the measures considered. The "Subtropical" community is the more balanced one. Instead, both "Tropical I" and "Tropical II" have more unbalanced food production shares compared to their population shares, in particular, the "Tropical II" community. These two communities mostly include developing countries, while the "Tempered" and "Subtropical" communities include mostly developed countries.

4 Discussion and concluding remarks

Studying the food system as a complex evolving network can provide relevant insights to characterize them and derive policy implications. In the last years, an increasing literature has focused on the way countries are interconnected in the food system through international-trade linkages and on the consequences that this may have in terms of food security and sustainability. Instead, little attention has been devoted to understanding how countries, given their capabilities, specialize in agricultural production, and what are the determinants of country specialization patterns.

Our main contribution lies in the analysis of the food system as an evolving complex network using production data for the period 1993 to 2013. We present the first analysis of the evolution of the food product space and the network of food producing countries, analyzing the emerging communities of products and countries, and we study its properties to understand how and why countries specialize in agricultural production given their capabilities.

We analyze countries' specialization patterns in agricultural production, considering their global competitiveness and the coherence of their production baskets in terms of required capabilities, using methodologies from network analysis and the theoretical framework that studies how capabilities are revealed in products and countries. We derive measures for the degree of relatedness between products, based on domestic production, which allows us to build the agricultural product space and the network of food producers countries.

We analyze the agricultural production space as a time-sequence of bipartite networks of agricultural products and countries, obtaining the product-product and country-country projected networks based on node similarity. This allows us to detect the structure of their communities, connecting countries to the agricultural commodities they produce, and we identify properties and determinants underlying their evolution.

We find that the agricultural product space is very dense, and that product relatedness depends on products' similar needs of natural conditions and other capabilities. Despite the high density of the network, we are able to detect that these products cluster in communities of very similar products.

Similarly, the network of countries is very dense but characterized by a small number of stable communities, which means that, given their capabilities, it is possible to consistently classify countries by their specialization patterns. We find that the probability that two countries belong to the same community depends not only on geographical conditions but also on other socio-political, institutional, technological, and economic factors.

Despite the unprecedented pressure that global food systems have been undergoing in recent years and the notably changes in terms of demand and dietary quality, we observe that the agricultural product space and the network of agricultural countries are very stable and display well-defined and stable communities over the period of twenty-one years.

Our findings have several implications for the understanding of the complex relationships involving production capabilities and specialization patterns of countries, the sustainability of systems, and the nutrition content of the domestic part of countries' food supplies.

The networks provide a picture of the specialization patterns of countries according to their production capabilities, where some countries are very specialized in one specific group of similar products (depicted by a specific community). Our analysis could help understanding whether certain specialization patterns and concentration of production could make countries more vulnerable to production shocks endangering their food security.

In addition, the communities of products are different in terms of kilocalories, proteins and fat content. Therefore, given their specialization patterns, some countries might be able to produce enough food in terms of a given measure but not in terms of others. A more detailed analysis of the nutrient content of products in the communities would provide an enhanced picture of the suitability of specialization patterns for the achievement of healthy diets for a country's population.

Food supply is also determined by the balance between exports and imports of food. Thus, our study would be improved by including the analysis of food international trade in order to have a more complete picture of food supply at the country level. The analysis of specialization patterns of food production already provides interesting insights related with the production side of food supply. For example, it implies that countries that are very specialized in one particular type of products would depend on exports to be able to provide a diverse and healthy diet for its population. In addition, this type of countries might have a higher probability of being affected by a trade or price shock.

Finally, this analysis has implications for the study of how sustainable are specialization patterns in terms of diets, biodiversity, and resilience; and might eventually contribute to policies seeking to achieve global food security and a more sustainable development of agriculture by providing inputs to understand specialization patterns of agricultural production and its dynamics.

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Supplementary Information

Table SI.1: List of countries and ISO codes

Country	ISO	Country	ISO	Country	ISO
Afghanistan	AFG	Gabon	GAB	Norway	NOR
Albania	ALB	Gambia	GMB	Oman	OMN
Algeria	DZA	Georgia	GEO	Pakistan	PAK
Angola	AGO	Germany	DEU	Panama	PAN
Antigua and Barbuda	ATG	Ghana	GHA	Paraguay	PRY
Argentina	ARG	Greece	GRC	Peru	PER
Armenia	ARM	Grenada	GRD	Philippines	PHL
Australia	AUS	Guatemala	GTM	Poland	POL
Austria	AUT	Guinea	GIN	Portugal	PRT
Azerbaijan	AZE	Guinea-Bissau	GNB	Rep. of Korea	KOR
Bahamas	BHS	Guyana	GUY	Rep. of Moldova	MDA
Bangladesh	BGD	Haiti	HTI	Romania	ROU
Barbados	BRB	Honduras	HND	Russian Federation	RUS
Belarus	BLR	Hungary	HUN	Rwanda	RWA
Belize	BLZ	Iceland	ISL	Saint Kitts and Nevis	KNA
Benin	BEN	India	IND	Saint Lucia	LCA
Bermuda	BMU	Indonesia	IDN	Saint Vincent and the Grenadines	VCT
Bolivia	BOL	Iran (Islamic Rep. of)	IRN	Samoa	WSM
Bosnia and Herzegovina	BIH	Iraq	IRQ	Sao Tome and Principe	STP
Botswana	BWA	Ireland	IRL	Saudi Arabia	SAU
Brazil	BRA	Israel	ISR	Senegal	SEN
Brunei Darussalam	BRN	Italy	ITA	Sierra Leone	SLE
Bulgaria	BGR	Jamaica	JAM	Slovakia	SVK
Burkina Faso	BFA	Japan	JPN	Slovenia	SVN
Cabo Verde	CPV	Jordan	JOR	Solomon Islands	SLB
Cambodia	KHM	Kazakhstan	KAZ	South Africa	ZAF
Cameroon	CMR	Kenya	KEN	Spain	ESP
Canada	CAN	Kiribati	KIR	Sri Lanka	LKA
Central African Rep.	CAF	Kuwait	KWT	Suriname	SUR
Chad	TCD	Kyrgyzstan	KGZ	Swaziland	SWZ
Chile	CHL	Lao People's Dem. Rep.	LAO	Sweden	SWE
China, Hong Kong SAR	HKG	Latvia	LVA	Switzerland	CHE
China, Macao SAR	MAC	Lebanon	LBN	Tajikistan	TJK
China, mainland	CHN	Lesotho	LSO	Thailand	THA
China, Taiwan Province of	TWN	Liberia	LBR	North Macedonia	MKD
Colombia	COL	Lithuania	LTU	Timor-Leste	TLS
Congo	COG	Madagascar	MDG	Togo	TGO
Costa Rica	CRI	Malawi	MWI	Trinidad and Tobago	TTO
Côte d'Ivoire	CIV	Malaysia	MYS	Tunisia	TUN
Croatia	HRV	Maldives	MDV	Turkey	TUR
Cuba	CUB	Mali	MLI	Turkmenistan	TKM
Cyprus	CYP	Malta	MLT	Uganda	UGA
Czechia	CZE	Mauritania	MRT	Ukraine	UKR
Dem. People's Rep. of Korea	PRK	Mauritius	MUS	United Arab Emirates	ARE
Denmark	DNK	Mexico	MEX	United Kingdom	GBR
Djibouti	DJI	Mongolia	MNG	United Rep. of Tanzania	TZA
Dominica	DMA	Morocco	MAR	United States of America	USA
Dominican Rep.	DOM	Mozambique	MOZ	Uruguay	URY
Ecuador	ECU	Myanmar	MMR	Uzbekistan	UZB
Egypt	EGY	Namibia	NAM	Vanuatu	VUT
El Salvador	SLV	Nepal	NPL	Venezuela (Bolivarian Rep. of)	VEN
Estonia	EST	Netherlands	NLD	Viet Nam	VNM
Ethiopia	ETH	New Caledonia	NCL	Yemen	YEM

Fiji	FJI	New Zealand	NZL	Zambia	ZMB
Finland	FIN	Nicaragua	NIC	Zimbabwe	ZWE
France	FRA	Niger	NER		
French Polynesia	PYF	Nigeria	NGA		

Table SI.2: List of agricultural products

Crops
Almonds, with shell; Anise, badian, fennel, coriander; Apples; Apricots; Artichokes; Asparagus; Avocados; Bambara beans; Bananas; Barley; Broad beans, horse beans, dry; Beans, dry; Beans, green; Berries nes; Blueberries; Brazil nuts, with shell; Buckwheat; Cabbages and other brassicas; Canary seed; Carobs; Carrots and turnips; Cashewapple; Cashew nuts, with shell; Cassava; Cassava leaves; Cauliflowers and broccoli; Cereals, nes; Cherries; Cherries, sour; Chestnut; Chick peas; Chicory roots; Chillies and peppers, green; Chillies and peppers, dry; Cinnamon (canella); Fruit, citrus nes; Cloves; Cocoa, beans; Coconuts; Coffee, green; Cottonseed; Cow peas, dry; Cranberries; Cucumbers and gherkins; Currants Dates; Eggplants (aubergines); Figs; Fonio; Fruit, fresh nes; Fruit, pome nes; Fruit, stone nes; Garlic; Ginger; Gooseberries; Grain, mixed; Grapefruit (inc. pomelos); Grapes; Groundnuts, with shell; Hazelnuts, with shell; Hempseed; Hops; Karite nuts (sheanuts); Kiwi fruit; Leeks, other alliaceous vegetables; Lemons and limes; Lentils; Lettuce and chicory; Linseed; Lupins; Maize; Maize, green; Mangoes, mangosteens, guavas; Mate; Melons, other (inc.cantaloupes); Melonseed; Millet; Mushrooms and truffles; Mustard seed; Nutmeg, mace and cardamoms; Areca nuts; Kola nuts; Nuts, nes; Oats; Oilseeds nes; Okra; Olives; Onions, dry; Onions, shallots, green; Oranges; Oil palm fruit; Palm kernels; Oil, palm; Papayas; Peaches and nectarines; Pears; Peas, dry; Peas, green; Pepper (piper spp.); Peppermint; Persimmons; Pigeon peas; Pineapples; Pistachios; Plantains and others; Plums and sloes; Poppy seed; Potatoes; Sweet potatoes; Pulses, nes; Pumpkins, squash and gourds; Quinces; Quinoa; Rapeseed; Raspberries; Rice, paddy; Roots and tubers, nes; Rye; Safflower seed; Sesame seed; Sorghum; Soybeans; Spices, nes; Spinach; Strawberries; String beans; Sugar beet; Sugar cane; Sugar crops, nes; Sunflower seed; Tangerines, mandarins, clementines, satsumas; Taro (cocoyam); Tea; Tomatoes; Triticale; Fruit, tropical fresh nes; Tung nuts; Vanilla; Vegetables, fresh nes; Vegetables, leguminous nes; Vetches; Walnuts, with shell; Watermelons; Wheat; Yams; Yautia (cocoyam)
Crops processed
Beer of barley; Oil, coconut (copra); Cottonseed; Oil, cottonseed; Oil, groundnut; Oil, linseed; Oil, maize; Margarine, short; Molasses; Oil, olive, virgin; Palm kernels; Oil, palm kernel; Oil, palm; Oil, rapeseed; Oil, safflower; Oil, sesame; Oil, soybean; Sugar Raw Centrifugal; Oil, sunflower; Wine
Livestock Primary
Meat, ass; Beeswax; Meat, bird nes; Meat, buffalo; Milk, whole fresh buffalo; Meat, other camelids; Milk, whole fresh camel; Meat, camel; Meat, cattle; Meat, chicken; Meat, duck; Eggs, hen, in shell; Eggs, other bird, in shell; Meat, game; Meat, goose and guinea fowl; Milk, whole fresh goat; Meat, goat; Honey, natural; Meat, horse; Meat, nes; Milk, whole fresh cow; Meat, mule; Offals, nes; Meat, pig; Meat, rabbit; Meat, other rodents; Meat, sheep; Milk, whole fresh sheep; Snails, not sea; Meat, turkey
Livestock Processed
Cheese, buffalo milk; Ghee, of buffalo milk; Butter, cow milk; Butter and Ghee; Cheese (All Kinds); Cheese, skimmed cow milk; Cheese, whole cow milk; Cream fresh; Ghee, butteroil of cow milk; Cheese of goat milk; Lard; Milk, skimmed cow; Evaporat & Condensed Milk; Milk, skimmed condensed; Milk, skimmed dried; Milk, skimmed evaporated; Milk, whole condensed; Milk, whole dried; Milk, whole evaporated; Cheese, sheep milk; Butter and ghee, sheep milk; Skim Milk & Buttermilk, dry; Whey, condensed; Whey, dry; Yoghurt

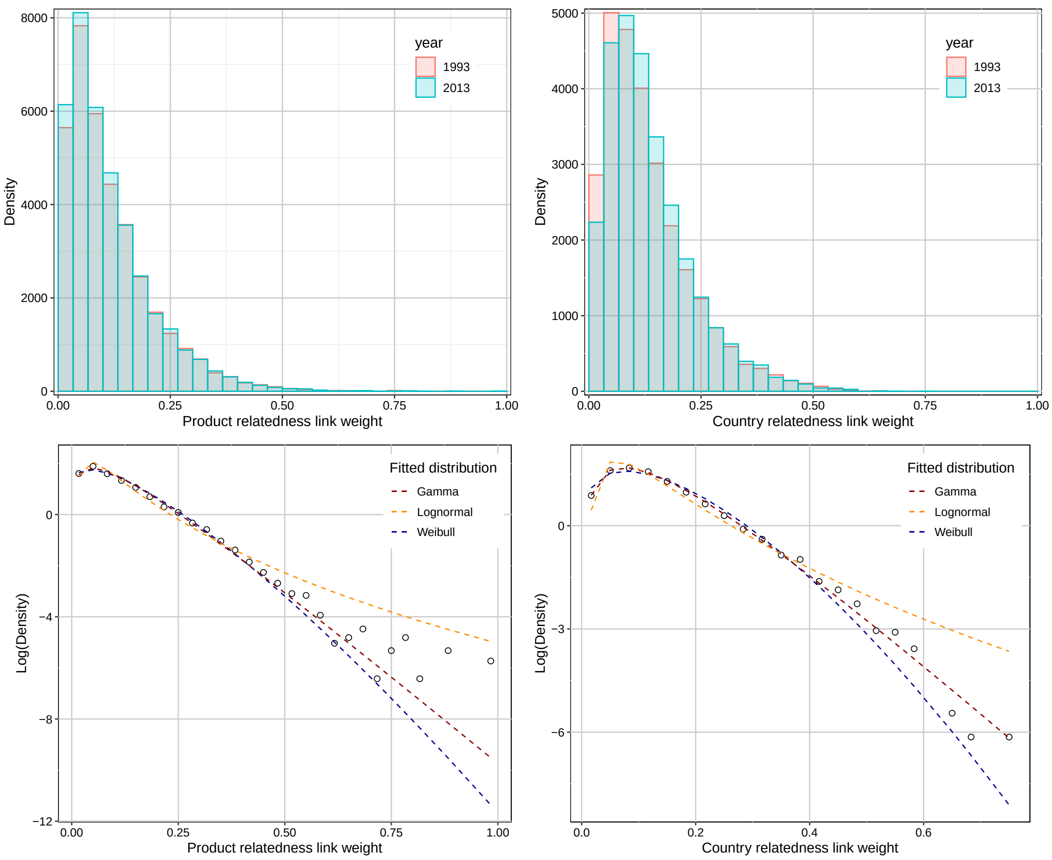

Figure SI.1: Products (left) and countries (right) link weight distribution (excluding zeros). Upper panel: Empirical distributions, 1993 and 2013. Lower panel: Fitted distributions, 2013

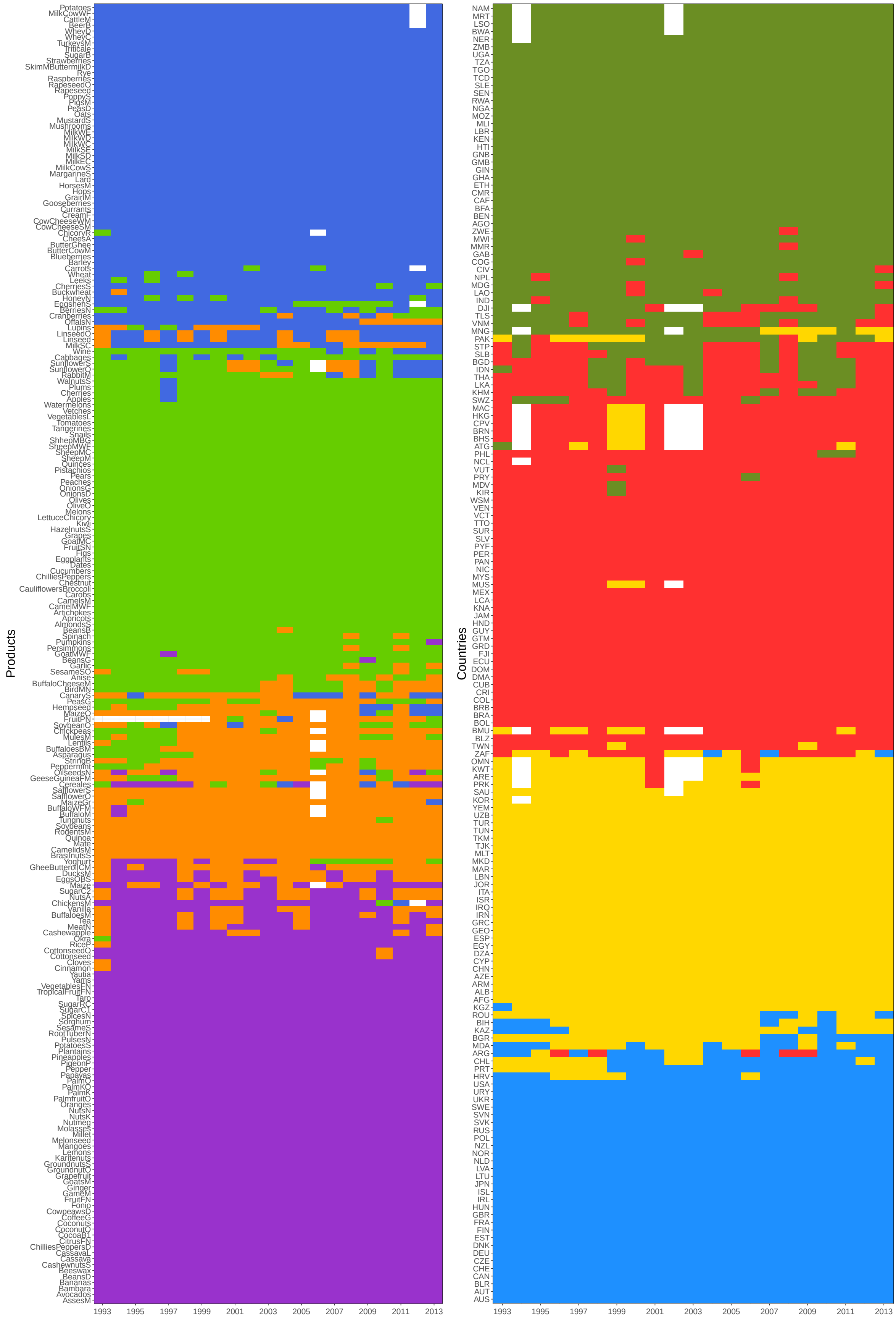

Figure SI.2: Composition of the communities in the agricultural product space and in the network of agricultural countries. 1993 to 2013. Colors represent communities as in the networks of Figures 1 and 2. White points appear when there is an additional community detected

Table SI.3: Variables used in the Logit estimations and sources

Name	Description	Source
Geographical distance	Geographical distance in km. between two countries (in ln)	BACI-CEPII*
Diff. in latitudes	Distance differences in countries' latitudes. It proxies differences in climate and agro-ecological zones (in ln)	BACI-CEPII*
Same region	Dummy that indicates if countries belong to the same geographical region: East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa	WDI**
Diff. in GDP per capita	Difference between the GDP per capita of a pair of countries (in ln)	Penn World Tables 9.0: Feenstra et al. (2015)
Diff. in human capital	Difference in the index of human capital (average years of schooling and the returns to education) of a pair of countries	Penn World Tables 9.0: Feenstra et al. (2015)
Diff. in political system	Difference in the level of democracy of a pair of countries	Systemic Peace: Polity IV***
Diff. in agricultural labor	Difference between the number of economically active adults in agriculture over agricultural land (in ln) of a pair of countries	ERS-USDA****
Diff. in agricultural machinery	Total stock of farm machinery over agricultural land (in ln) of a pair of countries	ERS-USDA****
Diff. in fertilizers consumption	Difference in fertilizers consumption (in metric tonnes of N, P2O5, and K2O) over agricultural land (in ln) of a pair of countries	ERS-USDA****
Diff. in irrigated land	Difference in the total area equipped for irrigation over agricultural land (in ln) of a pair of countries	ERS-USDA****

Notes: *www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=1, **databank.worldbank.org/source/world-development-indicators, ***www.systemicpeace.org/inscrdata.html, ****www.ers.usda.gov/data-products/international-agricultural-productivity (see, Fuglie (2012), for details on the methodology.). All differences are computed in absolute values

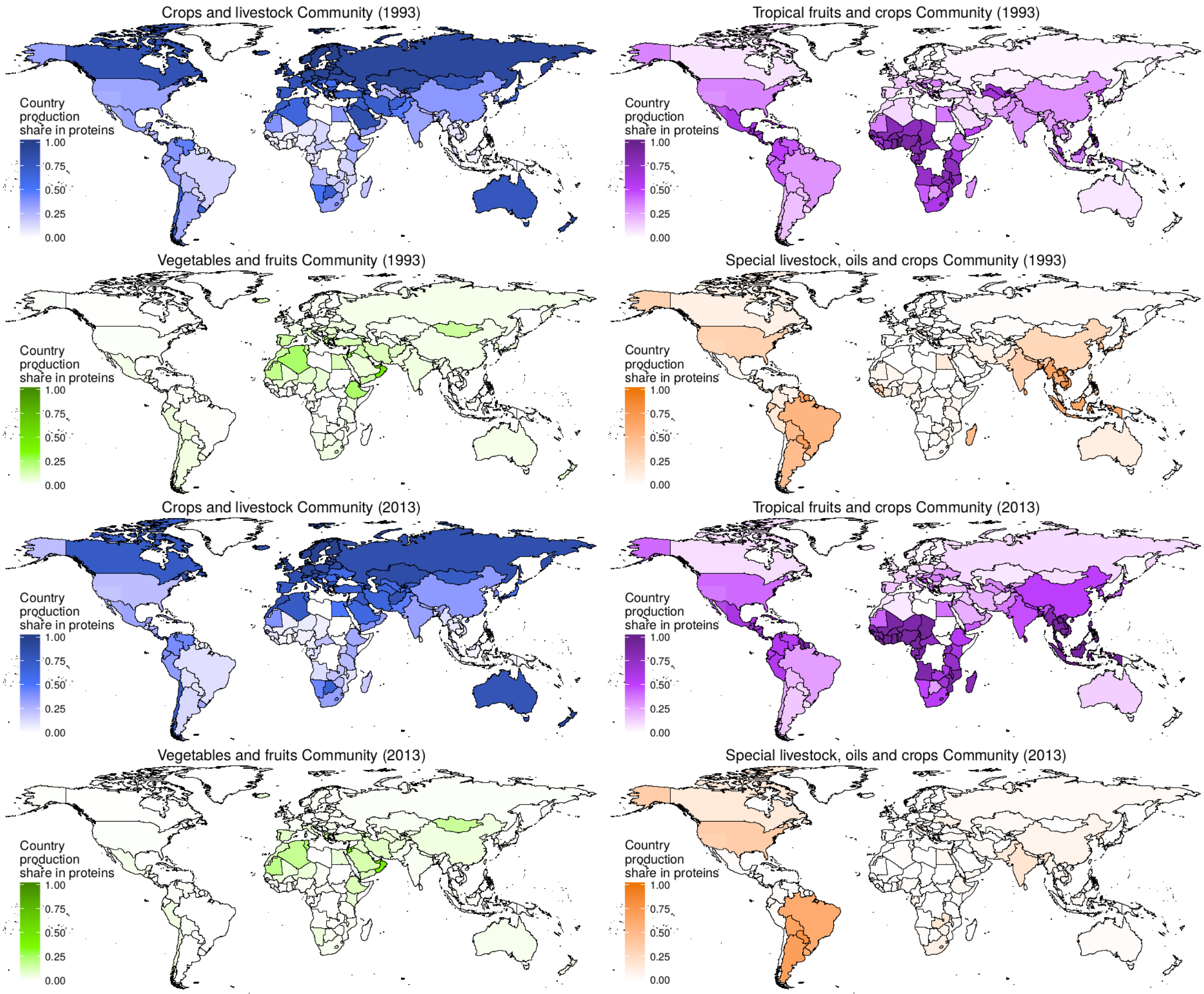

Figure SI.3: Production shares of countries in proteins in each community. 1993 and 2013. Colors represent communities as in the networks of Figure 1. Color intensity represents the share of a country's total production in the production of the community

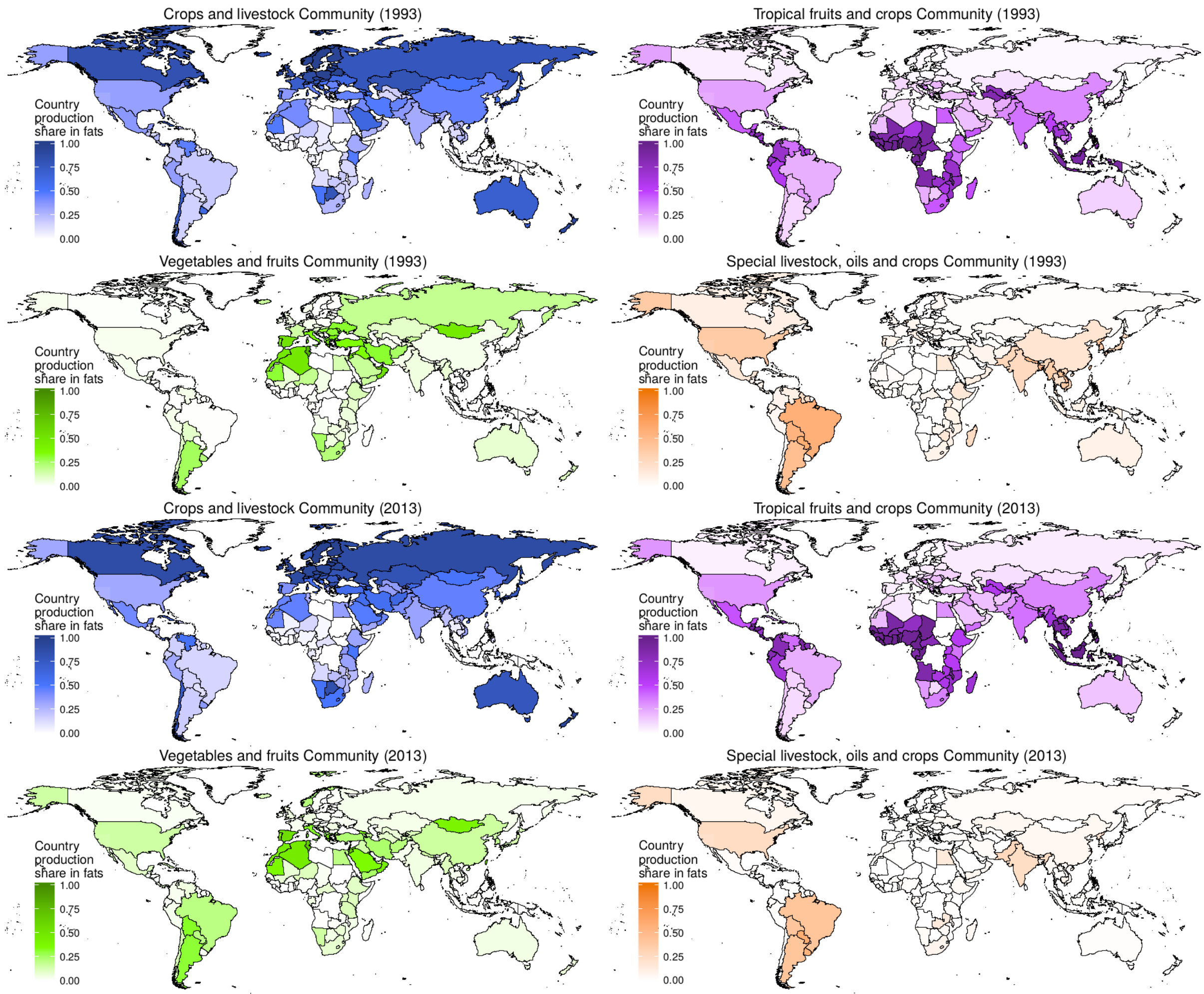

Figure SI.4: Production shares of countries in fats in each community. 1993 and 2013. Colors represent communities as in the networks of Figure 1. Color intensity represents the share of a country's total production in the production of the community