

Title: Global impacts of international food trade on biodiversity: Application of the telecoupling framework

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Presenter: Min Gon Chung

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Authors: Min Gon Chung, Jianguo (Jack) Liu

Affiliation:

Center for System Integration and Sustainability, Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI

International food trade is an important process that facilitates food supply and demand across the world ¹. Since food production is a basis for food trade but threatens biodiversity in many ways (e.g., conversion of wildlife habitat to cropland) ²⁻⁴, understanding food trade among countries with and without biodiversity hotspots is essential for uncovering the causes of biodiversity loss and for identifying responsible parties. Using a comprehensive dataset from 1992 to 2011, we found that biodiversity hotspot countries accounted for 87% of global food supply and approximately 76% of global food export while living 91% of world population in 82% of terrestrial land areas. The main drivers of food trade are total food production, per capita food production, and income level. The percentage of biodiversity hotspots is positively associated with food export while anthropogenic factors (the percentages of agricultural area and urban population) influence food import. Along with rapidly increasing food productivity and agricultural intensification in hotspot countries, agricultural activities for export in hotspot countries increase possible threats to species. The results suggest that non-hotspot countries share the responsibility of biodiversity loss and emissions of greenhouse gases from agriculture in biodiversity hotspot countries. New policies for the promotion of global incorporation, feedback embracement, the nurture of poor receiving countries, and food system enhancement in rich sending countries is needed to conserve biodiversity in the telecoupled world.

Global food production that is an important provisioning ecosystem service by providing the primary materials for livelihoods ⁵ can meet world food needs, but ineffective food distribution acts as a hurdle to improving global food security ⁶. With continued population growth ⁷ and income growth that is strongly associated with consumption ⁸, food trade is becoming an important telecoupling process that allows the world to meet increasing food demands ¹ while conserving biodiversity ⁹. The international food trade creates a balance between food supply and demand across regions ¹⁰ and is an insurance against natural disasters or political conflicts ¹¹. More countries depend on food import to meet their growing demands ¹¹⁻¹³, and it causes unpredictable environmental consequences in the world ²⁻⁴. Exported food products exert great pressures on land use ¹⁴, the possible threats to species ^{2,3,10}, and greenhouse gas emissions in agriculture ^{15,16}.

Understanding food trade among countries with and without biodiversity hotspots is essential for uncovering the causes of biodiversity loss and for identifying responsible parties. To clarify the role of biodiversity hotspots in the international food trade, we divided all countries into biodiversity hotspot and non-hotspot countries as two (hotspot and non-hotspot countries) and three coupled systems (high-hotspot, low-hotspot, and non-hotspot countries). We determined the complex interconnections between international food trade and biodiversity, using telecoupling framework (Supplementary Information).

Biodiversity hotspot countries produced six-fold more food than non-hotspot countries (Figure 1). In addition, because countries represented approximately 76% of global food export, they needed for global food supply and human livelihood. Hotspot countries accounted for 78% of CO₂ emissions by food transportation. Food export from hotspot countries accounted for 6% of total food production in non-hotspot countries. The population in hotspot countries was 10-fold higher than non-hotspot countries. At this time, the amounts of food export in hotspot countries increased 232% from 393 Mt in 1992 to 914 Mt in 2011 (Extended Data Figure 1). The amounts of food export from non-hotspot countries increased 221% from 135 Mt (accounting

for 26% of global food export) in 1992 to 299 Mt (25% of global food export) in 2011.

By using path analysis, total food production, per capita food production, and per capita GDP-PPP were the important factors for the international food trade (Extended Data Table 1). Food production is prerequisite for the international food trade. If food production in a country is extremely low, food export and import activities may be limited. When per capita food production increased in all countries, food import quantities tended to decrease. If per capita food production meets domestic human demands, food import may not be needed. In addition, per capita GDP-PPP was positively associated with food trade activities. Income level positively influences both per capita caloric and protein demands^{14,17}, and a high-income level is necessary to engage in land grabbing abroad in the globalization of food trade¹².

In the food export activities, the percentage of biodiversity hotspots was positively associated with food export quantities (Extended Data Table 1). Biodiversity hotspots, which have experienced the most deterioration of all natural habitats¹⁸, generally have the highest water provisioning¹⁹. Therefore, biodiversity hotspots have greater potential agricultural productivity than non-hotspot areas. Countries that have a high percentage of biodiversity hotspots can export more food because of high food productivity.

In the food import activities, anthropogenic determinants (the percentages of urban population and agricultural area) positively influenced food import quantities (Extended Data Table 1). Specifically, while food import quantities in non-hotspot countries were positively associated with the percentage of agricultural area, the percentage of urban population positively influenced food import quantities in hotspot countries (Extended Data Tables 2-3). This result showed that the main purpose of food import may differ between hotspot and non-hotspot countries. The percentage of urban population may represent human diet demands because urbanization and affluence from non-farm income lead to diet changes toward more consumption of meats, fats, and refined sugars²⁰. Additionally, countries that have a higher percentage of agricultural area may import more food from abroad. The percentage of agricultural area may represent the size of agricultural industries (e.g., for livestock feed, food processing, and industrial production). Particularly, high-income countries with a high percentage of agricultural area tend to have more food processing plants or agriculture-related companies than other countries with a low percentage of agricultural area. Therefore, hotspot countries may mainly import food for diet demands in urban areas, but non-hotspot countries may import food for livestock feed, food processed, and other industrial products.

At this time, importing hotspot countries shifted some parts of responsibility of deforestation and greenhouse gas emissions by agriculture to net exporting hotspot countries. In hotspot countries, while annual forest change rate was positively associated with food import quantities, greenhouse gas emissions by agriculture were negatively associated with food import quantities (Extended Data Table 2). Greenhouse gas emissions by agriculture could represent the size of agricultural activities. Some hotspot countries could not meet food demands themselves with the small agricultural size, and then they tended to import more food from abroad. Also, greenhouse gas emissions in developed countries were stabilized in part because of increasing imports from developing countries¹⁶. When forest areas in hotspot countries have increased from reforestation projects, they displace some demand for wood and agriculture productions to other countries¹². Land displacements were positively associated with deforestations in tropical hotspot countries¹³.

Along with the globalization of food trade, per agricultural area food production (food productivity) and agricultural intensifications in hotspot countries exceeded the uses in non-hotspot countries after the early 2000s (Figure 2). Because hotspot countries had biodiversity hotspots in terrestrial lands, higher food productivity and agricultural intensifications could severely deteriorate biodiversity and natural habitat. The number of threatened species in hotspot countries were positively associated with both food production and export (Extended Data Table 2), but the number of threatened species in non-hotspot countries were not significant with food production and export (Extended Data Table 3). This trend in non-hotspot countries led to insignificant relation between food export and the number of threatened species in all countries (Extended Data Table 1).

We summed the amounts of food products and exported from 1992 to 2011 to explain long-term effects of agricultural activities and food export on biodiversity²¹. Agricultural activities influence biodiversity and accumulate their negative impacts over time. While the number of threatened species in hotspot countries had a significantly positive association with food production and export, the number of threatened species in non-hotspot countries was not significant with food production and export (Figure 3). Although non-hotspot countries increased the amounts of food production and export, they did not significantly influence the number of threatened species.

The globalization of food trade may cause not only biodiversity loss in hotspot countries but also food insecurity in food importing countries. Food products for export were produced in approximately 20% of cropland in the world². The international food trade networks have increasingly become interconnected and vulnerable²², and importing countries depend on specific exporting countries, especially in hotspot countries²³. For example, seven countries (US, Germany, France, Netherlands, China, UK, and Italy) account for 30% of the total food trade. Therefore, if net exporting countries suffer national conflicts, change food export policy, or experience natural disasters, importing countries may suffer food shortage more often and lead to severe global food insecurity^{11,22}.

Table 1 showed consumers, producers, and traders in 2010. High-hotspot countries played a relatively important role for food export, and non-hotspot countries facilitated global food trade because of relatively high global food companies. Rapidly increased food consumptions may contribute to increase the number of farmers working for export in high-hotspot countries. Less than 1% of the workers produced food for export in low-hotspot countries, while 2.9% of the workers in high-hotspot countries produced food for export. In addition, although non-hotspot countries had lower consumers and producers than hotspot countries, they had 14 global food companies as traders.

New governance that considers the responsibilities of food exporting and importing countries with different environmental and socioeconomic determinants needs to conserve biodiversity in the telecoupled world. First, international initiatives and agreements are necessary to prevent biodiversity loss from food trade because biodiversity is distributed spatially heterogenous, aggregated in tropical hotspot countries²⁴. Second, developing countries that suffer rapid economy and population growth need to consider negative feedbacks. These countries have resolved the increasing food demand with food import abroad. This trend would decrease the capacity of domestic food production and exacerbate environment and biodiversity in food exporting hotspot countries. Third, the reduction of economic inequality among countries and within country helps to improve food distribution and security. Extreme

poor countries could not benefit from the globalized food networks because they import small amounts of food from a few countries. The international food trade would increasingly concentrate on among developed countries ²³.

In short, the international food trade is a complicated telecoupling process that interconnects with environmental and socioeconomic determinants. System integration requires to identify the interconnections and resolve sustainability problems in a telecoupled world.

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Tables

Table 1 Consumer, Producers, and Traders for Food in the three systems (high-hotspot countries (HHC), low-hotspot countries (LHC), and non-hotspot countries (NHC) in 2010. Data are from FAOSTAT (2014) and IMAP (2010).

	HC	HHC	LHC	NHC
Consumers*	6,188,854,484	1,445,850,777	4,743,003,707	607,144,055
Rural Population	3,088,604,083	660,913,643	2,427,690,440	201,081,388
Rural Population (%)	50%	46%	51%	33%
Workers in Agriculture Sectors**	1,258,942,000	245,171,000	1,013,771,000	46,714,000
Workers for Food Exports	16,034,540	7,089,025	8,945,515	1,188,226
Top 50 Global Food Companies	36	12	24	14

* Total population

** Economically active population in agriculture sectors

Figures

Figure 1 Food export flows and CO₂ emissions during international food transportations between hotspot and non-hotspot countries from 1992-2011; Hotspot countries had the higher amounts of food production and export than non-hotspot countries. While hotspot countries emitted high CO₂ for the international food trade, non-hotspot countries also emitted high CO₂ with inefficient food transportation. Raw data from FAOSTAT (2014) and Cristea et al. (2013).

Figure 2 Food productivity and per agricultural area agricultural intensifications in hotspot and non-hotspot countries; (A) Food productivity (ton/km²); food productivity in hotspot countries exceeded non-hotspot countries in 2000. **(B) Fertilizer use (ton/km²);** per agricultural area fertilizer uses in hotspot countries exceeded the use in non-hotspot countries in 1993. **(C) Pesticide use (ton/km²);** per agriculture area pesticide uses exceeded non-hotspot countries in 2005. **(D) Greenhouse gas emissions by agriculture (kg/km²);** greenhouse gas emissions by agriculture in hotspot countries exceeded non-hotspot countries in 1999. **(E) Agricultural water withdrawals (m³/km²);** Hotspot countries used six-fold more agricultural water withdrawals for irrigation and livestock than non-hotspot countries. Raw data from FAOSTAT (2014), The World Bank (2014), and WRI (2014).

Figure 3 The relations of food production and export on the number of threatened species from 1992-2011; (A) The relations between food production and the number of threatened species; While non-hotspot countries with higher food production did not significantly increase the number of threatened species, food export in hotspot countries rapidly increased the number of threatened species, particularly in the low amounts of food production. **(B) The relations between food export and the number of threatened species;** Whereas food export in non-hotspot countries was insignificant with the number of threatened species, food export in hotspot countries rapidly increased the number of threatened species, particularly in the low amounts of food export. Raw data from FAOSTAT (2014) and IUCN (2014).

Fig 1

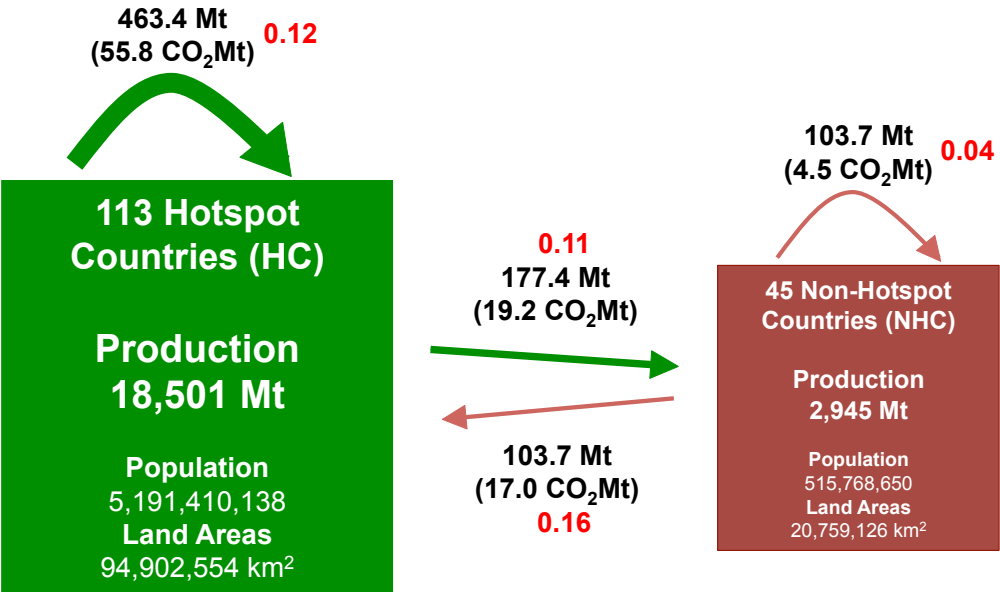


Fig 2

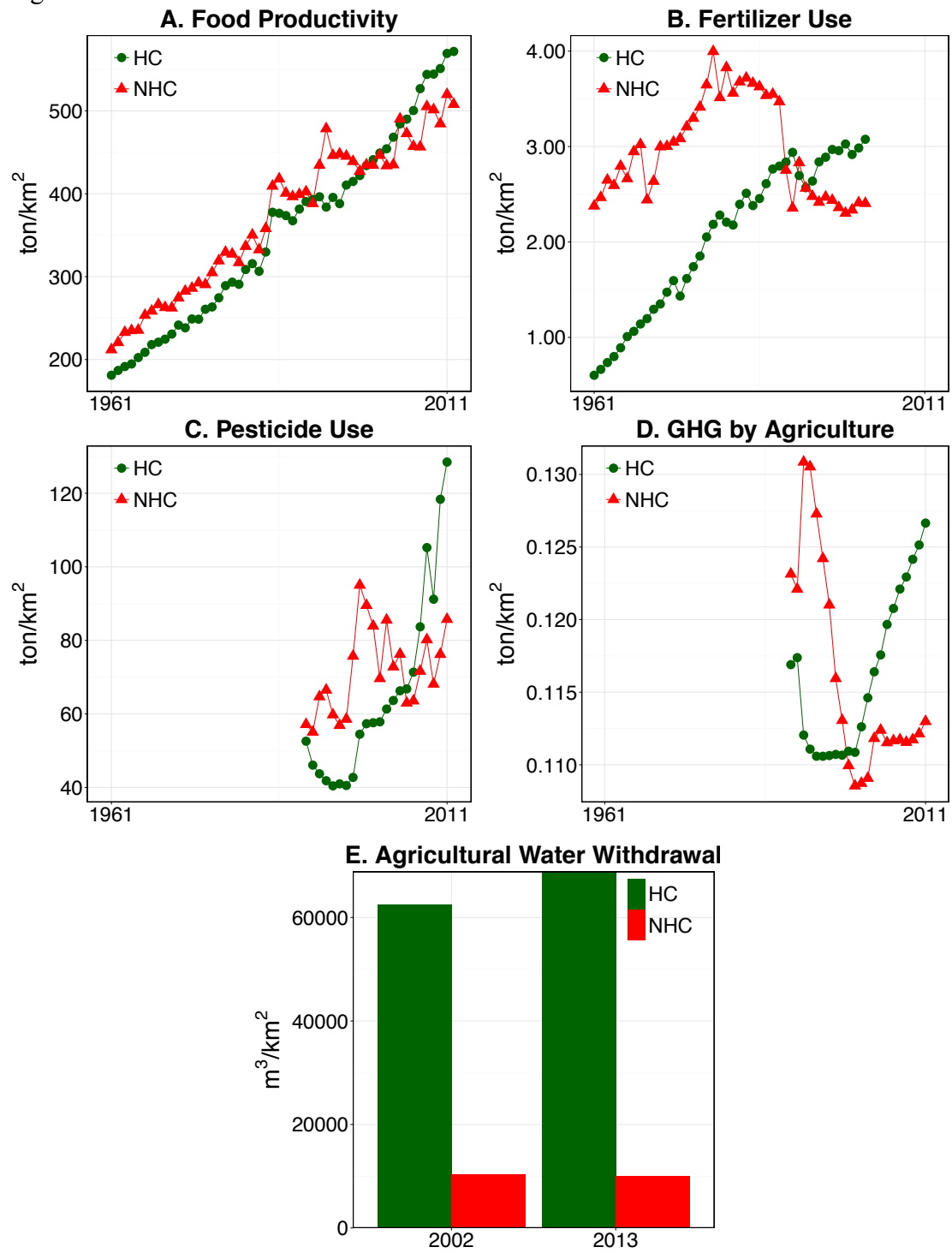
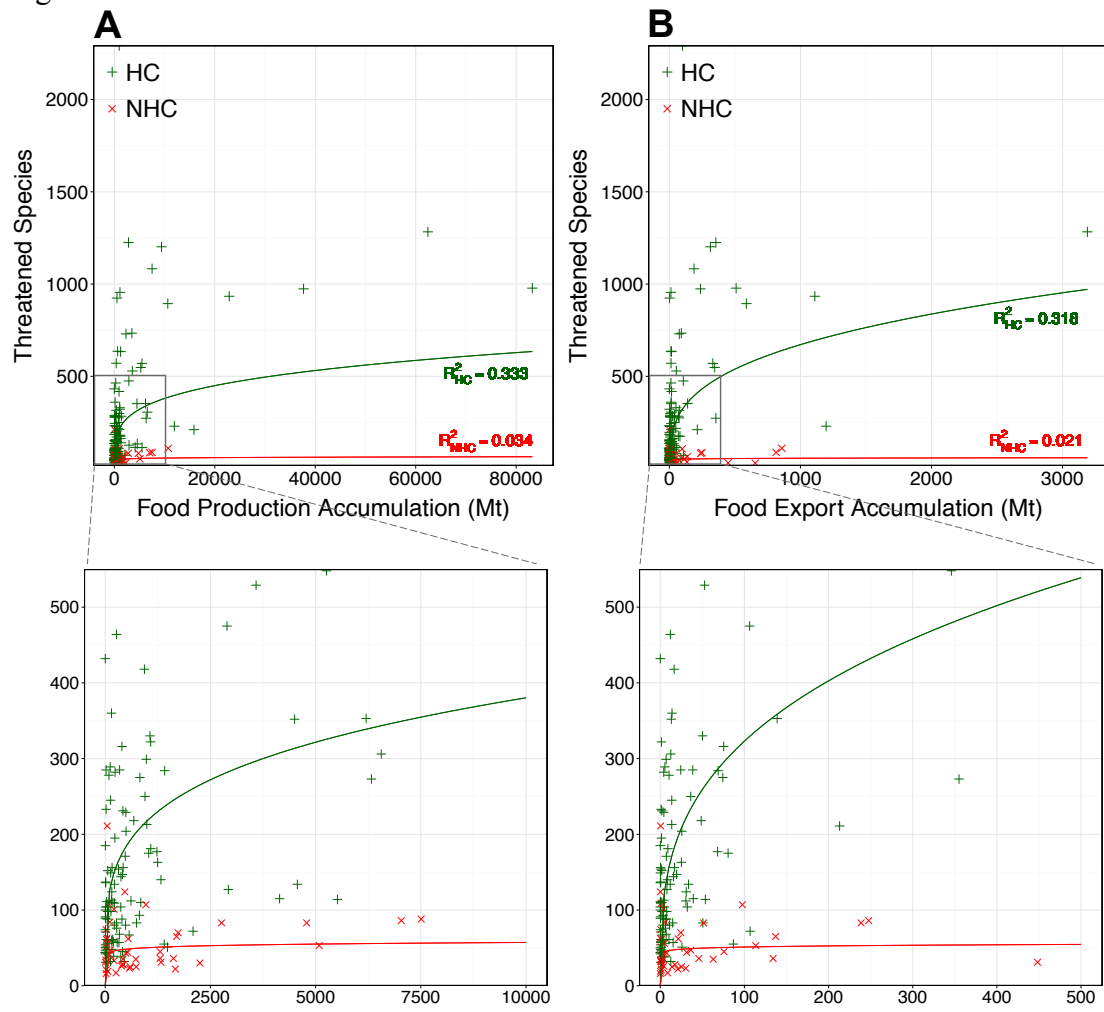


Fig 3



Extended Data Table 1. Results of path analysis for food export, import, and biodiversity in all countries with available data from 1992 to 2011. Raw data from FAOSTAT (2014), The World Bank (2014), WDPA (2014), WRI (2014), IUCN (2014), Myers et al. (2000), and Mittermeier and Cemex (2004).

Path analysis	Unstandardized coefficient (S.E.)		Standardized coefficient
Dependent variable: Food Export			
Food Production	0.915**	(0.091)	0.828**
Food production per capita	0.657*	(0.192)	0.156*
% of agriculture areas	0.088	(0.113)	0.029
GDP-PPP per capita (constant)	0.355*	(0.111)	0.178*
% of Urban population	0.120	(0.235)	0.025
Forest change rate	0.520	(0.406)	0.045
% of protected area	0.194	(0.099)	0.069
GHG emission in agriculture	-0.171	(0.124)	-0.105
% of biodiversity hotspots	0.105*	(0.043)	0.081*
Dependent variable: Food Import			
Food Production	0.939**	(0.045)	1.122**
Food production per capita	-1.382**	(0.096)	-0.434**
% of agriculture areas	0.148*	(0.057)	0.064*
GDP-PPP per capita (constant)	0.714**	(0.054)	0.473**
% of Urban population	0.381*	(0.115)	0.105*
Forest change rate	0.339	(0.199)	0.039
% of protected area	-0.060	(0.049)	-0.028
GHG emission in agriculture	-0.211*	(0.063)	-0.170*
% of biodiversity hotspots	0.051	(0.029)	0.052
Dependent variable: Number of threatened species			
Food Production	0.146*	(0.061)	0.315*
Food Export	0.055	(0.056)	0.132
Tests of model fit			
Chi-Square/degrees of freedom			144.005**/9
Comparative Fit Index (CFI)			0.848
Tucker-Lewis Index (TLI)			0.492

Values in parentheses are standard errors.

All variables are log transformation variables.

** p<0.001, * p<0.05

Extended Data Table 2. Results of path analysis for food export, import, and biodiversity in hotspot countries from 1992-2011. Raw data from FAOSTAT (2014), The World Bank (2014), WDPA (2014), WRI (2014), IUCN (2014), Myers et al. (2000), and Mittermeier and Cemex (2004).

Path analysis	Unstandardized coefficient (S.E.)		Standardized coefficient
Dependent variable: Food Export			
Food Production	0.802**	(0.103)	0.772**
Food production per capita	0.989**	(0.233)	0.209**
% of agriculture areas	-0.027	(0.137)	-0.009
GDP-PPP per capita (constant)	0.218	(0.134)	0.101
% of Urban population	0.345	(0.272)	0.071
Forest change rate	0.516	(0.421)	0.049
% of protected area	0.121	(0.109)	0.045
GHG emission in agriculture	-0.028	(0.144)	-0.018
% of biodiversity hotspots	0.117	(0.080)	0.058
Dependent variable: Food Import			
Food Production	0.964**	(0.046)	1.192**
Food production per capita	-1.487**	(0.104)	-0.403**
% of agriculture areas	0.108	(0.064)	0.044
GDP-PPP per capita (constant)	0.642**	(0.060)	0.382**
% of Urban population	0.505**	(0.121)	0.134**
Forest change rate	0.500*	(0.189)	0.061*
% of protected area	-0.043	(0.049)	-0.021
GHG emission in agriculture	-0.258**	(0.067)	-0.217**
% of biodiversity hotspots	0.086*	(0.040)	0.055*
Dependent variable: Number of threatened species			
Food Production	0.136*	(0.058)	0.332*
Food Export	0.110*	(0.056)	0.281*
Tests of model fit			
Chi-Square/degrees of freedom	56.617**/9		
Comparative Fit Index (CFI)	0.927		
Tucker-Lewis Index (TLI)	0.758		

Values in parentheses are standard errors.

All variables are log transformation variables.

** p<0.001, * p<0.05

Extended Data Table 3. Results of path analysis for food export, import, and biodiversity in non-hotspot countries from 1992-2011. Raw data from FAOSTAT (2014), The World Bank (2014), WDPA (2014), WRI (2014), IUCN (2014), Myers et al. (2000), and Mittermeier and Cemex (2004).

Path analysis	Unstandardized coefficient (S.E.)		Standardized coefficient
Dependent variable: Food Export			
Food Production	1.384**	(0.239)	1.034**
Food production per capita	-0.244	(0.413)	-0.069
% of agriculture areas	0.142	(0.199)	0.051
GDP-PPP per capita (constant)	0.375	(0.208)	0.203
% of Urban population	-0.082	(0.455)	-0.016
Forest change rate	0.805	(1.287)	0.049
% of protected area	0.312	(0.219)	0.094
GHG emission in agriculture	-0.638*	(0.262)	-0.303*
% of biodiversity hotspots			
Dependent variable: Food Import			
Food Production	0.725**	(0.126)	0.776**
Food production per capita	-0.967**	(0.226)	-0.391**
% of agriculture areas	0.349*	(0.105)	0.179*
GDP-PPP per capita (constant)	1.012**	(0.109)	0.787**
% of Urban population	0.005	(0.239)	-0.001
Forest change rate	-1.028	(0.675)	-0.089
% of protected area	-0.252*	(0.116)	-0.109*
GHG emission in agriculture	0.078	(0.137)	0.053
% of biodiversity hotspots			
Dependent variable: Number of threatened species			
Food Production	0.053	(0.084)	0.175
Food Export	0.002	(0.064)	0.009
Tests of model fit			
Chi-Square/degrees of freedom			18.794*/8
Comparative Fit Index (CFI)			0.944
Tucker-Lewis Index (TLI)			0.809

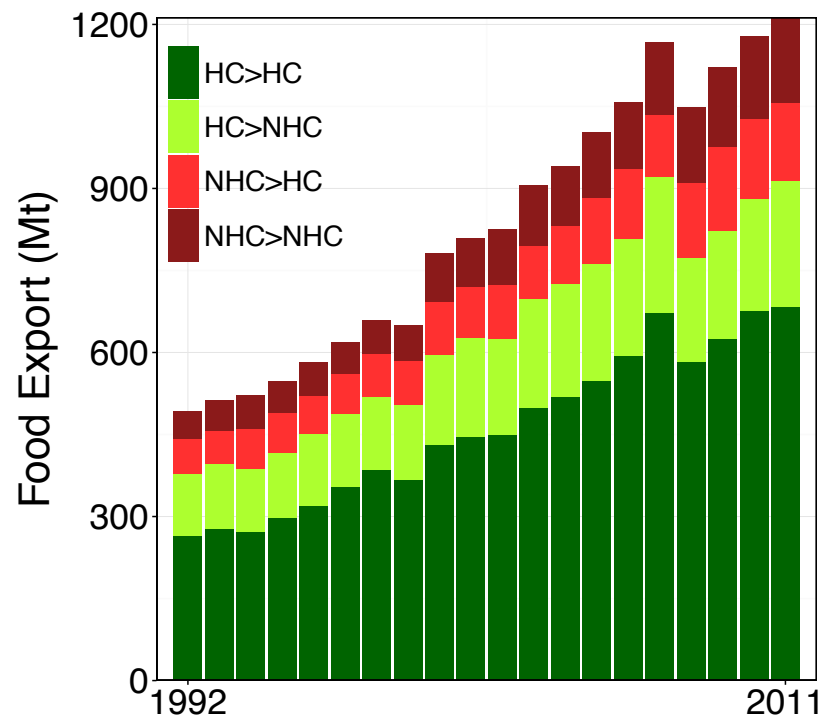
Values in parentheses are standard errors.

All variables are log transformation variables.

** p<0.001, * p<0.05

Extended Data Figure 1 Food export flows between hotspot and non-hotspot countries over the period 1992-2011; Food export flows had 114 hotspot countries and 45 non-hotspot countries. Hotspot countries produced 6 times more food than non-hotspot countries.

77% of global food exports came from hotspot countries, and the food export volumes from hotspot countries to non-hotspot countries were twice more than the latter to the former. The food exports of hotspot countries accounted for 8.4% of food productions in non-hotspot countries. Raw data from FAOSTAT (2014).



SUPPLEMENTARY INFORMATION

Global Impacts of International Food Trade on Biodiversity

Min Gon Chung and Jianguo Liu

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1. Supplementary Methods

1.1. System

Each country is treated as a coupled human and natural system. We divided all countries into hotspot countries (HC) and non-hotspot countries (NHC) as “Systems” in the telecoupling framework²⁵, which are listed in Supplementary Table S1. The telecoupling framework effectively ties multiple coupled human and natural systems over the long distances together, identifying flows, agents, causes, and effects in the coupled systems²⁵. The framework helps to understand socioeconomic and environmental interactions at a global level²⁶. Furthermore, because hotspot countries vary substantially in terms of hotspot areas, we divided hotspot countries into high-hotspot countries (HHC) in which biodiversity hotspot areas occupied more than 50% of terrestrial lands and low-hotspot countries (LHC) in which hotspot areas occupied less than 50% of terrestrial lands. Among low-hotspot countries, 79% had less than 30% of land areas as hotspot areas, and 78% of high-hotspot countries have biodiversity hotspot areas above 90% of land areas (Figure S1).

While the total number of hotspot countries was 135 (76 high-hotspot countries and 59 low-hotspot countries), there were 50 non-hotspot countries (Table S1 and Figure S2). Per capita GDP-PPP (Purchasing Power Parity) of non-hotspot countries in 2011 constant USD (\$27,206 in 2011) was twice as high as that of hotspot countries (\$12,605 in 2011). The proportion of urban population in hotspot countries had increased from 31% in 1961 to 51% in 2011 while the urban population in non-hotspot countries had increased from 55% in 1961 to 67% in 2011. After the early 1990s, the urbanization rate had stabilized in non-hotspot countries, but not in hotspot countries. The urban population in non-hotspot countries increased by 18% from 1992 to 2011, while the urban population in hotspot countries increased 59%. In 2011, the percentage of agricultural areas to total terrestrial land areas in hotspot countries (40%) was higher than in non-hotspot countries (27%). Total agricultural area in hotspot countries (41.23 million km²) was 6.4 times higher than in non-hotspot countries (6.44 million km²) in 2011.

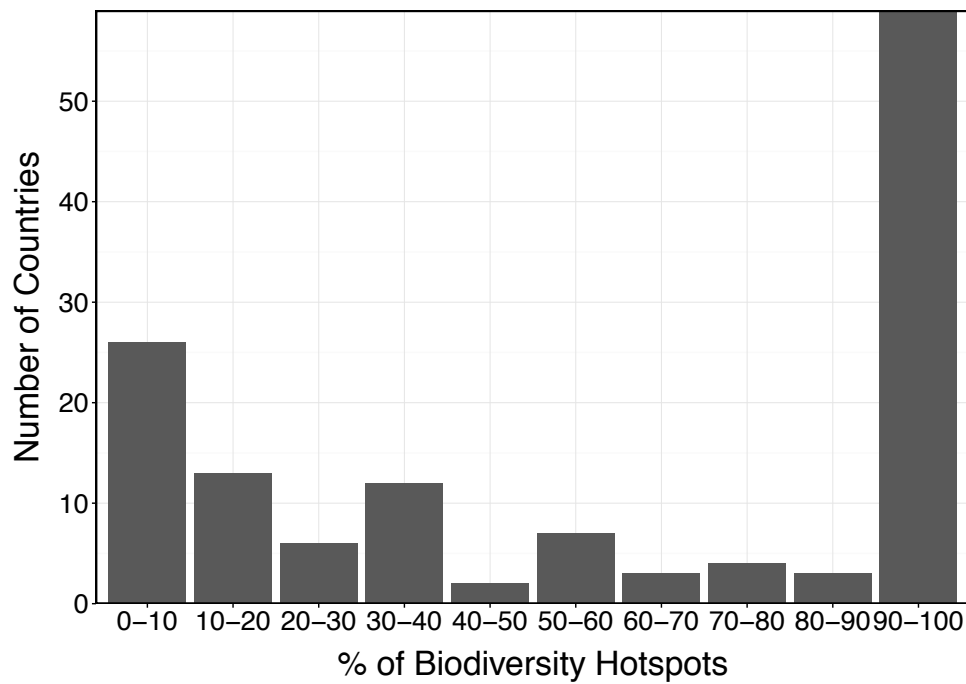


Figure S1 The number of countries with the percentage of biodiversity hotspot areas to terrestrial land areas. Raw data from Myers et al. (2000), and Mittermeier and Cemex (2004).

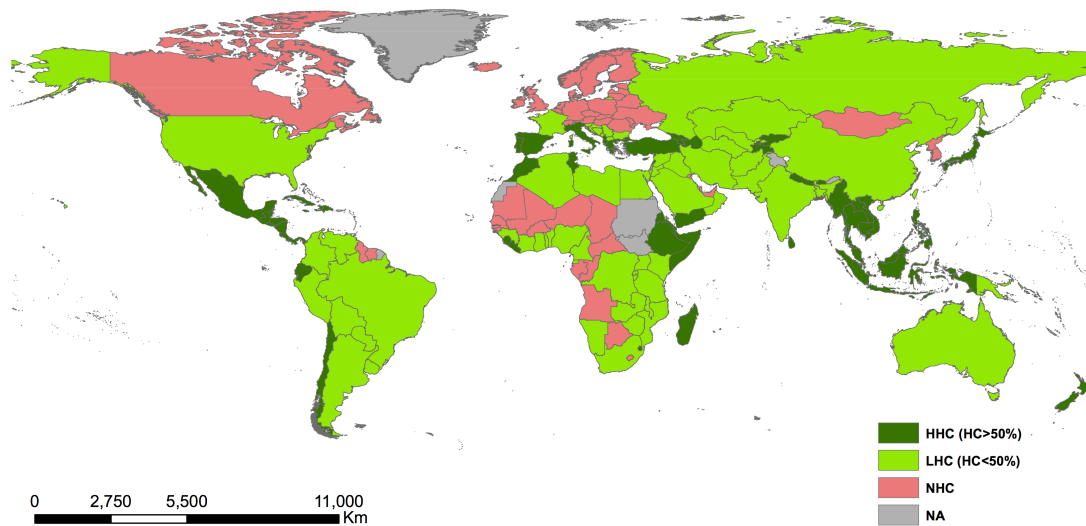


Figure S2 Hotspot and non-hotspot countries in the world; The number of hotspot countries was 136, and non-hotspot countries were 49. Two groups were coupled human and natural systems in telecoupling framework. Using the spatial data of biodiversity hotspots, when they had hotspots within their country boundaries, we classified countries into hotspot countries. Raw data from Myers et al. (2000), and Mittermeier and Cemex (2004).

Table S1. List of Hotspot and Non-hotspot Countries

High-hotspot Countries (HHC), N=76
Albania, Antigua and Barbuda, Armenia, Azerbaijan, Bahamas, Barbados, Belize, Bhutan, Brunei Darussalam, Cambodia, Cabo Verde, Chile, Comoros, Cook Islands , Costa Rica, Cuba, Cyprus, Djibouti , Dominica, Dominican Republic , Ecuador, El Salvador, Eritrea , Ethiopia, Fiji, Georgia, Greece, Grenada, Guatemala, Haiti , Honduras, Indonesia, Italy, Jamaica, Japan, Kyrgyzstan, Lao People's Democratic Republic , Lebanon, Liberia , Madagascar, Malaysia, Malta, Mauritius, Mexico, Morocco, Myanmar , Nepal, New Zealand, Nicaragua, Niue , Panama, Philippines, Portugal, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Samoa , Sao Tome and Principe, Seychelles, Sierra Leone , Singapore, Solomon Islands, Somalia , Spain, Sri Lanka, Swaziland, Tajikistan , Thailand, Timor-Leste , Tonga, Tunisia, Turkey, Tuvalu , Vanuatu, Viet Nam , Yemen
Low-hotspot Countries (LHC), N=59
Afghanistan, Algeria, <u>Argentina</u> , Australia, Bangladesh, Benin, Bolivia (Plurinational State of), Bosnia and Herzegovina, Brazil, Bulgaria, Burundi, Cameroon, China, Colombia , Croatia, Cote d'Ivoire, Democratic Republic of the Congo , Egypt, Equatorial Guinea , France, Ghana, Guinea, India, Iran (Islamic Republic of), Iraq , Israel, <u>Jordan</u> , Kazakhstan, Kenya , Kiribati, Libya , Malawi, <u>Montenegro</u> , Mozambique , Namibia, Nigeria, Oman, Pakistan, Papua New Guinea, Paraguay, Peru, Russian Federation, Rwanda, Saudi Arabia, <u>Serbia</u> , Slovenia, South Africa, <u>Syrian Arab Republic</u> , The former Yugoslav Republic of Macedonia, Togo, Turkmenistan , Uganda, United Republic of Tanzania, United States of America, Uruguay, Uzbekistan , Venezuela (Bolivarian Republic of), Zambia, Zimbabwe
Non-hotspot Countries (NHC), N=50
Angola , Austria, Bahrain, Belarus, Belgium, Botswana, Burkina Faso, Canada, Central African Republic, Chad , Congo, Czech Republic, Democratic People's Republic of Korea , Denmark, Estonia, Finland, Gabon, Gambia, Germany, Guinea-Bissau , Guyana, Hungary, Iceland, Ireland, Kuwait, Latvia, Lesotho , Lithuania, Luxembourg, <u>Maldives</u> , Mali, Mauritania, Mongolia, Netherlands, Niger, Norway, Poland, Qatar, Republic of Korea, Republic of Moldova, Romania, Senegal, Slovakia, Suriname, Sweden, Switzerland, Trinidad and Tobago, United Kingdom, Ukraine, United Arab Emirates

* Countries in bold did not have data for food trade dynamics (HHC=15, LHC=9, NHC=5).

** Countries in underline did not have data for path analysis and multiple regression analysis (HHC=7, LHC=5, NHC=3).

1.2. Data

Data were obtained from the UN FAO, the UN Data, the World Bank, and the World Resource Institute ²⁷⁻³⁰. The dataset composed 185 countries over the period 1961-2011. The dataset consisted of agriculture, environmental, and socioeconomic data. Agricultural data were obtained from the UN FAO ³⁰ and included food production, food trade, food trade balance, agricultural intensification, and agricultural water withdrawals data. We used agricultural commodities that had FAO item codes and classified them into crop primary, crop processed, livestock primary, livestock processed, and others, excluding aggregation item codes from # 1890 to # 2077 (Table S2). From 1961 to 2011, there were no significant within-year differences between total export and import quantities at the global level: within-each year quantities were almost equal.

The basic food trade unit in this research was the physical quantity (ton) of food produced, imported, and exported. The physical unit dataset reflects a global trend more reliable than a monetary dataset (US \$), because the number of countries in the quantity (ton) dataset was much higher (n=185) than in the monetary (dollar) dataset (n=154) and because the monetary value varied with price fluctuations. Indeed, since the purpose of this study was to assess the role of biodiversity hotspots in the international food trade, using the volume of food trade is appropriate for showing the extend to which the food trade is linked with agricultural areas and associated with coupled human and natural systems. The use of monetary value may bias the results. High-value commodities using small agricultural areas can overestimate ecological impacts more than low-value commodities using large agricultural areas. For example, 47% of global oil palm plantation areas used for exports, but they were a small proportion of total food export value ³¹. Several organizations provided environmental data: greenhouse gas emissions ²⁷, terrestrial protected areas ²⁹, and land use data ²⁸. Socioeconomic data such as population and per capita GDP-PPP came from the World Bank ²⁸. We also used published spatial data for identifying hotspot countries and measuring the proportion of biodiversity hotspots to protected areas. Hotspot countries were identified according to Conservation International (CI) ^{32,33}. Information on protected area locations came from the World Database on Protected Areas (WDPA) ³⁴.

Table S2. List of FAO Food Items. Data from FAOSTAT (2014).

Crop (192)
Alfalfa meal and pellets, Almonds shelled, Anise badian fennel coriander, Apples, Apricots, Apricots dry, Artichokes, Asparagus, Avocados, Bambara beans, Bananas, Barley, Barley pearled, Beans dry, Beans green, Blueberries, Bran buckwheat, Bran fonio, Bran maize, Bran millet, Bran rice, Bran sorghum, Bran wheat, Brazil nuts shelled, Broad beans horse beans dry, Buckwheat, Bulgur, Cabbages and other brassicas, Canary seed, Cane tops, Carrots and turnips, Cashew nuts shelled, Cashew nuts with shell, Cashewapple, Cassava, Cassava dried, Cauliflowers and broccoli, Cherries, Cherries sour, Chestnut, Chick peas, Chillies and peppers dry, Chillies and peppers green, Cinnamon (canella), Cloves, Cocoa beans, Coconuts, Coconuts desiccated, Cocoons unreelable & waste, Coffee green, Coffee husks and skins, Coffee roasted, Coffee substitutes containing coffee, Copra, Cotton lint, Cotton linter, Cotton waste, Cottonseed, Cranberries, Cucumbers and gherkins, Currants, Dates, Eggplants (aubergines), Figs, Figs dried, Flax fibre and tow, Flax fibre raw, Flax tow waste, Flour cereals, Flour fonio, Flour maize, Flour mixed grain, Flour mustard, Flour potatoes, Flour pulses, Flour roots and tubers nes, Flour wheat, Fonio, Forage and silage clover, Forage and silage grasses nes, Forage and silage legumes, Fruit dried nes, Fruit fresh nes, Fruit tropical fresh nes, Garlic, Germ maize, Ginger, Gooseberries, Grain mixed, Grapefruit (inc. pomelos), Grapes, Groundnuts shelled, Hay (clover lucerneetc), Hay (unspecified), Hazelnuts shelled, Hops, Jute, Kapok fibre, Kapokseed in shell, Kapokseed shelled, Kiwi fruit, Kola nuts, Leeks other alliaceous vegetables, Lemons and limes, Lentils, Lettuce and chicory, Linseed, Maize, Maize green, Malt, Mangoes mangosteens guavas, Manila fibre (abaca), Mat, Melons other (inc.cantaloupes), Millet, Mushrooms and truffles, Mustard seed, Nutmeg mace and cardamoms, Nuts nes, Nuts prepared (exc. groundnuts), Oats, Oats rolled, Oil palm, Oilseeds nes, Olives, Olives preserved, Onions dry, Onions shallots green, Oranges, Papayas, Peaches and nectarines, Pears, Peas dry, Peas green, Pepper (piper spp.), Peppermint, Persimmons, Pineapples, Pistachios, Plantains, Plums and sloes, Plums dried (prunes), Popcorn, Poppy seed, Potatoes, Potatoes frozen, Pumpkins squash and gourds, Pyrethrum dried, Quinces, Raisins, Rapeseed, Rice _ total (Rice milled equivalent), Rice husked, Rice paddy, Roots and tubers nes, Rubber natural dry, Rubber natural, Rye, Sesame seed, Sorghum, Soybeans, Spices nes, Spinach, Straw husks, Strawberries, Sugar beet, Sugar crops nes, Sunflower seed, Sweet corn frozen, Sweet potatoes, Tangerines mandarins clementines satsumas, Tea, Tobacco unmanufactured, Tomatoes, Triticale, Vanilla, Vegetable tallow, Vegetables in vinegar, Vegetables canned nes, Vegetables dehydrated, Vegetables dried nes, Vegetables fresh nes, Vegetables fresh or dried products nes, Vegetables frozen, Vegetables preserved nes, Vegetables preserved frozen, Vegetables temporarily preserved, Vetches, Walnuts shelled, Walnuts with shell, Watermelons, Wheat
Crop Processed (120)
Beer of barley, Beer of sorghum, Beeswax, Beet pulp, Beverages distilled alcoholic, Beverages fermented rice, Beverages non alcoholic, Bread, Cake copra, Cake cottonseed, Cake groundnuts, Cake hempseed, Cake kapok, Cake linseed, Cake maize, Cake mustard, Cake palm kernel, Cake rapeseed, Cake rice bran, Cake safflower, Cake sesame seed, Cake soybeans, Cake sunflower, Cereal preparations nes, Cereals breakfast, Chocolate products nes, Cider etc, Cigarettes,

Cigars cheroots, Cocoa butter, Cocoa paste, Cocoa powder & cake, Coffee extracts, Cotton carded combed, Dregs from brewing distillation, Feed and meal gluten, Feed minerals, Feed supplements, Feed compound nes, Feed pulp of fruit, Feed vegetable products nes, Food prep nes, Food preparations flour malt extract, Food wastes, Forage products, Fructose and syrup other, Fruit cooked homogenized preparations, Fruit prepared nes, Glucose and dextrose, Infant food, Juice citrus concentrated, Juice citrus single strength, Juice fruit nes, Juice grape, Juice grapefruit, Juice grapefruit concentrated, Juice lemon concentrated, Juice orange concentrated, Juice orange single strength, Juice pineapple, Juice pineapple concentrated, Juice plum concentrated, Juice plum single strength, Juice tomato, Lactose, Macaroni, Maple sugar and syrups, Margarine liquid, Margarine short, Mixes and doughs, Molasses, Mushrooms canned, Oil castor beans, Oil citronella, Oil coconut (copra), Oil cottonseed, Oil essential nes, Oil groundnut, Oil kapok, Oil linseed, Oil maize, Oil olive residues, Oil olive virgin, Oil palm kernel, Oil poppy, Oil rapeseed, Oil rice bran, Oil safflower, Oil sesame, Oil soybean, Oil sunflower, Oil vegetable origin nes, Pastry, Pineapples canned, Potato offals, Pyrethrum extraction, Rice broken, Rice milled, Rice milled/husked, Soya curd, Soya paste, Soya sauce, Starch cassava, Sugar confectionery, Sugar flavoured, Sugar non-centrifugal, Sugar Raw Centrifugal, Sugar refined, Sugar nes, Sweet corn prep or preserved, Tea mate extracts, Tobacco products nes, Tomatoes paste, Tomatoes peeled, Turnips for fodder, Vegetables homogenized preparations, Vermouths & similar, Wafers, Waxes vegetable, Wine

Livestock Primary (53)

Eggs dried, Eggs hen in shell, Eggs liquid, Eggs other bird in shell, Hair fine, Hair goat coarse, Hides and skins nes fresh, Hides buffalo dry salted, Hides buffalo fresh, Hides buffalo wet salted, Hides camel nes, Hides camel wet salted, Hides cattle fresh, Hides cattle wet salted, Hides horse dry salted, Hides nes, Honey natural, Meat ass, Meat cattle, Meat cattle boneless (beef & veal), Meat chicken, Meat duck, Meat game, Meat goat, Meat goose and guinea fowl, Meat horse, Meat nes, Meat pig, Meat pork, Meat rabbit, Meat sheep, Meat turkey, Milk whole fresh cow, Milk whole fresh sheep, Offals edible cattle, Offals edible goats, Offals liver chicken, Offals liver duck, Offals liver geese, Offals other camelids, Offals pigs edible, Offals sheepeedible, Silk-worm cocoons reelable, Skins calve wet salted, Skins goat fresh, Skins goat wet salted, Skins sheep dry salted, Skins sheep fresh, Skins sheep wet salted, Skins sheep with wool, Wool degreased, Wool greasy, Wool hair waste

Livestock Processed (40)

Bacon and ham, Butter of karite nuts, Butter cow milk, Buttermilk curdled acidified milk, Cheese processed, Cheese sheep milk, Cheese whole cow milk, Cream fresh, Fat camels, Fat cattle, Fat liver prepared (foie gras), Fat nes prepared, Fat pigs, Fatty acids, Fatty substance residues, Ghee of buffalo milk, Grease incl. lanolin wool, Ice cream and edible ice, Lard, Meal meat, Meat beef and veal sausages, Meat beef preparations, Meat chicken canned, Meat dried nes, Meat pig sausages, Meat pig preparations, Milk products of natural constituents nes, Milk reconstituted, Milk skimmed cow, Milk skimmed dried, Milk whole condensed, Milk whole dried, Milk whole evaporated, Oils fats of animal nes, Peanut butter, Silk raw, Tallow, Whey condensed, Whey dry, Yoghurt concentrated or not

Others (5)

Crude materials, Oil boiled etc., Vitamins, Waters ice etc.

1.3. Methods

The number of hotspot and non-hotspot countries included in this study was slightly adjusted depending on data availability. For example, whereas food production data included 135 hotspot countries and 50 non-hotspot countries, the data from the FAO food trade matrix listed 113 hotspot countries (61 high-hotspot countries and 52 low-hotspot countries) and 45 non-hotspot countries (Table S1). To avoid overestimation or underestimation during analyses, we excluded countries from analysis that had missing values.

In this study, we selected two time periods, from 1961 to 2011 and from 1992 to 2011. We selected different time periods for two reasons: data availability and the Soviet Union collapse. First, as international institutions provided data after the early 1990s, we could utilize various variables from 1992 to 2011. For example, after 1986, the raw data were available for food trade flows³⁰, and greenhouse gas emission data in agriculture sectors were available after 1990²⁷. The raw data for food productivity, agricultural intensification, and agent factors are available from 1961 to 2011. Second, many countries became independent after 1992 with the Soviet Union collapse, and thus the new countries did not have pre-1992 data from international institutions. Also, the Soviet Union collapse led to a revitalized international food trade. By selecting the period from 1992 to 2011, we could minimize the number of countries that had missing values for statistical analyses that dealt with global food trade. For 1961 to 2011, we calculated food productivity, agricultural intensification, and agent factors (consumers, producers, and traders) in the two-system model (hotspot and non-hotspot countries) and three-system model (high, low, and non-hotspot countries). For 1992 to 2011, we determined food trade flows, performed path analysis and multiple linear regression analysis, and estimated CO₂ emissions from international food transport.

Aggregate Level Analysis

We calculated per agricultural area food production (food productivity) and agricultural intensification from 1961 to 2011. By using agriculture and land use datasets, we divided food production and agricultural intensification variables by agricultural area in each country. The intensification variables involved the economically active population in the agriculture sector, fertilizer use, pesticide use, agricultural water withdrawals, and greenhouse gas emissions by agriculture.

To estimate the number of farmers who produced food for export, we calculated the volume exported food as the percentage of total food production. Then, the percentage was multiplying economically active population in the agriculture sector³⁰. We assumed that the percentage of export farmers to total farmers was the same as a volume exported food as the percentage of total food production.

We calculated per capita food supply (kcal/capita/day) of two systems (hotspot and non-hotspot countries) using data from the FAO Food Balance Sheets³⁰. First, using per capita food supply in each country from 1961 to 2011, we summed total food supply in the two systems. Then, we divided the total amount of the food supply by the total population in each system. Per capita food supply was the amount of food available for consumption in hotspot and non-hotspot countries.

We also estimated food trade flows between the hotspot and non-hotspot countries from 1992 to 2011. From the FAO food trade matrix dataset³⁰, we first calculated the food export volumes from each exporter to each importer. We summed the total volumes exported by each country in each year for two-system model (hotspot and non-hotspot countries) and three-system model (high, low, and non-

hotspot countries) from 1992 to 2011. We calculated mean annual food export flows to evaluate food trade dynamics within each model separately. In addition, we evaluated food export per agricultural area to quantify the effects of food trade on biodiversity hotspot areas. To assess the influence of food production and export on biodiversity, we first added the amounts of food production and exports from 1992 to 2011 in each country. Because prior agricultural activities impact current biodiversity over long-term³⁵, we summed the total agriculture yields from 1992 to 2011. Then, we analyzed the relations between the amount of food produced and exported and the number of IUCN threatened species using the R software^{36,37}. The data were log transformed for a regression analysis using the following equations:

$$Y = \alpha X^\beta$$

$$Y' = \log Y, X' = \log X$$

$$Y' = \log \alpha + \beta X'$$

where Y is the number of threatened species, X is food production or food export.

Path Analysis

To uncover the causes of international food trade and the food trade effects on biodiversity, we ran a path analysis. Path analysis is a type of structural equation model (SEM) for estimating causal relations among observed variables^{38,39}. Mplus was used to perform path analysis⁴⁰. After excluding countries with missing values, we selected 170 countries with valid values for all variables. Among 170 countries used for path analysis, 123 were hotspot countries and 47 were non-hotspot countries from 1992 to 2011 in path analysis. Based on previous research, we hypothesized that agricultural, socioeconomic, and environmental factors may affect the size of the food trade. Food production and export may directly and indirectly affect biodiversity status.

We constructed three structural models (all countries, hotspot countries, and non-hotspot countries). First, agricultural factors (food production, per capita food production, and percentage of agricultural areas), socioeconomic factors (per capita GDP-PPP and percentage of urban population), and environmental factors (annual forest change rate, percentage of protected areas, greenhouse gas emissions from agriculture, and percentage of biodiversity hotspot areas) were treated as exogenous variables. Then, the amount of food exported and imported was estimated as a function of the exogenous variables.

Biodiversity status (the number of threatened species) was determined as a function of the amount of food produced and exported. Although the amount of food exported was part of food production, the proportion of food exported to food produced differed among countries. The different proportion may affect biodiversity differently. For example, food import activities may displace the responsibility for biodiversity loss to the food exporting countries. In this case, some net food exporting countries would not produce extra food without food export, unless they could export it. We can explain it by using the amount of food exported. If food importing countries import food products due to increased food demand, food exporting countries may also increase the proportion of food exported. Furthermore, even if two food exporting countries produce the same amount of food, they may export different amount to a given importing countries. If the food demands of food importing countries increase because of urbanization and income growth, it may highly influence the amount of food produced by exporting countries. As a result, the

increased food production for export may exacerbate biodiversity loss in the food exporting countries.

We estimated coefficients using the Maximum Likelihood (ML) method and performed log transformation on all dependent and independent variables to correct for non-normality. The final models included all variables even though that were not statistically significant, because all three models had the lowest Akaike Information Criterion (AIC) when they contained all variables. The AIC measures the goodness of model fit and a smaller AIC indicates a better model fit ⁴¹.

Multiple linear regression models

To verify the results of path analysis, we performed ordinary least squares regressions using the R software package with routines `lm()` ³⁶. Data were available in 170 countries for multiple linear regression models. The number of hotspot countries was 123, and the number of non-hotspot countries was 47. We first established six regression models of food trade based on agricultural, environmental, and socioeconomic factors. Dependent variables were food export and food import quantities in all countries, hotspot countries, and non-hotspot countries. Independent variables included agricultural factors (food production, per capita food production, and percentage of agricultural areas), socioeconomic factors (per capita GDP-PPP and percentage of urban population), and environmental factors (annual forest change rate, percentage of protected areas, greenhouse gas emissions from the agriculture sector, and percentage of biodiversity hotspot areas). Then, for each country (1992-2011), we averaged each variable except forest change rate because not all countries had a perfect dataset for these years. Some countries had missing data for a specific year, but they had data before or after that year. Thus, we could minimize the missing values for statistical analyses by calculating the average value over the years from 1992 to 2011 for each country. We calculated annual forest change rates for each country and each year, because annual change in forest area reflects the demand for agriculture lands and exports in rural areas ^{42,43}. Then, we averaged the rates from 1992 to 2011.

We log-transformed all dependent and independent variables to achieve linearity for regression analysis. Using the diagnostic graphs by the `plot` command in R, we maintained the assumption of independence and homoskedasticity in residuals. We also performed collinearity diagnostics using variance inflation factors (VIF) (the `lm.beta` command in R). A VIF of 10 indicates a severe multicollinearity problem ⁴⁴. All VIF results in the regression models were less than 10. The results of multiple regression analysis coincided with the results of path analysis (Table S3 and S4).

Table S3 Results of ordinary least-squares regression for total food trade, export, and import from 1992-2011. Raw data from FAOSTAT (2014), The World Bank (2014), WDPA (2014), WRI (2014), Myers et al. (2000), and Mittermeier and Cemex (2004).

Variable	Export	Import
Food Production	0.915** (0.094)	0.947** (0.046)
Food production per capita	0.657** (0.198)	-1.340** (0.098)
% of agriculture areas	0.088 (0.116)	0.180* (0.058)
GDP-PPP per capita (constant)	0.355* (0.114)	0.714** (0.057)
% of Urban population	0.120 (0.243)	0.368* (0.120)
Forest change rate	0.520 (0.418)	0.364 (0.208)
% of protected area	0.194 (0.102)	-0.075 (0.051)
GHG emission in agriculture	-0.171 (-0.128)	-0.249** (0.063)
% of biodiversity hotspots	0.105* (0.045)	0.007 (0.022)
Intercept	-8.512**	-8.527**
R ²	0.824**	0.924**
F-statistic	82.04	216.4
DF	160	160

Values in parentheses are standardized errors.

All variables are log transformation variables.

** p<0.001, * p<0.05

Table S4 Results of ordinary least-squares regression for hotspot and non-hotspot countries from 1992-2011. Raw data from FAOSTAT (2014), The World Bank (2014), WDPA (2014), WRI (2014), Myers et al. (2000), and Mittermeier and Cemex (2004).

Variable	Export		Import	
	HC	NHC	HC	NHC
Food Production	0.802** (0.107)	1.384** (0.265)	0.972** (0.048)	0.706** (0.141)
Food production per capita	0.989** (0.243)	-0.244 (0.460)	-1.475** (0.189)	-0.877** (0.245)
% of agriculture areas	-0.027 (0.143)	0.142 (0.222)	0.129* (0.064)	0.370* (0.118)
GDP-PPP per capita (constant)	0.218 (0.140)	0.375 (0.231)	0.643** (0.063)	1.010** (0.123)
% of Urban population	0.345 (0.283)	-0.082 (0.506)	0.500** (0.127)	-0.032 (0.270)
Forest change rate	0.516 (0.440)	0.805 (1.431)	0.523* (0.197)	-0.948 (0.763)
% of protected area	0.121 (0.114)	0.312 (0.243)	-0.051 (0.051)	-0.276* (0.130)
GHG emission in agriculture	-0.028 (0.150)	-0.638* (0.291)	-0.281** (0.067)	0.073 (0.155)
% of biodiversity hotspots	0.117 (0.084)		0.067 (0.038)	
Intercept	-6.496**	-14.398*	-9.029**	-4.332
R ²	0.832**	0.838**	0.945**	0.904**
F-statistic	62.29	24.56	214	44.94
DF	113	38	113	38

Values in parentheses are standardized errors.

All variables are log transformation variables.

** p<0.001, * p<0.05

Distance and Volume Indices

Using GeoDa software⁴⁵, we calculated geographical distances (kilometer) from the centroid of one country to the centroid of all other countries (n=184) in the world. The distance data were used to represent trade distances between countries and to estimate CO₂ emissions by the international food trade. Then, we made a distance matrix among all countries and matrices of food export amounts between exporters and importers. From the food trade matrices, we extracted food export and import distances of each country's partners. Finally, we averaged export and import distances for each exporter and each year.

Because geographical locations of countries differ each other, we calculated the relative export and import distances using a distance index. European countries have shorter average distances from other countries rather than North American countries. To calculate the distance index, we divided the sum of food export and import distances by the sum of geographical distances for each country. When the distance index of a country is close to 1, the country exports or imports food globally. In contrast, when the distance index of a country is close to 0, the country trades food locally.

The volume index represents the amounts of food exported and imported per unit distance. To calculate the volume index, we divided the sum of food exported and imported by the sum of food export and import distances for each country. For example, France exported food to 181 countries, and therefore we summed food export distances and quantities from France to 181 partner countries. When a country has a high volume index, it tends to transport more food commodities to its partner countries.

CO₂ emissions from international food transport

Using mean annual export distances and quantities from 1992 to 2011 for each country, we estimated CO₂ emissions resulting from international food transport. Because less than 0.6% of the agriculture trade uses air transportation⁴⁶, we excluded air transportation but focused on land and sea transport for CO₂ estimations. First, because data on transport methods for trade did not exist for individual countries, we used 22 subregions data defined in FAOSTAT (Figure S3). We assumed that countries in the same sub-regions used land transportation. However, we assumed sea transportation for Caribbean, Melanesia, Micronesia, Polynesia, Eastern Asia, and Australia and New Zealand because countries in these subregions are separated by an ocean. In particular, the largest food trade partners within Eastern Asia also used sea transportation because of geopolitical barriers⁴⁶. Among different sub-regions, countries used maritime transportation.

Second, we calculated land transportation ratio between road and rail at a subregional level using modal shares data⁴⁶. Modal shares data indicated the percentage of freight transportation in mass among sea, rail, and road types. Then, we selected CO₂ emissions per ton-km of each transport mode⁴⁶. We estimated the CO₂ emissions by international food transport methods from each exporter to each importer. Finally, we summed CO₂ emissions between hotspot and non-hotspot countries and among high-hotspot, low-hotspot, and non-hotspot countries. Food transportation performance was calculated as the ratio between CO₂ emissions by international food transportation and the amounts of food exported. We calculated CO₂ emissions by international food transport as follows:

$$\begin{aligned} \text{CO}_2 \text{ Emissions by International Food Transport (CO}_2\text{g)} \\ &= (\text{Transportation ratio}) \times (\text{Export Volume (ton)}) \\ &\quad \times (\text{Export Distance (km)}) \times (\text{CO}_2 \text{ emission (CO}_2\text{g/ton/km)}) \end{aligned}$$

The CO₂ estimates resulting from international food transportation were underestimated for two reasons. First, we estimated CO₂ emissions using the shortest distances between food trade countries. In the real world, however, every transport service stops at several places for refueling and loading. Second, we did not consider air transportation. Although less than 0.6% of total food trade uses air transportation, CO₂ emissions by air transport are approximately 5 times, 24 times, and 46 times larger than the road, rail, and sea transportation respectively.

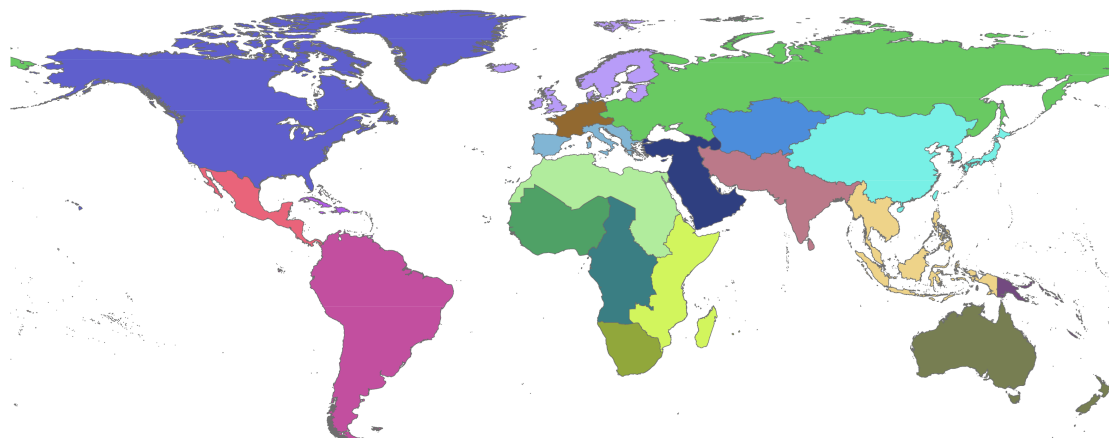


Figure S3 22 Sub-region areas in the world; Eastern Africa, Middle Africa, Northern Africa, Southern Africa, Western Africa, Northern America, Central America, Caribbean, South America, Central Asia, Eastern Asia, Southern Asia, South-Eastern Asia, Western Asia, Eastern Europe, Northern Europe, Southern Europe, Western Europe, Australia and New Zealand, Melanesia, Micronesia, Polynesia. Data from FAOSTAT (2014).

2. Supplementary Results and Discussion

2.1. Averaged food export and import distances

We calculated how long each country had average export distances from the centroid of food exporting country to the centroid of food importing country. When the average export distances increased, the number of countries was exponentially decreased from 3500-4500 kilometers (n=63) to 7500-8500 kilometers (n=4) (Figure S4a). Net exporting countries transported food commodities over greater distances for export (Figure S4b), whereas net importing countries exported food at shorter distances. 84% of net exporting countries that exported more food than food import were hotspot countries. Specifically, 40% of net exporting countries were high-hotspot countries, and 44% of them were low-hotspot countries. Hotspot countries were disproportionately net exporting countries. In the world, 73% of all countries were hotspot countries. 41% of all countries were high-hotspot countries, and low-hotspot countries were 32% of them.

The distribution of average import distances of countries was left-skewed on the range of 3500-4500 kilometers (Figure S4c). Whereas 63 countries ranged from 3,500 kilometers to 4,500 kilometers in average export distances, 81 countries had 3,500-4,500 kilometers in average import distances.

However, net exporting countries were not significantly different between the averaged export and import distances (Figure S4c and S4d). Net exporting countries exported and imported food products over the longer distances with relatively remote countries than net importing countries.

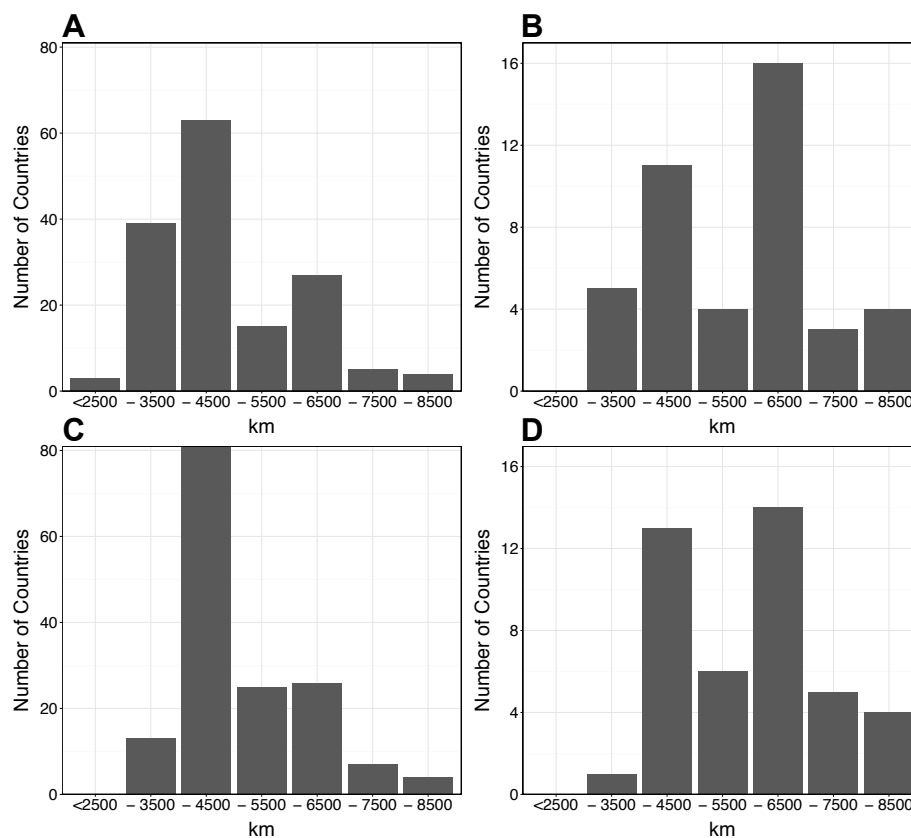


Figure S4 Average export distances in all countries and net exporters; (A) The distribution of average export distances of all countries was left-skewed, meaning that many countries had relatively shorter export distances. (B) On the contrast, net exporting countries had right-skewed distribution and therefore they tended to

transport food products for export over longer distances. (C) The average import distances of countries were longer than average export distances. (D). In net exporting countries, there was no significant difference between average food export and import distances. Raw data from FAOSTAT (2014).

2.2. Food trade dynamics in the three systems

Low-hotspot countries had the highest food production and population among high-hotspot, low-hotspot, and non-hotspot countries (Figure S5). Low-hotspot countries produced 4.5 times and 5.1 times more food than high-hotspot and non-hotspot countries respectively. Low-hotspot countries accounted for 52% of global food export. The population in low-hotspot countries was 7.9 times and 3.7 times higher than high-hotspot and non-hotspot countries. Low-hotspot countries (3%) had lower proportion of food export to the total food production than high-hotspot countries (6%) and non-hotspot countries (7%). The total amounts of food export in low-hotspot countries were approximately twice higher than the sum of high and non-hotspot countries. Low-hotspot countries provide twice more food to high-hotspot and non-hotspot countries than what the latter exported to the former. Thus, low-hotspot countries may be an important for global food supply and livelihoods by providing basic materials for living.

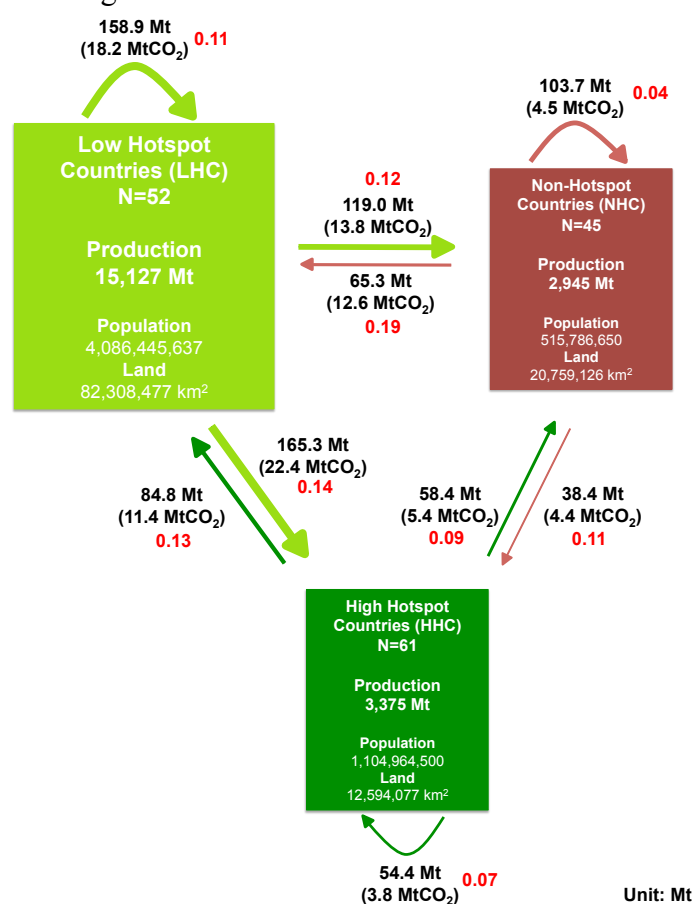


Figure S5 Food export flows and CO₂ emissions during international food transportations among high-hotspot, low-hotspot, and non-hotspot countries from 1992-2011; Low-hotspot countries had the highest amounts of food production and export among low-hotspot, high-hotspot, and non-hotspot countries. Low-hotspot countries also emitted the highest CO₂ for the international food trade. Non-hotspot

countries inefficiently transported food with high CO₂ emissions per food export volume toward low and high-hotspot countries. Raw data from FAOSTAT (2014) and Cristea et al. (2013).

The percentages of food export items were quite different among the three systems (Figure S6). Low-hotspot countries exported 90% of total food exports as crop products. While low-hotspot countries had a low export percentage for livestock products (5%), non-hotspot countries exported a higher percentage of livestock products (10-15%). The percentage of ‘other’ (mainly crude materials) in high-hotspot countries was extremely higher than other two systems. 20-30% of the total food exports in high-hotspot countries was ‘other’ items. Crude materials involve vegetable origin, vegetable saps, and extracts, and therefore they are used for other food processed and industrial productions³⁰.

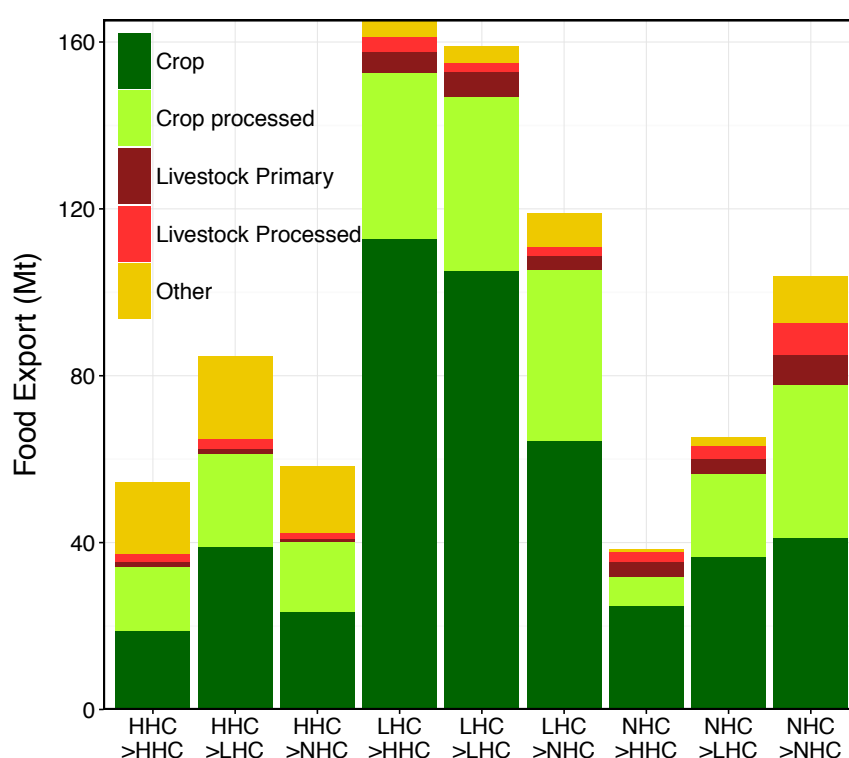


Figure S6 The proportions of food export items from 1992-2011; High-hotspot countries exported a high proportion of other products. While low-hotspot countries exported mainly crop products, non-hotspot countries exported high proportion of livestock products to other countries. Raw data from FAOSTAT (2014).

2.3. Food trade dynamics per agricultural area

For 1992 to 2011, we also calculated food productivities (ton/km²) and per agricultural area food export (ton/km²) between the two systems (Figure S7) and among the three systems (Figure S8). The flows of per agricultural area food export differed from food trade dynamics represented as the total amounts of food trade (Mt) (Figure S7). Per agricultural area food exports in non-hotspot countries were also higher than hotspot countries. In the three systems, although low-hotspot countries produced and exported the largest amounts of food, they had the lowest food productivities and per agricultural area exports (Figure S8).

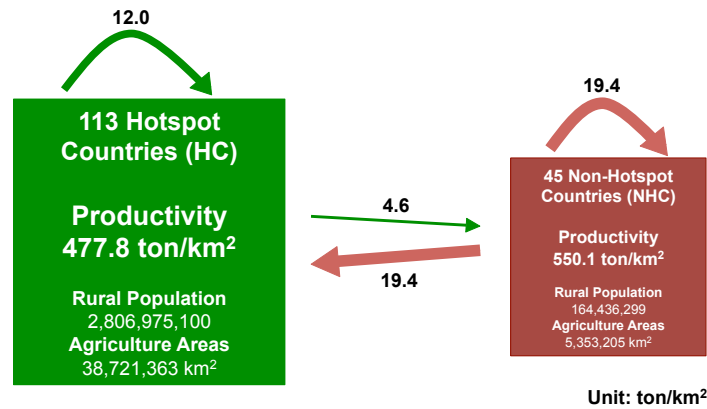


Figure S7 Per agriculture area food export flows between hotspot and non-hotspot countries from 1992-2011; Non-hotspot countries had higher food productivities than hotspot countries. Per agriculture area food exports in non-hotspot countries were also higher than hotspot countries. Raw data from FAOSTAT (2014) and The World Bank (2014).

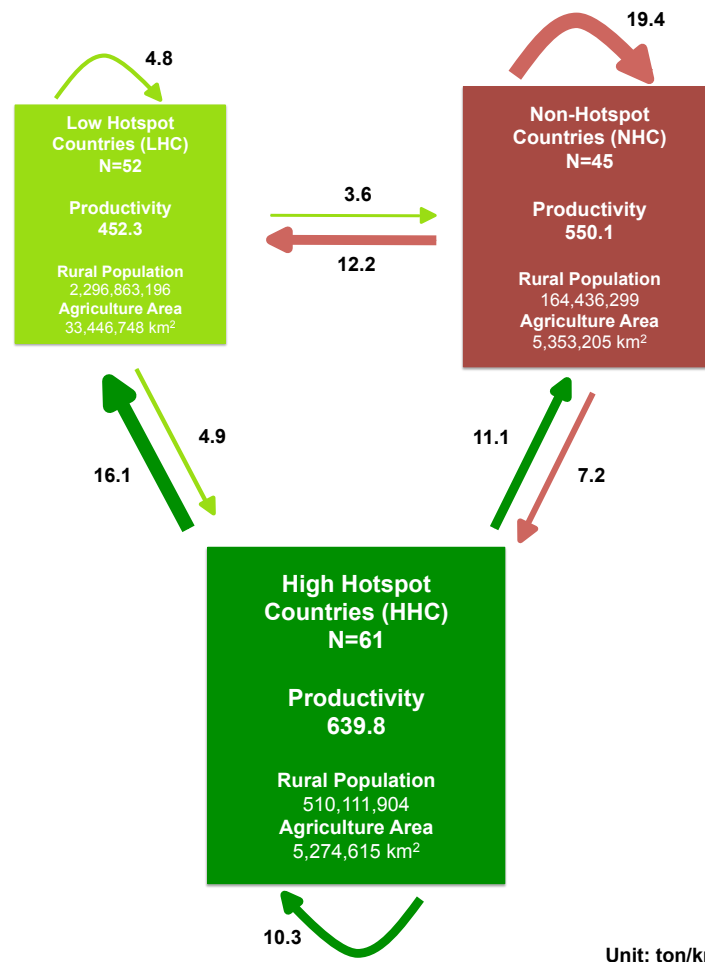


Figure S8 Per agriculture area food export flows among high-hotspot, low-hotspot, and non-hotspot countries from 1992-2011; While high-hotspot countries had the highest food productivities among high-hotspot, low-hotspot, and non-hotspot countries, low-hotspot countries had the lowest productivities. Per agriculture area food exports in both high-hotspot and non-hotspot countries were higher than low-hotspot countries. Raw data from FAOSTAT (2014) and The World Bank (2014).

Over the period from 1992 to 2011, food productivity in non-hotspot countries (550.1 ton/km²) was 15% higher than hotspot countries (477.8 ton/km²). However, since 2000, food productivity in hotspot countries has exceeded non-hotspot countries with higher agricultural intensification. Although per agricultural area greenhouse gas emissions by the agriculture sector and fertilizer use in hotspot countries were similar to non-hotspot countries from 1992 to 2011, per agriculture area pesticide use and agricultural water withdrawals in hotspot countries were 120% and 348% higher than non-hotspot countries.

In the three systems, high-hotspot countries had both the highest food productivities and per agricultural area food exports (Figure S8). High-hotspot countries had 41% and 16% higher food productivities than low-hotspot and non-hotspot countries. In addition, high-hotspot countries provided 3 times more per agricultural area food export to low-hotspot countries and approximately twice more to non-hotspot countries than what the latter exported to the former. It indicated that high-hotspot countries used high agricultural intensification. From 1992 to 2011, greenhouse gas emission of agriculture per agriculture area in high-hotspot countries (0.17 CO₂ekg/km²) was higher than low-hotspot (0.10 CO₂ekg/km²) and non-hotspot countries (0.12 CO₂ekg/km²). Per agriculture area fertilizer use in high-hotspot countries (3.63 ton/km²) was 26% and 22% higher than low-hotspot and non-hotspot countries respectively from 1992 to 2002. In 2002, high-hotspot countries used 88,389 m³/km² (74% of total water withdrawals) as agricultural water withdrawals, while low-hotspot countries used 56,038 m³/km² (71%) and non-hotspot countries used 14,883 m³/km² (20%). low-hotspot countries only had the highest per agriculture area pesticide use (0.20 ton/km²) than other two systems from 1992 to 2011; 0.12 ton/km² in high-hotspot countries and 0.08 ton/km² in non-hotspot countries.

Low and high-hotspot countries with higher food production and export increased the number of threatened species (Figure S9). Specifically, food production and export in high-hotspot countries influenced more the number of threatened species than low-hotspot countries.

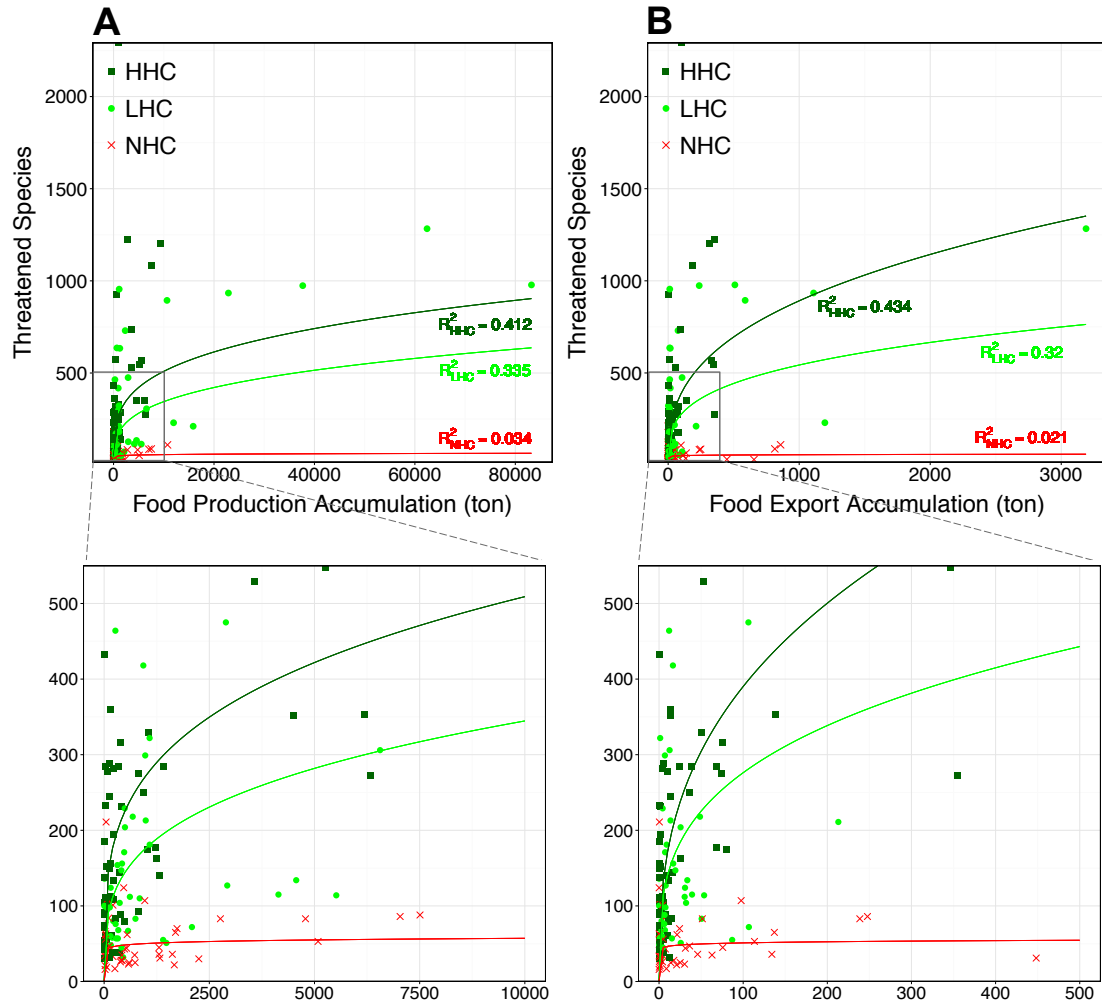


Figure S9 The influence of food production and export on the number of threatened species from 1992-2011; (A) The relations between food production and the number of threatened species; While non-hotspot countries with higher food production did not increase the number of threatened species, low and high-hotspot countries exponentially increased the number of threatened species with higher food productions. **(B) The relations between food export and the number of threatened species;** Both high and low-hotspot countries increased the number of threatened species with the low amounts of food export. Then, the increase rates of the number of threatened species in high and low-hotspot countries were decreased with the higher amounts of food export. Raw data from FAOSTAT (2014) and IUCN (2014).

2.4. Trade transportation distance and food volume index

We calculated volume index and distance index by using FAO food export matrix and average export distances in each country. When countries had greater distance index (export food globally), food export quantities exponentially increased (Figure S10a). As mentioned before, net food exporting countries had greater average export distances than the global average and 84% of them were hotspot countries. Countries with higher distance index rapidly increased the amounts of food import (Figure S10b). At this time, countries with both high volume and distance indices were different between food export and import, particularly in hotspot countries. In hotspot countries, USA, Thailand, South Africa, and France exported a lot of food

globally, but Japan and Mexico imported much food products over the long distances. In non-hotspot countries, Germany and the Netherlands exported and imported lots of food products across regions.

In addition, we averaged distance and volume indices between net food exporting and importing countries. Although the distant indices of net exporting countries were similar in both export (0.69) and import (0.66), net food importing countries had lower export distant index (0.54) than import (0.63). Net food importing countries also had higher import volume index (9.41) than export volume index (4.26), and thus they imported the high amounts of food over the longer distances than food export. On the other hand, net food exporting countries had higher export volume index (14.19) than import volume index (6.25).

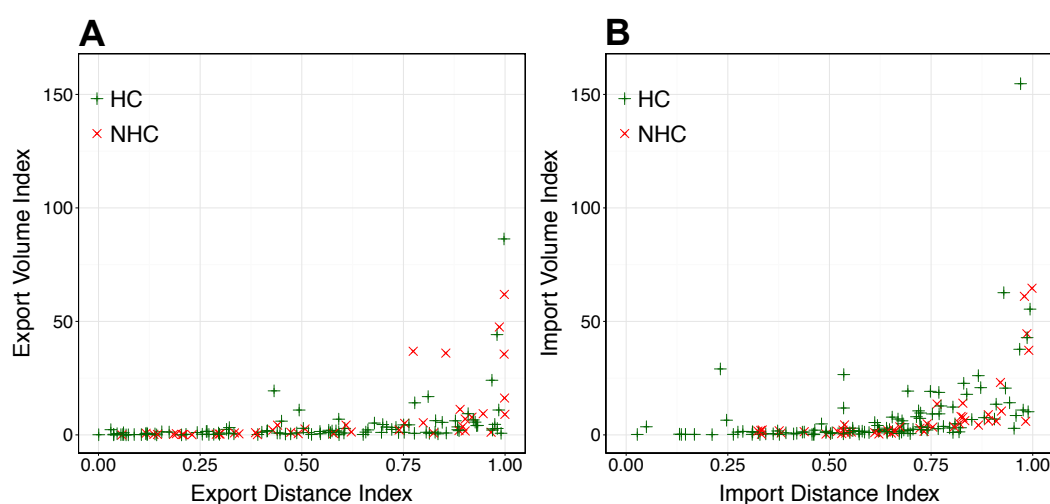


Figure S10 Relationships between distance index and volume index; Distance index indicated whether each country export food globally (close to 1) or locally (close to 0), and volume index indicated food export amounts in each country. (A) When countries tended to export food globally, their export amounts were exponentially increased. (B) Countries with higher distance index tended to import food over the great long distances. Raw data from FAOSTAT (2014).

2.5. CO₂ emissions by the international food transportation

We estimated CO₂ emissions by the international food transportation and calculated transportation performances by dividing CO₂ emissions (MtCO₂) into the amounts of food export (Mt). The transportation performances indicated how much carbon dioxide emitted per food export amount. In particular, low-hotspot countries contributed to 56% of total CO₂ emissions by food transportation (Figure S5). When countries exported more food products abroad, they tended to transport over the longer distances (Figure S10). It indicated that the CO₂ emissions for food transportation positively linked with the amounts of food exports.

High-hotspot (3.8 MtCO₂) and non-hotspot countries (4.5 MtCO₂) emitted low CO₂ for transportation when they transported food products within their systems. Although non-hotspot countries exported less food to low-hotspot countries than the latter to the former, non-hotspot countries emitted higher CO₂ by the transportation to low-hotspot countries. This is because non-hotspot countries tended to import food from neighboring low-hotspot countries, while they exported food to low-hotspot countries over the longer distances.

We also divided CO₂ emissions for food transportation into the amounts of food export (red numbers in Figure 1 and S5) as food transport performance. Non-

hotspot countries had higher ratio when exported food to other systems, particularly to low-hotspot countries. For example, the CO₂ ratios of food transportations from low-hotspot countries to high-hotspot countries (0.14) were similar to from high-hotspot countries to low-hotspot countries (0.13). However, the ratios from non-hotspot countries to low-hotspot countries (0.19) were higher than from low-hotspot countries to non-hotspot countries (0.12).

Because low-hotspot countries located in various sub-regions of the world (Figure S2), transportation distances from a low-hotspot country to other low-hotspot countries were similar to the distances from a low-hotspot country to high or non-hotspot countries. Thus, there was no difference in CO₂ emissions for international food transportation within the same system (e.g., from hotspot countries to other hotspot countries) and toward other systems (e.g., from hotspot countries to non-hotspot countries). Although high-hotspot countries scattered around the equator, they could reach other food importing countries with relatively shorter distances than non-hotspot countries (Figure S2). The geographic location of non-hotspot countries aggregated each other, especially in Europe and West Africa. Even though neighboring non-hotspot countries were close to each other, non-hotspot countries needed to transport food to low-hotspot and high-hotspot countries over the longer distances (Figure S2).

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