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Impacts of climate change on global food trade networks

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Abstract

Countries' reliance on global food trade networks implies that regionally different climate change impacts on crop yields will be transmitted across borders. This redistribution constitutes a significant challenge for climate adaptation planning and may affect how countries engage in cooperative action. This paper investigates the long-term (2070–2099) potential impacts of climate change on global food trade networks of three key crops: wheat, rice and maize. We propose a simple network model to project how climate change impacts on crop yields may be translated into changes in trade. Combining trade and climate impact data, our analysis proceeds in three steps. First, we use network community detection to analyse how the concentration of global production in present-day trade communities may become disrupted with climate change impacts. Second, we study how countries may change their network position following climate change impacts. Third, we study the total climate-induced change in production plus import within trade communities. Results indicate that the stability of food trade network structures compared to today differs between crops, and that countries' maize trade is least stable under climate change impacts. Results also project that threats to global food security may depend on production change in a few major global producers, and whether trade communities can balance production and import loss in some vulnerable countries. Overall, our model contributes a baseline analysis of cross-border climate impacts on food trade networks.

1. Introduction

Higher temperatures will significantly modify the production of crops (Parry *et al* 2004, Wheeler and Braun 2013, Challinor *et al* 2016, Bezner Kerr *et al* 2022). This impact constitutes a threat not only to individual producing countries but, because of an acceleration in countries' dependence on overseas trade for food supply, also to global food security (D'Odorico *et al* 2014, Janssens *et al* 2020). Disrupted production in one or a few countries can induce changes in the food trade network as a whole (Puma *et al* 2015), which is a primary example

of cross-border impacts of climate change (Bren D'Amour *et al* 2016, Hedlund *et al* 2018, Adams *et al* 2021, Carter *et al* 2021, Lager and Benzie 2022). Such redistribution of global climate risk constitutes a significant challenge for climate adaptation with regards to international cooperation (Challinor *et al* 2017).

Global food trade networks consist of densely connected trade communities (Torreggiani *et al* 2018, Gutiérrez-Moya *et al* 2021), in which countries (i.e. nodes) have a higher number of within-community trade relationships (i.e. links) than they have relations with countries outside their community. Networks with clearly distinguishable, but only loosely

connected, communities can have stabilising effects on certain changes within networks, such as limiting 'domino effects' of risks (May *et al* 2008, Scheffer *et al* 2012). However, the extent to which climate change impacts may change the structure of trade networks remains unknown.

This paper investigates how trade patterns between countries may be disrupted and reoriented under potential long-term (2070–2099) climate change impacts on food production. Using trade data for three key staple crops (wheat, rice and maize), we propose a baseline model for analysing potential structural redistributions of global food trade networks as a consequence of climate-induced production changes. We test the model for the three crops and develop projections by linking data on future climate impacts and current trade. Projected results are compared to present-day trade in order to assess the relative levels of disruption. For this, we use network community detection and functional cartography to analyse how trade community structures and countries' network roles change following adjustments to countries' trade patterns. The analysis is especially focused on identifying differences in structural changes across the selected key staple crops, and how trade might be concentrated differently compared to present-day. Our analysis is not a prediction of future trade. Rather, it is a baseline approach that—*ceteris paribus*—can generate knowledge on and how the trade system may need to reconfigure to manage future climate impacts. Our approach is useful to provide insights about the level to which the current food trade system is prepared for climate risks.

2. Methods and materials

2.1. Underlying model considerations

We study structural disruptions of global food trade networks by applying climate change impacts on production of wheat, rice and maize, and proportionally on trade. We hypothesise that climate change impacts on production might force a structural change in food trade networks, indirectly leading to cross-border disruptions in imports to other countries. To isolate the effect of climate change impacts on production and trade we develop a simplistic model. In our model, impacts on yields equal impacts on production and export–import flows. Everything else is assumed to not change and no other mechanisms increase supply. We are, for example, not considering behavioural changes and market effects or climate change impacts on transport routes, such as changes in the distribution or capacities of harbours and airports, nor on storage (Bailey and Wellesley 2017). Further, we are not considering second-order effects or more

'dynamic' responses that might occur as an adaptation to climate change, for example the effect of trade policies. The result is a model that highlights the isolated climate-induced cause-and-effect without introducing numerous detailed assumptions. Our model is therefore deliberately simple to allow for transparent and descriptive analyses of potential disruptions to the food trade networks. The model is not designed for predictions.
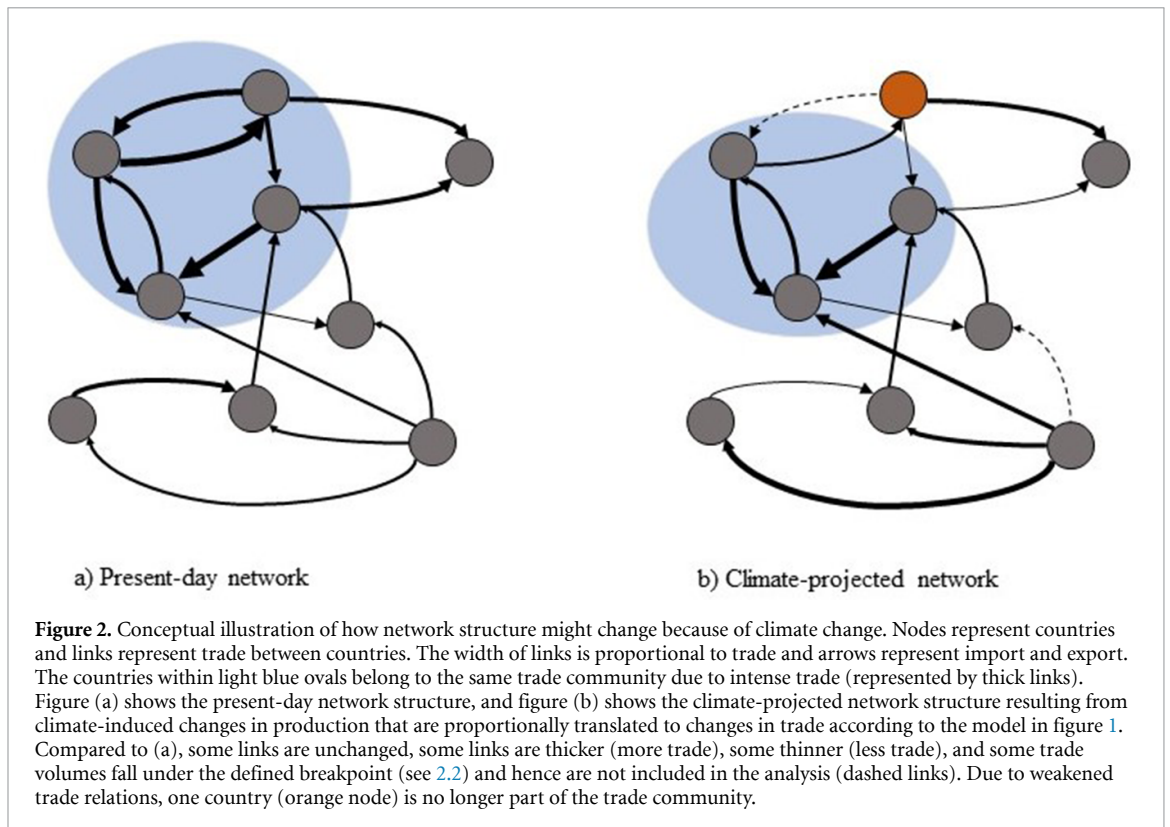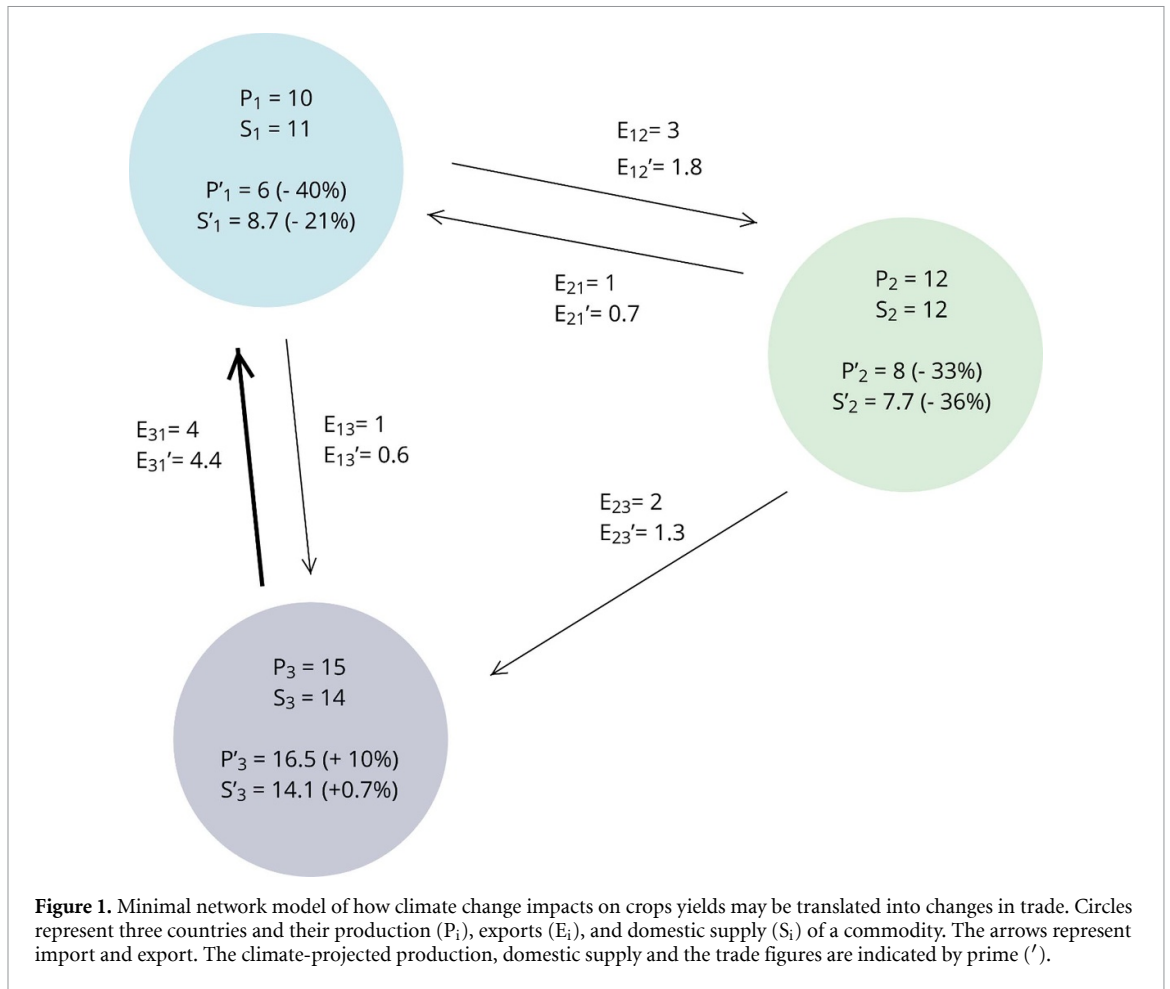
Figure 1 shows a schematic overview of the model. In this illustrative example, the production in three countries is affected by a climate-induced change of -40%, -33% and $+10\%$, respectively, which is proportionally translated into changes in exports (and hence, imports).

The model has two equilibrium states: The present-day sum of production (P_i) and a climate-projected sum of production (P'_i). Each of these two sums are distributed among all countries, i.e. $\sum P_i = \sum S_i$ and $\sum P'_i = \sum S'_i$. Hence, a global production increase of one crop would, in this model, imply increased consumption.

We develop a present-day and a climate-projected network for each crop (figure 2). Climate change impacts increase or decrease production, which changes export–import flows by the same percentage. Climate-projected trade networks are determined from multiplying climate change impact data (%) with current export data (tonnes). Changed export–import flows may modify the trade network structure, since a higher quantity of export–import determines if two countries have more concentrated trade. The trade concentration gives rise to structural differences in the trade system as a whole.

Our analysis consists of three steps. First, we analyse the stability (or lack thereof) of trade communities under climate change-affected crop production of wheat, rice and maize. We are investigating stability as the trade system's ability to maintain its structure when subjected to climate change impacts, yet considering the trade structure as formed only by export–import flows. To identify how exposed trade communities are to climate change impacts, we study changes in link strengths between countries in present-day and climate-projected trade and how these affect the community structures. Second, we study potential changes in countries' network positions, or 'roles', in the food trade networks.

Third, we identify how exposed individual countries are to changes in yield production and imports and the potential role of trade communities in balancing production loss. We use present-day production and trade data to analyse how a change in production is distributed among the countries within trade communities.

Figure 1. Minimal network model of how climate change impacts on crops yields may be translated into changes in trade. Circles represent three countries and their production (P_i), exports (E_i), and domestic supply (S_i) of a commodity. The arrows represent import and export. The climate-projected production, domestic supply and the trade figures are indicated by prime ($'$).

a) Present-day network   b) Climate-projected network

Figure 2. Conceptual illustration of how network structure might change because of climate change. Nodes represent countries and links represent trade between countries. The width of links is proportional to trade and arrows represent import and export. The countries within light blue ovals belong to the same trade community due to intense trade (represented by thick links). Figure (a) shows the present-day network structure, and figure (b) shows the climate-projected network structure resulting from climate-induced changes in production that are proportionally translated to changes in trade according to the model in figure 1. Compared to (a), some links are unchanged, some links are thicker (more trade), some thinner (less trade), and some trade volumes fall under the defined breakpoint (see 2.2) and hence are not included in the analysis (dashed links). Due to weakened trade relations, one country (orange node) is no longer part of the trade community.

2.2. Production and trade data

The Food and Agriculture Organization of the United Nations provides annual crop production and bilateral trade data for agricultural commodities (FAOSTAT 2021). We used crop production and detailed trade matrix data in tonnes for the most recently available data (2018) that were corrected for re-exports to represent point-of-origin-to-point-of-destination trade movements (Kastner *et al* 2011, Croft *et al* 2018). While trade may fluctuate across years, recent research shows that there is a high degree of 'stickiness' that makes the trade system less volatile and more stable than often assumed (Reis *et al* 2020, Adams *et al* 2021). We use primary commodity data for wheat and maize, but since the raw form of rice (paddy) is mainly traded in processed forms, we used the milled equivalent of paddy rice (FAO 1972).

To focus the analysis on relatively larger trade flows, bilateral trade flows below a certain threshold were excluded. We defined breakpoints for each crop at the 75th percentile (165.4 tonnes for wheat trade, 28.6 tonnes for rice trade, 26.6 tonnes for maize trade), which reduced noise but still maintained a relatively high number of countries (wheat 108, rice 108, maize 143) in the dataset.

2.3. Incorporating climate impacts

To consider climate impacts on crop production, we used data from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) (Jägermeyr *et al* 2021). ISIMIP offers intersectoral simulations that allow for the specification of risk factors for combined analysis, such as global climate models and impact models; global gridded crop models in our case.

We calculated a mean across relative changes projected by individual climate-crop model combinations compared to the reference period 1983–2013. We used ensemble data from the Global Gridded Crop Model Intercomparison Phase 3 simulations within ISIMIP, including five climate models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL) and twelve crop models (ACEA, CROVER, CYGMA1p74, DSSAT-Pythia, EPIC-IIASA, ISAM, LandscapeDNDC, LPJmL, pDSSAT, PEPIC, PROMET, SIMPLACE-LINTUL5) covering all three crops (Jägermeyr *et al* 2021), and include an CO_2 fertilisation effect (without this, the impacts of climate change may be more severe). For an overview of the climate models and crop models, see tables S1 and S3 respectively in (Jägermeyr *et al* 2021). Relative crop yield projections per grid were aggregated to country level through an area weighted mean. Grid cells were masked for currently cultivated areas and bias-corrected with observational yield levels. Areas not covered in cropland input and reference yield leave some countries reported as NA's (see supplementary material A).

Atmospheric concentration levels are given by the Representative Concentration Pathways (RCPs; van Vuuren *et al* 2011). We selected crop yield projections driven by climate scenarios for RCP 8.5, since this most closely agree with historical total cumulative CO_2 emissions (Schwalm *et al* 2020). Regarding time-perspective, we selected long term projections (the mean of the period 2070–2099) to generate more 'extreme' scenarios of trade impacts marking potential redistributions in trade communities.

2.4. Analysing network structures

We use the Louvain algorithm (Blondel *et al* 2008) to detect communities in the trade networks for the three selected crops. The Louvain algorithm defines a modularity function Q, which equals the fraction of links within communities minus the expected fraction of such weighted (i.e. non-binary) links (assuming a randomised network with the same numbers of nodes and links). The Louvain algorithm maximises Q over (optimally all) divisions of the network into communities. For the quality of the process of identifying trade communities, see supplementary material B.

We used two measures to evaluate changes between present-day and climate-projected network structures. First, we compared the similarity of network communities in present-day and climate-projected food trade networks using the Adjusted Rand Index (Hubert and Arabie 1985). The Rand Index is a measure for comparing similarity of two different partitions based on pair-wise comparison of included elements. Any two data points in one network can be in the same or in different communities and for each combination the Rand Index measures if these two points are in the same community, in one but not the other or in different communities in both networks. The result is the fraction between the agreement of two different partitions and the total number of pairs of elements. The Adjusted Rand Index (R) corrects for random assignments and the risk of overlap. R goes from 0 to 1, with 1 indicating an exact match between a pair of communities.

Second, to analyse how certain countries may change their network position before and after climate change, we used the method of functional cartography (Guimerà and Amaral 2005)[7]. This method assumes that nodes in a network fulfil certain roles based on how they are connected within, or across, communities. The role of a node is determined from two indices capturing how well a node is connected to other nodes in its community (z), and how

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[7] Note that while the full method also calculates modularity based on simulated annealing, we instead use Louvain community identification and subsequently apply the within-community degree and participation coefficient.

the node's links are distributed among other communities (*P*). The first index, the within-community degree, is defined as

$$z_i = \frac{K_i - \bar{K}_{s_i}}{\sigma_{K_{s_i}}},$$

where K_i is the number of links of node i to other nodes in its trade community s_i, $\bar{K}_{s_i}$ is the average of K over all the nodes in s_i, and $\sigma_{K_{s_i}}$ is the standard deviation of K in s_i. The second index, the participant coefficient, is defined as

$$P_i = 1 - \sum_{s=1}^{N} \left(\frac{K_{is}}{k_i} \right)^2,$$

where K_{is} is the number of links of node i to nodes in community s, k_i is the total number of links of node i and N is the number of communities.

These measures define a parameter space where different regions represent roles based on threshold values. Guimerà and Amaral distinguished seven roles for nodes. First, nodes are categorised along the *z*-dimension as hubs if $z \geqslant 2.5$, and non-hubs if $z < 2.5$. Second, nodes are categorised along the *P*-dimension. Non-hubs are divided into ultra-peripheral (all or almost all links within own community, $P \leqslant 0.05$), peripheral (most links within own community, $0.05 < P \leqslant 0.62$), connectors (many links across communities, $0.62 < P \leqslant 0.80$), and kin-less (homogenously distributed links across all trade communities, $P > 0.80$). The latter two roles bridge communities and are thereby important for network cohesion. Hubs are categorised as provincial (a vast majority of links within own community, $P \leqslant 0.30$), connector hubs (many links to most of the other communities, $0.30 < P \leqslant 0.75$) and kinless hubs (homogenously distributed links across all communities, $P > 0.75$). Hubs represent major traders; provincial hubs being of most importance for trade community cohesion, kinless hubs for global trade network cohesion, and connector hubs for both. The behaviour of *z* and *P* was further explored by changing threshold values (see supplementary material C).

3. Results

3.1. Climate change impacts on global trade patterns
Figures 3–5 show the community detection results for present-day and climate-projected trade (see supplementary material D for detailed lists of trade communities). Overall, these results suggest strong stability of trade communities under climate change impacts on production, and proportionally on trade. For wheat (figure 3), the trade community structure is identical between present-day and climate-projected trade, hence $R = 1$. For rice (figures 4(a) and (b); $R = 0.89$), one major producer, Vietnam, changes trade community from a community with four of the

major global producers, to a community with only two major producers, albeit the biggest one, China, and Cambodia. Zimbabwe, with a very small rice production, also changes trade community. For maize (figures 5(a) and (b); $R = 0.86$) the trade community structure between present-day and climate projected trade differs more, although the major maize producers remain in the same communities. Russia, Turkey and Sudan leave the trade community dominated by China and join the community with the five central Asian states.

Generally, the structure of the trade communities shows relatively strong patterns of geographical proximity: for all three crops, North and South America form two trade communities. Western and central Europe form a trade community, also for all three crops (note however small production of rice). Also, for Africa there are relatively strong patterns of food trade between neighbouring countries. The picture is slightly more scattered for Asia. For example, for rice there is a strong trade community in South Asia with important trade links to many Sub-Saharan African states, but weak links to North and South America.

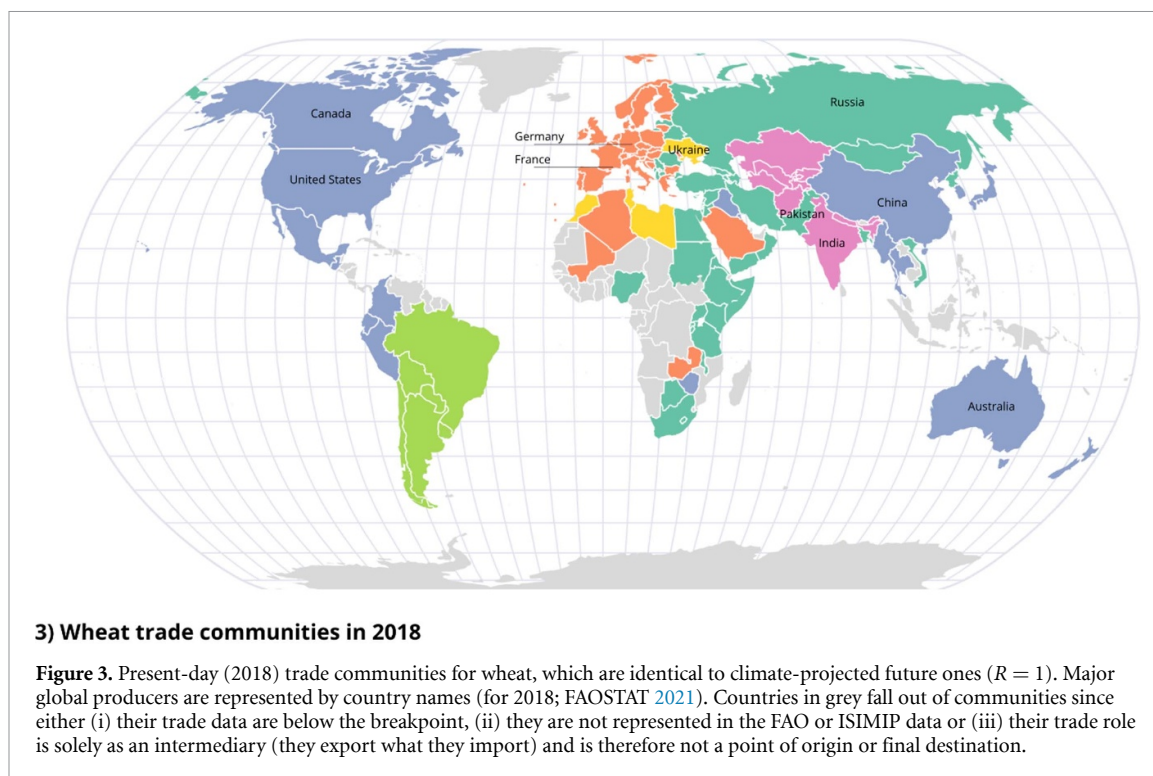### 3.2. Climate change impacts on network roles
Figures 6–8 illustrate network roles for countries in each present-day and climate-projected food trade network (see supplementary material E for full country lists). Figure 6 indicates that many major global wheat producers act as connector hubs, i.e. have many links within and across trade communities, and that this remains unchanged with projected climate change impacts. Thereby, results project that major global wheat producers are as important for the cohesion of the global wheat network as for their respective trade community.

For rice, the majority of countries remain in the same role (figures 7(a) and (b)). Of major global producers, only Cambodia shifts towards trading more across communities with projected climate change impacts (from non-hub to hub). Pakistan, with a mid-level sized production, increasingly distributes its rice trade by moving from connector to kinless hub with climate change impacts.

The largest changes in network roles are projected for maize trade, where major maize producers India, United States and Brazil increasingly distribute their trade across communities and are thus characterised as kinless hubs (figures 8(a) and (b)). Mid-level global producers such as Ethiopia, Egypt and Turkey shift to connector hubs, thereby becoming increasingly important as network brokers across trade communities.

3.3. Climate change impacts on production
In this section we study climate change impacts on production and how these affect trade communities. The trade communities studied here are based

3) Wheat trade communities in 2018

Figure 3. Present-day (2018) trade communities for wheat, which are identical to climate-projected future ones ($R = 1$). Major global producers are represented by country names (for 2018; FAOSTAT 2021). Countries in grey fall out of communities since either (i) their trade data are below the breakpoint, (ii) they are not represented in the FAO or ISIMIP data or (iii) their trade role is solely as an intermediary (they export what they import) and is therefore not a point of origin or final destination.

on present-day climate conditions (cf figures 3, 4(a) and 5(a)), i.e. we do not consider climate-projected trade communities in this section. Subsequently, we study disruptions to communities' domestic supply resulting from both projected climate-induced yield change and the share of countries' imports that originates from trade partners that face production changes (table 1; see supplementary material F for detailed lists of change for individual countries).

The global wheat production is dominated by four large trade communities. The production of wheat is projected to increase by 20% until 2099, and all six trade communities are projected to see increased production (column 3). As a result of the stability of the trade community structure, the import dependency for each community is almost unchanged under climate change impacts (cf columns 3 and 5).

The production of rice is dominated by three large trade communities of similar size, and two smaller ones in the Americas; the two latter are almost completely isolated from the rest of the world. The overall small increase in rice production and imports (4%; column 6) is not concentrated to one trade community, but distributed across the three major trade communities with community 3 showing a small overall increase (1%) and community 5 a larger increase (11%), whereas trade community 4 is projected to decrease with 6%. Trade community 1 increases its available amount of rice with 27% (note that this is a very small community). For all communities except
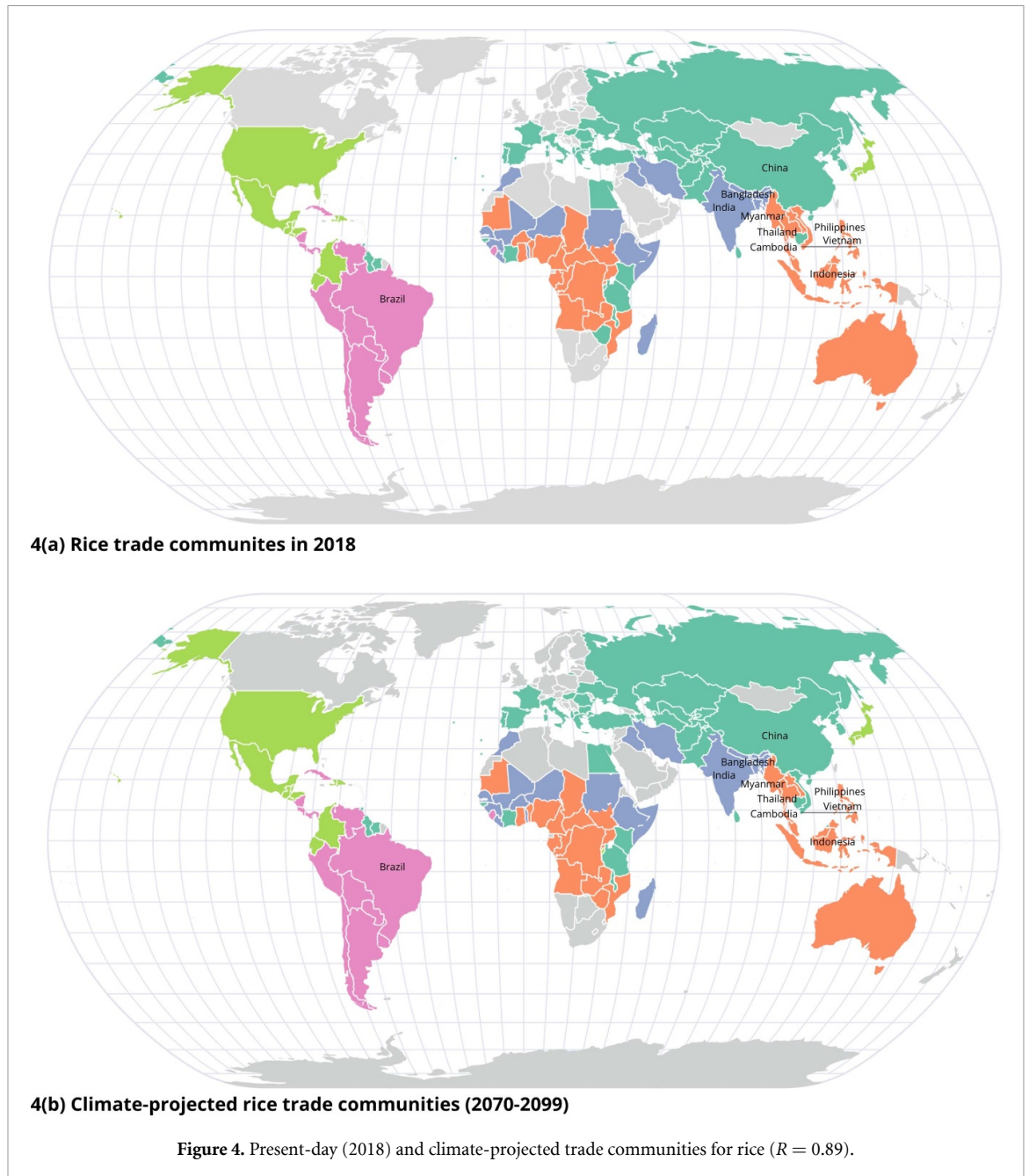
no. 4, production increases (column 3) while imports decrease (column 5). As a result, import dependency decreases. The situation for trade community 4 is especially problematic since both production and import decrease.

Lastly, the global maize production loss (-20%) hits all trade communities. The main producing community (2) is most exposed by combined climate-induced changes of -25% in total production and imports. For all trade communities except community 5, the production loss is roughly similar to decreased import.

4. Discussion

Our study identifies potential disruptions in food trade networks taking point-of-origin-to-point-of-destination trade movements into account. The strength of our method is to, through a transparent and tractable modelling approach, provide insight into how current trade patterns may be reoriented as a result of projected climate change impacts.

Our model projects high stability of trade community structures under climate change. Only for maize a more substantial change can be observed. Our results, however, also show that the yield level for a few major producers ultimately determines how vulnerable food trade networks may become under future climate change impacts. The movement of major global producers between communities, as exemplified by Vietnam and rice, indicates that trade

4(a) Rice trade communites in 2018

4(b) Climate-projected rice trade communities (2070-2099)

Figure 4. Present-day (2018) and climate-projected trade communities for rice ($R = 0.89$).
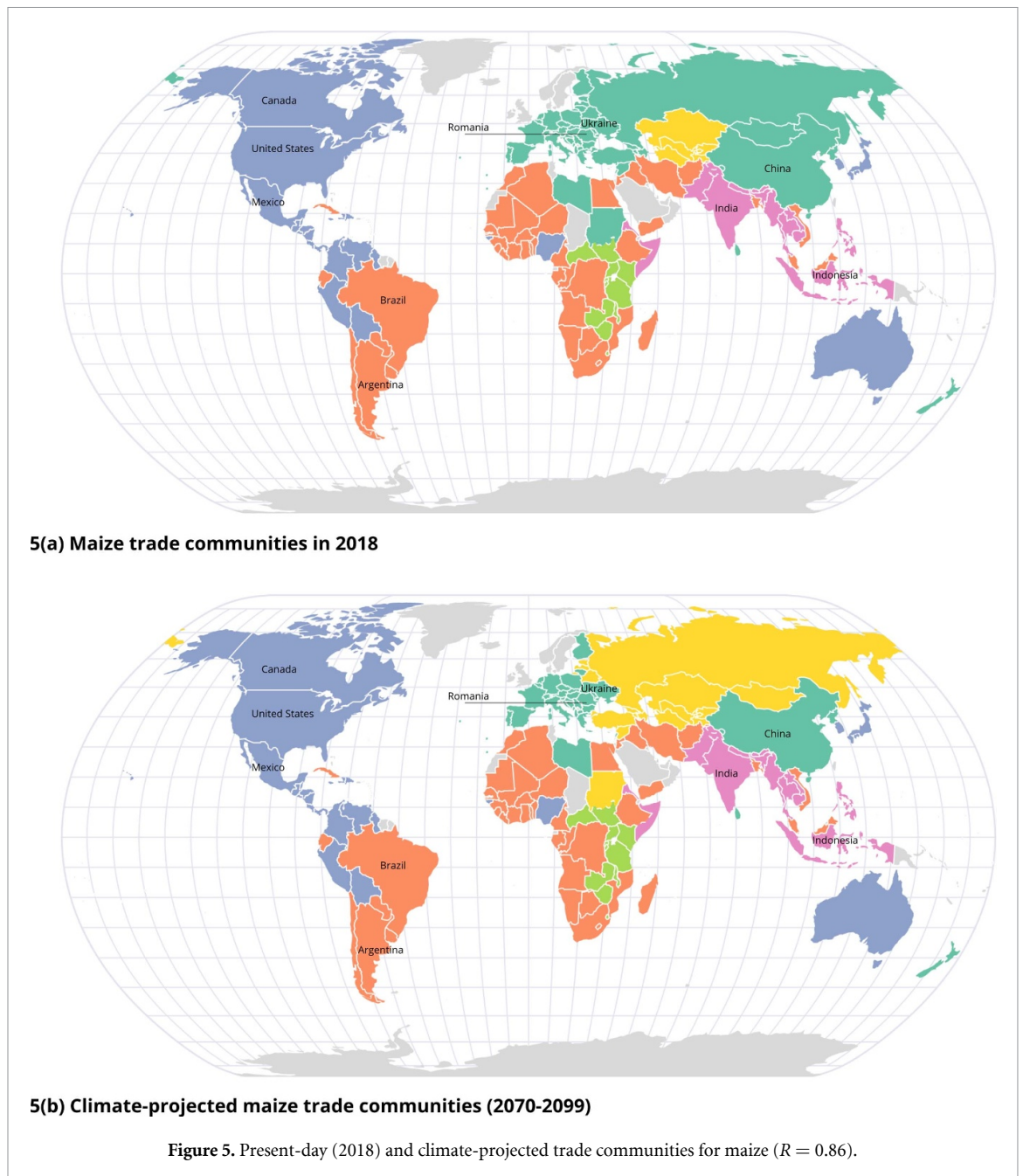
relationships may change despite overall stability of global trade structures.

These results show that a country's future trade-linked climate vulnerability will be a combined effect of yield change and the balance of production loss or gain among trade partners. According to our model, few countries may be able to buffer their production loss with imports from existing, close trade partners if maintaining current consumption levels, especially for maize. Rather, cross-border climate impacts are likely to cause disruptions to the available supply. Our model also illustrates how the distribution of cross-border production change in a community may be a

determinant of vulnerability for individual countries. For example, Mali and Saudi Arabia face wheat production loss, but imports from existing trade partners may maintain available supply. Contrastingly, larger production losses than gained imports will make balancing supply by imports impossible, as in the case of maize trade. Such conditions would introduce adaptation options beyond substituting trade partners. Our results do not support interpretation of such dynamic responses impacting future trade, yet indicate that trade as an adaptation mechanism may be more viable for wheat and rice than it is for maize.

5(a) Maize trade communities in 2018

5(b) Climate-projected maize trade communities (2070-2099)

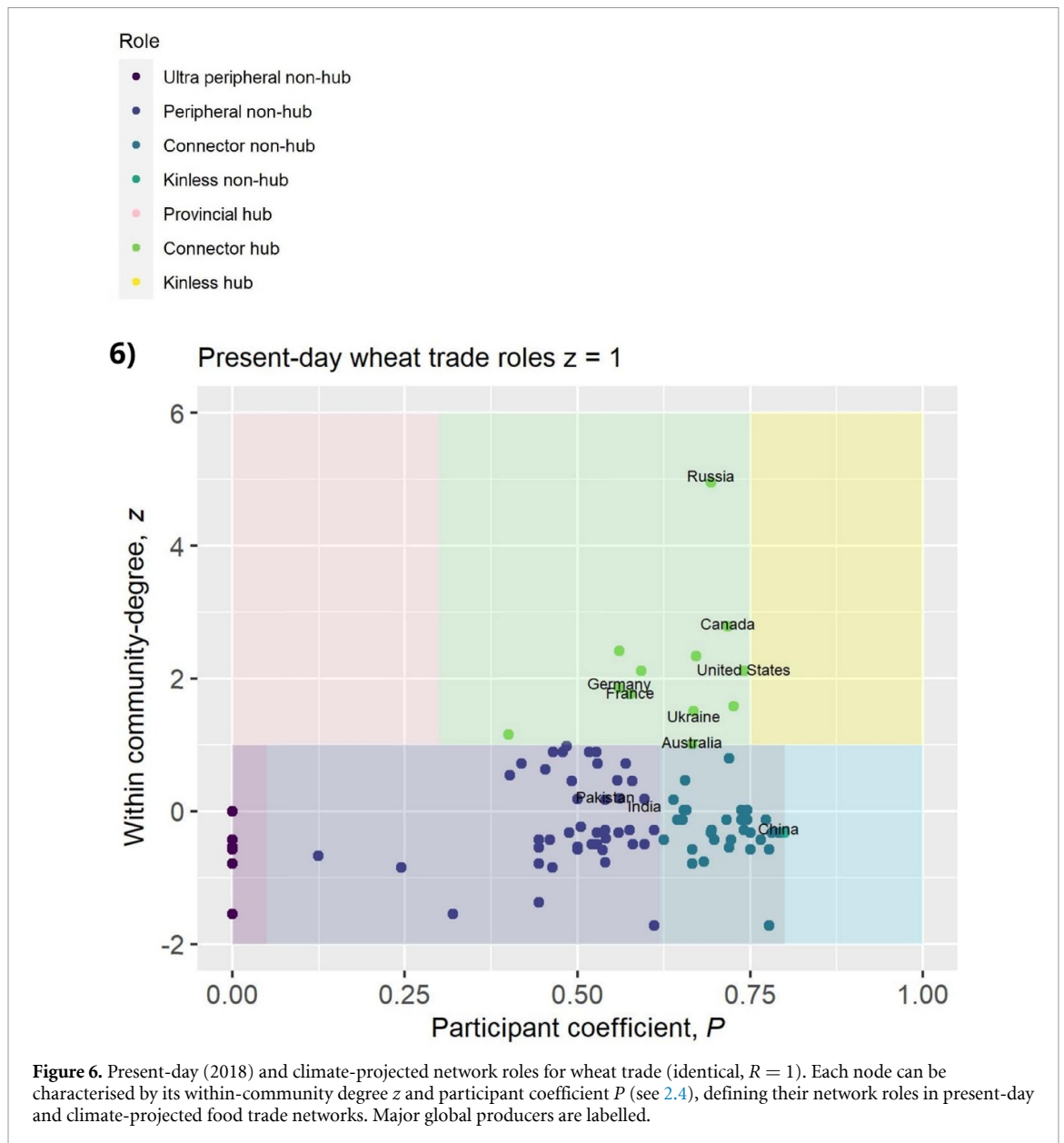**Figure 5.** Present-day (2018) and climate-projected trade communities for maize ($R = 0.86$).

5. Limitations and potential developments

Our model is inherently limited by its simplicity. For example, it only allows for considering first-order cross-border impacts. Reduced food production resulting in increased market prices will likely however lead to higher-order direct and/or indirect effects, with a substantial impact on trade patterns (Middelanis *et al* 2021). While model simplicity is required here for isolating the cause-and-effect relationship between climate change impacts and trade disruptions, future research could include economic modelling or the application of 'discount factors' to particular nodes to make them more likely to secure continued supply. Future analysis could also factor in the size and population of each country; in our analysis, each country (node) is treated the same way. Capturing these dynamics would entail the development of more complex models and associated assumptions, which whilst beyond the scope of this paper, offer a rich stream for future research activity focused on cross-border climate impacts.

Another limitation in our approach is that we utilise a future scenario with regards to atmospheric
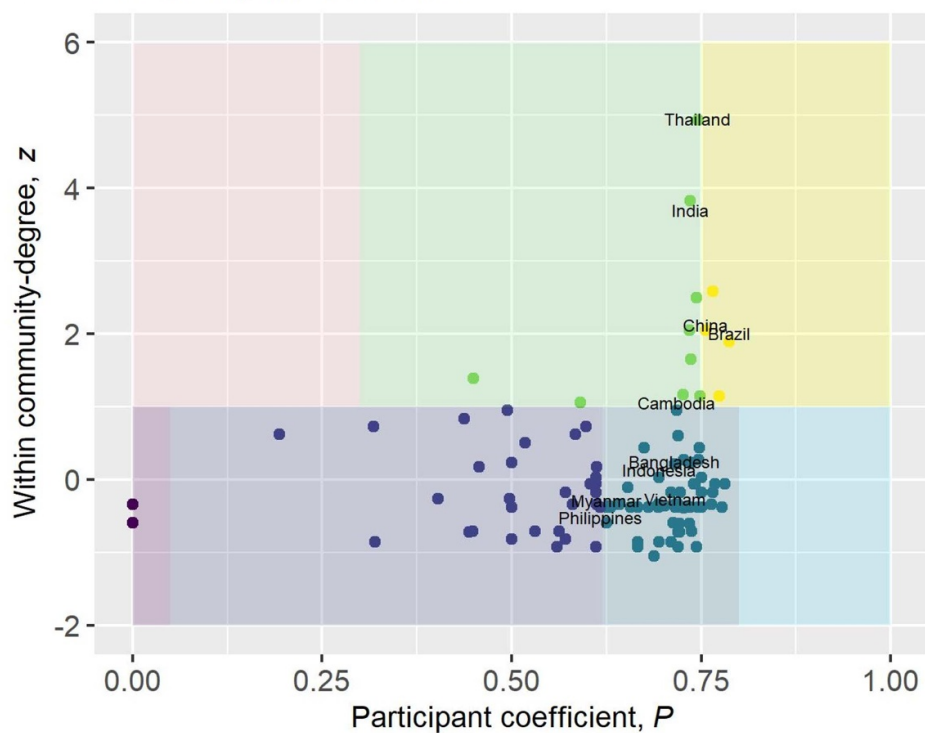
Figure 6. Present-day (2018) and climate-projected network roles for wheat trade (identical, $R = 1$). Each node can be characterised by its within-community degree z and participant coefficient P (see 2.4), defining their network roles in present-day and climate-projected food trade networks. Major global producers are labelled.

concentrations of greenhouse gases, and from this take projected future climate conditions and projected future impacts on crop yields, and apply it to a representation of today's trade patterns. There is—in general—a need for combining impact scenarios with scenarios of how the future society might evolve (O'Neill *et al* 2014, 2020). For example, future societies might see significant crop expansion, land use change and behavioural change, which could imply new conditions for today's production systems (Nelson *et al* 2014, Stevanovic *et al* 2016).

This analysis has been conducted using a single year's trade data, which may contain fluctuations or deviations from the average trade situation. As such, our baseline communities may not precisely represent the current reality. One option to account for this would be to average the trade data over a temporal window, but this introduces assumptions about how the averaging relates to where and when trade is re-exported. Averaging multiple climate and crop models could also have reduced the extremes of climate change impact projections, and averaging over multiple years may hide the more extreme years. More useful would be to test out a variety of years of trade data, along with a more exhaustive range of commodities, should this work be developed into more complex assessments.

Finally, our analysis does not capture substitution of products or the relative importance of the trade of secondary or derived commodities, and
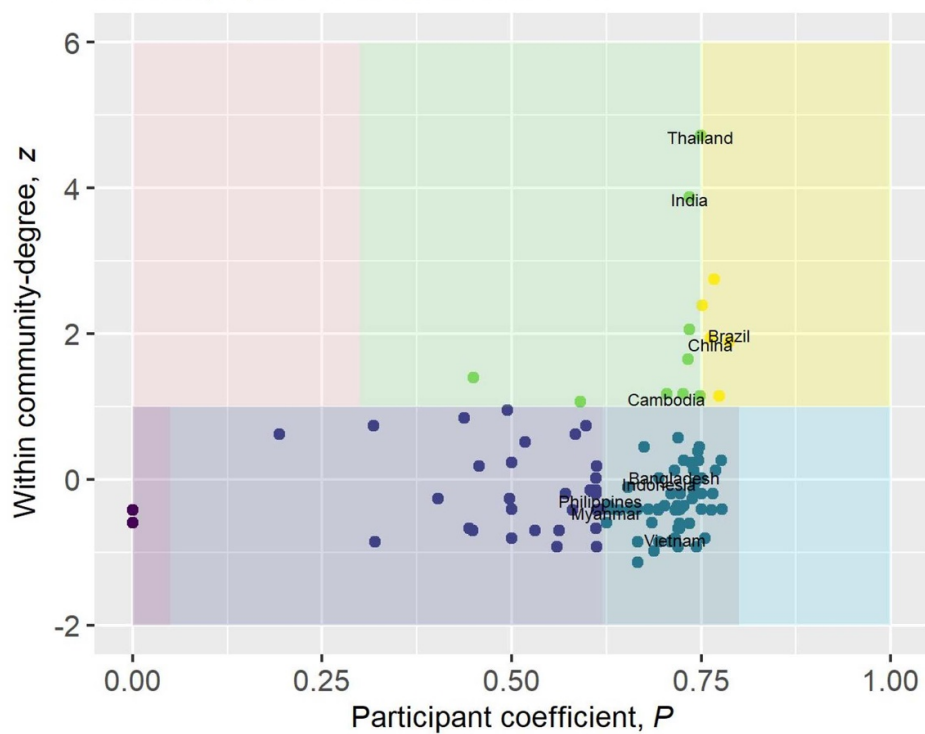
Figure 7. Present-day (2018) and climate-projected network roles for rice trade.
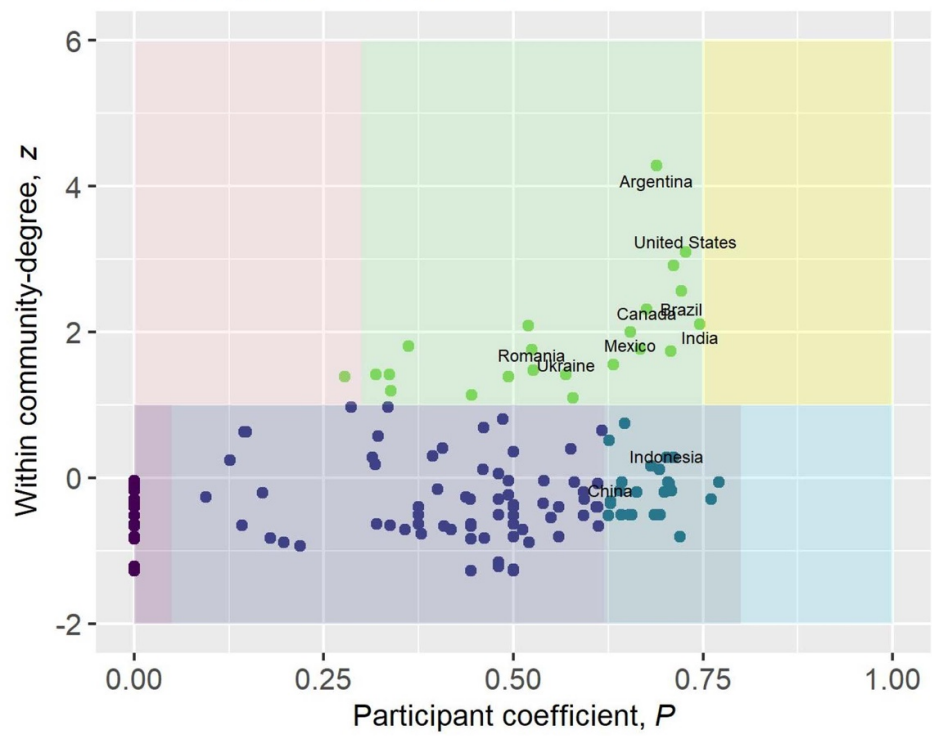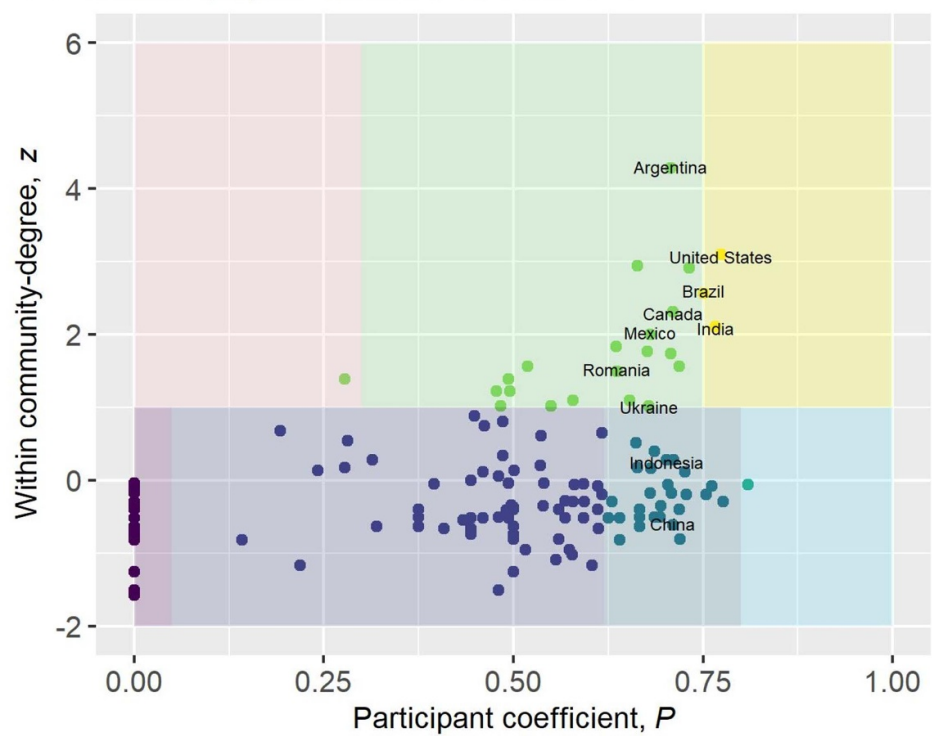
Figure 8. Present-day (2018) and climate-projected network roles for maize trade.

Table 1. Change in total production and imports per trade community for each crop. Colours correspond to present-day trade communities in figures 3, 4(a) and 5(a).

Wheat	1	2	3	4	5	6
Trade community	Community production—present-day climate conditions (tonnes)	Community production as % of world production	Climate-projected community production (tonnes) and change compared to present-day	Total import (tonnes) and share of production—present-day climate conditions	Climate-projected total import (tonnes) and change compared to present-day	Total climate-induced change in production plus import
1	26 869 848	4%	29 425 491 (10%)	8 149 390 (30%)	9 100 081 (12%)	10%
2	243 155 832	33%	304 516 255 (25%)	30 983 682 (13%)	38 242 929 (23%)	25%
3	133 234 315	18%	167 025 958 (25%)	43 620 994 (33%)	54 075 061 (24%)	25%
4	170 078 129	23%	197 181 129 (16%)	53 419 138 (31%)	62 246 560 (17%)	16%
5	33 612 230	5%	42 964 456 (28%)	7 473 730 (22%)	8 772 934 (17%)	26%
6	127 012 081	17%	140 853 917 (11%)	10 373 935 (8%)	12 645 044 (22%)	12%
TOTAL	733 962 435	100%	881 967 206 (20%)	154 020 868 (21%)	185 082 610 (20%)	20%

Rice	1	2	3	4	5	6
Trade community	Community production—present-day climate conditions (tonnes)	Community production as % of world production	Climate-projected community production (tonnes) and change compared to present-day	Total import (tonnes) and share of production—present-day climate conditions	Climate-projected total import (tonnes) and change compared to present-day	Total climate-induced change in production plus import
1	25 792 030	3%	33 585 808 (30%)	2 622 792 (10%)	2 367 407 (−10%)	27%
2	22 430 895	3%	24 602 262 (10%)	2 422 332 (11%)	2 164 986 (−11%)	8%
3	247 549 930	32%	250 751 903 (1%)	7 784 525 (3%)	7 780 355 (<1%)	1%
4	221 428 449	28%	207 892 155 (−6%)	8 507 224 (4%)	7 693 166 (−10%)	−6%
5	262 800 106	34%	293 214 047 (12%)	6 667 171 (3%)	6 385 300 (−4%)	11%
TOTAL	780 001 410	100.0%	810 046 176 (4%)	28 004 044 (4%)	26 391 214 (−6%)	4%

therefore potentially lacks significant trade relationships associated with the utilisation of primary commodities. However, while initial processing steps are quite simple to follow, derived products included in different processing streams become more complex to handle. Nonetheless, the extension of network models to include derived products would offer additional insight into these dependencies and their implications for climate change resilience.

Table 1. (Continued.)

Maize	1	2	3	4	5	6
Trade community	Community production—present-day climate conditions (tonnes)	Community production as % of world production	Climate-projected community production (tonnes) and change compared to present-day	Total import (tonnes) and share of production—present-day climate conditions	Climate-projected total import (tonnes) and change compared to present-day	Total climate-induced change in production plus import
1	83 554 440	7%	64 155 333 (−23%)	2072 181 (3%)	1582 681 (−24%)	−23%
2	453 883 616	40%	340 857 118 (−25%)	61 495 385 (14%)	46 564 236 (−24%)	−25%
3	192 959 809	17%	163 405 845 (−15%)	47 328 308 (25%)	39 980 756 (−16%)	−15%
4	394 390 952	34%	330 618 348 (−16%)	40 392 955 (10%)	34 084 162 (−16%)	−16%
5	19 757 003	2%	19 364 669 (−2%)	824 322 (4%)	731 770 (−11%)	−2%
6	2245 491	<1%	1877 669 (−16%)	55 790 (3%)	45 698 (−18%)	−16%
TOTAL	1146 791 311	100.0%	920 278 982 (−20%)	152 168 941 (13%)	122 943 606 (−19%)	−20%

6. Conclusion

This study develops a simple network modelling approach to explore how current food trade between countries may be disrupted under long-term climate change impacts. Our study complements previous work by focusing on climate change impacts on production and bilateral trade in global network structures. We find that, for wheat and rice, the trade community structure is either stable (wheat) or only slightly changed (rice). According to our model, countries with relatively large disruptions in both their domestic and trading partners' production face the largest challenges in meeting their demand for all three crops, but particularly so for maize. The degree to which the food trade system can withstand climate risks may thus largely depend on countries' abilities to balance production losses domestically and among vulnerable partners, relative reliance on specific crops, and relative levels of impacts differing between different producers and communities. Taken together, this analysis of climate-induced changes of current food trade networks provides a baseline framework for more detailed study of potential threats to global food security, and—most importantly—highlights the need for international cooperation on adaptation.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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