Global trade and the resilience of food supply to extreme weather exposure

Daniel P. Bebber[1,3,*], Carole Dalin[2], Emma W. Littleton[3], Pete Falloon[4,5], Andrew J. Challinor[6], Steve McCorriston[7], Tim Lloyd[8], Matteo Zampieri[9].

[1] Department of Biosciences, University of Exeter, Exeter, UK

[2] Institute for Sustainable Resources, University College London, London, UK

[3] Global Systems Institute, University of Exeter, UK

[4] Met Office Hadley Centre, Met Office, Exeter, UK

[5] School of Biological Sciences, University of Bristol, Bristol, UK

[6] Institute of Climate and Atmospheric Science (ICAS), School of Earth and Environment, University of Leeds, Leeds, UK

[7] Department of Economics, University of Exeter, Exeter, UK

[8] Bournemouth University Business School, Bournemouth University, Bournemouth, UK

[9] King Abdullah University of Science and Technology, Thuwal, Kingdom of Saudi Arabia

* Correspondence to d.bebber@exeter.ac.uk

This manuscript is a non-peer reviewed preprint submitted to EarthArxiv.

This manuscript has been submitted to the journal *Nature Communications* for peer review.

Summary paragraph

Climate change is increasing the risk of extreme weather events, potentially threatening crop yields and global food security. A key benefit of international free trade is risk sharing, because global aggregate production is more stable than that of individual countries which may be adversely affected by extremes. Here we test the hypothesis that diverse sourcing of crops from multiple trading partners reduces exposure to extreme weather, using a detailed trade matrix and range of extreme weather indices. We find that countries with high source diversity have moderate exposure, but that there is wide variation in the degree of exposure in countries reliant on domestic crop production. Global aggregate production and export volatility is stable or declining for most crops, suggesting that source diversification will increase resilience to both climatic and non-climatic supply shocks.

Main text

The history of the global food system is characterized by increasing international trade of agricultural commodities. Archaeological evidence indicates that Egypt imported palm oil from the Sudan more than 5000 years ago [1], and today the total value of agricultural exports is around US$1.8 trillion [2]. The contribution of imports to domestic consumption of major grains doubled in volume between 1995 and 2018, to 9 % for rice, 15 % for maize, 24 % for wheat and 42 % for soybeans [2]. Participation in the global food trade network is increasing in size and complexity. The number of participating countries and the number of links between countries has grown dramatically in recent decades [3,4]. The network became tighter and more efficient in terms of a growing number of links per country and more direct connections between countries, though trade is not entirely free and a set of trading clusters, or communities, remains [4].

The size, structure and function of the international food trade network are of paramount importance to global food security [3]. Consumers benefit from access to international markets through lower prices and availability of products which cannot be produced locally or are out of season, while producers benefit from better prices for marketable surpluses [2]. Food prices increase when governments impose restrictions on free trade such as export bans, as demonstrated by the 2007-8 global food price crisis [5,6] and responses to the Russian invasion of Ukraine [7,8]. Though globally deleterious to food security, such actions can protect poorer consumers against transient production shortfalls or price spikes, and may be the only policy tools available in low income countries [2].

A key benefit of international free trade is risk sharing [9]. Because production shocks are largely uncorrelated among countries, global aggregate production is very stable compared to that of individual countries. Stocks of surpluses that can be released onto the market in times of scarcity contribute to this stability, while low stocks can trigger behaviours that cause price spikes [10]. Therefore, consumers with wider access to markets will benefit from more stable supplies and lower risk of price shocks. While not perfect, the global grain markets provide over 80 % insurance against shocks, estimated from the contribution of changes in country production to changes in country consumption, with the wheat market performing most efficiently [9]. Stocks contribute nearly half of this consumption shock smoothing effect by providing a buffer against production shocks.

Empirical analyses thus support, to a large degree, the theory that international free trade increases food security via risk sharing. However, there are several caveats. Firstly, trade participation is strongly linked to wealth. For example, low income countries achieve just 52% of full risk insurance for rice, compared with 93% for high income countries [9]. Simulations suggest that low income countries tend to be more exposed to external production shocks [11]. Secondly, global markets are not perfectly free, with persistent connected clusters demonstrating limited access to globally-stable supplies [4]. Thirdly, climate change may increase the exposure of crop producing regions to adverse weather and climate shocks [12–15], thus challenging both the resilience of the global market and resulting levels of food security [16]. The cascading effect of increasingly frequent and severe extreme events, in addition to other stressors for agricultural productions, could affect the entire interconnected system jeopardizing food security and markets stability through escalating global prices of agricultural commodities [17,18]. Ongoing global socio-political and environmental trends will exacerbate economic uncertainty [19,20], thus reducing risk insurance in concert with increasing climate risks [21]. Assessing the resilience of food supplies, as mediated – at least partially – via global markets, is critical to understanding the implications of these ongoing and projected changes [11]. Accordingly, we test the hypotheses that global food supplies have become more secure against extreme weather shocks through source diversification, and that source diversification reduces risks of exposure to adverse weather conditions in crop producing regions.

Results and discussion

Extreme weather exposure indices and yield shocks

We analysed the relationships between global crop yield shocks and a set of extreme weather indices: the Agriculturally Relevant Exposure to Shocks (ARES) [22], and derivatives of a subset of the Climate Extreme Indices (CEI) [23] and the Emergency Event Database (EM-DAT) [24]. We analysed 16 crops included in the ARES analysis (Supplementary Table S 1), omitting yam due to a lack of international trade data. The various extreme indices appeared largely independent, showing very little correlation among one another (Supplementary Fig. S 1). Moderately positive correlations (around 0.3) were found between ARES hot and cold indices, ARES cold and CEI cold, and CEI cold and CEI dry. A moderate negative correlation (-0.41) was found between EM-DAT dry and EM-DAT wet indices. We tested whether extreme indices were negatively correlated with annual yield shocks (Supplementary Fig. S 2). None of the ARES indices, and none of the cold shock indices, showed consistently positive or negative correlations with yield shocks (Supplementary Fig. S 3). The CEI and EM-DAT dry and hot indices showed more negative correlations with yield shocks than did the ARES indices. The CEI wet index had a generally positive correlation with yield shocks for most crops, suggesting that this metric is actually indicative of better growing conditions. To investigate the role of source diversity in reducing exposure to supply shocks caused by extreme weather, we selected the CEI hot and EM-DAT dry indices for further analysis.

Diversification of commodity sourcing

Diverse sourcing of food crops theoretically spreads the risk of scarcity from supply shocks. Similar patterns in source diversity were found for most crops, with major producers tending to rely on domestic production (low diversity, small import fraction), though there were varying numbers of countries dependent upon imports (Fig. 1). Overall, mean import fraction and mean source diversity over time for each country and each crop were highly correlated (Kendall correlation = 0.80), and there were very few cases where a country reliant on imports sourced these from few partners. Cassava, oat, potato, rye and sorghum had generally lower source diversity than crops like rice, sunflower and wheat. Source diversity increased over time for most countries and most crops. For major commodity crops, we found almost universal increases in source diversity, but without consistent geographical patterns in either means or trends (Fig. 2). Maize sourcing was most diverse in parts of Latin America, North Africa, and Europe, and increased most in parts of North Africa and Europe. Rice sourcing was most diverse in Europe, and increased most in Eastern Europe. Soybean source diversity was greatest in northern South America, and across much of Europe and Asia, and is increasing most rapidly in Asia and parts of Africa. The soybean supply has become more concentrated in a few countries (Fig. 2c). For example, New Zealand has become almost entirely dependent on Argentina for soybean imports since 2010. Wheat sourcing is most diverse in Latin America and Africa, and has increased most rapidly in parts of Africa and the Arabian peninsula. Increasing diversification of supply across most commodities and countries suggests reduced risk of exposure to extreme weather shocks that could impact production.

Source diversity and extreme exposure risk

We found that the relationship between extreme weather exposure and source diversity was more complex than a simple inverse correlation (Fig. 3, Fig. 4). Self-sufficient countries with low import diversity tend to have a wide range of exposures while those reliant on imports from a wide range sources tend to have low overall exposure but not as low as the least-exposed self-sufficient countries. Taking rice as an example, some largely self-sufficient countries like Cuba, the Philippines and Papua New Guinea experience high risk of extreme heat exposure, while Angola, Argentina and Brazil do not (Fig. 3). Similarly, self-sufficient countries like China, Madagascar and Tanzania are highly exposed to drought while Belize, Dominican Republic and Ivory Coast are not (Fig. 4). Importers like Denmark, France and the United Kingdom are only moderately exposed to heat and drought due to their high source diversity. Overall, we see a wide range of exposures to extreme weather for self-sufficient countries and a lower, less variable range of exposures for importers. Countries vary in import fraction and source diversity over time, and we would expect a negative correlation between diversity and extreme exposure within countries under the hypothesis of reduced risk through diversification. However, we found these correlations to be highly variable, both for the CEI hot index and the EM-DAT dry index (Supplementary Fig. S 4). Therefore, there is no general pattern that supply diversity decreases exposure to extreme weather.

While climate variability can affect one third to one half of the global production variability for some crops [25,26] extreme weather (variously defined) contributes only a small fraction of variance in production [27]. Therefore supply shocks are primarily due to other factors including energy prices, interest rate fluctuations, commodity speculation, trade embargoes and global stock shortages [10]. Greater source diversity could in theory reduce the risk of supply shocks, but we found equivocal evidence to support this hypothesis (Fig. 5). Negative correlations between source diversity and supply shocks were found for barley, groundnut, maize, oat, rye, soybean and sunflower, while positive correlations were found for cassava, millet, potato, sorghum, sugarcane and sweet potato. Correlations for rapeseed, rice and wheat were very weak ($-0.1 < \tau < 0.1$). Thus, it is not necessarily the case that supply diversity is related to supply stability. There was substantial interannual variability in total supply for certain crops in some countries, meaning that detrending to quantify expected supply and supply shocks could result in extremely large relative supply shock values (Supplementary Fig. S 5).

Variability in global production and exports

There is growing concern that climate change will increase extreme weather impacts on agriculture, threatening global food security [28]. The CEI hot index showed a substantial increase over time for the major grains, particularly after 2010, while the EM-DAT dry index showed no marked trends over time (Supplementary Fig. S 6). We tested whether global crop production and export volatility has increased over time, as might be expected under growing risks of extreme weather impacts.

We found no evidence for changes in global aggregate production variability over time for most crops (Supplementary Fig. S 7, Supplementary Table S 1), and declining of variability of exports to international markets for many crops (Supplementary Fig. S 8, Supplementary Table S 1). Average annual production shocks over the period 1961 to 2020, estimated as absolute deviations from expected production, varied between 1.5 ± 0.2 % for rice and 7.9 ± 0.8 % for rye. Production shocks declined significantly over time for rice, but not for other crops. For total global exports, average annual shocks varied between 3.2 ± 0.4 % for sugarcane and 23.7 ± 2.7 % for rye, and were greater than production shocks for all crops. However, export shocks declined significantly for maize, oat, rapeseed, sunflower and wheat, and the trend was more negative than for production shocks for almost all crops. No trends in production shocks or export shocks were significantly positive. Stable or declining variability in global production and exports to international markets to some extent ameliorates concerns of increasing risks from synchronized global shocks to the food system [15,28,29]. Previous analysis has shown that global production of agricultural commodities has been temporally stable compared with production within individual countries, potentially reducing the risk of supply shocks for countries able to import from global markets [9].

Conclusions

We have investigated whether source diversity – the import of agricultural commodities from a wide range of exporters – reduces the risk of exposure to weather-related supply shocks, in the knowledge that global supplies are less erratic than national production and have become more stable for many crops in recent decades. We found that the hypothesis is supported in part. Aggregate exposure to weather shocks is relatively low in countries with high source diversity, but not as low as those self-sufficient countries that are not often exposed to extreme weather events. However, a substantial number of countries are self-sufficient but are also highly exposed to weather extremes. This general pattern holds for most of the crops, and both of the extreme weather indices, that we investigated. We can therefore classify countries into three broad grouping, the Safe Self-sufficient, Exposed Self-sufficient and Sheltered Importers, acknowledging a continuum spanning these extremes (Fig. 6). We found strong evidence that global crop production and exports to global commodity markets have become more stable over time. There is no evidence for increasing risks of 'simultaneous breadbasket failures' over the past 60 years, although this does not mean that such coincidences will not become more common in future [13,15,28,29].

We compared three independent metrics of exposure to extreme weather, ARES, CEI and EM-DAT. A surprising result was the lack of correlations between the ARES indices and country-level annual yield shocks, given that ARES was designed to improve upon previous definitions of extreme events by including estimates of crop physiological tolerances. ARES was also important in that it included 17 diverse crops, while the majority of studies on food supply shock has focussed on the major grains [17]. Many previous studies have detected weak but significant negative impacts of extreme events on crop yields, whether based on climate disaster databases [27,30,31] or the statistical distributions of weather variables [25,32,33]. Jackson et al. [22] suggest a number of potential limitations in the ARES approach, including farmer adaptation (such as variation in sowing and planting dates), crop physiological adaptation in time and space (such as plant breeding and variety selection), and the effects of irrigation. However, these limitations do not explain why the CEI indices, based on statistical distributions of weather variables, and the EM-DAT indices, based only on country-level reports of events, were more strongly correlated with yield shocks than ARES. Further investigation will be required to understand the importance of these factors and make ARES truly relevant to agriculture. The generally poor correlations with yield shocks could indicate that some countries are better able to cope with extreme exposure than others, for example due to better access to mitigating technologies such as irrigation or data [34,35]. Large-scale patterns in vulnerability might be expected because wealth, and hence access to technology, vary latitudinally [36]. We saw no such global trends, however. Another reason for the weak correlations of weather extremes with yield shocks is likely to be that non-extreme weather conditions throughout the growing season are probably the most important climatic determinant of final yield, particularly conditions during key crop development phases. Crop models which simulate crop physiological responses to weather conditions throughout the growing season often provide highly accurate yield estimates, once calibrated to local conditions [e.g. 37]. Crop specific indicators such as the Combined Stress Index (CSI) [26,33] might provide higher predicting power for certain crops. However, the CSI requires extensive analysis for each commodity, making it less suitable for global food security studies. An AI enhanced procedure to identify the most sensitive period of the growing season for each crop and weather event could be envisaged to develop specific impact indicators for all commodities.

Climate change is increasing exposure of crops to extreme weather events, potentially reducing yields and threatening food security. Climate is among the most important determinants of plant productivity, explaining up to half of global crop yield variation [25,26]. Extreme weather events significantly reduce crop yields [25,27,31–33,38–41]. Crop exposure to extreme weather has been increasing in many regions [22,42] with risks of concurrent extremes in key producing regions [13], exerting a strong influence on crop production [43]. However, increasing negative impacts on crop production are not universal. For example, although extreme heat reduces grain yields in the USA [40], warming over recent decades has resulted in longer growing seasons and increased yields in maize [44]. In general, crop models and observational data indicate a latitudinal trend in the effect of climate change on yields in coming decades, with more negative yield impacts in the tropics and neutral or positive responses at higher latitudes [45,46]. The recent international concern over grain supplies to Sub-Saharan Africa caused by the Russian invasion of Ukraine highlights the importance of international trade to food security. Access to global trade networks is therefore critical, even if extreme weather events are not the main threat to supply.

Methods

Overall approach

Our primary aim was to test the hypothesis that crop source diversity (domestic supply plus imports) was negatively correlated with a source-weighted aggregate index of exposure to extreme weather across supplier countries. To select appropriate extreme weather indices for analysis, we tested a set of indices derived from different data sources for significant negative correlations with yield shocks. We also tested whether global production and export shocks have increased over time. Our analyses considered a range of time periods, depending on the constituent data sources. Following Jackson et al. [22] we including the following crops: Barley, cassava, groundnut, maize, millet, oat, potato, rapeseed, rice, rye, sorghum, soybean, sugarcane, sunflower, sweet potato and wheat. We omitted yam due to a lack of international trade data.

Crop production and trade data

For tracking food trade between countries, we used detailed bilateral trade data from 1987 to 2014 provided by the Food and Agriculture Organization of the United Nations [47]. The FAO collects and processes the data according to the standard International Merchandise Trade Statistics Methodology. This methodology is based on source data provided by the United Nations Statistics Division, Eurostat, and other national authorities. The FAO has checked the source data for outliers, added data on food aid, and built statistical models to derive estimates for non-reporting countries and to fill data gaps. The trade database includes all food and agricultural products imported and exported annually by country. Data for the following crops were obtained, to match the ARES extreme weather exposure analyses [22]: Barley, cassava, groundnut (peanut), maize, millet, oat, potato, rapeseed, rice, rye, sorghum, soybean (soya bean), sugarcane, sunflower, sweet potato, wheat and yam. No import data were reported for yam, therefore this crop was omitted from import-related analyses.

In the bilateral trade data provided by the FAO, the source country is usually the country where the last value-added production step has taken place. For example, when a country imports raw material, processes it and re-exports the product, it will be listed as the source country. We used a balancing algorithm to clearly link final demand to the origin of the primary product [48,49]. The algorithm is based on production data of primary products, bilateral trade data for primary products and the secondary products derived from those (e.g. oils), and conversion factors for converting secondary products into primary equivalents based on caloric content and using extraction rates. Total supply of each crop per country and year was calculated as the sum of all imports plus domestic supply (production minus imports).

Total annual global production and exports were obtained from FAOSTAT from 1961 to 2019. We stopped the analysis at 2019 to omit the unusual year of 2020, during which the COVID19 pandemic affected the global food system [50]. All exported crop derivatives were combined to give a total export tonnage per crop. For example, total maize exports were comprised of the following categories: Bran, maize; Cake, maize; Flour, maize; Germ, maize; Maize; Maize, green; Oil, maize. The main category Maize made up 97 % of the mean annual export.

The Shannon diversity index (exponent of Shannon entropy) was used to quantify the diversity of crop sources for importing country i in each year:

$$H_i = -\sum_{j=1} p_{ij} \ln p_{ij}$$

where p_{ij} is the fraction of a crop imported from the jth source (domestic production and importers).

Extreme weather indices

We compared three independent sources of extreme weather exposure, the Agriculturally Relevant Exposure to Shocks (ARES) [22], and derivatives of a subset of the Climate Extreme Indices (CEI) [23] and the Emergency Event Database (EM-DAT) [24]. Crops vary in their climatic tolerances and growing seasons, meaning that exposure to climatic extremes is dependent upon the crop, its geographical location and the timing of extreme events. A recent analysis has estimated crop-specific exposure to hot, cold, wet and dry conditions expected to negatively affect plant growth around the world from 1961 to 2014, showing that exposure to drought has grown most rapidly for most crops [22]. We used these ARES indices as a measure of crop exposure to hot, wet, cold and dry conditions in each country. Briefly, the ARES methodology combines gridded estimates of crop areas, crop calendars, daily weather data (minimum and maximum temperature, precipitation and reference evapotranspiration) with crop-specific thermal and hydrological tolerances to determine when and where crops have been exposed to extreme climatic conditions. ARES was developed to improve upon estimates of extreme exposure based solely on meteorology without consideration of crop physiology and distribution in time and space.

We calculated the annual exposure to extreme weather shocks per importer per crop to shocks by a supply-weighted sum of each ARES extreme index S_i:

$$S_i = \sum_{j=1} p_{ij} s_j$$

where i denotes the importing country, p_{ij} is the fraction of a crop imported from the jth source country, and s_j is the ARES index for that crop in the jth source in a particular year.

We selected four of the 71 CEI datasets to follow the hot, cold, wet and dry ARES indices. These were monthly Frost Days (number of days when minimum temperature is below freezing), annual Warm Spell Duration (number of days where six or more consecutive days experience daily maximum temperature above the 90th percentile), monthly Consecutive Dry Days (maximum number of consecutive days in which rainfall is below 1 mm) and monthly Very Heavy Rain Days (number of days in which rainfall exceeds 20 mm). The CEI data are provided at 0.25° resolution for the period 1970 to 2016. We assumed that all Warm Spell Duration days occurred during the growing season (e.g. not during winter) and so did not temporally mask this variable. The other three indices, provided at monthly resolution, were temporally masked using the growing seasons in the MIRCA2000 dataset [51]. MIRCA2000 contains sub-crops of the same crop type within a grid cell – irrigated and rainfed, and up to three sub-crops/rotation schedules, at 5 arc minute resolution. All of these sub-crops were combined to give a single presence/absence for each month. This was then used to mask the monthly values of extreme weather, such that climatic extremes occurring outside the growing season were ignored. The extreme indices for each valid month were summed to give a total extreme index per year. Crop spatial distributions were obtained from the SPAM 2010 v2 dataset [52] at 5 arc minute resolution.

We calculated a crop area-weighted mean CEI for each crop, country and year:

$$C = \frac{1}{A} \sum_{g=1}^{n} c_g a_g$$

Where A is the total crop area within a country, n is the number of 5 arc minute grid cells within a country (using the country definitions for each grid cell within the SPAM dataset), c_g is the CEI value of the gth grid cell obtained from the 0.25° CEI dataset, and a_g is the SPAM crop area in the gth grid cell. C was set to zero when crop area was zero for a particular country.

The EM-DAT database contains records of a range of emergency events including climate extremes such as heat waves, cold waves, droughts and storms, along with start and end dates for most events. We used these to construct extreme weather indices to approximate the hot, cold, dry and wet ARES indices by calculating the number of affected days per country per year. If the start and end days were missing, we assumed that the event lasted the entire month. If only year was listed, we assumed the event lasted the whole year (360 days). Our EM-DAT indices were therefore the least crop- and region-specific of the three.

Statistical analyses of crop yield shock relationships with exposure to extreme weather

Shocks in production and yield were defined as deviations of annual values from local polynomial (quadratic) regression fits using the *loess* function in R v. 4.2.1. The smoothing parameter α was set to 0.5 to follow the long-term trends without over-fitting to annual variability [53]. Relative absolute shocks were defined as the absolute deviation from the fitted value, divided by the fitted value (expressed as a percentage), as in other similar studies [53]. Temporal trends in relative absolute shocks in production or export were estimated using generalized least squares models, fitted using the *gls* function in R. Temporal autocorrelation in residuals was modelled using first order correlations using the *corAR1* function. Generalize Additive Models (GAMs) were fitted to linear trends in extreme exposure against mean source diversity for the major grains, using the *gam* function for the *mgcv* package for R [54].

Acknowledgements

The discussions that led to this paper were part of a Met Office Academic Partnership (www.metoffice.gov.uk/ research/approach/collaboration/partnership) activity.

Conflict of interest

The authors declare no conflicts of interest.

Data Availability

The data analysed in this paper are available from the following sources:

Corrected trade matrices	Prof. Carol Dalin (c.dalin@ucl.ac.uk)
Agriculturally Relevant Exposure to Shocks (ARES)	https://doi.org/10.13012/B2IDB5457902_V1
Climate Extreme Indices (CEI)	https://doi.pangaea.de/10.1594/PANGAEA.898014

Emergency Event Database (EM-DAT)	https://www.emdat.be/
National crop yield, production and export	https://www.fao.org/faostat
MIRCA2000 crop calendars	https://www.uni-frankfurt.de/45218031/Data_download_center_for_MIRCA2000
Spatial Production Allocation Model (SPAM) crop distributions	https://mapspam.info/

References

1. Saffirio, L. Food and dietary habits in ancient Egypt. *J. Hum. Evol.* **1**, 297–305 (1972).
2. Smith, V. H. & Glauber, J. W. Trade, policy, and food security. *Agric. Econ.* **51**, 159–171 (2020).
3. FAO. *The State of Agricultural Commodity Markets 2022*. (FAO, 2022). doi:10.4060/cc0471en.
4. Wang, J. & Dai, C. Evolution of Global Food Trade Patterns and Its Implications for Food Security Based on Complex Network Analysis. *Foods* **10**, 2657 (2021).
5. Anderson, K. & Nelgen, S. Agricultural trade distortions during the global financial crisis. *Oxf. Rev. Econ. Policy* **28**, 235–260 (2012).
6. Headey, D. Rethinking the global food crisis: The role of trade shocks. *Food Policy* **36**, 136–146 (2011).
7. Glauber, J., Laborde, D. & Mamun, A. From bad to worse: How Russia-Ukraine war-related export restrictions exacerbate global food insecurity. *International Food Policy Research Institute* https://www.ifpri.org/blog/bad-worse-how-export-restrictions-exacerbate-global-food-security (2022).
8. Laber, M., Klimek, P., Bruckner, M., Yang, L. & Thurner, S. Shock propagation from the Russia–Ukraine conflict on international multilayer food production network determines global food availability. *Nat. Food* **4**, 508–517 (2023).
9. Negi, D. S. & Ramaswami, B. *International risk sharing for food staples*. *Indira Gandhi Institute of Development Research, Mumbai Working Papers* https://ideas.repec.org/p/ind/igiwpp/2020-002.html (2020).
10. Wright, B. D. The economics of grain price volatility. *Appl. Econ. Perspect. Policy* **33**, 32–58 (2011).
11. Grassia, M., Mangioni, G., Schiavo, S. & Traverso, S. Insights into countries' exposure and vulnerability to food trade shocks from network-based simulations. *Sci. Rep.* **12**, 4644 (2022).
12. Bai, H. *et al.* Multi-model ensemble of CMIP6 projections for future extreme climate stress on wheat in the North China plain. *Int. J. Climatol.* **41**, E171–E186 (2021).

13. Chatzopoulos, T., Domínguez, I. P., Toreti, A., Adenäuer, M. & Zampieri, M. Potential impacts of concurrent and recurrent climate extremes on the global food system by 2030. *Environ. Res. Lett.* **16**, 124021 (2021).
14. Falloon, P. *et al.* What do changing weather and climate shocks and stresses mean for the UK food system? *Environ. Res. Lett.* **17**, 051001 (2022).
15. Zscheischler, J. *et al.* Future climate risk from compound events. *Nat. Clim. Change* **8**, 469–477 (2018).
16. Challinor, A. J. *et al.* Transmission of climate risks across sectors and borders. *Philos. Trans. R. Soc. Math. Phys. Eng. Sci.* **376**, 20170301 (2018).
17. Davis, K. F., Downs, S. & Gephart, J. A. Towards food supply chain resilience to environmental shocks. *Nat. Food* **2**, 54–65 (2021).
18. Gaupp, F. Extreme Events in a Globalized Food System. *One Earth* **2**, 518–521 (2020).
19. Schulz, C. *Global economic outlook: heading for a fall?* https://ifs.org.uk/publications/global-economic-outlook-heading-fall (2022).
20. World Bank. *Global Economic Prospects*. 150 https://www.worldbank.org/en/publication/global-economic-prospects (2022).
21. Challinor, A. J. & Benton, T. G. International Dimensions. in *The Third UK Climate Change Risk Assessment Technical Report* (eds. Betts, R. A., Haward, A. B. & Pearson, K. V.) 119 (The Climate Change Committee, 2021).
22. Jackson, N. D., Konar, M., Debaere, P. & Sheffield, J. Crop-specific exposure to extreme temperature and moisture for the globe for the last half century. *Environ. Res. Lett.* **16**, 064006 (2021).
23. Mistry, M. N. A High-Resolution Global Gridded Historical Dataset of Climate Extreme Indices. *Data* **4**, 41 (2019).
24. CRED. EM-DAT - The international disaster database. (2022).
25. Ray, D. K., Gerber, J. S., MacDonald, G. K. & West, P. C. Climate variation explains a third of global crop yield variability. *Nat. Commun.* **6**, 5989 (2015).

26. Zampieri, M. *et al.* When Will Current Climate Extremes Affecting Maize Production Become the Norm? *Earths Future* **7**, 113–122 (2019).

27. Brás, T. A., Jägermeyr, J. & Seixas, J. Exposure of the EU-28 food imports to extreme weather disasters in exporting countries. *Food Secur.* **11**, 1373–1393 (2019).

28. Mehrabi, Z. & Ramankutty, N. Synchronized failure of global crop production. *Nat. Ecol. Evol.* **3**, 780–786 (2019).

29. Gaupp, F., Hall, J., Hochrainer-Stigler, S. & Dadson, S. Changing risks of simultaneous global breadbasket failure. *Nat. Clim. Change* **10**, 54–57 (2020).

30. Heinicke, S., Frieler, K., Jägermeyr, J. & Mengel, M. Global gridded crop models underestimate yield responses to droughts and heatwaves. *Environ. Res. Lett.* **17**, 044026 (2022).

31. Lesk, C., Rowhani, P. & Ramankutty, N. Influence of extreme weather disasters on global crop production. *Nature* **529**, 84–87 (2016).

32. Vogel, E. *et al.* The effects of climate extremes on global agricultural yields. *Environ. Res. Lett.* **14**, 054010 (2019).

33. Zampieri, M., Ceglar, A., Dentener, F. & Toreti, A. Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environ. Res. Lett.* **12**, 064008 (2017).

34. Mehrabi, Z. *et al.* The global divide in data-driven farming. *Nat. Sustain.* **4**, 154–160 (2021).

35. Wang, X. *et al.* Global irrigation contribution to wheat and maize yield. *Nat. Commun.* **12**, 1235 (2021).

36. Kummu, M. & Varis, O. The world by latitudes: A global analysis of human population, development level and environment across the north–south axis over the past half century. *Appl. Geogr.* **31**, 495–507 (2011).

37. Feleke, H. G., Savage, M. & Tesfaye, K. Calibration and validation of APSIM–Maize, DSSAT CERES–Maize and AquaCrop models for Ethiopian tropical environments. *South Afr. J. Plant Soil* **38**, 36–51 (2021).

38. Cottrell, R. S. *et al.* Food production shocks across land and sea. *Nat. Sustain.* **2**, 130–137 (2019).

39. Madadgar, S., AghaKouchak, A., Farahmand, A. & Davis, S. J. Probabilistic estimates of drought impacts on agricultural production. *Geophys. Res. Lett.* **44**, 7799–7807 (2017).
40. Schauberger, B. *et al.* Consistent negative response of US crops to high temperatures in observations and crop models. *Nat. Commun.* **8**, 13931 (2017).
41. Zhao, C. *et al.* Temperature increase reduces global yields of major crops in four independent estimates. *Proc. Natl. Acad. Sci.* **114**, 9326–9331 (2017).
42. Zhu, X. & Troy, T. J. Agriculturally Relevant Climate Extremes and Their Trends in the World's Major Growing Regions. *Earths Future* **6**, 656–672 (2018).
43. Iizumi, T. *et al.* Impacts of El Niño Southern Oscillation on the global yields of major crops. *Nat. Commun.* **5**, 3712 (2014).
44. Butler, E. E., Mueller, N. D. & Huybers, P. Peculiarly pleasant weather for US maize. *Proc. Natl. Acad. Sci.* **115**, 11935–11940 (2018).
45. Chaloner, T. M., Gurr, S. J. & Bebber, D. P. Plant pathogen infection risk tracks global crop yields under climate change. *Nat. Clim. Change* **11**, 710–715 (2021).
46. Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G. & Lobell, D. B. Anthropogenic climate change has slowed global agricultural productivity growth. *Nat. Clim. Change* **11**, 306–312 (2021).
47. FAO. FAOSTAT. http://faostat.fao.org/ (2020).
48. Dalin, C., Wada, Y., Kastner, T. & Puma, M. J. Groundwater depletion embedded in international food trade. *Nature* **543**, 700–704 (2017).
49. Kastner, T., Kastner, M. & Nonhebel, S. Tracing distant environmental impacts of agricultural products from a consumer perspective. *Ecol. Econ.* **70**, 1032–1040 (2011).
50. Béné, C. *et al.* Global assessment of the impacts of COVID-19 on food security. *Glob. Food Secur.* **31**, 100575 (2021).
51. Portmann, F. T., Siebert, S. & Döll, P. MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. *Glob. Biogeochem. Cycles* **24**, 1–24 (2010).

52. International Food Policy Research Institute. Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 2.0. (2020).

53. Zampieri, M. *et al.* Estimating resilience of crop production systems: From theory to practice. *Sci. Total Environ.* **735**, 139378 (2020).

54. Wood, S. N. Package ‘mgcv’. (2012).

Figures

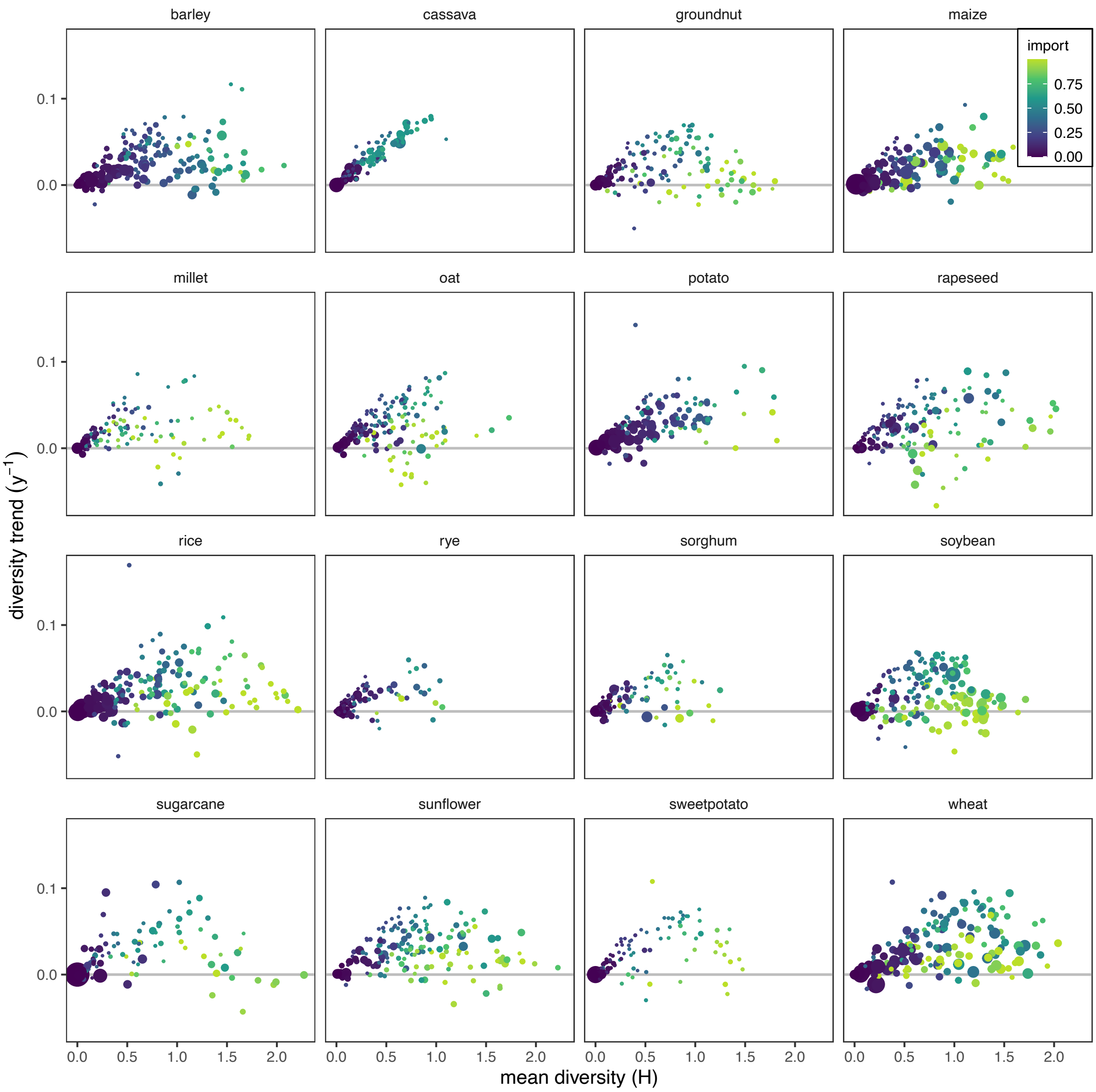


Fig. 1. Supply diversity trend vs mean (1987-2019).

Points are countries with point size indicating mean annual supply (domestic plus imports) and colour indicating mean fraction imported over the sample period.

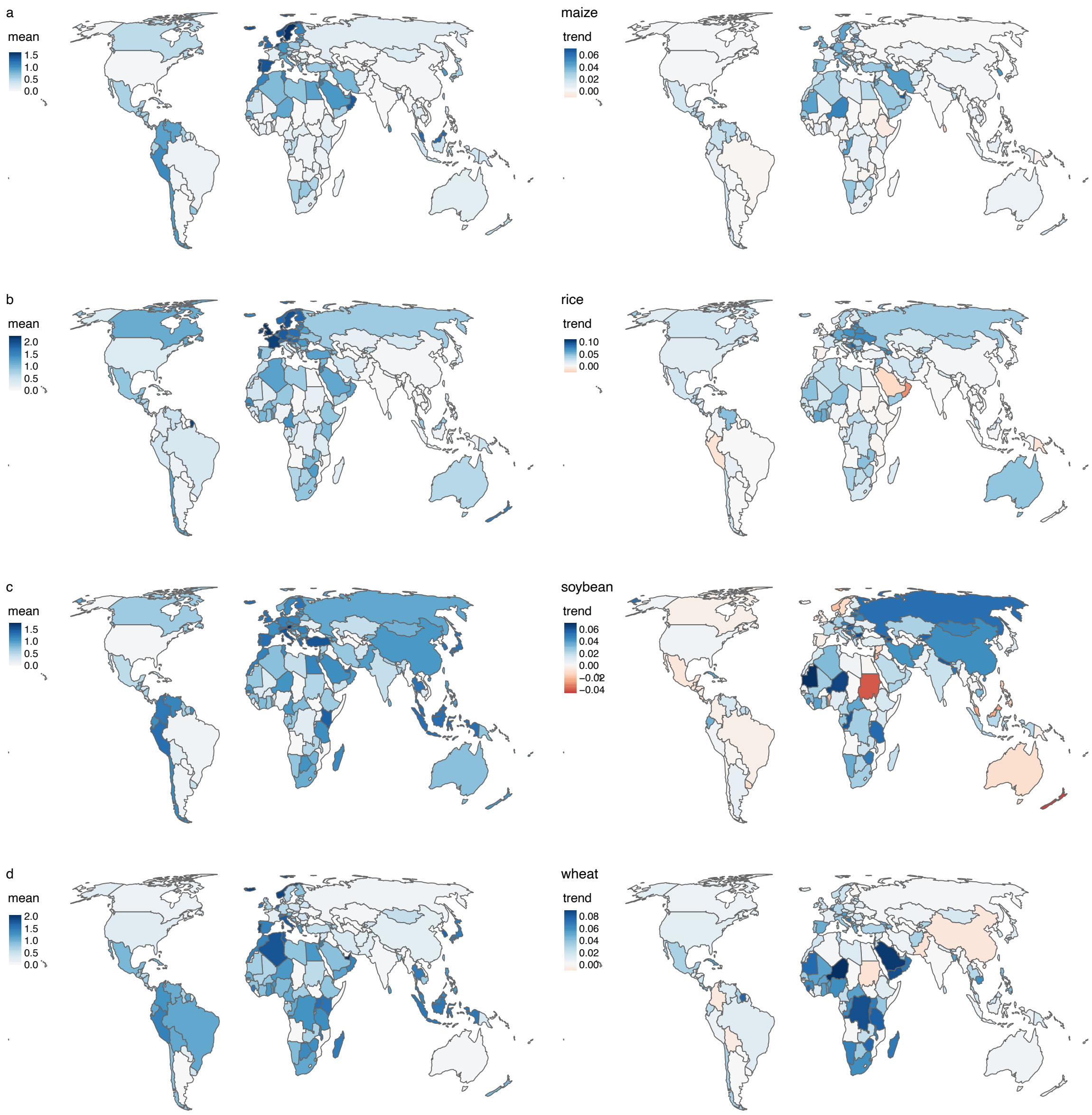


Fig. 2. Diversity of grain sources, 1987-2019.

a. Maize, b. Rice, c. Soybean, d. Wheat. Mean Shannon diversity of all sources including domestic production (left-hand panels) and annual linear trend in diversity (right-hand panels).

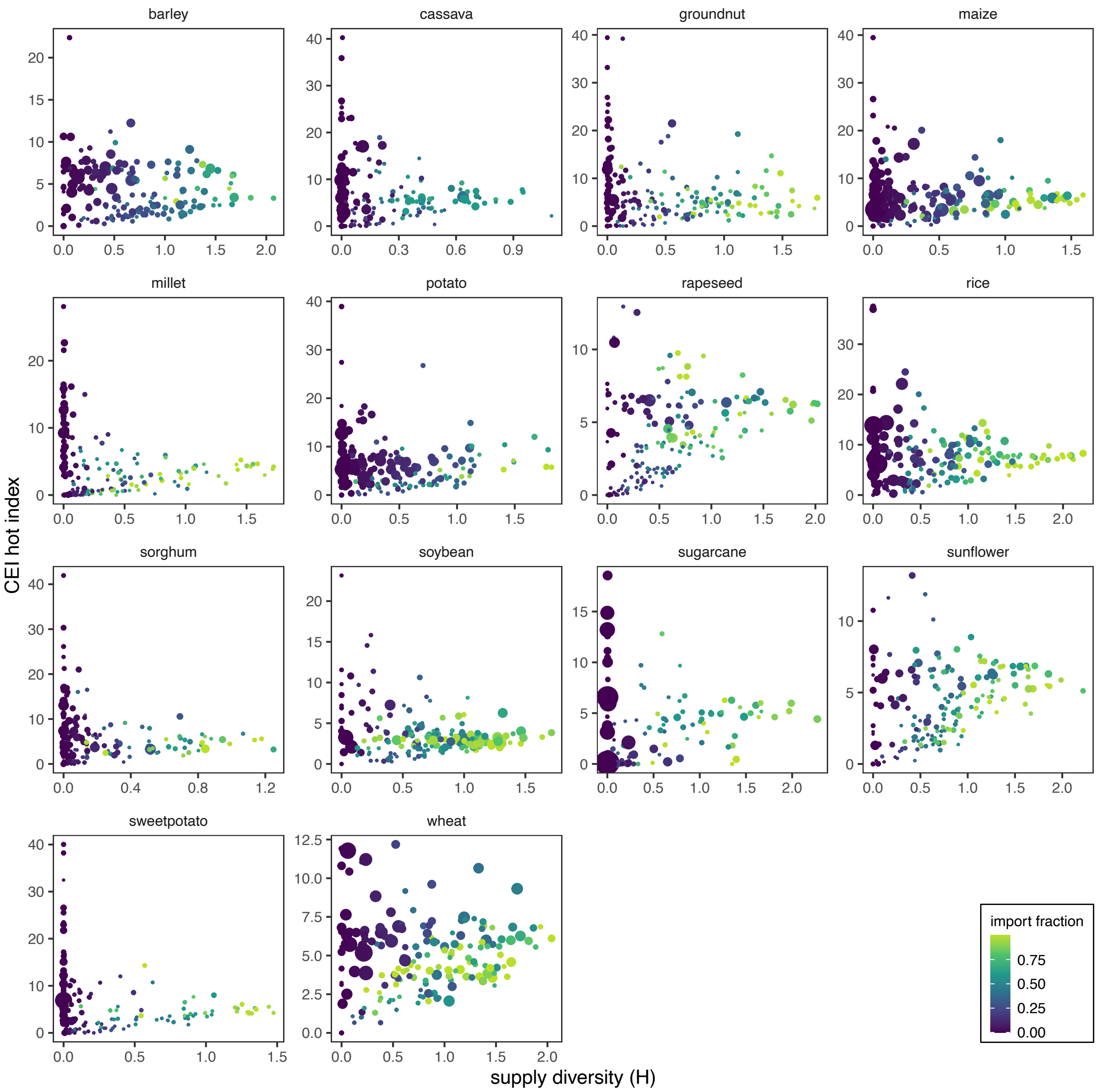


Fig. 3. CEI hot index vs. source diversity (1987–2019).

Points show mean value per country with size relative to mean supply (domestic plus import) and colour indicating mean import fraction. Oat and rye not shown due to missing crop distribution data.

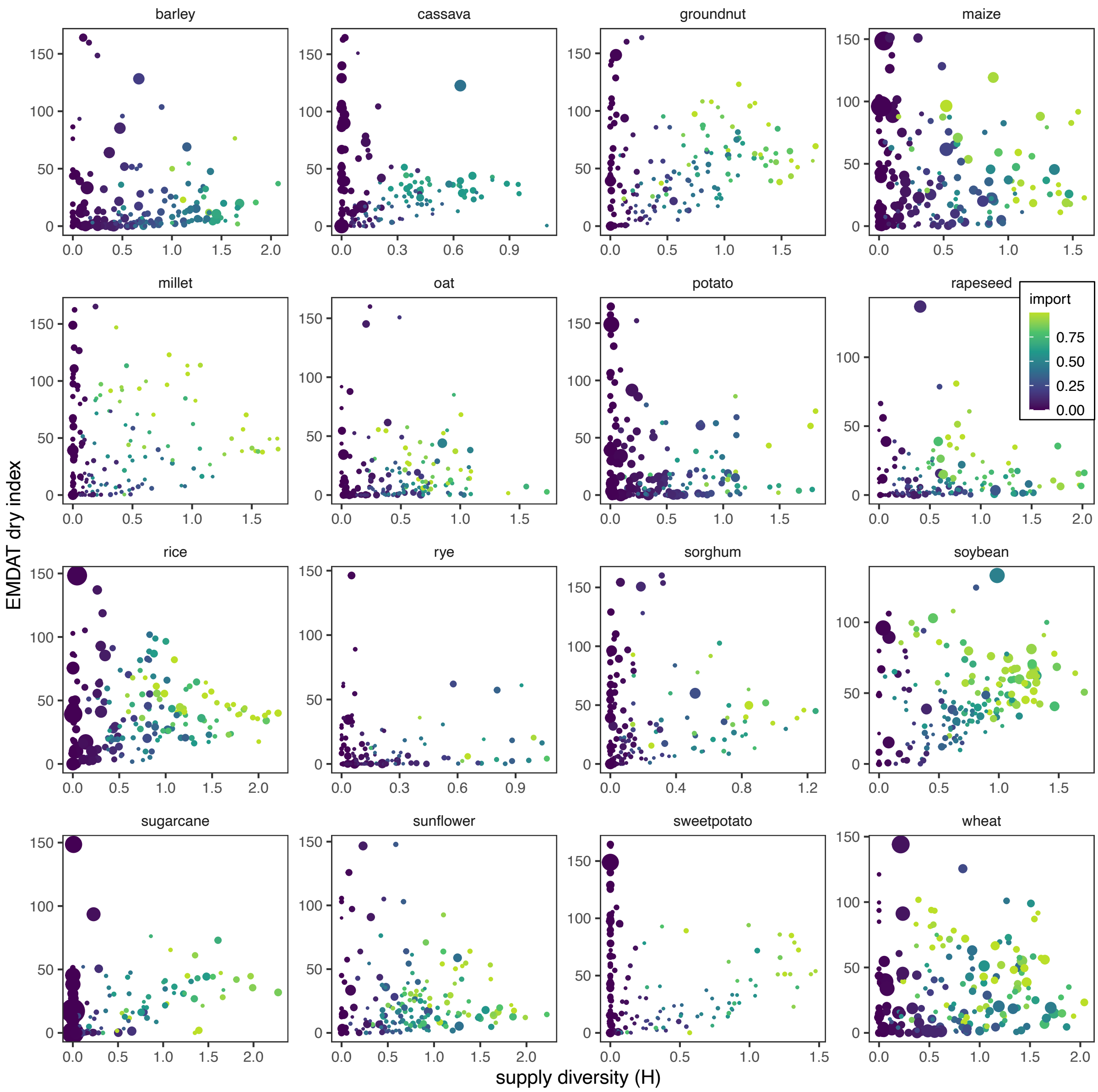


Fig. 4. EM-DAT dry index vs. source diversity (1987–2019).

Points show mean value per country with size relative to mean supply (domestic plus import) and colour indicating mean import fraction.

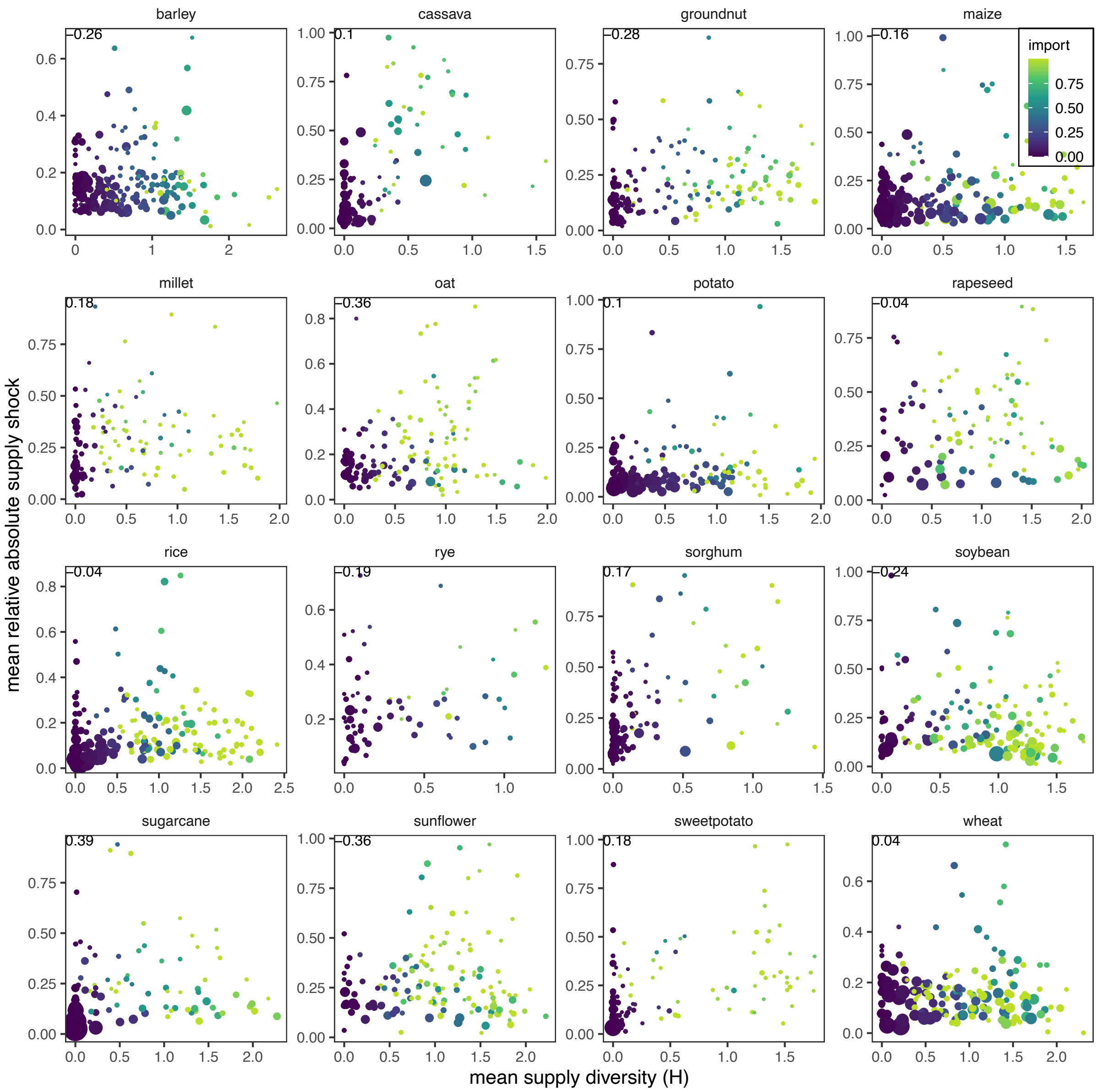


Fig. 5. Supply shocks vs. source diversity (1987–2019).

Points show mean relative absolute supply shock calculated from a smooth fit to supply (domestic plus import) by year per country, with size relative to mean supply and colour indicating import fraction. Cases for which the mean relative supply shock was extreme (> 1) are not shown (207 of 2594 data points). Kendall's τ correlation coefficients weighted by mean supply are given in the top left of each panel.

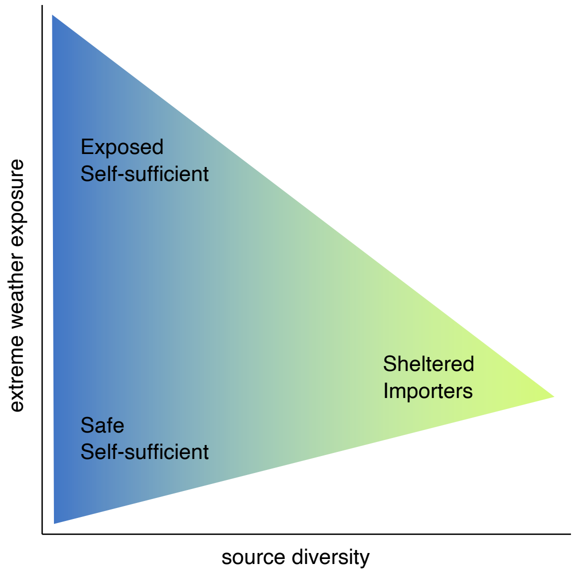
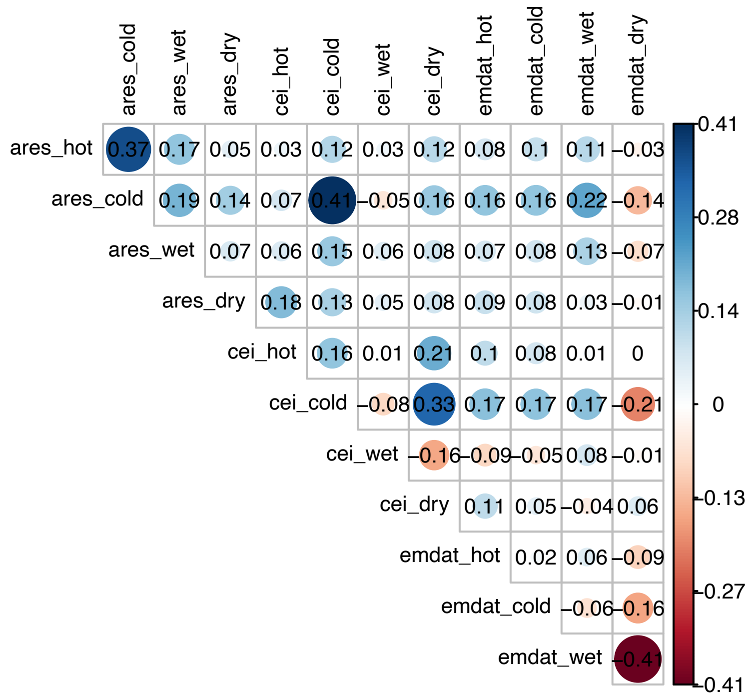


Fig. 6. Schematic classification of countries by extreme exposure and source diversity.

Our analyses indicate that countries with low source diversity, which are almost always self-sufficient, experience a wide range of extreme exposure. As source diversity increases, extreme exposure tends towards intermediate levels.

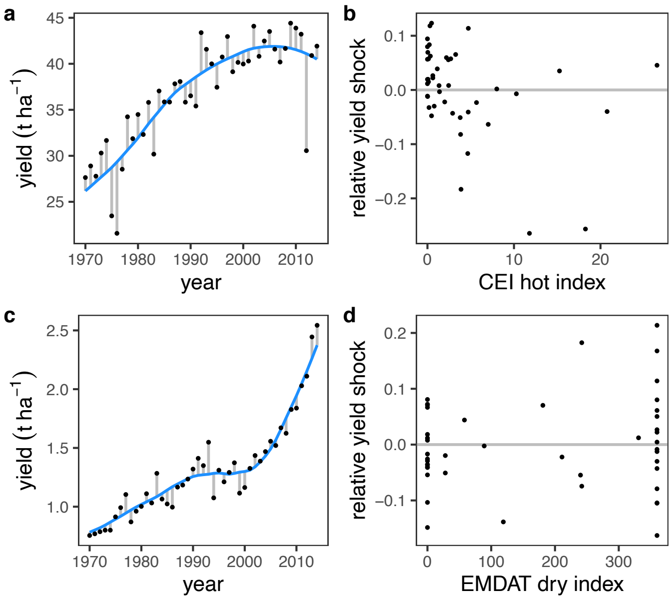
Supplementary Material

Supplementary Figures



Supplementary Fig. S 1. Kendall correlations among extreme exposure indices (1970 – 2014).

ARES crop-specific indices were matched to CEI and EM-DAT indices by country and year. Blue indicates positive correlations, red indicates negative correlations, with the area of the circle proportional to the strength of the correlation.



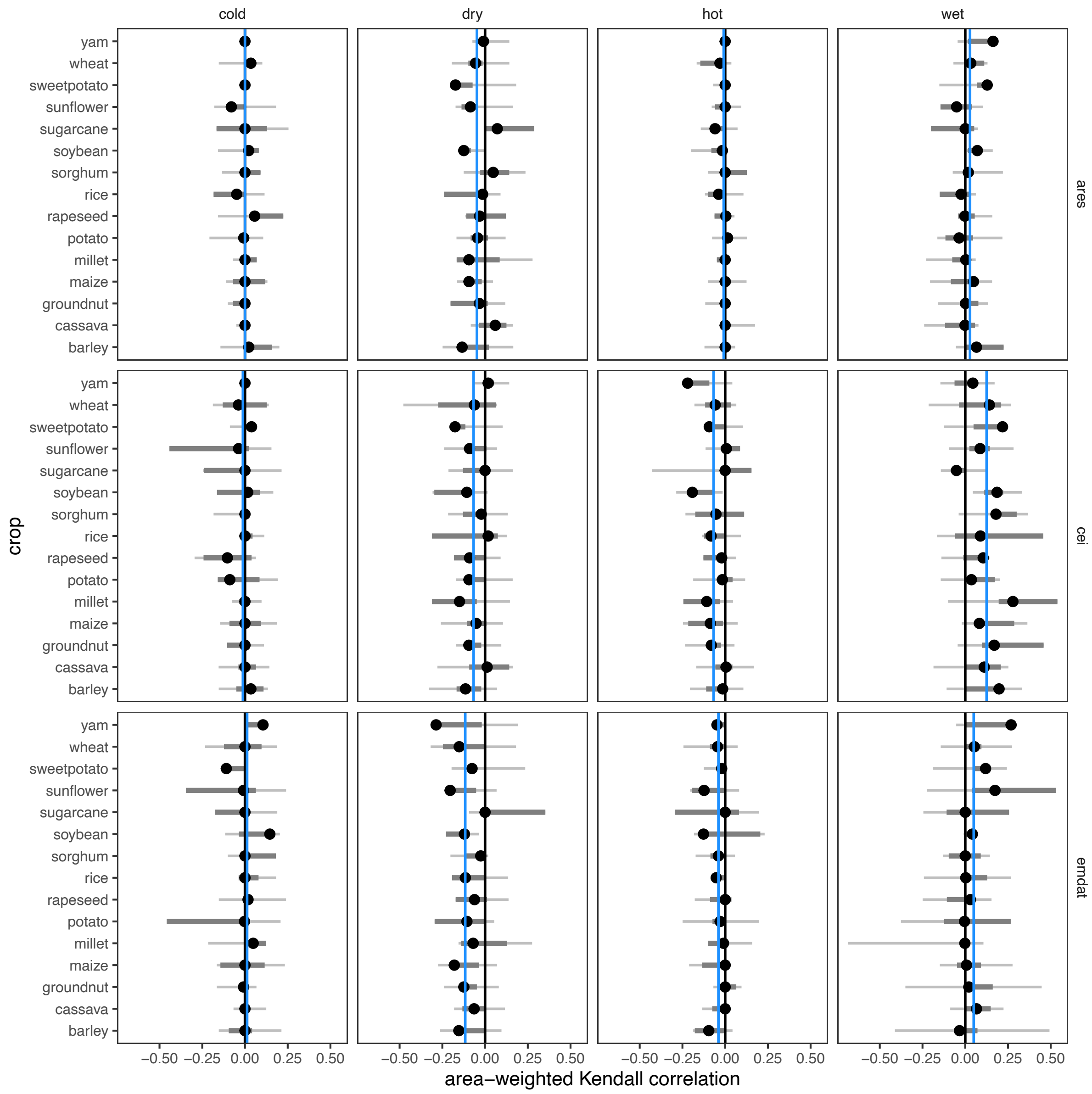
Supplementary Fig. S 2. Yield shocks vs. extreme weather indices (1970-2014).

a. Annual UK potato yield over time (black points), with yield shocks (grey lines) from a long term trend fitted by locally-weighted polynomial regression (blue line).

b. Relative yield shocks (yield shock divided by expected yield) vs. CEI hot index for UK potato yield. The Kendall correlation is -0.30.

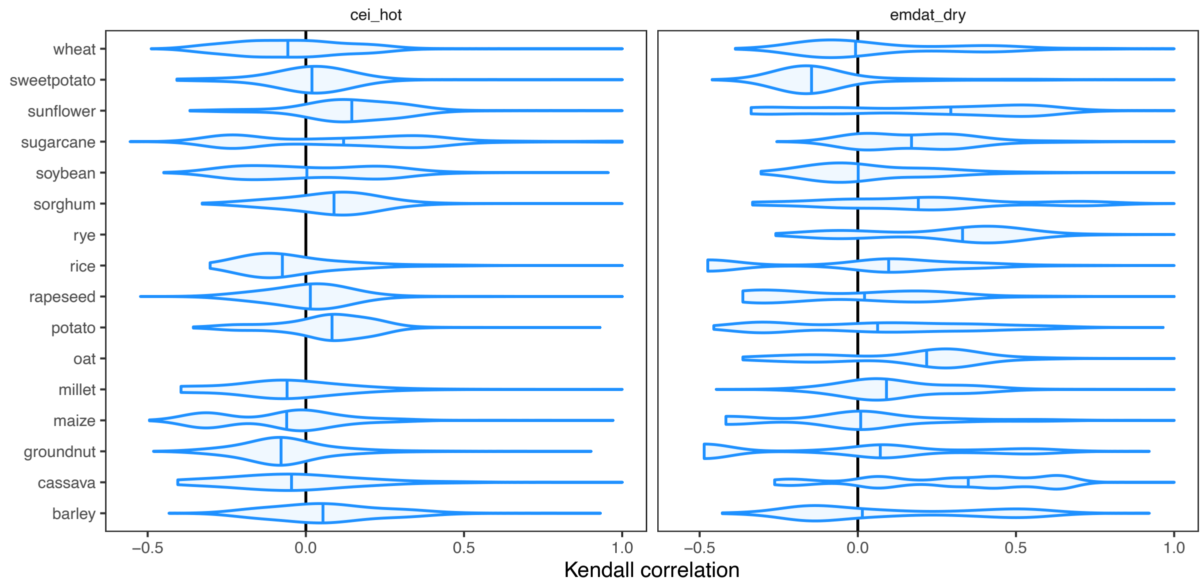
c. As a. but for Ethiopian wheat production.

d. As b. but for Ethiopian wheat production vs. the EM-DAT dry index. The Kendall correlation is 0.07.



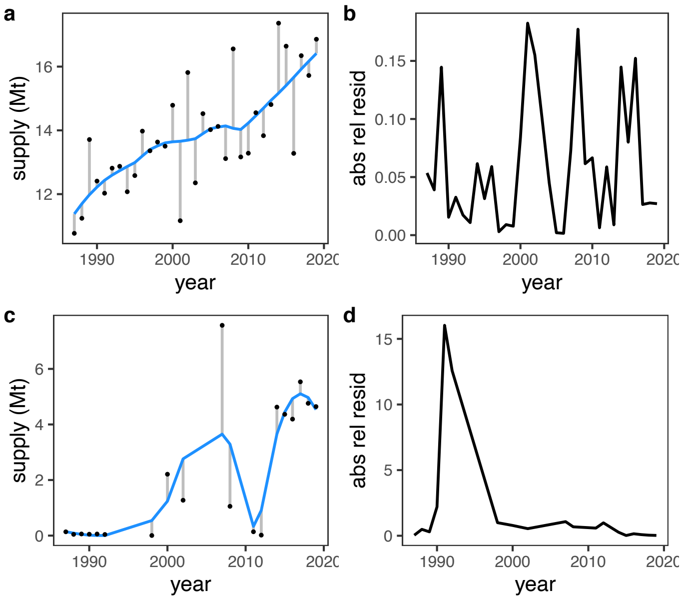
Supplementary Fig. S 3. Crop area-weighted Kendall correlations between extreme indices and yield shocks (1970 – 2014).

Panels show correlations for cold, dry, hot and wet extremes (left–right), and ARES, CEI and EM-DAT extremes (top–bottom). The EM-DAT 'wet' index refers to storm incidences (see Methods). Points indicate weighted medians, wide bars are weighted interquartile ranges, and lines are weighted 90th percentile ranges. Blue vertical lines show the mean of the area-weighted median correlations across crops. Oat and rye are omitted as CEI values could not be calculated for them.



Supplementary Fig. S 4. Within-country correlations between extreme weather indices and source diversity.

Width of the violin plots indicates probability density of correlations weighted by mean total supply (domestic plus imports) across countries. Oat and rye are not available for CEI hot index. Vertical blue lines within violin plots indicate the weighted median correlation.



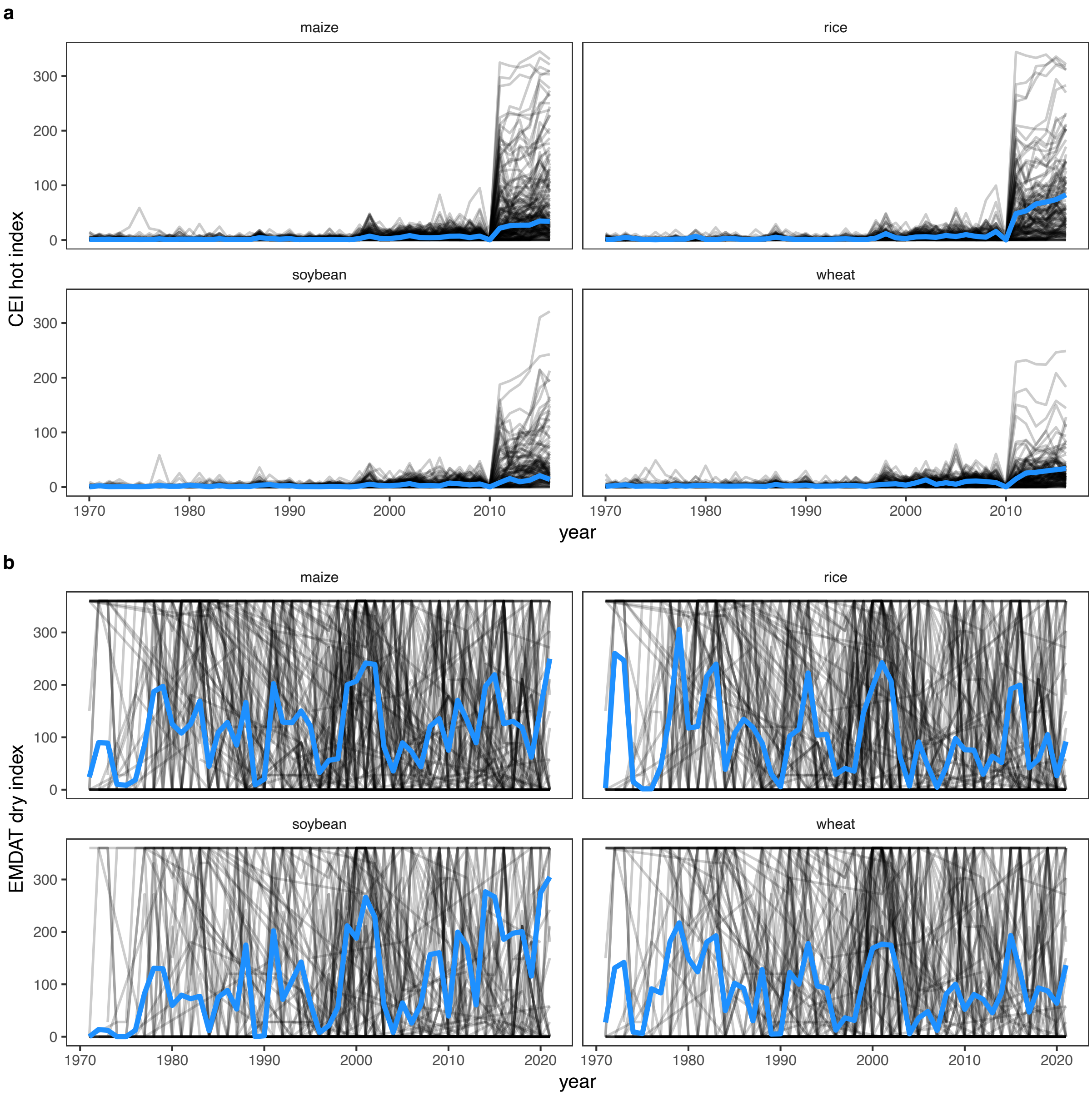
Supplementary Fig. S 5. Supply shocks for wheat in the UK and Nigeria (1987–2019).

a. Annual UK wheat supply over time (black points), with supply shocks (grey lines) from a long term trend fitted by locally-weighted polynomial regression (blue line).

b. Absolute relative residuals for UK wheat supply calculated as the modulus of the residual divided by the trend value. Shocks vary between zero and 18 per cent of the expected supply.

c. As a., but for Nigeria wheat supply.

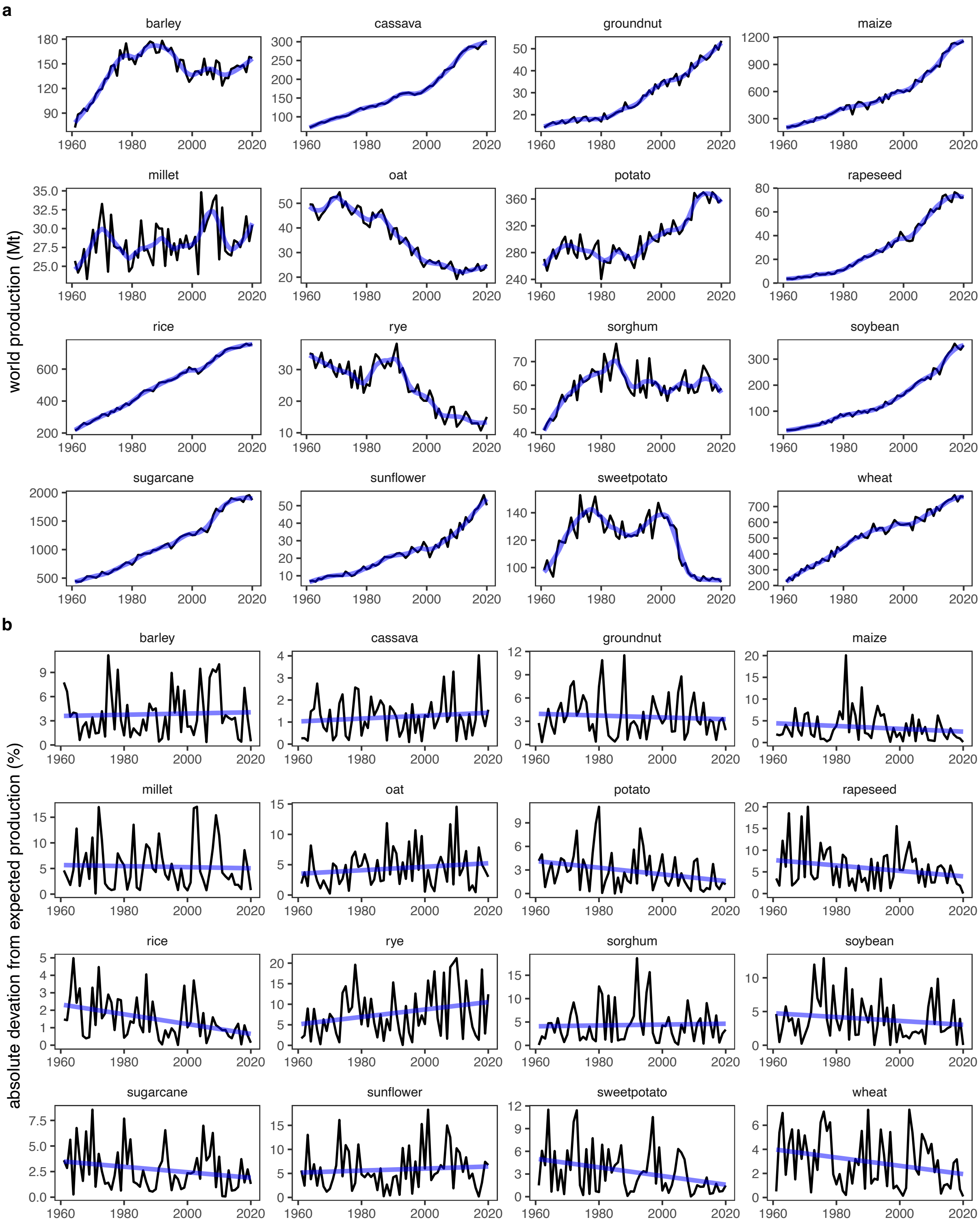
d. As b., but for Nigeria wheat supply. The highly erratic wheat supply over time results in a maximum absolute relative residual of 1600 per cent of the expected supply when supply quantities are very low.



Supplementary Fig. S 6. Extreme weather indices over time for major grain crops.

a. Grey lines show the CEI hot index for individual countries, and the blue line shows the production area-weighted mean.

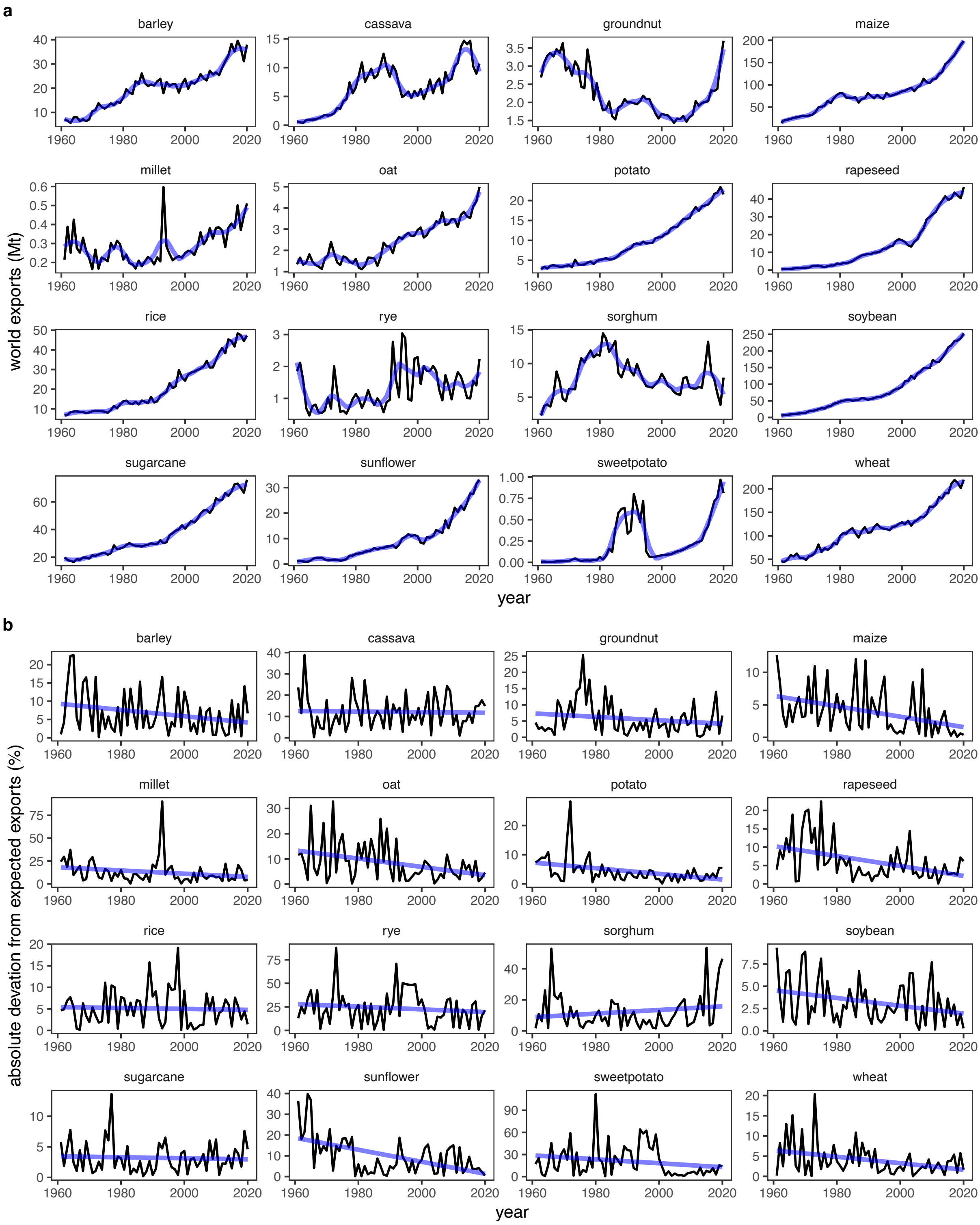
b. As for a. but for the EM-DAT dry index. The grey lines are identical in each panel because the EM-DAT index is calculated per country rather than by crop. The area-weighted means (blue lines) differ among crops.



Supplementary Fig. S 7. Volatility of global crop production.

a. Total annual global production, FAOSTAT data, 1961-2020. Black line shows reported data, blue line shows a locally-weighted polynomial regression.

b. Annual global production shocks, as percentage absolute deviations from expected production (locally-weighted polynomial regression). Black line shows deviations, blue line shows fit from generalized least squares regression with temporally autocorrelated errors.



Supplementary Fig. S 8. Volatility of global grain exports.

a. Total annual global exports, FAOSTAT data, 1961-2020. Black line shows reported data, blue line shows locally-weighted polynomial regression. Exports include primary derivatives e.g. maize cake, milled rice. See Methods for details.

b. Annual global export shocks, as percentage absolute deviations from expected export. Black line shows deviations, blue line shows fit from generalized least squares regression with temporally autocorrelated errors.

Supplementary Tables

Supplementary Table S 1. Trends in world production and export shocks, 1961 – 2020. Generalized least squares (GLS) regressions fitted with first order temporal autocorrelation in errors. Separate regressions for each crop. Mean and SE are average values for relative absolute deviations (%) over the entire period, fitted by GLS. Trend values are relative absolute deviations (%) per year, SE is the standard error of the estimate, with t-test and p-value of tests vs. zero. Phi is the autocorrelation coefficient. Error d.f. = 58. Trends with p < 0.005 are highlighted in bold to indicate which may be statistically significant. Data from FAOSTAT.

PRODUCTION							
Crop	Mean	SE	Trend	SE	t	p	Phi
Barley	3.83	0.44	0.008	0.026	0.296	0.768	0.169
Cassava	1.23	0.11	0.007	0.006	1.009	0.317	0.019
Groundnut	3.61	0.4	-0.012	0.023	-0.503	0.617	0.192
Maize	3.47	0.48	-0.032	0.028	-1.177	0.244	0.068
Millet	5.36	0.72	-0.01	0.043	-0.245	0.807	0.219
Oat	4.39	0.34	0.029	0.019	1.516	0.135	-0.204
Potato	2.85	0.37	-0.042	0.019	-2.246	0.029	0.1
Rapeseed	5.82	0.55	-0.063	0.029	-2.145	0.036	-0.123
Rice	1.47	0.19	**-0.028**	**0.008**	**-3.334**	**0.001**	**0.048**
Rye	7.86	0.83	0.091	0.045	2.023	0.048	0.04
Sorghum	4.36	0.59	0.009	0.035	0.267	0.791	0.141
Soybean	3.88	0.41	-0.029	0.023	-1.23	0.224	-0.01
Sugarcane	2.69	0.26	-0.027	0.014	-1.887	0.064	-0.068
Sunflower	5.81	0.54	0.021	0.031	0.679	0.5	-0.01
Sweet potato	3.27	0.44	-0.057	0.022	-2.634	0.011	0.017
Wheat	2.95	0.34	-0.034	0.018	-1.941	0.057	0.116
EXPORTS							
Crop	Mean	SE	Trend	SE	t	p	Phi
Barley	6.7	0.8	-0.086	0.042	-2.05	0.045	0.003
Cassava	12.14	0.96	-0.014	0.057	-0.24	0.811	-0.021
Groundnut	5.75	0.91	-0.053	0.051	-1.037	0.304	0.305
Maize	3.96	0.47	**-0.08**	**0.021**	**-3.79**	**0.000**	**-0.112**
Millet	12.77	2.24	-0.177	0.124	-1.419	0.161	0.25
Oat	8.4	0.92	**-0.164**	**0.042**	**-3.895**	**0.000**	**-0.226**
Potato	4.36	0.82	-0.097	0.039	-2.495	0.015	0.269
Rapeseed	6.16	0.95	**-0.136**	**0.041**	**-3.293**	**0.002**	**0.13**
Rice	5.09	0.56	-0.011	0.033	-0.321	0.749	0.105
Rye	23.71	2.67	-0.142	0.153	-0.923	0.360	0.149
Sorghum	12.32	1.98	0.117	0.116	1.013	0.315	0.261
Soybean	3.23	0.36	-0.044	0.019	-2.306	0.025	0.077
Sugarcane	3.21	0.35	-0.008	0.02	-0.396	0.693	0.098
Sunflower	10.03	2.17	**-0.29**	**0.084**	**-3.443**	**0.001**	**0.349**
Sweet potato	20.72	3.62	-0.268	0.2	-1.336	0.187	0.23
Wheat	4.01	0.47	**-0.08**	**0.022**	**-3.657**	**0.001**	**-0.225**