Impacts of extreme weather stress and synchronous yield fluctuation on international wheat trade network

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Abstract

One of the central challenges for global food security is the growing pressure from increasingly frequent extreme weather events that results in sharp drops in crop yield and disruptions in the food supply. Such pressure can potentially be alleviated by international crop trade, which plays a crucial role in reallocating food commodities from surplus to deficit regions. However, few studies have examined the influence of extreme weather events and the synchrony of crop yield anomalies on trade linkages among nations. To investigate such influence, we used the international trade network of wheat as an example, developed relevant covariates, and tested specialized statistical and machine-learning methods. The results show that countries with higher differences in extreme weather stress tend to have higher import volumes and more trade partners. Trade partnerships are more likely to be established between countries with synchronous yield variations. These findings indicate that increase in heat stress and co-occurring yield loss could lead to future higher dependence on imports, especially for vulnerable import-dependent nations, and affect the stability of wheat supply. Hence, the current international trade network needs to be improved by contemplating the patterns of extreme weather and yield synchrony among countries.

Introduction

Extreme weather events, such as drought, flood, and heatwave threaten food security from regional to global scales through the resulting sharp decline in the availability, affordability and adequate utilization of food (1, 2). During 2003–2013, extreme weather events have caused marked damage of USD 30 billion to the agricultural productivity (3). Crop production was impacted the most, with yield reductions (3–7) introducing price volatility in the food systems (1, 8), affecting food trade, welfare of farmers, and economic development, especially in low-income or import-dependent countries (1, 9–11).

International crop trade can potentially alleviate the negative impacts of extreme weather events on food security by exporting food commodities from surplus to deficit regions (12). Currently, international trade accounts for 80% of the global crop supply, and wheat, a crop essential for people's daily caloric and protein needs, accounts for 22% of the crop trade (in caloric content) (13). However, heavy reliance on the import from other countries or the global market may expose a country to the yield and market variations outside of the country's jurisdiction and consequently introduce additional risk to the country's food supply. For example, the 2010 heatwave in Russia triggered export restrictions for wheat, led to wheat shortage and price spike in Middle East, where over 1/3 of the wheat supply is from Russia, and potentially contributed to the destabilization of the region (9, 14). A simultaneous drop in yields of major exporters may destabilize the global trade network and food supply. Therefore, the controversial role of international trade in addressing the food security challenge is associated with patterns of extreme weather events and yield variability, however, such associations remain poorly understood and require an in-depth investigation (15).

The occurrence and volume of the trade between countries have been often investigated as results of comparative advantages in producing food commodities (e.g., more efficient use of water and land resources), as well as many socioeconomic factors such as geographical proximity of countries, population, agricultural productivity language, contiguity, level of economic development, and trade agreements (16–20). Several recent studies have evaluated the impacts of climate factors (17), such as annual rainfall and annual evapotranspiration. Only a few studies investigated the impacts of extreme weather stress and synchronous crop yield fluctuations (21–24); but their focus was on the impacts on food price fluctuations or trade volumes for individual countries, and not on the changes in the bilateral trade network.

In addition, the investigation of drivers for trade links has been limited to statistical approaches that were not designed to handle complex network data or derive data-driven relationships. Prior research of the potential drivers used linear regression models (25–27) that impose multiple restrictive assumptions on the shapes of relationships and distribution of the data, while application of statistical network analysis and machine learning methods has been limited. Only recently, the statistical exponential random graph models (ERGMs) have been used to investigate the relationships between international trade links (or volume) and their potential drivers (20, 28, 29). However, these recent studies still impose parametric assumptions and do not consider non-linearity in the data. Despite the success of machine learning approaches such as random forest (RF) in handling large volumes of complex data and deriving non-linear relationships from the data, such data-driven approaches have been rarely utilized in trade analysis (30).

To address these knowledge gaps, we proposed network-based covariates for studying international trade network of wheat using modern statistical and machine learning models. In addition to commonly used geopolitical factors (e.g., contiguity) two network-based covariates were developed to characterize the extreme weather stress and yield synchrony, namely the difference in extreme weather stress (DEWS) and short-term synchrony (STS) of crop yield anomalies between countries. To accommodate the complexity and network structure of the data, we applied ERGM and RF, the modern specialized statistical and machine learning methods, to model trade linkages and volume between countries (see Methods section for details). With the developed models, we investigated potential changes in trade relationships under future climate conditions and discussed their implications for the global food security.

Results

Extreme weather stress for wheat production

Cold and heat stresses were identified as the major contributors to the variability of extreme weather indices developed for a country's wheat production. A total of 17 indices were used to quantify weather stresses (including heat stress, cold stress, flood, and drought) during the growing period for wheat in 115 countries for the years 2005–2014 (see Methods and SI Appendix, Section S3). The first two principal components of the 17 indices, dominated by cold and heat stress, represent 65% and 22.7% variance of the weather index matrix, respectively (SI Appendix, Fig. S2).

The dominant principal components of the extreme weather indices are not significantly correlated with production level across countries, while the heat stress indices are correlated with the import dependency (Fig. 1; detailed results in SI Appendix, Table S3). It suggests that the scale of wheat production in a country was not necessarily affected by the extreme weather stress in the wheat producing region, but a country's dependency on wheat import was associated with higher heat stress. The pairwise relationships between weather stress and other major characteristics of trade (such as number of linkages and trade volume) are similar: the countries facing higher heat stress (or lower cold stress) are likely to have fewer trade partners for exports; and countries with higher cold stress tend to have higher import trade partners (SI Appendix, Figs. S8–S11 and Table S3).

Relationships between trade networks and extreme weather stress

Using the principal components of extreme weather indices as part of the covariates, we modeled the bilateral trade networks (one weighted by trade volume and one without the weights) of wheat with ERGM and RF model separately. The two models observe similar general relationships between trade networks and their potential drivers, but the performances of the two models vary. To evaluate the performance of each model, we conducted a cross-validation. The results show that ERGM, with an error rate of 5.35%, was more accurate than RF in predicting trade presence/absence (i.e. the trade network without weight by trade volume), while RF was more accurate in predicting trade volume (Table 1). Hence, throughout the rest of the paper, we report the modeling results for trade linkages and trade volumes based on ERGM and RF, respectively.

Modeling results from both ERGM and RF show that country pairs with larger differences in the levels of extreme weather stresses are more likely to be trade partners. The ERGM shows that a more severe heat stress in importing country compared to an exporting country (i.e., $DEWS_{heat} < 0$) corresponds to a higher likelihood of trade link formation. Vice versa, trade partnerships are less likely if the exporting country is experiencing a larger heat stress than the importer does (i.e., $DEWS_{heat} > 0$; Table 1, and SI Appendix, Fig. S12). These model results align with the observed relationship between import dependency and heat stress (Fig. 1b).

The differences of both heat and cold stress between countries have significant relationships with trade volume. The RF shows overall higher trade volumes correspond to a higher heat stress in importing country (i.e., when $DEWS_{heat} < 0$, compared with $DEWS_{heat} > 0$, similar to the ERGM results), however, the relationship is not exactly linear and the trade volumes increase marginally for $DEWS_{heat}$ around zero (Fig. 2b). Higher trade volume is predicted when differences in cold stress between partners exist (i.e., $DEWS_{cold} \neq 0$; Fig. 2a), however, in contrast to the heat stress, two upper deciles of $DEWS_{cold}$ are associated with higher trade volumes. In particular, two biggest spikes in Fig. 2a are driven by France and Germany, i.e., large exporters that may often experience more severe cold stress than their trade partners do ($DEWS_{cold} > 0$). The cases of $DEWS_{cold} > 3000$ are dominated by Japan, Mongolia, and South Korea in the exporter role, hence the corresponding average trade volumes decline from the peak values (Fig. 2a).

The role of yield synchrony

In addition to extreme weather stress, the STS of crop yield anomalies also demonstrates significant relationship with the wheat trade networks regarding the presence/absence of trade links and trade volumes. More specifically, the ERGM for unweighted network shows that STS is positively associated with the likelihood of trade partnerships (Table 1). In the weighted trade network, RF detects a non-linear relationship characterized by the overall accelerating increase of trade volume with the increase in STS (main body of the distribution; Fig. 2c). However, the first decile of STS, comprising the most asynchronous pairs of countries, is also characterized by a spike in trade volume (Fig. 2c). This illustrates that countries with perfect asynchrony ($STS \approx -1$) and synchrony ($STS \approx 1$) of yield fluctuations tend to trade more.

The role of other factors

All our ERGM and RF models also include the following covariates that have been considered as important for the formation of trade linkages: population-weighed distance, contiguity, and common official language between countries. Our modeling results further confirmed the important role of these factors. The ERGM results show that the trade partnerships are more likely to occur between countries that are closer to each other, contiguous, or have a common official language (Table 1), what aligns well with the existing findings in the literature. The RF results show, similarly to ERGM, higher trade volumes for countries that are contiguous and have a common official language (Figs. 2d and 2f), and an overall negative relationship between trade volume and distance (Fig. 2e). However, RF was also able to model non-linearity in the latter relationship, characterized by substantial spikes in trade volume around the deciles 3–4 and 9–10 of the population-weighted distance (Fig. 2e).

The inclusion/exclusion of these covariates in the ERGM and RF models does not affect the above results regarding the relationships between trade networks and extreme weather stresses, as well as yield synchrony, further confirming the robustness of the modeling results. For example, countries closer to each other tend to have more synchronized yield; however, the ERGM results show significant positive association of trade partnerships with STS regardless of whether the distance variable is included or excluded (SI Appendix, Table S4). This test suggests that the positive relationship between trade networks and STS is not only due to the positive relationship between STS and distance, but could be an outcome of other factors that are not included in the models (e.g., level of economic development, cultivars, and technology and management practices in agriculture).

Conclusions

Our analysis suggests that the two factors, the level of extreme weather stress and synchrony of crop yield fluctuations, significantly affect the international wheat trade network. Country-pairs with larger differences in heat stress are more likely to have trade connections and higher trade volumes. Meanwhile, in the current wheat trade network, trade partnerships are more likely to be established between countries with synchronized yield fluctuations. This represents a systemic risk in the current global wheat market, since synchronized yield failure can disrupt the wheat supply and intensify food insecurity for both partnering countries. Our results demonstrate the need to consider the extreme weather stress and yield synchrony in the trade policy framework in order to improve the stability and fairness of the global food system.

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References

1. FAO, IFAD, UNICEF, WFP, WHO, “The State of Food Security and Nutrition in the World 2019. Safeguarding against economic slowdowns and downturns.” (2019).
2. F. Gaupp, G. Pflug, S. Hochrainer-Stigler, J. Hall, S. Dadson, Dependency of Crop Production between Global Breadbaskets: A Copula Approach for the Assessment of Global and Regional Risk Pools. *Risk Anal.* **37**, 2212–2228 (2017).
3. FAO, “Impact of Natural Hazards and Disasters on Agriculture and food security and nutrition: a Call for Action to build resilient livelihoods” (2015).

4. S. S. Myers, *et al.*, Climate Change and Global Food Systems: Potential Impacts on Food Security and Undernutrition. *Annu. Rev. Public Health* **38**, 259–277 (2017).
5. C. Rosenzweig, *et al.*, Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proc. Natl. Acad. Sci. U. S. A.* **111**, 3268–3273 (2014).
6. E. E. Butler, N. D. Mueller, P. Huybers, Peculiarly pleasant weather for US maize. *Proc. Natl. Acad. Sci.* **115**, 11935–11940 (2018).
7. D. B. Lobell, W. Schlenker, J. Costa-Roberts, Climate Trends and Global Crop Production Since 1980. *Science* **333**, 616–620 (2011).
8. U. L. C. Baldos, T. W. Hertel, The role of international trade in managing food security risks from climate change. *Food Secur.* **7**, 275–290 (2015).
9. S. Mitra, T. Josling, “Agricultural Export Restrictions: Welfare Implications and Trade Disciplines” (2009).
10. R. Dellink, H. Hwang, E. Lanzi, J. Chateau, “International trade consequences of climate change” (2017) https:/doi.org/10.1787/9f446180-en.
11. M. J. Puma, S. Bose, S. Y. Chon, B. I. Cook, Assessing the evolving fragility of the global food system. *Environ. Res. Lett.* **10**, 024007 (2015).
12. W. B. Anderson, R. Seager, W. Baethgen, M. Cane, L. You, Synchronous crop failures and climate-forced production variability. *Sci. Adv.* **5**, 1–10 (2019).
13. P. D. Odorico, J. A. Carr, F. Laio, L. Ridolfi, S. Vandoni, Feeding humanity through global food trade. *Earth’s Futur.* **2**, 458–469 (2014).
14. C. B. D’Amour, L. Wenz, M. Kalkuhl, J. Christoph Steckel, F. Creutzig, Teleconnected food supply shocks. *Environ. Res. Lett.* **11**, 035007 (2016).
15. M. E. Brown, *et al.*, Do markets and trade help or hurt the global food system adapt to climate change? *Food Policy* **68**, 154–159 (2017).
16. T. Distefano, M. Tuninetti, F. Laio, L. Ridolfi, Tools for reconstructing the bilateral trade network: a critical assessment. *Econ. Syst. Res.* **32**, 378–394 (2019).
17. M. Tuninetti, S. Tamea, F. Laio, L. Ridolfi, To trade or not to trade: Link prediction in the virtual water network. *Adv. Water Resour.* **110**, 528–537 (2017).
18. G. Fagiolo, J. Reyes, S. Schiavo, On the topological properties of the world trade web: A weighted network analysis. *Phys. A Stat. Mech. its Appl.* **387**, 3868–3873 (2008).
19. G. Fagiolo, J. Reyes, S. Schiavo, The evolution of the world trade web: A weighted-network analysis. *J. Evol. Econ.* **20**, 479–514 (2010).
20. P. R. Herman, “Identifying multilateral dependencies in the world trade network” (2017).
21. D. Willenbockel, “Extreme weather events and crop price spikes in a changing climate. Illustrative global simulation scenarios” (2012).
22. M. Verma, T. Hertel, N. Diffenbaugh, Market-oriented ethanol and corn-trade policies can reduce climate-induced US corn price volatility. *Environ. Res. Lett.* **9**, 064028 (2014).
23. M. Tigchelaar, D. S. Battisti, R. L. Naylor, D. K. Ray, Future warming increases probability of globally synchronized maize production shocks. *Proc. Natl. Acad. Sci. U. S. A.* **115**, 6644–6649 (2018).

24. F. Gaupp, J. Hall, S. Hochrainer-Stigler, S. Dadson, Changing risks of simultaneous global breadbasket failure. *Nat. Clim. Chang.* **10**, 54–57 (2020).
25. I. Bostan, C. Toderașcu (Sandu), B.-N. Firtescu, Exchange Rate Effects on International Commercial Trade Competitiveness. *J. Risk Financ. Manag.* **11**, 1–11 (2018).
26. J. E. Anderson, A theoretical foundation for the gravity equation. *Am. Econ. Rev.* **69**, 106–116 (1979).
27. J. E. Sohn, "The impact of aid for trade on the cost and time to trade: The case of Latin America and the Caribbean" (United Nations Publications, 2013).
28. P. R. Herman, "Essays on network effects in international trade and markets for differentiated goods." (2016).
29. E. Gutiérrez-Moya, S. Lozano, B. Adenso-Díaz, Analysing the structure of the global wheat trade network: An ERGM approach. *Agronomy* **10**, 1–19 (2020).
30. M. Gopinath, F. A. Batarseh, J. Beckman, A. Kulkarni, S. Jeong, International agricultural trade forecasting using machine learning. *Data Policy* **3**, 1–20 (2021).

Figures and Tables

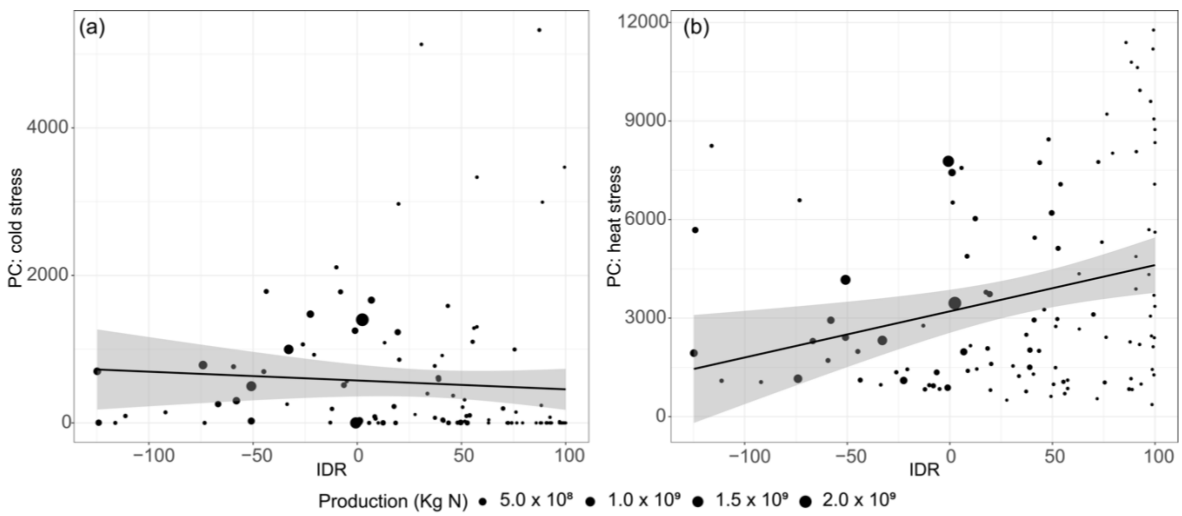

Fig. 1. Relationships between the 2005–2014 import dependency ratio (IDR; Eq. 1) and derived principal components (PC) representing the weather stress: (a) cold stress, (b) heat stress. Positive IDR means higher import dependency, while a negative IDR means that a country is a net exporter. Each point represents a country, size of the point corresponds to the average wheat production level during 2005–2014. The lines represent the estimated linear relationships between weather stress and IDR (p-value = 0.460 and 0.005, respectively), shaded areas correspond to 95% confidence intervals.

Table 1. Summaries of the models for 2005–2014 international wheat trade

Response	Model	Covariate	Coefficient	Error
Trade presence (unweighted directed network)	ERGM	$DEWS_{heat}$	-2.30×10^{-5} (4.20×10^{-6})	5.35%
		STS	0.111 (4.22×10^{-2})	
		Distance	-2.17×10^{-5} (1.28×10^{-6})	
		Contiguity	2.25 (0.164)	
		Common official language	0.272 (5.80×10^{-2})	
	RF	$DEWS_{heat}$, $DEWS_{cold}$ STS Distance Contiguity Common official language	Fig. S4	37%
Trade volume (weighted directed network)	ERGM	$DEWS_{heat}$	-1.76×10^{-5} (1.00×10^{-6})	1.64
		STS	2.08×10^{-2} (4.62×10^{-4})	
		Distance	-3.06×10^{-5} (3.30×10^{-7})	
		Contiguity	0.498 (9.12×10^{-4})	
		Common official language	1.92×10^{-3} (6.32×10^{-4})	
	RF	$DEWS_{heat}$, $DEWS_{cold}$ STS Distance Contiguity Common official language	Fig. 2	1.36

ERGM: exponential random graph model, RF: random forest, DEWS: difference in extreme weather stress, STS: short-term synchrony. Standard errors of the coefficients are shown in parentheses. Errors are the cross-validated misclassification error for trade presence, and mixed error for trade volume.

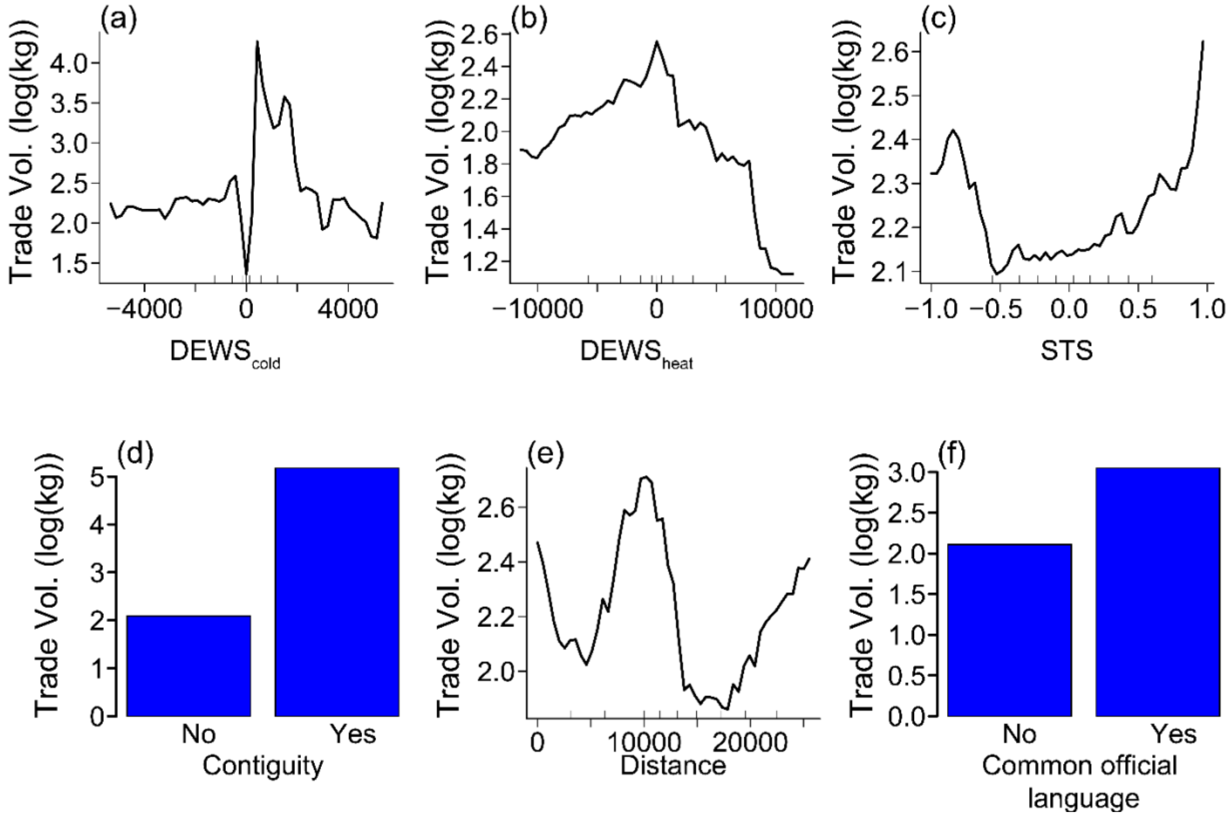

Fig. 2. Random forest partial dependence plots for trade volume in 2005–2014. The x-axes represent the considered covariates, where DEWS is difference in extreme weather stress, STS is short-term synchrony. The inner tickmarks on the x-axes represent deciles of the variables. The y-axis represents the marginal effect of the covariate on wheat trade volume.