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The water footprint of staple crop trade under climate and policy scenarios

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Abstract

Trade in staple crop commodities has become increasingly important in the global food system, with ramifications for both food security and water resources sustainability. It is thus essential to understand how the water footprint (WF) of staple crop trade may change in the future. To this end, we project international staple crop trade and its WF under climate and policy scenarios for the year 2030. We use the H08 global hydrologic model to determine the impact of climatic changes to staple crop yields and evapotranspiration. Using the yield changes projected with the H08 model, we estimate the bilateral trade of staple crops using the Global Trade Analysis Project model. We combine these projections to obtain the total and blue WF of agricultural trade and global water savings (GWS) across scenarios. This approach enables us to determine the direct impact of climate change and trade liberalization—together and in isolation—on the WF of staple crop trade. Importantly, we show that trade liberalization leads to greater WF, making it a potentially important adaptation measure to a changing climate, although future work is needed to distinguish high resolution crop water use, water stress, and commodity transfers.

1. Introduction

Despite widespread and growing interest in the implications of climate change for food security, most research focuses on the direct impact of climate change to food production [1]. It is increasingly important to understand how human adaptation actions will interact with future food security and resource scarcity, particularly since water scarcity may be over-estimated if adaptation is not accounted for [2]. Thus, it is essential to start incorporating human adaptation into models of future projections [3]. International trade liberalization has been shown to enhance global food security [4], making it one potential adaptation measure to a changing climate [1, 5, 6]. The main goal of this paper is to understand how one potential human adaptation to a changing climate—trade policy—impacts food trade and its water footprint (WF).

The global food system is a coupled human and natural system [7], in which policy, technological advancement, and culture impact agricultural productivity and food security as significantly as climate [8, 9]. Global food trade has increased over the last few decades [10–12], with ramifications for virtual water [13, 14], overexploited aquifers [15], embodied carbon [16], land [17, 18], nutrients [19, 20] and transportation infrastructure [21], among others. Food trade enables the spatial decoupling of agricultural production and consumption [22], highlighting the importance of understanding distant teleconnections for sustainability [23, 24].

The global WF of humanity is dominated by agricultural production (92%). The global WF of agriculture is 8360 $km^3\ yr^{-1}$ [25]. The gross international virtual water flows associated with trade in agricultural products is 2038 $km^3\ yr^{-1}$ [25]. Thus, almost a quarter ($24.4\% = 2038\ km^3\ yr^{-1}/8360\ km^3\ yr^{-1}$) of the total WF of agriculture is embodied in the international trade of agricultural commodities. For this reason, it is essential to understand interactions between global food trade, food security, and water resources sustainability, including the role of trade policy.

Global water savings (GWS) is an important metric of the water resources efficiency of global trade. International food trade saves water globally [26–28] and relieves local water scarcity [29]. Global water savings has increased over the last several decades [14], particularly for blue (irrigation) water sources [30], where the blue water saved via trade is estimated to be worth 2.4 billion $US [31]. As such, when determining if trade liberalization is an effective adaptation measure to climate change it is important to understand if it will increase or decrease WF, particularly for blue water sources [18].

This paper builds on existing literature. Kastner *et al* [32] find that trade currently flows from high-yield to low-yield countries, on average. [31] show that trade saves water globally and improves water scarcity in some locations, while exacerbating it in others. Hertel *et al* [33] examine how climate change impacts to agricultural trade will impact poverty in developing countries. Orlowsky *et al* [34] estimates how future water scarcity will impact virtual water trade. Ercin and Hoekstra [35] develop future WF scenarios across a multitude of drivers of change, highlighting the importance of consumption patterns. Schmitz *et al* [36] project that future water scarcity can be alleviated with trade liberalization and reduced livestock consumption. Liu *et al* [37] and Reimer [38] demonstrate that international trade can help humanity adapt to climate change by buffering projected irrigation shortfalls. Reimer [38] finds that under some forms of trade liberalization, wherein there is a migration of crop production towards countries with lower production costs, there could be higher rates of water use overall at the global level. However, Reimer [38] do not consider full trade liberalization nor the implications of climate change. Konar *et al* [39] quantify virtual water trade flows and WF under climate change. This paper builds on Konar *et al* [39] by considering adaptation to climate change through trade liberalization.

Despite the increase in trade in recent decades, the share of agricultural output that is traded remains much smaller than with most other sectors [40, 41]. One reason is relatively high freight costs; specifically, the value-to-weight ratio of most agricultural products is low, which limits the profit that traders can earn and thus their incentive to trade internationally. Another reason is an extensive array of policy barriers to trade at national borders, including tariffs, tariff-rate quotas, and non-tariff barriers to trade (e.g. commodity standard disparities, voluntary export restrictions [4], etc). These policies were left in place after the Uruguay round of World Trade Organization agreements. Many of these policies are designed to encourage local food production, or perhaps are due to political considerations, i.e., lobbying power of certain farm groups. Disagreement over agricultural policies and protectionism is one reason why the Doha round of multilateral trade negotiations has made little progress [38].

The effect of policy barriers to trade is to distort local prices away from world prices. Domestic rice prices in May 2015, for example, exhibited great variation across the globe: \$0.39 kg^{-1} in Cambodia, \$0.61 kg^{-1} in Mali, \$3.06 kg^{-1} in Angola, and \$3.80 kg^{-1} in Japan [41]. Some of these differences may reflect varietal and quality differences, but as mentioned, policy barriers that protect farmers in some markets are a major factor [42]. If these policies were relaxed, international prices should vary by little more than freight costs and associated transaction costs. Commodity prices would not perfectly equalize under free trade (due to freight and transaction costs), but greater spatial arbitrage would take place and prices would be more equivalent around the world [40]. Such trade liberalization would dramatically impact the pattern of trade flows, and, therefore, virtual water trade, the focus of this paper.

As such, this paper incorporates one potential human adaptation to climate change in a modeling framework. We estimate the relative implications of trade liberalization and climate change—both alone and in combination—for the WF of agricultural trade, and its WF. There are numerous factors excluded from the analysis that will determine future scenarios, so this study should not be viewed as making predictions. Rather, we isolate the impacts of two factors that have received relatively little joint attention in the literature; namely, trade policy and crop yield changes associated with climate change. The paper is organized as follows. Section 2 describes our modeling framework and methods. Section 3 presents our results. We conclude in section 4.

2. Methods

We quantify the staple crop trade between nations under a global free trade policy and a changing climate, with 2001 as the baseline year and projections to 2030. To do this, we employ a global model of international trade (the Global Trade Analysis Project, GTAP) and a global hydrology model (H08). A schematic of the methodology is provided in figure 1. Our methodology closely follows that of Konar *et al* [39] with three important improvements. First, we loosely couple the H08 and GTAP models. We do this by using H08 output of projected yield changes [%] to drive GTAP. Second, we consider the global free trade policy scenario both with and without climate change. Third, we explicitly consider blue virtual water flows.

The main goal of our paper is to understand how climate change and trade liberalization—in isolation and combination—impact the WF of agricultural trade. For this reason, we employ a static comparison modeling approach, in which we perturb only climate and trade liberalization input, in order to identify their

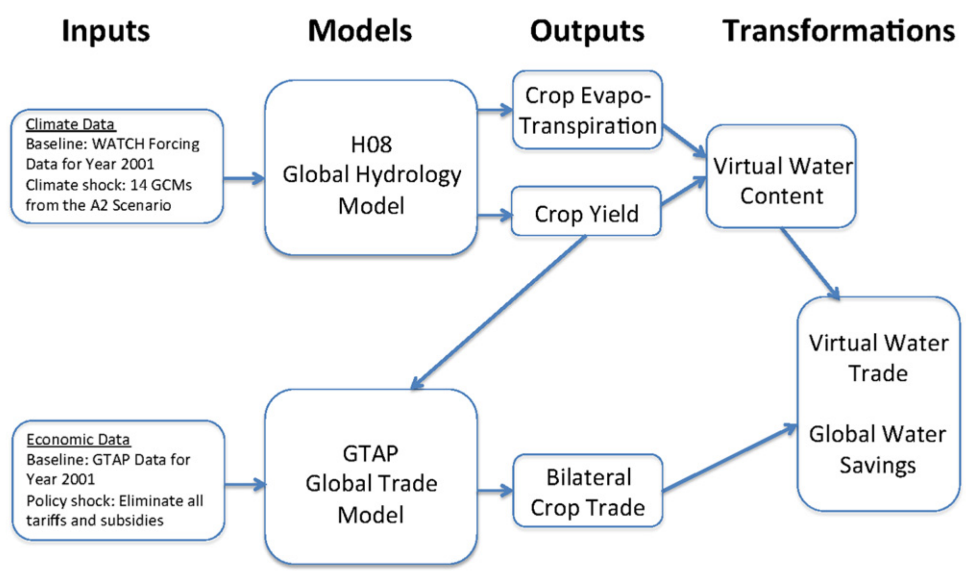

Figure 1. Schematic of methodology, which employs H08 hydrology and GTAP trade models.

causal role. However, this approach comes at the expense of obtaining a realistic projection of the future. In modeling, there is a trade-off between model 'realism', 'precision', and 'generality (e.g. refer to Troy *et al* [43] and Levins [44]). If we perturb all potential variables simultaneously (i.e. population, demand, land-use, agricultural technologies, etc) it would limit our ability to distinguish the distinct impacts of climate change and trade liberalization on the outcome variables of interest.

2.1. Global hydrology model: H08

We utilize the H08 global hydrology model [45] to estimate crop virtual water content (VWC) and projected changes in crop yield (Y). The H08 model is a state-of-the-art hydrologic model incorporating both natural and anthropogenic water flows, with energy and water balance closure. The model runs globally on a $0.5^\circ \times 0.5^\circ$ spatial resolution and daily time step. H08 models crop growth, land surface hydrology, river routing, reservoir operation, environmental flow requirements, and water withdrawals for human use, which, importantly, enables crop irrigation supplies to be separated into blue and green components [45–47].

Two types of input data are used to force the H08 model: land use and meteorological (refer to figure 1). For land use, the global distribution of cropland [48], major crops [49], irrigated areas [50], and cropping intensity [51] were used to run the model. These land use data were fixed to the year 2000.

The base meteorological forcing data for the year 2000 is obtained from the Integrated Project Water and Global Change (EU WATCH) meteorological data [52]. Projections under climate change were obtained by forcing the H08 model with climate data from 14 global climate models (GCMs) driven with emissions from the IPCC SRES A2 scenario [53] for 2030, which is the second highest carbon emission scenario [53]. Refer to Rogelj *et al* [54] for a comparison between SRES and SSP scenarios. A list of the 14 GCMs used to obtain climate change projections are provided in the supplementary information (SI) document. Projections of air temperature, incoming long wave radiation, and precipitation were obtained from each of the 14 GCMs. Climate grids for each of the GCMs were input separately into the H08 model. In this way, we obtain output for each of the 14 GCMs.

2.1.1. VWC

VWC is an estimate of the volume of water used to produce a unit of agricultural output [45]. VWC is defined as the total evapotranspiration ($\overline{\mathrm{ET}}$) during a cropping period (kg m^{-2}) divided by the total crop yield (Y) (kg m^{-2}), i.e. $\mathrm{VWC} = \overline{\mathrm{ET}}/Y$. H08 tracks the source of crop irrigation, such that $\overline{\mathrm{ET}}$ of a particular crop in each cell can be broken down into the fraction of ET originating from blue and green water sources.

Using the H08 model, we estimate current (i.e. year 2000) and future (i.e. year 2030) VWC of four staple crops: corn, rice, soy, and wheat. An estimate of total, blue, and green VWC is obtained for each grid cell of the H08 model (i.e. $0.5^\circ \times 0.5^\circ$), which is amongst the highest spatial resolution currently available in the literature [55]. The grids with crop-specific VWC estimates are then averaged to obtain a national VWC estimate. For climate change, VWC is estimated for each country-crop pair under each of the 14 GCMs. The time average of VWC from 2020–2039 is used to represent VWC for 2030.

2.1.2. Crop yield

Using the H08 model, we estimate current (i.e. year 2000) and future (i.e. year 2030) Y of four staple crops:

corn, rice, soy, and wheat. The H08 model includes the crop growth sub-model in order to estimate the cropping calendar (i.e. planting and harvesting date) of major crops around the world, which is essential to estimate agricultural crop water requirements and VWC. The crop growth sub-model is compatible with the widely used SWAT model [56]. The cropping calendar for major crops have been intensively validated [45, 46], but not crop yield. To estimate crop yield, numerous parameters by crop and region require calibration using quality-controlled yield statistics, which is challenging [57].

We estimated the yield for each nation:

$$Y_{c,n} = \frac{\sum_n Y_{c,i} * A_{c,i}}{\sum_n A_{c,i}}, \quad (1)$$

where Y is yield (kg ha^{-1}), A is harvested area (ha) in the year 2000, c denotes crop, n denotes nation, and i denotes cell. Here $\sum_n$ indicates the aggregation of cells for each nation. $Y_{\min}$ is a threshold for cell aggregation. Note that $Y_{c,i} > Y_{\min}$.

In this study, we estimate the percentage change in yield (%) from 2000 to 2030 with the H08 model, which we then use to force the GTAP model. For climate change, 14 estimates of Y are obtained for each country-crop pair. The time average of Y from 2020–2039 is used to represent Y in the year 2030. Climate change in H08 impacts the cropping period. The crop planting date is fixed in H08 (optimized for the 2000 climate), but the harvesting date is simulated based on crop growth. Importantly, farmer adaptations that impact Y are not included in H08. Thus, Y is only impacted by changes to the climate, but farmer adaptation measures—such as nutrient management, genetic modification, or other technological improvements—are not considered, which may be important in some locations, even with adequate water resources [58]. For countries in which H08 does not output yield changes, we use the crop-specific yield projections provided in [33].

2.2. Global trade model: GTAP

To project crop trade we use the Global Trade Analysis Project (GTAP) model. GTAP provides a detailed characterization of the supply and demand for multiple commodities. In each country, producers and consumers of a commodity are modeled as adjusting their behavior in response to exogenous shocks to the system [59]. Producers maximize profits, choosing what and how much to supply, based upon numerous factors including prices received and prices of inputs. Production is linked back to the need for labor (skilled and unskilled), capital, natural resources, and land. Consumers in each country maximize utility, choosing what and how much to buy, based upon a variety of factors, including preferences, the substitutability of commodities, and the price of alternative suppliers. Individually modeled national economies are linked through a detailed characterization of international trade behavior, with the model able to account for product differentiation and substitution possibilities. Of importance to this study, and in contrast to most other approaches in the literature, GTAP models bilateral trade flows using methodology that has been well established in the economics literature.

We develop a regionally disaggregated version of GTAP with 76 countries for the base year 2001. The list of countries is provided in the SI. Note that countries with incomplete economic data are placed into a 'Rest of the World (ROW)' category, which allows us to maintain exhaustive global coverage. From GTAP, we obtain baseline data and projections of bilateral trade flows for the four staple crops of this study: corn, rice, soy, and wheat. Output is in value terms (millions $USD). We convert to mass using the GTAP projected price data along each trade link. GTAP makes predictions about price changes in percentage terms. These are converted to absolute changes using agricultural price data for 2001 from the Food and Agricultural Organization [41]. When there is no price data for a country, data from the nearest neighbor country was used. For the ROW, the average price across countries within ROW was used.

Critical parameters of the model include price elasticities of demand and supply, as these largely determine how yield shocks are translated into changes in prices and changes in quantity demanded, by country. These and other key elasticities in the model are specified from a combination of econometric evidence, when possible, but mainly from calibration. In the latter case, parameters are adjusted by algorithm until the model can reproduce economic values for the base year, including numerous economic transactions among producers, consumers, and government within each country and across countries.

The GTAP data base provides highly detailed records of individual taxes by commodity and country pair. The associated parameters are *txs* for an export tax and *tms* for an import tariff, with negative values representing subsidies, and indexed by commodity, source country, and destination country. In the policy simulations below, these model parameters are changed such that the ad valorem taxes and subsidies become zero and no longer have any effect on bilateral trade patterns. Note that while export subsidies may encourage trade, these are much less common and typically much smaller in magnitude and importance than the import tariffs evident in the GTAP data base.

To ensure that supply response under policy liberalization simulations is biophysically realistic [22], the economic model has a number of constraints, including agricultural land and natural resources, which implicitly account for water. Information on these constraints is sourced from the economic literature on primary factor shares in agriculture, and are then altered so that they are consistent with estimates of the global supply elasticity for agricultural output as a whole. Note that supply is also constrained by a countrys endowment of physical capital (e.g. machinery), skilled labor and unskilled labor. All of these constraints impose a limit on agricultural supply response.

Even with no subsidies or tariffs, there are still non-policy barriers to trade, including freight costs, exchange rate imperfections, and frictions regarding the ability of countries to switch suppliers [42]. The standard method in economic modeling to represent this is to characterize supply from one country as not perfectly substitutable for supply from another. As a result, the four staple commodities are differentiated by country, with substitution among foreign importers only imperfect at best; the associated parameters are calibrated such that the model can replicate the trade patterns exhibited in the GTAP bilateral trade data base.

2.3. Scenarios

We compare four scenarios: (1) baseline data only (i.e. year 2001), (2) free trade only, (3) climate change only, and (4) both free trade and climate shocks. We refer to these scenarios as 'Baseline', 'Policy', 'Yield', and 'All', respectively. 'Baseline' refers to the GTAP baseline data for the year 2001. 'Policy' refers to the free trade only scenario in which all tariffs and subsidies are eliminated for corn, rice, soy, and wheat in GTAP. 'Yield' refers to the climate change only scenarios, in which yield changes (%) are output from H08 and used as input to GTAP. Note that there are 14 yield scenarios corresponding to the list of climate models provided in the SI. 'All' refers to the scenario in which both free trade and yield changes are implemented. Non-agricultural commodities are not shocked in any way across the scenarios.

2.4. WF of staple crop trade

The WF of agricultural trade is calculated by multiplying the international trade of a particular crop (CT) by its associated (VWC) in the country of export [25]. The WF of agricultural trade is:

$$\mathrm{WF}_{s,w} = \sum_{e,i,c} \mathrm{VWC}_{e,s,w} \cdot \mathrm{CT}_{e,i,s} \tag{2}$$

where the subscripts e, i, *and* c denote country of export, country of import, and crop commodity, respectively. The subscript s indicates the scenario (i.e. 'Baseline', 'Policy', 'Yield', and 'All'). The subscript w indicates the water sources (i.e. total or blue). The WF of trade is summed across all trade links. In the above equation WF is summed across commodities; we refer to this as the 'aggregate' WF. For the WF associated with a particular crop, we refer to the commodity by name (i.e. corn, rice, soy, or wheat).

2.5. Global water savings (GWS) of staple crop trade

GWS is a theoretical measure of how much water is saved by trade [26–28]. For each trade link, the VWC of the country of export is subtracted from the VWC of the country of import. Positive values indicate that water is being saved by that trade link; negative values indicate trade-based water losses. The difference in VWC between trading partners is multiplied by the mass of crop trade occurring on that trade link. GWS is the sum across all trade links. We calculate GWS as:

$$\mathrm{GWS}_{s,w} = \sum_{e,i,c} T_{e,i,c,s} * (\mathrm{VWC}_{i,c,s,w} - \mathrm{VWC}_{e,c,s,w}), \tag{3}$$

where the subscripts e, i, c, s, and w are as above. T is the volume of commodity c traded from exporting country e to importing country i. The difference in water use efficiency between i and e is $\mathrm{VWC}_{i,c,s,w} - \mathrm{VWC}_{e,c,s,w}$, which is indexed by country, crop, scenario, and water source. Water savings (WS) refers to the WS associated with a particular country or trade-link.

2.6. Water stress data

We collected data on water scarcity from the World Resources Institute (WRI) Aqueduct Projected Water Stress database. This database contains information on projected country-level water stress for the years 2020, 2030, and 2040. The WRI data presents data for 167 countries under three scenarios: business-as-usual, pessimistic, and optimistic. Scores are available for total water stress, as well as stress for industrial, agricultural, and domestic users [60]. We selected agricultural water stress data for the year 2030 under the business-as-usual scenario.

Aqueduct water stress data is presented with five thresholds. Each country is assigned a score from 1 to 5. A score of 1 indicates low stress (<10% available water withdrawn), 2 indicates low to medium stress (10%–20% available water withdrawn), 3 indicates medium to high stress (20%–40% available water withdrawn), 4 indicates high stress (40%–80% available water withdrawn), and 5 indicates extremely high stress (> 80% available water withdrawn) [61].

3. Results and discussion

3.1. Yield changes

The global average yield changes are 13.0% for corn, –2.1% for rice, 7.1% for soy, and –6.5% for wheat (or 2.9% across all crops). However, these values are relatively uninformative, because they are averaged across all climate scenarios and countries. Global averages do not capture spatial heterogeneities in yield changes that drive bilateral trade flows. Yield changes in one country impact other countries through changing crop prices and subsequent trade patterns. The range of yield shocks for major agricultural producers are provided in table 1. The average and range of the yield changes for all countries and crops are provided in the SI.

H08 estimates of the percentage change in yield compare relatively well with those provided by Hertel

Table 1. Yield shock range across the 14 global climate models (GCMs) of major producers. Starred values (*) indicate that output data is not available from H08; projections from [33] were used instead. Values are reported in percentage terms (%).

Country	Corn	Rice	Soy	Wheat
Argentina	[–16, 4]	[–19, 9]	[–21, 4]	[–21, 2]
Australia	[–13, 5]	[–5, 19]*	[–10, 14]*	[–21, 0.2]
Brazil	[–5, 1]	[–6, -1]	[–4, –0.2]	[–18, –1]
India	[–8, 2]	[–4, 0]	[–4, 1]	[–42, 17]
United States	[15, 116]	[–25, –1]	[16, 64]	[–16, 4]

et al [33], except for some countries and crops. For example, the yield change of corn in the USA and yield change of soy in China are unexpectedly high. From H08, the upper bound on corn yield change is +116%, while it ranges from approximately –5 to –35% in Hertel *et al* [33]. Similarly, the range of soy yield change from H08 is +147% to +230%, while it is –12%–12% in Hertel *et al* [33]. These discrepancies are partly due to differences in climate forcing grids, but largely due to the H08 method of spatial aggregation of yield. Since the crop yield parameters are not calibrated in H08, the default parameters do not always reflect the region-specific cultivars. This results in erroneously low crop yield under some conditions. To exclude these cases, we used a global threshold of $Y_{\text{min}} = 100\ \text{kg ha}^{-1}$. This is reasonable for many crops and nations, but is likely too small for corn in the USA and soy in China. Note that if we change the threshold value to be 1000 kg ha^{-1} the upper bound of the yield change for corn in the USA becomes 57% (refer to Table S 4), which is closer to the value provided by Hertel *et al* [33]. However, to be consistent, we chose a single threshold value for all crops and nations. We decided to implement a smaller threshold value for Y_{min}, since larger Y_{min} values decrease the number of cells to aggregate, which is problematic for nations with few cells.

The H08 model only estimates yield changes for locations that are currently major producers of a given crop. Changing the spatial distribution of crop production is an important adaptation measure to climate change that is not captured in this modeling framework.

3.2. WF of staple crop trade

The total WF (m^3) of aggregate crop trade across scenarios is provided in figure 2. The base level is 245 billion cubic meters. This rises by 29.5% under the trade liberalization scenario ('Policy'). This is a substantial rise that illustrates the magnitude of the policy barriers that currently exist at the global level for the staple commodities being analyzed. Elimination of tariffs and subsidies to trade dramatically increases trade in dollar terms (refer to SI). Under yield changes (only) ('Yield') there is an average 16.0% rise in the WF. So while the WF of food trade increases across all climate scenarios, it increases even more under the free trade scenario. In turn, under the combined trade liberalization and climate change scenarios ('All'), the WF of trade increases by an average of 49.8% over the baseline. The value of the All scenario is distinct to a simple sum across the Policy and Yield scenarios, due to complex interactions that arise from the spatial distribution of climate and policy changes.

The WF of crop-specific trade across scenarios is provided in figure 3. Figure 3 highlights that the rice trade is most impacted by free trade. Its WF of trade increases by approximately 400% under the combined trade liberalization and climate change scenarios, although nearly all of this change comes from the policy change. It is important to note that while this increase is very large in percentage terms, in absolute terms it is fairly modest because the base level of trade for rice is so small, and because natural resource constraints within the GTAP model inhibit the model from making over-predictions in this regard. Rice has particularly high trade policy barriers in some countries [62], such that the free trade policy implemented here—in which all tariffs and subsidies are eliminated—has more of an impact relative to the yield-focused climate scenarios. This is exhibited by Thailand, a

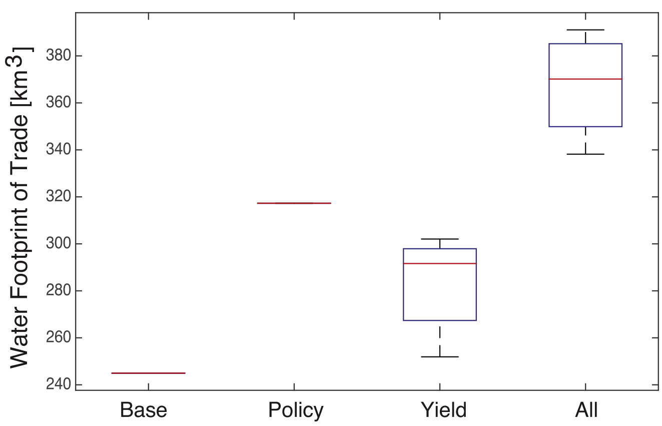

Figure 2. The total water footprint of staple crop trade across scenarios. The yield gains that increase trade also lead to smaller virtual water contents.

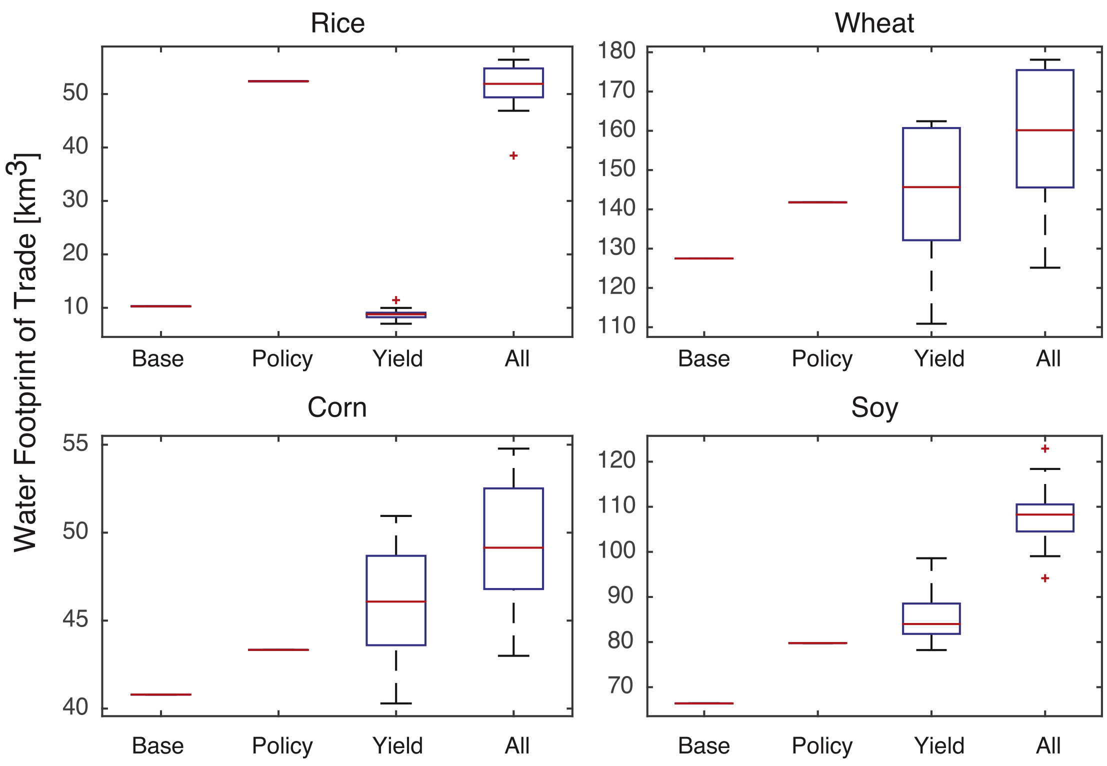

Figure 3. Crop-specific water footprint of trade across scenarios. Note that rice is most impacted under the free trade policy scenario.

major rice producer, moving into the top 10 net traders of total virtual water under the free trade scenario (refer to table S10).

Blue water resources play a more direct role in freshwater scarcity and have a distinctive geographic pattern to agricultural land areas [18]. As such, it is important to explicitly consider the blue WF of trade. Maps of changes in net blue virtual water trade (km^3) for each country and scenario are presented in figure 4. Warm shades indicate reductions in net blue virtual water trade, while cool shades show positive changes. Not all countries are modeled under our framework, as GTAP provides output for only 76 countries (refer to the SI for the full list). Countries for which we do not have model results are shaded white.

A list of the largest changes in net blue virtual water trade by scenario is presented in table 2. Table 2 presents changes from the baseline scenario. China and the USA both export more blue virtual water across all scenarios, although the volume change is most positive under the policy only scenario. Japan exports less blue virtual water across all scenarios, but exhibits the largest negative change in net blue virtual water trade under the policy only scenario. Interestingly, India demonstrates the largest negative change in net blue virtual water trade under the climate change scenarios, but is amongst the top 10 positive changes under the policy only scenario. This illustrates the differing impacts of trade policy and climate change across countries.

Due to model limitations, we do not consider some important water-intensive agricultural commodities in this study, such as cotton and animal products. Trade in oil crops (cotton, soybean, oil palm, sunflower, rapeseed, and others) and derived products accounts for the largest share of international virtual water flows (43%) [25]). Approximately 20% of this amount is due to trade in soy, while over half of the oil crops category is due to trade in cotton. Beef cattle products comprise approximately 6.7% of total international virtual water flows [25]. By not including these items in our study, we under-estimate the WF of agricultural trade. However, we focus on staple crops that are critical for global food security [58].

3.3. Global water savings (GWS)

The blue GWS (km^3) of aggregate crop trade across scenarios is provided in figure 5. Blue GWS is highest under climate change when free trade is allowed. Total GWS exhibits the same pattern (refer to figure S 6). Even under the most pessimistic of yield changes, there is WS. This happens because, on average, there is switching of exporters away from those with low water use efficiency to those with high water use efficiency. In effect, by lowering policy barriers, the sourcing of staple commodities is re-routed to suppliers which are not only lower cost producers but also more efficient water users.

More detail can be seen by examining blue GWS of crop-specific trade across scenarios, provided in figure 6. In all cases trade liberalization leads to greater

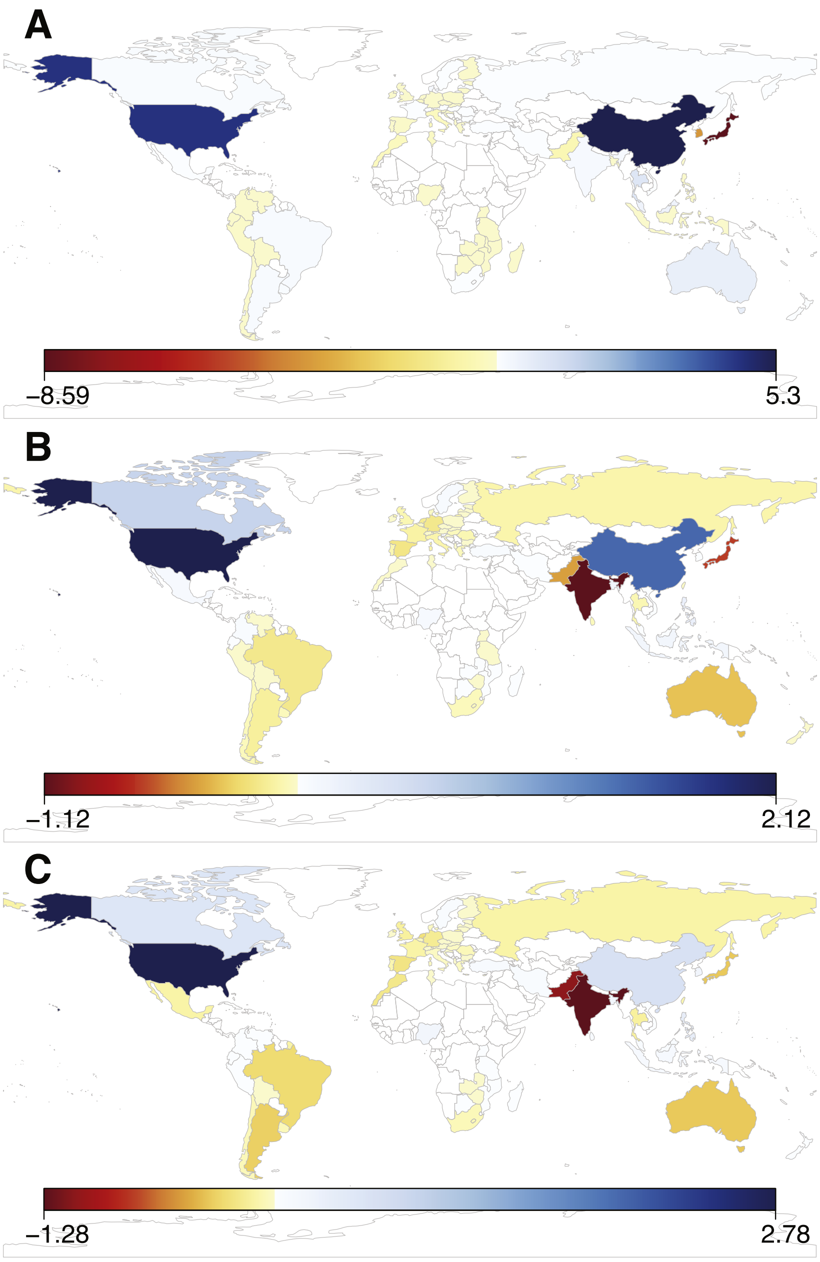

Figure 4. Maps of changes in net blue virtual water trade (km^3) for each country from the baseline scenario to the (A) policy only, (B) climate change only, and (C) climate change and policy scenario. Warm shades indicate reductions in net blue virtual water trade, while cool shades show positive changes. Countries that are shaded white indicates that model results are not available. Note that the ranges on the color bars are different across scenarios.

GWS, most importantly in the case of rice and soy. It is less effective for corn, but that is because it is comparatively more liberalized at present, as reflected in the baseline GTAP tariff data. This indicates that future scenarios with status quo trade policy will likely lead to greater global irrigation use, rather than one in which free trade is enabled.

Maps of changes in national blue WS (km^3) for each country and scenario are presented in figure 7. Warm shades indicate reductions in blue WS, while cool shades show positive changes. Notably, Brazil moves from a warm shade under climate change only (panel B), but is a cool shade under the free trade scenarios (panels A and C). Table 3 details that Brazil contributes 3.34 km^3 under free trade only and 1.01 km^3 under the free trade and climate change scenario to GWS. However, under only climate change, Brazil shows a reduction of 2.16 km^3 to WS. This highlights that the impacts of policy and climate change differ both within and across countries. It is important to note that changes from the baseline are shown in table 3 and that Brazil contributes to blue WS across all scenarios, but contributes to losses in total WS (refer to table S12).

Figure 8 maps the largest changes in link-level blue WS from the baseline to the climate change and policy scenario. Positive (panel A) and negative (panel B) changes are shown. Table 4 details these link-level

Table 2. Largest changes in national net blue virtual water trade (km^3) across scenarios.

Positive changes	Policy		Yield		All	
Rank	country	Volume	Country	Volume	Country	Volume
1	China	5.30	USA	2.12	USA	2.78
2	USA	4.57	China	1.46	China	0.58
3	Thailand	0.87	Canada	0.60	Canada	0.49
4	Australia	0.579	Philippines	0.20	Philippines	0.33
5	Malaysia	0.37	Bangladesh	0.14	Korea	0.18
6	Denmark	0.19	Indonesia	0.11	Nigeria	0.15
7	India	0.16	Mexico	0.07	Bangladesh	0.15
8	Argentina	0.14	Nigeria	0.072	Indonesia	0.10
9	Brazil	0.14	Sweden	0.06	Turkey	0.07
10	Canada	0.10	Turkey	0.04	Sri Lanka	0.06
Negative changes	Policy		Yield		All	
Rank	Country	Volume	Country	Volume	Country	Volume
1	Japan	−8.56	India	−1.11	India	–1.27
2	Korea	−3.66	Japan	−0.69	Pakistan	–1.11
3	Pakistan	−0.53	Pakistan	−0.45	Australia	–0.39
4	Italy	−0.28	Australia	−0.35	Japan	–0.36
5	Morocco	−0.28	Spain	−0.20	Argentina	–0.35
6	Tunisia	−0.18	Brazil	−0.18	Brazil	–0.29
7	Belgium	−0.18	Germany	−0.18	Netherlands	–0.27
8	Spain	−0.08	Netherlands	−0.17	Spain	–0.23
9	Peru	−0.07	Argentina	−0.14	Morocco	–0.20
10	Colombia	−0.04	France	−0.12	Germany	–0.18

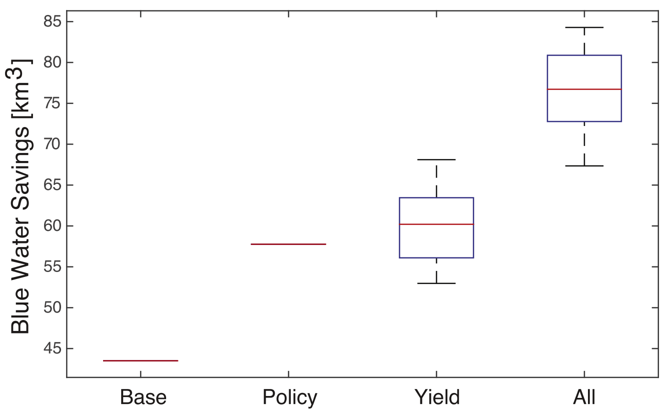

Figure 5. Blue global water savings across scenarios. Note that aggregate blue global water savings is highest under climate change when free trade is enabled.

changes. The largest gain is from Brazil to China, with an additional 1.04 km^3 being saved along this trade link. Trade from the USA to Japan indicates that an additional 6.10 km^3 will be lost along this trade link. This highlights the fact that staple crop trade relationships are not influenced solely by water factor efficiency and trade policies, but that there may also be other considerations, such as politics, the logistics of transportation, or the national availability of arable land [18].

3.4. Water stress relationships

We present regressions between national blue WFs and water stress in 2030 in figure 9. Panels A, B, and C presents relationships between log (total blue water exports (m^3)) and agricultural water stress. Panels D–F present relationships between log (blue GWS (m^3)) and agricultural water stress. The agricultural water stress scenario is under business-as-usual conditions. Panels A and D show the policy only scenario, panels B and E show the climate change only scenario, and panels C and F show the climate change and policy scenario.

Values of R-squared are fairly constant for log (total blue water exports) (approximately 0.27 for all scenarios). This indicates that there is a positive relationship between national water stress and log (total blue water exports). In other words, some

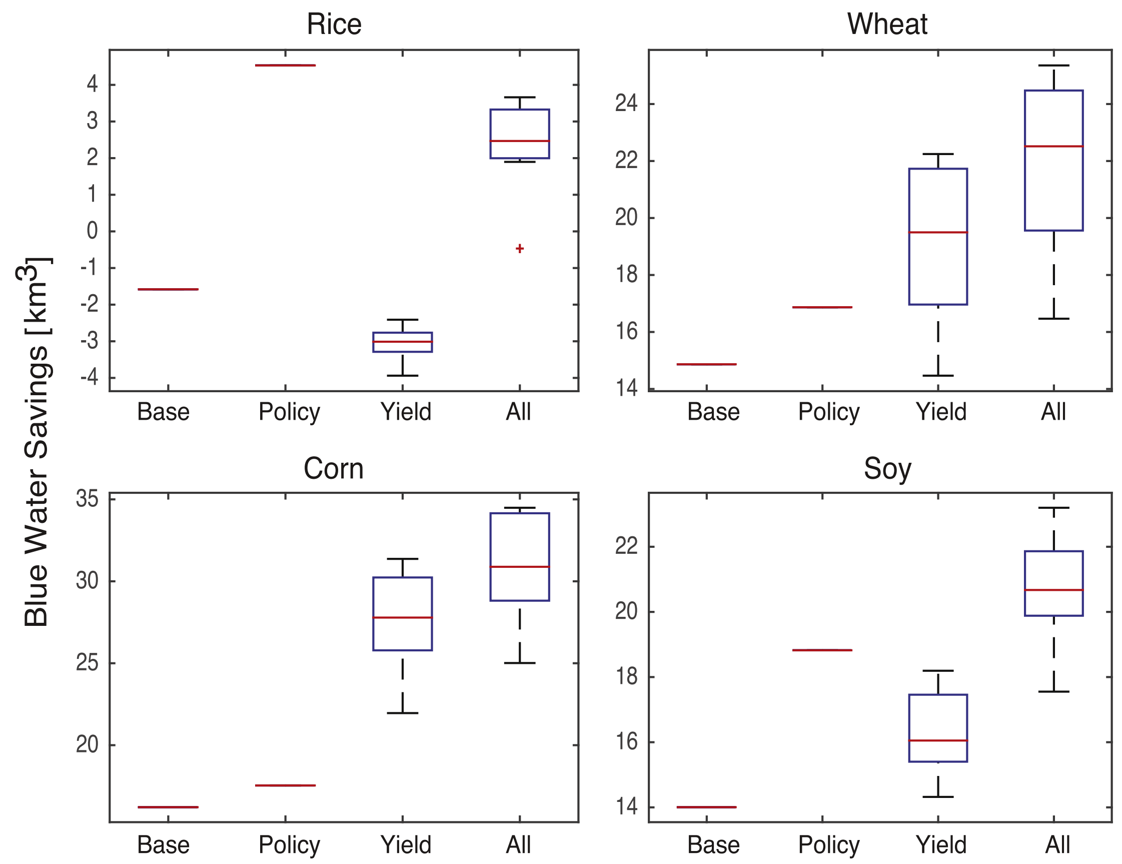

Figure 6. Blue crop-specific global water savings across scenarios. Note that rice and soy exhibit large water-efficiency gains in trade under free trade policies.

countries with relatively high values of water stress are projected to export large volumes of blue water across all scenarios. For log (blue GWS), the largest R-squared value is present for the policy only scenario (panel D). This shows that the countries that are projected to be the largest contributors to GWS are also projected to experience the largest levels of water stress.

It is important to highlight that many of the countries driving the relationships in figure 9 are large, with much spatial heterogeneity in water stress. For example, Brazil, China, and the United States have significant regional variations in water demand and supply that may not be captured properly when aggregating to the national level [61]. These countries are amongst the largest contributors to blue water exports and savings. As such, it is critical that future research takes sub-national variation into account and spatially co-locates high resolution agricultural water use with water stress. Another important area of future work will be to distinguish sub-national agricultural production and consumption flows to most accurately determine contributions to WF. Trade data and models typically operate at the national scale, making this challenging.

4. Conclusions

The need to investigate the international dimensions of water use has become increasingly important as climate change and economic growth put greater pressure on the water resources of many countries. The study at hand sheds light on how international trade can serve as a vehicle for adaptation to climate change, and how international trade policy affects the global redistribution of water resources. A joint hydrologic–economic modeling framework is developed to study the link between water usage for four staple crops (corn, rice, soy, and wheat) and international trade, using well established models in the hydrology and economics literatures. This modeling framework was used to quantify the impact of climate change and trade liberalization on the WF of agricultural trade, and its WF.

The WF of trade is found to greatly increase under trade liberalization, and is limited primarily by the natural resource constraints by country that are imposed by the economic model. There is also increased total and blue WS at the global scale with lower trade barriers. By eliminating distortionary policy barriers, some countries are able to import

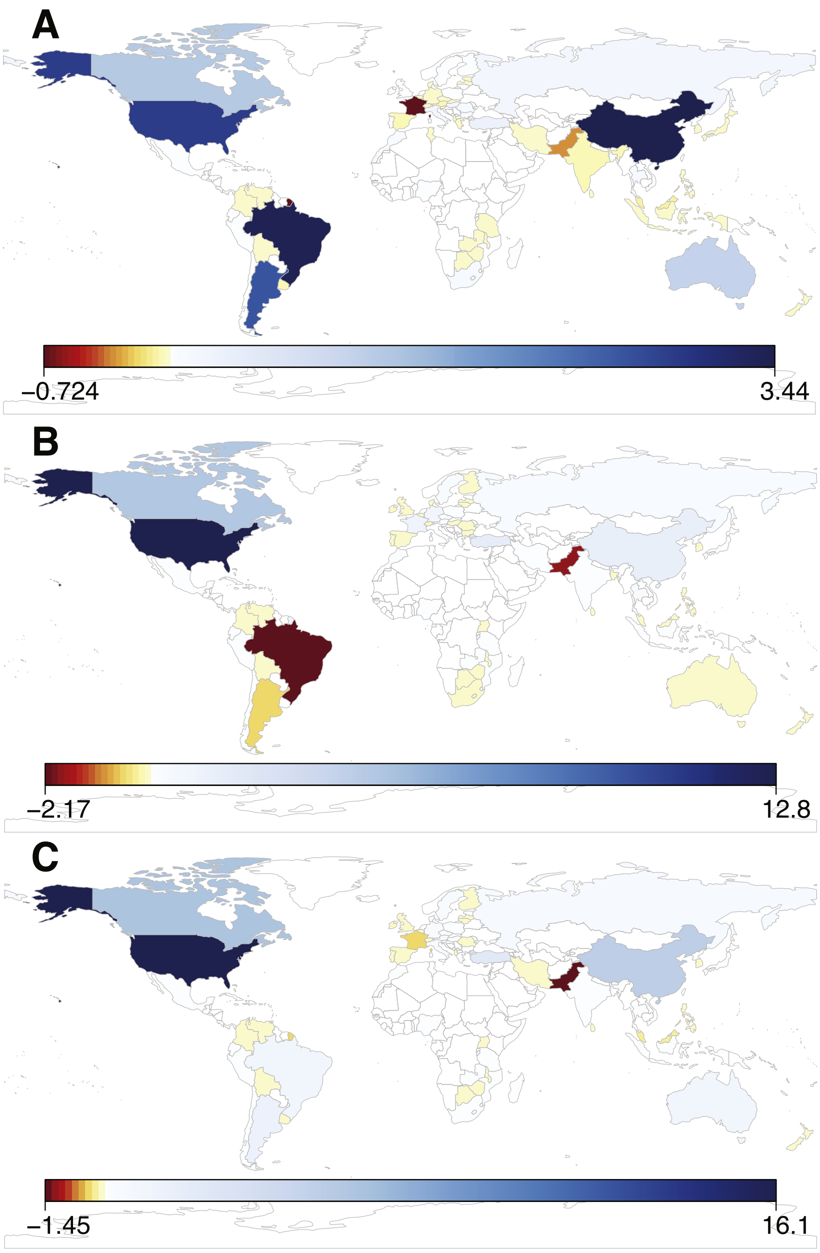

Figure 7. Maps of changes in blue global water savings (km^3) for each country from the baseline scenario to the (A) policy only, (B) climate change only, and (C) climate change and policy scenario. Warm shades indicate reductions in blue global water savings, while cool shades show gains. Countries that are shaded white indicates that model results are not available. Note that the ranges on the color bars are different across scenarios.

agricultural goods from other countries where water is used more efficiently, due to reasons of climate, soil, management techniques, or other factors. As such, this study adds another dimension to some of the established benefits of trade liberalization of agricultural markets, which has been shown to improve global food security and welfare, while simultaneously mitigating price volatility [4]. This study indicates that full liberalization—alone and in combination with climate change—will enhance WF, making it one potential lever in a suite of adaptation measures to a changing climate. As such, this analysis provides an additional element of support for policy-makers who are presently pushing for further agricultural trade liberalization in the Doha round multilateral trade negotiations. To our knowledge, such considerations have been largely absent from the trade negotiations.

This study also highlights that there is a positive relationship between national level contributions to WF and water stress. These results must be interpreted carefully though, as many large countries exhibit significant spatial heterogeneity in regional water stress that may not be adequately captured by a national indicator of water stress. To this end, an important area for future research could be integrating understanding of WF with local water scarcity, particularly in light of the fact that the value of water varies by source and commodity, as well as in space and time [63]. Future work should develop accounting

Table 3. Largest changes in national blue WS (km^3) of export across scenarios.

Positive changes	Policy		Yield		All	
Rank	Country	Volume	Country	Volume	Country	Volume
1	China	3.44	USA	12.78	USA	16.09
2	Brazil	3.34	Canada	4.56	Canada	5.99
3	USA	2.85	Turkey	1.49	China	5.03
4	Argentina	2.56	China	1.35	Turkey	2.40
5	Canada	1.18	France	0.94	Argentina	1.30
6	Australia	1.03	Germany	0.71	Brazil	1.01
7	Turkey	0.28	Russia	0.30	Australia	1.00
8	Hungary	0.17	Sweden	0.18	Russia	0.52
9	Italy	0.15	Thailand	0.13	Denmark	0.37
10	Russia	0.14	India	0.08	Italy	0.32
Negative changes	**Policy**		**Yield**		**All**	
Rank	Country	Volume	Country	Volume	Country	Volume
1	France	−0.72	Brazil	−2.16	Pakistan	–1.38
2	Pakistan	−0.33	Pakistan	−1.91	France	–0.43
3	Malaysia	−0.08	Argentina	−0.53	Malaysia	–0.18
4	Uruguay	−0.07	Spain	−0.12	Spain	–0.15
5	Spain	−0.06	Romania	−0.10	Korea	–0.09
6	India	−0.06	Malaysia	−0.08	UK	–0.05
7	Austria	−0.04	UK	−0.08	Uruguay	–0.03
8	Denmark	−0.03	Bulgaria	−0.05	Romania	–0.03
9	Sri Lanka	−0.02	Hungary	−0.05	Sri Lanka	–0.01
10	Indonesia	−0.01	Australia	−0.04	Bolivia	–0.01

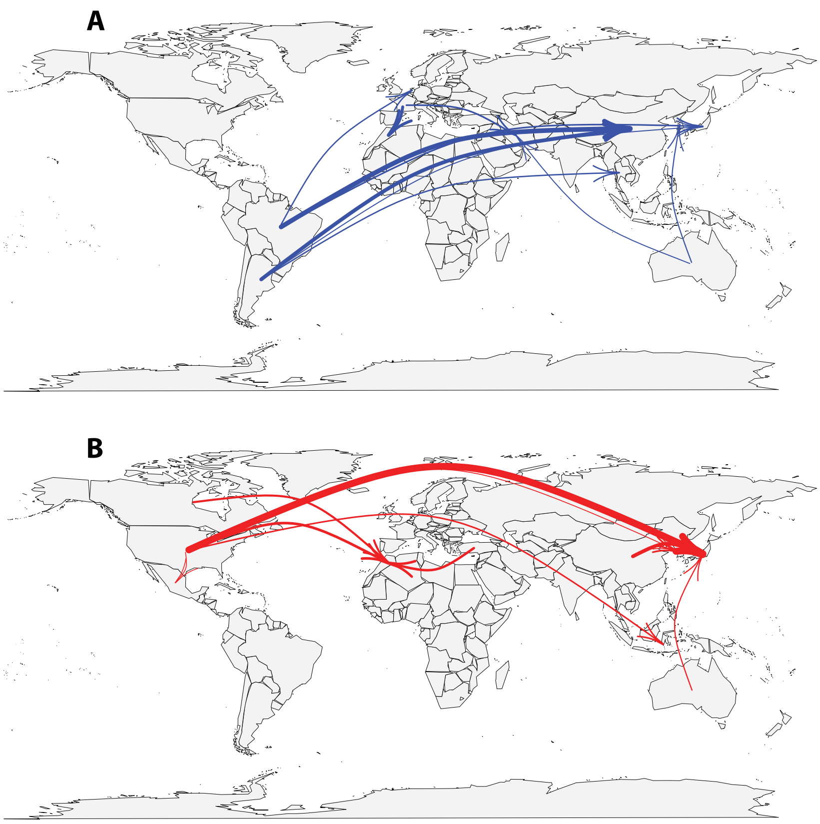

Figure 8. Maps of 10 largest changes in link-level blue WS (km^3) from the baseline scenario to the climate change and policy scenario. (A) Blue links indicate positive changes, while (B) red links illustrate negative changes. Details are provided in table 4.

Table 4. Largest changes in link-level blue WS (km^3) from the baseline scenario to the combined climate change and policy scenario. Note that 'Export' refers to the country of export and 'Import' refers to the country of import.

	Positive changes			Negative changes		
Rank	Volume	Export	Import	Volume	Export	Import
1	1.04	Brazil	China	−6.10	USA	Japan
2	0.83	Argentina	China	−3.20	China	USA
3	0.64	France	Morocco	−2.29	USA	Morocco
4	0.36	France	Iran	−2.18	Turkey	Morocco
5	0.35	Brazil	Japan	−1.83	Canada	Morocco
6	0.30	Argentina	Thailand	−1.48	China	Korea
7	0.30	Brazil	Netherlands	−1.35	USA	Indonesia
8	0.25	Australia	Korea	−1.02	Australia	Japan
9	0.22	Argentina	Japan	−0.76	USA	Korea
10	0.22	Australia	Iran	−0.71	USA	Mexico

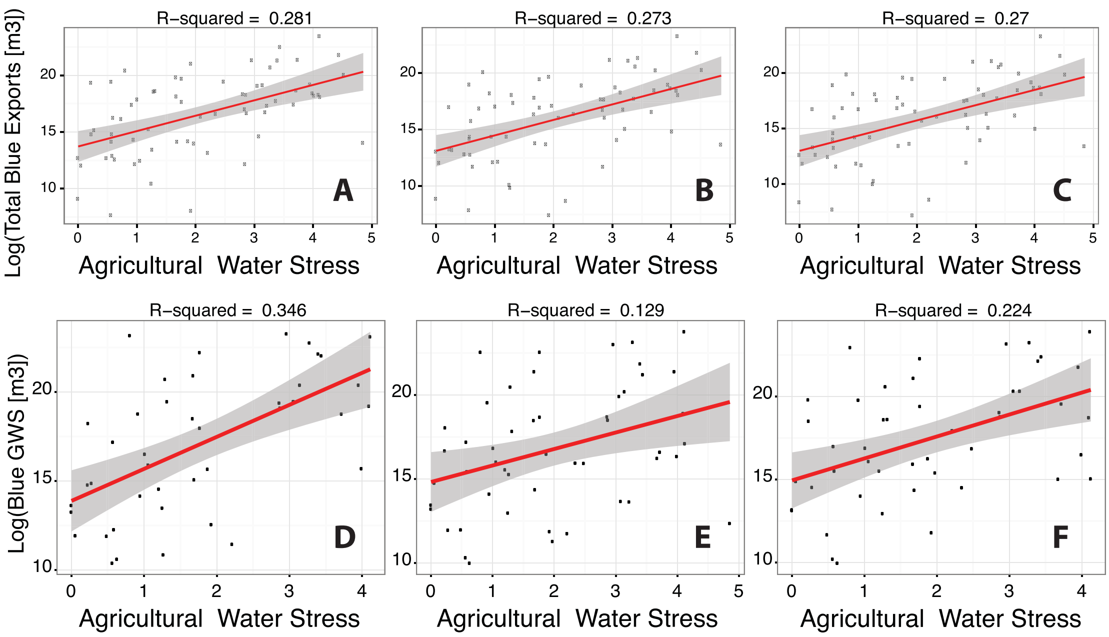

Figure 9. Relationships between national blue water footprint and water stress in 2030. The top row (panels A–C) shows regressions between total blue virtual water exports and agricultural water stress. The bottom row (panels D–F) presents regressions between blue global water savings of exports and agricultural water stress. Panels A and D present the policy only scenario, panels B and E present the climate change only scenario, and panels C & F presents the climate change and policy scenario.

procedures to track water scarcity implications of agricultural production in the exporter country with water scarcity outcomes for the consuming location in the absence of that virtual water transfer, such that a unit of water is not weighted equally across all times and locations.

This paper represents an important step in incorporating human adaptation into models that make climate change projections. However, future work in this area should consider additional human adaptation measures, such as changing the spatial distribution of agricultural production and building irrigation infrastructure. It would also be fruitful for future work to incorporate additional water-intensive commodities and examine the role of specific policy instruments, such as those governing the allocation of irrigation water for agricultural purposes.

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