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Research Article

Rewiring the Domestic U.S. Rice Trade for Reducing Irrigation Impacts—Implications for the Food−Energy−Water Nexus

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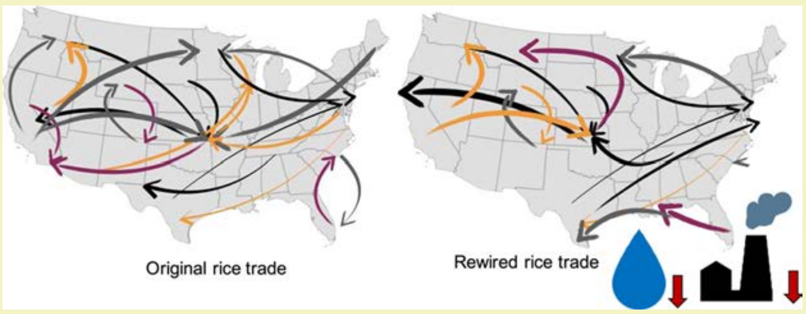

ABSTRACT: Food trade connects distant places of food production to places of consumption. Through traded food, associated environmental impacts are also displaced as the consumer benefits from the product without incurring the externalities of production. Taking U.S. rice as an example, we discuss the sustainability implications of rewiring U.S. rice production and trade for reducing the impacts of irrigation (water and energy) and transportation greenhouse gas (GHG) emissions. We model a series of robust optimization scenarios that re-arrange the origin of trade and therefore the production to target virtual water use and GHG emission reductions. For the baseline case, virtual water trade amounts to 35 billion m^3, and embodied irrigation and transportation GHG emissions amount to 6 billion kg CO_2-equivalent and 0.7 billion kg CO_2-equivalent, respectively. Rewiring consistently achieves better results compared to the baseline even in the presence of uncertainty. However, our findings reveal strikingly sobering national-level savings in optimizing the water use (2%) and GHG emissions (14%) with tradeoffs in other impacts. To achieve these results, all rice-producing states undergo changes, with the state of Mississippi completely stopping production. California's unique ability to produce medium-grain rice at a large scale makes it indispensable for current rice production and hence a major constraint for rewiring rice production. The findings of this work reveal the inflexibility of our food system in balancing the food−energy−water nexus tradeoffs through restructuring trade.

KEYWORDS: *food−energy−water nexus, optimization, food trade, crop re-distribution*

INTRODUCTION

Trade liberalization has played a major role in avoiding the Malthusian catastrophe of over-population and insufficient food.[1,2] Availability of food does not solely depend on a region's capacity for agricultural production but also on access to food. A nation's inability to reach food self-sufficiency either due to local crop failure, increasing population, or limited agriculture potential can be met through food trade or assistance. At present, 66 countries rely on agriculture imports as they do not have access to sufficient land and water resources to produce adequate food.[3] Additionally, a substantial population depends on food trade for access to diverse and out-of-season items available at competitive prices.

Proponents of trade for food security argue that trade provides an opportunity for nations to improve agricultural efficiencies by focusing on suitable regional crops while importing others.[4] Additionally, diversity in agricultural practices, resource endowment, and local policies can impact how identical crops are produced in different locations. However, trade is not structured solely based on the suitability of regional crops but as a result of environmental factors, demographics, market demand, and policies. Therefore, depending on the origin of production, food trade can decrease or increase environmental impacts and associated risks.[5]

A growing body of literature has discussed indirect trade of resources and environmental consequences of physical food trade.[6−9] Studies have shown that global trade of food has resulted in overall water savings[10,11] with exporting countries

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being water-efficient in agriculture, particularly with large-quantity exports of soybeans driving the savings.[10] Similarly, studies have assessed embodied impacts in trade to assess land,[12,13] biodiversity,[14] and nutrients displaced through trade[6,15,16] with the goal of promoting discourse on internalizing the environmental cost of externalities. Such comparison of relative impacts of agriculture through traded food has highlighted the role of trade in alleviating or acerbating resource depletion. However, national and international trade is not designed with the specific purpose of reducing environmental impacts and may not always be environmentally sustainable.[5] For example, global demand of commodities such as palm oil,[17] soy,[18] coffee,[19] shrimps,[20] and so forth and their increasing agricultural expansion in specific regions have resulted in loss of biodiversity. Similarly, studies have reported supply risk associated with reliance on depleted groundwater aquifers[21,22] and ecological risk of fish extinction due to overreliance on freshwater rivers for U.S. domestic trade and exports.[23]

Taking a step beyond quantification, studies have also investigated the possibility of re-distributing crops to maximize benefits such as nutritional gains and climate resilience while reducing resource demand and greenhouse gas (GHG) emissions at regional[24,25] and global levels.[26] For instance, Davis et al. recommend adopting a multi-dimensional approach for agriculture in India that moves away from growing high-output crops (rice, wheat, and sugar) and plant coarse grain crops such as millet and sorghum to increase synergies in agriculture benefits.[25] Despite the benefits of conscious crop re-distribution and arguments against monoculture centric agriculture, there are complex cultural and socio-economic implications associated with changing the agriculture landscape and consequently diet that would require a bigger systemic overhaul and a longer timeframe for implementation.[27]

We present an optimization-based approach to explore the feasibility of re-distributing currently grown crops for reducing environmental impact with U.S rice production as a case study. Rice is a staple food to more than half of the global population with significant cultural and economic importance.[28] The United States exports 45% of its total rice production and ranks in the top five largest exporters.[29] Additionally, U.S. rice is completely irrigated, making an excellent case study to assess (i) current food–energy–water (FEW) tradeoffs and synergies existing between rice irrigation systems (ii) whether re-structuring alleviates or exacerbates energy–water tradeoffs. Here, we employ trade restructuring as a lever to identify the crop re-distribution potential of regions. We refer to rewiring or restructuring as altering the trade connections between two regions by either reducing, forming new, or eliminating trade links. Re-distribution refers to displacing a portion or entirety of crop production from one place to another. We use U.S. shipment data to create a domestic rice trade network consisting of 6 major rice-producing states and 51 receiving states. Combining the U.S. agriculture census data on irrigation, energy prices, and life-cycle assessment (LCA) methods, we create four distinct layered networks of (i) physical rice trade, (ii) irrigation water (referred to as virtual water in this article), (iii) transportation GHG emissions associated with shipment of food, and (iv) GHG emissions embodied in irrigation (referred to as irrigation GHG emissions). Finally, we use an optimization-based approach to assess the extent to which irrigation water, transportation GHG emissions, and irrigation emissions can be reduced by rewiring rice trade. The details of the layered networks, underlying data, and optimization model are described next. To capture uncertainty in our data calibration, in addition to deterministic optimization models, we also implement a robust optimization routine.[30]

DATA AND METHODS

Trade and Production Data. The U.S. food trade network model was built leveraging existing freight shipment data from the Freight Analysis Framework (FAF).[31] FAF is jointly published by the Bureau of Transportation Statistics (BTS) and U.S. Federal Highway Administration and provides estimates for tonnage, value, mode of transport, and distance of freight transported across the United States. We use data for year 2012 in our analysis. The FAF shipment data are provided for aggregated commodity groups represented by Standard Classification of Transported Goods (SCTG) classes. This study used commodity group of cereal grains (SCTG code 02) and applied production data from the United States Department of Agriculture (USDA) to disaggregate into raw grain rice shipments. For example, if rice accounted for 97% of total grain production in Arkansas, then 97% of grains shipped from Arkansas were assumed to be rice transfers. As approximately 30–40% of rice exports contain rough grain rice, we included domestic shipments as well as shipments intended for exports.[29] For international shipments, FAF includes the domestic origin–destination pair as well as their international counterpart (e.g., for exports, the data include origin of the shipment and the port of exit). However, since the analysis is limited to the United States, only the domestic leg of the exports is analyzed. FAF reports trade directly from farms as well as manufacturing/distribution centers without making a distinction regarding place of origin. For the optimization exercise, it is imperative to link the origin of trade with the origin of crop production as we further optimize for resource use and emissions. Therefore, we do not select trade of milled grains (SCTG 06) to actively eliminate any distribution centers/rice mills from the networks. However, for exports, we may still inadvertently account for them as trade may be reported from distribution centers to the point of destination. We hedge against this by coupling production data with trade data for disaggregation and ensure that the origin of trade aligns with rice-producing states. For example, rice produced in California may travel to Pennsylvania through Colorado. The challenge is to identify California as the origin to accurately account for local water and energy use. By using production-based disaggregation, we do not apportion any trade from Colorado to Pennsylvania as raw grain rice trade. The drawback of this method is that we do not trace the final point of consumption and therefore we cannot trace the entire supply chain. However, we argue that the analysis and discussion still remain relevant as often the supply chain decisions regarding raw grains are on rice mills and large food companies as opposed to the final consumer. Another shortcoming of the FAF data set is related to their accounting of farm-based shipments. These shipments are traced using 2002 BTS vehicle inventory and use survey. It is likely that farm movements may have changed within 10 years but are not reflected in FAF. Despite the shortcomings, FAF remains the best available data on sub-national trade.

Based on the 2012 survey data from USDA, there were six states that accounted for 99% of the total U.S. rice production: Arkansas, California, Louisiana, Missouri, Texas, and Mississippi. However, not all states produce the same type of rice. To represent a more realistic scenario for crop re-distribution, we differentiated between distinct classes of rice grown across the United States, namely, long grain, medium grain, and short grain. Due to favorable soil and climate conditions, majority of medium grain rice is produced in California, while the rest of the states mostly produce long-grain rice. Short grain rice production is limited to California and to a smaller extent Arkansas. Therefore, the trade rewiring occurs keeping in mind the growing potential of each class in a specific state. Due to a lack of class-specific demand data, the demand composition is kept consistent with the production composition of rice. All production-related data are obtained from USDA's agriculture survey. As FAF data were the year-limiting data set at the time of conducting this study, all the production, water, and energy data are for 2012 or the nearest year available unless stated otherwise. In order to model the rice-associated FEW nexus as an applied network optimization problem, we define the set N as the nodes of the network, where each node $i \in N$ represents a state. Let $N_p \in N$ be the set of rice-producing states. Then, the set A of directed links (i, j) between node pairs i and j represents trade of rice between rice-producing states $i \in N_p$ and the other states, including self-loops for a state's production sent to itself. Each rice-producing state N_p produces one or several types of rice, designated $k \in K$, where K is long-, medium-, and short-grain rice.

Virtual Water Transfers. Virtual water transfers were obtained by combining physical trade data (i.e., tons of rice traded) with water application intensities (m^3/ton) for the type of rice in a specific region. State- and crop-specific water applied per acre (m^3/acre) was obtained from the Farm and Ranch Irrigation Survey 2013.[32] The water applied per acre was combined with yield data (ton/acre) to arrive at water application intensities. The yields for specific rice type (i.e., long, medium, and short grains) were obtained from the USDA. To account for yield anomalies (i.e., 2012 drought in Texas) for specific years, we selected a 5 year timeframe (2010−2014) to minimize yield trend effects (e.g., increase in yields due to technology improvement) over time.[33] The yield values were assumed to follow a uniform distribution. Based on the minimum and maximum values of yields, we simulated 10,000 samples to incorporate sensitivity analysis in our estimates.

$$w_i = \sum_{k \in K} c_{ik}^{w} \sum_{j \in N} t_{ij,k} \qquad i \in N_p,\ j \in N,\ k \in K \tag{1}$$

N_p = rice-producing states (6 states), N = exporting states (51 states), K = set of rice types. w_i = virtual water used in producing the commodity at the origin state i in (m^3). $t_{ij,k}$ = trade of commodity k from origin state i to destination state j (U.S. ton). c_{ik}^{w} = water applied per unit crop type (k) produced (m^3/ton)

Transportation Emissions. The FAF data labels transportation modes in six categories: truck, rail, water, air, multiple modes, and mail, and other or unknown. Shipments tagged with the other and unknown category were assigned a transportation mode following the FAF mode reassignment method: if a shipment was greater than 80,000 pounds (40 tons), then it was assumed to be transported through rail or else truck. Multiple modes and mail category may include travel by a combination of truck−rail, truck−water, and rail−water or though parcel delivery services, for any of which specific data were not available.[34] Additionally, depending on the type of transportation mode, vehicle freight capacity, and any combination of distance traveled by specific modes, the associated GHG emissions could vary significantly.[35,36] Considering that multiple mode shipment routes carried less than 5% of tonnage for the six rice-producing states (Figure S1), we replaced the category with the dominant shipment mode for that route. The life-cycle GHG emissions associated with each of the four type of modes considered are obtained from the Ecoinvent[37] database and listed in the Supporting Information.

$$g_{ij} = m_{ij} c_{ij}^{gt} \sum_{k \in K} t_{ij,k} \tag{2}$$

g_{ij} = life-cycle transportation emissions in kg CO_2-equivalent. m_{ij} = mean distance from i to j as total ton miles per ton to get a weighted average distance by tonnage. c_{ij}^{gt} = GHG emissions associated with shipping from i to j weighted based on transportation mode (kg CO_2-equivalent/ton-mile)

Irrigation GHG Emissions. The irrigation GHG emissions were derived from Vora et al.[8,38] and included GHG emissions associated with on-farm irrigation pumping. The primary data source for pumping energy expenses was the Farm and Ranch Irrigation Survey (FRIS) 2013.[32] Specifically, we use data from Table 12 from FRIS-2013 that details energy expenses for pumping by water source type (surface water vs ground water) and type of energy (electricity, diesel, gasoline, natural gas, LP gas, propane, and butane). These reported expenses were converted into energy quantities by obtaining energy prices from the U.S. Energy Information Administration.[39] Energy prices and the electricity grid mix are for year 2012. The pumping energy expenses account for varying pumping requirements from both groundwater and surface water sources and type of irrigation system employed. Life-cycle GHG emissions were calculated based on the IPCC 100 year global warming potential[40] using Ecoinvent[37] and the U.S. Life Cycle Inventory Database.[41] The irrigation GHG emissions were combined with estimates of virtual water to arrive at embodied GHG emissions.

$$g_i = c_i^{gw} w_i \tag{3}$$

g_i = embodied irrigation GHG emissions trade in kg CO_2-equivalent. c_i^{gw} = embodied GHG emissions per unit water applied (kg CO_2-equivalent/m^3)

Deterministic Optimization Model. The optimization model was formulated with linear programming techniques and implemented in C++ using the IBM CPLEX concert technology solver.[42] The decision variables for the model encompass both production and transportation decisions. Thus, we feed into the model quantity of each type of rice produced as well as the amount shipped to/from each state along the link (i, j). We explored four scenarios: (i) minimize overall virtual water usage, (ii) minimize irrigation GHG emissions, (iii) minimize transport emissions, and (iv) reduce all three impacts simultaneously. We present three models to explore all four scenarios.

In model 1, the overarching objective was to minimize virtual water usage; we also defined input parameters α (for transport) and β (irrigation), which represented the factor by which irrigation and transportation GHGs were allowed to increase over their present values or permitted to decrease. That is, let $\overline{g}_o^{gt}$ be the initial amount of total transportation GHG emissions produced by the system; then, we constrain $\sum_{(i,j)\in A} g_{ij} \leq \alpha \overline{g}_o^{gt}$ for some factor $\alpha > 0$. Similarly, let $\overline{g}_o^{gw}$ be the initial amount of total irrigation GHG emissions, and then we constrain $\sum_{i\in N_p} g_i \leq \beta \overline{g}_o^{gw}$ for some factor $\beta > 0$. Through tuning of values of α and β, we explored the case of minimizing virtual water as well as a case where we simultaneously reduced all impacts.

Model 2 describes minimizing irrigation GHG emissions and model 3 describes transportation GHG emissions. The constraints represented by eqs 4 and 5 remain consistent for all the models. The constraint in eq 4 enforces that each state should continue to receive the same amount of type of rice it receives. The constraint in eq 5 ensures that yields do not exceed the defined upper bound yields (described in detail next).

$$\min \sum_{i \in N_p} w_i \text{ (model 1)}$$

$$\min \sum_{i \in N_p} g_i \text{ (model 2)}$$

$$\min \sum_{i \in N_p, j \in N} g_{ij} \text{ (model 3)}$$

$$\text{subject to: } \sum_{i \in N_p} t_{ijk} \geq d_{jk} \tag{4}$$

$$y_{ik} \leq y_{ik}^{UB} \tag{5}$$

Land Constraints and Potential Yields. There has been a decrease in land allocated for rice production in recent years with the national rice acreage declining by 20% in 2018 compared to 2010.[43] Therefore, the model was constricted to only consider the current acreage (year 2012) when re-distributing trade. Instead, we allowed the yield values to increase up to its yield potential. The potential yields, also known as yield ceilings, represent maximum achievable

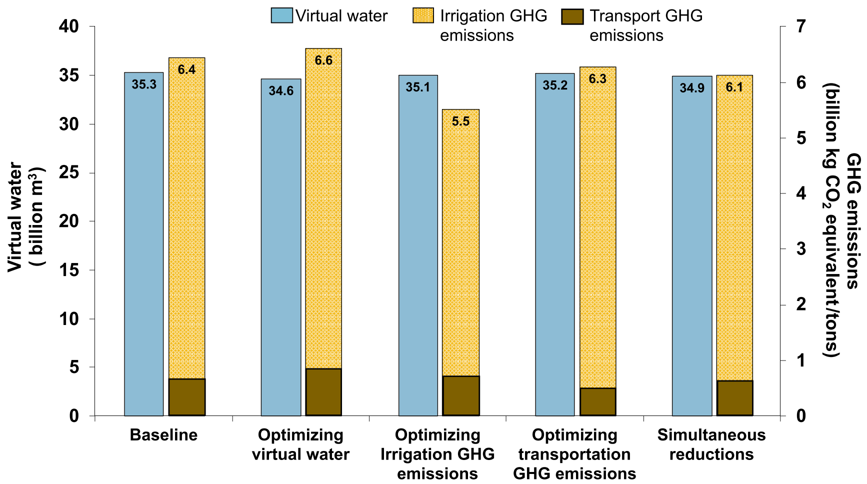

Figure 1. Network-wide rewiring results for virtual water and embodied GHG emission estimates for scenarios: (i) baseline, (ii) optimizing virtual water, (iii) embodied irrigation GHG emissions, (iv) embodied transportation GHG emissions, and (v) simultaneous reductions in all three impacts. The solid bars in GHG emissions represent the contribution of transportation GHG emissions and the cross-hatched bar represents the irrigation GHG emissions. Baseline represents status quo estimates of virtual water and embodied GHG emissions for the rice production.

yields for the given crop in a given location without constraints from water, nutrients, pests, and diseases.[44] The data for potential yields for rice were obtained from the global yield gap atlas.[45] The potential yields were calculated for 14 weather stations spanning six major rice-producing states. Based on the modeled acreage, we scaled up data at the state level. Due to diminishing economic returns on investment for yields, farmers may not target achieving 100% of the yield potential. Therefore, based on literature, we assume 85% of the reported yield potential can be exploited and use it as our yield ceiling.[33] The exploitable yields are provided as the upper bound in eq 5. The potential yields are estimated without differentiating between rice classes and represent values for the dominant rice systems in a given region. A dominant system for a given state is determined based on maximum acreage dedicated to a particular rice class (e.g., California's dominant system is medium-grain rice). To estimate yield potentials for secondary systems (i.e., long-grain rice production in CA), we assumed the same percentage increase in yield can be achieved as the dominant system. For example, if current yields have reached 70% of their yield potential for the dominant system, a similar efficiency is assumed to be possible to achieve for the secondary system. Table S1 shows exploitable yields for all states and rice types. The yield values reported by the optimization model indicate a minimum yield that would be required (on the existing land) to support the desired level of production. The minimum yields were based on the current yield data. Hence, it is possible that lower yields could be reported by the model, but the interpretation is that, since production would have decreased, a smaller yield would be required. This is interpreted as decrease in the land usage.

Capturing Uncertainty through Robust Optimization. Any systems-level analysis as well as the underlying data are subject to uncertainties. We address this by using methods of robust optimization in order to maintain the computational tractability of optimization.[30,46] We assumed that c_{ik}^{w}, c_i^{gw}, c_i^{gt} are unknown quantities, but the bounds on their ranges could be established. We use Monte Carlo simulations to account for uncertainty and propagation of uncertainty in the model. For c_{ik}^{w}, we combined uncertainty in yields with water applied per unit land. We simulated 10,000 samples for yields (long, medium, and short) assuming a uniform distribution to arrive at 10,000 values of c_{ik}^{w} for each state. Here, we assumed water applied per unit land to be constant. The uncertainty values for life-cycle GHG emissions of transportation were obtained from the LCA database ecoinvent[37] using SimaPro.[47] We used the simulated 10,000 values for each mode and combined it with m_{ij} to estimate bounds for transportation emissions associated with a specific route. For irrigation emissions, we followed a similar procedure as transportation for estimating uncertainty. These values were propagated with energy pricing data and virtual water estimates to arrive at 10,000 simulated values for embodied irrigation emissions from i to j. The average and 95% confidence bounds were estimated for each simulation.

For the robust optimization model, we follow the approach of Bertsimas and Sim[30] and introduce a parameter Γ that controls the level of uncertainty a decision-maker is willing to tolerate—higher values ensure that the optimal solution to the robust model will remain feasible given increasingly worse-case realizations of the data. Conversely, values of $\Gamma = 0$ would imply that the decision-maker is absolutely certain of the data, and the problem reduces to the deterministic optimization discussed here. We use $\Gamma = (1, 10, 1, 0.05)$ as being reasonably confident in data and $\Gamma = (4, 40, 4, 0.20)$ as a higher guarantee of feasibility but less confident. There are 14 state-rice-type combinations and approximately 10 times as many links between them for trade. Therefore, $\Gamma = (1, 10, 1, 0.05)$ refers to changing one state-rice-type combination for virtual water, 10 links for associated transportation uncertainty, one state-rice-type for irrigation emissions, and 0.05 for mileage range. Similarly, for $\Gamma = (4, 40, 4,$ and $0.20)$, we change four states, 40 links, and 0.20 for mileage range. These number of parameters are changed to the top of their allowed ranges (upper bound on the confidence interval). Depending on the objective (i.e., minimizing virtual water), the robust optimization selects the solution in a way that considers all possible worst-case scenarios by changing Γ number of parameters and still obtain a feasible solution. The Supporting Information contains detailed equations and derivations for the deterministic and robust optimization models.

■ RESULTS

Rewiring Rice Trade. Figure 1 represents network-wide optimization results for virtual water and embodied GHG emissions. The solid bars in GHG emissions represent contribution of GHG emissions from rice shipment transportation and the hatched bar represents irrigation GHG emissions. For the baseline case, embodied irrigation GHG emissions amount to 5.8 billion kg CO_2-equivalent and transportation GHG emissions 0.7 billion kg CO_2-equivalent. The higher contribution from irrigation emissions can be attributed to the large quantities of irrigation water used in rice production and associated GHG emissions resulting from irrigation pumping. Scenario ii (optimizing virtual water) results in modest reductions in virtual water (2%) compared to the baseline case. Further, these reductions come at the expense of increase in transportation-related GHG emissions

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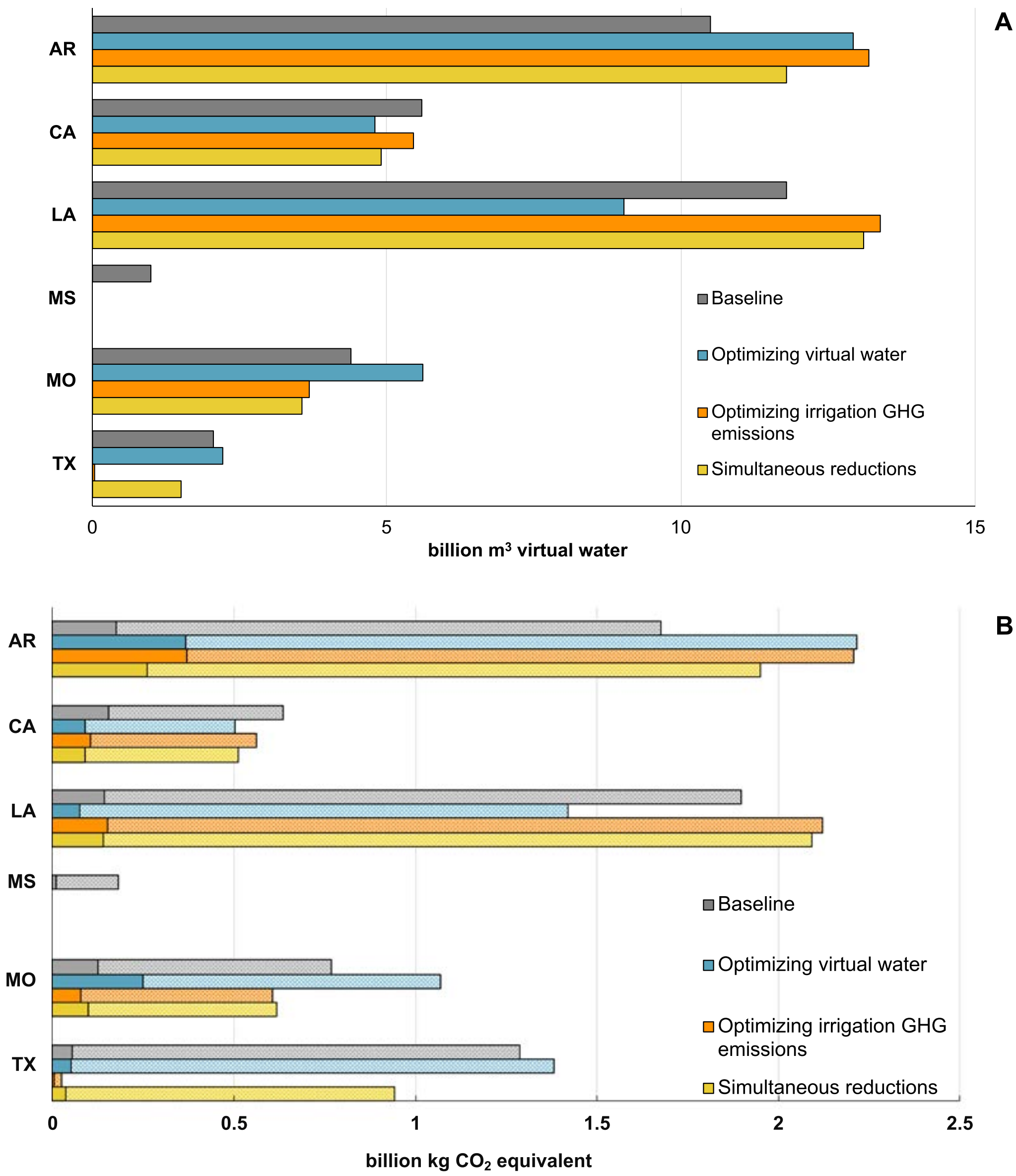

Figure 2. State-level changes in (a) virtual water and (b) embodied emissions for scenarios: (i) baseline, (ii) optimizing virtual water, (iii) optimizing irrigation GHG emissions, and (iv) simultaneous reductions compared to baseline state-level exports. The cross-hatched bars represent emissions from irrigation and solid bars represent emissions from transport. AR = Arkansas, CA = California, LA = Louisiana, MS = Mississippi, MO = Missouri, TX = Texas.

(26% increase), thus highlighting the tradeoff between water consumption and GHG emissions. Irrigation-related emissions remain unchanged and are an order of magnitude higher than that of transportation, resulting in a 3% increase in net GHG emissions.

Scenario (iii) (optimizing irrigation GHG emissions) results in irrigation GHG emission reduction by 17% with 1% reduction in virtual water and 7% increase in transportation-related GHG emissions. Scenario (iv) (optimizing transportation emissions) results in transportation GHG emission reduction by 25% with no reduction in irrigation emissions and half percent reduction in virtual water. Scenario (v) explores maximum virtual water reduction while also simultaneously reducing GHG emissions from transportation and irrigation. The outcome of this strategy is 5% reduction in net GHG emissions (both transportation and irrigation) with a corresponding 1% reduction in virtual water. While the results show that there is potential for improvements with respect to virtual water and GHG emissions, they also point to the inflexibility of the U.S. rice production system due to biophysical constraints and overall inability to cope with a marked reduction in certain areas.

The present study focuses on GHG emissions from transport and on-farm irrigation of rice. Other major sources of emissions include GHG emissions from submerged rice fields due to methanogenesis[48] and post-harvest crop burning to clear rice stubble.[49] Specifically, GHG emissions from methanogenesis are an order of magnitude greater than irrigation-associated emissions estimated here. However, they depend on many factors including soil characteristics, climate, on-farm water management such as aeration, and continuous flooding practices.[48] These emissions can be managed with better on-farm practices despite crop re-distribution and therefore not considered in the study. Additionally, prior

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LCA work has found emissions due to irrigation being the second largest contributor to total life-cycle GHG emissions after direct methane emissions from paddy fields.[50]

Changes at the State Level. Next, we assess changes in state-level rice production and impacts resulting from rewiring. Figure 2 represents state-level changes in virtual water (2A) and net GHG emissions (2B) under various scenarios. In Figure 2B, the solid bars represent transportation emissions and hatched bars represent irrigation emissions. For all scenarios, the total number of trade links are reduced with a corresponding increase in number of shipments carrying a large volume, concentrating the trade. The states that increase production do so by increasing the yield up to maximum exploitable yield specified in the optimization model. This strategy of both increasing yield up to a maximum physical limit in some states while reducing production in other states results in 12% reduction in total land use for optimizing the virtual water scenario. The model results in land use decrease by 11% for optimizing irrigation GHG emissions and 8% for simultaneous reductions.

Across the modeled scenarios, California's rice production is reduced by 5% (optimizing GHG emissions)−14% (optimizing virtual water) with corresponding reductions of 5−14% in virtual water and 11−21% in total GHG emissions. CA has the highest water footprint (m^3/ton) across all three rice types, prompting the model to reduce production and shift it to states with a comparatively lower water footprint. It is to be noted that the model takes into account the suitability of rice produced in each state when adjusting production and rewiring trade links. For example, majority of medium- and short-grain rice is produced in California. Therefore, despite high water intensity for CA rice, the model does not shift large production from CA to other states due to their inability to produce medium-/short-grain rice at a competitive scale. On the other hand, CA has the lowest irrigation emission intensity (kg CO_2-equivalent/m^3 water applied), prompting the model to not penalize CA by slashing production at a large scale when emissions are considered. The embodied irrigation GHG emissions are a function of the energy type used in pumping. According to 2013 FRIS data, 85% of the total pumps were powered by electricity in California (with 60% grid generation from natural gas in 2012). Electricity-based pumps combined with gravity systems for irrigation results in lower GHG emissions per cubic meter of water withdrawn. Figure S2 visualizes state-level changes in transfers by rice type for all scenarios including transport.

When rewiring for minimizing virtual water, Texas increases its production and associated virtual water and irrigation impacts by 8%. For simultaneous reductions, Texas reduces production and irrigation impacts by 26% and for optimizing irrigation GHG emissions 98%. In all scenarios, individual changes in impacts (water and irrigation GHG) follow identical percent changes to the production. As seen from Figure 2B, Texas has relatively large overall GHG emissions (1.3 billion kg CO_2-equivalent) compared to other states despite not having a large virtual water footprint (2 billion m^3). This is primarily due to Texas's high irrigation emission intensity per m^3 of water applied (Table S2). However, more than half of Texas's pumping fuel mix is powered by natural gas including pumps dependent on grid electricity. Natural gas has one of the lowest life-cycle GHG emissions compared to other fuels used for irrigation pumps. Over 90% of the acres irrigated in Texas use ground water from wells as the only source of irrigation.[32] Additionally, Texas had the largest number of wells (46,948) across the considered states with a reported 5-yr decrease in well depth to water.[32] Therefore, the large GHG emissions intensity may reflect the situation of low groundwater levels requiring greater depths for lifting water. Texas is one of the interesting cases where FEW goals are in apparent synergy with respect to virtual water use and use of irrigation pumping fuel but in an attempt to reduce emissions due to declining water depth, the model slashes production.

As Mississippi has the second largest water footprint after California, the model manages to eliminate the production completely to gain modest national water savings. In fact, in all of the scenarios, Mississippi stops producing rice entirely, as it also has the second largest irrigation emission intensity after Texas. This is one of the most drastic results where the model recommends completely stopping production in all scenarios considered. One of the disadvantages of rice production shifting is the inability to produce other crops/rotations in place of rice. Rice can only be grown in soil with ability to retain water, which makes it unsuitable for growing a host of other crops. Mississippi is one of the few states that grows other crops for rotation along with rice and therefore demonstrates land suitability for alternative cropping.[29] Currently, Mississippi farmers do not purchase irrigation water and rely on groundwater from the underlying aquifer system.[29] Therefore, unlike other states, irrigation costs are not prohibitive to continued production. However, declining groundwater levels have prompted the state government to stipulate farm level water conservation efforts and install meters for the continued access to groundwater for irrigation.

Arkansas is the only state that increases production in all scenarios ranging from 12% for simultaneous reductions to 23% for optimizing virtual water. Accordingly, similar % changes are observed in both virtual water and irrigation GHG emissions. Arkansas has the lowest water footprint among all states and the second lowest irrigation GHG emission intensity. Additionally, it has the ability to produce all three types of rice, although not at the scale of California. Therefore, the model maximizes on benefits by increasing production. Currently, Arkansas farmers do not purchase water and primarily rely on groundwater for irrigation.[29] However, declining groundwater levels could make future expansion expensive. From the irrigation GHG emission perspective, Arkansas primarily relies on electricity and diesel-based pumps, with grid electricity primarily consisting of coal (44%), natural gas (26%), and nuclear (24%). Thus, there is room for improvement in switching away from diesel-based pumps and reducing emissions. State-level optimization results observed for Missouri and Louisiana are a result of a combination of high emission intensities and model's adjustments for inability to reduce California's water-intensive rice production.

Rewiring for Optimizing Transportation Emissions. While the GHG emissions from transportation are an order of magnitude less than irrigation GHG emissions, they are direct emissions compared to the latter being a second-order impact in the food supply chain.[51] As such, they could be used as a separate and more apparent lever in managing GHG emissions related to food trade. In this case, reducing transportation emissions does not result in a marked change in either irrigation GHG emissions or virtual water (Figure 1). However, in optimizing the other two, transportation emissions increase by 26% in optimizing for virtual water scenario and 7% in irrigation GHG emissions scenario. This

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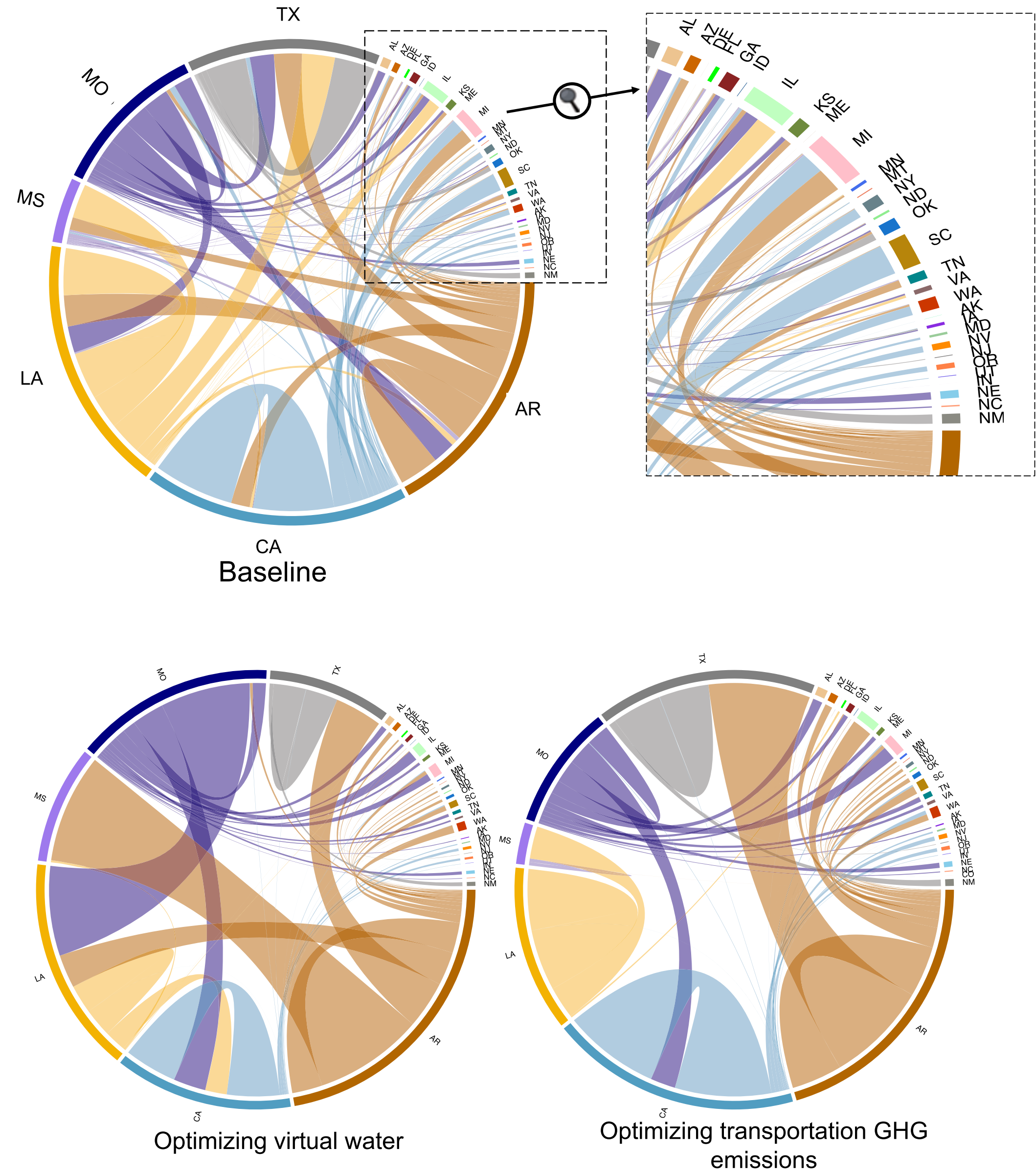

Figure 3. Rewiring resulting from baseline, optimizing virtual water, and transportation GHG emissions. The figures portray embodied GHG emissions for rice transportation. The size of each segment representing a state inside the diagram is based on the relative contribution to embodied GHG emissions for that network. The similar colored segments and links represent export links and different colored links represent imports. The size of the segment represents the total incoming and outgoing links.

occurs due to states transitioning from within-state flows (i.e., local transportation) to sourcing from states with lower water and irrigation GHG emission intensities. In the virtual water scenario, Arkansas and Missouri increase their rice production and supply it to other states, reducing other state's own within-state flows.

In Figure 3, we compare transportation emissions from the baseline scenario with emissions from virtual water reduction (largest transportation emissions amongst all cases considered) and with the scenario of minimizing transportation emissions. The size of each segment representing a state is based on relative contribution to transportation GHG emissions. Compared to the baseline, both scenarios have fewer but larger links. For example, in the baseline scenario, Texas imports rice from four other states (Louisiana, Arkansas, Missouri, and California) and has a within-state flow. For virtual water and transportation emissions scenario, Texas reduces its number of import partners and satisfies the same demand with comparatively larger flow from Arkansas and a larger within-state flow (the California supply remains consistent due to specific rice type demand). For optimizing transportation emissions, the model manages to satisfy a majority of demand though directing within-state flows as seen from larger self-loops for Louisiana, California, and Arkansas. Optimizing transportation is the only case where production from Mississippi is not significantly reduced. However, the rewiring routes all the flows from Mississippi to within-itself to partially satisfy demand and the rest is sourced from Louisiana.

Generally, rice mills are located in or nearby states with rice production,[52] contributing to large within-state demands for coarse grain rice. The United States also exports raw grain rice directly to international destinations;[29] therefore, some of the flow actually goes to international shipping hubs. For rice trade, the largest mode of shipment carrying significant

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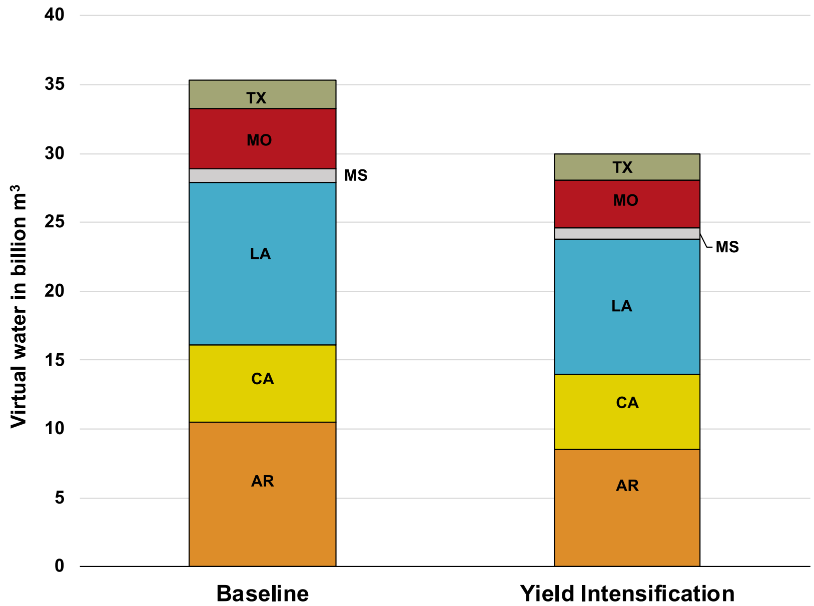

Figure 4. Comparison of virtual water savings from achieving maximum exploitable yields for all rice types in each state.

tonnage is trucks, followed by rail and water-based shipments (Figure S1). Water-based shipping has the lowest life-cycle GHG emissions followed by rail and truck. Specifically, Louisiana and Mississippi have on average higher water-based shipments, reducing their transportation emission intensity, while California, Texas, and Arkansas ship significantly through trucks. A clear alternative is to move away from truck-based shipments, specifically for longer distances travel where rail or multiple-mode transportation might be available. However, previous studies have discussed the limited opportunities for shifting modes to reduce emissions and have called for the more aggressive penetration of zero emission vehicles.[53]

Relaxing the Rice-Type Constraint on the Rewiring Scheme. A priori, we find that we do not obtain significant reduction for virtual water in the network through optimization. The biophysical constraints for rice type impose very stringent requirements on the rewiring scheme. As a theoretical exercise, we remove the constraint for rice type and assume all types can be grown in the production states analyzed in our work. The findings reveal reduction in virtual water up to 5% from the baseline scenario. The modest results despite relaxation of the rice type constraint are not surprising and corroborate previous findings.[24]

Robust Optimization. Figures S3 and S4 in the Supporting Information show solutions for robust optimization. For robust modeling, we minimized virtual water subject to emission constraints (controlled through α and β) that were Pareto optimal. As embodied irrigation emissions are derived from virtual water values, we focused on virtual water alone as the irrigation emissions would follow a similar trend. However, to prevent from getting a suboptimal solution than the baseline, we constrained the model to not increase irrigation emissions compared to the status quo.

In minimizing virtual water, we increase transportation emissions by 22−25% with no changes in irrigation emissions. For the next strategy, we attempted to minimize water while asking the model to minimize transportation GHG emissions as much as possible. As a result, the model managed to reduce transportation emissions by 25−28% but provided minor reductions in water use (0.09−0.36%). Finally, we implemented a simultaneous reduction strategy where virtual water was reduced by 0.8−1.2%, irrigation GHG emissions by 5−6%, and transportation emissions by 6−8%. In examining results for both deterministic and robust optimization, the models managed to achieve reductions in GHG emissions but yielded only a marginal reduction in virtual water. Rice fields need to be flooded up to a certain level, which drives up water use as well as energy requirements.[29] However, there is a limit to implementing on-farm water conservation strategies as crop water requirements have to be met. Conversely, large-scale energy decisions are easier to implement including investment in renewable energy transitions.

Closing the Yield Gap. Apart from implementing on-farm best management practices through improvements in water use and irrigation efficiencies, focusing on improving yields[54] is another strategy for sustainable agriculture. As such, we explore an alternative to rewiring for reducing virtual water and GHG emission impacts: namely, targeting maximum exploitable yields to achieve resource savings. Here, we make an important assumption that exploitable yields are not water-limited and therefore no additional water is applied to increase the yield. We justify this assumption as for all states and rice types, at least 70−75% of exploitable yields have already been achieved. We assume the small yield gap can be closed with the help of proper nutrient and agriculture management practices.[55] Figure 4 compares baseline virtual water use for exports with yield intensification values. Our estimate suggests that by reaching maximum exploitable yields, production increases by 7%. The resulting network-level water savings are 15% with corresponding similar percentage reductions in irrigation GHG emissions. The reduction for virtual water is significantly larger than all the optimization scenarios considered here. Although rewiring for optimizing irrigation GHG emissions results in a larger reduction in irrigation GHG emissions, it also increases transport emissions. Since there is no rewiring for yield intensification, transport emissions remain the same.

Discussion and Conclusions. Sustainable intensification of agriculture involves increasing yields while minimizing environmental impacts. In this study, we explore the potential

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of selective sustainable intensification where we recommend intensifying systems that are efficient at producing a crop with respect to water and energy and shifting away production from more resource-intensive locations. This strategy recommends growing more with current resources by penalizing locations that are using excessive resources. We compare these results to a yield intensification strategy by keeping all other agricultural inputs unchanged. For producing rice in the United States, this appears to be a better strategy than re-distributing production as it yields large network-level savings for virtual water and irrigation GHG emissions. However, the utility of widespread intensification is case-specific as other studies have reported a large increase in water and fertilizer use.[56] The optimization scenarios we explore for singular objectives (i.e., optimizing for virtual water, irrigation, and transport emissions) represent extreme cases. While network-level savings are modest for all analyzed scenarios, the rewiring results in drastic changes at the state level. This also poses a question on the usefulness of assessing national savings for virtual resource studies as water use and emissions resulting from inefficient water and irrigation systems have a larger impact on the local environment.

While there are no national estimates published on the proportion of rice irrigated through surface water or ground water, based on total acreage under each source, we can estimate that majority of rice in Arkansas, Mississippi, Texas, Louisiana, and Missouri is irrigated using groundwater and California's from surface water, although there may be exceptions at county or farm level. If economics of irrigation are considered, then, the states such as Missouri that use groundwater would benefit over states such as California that purchase irrigation water at a significant price.[29]

Although there is increased attention to issues associated with overdrawing groundwater, penalizing a state for using more groundwater may not work as the hydrology between the surface and groundwater is complex and connected, and overuse of one may pose a deleterious effect on another. A significant improvement going forward would be to integrate basin-level water scarcity risks to contextualize water savings, keeping in mind data assimilation issues across spatial scales. It is important to note that the values reported here are for water applied for irrigation and not consumptive water use; as such, a portion of the water applied could be collected back. In such cases, the resulting water savings would be larger.

Finally, a majority of rice is irrigated through gravity systems. Therefore, it is important to consider improving resource use efficiency using water management and conservation practices such as using tail water pipes, dikes, precision-leveling, and alternative row irrigation along with gravity irrigation. Implementing advanced irrigation technologies may result in more water savings as well as energy savings. However, studies have reported that declining water levels coupled with Jevon's paradox (more irrigation resulting from water savings) have increased GHG and the carbon footprint of irrigated agriculture.[57,58] California, followed by Texas and Missouri have the most acreage under some kind of water management systems while Mississippi, Louisiana, and Arkansas have less, indicating scope for improvement.[59] However, our model's attempt to reduce production in California and Texas signals that these conventional practices may not be sufficient. At the same time, improving water efficiency of rice irrigation in Arkansas and Louisiana indicates that more water savings can be achieved while intensifying production in these areas. Another area of promise in rice irrigation research is exploring the potential of an alternative wet and dry technique for rice irrigation where the fields are only periodically flooded and then flushed out to dry in-between. Apart from saving water, the technique has the added benefit of also reducing atmospheric methane emissions associated with methanogenesis in rice fields. The disadvantage with the method is reported loss of yields in rice due to low water stress tolerance[54] and increase in nitrous oxide emissions,[60] and therefore such methods require more analysis and region-specific field trials before widespread adoption. Finally, improper management of rice residues is an important source of GHG emissions as disposal through incineration causes GHG emissions, while incorporating residues back into the field causes decomposition and ultimately emissions. Solutions ranging from applying biochar to increase soil carbon sequestration to tillage practices can reduce adverse effects. However, rather than depending on universal solutions, site-specific management may be more appropriate for reducing GHG emissions.[61]

The scenarios modeled in this work result in net land savings, but production reductions also mean loss of livelihood. Any scenario that reduces or eliminates production requires a careful evaluation on socio-economic implications. Richter et al.[23] discuss rotational land fallowing practices in California and its success. Generally, crops with a lower selling price are fallowed and rice may not fall into the category unless a competitive renumeration is provided or market demand for U.S. rice reduces. However, there is some incentive to farmers on choosing to receive continuous payment through fallowing programs as opposed to fluctuating revenue dependent on market demand and success of crop. A complementary strategy would be to encourage farmers to plant alternative suitable crops, which may result in less resource savings (as opposed to completely fallowing the land), although land suitable for rice may not be suitable for a variety of other crops that yield similar or more revenue. Another drawback to reduction would be loss of biodiversity and other ecosystem services as submerged rice fields provide a habitat for diverse living organisms.[62] The message from this work should not be interpreted as suggesting that closing the yield gap is a panacea for sustainable intensification. Strategies such as boosting yields will require integrating diverse feedback, stakeholder engagement encompassing all levels from policymakers to farmers, being conscious of dissenting opinions, and recognizing tradeoffs resulting from crop intensification. The goal should be creating equitable and fair strategies to reduce impact and boost production[63] while recognizing that reducing one impact may exacerbate others.

Our work focuses on two environmental sustainability metrics: water use and GHG emissions. Other impacts such biodiversity loss, eutrophication, and land use should be evaluated in future studies to avoid unintended consequences. The optimization framework presented in this work is general enough to include other environmental impacts. Finally, we recognize that national trade cannot be realistically optimized to save embodied resources; however, many farmers make production decisions keeping water supply in mind, specifically in times of drought or in water-scarce areas.[64] The results also indicate that for water-intensive crops such as rice that are produced in very limited areas, regional crop replacement shifting may reduce overall production as the limited areas may not have capacity to grow sufficient quantity to meet the

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demand. This would affect the downstream supply chain including loss in national revenue and such effects should be analyzed in future studies.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acssuschemeng.1c00776.

Details of various modes of transportation of tonnage; data for rice-producing states on exploitable yield, virtual water density for each rice type, and embodied irrigation emission intensity; comparison of state-level export changes in rice types; robust optimization results; and the optimization model (PDF)

Trade, agriculture, water, and energy data (XLSX)

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Notes

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