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Explaining virtual water trade: A spatial-temporal analysis of the comparative advantage of land, labor and water in China

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ABSTRACT

The well-known "virtual water hypothesis" states that water-deficient regions/countries could alleviate water stress through importing water-intensive products from water-abundant regions/countries. Although observed trading patterns do often not support this hypothesis, there is a lack of research to explore the reasons why trade patterns often do not support the intuitive virtual water hypothesis. To fill this important gap, we introduce comparative advantage theory in a quantitative way to track the driving forces of net virtual water export based on the spatial-temporal distribution of resource productivity and opportunity costs of land, labor and water use in agricultural and non-agricultural sectors across Chinese provinces between 1995 and 2015. The results show that regional differences in land productivity between agricultural and non-agricultural sectors are the main forces determining the pattern of virtual water flows across major regions, and other resources such as labor and water have played only a limited role. Our study shows that the current market forces reflect the scarcity of land resources, but does not reflect the water scarcity in the context of interregional trade in China. Our findings suggest that the ongoing efforts to increase land productivity of agriculture in the southern regions would contribute to reducing water scarcity in the North and Northeast China Plain.

1. Introduction

Substantial attention has been paid to the topic of "virtual water" in recent years since Tony Allan coined the term to describe water used for the production of crops traded in international markets (Allan 1996, 2002, 2003). Numerous studies have estimated virtual water flows by calculating how much water is used to produce goods and services at the river basin, regional, national and global scales (Chapagain and Hoekstra, 2008; Feng and Hubacek, 2015; Feng et al., 2012; Guan and Hubacek, 2007; Mekonnen and Hoekstra, 2011; Hoekstra and Hung, 2005; Serrano et al., 2016; Zhao et al. 2015, 2016, 2017). Estimates of virtual water flows largely reflect international trade statistics; whereby major food exporting countries such as Argentina, Australia and the USA are large net virtual water exporters, while major food importing countries such as Japan, North African and Europe are large net virtual water importers (Mekonnen and Hoekstra, 2011).

The virtual water perspective was initially proposed as a strategy for countries with water-shortage to import commodities that consume substantial amounts of water and are produced in water-abundant countries to alleviate existing water stress. However, numerous studies show that this strategy is not reflected in the international trade data. For example, Ramirez-Vallejo and Rogers (2004) find that observed trading patterns are independent of water resources endowments (Ramirez-Vallejo and Rogers, 2004). Du Fraiture (2004) suggest that water savings cannot always be

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reallocated to other beneficial purposes (including relieving ecological scarcities) to mitigate water scarcity, implying that economic and political considerations may have more influence than water scarcity in determining national trade strategies (Du Fraiture, 2004). Wichelns (2010) shows that trading strategies based on the virtual water perspective are not consistent with the economic concept of comparative advantage (CA) and cannot be used alone as a criterion for developing optimal policies (Wichelns, 2010). Similarly, a number of studies have found that often, water-abundant countries import water-intensive products, while water-scarce countries export water-intensive products due to the dominating influence of others factors such as land endowment, labor costs, and institutions (Kumar and Singh, 2005).

Similar results can also be found in the context of studies on water flows in China. For example, Guan and Hubacek (2007) find that the water-scarce northern areas of China predominantly export water-intensive goods, while the water-abundant southern areas import water-intensive goods. Feng et al. (2014) expand the scope by including all provinces and incorporated water stress index into the virtual water flow analysis and they found that water consumption in highly developed and water-rich coastal provinces largely rely on virtual water inflows from water-scarce northern provinces, such as Xinjiang, Hebei and Inner Mongolia, thus, significantly increasing water scarcity in these regions. Similarly, Zhao et al. (2015) show that major virtual water flows from the economically poor and water-scarce northwest areas to the more affluent and water-abundant coastal areas by far exceed the annual real water transfer proposed by the South-North Water Transfer Project. Zhuo et al. (2016a,b) demonstrate that crop-related virtual water flows within China was from North to South since 2000, thus South China gradually became dependent on food supply from the water-scarce North. Their results confirm the view that domestic virtual water trade is dominated by economic and government policies rather than regional disparity in water endowments.

One important conclusion of these studies is that factors such as population density, land endowment, policy considerations, and water pricing, may be more important than water endowment for guiding trade and virtual water flows. CA theory is an economic theory about the benefits that individuals, firms or nations achieve from trade that originated from differences in their factor endowments or technological progress, and opportunity cost is a key concept in CA theory (Deardorff 2005, 2014; Dornbusch et al., 1977, 2004; Hidalgo and Hausmann, 2009; Hartmann et al., 2015). This theory provides a powerful perspective that could explain the driving forces of commodity trade. Similarly, all of these factors related to virtual water trade could also be reflected in the notion of CA disparity across trading partners and the distribution patterns of resource productivity. However, previous studies supply only some narrative explanations or hypothetical examples. An exception is the work by Duchin and Morales (2015) who introduced the rectangular choice of technology (RCOT) model within an input-output framework to quantify the CA of food production in water-rich regions. Nevertheless, their model focuses on the constraints of water endowment to agriculture production, without attention to land and the competition for land, water, and labor between agricultural and non-agricultural sectors. Other studies are more conceptual. For example, Wichelns (2010) used one hypothetical example to demonstrate how optimal trading strategies would be influenced by a CA of water endowment in two virtual small countries. Most studies do not quantify the CA of production factors associated with the virtual water trade in a multi-regional context empirically. To fill this research gap, we select land use, labor input and water consumption as the main production factors to model the linkages between virtual water trade and CA in terms of opportunity costs in a multi-sectoral framework. First, we assess the spatial distribution of resource productivity in China's 31 provinces in 2015 (excluding Hong Kong, Macao and Taiwan); then, we show how these productivities change between 1995 and 2015. Furthermore, based on CA theory, we assess the CA of each resource in three aggregate sectors (agriculture, industry and services) at the provincial scale to detect whether the spatial distribution of these factors has a significant association with the patterns of China's virtual water trade across provinces.

There are several reasons why we choose China as our research focus. First, China's regional development shows a persistent imbalance. This imbalance has been associated with pronounced disparity in factor productivity and differences in resource endowment. Regional specialization and economic booming during the reform and opening era have led to significant increase in interregional commodity trade. As a result, the virtual water flows embodied in trade across regions is extensive (Wang and Mao, 2017; Sheng et al., 2014). Second, as the largest exporting country and the second largest economy in the world, China's exports present a significant part of the global economy. Dynamics of interregional trade structure within China would have significant implications for the global trade and global economy. Nevertheless, the reasons underpinning the persistent unsustainable trading structure with water-deficient regions exporting virtual water to water-abundant regions in China has not yet been found. To fill in this important gap, a systematic analysis of key production factors that shape the patterns of virtual water trading becomes essential.

2. Methods and data

2.1. Method

Productivity refers to the amount of output in physical or monetary units per unit of resource input (Upadhyaya and Alok, 2016). To allow for the comparison of productivity across different input categories, we use monetary units. Equations (1)–(3) refer to land, labor and water productivity per unit of land (in km^2), labor (per worker) and water (in m^3):

$$p_l^{ij} = e^{ij} \Big/ l_a^{ij} \quad (i = 1, 2, 3; j = 1, 2 \ldots 31) \tag{1}$$

$$p_{lf}^{ij} = e^{ij} \Big/ lf_w^{ij} \quad (i = 1, 2, 3; j = 1, 2 \ldots 31) \tag{2}$$

$$p_w^{ij} = e^{ij} \Big/ w_c^{ij} \quad (i = 1, 2, 3; j = 1, 2 \ldots 31) \tag{3}$$

where, e^{ij} represents domestic total output of industry i in region j (million CNY/yr), p_l^{ij} represents land productivity of industry i in region j (million CNY/km^2), l_a^{ij} refers to the land use area of industry i in region j (km^2/yr), p_{lf}^{ij} refers to the labor force productivity of industry i in region j (CNY/cap), lf_w^{ij} refers to the total employment of labor in industry i in region j (cap/yr), p_w^{ij} is the water productivity of industry i in region j (CNY/m^3), and w_c^{ij} is the water consumption of industry i in region j (m^3/yr). In this study, we work with three aggregate economic sectors: agriculture, industry sector (including industry, manufacturing and construction) and services.

We introduce the concepts of opportunity cost (OC) and comparative advantage (CA) to assess one region's productive advantage in one sector when compared with another region (Deardorff, 2014). Opportunity cost is a key concept in economics. It represents the benefits an individual, investor or business misses from all other alternatives when one alternative is chosen (Buchanan, 2008). That means for example in our case, when using a specific unit of a resource (e.g. water) for producing agricultural goods, the region has to simultaneously give up its use for producing non-agricultural goods, and vice versa. In other words, this specific unit of the resource is no longer available anymore for other uses, and the opportunity costs are the benefits that would have been incurred for the best alternative use of this unit. Equations (4) and (5) refer to the OC of agricultural goods and non-agricultural good per unit of land (in km^2), labor (per worker) and water (in m^3).

$$OC_r^{Agriculture} = \max\left\{p_j^{Secondary}, p_j^{Tertiary}\right\}, (r = 1, 2, 3; j = 1, 2\ldots 31) \tag{4}$$

$$OC_r^{Non-Agriculture} = p_j^{Agriculture}, \quad (r = 1, 2, 3; j = 1, 2, 3\ldots 31) \tag{5}$$

Where $OC_r^{Agriculture}$ is the OC of agriculture goods, which equals the maximum value between the industry sector's productivity and the service sector's productivity for resource r (land, labor force and water); $OC_r^{Non-Agriculture}$ is the OC of non-agriculture goods, which equals the agriculture productivity for resource r.

Across regions and sectors, different economic benefits will be obtained from one unit of resource (land, labor force and water) consumption. CA is a way to compare such differences based on the OC measurements, as presented in Equation (6) below.

$$CA_r^j = \frac{OC_r^{j,Agriculutre}}{OC_r^{j,\ Non-Agriculture}} > CA_r^k = \frac{OC_r^{k,\ \ Agriculture}}{OC_r^{k,Non-Agriculture}} \tag{6}$$

Equation (6) indicates that region j has a CA in terms of r resource use for producing non-agricultural commodities, relative to producing agriculture goods, compared to region k.

To explore the association between the CA of a specific resource and virtual water flows, in other words, to investigate which resource's CA is a significant factor in driving virtual water export, we conduct a multivariate linear regression analysis to test the statistical connection between the OC and net virtual water flows, controlling for relevant geographical features (Hartmann et al., 2015). The following regression is the baseline specification that we use to study the role of the three resources:

$$\begin{aligned} y_p = {} & \delta_1 d_{east} + \delta_2 d_{middle} + \delta_3 d_{10} + \delta_4 d_{12} + \beta_1 X_{1p} + \beta_2 X_{2p} \\ & + \beta_3 X_{3p} + \beta_4 X_{4p} + \beta_5 X_{5p} + \beta_6 X_{6p} + \beta_7 Log(pop) \\ & + \beta_8 Log(irr) + \beta_0 + \varepsilon \end{aligned} \tag{7}$$

Where y_p measures net virtual water exports from province p to all other provinces in China. d_{east} and d_{middle} are regional dummy variables that capture regional differences in terms of geographical features, development levels and average technological levels. “East,” “middle,” and “west” regions are classified by regional GDP per capita, and the regional affiliations of provinces are listed in Supplementary Table S1, $Log(pop)$ refers to regional population, $Log(irr)$ represents regional irrigation area. d_{10} and d_{12} are time dummy variables that capture time heterogeneity. X_{1p} to X_{6p} are six key factors in our analysis, and they measure Land's OC for agricultural production (X_{1p}), Land's OC for non-agricultural production (X_{2p}), Labor's OC for agricultural production (X_{3p}), Labor's OC for non-agriculture production (X_{4p}), Water's OC for agriculture production (X_{5p}) and Water's OC for non-agriculture production (X_{6p}), respectively. A positive and statistically significant coefficient in the equation indicates that virtual water export increases with an increase in OC. In contrast, a negative and statistically significant coefficient means that there is a negative relation between virtual water exports and OC. Please note that the six explanatory variables in equations (1)–(5) include the essential components of regional GDP and therefore we do not include GDP as a separate variable to avoid a high level of implicit multicollinearity. In other words, our study puts the essential components of regional GDP into comparative advantage measures so that we can see whether the disparity of resource's comparative advantage exerts a significance influence on virtual water flow.

In our study, the net virtual water outflow by sector and province is the dependent variable, and independent variables include OCs of three resources used for agriculture production, industrial production and services. We use “Variance Inflation Factors (VIF)” to detect collinearity among all independent variables, the results show that all the VIFs are smaller than 10 (empirical threshold), so there is no severe collinearity among these variables. Table S2 shows VIF details. Given data availability, our econometric modeling is based on a panel dataset of 30 provinces for the years 2007, 2010 and 2012.

y_p measures the net virtual water exports from province p to all other provinces in China. There are two types of approaches that are frequently used to calculate virtual water flows. One is the bottom-up approach commonly used for water footprint accounting, which estimates virtual water flows by multiplying the amount of water used per unit of product by the amount of the product that is traded by using detailed trade data (Chapagain and Hoekstra, 2008; da Silva et al., 2016; Zhuo et al., 2016; Orlowsky et al., 2014). This approach has been one of the most popular approaches in water footprint studies because data is available from a relatively good database (Mekonnen and Hoekstra, 2010; Hoekstra and Mekonnen, 2012). The other one is the top-down approach, which calculates the virtual water flow by tracing entire regional, national or global supply chains based on input-output tables provided by national statistical agencies. In this way, water consumed during production is attributed to final consumers rather than intermediate consumers. This approach aggregates the processes and products at the level of economic sectors, usually coupling water consumption in economic sectors with environmental input-output analysis (Zhao et al. 2015, 2017; Cai et al., 2019; White et al., 2018; Raul et al., 2017). Feng et al. (2014) and Hubacek and Feng (2016) present a detailed comparison of the two approaches.

China's virtual water flows among 30 provinces in 2007, 2010 and 2012 are calculated based on environmental multiregional input-output analysis (excluding international imports and exports), as presented in Equations (8) and (9) below.

$$\mathrm{vwe^s} = \mathrm{d^s}(\mathrm{I} - \mathrm{A^{ss}})^{-1}\sum_{r \neq s}\mathrm{e^{sr}} \tag{8}$$

$$\mathrm{vwi^s} = \sum_{r \neq s}\mathrm{d^r}(\mathrm{I} - \mathrm{A^{rr}})^{-1}\mathrm{e^{rs}} \tag{9}$$

$\mathrm{d^s}$, $\mathrm{A^{ss}}$ and $\mathrm{e^{rs}}$ of region s are direct water use intensity, technical coefficients of domestic intermediate inputs, and imports of province r from province s. $\mathrm{d^r}$, $\mathrm{A^{rr}}$ and $\mathrm{e^{sr}}$ of region r represent direct water use intensity, technical coefficients of domestic intermediate inputs, and exports from province r to province s. Virtual water export of province s, $\mathrm{vwe^s}$, represents the virtual water imports of other regions from province s. We calculate $\mathrm{vwe^s}$ by summing the virtual water imports of other regions from province s. Virtual water import of province s, $\mathrm{vwi^s}$, represents the virtual water export from other regions to province s. We calculate $\mathrm{vwi^s}$ by summing the virtual water exports of other regions to province s.

Net virtual water export (y_p) in province s is equal to virtual water that province s exports to other provinces minus virtual water that province s imports from other provinces, as presented in Equation (10):

$$y_p = vwe^s - vwi^s \quad (10)$$

More details can be found in Zhao et al. (2017). For the purpose of this study, we have aggregated virtual water across 30 economic sectors for every provinces. Table S3 shows virtual water trade of individual provinces in China for the years 2007, 2010 and 2012.

The water stress index (W_s) refers to the tension between water consumption (w_c) and available local water resources (Q) and is expressed as:

$$W_s = \frac{w_c}{Q} \quad (11)$$

Water consumption refers to the gross quantity of water consumed by users; Q represents renewable freshwater availability. The categories of W_s that evaluate stress levels are listed in Supplementary Table S4 (Zhao et al., 2015). Supplementary Table S5 shows the provincial water stress index (WSI).

2.2. Data sources

To calculate resource productivity at the province level based on Equations (1)–(3), we need regional domestic production (or economic output), land use, labor input, and water consumption for agriculture, industry and services. We collect regional domestic production from the China Statistical Yearbook (National Bureau of Statistics of China, 1996a, 2001a, 2006a, 2011a, 2016a), the Chinese Agricultural Yearbook (Ministry of Agriculture, 1996, 2001, 2006, 2011, 2016) and the China Rural Statistical Yearbook (National Bureau of Statistics of China, 1996b, 2001b, 2006b, 2011b, 2016b). Regional domestic production values are deflated to 2005 constant prices. Land use area for each industry are provided by the Ministry of Housing and Urban-rural Development (Ministry of Housing and Urban-rural Development 2006; 2010, 2015). The yearbooks supply land use data at different scales; therefore, we aggregated this data into the same scale as regional GDP according to the “Standard on current land use classification of China” (Ministry of Land and Resources of China) and the “Standard classification of national economy” (National Bureau of Statistics of China, 2011c). The working labor force for each sector at the regional scale was obtained from the China Labor Statistical Yearbook (National Bureau of Statistics of China, 1996c, 2001c, 2006c, 2011d, 2016), the China Statistical Yearbook (National Bureau of Statistics of China, 1996a, 2001a, 2006a, 2011a, 2016a) and the China Rural Statistical Yearbook (National Bureau of Statistics of China, 1996b, 2001b, 2006b, 2011b, 2016b). Based on Equations (9) – (10), we calculated virtual water trade among provinces, using China multi-regional input-output table for years 2007, 2010 and 2012 compiled by Liu et al. (2014) and Mi et al. (2017). We collected data on water consumption and annual local water availability from the Provincial Water Resource Bulletin (The Ministry of Water Resources of China, 1998; 2001, 2006, 2011, 2016), and we used the urbanization rate to estimate water consumption of the service sector in each province. Table S6 shows the correspondence between urbanization rate and service's water consumption. Detailed procedures could be found in Liu (2016).

3. Results

3.1. The spatial distribution of land, labor and water productivity in 2015

Fig. 1 and Table 1 show the spatial distribution of land, labor and water productivity in 2015. In China in 2015, the average land productivity was 1.5 million CNY/km^2 for agriculture, 744.2 million CNY/km^2 for industry and 575 million CNY/km^2 for services (Note that 1 CNY equals 0.1582 US$). Land productivity of the industry sector was nearly 510 times greater than that of agriculture (see Table 2). Land productivity varied between 1411.3 million CNY/km^2 in Tianjin for the industry sector and 0.9 million CNY/km^2 in Ningxia for agriculture. Beijing, as the capital, had the highest land productivity for both agriculture and services, with 3.0 million CNY/km^2 and 1392.1 million CNY/km^2, respectively. However, because of its special role in China, Beijing was changing its industrial structure from resource-intensive products to advanced service products, and the livelihood of most of its citizens and most necessities relied on imports from other regions or abroad. As a result, although Beijing showed very high productivity for agriculture, much higher land productivity was actually captured by services.

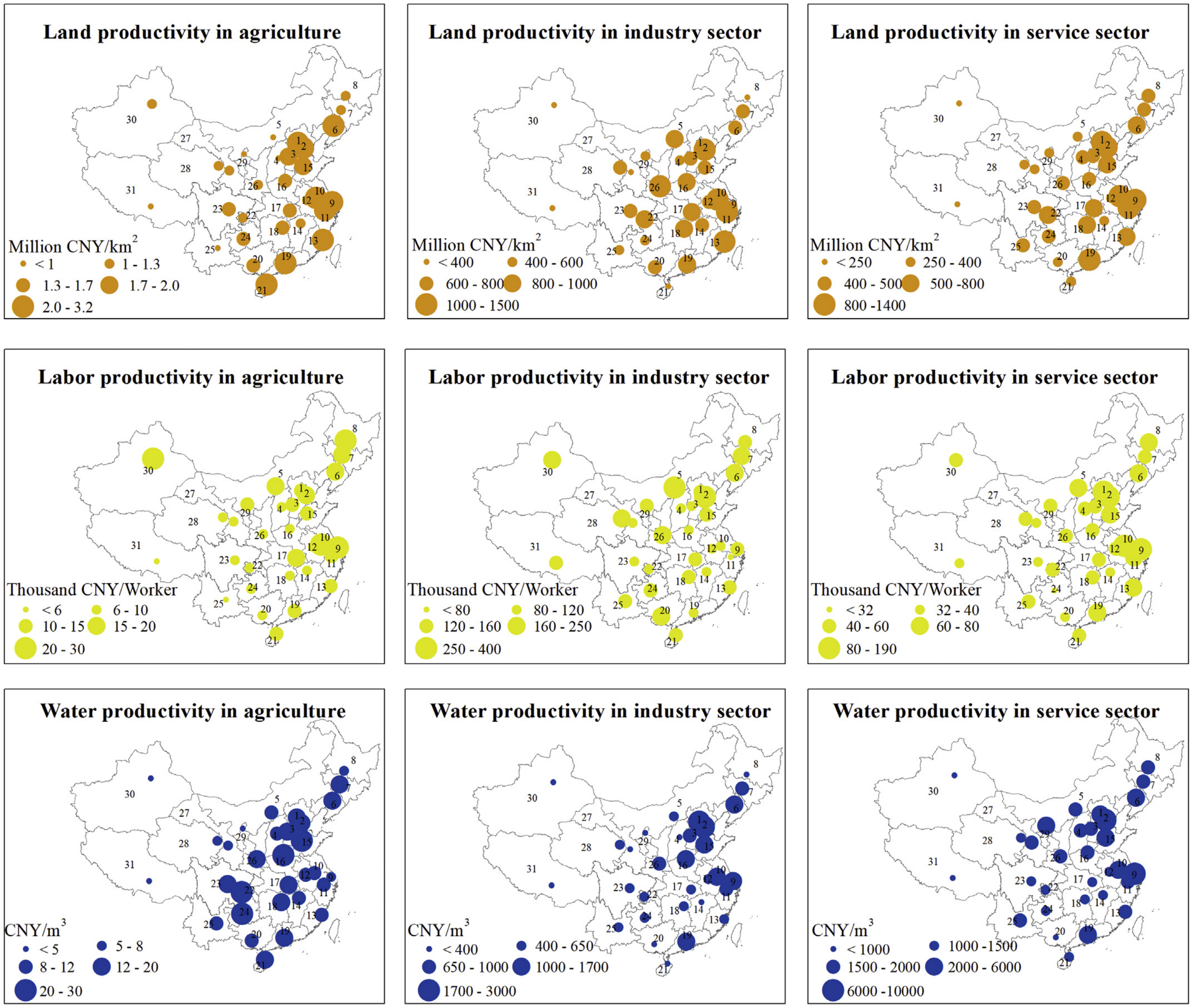
The top three maps in Fig. 1 indicate that most of the high values of land productivity were clustered in the eastern coastal areas of China, especially in the Yangtze River Delta (YRD), the Bohai Economic Rim (BER) (except Hebei) and the Pearl River Delta (PRD), whereas nearly all of the low values were located in the economically less developed northwest areas of China.

In terms of the spatial pattern of labor productivity, one worker would create either 11.8 thousand CNY, 115.2 thousand CNY or 59.3 thousand CNY if he or she had ability to freely enter the agriculture, industry or service sector, respectively (see Table 1). Labor productivity of the industry sector was ten times greater than that of agriculture and twice that of services. Specifically, we noticed that labor productivity in agriculture ranged from 4.7 thousand CNY/worker in Tibet to 28 thousand CNY/worker in Jiangsu. This value varied from 66.6 thousand CNY/worker in Zhejiang to 374.2 thousand CNY/worker in Inner Mongolia for industry; and services ranged from 31.2 thousand CNY/worker in Guizhou to 189.5 thousand CNY/worker in Tianjin. In terms of the spatial pattern of labor productivity, we noticed that the high values of agricultural labor productivity were dispersed in different regions (including Jiangsu, Shanghai, Heilongjiang, Xinjiang and Tianjin); but industry's hotpots were concentrated in several northern regions, such as Inner Mongolia, Tianjin, Xinjiang and Jilin. The eastern regions had a flourishing service economy. The southwest regions lagged far behind in labor productivity for both agriculture and services.

As for water productivity, the results show that service enterprises reaped the highest economic benefit per unit of water use (1846.4 CNY/m^3), followed by industry and agriculture, for which the corresponding figures were 729.5 CNY/m^3 and 11.5 CNY/m^3, respectively (see Table 1). These findings are similar to Ye et al. (2018), in that agriculture had the lowest water productivity but consumed the most water resources, and was the predominant water user. There was a huge difference between the region with the highest and that with the lowest water productivity across the three economic sectors. This disparity was 19 times in agriculture, 30 times in industry and 20 times in services, respectively. Regarding to the spatial pattern of water productivity, as Fig. 1 shows, high water productivity in the agricultural sector was mainly located in the main diagonal section of China (Chongqing, Guizhou, Henan, Shandong, etc.). Similar to land productivity, high values of water productivity in the industry and service sector were clustered in the YRD, the BER (except Hebei) and the PRD, but low values were clustered in the western regions.

3.2. The spatial pattern of comparative advantage in China in 2015

Fig. 2 shows the spatial distribution of CA for agriculture and the non-agricultural sectors in 2015, and more detailed information is provided in Table 2. At the national average, OC of agricultural use was 508.5, 9.8 and 160 times higher than the productivity of



Province numbers:

Yangtze River Delta (YRD): 9, 10, 11 **Bohai Economic Rim (BER): 1, 2, 3, 5, 15** **Pearl River Delta (PRD): 19**

1. Beijing 2. Tianjin 3. Hebei 4. Shanxi 5. Inner Mongolia 6. Liaoning 7.Jilin 8. Heilongjiang 9. Shanghai 10. Jiangsu
11. Zhejiang 12. Anhui 13. Fujian 14. Jiangxi 15. Shandong 16. Henan 17. Hubei 18. Hunan 19. Guangdong 20. Guangxi
21. Hainan 22. Chongqing 23. Sichuan 24. Guizhou 25.Yunnan 26. Shaanxi 27. Gansu 28. Qinghai 29. Ningxia 30. Xinjiang
31. Tibet

Fig. 1. The spatial distribution of land, labor and water productivity.

agriculture in terms of land, labor and water, respectively. In terms of land, Shaanxi would suffer the highest OC if land changed from non-agricultural use to crop planting, which was equivalent to non-agricultural land being 900 times more productive than agricultural land productivity. On the other hand, Hainan had the lowest OC because of the small resource productivity gap across the three sectors, followed by Xinjiang. In terms of the labor force, the CA ratios varied from 32.6 in Tibet to 3.2 in Jiangsu, and we noticed that in most western regions (Tibet, Qinghai, Yunnan, and Guangxi), with a considerable labor productivity gap between the agricultural and non-agricultural sectors, the CA ratio was over 20, but for the developed coastal areas (Zhejiang, Shanghai and Jiangsu), this value was lower than six. As for CA of water, our results show considerable differences across regions. The highest CA value was located in Shanghai, which was higher than 1600, while the lowest value was in Guizhou with just 43. Furthermore, most of water-scarce regions in north China (except Jilin and Shaanxi) had significant CA of water in industry.

3.3. The changes in resource productivity and comparative advantage (from 1995 to 2015)

Fig. 3 and Table S7 show the changes in resource productivity and CA of land, labor and water over the past two decades (from 1995 to 2015). We see from the figure that all the indicators increased over time; the productivity per unit of land for

Table 1
Resource productivity in 2015.

2015	Agriculture land productivity [Million CNY/ km^2]	Industry land productivity [Million CNY/ km2]	Service land productivity [Million CNY/ km2]	Agriculture labor productivity Thousand CNY/ Cap	Industry labor productivity Thousand CNY/ Cap	Service labor productivity Thousand CNY/ Cap	Agriculture water productivity CNY/m^3	Industry water productivity CNY/m^3	Service water productivity CNY/m^3
Beijing	3.0	548.6	1392.1	13.2	122.3	93.8	13.8	2346.5	4725.8
Tianjin	2.3	1411.3	1121.9	19.9	253.1	189.5	13.4	2870.0	6035.2
Hebei	1.7	727.0	412.3	13.6	109.3	57.8	14.9	696.6	1680.1
Shanxi	0.9	532.4	434.7	7.2	95.4	56.1	10.3	311.6	1860.3
Inner Mongolia	0.9	834.7	365.9	17.5	374.2	65.6	9.5	539.1	1835.4
Liaoning	2.1	683.4	672.4	18.0	170.2	73.5	15.1	1103.0	2125.0
Jilin	1.2	664.2	471.1	17.9	192.5	50.5	15.3	810.4	1519.8
Heilongjiang	1.2	307.7	436.7	24.2	159.5	78.8	7.0	362.2	1747.3
Shanghai	2.0	366.6	890.5	26.7	121.0	89.9	7.2	1549.4	11911.1
Jiangsu	2.3	1016.9	884.8	28.0	87.9	90.3	9.8	1162.3	3246.6
Zhejiang	2.3	1032.1	852.2	13.2	66.6	63.4	11.0	804.2	1949.4
Anhui	1.1	601.8	323.9	8.5	98.5	40.2	10.6	540.1	1118.3
Fujian	2.6	1169.7	733.7	13.9	123.6	61.3	10.7	644.5	1962.3
Jiangxi	1.1	671.4	337.3	9.0	101.4	36.9	8.1	344.7	1004.1
Shandong	1.8	791.6	609.7	13.7	129.8	68.1	22.9	1677.1	3258.2
Henan	1.4	838.2	409.3	9.8	96.6	51.9	25.5	1121.3	1531.5
Hubei	1.6	854.6	596.3	18.3	140.7	41.5	16.1	491.2	1194.0
Hunan	1.6	912.9	569.7	10.0	140.3	52.2	14.7	595.9	1429.3
Guangdong	2.4	877.8	910.5	10.6	108.3	67.0	13.2	1337.3	2083.8
Guangxi	1.5	725.3	395.5	7.7	165.7	34.4	11.0	314.9	604.9
Hainan	2.3	363.5	353.4	12.4	129.2	52.2	14.4	363.1	1351.1
Chongqing	1.2	867.9	697.8	9.8	111.9	42.6	28.3	400.7	1322.2
Sichuan	1.4	638.5	437.0	8.8	106.0	38.3	18.8	487.9	1007.8
Guizhou	1.4	540.2	405.6	8.7	125.6	31.2	26.5	432.6	1142.6
Yunnan	0.9	597.9	411.6	5.6	122.2	43.4	11.4	445.5	1623.9
Shaanxi	1.3	1161.0	410.4	8.6	173.7	50.4	18.3	943.4	1538.5
Gansu	1.1	397.6	292.4	8.1	87.7	34.9	7.3	384.6	1745.8
Qinghai	1.0	646.8	377.7	8.0	186.1	53.8	6.5	565.2	1371.2
Ningxia	0.9	473.1	252.1	12.0	152.6	45.4	4.7	277.7	3293.6
Xinjiang	1.2	279.0	218.3	20.3	200.1	58.9	2.5	395.3	873.7
Tibet	1.0	267.7	194.9	4.7	154.7	35.3	1.5	95.7	721.2
Average	1.5	744.2	575.0	11.8	115.2	59.3	11.5	729.5	1846.4

Table 2
Comparative advantage in 2015.

2015	CA for per unit of land	CA for per unit of labor force	CA for per unit of water
Beijing	461.3	9.2	342.5
Tianjin	610.4	12.7	450.8
Hebei	427.2	8.0	112.7
Shanxi	578.7	13.2	181.4
Inner Mongolia	887.1	21.3	193.6
Liaoning	323.2	9.4	141.0
Jilin	544.3	10.8	99.4
Heilongjiang	378.6	6.6	249.1
Shanghai	437.4	4.5	1650.9
Jiangsu	436.9	3.2	331.0
Zhejiang	448.4	5.1	177.8
Anhui	544.7	11.6	105.2
Fujian	455.6	8.9	183.3
Jiangxi	636.4	11.2	123.5
Shandong	428.2	9.5	142.4
Henan	607.0	9.8	60.1
Hubei	532.5	7.7	74.0
Hunan	581.5	14.1	97.3
Guangdong	386.0	10.3	157.5
Guangxi	494.2	21.4	54.8
Hainan	155.7	10.4	93.8
Chongqing	716.1	11.4	46.7
Sichuan	453.1	12.1	53.5
Guizhou	379.1	14.5	43.1
Yunnan	636.9	21.7	142.3
Shaanxi	903.1	20.2	84.1
Gansu	369.9	10.8	240.3
Qinghai	638.0	23.3	210.8
Ningxia	514.5	12.7	699.6
Xinjiang	230.9	9.8	352.6
Tibet	281.0	32.6	485.2
Average	508.5	9.8	160.0

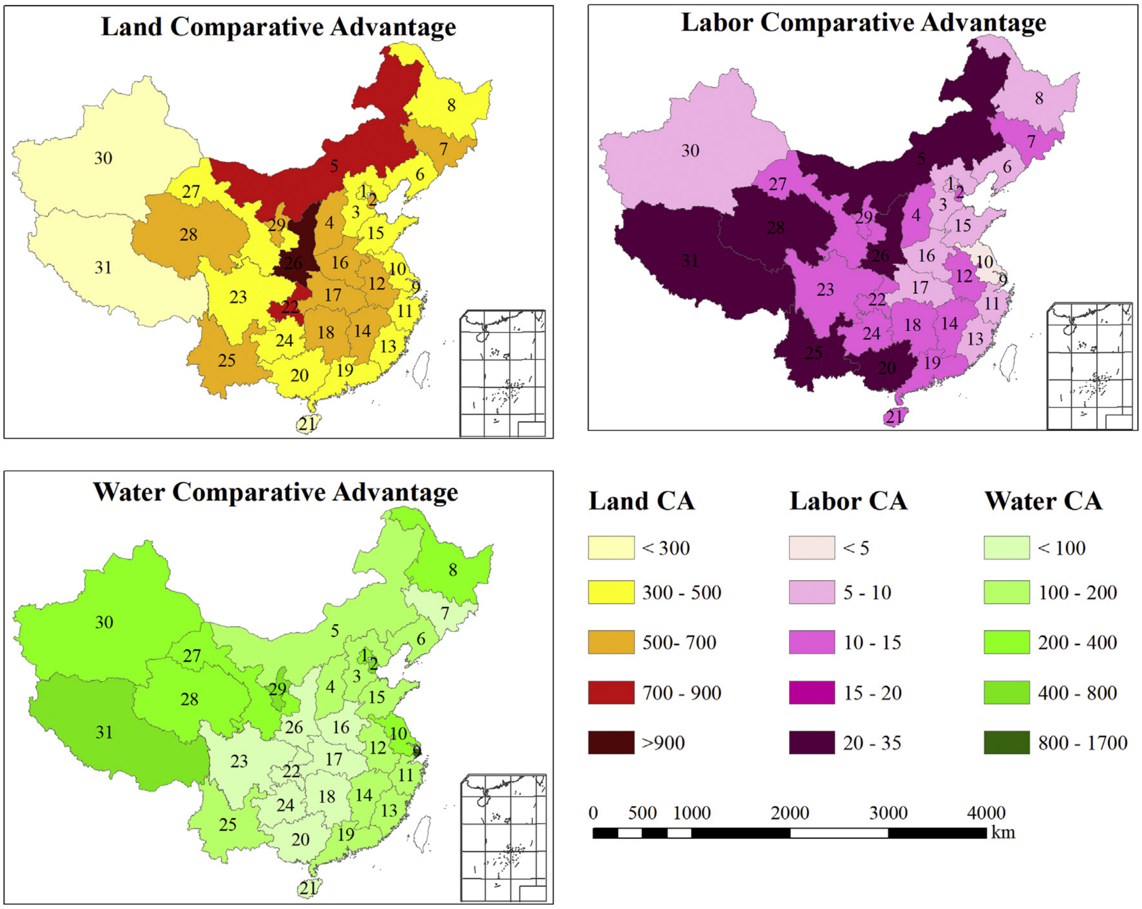


Fig. 2. Comparative advantage of land, labor and water in China.

agriculture increased slightly, from just 0.97 million CNY/km^2 to 1.46 million CNY/km^2, labor productivity increased from 4645 CNY/worker to 11,758 CNY/worker and water yield increased from 6 CNY/m^3 to 12 CNY/m^3. However, industrial productivity grew sharply by 3.6 times in land productivity, 5.9 times in labor and 8.5 times in water productivity. Similar results are found in the service sector. The results demonstrate that the national average resource productivity between the agricultural and non-agricultural sectors was increasing over the 20 years. Most significantly, the discrepancy of land resource productivity between agriculture and non-agricultural sectors has grown from 209 times in 1995 to 510 times in 2015. In contrast, the range of national average CA varies from 4.2 to 9.8 per unit of labor; for water, this value changed from 38 in 1995 to 154 in 2015.

3.4. Net virtual water outflows and opportunity cost at provincial scale

Table 3 reports the results of nine multivariate (pooled) panel regressions between the net virtual water outflow as dependent variable and OCs of resources for agriculture and non-agricultural production as the key explanatory variables. Columns 1–9 illustrated a sequence of nested models that regressed the net virtual water exports against X_{1p} (land's OC for agriculture production), X_{2p} (land's OC for non-agricultural production), X_{3p} (labor's OC for agriculture production), X_{4p} (labor's OC for non-agricultural production), X_{5p} (water's OC for agriculture production), X_{6p} (water's OC for non-agricultural production), Log(pop) (population) and Log(irr) (irrigation land).

In nearly every model, the X_{2p} (land's OC for non-agricultural production) is positive and significant predictors of net virtual water exports; whereas, X_{1p} (land's OC for agriculture) is negatively correlated with the dependent variable. Together, all the variables explained 53% of the variance in net virtual water exports across the 30 provinces over the period (Table 3, Column 1). However, X_{2p} (land's OC for non-agricultural production) proved to be the most significant variable in the regression analysis and explained the largest percentage of the variance in net virtual water exports after the effects of all other variables have been considered. In more detail, the semi-partial correlation of X_{2p} (the difference in the adjusted R^2 between the full model and one for which only X_{2p} was removed) was 5.4% (0.53−0.476), meaning that 5.4% of the variance in net virtual water exports was explained by X_{2p} (Table 1), followed by X_{1p}. In contrast, other key explanatory variables (X_{3p} to X_{6p}) are not statistically significant across models 1–8 and did not improve the accuracy of the model. When irrigation land is excluded from the model (see column IX), X_{4p} and X_{5p} show statistically significant influence on virtual water flow at the 10% level, with the marginal effect lower and significant level less than X_{1p}, thus we find that other resources' comparative advantages do not play an important role in shaping virtual water trade. As a matter of fact, a one standard deviation increase in X_{1p} decreased net virtual water exports by approximately 0.295 standard deviation and a one standard deviation increase of X_{2p} increased net virtual water exports by about 0.656 standard deviation in the most completely-specified model (see column I). As a result, net virtual water

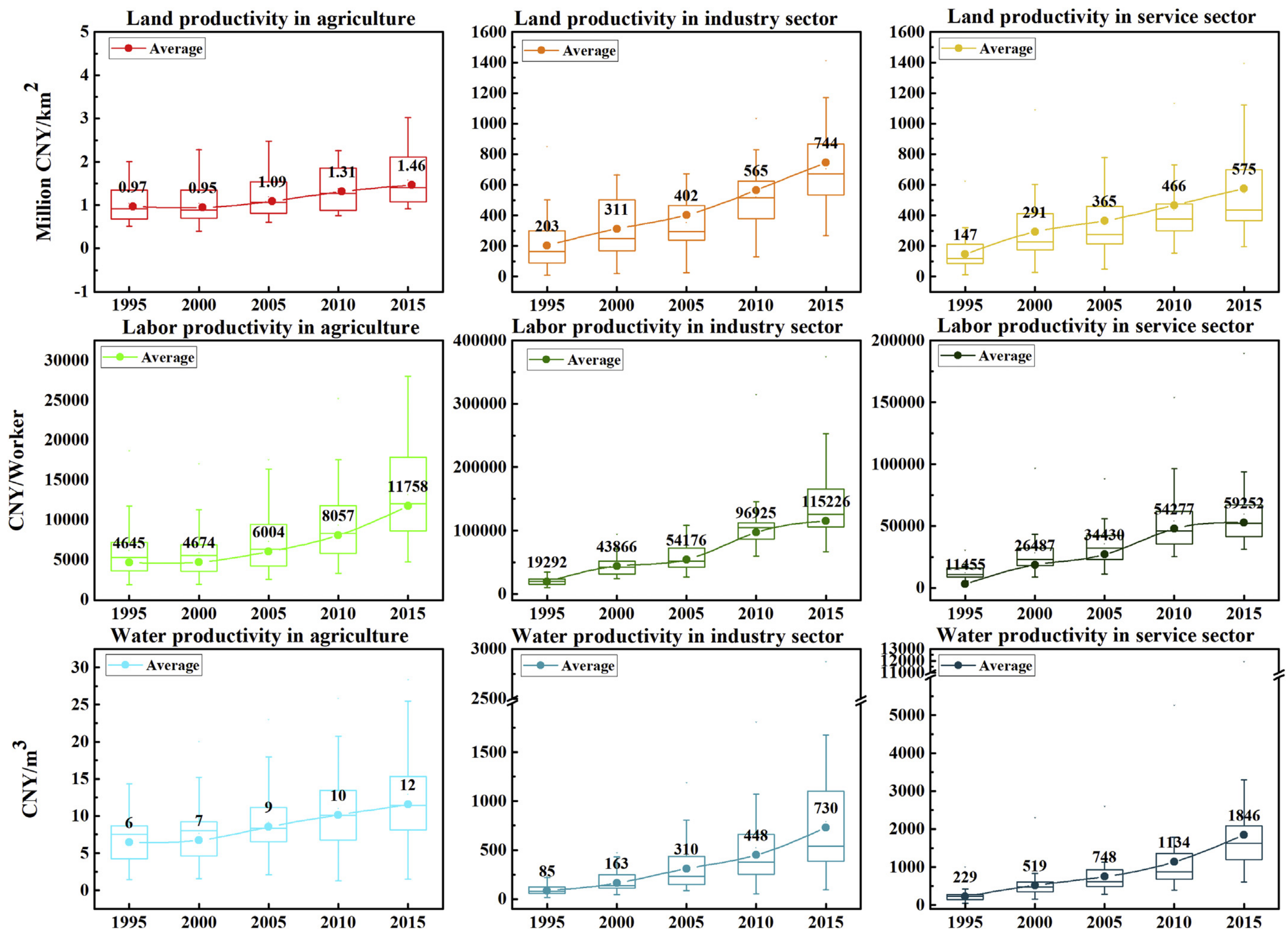


Fig. 3. Temporal changes in resource productivity. Note: The bottom and top of the box represent the 25th and 75th percentiles; the error bars refer to maximum and minimum values.

exports was most significantly associated with the change of X_{2p} and X_{1p}.

4. Discussion

This study investigated the spatial-temporal distribution of resource productivity and comparative advantage (CA) for land, labor and water based on economic output per unit of resource consumption in 31 provinces of China from 1995 to 2015. For the first time, we introduced CA theory to study the driving forces of virtual water exports. The results show that the provinces with high land productivity were clustered in the eastern coastal areas of China, especially in the Yellow River Delta, the Bohai Economic Rim (except Hebei) and the Pearl River Delta. However, high values of labor productivity were dispersed throughout different regions; for instance, a hotspot of the industry sector was found in the northern regions, whereas the eastern regions were dominated by service sectors. The findings show that there were huge differences in water productivity across sectors and regions. The CA analysis reveals that the average opportunity cost (OC) of agricultural production was 510, 9.8 and 160 times higher than the agricultural productivity of land, labor, and water, respectively.

Our pooled panel data regression results demonstrate that increases in land's OC for agricultural use would curb virtual water exports, whereas an increase in land's OC for non-agricultural use would tend to be accompanied by an increase in virtual water exports. In other words, if land produces higher returns outside agricultural production then the net outflow of virtual water tends to be lower. This conclusion is similar to the observations in Feng et al. (2014), Zhao et al. (2015), Ye et al. (2018) and Chen et al. (2017). In these studies, Xinjiang, as the biggest virtual water exporter, had exported a large amount of virtual water through exporting water-intensive food commodities to other provinces, particularly to the eastern coastal provinces, such as Shandong, Shanghai, Tianjin and Jiangsu. The results for land CA confirm the existing huge disparity between Xinjiang and the regions receiving its virtual water, such as Shanghai. In Shanghai, we found that land productivity in services was about 440 times higher than that in agriculture. For Xinjiang, this value was just 230, which is the second smallest in China, as a result, Shanghai will purchase water-intensive commodities from these regions that have lower land OC for agricultural production. In Tianjin, another high net importer of virtual water, one km^2 of land will produce 1411.3 million CNY for non-agricultural enterprises, which is 610 times bigger than that for agricultural land; however, in Xinjiang, this gap is only 230 times. Similar results could also be found between the second biggest virtual water exporter, Hebei and its water receiving regions. In other words, water net importers have higher returns of land from industrial production or services and thus import more agricultural products.

Table 3
Multivariate (pooled) panel regression results.

Dependent variable: Net virtual water export									
	I	II	III	IV	V	VI	VII	VIII	IX
deast	−1.212***	−1.174***	−0.506*	−1.216***	−1.183***	−1.107***	−1.221***	−1.164***	−0.966**
	(0.33)	(0.34)	(0.26)	(0.33)	(0.33)	(0.32)	(0.33)	(0.37)	(0.39)
dmiddle	−0.556***	−0.581***	−0.558**	−0.563***	−0.592***	−0.557***	−0.556***	−0.622***	−0.487**
	(0.20)	(0.21)	(0.22)	(0.20)	(0.20)	(0.21)	(0.20)	(0.23)	(0.24)
d10	−0.146	−0.185	−0.015	−0.134	−0.116	−0.104	−0.142	−0.084	0.007
	(0.21)	(0.22)	(0.22)	(0.20)	(0.21)	(0.21)	(0.21)	(0.24)	(0.25)
d12	−0.211	−0.335	−0.015	−0.198	−0.194	−0.12	−0.2	−0.028	0.135
	(0.28)	(0.27)	(0.28)	(0.26)	(0.28)	(0.27)	(0.27)	(0.31)	(0.32)
X_{1p} (Land's OC for Agriculture)	−0.295**		−0.105	−0.286**	−0.271*	−0.246*	−0.290**	−0.443***	−0.426**
	(0.15)		(0.14)	(0.14)	(0.15)	(0.14)	(0.15)	(0.16)	(0.18)
X_{2p} (Land's OC for Non-Agriculture)	0.656***	0.485**		0.651***	0.549***	0.544***	0.657***	0.375*	0.171
	(0.21)	(0.19)		(0.20)	(0.18)	(0.19)	(0.21)	(0.22)	(0.23)
X_{3p} (Labor's OC for Agriculture)	0.021	−0.068	−0.032		−0.018	0.004	0.022	0.211	0.194
	(0.12)	(0.12)	(0.13)		(0.11)	(0.12)	(0.12)	(0.13)	(0.14)
X_{4p} (Labor's OC for Non-Agriculture)	−0.152	−0.1	0.1	−0.143		−0.02	−0.155	0.111	0.302*
	(0.15)	(0.15)	(0.14)	(0.14)		(0.12)	(0.15)	(0.16)	(0.16)
X_{5p} (Water's OC for Agriculture)	0.186	0.118	0.015	0.184	0.1		0.182	−0.05	−0.262*
	(0.14)	(0.14)	(0.13)	(0.14)	(0.11)		(0.14)	(0.14)	(0.14)
X_{6p} (Water's OC for Non-Agriculture)	0.021	−0.008	0.032	0.021	0.028	0.006		−0.114	−0.082
	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)		(0.10)	(0.11)
Log(pop)	−0.906***	−0.994***	−0.718***	−0.918***	−0.831***	−0.803***	−0.892***		0.143
	(0.20)	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)	(0.19)		(0.11)
Log(irr)	1.229***	1.291***	0.972***	1.237***	1.127***	1.074***	1.220***	0.396***	
	(0.21)	(0.21)	(0.20)	(0.20)	(0.18)	(0.17)	(0.20)	(0.11)	
Intercept	0.712***	0.759***	0.345	0.706***	0.695***	0.629**	0.710***	0.630**	0.437
	(0.25)	(0.25)	(0.23)	(0.24)	(0.25)	(0.24)	(0.25)	(0.28)	(0.29)
Observations	90	90	90	90	90	90	90	90	90
Adjusted R^2	0.53	0.512	0.476	0.536	0.53	0.525	0.536	0.412	0.325
F Statistic	9.373***	9.494***	8.359***	10.352***	10.139***	9.951***	10.347***	6.678***	4.887***
Degrees of freedom	(12; 77)	(11; 78)	(11; 78)	(11; 78)	(11; 78)	(11; 78)	(11; 78)	(11; 78)	(11; 78)
p-value	7.24E-11	1.35E-10	1.68E-09	2.20E-11	3.42E-11	5.08E-11	2.22E-11	9.39E-08	1.04E-05

Note:* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Column I includes all the variables, and ColumnsII-IX exclude blocks of variables to explore the contribution of each group of variables to the full model. All explanatory variables are standardized, the estimated standard errors appear in parenthesis.

Our regression analysis highlights the dominant role played by land in shaping virtual water export. This finding is notably interesting. Our explanation is as follows. Land is a capital-intensive and indispensable production factor for all sectors and is not movable across regions. In contrast, labor in general and skilled labor in particular have become increasingly mobile in China. At the same time, landholders aim to utilize their land resources to produce products with the highest CA and import commodities with a comparative disadvantage. In less developed regions, the gap of land productivity between non-agricultural and agricultural sectors has been smaller than that in developed regions, in addition, non-agricultural job opportunities are more limited in less developed regions. These together drive land holders in less developed regions to explore comparative advantage in producing and exporting food-related commodities. For example, the North China Plain and the northeast region, despite being water-scarce, have become major exporters of (water intensive) food products to more industrialized and water-rich regions. The intensification and expansion of agricultural production in these two water-scarce regions have led to over-exploitation of ground water. The rapid drop of groundwater tables in the North China Plain has caused many environmental problems such as dried up rivers and lakes, seawater intrusion, land subsidence and ground fissures (Xu et al., 2015; Zhang et al., 2009) as well as health problems when pumping reaches deep layers with water containing toxic levels of fluoride and arsenic (Currell et al., 2012). The above tension means that how to recover local groundwater tables without undermining regional grain production level has become the most important policy challenge in the region (Zhong et al., 2017). Our research highlights the nationwide drivers of this tension — the relative gaps of land productivity between non-agricultural and agricultural production across regions.

Moreover, in China, the spatial distribution of industry is mainly determined by scarcity of land resources, and the effects of labor and water resources are secondary. In the water-rich regions of China, arable land per capita is smaller and the land productivity gap between non-agricultural and agricultural production is much bigger than those in water-scarce regions. The above economic logic means that it is more profitable for water-rich regions to use their scarce land resources for non-agricultural production and import land-intensive products from other regions. For example, Guangdong and Zhejiang, two water-rich but land scarce provinces, have become highly industrialized and urbanized and are increasingly dependent on importing land- and water-intensive goods like food from other regions and abroad.

Our findings reveal that the gap between agricultural productivity and non-agricultural productivity in the three resource categories have increased during the past two decades, which means that the growth in resource productivity of agriculture is much slower than that of the non-agricultural sectors, especially in the northern regions. Our results indicate that the northern regions can export large amounts of food products to southern provinces because of their high total production driven by more available land, and not because they have higher land productivity in comparison with the southern provinces. Because agricultural production is land- and water-intensive, improving resource productivity of the agricultural sector is of fundamental importance for alleviating arable land scarcity and reducing water stress in China. Our findings further indicate that increasing land productivity of agriculture in the southern regions will contribute to water-stress reduction in the North and Northeast China Plains.

In our study, the CA of labor and water do not play an important role in shaping net virtual water exports. This is not surprising because of the following reasons: First, skilled labor is mobile and can relatively easily move from one place to another, especially if it is within the same country. Vast numbers of manufacturing centers in the southern regions like Guangdong and Zhejiang have been manpowered by cheap labor of immigrants from other regions. As a result, the gap of labor productivity in non-agricultural sectors between water-scarce and water-rich regions are more a reflection of differences in living-costs, earning opportunity and overall economic development, which are fundamentally different from differences in land productivity. Second, the production of goods and services requires water. However, in many instances, water is an open access resource that is subject to the tragedy of the commons, which explains why water is often freely used and water resources are over-exploited, especially in agriculture. Our study shows that the current market forces reflect the scarcity of land resources, it does not reflect the scarcity of water resources in the context of interregional trade in China.

A number of limitations should be taken into consideration when interpreting the main results of this study. First, spatial resolution is restricted to provincial administrative boundaries rather than watershed level due to a lack of trade and thus virtual water flow data at the sub province level. Second, our analysis focuses on three aggregated sectors (agriculture, industry, and the services). However, different crops have very different land productivity. Nevertheless, the comparison across aggregated sectors is a suitable starting point. Third, the data constraints and the resultant small sample size do not allow us to run more complicated panel regressions than the pooled OLS. Although we introduced regional and time dummy variables to represent regional and temporal variations, the two regional dummy variables may not be sufficient to capture specificities of individual provinces, for example, the difference in crop mix and productive specialization. In the future, once more data become available, it will be straightforward to extend our analysis using fixed effect and other regression techniques. Another potential extension can be based on a bilateral measurements of virtual water flows and CAs between two regions, when such bilateral flow data become available for multiple years. Finally, similar to most other scholars exploring water issues at the national and provincial level we rely on official Chinese statistics both at the national scale, such as data obtained from the China Statistical Yearbook and the Chinese Agricultural Yearbook, and at the provincial scale, such as data obtained from Provincial Water Resources Bulletin. The reliability of Chinese statistics has often been questioned but still presents the best available comprehensive secondary datasets available for our research questions (Zhao et al. 2015, 2016).

5. Conclusion

This study introduces a quantitative framework to comparative advantage theory and then uses it to track the driving forces of virtual water exports based on the spatial-temporal distribution of resource productivity and opportunity cost of land, labor and water use in agricultural and non-agricultural sectors across Chinese provinces. Our findings reveal that the regional differences in land productivity between agricultural and non-agricultural sectors are the main forces shaping the pattern of virtual water flows across regions, whereas other resources such as labor and water have played a less important role. The regions that tend to show a net import of virtual water flows, such as southern China, are also the ones that have high opportunity costs for their land resources and gain higher shares of value added by using their land for non-agricultural production and import agricultural products, even if they have fertile land and rich water resources. Our findings suggest that efforts to increase land productivity of agriculture in the southern regions would contribute to reducing water scarcity in the North and Northeast China Plains. In this way, our study presents an excellent example of how an innovative coupling of economic theories with natural resource management can explain the counter-intuitive phenomenon of the virtual water flows in trade from water-scarce regions to water-rich regions in the context of China.

Author contributions

J.L., D.Z., K.H., K.F., and L.S. conceived the central idea. D.Z. collected the data, performed the calculations, and created all figures. D.Z., J.L., and K.H. wrote the first draft. All authors contributed to the analysis and developed the manuscript.

Declarations of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.watres.2019.01.025.

References

Allan, J.A., 1996. Water use and development in Arid regions: environment, economic development and water resource politics and policy. Review of European, Comparative & International Environmental Law 5 (2), 107–115.
Allan, J.A., 2002. Hydro-peace in the Middle East: why no water wars?: a case study of the Jordan River Basin. SAIS Rev. 22 (2), 255–272.
Allan, J.A., 2003. Virtual water-the water, food, and trade nexus. Useful concept or misleading metaphor? Water Int. 28 (1), 106–113.
Buchanan, J.M., 2008. Opportunity Cost. The New Plalgrave Dictionary of Economics Online, second ed. Palgrave Macmillan, London, United Kingdom.
Cai, B.C., Zhang, W., Hubacek, K., Feng, K.S., Li, Z.L., Liu, Y.W., Liu, Y., 2019. Drivers of virtual water flows on regional water scarcity in China. J. Clean. Prod. 207 (10), 1112–1122.
Chapagain, A.K., Hoekstra, A.Y., 2008. The global component of freshwater demand and supply: an assessment of virtual water flows between nations as a result of trade in agricultural and industrial products. Water Int. 33 (1), 19–32.

Chen, W., Wu, S., Lei, Y., Li, S., 2017. China's water footprint by province, and inter-provincial transfer of virtual water. Ecol. Indicat. 74, 321–333.
Currell, M.J., Han, D., Chen, Z., Cartwright, I., 2012. Sustainability of groundwater usage in northern China: dependence on palaeowaters and effects on water quality, quantity and ecosystem health. Hydrol. Process. 26 (26), 4050–4066.
da Silva, V.d.P.R., de Oliveira, S.D., Hoekstra, A.Y., Dantas Neto, J., Campos, J.H.B., Braga, C.C., de Araújo, L.E., Aleixo, D.d.O., de Brito, J.I.B., de Souza, M.D., 2016. Water footprint and virtual water trade of Brazil. Water 8 (11), 517.
Deardorff, A.V., 2004. Local Comparative Advantage: Trade Costs and the Pattern of Trade.
Deardorff, A.V., 2005. How robust is comparative advantage? Rev. Int. Econ. 13 (5), 1004–1016.
Deardorff, A.V., 2014. Local comparative advantage: trade costs and the pattern of trade. Int. J. Econ. Theor. 10 (1), 9–35.
Dornbusch, R., Fischer, S., Samuelson, P.A., 1977. Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods. Am. Econ. Rev. 67 (5), 823–839.
Du Fraiture, C., 2004. Does International Cereal Trade Save Water?: the Impact of Virtual Water Trade on Global Water Use. Iwmi.
Duchin, F., Morales, L.C., 2015. Do water-rich regions have a comparative advantage in food production?improving the representation of water for agriculture in economic models. Econ. Syst. Res. 24 (4), 371–389.
Feng, K., Hubacek, K., 2015. 10 A multi-region input–output analysis of global virtual water flows. In: Handbook of Research Methods and Applications in Environmental Studies, p. 225.
Feng, K., Siu, Y.L., Guan, D., Hubacek, K., 2012. Assessing regional virtual water flows and water footprints in the Yellow River Basin, China: a consumption based approach. Appl. Geogr. 32 (2), 691–701.
Feng, K., Hubacek, K., Pfister, S., Yu, Y., Sun, L., 2014. Virtual scarce water in China. Environ. Sci. Technol. 48 (14), 7704–7713.
Guan, D., Hubacek, K., 2007. Assessment of regional trade and virtual water flows in China. Ecol. Econ. 61 (1), 159–170.
Hartmann, D., Guevara, M., Jara-Figueroa, C., Aristarán, M., Hidalgo, C., 2015. Linking Economic Complexity, Institutions and Income Inequality. World Development.
Hidalgo, C.A., Hausmann, R., 2009. The building blocks of economic complexity. Proc. Natl. Acad. Sci. Unit. States Am. 106 (26), 10570–10575.
Hoekstra, A.Y., Hung, P.Q., 2005. Globalisation of water resources: international virtual water flows in relation to crop trade. Glob. Environ. Chang. 15 (1), 45–56.
Hoekstra, A.Y., Mekonnen, M.M., 2012. The water footprint of humanity. Proc. Natl. Acad. Sci. Unit. States Am. 109 (9), 3232–3237.
Hubacek, K., Feng, K., 2016. Comparing apples and oranges: some confusion about using and interpreting physical trade matrices versus multi-regional input–output analysis. Land Use Pol. 50, 194–201.
Kumar, M.D., Singh, O.P., 2005. Virtual water in global food and water policy making: is there a need for rethinking? Water Resour. Manag. 19 (6), 759–789.
Liu, Y., 2016. The Analysis of Water Footprint Changes and Driving Mechanism in Beijing-Tianjin-Hebei. Beijing Forestry University, Beijing, China.
Liu, W.D., Tang, Z.P., Chen, J., Yang, B., 2014. Multi-regional Input-Output Model for 30 Provinces of China in 2007 and 2010. China Statistics Press, Beijing.
Mekonnen, M.M., Hoekstra, A.Y., 2010. The Green, Blue and Grey Water Footprint of Crops and Derived Crop Products. UNESCO-IHE, Delft, the Netherlands.
Mekonnen, M.M., Hoekstra, A.Y., 2011. National Water Footprint Accounts: the Green, Blue and Grey Water Footprint of Production and Consumption.
Mi, Z.F., Meng, J., Guan, D.B., Shan, Y.L., Song, M.L., Wei, Y.M., Liu, Z., Hubacek, K., 2017. Chinese CO2 emission flows have reversed since the global financial crisis. Nat. Commun. 8, 1712.
Ministry of Agriculture, 1996. Chinese Agricultural Yearbook. China Agriculture Press, Beijing, China.
Ministry of Agriculture, 2001. Chinese Agricultural Yearbook. China Agriculture Press, Beijing, China.
Ministry of Agriculture, 2006. Chinese Agricultural Yearbook. China Agriculture Press, Beijing, China.
Ministry of Agriculture, 2011. Chinese Agricultural Yearbook. China Agriculture Press, Beijing, China.
Ministry of Agriculture, 2016. Chinese Agricultural Yearbook. China Agriculture Press, Beijing, China.
Ministry of Housing and Urban-rural Development, 2006. Urban-rural Development Statistical Yearbook. China Planning Press, Beijing, China.
Ministry of Housing and Urban-rural Development, 2010. Urban-rural Development Statistical Yearbook. China Planning Press, Beijing, China.
Ministry of Housing and Urban-rural Development, 2015. Urban-rural Development Statistical Yearbook. China Planning Press, Beijing, China.
Ministry of Land and Resources of China, 2007. Standard on Current Land Use Classification of China (GB/T21010). Standards Press of China Beijing, China.
National Bureau of Statistics of China, 1996a. China Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 1996b. China Rural Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 1996c. China Labor Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2001a. China Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2001b. China Rural Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2001c. China Labor Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2006a. China Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2006b. China Rural Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2006c. China Labor Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2011a. China Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2011b. China Rural Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2011c. Standard Classification of National Economy (GB/T 4754-2011). Standards Press of China Beijing, China.
National Bureau of Statistics of China, 2011d. China Labor Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2016. China Labor Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2016a. China Statistical Yearbook. China Statistics Press, Beijing, China.
National Bureau of Statistics of China, 2016b. China Rural Statistical Yearbook. China Statistics Press, Beijing, China.
Orlowsky, B., Hoekstra, A.Y., Gudmundsson, L., Seneviratne, S.I., 2014. Today's virtual water consumption and trade under future water scarcity. Environ. Res. Lett. 9 (7), 074007.
Ramirez-Vallejo, J., Rogers, P., 2004. Virtual water flows and trade liberalization. Water Sci. Technol. 49 (7), 25–32.
Raul, M.C., Feng, K.S., Hubacek, K., Sun, L.X., Guilhoto, J., Wilhelm, F.M., 2017. Uncovering the green, blue and grey water footprint and virtual water of biofuel production in Brazil, a nexus perspective. Sustainability 9, 2049. https://doi.org/10.3390/su9112049.
Serrano, A., Guan, D., Duarte, R., Paavola, J., 2016. Virtual water flows in the EU27: a consumption-based approach. J. Ind. Ecol. 20 (3), 547–558.
Sheng, Y., Shi, X., Zhang, D., 2014. Economic growth, regional disparities and energy demand in China. Energy Policy 71, 31–39.
The Ministry of Water Resources of China, 1998. Provincial Water Resource Bulletin. China Water & Power Press, Beijing, China.
The Ministry of Water Resources of China, 2001. Provincial Water Resource Bulletin. China Water & Power Press, Beijing, China.
The Ministry of Water Resources of China, 2006. Provincial Water Resource Bulletin. China Water & Power Press, Beijing, China.
The Ministry of Water Resources of China, 2011. Provincial Water Resource Bulletin. China Water & Power Press, Beijing, China.
The Ministry of Water Resources of China, 2016. Provincial Water Resource Bulletin. China Water & Power Press, Beijing, China.
Upadhyaya, A., Alok, K.S., 2016. Concept of water, land and energy productivity in agriculture and pathways for improvement. Irrigat. Drain. Syst. Eng. 5 (1), 154.
Wang, F., Mao, Q., 2017. Spatial dynamics of Chinese manufacturing industries: comparative advantage versus new economic geography. Appl. Econ. Finan. 4 (3), 30–46.
White, D., Hubacek, K., Feng, K.S., Sun, L.X., Meng, B., 2018. The water-energy-food nexus in East Asia: a tele-connected value chain analysis using inter-regional input-output analysis. Appl. Energy 210, 550–567. https://doi.org/10.1016/j.apenergy.2017.05.159.
Wichelns, D., 2010. Virtual water: a helpful perspective, but not a sufficient policy criterion. Water Resour. Manag. 24 (10), 2203–2219.
Xu, J., Li, C., Liu, H., Zhou, P., Tao, Z., Wang, P., Meng, Q., Zhao, M., 2015. The Effects of Plastic Film Mulching on Maize Growth and Water Use in Dry and Rainy Years in Northeast China. PLoS One 10 (5), e0125781.
Ye, Q.L., Li, Y., Zhuo, L., Zhang, W.L., Wei, X., Wang, C., 2018. Optimal allocation of physical water resources integrated with virtual water trade in water scarce regions: a case study for Beijing, China. Water Res. 129, 264–276.
Zhang, Z., Shen, Z., Xue, Y., Ren, F., Shi, D., Yin, Z., 2009. Evolution and Development of Groundwater Environment in North China Plain under Human Activities. Geological Publishing House, Beijing.
Zhao, X., Liu, J., Liu, Q., Tillotson, M.R., Guan, D., Hubacek, K., 2015. Physical and virtual water transfers for regional water stress alleviation in China. Proc. Natl. Acad. Sci. Unit. States Am. 112 (4), 1031–1035.
Zhao, X., Liu, J., Yang, H., Duarte, R., Tillotson, M.R., Hubacek, K., 2016. Burden shifting of water quantity and quality stress from megacity Shanghai. Water Resour. Res. 52 (9), 6916–6927.
Zhao, D., Tang, Y., Junguo, L., Tillotson, M.R., 2017. Water footprint of Jing-Jin-Ji urban agglomeration in China. J. Clean. Prod. 167, 919–928.
Zhong, H., Sun, L., Fischer, G., Tian, Z., Velthuizen, H., Liang, Z., 2017. Mission Impossible? Maintaining regional grain production level and recovering local groundwater table by cropping system adaptation across the North China Plain. Agric. Water Manag. 193, 1–12.
Zhuo, L., Mekonnen, M.M., Hoekstra, A.Y., 2016a. Consumptive water footprint and virtual water trade scenarios for China—with a focus on crop production, consumption and trade. Environ. Int. 94, 211–223.
Zhuo, L., Mekonnen, M.M., Hoekstra, A.Y., 2016b. The effect of inter-annual variability of consumption, production, trade and climate on crop-related green and blue water footprints and inter-regional virtual water trade: a study for China (1978-2008). Water Res. 94, 73–85.