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Agricultural infrastructure: The forgotten key driving force of crop-related water footprints and virtual water flows in China

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ABSTRACT

Here we identified and evaluated the strengths and spatio-temporal heterogeneities in 12 main socio-economic driving factors of water footprints and inter-provincial virtual water flows related to three staple crops (rice, wheat, and maize) within mainland China for 2000–2017, in consideration of the infrastructure related to irrigation, agricultural electricity and road for the first time. The irrigation, agricultural electricity, and road infrastructures in China expanded by 33.8, 4.5, and 2.4 folds, respectively, throughout the course of this study. The results show that irrigation infrastructure in water-scarce regions was the most critical driver for the effective reduction of the water footprint per unit mass of crops, particularly the blue water footprints (i.e. increasing water efficiency). As the irrigation infrastructure per unit area doubled for 2000–2008, blue water use efficiency and total blue water consumption decreased by 58% and 71%, respectively. However, the development of irrigation infrastructure has led to a larger total water footprint in crop production. Agricultural electricity and road infrastructures had increasing effects on provincial virtual water export, with varied corresponding driving strengths across spaces. The visible effects of agricultural infrastructure on regional water productivity, water consumption, and virtual water patterns should not be neglected. This analysis suggests that investments in agricultural infrastructure should consider the spatio-temporal heterogeneity of these infrastructures on local water productivity and water consumption in addition to the economic benefits.

1. Introduction

The development of infrastructure has significantly promoted the process of global urbanization and industrialisation, providing a material basis to realise efficient agricultural production systems (Leshner, 2016; Muller et al., 2015). Global investment in infrastructure is mainly concentrated in developing economies. Currently, 90% of the approximately one trillion USD annual investment demand into infrastructure, is focused on developing countries (Thacker et al., 2019; Laurance, 2018). China is the largest developing country and possesses the largest infrastructure and investment demand in the world (Thacker et al., 2019). Agricultural infrastructures are a key component of infrastructure, which improves agricultural production and trade (Li et al., 2012; Mamatzakis, 2003). In the past decade, China has launched a series of relevant policies to continuously increase the budget for agricultural infrastructures, including irrigation (II), agricultural electricity infrastructure (AEI), and road infrastructure (RI). In 2008, the Chinese government released the annual 'No. 1 Central Document' (The State Council of China, 2008), which pledged to 'strengthen agricultural infrastructure', emphasising that agricultural infrastructure construction was a priority for the country. The subsequently published No. 1 document (The State Council of China, 2011) proposed a plan to invest in excess of 619.3 billion USD in water conservancy infrastructure over the next decade (Liu and Yang, 2012). However, infrastructure can have negative environmental impacts, such as increased ecological degradation and the direct or indirect generation of greenhouse gas emissions

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(Laurance et al., 2015; Tsui, 2011; Doyle and Havlick, 2009). Infrastructures are widely used to extract, control, and transport natural resources. As such, understanding the potential impact of infrastructure on the environment is crucial to formulate effective environmental protection policies. To date, several studies have focused on the impacts of dam, energy, and road infrastructures on biodiversity loss and carbon emissions (e.g. Ryu et al., 2019; Laurance et al., 2014; Davis et al., 2010). However, there is limited research on the impacts of agricultural infrastructures on water resource consumption and flows related to agricultural production and trade (Liu et al., 2013; Palmer, 2010). This knowledge is particularly useful in developing countries that are undergoing rapid developments in agricultural infrastructure investment and demand, while experiencing increasing water scarcity.

The water footprint (WF) (Hoekstra, 2003) measures indirect and direct water appropriation by anthropogenic activities. It is measured in terms of the source and volume of water consumption and its associated impacts on the environment. The WFs to produce traded products and services constitute the embedded virtual water (VW) flows through trade (Allan, 1998). With intensive trade across the world, the VW cycle has become an integral and important part of the modern global water cycle (D'Odorico et al., 2019). The VW cycle sheds light on the redistribution of water resources and the increasing water crisis due to trading within an open and globalised economic framework (Zhao et al., 2015; Dalin et al., 2012). Crop production is the largest consumer of water resources (by 92%) and is also the largest contributor of the global VW trade (by ~20%) (Hoekstra and Mekonnen, 2012). As such, a growing number of studies have focused on the socio-economic driving forces of the formation and spatio-temporal evolution of crop-related WF and VW flows at global and local scales (Soligno et al., 2019; Qian et al., 2018; Wang et al., 2016; Xu et al., 2015; Tamea et al., 2014; Zhao et al., 2014a; Dalin et al., 2012). Table 1 summarises the representative literature on the driving factor analysis of crop-related WFs and VW flows. At the global scale, population (Soligno et al., 2019) and economic development (Wang et al., 2016) were considered the most important factors influencing crop WFs and VW flows. At the sub-national scale, the dominant driving factors vary between regions, particularly in China. Xu et al. (2015) showed that production scale was one of the dominant driving factors of crop WFs in Beijing city, while Feng et al. (2017) demonstrated that the urbanization rate is the most important driver for crop WFs during the rapid urbanization in Zhangye city. Finally, Qian et al. (2018) reported that economic scale was the driving factor governing the water-rich yet underdeveloped Yunnan Province. Similarly, Zhao et al. (2019) claimed that land productivity differences were key influencing factors in promoting inter-provincial VW flows in China.

However, few studies have considered the spatio-temporal differences in the drivers of crop-related WFs and VW flows across various regions and periods of time. These spatio-temporal differences hold key insights that may inform precise water resource management and differentiated decision-making among regions that differ in terms of economic structure and water endowments (Li et al., 2021). Li et al. (2021) showed significant spatial heterogeneity in the driving forces of crop-related WFs and VW flows; however, they only focused on the Beijing-Tianjin-Hebei region. In the context of huge imbalances within China, research on the heterogeneity of the driving forces of crop WFs and VW flows is the foundation for customised water resource management for regions endowed with different water resources. Existing studies have investigated the driving forces of crop-related WFs or VW flows independently, and few studies have comprehensively analysed the drivers of WFs and VW flows. Such a comprehensive analysis can provide feasible solutions that address water problems from the agricultural production, consumption, and trade perspectives.

Overall, there have been three approaches widely used to investigate the driving forces of crop-related WFs and VW flows: logarithmic-mean divisia index (LMDI) exponential decomposition (e.g. Qian et al., 2019; Xu et al., 2015; Zhao et al., 2014b), structural decomposition analysis

Table 1
Summary of representative literature on the driving forces of crop-related water footprints (WFs) and virtual water (VW) flows relating to crop production, consumption, and trade.

References	Methods	Object	Main positive (+) and negative (−) driving forces
Zhao and Chen (2014a)	LMDI	WF	Per capital GDP (+); population (+); diet structure (+); water use intensity (−)
Zhao et al. (2014b)	STIRPAT	WF	Population (+); per capital GDP (+); diet structure (+); urbanization (+)
Xu et al. (2015)	LMDI	WF	Population (+); production scale (+); plantation structure (+); technology effect (−); urbanization (−)
Jin et al. (2016)	STIRPAT	WF	Engel coefficient (+); urbanization (+); total agricultural electricity (−); population (−); per capital GDP (−)
Wang et al. (2016)	STIRPAT	WF, VW	Per capital GDP (+); population (+); arable land availability (+); proportion of domestic water (−)
Feng et al. (2017)	SDA	WF	Urbanization (+); per capital GDP (+); water use intensity (−); industrial structure (−); planting structure (−)
Qian et al. (2018)	SDA	WF	Gross economic scale (+); economic structure (−); technology (−)
Soligno et al. (2019)	SDA	WF	Per capital GDP (+); population (+); water use intensity (−)
Dalin et al. (2012)	Fitness model	VW	Population (+); total GDP (+); rainfall (+); agricultural area (+)
Tamea et al. (2014)	Gravity law	VW	Population (+); total GDP (+); geographical trade distances (−)
Qian et al. (2019)	LMDI	VW	Trade structure (+); water use intensity (−); product structure (−); trade scale (−)
Cai et al. (2019)	SDA	VW	Per capital GDP (+); production structure (+); trade structure (+); water use intensity (−)
Zhao et al. (2019)	Liner regression	VW	Land productivity (+); irrigation land (+); population (−)
This study	STIRPAT	WF, VW	Agricultural infrastructures; population; per capital GDP; water use intensity

(SDA) (e.g. Soligno et al., 2019; Cai et al., 2019; Qian et al., 2018; Feng et al., 2017), and stochastic impacts by regression on population, affluence, and technology (STIRPAT) (e.g. Wang et al., 2016; Jin et al., 2016; Zhao et al., 2014) (see Table 1). The LMDI has no residual error (Ang, 2005), and the SDA is based on input-output analysis to subdivide the research object into various departments for decomposition (Su and Ang, 2012); however, these two methods have limitations. Although the LMDI can achieve non-residual decomposition and quantify the contribution from each influencing factor, it is unable to examine the elasticity of each factor. This elasticity refers to the change in the dependent variable caused by a change in an independent variable, while other factors remain static. In the SDA method, data needs to be acquired for consecutive years, which is a major obstacle when there is limited availability of input–output tables (Zhao et al., 2014). The advantage of the STIRPAT model is that the model estimates the influence of various factors as parameters, and the model may be extended based on its own research purposes (Waggoner and Ausubel, 2002). The STIRPAT model has been widely used, including in research on the driving factors of environmental impacts (e.g. Gao et al., 2019; Ren et al., 2018; Zhao et al., 2014b; York et al., 2003).

This study aims to investigate the driving forces of WF and VW flows in terms of their magnitudes and spatio-temporal differences as it relates to the production, consumption, and trade of staple crops (including rice, wheat, and maize) in mainland China from 2000–2017 at the provincial scale (Fig. 1). This study uses China as a case study; compared to the existing research, a number of improvements have been made for three aspects:

Fig. 1. Provinces in mainland China divided into eight economic regions based on the socio-economic development of different regions (Zhuo et al., 2016; Dalin et al., 2014; Ma et al., 2006).

(i) To the best of our knowledge, this is the first study in which the development of major agricultural infrastructures (irrigation, agricultural electricity, and roads) is considered in the driver evaluation of crop-related water consumption and VW flows;
(ii) This study provides a comprehensive analysis of the driving forces of crop-related WFs and VW flows, distinguishing blue water (surface water and groundwater), and green water (rainwater); and
(iii) This study investigates the spatio-temporal variations in the driving forces of crop-related WFs and VW flows.

2. Methods and data

2.1. Estimation of WFs in crop production and consumption

The total green and blue WFs ($m^3 \cdot y^{-1}$) to produce a crop in a province were the product of total production ($t \cdot y^{-1}$) and the WF of the unit mass of the crop; this is the unit crop WF (*uWFP*, in $m^3 \cdot t^{-1}$). The annual green and blue WFs per unit mass of a crop at the provincial scale over 2000–2008 were obtained from Zhuo et al. (2016). The WFs values for crop production from 2009 to 2017 were estimated using the 'Fast Track' approach (Tuninetti et al., 2017), where the year 2008 was used as the reference:

$$uWFP_t[c] = \frac{uWFP_{2008}[c] \ \times \ Y_{2008}[c]}{Y_t[c]} \tag{1}$$

where $uWFP_t[c]$ and $uWFP_{2008}[c]$ ($m^3 \cdot t^{-1}$) refer to the production WF of the unit mass of crop, *c*, in year *t* (t = 2009, 2010 … 2017) and 2008, respectively; and $Y_t[c]$ and $Y_{2008}[c]$ ($t \cdot ha^{-1}$) are the yield per unit area of crop, *c*, in year *t* (t = 2009,2010,2017) and 2008, respectively. Tuninetti et al. (2017) demonstrated that the annual variability of unit crop WF is mainly determined by the crop yield, where the former has a negative linear relationship with the latter. This Fast Track method has been widely applied to calculate the unit crop WF (Tuninetti et al., 2017), owing to its lower computational cost and error (less than 0.1) (Gao et al., 2020; Soligno et al., 2019; Abdelkader et al., 2018).

The total green and blue WFs ($m^3 \cdot y^{-1}$) of crop consumption in a province were defined as the local crop production and trade together with the corresponding unit crop WF of the province in exporting regions (Hoekstra et al., 2011). The consumption WF of a unit mass (*uWFC*, in $m^3 \cdot t^{-1}$) within a province may be expressed as:

$$uWFC_{prov}[c] = \begin{cases} \dfrac{P_{prov}[c] \times uWFP[c] \ + \Sigma_e (NI_e[c] \times uWFP_e[c])}{P_{prov}[c] + \Sigma_e NI_e[c]} & (NI_e[c] \geq 0) \\ uWFP[c](NI_e[c] < 0) & \end{cases} \tag{2}$$

where $P_{prov}[c]$ ($t \cdot y^{-1}$) denotes the production volume of crop, *c*, within the province; $NI_e[c]$ ($t \cdot y^{-1}$) refers to the net import volume of crop, *c*, from exporter, *e* (outside provinces in China or exterior countries); $uWFP[c]$ ($m^3 \cdot t^{-1}$) is the unit WF of crop, *c*, produced in the province; and $uWFP_e[c]$ ($m^3 \cdot t^{-1}$) is the unit WF of crop, *c*, produced in the exporting region, *e*.

2.2. Estimation of crop-related provincial VW balances

The total net VW import (*VWI[c]*, $m^3 \cdot y^{-1}$) related to crop, *c*, was defined by the net import volume (*NI [c]*, $t \cdot y^{-1}$) and the unit WF of crop production (*uWFP [c]*, $m^3 \cdot t^{-1}$):

$$VWI[c] = NI_{dom}[c] \times uWFP_{dom}[c] + NI_{int}[c] \times uWFP_{int}[c] \tag{3}$$

where $NI_{dom}[c]$ and $NI_{int}[c]$ refer to the total net import volume of crop, *c*, from outside provinces in China and other countries, respectively; and $uWFP_{dom}[c]$ and $uWFP_{int}[c]$ are the unit WFs of crop production in the corresponding domestic and international export regions, respectively. Data on WFs ($m^3 \cdot t^{-1}$) for exterior countries were obtained from Mekonnen and Hoekstra (2011), and the domestic provincial net VW imports ($m^3 \cdot y^{-1}$) of crop, *c*, were calculated as per Zhuo et al. (2016).

The trade balance of each crop per province was estimated by downscaling the Food and Agriculture Organisation (FAO) food balance sheet (FAO, 2020) based on the assumptions of Ma et al. (2006); this has been widely used to simulate Chinese sub-national food trade networks (Gao et al., 2020; Zhuo et al., 2016; Dalin et al., 2014). Specifically, we assumed that international imports and exports of a crop occur in provinces experiencing crop deficits and surpluses, respectively. Following the consideration of international imports and exports, the provincial import and export quantity of a crop were estimated by subtracting the production in the entire province from its consumption, assuming no changes in food stock.

Rice, wheat, and maize are staple food crops in mainland China, and their annual average production accounts for 87% of the total grain production in China (Jiang et al., 2017); as such, the WFs and VW flows of these three crops are the focus of this study.

2.3. The extended STIRPAT model

In this study, the extended STIRPAT model was used to identify the driving forces of WFs and VW flows relating to crop production, consumption, and trade. The basic and logarithmic forms of STIRPAT proposed by Dietz and Rosa (1997) are:

$$I = aP^b A^c T^d e \tag{4}$$

$$\ln I = a + b(\ln P) + c(\ln A) + d(\ln T) + lne \tag{5}$$

where I, P, A, and T refer to the environmental impact, population, affluence, and technology, respectively; a is a constant term; b, c, and d are estimated model coefficients; and e is the random error. In logarithmic form, b, c, and d represent the elasticity of P, A, and T, respectively, on environmental impact. This indicates the percentage change in environmental impact caused by a 1% change in a specific independent variable when all other independent variables are constant.

The STIRPAT model may be extended by adding, reducing, or decomposing factors to improve model analysis and interpretation (York et al., 2003). To comprehensively investigate the driving forces of WFs and VW flows related to crop production, consumption, and trade, we extended the STIRPAT model by including three categories of twelve variables into the model. The selection of these variables was based on widely validated indicators in the literature (see Table 1) and the results from stepwise regression. The three categories of variables include indicators relating to agricultural infrastructure, population scale and economic development, and agricultural production. Using the WF of crop production as an example, the improved STIRPAT model may be expressed as:

$$lnWFP_i = a_i + \beta_1 \ln II_i + \beta_2 \ln AEI_i + \beta_3 \ln RI_i + \beta_4 \ln POP_i + \beta_5 \ln pGDP_i + \beta_6 \ln\%TIA_i + \beta_7 \ln\%TIA_i + \beta_8 \ln AWI_i + \beta_9 \ln WSI_i^{\cdot} + \beta_{10} \ln PS_i^{\cdot} + \beta_{11} \ln ALA_i^{\cdot} + \beta_{12} \ln FER_i^{\cdot} + \varepsilon_i^{\cdot} \tag{6}$$

where WFP_i is the WF of crop production in province, i; II represents irrigation infrastructure (expressed as irrigation investment per unit effective irrigation area); AEI refers to agricultural electricity infrastructure (expressed as per capita electricity consumption of the agricultural population); RI denotes road infrastructure (expressed by road mileage per unit territory area); POP refers to population size (expressed by total population); $pGDP$ represents affluence (expressed by per capita GDP); $\%PIA$ refers to the proportion of the primary industry; $\%TIA$ represents the proportion of the tertiary industry; AWI denotes the agricultural water use intensity; WSI is the water stress index; PS refers to planting structure; $pALA$ denotes the per capita arable land area; and FER is the fertiliser amount.

The II, being one of the core explanatory variables in this study, may be measured in two ways: (1) the level of public investment (Mamatzakis, 2003) and (2) the use of physical objects (such as effective irrigation area) to represent its development level (Teruel and Kuroda, 2005). The uncertainty caused by increasing private investment, maintenance, and regional price differences is neglected by (1), while (2) is unable to fully represent the infrastructure development (Teruel and Kuroda, 2005). As such, (1) and (2) were combined, whereby the amount of irrigation investment per unit effective irrigation area was used to characterise the development level of II. AEI was represented by the per capita electricity consumption of the agricultural population, as per previous studies (Jin et al., 2016; Mamatzakis, 2003). Although it includes the electricity consumption of the agricultural population in day-to-day life, it is typically a small component of the total electricity consumption (~13% in China in 2017) based on data from the China National Energy Administration (2018). RI was denoted by road density (mileage of roads per km^2) (Tan et al., 2018). Table 2 provides the descriptive statistics of the variables used in this study.

A multicollinearity diagnosis of the independent variables was required prior to regression. The variance inflation factor (VIF) is the most commonly used index to test collinearity (Stine, 1995). Generally, if VIF $\leq$10, there is no clear multicollinearity (Freund et al., 2006). Table S1 presents collinearity diagnosis information of the independent variables. The results indicate that the VIFs of all variables were less than the threshold of 10; this means that there was no clear multicollinearity.

Table 2
Descriptive statistics of dependent and independent variables used in this study.

		Symbol	Variables	Unit	Mean (logarithm)	SD (logarithm)
Dependent Variables		$uWFP_b$	Unit blue water footprint of crop production	m^3 t^{-1}	5.11	1.29
		uWFP	Unit green-blue water footprint of crop production	m^3 t^{-1}	7.00	0.39
		WFP_b	Total blue water footprint of crop production	Gm^3 y^{-1}	7.23	1.82
		WFP	Total green-blue water footprint of crop production	Gm^3 y^{-1}	9.13	1.41
		WFC_b	Total blue water footprint of crop consumption	Gm^3 y^{-1}	7.86	0.99
		WFC	Total green-blue water footprint of crop consumption	Gm^3 y^{-1}	9.46	0.91
		VWI_b	Total domestic blue virtual water import	Gm^3 y^{-1}	7.00	0.94
		VWI	Total domestic green-blue virtual water import	Gm^3 y^{-1}	8.56	0.87
		VWE_b	Total domestic blue virtual water export	Gm^3 y^{-1}	4.46	3.42
		VWE	Total domestic green-blue virtual water export	Gm^3 y^{-1}	6.15	3.9
Independent Variables	I	II	Irrigation infrastructure	USD ha^{-1}	4.27	1.40
		AEI	Agricultural electricity infrastructure	kW·h pp^{-1}	6.15	1.27
		RI	Road infrastructure	km km^{-2}	3.91	0.94
	II	POP	Total population	10^3	10.38	0.86
		pGDP	Per capita GDP	Dollars pp^{-1}	7.79	0.81
		%PIA	Proportion of primary industry added value to GDP	%	10.97	6.79
		%TIA	Proportion of tertiary industry added value to GDP	%	41.01	7.28
	III	AWI	Agricultural water consumption per 1000 dollars GDP	m^{3}10^{-3} dollars	3.23	0.66
		WSI	Total water consumption divided by freshwater availability		0.53	0.58
		PS	Proportion of three staple food crops to total crops sown area	%	65.54	12.27
		pALA	Per capita arable land area	ha	6.77	0.77
		FER	Fertilizer amount	10^3 t	5.75	0.37

2.4. Geographic weighted regression

To further investigate the spatial differences of driving factors at the provincial scale, we adopted the geographically weighted regression (GWR) method. The GWR embeds spatial coordinates into the regression parameters and replaces global parameter estimation with local parameter estimation for each sample point. This compensates for the inability of estimated parameters to vary with the spatial position of ordinary least squares (OLS) regression in the global regression model (Brunsdon et al., 1998). Therefore, GWR is more conducive to exploring spatial non-stationary characteristics in real situations with heterogeneity of sample points over spaces (Fotheringham et al., 2002). The basic form of the GWR model is:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \tag{7}$$

where y_i denotes the dependent variable of point, i; X_{ik} is the independent variable; k is the number of independent variables ($k = 1, 2, 3, p$); (u_i, v_i) represents the spatial coordinates of point, i; $\beta_0(u_i, v_i)$ indicates the intercept; $\beta_k(u_i, v_i)$ is the local parameter estimate of the kth variable with coordinates of point, i; and ε_i stands for the random error of point, i.

The weighted least square was selected to estimate the parameters of each observation point in the GWR model. Additionally, the Gaussian kernel function was used to construct the weighting function (Fotheringham et al., 2002):

$$w_{ij} = \exp\left[-\left(\frac{d_{ij}}{b} \right)^2 \right] \tag{8}$$

where w_{ij} is the weight of point, j, to observation point, i; b is the bandwidth; and d_{ij} is the distance between points i and j. If the data of i is observed, the weights of other points will decrease with an increase in d_{ij} as per the Gaussian curve (Fotheringham et al., 2002). The optimal bandwidth was determined based on the minimum Akaike information criterion (AICc) proposed by Fotheringham et al. (2002):

In this study, the GWR model was applied to analyse the spatial effect of driving factors. Using WFP as an example, the regression model is:

$$WFP_i[c] = \beta_0(u_i, v_i) + \sum_{k=1}^{12} \beta_1(u_i, v_i) LnII_i + \varepsilon_i \tag{9}$$

where $WFP_i[c]$ is the crop production WF of province, i; II_i represents the driving factor of II in province, i; k denotes the number of independent variables ($k = 1,2 \ldots 12$); and i refers to different provinces ($i = 1, 2, 3 \ldots, 31$).

2.5. Structural equation model (SEM)

The STIRPAT model is only able to reflect the total influence of specific driving factors on the dependent variable, and it fails to measure direct and indirect effects separately (Li et al., 2011). The structural equation model (SEM) is a priori model which can address complicated causality between variables (Schreiber et al., 2006); this model has been widely used in the fields of psychology, environmental science, and ecology (Colman and Schimel, 2013; Cubaynes et al., 2012; MacCallum and Austin, 2000). In this study the SEM was used to quantify the causal mechanism of the main drivers (identified by the STIRPAT model) that affect WFP. Specifically, the model may be further decomposed into direct, indirect, and net effects based on the path coefficient. The explanatory variables were divided into two groups: exogenous variables and endogenous variables. The former includes II, population, per capita GDP, agricultural water intensity, and per capita arable land area; these were selected based on the results of the former driving force analysis. The endogenous variables include crop yield and uWFP.

2.6. Data sources

Data on agricultural infrastructure variables were sourced from the Chinese Water Conservancy Statistical Yearbook cited in the China National Knowledge Infrastructure project (CNKI, 2020); this includes the data on the amount of irrigation investment in each province. Data on the per capita arable land area was sourced from the Chinese Rural Statistical Yearbook of China National Knowledge Infrastructure project (CNKI, 2020). Data on the effective irrigation area, agricultural electricity consumption, agricultural population, road mileage, and land area for each province, data on the socio-economic variables (i.e. provincial population, per capita GDP, and the added value of primary and tertiary industries), and data on the agricultural production variables (i.e. crop yield, production, planting area, and amount of fertiliser application at the provincial scale) were obtained from the national data network of the National Bureau of Statistics of China (NBSC, 2020). Data on the total and agricultural water withdrawal were sourced from the Water Resources Bulletin of the Ministry of Water Resources of the People's Republic of China (MWRC, 2020). The data on per capita consumption and international trade volume of each crop were extracted from FAOSTAT (FAO, 2020). To eliminate the impact of price change and ensure comparability, data on economic-related variables (i.e. irrigation investment, per capita GDP, the added value of primary and tertiary industries) were converted into constant prices based on the year 2000.

3. Results

3.1. Rapid development of agricultural infrastructure in China

The agricultural infrastructure in China has grown rapidly in the first 18 years of the 21st century (Fig. 2a). Over the period from 2000 to 2017, II increased by 33.8, whereas the AEI and RI increased by 4.5 and 2.4 times for mainland China, respectively. The investment in II per hectare of effective irrigation area increased from only 12.1 USD in 2000 to 420.2 USD in 2017; this signifies an average annual growth rate of 190.0% (Fig. 2a). This high-speed growth trend commenced in 2009, with a growth rate of 585.2% from 2009 to 2017, compared to a growth rate of 138.7% from 2000 to 2008. This major growth surge from 2009 to 2017 may be due to the Chinese government adopting an investment plan of ~619.3 billion USD in water conservancy infrastructure, following the 2008 economic crisis. Note that the multi-year average proportion of II investment to water conservancy infrastructure investment was 14.5% (Liu and Yang, 2012).

In terms of provincial variations in agricultural infrastructure development within China, the distribution of II was related to national policies (Fig. 2b), while AEI and RI were mainly restricted by regional economic development levels (Fig. 2c and d). The II in northern regions such as Tibet, Qinghai, and Heilongjiang with a relatively slow-growing economy was higher than that in eastern regions, such as Jiangsu and Zhejiang that have a relatively developed economy. This shows that under national policies such as the strategies of western development and the revitalisation of Northeast China, the investments for II were focused on the northern areas that were characterised by better land, radiation resources, and higher land productivity. Over the study period, Beijing and Shanghai were provinces experiencing the most rapid growth in II, by 123.8 times and 64.8 times, respectively. Despite the decreasing irrigation area in these municipalities, the investment amount into irrigation was constantly increasing, leading to a boom in II. The AEI and RI variables showed the opposite trend; by 2017, the AEI and RI in Beijing, Guangdong, Shanghai, and Jiangsu were higher than those in other provinces, and the per capita GDP of these four provinces were also higher than other provinces. This means that the AEI and RI were consistent with the level of regional economic development. Although the level of agricultural infrastructure was relatively low in 2017 in several provinces, there were rapid growth rates; this includes II

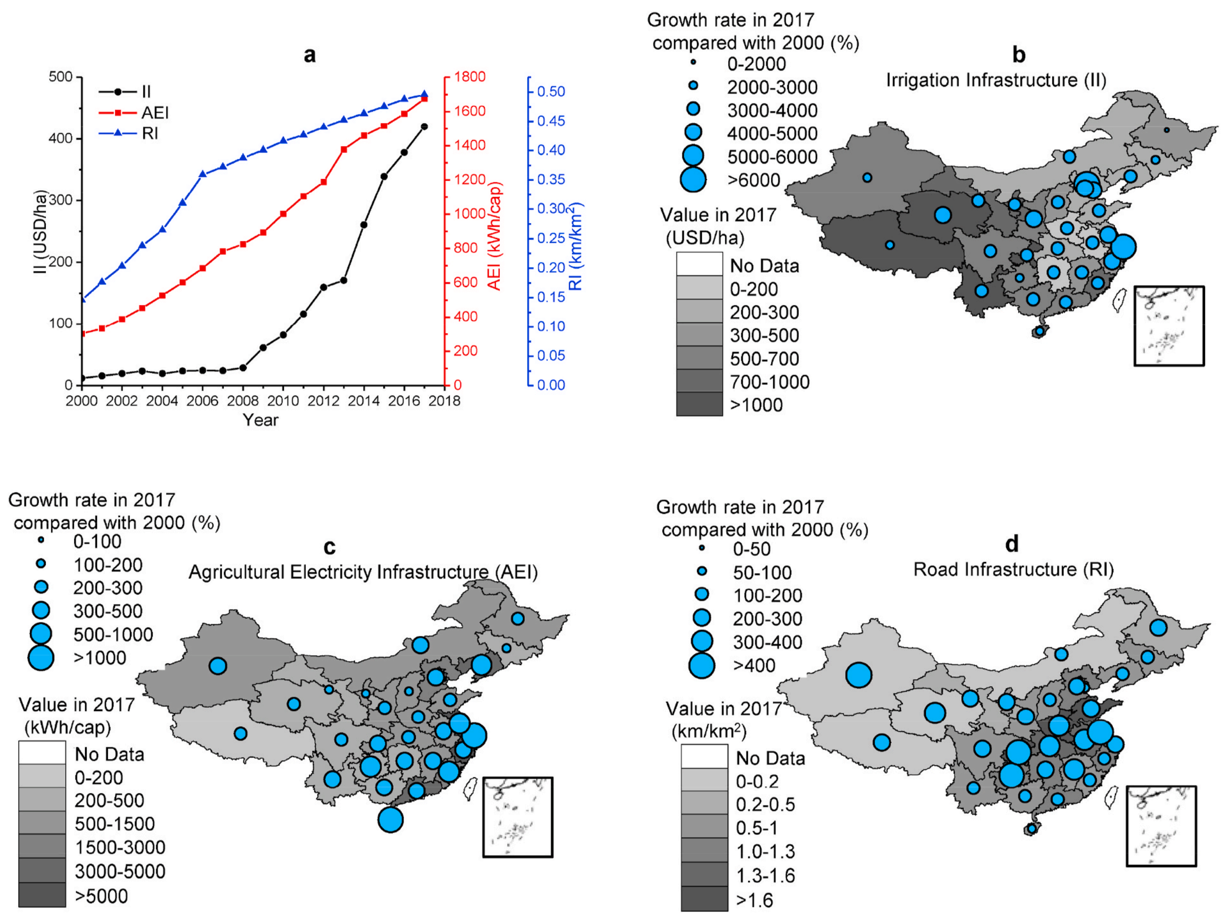

Fig. 2. Development in agricultural infrastructures within mainland China: (a) annual development of three types of agricultural infrastructure for the entire country from 2000 to 2017; (b)–(d) represents the development level (grey background) of irrigation infrastructure (II), agricultural electricity infrastructure (AEI), and road infrastructure (RI), respectively, at the provincial scale in 2017 and the growth rate (blue circle) compared with 2000.

Table 3
Crop related total and blue water footprints (WFs), and virtual water (VW) flows at the national scale in 2000 and 2017.

WF/VW	2000			2017		
	Rice	Wheat	Maize	Rice	Wheat	Maize
$uWFP_b$ (m^3t^{-1})	408.8	538.2	87.69	362.9	306.2	47.85
uWFP (m^3t^{-1})	1409	1738	908.0	1269	1195	677.7
WFP_b (Gm^3y^{-1})	76.83	53.62	9.295	77.19	41.13	12.40
WFP (Gm^3y^{-1})	264.7	173.2	96.26	269.9	160.5	175.6
WFC_b (Gm^3y^{-1})	75.72	53.92	8.378	78.15	42.64	12.53
WFC (Gm^3y^{-1})	260.9	174.6	86.76	274.1	167.7	177.4
*$VWI_{b,int}$ (Gm^3y^{-1})	0	0.2991	0	0.8201	0.9105	0.1296
*VWI_{int} (Gm^3y^{-1})	0	1.415	0	3.581	5.044	1.796
*$VWE_{b,int}$ (Gm^3y^{-1})	1.102	0	0.9175	0	0	0
*VWE_{int} (Gm^3y^{-1})	3.796	0	9.501	0	0	0

*$VWI_{b,\ int}$.
*VWI_{int}.
*$VWE_{b,\ int}$.
*VWE_{int} denote the international blue VW import, green-blue VW import, blue VW export and green-blue VW export, respectively.

in Beijing, Tianjin, and Hebei, AEI in Guizhou and Liaoning, and RI in Guizhou and Chongqing.

3.2. *Spatio-temporal evolution of crop-related WFs and VW flows*

At the national scale, the uWFPs of rice, wheat, and maize decreased by 9.9%, 31.3%, and 25.4%, respectively, over the study period. The $uWFP_b$ experienced a decrease of 11.2%, 43.1%, and 45.4% for rice, wheat, and maize, respectively, as the crop yield increased by 10.5%, 46.6%, and 32.9%, respectively (Table 3). The national WFP of maize increased by 82.5% due to a 144.5% increase in the crop production. By contrast, the WFP_b of wheat experienced a downward trend by 23.3%, while maize experienced a rising trend of 33.4%. This is mainly because the area of wheat sown decreased by 8.0% over the study period, while that of maize increased by 84.0%. Over the study period, WFC decreased by 4.0% for wheat and increased by 104.5% for maize; this may be related to the transformation of dietary structure in China. Correspondingly, the related international total net VW import of these three crops increased by 6.4 times (~10.42 Gm^3 y^{-1} in 2017) driven by a 2.6-fold import of wheat.

Among the eight economic regions within China, the largest drop in uWFP was observed in the southwest (38.0%) and north coast (34.4%) regions. The Jing-Jin region experienced the highest decline (56.0%) in $uWFP_b$, followed by the north coast, with a decrease of 52.3% (Fig. 3a). The WFP increased by 108.2% in the northeast region and decreased by 33.3% in the south coast region (Fig. 3b). With the exception of a slight increase in WFP_b in the central region, this variable decreased in each region; this decrease amounted to >50% in the Jing-Jin region due to

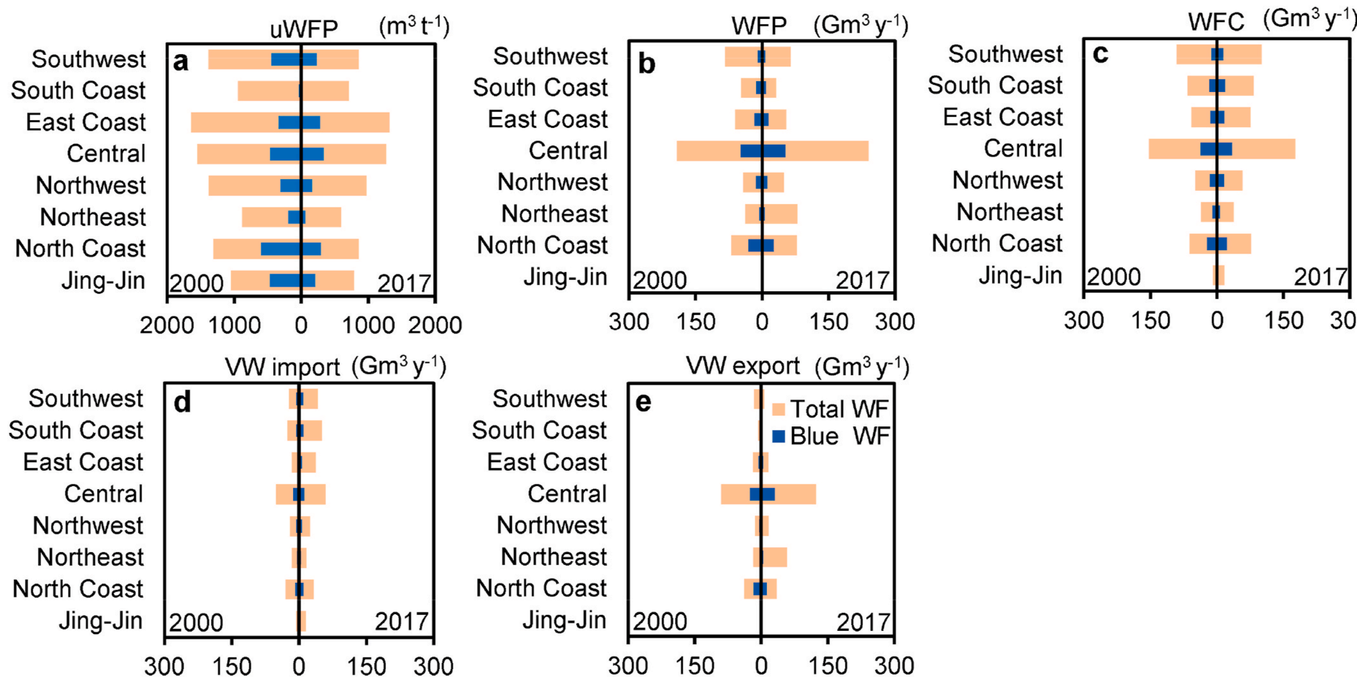

Fig. 3. Crop related water footprints (WFs) and virtual water (VW) flows in eight regions within mainland China in 2000 (left side of coordinate origin) and 2017 (right side of coordinate origin): (a)–(e) represents the unit WF of crop production (uWFP), total WF of crop production (WFP), total WF of crop consumption (WFC), total VW import (VWI), and total VW export (VWE), respectively. The orange and blue columns indicate the green-blue WFs and blue WF, respectively.

shrinking the production scale of water-intensive crops such as wheat. With a 131.2% increase in crop consumption, the WFC in the Jing-Jin region increased by 80% over the study period (Fig. 3c). The east coast, Jing-Jin, and south coast were regions with the fastest growth of VWI, increasing by 131.5%, 125.5%, and 98.4%, respectively (Fig. 3d). By 2017, the VWE and VWE_b increased by 221.7% and 261.6% in the northeast region, respectively (Fig. 3e). The central and northeast regions supported 71.4% of the VWE, placing substantial pressure on the sustainability of regional water resources in these regions, particularly groundwater resources extracted for irrigation.

3.3. Driving force analysis

3.3.1. Driving force results at the national level

For China in its entirety, the OLS results on the national scale show that the II was a significant negative driver of $uWFP_b$, WFP_b, and WFP. Additionally, the role of II in reducing $uWFP_b$ and WFP_b was more critical than the main drivers identified in previous studies, such as per capita GDP and agricultural water use intensity. Population was the most positive driver of WFP, WFC, and VW flows (Table 4). The elasticity coefficient of II on $uWFP_b$ was higher than uWFP. When II increased by 1%, the $uWFP_b$ decreased by 0.58% over the 2000–2008 period, and this value decreased to 0.26% for 2009–2017. This indicates that the effect of II on $uWFP_b$ weakened as the marginal effect of II investment was diminishing. A same tendency was consistently observed in WFP_b. The absolute value of the regression coefficient of II to the WFP_b decreased from 0.71 to 0.27 for 2000–2008 and 2009–2017, respectively; this represents a decrease of 62.0%. From 2000–2008, for each 1% growth in population, the agricultural water intensity, and fertiliser application, the WFP increased by 1.25%, 0.55%, and 0.31%, respectively; in 2009–2017, these values were 1.39%, 0.71%, and 0.16%, respectively. These results demonstrate that the role of population and agricultural water intensity strengthened as the former exerted increasing pressure on the water resources systems used for crop production. The population was the most significant positive driving factor affecting WFC. Per capita GDP had a considerable positive effect on the international crop-related VW imports and exports, showing that affluence was likely to accelerate crop VW flows. The three types of agricultural infrastructures significantly influenced the national crop-related VWEs to different extents and in various directions.

3.3.2. Spatio-temporal differences of driving forces—uWFPb, WFPb, VWIb, and VWEb

Based on the local regression results of GWR, four blue WFs or VW flow variables (i.e. $uWFP_b$, WFP_b, VWI_b, and VWE_b) with significant spatial differences were selected for analysis to understand the more important role of blue water (Wang et al., 2016; Soligno et al., 2019). Notably, the WFC_b was mainly driven by population, while the other factors had less influence; as such, it was not analysed separately here. Additionally, the driving forces were found to have little change between provinces within the same economic region as those adjacent characteristics and structure of crop production and trade in provinces within a specific region. Therefore, the analysis focused on eight areas.

Fig. 4 shows the spatial heterogeneity of the driving forces on crop-related WF and VW flows at the provincial scale in China for the two stages in 2000–2008 and 2009–2017. In terms of $uWFP_b$ for the first half of the study period (i.e. 2000–2008), the per capita GDP was the cardinal negative driving factor in the Jing-Jin, north coast, and northeast regions, whereas II was the equivalent for the northwest, central, and southwest regions (Fig. 4a). For the second half of the study period (Fig. 4b) (i.e. 2009–2017), the per capita GDP became a positive driver of $uWFP_b$ in the central, south coast, and southwest regions; the role of II had decreased over this period. Agricultural water use intensity and the amount of fertiliser application were consistently the strongest positive driving factors for $uWFP_b$; however, the impact of these two factors continued to weaken in the Jing-Jin and north coast regions.

In terms of the WFP_b (Fig. 4c and d), II continued to be the main negative driving factor, particularly in the Jing-Jin, north coast, and northwest regions. By contrast, II was a slight positive driver of WFP in 12 provinces experiencing water shortage; these were mainly located in the north coast and central regions; this indicates that the development of II may prompt more water resource consumption in these major crop production regions (Fig. S1). Population, per capita GDP, agricultural water intensity, and the amount of fertiliser application were the main

Table 4
Driving force results on crop related water footprints (WFs) and virtual water (VW) flows at the national scale.

Time	Dependent variables	II	AEI	RI	POP	pGDP	%PIA	%TIA	AWI	WSI	PS	pALA	FER
2000–2008	$uWFP_b$	−0.58***	−0.23*	−0.44***	–	−0.46**	−0.09***	−0.07***	1.52***	–	0.01	−1.36***	1.31***
	uWFP	0.02	−0.01	0.05	–	−0.38***	0.00	−0.02***	0.24***	–	0.00	−0.45***	0.28***
	WFP_b	−0.71***	−0.42***	−0.27*	1.48***	0.01	−0.07***	−0.08***	1.85***	−0.01	0.02***	−0.81***	1.38***
	WFP	−0.19***	−0.09	0.33***	1.25***	−0.08	0.01*	−0.04***	0.55***	−0.12*	0.01***	0.15*	0.31***
	WFC_b	−0.28***	−0.01	−0.13*	0.92***	−0.07	−0.03***	−0.02***	0.62***	−0.04	0.00	−0.31***	0.49***
	WFC	−0.03	−0.02	0.06**	0.99***	−0.13***	−0.01*	−0.01**	0.18***	−0.09***	0.00	−0.16***	0.20***
	*$VWI_{b,\ int}$	−0.08	−0.01	−0.40***	0.79***	0.30	−0.02	0.01	−0.37***	0.04	−0.01	−0.10	−0.21
	*VWI_{int}	−0.13**	−0.04	−0.25***	0.81***	0.36***	−0.01	0.01	−0.17*	−0.18*	−0.01*	−0.27***	−0.15
	*$VWE_{b,\ int}$	−1.44***	−1.93***	−0.80**	2.24***	0.92*	−0.04	−0.16***	2.67***	0.95**	0.04**	−0.84*	3.01***
	*VWE_{int}	−1.20***	−1.40***	−0.59	2.14***	1.09*	0.06	−0.12***	1.43***	0.68	0.07***	0.44	2.26***
2009–2017	$uWFP_b$	−0.26***	−0.10	−0.35**	–	−0.06	−0.10***	−0.06***	1.19***	–	−0.01	−0.84***	1.40***
	uWFP	0.03	−0.04	0.15***	–	−0.01	0.02*	−0.02***	0.19***	–	−0.01***	−0.27***	0.13
	WFP_b	−0.27***	−0.46***	−0.26	1.97***	0.97***	−0.04	−0.06***	1.65***	0.29*	0.00	−0.19	1.25***
	WFP	−0.09***	−0.19***	0.59***	1.39***	0.70***	0.06***	−0.03***	0.71***	−0.16***	0.00	0.60***	0.16*
	WFC_b	−0.05	−0.06	−0.26***	1.11***	0.15	−0.05***	−0.01	0.18*	0.25***	−0.01***	0.02	0.39***
	WFC	0.05***	−0.09***	0.09**	1.04***	0.13**	−0.01	0.00	0.13***	−0.04	0.00**	−0.04	0.17***
	*$VWI_{b,\ int}$	0.07	0.08	−0.67***	0.91***	−0.07	−0.04**	0.02**	−0.68***	0.24**	−0.01**	−0.13	−0.13
	*VWI_{int}	0.02	−0.01	−0.30***	0.90***	0.21*	−0.02*	0.01**	−0.27***	−0.1	−0.01*	−0.28***	−0.13
	*$VWE_{b,\ int}$	−0.88***	−2.03***	0.95**	3.23***	4.33***	0.17***	−0.04*	2.67***	1.68***	−0.02	1.41***	0.14
	*VWE_{int}	−0.83***	−1.74***	1.49***	2.82***	4.58***	0.30***	−0.04	2.11***	1.62***	0.03	2.32***	−0.10

Note: * * * $P < 0.001$, * * $P < 0.01$, and * $P < 0.05$.

contributors to the increased WFP_b; in particular, the role of per capita GDP had significantly increased during the later stage.

In terms of crop-related VWI_b per province (Fig. 4e and f), population was the largest positive driving force with enhanced effects over the study period. Agricultural water intensity and RI were the largest negative driving factors, where significant regional differences were observed. The impacts of II and AEI varied throughout the study period. For 2000–2008, II played a only positive driving role in the Jing-Jin and east coast regions, while it had a positive driving effect in all regions with the exception of the northwest and southwest regions over 2009–2017. In addition, the elasticity coefficient of per capita GDP changed from a positive driving force (~0.30) in 2000–2008 to a weakly negative driving force (−0.07) in 2009–2017; it had higher impacts in the Jing-Jin and north coast regions than all other regions.

With respect to the VWE_b of provinces (Fig. 4g and h), the population, per capita GDP, agricultural water intensity, and water pressure index were the major positive drivers, while II and AEI had an opposing effect. The effects of RI and per capita arable land area changed from being clearly negative in most provinces for 2000–2008 to positive for 2009–2017. This indicates that the development of RI and per capita arable land promotes regional.

3.3.3. Paths and contributions of driving forces affecting WFP

The main driving factors (i.e. II, POP, pGDP, AWI, and pALA) affecting WFP identified in Section 3.3.2 were selected to further explore the impact mechanisms and causal relationships with WFP (Fig. 5). Crop yield and production were also considered as they may affect WFP as intermediate variables.

By analysing the direct and indirect paths of driving factors through SEM, II was found to have an indirect negative link with WFP. The direct standardised path coefficient was −0.10 ($P > 0.05$), while it indirectly affected $uWFP_b$ and uWFP with a standard path coefficient of −0.49 ($P < 0.01$) and −0.20 ($P < 0.05$), respectively (Fig. 5). The per capita GDP influenced the WFP through two contradictive paths: (1) directly improving yield, and then increasing the WFP through yield; and (2) decreasing the uWFP, and then promoting the WFP through the uWFP. The most direct positive effect mediated by water use intensity may have prompted the decrease in $uWFP_b$. Per capita arable land area was the most important direct driver to reduce $uWFP_b$, with the exception of II.

3.4. Discussion

This study investigates the driving forces of WFs and VW flows related to crop production, consumption, and trade at the national and intra-national scales, while accounting for agricultural infrastructure. The results reveal that the development of agricultural infrastructures was one of the key driving factors for crop related water consumption and VW flows. In particular, the driving intensity of II was stronger than traditional major drivers, such as per capita GDP and agricultural water intensity. It was confirmed that agricultural infrastructures should not be neglected when considering the driving forces of crop-related WFs and VW flows.

Interestingly, although II was one of the most critical drivers for reducing the $uWFP_b$, the ongoing development of II will lead to an increasing WFP in provinces experiencing water scarcity. This phenomenon shows that the development of II via advanced technologies can improve the utilisation efficiency of crop water resources; however, it may also result in more total water consumption during crop production with growing food demand and intensive crop trade. This is demonstrated by the 26.0% increase in the total effective irrigation area in China (Fig. S2); this finding supports the conclusions from Grafton et al. (2018) and Palmer (2010).

AEI and RI had positive effects on regional crop related VWE; this is a benefit from the political promotions in agricultural modernisation by the Chinese government. These infrastructure constructions have created conditions for agricultural modernisation, such as popularising

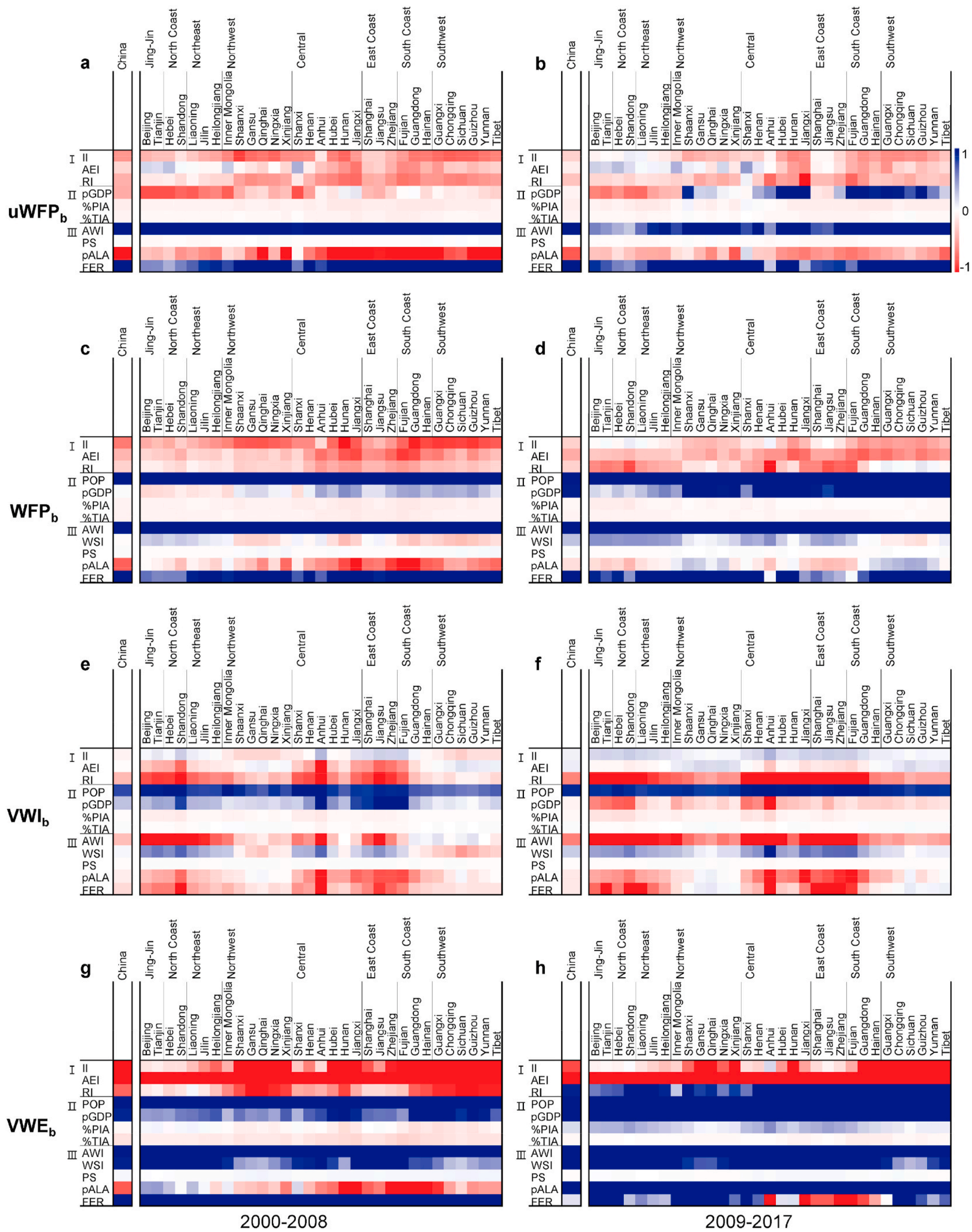

Fig. 4. Spatio-temporal differences in the driving forces of crop-related water footprints (WFs) and virtual water (VW) flows: (a)–(h) represent unit blue WF of crop production ($uWFP_b$), total blue WF of crop production (WFP_b), total blue VW import (VWI_b), and total blue VW export (VWE_b), respectively, for 2000–2008 (left) and 2009–2017 (right). Red and blue indicate negative and positive driving effects, respectively.

agricultural machinery in fields and improving the logistics of agricultural products. The No. 1 Central Document in 2008 of China (The State Council of China, 2008) focused on 'realising agricultural modernisation' and 'strengthening agricultural infrastructure construction'. Such policies accelerate the transformation in the Chinese agricultural industry from the traditional, extensive agricultural system to the modern, precise agriculture system (Bryan et al., 2018).

The significant spatio-temporal heterogeneity of driving forces was also demonstrated in this analysis. The coefficient of II on uWFP over the 2009–2017 period decreased by more than 50% compared to the first half of the study period. This suggests that it is imperative to consider the diminishing marginal effect to make wise II investments. The negative driving effect of II on $uWFP_b$ was significantly higher in the northwest region and in parts of provinces (e.g. Henan, Hunan, and Jiangxi) in the central region than all other regions. This demonstrates the potential of II for 'more crop per drop' in the regions experiencing water resource shortages, and the result is consistent with the results reported by Dalin et al. (2014).

Per capita GDP showed contrasting driving effects on WFP_b in various regions. This is likely to reflect the degree of water shortages and the development of agricultural production technologies. The Jing-Jin, north coast, and northeast regions were forced to plan more budget shares to save irrigation water and reduce the WFP_b due to severe water scarcity. Despite the abundant water resources and per capita GDP

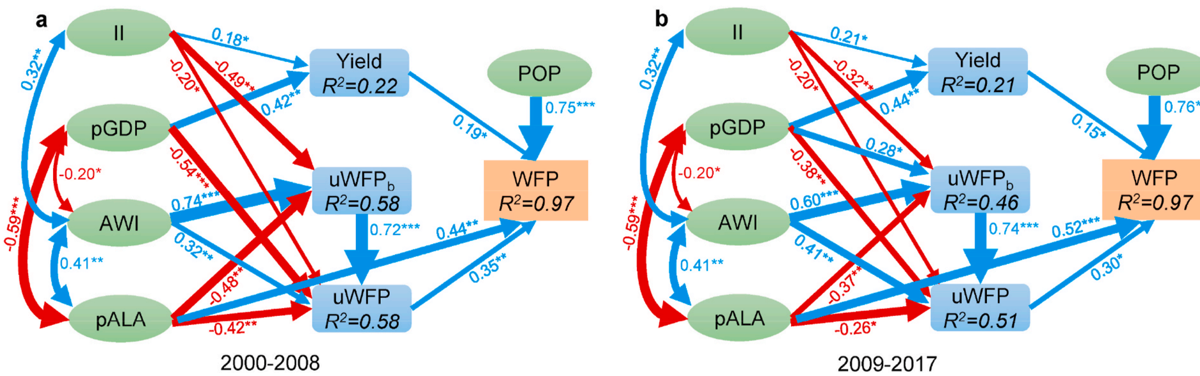

Fig. 5. Path diagrams for water footprints (WFs) of crop production: (a) and (b) represent the two stages of 2000–2008 and 2009–2017, respectively. The green ellipse refers to the exogenous variables; the blue represents the endogenous variables; and the orange rectangle represents the dependent variable. R^2 indicates the coefficients of determination. * * *$P < 0.001$, * *$P < 0.01$, and *$P < 0.05$. The significant positive and negative standardised path coefficients are depicted by the blue and red lines, respectively, at a significance level of $P < 0.05$; the insignificant coefficients have been omitted. Positive relationship between the absolute value of standardised path coefficient and line thickness.

superiority in parts of the central region and the south coast and southwest regions, these areas continue to adopt relatively extensive irrigation management strategies in crop production due to the comparative advantages of other industries (e.g. textiles, catering, and finance) over crop production (Zhao et al., 2019).

This study has four major limitations. First, the uWFP for 2009–2017 was estimated using the Fast Track approach; this approach is mainly driven by the temporal variation in yield. Tuninetti et al. (2017) demonstrated the applicability of Fast Track by comparing it with the uWFP from crop evapotranspiration while accounting for the effects of climatic variations and soil conditions. The uncertainty analysis shows that the standard deviation in the error of the Fast Track estimation was approximately 10% globally, while Gao et al. (2020) verified that this deviation was less than 20% at the provincial scale in mainland China; this error margin is acceptable for the purpose of the current study. Second, this study only focused on the major staple crops; additional crops, and animal and industrial products need to be incorporated in further research. Third, this study only considered the impact of agricultural infrastructures on water quantity; future research on water quality and other environmental factors is highly recommended. Lastly, this study only focused on part of the environmental effects (water consumption) of agricultural infrastructures and did not undertake an analysis of the economic benefits. There is an urgent and significant need to comprehensively evaluate the economic and environmental effects of agricultural and other socio-economic infrastructures.

Based on the results and discussion, we propose two policy recommendations for agricultural infrastructure investments and water security in developing countries. First, in terms of water productivity and total water consumption, although II plays a key role in reducing $uWFP_b$ and WFP_b, it indirectly increases WFP. Similarly, the environmental benefits of potential investments in AEI and RI should also be considered. AEI and RI play an increasingly important role in crop VW trade; it is recommended that attention should be paid to the environmental unsustainability caused by enormous VWE for regions with undeveloped AEI and RI, such as the northwest and northeast region. Second, customised strategies may be developed by thoroughly considering the spatiotemporal heterogeneity of driving factors. In the Jing-Jin and north coast regions that have relatively developed economies while experiencing severe water shortages, II should be continually developed to improve water use efficiency and formulate agricultural water quotas. To achieve sustainability in the northwest region, which suffers from a relatively slow-growing economy and serious water shortages, AEI and RI should be investment priorities, while VWE should be strictly controlled. The central region and northeast regions are major areas for VWE; these regions require further II investments and the achievement of an efficient VWE. In the east coast and south coast regions that have the benefit of a water-rich and developed economy, it is wise to adjust the industry structure to improve the capacity of local crop production and reduce the dependence on VWI. In the southwest region, which is abundant in water resources yet has an underdeveloped economy, a better choice is to export more water-intensive products in exchange for economic benefits (Qian et al., 2018).

4. Conclusion

This study focused on agricultural infrastructures (irrigation, agricultural electricity, and roads) to investigate the main socio-economic driving factors of crop-related WFs and VW flows in the production, consumption, and trade of three staple crops (rice, wheat, and maize) in China. An analysis of the spatio-temporal differences in the driving forces of crop-related WFs and VW flows was also carried out. The results demonstrate that agricultural infrastructures have a more driving strength than the common major drivers of crop-related WFs and VW flows, such as per capita GDP and agricultural water intensity. In particular, II was one of the key driving factors for reducing crop WF. When II increased by 1%, uWF_b and WFP_b decreased by 0.71% and 0.58%, respectively. The results also demonstrated the evidence of spatio-temporal heterogeneity in the driving forces. Agricultural infrastructures may play a more significant role in regions experiencing water shortage such as Jing-Jin, north Coast, and the northwest. For mainland China, we suggest that water productivity, total water consumption, and the spatial-temporal heterogeneity of driving factors should be thoroughly considered to develop customised strategies for effective water resources management. This analysis provides a scientific reference for sustainable investment in agricultural infrastructures relating to regional physical and virtual water consumption and flow management in countries possessing similar natural water resources and infrastructure investments as China. Future research needs to incorporate the synergy or trade-offs between the economic and environmental effects of agricultural infrastructure. Furthermore, it is important to consider the extent to which agricultural infrastructure affects water quality in future.

CRediT authorship contribution statement

Hongrong Huang: Software, Methodology, Validation, Formal analysis, Writing – original draft. **La Zhuo:** Conceptualization, Writing – review & editing, Supervision. **Ranran Wang:** Conceptualization, Writing – review & editing, Supervision. **Kehui Shang:** Visualization, Data curation. **Meng Li:** Visualization, Data curation. **Xi Yang:** Visualization, Data curation. **Pute Wu:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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