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Index decomposition analysis of urban crop water footprint

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Abstract

Rapid urbanization has resulted in often unplanned increases in population, and food demand in cities. Historically, hinterlands to these cities have acted as breadbaskets producing food to the urban residents. Accordingly, a large amount of available freshwater has been needed to support these croplands. However, the rapid expansion of cities in developing countries has significantly changed both the croplands around cities and the water demand. It is thus important to quantitatively investigate the water-food nexus of cities related to the changing hinterland agriculture. Water footprint is an indicator reflecting the human impact on water. In this study, we quantified both the blue and green water footprint of major crop products in Suzhou city, China using a bottom-up accounting method. A novel decomposition analysis was carried out with a Logarithmic Mean Divisia Index (LMDI) method to study the driving forces that changed the water footprint during the period 2001-2010. The drivers were designed to

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reflect the factors related to farmland, such as yield and crop area. This is different from previous decomposition analyses, which focused on economic factors such as GDP. The results show that the crop water footprint of Suzhou city has seen a general decreasing trend between 2001 and 2010. The decomposition analysis showed that the decline of crop area was the main driver that decreased the crop water footprint, followed by the virtual water content (water consumption per unit of production). In contrast the changes of crop combination and yield contributed to an increase in the crop water footprint. Although the shrink of urban croplands decreased the water footprint of crop products. Cities' increasing demand for food will increase the crop water footprint of consumption. This will increase the dependence of cities on external water footprint of crop products (water embodied in imported crops), which may impact upon food security in cities in the long term.

Keywords: hinterland agriculture, crop water footprint, decomposition analysis, LMDI

Highlights

Redesign of driving forces for crop water footprint changes

Analysis of interaction between hinterland agriculture and water demand

Discussion of farmland impact upon urban water demand

1. Introduction

Cities constitute primary agglomerations of people. In 2014 54% of the world's population lived in cities, and this is forecast to rise to 66% by 2050 (United Nations, 2014). One of the key challenges faced by cities around the world is to meet food demand for residents (Barthel and Isendahl, 2013; Lynch et al., 2013). Traditionally, farmlands around cities, also known as hinterlands, have supported this food demand (Zezza and Tasciotti, 2010). Such urban agriculture has historically been critical to achieving food security in cities (Lynch et al., 2013). However, the huge water demand associated with agricultural production conflicts with the increasing water demand due to urban population growth. Current trends of rapid expansion of cities, especially in developing countries, has significantly changed both the croplands around cities and the associated water demand. To the best of our knowledge, few studies have focused on the interactions between hinterland agriculture and the water demand associated with urbanization.

The water-food nexus of cities related to changing hinterland agriculture can be evaluated using the water footprint (WF) concept. The WF is defined as the volume of freshwater used during the production process (Hoekstra et al., 2011). It has been widely used in quantifying and assessing freshwater consumption in crop production (e.g. Chapagain and Hoekstra, 2011; Mekonnen and Hoekstra, 2011; Vanham et al., 2013). Freshwater refers to both green water and blue water. Green water is the precipitation on land which does not run-off or recharge groundwater but is stored in the soil or remains on the surface of the soil or vegetation. The accounting of green water footprint is closely related to crop growth. The blue water for crop growth can be substituted by green water, so a complete picture can be obtained only by accounting for both (Hoekstra et al., 2011). A bottom-up method is widely applied to accounting for the crop WF, which starts from the smallest unit feasible in assessing the WF and aggregates each unit to the desired scale and period (Yang et al., 2013).

The changes in the WF of crops can be related to crop production and changes in hinterland usage, with drivers such as water productivity, yield, agricultural area etc., to understand the interactions between hinterland agriculture changes and freshwater consumption. In recent years, decomposition analyses has been applied to study the driving forces or determinants that underlie changes to the WF (Feng et al., 2015). For example, Zhang (2012) decomposed the effects of contributing factors to Beijing's WF changes during 1997-2007. The contributing factors were technological, economic system efficiency, scale, and structural effects. Zhao et al. (2014) investigated the impact of population, affluence, urbanization level, and diet factors on the WF of agricultural products in China based on an extended STIRPAT model. The above decomposition analyses, however, were not designed to reflect the factors related to changing farmland, such as crop yield or area, and thus were unable to identify the interrelationships between hinterland agricultural changes and associated water consumption. In addtion, green water was excluded from most decomposition analyses of WF changes.

In the context of increasing urbanization in developing countries, this study has quantitatively investigated the water-food nexus in Suzhou city, China by performing a novel decomposition analysis with a Logarithmic Mean Divisia Index (LMDI) model. The aim was to study the contributing factors to urban crop WF changes, including virtual water content (reciprocal of water productivity), yield, crop structure, and crop area. To best of our knowledge the driving forces related to crop production that changes both green and blue WF has been rarely reported. The driving forces and the implications to water-food security at urban scale are also discussed.

2 Water endowment and water stress in Suzhou city

Fig. 1. Location of Suzhou city, China

Suzhou city is located in the Taihu Lake Basin, which is a subtropical humid area of plentiful rainfall. The annual available water resource in Suzhou is 2.98 billion m^3 (in 2010). The total administrative area of Suzhou is 8,488 km^2, with 3,609 km^2 covered by water (Suzhou Water Resources Bureau, 2010). Lake Taihu, a large shallow freshwater lake in the lower Yangtze Delta, is close to Suzhou (Fig. 1), and is the main water resource for Suzhou. Significant nutrient pollution from wastewater discharges, along with agricultural run-off from the northwestern shores flows into Lake Taihu. Nutrient concentrations decrease with the current towards the eastern and southern reaches of the lake which, as a result, have better water quality i.e. the reaches close to Suzhou city, despite extensive blue-green algae problems in the northwestern part of the lake (Hu et al., 2010).

Suzhou is an ideal case for illustrating how hinterland agriculture can be changed through urbanization and industrialization. Although in contemporary China, Suzhou is known as an industrialized city with many high-tech industries, it was until the 1980's on of China's grain production center. The Taihu Lake Basin has long been known as "the land of rice and fish" in China. Agriculture in the Taihu Lake Basin sustained high productivity for more than nine centuries (Ellis and Wang, 1997). As such, Suzhou has historically had a large amount of hinterland agriculture dedicated to producing rice and other grain products for both local consumption and export to other regions in China. After the foundation of the People's Republic of China in 1949, Suzhou was established as a grain production base (Wang et al., 2015). In 1984, the sown area was about 5000 km^2 with grain production peaking at 3.1 million tons (Suzhou Statistics Bureau, 2011). Since then Suzhou has accelerated its industrialization transformation process by creating a series of industrial park and development zones to stimulate industrial development and attract Foreign Direct Investment (Wang et al., 2015). Today, Suzhou has become one of the wealthiest industrial cities in China. In 2010, GDP in Suzhou ranked 5th among China's 337 cities, following the mega-cities of Beijing, Shanghai, Guangzhou, and Shenzhen. Per capita GDP was about 87,607 CNY (about 12,800 US dollars) (Suzhou Statistics Bureau, 2011). Urbanization in Suzhou, as with other Chinese cities, has experienced land grab and population growth, which have substantial impacts on hinterland agriculture.

Despite its location in a subtropical and humid area, Suzhou as a developed city in China faces water stress. We evaluated water stress in Suzhou during 2007-2010 with two well-known water scarcity indices. The Falkenmark Index evaluates water stress through the total annual renewable water resource per capita (Falkenmark et al., 1989), and the "Criticality ratio" evaluates water stress using the ratio of total annual withdrawals to renewable water resources (Alcamo et al., 2000). The classification of both indices was adjusted according to Zeng (2013) and Zhao (2016) following China's water endowment. As a result, four classifications were generated with C as the "Criticality ratio" and F as the Falkenmark Index: Absolute Scarcity (C >1 or F< 500 m^3/capita); Scarcity (1> C > 0.4 or 1000 m^3/capita > F > 500 m^3/capita); Stress (0.4 > C > 0.2 or 1700 m^3/capita > F > 1000 m^3/capita); and No Stress (C < 0.2 or F > 1700 m^3/capita). The results for the Criticality ratio show the highest level of water stress in Suzhou (Table 1), while the results for the Falkenmark Index show the second highest level of water stress during 2007-2009, and the highest level in 2010. These results suggest that intensive water use and high population density are the main causes of Suzhou's water stress.

Table 1 Results of water scarcity indices in Suzhou city

Year	Annual renewable water resources(billion m^3)	Population	Water withdrawal (billion m^3)	Falkenmark Index (F)	Criticality Ratio (C)
2007	3.2	6244311	7.7	515	2.3
2008	3.3	6297530	7.5	522	2.3
2009	4.4	6332903	7.7	702	1.7
2010	3.0	6376558	7.8	468	2.6

3. Method and data

3.1. Quantification of blue and green water footprint of crop products

The WF of crop products in this study refers to the WF of crop growth. The indirect water requirement for crop production, i.e. the water required in production of upstream products only takes a small share of the total crop WF (Zhao et al., 2009), thus is ignored in this study. A bottom-up method to quantify the WF of crop products can be expressed as follows:

$$WF_{tot} = WF_g + WF_b = \sum_i [CWR_{g.i} \cdot A_i] + \sum_i [CWR_{b.i} \cdot A_i] \quad (1)$$

Where WF_{tot}, WF_g and WF_b refer to the total, green and blue water footprint of crops, *i* is the type of crops planted, A_i is the plant area of crop *i*, $CWR_{g.i}$ and $CWR_{b.i}$ are annual green and blue crop water requirements per hectare of crop *i*. Crop water requirement can be calculated using the CROPWAT model developed by the Food and Agriculture Organization (FAO) (available at http://www.fao.org/nr/water/infores databases cropwat.html). The CROPWAT model takes into account both rainfed and irrigated conditions. So in the CROPWAT model, the green crop water requirement is obtained through quantifying effective rainfall, while the blue crop water requirement is obtained through quantifying irrigation.

3.2. LMDI model

We used the LMDI model to decompose the WF of crops in Suzhou city. The LMDI method was initially developed by Ang and Liu (2001), and has been widely used in analyzing the driving forces of carbon dioxide (CO_2) emissions or energy efficiency (e.g. Ang, 2004; Dai and Gao, 2016; Fernández González et al., 2014; Liu et al., 2012), and a small number of applications in analyzing WF changes (Xu et al., 2015; Zhao and Chen, 2014). The method has the advantages of expressing in a simple form with no residual errors, so has been recommended for general use (Ang, 2004).

In this study, we redesigned the driving forces of the crop WF to reflect the interrelationships between urban agriculture and associated freshwater consumption. The total WF of crops in Suzhou was decomposed into four driving forces: virtual water content, yield, crop structure, and crop area. Virtual water content (VWC) is the amount of water consumed to produce a unit of each crop, which is also the reciprocal of water productivity. Yield is production volume per unit area. Crop structure is the proportion of specific crop area to total area of all crops, and crop area is the total planting area for all crops. The total WF of crops can be expressed with the above four driving forces as follows:

$$WF(\mathrm{t}) = \sum_i [V_i(\mathrm{t}) \cdot Y_i(\mathrm{t}) \cdot S_i(\mathrm{t}) \cdot A(\mathrm{t})] = \sum_i [\frac{WF_i(\mathrm{t})}{P_i(\mathrm{t})} \frac{P_i(\mathrm{t})}{A_i(\mathrm{t})} \frac{A_i(\mathrm{t})}{A(\mathrm{t})} A(\mathrm{t})] \quad (2)$$

Where $WF(\mathrm{t})$ is the water footprint of all crops, $V_i(\mathrm{t})$, $Y_i(\mathrm{t})$, and $S_i(\mathrm{t})$ represent VWC, yield, and crop structure for crop *i* in year t respectively. $A(\mathrm{t})$ is the total crop area in year t. $P_i(\mathrm{t})$ is the production volume of crop *i* in year t, and $A_i(\mathrm{t})$ is the crop area of crop *i* in year t.

According to LMDI, the variation of WF (ΔWF) from year 0 to year t can be decomposed into four parts: the variation of WF caused by change in VWC (ΔWF_{v}), the variation of WF related to change in yield (ΔWF_y), the variation of WF which is due to change in the proportion of a crop area in the total area (ΔWF_s), and the variation of WF caused by changes to the total area (ΔWF_a). The decomposition form is shown in Eq. (3):

$$\Delta WF = WF(t) - WF(0) = \Delta WF_{\mathrm{v}} + \Delta WF_s + \Delta WF_y + \Delta WF_a \quad (3)$$

The four driving forces in Eq. (3) can be quantified as:

$$\Delta WF_{\mathrm{v}} = \sum_i [\varphi[WF_i(\mathrm{t}), WF_i(0)] \ln \frac{V_i(\mathrm{t})}{V_i(0)}] \quad (4)$$

$$\Delta WF_s = \sum_i [\varphi[WF_i(\mathrm{t}), WF_i(0)] \ln \frac{S_i(\mathrm{t})}{S_i(0)}] \quad (5)$$

$$\Delta WF_y = \sum_i [\varphi[WF_i(\mathrm{t}), WF_i(0)] \ln \frac{Y_i(\mathrm{t})}{Y_i(0)}] \quad (6)$$

$$\Delta WF_a = \sum_i [\varphi[WF_i(\mathrm{t}), WF_i(0)] \ln \frac{A(\mathrm{t})}{A(0)}] \quad (7)$$

where function $\varphi[WF_i(\mathrm{t}), WF_i(0)]$ is the logarithmic average of two positive numbers $WF_i(\mathrm{t})$ and $WF_i(0)$ which are given by:

$$\varphi[WF_i(\mathrm{t}), WF_i(0)] = \begin{cases} \dfrac{WF_i(\mathrm{t}) - WF_i(0)}{\ln WF_i(\mathrm{t}) - \ln WF_i(0)}, WF_i(\mathrm{t}) \neq WF_i(0) \\ WF_i(0), WF_i(\mathrm{t}) = WF_i(0) \end{cases} \quad (8)$$

3.3. Data source

In this study, the four main crops in Suzhou were considered: wheat, rice, cotton, and rapeseed. The total cultivated area of the four crops accounted for about 70% of the total cultivated area in Suzhou (Suzhou Statistics Bureau, 2011). The input data of the CROPWAT model included climatic, crop and soil parameters. Climatic inputs included average maximum and minimum air temperature, precipitation, relative humidity, sunlight duration, radiation and wind speed, which were obtained from the China Meteorological Data Sharing Service System (http://data.cma.cn/). Crop and soil parameters were taken from the default values in the CROPWAT software provided by FAO. The data for crop production and crop areas were obtained from the Suzhou Statistical Yearbook (Suzhou Statistics Bureau, 2011).

4. Results and Discussion

4.1. Water footprint of major crops in Suzhou from 2001-2010

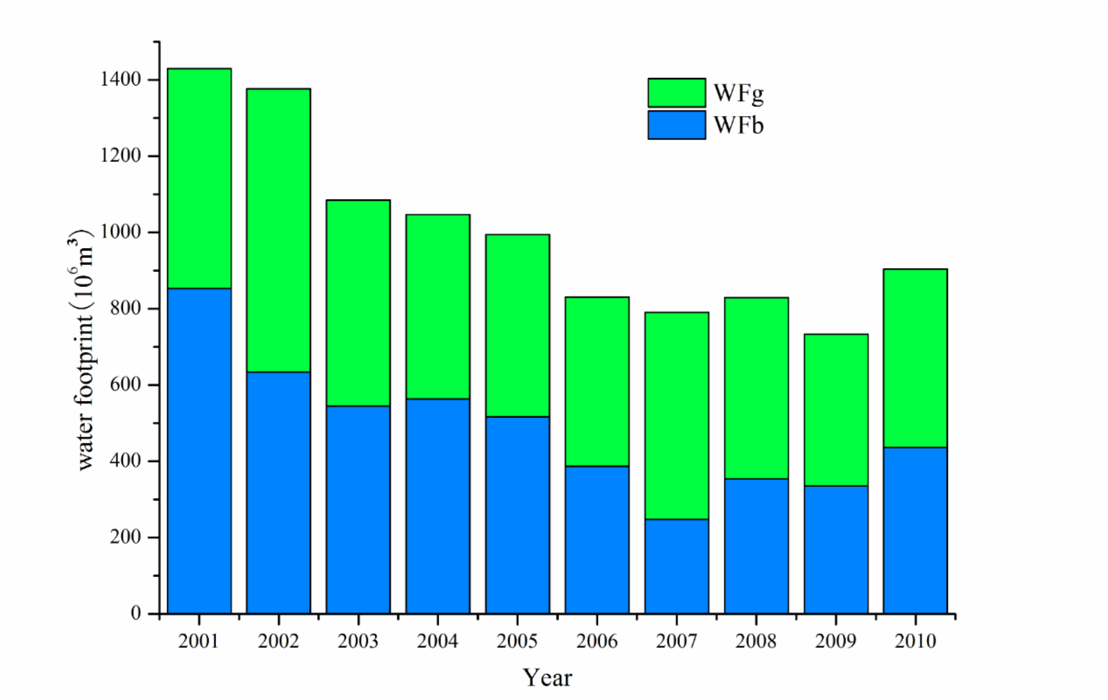

Fig. 2. Changes of blue and green water footprint of crop products in Suzhou (2001-2010)

The average crop WF in Suzhou was 1001.9 million m^3 during 2001-2010, incorporating 487.5 m^3 of blue WF and 514.4 m^3 of green WF. Green WF dominated the WF for wheat, cotton, and rapeseed, accounting for 73%-79% of the total WF on average for these three crops. Blue WF dominated the WF of rice, accounting for 62% of the total WF on average. The average WF for rice took the greatest share amongst the WF of the four crops studied, accounting for 63% of the total, followed by the WF of wheat which accounted for 29% of the total. As shown in Fig. 2, the crop WF experienced a general decreasing trend from 2001 to 2010. Specifically, the crop WF experienced continued reduction between 2001 and 2007, before fluctuating slightly from 2007 to 2010. Blue WF decreased from 853.04 million m^3 in 2001 to 247.53 million m^3 in 2007, before increasing to 436.38 million m^3 in 2010. Green WF fluctuated between 397.41 million m^3 to 742.75 million m^3 during the 10 study years. The biggest share of the blue WF to total WF of crop products was 59.64% in 2001, and the smallest share was 31.32% in 2007.

4.2. The driving force analysis of crop water footprint changes in Suzhou

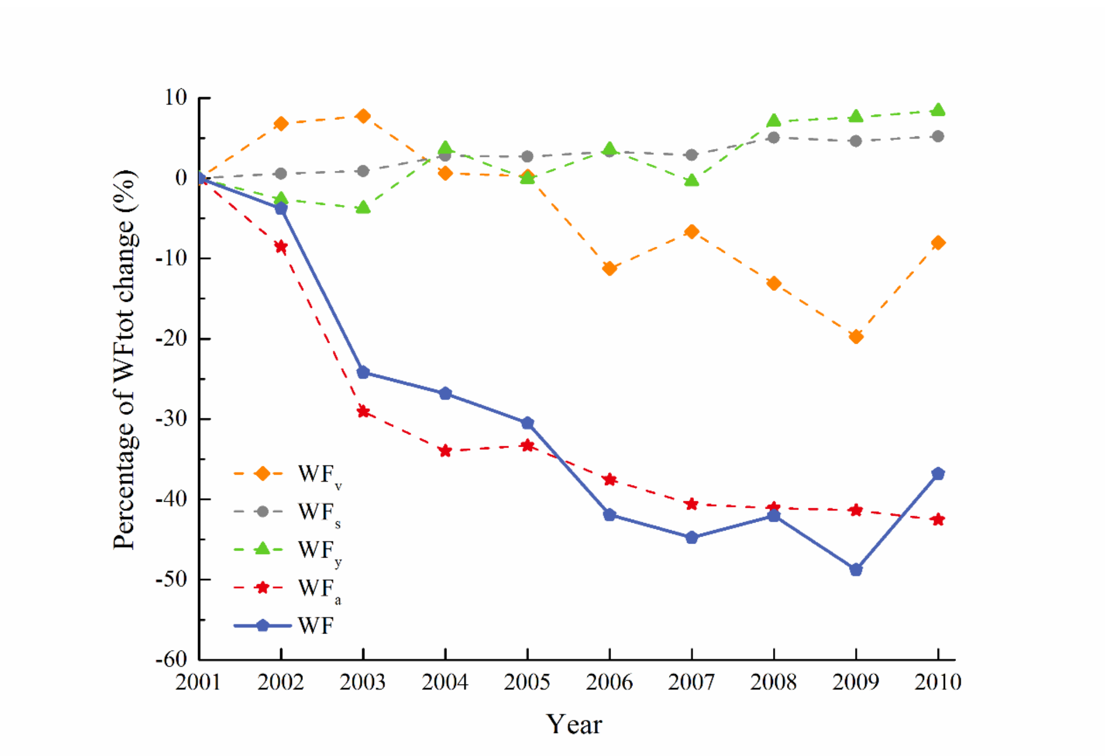

Fig. 3. Driving forces of crop WF during the study period of 2001-2010

As shown in Fig. 3, the total crop WF decreased by 526 million m^3 during 2001-

2010, with total area contributing the most to this reduction. The decrease of total area would have decreased the crop WF by a total of 608 million m^3, if other factors (VWC, crop structure, and crop yield) had remained static at 2001 levels. In the study period (2001-2010)， area changes were the main driving forces in crop WF reduction. According to Fig. 3, area changes sharply reduced crop WF from 2001 to 2004, continued to cause a gentle reduction between 2004 and 2007, finally having less impact between 2007 and 2010. The impact of VWC fluctuated over the study period, but decreased by a total of 115 million m^3 of the crop WF during 2001-2010. For example, the VWC decreased the crop WF by 164.52 million m^3 during 2005-2006, but increased by 167.68 million m^3 of the crop WF during 2009-2010. The change in crop yield and crop structure would have increased the crop WF by 120 and 75 million m^3 respectively. It is obvious that the crop WF growth due to the effects of crop yield and crop structure could not offset the crop WF reduction owing to the effects of crop area and VWC.

4.2.1. Virtual water content effect

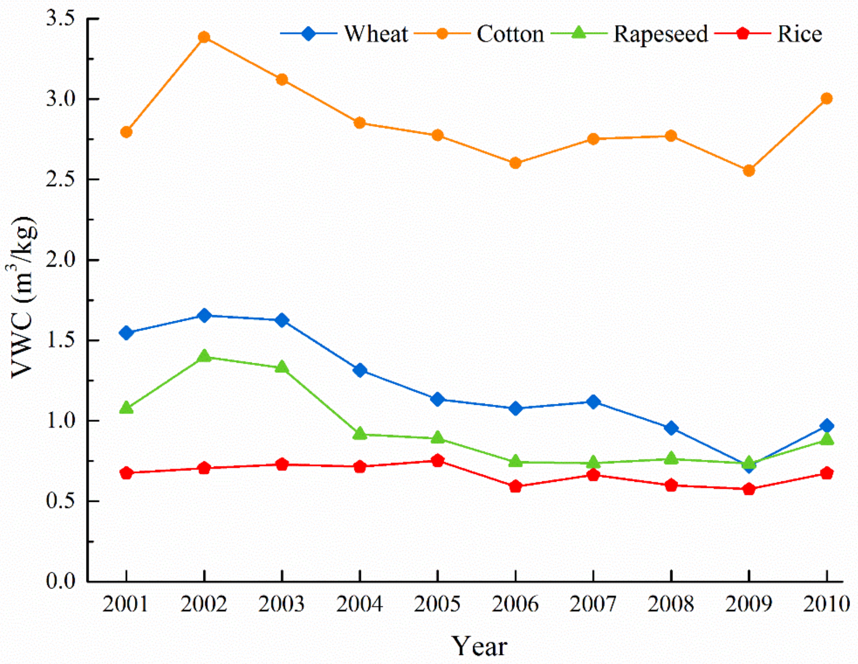

Fig. 4. Virtual water content changes for four major crops

Fig. 3 shows that the pattern of crop WF change is highly related to the change of the VWC which fluctuated over the study period. Such fluctuation can be linked to changes in climatic factors such as temperature, sunlight, and precipitation etc. Climatic factors can change both crop output and associated water consumption, and as a result, have impact on the VWC. For example, Bocchiola and Soncini (2013) found that crop yield decreased and the WF increased with increasing temperature and decreasing precipitation. Kang et al. (2009) found that climate change led to changes in soil evaporation and plant transpiration and consequently the crop growth period may be changed having influence on crop water productivity, i.e. the reciprocal of the VWC. Some previous studies assumed the same VWC for different years e.g. (Liu et al., 2007), which ignored the impact of the changing VWC on the crop WF. However, our results show that ignoring the difference of the VWC will lead to noticeable bias for crop WF accounting.

4.2.2. Crop area effect

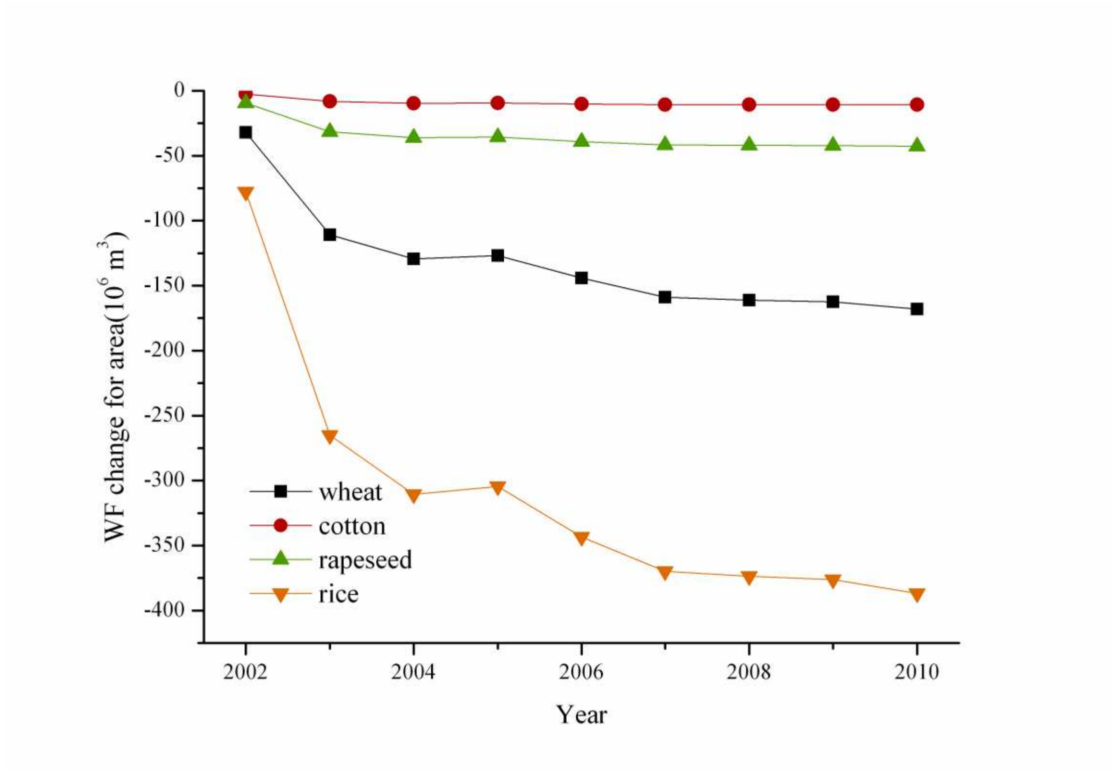

Fig. 5. Contribution of crop area to crop WF changes

During the study period (2001-2010) area changes were the main driving force in crop WF reduction. According to Fig. 3, area changes sharply reduced crop WF between 2001 and 2004, continued to cause a gentle reduction between 2004 and 2007, and had less impact from 2007 to 2010. The above changes correlated with crop area changes in Suzhou. The crop area reduction per annum was 136.6 km^2 from 2001 to 2004, 76 km^2 from 2004 to 2007, and 31.6 km^2 from 2007 to 2010. The main cause of crop area reduction is attributed to rapid urbanization in China, along with urban land expansion. In urban expansion it is common to see crop land occupied by newly built urban infrastructure, such as dwellings and factories. Consistent with China's national urbanization trend, the urban land take around Suzhou in the early 21st century has also undergone rapid expansion (Wang et al., 2015). As a result, agricultural land around Suzhou has shrunk rapidly since 2001. Such reductions have attracted the attention of government and scientists: a major concern is that rapid urban expansion will threaten food security in China. In 2006, 0.12 billion ha of arable land area was set as a cap, i.e.

a redline to limit arable land reduction (State Council of the People's Republic of China, 2006). Consequently, the downward trend of crop area has slowed since 2007.

4.2.3. Crop structure effect

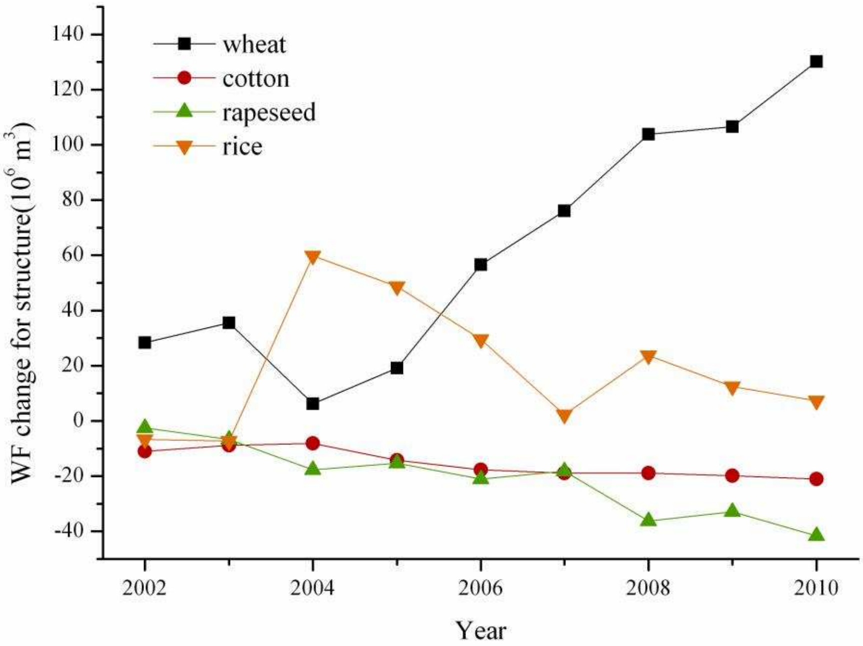

Fig. 6. Contribution of crop structure to WF change

The overall impact of crop structure on crop WF was small but resulted in a steady increase in crop WF during the study period. As shown in Fig. 6, the proportion of wheat area amongst the major crop areas increased between 2004 and 2010, while the area proportion for the other crops decreased. The increasing crop area proportion of wheat possibly reflects a decreased labour force for Suzhou's crop production. In 2010, labour costs for wheat production in Suzhou was the lowest of the four crops at about 1950 CNY/ha (285 dollars/ha), whilst labour costs for rapeseed was highest, at about 4440 CNY/ha (650 dollars/ha) (National Development and Reform Commission, 2010). Since the population working on Suzhou's hinterland agriculture decreased by 218 thousand from 2001 to 2010, it is reasonable to infer that more farmers chose to cultivate wheat to overcome labour shortage. Since wheat had the second largest VWC among the four crops studied, and the largest plant area, the increased proportion of wheat also increased the total WF.

4.2.4. Yield effect

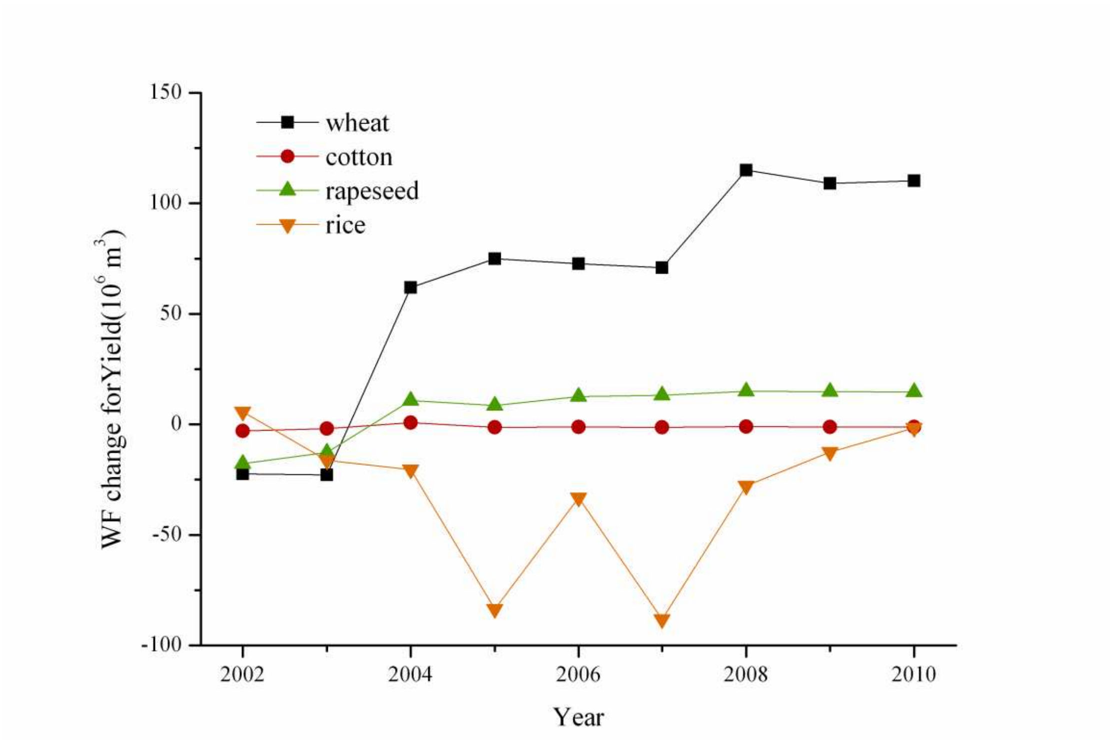

Fig. 7. Contribution of yield to WF changes

From 2001 to 2010 yield generally increased crop WF for Suzhou. As shown in Fig. 7 the yield of wheat contributed most to crop WF increase, rising from 3,136 ton/thousand ha to 4,727 ton/thousand ha, about a 51% increase during the study period. It can be inferred that the increase in wheat yield also stimulated the increased proportion of wheat planting area to the total areas of the four studied crops. The yield for rice decreased in 2005 and 2007, and then increased to reflect the general trend in subsequent years. Crop yield is highly related to climatic factors such as radiation, temperature, and precipitation etc. (Liu et al., 2016), and will thus be considered in the decomposition analysis of crop WF in future work.

5. Conclusions

China has long advocated food self-sufficiency; even developed cities take a significant stake in governing agricultural land use. Such efforts provide an effective way of supporting food security, but also increase the pressure on urban water supplies. This study has proposed a new set of parameters including virtual water content, yield, crop structure, and crop area to reflect the interactions of hinterland agriculture and water demand on a developed Chinese city. Our attempt highlights the importance of incorporating drivers related to agricultural land changes into urban land and water management, thus can support decision making in balancing the trade-offs between local food demand and water resource allocation. Decreased WF of crop products mitigate urban water stress to an extent, but increase the reliance of the city on external water supplies which can be acquired through both physical and virtual forms. Research and modelling on the sustainability and equity for large cities relying on external water supply is an urgent issue.

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Reference

Alcamo, J., Henrichs, T., Rösch, T., 2000. World water in 2025: Global modeling and scenario analysis for the world commission on water for the 21st century. Center for Environmental Systems Research, University of Kassel.

Ang, B.W., 2004. Decomposition analysis for policymaking in energy. Energ Policy 32, 1131-1139.

Ang, B.W., Liu, F.L., 2001. A new energy decomposition method: perfect in decomposition and consistent in aggregation. Energy 26, 537-548.

Authro, 2014. World urbanization prospects: The 2014 revision, Highlights (ST/ESA/SER.A/352).

Barthel, S., Isendahl, C., 2013. Urban gardens, agriculture, and water management: Sources of resilience for long-term food security in cities. Ecological Economics 86, 224-234.

Bocchiola, D., Nana, E., Soncini, A., 2013. Impact of climate change scenarios on crop yield and water footprint of maize in the Po valley of Italy. Agricultural Water Management 116, 50-61.

Chapagain, A.K., Hoekstra, A.Y., 2011. The blue, green and grey water footprint of rice from production and consumption perspectives. Ecological Economics 70, 749-758.

Dai, Y., Gao, H.O., 2016. Energy consumption in China's logistics industry: A decomposition analysis using the LMDI approach. Transportation Research Part D: Transport and Environment 46, 69-80.

Ellis, E.C., Wang, S.M., 1997. Sustainable Traditional Agriculture in the Tai Lake Region of China. Agriculture, Ecosystems & Environment 61, 177-193.

Falkenmark, M., Lundqvist, J., Widstrand, C., 1989. Macro‐scale water scarcity requires micro‐scale approaches, Natural resources forum. Wiley Online Library, pp. 258-267.

Feng, L., Chen, B., Hayat, T., Alsaedi, A., Ahmad, B., 2015. The driving force of water footprint under the rapid urbanization process: a structural decomposition analysis for Zhangye city in China. Journal of Cleaner Production, In press.

Fernández González, P., Landajo, M., Presno, M.J., 2014. Tracking European Union CO2 emissions through LMDI (logarithmic-mean Divisia index) decomposition. The activity revaluation approach. Energy 73, 741-750.

Hoekstra, A.Y., Chapagain, A.K., Aldaya, M.M., Mekonnen, M.M., 2011. The water footprint assessment manual: Setting the global standard. Earthscan 224 pp.

Hu, L., Hu, W., Zhai, S., Wu, H., 2010. Effects on water quality following water transfer in Lake Taihu, China. Ecological Engineering 36, 471-481.

Kang, Y., Khan, S., Ma, X., 2009. Climate change impacts on crop yield, crop water productivity and food security – A review. Progress in Natural Science 19, 1665-1674.

Liu, J., Zehnder, A.J.B., Yang, H., 2007. Historical Trends in China's Virtual Water Trade. Water Int 32, 78-90.

Liu, S.L., Pu, C., Ren, Y.X., Zhao, X.L., Zhao, X., Chen, F., Xiao, X.P., Zhang, H.L., 2016. Yield variation of double-rice in response to climate change in Southern China. European Journal of Agronomy.

Liu, Z., Liang, S., Geng, Y., Xue, B., Xi, F., Pan, Y., Zhang, T., Fujita, T., 2012. Features, trajectories and driving forces for energy-related GHG emissions from Chinese mega cites: The case of Beijing, Tianjin, Shanghai and Chongqing. Energy 37, 245-254.

Lynch, K., Maconachie, R., Binns, T., Tengbe, P., Bangura, K., 2013. Meeting the urban challenge? Urban agriculture and food security in post-conflict Freetown, Sierra Leone. Appl Geogr 36, 31-39.

Mekonnen, M.M., Hoekstra, A.Y., 2011. The green, blue and grey water footprint of crops and derived crop products. Hydrology and Earth System Sciences 15, 1577-1600.

National Bureau of Statistics of China, 2011. Chinese Statistical Yearbook 2011. China Statistics Press, Beijing, China.

National Development and Reform Commission, 2010. Collection on cost and benefit data of national agricultural products, China Statistics Press.

State Council of the People's Republic of China, 2006. The outline of the 11th Five-year pland of Economy and Social Development.

Suzhou Statistics Bureau, 2011. Suzhou Statistical Yearbook. China Statistics Press.

Suzhou Water Resources Bureau, 2010. Suzhou Water Resource Bulletin (in Chinese). China Water Power Press, Beijing.

Vanham, D., Mekonnen, M.M., Hoekstra, A.Y., 2013. The water footprint of the EU for different diets. Ecological Indicators 32, 1-8.

Wang, L., Shen, J., Chung, C.K.L., 2015. City profile: Suzhou - a Chinese city under transformation. Cities 44, 60-72.

Xu, Y., Huang, K., Yu, Y., Wang, X., 2015. Changes in water footprint of crop production in Beijing from 1978 to 2012: a logarithmic mean Divisia index decomposition analysis. Journal of Cleaner Production 87, 180-187.

Yang, H., Pfister, S., Bhaduri, A., 2013. Accounting for a scarce resource: virtual water and water footprint in the global water system. Current Opinion in Environmental Sustainability 5, 599-606.

Zeng, Z., Liu, J., Savenije, H.H.G., 2013. A simple approach to assess water scarcity integrating water quantity and quality. Ecological Indicators 34, 441-449.

Zezza, A., Tasciotti, L., 2010. Urban agriculture, poverty, and food security: Empirical evidence from a sample of developing countries. Food Policy 35, 265-273.

Zhang, Z., Shi, M., Yang, H., 2012. Understanding Beijing's water challenge: A decomposition analysis of changes in Beijing's water footprint between 1997 and 2007. Environmental Science & Technology 46, 12373−12380.

Zhao, C., Chen, B., 2014. Driving force analysis of the agricultural water footprint in China based on the LMDI method. Environmental Science & Technology 48, 12723-12731.

Zhao, C., Chen, B., Hayat, T., Alsaedi, A., Ahmad, B., 2014. Driving force analysis of water footprint change based on extended STIRPAT model: Evidence from the Chinese agricultural sector. Ecological Indicators 47, 43-49.

Zhao, X., Chen, B., Yang, Z.F., 2009. National water footprint in an input-output framework- a case study of China 2002. Ecological Modelling 220, 245-253.

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 Resoures Research, 10.1002/2016WR018595.