Journal of Hydrology 384 (2010) 187–197

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Spatially explicit assessment of global consumptive water uses in cropland: Green and blue water

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ARTICLE INFO

Keywords:
Water scarcity
Consumptive water use
Virtual water
EPIC
GEPIC
Green water

SUMMARY

An accurate estimate of global water uses with high spatial resolution is a key to assessing global water scarcity and to understanding human's interference with the ecosystems. In spite of the progress made previously, there is a lack of spatially explicit assessment of both green and blue water uses in agriculture. In this paper, we estimated consumptive water use (CWU) in cropland on a global scale with a spatial resolution of 30 arc-minutes. A GIS-based version of the EPIC model, GEPIC, is used for the estimation. The results show that in crop growing periods, global CWU was 5938 $km^3\ a^{-1}$ in cropland around the year 2000, of which green water contributed to 84%. On an annual basis, global CWU was 7323 $km^3\ a^{-1}$ in cropland, of which green water contributed to 87%. We compared the simulated consumptive blue water use (CBWU) with the statistical CBWU at the national level among individual countries, and at the federal state or province level in the USA and China. The comparison indicates a good agreement between the simulated and statistical CBWU, suggesting a satisfactory performance of the GEPIC model and reliability of the estimation in irrigated cropland. The importance of green water in both crop production and food trade calls for a better management of green water, in addition to blue water.

Introduction

Water scarcity has become one major threat to the sustainable development in an increasing number of countries (Liu et al., 2007c; Oki and Kanae, 2006; Postel et al., 1996; Vörösmarty et al., 2000; Yang et al., 2007). Currently, around one third of the world population are suffering from different levels of water stress (Oki and Kanae, 2006), while water scarcity is likely to affect up to two thirds of the world population over the next decades (Oki and Kanae, 2006; Vörösmarty et al., 2000). Water scarcity is often intuitionally associated with lack of drinking water of adequate quality, but it is mainly a result of insufficient water for agricultural uses, in particular, food production (Savenije, 2000). Globally, agricultural water use accounts for around 70% of the total "blue" water withdrawn (IWMI, 2000). When "green" water is also considered, agricultural water use likely consists of over 90% of the total water uses (Savenije, 2000). Here, blue water refers to the water in surface water bodies and groundwater; while green water is essentially the rainfall that (after infiltration in the unsaturated zone) is directly consumed by plants to produce biomass (Falkenmark and Rockström, 2006; Liu and Savenije, 2008a; Savenije, 2000).

Accurate assessment of global water uses with high spatial resolution, particularly agricultural water use, is a key to quantifying the level of water scarcity. Water scarcity is often assessed by comparing water availability with water demand. Water scarcity within a given spatial unit can be assumed when water consumption is close to water availability. It is also a key to understanding the potential pathways of water cycle and to evaluating human interference with the ecosystems. Significant progress has been achieved in assessing global water uses in the past two decades. One major achievement is the move from coarse spatial resolutions to finer ones in the assessment. Prior to 2000, almost all global assessments were conducted with very coarse spatial resolutions, i.e. treating the entire world or a country as a whole. Shiklomanov (1991) performed one of the first assessments, and he estimated blue water withdrawal for each country in four user groups, i.e. agriculture, industry, municipalities and reservoir. Estimation of blue water withdrawal at the national level for different sectors can also be found in Raskin et al. (1997), Seckler et al. (1998) and Shiklomanov (2000). In addition, several studies have dealt with the assessment of blue water consumption at the national level, such as Seckler et al. (1998) and Shiklomanov (2000). Here blue water consumption refers to the water withdrawn from a source and made unusable for reuse (Gleick, 2003). Another early

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doi:10.1016/j.jhydrol.2009.11.024

assessment was done by Postel et al. (1996), who estimated blue water withdrawal as well as blue water consumption in different economic sectors on a global scale. In addition, the authors estimated the total amount of water used in terms of evapotranspiration in cultivated land, grazing land, forest land and human-occupied areas. The assessment in this study was very rough because it treated the entire world as a whole, and it used several simple assumptions. For example, blue water consumption was assumed to be equal to 65% of withdrawal. Since the late 1990s and early 2000s, high-resolution assessments of global water uses have emerged, and the typical resolution is 30 arc-minutes (approximately 50 km × 50 km for each pixel nearby the equator). These assessments are conducted for blue water withdrawal (Döll et al., 1999; Vörösmarty et al., 2000; Alcamo et al., 2000), blue water consumption (Döll et al., 1999; Alcamo et al., 2000) and irrigation water requirements (Döll and Siebert, 2002).

The above literature review reveals a significant improvement in the assessment of blue water uses. However, green water uses have drawn less attention. Green water is almost exclusively used by the agricultural sector and other terrestrial ecosystems. Consumptive water use, defined as the total evapotranspiration of a crop during the crop growth period (Falkenmark and Lannerstad, 2005; Liu et al., 2009b), is a concept that covers both the uses of blue water and green water in agriculture. So far, global consumptive water use covering both the elements has mainly been assessed with coarse spatial resolutions, i.e. the entire world as a whole e.g. (Postel et al., 1996; Rockström et al., 1999) or at the national level e.g. in Chapagain and Hoekstra (2004). Little research has been conducted to address the following two issues: (1) assessment of consumptive water use on a global scale with high spatial resolutions; (2) separated assessment of green and blue water uses. Against this background, we conducted a comprehensive assessment of global consumptive water use in cropland with a spatial resolution of 30 arc-minutes. We also evaluated the role of both green and blue water with the same spatial resolution.

Methods and data

The GEPIC model

In this paper, we used the GEPIC model (GIS-based environmental policy integrated climate), which is designed to simulate the spatial and temporal dynamics of the major processes of the soil–plant–atmosphere-management system (Liu et al., 2007a,b). GEPIC integrates a geographical information system (GIS) with a widely-used EPIC model (version EPIC0509), which explicitly considers key processes in ecosystems such as weather, hydrology, vegetation growth, nutrient and carbon cycling, soil erosion, tillage, and plant environmental control. The integration allows GEPIC to use all the functions of the EPIC model to simulate the above processes on a daily time step for more than 100 vegetations including crops, grass, and trees (Liu, 2009). Climate data, soil parameters, crop distribution, terrain properties (elevation and slope) and crop management are needed for the calculation of consumptive water use. Sources of the input data are described in detail in Sections "High-resolution data of harvested area and Other data sets". Details of the GEPIC and EPIC models are described in Liu et al. (2007b) and Williams et al. (1989), respectively.

Consumptive water use (CWU)

In this study, consumptive water use (CWU) refers to the total amount of water consumed by crops in terms of evapotranspiration. In each grid cell, CWU is calculated as:

$$\mathrm{CWU} = \mathrm{CWU}_r + \mathrm{CWU}_i \tag{1}$$

$$\mathrm{CWU}_r = \sum_c \mathrm{CWU}_r^c = 10 \times \sum_c (\mathrm{ET}_r^c \times A_r^c) \tag{2}$$

$$\mathrm{CWU}_i = \sum_c \mathrm{CWU}_i^c = 10 \times \sum_c (\mathrm{ET}_i^c \times A_i^c) \tag{3}$$

where CWU is consumptive water use in $m^3\,a^{-1}$ in one grid cell, subscript r and i refer to rainfed and irrigated agricultural systems, respectively. The subscript c represents the crop code. ET is evapotranspiration of crop c under rainfed conditions (r) or irrigated conditions (i) in $mm\,a^{-1}$, while A is area of crop c under rainfed or irrigated conditions in ha. The constant 10 converts mm into $m^3\,ha^{-1}$. In this paper, we calculated CWU both in crop growing periods and in the entire year in cropland. When CWU in crop growing periods was calculated, ET in crop growing periods was used. The annual CWU was calculated based on ET in the entire year. After harvest of crops weeds start to grow, particularly in humid regions. In addition, intercrops are increasingly used by farmers for soil conservation or nutrient trapping. In this article, we did not take weeds and intercropping into account mainly due to the lack of data.

The Hargreaves method (Hargreaves and Samani, 1985) is selected to calculate reference evapotranspiration (E_0) at a daily time step. The selection of this method is mainly due to two reasons. First, this method has a relatively low data requirement compared to other methods such as Penman (1948) or Penman–Monteith (Monteith, 1965). Second, the Hargreaves method has been demonstrated as an effective method to estimate crop yield and crop water use for large scales with a high spatial resolution, e.g. the entire world (Liu, 2009; Liu et al., 2007b), China (Liu et al., 2007a) and Sub-Saharan Africa (Liu et al., 2008). Evaporation from soil and transpiration from plants are calculated separately by an approach similar to that of Ritchie (1972). Interception of rainfall from crop canopy is not calculated by the EPIC model. The daily evapotranspiration is the sum of plant transpiration and soil evaporation. CWU is calculated as the sum of daily evapotranspiration within the growing season or the entire year.

Calculation of consumptive green and blue water uses

For rainfed crops, CWU_r is all from green water. For irrigated crops, CWU_i is partly from green water and partly from blue water. In order to estimate the proportion of green and blue water uses in irrigated agriculture, two different soil water balances are performed for irrigated crops according to FAO (2005).

(1) Soil water balance I is carried out by assuming that the soil does not receive any irrigation water. Seasonal evapotranspiration computed using this soil water balance is referred to as *SET1*.
(2) Soil water balance II is carried out by assuming the soil receives sufficient irrigation water. Seasonal evapotranspiration computed using this soil water balance is referred to as *SET2*.

For a specific crop under irrigated conditions, according to FAO (2005), green water use is equal to *SET1*, while blue water use is equal to the difference between *SET2* and *SET1*, or *SET2–SET1* in crop growing periods. Hence, for a specific crop under irrigated conditions, the proportion of blue water in crop growing periods is calculated as:

$$b_i^c = \frac{SET2^c - SET1^c}{SET2^c} \tag{4}$$

where b is the blue water proportion of crop c under irrigated conditions i.

It needs to be pointed out that *SET1* is not exactly the "green" part of seasonal evapotranspiration in the irrigated systems. Particularly in semi-arid and arid regions, crops in rainfed systems generally grow slower than those under irrigated systems, partly due to the lack of water and fertilizer. Smaller crops in rainfed systems often abstract less rain water from unsaturated soil; hence, *SET1* may underestimate the green water proportion. That is to say, the blue water proportion may be overestimated by Eq. (4).

In a grid cell, consumptive blue water use (CBWU) is equal to the CBWU under irrigated conditions ($CBWU_i$) for all crops as below:

$$CBWU = \sum_{c} (b_i^c \times CWU_i^c) \tag{5}$$

The blue water proportion (B) and green water proportion (G) in each grid cell are calculated as follows:

$$B = \frac{CBWU}{CWU} \tag{6}$$

$$G = 1 - B \tag{7}$$

with Eq. (6), blue water proportion in both crop growing periods and in the entire year are calculated. It is assumed that irrigation is not applied in non-growing periods. Hence, CBWU remains the same for the crop growing periods and the entire year. CWU during the growing periods differs from that during the entire year, leading to different blue water proportion in the two calculations.

High-resolution data of harvested area

Two data sources are used in this study for the harvest area of crops. One source is the center for sustainability and the global environment (SAGE) of the University of Wisconsin at Madison, USA (Ramankutty et al., 2008). The SAGE dataset provides harvested area of 175 primary crops in the year 2000 with spatial resolutions of 30 arc-minutes. In this dataset, the harvested area is the sum of the rainfed and irrigated crop area. Another source is the Institute of Physical Geography of the University of Frankfurt (Main), Germany (hereafter referred to as "MIRCA2000 dataset"). The MIRCA2000 dataset provides harvested area of 26 irrigated crops around 2000 with a spatial resolution of 30 arc-minutes (Portmann et al., 2008). The harvested area of these irrigated crops are calculated mainly based on the SAGE harvested area data and the global map of irrigated areas (Siebert et al., 2007). The harvested area (rainfed plus irrigated) of the 26 crops is also integrated from the SAGE dataset by Portmann et al. (2008). For these crops, the harvested area of a rainfed crop is assumed to be the difference between the harvested area and the irrigated harvested area of the corresponding crop in each grid cell. In case that the irrigated harvested area is higher than the total harvested area, we assume there is no rainfed harvested area for the corresponding crop.

After obtaining the harvested area data for both rainfed and irrigated crops, we regrouped the 26 crops into 22 crop categories (Table 1). The four crop types ("citrus", "date palm", "grapes/vine", and "others perennial") are combined into one category "fruits". Grape is the most planted fruit in terms of harvested area (FAO, 2006); hence, it is used as a representative crop for the simulation of fruits by the GEPIC model. Similarly, tomato is the most planted vegetable in terms of harvested area (FAO, 2006), and it is selected as a representative crop type for the simulation of vegetables. Fruits and vegetables only account for 3.7% and 3.4% of the total cropland (Ramankutty et al., 2008). They account for 6.0% and 6.4% of the total irrigated cropland. Hence, the use of representative crops will not significantly affect the simulation results of CWU. Since cocoa is not included in the GEPIC model, it is categorized together with coffee in this study. The crop group "cocoa and coffee" is represented by coffee. Potential heat unit (PHU) of each crop is shown in Table 1, and the values of PHU are based on expert judgment. In general, PHU varies in different locations even for the same crop. However, the spatial distribution of PHU is rarely studied in literature. Sensitivity of simulation outputs to PHU is demonstrated by Liu (2009). In each grid cell, we assume that all crops are planted on the same soil. The source of soil parameters are introduced in Section "Other data sets". The crop-specific fertilizer application rates at the national level are obtained from the statistical report by the International Fertilizer Industry Association with its partners (IFA, 2002). Grid-based fertilizer application rates are not available. It is assumed that a crop receives the same amount of fertilizer per hectare in all grid cells within a county. This assumption may lead to overestimation of CWU in grid cells with low fertilizer application rates, while underestimation of CWU in grid cells with high fertilizer application rates.

Table 1
The 22 crop categories used in this study.

Crop category in this study	Corresponding crop category in MIRCA2000	Representative crop for simulation	Potential heat unit (°C)
Wheat	Wheat	Wheat	1750
Maize	Maize	Maize	1000
Rice	Rice	Rice	1500
Barley	Barley	Barley	1000
Rye	Rye	Rye	1750
Millet	Millet	Millet	1500
Sorghum	Sorghum	Sorghum	1500
Soybeans	Soybeans	Soybean	1800
Sunflower	Sunflower	Sunflower	1500
Potatoes	Potatoes	Potato	1500
Cassava	Cassava	Cassava	1500
Sugar cane	Sugar cane	Sugar cane	1500
Sugar beets	Sugar beets	Sugar beet	1500
Oil palm	Oil palm	–	–
Rapeseed/canola	Rapeseed/canola	Rapeseed	1500
Groundnuts/peanuts	Groundnuts/peanuts	Groundnut	1500
Cotton	Cotton	Cotton	1500
Pulses	Pulses	Peas	1600
Coffee and cocoa	Coffee, cocoa	Coffee	1700
Fruits	Citrus, date palm, grapes/vine, others perennial	Grape	2223
Vegetables	Others annual	Tomato	1700
Managed grassland/pasture	Managed grassland/pasture	Pasture	2000

Oil palm cannot be simulated by the GEPIC model. The estimation of CWU of oil palm is mentioned in Section "High-resolution data of harvested area" in this paper.

It needs to be pointed out that oil palm cannot be estimated by the GEPIC model. Oil palm only accounts for about 0.6% of total cropland area. In addition, oil palm is mostly concentrated in very few countries in the tropical areas, such as Indonesia, Thailand, Malaysia, and Papua New Guinea. Due to the small share and high spatial concentration, we assume identical evapotranspiration of oil palm. Radersma and De Ridder (1996) calculate the evapotranspiration of oil palm to be 1018 mm a^{-1}. This level of evapotranspiration is used in the paper. Globally, only 0.1% of the area of oil palm applies irrigation (Portmann et al., 2008). Therefore, we ignored the irrigation for oil palm in the estimation of CWU.

Other data sets

Historical monthly data on maximum temperature, minimum temperature, precipitation and number of wet days between 1998 and 2002 are obtained with a spatial resolution of 30 arc-minute from the Climate Research Unit of the University of East Anglia (CRU TS2.1) (Mitchell and Jones, 2005). A MOnthly to DAily

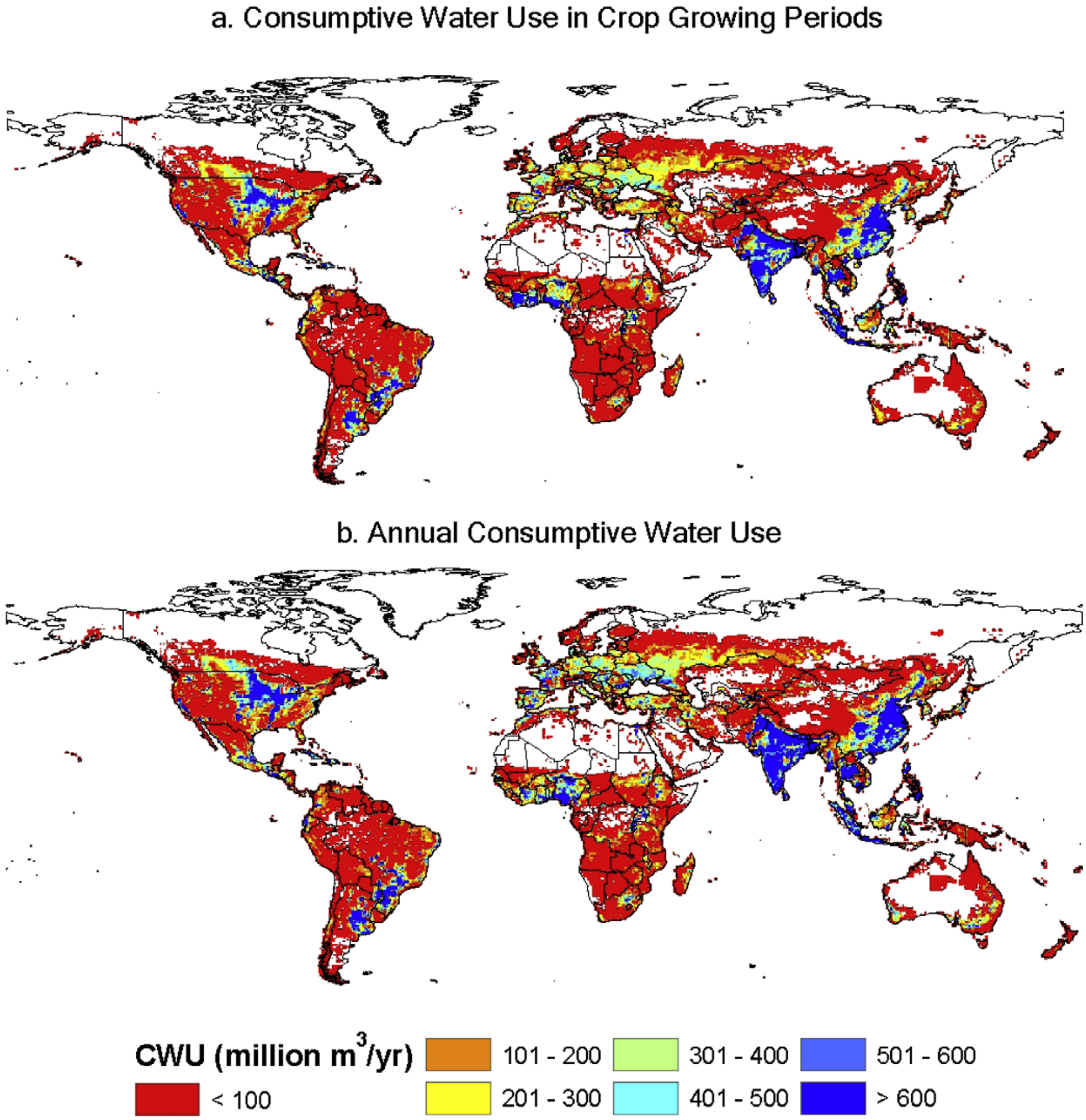

Fig. 1. Spatial pattern of consumptive water use in cropland around the year 2000: (a) in crop growing periods and (b) in the entire year.

WEather Converter (MODAWEC) model is used to generate the daily weather data (Liu et al., 2009a). Soil parameters of soil depth, percent sand and silt, bulk density, pH, organic carbon content are obtained from Batjes (2006). Soil parameters are available for five soil layers (0–20, 20–40, 40–60, 60–80, 80–100 cm). All other data used for the GEPIC model have been described in detail in Liu et al. (2007b).

Results and discussion

Consumptive water use (CWU)

Spatial pattern

The global CWU in crop growing periods was 5938 $km^3\ a^{-1}$ in cropland around the year 2000 (the average of the years 1998–2002). Spatial patterns of CWU are demonstrated in Fig. 1a. The highest CWU per grid cell (e.g. >400 million $m^3\ a^{-1}$) was found in most part of India, eastern part of China, some countries in Southeast Asia such as Indonesia, Mid Central of the USA, part of Argentina and Brazil, and very few countries in Africa (e.g. Nigeria, Ghana, and Ivory Coast). These regions represent the most intensive agricultural production area in the world. In Europe, CWU in most grid cells is between 300 and 400 million $m^3\ a^{-1}$. In other parts of the world, CWU was generally lower than 100 million $m^3\ a^{-1}$.

Spatial pattern of annual CWU in the entire year is similar to that of CWU in the crop growing periods (Fig. 1a vs. Fig. 1b). At the global level, annual CWU was 7323 $km^3\ a^{-1}$ in cropland around the year 2000. This means that 81% of the annual CWU was used in the crop growing periods, while the remaining 19% occurred in the non-growing periods. At the river basin level, Mississippi, Yangtze, Ganges and Nile are the four river basins with the highest CWU both during the growing periods and for the entire year (Table 2). These four river basins account for around 20% of the global CWU.

The spatial distribution of CWU closely follows the land use patterns, with high proportions in the belt between 10°N and 40°N,

Table 2
Consumptive water use and blue water proportion in major river basins.

Name of river basin	Annual consumptive water use ($km^3\ a^{-1}$)	Consumptive water use in crop growing periods ($km^3\ a^{-1}$)	Consumptive blue water use ($km^3\ a^{-1}$)	Blue water proportion in the entire year (%)	Blue water proportion in crop growing periods (%)
Mississippi	538.3	445.6	58.4	10.8	13.1
Yangtze	441.7	338.5	65.0	14.7	19.2
Ganges	407.0	296.7	57.0	14.0	19.2
Nile	144.2	114.1	19.1	13.2	16.7
Danube	104.2	77.8	2.0	1.9	2.6
Yellow	94.7	73.3	24.5	25.9	33.4
Murray–Darling	56.1	37.0	9.3	16.6	25.1
Amazon	55.6	48.8	1.4	2.5	2.8
Orange	25.4	19.5	1.4	5.3	6.9
Mac Kenzie	7.2	5.5	0.002	0.0	0.0
Lena	0.24	0.19	0.043	17.9	22.6

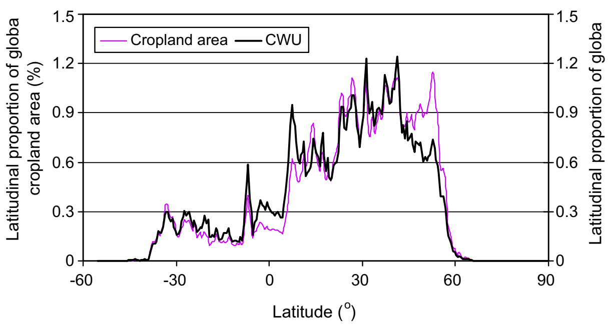

Fig. 2. Latitudinal breakdown of cropland area and CWU in crop growing periods around the year 2000.

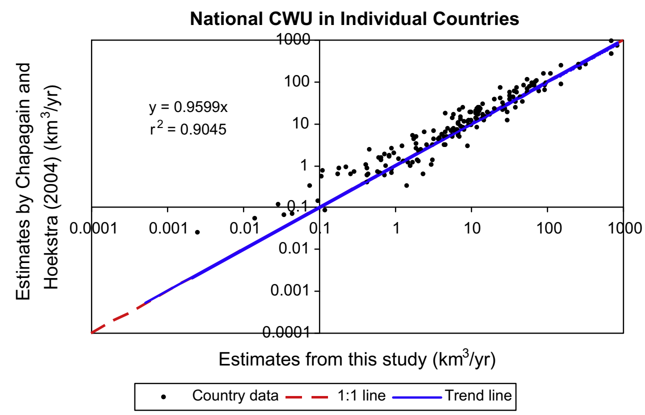

Fig. 3. Comparison of national consumptive water use (CWU) between this study and Chapagain and Hoekstra (2004). Each dot represents one country. The full line is the trend line. The dashed line is the 1:1 line.

and low proportions in the South Hemisphere, tropical regions and high latitudinal regions in the North Hemisphere (Fig. 2). The belt between 10°N and 40°N is a very important agricultural production region, and it includes the major agricultural production areas of China, India and the USA. It accounts for 48% of total world cropland area, as well as 48% of the total world CWU. Compared to cropland area, CWU has a relatively high proportion in the tropical regions, while a relatively low proportion in the high latitude (e.g. >45°N) (Fig. 2). The high temperature and precipitation in the tropical regions lead to high water use per unit of cropland area (or high evapotranspiration), while the relatively low temperature in the high latitudinal regions results in low evapotranspiration there. Different climate conditions are an important factor for the disproportions of cropland area and CWU in the equator and at higher latitude areas.

There have been several estimates of global CWU available in the literature. These estimates range from around 3500 $km^3\ a^{-1}$ (Zehnder, 1997) to 7400 $km^3\ a^{-1}$ (Postel et al., 1996), depending on the land types and the methods used for the estimation. Postel et al. (1996) provide a CWU value of 7370 $km^3\ a^{-1}$ in cultivated land in 1990. Cultivated land area refers to arable land and land under permanent crops. Cultivated land area is almost equal to cropland area; hence, the above estimate can be regarded as CWU for cropland. The estimation by Postel et al. (1996) is very rough with several strong assumptions. For example, Postel et al. assume an average irrigation depth of 1200 mm a^{-1} in agricultural land, which is likely too high compared to reality. Rockström et al. (1999) calculate global CWU at 6800 $km^3\ a^{-1}$ for the period 1992–1996 by using crop production and crop water productivity of 18 crop groups, with differentiation of tropical and temperate climate zones. Crop water productivity of various crop groups was based on extensive literature review. Chapagain and Hoekstra (2004) calculate the global CWU as 6390 $km^3\ a^{-1}$ for 164 crops based on national average crop production and national average crop water productivity (CWP) for the period 1997–2001. This estimate considers crop production and crop water productivity in individual countries, but it does not take into account the variations within a country. The estimate from Chapagain and Hoekstra (2004) is very close to our estimate of 5938 $km^3\ a^{-1}$ in crop growing periods.

Country-specific CWU in crop growing periods

The top six countries with the highest CWU are China, USA, India, Brazil, Russia and Indonesia (Appendix A). These six countries account for over half (i.e. 51.4%) of the global total CWU. The high CWU in these countries is mainly due to the large cropland area. These countries account for almost half (i.e. 47%) of the total global cropland (Ramankutty et al., 2008).

CWU is seldom reported in statistics. This makes the validation of our results difficult. In this paper, the validation is conducted in two ways: (1) the national CWU calculated in this study is compared with that calculated by Chapagain and Hoekstra (2004). This is a compromise for model inter-comparison when statistical data are not available; (2) the simulated CBWU is compared with national statistics for irrigation, as shown in Section "Comparison between simulated and statistical CBWU at the national level". In addition, the simulated CBWU in the USA and China is compared with the statistical CBWU at the state or provincial level.

The national CWU from this study compares very well with that from Chapagain and Hoekstra (2004) with a high r^2 value of 0.90 (Fig. 3). The trend line ($y = 0.9599x$) is almost exactly the same as the 1:1 line. All the dots are scattered near the 1:1 line except for those with very low CWU values (e.g. <1 $km^3\ a^{-1}$). The disagreement for the countries with very low CWU values is largely caused by their small cropland area and the logarithmic scale,

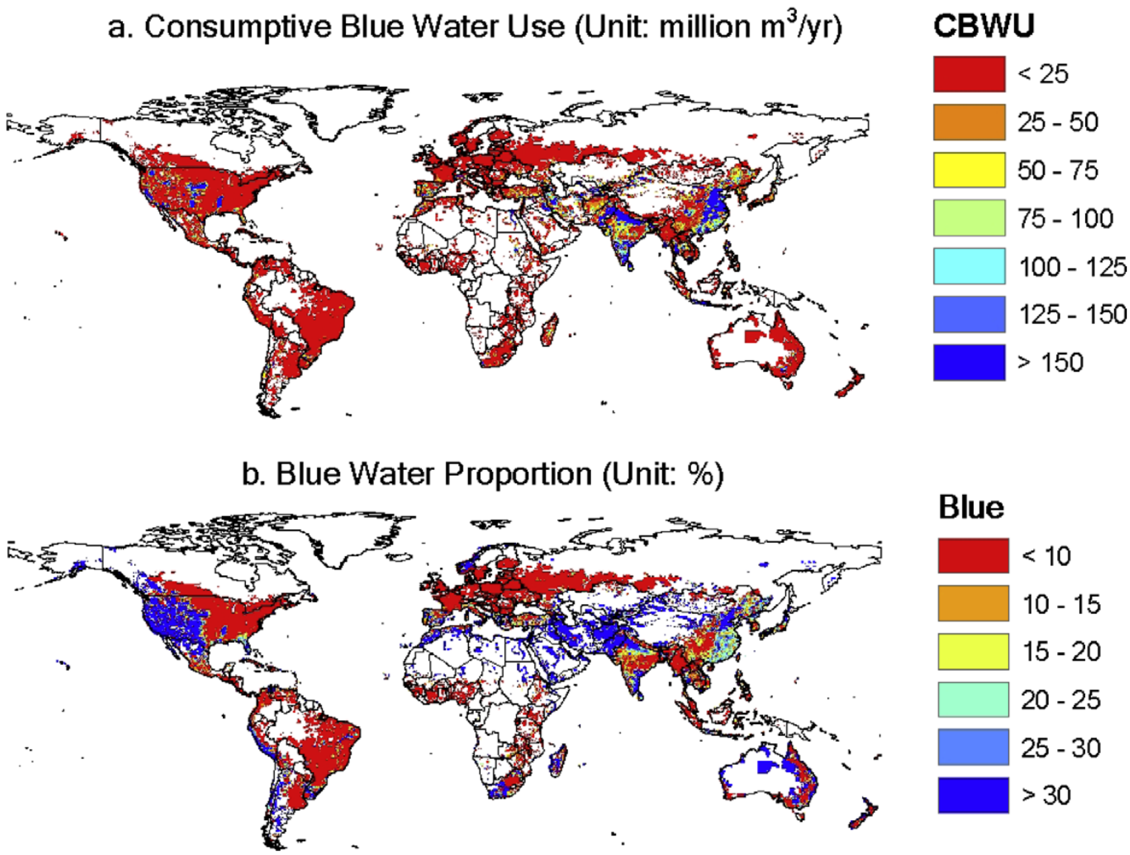

Fig. 4. Spatial pattern of: (a) consumptive blue water use and (b) blue water proportion in crop growing periods in cropland.

which often leads to errors when aggregating grid cell CWU to the national total. However, these countries only account for 0.2% of the total global CWU. The disagreement of CWU in these countries will not significantly affect the estimated total global CWU.

Consumptive blue water use (CBWU)

Spatial pattern

The consumptive blue water use (CBWU) was 927 $km^3\,a^{-1}$ in cropland on a global scale based on land cover and climate data around the year 2000. Hence, in crop growing period, blue water accounts for 16% of the global CWU, while green water accounts for 84%. On an annual basis, the figures are 13% and 87% for blue water and green water, respectively. High CBWU occurs in northern and southern India, eastern part of China, and the Mid Central of the USA (Fig. 4a). As discussed previously, these regions are the major agricultural production regions in the world, and they also have very high CWU. When irrigation infrastructure exists, these regions often use a large volume of blue water, mainly due to the large agricultural area there. As for the blue water proportion, regions with high values are located in the northern part of China, several West Asian countries, Middle East and North Africa (MENA), the western part of the USA, and Chile (Fig. 4b). These regions mostly have arid or semi-arid climate with low precipitation. Precipitation can only meet part of the water required by crops. In order to achieve high crop yields, irrigation water has to be supplied in addition to precipitation. Largely due to the low precipitation, irrigation depth is generally very high, resulting in high blue water proportion.

The spatial distribution of CBWU closely follows the pattern of irrigated area, with high proportions in the belt between 25°N and 40°N, and low proportions in the South Hemisphere, tropical regions and high latitudinal regions in the North Hemisphere (Fig. 5). The belt between 25°N and 40°N covers the major agricultural production regions in China, the USA and India. This belt accounts for 51% of the total world irrigated area as well as 55% of the total world CBWU. The shares of both irrigated area and CBWU are small in the South Hemisphere. This is largely due to two reasons: first, the share of cropland in the South Hemisphere is low, as shown in Fig. 2. Second, rainfed agriculture is the dominant agricultural systems in most regions in the South Hemisphere. The dominance of rainfed agriculture is in part due to high precipitation such as in many countries in South America, or the low financial capacity to develop irrigation infrastructure such as in many African countries, or both the reasons. Besides, maize and wheat are often the major crops in South America and Sub-Saharan African. Both the crops have lower water use (particularly irrigation) than e.g. rice. In addition, there is no tradition and indigenous know-how of irrigation in many areas in the two continents.

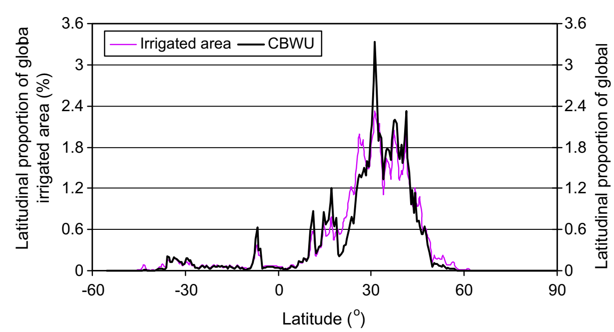

Fig. 5. Latitudinal breakdown of irrigated area and CBWU around the year 2000.

At the river basin level, the Yellow River, Lena and Murray–Darling River basins had the highest blue water proportion (Table 2). These river basins are located in arid or semi-arid climates with low precipitation. For example, the mean annual rainfall in the Yellow River basin is 452 mm a^{-1}. Meanwhile, this river basin is an important food producing region in China (Yang and Jia, 2008), and almost three fourths of the population lived in rural areas of the basin in 2000. Irrigation is vital to maintain high agricultural productivity, leading to relatively higher blue water proportion compared to other river basins. In contrast, the Mac Kenzie, Danube and Amazon River basins had the lowest blue water proportions (Table 2).

Comparison between simulated and statistical CBWU at the national level

Statistical data on CBWU are not available, but data on both irrigation water withdrawal and project efficiency are available. Project efficiency reflects that fraction of the water diverted from a source for irrigation purposes, which is available for beneficial crop evapotranspiration (Rohwer et al., 2007). Hence, CBWU can be calculated by multiplying statistical irrigation water withdrawal by project efficiency at the national level. We refer this calculated CBWU as statistical CBWU. The country-specific project efficiency was obtained from Rohwer et al. (2007). Statistical data on agricultural water withdrawal were reported by AQUASTAT (2008) at the national level. Agricultural water withdrawal data were available for 139 countries, of which 129 countries had data for the year 2000. For the remaining 10 countries, agricultural water withdrawal in the year nearest to 2000 was used depending on the data availability. We assume that irrigation water withdrawal is equal to agricultural water withdrawal at the national level. This may slightly overestimate CBWU because agricultural water withdrawal is also used for domestic purposes by rural population and animal husbandry in addition to irrigation. For example, in China, 91.6% of agricultural water withdrawal is used for irrigation, while the rest is used for other purposes (MWR, 2001).

In general, the simulated CBWU by the GEPIC model compares well with the statistical CBWU with a high r^2 value of 0.886 (Fig. 6). The trend line is close to the 1:1 line. The slope of the trend line, or 0.941, indicates that our simulated CBWU slightly underestimates the actual CBWU. This is partly caused by our assumption that irrigation water withdrawal is equal to agricultural water withdrawal, which results in overestimation of the statistical CBWU. In addition, the statistical data on agricultural water withdrawal also bear high uncertainties, which may be one important reason for the overestimation. For example, According to the China Water Resources Bulletin, agricultural water withdrawal was 378.4 km^3 a^{-1} in China in 2000. However, according to AQUASTAT (2008), it was 427 km^3 a^{-1}, or 12.8% higher than that reported in the China Water Resources Bulletin. In Fig. 6, the AQUASTAT data are used for all countries including China to keep the source of statistical data consistent.

Comparison between simulated and statistical CBWU in the USA

Irrigation water withdrawal was reported at the level of the federal state in the USA for 2000 (Hutson et al., 2004) and 1995 (Solley et al., 1998). Consumptive irrigation water use, which is equivalent to CBWU in this paper, was reported for 1995, but not for 2000. In order to calculate the CBWU in each state in 2000, we assume the same project efficiency in 2000 as that in 1995 for all the states. Based on this assumption and irrigation water withdrawal data, the total CBWU in the USA is calculated to be 117 km^3 a^{-1} (this is referred to as statistical CBWU in this paper). In each state, project efficiency may be slightly higher in 2000 than that in 1995 due to the technological progress. Hence, the assumption of the same project efficiency may lead to an underestimation of statistical CBWU. Our simulated CBWU (i.e. 138 km^3 a^{-1}) is about 19% higher than the statistical CBWU. The assumption on constant project efficiency in part explains the difference between the simulated CBWU and the statistical CBWU for the USA. It is interesting to note that Siebert and Döll (2008) estimate the CBWU to be 139 km^3 a^{-1} in the USA, which is exactly the same as our estimate.

The simulated CBWU by the GEPIC model agrees well with the statistical CBWU on the state level (Fig. 7). The two data sets were correlated with an r^2 value of 0.945 when setting intercept to 0. California is a state with the highest CBWU. The CBWU in California from both the sources is almost the same (32.6 km^3 a^{-1} by GEPIC vs. 34.3 km^3 a^{-1} in statistics). Large differences exist in the states where CBWU is low, such as West Virginia, Alaska, and New Hampshire. Among others, two reasons explain the differences in these states. First, uncertainty is generally high for statistics for the states with low CBWU. For example, the statistics show the project efficiency is 1 in West Virginia, which has the lowest CBWU among all the states (Solley et al., 1998). This project efficiency is likely to be too high according to our knowledge. Second, these states generally have small cropland area, or very few grid cells for simulation. The small number of grid cells often leads to aggregation errors at a high level.

Comparison between simulated and statistical CBWU in China

According to the China Water Resources Bulletin (MWR, 2001), the total agricultural water use was 378.4 km^3 a^{-1} in 2000 in China, of which about 91.6% was for irrigation purposes. On average, 37% of the irrigation water use was lost during the delivery processes from water source to crops (MWR, 2001). This means that only 63% of irrigation water can be used by crops, or project

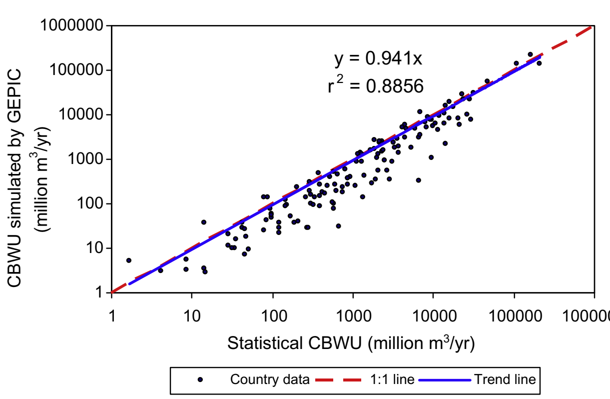

Fig. 6. Comparison between the statistical CBWU and the simulated CBWU by the GEPIC model at a national level.

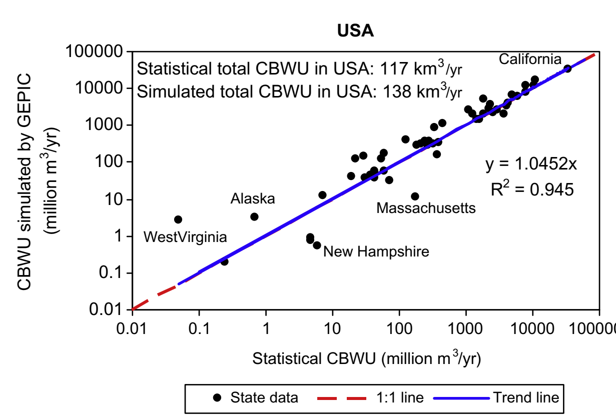

Fig. 7. Comparison between statistical and simulated CBWU at state level in the USA.

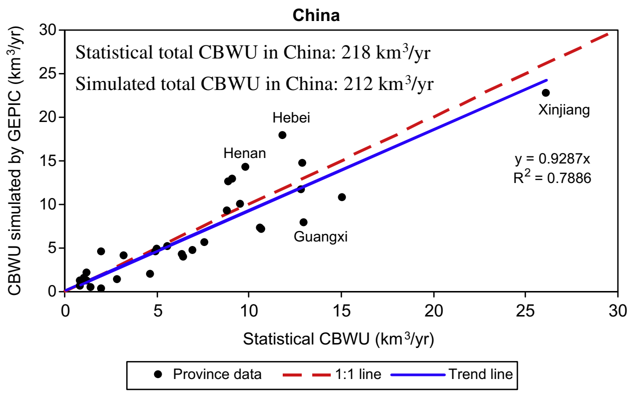

Fig. 8. Comparison between statistical and simulated CBWU at provincial level in China.

efficiency is 0.63. As a result, the total statistical CBWU was 218 $km^3\ a^{-1}$ in 2000 in China.

The simulated CBWU in this paper was 212 $km^3\ a^{-1}$ for China around the year 2000. This estimate is almost the same as the statistical CBWU, indicating the high accuracy of the simulated CBWU for China. According to Siebert and Döll (2008), CBWU was 147 $km^3\ a^{-1}$ for China over 1998–2002. Their estimate is about 30% lower than both our estimate and the statistical CBWU.

The Water Resources Bulletin also reported agricultural water uses in 31 individual provinces in China. CBWU was calculated for each province by multiplying the total irrigation water use by project efficiency. We use the same project efficiency at the national average for all provinces except for those located in the Haihe River basin and Guangdong province. The project efficiency in the Haihe River basin is about 80% according to the Water Resources Bulletin for the Haihe River basin, well above the national average. Guangdong province is located in the Southern part of China with high precipitation. The project efficiency there is well below the national average, only 45% according to the Water Resources Bulletin of the Guangdong Province.

CBWU simulated in this paper agrees well with the statistical CBWU for 31 provinces in the mainland China with an r^2 value of 0.789 when setting intercept to 0 (Fig. 8). The trend line ($y = 0.9287x$) is close to the 1:1 line. The province with the highest CBWU is Xinjiang. According to our calculation, CBWU in this province is 22.7 $km^3\ a^{-1}$, which compares very well with the statistics (i.e. 26.2 $km^3\ a^{-1}$). Despite the good agreement, there are still a few provinces where our simulated CBWU largely diverges from the statistical CBWU (e.g. Hebei, Henan and Guangxi provinces). In our simulation, we assume that irrigation water is always available when irrigation infrastructure exists. This assumption leads to overestimation of CBWU for the regions where only deficit irrigation is applied. Hebei and Henan provinces are located in the North China Plain, where water scarcity is serious (Liu et al., 2007a,c; Liu and Savenije, 2008b; Yang and Zehnder, 2001). Farmers in these two provinces generally apply less irrigation water than crop water requirement. Largely due to this situation, our results overestimate CBWU in both the provinces. For other provinces, the use of the national average project efficiency may partly explain the differences between the simulated and statistical CBWU.

Consumptive water use vs. virtual water trade at the national level on a per capita basis

On a per capita basis, the countries with large CWU (e.g. >1400 $m^3\ cap^{-1}\ a^{-1}$) are located in North America, many South American countries, Oceania, several Southeastern Asian countries, and Russia, while the countries with low CWU (e.g. <400 $m^3\ cap^{-1}\ a^{-1}$) are mainly in MENA and several Sub-Saharan

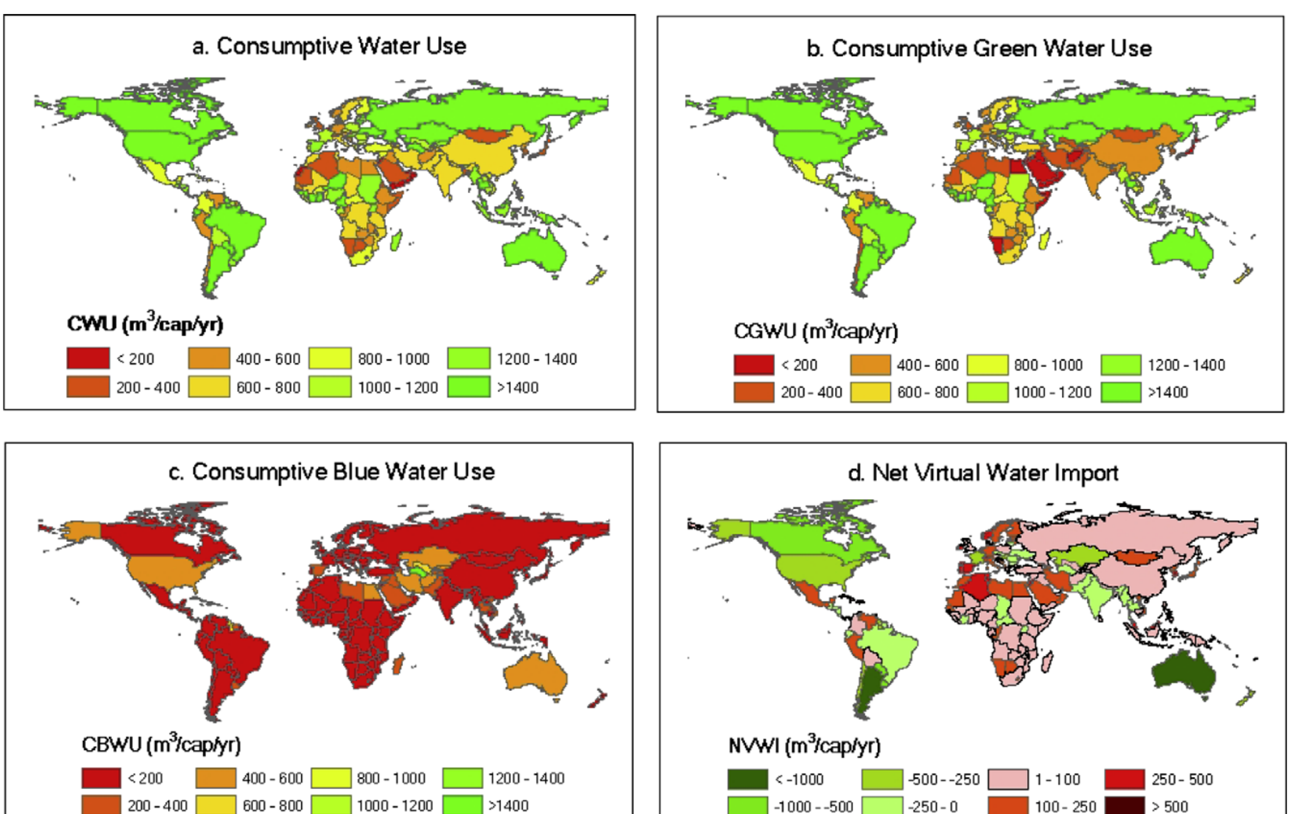

Fig. 9. Consumptive water use (CWU), consumptive green water use (CGWU), consumptive blue water use (CBWU) and net virtual water import (NVWI) at the national level on a per capita basis.

African countries (Fig. 9a). The countries with low CWU are either too arid to support large-area agricultural production or too poor to support high-production agriculture. The distribution of consumptive green water use (CGWU) on a per capita basis is very similar to that of CWU (Fig. 9b), reflecting the dominance of green water in CWU. The high consumptive blue water use (CBWU) on a per capita basis is in the USA, Australia, several countries in the Central Asia, Middle East, Egypt, Libya, and Spain (Fig. 9c). These countries either have a high blue water proportion (e.g. Egypt), or a very low population that leads to high per capita irrigated area (e.g. Australia).

In the recent decade, virtual water has been recognized as an option for integrated water resources management. Virtual water describes the amount of water consumed in the production process of a product (Allan, 1998). The concept of virtual water import implies that water scarce countries could mitigate water scarcity by importing water intensive food (Hoekstra and Hung, 2005; Liu and Savenije, 2008b; Liu et al., 2007c; Yang et al., 2003). We estimate net virtual water import (NVWI) on a per capita basis (Fig. 9d). When NVWI has a positive sign, the country is a net importing country with respect to virtual water trade; the opposite sign indicates a net exporting country.

The countries with large per capita NVWI are mainly located in the regions where poor climatic conditions do not allow large area of agricultural production (as a result, CWU is also low in these countries), e.g. the arid MENA region, and the low-temperature countries e.g. Northern Europe and Mongolia. Particularly in the MENA countries, the current NVWI already reaches or even exceeds combined green and blue water uses in domestic agriculture. Virtual water imports play a vital role in mitigating the regional water scarcity and in guaranteeing the regional food security. Given the strong agreement among climate models for less precipitation in the future in the MENA region, virtual water trade will become more important for the regional water and food security.

It should be pointed out that virtual water import is influenced not only by climatic conditions, but also by economic conditions and other factors. The top two largest virtual water importers are the Netherlands and Belgium. Although both the countries are big meat exporters with over 120 kg cap^{-1} a^{-1} of meat exports, they import a large amount of feed concentrates and raw materials e.g. cassava and soybeans. Virtual water import through the trade of raw materials is much larger than virtual water export through meat trade in these countries (Liu et al., 2009b). Our findings show that many African countries have low CWU, but they do not have high NVWI. Low financial capacity poses a constraint to food imports from international market (Liu et al., 2009b).

The large countries in terms of per capita net virtual water export (NVWE) are mainly in North America, Oceania, and South America. Australia and Argentina are the top two largest virtual water exporters. They have 1665 and 1235 m^3 cap^{-1} a^{-1} of NVWE, respectively. A large area of cropland on a per capita basis is one important reason leading to the high NVWE. The area for arable and permanent crops was around 2.49 and 0.78 ha cap^{-1} a^{-1}, much higher than the world average of 0.25 ha cap^{-1} a^{-1} in 2000 (FAO, 2006). Another interesting phenomenon is that large exporting countries generally have lower blue water proportion in virtual water trade than that in domestic food production. According to Liu et al. (2009b), except for Thailand, all the 10 major virtual water exporting countries have lower blue water proportion in virtual water trade than that in domestic food production.

Improvement of crop water productivity (CWP) by better water and nutrient management

Blue water has become scarcer and scarcer in an increasing number of countries with population growth and economic devel-

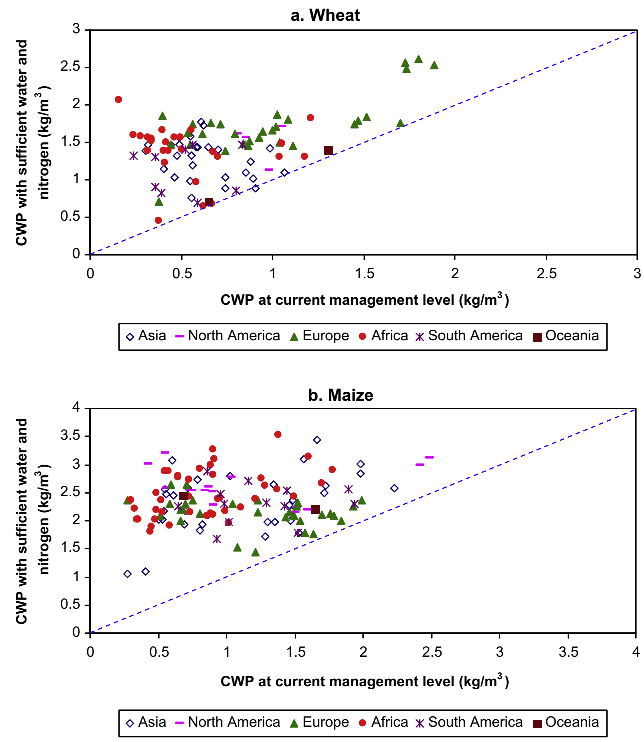

Fig. 10. Crop water productivity (CWP) at the current management level vs. CWP with sufficient water and nitrogen application.

opment. Agriculture will face a great challenge to produce more food with less available blue water in the next half century. This requires an improvement of CWP to increase crops per drop. Among others, water and nutrient management are two important issues for this purpose. We compare the national average CWP of wheat and maize under two situations: the current situation (CWP_c) and the situation with sufficient water and nitrogen (CWP_s). At the grid cell level, for the current situation, CWP is simulated under rainfed and irrigated conditions. Crop-specific fertilizer application rates are obtained from statistical data reported by the International Fertilizer Industry Association. For the situation with sufficient water and nitrogen, we assume that all rainfed croplands are converted into irrigated cropland. In addition, crops can always obtain sufficient irrigation water and fertilizer when water stress or nitrogen stress occur. The grid-based CWP is aggregated to the national level based on crop harvest area of each crop. For both crops considered, CWP_s is higher than CWP_c in all countries (Fig. 10). The difference between CWP_s and CWP_c is particularly large in Africa. For example, CWP_c of wheat is generally lower than 0.75 kg m^{-3} in the African countries, but CWP_s can reach a level as high as around 1.5 kg m^{-3} (Fig. 10a). Water and nutrient management plays an important role also for maize in increasing CWP (Fig. 10b). With sufficient water and nitrogen supply, CWP_s of maize can reach 2 kg m^{-3} in most African countries, although the current CWP_c is lower than 1 kg m^{-3} in many of these countries.

Our findings show the importance of supplying water together with nitrogen to crops. However, blue water is becoming increasingly scarce. This implies higher opportunity costs of blue water, and lower economic efficiency of traditional water management (e.g. expansion of irrigated area) in many regions. It needs to be pointed out that there are many low-cost techniques for water management, including soil conservation tillage and rain water harvesting techniques (Schiermeier, 2008). These techniques may significantly increase crop yields of major crops (Rockström, 2003). Attention should be paid to the knowledge transfer of these cheap but often sophisticated water management techniques. Low

CWP in Africa is among other reasons a result of low fertilizer application, which is often caused by high fertilizer prices. The Africa's fertilizer prices are typically 2–6 times higher than those in Europe, North America or Asia (Sanchez, 2002) mainly due to high taxes on imported fertilizers, poor infrastructure, and consequently high transport costs and low access to markets and utilities (Haile, 2005). In order to enhance farmers' access to fertilizer, future development policies need to emphasize investment in rural infrastructure.

Conclusion

We quantified consumptive water use (CWU) in cropland in a spatially explicit way by taking into account both green and blue water components. The results show that the global CWU was 5938 $km^3\ a^{-1}$ in the crop growing periods and 7323 $km^3\ a^{-1}$ in the entire year in cropland around the year 2000. Green water contributed to 84% of the global CWU in the crop growing periods and 87% of the global CWU on an annual basis. The high proportion of green water was in part due to the dominance of rainfed agriculture, which consumed 4068 $km^3\ a^{-1}$ of water in the crop growing periods and 5105 $km^3\ a^{-1}$ of water in the entire year. In addition, in irrigated cropland, green water contributed to 50% of the total CWU in the crop growing periods, and over 60% of the annual total CWU.

The important role of green water in crop production gives rise to the need for a better management of this water resource. However, in the past, water engineers and managers have mainly focused on expansion of irrigation infrastructure, particularly in many Asian countries. There is a general lack of green water management. Nowadays, further developing irrigation infrastructure becomes more and more difficult. There is not much potential to build large dams in most countries because water projects have been developed in the most suitable locations. Against this background, improving green water management should be an important option to guarantee world food security in the future.

There are several uncertainties in this study for the quantification of consumptive water use and the partitioning into green and blue components. First, many assumptions have to be made due to the lack of data. Intercropping is often in practice, but it is not explicitly considered in this study. Harvest area of different crops can partly reflect the pattern of intercropping, but the exact planting and harvest dates are not available. An automatic calendar algorithm is used, which calculates crop yields by using a series of planting and harvest dates. The crop calendar with the highest crop yield is selected. This algorithm theoretically involves an assumption that local farmers have perfect knowledge in selecting planting and harvesting dates (Liu et al., 2008). Another assumption is that the same crop receives the same amount of fertilizer under both rainfed and irrigated systems. In the real world, irrigated crops generally receive more fertilizer than rainfed crops. Our assumption may lead to underestimation of consumptive water use for irrigated systems, while overestimation for rainfed systems. Second, the EPIC model is well established for conventional crops e.g. wheat and maize of the US. However, there are few reports on the performance and reliability of the model to simulate crops such as cassava, potato, sugar beet, groundnut, cotton, cowpea and pasture. Although simulated national average yields compare well with statistics, more efforts are needed to validate the performance of the EPIC model in simulating the unconventional crops on different sites all over the world. Third, for irrigated system, variations in irrigation methods (e.g. surface, sprinkler, sub surface, micro) were not considered. Flood irrigation was used for all irrigated crops for all grid cells. Since advanced irrigation systems (sprinkler, sub surface, micro) only account for a small share in irrigated cropland, this assumption may not lead to large errors.

Acknowledgements

This study was supported by the Outstanding Scholar Program of Beijing Forestry University, Beijing, China (Grant No. BLJC200909). It is also supported by the Beijing Municipal Science and Technology Commission Project (Grant No. D090409004009003).

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jhydrol.2009.11.024.

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