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The water productivity score (WPS) at global and regional level: Methodology and first results from remote sensing measurements of wheat, rice and maize

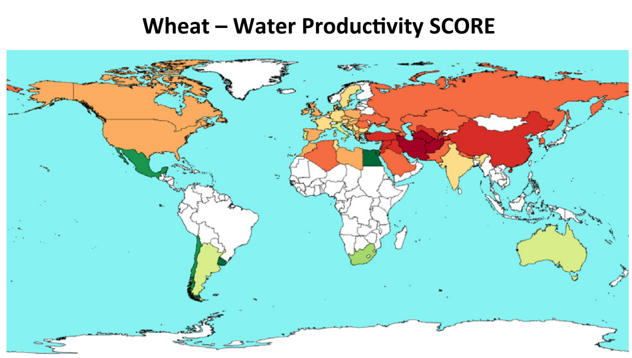
Wim G.M. Bastiaanssen [a,b,*], Pasquale Steduto [c]

[a] UNESCO-IHE Institute for Water Education, Westvest 7, P.O. Box 3015, 2611, DA, Delft, The Netherlands
[b] Delft University of Technology, Faculty of Civil Engineering and Geosciences, Stevinweg 1, 2628, CN, Delft, The Netherlands
[c] FAO, UN Food and Agricultural Organization, 11 El Eslah El Zerai Street, Dokki, P.O. Box 2223, Cairo, Egypt

HIGHLIGHTS

- First global scale high resolution map of crop water productivity for wheat, rice and maize
- First introduction of Water Productivity Score (WPS) to facilitate benchmarking of water consumption in agriculture
- Normalizing water productivity against crop type, climate and production potential
- Identification of local gaps and target values for crop water productivity that can be used for Sustainable Development Goals
- Analytical equations to express upper and lower boundaries by production potential zone

GRAPHICAL ABSTRACT



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ABSTRACT

Scarce water resources are one of the major constraints to achieve more food production. Food production needs therefore also to be evaluated in terms of water consumption, besides the conventional unit of land. Crop Water Productivity (CWP) is defined as the crop yield per unit of water evaporated. Contrary to crop yield, local benchmark values for CWP do not exist. This paper shows how operational earth observation satellites can measure CWP indirectly on a pixel-by-pixel basis, which provides an opportunity to define local, regional and global benchmark values. In analogy to a grading system for earthquakes (Richter) or wind force (Beaufort), a grading system for CWP is introduced: the Water Productivity Score (WPS). A regional scale WPS and a global version - Global Water Productivity Score (GWPS) - are presented. Crop yield zones are used to reflect local production potential, which reflects also the presence of irrigation systems besides general physio-graphical conditions. The 99th percentiles of climatic normalized CWP values at global scale are 2.45, 2.3 and 4.9 kg m^{-3} for wheat, rice and maize respectively. There is significant scope to produce the same - or more - food from less water resources, provided that locally specific best on-farm practices are implemented. At the upstream level, Governments can use (G)WPS to define national water and food policies and use it as a means to report to the Sustainable

* Corresponding author at: UNESCO-IHE Institute for Water Education, Westvest 7, P.O. Box 3015, 2611, DA, Delft, The Netherlands.
E-mail address: w.bastiaanssen@unesco-ihe.org (W.G.M. Bastiaanssen).

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Development Goal standards. At the downstream level, WPS helps to improve on-farm water management practices by growers, both for rainfed and irrigated crops. While the current paper is based on wheat, rice and maize, the same framework can be expanded to potatoes, sugarbeet, sugarcane, fruit trees, cotton and other crops.

1. Introduction

It is estimated that in the next 40 years, food production needs to increase by 60% in developed countries and up to 100% in developing countries (Alexandratos and Bruinsma, 2012). The main strategies for securing future food demands are: (i) reducing the existing yield gap; (ii) increasing water productivity and efficient use of other natural resources; (iii) avoiding land degradation, (iv) reducing losses and waste of food, and (v) adopting more sustainable diets (Foley et al., 2011; Steduto et al., 2012). Expansion of cultivated lands is not considered appropriate as it causes an unacceptable impact on losses of biodiversity and an increase in greenhouse gas emissions (Foley et al., 2011). Over the last 50 years the world has dramatically changed from a situation of apparent abundance of water to a situation of water scarcity (e.g. Steduto et al., 2012). While an individual may need 50 to 150 l of water a day for personal use, seventy times more water is needed to produce an individual's daily food requirement. Agriculture is responsible for about 60% to 90% of global freshwater withdrawals, mostly through irrigation, which significantly reduces river outflow to oceans (Falkenmark and Molden, 2008), substantially lowers groundwater tables (Siebert et al., 2010; Wada et al., 2010), and causes degradation of water quality (UNDP, 2008). Anthropogenic pressure on land and water resources is stretching the planet's sustainability to its limits (Rockstrom et al., 2009). Given this scarcity of land and water resources, the key strategy to increase food security should be through the increase of production per unit resources, i.e., the combined increase of production per unit land (crop yield expressed in kg ha^{-1}) and the increase of production per unit water consumed (water productivity expressed in kg m^{-3}). These water and food security concerns have prompted the Food and Agriculture Organization of the United Nations (FAO), UN Water and other international organizations to engage in programs to improve Crop Water Productivity (CWP). The United Nations embraced CWP as one of the Sustainable Development Goals (SDGs) in their General Assembly (September 2015), although it is referred to as water use efficiency in SDG 6.4.

While a wealth of knowledge is associated to land productivity statistics (kg ha^{-1}), information and guidelines on CWP (kg m^{-3}) are lacking. Only experimental studies provide estimates on physical ranges of CWP, though in a scattered manner. Zwart and Bastiaanssen (2004) created a worldwide database of CWP, based on a literature review, which was further expanded by Bastiaanssen et al. (2012a) to establish the "FAO-CWP" database. This FAO-CWP database is based on 96 research papers for wheat, 46 papers for maize and 29 papers for rice. Fig. 1 illustrates diagrams between experimental crop yield data (Y) and the associated actual evapotranspiration data (ET) required to achieve that yield. Only field experiments with well described techniques to measure actual crop ET were included in the database. The field experiments took place in the period 2000 to 2010 and reflect the crop conditions from 17 countries spread over five continents. A total of 840 data points are included for wheat, 242 data points for rice and 410 data points for maize. Fig. 1 shows that wheat ET ranges from 1000 m^3 ha^{-1} to 9000 m^3 ha^{-1}, while crop yield ranges between 500 kg ha^{-1} to 8500 kg ha^{-1}. More recently, certain countries report an average wheat yield of 9000 kg ha^{-1}, so there should be several individual fields with a higher wheat yield (e.g. 10,000 to 12,000 kg ha^{-1}). Rice yield in Fig. 1 can be as high as 13,500 kg ha^{-1}, being in better agreement with optimum farming practices. The production of maize can reach levels of 20,000 kg ha^{-1}. The fitted line in Fig. 1 describes the maximum slope $\partial Y/\partial ET$ being 2.6, 2.5 and 6.9 kg m^{-3} for wheat, rice and maize respectively. These slopes can be considered as the first estimates of maximum attainable CWP values under academic field research conditions.

The CWP values depend on crop yield, Y (which varies with factors such as variety, diseases, soil fertility, drought, and overall management practices), and ET (which depend on factors such as climatology, soil moisture, cropping calendars, soil treatment, mulching, rainfall patterns, irrigation scheduling, irrigation and drainage systems, depth to water table). Basin irrigation has large evaporation rates due to the water standing on the land surface. Furrow and border irrigation saturates the soil intermittently, which unavoidably increases soil evaporation during wetting events and creates ponded surface at the tail end of the field. A recent overview on ET savings is provided by Chukkalla et al. (2015). The ET of rainfed crops can be reduced by agricultural practices including, but not limited to, means of mulching, weed control, row spacing. Hence on-farm management options play a significant role in determining Y, ET and hence CWP. The best solution for CWP improvement has to be determined from this range of options, and as a pre-requisite, a measurement system that can be used to spatially detect these superior on-farm management practices must be set in place. IT technology should bring this real time information to farmers on a field by field basis.

In situ crop ET under actual field conditions is hard to measure on a routine basis (e.g. Teixeira de and Bastiaanssen, 2012). Instead the ET_0 of a reference crop (e.g. grass) is often considered that can be computed from routine weather station data. The potential ET (ET_{pot}) follows from ET_0 and a set of standard crop coefficients (K_c) that assume pristine growing conditions (e.g., Doorenbos and Pruitt, 1973; Allen et al., 1998). In either case, ET_0 and ET_{pot} are proxies of ET, with the actual ET values usually being lower. A crop stress coefficient K_s, being either a linear or convex function of root zone soil moisture and soil salinity, needs to be involved to obtain ET_{act} from ET_{pot} (Steduto et al., 2012). The latter requires access to soil, rainfall and irrigation data sets at global scale (e.g. Jagermeyr et al., 2015). In absence of these data sets, ET in many studies is assumed to be similar to ET_{pot}.

Alternatively, ET under actual growing conditions can be quantified from satellite multi-spectral measurements in conjunction with surface energy balance models (e.g. Jackson et al., 1977; Anderson et al., 1997; Allen et al., 2011). This excludes the need to have access to in situ soil moisture data. Satellite-based monitoring makes it feasible to determine actual ET worldwide by one single sensing system (e.g. Guerschman et al., 2009; Senay et al., 2013). The spatial distribution of crop yield, Y, can also be determined from satellite measurements by applying the concepts of Light Use Efficiency (e.g. Anderson et al., 2000; Bastiaanssen and Ali, 2003; Schull et al., 2015) or Water Use Efficiency (WUE) (e.g.,Steduto and Albrizio, 2005; Steduto et al., 2007, 2009). Remote-sensing based estimates of Y and ET allow us to generate populations of CWP data from which yield and water productivity gaps can be determined (Sadras et al., 2015). Remote sensing is essential for providing a data set independent from statistics, tabulated crop coefficients and soil water balance models.

Only a few studies cover global analysis of attainable ranges of CWP (see Table 1). The water footprint ET values published by Chapagain and Hoekstra (2004) and Mekonnen and Hoekstra (2011) are generally high, resulting in lower CWP values. Recent work by Siebert and Döll (2010) support these lower values. In a recent benchmark paper, Mekonnen and Hoekstra (2014) indicated the average CWP values to be 0.42, 0.67 and 0.98 kg/m^3 for wheat, rice and maize respectively.

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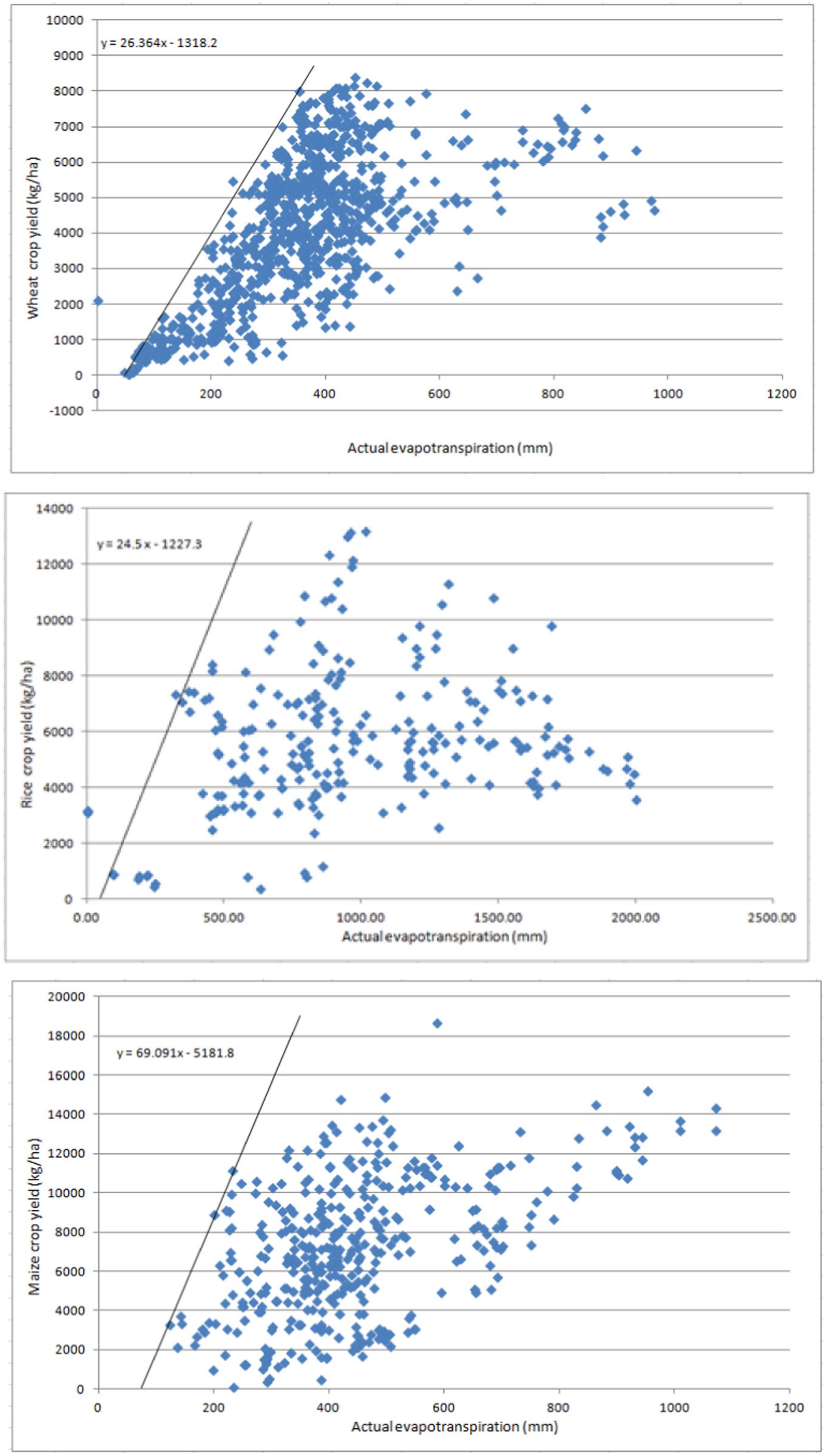

Fig. 1. Crop yield vs. water consumption (i.e. actual evapotranspiration) measured in experimental fields for wheat, rice and maize during the period of 2000 to 2010 in 17 countries (source: Bastiaanssen et al., 2012a).

These low values can be understood by the applied estimation procedures of crop ET_{pot} from ET_0. The difference in methodologies, spatial coverage, duration of cropping seasons and especially the years of analysis explains the differences in global CWP statistics presented in Table 1. The CWP values found on experimental farms seem to be the highest, because these crops are managed by academia on small fields with little spatial variability.

Without standards and target values, it is not feasible to benchmark CWP values, monitor progress of CWP improvement and report them to policy makers. By absence of a proper standard, the public and private sector are not adopting the CWP concept to increase the efficiency of scarce water resources and adapt policy guidelines. They simply do not know what their target values are. Some first benchmark numbers at global scale were published by Zwart and Bastiaanssen (2004) and

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Table 1
Published data on global scale mean crop water productivity values (Y/ET). Standard deviations are provided in parenthesis, when the required data was available.

Source	Methodology	Wheat ($kg\ m^{-3}$)	Rice ($kg\ m^{-3}$)	Maize ($kg\ m^{-3}$)
Doorenbos and Pruitt (1973), FAO33	Statistical data	0.9 (0.1)	0.9 (0.2)	1.2 (0.4)
Chapagain and Hoekstra (2004), Water Footprint Network	FAOStat & FAO56	0.84 (0.40)		
Zwart and Bastiaanssen (2004)	International literature review	1.09 (0.44)	1.09 (0.40)	1.80 (0.69)
Liu et al. (2007)	GEPIC water balance model	0.91 (0.31)	Na	na
Siebert and Döll (2010)	GCWM water balance model	0.68	0.72	0.92
Zwart et al. (2010a)	WATPRO Remote sensing model	0.93 (0.29)	Na	na
Bastiaanssen et al. (2010)	WATPRO Remote sensing model	0.98 (0.55)	0.98 (0.45)	2.25 (0.94)
Mekonnen and Hoekstra (2011), Water Footprint Network	FAOStat & FAO56	0.55	0.75	0.82
Bastiaanssen et al. (2012a)	International literature review	1.13 (0.44)	0.68 (0.39)	1.70 (0.82)
Mekonnen and Hoekstra (2014)	FAOStat & FAO56	0.42	0.67	0.98

Mekonnen and Hoekstra (2014). The 95% percentile for wheat was according to Zwart and Bastiaanssen 1.7 kg/m^3, while Mekonnen and Hoekstra report 1.72 kg/m^3 for 90% percentile. Although interesting to know and good to observe similarities, global benchmark values are not useful for local agricultural water management policies.

In analogy to a grading system for earthquakes (Richter) or wind force (Beaufort), the current paper introduces a grading system for CWP: the Water Productivity Score (WPS). The objective of this paper is therefore to define a standard WPS that is easy to understand and can be implemented for practical applications by a wide range of decision makers and professionals in the agribusiness, agricultural water management sector. The WPS for wheat, rice and maize is presented for both global and regional scale.

2. Some essential crop water productivity definitions

Agricultural production - and the gap thereof - needs to be expressed both in terms of land productivity ($kg\ ha^{-1}$) and water productivity ($kg\ m^{-3}$), see for instance Brauman et al. (2013) and Sadras et al. (2015). WUE is a terminology classically used primarily by agronomists and breeders. WUE depicts the output per unit of transpiration or evapotranspiration at the field scale ($kg\ m^{-3}$), e.g. Hanks and Tanner (1952); Bierhuizen and Slayter (1965). The concept of Water Productivity (WP) is comprehensively described by Kijne et al. (2003) to express the greater context of water consumption in relation to a wide range of benefits, goods and services produced, including fisheries, livestock, crop, agro-forestry and mixed systems (e.g., kg, $, calories, proteins, sucrose, jobs per m^3 of water). Crop Water Productivity (CWP) evolved from WUE and WP, and describes the fresh crop yield per unit of water consumed (Y/ET). It is the final indicator for efficient use of water in agriculture (Molden, 2007; Tolk and Howell, 2012):

$$CWP = \frac{Y}{\sum ET}\ \left(kg\ m^{-3}\right) \tag{1}$$

where Y ($kg\ ha^{-1}$) is the actual crop yield (at given moisture content of the harvested product) and $\sum$ET ($m^3\ ha^{-1}$) represents the actual evapotranspiration accumulated for a growing season, including the evaporation from bare soil (E_s), from water logging and ponding (E_w), from interception (E_i) and from canopy transpiration (T). Consumed water expresses that certain water resources are no longer available for other water users in the basin; it is a sink term of the water balance. Consumptive use can also occur due to contamination and water in products (Molden, 1997; Karimi et al., 2013). Crop evapotranspiration is a preferred water term over rainfall, irrigation, capillary rise, change in soil moisture and other sources of water; it integrates the different sources of water, which can be fully attributed to the cultivation practices of a certain crop.

The concept of CWP applies to both rainfed and irrigated crops. Because of the influence of on-farm management on CWP (Sarwar and Perry, 2002; Geerts and Raes, 2009), it is interesting to isolate the impact of irrigation, especially when rainfall and irrigation occurs simultaneously. Irrigation Crop Water Productivity (ICWP) can be explicitly related to on-farm irrigation management practices by obeying the following expression (e.g. Feddes et al., 1978):

$$ICWP = \frac{\Delta Y}{\Delta \sum ET}\ \left(kg\ m^{-3}\right) \tag{2}$$

where ΔY ($kg\ m^{-2}$) represents the incremental crop yield due to irrigation and $\Delta\sum$ET ($m_3 m_{-2}$) the incremental ET due to irrigation. Variability in ET is mainly driven by climatic, leaf area index and soil moisture conditions. For instance, arid and semi-arid climates with a high evaporative demand (i.e., high reference ET_0) will result in consistently higher $\sum$ET values, provided that crops have no constraints in water availability. A high $\sum$ET value has a negative impact on CWP. For this reason, the analysis of CWP requires a climatic normalization to make meaningful comparisons between CWP values in different climates feasible. A climatic normalization using ET_0, such as also proposed by Steduto et al. (2007) for the biomass production vs. transpiration relationship, is followed to describe the climatic normalization of CWP into CWP_c:

$$CWPc = \frac{Y}{\sum ET} \times \frac{\sum ET_0(a)}{\sum ET_0(c)}\ \left(kg\ m^{-3}\right) \tag{3}$$

where $\sum ET_0(c)$ is the climatologically averaged ET_0 value worldwide for a given crop (during its growing cycle) over the reference time period, in our case the period from 1960 to 1990 and $\sum ET_0(a)$ is the reference ET_0 for a particular growing season in a certain region or country. Hence the intra-annual weather variability is encompassed in CWP_c. Some kind of trade off in accumulated $\sum$ET occurs because warmer climates with a higher ET_0 have a shorter duration of the cropping cycle than the same crop grown in a colder climate.

As mentioned before, two types of CWP approaches are identified, one for global analysis and one for regional scale applications. A further normalization for crop types is required in order to report the CWP_c on a common standard scale (scoring) in order to abstract the 'intrinsic' variation of agricultural systems around the world in terms of bio-physical water productivity. This normalization of CWP_c for crop types, and its standard scoring, is achieved by first considering the minimum and maximum values of CWP_c for each crop type. However, extreme values are not recommended as they can represent outliers. Therefore, upper and lower percentiles are used to represent the minimum and maximum values of the CWP_c scale for each crop. Due to inaccurate crop classifications, the uncertainties at the lower end of the CWP_c are larger than those of the higher end. The 5^{th} percentile is therefore taken for the minimum CWP_c value (CWP_c^5), while the 99^{th} percentile is taken for the maximum CWP_c value (CWP_c^{99}).

The next step consists in setting a common standard scale for scoring the CWP_c of the different crops. The Global Water Productivity Score (GWPS) is proposed to set the scale between 1 and 10, where 1

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indicates extremely poor values of CWP_c and 10 indicates the excellent ones. Accordingly, the GWPS can be expressed numerically as:

$$GWPS = 9 \times \frac{CWP_c - CWP_c^5}{CWP_c^{99} - CWP_c^5} + 1\ (-) \quad (4)$$

This crop normalization is repeated for any crop type for which CWP_c^5 and CWP_c^{99} is available, requiring an analysis at global level to be performed first. Due to the relative unit, GWPS can be applied to report for a set of crops of interest (e.g., cereals, fruit tree crops) rather for one particular type of crop. Depending on the set chosen, the GWPS reflects an intrinsic water-productivity capacity of the selected cropping system. This information is important for Departments of Agriculture, who are responsible for preparing plans to become more resilient to climate variability and produce more food from less water. An example of the frequency distribution for staple crops (cereals) at global level is reported in Fig. 2. It reveals a skewed distribution for cereal crops at the global scale, which implies that the majority of the fields are not even reaching an average CWP_c performance (WPS = 5). Sixty-six percent of the cereal area has a WPS value lower than 5.0, and water productivity in these areas need to be improved urgently. This simple diagram proofs the existence of a CWP gap.

While GWPS has its own value for investigating and monitoring intrinsic agricultural water productivity at global level and understanding planetary boundaries, it does not help the local farmers, cooperatives, irrigation districts and other practitioners to assess their local CWP status. Rainfed wheat yield on poor soils in the hills of Uzbekistan can, for instance, not be compared with the yield of irrigated wheat in the fertile Egyptian Nile delta. Regional scale governance ought to know the extent of CWP variability in their "own" irrigation district, watersheds or a delta, as well as, the magnitude of its gap towards optimization. Given that the CWP variability can be attributed to both 'management' and 'physical' factors, the practitioners' interest is also to decouple these two factors to better understand the type of interventions required to raise the CWP value and possibly bridge the gap. Normalizations are also required in this case. A practical solution for data poor areas is to investigate the local production potential by subdividing the full yield-range into discrete 'yield-zones' (Fig. 3).

Fig. 3 presents data from a recent remote sensing study on Y, ET and CWP for the Doukalla irrigation scheme (Morocco) based on satellite data taken from Goudriaan and Bastiaanssen (2012) and redrawn from Sadras et al. (2015). The variability of the CWP_c for maize in the

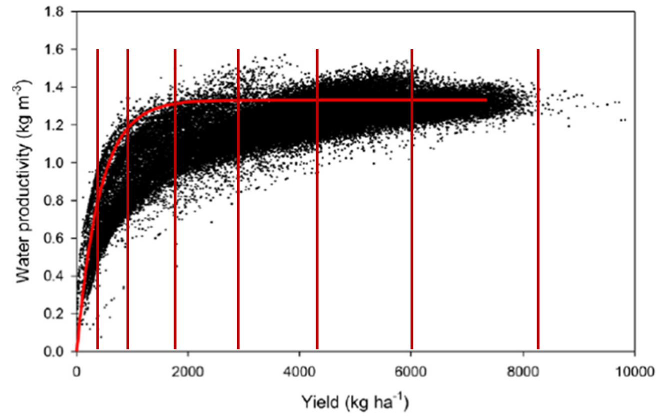

Fig. 3. Relationship between land and water productivity for maize fields in the Doukalla irrigation system, Morocco. The x-axis is subdivided in 'yield-zones' to reflect different local growing conditions and hence define a spectrum of target values of CWP (adjusted after Sadras et al., 2015).

Doukalla irrigation scheme is based on Landsat 30 m × 30 m pixels using a supervised crop classification methodology and the ETLook model (Samain et al., 2012; Bastiaanssen et al., 2012b) for the computation of Y, ET and CWP. Similar to Molden (2007) who was the first to display these types of CWP(Y) graphs, the population of pixel values confirms that lower yield zones exhibit more variability in CWP than at higher crop yield zones. The variability of CWP_c in the lower range of crop yield is large due to highly uncertain crop inputs including water resources. At a high crop yield, the range of CWP is small because the farmer has excluded most risks by investing in technologies and optimizing the business, through measures such as provision of water supply with own tubewells, supplying water to low pressure drip systems, fertigation to provide optimum crop nutrient status and variable plant spacings following soil property variability. Consequently, there is ample scope to establish higher CWP_c values in low-yielding rainfed areas and in poorly performing irrigation systems where poverty and food insecurity prevail, an important conclusion also drawn by Molden (2007).

Similar to the global scale, a scoring system can be established at 'regional' scale. Here it is proposed to use the Water Productivity Score (WPS) for each crop yield zone, instead of relating it to national or international standards. Following the same principles as for GWPS, the WPS is scaled between the 5th and 99th percentile of the CWP_c values. The

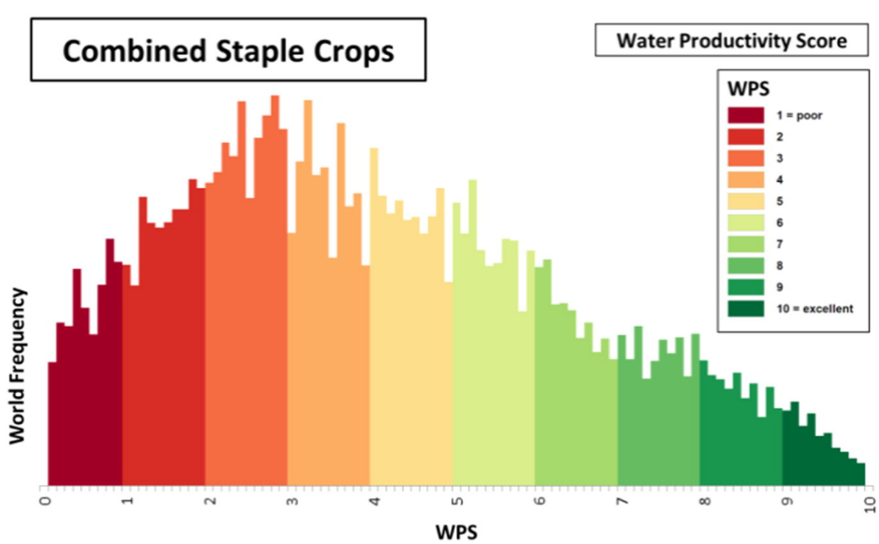

Fig. 2. Frequency distribution of GWPS reflecting wheat, rice and maize crops at the global scale. This graph could be created due to climate and crop normalization of CWP (after Bastiaanssen et al., 2010).

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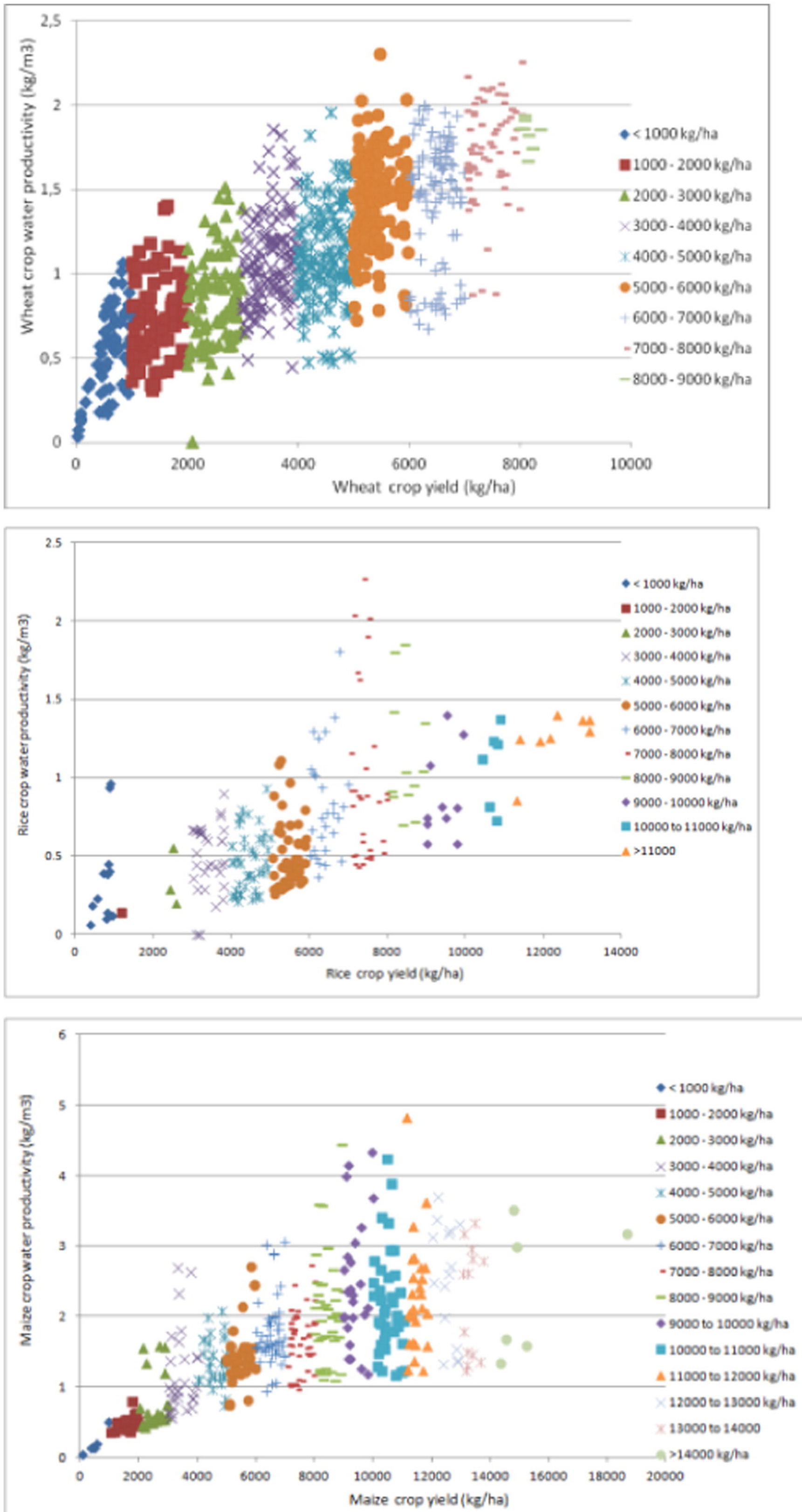

Fig. 4. Crop water productivity variability by crop yield zones for wheat, rice and maize. The data points are taken from Fig. 1 and are based on experimental research from 17 different countries.

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only difference is that the CWP_c values need to be determined by crop yield zone (y) rather than having one single global benchmark value. Hence,

$$WPS = 9 \times \frac{CWP_c(y) - CWP_c^5(y)}{CWP_c^{99}(y) - CWP_c^5(y)} + 1\ (-) \quad (5)$$

where $CWP_c^5(y)$ is the 5th percentile of CWP_c value in yield zone, y, and $CWP_c^{99}(y)$ is the 99th percentile of the same yield zone. Practical values for $CWP_c(y)$ are defined in the results section where literature data is merged with data from a few regional scale studies. The concept of Eq. (5) can be explained by analyzing the experimental data of the FAO database portrayed in Fig. 1. Fig. 4 shows the band width of CWP values if the influence of climate is ignored (thus assuming $CWP_c = CWP$ by absence of information on local ET_0 values from all these global experiments). The variability in the yield zone for <1000 kg ha^{-1} appears indeed to be large in accordance with the expectations, and the crop yield zone for >9000 kg ha^{-1} and higher exhibits a limited spatial variability due to more uniform and optimal on-farm practices. The results of Fig. 4 confirm the principles underlying Fig. 3. The Coefficient of Variation (CV) values for all three cereal crops are presented in Table 2. Due to the nature of the data set, the maximum CV value in the crop yield zone <1000 kg ha^{-1} is approximately CV ~ 0.5 for wheat, while for rice and maize the maximum CV is substantially higher (CV ~ 0.9). The variability of CWP decreases to a CV of 0.05, 0.15 and 0.30 for wheat, rice and maize respectively, when production is optimized. The data suggests that maize contains a high variability between Y and ET (see also Fig. 1). The wide variety of growing conditions of maize in mountains, plains and deltas and the large range of sowing dates and cropping calendars and for cash crop and staple crop can be a reason for the large variability detected.

The 5th and 99th percentile values are added in Table 2 to provide a first guess of CWP_c target values in each crop yield zone. The highest CWP_c ^{99} values are 2.12, 2.27 and 4.82 kg m^{-3} for wheat, rice and maize respectively. Note that these numbers are similar to the slopes provided in Fig. 1.

The maximum CWP_c value in the low crop yield zones is lower than the minimum CWP_c value for land located in the high crop yield zones. This demonstrates the need to normalize by production potential, reflecting the presence of irrigation and drainage system, the type of irrigation systems in place and other on-farm management factors. This goes further than the concept of Agro Ecological Zonation (AEZ) being published by Fischer et al. (2010) that is based on physical factors only (i.e. soil, geography, land use, climate). Hence, GWPS and the WPS follow a similar benchmarking approach, and normalize for variabilities of climate, crop type and production potential at different spatial scales.

3. Materials and methods

3.1. Materials

While Section 2 is based on experimental data from the FAO-CWP database, the current section describes the materials and methods related to the earth observation measurements used to describe real world CWP_c variability. The global analysis on CWP, CWP_c and WPS requires a map with the location of the major crop types. The crop dominance map of Leff et al. (2004), with a spatial resolution of 10 km, has been merged with 10 km data from Monthly Irrigated and Rainfed Crop Areas MIRCA-2000 (Portmann et al., 2010). Following Zwart et al. (2010a), these global maps of wheat, rice and maize were verified, improved and dis-aggregated towards a 1 km × 1 km grid using satellite measurements of the Normalized Difference Vegetation Index (NDVI). The NDVI describes the photosynthetical activity of crops (e.g. Tucker, 1979; Jackson et al., 1983). Temporal profiles of global SPOT-Vegetation NDVI measurements with 10 day intervals from the period 1998 to 2008 have been used. Hence, the results of this paper describe the average conditions for the period 1998 to 2008.The NDVI time profile for each 1 km × 1 km pixel covering this 10 year period has been used to verify whether a certain pixel is indeed categorized by that given dominant crop. Pixels with weak signals in NDVI and with a length of the growing season not matching standard cropping calendars have been eliminated. Both summer and winter cereals were considered. A consequence of using 1 km pixels of 100 ha each, is that only cereal regions with a contiguous coverage are incorporated in the analysis. Regions with crop mosaics due to rotational schedules with small fraction of cereals are declined. For this reason, only global regions with dominant wheat, rice and maize crops could be analyzed.

Additional to satellite images, longer term climatic data has been used for the computation of reference ET_0 using the standard FAO 56 methodology (Allen et al., 1998). Data for the 1960 to 1990 period has been inferred from the Climate and Research Unit (CRU). The reference ET_0 is needed for the climatic normalization of $ET_0(c)$ in Eq. (3). In addition, crop specific parameters need to be defined. The spatially constant input parameters are the moisture content of the harvestable product (θ_{crop}), the maximum Light Use Efficiency (ε_{max}) and the reference harvest index h_0, see Table 3.

Table 2
CWP statistics for the CWP of wheat, rice and maize within crop yield zones with increments of 1000 kg ha^{-1} compiled from Fig. 4.

Crop yield zone	Wheat			Rice			Maize		
(kg ha^{-1})	(CV)	CWP_c 5%	CWP_c 99%	(CV)	CWP_c 5%	CWP_c 99%	(CV)	CWP_c 5%	CWP_c 99%
<1000	0.453	0.14	1.06	0.837	0.06	0.96	0.883	0.04	0.50
1000–2000	0.326	0.34	1.39	na	0.54	0.54	0.218	0.36	0.80
2000–3000	0.302	0.48	1.51	0.522	0.20	0.55	0.494	0.44	1.59
3000–4000	0.251	0.68	1.82	0.338	0.18	0.67	0.499	0.56	2.69
4000–5000	0.257	0.51	1.82	0.391	0.21	0.93	0.238	0.75	2.08
5000–6000	0.196	0.87	2.03	0.408	0.26	1.11	0.297	0.75	2.71
6000–7000	0.254	0.77	1.97	0.414	0.37	1.81	0.265	0.93	3.07
7000–8000	0.174	0.88	**2.12**	0.555	0.43	**2.27**	0.227	0.98	2.74
8000–9000	0.048	1.67	1.94	0.346	0.70	1.85	0.355	1.10	4.45
9000–10,000				0.324	0.58	1.40	0.362	1.19	4.33
10,000–11,000				0.235	0.73	1.38	0.330	1.17	4.24
11,000–12,000				0.137	0.86	1.40	0.347	1.24	**4.82**
12,000–13,000							0.326	1.33	3.70
13,000–14,000							0.347	1.23	3.24
14,000–15,000							0.397	1.34	3.51

Bold values reflect the maximum CWP_c values achieved for each cereal crop.

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Table 3
Global constant crop parameters for the main cereal crops used in this global earth observation study.

Description	Symbol	Unit	Wheat	Rice	Maize
Moisture content of harvestable product	θ_{crop}	gr gr^{-1}	0.15	0.14	0.26
Maximum Light Use Efficiency	ε_{max}	gr MJ^{-1}	2.5	2.5	3.75
Reference harvest index	h_o	–	0.50	0.55	0.55
Slope fPAR(NDVI) relationship		–	1.23	1.24	1.40
Offset fPAR(NDVI) relationship		–	−0.12	−0.27	−0.36

3.2. Methodology

Apart from parameters described in Table 3, other crop parameters in the mathematical framework are kept spatially variable. Among them are the actual harvest index, the fraction of Absorbed Photosynthetical Active Radiation (fPAR), the surface albedo and the sowing and harvesting dates. The spatial variability of surface albedo has been computed from the MODIS product (MOD43) with 16 day interval on whitesky and blacksky albedo. The atmospheric transmissivity for shortwave solar radiation is used to distinguish between direct and diffusive radiation. The fPAR(NDVI) relationship for wheat is based on measurements undertaken by Asrar et al. (1984), Hatfield et al. (1984) and Baret and Olioso (1989). The offset and slope of the fPAR = f(NDVI) relationship following these publications are added to Table 3. The fPAR curve for rice is slightly different, and the work of Casanova et al. (1998), Wahid et al. (2003), Wiegand et al. (1989) and Inoue et al. (2008) have been used to assess fPAR from NDVI. Similarly for maize, the publication of Lapita (1986), Wiegand et al. (1991) and Daughtry et al. (1992) were consulted.

The Harvest Index, h, describes the harvested portion of the accumulated dry matter. The reference Harvest Index, h_o, is the ratio of the yield dry mass to the total above ground biomass that will be reached at maturity for non-stressed conditions (Raes et al., 2012). The reference h_o values of Table 3 will be adjusted for every pixel based on failure of pollination and inadequate photosynthesis due to water stress and heat stress. These non-optimum conditions are described by means of a coefficient h_i:

$$h = hi \times h0\ (-) \tag{6}$$

Fereres and Soriano (2007) and Nangia et al. (2008) showed that the stress function for harvest index h_i can be approximated from a quadratic function of the relative biomass production B_{ior}:

$$hi = -1.468\ \times B_{ior^2} + 2.685 \times B_{ior} - 0.208\ (-) \tag{7}$$

Relative NDVI values were considered instead of Bior relative biomass production values for the sake of simplicity. The crop yield, Y, (kg ha^{-1}) can be determined from the accumulated biomass production $\sum$ Bio (kg ha^{-1}) between the start and the end of the growing season:

$$Y = \frac{h\ \sum_{start}^{end} Bio}{(1-\theta crop)} \left(\text{kg ha}^{-1}\right) \tag{8}$$

where θ_{crop} (gr gr^{-1}) is the moisture content of the harvestable product (see Table 3) and h (−) is actual harvest index. The accumulated biomass production $\sum$ Bio can be determined on the basis of the Light Use Efficiency model first published by Monteith (1972), and reconfirmed by many others (e.g., Kiniry et al., 1989; Bastiaanssen and Ali, 2003; Sadana and Pinochet, 2014):

$$\text{Bio} = 0.864 \times \text{APAR}_{24} \times \varepsilon \left(\text{kg ha}^{-1}\ \text{d}^{-1}\right) \tag{9}$$

where $APAR_{24}$ (Wm^{-2}) represents the 24 h averaged Absorbed Photosynthetically Active Radiation and ε (gr MJ^{-1}) is the actual Light Use Efficiency. $APAR_{24}$ is the at-surface solar radiation absorbed by chlorophyll in the 0.4 to 0.7 μm range. The APAR radiation is approximated as being a fraction of the at-surface solar radiation (e.g. 0.48):

$$\text{APAR}_{24} = 0.48 \times \text{fPAR} \times \tau \times \text{S}{\downarrow}\text{exo}\left(\text{W m}^{-2}\right) \tag{10}$$

where fPAR (−) is the fraction of 24 h Absorbed Photosynthetical Active Radiation, τ (−) is the atmospheric transmissivity for solar radiation and $S^{\downarrow}_{exo}$ (W m^{-2}) is the 24 h averaged extra-terrestrial solar radiation. The Light Use Efficiency model chosen in this global study follows the main principles of the Jarvis-Stewart model for stomatal regulation: there is a maximum conductivity (in this case a maximum Light Use Efficiency) and reduction functions that describe the partial closure of the stomates according to scalars (e.g. Field et al., 1995; Nouvellon et al., 2000):

$$\varepsilon = \varepsilon_{max} \times g(T) \times g(D) \times g(\theta)\ \left(\text{gr MJ}^{-1}\right) \tag{11}$$

where ε_{max} (gr MJ^{-1}) is the maximum Light Use Efficiency and g(T), g(D) and g(θ) are the scalars for air temperature (T), vapor pressure deficit (D) and soil moisture in the root zone (θ). More background information on these functions can be found in Bastiaanssen et al. (2010). Hence the total function for crop yield Y can be expressed as:

$$Y = \frac{0.864 \times h \times \sum_{start}^{end}\{0.48 \times fPAR \times \tau \times \text{S}{\downarrow}\text{exo} \times \varepsilon_{max} \times g(T) \times g(D) \times g(\theta)\}}{(1-\theta crop)} \left(\text{kg ha}^{-1}\right) \tag{12}$$

The ET is computed in an entirely different and independent manner. The actual evapotranspiration process follows from the surface energy balance expressed as a latent heat flux density:

$$LE_{24} = \Lambda \times (Rn_{24} - G_{24})\ \left(\text{W m}^{-2}\right) \tag{13}$$

where LE_{24} (W m^{-2}) is the latent heat flux averaged for 24 h, Λ (−) is the instantaneous evaporative fraction during daytime, Rn_{24} (W m^{-2}) is the net radiation for 24 h and G_{24} (W m^{-2}) is the soil heat flux for 24 h. The instantaneous evaporative fraction can be expressed as (Shuttleworth et al., 1989; Bastiaanssen and Roebeling, 1993):

$$\Lambda = \frac{LE}{Rn-G}\ (-) \tag{14}$$

where R_n, G, and LE (W m^{-2}) are the instantaneous flux densities -for net radiation, soil heat flux and latent heat flux respectively - that are usually determined during the moment of satellite overpass. Due to the cancellation of soil heating and cooling across one daily cycle. G_{24} can be ignored. This reduces Eq. (13) into:

$$LE_{24} = \Lambda \times Rn_{24}\ \left(\text{W m}^{-2}\right) \tag{15}$$

Furthermore, the ET flux can be derived from LE_{24} using physical constants as:

$$ET = 86.4 \times 10^6 \times \frac{LE_{24}}{\rho w \times L}\ \left(\text{mm d}^{-1}\right) \tag{16}$$

where ρ_w (kg m^{-3}) is the density of water and L (J kg^{-1}) is the latent heat of vaporization, i.e. the amount of energy required to let 1 kg of water evaporate. Certain existing remote sensing surface energy balance models with a biomass production and ET component such as ALEXI (Anderson et al., 2000), SEBAL (Teixeira de Castro et al., 2008) and ETLook (Bastiaanssen et al., 2012a) are able to solve Eqs. (12) to (16).

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CWP can also be computed directly if Eqs. (12) and (16) are combined. In the case that the evaporative fraction (Λ) is used as an indicator for water stress - instead of g(θ), e.g. Field et al. (1995) - the soil moisture can be eliminated from the CWP expression as it regulates both biomass production and ET. This cancellation, strongly simplifies this CWP computation because soil moisture in the root zone is difficult to model or measure. Furthermore, if the 24 h net radiation Rn_{24} is described with the Slob equation (de Bruin and Stricker, 2000), the combination equation for CWP becomes:

$$CWP = \frac{0.864 \times h \times \sum_{start}^{end} \{0.48 \times fPAR \times S{\downarrow}exo \times \varepsilon_{max} \times g(T) \times g(D)\}}{(1-\theta crop) \times \sum_{start}^{end} \{0.35 \times \{(1-\alpha) \times S{\downarrow}exo - s(T)\}\}} \left(\mathrm{kg\ m^{-3}}\right) \tag{17}$$

where α (—) is the surface albedo, s(T) is an empirical solution for net longwave radiation (see Bastiaanssen et al., 2010) and 0.35 is a conversion factor from radiation to an ET rate. Eq. (17) is also known as the WATPRO model (Zwart et al., 2010b). The atmospheric transmissivity, τ, is eliminated from Eq. (17) as it affects both photosynthesis and ET. To reduce the computational burden, Eq. (17) was applied in this paper with seasonal averaged input data for the global scale. The update of WATPRO as compared to the original publication relates to improved functions for α, fPAR, g(T), g(D) and s(T). The attractiveness of Eq. (17) is the direct computation of CWP. The drawback is that crop yield and ET are not explicitly quantified. The latter can be considered a rationale to apply Eqs. (12) to (16).

4. Results

4.1. Global water productivity score (GWPS) computed with the updated WATPRO model

Cereals are the main staple crops. They are grown under a wide variety of climatic conditions ranging from the hyper-arid climates in the Middle East to the Humid Tropics of South East Asia and Central Africa. The global cropped area statistics according to FAOStat for wheat, rice and maize in the period from 1998 to 2008 are provided in Table 4. The area covered by the current crop identification is inserted in Table 4 to demonstrate the degree of representation of the current study. The remote sensing acreage for rice and maize is smaller than FAOStat, but for wheat it suggests that a larger area is covered by the satellite images. The 1 km × 1 km pixel data rarely covers one monoculture of 100 ha. If we assume that 50% of a pixel is covered with a particular monoculture, then 40% of the world cereals fields are encompassed in the current study. This implies that the CWP analysis discussed in this paper is indeed representative, with wheat having the highest representation (64.3%), followed by maize (28.4%) and rice (10.7%).

Following Fischer (1994) and Zwart et al. (2010a), the cropping calendar was determined for each crop type and each pixel to estimate the actual length of the growing season. The start and end of season was used to estimate the pixel dependent seasonal average values of α, fPAR, $S^{\downarrow}{}_{exo}$, g(T), g(D) and s(T). Eq. (17) has been applied to all the global scale 1 km × 1 km pixels for wheat, rice and maize. As a result, a comprehensive data base with plausible ranges of CWP and CWP_c values for the period 1998 to 2008 has been created. Fig. 5 shows the 1 km pixel results for Europe and North Africa for wheat. The harvest index (h) and crop water productivity (CWP) is generally higher in Europe. However, after the climatic normalization for the higher reference ET_0 in North African and the longer duration of the season, the CWP_c values are generally higher in North Africa.

Table 4
Acreage statistics of the major cereal crops included in the GWPS study for the period from 1998 to 2008.

	This study (assuming 100% monocrop) (ha)	This study (assuming 50% monocrop) (ha)	FAOStat (ha)	Relative area coverage (assuming 50% monocrop) (%)
Wheat	278,426,129	139,213,065	216,192,046	64.3
Rice	30,641,204	15,320,602	142,571,868	10.7
Maize	50,455,017	25,227,509	88,594,590	28.4
Total	359,522,350	179,761,175	447,358,504	40.2

The mean seasonal values of certain key crop parameters are summarized in Table 5. Rice has an average worldwide growing season of 136 days from crop emergence to harvest including mountain and lowland rice. Wheat's and maize's seasons are approximately one month longer (169 days). The $\sum ET_0(c)$ value for maize is 690 mm (or 4.1 mm d^{-1}), thus being larger than for wheat ($\sum ET_0(c) = 545$ mm or 3.3 mm d^{-1}) and rice ($\sum ET_0(c) = 555$ mm or 4.1 mm d^{-1}). Wheat is often grown as a winter crop with lower ET_0 rates, while maize and rice are typical summer crops with larger average ET_0 values. The short duration for rice is the reason for the relatively low accumulated $\sum ET_0(c)$ value of 555 mm during the summer. Maize has the highest NDVI value averaged across the entire growing season (NDVI = 0.54), because maize has a higher leaf area index and more chlorophyll per unit land. The average global CWP values for both wheat and rice (being C3 crops) is 0.98 kg m^{-3}. At 2.25 kg m^{-3} maize has more than double the global average CWP value of rice and wheat due to its C4 character.

The frequency distributions of CWP and CWP_c for the world's major cereal crops are presented in Fig. 6. In all 3 cases, the range of CWP and CWP_c values are approximately similar. The $ET_0(a)/ET_0(c)$ normalization introduces local modifications as can be seen on Fig. 5, but there is a tradeoff between positive and negative corrections that -apparently - conserves the total range. Wheat and rice show the modus located towards the lower end of the CWP spectrum. There is thus a relative large portion of farmland that has a relatively low CWP value between 0.5 to 1.0 kg m^{-3}, which pertains to poor farming and water management practices. The total range of CWP_c for wheat varies approximately between 0.1 to 2.0 kg m^{-3} with the mean value being 0.92 kg m^{-3}. The good CWP performance of wheat from higher latitudes will be negatively corrected with relatively low $\sum ET_0(a)/\sum ET_0(c)$ values so that CWP_c becomes lower. The climatic normalization shows a mirror result for wheat; the low values for CWP in the semi-arid and arid zones after ET_0 correction will result into a more favorable CWP_c performance. After climatic normalization, Egypt, Uruguay and Mexico are the three countries with the largest CWP_c values for wheat, being 2.65, 2.40 and 2.18 kg m^{-3} at national scale respectively.

The highland rice areas represent the lower end of CWP values (0.5 to 1.0 kg m^{-3}). Since their ET_0 is neither excessive nor low (otherwise rice cannot be cultivated), the frequency distribution of CWP_c will have the same skewed behavior. A large group of rice pixels are located in the humid tropics of South and Southeast Asia where ET_0 is low due to frequent cloud cover and high air humidity. There is a small particular group of rice areas that are now identified as being extremely productive water users with CWP_c values varying between 1.5 to 2.0 kg m^{-3}. Interestingly, the top countries in terms of CWP_c score are located in different continents, ranging from USA (1.77 kg m^{-3}), to Sri Lanka (1.75 kg m^{-3}) and Spain (1.51 kg m^{-3}).

This skewed CWP phenomenon was not observed for maize, which shows the features of a normal distribution with a peak at 2.3 kg m^{-3}. One plausible explanation is that maize is grown under a wide range of climatic and soil conditions, both rainfed and irrigated, both smallholder and commercial farming, subsistence and cash crops. The impact of climate normalization of maize on the frequency distribution is greater than for wheat and rice. The bi-modal structure of the CWP_c histogram of maize is believed to reflect arid zones (high $\sum ET_0(a)/\sum ET_0(c)$; high CWP_c) and humid zones (low $\sum ET_0(a)/\sum ET_0(c)$; low CWP_c). Paraguay, Argentina and Bolivia are the countries that are

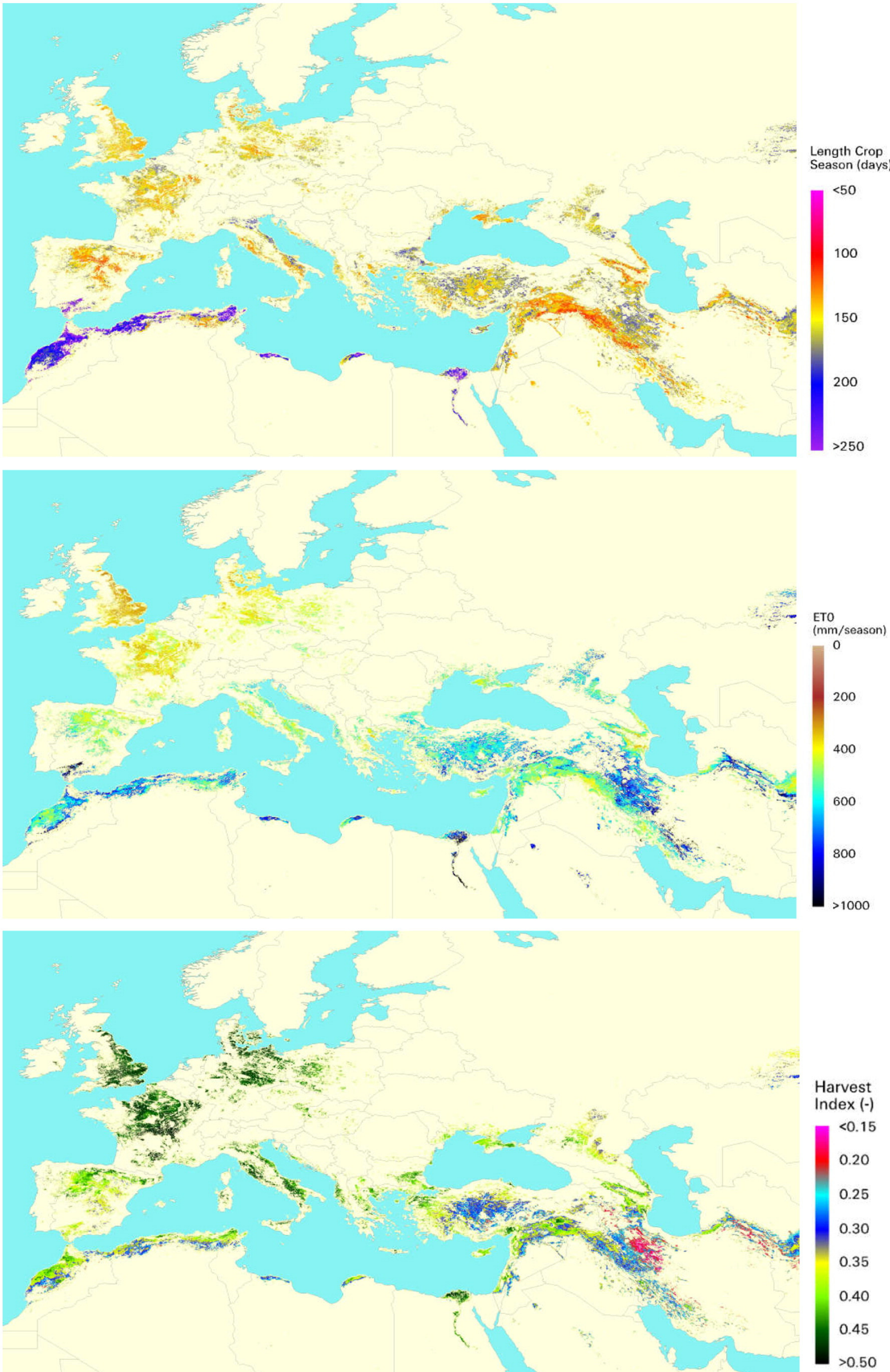
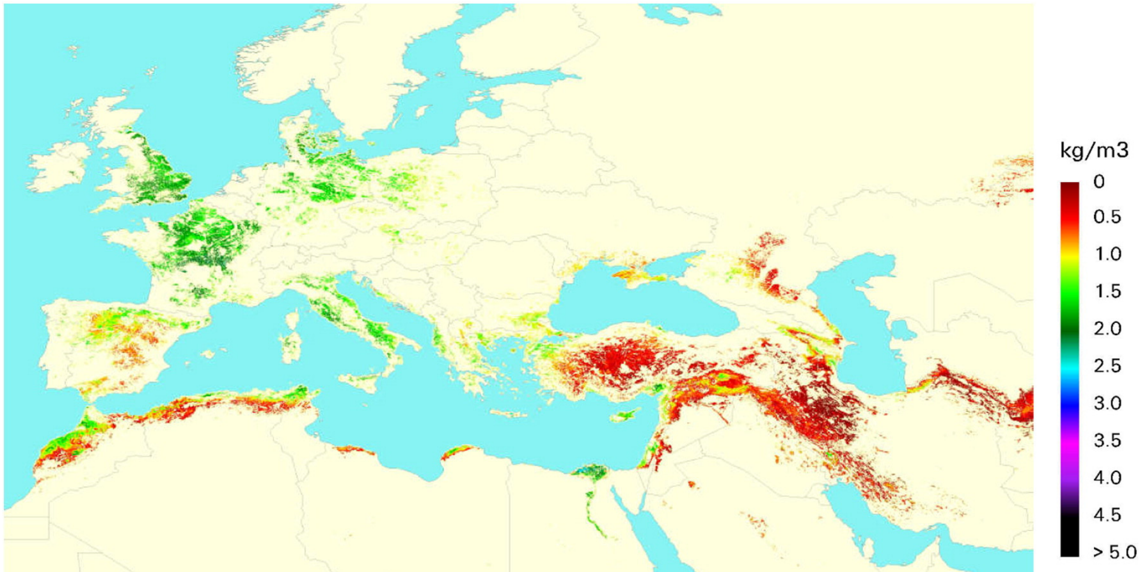


Fig. 5. Spatial variability of crop water productivity related parameters for wheat during the period 1998 to 2008. Duration of season (Part A), reference ET_0 (Part B), Harvest index (Part C), crop water productivity CWP (Part D) and crop water productivity normalized for climate effects CWP_c (Part E).



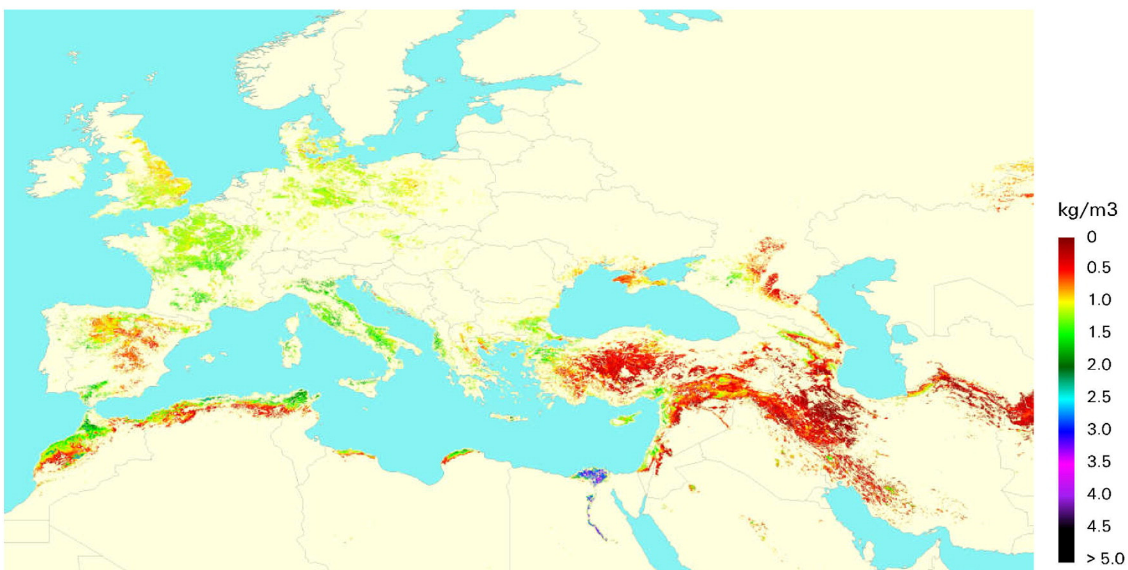


Fig. 5 (*continued*).

most efficient with water, in terms of CWP, in agriculture. The country wide CWP_c values are 3.77, 3.42 and 3.09 kg m^{-3} respectively.

The CV of CWP ranges between 0.43 (maize) to 0.56 (wheat), see Table 6. The same finding applies to CWP_c. The area under wheat is, however, much larger. The difference between the 5th and 95th percentile values for CWP is a factor of 9 for wheat, of 5 for rice and of 6 for maize. The interim conclusion is that - even after climatic normalization - the world has a substantial diversity of CWP values. Wheat exhibits the largest variability and certain locations are more suitable to cultivate a particular crop than other locations. This aspect deserves more attention in international policy on water and food security.

The results of the updated WATPRO model were validated against the statistics derived from the international FAO-CWP database, with the period of the literature review almost coinciding with the period of the global remote sensing analysis. Despite different growing conditions (experimental vs. farm practices) and spatial coverage (the entire world vs. 1492 points), the statistical agreement is high ($R^2 = 0.97$). The validation graph in Fig. 7 suggests that WATPRO is systematically higher (17%). This could be related to the differences in sampling size (1492 fields vs 179,761,175 ha), the physical crop environmental conditions or an-overestimation of either the harvest index (h) or the maximum Light Use Efficiency as presented in Table 5.

The CWP_c frequency distributions of Fig. 6 form the fundamental basis for defining the GWPS values. The CWP_c values were sliced linearly between CWP_c of 5th and 99th percentiles. The values for each interval are specified in Table 7. The maximum CWP_c value for wheat found by WATPRO is 2.45 kg m^{-3}, which is higher than 2.03 kg m^{-3} found in

Table 5
Global main crop statistics inferred for the period from 1998 to 2008. The average values for the season are presented.

	Unit	Wheat		Rice		Maize	
		Mean	Std	Mean	Std	Mean	Std
Growing season	Days	166	32	136	17	169	27
Mean NDVI	–	0.43	0.13	0.52	0.07	0.54	0.09
Mean surface albedo α	–	0.172	0.026	0.163	0.016	0.155	0.019
Harvest index h	–	0.37	0.07	0.38	0.08	0.38	0.07
$\sum ET_0(c)$	mm season^{-1}	545	161	555	142	690	121
CWP	kg m^{-3}	0.98	0.55	0.98	0.45	2.25	0.94
CWP_c	kg m^{-3}	0.92	0.51	0.95	0.43	2.25	0.96

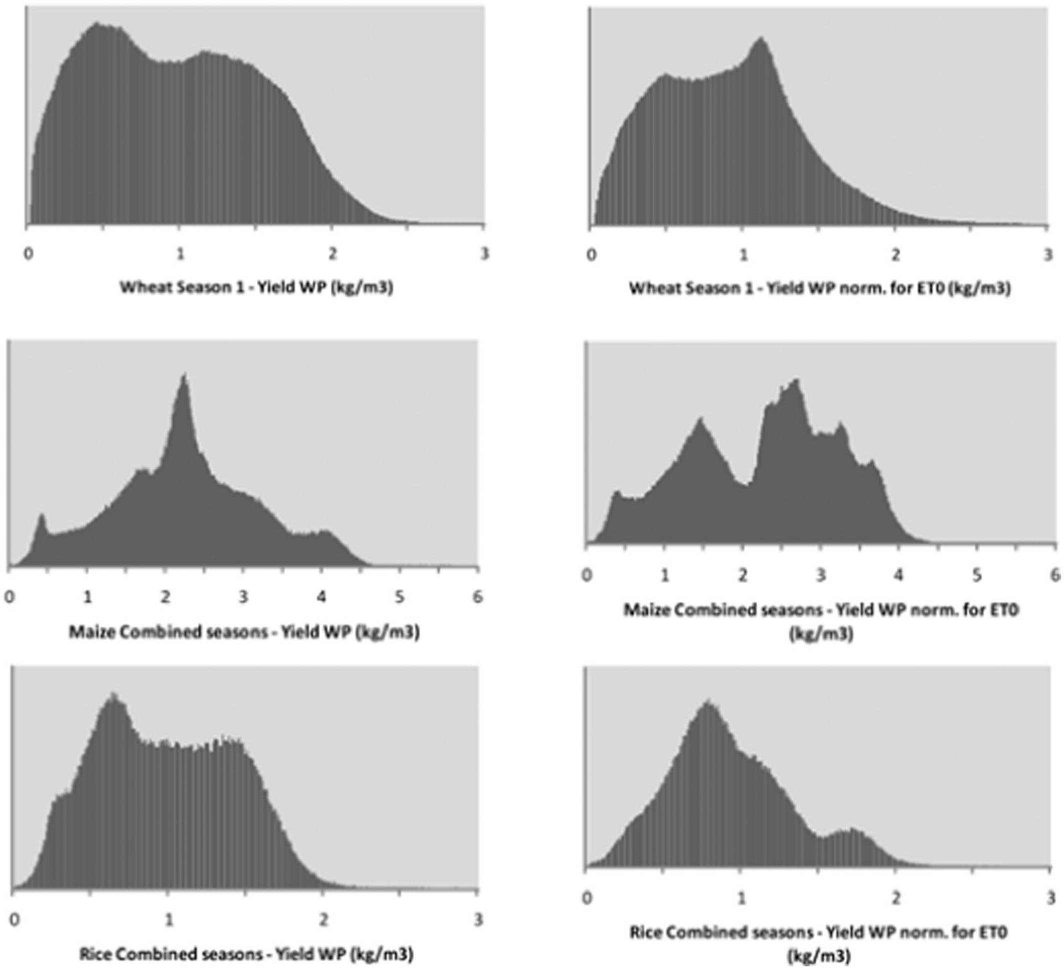


Fig. 6. Frequency distribution of the CWP and CWP_c results for wheat, rice and maize at the global scale during the period from 1998 to 2008 computed with the WATPRO model (Eq. (17)). Forty percent of the world's fields are included in the analysis.

the literature database of Table 2. Sadras and Angus (2006) found for rainfed wheat a maximum achievable CWP of 2.2 kg m^{-3}, hence this is a good agreement. Fig. 8 demonstrates a pixel map of GWPS for the most intensive wheat belt of the world: the Indo-Gangetic plain. It is interesting to note that significant spatial differences are present between Pakistan and India. Considering that this is one agro-ecological zone, the differences must be prescribed to water management, agronomical practices and policy making. The 99th percentile WATPRO-based CWP_c value for rice is 2.11 kg m^{-3}, while the database showed 2.27 kg m^{-3}, consequently the maximum value has been fixed at 2.3 kg m^{-3}. Dong et al. (2001) reports on a maximum CWP value for rice crop in the Zhangye irrigation system in China to be 2.20 kg m^{-3}. The 99th percentile of CWP_c for maize computed with WATPRO is 4.01 kg m^{-3}, which is lower than the 4.82 kg m^{-3} described in Table 2. To ensure that values can be higher than 4.01 kg m^{-3}, the value where WPS is 10 prevails and has been fixed at 4.9 kg m^{-3} (see Table 7). Hence, every CWP_c value can be converted into GWPS using the key provided in Table 7.

Table 6
Global main crop water productivity statistics derived from the updated WATPRO model (Eq. (17)) for the period 1998 to 2008.

	Wheat	Rice	Maize
CWP - mean	0.98	0.98	2.25
CWP - std	0.55	0.45	0.96
CWP - CV	0.56	0.46	0.43
CWP - 5%	0.20	0.30	0.60
CWP - 95%	1.90	1.70	4.00
CWP_c - mean	0.92	0.95	2.25
CWP_c - std	0.51	0.43	0.96
CWP_c - CV	0.55	0.45	0.43
CWP_c - 5%	0.20	0.32	0.57
CWP_c - 99%	2.45	2.11	4.01

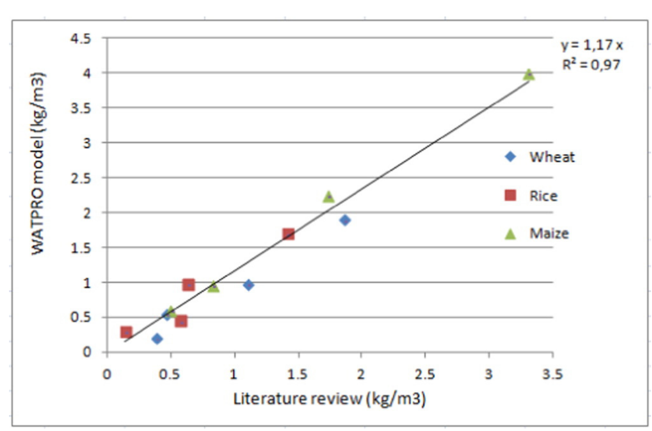


Fig. 7. Comparison of the global water productivity statistics (mean, median, standard deviation (std)) produced by the improved WATPRO remote sensing model and the international database.

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Table 7
Definition of the GWPS for wheat, rice and maize according to CWP_c frequency distributions.

GWPS	CWP_c Wheat ($kg\ m^{-3}$)	CWP_c Rice ($kg\ m^{-3}$)	CWP_c Maize ($kg\ m^{-3}$)
1	≤0.2	≤0.32	≤0.57
2	0.45	0.54	1.05
3	0.70	0.76	1.53
4	0.95	0.98	2.01
5	1.20	1.20	2.49
6	1.45	1.42	2.98
7	1.70	1.64	3.46
8	1.95	1.86	3.94
9	2.20	2.08	4.42
10	≥2.45	≥2.30	≥4.90

Due to the shape of the frequency distribution, the average GWPS value for wheat and rice is systematically lower (GWPS = 4.2 and GWPS 4.5 respectively) than for maize (GWPS = 5.9). The underlying reasons were not investigated further, this should be done by linking geographical attributes to these WPS values. Climatic conditions could also explain this, as certain crop production and risk of diseases are coupled to climate. The climatic normalization from CWP to CWP_c is merely an ET correction for low and high ET_0 values and does not correct for the climate effect on crop yield.

Table 8 summarizes the GWPS results for sub-continents. Wheat and maize are cultivated most water efficiently in South America (average GWPS 8.1 and 6.1 for wheat and maize respectively). The North American continent has the largest GWPS score for rice (GWPS = 7.6) and this occurs in the delta's of the Mississippi and Sacramento. The Russian Federation and its former members in Central Asia are the least water productive: the average GWPS for wheat is 2.9. A similar low value applies to several countries in Asia (GWPS is 2.9). South and south-east Asia have a better GWPS performance (4.0) than the other countries in Asia where rice and wheat have a GWPS of 3.5 and 2.9 respectively. The Middle East and North Africa have a GWPS of 4.5, close to the values observed for Eastern Europe (4.5) and Western Europe (5.0). Rice is doing quite well in the deltas of the Po, Ebro and Quadalqivier, which increases the average score. The interim conclusion is that the America's - and South America in particular - are most productive with water resources, both for rainfed and irrigated cereals.

4.2. Regional water productivity score (WPS) computed with ETLook

While it is useful to have an understanding of GWPS variability to learn of the caps of GWPS and where on earth certain crop type can be cultivated most efficiently and by which on-farm practices, it is inadequate to define one single maximum CWP_c target value for particular landforms such as river plains, deltas, polders, oases, hill slopes, mountain valleys, high plateaus. The presence of on-farm irrigation systems increases the expected CWP value considerably because the role of erratic rainfall is excluded. The latter example demonstrates that a WPS system based on climate and soil types is insufficient, and that the role of infrastructure investment should be included. WPS targets should therefore not be defined by agro-ecological zones. WPS by crop yield zone is a better methodology to define WPS targets by specific physical and management conditions. For instance, rainfed cereals cultivated on a poor mountain soil in the upstream end of a river basin that receives erratic rainfall should have a target WPS value that differs from irrigated cereals cultivated on alluvial soils in the downstream end.

Contrary to GWPS, populations with data on CWP_c within a single crop yield zone are required for the computation of a more geographically specific WPS. An example of the Indo-Gangetic plain is illustrated in Fig. 9. The Y and CWP_c values are computed with Eqs. (12) and (16). The wheat map is taken from Cheema and Bastiaanssen (2010), the ET values from Bastiaanssen et al. (2012) and the crop yield was obtained from the biomass production functions in ETLook based on Eq. (12) using a constant harvest index, h = 0.26 and a moisture content, $\theta_{crop,} = 0.15\ gr\ gr^{-1}$. Although the value for the harvest index is low, it is representative for the wheat varieties and the yield in Pakistan (e.g. Hussain et al., 2003). The CWP_c in the crop yield zone <1000 kg ha^{-1} shows a CV of 0.41, which reduces to a CV of 0.08 for the crop yield zone 6.000 to 7000 kg ha^{-1}. These results reveal large similarities to the CV values found in the literature review presented in Table 2. A WPS of 10 is associated with the 99th percentile of CWP_c within each crop yield zone, similarly the 5th percentile is linked to a WPS of 1. The definition is thus similar to GWPS, but the reference values are variable by crop yield zone.

The 5th and 99th percentiles of CWP_c for each crop yield zone in the Indus basin (see Fig. 9) were estimated and combined with the experimental data from the 17 countries in the FAO-CWP database and with the Doukkala irrigation scheme in Morocco. Fig. 10 shows the upper

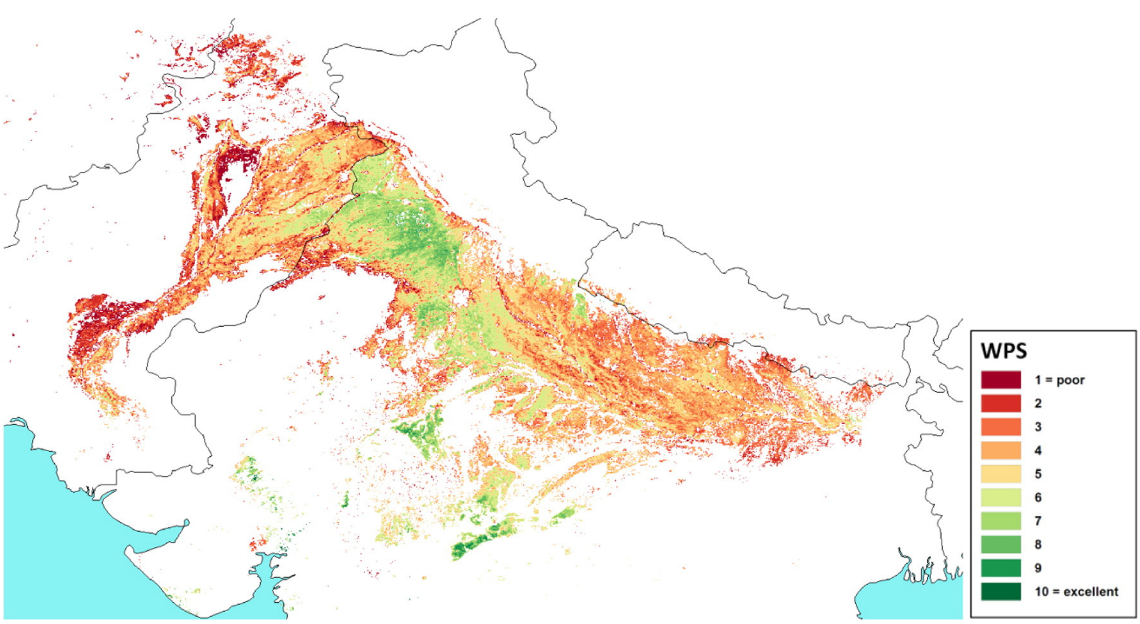

Fig. 8. Distribution of GWPS in the Indo-Gangetic plain. Strong geographical contrasts between India and Pakistan are visible.

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Table 8
GWPS by sub-continent for wheat, rice, maize and their average value to present cereals more generally.

Sub-continent	Countries	Wheat		Rice		Maize		Cereals
		CWP_c (kg m^{-3})	GWPS (−)	CWP_c (kg m^{-3})	GWPS (−)	CWP_c (kg m^{-3})	GWPS (−)	GWPS (−)
South America	Uruguay, Argentina, Chili, Surinam, Brazil, Peru, Paraguay, Bolivia	1.97	**8.1**	0.97	4.0	3.04	**6.1**	7.5
North America	Mexico, USA, Canada	1.39	5.8	1.77	**7.6**	2.43	4.9	5.8
Western -Europe	UK, Netherlands, France, Spain, Italy, Germany, Denmark, Greece, Sweden, Austria, Ireland, Croatia, Portugal, Bosnia, Albania	1.20	5.0	1.31	5.5	2.24	4.5	5.0
Eastern-Europe	Poland, Romania, Hungary, Czech Republic, Bulgaria, Slovakia	1.08	4.5	–	–	–	–	4.5
Middle East and North Africa	Saudi Arabia, Egypt, Morocco, Syria, Algeria, Tunisia, Lybia, Jordan, Lebanon, Israel	1.06	4.4	1.24	5.2	–	–	4.5
Africa	South Africa, Mali	1.79	7.4	0.71	2.8	1.24	2.4	6.3
Russia and former USSR	Russia, Kazakhstan, Ukraine, Turkmenistan, Tajikistan	0.67	2.9	–	–	–	–	2.9
South and southeast Asia	Pakistan, India, Nepal, Bangladesh, Indonesia, Thailand, Vietnam, Philippines, Cambodia, Sri Lanka, Malaysia	0.94	4.0	0.98	4.0	–	–	4.0
Asia	China, Turkey, Iran, Iraq, Afghanistan, Azerbaijan, Armenia, Georgia, Cyprus, Japan	0.68	2.9	0.87	3.5	1.22	2.4	2.9
Australia		1.37	5.7	1.09	4.5	–	–	5.6
World		0.92	**3.9**	0.95	**3.9**	2.25	**4.5**	4.0

Bold values represent the sub-continents with the maximum GWPS performance.

and lower envelopes of CWP_c analytically by means of curve fitting. The lower boundaries of CWP_c appeared to increase linearly with crop yield zones. The upper boundary shows more of a plateau value for wheat and maize and to a lesser extent for rice. The data of the upper edge follows a logarithm behavior, with a steep change in CWP_c maximum values at low productivity fields. The functions for wheat, rice and maize are inserted. With these CWP_c functions, WPS for every crop yield zone on earth can be computed. Remotely sensed maps of (i) crop type, (ii) crop yield Y and (iii) CWP_c can be combined in a simple model to produce maps of WPS that have a local practical value.

With these approximations of the magnitudes of CWP_c for each crop and for each yield zone, it is deemed possible to assess the local minimum and maximum values of CWP_c. For instance, a wheat yield of 4500 kg ha^{-1}, will have a CWP_c varying between 0.48 (WPS = 1) to 2.14 kg m^{-3} (WPS = 10). These WPS boundaries for Y = 4500 kg ha^{-1} are achieved for $\sum$ET values ranging between 210 to 938 mm per season. For simplicity it is assumed that CWP is equal to CWP_c. $\sum$ET values of 600 mm and more are thus unacceptable (WPS < 2.5), and $\sum$ET lower than 375 mm desirable (WPS > 5.0). A WPS of 7.5 or higher would be obtained if $\sum$ET ≤ 268 mm or lower. Growers and irrigation advisors should work together to achieve such lower $\sum$ET value. Chukkalla et al. (2015) demonstrate that this is feasible.

5. Limitations and way forward

WATPRO has been applied at the global scale using seasonal averaged input parameters. This can be further improved by considering weekly inputs. With weekly inputs, CWP variability during the season can be monitored, which is a very practical approach for policy makers and farming communities to gauge progress. Instead of CWP, separated computations for weekly biomass production and ET values are preferred. With cloud computation capabilities and new satellites such as NPP-VIIRS and PROBA-V being available, the opportunities are becoming rapidly realistic. Grower access to this technology is important to increase WPS in the field in a timely manner. The largest challenge is to generate annual maps of field crops, both national and at international scale. The scientific progress at this front is not satisfactory.

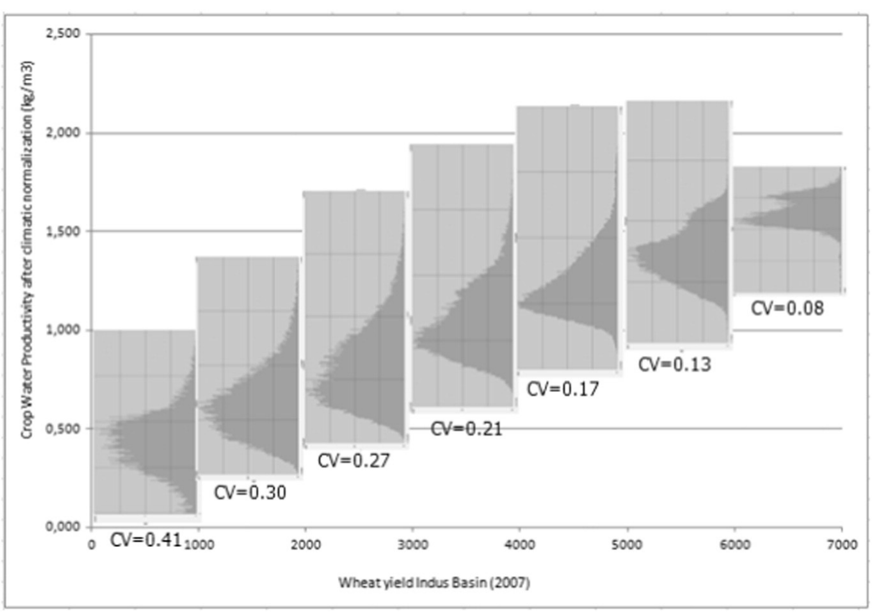


Fig. 9. Variability of climate normalized Crop Water Productivity (CWP_c) within crop yield zones for wheat growing in the Indus Basin in Pakistan and India computed with the ETLook model.

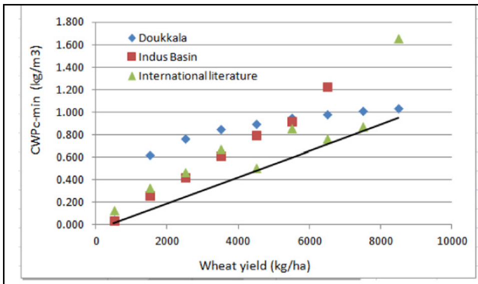
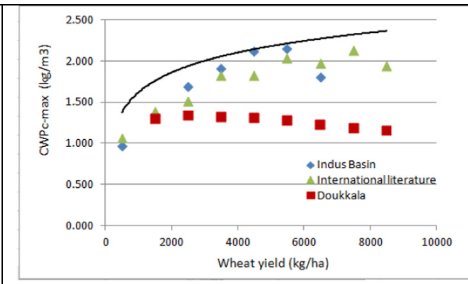
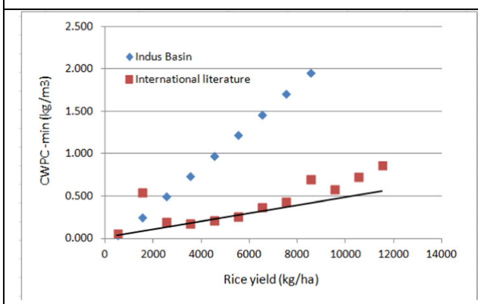
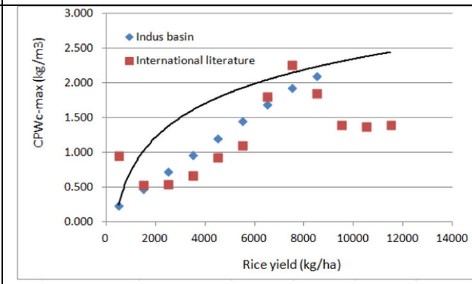
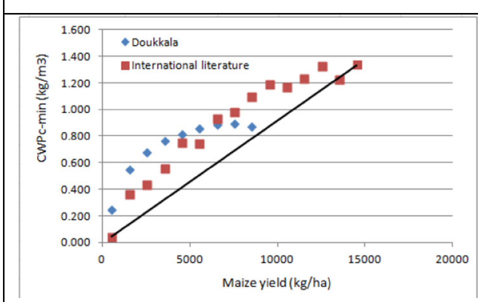
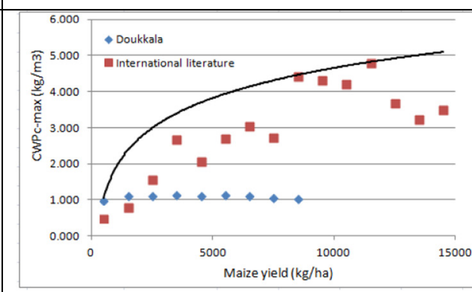
	
5th percentile variability of CWP_c by wheat yield zone. CWP_c^{5} *wheat* $= -0.05 + 1.176\times10^{-4}\ Y$	99th percentile variability of CWP_c by wheat yield zone. CWP_c^{99} *wheat* $= 0.35 \ln(Y) - 0.8$
	
5th percentile variability of CWP_c by rice yield zone. CWP_c^{5} *rice* $= 0.015 + 4.6\times10^{-5}\ Y$	99th percentile variability of CWP_c by rice yield zone. CWP_c^{99} *rice* $= 0.7\ln(Y) - 4.1$
	
5th percentile variability of CWP_c by maize yield zone. CWP_c^{5} *maize* $= 0.0 + 9.2\times10^{-5}\ Y$	99th percentile variability of CWP_c by maize yield zone. CWP_c^{99} *maize* $= 1.2\ln(Y) - 6.4$

Fig. 10. Estimations of the lower and upper boundaries of CWP_c for the major cereal crops including the analytical relationships to describe them.

While the biomass production models are believed to be rather good, the harvest index models such as those presented along with Eqs. (6) and (7) need further testing and improvement. In particular, the role of soil moisture during flowering stage and crop nutrition in critical growth stages affect the harvest index. The AquaCrop-based harvest index model (Raes et al., 2012) provides a sound theoretical basis, and need to be applied in a spatially distributed context. Models such as WOFOST (Bogaard et al., 1998), DSSAT (Jones et al., 2003), STICS (Brisson et al., 2003) and AquaCrop (Raes et al., 2009) can simulate crop growth process in more detail for specific fields and can be used to study the harvest index in more detail. A recent paper of Leroux et al. (2016) utilizes the Crop Water Stress Index (CWSI) to determine a pixel dependent harvest index, and these type of solutions are believed to be of great value.

The separation of ET into soil evaporation, E, and crop transpiration, T, can be considered as being fundamental for achieving progress in CWP modelling because it provides ranges on possible savings in E without affecting T. Measures to reduce E will contribute to the vapor shift and increase CWP (e.g. Rost et al., 2009). Two-layer surface energy balance models such as TSEB (Norman et al., 1995), ALEXI (Anderson et al., 2000), ETLook (Bastiaanssen et al., 2012a) and ETMonitor (Jia et al., 2009) have the technical capabilities to estimate E in future analyses.

6. Conclusions

The main objective of this research was to understand the current levels of CWP and develop a simple scoring system that all stakeholders understand, accept and can work with. With the theoretical framework provided, it is now feasible to compute a WPS and GWPS for pixels with spatial dimensions ranging from a few decimeters (aircraft and drones) to the world (wide swath polar orbiting satellites). International efforts are underway to provide this type of data from earth observation satellites on a regular manner and for free. (G)WPS normalizes for (i) crop types and (ii) climates so that some first comparison between regions and global cropping systems can be made. In addition, WPS includes local production potential, which makes it feasible to apply the concept in a wide range of agricultural conditions.

Since the CV of CWP varies between 0.88 in unfavorable conditions (low crop yield zones, <1000 kg ha^{-1}) to 0.05 in perfect on-farm management conditions (high crop yield zones, >8000 kg ha^{-1}), it is realistically feasible to increase the WPS. Spatial WPS maps make it feasible to identify discrete areas and farmer fields with good and poor WPS values. The underpinning reasons for variability can be attributed to many factors including rainfall variability, soil physical properties, soil fertility, slopes, irrigation management and drainage management. The way forward is to interpret and explain this variability by physical and management factors. The part that cannot be explained by physical factors can be associated with on-farm decision making. Fields with high WPS can be used by local growers and their supporting cooperatives and agencies to diagnose the best practices and disseminate them to areas with lower WPS values. Growers should be exposed to these new technologies and receive the required training.

This paper presents a methodology to map the boundaries and present the results for wheat, rice and maize for both local and global scale. It is suggested to continue this work to other crops and build further on the work of cotton (Tennakoon and Milroy, 2003), potatoes (e.g. Darwish et al., 2006), fruit trees (e.g. Teixeira de Castro et al., 2008), sugarcane (e.g. daSilva et al., 2013) and sunflower (e.g. Howell et al., 2015).

The Sustainable Development Goals (SDGs) and several world forums advocate the need to improve Crop Water Productivity (CWP). This type of upstream policy making needs to be integrated with downstream implementation by growers. GWPS provides leading insight into differences between basins, provinces, states and countries. It also allows the global community to monitor and facilitate discussion on the efficient use of scarce water resources. GWPS is based on this first global determination of the plausible ranges of climatologically corrected crop water productivity CWP_c for wheat, rice and maize. WPS maps are meant for describing typical values of CWP_c that can be achieved under local production circumstances. WPS will support the downstream agronomy and (irrigation) water resources community. We believe that (G)WPS represents a straightforward and scientifically sound basis for better discussions on efficient water use in agriculture as it meets the requirement to define baselines, set targets, and monitor progress towards their achievement in an easy to understand format.

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