Historical simulation of maize water footprints with a new global gridded crop model ACEA

Oleksandr Mialyk[1], Joep F. Schyns[1], Martijn J. Booij[1], Rick J. Hogeboom[1,2]

[1]Multidisciplinary Water Management group, Faculty of Engineering Technology, University of Twente, Enschede, The Netherlands
[2]Water Footprint Network, Enschede, The Netherlands

Correspondence to: Oleksandr Mialyk (o.mialyk@utwente.nl)

Abstract. Crop water productivity is a key element of water and food security in the world and can be quantified by the water footprint (WF). Previous studies have looked at the spatially explicit distribution of crop WFs but little is known about ~~the~~their temporal dynamics. ~~We develop a new global gridded crop model –~~ Here, we present AquaCrop-Earth@lternatives (ACEA) – a new process-based global gridded crop model that can simulate three consumptive WF components: green (WF_g), blue from irrigation (WF_{bi}), and blue from capillary rise (WF_{bc}~~) at high temporal and spatial resolutions.~~). The model is applied to analyse global maize production ~~during~~in 1986-2016 at 5 x 5 arc minute ~~grid.~~spatial resolution. Our results show that ~~in~~over the 2012-2016 period, the global average unit WF of maize is ~~723.2~~728.0 m^3 t^{-1} y^{-1} (~~89.5~~91.2 % WF_g, ~~8.3~~7.6 % WF_{bi}, ~~2~~1.2 % WF_{bc}) with values varying greatly around the world. Regions ~~characterised by high agricultural development generally show a small unit WF and its interannual variation, such as~~with high-input agriculture (e.g. Western Europe and Northern America ~~(WF < 500 m^3 t^{-1} y^{-1}, CV < 15%). On the contrary,~~) show small unit WFs and low interannual variability, while low-input regions ~~with low agricultural development~~ show opposite outcomes~~, such as~~ (e.g. Middle and Eastern Africa ~~(WF > 2500 m^3 t^{-1} y^{-1}, CV > 40%). Since~~). From 1986 to 2016, the global average unit WF ~~of maize~~ has reduced by ~~34.6 %~~a third, mainly due to the historical ~~decrease~~increase in ~~yield gaps~~maize yields. However, due to the rapid expansion of rainfed and irrigated ~~cropland~~areas, the global WF of maize production has increased by ~~48.8 %~~half, peaking at ~~762.9~~768.3 x 10^9 m^3 y^{-1} in 2016. As many regions still have a high potential in ~~decreasing~~closing yield gaps, ~~the~~ unit ~~WF of maize is likely to continue reducing, whereas the WF of maize production is~~WFs are likely to ~~continue growing as~~reduce further. Simultaneously, humanity's rising ~~appetite can lead~~demand for food and biofuels may further expand maize areas, hence increase WFs of production. Thus, it is important to ~~further cropland expansion. The simulation of other crops with ACEA is necessary to assess the pressure of overall crop production on~~address the sustainability and purpose of maize production, especially in those regions where it might endanger ecosystems and ~~freshwater resources worldwide~~human livelihoods.

1 Introduction

The ever-increasing ~~demand for crops pushes~~crop production is one of the reasons why humanity ~~towards the environmental limits of our planet~~transgresses planetary boundaries (Campbell et al., 2017; Jaramillo and Destouni, 2015). In particular, crop production is ~~responsible~~estimated to account for around 87 % of humanity's total water consumption~~ in the world~~ (Hoekstra and Mekonnen, 2012)~~ which, in many places, already exceeds the sustainable limits posing risks to local water security (Hoekstra et al., 2012b; Schyns et al., 2019) and further deterioration can be expected in the future~~, which in some places already exceeds the environmental limits endangering local ecosystems and water security (Hoekstra et al., 2012b; Schyns et al., 2019; Verones et al., 2017). Moreover, the situation is likely to worsen in the future as crop water consumption continues to grow (Wada and Bierkens, 2014; Greve et al., 2018).

One way to minimize ~~the~~crops' pressure on water resources ~~posed by crop production~~ is to increase crop water productivity, i.e. have "more crop per drop" (Giordano et al., 2006). The volume of water needed to produce a unit of a crop can be measured by the consumptive water footprint (WF). ~~The consumptive WF of a crop~~It is calculated as the ~~ratio of~~ crop water use (CWU) ~~to~~over crop yield (Hoekstra, 2011). ~~CWU reflects the amount of accumulated evapotranspiration (ET) over the crop's growing season and can be attributed to two water types: green — water from rainfall, and blue — water from capillary rise and/or irrigation. ET is usually modelled rather than measured in the field, especially if the focus of studies covers large areas or several alternative crop management practices are assessed (e.g. different irrigation strategies or mulches). Crop yields are commonly measured during the harvest but can be also modelled together with ET to explore feedback loops between crop growth and water availability (Hoekstra, 2011).~~CWU reflects the amount of accumulated evapotranspiration (ET) over the growing season and can be attributed to green (from precipitation) and blue water (from capillary rise (CR) and irrigation). Crop yield reflects the harvestable part of crop biomass.

Since its introduction in 2002, the WF concept has been widely applied to analyse crop water ~~use in crop production~~productivity (Feng et al., 2021; Lovarelli et al., 2016). However, most studies either focus on a small geographical extent (e.g. specific ~~watersheds~~catchments or administrative units) or consider a short time period. The~~ only~~ few existing global studies focus on the average year 2000 (Mekonnen and Hoekstra, 2011; Siebert and Döll, 2010; Tuninetti et al., 2015), and thus ~~they~~ lack the analysis of historical trends and interannual variability~~ in crop WFs~~. Moreover, ~~the~~their methods ~~used~~ to estimate ~~the~~ green and blue ~~WFs in these studies can be improved in various aspects~~crop WFs have several limitations: (i) ~~they apply a~~the applied crop water requirement approach ~~which~~ does not simulate crop growth and its response to ~~abiotic~~thermal stresses~~ (e.g. from extreme temperatures or water deficits);~~; (ii) the water balance is simulated without considering ~~capillary rise~~CR that can be~~ quite~~ relevant in areas with shallow groundwater (Hoekstra et al., 2012a); (iii) the green-blue water ~~separation~~partitioning is performed in post-processing ~~rather than tracing it directly during the modelling,~~ which ~~leads to~~does not account for the ~~lower accuracy~~full dynamics of ~~WF estimates~~green and blue water fluxes in the soil water balance (Hoekstra, 2019). Alternatively to these studies, crop WFs can be ~~calculated at high spatial and temporal resolutions~~simulated with ~~process-based~~ global gridded crop models (~~GGCMs~~GGCM). These models (~~such as~~e.g. LPJmL, EPIC, and DSSAT) typically simulate crop growth and water use from the underlying biophysical processes in the atmosphere-plant-soil continuum ~~for~~in each grid cell~~ independently or with couplings between grid cells~~ (Müller et al., 2017). Due to high computational demands, ~~there is a limited body of literature that applies GGCMs, with topics varying from irrigation demand estimation (McNider et al., 2015), climate change impact assessment (Rosenzweig et al., 2014; Ruane et al., 2018), and yield~~

~~gap analysis (Wang et al., 2021). To our knowledge, global crop WFs have never been studied with GGCMs.~~a limited body of literature applies GGCMs. The most prominent studies come from the Global Gridded Crop Model Intercomparison (GGCMI) within the Agricultural Model Intercomparison and Improvement Project (Rosenzweig et al., 2013; Elliott et al., 2015) that mainly uses ensembles of GGCMs to analyse climate change impacts on crop production (Ruane et al., 2018; Jägermeyr et al., 2021a; Minoli et al., 2019; Zabel et al., 2021; Deryng et al., 2016). Besides GGCMI, several studies look into spatial patterns of crop water productivity but not into historical dynamics (Liu et al., 2009; Fader et al., 2010; Liu et al., 2016). ~~In this paper, we present a new GGCM – AquaCrop-Earth@lternatives (ACEA) – with a primary focus on crop water productivity. ACEA is a gridded version of FAO's standalone process-based and water-driven crop growth model AquaCrop (Steduto et al., 2009). This model is widely applied for crop water productivity studies because it requires a small number of inputs to produce reliable estimates of crop yields as well as CWU under different~~In this paper, we present AquaCrop-Earth@lternatives (ACEA) – a global gridded version of FAO's water-driven, process- and site-based crop growth model AquaCrop (Vanuytrecht et al., 2014; Steduto et al., 2009). We use AquaCrop because it requires a small number of inputs to produce reliable estimates of crop yield and CWU under various agro-climatic conditions (Araya et al., 2016; Greaves and Wang, 2016; Karandish and Hoekstra, 2017; Maniruzzaman et al., 2015; Chukalla et al., 2015; Zhuo et al., 2016). In recent years, several studies applied ~~originally site-based AquaCrop~~ it at the regional scale ~~by coupling it with a~~via GIS software (Lorite et al., 2013; Huang et al., 2019; Han et al., 2020). However, in this implementation, AquaCrop demands inputs for each simulation site ~~as~~in separate files, which ~~increases modelling complexity and makes global crop simulations extremely demanding on computational resources.~~can be computationally inefficient. To overcome this limitation ~~in~~, ACEA~~, we utilise~~ utilises the open-source version ~~of AquaCrop~~ developed by ~~Foster et al. (2017) – AquaCrop-OS.~~Kelly and Foster (2021) – AquaCrop-OSPy. We optimise ~~AquaCrop-OS for computationally efficient~~ACEA for large scale simulations by minimising the number of input ~~and output~~ files and by parallelising the modelling procedure. Furthermore, we implement the daily ~~tracing~~accounting of green and blue water fluxes in ~~each grid cell to allow accurate estimation of green and blue crop water productivity~~the soil profile, including CR contributions from shallow groundwater.

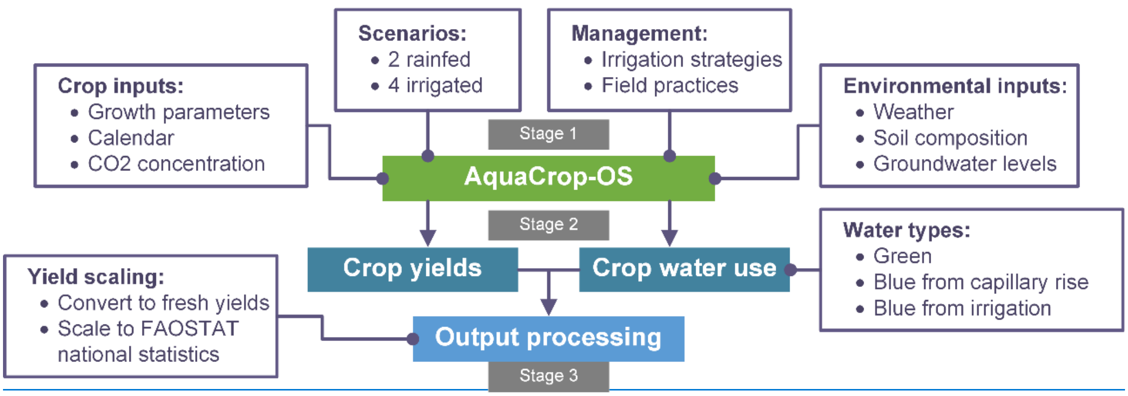
~~To~~ Although ACEA can be applied to simulate all crops that are compatible with AquaCrop, we demonstrate ~~its~~ACEA's performance~~, we apply ACEA to simulate~~ by simulating global WFs of maize ~~WFs during 1986-2016~~ (*Zea mays* L.) at 5 x 5 arc minute resolution (~8.3 km x 8.3 km~~), while accounting for~~). We cover the 1986-2016 period, considering historical changes in ~~cropland extent.~~harvested areas and crop yields. We focus on maize because of several reasons. First, it is the most-produced ~~crop~~grain in the world (FAOSTAT, 2021)~~ and its WFs are not as extensively researched as WFs of other major crops~~. Second, it plays a major role in the global economy by being used not only as food for animals (including humans) but also to produce biofuels and other biochemicals (Ranum et al., 2014). Finally, maize WFs are not as extensively researched as WFs of other major grains, such as rice and wheat (Chapagain and Hoekstra, 2011; Mekonnen and Hoekstra, 2010). In our analysis, we reveal temporal and spatial patterns in both unit WFs of maize (in m^3 t^{-1} y^{-1}) and ~~total~~ WFs of maize production (in m^3 y^{-1}) at global and regional levels. ~~In the end, we compare~~We conclude by comparing our results to estimates from previous studies~~ and discuss~~, discussing both limitations and advantages of crop water productivity analysis with ACEA, and addressing the sustainability of maize production.

2 Data and methods

2.1 Global gridded crop model ACEA

2.1.1 General ~~model~~ description

~~The AquaCrop-Earth@lternatives (~~ACEA~~) model~~ is ~~a process-based global gridded crop model (GGCM) specifically developed to calculate crop water productivity at high spatial~~ written in Python and ~~temporal resolutions while requiring a minimum set of input data. Each grid cell is simulated independently via a three-stage procedure~~its simulation procedure has three main stages as shown in Fig. 1.



~~**Figure 1: Schematic representation of ACEA's simulation procedure in each grid cell.**~~

In the first stage, ACEA collects crop and environmental input data for each grid cell within the study area~~. The~~ (elaborated in Sect. 2.2). The spatial resolution of input data determines the size of grid cells, ~~and~~while the geographical extent of rainfed and irrigated ~~crop~~ production systems determines the number of ~~grid~~ cells. Depending on ~~the production system, one or multiple simulation scenarios are~~water availability, several rainfed and irrigation setups can be selected. The rainfed ~~scenarios~~setups include fully rainfed (~~scenario 1~~*s1*) and rainfed with ~~a~~ presence of shallow groundwater (~~scenario 2~~*s2*). The irrigation ~~scenarios~~setups include surface irrigation (~~scenario 3~~*s3*), sprinkler irrigation (~~scenario 4~~*s4*), drip irrigation (~~scenario 5~~*s5*), and surface irrigation with ~~a~~ presence of shallow groundwater (~~scenario 6~~*s6*). Besides ~~the simulation scenarios, field~~ water availability setups, crop management can be customised by selecting field practices (mulches, weed control, and bunds) and ~~customized~~adjusting irrigation strategies~~ are chosen if appropriate. A detailed simulation setup for this study is provided in Sect. 2.1.4.~~

In the second stage, ACEA runs ~~the~~ AquaCrop-~~OS crop model (see~~OSPy (described in Sect. 2.1.2) ~~by iterating the grid cells within the study area. AquaCrop-OS simulates the crop growth and soil water balance on a daily time step without considering~~

in each grid cell independently, meaning that lateral ~~flows to other grid cells. Thus, the grid cells are independent from each other and can be run in parallel depending on the available computational resources.~~processes, such as water inflow from adjacent cells, are not considered. Main output variables are crop yield and CWU ~~that is attributed to one of the three water types: green, blue from irrigation, and blue from capillary rise. More information about the output variables is provided~~ (see all outputs in Sect. S1.1~~.~~

). In the third stage, ACEA aggregates the raw outputs from each grid cell into global gridded datasets~~.~~ in NetCDF format. Then, it runs optional post-processing procedures, ~~such as WF calculation (see Sect. 2.1.3),~~ including crop yield scaling (see Sect. 2.1.4), ~~and~~ WF calculation (Sect. 2.1.3), statistical ~~analyses (see Sect. 2.1.5). The final gridded datasets are saved in a NetCDF format, which allows further crop water productivity~~ analysis ~~in any programming language or GIS software.~~(see Sect. 2.1.5) and visualisation.

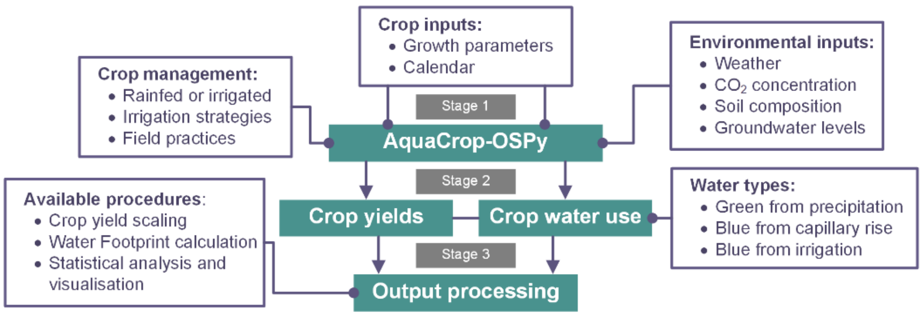


Figure 1: Schematic representation of ACEA's simulation framework.

2.1.2 AquaCrop-~~OS~~OSPy and green-blue water accounting

~~We use AquaCrop-OS version 6.0 (Foster et al., 2017) which is an open-source implementation of FAO's standalone AquaCrop application (Vanuytrecht et al., 2014; Steduto et al., 2009). This crop model is process-based and uses crop, soil, climate, field and irrigation management data to simulate daily crop growth and the soil water balance. The soil water balance is calculated as the sum of water inflow (rainfall, irrigation, and capillary rise) and outflow fluxes (runoff, evapotranspiration, and deep percolation) among soil compartments. Crop development is temperature-driven via growing degree days (GDDs) and is ultimately expressed in biomass build-up. At the end of the growing season, the accumulated biomass is converted into a simulated crop yield via the harvest index, which is affected by water and temperature stresses. Note that AquaCrop-OS v6.0 cannot simulate the nutrient cycle or water salinity. For more information about AquaCrop, please refer to the associated literature~~We use AquaCrop-OSPy (Kelly and Foster, 2021) which is a Python implementation of FAO's AquaCrop application version 6.1. This crop model uses crop, soil, climate, field and irrigation management data (see Fig. 1) to simulate daily crop growth and the soil water balance (Vanuytrecht et al., 2014). The latter includes water input (precipitation, irrigation, and CR) and output (runoff, evaporation (E), transpiration (T), and deep percolation) fluxes as well as upward and downward fluxes between soil compartments (see Fig. 2). Crop growth is temperature-driven via growing degree days (GDDs) and expressed by the variable effective rooting depth and canopy cover. Canopy cover is used to convert the potential evapotranspiration

(ET_0) into T which drives dry above-ground biomass growth via a CO_2-adjusted water productivity factor. At the end of the growing season, the accumulated biomass is converted into a dry crop yield via a harvest index. The crop growth is affected by thermal and water stresses. For example, the latter can induce stomatal closure and constrain canopy expansion which would lead to reduced T and biomass growth. Note that the nutrient cycle and water salinity are not simulated in AquaCrop-OSPy. For more information on AquaCrop, please refer to user manuals (Raes et al., 2009; Steduto et al., 2009; Hsiao et al., 2009).

~~We have implemented several changes to the original code (see Sect. S1.2). The most important change is the direct separation between green and blue water fluxes based on the method suggested by Hoekstra (2019). On a daily time step, all inflow and outflow water fluxes are accounted separately for every soil compartment. Each of these fluxes is attributed to one of three water types: green, blue from irrigation, and blue from capillary rise. Thus, it is possible to know the composition of soil moisture in terms of these three types when soil evaporation and root water abstraction (equal to crop's transpiration) are calculated. The composition of consumed water is proportional to the water types stored in each soil compartment on a specific time step.~~

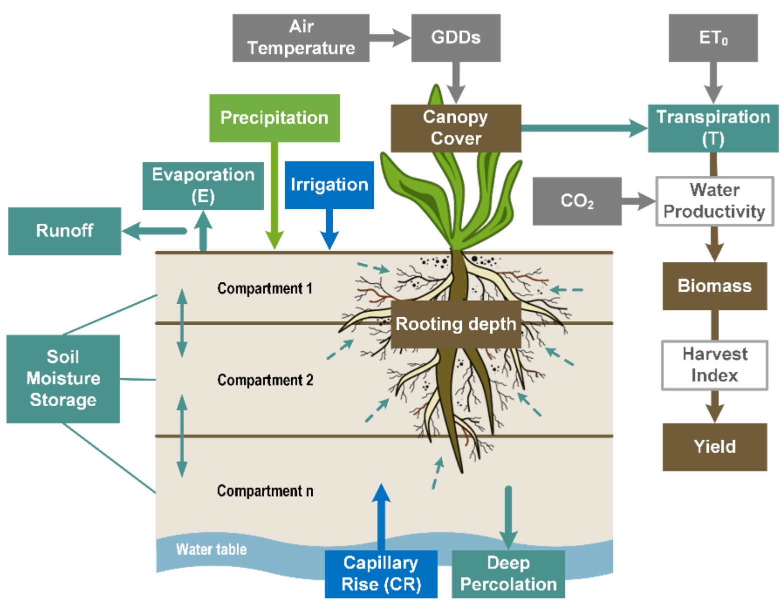


Figure 2: AquaCrop simulation scheme. Green, blue, and cyan boxes represent variables related to the soil water balance, brown boxes to crop growth, and grey boxes to climate. We only abbreviate the terms that are often used in the text.

The green-blue water accounting is our most important addition to the AquaCrop-OSPy code (see other changes in Sect. S1.2). According to Hoekstra (2019), each of the input fluxes is attributed to one of the three water types: green from precipitation, blue from CR, or blue from irrigation (see the respective coloured boxes in Fig. 2). Once entered, these fluxes are assumed to mix evenly with moisture in soil compartments at the top or the bottom of the soil profile. Then, the mixed water is partly redistributed via the upward and downward fluxes between the compartments due to gravitational and capillary forces. The mixed water is taken up for ET – from the upper part of the soil profile for E and from all compartments within the effective rooting depth for T. Therefore, the volumes of the three water types stored in each soil compartment constantly change. This implies that the composition of ET varies per day too, and, consequently, we can estimate precise CWU for each of the three water types. For more details about green-blue water accounting, please refer to Hoekstra (2019).

2.1.3 Water footprint calculation

ACEA calculates the annual consumptive unit *WF* ($m^3\ t^{-1}\ y^{-1}$) of a crop as the sum of three WF components (Hoekstra, 2011):

$$WF = WF_g + WF_{bc} + WF_{bi} \tag{1}$$

where WF_g is the green WF, WF_{bc} is the blue WF from ~~capillary rise~~CR, and WF_{bi} is the blue WF from irrigation. Each *WF* component is calculated as the ~~ratio of~~ crop water use CWU_x ($mm\ y^{-1}$) of a water type *x* (*g*, *bc*, or *bi*) ~~to~~over crop yield *Y* ($t\ ha^{-1}\ y^{-1}$). To convert from $mm\ y^{-1}$ into $m^3\ ha^{-1}\ y^{-1}$, CWU_x is multiplied by 10:

$$WF_x = \frac{CWU_x * 10}{Y} \tag{2}$$

To obtain *Y*, the simulated crop yield Y_s in AquaCrop-~~OS~~OSPy is corrected by two unitless coefficients. The first one is a conversion coefficient from dry to fresh crop yield K_f (0.87 for maize); the second one is a yield scaling factor *S*, which is introduced to account for external developments not modelled ~~by~~in ACEA (explained in Sect. 2.1.4):

$$Y = \frac{Y_s * S}{K_f} \tag{3}$$

The simulated ~~rainfed and irrigated scenarios~~water availability setups are combined to analyse rainfed and irrigated production systems. In the case of rainfed systems, ~~the~~ *WFs* of a water type *x* from ~~scenario 1 (~~setups *s1*~~)~~ and ~~2 (~~*s2*~~)~~ (defined in Sect. 2.1.1) are simply summed ~~up~~ as rainfed grid cells always have only one ~~of those two scenarios.~~setup. On the other hand, in irrigated systems, the same grid cell can have several irrigated ~~scenarios at once~~setups (*s3* to *s6*~~).~~) at once. Therefore, ~~the WF of a water type *x* from each of the scenarios is~~irrigated *WFs* are multiplied by irrigation factor K_i~~.~~ before being summed. The latter ~~is the~~reflects a fraction of irrigated ~~harvested~~ area under the respective irrigation method obtained from Jägermeyr et al. (2015):

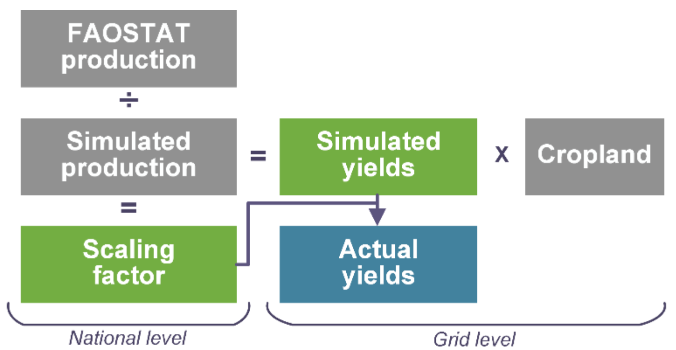
$$\begin{cases} Rainfed\ WF_x = WF_{x,s1} + WF_{x,s2} \\ Irrigated\ WF_x = \sum_{i=s3}^{s6} WF_{x,i} * K_i \end{cases} \tag{4}$$

Note that we differentiate between the unit *WF* (always written in italic) and the WF of crop production. The latter is calculated by multiplying *WF* with the annual crop production, and thus it is measured in $m^3\ y^{-1}$.

2.1.4 Crop yield scaling

~~Crop yield is scaled to incorporate external developments that cannot be modelled in ACEA. Some developments affect long-term trends in crop yields, such as changes in agricultural inputs (e.g. fertilizers, better crop varieties, machinery) or in environmental conditions (e.g. irrigation water quality). Some developments are short-term and cause interannual variability,~~

~~such as~~During the last decades, maize yields have increased globally due to various long-term agricultural developments, namely advances in agricultural inputs (e.g. irrigation, fertilizers, machinery, chemical control of weeds and insects) and better crop varieties (e.g. higher plant density, improved biotic and abiotic stress resistance) (Duvick, 2005; Lorenz et al., 2010). At the same time, there have been short-term developments that caused interannual variability in maize yields, namely disruptions due to political (e.g. civil wars), economic (e.g. food prices), and natural reasons (e.g. locust plague, flooding~~). Since these developments are not modelled in ACEA, Y_s represents the maximum attainable values under water and temperature stresses only. Therefore, following~~) (Woo-Cumings, 2002; Smale et al., 2011). Both long-term and short-term developments are not modelled in ACEA, either because of input data limitations or because required processes are not included in AquaCrop-OSPy. However, following the logic of previous studies (Mekonnen and Hoekstra, 2011; Siebert and Döll, 2010), we ~~use~~attempt to represent the combined effect of these developments via yield scaling factors ~~to~~(*S*) that scale Y_s to the ~~official~~ annual statistics ~~reported by~~from FAO (FAOSTAT, 2021).~~ Because FAO reports crop production at the national scale, these factors are the same for all grid cells within one country regardless of the production system (see Fig. 2).~~



~~**Figure 2: Calculation procedure of yield scaling factor at the national level.**~~

~~The yield scaling factors *S* are~~Because FAO reports the total crop production at the national scale, *S* values are the same for each grid cells within a country (see Fig. 3). *S* is calculated per country per year as the ratio of the official crop production P_{FAO} (t y^{-1}) reported by FAO to the simulated crop production P_{ACEA} in ACEA. The latter is calculated as the sum of rainfed and irrigated production:

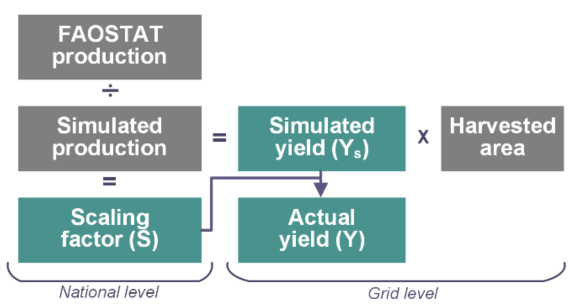


Figure 3: Calculation procedure of yield scaling factors at the national level.

$$S = \frac{P_{FAO}}{\sum Rainfed\ P_{ACEA} + \sum Irrigated\ P_{ACEA}} \tag{5}$$

$$\begin{cases} Rainfed\ P_{ACEA} = \dfrac{(Y_{s,s1} + Y_{s,s2}) * A_{rainfed}}{K_f} \\ Irrigated\ P_{ACEA} = \left(\displaystyle\sum_{i=s3}^{s6} \frac{Y_{s,i} * K_i}{K_f} \right) * A_{irrigated} \end{cases} \tag{6}$$

where Y_s is the simulated crop yield (t ha^{-1} y^{-1}) in a specific ~~scenario~~water availability setup (rainfed: *s1* and *s2*, irrigated: *s3* - *s6*), $A_{rainfed}$ and $A_{irrigated}$ are historical rainfed and irrigated harvested areas (ha y^{-1}), K_i ~~is the fraction of irrigated harvested area covered by the respective irrigation method in each scenario, and K_f is the conversion coefficient from dry to fresh crop yield~~and K_f are defined in Sect. 2.1.3.

~~To account for the historical changes in harvested areas, we extrapolate the MIRCA2000 data to the period of 1986-2016. The extrapolation is performed using two historical datasets on cropland extent HYDE 3.2 and HID (see Table 1) under the assumption that maize harvested areas experienced the same dynamics as the croplands did. A detailed description of the extrapolation procedure is provided in Sect. S1.7.~~

~~The interannual~~Interannual variability in *S* ~~can lead~~leads to ~~large~~ interannual variability in crop yields, ~~and~~ hence in WFs. However, we aim to capture the effect of long-term external conditions while maintaining the modelled climate-related interannual variability. Therefore, we take a three~~-~~-year moving average of scaling factors for each country (using the previous, current, and next year's factors). This allows ~~to keep~~keeping the overall trend and variability in historical crop yields ~~and attenuate~~while attenuating extreme responses to short-term external developments.

One could argue to scale CWU as well. However, we only scale Y_s due to several reasons. First, improvements in crop varieties (e.g. angle and size of leaves) can change the ratio of T to E, but this has minor effects on CWU as an increase (or decrease) in T is compensated by a decrease (or increase) in E (Xu et al., 2018; Nagore et al., 2014). Both E and T consume green and blue water, and thus we do not expect major changes in green and blue CWUs either. Second, the historical increase in plant density mainly increases maize yields while CWU values stay relatively similar for the same reasons as mentioned above. A sensitivity analysis with our model (see Sect. S1.3) confirms this. Third, an input of nitrogen fertilizer can marginally increase CWU when first applied, but additional fertilizer amounts would not always lead to a larger CWU (Rudnick et al., 2017). In our study, we have to assume no nutrient stress (i.e. optimal nutrient supply) as AquaCrop-OSPy cannot simulate the nutrient cycle. This might lead to an overestimation of CWU in places that do not use fertilizers. However, we assume that the majority of maize is produced by high-input farms with sufficient nutrient supply, and thus our CWU estimates over large scales should be hardly affected. To sum up, the literature indicates that historical changes in crop varieties and agricultural inputs have only minor effects on maize CWU compared to yields. Therefore, scaling the yields should be sufficient to represent historical dynamics in maize WFs.

2.1.5 Statistical ~~analyses~~analysis of results

~~The statistical analyses in our study are~~Statistical analysis is performed at several spatial scales according to the UN classification (UNSD, 2021): global, (sub)regional, and national. To obtain representative values for each scale, ~~the~~ WFs are averaged based on the production amounts, and related WF variables (*Y*, *CWU*, and *S*) are averaged based on the harvested ~~areas~~area in each grid cell.

We also focus on two timeframes: i) the last five-year period (2012-2016) as a proxy for the current state of WFs, and ii) the whole 1986 to 2016 period to analyse historical changes. For the trend analysis of WFs and related variables, we use the Mann–Kendall test, which identifies the direction and significance of a trend in time series (Hussain and Mahmud, 2019)~~, which identifies the direction and significance of a trend in time series.~~. We further detrend the variables with significant trends to analyse interannual variations by removing a linear trend. The interannual variability is measured by estimating the coefficient of variation (CV) of detrended timeseries and the dependency between different variables is determined by the Pearson linear correlation coefficient (Brown, 1998).

2.2 Simulation setup

Data needed to run ACEA for global maize production ~~during 1986-2016~~ are summarised in Table 1. We ~~run ACEA~~simulate maize WFs over the 1986-2016 period at 30 x 30 arc minute resolution (~50 km x 50 km), which is ~~a~~also common ~~resolution in many GGCMs~~for GGCMI studies (Franke et al., 2020)~~. The grid cells are selected according to the location of maize production systems obtained from MIRCA2000 (Portmann et al., 2010). We consider one growing season per year and simulation scenarios *s1* to *s4* (see Sect. 2.1.1) as *s5* and *s6* are not common in maize production.~~

. The maize-growing grid cells are selected according to the location of maize production systems obtained from SPAM2010 (Yu et al., 2020). Note that we do not differentiate between the various types of maize (e.g., pop, dent, flour, and sweet corns) due to a lack of input data. We consider only one growing season per year, as double cropping of maize is negligible at the global scale (Portmann et al., 2010). The periods between growing seasons are also simulated to account for soil moisture changes. We exclusively use water availability setups *s1* to *s4* (defined in Sect. 2.1.1), as *s5* and *s6* are not common for maize production. The 30 x 30 arc minute modelling outputs are distributed among its underlying 5 x 5 arc minute grid cells from SPAM2010, and hence the post-processing (see Sect. 2.1.1) is performed at 5 x 5 arc minute resolution.

Table 1: Summary of input data used for maize crop modelling and post-processing in ACEA.

Type	Period	Timestep	Resolution	Source
Data for crop modelling in AquaCrop-~~OS~~OSPy (1984-2016)				
Climate inputs	1984-2016	daily	30 x 30 arc minutes	GSWP3-W5E5 v1.0 (Lange, 2019)~~GSWP3-W5E5 composite product (Lange, 2019)~~
Atmospheric CO2 concentration	1984-2016	annual	Global average	~~NOAA (Dlugokencky and Tans, 2020)~~NOAA (Dlugokencky and Tans, 2020)
Crop parameters	-	-	-	AquaCrop's manual and crop files
Crop calendar	-	-	30 x 30 arc minutes	~~ISIMIP3 project (ISIMIP, 2020)~~Jägermeyr et al. (2021b)

Soil composition	-	-	30 x 30 arc minutes	~~ISIMIP3 project (ISIMIP, 2020) based on Harmonized World Soil Database 1.12 (Nachtergaele et al., 2008)~~ISIMIP3 project (ISIMIP, 2020) based on Harmonized World Soil Database 1.12 (Nachtergaele et al., 2008)
Groundwater levels	Average of 2004-2014	monthly	5 x 5 arc minutes	~~Fan et al. (2013)~~Fan et al. (2013)
Data for setup and post-processing (1986-2016)				
Harvested areas	Around ~~2000~~2010	annual	5 x 5 arc minutes	~~MIRCA 2000 (Portmann et al., 2010)~~SPAM2010 (Yu et al., 2020)
Irrigated cropland	1985-2005	5~~-~~-year	5 x 5 arc minutes	~~HID (Siebert et al., 2015)~~HID (Siebert et al., 2015)
Irrigated and rainfed cropland	1980-2017	10~~-~~-year till 2000 then annual	5 x 5 arc minutes	~~HYDE 3.2 (Klein Goldewijk et al., 2017)~~HYDE 3.2 (Klein Goldewijk et al., 2017)
Maize production statistics	1986-2016	annual	National	~~FAO (FAOSTAT, 2020)~~FAO (FAOSTAT, 2021)

~~Climate inputs for AquaCrop-OS are obtained from the GSWP3-W5E5 composite product~~Climate inputs for AquaCrop-OSPy are obtained from the bias-corrected reanalysis product GSWP3-W5E5 v1.0 (Lange, 2019) ~~(Lange, 2019)~~ ~~which~~that provides historical daily rainfall, temperature, surface shortwave radiation, wind speed, and relative humidity. These variables (except rainfall) are used together with a global elevation model (Amante, 2009) to estimate ~~the potential evapotranspiration~~ET_0 according to the Penman-Monteith equation (Allen et al., 1998).

Crop parameters are obtained from the AquaCrop manual (Raes et al., 2018) and ~~default maize crop file provided with AquaCrop-OS. In case of inconsistencies among these two sources, priority is given to data from the manual. The resulting set of maize parameters is generic, and thus crop development stages (in GDDs) for every grid cell are recalculated to ensure that the average growing season duration is similar to the one from the crop calendar (ISIMIP, 2020). This calendar is a composite of multiple recent data sources that rely on national and subnational statistics, remote sensing products, and modelling. Additional information on crop parametrisation is provided in Sect. S1.3~~the default maize crop file provided with AquaCrop-OSPy. In case of inconsistencies among these two sources, priority is given to data from the manual. The considered crop calendar (Jägermeyr et al., 2021b) is a composite of multiple recent data sources that rely on national and subnational statistics, remote sensing products, and modelling. The planting and harvest dates from the crop calendar are used to calculate GDDs with the third calculation method from AquaCrop (Raes et al., 2018). Crop development stages (in GDDs) for each grid cell are recalculated with the method of Minoli et al. (2019) to ensure that the average growing season duration is similar to the one from the crop calendar. Since some growing seasons are colder than average, they are allowed to be up to 15 % longer for the crop to reach maturity. Additional information on maize parametrisation is provided in Sect. S1.4.

The soil profile is defined as one layer of 3 m depth with eight compartments ranging from 0.1 to 0.7 m in thickness. The selection of soil compartments is based on the analysis described in Sect. S1.~~4~~5. Sand, silt, and clay fractions for each grid cell are obtained from the ISIMIP3 project ~~(ISIMIP, 2020)~~(ISIMIP, 2020) which provides the fractions from the Harmonized World Soil Database 1.12 ~~(Nachtergaele et al., 2008)~~(Nachtergaele et al., 2008) upscaled to 30 x 30 arc minutes. The soil composition is then converted into hydraulic parameters using a pedotransfer function (Saxton and Rawls, 2006) ~~provided~~included in AquaCrop-~~OS~~OSPy. To ensure realistic initial soil moisture values, we run the model two years in advance of our study period (~~as~~ described in Sect. S1.~~5~~6).

The average monthly groundwater levels are taken from ~~Fan et al. (2013)~~Fan et al. (2013) and initially upscaled to 5 x 5 arc minutes using a resample function in QGIS (QGIS, 2021). ~~We further upscale them to 30 x 30 arc minutes by taking average monthly values over underlying 5 x 5 arc minute grid cells where maize production and shallow groundwater (0-3 m in depth) are present. The final groundwater levels~~Then, the near-to-surface values are lowered to 1 m depth under the assumption that farmers drain the agricultural field to avoid aeration stress (see Sect. ~~S1.6).~~S1.7). We further upscale monthly groundwater levels to 30 x 30 arc minutes by taking an average over the underlying 5 x 5 arc minute grid cells where maize production and shallow groundwater (< 3 m in depth) are present. Finally, we interpolate the monthly values to obtain daily groundwater levels. Note that Fan et al. (2013) report values in a natural state for only one year, and thus short- and long-term effects of groundwater pumping and natural annual fluctuations are not considered.

Following previous studies (Andarzian et al., 2011; Khoshravesh et al., 2013), irrigation events are triggered as soon as the soil moisture drops below 50 % of the maximum available soil water within the root zone. The amount of irrigated water in each of the irrigated ~~scenarios~~setups is limited ~~to~~by field capacity and depends on the percentage of wetted area by the respective irrigation method (Chukalla et al., 2015). The conveyance efficiency is set to 100 % to provide the net irrigation requirement. No particular field management practices are activated due to a lack of data on where they are applied.

~~The simulation results are downscaled to 5 x 5 arc minutes according to the location of rainfed and irrigated maize production systems in MIRCA2000 and location of shallow groundwater levels (only for *sc2*) of the same resolution.~~

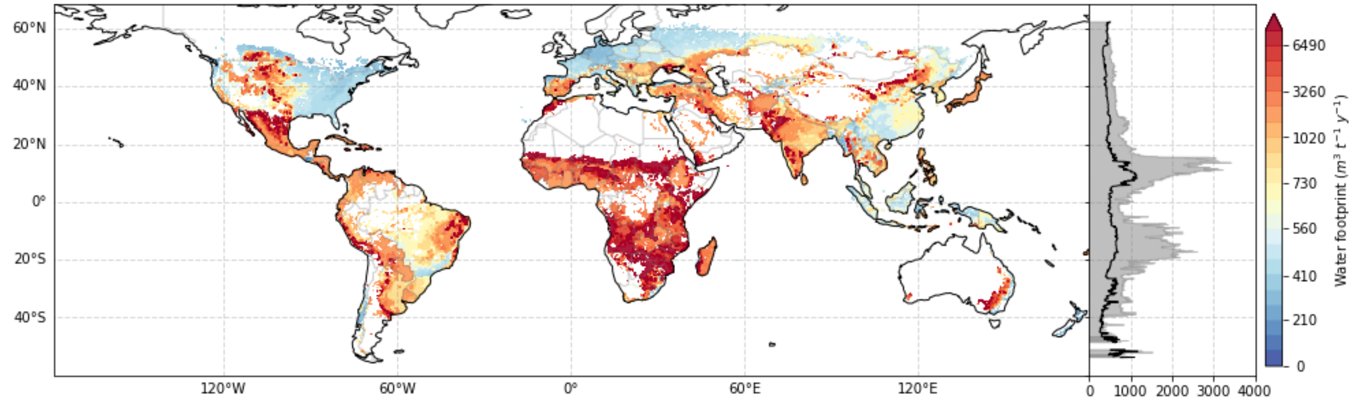
To account for the historical changes in harvested areas, we extrapolate SPAM2010 to the 1986-2016 period. The extrapolation is performed using two historical datasets on rainfed and irrigated cropland extent, i.e. HYDE 3.2 (Klein Goldewijk et al., 2017) and HID (Siebert et al., 2015), under the assumption that maize harvested areas from SPAM2010 experienced the same dynamics as the croplands did. Then, the extrapolated areas are scaled to FAOSTAT (2021). A detailed description of the extrapolation and scaling procedures are provided in Sect. S1.8.

3 Results

3.1 Average ~~maize~~ water footprints in 2012-2016

The global average unit *WF* of maize is ~~723.2~~728.0 $m^3\ t^{-1}\ y^{-1}$ ~~in~~over the 2012-2016 period. The share of green water (WF_g) is ~~89.5~~91.2 %, while the shares of blue water from ~~capillary rise~~CR (WF_{bc}) and irrigation (WF_{bi}) are ~~2~~1.2 % and ~~8.3~~7.6 %, respectively. ~~The distribution of~~ *WF* ~~around the world is shown in Fig. 3. The map indicates~~has a distinct latitudinal distribution~~, which corresponds to~~ (see Fig. 4a ~~similar one in maize~~) following the same patterns as crop yields (see Fig. ~~S1). Small~~S1a). High yields and small *WF* values north of 20°N are ~~mainly~~ due to ~~the~~ high ~~yields~~-input production systems in the main ~~producing~~maize-growing regions: Northern America (*WF* is ~~481.2~~483.1 $m^3\ t^{-1}\ y^{-1}$; yield is 10.1 $t\ ha^{-1}$), Europe (~~581~~597.5 $m^3\ t^{-1}\ y^{-1}$; 6.2 $t\ ha^{-1}$), and Eastern Asia (~~624.6~~615.7 $m^3\ t^{-1}\ y^{-1}$; 5.9 $t\ ha^{-1}$). On the other hand, the regions with low ~~maize~~ yields have substantially larger *WF* values and are mostly located in arid parts of the world that mainly rely on low-input rainfed production systems (e.g. Middle and Eastern Africa).

Rainfed systems ~~(741.9 m^3 t^{-1} y^{-1})~~produce 76.5 % of maize and show on average a 10.5 % larger ~~unit~~ *WF* (744.9 m^3 t^{-1} y^{-1}) than irrigated systems (674.1 m^3 t^{-1} y^{-1}). However, both the smallest and the largest regional *WF* (among regions with at least 0.5 % of global maize production) are located in areas dominated by rainfed production (see Table 2), with the largest one in Middle Africa (~~3379~~3157.9 m^3 t^{-1} y^{-1}) and the smallest one in Western Europe (~~416~~433.2 m^3 t^{-1} y^{-1}). The smaller *WF* in the latter region can be explained by both a smaller CWU (i.e. lower ET rates) and a higher crop yield (see Fig. S1). The *WF* values also vary among areas dominated by irrigated production. For example, ~~Eastern~~the *WF* in Western Asia (~~624~~569.6 m^3 t^{-1} y^{-1}) ~~has a twice smaller *WF* than~~ is almost half of that in Northern Africa (~~1170~~1035.5 m^3 t^{-1} y^{-1}) due to a smaller CWU, while ~~the~~maize yields in both regions are similar. The global maps with separated rainfed and irrigated ~~maize~~ *WF* can be found in Fig. S2.



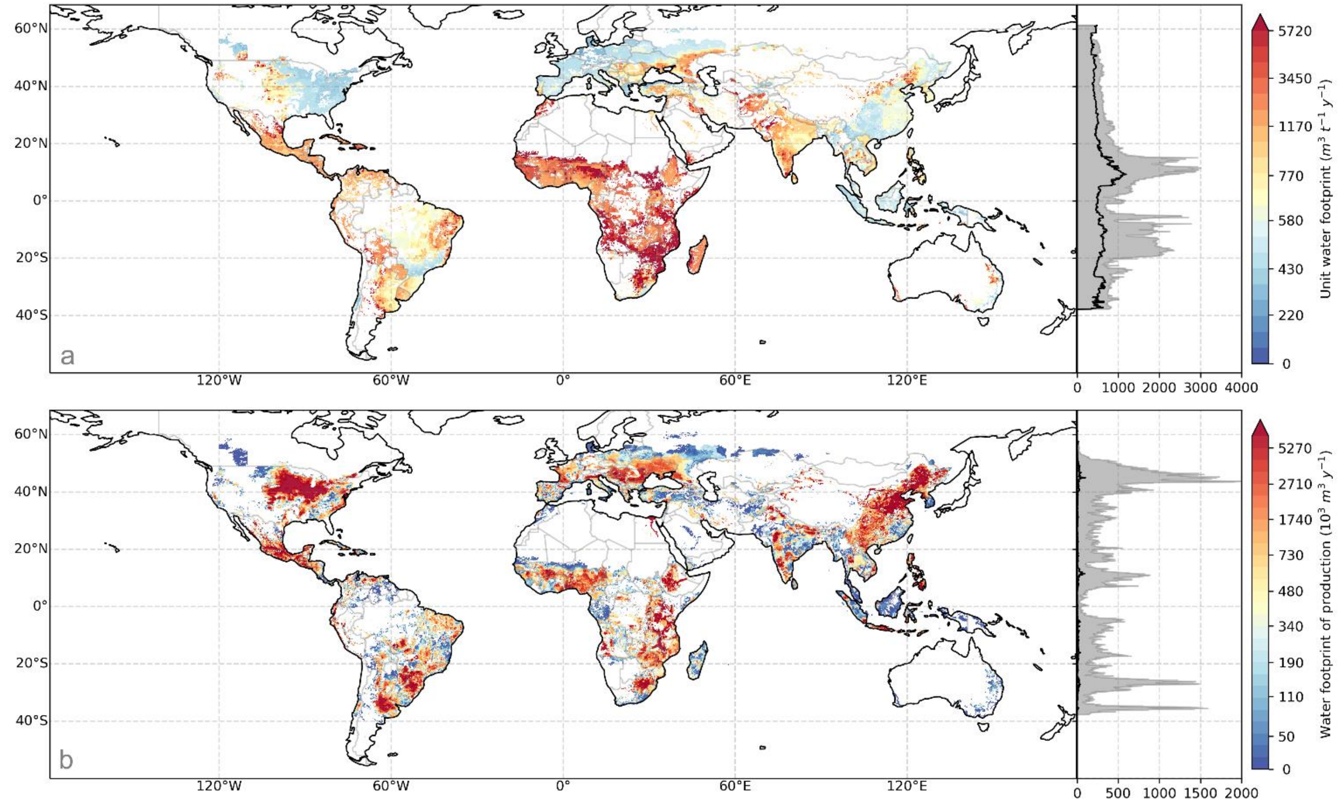


Figure 4~~: Average unit~~: Unit water footprint (a) (m^3 t^{-1} y^{-1}) and water footprint of production (b) (10^3 m^3 y^{-1}) of maize ~~in m^3 t^{-1} y^{-1}~~ as the average over 2012-2016 at 5 x 5 arc minute resolution. The grey area in the side chart represents the median of all data points along the respective latitude and the black line is the ~~10 %~~10th percentile ~~of them~~.

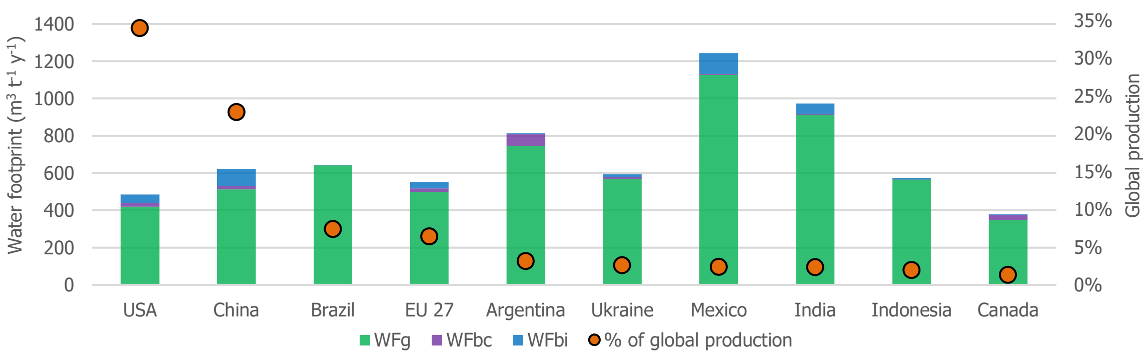
Table 2: Overview of global maize production and water footprint statistics as the average over 2012-2016 (except the coefficient of variation (CV) which is estimated for 1986-2016). CWU is crop water use and WF is water footprint (g - green, bc - blue from capillary rise, bi - blue from irrigation). The selection of regions is based on the UN classification (UNSD, 2021).

Region	Maize production (% of global)	Irrigated [%(% of production])	WF of production (% of global)	Crop yield (t ha^{-1} y^{-1})	Yield gap*	CWU (mm y^{-1})	WF_g (% of unit WF)	WF_{bc} (% of unit WF)	WF_{bi} (% of unit WF)	Unit WF (m^3 t-1 y^{-1})	Change in unit WF (relative to 1986-1990)	CV of unit WF
EasternNorthern Africa	3.0.8 %	3.798.6 %	11.31.1 %	1.86.7	88.158.7 %	505.8691.9	98.35.1 %	0.21 %	1.594.8 %	2746.41035.5	-24.334.0 %	55.47.5 %
MiddleEastern Africa	3.0.6 %	1.04 %	2.911.4 %	1.18	90.688.7 %	375.0513.3	99.24 %	0.41 %	0.34 %	3378.92763.5	-34.922.8 %	41.833.9 %
NorthernMiddle Africa	0.86 %	98.61.4 %	1.32.8 %	5.81.1	64.289.7 %	674.7363.5	15.198.9 %	0.07 %	84.90.4 %	1170.13157.9	-29.430.1 %	830.1 %
Southern Africa	1.21 %	20.032.9 %	1.67 %	4.21	35.446.6 %	429.7456.5	9588.7 %	0.0 %	411.3 %	9491067.3	-65.260.3 %	8374.5 %
Western Africa	1.9 %	0.7 %	5.43 %	1.6	85.20 %	335.8332.5	99.57 %	0.31 %	0.21 %	2066.42008.9	-22.83 %	46.440.0 %
Africa	**7.4 %**	**15.29 %**	**22.54 %**	**2.0**	**84.58 %**	**435.5437.2**	**93.79 %**	**0.32 %**	**6.10 %**	**2169.72157.0**	**-28.126.6 %**	**51.338.5 %**
Caribbean	0.1 %	56.69.1 %	0.2 %	1.3	86.487.0 %	299.7308.1	95.398.6 %	0.12 %	4.61.2 %	2233.52299.8	-25.35 %	25.722.9 %
Central America	2.78 %	26.424.3 %	4.58 %	3.31	74.778.4 %	364.7394.9	91.40 %	0.41 %	8.29 %	1179.11278.7	-42.73 %	16.113.2 %
NorthernSouth America	35.311.9 %	18.4.5 %	23.112.2 %	10.15.2	30.564.2 %	478.1389.8	8696.8 %	4.01.3 %	1.9.3 %	481.2746.6	-28.657.7 %	13.97 %
SouthNorthern America	11.935.1 %	4.717.0 %	12.222.9 %	5.210.1	63.431.0 %	386.4476.8	96.690.3 %	2.21.7 %	1.28.0 %	741.5483.1	-57.228.8 %	20.516.1 %

Americas	**~~50.0~~49.9 %**	**~~15.6~~14.4 %**	**40.~~0~~2 %**	**7.4**	**~~47.4~~48.8 %**	**~~430.6~~435.0**	**~~90.3~~92.4 %**	**~~3.0~~1.4 %**	**6.~~7~~2 %**	**~~583.8~~592.6**	**-37.~~1~~4 %**	**15.~~6~~4 %**
Central Asia	0.2 %	~~100.0~~88.3 %	0.2 %	6.~~1~~2	~~46.7~~47.4 %	~~478.3~~456.5	~~31.9~~36.1 %	0.~~0~~9 %	~~68.1~~63.0 %	~~778.9~~756.4	-~~43~~45.2 %	~~22.4~~18.8 %
Eastern Asia	23.~~1~~2 %	~~61.0~~46.4 %	19.~~9~~5 %	5.9	55.7 %	~~367.4~~362.3	~~82.3~~85.6 %	~~2.7~~1.9 %	~~15.0~~12.5 %	~~624.6~~615.7	-~~28.6~~29.5 %	~~14.4~~19.3 %
South-eastern Asia	4.~~0~~1 %	~~10.4~~9.3 %	3.6 %	4.~~3~~2	~~59.5~~60.6 %	~~277.6~~273.8	98.~~2~~4 %	0.~~9~~3 %	~~0.9~~1.3 %	~~653.9~~643.5	-59.~~9~~1 %	~~24.1~~15.7 %
Southern Asia	3.4 %	38.~~3~~0 %	4.~~3~~5 %	2.9	~~71.8~~72.5 %	~~265.4~~276.8	87.~~4~~1 %	0.~~4~~2 %	12.~~2~~7 %	~~906.9~~941.8	-~~52.6~~49.1 %	~~26.4~~21.3 %
Western Asia	0.7 %	~~38.9~~49.3 %	0.5 %	7.~~0~~1	~~31.6~~22.1 %	~~394~~372.2	~~63~~65.1 %	0.~~4~~5 %	~~36.5~~34.4 %	~~562.4~~569.6	-~~41.1~~36.9 %	~~33.8~~36.7 %
Asia	**31.~~4~~5 %**	**~~51.7~~41.0 %**	**28.~~6~~3 %**	**5.1**	**58.~~4~~7 %**	**~~335.1~~333.0**	**~~84.4~~86.8 %**	**~~2.~~1.4 %**	**~~13.6~~11.9 %**	**~~658.6~~654.7**	**-~~39.1~~38.5 %**	**~~17~~19.4 %**
Eastern Europe	6.5 %	~~5.2~~3.8 %	~~5.8~~6.0 %	5.3	~~52.7~~53.4 %	~~342.2~~351.6	~~94.4~~96.7 %	~~4.0~~2.2 %	1.~~5~~1 %	~~655.0~~669.5	-~~28.0~~30.1 %	~~53.6~~44.9 %
Northern Europe	0.015 %	~~12.~~0.0 %	0.~~1~~0 %	6.~~4~~3	~~37.5~~39.4 %	~~255.0~~247.6	~~95.6~~99.0 %	~~3.5~~1.0 %	~~1.~~0.0 %	~~401.7~~392.1	-~~50.2~~54.5 %	~~56.2~~52.3 %
Southern Europe	2.4 %	~~51.8~~43.5 %	1.8 %	7.9	~~41.3~~44.7 %	~~427.5~~442.1	79.~~5~~8 %	~~5.1~~3.6 %	~~15.4~~16.6 %	~~543.2~~562.5	-~~28.2~~30.3 %	~~17~~14.7 %
Western Europe	2.2 %	~~21.4~~39.7 %	1.3 %	9.1	~~32.3~~35.9 %	~~379.4~~394.6	~~95.6~~94.3 %	~~1.3~~0.4 %	5.3~~.0~~ %	~~416~~433.2	-~~19.7~~20.5 %	~~9.5~~8.8 %
Europe	**11.~~1~~2 %**	**~~18~~19.5 %**	**~~8.~~9.1 %**	**6.2**	**~~47.2~~48.9 %**	**~~361.0~~372.9**	**~~91.6~~93.0 %**	**~~3.9~~2.2 %**	**4.~~5~~8 %**	**~~581~~597.5**	**-~~24.2~~26.4 %**	**~~37.1~~31.2 %**
Australia & New Zealand	0.1 %	~~95.4~~57.0 %	0.~~04~~05 %	8.~~2~~1	~~30.8~~34.6 %	~~399.5~~426.7	~~66.8~~72.3 %	0.~~0~~3 %	~~33.1~~27.4 %	~~490.9~~529.8	-~~41.7~~32.8 %	~~10.5~~14.3 %
Melanesia	0.001 %	0.0 %	0.001 %	~~5.1~~3.4	~~66.1~~65.2 %	~~320.7~~191.6	~~99.2~~100.0 %	0.~~8~~0 %	0.0 %	~~636.6~~572.7	-~~72.0~~60.1 %	~~15.6~~18.1 %
Oceania	**0.1 %**	**~~93.5~~55.9 %**	**0.~~04~~05 %**	**~~8.1~~7.9**	**~~32.1~~35.8 %**	**~~397.0~~415.4**	**~~67.6~~72.9 %**	**0.~~1~~3 %**	**~~32.3~~26.8 %**	**~~493~~530.7**	**-~~42.3~~33.2 %**	**~~10.6~~14.3 %**
Average world	**-**	**~~27.3~~23.5 %**	**-**	**5.4**	**~~58.3~~59.0 %**	**~~392.7~~395.3**	**~~89.5~~91.2 %**	**1.2~~.2~~ %**	**~~8.3~~7.6 %**	**~~723.2~~728.0**	**-34.~~6~~5 %**	**~~21.3~~19.8 %**

* yield gap is estimated as: 100 % - yield scaling factor.

Zooming to the national level, the average ~~unit~~ *WF* of ~~maize of~~ the nine biggest producing ~~nations~~countries plus the EU 27 is ~~592.3~~591.0 m^3 t^{-1} y^{-1} (~~88.3~~90.5 % WF_g, ~~2.9~~1.6 % WF_{bc}, and ~~8~~7.9 % WF_{bi}). ~~Together, they produce 84.3 % of maize globally. The~~ *WF* values range from ~~485.3~~487.2 m^3 t^{-1} y^{-1} in the USA to ~~1244~~1252.4 m^3 t^{-1} y^{-1} in Mexico (see Fig. ~~4~~5~~). The contribution of blue water from capillary rise)~~. WF_{bc} is substantial in Argentina (~~7~~4.6 % of *WF*), ~~the USA (3.9 %),~~ and the EU 27 (~~3~~2.4 %). Among the EU 27 countries, the largest WF_{bc} shares are in Slovakia (8.1 %), the Netherlands (~~26.1 %), Slovakia (13.~~7.2 %), and Hungary (~~9.6 %).~~6.9 %). Together, these ten biggest producers account for 68.1 % of the global WF of maize production with the USA (22.5 %) and China (19.3 %) contributing the most (see Fig. 4b). The complete table with maize WFs of ~~148~~149 countries can be found in Table ~~S2~~S3.



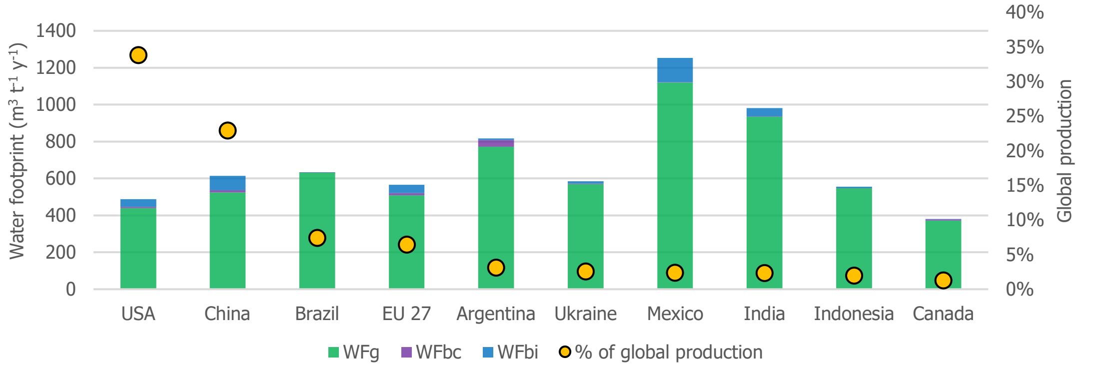


Figure 5: Average unit water footprint of maize (g - green, bc - blue from capillary rise, bi - blue from irrigation) in m^3 t^{-1} y^{-1} and percentage of global production of ~~maize in~~ the ten biggest maize producers during 2012-2016.

~~In terms of the global WF of maize production (i.e. total water consumption), more than 91 % of water is consumed in Americas (40.0%), Asia (28.6%), and Africa (22.5%) as shown in Table 2. The shares of global production in Americas (50.0%) and Asia (31.4%) are larger than the shares of global WF, which indicates high crop water productivities. On the contrary, Africa's share of global production is three times smaller than its share of the global WF, which indicates a low crop water productivity.~~

3.2 Historical trends ~~in maize water footprints~~

The global average unit *WF* of maize has reduced over the last decades as shown in Fig. ~~5~~6. When compared to 1986-1990, the average *WF* of 2012-2016 is 34.~~6~~5 % smaller. However, not all *WF* components ~~reduce~~have reduced by the same magnitude. WF_g and WF_{bc} have reduced by ~~more than~~nearly one third between the two periods (-35.~~8~~7 % and -~~39.4~~31.0 %, respectively), while WF_{bi} has reduced by ~~14~~only 16.6 %. Therefore, the fraction of blue water in total unit *WF* has increased by 23.9 % (+5.4 % for WF_{bc} and +27.4 ~~%.~~ % for WF_{bi}).

To explain the decreasing trend in *WF*, the main contributing factors – Y_s, *CWU*, and *S* (see Sect. 2.1.3)~~ – simulated yield (Y_s), crop water use (*CWU*), and yield scaling factor (*S*)~~ – are analysed with the Mann–Kendall trend test (Hussain and Mahmud, 2019). ~~This test detects significant~~ We detect significantly increasing trends in *S* (+~~56.1~~51.5 % since 1986; p = ~~1.35~~5.74 x $10^{-\cancel{14}13}$) and CWU ~~(+~~(-0.~~1~~37 % since 1986; p = 2.5~~.90~~ x $10^{-\cancel{3}2}$), and no significant trend in Y_s (p = 0.~~29~~54). Subsequent correlation analysis shows that *WF* significantly correlates only with *S* (r = -0.~~97~~96, t = -~~20.64~~19.5) and *CWU* (r = -0.~~51~~45, t = -~~3.19~~2.7). Hence, the reduction in *WF* can be mainly attributed to the increase in *S*, which ~~is a factor that~~ reflects ~~external developments that cannot be modelled with ACEA~~the historical agricultural advances (see Sect. 2.1.4). Once detrended, *WF* correlates significantly only with Y_s (r = -0.~~73~~77; t = -~~5.69~~6.4), and thus the interannual variations in *WF* are mainly driven by ~~crop~~Y_s response to climatic variability~~ reflected in Y_s~~. For example, the *WF* peaks around 1988 and 2012 (see Fig. ~~5~~6) are likely due to extreme La Nina-driven droughts in major maize producing areas which caused substantial drops in crop yields (Iizumi et al., 2014; Rippey, 2015). A summary of global annual *WFs* and main contributing factors during 1986-2016 is provided in Table ~~S3~~S4.

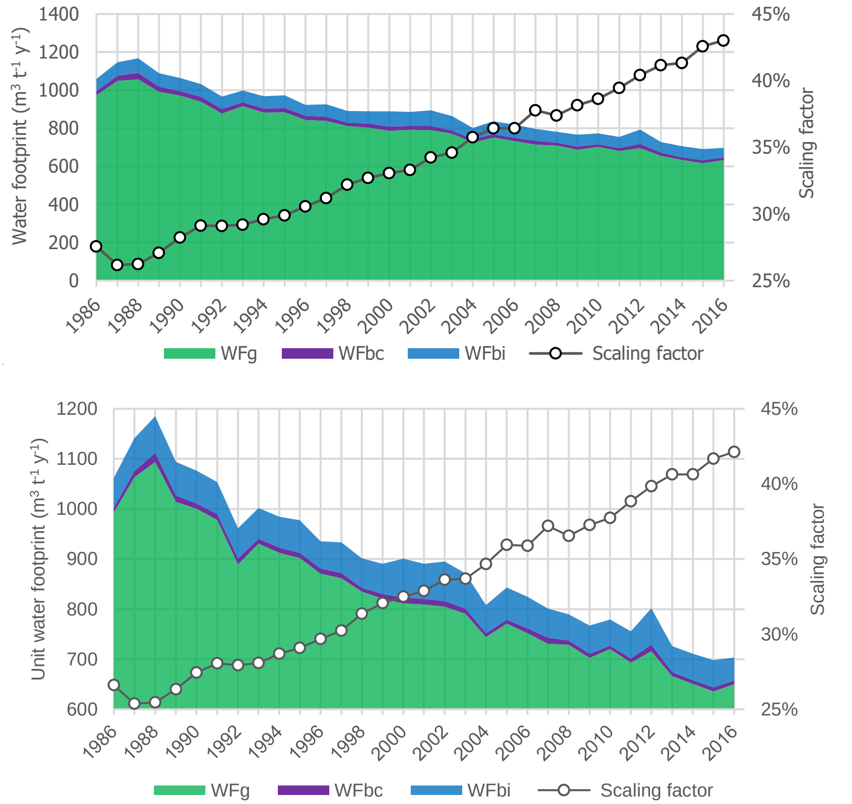


Figure 6: Global trends in average unit water footprints~~ of maize~~ (g - green, bc - blue from capillary rise, bi - blue from irrigation) in m^3 t^{-1} y^{-1} and yield scaling factors of maize from 1986 to 2016. Note that both y-axes do not start at zero.

All major maize producing areas show a smaller ~~unit *WF* of maize (i.e. increase in crop water productivity)~~*WF* in 2012-2016 compared to 1986-1990 (see Fig. ~~6~~7). The regions with the largest *WF* reductions are ~~Melanesia (-72.0 %), ~~Southern Africa (-~~65.2~~60.3 %), Melanesia (-60.1 %), and South-eastern Asia (-59.~~9~~1 %), which indicates substantial increases in ~~their ~~maize yields. On the other hand, the regions with the smallest reductions are Western Europe (-~~19.7 %) and~~20.5 %), Western Africa (-22.3 %), and Eastern Africa (-22.8 %). In the case of Western Europe, this is ~~a result of~~due to the already small *WF* in 1986-1990 (~~518.4~~545.1 m^3 t^{-1} y^{-1}), and thus there was a low potential for *WF* reduction. In the case of Western and Eastern Africa, there was a high reduction potential, but it was barely realised likely due to underlying socio-economic limitations (Smale et al., 2011).

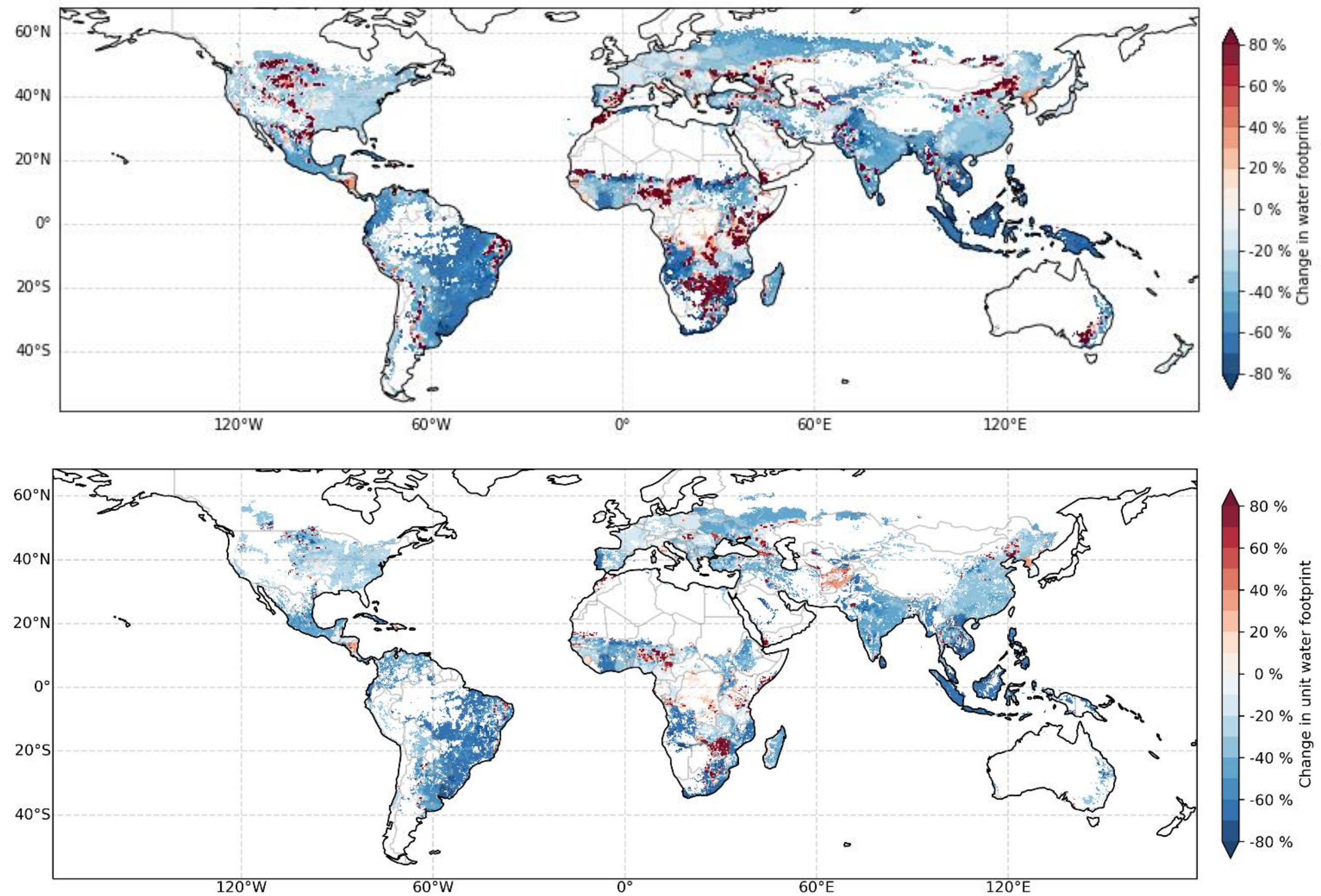


Figure 7: Relative change ~~of~~in unit water footprint of maize from the average of 1986-1990 to the average of 2012-2016 at 5 x 5 arc minute resolution.

~~At~~Among the~~ national scale,~~ countries that together account for 95 % of global maize production~~ show a 32.9 % smaller unit *WF* of maize in 2012-2016 compared to 1986-1990 (see Fig. 7). Reductions~~, reductions of more than 50 % are in Brazil, Indonesia, South Africa, the Philippines, Vietnam, Pakistan, and Paraguay (see Table ~~S2). These countries mostly rely on rainfed systems, and thus the *WF* reduction is mainly due to a smaller *WF*g.~~S3). On the other hand, ~~there are ~~three countries ~~with a *WF* increase: +10.0 % in ~~that have increases in *WFs* (see Fig. 8), but together produce only 0.77 % of maize globally, are the Democratic Republic of Congo~~, +13.1 % in~~ (+9.7 %), Kenya~~,~~ (+12.7 %), and ~~+33.1 % in ~~the Democratic People's Republic of Korea~~. In total, these three countries produce only 0.77 % of maize globally.~~ (+32.2 %). In the first two countries, this is due to an overall decreasing trend in maize yields and high interannual variability (see Sect. 3.3). Different dynamics can be observed in North Korea where maize yields have dropped dramatically since the mid-1990s – the period known as "*The North Korean famine*" (Woo-Cumings, 2002). The yields have not yet recovered resulting in a larger unit *WF*.

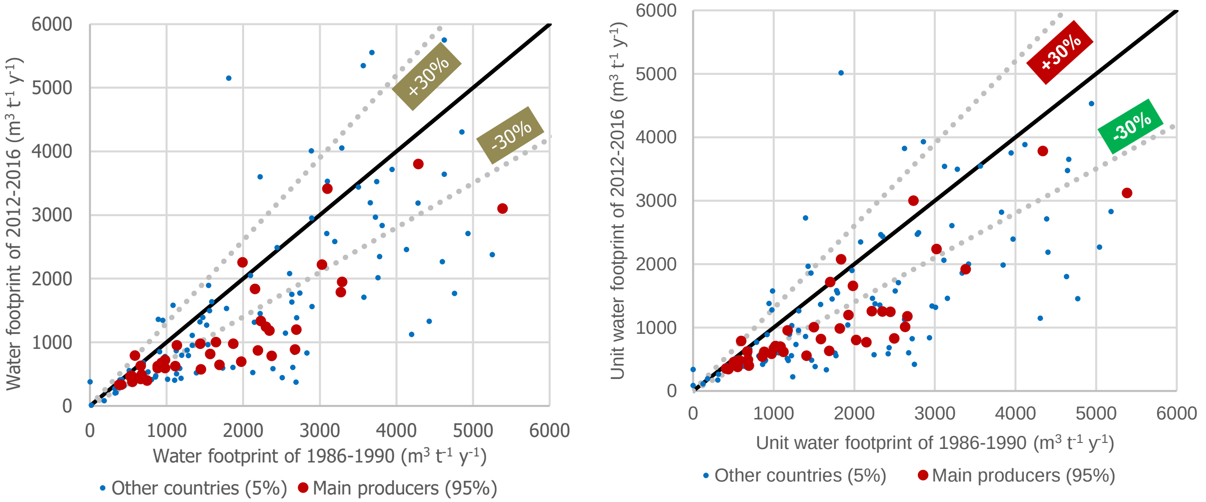


Figure 8: Comparison of the national unit water footprints of maize (m^3 t^{-1} y^{-1}) between the average of 1986-1990 and the average of 2012-2016. The black line represents no change and the grey dotted lines show +30 % and -30 % changes~~ in unit water footprint~~.

The global WF of maize production has increased by ~~48.8~~49.6 % since 1986 (see Fig. 9) peaking at ~~762.9~~768.3 x 10^9 m^3 y^{-1} in 2016~~ (see Fig. 8).~~. This increase differs among ~~rainfed and irrigated~~production systems. In rainfed systems, the consumption of green ~~water~~ and blue water from ~~capillary rise have~~ CR has increased by ~~36.3~~39.9 % and ~~33.8~~67.0 %, respectively. In irrigated systems, ~~the consumption of green water and blue water from irrigation~~they have increased by ~~114~~108.4 % and ~~76.4~~72.5 %, respectively. The Mann–Kendall trend test detects ~~significant~~ significantly increasing trends in the two main contributing factors~~ to the global WF of maize production~~: rainfed harvested area (+~~36.7~~39.5 % since 1986; p = ~~2.48~~5.0 x $10^{-\cancel{8}9}$) and irrigated harvested area (+~~110.0~~107.2 % since 1986; p = 1.~~55~~2 x 10^{-14}). Subsequent correlation analysis shows a significant correlation with both factors (r = 0.98 each). Hence, the expansion of ~~maize cropland~~ harvested areas increases global maize water consumption despite the reduction in ~~unit~~ *WF*. The detrended ~~WF of maize production correlate~~global WF correlates significantly with the detrended harvested areas (rainfed r = 0.95; irrigated r = 0.~~88~~86), which means that historical changes in ~~maize cropland~~ the harvested areas are responsible for ~~its~~ interannual variations in the global WF.

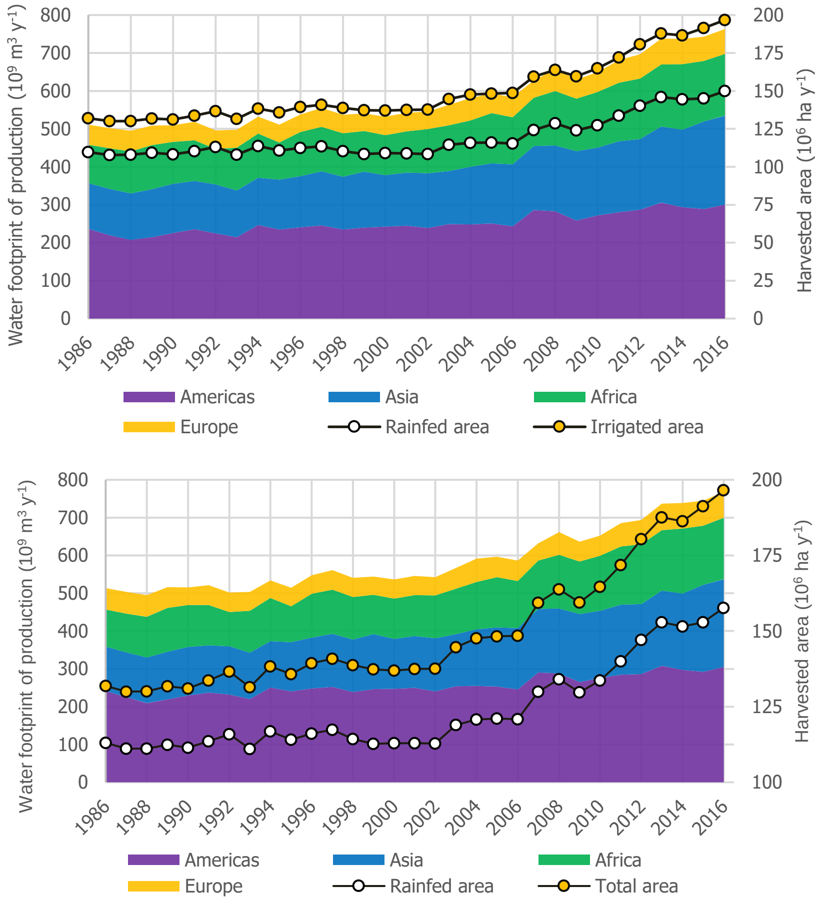


Figure 9: ~~Regional trends~~Trends in the regional water footprints of ~~maize~~ production (10^9 m^3 y^{-1}) and global harvested areas (10^6 ha y^{-1}) of maize from 1986 to 2016. Oceania is not shown due to its negligible contribution. Note that right y-axis does not start at zero.

Most of the ~~maize cropland~~harvested area expansion since 1986 has occurred in Asia and Africa (+81.~~6~~7 % and +76.~~5~~1 %, respectively), which has led to substantial increases in the WFs of maize production (+~~94.4~~96.8 % and +~~60.2~~67 %). At the same time, Americas and Europe have also increased their WFs of production (+~~27.1~~26.3 % and +~~24~~20.8 %), but the ~~cropland~~ harvested areas have expanded moderately (+25.7 % and +~~15~~14.4 %). One of the main reasons behind a larger increase in WFs of production than in harvested areas lies in the ~~substantial~~ expansion of irrigated systems. They have a larger CWU than rainfed systems (+~~14~~17.3 % on average), and hence the regions with a ~~rapid~~larger expansion of ~~them~~irrigated systems, such as +~~175.9~~204.7 % in Asia (compared to +~~37.1~~45.0 % in rainfed systems), experience an increase in the average CWU. As a result, the share of irrigated maize in the global WF of ~~maize~~ production has increased from ~~19.1~~16.8 % in 1986 to ~~26~~22.0 % in 2016. Besides the increase in feed demand, one of the main driving forces for maize area expansion is biofuel production. For example, nearly 40 % of maize in the USA is grown to produce bioethanol (Ranum et al., 2014).

3.3 Interannual variability ~~in maize water footprints~~

The interannual variability in detrended unit ~~*WF*~~*WFs* of maize is analysed using the coefficient of variation (*CV*~~) estimated for the detrended values during 1986-2016.~~). The global average *CV* ~~for this~~over the 1986-2016 period is ~~21.3 %: 8.4 % in irrigated systems and 28.8 % in rainfed systems.~~19.8 %. The variability in rainfed systems (average *CV* of 26.1 %) differs around the world depending on ~~maize yield response to~~ water availability. For instance, the average *CV* of regions with ~~capillary rise~~CR contribution is ~~14.7~~16.8 %, while many arid parts of Sub-Saharan Africa that completely rely on rainfall have *CV* values higher than ~~100~~70 % (see Fig. ~~9~~10~~).~~). As a result, some years may have extremely low yields leading to *WF* peaks of more than 5000 m^3 t^{-1} y^{-1} (see Fig. 4a). On the other hand, the *WF* variability in irrigated systems (average *CV* of 8.2 %) is generally low in all regions as also suggested by previous studies (Kucharik and Ramankutty, 2005; Osborne and Wheeler, 2013). The interannual variability also depends on the level of agricultural development and socio-economic stability ~~(as reflected by yield scaling factors). In Western Europe~~. For example, the average *CV* ~~is 9.5 % despite being~~ of the mostly rainfed~~,~~ maize in Western Europe is 8.8 %, while ~~in Central Asia~~ the average *CV* ~~is 22.4 % despite being 100 %~~of the mostly irrigated~~.~~ maize in Central Asia is 18.8 %. The *CV* values of other regions are listed in Table 2.

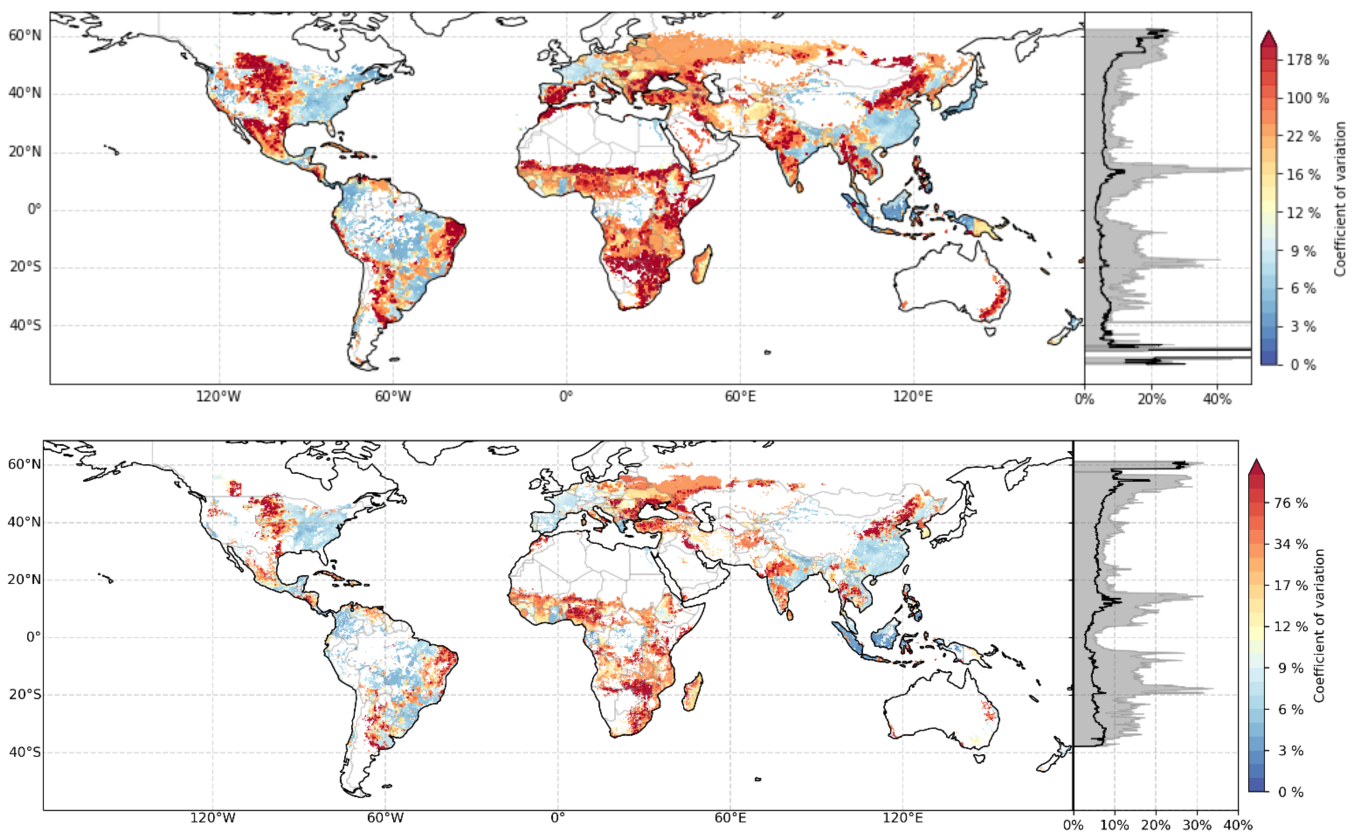


Figure 10: Coefficient of variation of the detrended unit water footprints of maize during 1986-2016 at 5 x 5 arc minute resolution. The grey area in the side chart represents the median of all data points along the respective latitude and the black line is the ~~10 %~~10th percentile ~~of them~~.

4 Discussion

4.1 Comparison ~~of results~~ with literature

4.1.1 Average ~~maize~~ water footprints around 2000

Three previous studies have estimated maize WFs at the global scale with a distinction between green and blue water (see Table 3~~). All three focus on the period around the year 2000, and thus we average our results for a similar period to make the comparison (1996-2005). Both our and previous studies agree on the dominant role of green water in the global average unit *WF* of maize (~90%). However, previous studies show larger unit *WF* estimates compared to the present study: +24 % by Siebert and Döll (2010), +20 % by Mekonnen and Hoekstra (2011), and +12 % by Tuninetti et al. (2015). These *WF* differences are likely caused by different methods applied to estimate *CWU* since the differences in the global average crop yields are relatively small (-4 % to +12 %).~~

). All three focus on the period around year 2000. Therefore, we average our results over the 1996-2005 period to make the comparison. The previous studies agree with ours on the dominant role of green water. They also show larger global average unit *WF* estimates (ranging from +5 % to +23 %). Since the differences in the global average crop yields are relatively small (-4 % to +12 %), these larger *WF* estimates are likely caused by different methods of CWU estimation.

Table 3: Comparison of ACEA results for maize with other global gridded studies. Numbers in brackets indicate the difference compared to the results of ACEA.

Source	Water footprint calculation approach	Shallow groundwater	Averaging period	Crop yield ~~[~~(t^{-1} ha^{-1}~~]~~)		Average unit water footprint ~~[~~(m^3 t^{-1} y^{-1}~~]~~)		
				Rainfed	Irrigated	Green	Blue	Total
Our study	Process-based and water-driven model in growing degree days with incorporated green-blue separation	Considered	1996-2005 (with trend)	4.3	5.~~4~~5	~~792~~812	~~88~~75	~~880~~887
Siebert and Döll (2010)	Daily soil water balance model and crop coefficient approach with green-blue separation in post-processing	Not Considered	1998-2002 (with trend)	4.1 (-~~4~~3 %)	5.7 (+~~6~~3 %)	969 (+~~22~~19 %)	120 (+~~36~~60 %)	1089 (+~~24~~23 %)
Mekonnen and Hoekstra (2011)	Similar to Siebert and Döll (2010), but for one representative year	Not Considered	1996-2005 (no trend)	4.1 (-4 %)	6 (+~~12~~9 %)	947 (+~~20~~17 %)	81 ~~(-~~(+8 %)	1028 (+~~17~~16 %)
Tuninetti et al. (2015)	Crop coefficient approach with evapotranspiration and crop yields from literature	Not Considered	1996-2005 (with trend)	-	-	886* (+~~12~~9 %)	47* (-~~47~~38 %)	933 (+~~6~~5 %)

* approximate estimates from the reported total water consumption as unit water footprint components were not explicitly provided.

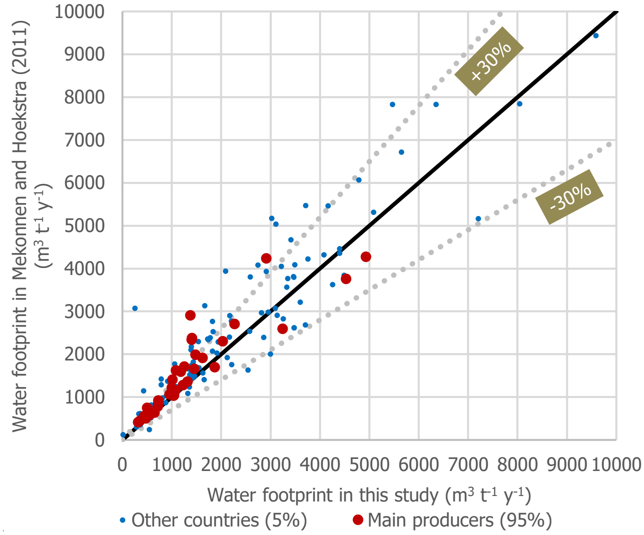
~~The study by~~ Siebert and Döll (2010) ~~estimates a~~estimate larger global average green ~~(+22 %)~~ and blue ~~*CWU* (+36 %)~~*WFs* compared to our study. ~~One of the reasons for these higher estimates is that the~~The authors assume a pre-defined root depth and canopy development (~~linear interpolation between crop factors~~ in the initial, mid-, and late-~~-~~season stages~~), whereas in~~). In our study, both of them are driven by daily temperature and water availability~~. The latter is particularly important since~~, and thus the ability of maize to take up water ~~stress leads to~~ and to transpire it can be limited by abiotic stresses (e.g. constrained root and canopy expansion, induced stomatal closure~~, which reduces crop transpiration.~~). Therefore, ~~crop transpiration and~~

~~root water uptake in ACEA are~~we likely ~~to be~~simulate a smaller ~~leading~~CWU compared to ~~reduction in *CWU* values. There are several other reasons for differences in *CWU* between the two studies, but to what degree they explain the lower estimates in ACEA is difficult to answer.~~ Siebert and Döll (2010). There are several other reasons for differences in CWU, but to what degree they explain the smaller estimates in ACEA is difficult to answer. Siebert and Döll (2010) consider a constant growing season duration using the crop calendar based on ~~the~~ year 2000, while in our model the growing season duration is temperature-dependent and the crop calendar is a composite of multiple recent data sources (see Sect. 2.1.4). Consequently, crop calendar days differ among the two studies leading to different daily weather conditions and growing season durations. This results in different ET rates ~~accumulated over the crop cycle, and~~, hence different ~~*CWU* values~~CWUs. Moreover, the authors estimate green and blue CWU ~~in post-processing, which is~~ with methods that are less ~~accurate~~precise than ~~tracing it directly during the modelling as~~the daily green-blue accounting in ACEA (see Sect. 2.1.2). ~~The authors~~Siebert and Döll (2010) also cover a shorter historical period and use two older input datasets~~:~~, i.e. climatic data that directly affects water availability and ET rates, and harvested area data that ~~results in different sizes of rainfed and irrigated systems, which are important in the global~~affects the averaging of results.

~~The study by~~ Mekonnen and Hoekstra (2011) also ~~shows a~~show larger green ~~*CWU* (+20 %) but a~~and blue ~~*CWU* is smaller (-8 %).~~*WFs.* The authors use a ~~relatively~~ similar modelling approach as Siebert and Döll (2010), but they simulate only one representative year, which neglects the interannual variability in climatic variables as well as trends in agricultural ~~development~~developments and harvested areas. Therefore, CWU estimates do not capture years with abnormal weather (wet, dry, cold, warm). Nevertheless, at the national level, both studies correlate well (r = 0.95).

Tuninetti et al. (2015) ~~also~~ report ~~a~~ larger green ~~*CWU* (+12 %)~~ but smaller blue ~~*CWU* (-47 %).~~*WFs.* The authors do not model the reference evapotranspiration and crop yields (as the other studies do) but take ~~them~~both from literature instead. Moreover, they equalize the blue CWU to irrigation supply which is calculated using independent data sources of different temporal and spatial resolutions.

~~Due to limitations on data availability, we only compare our national unit *WF* estimates to Mekonnen and Hoekstra (2011). Both studies correlate well (r = 0.95) as shown in Fig. 10. Among 148 considered countries, 52 have a unit *WF* difference of more than 30 % and countries that produce 95 % of maize globally have on average the difference of 15.3 %.~~



~~**Figure 10: National comparison of unit water footprints of maize ($m^3\ t^{-1}\ y^{-1}$) around 2000 with Mekonnen and Hoekstra (2011). The black line represents no difference and the grey dotted lines show +30 % and -30 % differences in unit water footprint.**~~

The methodological differences among these three studies also lead to different estimates of the global ~~WFs~~WF of maize production. Compared to our study, Siebert and Döll (2010) and Mekonnen and Hoekstra (2011)~~ show similar directions and magnitudes of differences and~~ report ~~17-19~~16-18 % larger ~~estimates (37-40~~global WFs (15-17 % larger green and 8-53 % larger blue), while Tuninetti et al. (2015) report a half larger global WF (55 % larger green but ~~43-60~~12 % smaller blue~~), while Tuninetti et al. (2015) report a 50 % larger estimate (85 % larger green but 68 % smaller blue).~~).

4.1.2 ~~Historical trends and variability in maize water footprints~~

~~We are not aware of any other study that simulates maize WFs for the same time period as our study. However, the~~Other comparisons~~ of WFs and main contributing factors can be done for a few historical periods. For example, the~~

The recent literature review of 70 related studies~~ (during 2002-2018)~~ by Feng et al. (2021) reports ~~a global average unit *WF* of maize of 730 $m^3\ t^{-1}\ y^{-1}$ with a *CV* of 15.9 %. This aligns well with our estimate of 723.2 $m^3\ t^{-1}\ y^{-1}$ with a *CV* of 21.3%. ~~the global average unit *WF* of maize of 730 $m^3\ t^{-1}\ y^{-1}$ (*CV* of 15.9 %) in 2002-2018. This aligns well with our estimate of 728.0 $m^3\ t^{-1}\ y^{-1}$ (*CV* of 19.8 %) in 2012-2016. Our estimates of maize CWU and yields also align well with the literature. Jägermeyr et al. (2021) simulate CWU for both rainfed and irrigated maize with multiple GGCMs at 30 x 30 arc minute resolution. The global medians are similar to ours as can be observed in Fig. S3. Moreover, we compare our maize CWU estimates to several field studies in various years and locations (see Table 4). The differences between ACEA's values and the ones reported in literature vary between -9.4 % to +14.8 %. Irrigated maize shows smaller differences than rainfed maize for most of the considered studies. This may not be a model but rather a data accuracy issue. It is likely that the gridded meteorological data we use with a spatial resolution of 30 x 30 arc minutes (see Sect. 2.2) deviates from measured data at the fields in the other studies. This is particularly relevant for rainfall which shows strong spatial variability at small scales.

Table 4: Comparison of crop water use (CWU) of rainfed and irrigated maize with field studies.

	Location	Period	Country	Production system	Evapotranspiration measuring method*	Average maize CWU difference relative to ACEA (range of values)**	Reference
1	40°39 N, 104°59 W	2006-2010	USA	Irrigated	Soil water balance	-5.4 % (-13.3 % to +4.7 %)	DeJonge et al. (2012)
2	36°69 N, 108°31 W	2011-2014	USA	Irrigated	Meteorological	-8.5 % (-12.4 % to -5.8 %)	Djaman et al. (2018)
3	41°09 N, 96°28 W	2002-2006	USA	Irrigated	Energy balance	+9.4 % (+1.6 % to +24.4 %)	Suyker and Verma (2009)
4	41°10 N, 96°26 W			Rainfed		-7.8 % (-22.6 % to +20.6 %)	
5	42°24 N, 85°24 W	2010-2016	USA	Rainfed	Meteorological	+14.8 % (+7.2 % to +24 %)	Abraha et al. (2020)
6	40°43 N, 98°8 W	2011-2012	USA	Rainfed	Soil water balance	-9.4 % (-19.9 % to +1.1 %)	Irmak and Djaman (2016)
7	37°45 S, 58°18 W	1995/1996	Argentina	Irrigated	Energy balance	-0.9 %	Gardiol et al. (2003)
8	45°10 N, 12°13 E	2011-2012	Italy	Rainfed	Remote sensing	+11.9 % (+3.1 % to +20.7 %)	Grosso et al., (2018)

* according to FAO classification (Allen et al., 1998), ** estimated as: (Observed CWU in a study / ACEA's CWU) - 100 %

Approximate comparisons can be also done for maize yield gaps. Three studies estimate the global yield gaps around 2000 in a range of 50-64 % (Licker et al., 2010; Mueller et al., 2012; Neumann et al., 2010). Our estimate of the water-limited yield gap for 1996-2005 in ACEA is 67.3 %. Two more recent studies report yield gaps around 2010 for several locations in different regions (Hoffmann et al., 2018; Edreira et al., 2018). Their estimates show similarities to our study (calculated for 2012-2016): 80 % yield gap in Sub-Saharan Africa (~~75~~77.5 % in ACEA), 20 % in Northern America (~~30.5~~31.0 % in ACEA), and 38 % in East Asia (55.7 % in ACEA). ~~More~~The more pessimistic results of our study are likely due to differences in yield-limiting factors and ~~cropland extents~~harvested areas.

4.2 Strengths and weaknesses of ACEA

4.2.1 Advancing crop water productivity research

~~ACEA is the first process-based GGCM that can trace the fluxes of green water, blue water from capillary rise, and blue water from irrigation within the soil profile on a daily time step. This allows to accurately distinguish between green and blue crop water productivity (Hoekstra, 2019). To demonstrate usefulness of this distinction, we highlight the importance of accounting blue water from capillary rise as its contribution to the national WF of maize production can amount to 25 % (see Sect. 3.1). Furthermore, the open-source nature and advanced functionality of ACEA facilitates simulations of various alternative management packages (e.g. field management practices, irrigation methods and strategies). This allows studying responses of crop water productivity to various environmental and managerial changes.~~

ACEA is a new GGCM that can estimate crop yield and CWU distinguishing three water types: green water, blue water from CR, and blue water from irrigation. The open-source nature and easy customisation in ACEA facilitate the analyses of crop water productivity responses to various environmental and managerial changes. Furthermore, the optimised modelling procedure allows computationally-efficient large scale simulations. In our case, ACEA took 12 hours to simulate 57 000 combinations of grid cells and setups (34-year long each, see Sect. 2.2) on a working station with 12 CPUs. This corresponds to 160 000 simulated years per computational hour. Compared to the reported performance of AquaCrop-GIS (Lorite et al., 2013), ACEA is up to 25 times faster. Simulation inputs for this study take more than 27.3 GB of space and outputs more than 30.2 GBs.

4.2.2 Uncertainties in global crop modelling

Global gridded crop modelling is a complex process that contains ~~several~~many uncertainties (Folberth et al., 2019) and ACEA is not an exception. Most of the uncertainties likely originate from spatial and temporal resolutions of input datasets rather than from the model itself. ~~In our study, we model~~We simulate maize production at 30 x 30 arc minute resolution meaning that input datasets with finer resolutions have to be upscaled, such as soil characteristics and shallow groundwater levels (see Sect. 2.2). Then, we ~~downscale simulation~~distribute the results ~~to~~among 5 x 5 arc minute ~~resolution, which~~grid cells according to the spatial distribution of harvested areas. This leads to uncertainty ~~in crop yields and *CWU* estimates~~ as ~~they~~the distributed results do not reflect the exact environmental conditions in each 5 x 5 arc minute grid cell. Alternatively, we could run ACEA ~~can be run~~ at ~~5 x 5 arc minutes~~a finer resolution, but this ~~is~~was not feasible ~~for our study~~ due to input data limitations and high computational requirements~~ and input data limitations (see Sect. 2.2).~~. Next, ~~maize~~selected crop parameters are based on a single maize cultivar ~~calibrated for several agro-climatic conditions by~~from FAO (Hsiao et al., 2009). Therefore, the regional and historical differences in crop ~~genetics such as water productivity, root depth, and abiotic stress responses~~variety are not directly considered~~.~~ but incorporated in yield scaling factors (see Sect. 2.1.4). Moreover, the lack of subnational data needed to generate reliable crop calendars results in a ~~poor~~rough representation of spatial variability in planting and harvest dates. Thus, the start and duration of growing seasons might be miscalculated. As the current version of ACEA does not consider chemical cycles between a crop and the environment, the biophysical stresses from water salinity and insufficient nutrient intake are not simulated, which~~,~~ again~~,~~ leads to uncertainties in ~~simulated crop yields and *CWU*.~~ our results.

We also assume the same soil moisture-based rule for irrigation application in all grid cells. In reality, farmers decide when and how much to irrigate based on site-specific conditions such as access to water and technological inputs. ~~Note that the current version of ACEA does not consider chemical cycles between a crop and the environment. Therefore, the biomass accumulation stresses from water salinity and insufficient nutrient intake are not simulated but captured in the national yield scaling factors (see Sect. 2.1.4).~~ Furthermore, the water consumed by irrigation conveyance is not accounted for. Therefore, the timing and volume of irrigation events simulated in ACEA can deviate from the actual ones. As for CR, we consider neither interannual variations in groundwater levels nor the effects of pumping, and thus our WF_{bc} estimates rather reflect potential values under steady-state conditions.

~~The~~Finally, the post-processing of results also contains uncertainties. In particular, the ~~geographical extent~~distribution of ~~maize production~~extrapolated harvested areas (see Sect. 2.2) plays an important role during spatial averaging. ~~To our knowledge, we make the first-ever attempt to temporally extrapolate maize harvested areas (see Sect. S1.6); hence, our gridded estimates for rainfed and irrigated systems are only approximate. These~~The resulted uncertainties are particularly relevant when zooming to smaller geographical scales (e.g. analysis of small countries).

4.~~2.~~3 ~~Future prospects~~

~~In this paper, we apply ACEA to study the historic and current state~~Sustainability of maize ~~WFs in the world. However, maize covers only a fraction of overall crop production globally, and hence WFs of other crops should be analysed to provide a complete overview of developments in crop water productivity and water consumption worldwide. Furthermore, regional impacts of crop production on ecosystems and freshwater resources can only be assessed by relating the total WF of production (agricultural, industrial, and domestic) to maximum sustainable levels within a given geographical unit (Bunsen et al., 2021; Hoekstra et al., 2012b; Liu et al., 2017; Hogeboom et al., 2020). WFs in crop growing areas that already overshoot (or soon to overshoot) these levels can be further assessed in ACEA to propose potential measures of WF reduction, such as more efficient irrigation and field management (Chukalla et al., 2015, 2017; Campbell et al., 2017; Nouri et al., 2019) or change of cropping patterns (Chouchane et al., 2020).~~production

Global maize production has soared in recent decades due to high demands from livestock and biofuel industries. For example, in the USA, these industries consume almost 90% of all domestically produced maize (Ranum et al., 2014), and thus only a small fraction ends up on human's plates. This does not only lead to debates of "food versus fuel" and "food versus feed" but also raises the question of environmental impacts of maize production (Wallington et al., 2012). Although assessing the latter is out of the scope of our study, we highlight several sustainability aspects of maize production that could be addressed in further research. Concerning water resources, there are three key aspects:

- To what extent WFs of maize production contribute to local green (Schyns et al., 2019) and blue water scarcity (Mekonnen and Hoekstra, 2016). For example, WFs of production can be compared to local time-specific environmental limits of water consumption (Hogeboom et al., 2020; Mekonnen and Hoekstra, 2020).
- How local unit *WFs* of maize compare to appropriate benchmarks. These benchmarks refer to *WFs* that are either obtained by the best producers in other areas with similar agro-environmental conditions or can be achieved using best available practices (Mekonnen and Hoekstra, 2014). Examples of such practices are the application of mulches, selection of better crop varieties, optimization of irrigation and nutrient supply (Chukalla et al., 2015; Rusinamhodzi et al., 2012).
- To what extent maize production pollutes the local water resources via applied fertilisers, herbicides, and pesticides. This pollution can be quantified by water quality indicators, such as the grey WF (Chukalla et al., 2018a; Mekonnen and Hoekstra, 2010; Liu et al., 2017), which refers to the volume of water needed to assimilate a load of pollutants to freshwater bodies. This load can be minimised with agroecological practices, such as the application of organic alternatives to agrochemicals and intercropping (or crop rotation) with nitrogen-fixing plants (e.g. alfalfa, soybeans) (Capellesso et al., 2016). In this context, it is also worthwhile to study the trade-offs between the consumptive (green plus blue) and grey WFs, as the alternative agroecological practices also affect the former (Chukalla et al., 2018b).

The sustainability of maize production can be also assessed from other than water perspectives, e.g. by addressing questions around impacts on ecosystems (Fletcher et al., 2011; Immerzeel et al., 2014), associated GHG emissions (Yang and Chen, 2013; Dias De Oliveira et al., 2005), equitable crop markets (Marenya et al., 2017; Mmbando et al., 2015), and economic value (Wallington et al., 2012; Baffes et al., 2019).

5 Conclusions

~~This study introduces~~ ACEA is a new process-based ~~global gridded~~ crop model ~~— AquaCrop-Earth@lternatives (ACEA) —~~ that ~~can simulate~~ allows the assessment of green and blue crop water productivity at ~~high~~large spatial ~~and temporal resolutions. The main novelty of ACEA lies in its ability to trace fluxes of green water, blue water from capillary rise, and blue water from irrigation within the soil profile on a daily time step. This allows to estimate the precise contribution of these three water types to the final crop WF.~~

~~We apply ACEA to analyse~~scales, which we demonstrate by simulating global maize WFs ~~during~~over the 1986-2016 ~~at 5 x 5 arc minute resolution.~~period. Our results show that~~, in 2012-2016,~~ the current global average unit *WF* of maize is ~~723.2~~728.0 m^3 t^{-1} y^{-1}~~ with a dominant role of~~. The *WF* composition is dominated by green water ~~(89.5 % of total), followed by~~ but the share of blue water from irrigation is increasing. The share of blue water from ~~irrigation (8.3%), and blue water from capillary rise (2.2%). Despite being~~ CR is minor at the global scale~~, the role of blue WF from capillary rise becomes~~ but can be substantial ~~when zooming to regions~~in areas with ~~a wide~~ presence of shallow groundwater~~ tables. We also find that rainfed areas with capillary rise contribution have a twice lower interannual variability in unit WF (CV of 14.7%) than rainfed areas without such contribution (28.8%). However, the lowest interannual variability is found in irrigated areas (8.4%).~~ ~~Spatial and temporal patterns in maize unit~~. Unit *WFs* ~~are mostly determined by crop yields.~~ vary greatly around the world. Regions ~~with~~ characterised by high-input agriculture generally have a small ~~yield gaps and/or favourable climate conditions (e.g. low ET rates, sufficient rainfall) have a small unit WF and its interannual variation~~*WF* and its *CV*, such as Western Europe and Northern America (*WF* < 500 m^3 t^{-1} y^{-1}, *CV* < ~~15%). Regions with large yield gaps have~~17 %). On the contrary, low-input regions show opposite outcomes, such as Middle and Eastern Africa (*WF* > 2500 m^3 t^{-1} y^{-1}, *CV* > ~~40%). Consequently, these~~30%). Nevertheless, we observe *WF* reductions in most regions ~~have potential to substantially reduce their unit WFs of maize, and hence to improve local food and water security.~~

~~Our results also reveal a rebound effect of global crop water productivity gains:~~ due to the historical increase in maize yields. As a result, the global average ~~unit~~ *WF* ~~of maize~~ has ~~decreased~~reduced by ~~one third~~34.5 % since 1986~~, but the~~. Despite this productivity gain, the global WF of maize production has increased by ~~almost one half reaching 762.9 x 10^9 m^3 y^-1 in 2016. This dynamic is mainly driven by two factors: decreasing yield gaps and expanding croplands. Since decreasing~~ 49.6 % due to the expansion of rainfed and irrigated areas. Both trends are likely to continue as the yield gaps are ~~insufficient to satisfy the global maize demand, farmers started expanding both rainfed and irrigated croplands. Consequently, more and more maize is cultivated which increases maize's water consumption worldwide (mostly in Asia and Africa).~~

~~As maize production consumes more water than ever before~~closing and maize areas are further expanding driven by demands from food, livestock, and biofuel industries. Therefore, it is important to ~~evaluate other crops in ACEA too. This would advance the understanding of temporal and spatial patterns in WFs of crops as well~~ address the sustainability and purpose of maize production as ~~allow assessing the pressure of crop production on~~ it might endanger local ecosystems and ~~freshwater~~ human livelihoods, e.g. by polluting water resources ~~worldwide~~and contributing to water scarcity.

Code and data availability

Input and output datasets that are not provided in the paper or the supplement as well as Python ~~and MATLAB~~ scripts ~~can~~may be provided by the corresponding author upon request.

Author contributions

OM, JFS, and MJB designed the study and the model. OM wrote the code and carried out the simulations. ~~All~~ With contributions from all co-authors, OM did the analysis~~. OM~~ and prepared the manuscript ~~with contributions from all co-authors~~.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

We dedicate our study to Prof. Arjen Y. Hoekstra (1967-2019) who initiated this research but unfortunately passed away before it was published. All authors were supported by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (Earth@lternatives project, grant agreement No 834716). The ACEA simulations were ~~mostly~~partly carried out using the Dutch national e-infrastructure with the support of SURF Cooperative.

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