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DROPS FOR CROPS: MODELLING CROP WATER PRODUCTIVITY ON A GLOBAL SCALE

J. LIU[1,*]
A.J.B. ZEHNDER[2]
H. YANG[1]

[1]*Swiss Federal Institute of Aquatic Science and Technology (Eawag), P.O. Box 611, Ueberlandstrasse 133 CH8600, Duebendorf, Switzerland*
[2] *Board of the Swiss Federal Institute of Technology ETH-Board, CH8092 Zurich, Switzerland*

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*to whom all correspondence should be addressed:
e-mail: junguo.liu@eawag.ch; water21water@yahoo.com

ABSTRACT

There is an emerging need to support water and food policy and decision making at the global and national levels. A systematic tool that is capable of analyzing water-food relationships with high spatial resolutions would be very useful. A GEPIC model has recently been developed by integrating a crop growth model with a Geographic Information System (GIS). The GEPIC model was applied to simulate crop yield and crop water productivity (CWP) for maize at a spatial resolution of 30 arc-minutes on a global scale. A comparison between simulated yields and FAO statistical yields in 124 countries shows a good agreement. The simulated CWP values are mainly in line with the measured values reported in literature. The crop yield and CWP were simulated with the assumption of sufficient water and fertilizer supply, holding other factors unchanged. The simulation results show that many countries have the potentials in achieving high maize yields and CWP. More than 80% of African countries have the potential to double their CWP. This reflects the current poor water and fertilizer management there. The results imply that efforts have to be strengthened to improve water and fertilizer management should the malnutrition be reduced or even eliminated.

KEYWORDS: GEPIC, maize, water scarcity, fertilizer.

1. INTRODUCTION

With the population growth and relevant development, water has become increasingly scarce in a growing number of countries and regions in the world. As the largest water user, the agricultural sector is facing a challenge to produce more food with less water, or to produce more crops per drop (Molden *et al.*, 2003).

To better understand the global water-food relationship, it is necessary to provide accurate crop yield and crop water productivity (CWP, defined as the ratio of crop yield to actual evapotranspiration) data at a large scale and with a high resolution. However, traditional methods are not sufficient for estimating crop yield and CWP on a global scale given large spatial and temporal variations across different geographical locations (Liu *et al.*, 2007a). As the escalation of water scarcity and the integration of world economy, there is an emerging need to support water and food policy and decision making at the global and national levels. A systematic tool that is capable of analyzing water-food relationships at high spatial resolutions would be very useful.

The integration of GIS with a crop growth model can increase the range of applicability of the crop growth model. In this paper, we developed and tested a GIS-based EPIC (Environmental Policy Integrated Climate) model to simulate crop yield and CWP by considering different factors such as climate conditions, soil properties, land use, water and fertilizer management etc. GEPIC was applied to simulate yield and CWP for maize on a global scale at a grid resolution of 30 arc-minute on the land surface.

2. MODEL DESCRIPTION AND DATA USED

2.1. The GEPIC model

The GEPIC model is a GIS-based EPIC model designed to simulate the spatial and temporal dynamics of the major processes of the soil-crop-atmosphere-management system (Liu *et al*., 2007a; 2007b). The core of the GEPIC model is a widely applied and well calibrated EPIC model, which uses a daily time step to simulate the processes of weather, hydrology, crop growth, nutrient cycling, tillage, plant environmental control and agronomics. EPIC uses radiation-use efficiency in calculating photosynthetic production of biomass. Intercepted photosynthetic active radiation is estimated with a Beer's law equation (Monsi *et al*., 1953). Potential increase in biomass for a day is estimated using Monteith's approach (Monteith, 1977). Actual daily biomass is calculated by accounting for stresses from water shortage, unfavorable temperature conditions, nitrogen and phosphorus deficiencies, and poor soil aeration. Dry crop yield is estimated by multiplying the above-ground biomass at maturity by a water stress adjusted harvest index. Five methods are offered to estimate potential evapotranspiration, including the Hargreaves method (Hargreaves and Samani,1985). The Hargreaves method is employed in this study because all required input data of this method are available. Actual evapotranspiration is calculated by an approach similar to that of Ritchie (Ritchie, 1972). Detailed description of the EPIC model can be found in Williams *et al.* (Williams *et al*., 1989). In the GEPIC model, CWP is estimated by dividing a fresh yield by the actual evapotranspiration. The fresh yield is calculated by adjusting the dry yield with a moisture content of 14% in maize seeds.

Loose coupling approach is used to integrate EPIC with GIS. This approach relies on the transfer of data files between a simulation model and GIS. With this approach, the simulation model does not need to be redesigned, and much redundant programming can be avoided. The resultant GEPIC model has specific input and output data translation modules designed in ArcGIS (version 9.0). Some features of a data file editor, or Universal Text Integration Language (UTIL), are also used in the process of transferring raw input data into EPIC required inputs. The flow chart of the integration is illustrated in Figure 1, and detailed description of the integration is given in (Liu *et al*., 2007a).

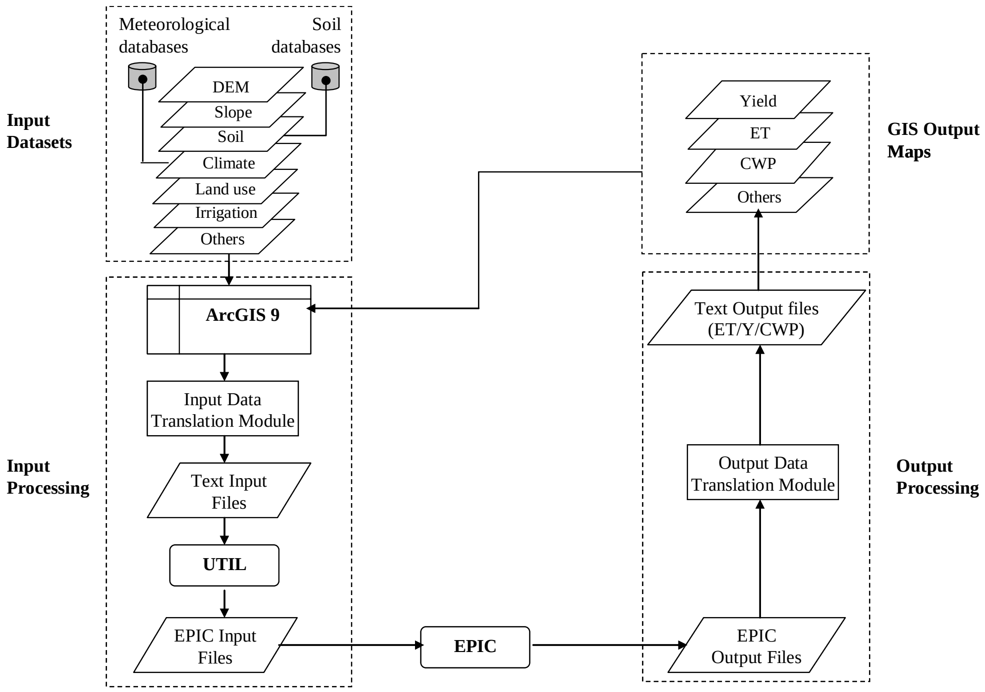

Figure 1. The schematic representation of the integration of EPIC with GIS (according to Liu *et al*., 2007a)

2.2. Data

Six types of data are necessary for the GEPIC model: site information (latitude, longitude, elevation and slope), soil parameters, land use data, climate data, plant parameters, and management data, such as irrigation and fertilizer application. The data on elevation, slope, soil parameters, land use, and irrigation were collected in a raster data format. The elevation data were obtained from the 30 arc-second digital elevation model GTOPO30 of the United States Geological Survey (USGS). Terrain slopes were from the 30 arc-second HYDRO1K digital raster slope map, which defines the maximum change in the elevations between each cell and its eight neighbors. Soil data of depth and texture (percent sand and silt) were obtained from the Digital Soil Map of the World (DSMW) (FAO, 1990). Soil data of pH, organic carbon content, and calcium carbonate fraction were from ISRIC-WISE International Soil Profile Data Set (Batjes, 1995), which presents these soil parameters at a spatial resolution of 30 arc-minutes. Bulk density is calculated with pedotransfer function (Saxton *et al.*, 1986) based on the thickness and texture in each soil layer. The geographic distribution map of maize is obtained from (Leff *et al*., 2004). This map describes the fraction of a grid cell occupied by maize with a spatial resolution of 30 arc-minutes. The irrigated area data were obtained from a 30 arc-minute global map of irrigated areas generated by the Center for Environmental Systems Research, University of Kassel (Döll and Siebert, 2000). All the above datasets were converted into those with the simulation resolution of 30 arc-minutes (Liu *et al*., 2007a).

The daily maximum and minimum temperatures and precipitation data over 1977-1993 were derived from the Global Daily Climatology Network (GDCN) (Version 1.0) (Gleason *et al.*, 2002). Daily climate data from 1994 to 2004 were downloaded from the website of the National Climate Data Center (NCDC) (www.ncdc.noaa.gov). The amount of fertilizer applied per country and crop was mainly derived from the international fertilizer association. The default crop parameters of maize were used in the GEPIC model. The statistical national average yields of maize were obtained from FAOSTAT (FAO, 2006).

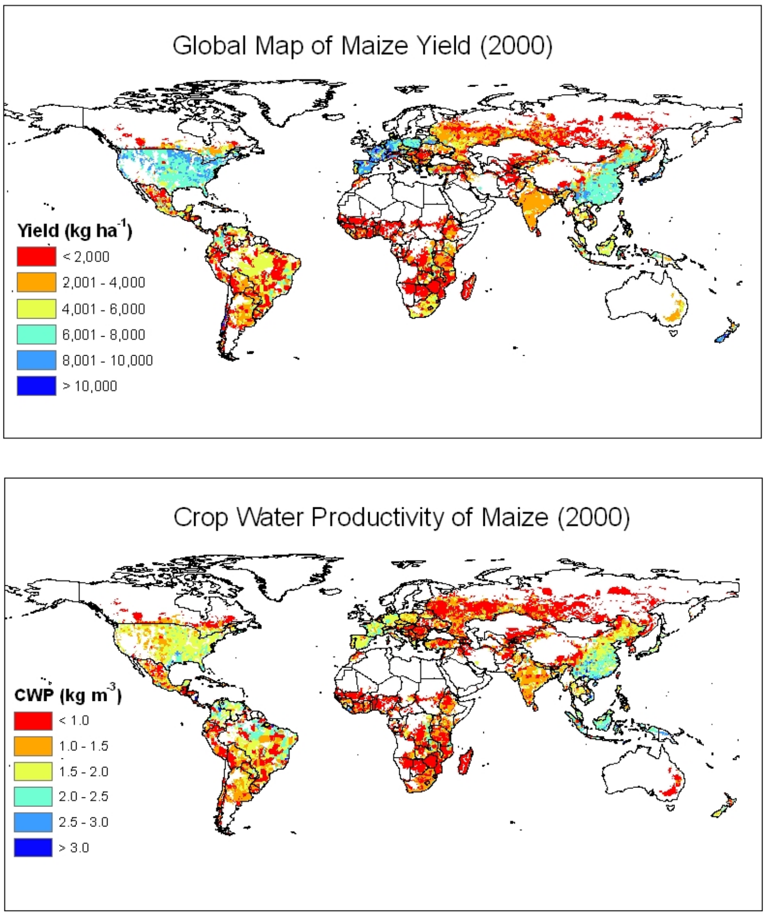

Figure 2. Spatial distribution of crop yield and crop water productivity of maize

3. RESULTS

3.1. Spatial distribution of crop yield and crop water productivity (CWP)

Figure 2 shows the worldwide distributions of crop yield and CWP of maize in 2000. Both crop yield and CWP differ significantly across countries and even within a country. In 2000, the USA, China, and several Western European countries achieved high yields (>6000 kg ha^{-1}), as well as high CWP (>1.5 kg m^{-3}), while many African countries generally suffered from low yields (< 2000 kg ha^{-1}), and low CWP (<1 kg m^{-3}).

To our best knowledge, there exists no statistical yield data in raster format on a global scale. This makes grid-grid comparison between statistical yield and simulated yield impossible. The FAO, in collaboration with the International Institute for Applied Systems Analysis (IIASA), estimated the global potential crop yield (Fischer *et al.,* 2002). Although valuable, this product only indicates the potentials of crop yield with different input combinations, and does not reflect the current levels of maize yield.

The lack of comparable data makes our effort unique, but also presents us with the challenge of performing a comprehensive quality assessment. To quantitatively assess the performance of the model, the simulated yield data in individual grids were aggregated into national averages. The GEPIC model is tested by comparing the simulated national average yields with the statistical averages (Figure 3). A total of 124 countries were compared, where both simulated and statistical yields were available. The total maize production in these countries accounted for about 98% of the total world maize production (FAO, 2006).

In Figure 3, the dashed line is the 1:1 line and the solid line is the linear trend line setting intercept at the origin. The trend line is close to the 1:1 line. The simulated yields and the statistical yields are quite comparable, as indicated by a highly significant *F*-test (the *P* value is higher than 95%) and a high R^2 value (0.70). The slope is not significantly different from 1. The statistical tests indicate a good performance of the GEPIC model in simulating crop yields for maize.

The deviations of simulated yield from statistical yield are small in most countries, except in some high-yielding ones (Figure 3). One major reason is the assumption of the automatic flood irrigation used in the GEPIC model. This assumption does not take different irrigation technology and irrigation management level into account. However, in reality, irrigation technology and management may likely developed unevenly across countries. For example, technological breakthrough has helped Israel develop advanced water-saving irrigation, which increase both crop yield and water use efficiency (Shanan and Berkowicz, 1995). The assumption of universal flood irrigation does not reflect the technology breakthrough in irrigation, and therefore may lead to the underestimation of maize yield and CWP in the countries with wide application of advanced irrigation techniques (e.g. in Israel). Some developing countries, e.g. Poland and Slovakia, have overestimation of crop yield. This is possibly caused by the higher management level assumed in the GEPIC model than that in these countries.

Similarly, there exist no statistical data that indicates the CWP values for maize in raster format on a global scale. There are even no statistical data for national average CWP. Zwart and Bastiaanssen (2004) reviewed the measured CWP values for irrigated wheat, rice, cotton and maize at the global level by using 84 literature sources. This study, to our knowledge, is the most comprehensive study on the measured CWP of maize on the global scale. Zwart and Bastiaanssen (2004) listed the ranges and the means of CWP for 20 cities or regions. Among them, 15 locations can be precisely located as a point in a global map. The results show that 11 out of the 15 locations (or appropriately 73%) have simulated CWP values falling into the minimum-maximum CWP ranges (Figure 4). The simulated values from GEPIC are mostly in line with the measured values reported in Zwart and Bastiaanssen (2004).

3.2. Crop yield and CWP with sufficient water and fertilizer supply

In order to examine the effect of water availability and fertilizer application on yield and CWP, a simulation was performed using GEPIC with the assumption of sufficient water and fertilizer supply, holding other factors unchanged. The current crop yield and CWP and the potential yield and CWP are presented in Figure 5.

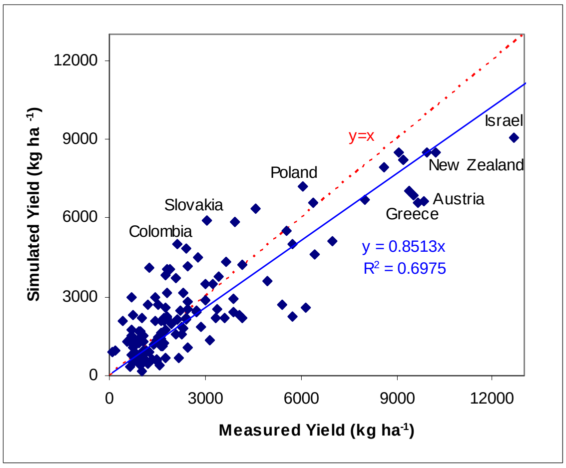

Figure 3. Comparison between simulated and statistical maize yield at national level

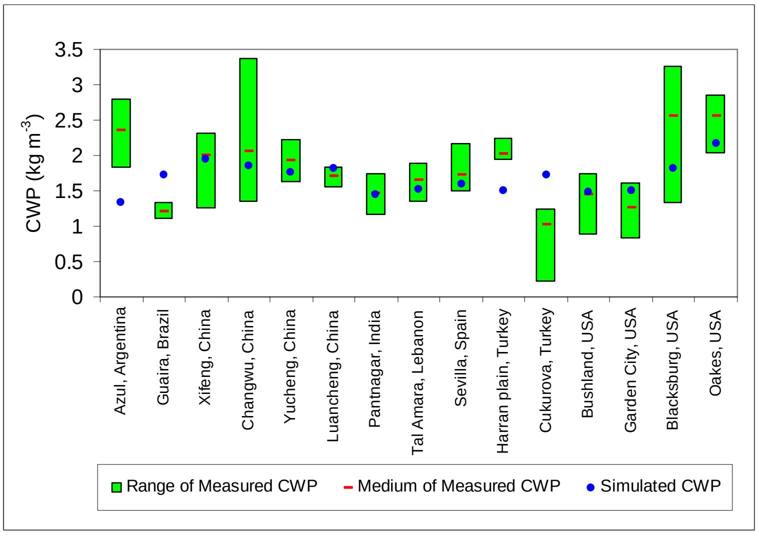

Figure 4. Comparison between simulated and measured CWP

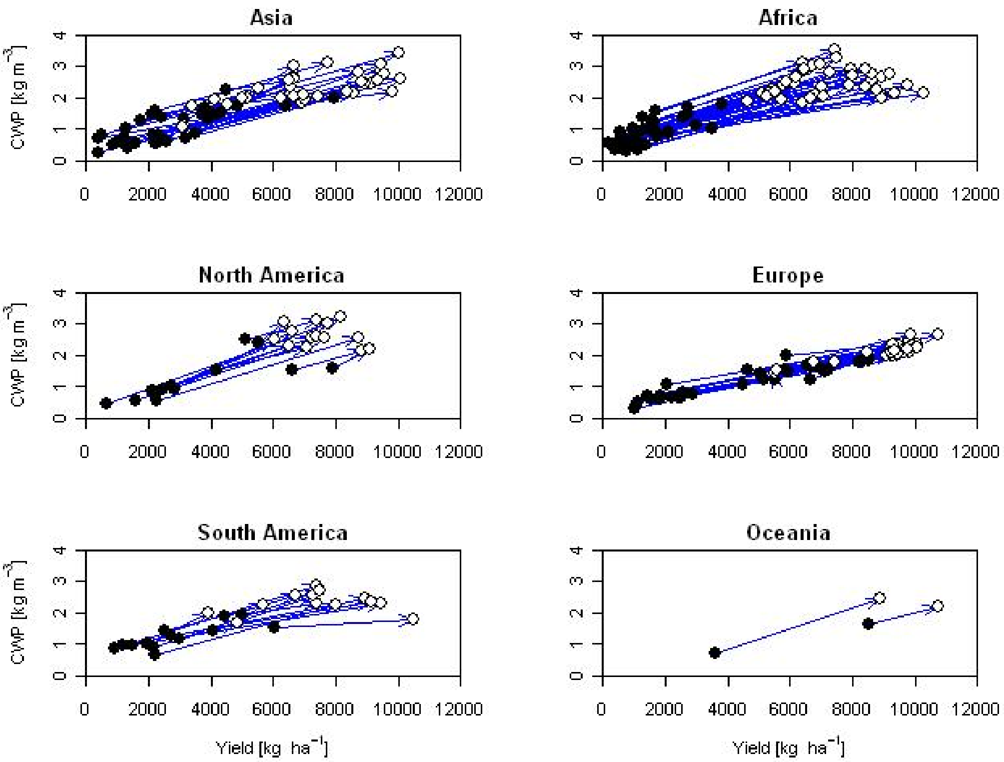

Figure 5. National average yield and CWP in 2000 (solid dots) vs. potential national average yield and CWP (open dots). The arrows connect the current achieved values with the potentials for individual countries

CWP can be increased in all the countries by increasing water and fertilizer supply. African countries show the most significant potential improvements in CWP. In Africa, the minimum potential national average CWP (i.e. 1.814 kg m^{-3} in Namibia) is higher than the currently achieved maximum national average CWP (i.e. 1.701 kg m^{-3} in Liberia). Statistically, about 83%, 64%, 50%, 40%, 38% and 33% of the countries in Africa, North America, Oceania, Europe, South America and Asia respectively have the possibility to double their CWP by good management of water and fertilizer.

4. CONCLUSION

The GEPIC model provides a practical tool for simulating crop yield and crop water productivity (CWP) by integrating the EPIC model with GIS. The integration facilitates the effective use of spatially distributed climatic, soil, land use, and irrigation data to estimate yield and CWP for each grid with a global coverage. The results show the GEPIC model can simulate global maize yield and CWP with acceptable accuracy. The global maps visually demonstrate the geographical variations of crop yield and CWP across regions. The national average yield and CWP can be used to analyze global, regional, national water-food relationship, and can provide useful information for global virtual water assessment, which should be elaborated on in future research.

The potential yield and CWP can be improved in all the countries. This means that better water and fertilizer management can enhance both the food production and the crops produced per drop. Most African countries have the potentials in achieving high maize yield and CWP. The current low values are to a large extent due to the poor water management or the low fertilizer application. Efforts have to be strengthened in water and soil management should the malnutrition be reduced or even eliminated in the near future.

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