Available online at www.sciencedirect.com

ScienceDirect

Agricultural Systems 94 (2007) 478–493

AGRICULTURAL SYSTEMS

www.elsevier.com/locate/agsy

GEPIC – modelling wheat yield and crop water productivity with high resolution on a global scale

Junguo Liu [a,*], Jimmy R. Williams [b], Alexander J.B. Zehnder [c], Hong Yang [a]

[a] *Swiss Federal Institute of Aquatic Science and Technology (Eawag), P.O. Box 611, Ueberlandstrass 133, CH-8600 Duebendorf, Switzerland*
[b] *Texas Agricultural Experiment Station, Blackland Research and Extension Center, 720 E. Blackland Road, Temple, TX 76502, USA*
[c] *Board of the Swiss Federal Institutes of Technology, ETH-Zentrum, CH-8092 Zurich, Switzerland*

Received 20 January 2006; received in revised form 28 September 2006; accepted 22 November 2006

Abstract

With population growth and economic development, the agricultural sector is facing the challenge to produce more food with less water. Crop water productivity (CWP) is important for understanding water–food relationships. It also provides a basis for the assessment of water use efficiency embodied in global food trade. However, traditional methods are not sufficient for estimating CWP on a global scale considering large spatial and temporal variations across different geographical locations. In this paper, a GIS-based EPIC model (GEPIC) is developed and tested to estimate wheat (*Triticum aestivum* L.) yield and CWP at a grid resolution of 30′ on the land surface. A comparison between simulated yields and FAO statistical yields in 102 countries over 10 years shows a good agreement. The simulated CWP is also mostly in line with the CWP reported in the literature.

The simulation results show that compared with rainfed wheat, irrigated wheat has higher frequencies for high CWP (>0.8 kg m^{-3}) and lower frequencies for low CWP (<0.8 kg m^{-3}). This is likely because irrigation can provide timely water supply to crop development and the management of irrigated crops is usually more intensive than in rainfed production. A strong linear relation is found between CWP and yield. High wheat yield and CWP appear in the European countries, especially those in western and northern Europe. Low wheat yield and CWP are seen in most African countries. The simulation using GEPIC, however, shows that wheat yield and CWP in many African countries could increase substantially with sufficient water supply and fertilizer application. Variations in CWP across countries suggest that global water use could be reduced through food trade. Calculations indicate a saving of 77×10^9 m^3 of water in 2000 through international wheat trade as a result of relatively high CWP in major exporting countries. However, the simulation results also suggest that an overall improvement in CWP through better crop management practices in local areas could make a greater contribution to the reduction in global water use.

Keywords: EPIC; GIS; Irrigated and rainfed production; Virtual water trade

1. Introduction

Water is essential for both the human society and the ecological systems that humans rely on. But this essential resource is finite. With the population growth and economic 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. This requires an increase in crop water productivity (CWP), which is defined as the marketable crop yield over actual evapotranspiration (ET) (Kijne et al., 2003; Zwart and Bastiaanssen, 2004). CWP is a function of many factors like the water vapour pressure deficit of the atmosphere, soil fertility, irrigation, pest and disease control. As a rule, any management factors that increase crop yield also increase CWP because evapotranspiration is generally less responsive than yield to the changes in these factors.

* Corresponding author. Tel.: +41 18235012; fax: +41 18235375.
E-mail addresses: Junguo.liu@eawag.ch, water21water@yahoo.com (J. Liu).

0308-521X/$ - see front matter
doi:10.1016/j.agsy.2006.11.019

CWP is important for understanding water–food relationships. It is also a basis for assessing water use efficiency through the trade of food in the virtual water form, both at the international and intra-national level. Introduced by Allan (1998), "virtual water" describes the amount of water consumed in the production process of a product. The concept of virtual water implies that water scarce countries could mitigate water scarcity by importing water intensive food. In recent years, there have been many studies of virtual water trade and relevant issues at global, regional and national levels (Hoekstra and Hung, 2002, 2003; Yang and Zehnder, 2002; Yang et al., 2003, 2006; Oki et al., 2003; Chapagain and Hoekstra, 2004; World Water Council, 2004; Fraiture et al., 2004; Ramirez-Vallejo and Rogers, 2004; Wichelns, 2001; Liu et al., in press; Chapagain et al., 2006). These studies have contributed greatly to the understanding of water–food relations and the roles of food trade in balancing local and national water budgets. Globally, water resources may be used more efficiently when food flows from the countries with high CWP to the countries with low CWP. With the increasing integration of the world economy, there is an emerging need to support water and food policy formulation and decision making at the global level. A systematic tool that is capable of estimating CWP on a global scale and at high spatial resolution would be very useful for this purpose.

In the literature, three methods have been applied to estimate CWP: "rule of thumb", field experiments, and crop growth models. The "rule of thumb" method assumes the CWP as a roughly constant value. This method has been applied in many virtual water related studies. A commonly used approximation is that 1 m^3 of water can roughly produce 1 kg of cereal, or around 1 kg m^{-3} of CWP for cereal (Allan, 1998; Yang and Zehnder, 2002). This method allows a quick estimation of CWP but suffers from inaccuracy in explaining local variations. In field experiments, CWP is determined by measuring seasonal crop ET and crop yield. Such experiments are time consuming, costly and cannot be easily extrapolated to other seasons and geographic locations (Ines et al., 2002). With crop growth models, ET and crop yield can be simulated simultaneously; hence, CWP can be estimated. However, most existing crop growth models are mainly used for point or site specific applications. There is a lack of models that are suitable for global scale applications accounting for variations in local conditions across regions.

Integrating crop growth models with a Geographic Information System (GIS) provides a way to increase the range of applicability of crop growth models. Combined with the powerful function of spatial data storage and management in GIS, a crop growth model may be extended to address spatial variability of yield and ET as affected by climate, soil, and management factors. There have been some attempts to integrate crop growth models with GIS (Curry et al., 1990; Thornton, 1990; Vossen and Rijks, 1995; Rao et al., 2000; Priya and Shibasaki, 2001; Ines et al., 2002; Stöckle et al., 2003). However, a GIS-based model for CWP simulation on a global scale has not been developed prior to this study.

In the present paper, we develop and test a GIS-based EPIC model to simulate yield and CWP at the resolution of 30′ with global coverage. Here GEPIC is also used to estimate potential yield and CWP assuming sufficient water and fertilizer supply, holding other factors constant. The paper ends with an estimation of the magnitude of global virtual water flows and water savings embodied in the international wheat trade, and a potential reduction in global water use through improved water and fertilizer management taking the year 2000 as reference.

2. The EPIC model

2.1. The selection of the EPIC model

To satisfy the objectives of this study, a crop growth model needs to possess the following characteristics: flexibility for the simulation of different crops under a variety of climatic conditions, ability to simulate ET and yield, availability of and easy access to the model, minimum data requirements, and technical feasibility for the integration with a GIS. The following models were considered and compared: DSSAT, WOFOST, CropSyst, YIELD, CENTURY, CropWat, APSIM, and EPIC. DSSAT does not provide one unified model to simulate different crops; instead, it brings together a number of crop models for specific crops (IBSNAT, 1989). Crop growth models like APSIM, CropWat and CropSyst are not suitable for simulating rice because the rice parameters are not well calibrated or because rice is not included (Keating et al., 2003; Confalonieri and Bocchi, 2005). The WOFOST model is sophisticated in describing crop physiology, thus needs detailed input data (Monteith, 1996). CENTURY is focused on element and material cycles. It is more specifically designed for soil processes, such as organic matter decomposition, nitrification, and denitrification (Zhang et al., 2002).

Compared to the other models, the EPIC model uses a unified approach to simulate more than 100 types of crops (Williams, 1995; Wang et al., 2005). It has been successfully applied in simulating crop yields for various combinations of weather conditions, soil properties, crops, and management schemes in many countries all over the world. Williams et al. (1989) tested the EPIC model for the yields of wheat, corn, rice, soybean, corn soybean and sunflower at several US locations and on sites in Asia, France, and South America, and concluded that the difference between simulated and measured yields was always within 7% of the average measured yields. Bernardos et al. (2001) demonstrated that the estimated yield trend by the EPIC model superimposed well with the recorded yield trend for wheat ($r^2 = 0.63$) and maize ($r^2 = 0.71$) during a 93-year period (1907–1999) in the Argentine pampas. Priya and Shibasaki (2001) found only small differences between simulated and predicted wheat and maize yields in Bihar, India. More detailed description of the EPIC application in simulating crop yields can be found in Gassman et al. (2005). Besides the wide application and good performance, EPIC is a public domain software. It can be downloaded with its source code free of charge (http://www.brc.tamus.edu/epic/index.html). Furthermore, there have been some attempts to integrate EPIC with GIS, such as Spatial-EPIC for crop production simulation at the national level in India (Priya and Shibasaki, 2001) and EPIC-View for sustainable farm management practices (Rao et al., 2000). The data required by EPIC are relatively minimal (Dumesnil, 1993). Given all these advantages, EPIC was selected for further development under the framework of this study.

2.2. Methods for estimating crop yield, ET, and CWP in EPIC

Developed by the USDA-ARS and TAES, the EPIC model (Environmental Policy Integrated Climate, originally known as Erosion Productivity Impact Calculator) uses a daily time step to simulate the major processes that occur in soil-crop-atmosphere-management system, such as weather, hydrology, nutrient cycling, tillage, plant environmental control and agronomics. In EPIC, potential crop yield is simulated based on the interception of solar radiation, crop parameters, leaf area index (LAI) and harvest index (HI). The daily potential growth is decreased by stresses caused by water, nitrogen and phosphorus deficiencies, extreme temperatures, and poor soil aeration. EPIC uses radiation-use efficiency in calculating photosynthetic production of biomass. Intercepted photosynthetic active radiation is estimated with a Beer's law equation (Monsi and Saeki, 1953). Potential increase in biomass for a day is estimated using Monteith's approach (Monteith, 1977). Simulated potential biomass is adjusted daily for stress from five factors (water, temperature, nitrogen, phosphorus and aeration) in proportion to the extent of the most severe stress during that day. Crop yield is defined as the marketable part of the total above ground biomass produced. It is estimated by multiplying the above-ground biomass at maturity by a water stress adjusted harvest index for the particular crop. In our study, a fresh yield is calculated using a moisture content of 14% in wheat seeds as suggested by Bessembinder et al. (2005). The fresh yield is estimated by dividing the dry yield by 0.86.

The EPIC model offers five methods for estimating potential evapotranspiration: Hargreaves (Hargreaves and Samani, 1985), Penman (Penman, 1948), Priestley–Taylor (Priestley and Taylor, 1972), Penman–Monteith (Monteith, 1965), and Baier–Robertson (Baier and Robertson, 1965). When wind speed, relative humidity, and solar radiation data are not available, the Hargreaves or Priestley–Taylor methods provide options that give realistic results in most cases. In this study, the Hargreaves method was chosen to estimate potential evapotranspiration. The Hargreaves method estimates potential evapotranspiration as a function of extraterrestrial radiation and air temperature. The actual ET is the sum of transpiration and evaporation. The EPIC model computes evaporation from soil and transpiration from plants separately by an approach similar to that of Ritchie (1972). Detailed description on the EPIC model can be found in Williams (1995).

Crop water productivity is defined as the crop yield over actual evapotranspiration:

$$\mathrm{CWP} = \frac{Y_{\mathrm{act}}}{ET_{\mathrm{act}}} \tag{1}$$

where CWP is the crop water productivity in kg m^{-3}, ET_{act} is the actual seasonal crop water consumption in $\mathrm{m}^3\ \mathrm{ha}^{-1}$, and Y_{act} is the actual crop yield in kg ha^{-1}.

There are a number of definitions of CWP depending on the specific aim, stakeholder interest, and scale under consideration (Molden, 1997). The definition with respect to crop yield and ET is a valuable index for judging the water productivity for a specific crop variety under various agronomic practices. It is useful to compare the water productivity in different regions for the same crops, the water productivity of different crops in the same region, and the water productivity for other possible uses. ET is the total water consumption that will no longer be available for uses in an agricultural system. By integrating crop yield and ET into one concept, CWP can answer the question of how much food can be typically produced by consuming a unit of water resources. This concept is particularly useful in optimizing water uses among different agricultural sectors in water-scarce regions.

ET is composed of two factors, transpiration and evaporation. Transpiration is the water flow that is used for crop growth. Since on a local scale, there is a certain equilibrium and interdependency between the water taken up by the roots of a plant and the water in and on the soil in close vicinity of the plant, a separation between the water to be transpired through the plant and the water directly evaporated into the atmosphere close to the plant has little practical meaning. Thus, it makes sense to define crop water productivity using ET rather than solely transpiration (Zwart and Bastiaanssen, 2004).

3. Integration of EPIC with GIS – The GEPIC model

Loose coupling and tight coupling are two generally used approaches to integrate simulation models with GIS (Sui and Maggio, 1999; Huang and Jiang, 2002). The loose coupling approach relies on the transfer of data files between GIS and simulation models (Huang and Jiang, 2002). In contrast, the tight coupling approach is to develop models within a GIS (Huang and Jiang, 2002). In this study, the loose coupling approach was used mainly to avoid much redundant programming.

The GIS software ArcGIS (Version 9.0) was selected for the development of the GEPIC model. ArcGIS is used as input editor, programmer and output displayer. Visual Basic for Applications (VBA) is the main computer language used by the GEPIC model to develop the user interface, access input data, generate EPIC required input files, control the execution of the EPIC model, create output data, and visualize the output maps. VBA is a simplified version of Visual Basic and is embedded in ArcGIS. VBA can use the ArcGIS Desktop's built-in functionalities, making the programming much easier.

Some features of UTIL (Universal Text Integration Language) are used in the process of transferring raw input data into EPIC required inputs. UTIL is a data file editor that comes with the EPIC model, and can edit the EPIC specific input data files by executing a series of command-lines (Dumesnil, 1993).

The steps of the development of the GEPIC model are illustrated in Fig. 1. Input data are first added into GEPIC in terms of GIS raster datasets. Basic "GIS input datasets" include maps of DEM (Digital Elevation Model), slope, soil, climate, land use, irrigation and fertilizer. Climate and soil maps show the "code number" of the climate and soil files in each grid. These code numbers are connected with corresponding climate and soil files. The land use map indicates different land use types, including irrigated and rainfed agriculture. Maps of DEM, slope, irrigation, and fertilizer show the real values of elevation (m), slope (dimensionless), maximum annual irrigation (mm), and maximum annual fertilizer application (kg ha^{-1}).

After adding the raster "GIS input datasets" into GEPIC, an "input data translation module" reads and writes input information to a "text input file". In the text input file, each line stands for one simulated grid, and consists of latitude, longitude, elevation, slope, land use, soil code, climate code, maximum annual irrigation, and maximum fertilizer application. The information is then used to generate specific "EPIC input files" with the help of a "UTIL" program. This process is achieved by writing command lines into a "batch file". The batch file consists of two types of command lines: UTIL command line, and EPIC executive command line. UTIL command lines are used to edit specific "EPIC input files", and EPIC executive command lines control the running of the EPIC model. By executing the batch file, GEPIC runs the EPIC model for each simulated grid one by one. After one simulation, a set of "EPIC output files" are generated. With an "output data translation module", output variables, such as yield, evapotranspiration, crop water productivity, are written into a "text output file". Each line of the "text output file" presents latitude, longitude, and output variables for one simulation. This output file is used to generate "GIS output maps", such as yield, ET, and CWP maps. These maps can be visualized in GEPIC and can be edited by the user.

The GEPIC model has two unique advantages. First, it can estimate crop yield, ET, and CWP by considering the influencing factors with a flexible spatial scale ranging from field to catchment to national and global. Second, it has an easy to use Graphical User Interface to access GIS data, to conduct the simulation, and to visualize the results.

4. Simulation of yield and ET with the GEPIC model

The simulation of yield and ET is conducted at a resolution of 30′ (about 50 km × 50 km in each grid near the equator), covering the whole world (from longitude 180 °W to 180 °E and from latitude 90 °N to 90 °S).

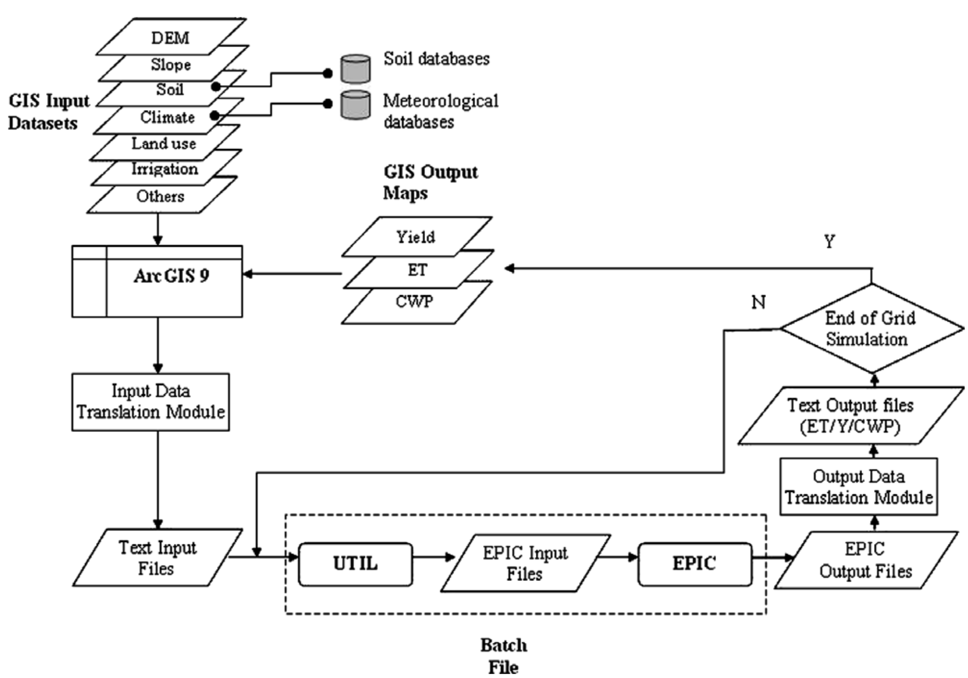

Fig. 1. The schematic representation of the integration of EPIC with GIS.

4.1. Data source, database development and simulation results

Six types of input data are used for the GEPIC model: (1) information on location (latitude, longitude, DEM and slope), (2) climate data, (3) soil physical parameters, (4) land use data, (5) plant parameters, and (6) management data, such as irrigation and fertilizer application.

The DEM data are obtained from the 1-km resolution (30″) digital elevation model GTOPO30 of the United States Geological Survey (USGS) (EROS Data Center, 1998). Terrain slopes are from the 1-km resolution (30″) HYDRO1K digital raster slope map, which defines the maximum change in the elevations between each cell and its eight neighbors (USGS, 2000). Both the DEM and slope maps are transformed into 30′ maps, in which the value of each grid is equal to the averages in the corresponding higher resolution maps.

Actual daily weather records may be used, or EPIC can generate daily weather using a stochastic weather generator [described by Richardson and Nicks (1990)]. Inputs to the weather generator include average monthly temperature, precipitation, solar radiation, relative humidity, and wind speed. In this study, the daily maximum and minimum temperatures and precipitation data are derived from the Global Daily Climatology Network (GDCN) (Version 1.0) (Gleason et al., 2002). The GDCN contains daily precipitation and maximum and minimum temperature for more than 32,000 stations worldwide for the period 1977 to 1993. Daily climate data from 1994 to 2004 is downloadable from the website of the National Climate Data Center (NCDC) (www.ncdc.noaa.gov). Suitable climate stations (11,729 stations) were selected. Stations covering all daily climate data from 1977 to 2004 were considered "suitable". The EPIC specific monthly statistical climate data were estimated based on the daily climate data, such as average monthly maximum/minimum temperature, monthly standard deviation of maximum/minimum daily temperature, average monthly precipitation, monthly standard deviation of daily precipitation, monthly skew coefficient for daily precipitation, and average monthly number days of rain. These statistical monthly data are used to generate the missing daily data where necessary. Average daily relative humidity, sunshine hours, and wind speed per month were taken from the FAO CLIMWAT database, which includes a total of 3262 meteorological stations from 144 countries (FAO, 1993). Solar radiation was estimated from sunshine hours (Ångström, 1956). The climate parameters of each grid are assumed the same as those in the "closest" climate stations. The boundary of a region within which all the grids share the same set of climatic variables is created with a method of Thiessen Polygons (Isaaks and Srivastava, 1989). We are aware that climatic factors influencing CWP may change within very short distances, and different interpolation procedures can result in different simulation results. Comparing the results from different interpolation procedures may be helpful, but it is beyond the scope of this study.

A minimum of seven soil parameters is required for simulation: depth, percent sand, percent silt, bulk density, pH, organic carbon content, and fraction of calcium carbonate. Other soil parameters could either be inputs or estimated by EPIC. Soil data of depth and texture (percent sand and silt) are obtained from the Digital Soil Map of the World (DSMW) (FAO, 1990). DSMW is derived from the FAO-UNESCO Soil Map of the World (SMW) at an original scale of 1:5 million, and presents soil parameters in grid-cells of a 5′ latitude/longitude resolution. Soil pH, organic carbon content, and calcium carbonate fraction are from ISRIC-WISE International Soil Profile Data Set (Batjes, 1995), which presents soil parameters on spatial soil data layers on a 30 by 30′ grid. Bulk density is calculated with pedotransfer function (Saxton et al., 1986) based on the thickness and texture in each soil layer.

Land use data are from Global Land Cover Characterization (GLCC), which is a 1-km resolution (30″) global land cover generated by USGS (Reed, 1997). GLCC divides the world into 24 land use classes, including rainfed and irrigated crop land. In this study, the 30″ global land cover map was converted into a 30′ map, in which each grid shows the dominant land use type. The simulation was performed for all the dryland cropland and pasture, and irrigated cropland and pasture grids in the global land use map. As pointed out by one of the referees of this paper, locating the growing areas of wheat precisely is important with regard to climatic conditions, edaphic conditions and management practices which are key factors influencing CWP. The crudeness of the land use data could lead to errors in the simulation results. However, prior to the availability of detailed information on global wheat distribution, the use of the GLCC land cover data is a practical compromise.

The irrigated area data were obtained from a digital global map of irrigated areas generated by the Center for Environmental Systems Research, University of Kassel (Döll and Siebert, 2000; Siebert et al., 2002). This map shows the total area percentage that is equipped for irrigation in each grid. It has two versions with resolutions of 30 and 5′. The 30′ map is used in this study. In addition, AQUASTAT (FAO, 2005a) provides the data for agricultural water withdrawal and irrigation efficiency in individual countries. The volume of irrigation water delivered to the crop field, or irrigation water use, can be calculated by multiplying agricultural water withdrawal by irrigation water use efficiency. We assume that, in each country, the irrigation water use is equally distributed among the area equipped for irrigation in the global irrigation map. The annual irrigation depth is calculated by dividing the irrigation water use by total irrigation area in individual countries.

The data for total fertilizer consumption and total hectares of arable and permanent cropland of each country are available from FAOSTAT (FAO, 2005b). Average fertilizer use (kg ha^{-1}) during 1977 and 2004 for each country was estimated by a country's total fertilizer consumption divided by its total hectares of arable and permanent cropland. Also, the allocation of fertilizer to crops is influenced by the importance of specific crops and the intensity of production. Evidence shows that irrigated crops receive higher amounts of fertilizer than rainfed crops and important crops receive more fertilizer than less important crops (Fischer, 2005). The date limitation, however, impedes a further specification of fertilizer application for individual crops in this study.

Crop parameters of the Wheat (*Triticum aestivum* L.) are obtained from the default crop parameter file in EPIC. One set of parameters for spring wheat and one set of parameters for winter wheat were applied. We assumed that spring wheat was planted in regions with latitudes between 30 °S and 30 °N and winter wheat was planted in regions with greater latitudes. Crop calendar data are obtained from FAO (2005c), which provides the data for 90 countries. For the countries that are not included in FAO (2005c), the calendar data from their neighbouring countries with the nearest latitudes are used.

Wheat yields, ET, and CWP were simulated on a global scale over the period 1977–2004 using GEPIC. The resulting rainfed and irrigated wheat yields for the year 2000 were combined and are shown in Fig. 2.

4.2. Test of the GEPIC performance

The lack of statistical yield on a comparable spatial resolution makes grid to grid comparison between statistical yields and simulated yields impossible. In order to quantitatively assess the performance of the GEPIC model, the simulated yields in individual grids are aggregated into national averages. The GEPIC model is tested by comparing the simulated national average wheat yields with the statistical wheat yields from FAOSTAT (FAO, 2005b). Wheat yield records exist in 105 countries. By excluding three countries (Mauritania, Mozambique, and Honduras) with evident yield errors, 102 countries were selected for comparison.

The national average yield was calculated with the following equation:

$$\overline{Y[i]} = \frac{\sum_{j=1}^{N[i]} Y[i,j] \times A[i,j]}{\sum_{j=1}^{N(i)} A[i,j]} \tag{2}$$

where $\overline{Y[i]}$ is the national average yield of wheat for country i, $Y[i,j]$ is the wheat yield in the jth grid of country i, $A[i,j]$ is the wheat planting area in the jth grid of country i, $N[i]$ is the total number of simulated grids in country i.

Several statistics were used to evaluate the model performance: coefficient of determination (R^2), slope and intercept of the regression function, Nash–Sutcliffe efficiency (EF) (Nash and Sutcliffe, 1970), normalized mean square error (NMSE) (Hanna, 1988), and index of agreement (d) (Willmott, 1982). EF compares the simulated values with the mean of the observed values. A positive value indicates a better predictor than the mean of the observed values. NMSE ranges from 0 to 1, and a value of 0 implies perfect agreement. Generally, a model with NMSE of 0.4 or lower is considered good (Hanna, 1988). The index of agreement (d) ranges from 0 to 1, and a value of 1 implies perfect agreement.

The statistical and simulated national average yields and the difference between them are reported in Table 1. A graphical comparison between simulated and FAO statistical wheat yields is depicted in Fig. 3 for 102 countries during 1995–2004. The indices for testing model performance are given in Table 2.

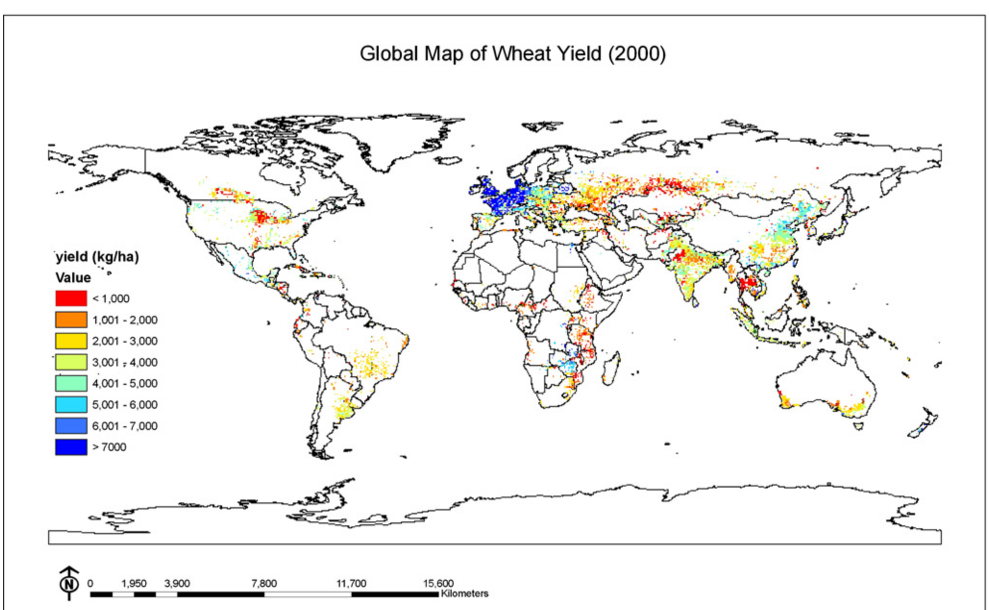

Fig. 2. Global map of simulated wheat yield (2000).

Table 1
National averages of statistical yields (Y_{sta}), simulated yields (Y_{sim}), simulated crop water productivity (CWP), and values of crop water productivity in literature (CWP*)

Country	Y_{sta} (kg ha^{-1})	Y_{sim} (kg ha^{-1})	Y_{dif}[a] (%)	CWP (kg m^{-3})	CWP*[b] (kg m^{-3})	CWP_{dif}[c] (%)
Albania	3046	3625	19	0.926	–	–
Algeria	919	1155	26	0.319	0.368	15
Angola	1739	1652	−5	0.557	0.382	−31
Argentina	2493	2855	15	0.531	1.355	155
Armenia	1706	1404	−18	0.491	0.627	28
Australia	1821	2356	29	0.646	0.630	−3
Austria	4469	4859	9	1.021	1.019	0
Azerbaijan	2322	2389	3	0.609	0.681	12
Bangladesh	2210	2912	32	0.742	0.710	−4
Belgium	7920	8377	6	1.704	0.856	−50
Bolivia	887	959	8	0.238	0.282	18
Bosnia	3229	1808	−44	0.619	0.426	−31
Botswana	1667	1645	−1	0.702	0.592	−16
Brazil	1559	2217	42	0.522	0.619	18
Bulgaria	2842	2518	−11	0.712	1.221	71
Burundi	677	941	39	0.339	0.214	−37
Cameroon	1333	1167	−12	0.431	0.483	12
Canada	2444	2529	3	0.855	0.671	−22
Chad	1434	1435	0	0.375	0.330	−12
Chile	3812	4046	6	0.801	0.693	−13
China	3738	3658	−2	0.790	1.449	83
Colombia	2142	2589	21	0.837	0.668	−20
Congo	1285	1494	16	0.407	0.385	−5
Croatia	4374	3558	−19	0.797	0.599	−25
Czech Rep	4209	3122	−26	0.946	0.847	−10
Denmark	7480	7820	5	1.733	1.497	−14
Ecuador	621	890	43	0.564	0.234	−58
Egypt	6342	6447	2	1.181	1.075	−9
Eritrea	594	600	1	0.581	0.140	−76
Ethiopia	1163	1141	−2	0.396	0.396	0
Finland	3601	3150	−13	0.693	0.785	13
France	7117	7191	1	1.449	1.117	−23
Georgia	1043	1410	35	0.548	0.688	25
Germany	7283	7394	2	1.471	1.326	−10
Greece	2539	2314	−9	0.536	0.824	54
Guatemala	2093	3156	51	1.052	0.500	−52
Hungary	3604	3190	−11	0.877	1.799	105
India	2779	2871	3	0.893	0.605	−32
Iran	1586	1666	5	0.563	0.342	−39
Ireland	9454	8625	−9	1.887	1.946	3
Italy	3213	4241	32	1.087	0.413	−62
Japan	3761	3421	−9	0.590	1.362	131
Jordan	1397	1400	0	0.302	0.276	−9
Kazakhstan	903	886	−2	0.487	0.453	−7
Kenya	1547	1634	6	0.461	0.469	2
Kyrgyzstan	2342	1491	−36	0.441	0.307	−30
Latvia	2704	1765	−35	0.380	1.642	332
Lebanon	2703	2694	0	0.480	0.609	27
Lithuania	3341	4547	36	1.025	1.706	67
Macedonia	2469	2645	7	0.548	1.001	83
Madagascar	2250	2443	9	0.676	0.861	27
Malawi	797	866	9	0.236	0.221	−6
Mali	2352	1987	−16	0.620	0.302	−51
Mexico	4936	4720	−4	0.983	0.938	−5
Moldova	1951	2027	4	0.442	1.218	176
Mongolia	777	1141	47	0.742	0.117	−84
Morocco	476	1556	227	0.418	0.218	−48
Myanmar	1167	1691	45	0.463	0.377	−19
Namibia	3429	5294	54	1.042	1.639	57
Nepal	1793	2194	22	0.584	0.530	−9
Netherlands	8359	8542	2	1.515	1.616	7
New Caledonia	1667	1082	−35	0.659	0.691	5
New Zealand	6210	6412	3	1.305	1.445	11
Nigeria	1404	846	−40	0.335	0.281	−16
North Korea	848	1146	35	0.319	0.601	89
Norway	4533	4480	−1	1.126	1.255	11
Oman	3190	2788	−13	0.881	0.475	−46
Pakistan	2491	3377	36	0.907	0.304	−66
Paraguay	1381	1529	11	0.394	0.454	15
Peru	1288	1761	37	0.358	0.439	23
Poland	3227	4395	36	1.040	1.988	91
Portugal	1569	1633	4	0.394	0.470	19
Romania	2300	1990	−13	0.664	1.318	99
Russia	1614	1899	18	0.621	0.421	−32
Rwanda	642	788	23	0.160	0.219	37
Saudi Arabia	4264	4565	7	1.066	0.508	−52
Serbia	3150	3672	17	0.870	1.456	67
Slovakia	3095	3416	10	0.740	2.151	191
Slovenia	4249	4520	6	1.000	–	–
South Africa	2843	2240	−21	0.504	0.732	45
South Korea	2545	2836	11	0.705	1.012	44
Spain	3100	3636	17	0.840	0.815	−3
Sudan	2327	2441	5	0.668	0.322	−52
Swaziland	1500	1485	−1	0.281	0.525	87
Sweden	5982	5990	0	1.727	1.282	−26
Switzerland	6132	6164	1	1.112	1.337	20
Syria	1850	2796	51	0.559	0.452	−19
Tajikistan	1184	1271	7	0.407	0.151	−63
Tanzania	1301	1175	−10	0.321	0.396	23
Thailand	667	541	−19	0.556	0.197	−65
Tunisia	1173	1808	54	0.407	0.359	−12
Turkey	2235	2426	9	0.650	0.653	1
Turkmenistan	1643	1688	3	0.549	0.524	−5
Uganda	1714	1793	5	0.497	0.441	−11
Ukraine	1976	2199	11	0.563	1.389	147
United Kingdom	8008	8886	11	1.799	1.996	11
USA	2826	2571	−9	0.810	1.178	45
Uruguay	2534	2516	−1	0.589	1.106	88
Uzbekistan	2605	3100	19	0.857	0.733	−14
Venezuela	369	447	21	0.360	0.106	−70
Zambia	6210	5584	−10	1.214	1.264	4
Zimbabwe	5391	4682	−13	1.053	1.279	21
World	2720	2939	8	0.798	0.750	−6

[a] Y_{dif} is defined as $(Y_{sim} - Y_{sta})/Y_{sta} \times 100\%$.
[b] The values are estimated as the inverse of virtual water content from Chapagain and Hoekstra (2004).
[c] CWP_{dif} is defined as $(CWP^* - CWP)/CWP \times 100\%$.

The simulated yields and the statistical yields are quite comparable. All the trend lines in Fig. 3 are close to the 1:1 lines. *F*-tests (the *P* value is higher than 99%) are highly significant and R^2 values are high (Table 2). The mean of the R^2 values in the 10 years is 0.86 with a S.D. of 0.05. All the slopes are close to 1. The intercepts are small, and are not significantly different from 0. The values of EF, NMSE, and *d* also indicate a good performance of the model.

The statistical analyses indicate that the GEPIC model performs well in simulating wheat yields throughout the world.

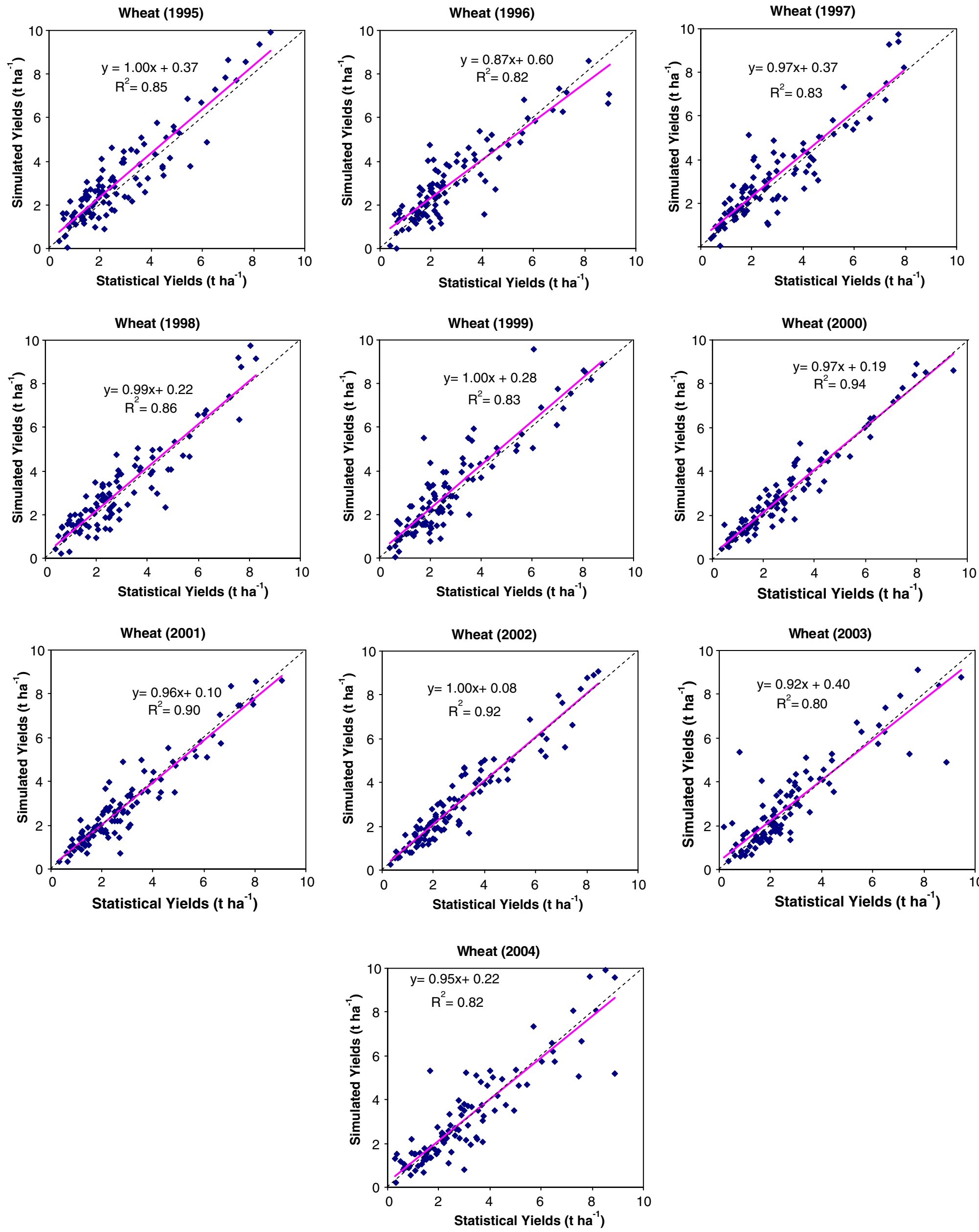

Fig. 3. Comparison between simulated wheat yields and FAO statistical wheat yields in 102 countries in the years 1995–2004.

5. Estimation of crop water productivity

Based on the simulated yields and ET with GEPIC, CWP can be estimated at the same spatial resolution. The global map of CWP is shown in Fig. 4. It can be seen that CWP differs significantly across countries and within countries. In general, western European countries have relatively high CWP values (>1.2 kg m^{-3}), whereas most African countries have low CWP (<0.4 kg m^{-3}).

To our best knowledge, CWP has so far not been estimated with such a high spatial resolution on a global scale. This makes our effort unique, but also results in difficulties in conducting a grid to grid comparison with other researches. Two approaches are used for comparison: aggregate the grid-based CWP to the national average values and compare them with the national average values given by Chapagain and Hoekstra (2004); and compare the simulated grid values of CWP with the measured values on a number of sites reported in the literature.

The values of the simulated national average CWP (marked as CWP in Table 1) are compared with those from Chapagain and Hoekstra (2004) (marked as CWP* in Table 1) for 98 countries. The results show that, in 55 countries (or more than half of the compared countries) the difference between CWP* and CWP is within the range of 30%. The world average water productivity of wheat is similar in the two studies. The comparison, however, shows large discrepancies in some countries notably the USA,

Table 2
Statistical index for the assessment of the model performance

Year	R^2	Slope	Intercept	EF[a]	NMSE[b]	d[c]
1995	0.85	1.00	0.37	0.77	0.08	0.95
1996	0.82	0.87	0.60	0.80	0.08	0.95
1997	0.83	0.97	0.37	0.77	0.08	0.95
1998	0.86	0.99	0.22	0.83	0.07	0.96
1999	0.83	1.00	0.28	0.78	0.09	0.95
2000	0.94	0.97	0.19	0.93	0.03	0.98
2001	0.90	0.96	0.10	0.90	0.04	0.97
2002	0.92	1.00	0.08	0.91	0.04	0.98
2003	0.80	0.92	0.40	0.77	0.10	0.94
2004	0.82	0.95	0.22	0.80	0.09	0.95
Mean	*0.86*	*0.96*	*0.28*	*0.83*	*0.07*	*0.96*
S.D.	*0.05*	*0.04*	*0.16*	*0.06*	*0.02*	*0.01*

[a] EF is Nash–Sutcliffe efficiency.
[b] NMSE is normalized mean square error.
[c] d is index of agreement.

the largest exporting country in wheat. The USA had a yield close to the world average level, corresponding to the simulated CWP in our study which is also close to the world average CWP (Table 1). In Chapagain and Hoekstra (2004), the value of CWP* is more than 50% higher than the world average CWP*. This value is likely to be overestimated. The reason may be partly because Chapagain and Hoekstra (2004) calculate CWP* with country average climate data, which ignores the spatial variations, leading to errors in the simulation results, especially in large countries like USA.

The simulated values of CWP from GEPIC were compared with the on site measurements reported in the literature. 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 with results of experiments not older than 25 years. Our results are mostly in line with the measured values (Table 3). Among 26 sites listed, 19 sites or 73%, have simulated CWP values falling into the minimum–maximum CWP ranges. However, GEPIC fails to model CWP in some locations with high measured CWP values, such as Wangtong and Quzhou in China. This is not surprising. In this study, the country average irrigation and fertilizer rates are used as input parameters. Those high CWP sites may profit from an above average level crop management. For example, in Wangtong, the high CWP values may be partly due to the intensive application of manure and straw mulching, factors which are not specifically considered in this study.

The frequency distribution of CWP for wheat shows obvious differences between irrigated and rainfed conditions (Fig. 5). Irrigated wheat has generally higher frequencies in the ranges of high CWP and lower frequencies in the ranges of low CWP. An opposite situation is evident for rainfed wheat. For the ranges with CWP higher than 0.8 kg m^{-3}, irrigated wheat always has higher frequencies of CWP; while for the ranges with CWP lower than 0.8 kg m^{-3}, irrigated wheat has lower frequencies. In the range from 0.8 to 1.2 kg m^{-3}, the frequency of CWP of irrigated wheat is about 40% (this number is in agreement with the value of 39% given by Zwart and Bastiaanssen (2004) for irrigated wheat in the same range based on 412 experimental points). The frequency of rainfed wheat is only 23%. In the range from 0.2 to 0.6 kg m^{-3}, the frequency of CWP of irrigated wheat is about 23%, while the frequency of rainfed wheat is about 43%. The low CWP in rainfed wheat production is partly due to water availability restricting crop development. In irrigated fields, water can be applied in times of deficiencies otherwise restricting wheat growth. Especially in the critical periods of crop

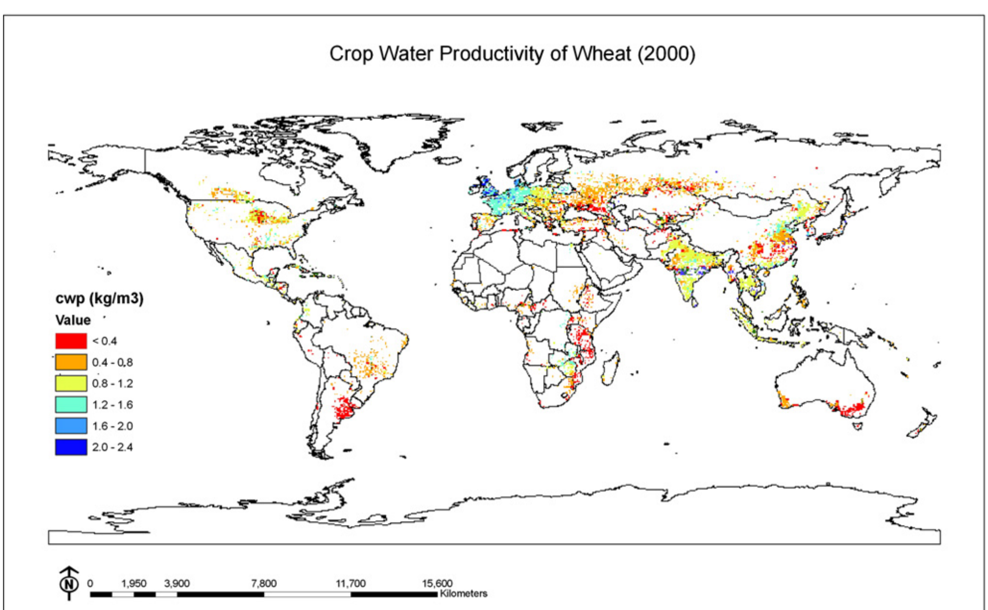

Fig. 4. Global map of simulated crop water productivity of wheat (2000).

Table 3
Comparison of the simulated CWP values with the measured CWP values in the literature

Location	Minimum ($kg\ m^{-3}$)[a]	Maximum ($kg\ m^{-3}$)[a]	Median ($kg\ m^{-3}$)[a]	Simulated CWP ($kg\ m^{-3}$)[b]	Simulated CWP in the minimum–maximum range?[c]
Parana, Argentina	0.55	1.49	1.04	0.65	*Y*
Merredin, Australia	0.56	1.14	0.95	0.82	*Y*
Merredin & Mullewa, Australia	0.55	1.65	0.88	0.62, 0.82	*Y*
Benerpota, Bangladesh	0.52	1.34	0.91	0.99	*Y*
Quzhou, China	1.38	1.95	1.58	0.84	*N*
Xifeng, China	0.65	1.21	0.84	0.67	*Y*
Wangtong, China	1.49	2.67	2.23	1.14	*N*
Gansu Province, China	0.58	1.45	1	1.05	*Y*
Luancheng, China	1.07	1.29	1.26	1.23	*Y*
Yucheng, China	0.88	1.16	1.04	1.01	*Y*
Beijing, China	0.92	1.55	1.19	1.23	*Y*
Luancheng, China	1.28	1.82	1.63	1.23	*N*
West Bengal, India	1.11	1.29	1.19	0.87	*N*
Pantnagar, India	0.86	1.31	1.11	0.87	*Y*
Uttar Prades, India	0.48	0.71	0.64	0.51	*Y*
Karnal, India	0.27	0.82	0.67	0.49	*Y*
Pantnagar, India	1.06	1.23	1.1	0.87	*N*
Gilat, Israel	0.6	1.6	0.85	0.63	*Y*
Meknes, Morocco	0.11	1.15	0.58	0.48	*Y*
Sidi El Aydi, Morocco	0.32	1.06	0.61	0.45	*Y*
Faisalabad, Pakistan	0.7	2.19	1.28	0.71	*Y*
Tel Hadya, Syria	0.48	1.1	0.78	0.56	*Y*
Cukurova, Turkey	1.33	1.45	1.39	1.14	*N*
Yellow Jacket (CO), USA	0.47	1.08	0.77	0.56	*Y*
Grand Valley(CO), USA	1.53	2.42	1.72	0.56	*N*
Tashkent, Uzbekistan	0.44	1.02	0.73	0.75	*Y*

[a] Data from Zwart and Bastiaanssen (2004).
[b] Data from this study.
[c] *Y* indicates the simulated CWP values are within the minimum–maximum range, while *N* indicates the simulated CWP values are out of the minimum–maximum range.

growth, application of irrigation can improve wheat yield significantly.

Our simulation results do not show a clear division of CWP between irrigated and rainfed fields, whereas Mo et al. (2005) find such a division in frequencies between the two. This is largely due to the differences in scale and range of climatic conditions. In the Hebei province in China, for example, winter wheat is planted in autumn and harvested early next summer. Precipitation in spring is unreliable and insufficient for wheat growth, leading to

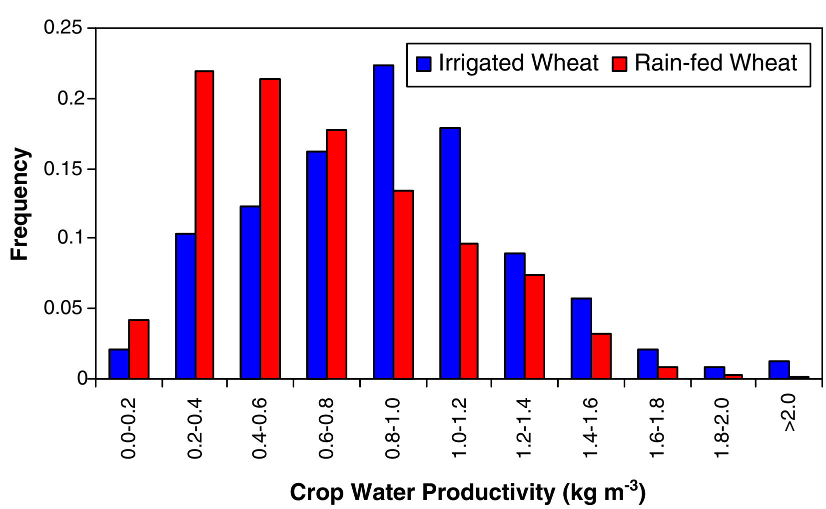

Fig. 5. Frequency histogram of crop water productivity of wheat (2000) under irrigated and rainfed conditions.

low yields and CWP values in rainfed fields. With irrigation, both wheat yield and ET raise but yield increases are more pronounced (Mo et al., 2005). Hence, the values of CWP for irrigated wheat become much higher.

6. Discussion

6.1. Yield and CWP

The estimated national average crop yield and CWP show a strong linear relation ($R^2 = 0.88$) (Fig. 6). High yields and CWP are seen in Europe, especially in Western and Northern Europe. Most African countries have low CWP and low wheat yields. The national average CWP ranges from 0.160 kg m^{-3} in Rwanda to 1.887 kg m^{-3} in Ireland. The difference is a result of many factors affecting plant growth, such as the water vapor pressure deficit of the atmosphere during the crop growing period, the availability of water when it is most needed, soil fertility, fertilizer application, general climatic conditions, etc. In general the CWP differs for given agronomic practices and environmental conditions. In some areas in Western European countries, the simulated CWP values exceed 2 kg m^{-3} (Fig. 6). These numbers come close to the maximum when there is no limitation of production by nutrients or reduction of production by the presence of weeds, pests and diseases (Bessembinder et al., 2005).

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

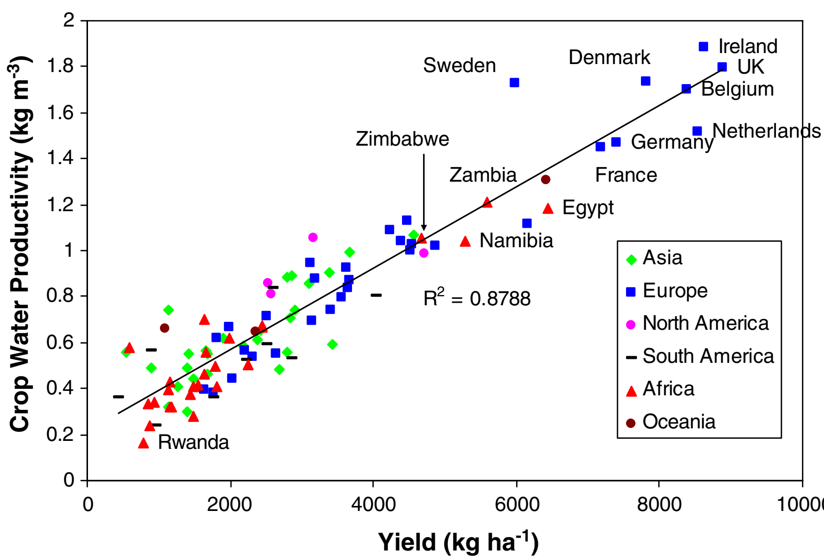

Fig. 6. Relationship between national average yield and CWP (2000).

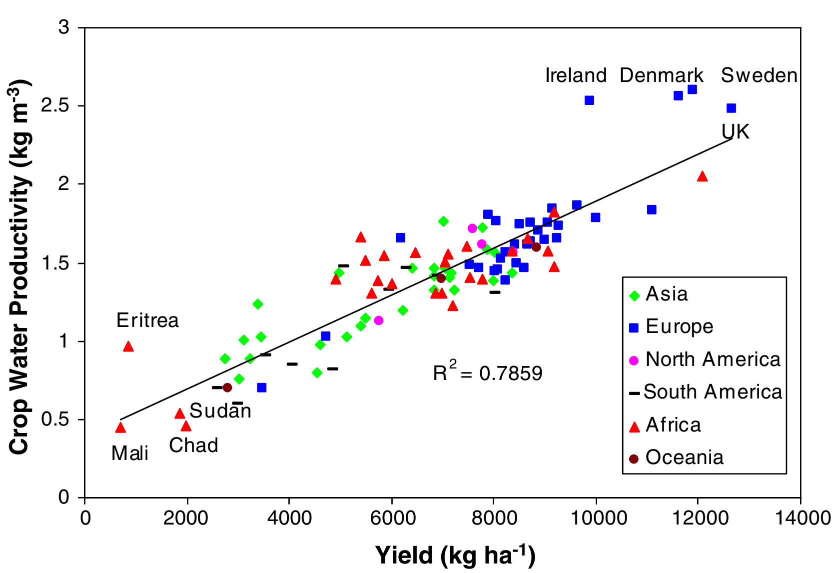

Fig. 7. Wheat yield vs. CWP under assumption of sufficient water and fertilizer supply (2000).

Table 4
Potential yield (Y_p), yield gap (Y_{gap}) between Y_p and actual yield (Y_{sta}), the percentage of Y_{gap} to Y_p (Y_{gap}%), potential crop water productivity (CWP_p), CWP gap (CWP_{gap}) between CWP_p and actual crop water productivity (CWP), and the percentage of CWP_{gap} to CWP_p (wheat, 2000)

Country	Y_p (kg ha^{-1})	Y_{gap} (kg ha^{-1})	Y_{gap} (%)	CWP_p (kg m^{-3})	CWP_{gap} (kg m^{-3})	CWP_{gap} (%)
Albania	8223	5177	63	1.564	0.638	41
Algeria	7773	6854	88	1.391	1.072	77
Angola	5406	3667	68	1.668	1.111	67
Argentina	3000	507	17	0.600	0.069	12
Armenia	8008	6302	79	1.567	1.076	69
Australia	2796	975	35	0.702	0.056	8
Austria	8885	4416	50	1.707	0.686	40
Azerbaijan	7022	4700	67	1.768	1.159	66
Bangladesh	3246	1036	32	0.885	0.143	16
Belgium	9059	1139	13	1.751	0.047	3
Bolivia	5954	5067	85	1.323	1.085	82
Bosnia	8430	5201	62	1.610	0.991	62
Botswana	6859	5192	76	1.306	0.604	46
Brazil	6893	5334	77	1.411	0.889	63
Bulgaria	8725	5883	67	1.750	1.038	59
Burundi	5849	5172	88	1.544	1.205	78
Cameroon	5723	4390	77	1.388	0.957	69
Canada	8391	5947	71	1.567	0.712	45
Chad	1988	554	28	0.455	0.080	18
Chile	4056	244	6	0.850	0.049	6
China	6836	3098	45	1.414	0.624	44
Colombia	6285	4143	66	1.469	0.632	43
Congo	4919	3634	74	1.392	0.985	71
Croatia	8649	4275	49	1.617	0.820	51
Czech Rep	8989	4780	53	1.648	0.702	43
Denmark	12,645	5165	41	2.480	0.747	30
Ecuador	5070	4449	88	1.472	0.908	62
Egypt	6617	275	4	1.308	0.127	10
Eritrea	849	255	30	0.970	0.389	40
Ethiopia	8671	7508	87	1.658	1.262	76
Finland	4738	1137	24	1.030	0.337	33
France	9277	2160	23	1.737	0.288	17
Georgia	7880	6837	87	1.582	1.034	65
Germany	9992	2709	27	1.783	0.312	18
Greece	8722	6183	71	1.632	1.096	67
Guatemala	7584	5491	72	1.717	0.665	39
Hungary	8130	4526	56	1.521	0.644	42
India	3100	321	10	1.010	0.117	12
Iran	6209	4623	74	1.200	0.637	53
Ireland	9883	429	4	2.528	0.641	25
Italy	7903	4690	59	1.800	0.713	40
Japan	7174	3413	48	1.437	0.847	59
Jordan	7988	6591	83	1.386	1.084	78
Kazakhstan	6830	5927	87	1.467	0.980	67
Kenya	8370	6823	82	1.571	1.110	71
Kyrgyzstan	6408	4066	63	1.467	1.026	70
Latvia	3488	784	22	0.702	0.322	46
Lebanon	7233	4530	63	1.328	0.848	64
Lithuania	9637	6296	65	1.867	0.842	45
Macedonia	8604	6135	71	1.468	0.920	63
Madagascar	6022	3772	63	1.364	0.688	50
Malawi	7477	6680	89	1.600	1.364	85
Mali	2698	346	13	0.646	0.026	4
Mexico	5777	841	15	1.124	0.141	13
Moldova	7714	5763	75	1.466	1.024	70
Mongolia	5128	4351	85	1.027	0.285	28
Morocco	7058	6582	93	1.503	1.085	72
Myanmar	3437	2270	66	1.028	0.565	55
Namibia	6979	3550	51	1.309	0.267	20
Nepal	4963	3170	64	1.439	0.855	59
Netherlands	11,099	2740	25	1.832	0.317	17
New Caledonia	8849	7182	81	1.590	0.931	59
New Zealand	6985	775	11	1.400	0.095	7
Nigeria	5484	4080	74	1.518	1.183	78
North Korea	7051	6203	88	1.464	1.145	78
Norway	6202	1669	27	1.651	0.525	32
Oman	3384	194	6	1.235	0.354	29
Pakistan	2748	257	9	0.913	0.006	1
Paraguay	4851	3470	72	0.820	0.426	52
Peru	8033	6745	84	1.308	0.950	73
Poland	8461	5234	62	1.492	0.452	30
Portugal	9151	7582	83	1.848	1.454	79
Romania	8046	5746	71	1.761	1.097	62
Russia	7780	6166	79	1.728	1.107	64
Rwanda	12,081	11,439	95	2.058	1.898	92
Saudi Arabia	4558	294	6	1.081	0.015	1
Serbia	8034	4884	61	1.445	0.575	40
Slovakia	8224	5129	62	1.388	0.648	47
Slovenia	9246	4997	54	1.657	0.657	40
South Africa	7527	4684	62	1.409	0.905	64
South Korea	7134	4589	64	1.409	0.704	50
Spain	7545	4445	59	1.481	0.641	43
Sudan	2849	522	18	0.738	0.070	9
Swaziland	9047	7547	83	1.577	1.296	82
Sweden	11,634	5652	49	2.560	0.833	33
Switzerland	8093	1961	24	1.451	0.339	23
Syria	6843	4993	73	1.322	0.763	58
Tajikistan	5479	4295	78	1.147	0.740	65
Tanzania	6478	5177	80	1.567	1.246	80
Thailand	3027	2360	78	0.762	0.206	27
Tunisia	7209	6036	84	1.230	0.823	67
Turkey	8366	6131	73	1.439	0.789	55
Turkmenistan	4603	2960	64	0.977	0.428	44
Uganda	7107	5393	76	1.559	1.062	68
Ukraine	8515	6539	77	1.742	1.179	68
United Kingdom	11,904	3896	33	2.605	0.806	31
USA	7791	4965	64	1.619	0.809	50
Uruguay	2600	66	3	0.700	0.111	16
Uzbekistan	5388	2783	52	1.099	0.242	22
Venezuela	3531	3162	90	0.902	0.542	60
Zambia	9189	2979	32	1.826	0.612	34
Zimbabwe	9189	3798	41	1.479	0.426	29

Actual yield and actual crop water productivity are the same as Y_{sta} and CWP respectively in Table 1.

water and fertilizer supply, holding other factors unchanged. The estimated yield and CWP values are provided in Fig. 7, and the detailed values for each country are reported in Table 4.

Many countries in Europe, Africa, and North America have advantages in achieving high wheat yield and high CWP with sufficient water and fertilizer supply (Fig. 7 and Table 4). The highest CWP and yields are found in UK, Denmark, Sweden and Ireland. The highest CWP in these countries may be closely related to the vapor pressure deficit of the air. There is a proportionally inverse relation between vapor pressure deficit of the atmosphere and CWP

(Bierhuizen and Slayter, 1965; Tanner and Sinclair, 1983). The four countries have much lower vapor pressure deficits compared to other countries (this has been verified by the GEPIC model, but the data are not shown in this paper). It is not surprising that they have the highest CWP. Most European countries have the potential to achieve wheat yields over 7000 kg ha^{-1} and CWP over 1.2 kg m^{-3}. Compared with Fig. 6, the gap between the currently achieved yield and CWP and their potentials is relatively small. This reflects the fact that in many European countries, water and fertilizer supply, and other management factors, are already in near-optimum conditions. In contrast, the large gap appears in African countries. The results also show that, except for Mali, Chad, Sudan and Eritrea, most African countries have high potential wheat yield and CWP (Fig. 7 and Table 4). Wheat yields could reach 5000 to 9000 kg ha^{-1} with CWP between 1.2 and 1.8 kg m^{-3}, if the water supply and fertilizer application were sufficient. The high potential yields and CWP suggest that increasing water and fertilizer supply would improve wheat production in Africa, although other management factors may also have to be improved. In the four exceptional countries, biophysical conditions, e.g. the prevailing soils, may restrict the growth of wheat, leading to low potential yield and CWP even with sufficient water and fertilizer supply. Fischer et al. (2002) show that the soil texture in the four countries has partly constrained crop growth.

6.2. Virtual water flows embodied in the international wheat trade

The variation in CWP has important implication for global water resources utilization. On the global scale, water can be saved through wheat trade when the flow is from countries with high CWP to countries with low CWP countries. The magnitude of the virtual water through wheat trade is estimated in this section.

Virtual water volumes can be calculated by dividing food trade volume by CWP in each country. For a country, virtual water export (VWE) is calculated by dividing the volume of wheat exports by the national average CWP of this country. The global virtual water export (GVWE) is equal to the sum of the VWE in all the exporting countries, and it indicates the volume of virtual water leaving all the exporters to the importers. Likewise, virtual water import (VWI) is calculated by dividing the volume of wheat imports by the national average CWP in the respective importing countries. For those wheat-importing countries that are not listed in Table 1, the global average CWP for all the wheat-importers is used to calculate VWI. The global virtual water import (GVWI) is equal to the sum of the VWI in all the importing countries, and it indicates the volume of virtual water that the importing countries would have used to produce the amount of wheat imports if no wheat were traded. In 2000, around 129×10^9 kg of wheat (refers to the wheat equivalent, which includes wheat and wheat flour) was traded in the international food market (FAO, 2005b). The calculation shows that corresponding GVWI and GWVE were 236×10^9 m^3 and 159×10^9 m^3, respectively. The difference of 77×10^9 m^3 represents the global water saving through wheat trade in the year. The top five exporting countries (USA, Canada, France, Australia, and Argentina) were responsible for some 80% of the wheat export in 2000 (FAO, 2005b). Except for Argentina, the other major exporting countries all have CWP values higher than 0.8 kg m^{-3} (Table 1). In contrast, the top five importing countries (Brazil, Italy, Iran, Japan, and Algeria) have values of CWP lower than 0.6 m^3 kg^{-1} except for Italy. The difference in CWP among importing and exporting countries resulted in the global water saving through international wheat trade.

The volume of global water saving through wheat trade from this study is appropriately 25% lower than the 103×10^9 m^3 estimated by Chapagain et al. (2006). This value is for an average during the period 1997–2001, and was calculated based on the estimated CWP from Chapagain and Hoekstra (2004). The trade volume of wheat is only appropriately 4% higher in 2000 than that the average over 1997–2001 (FAO, 2005b). Thus, the difference in global water savings in the two studies stems mainly from the different values of the national average CWP. Taking USA as an example, the difference in the national average CWP leads to as high as 12×10^9 m^3 more water saving using Chapagain and Hoekstra (2004) estimates compared with those reported here. Another example is for Italy, the second largest wheat importer. The lower national average CWP reported by Chapagain and Hoekstra (2004) resulted in water savings 2.5 times the value reported here. The large discrepancy in the estimation of global water saving through trade of wheat suggests that the values of CWP are of great importance for global virtual water study, and accurate estimation of CWP is necessary.

GEPIC is also used to estimate the potential global water saving in wheat production in the year 2000 with the potential CWP that could be achieved under optimal water and fertilizer supply. Globally, about 278×10^9 m^3 of crop water use could be saved with the same amount of wheat production in 2000 (160×10^9 and 118×10^9 m^3 in importing and exporting countries, respectively). The results suggest that the magnitude of the water saving by narrowing the gap between actual and potential CWP is much larger than that of the water saving achieved through wheat trade. This indicates that efforts to enhance wheat yield and CWP are very important in efficiently use of the global water resources.

7. Conclusion

GEPIC 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 comparison between simulated yields and FAO statistical yields in 102 countries over 10 years suggests a good performance of the model. The simulated CWP is also mostly in line with the measured CWP in the literature. With its capability of simulating yield and CWP in the past, present and future under real or assumed conditions, GEPIC also has potential to be used to support policy formulation concerning water use and food trade at both global and regional levels.

A comparison between the grid-based global maps of wheat yield and CWP generated by GEPIC reveals a spatial relation between them: high-yielding regions have high CWP, and low-yielding regions have low CWP. The relation can also be observed between the national average yield and CWP. In many European countries, the current wheat yield and CWP are high due to relatively sufficient water and fertilizer supply. In contrast, the current wheat yield and CWP are very low in many African countries. Simulating wheat yields assuming sufficient water and fertilizer supply reveals that African countries can improve yields and CWP significantly through better water and fertilizer management. The difference in CWP among regions has resulted in a global saving of water through international wheat trade. The simulation, however, also suggests that a greater and more meaningful global water saving can be achieved by narrowing the gap between the potential and actual CWP in individual countries.

The accuracy of the GEPIC output depends largely on the quality of the input data. Since we do not have land use map indicating spatial distribution of specific crops, the simulation is based on all the grids with legend of dryland cropland and pasture or irrigated cropland and pasture in the global land use map. The real wheat planting pattern in a specific location may be different from the global land use map, which may lead to simulation errors. For example, our results did not indicate that Kansas is one of the major wheat producing areas in the USA. This is mainly because the global land use map shows only a few grids in this region marked with the cropland legend. A better quality of GIS data, including a global map of crop planting patterns, would help improve the simulation accuracy of the GEPIC model.

The application of the GEPIC model is restricted by the setup of the EPIC model. For instance, pest can lead to yield losses, but the effects of pests on crop yield were not addressed here. As a result, the GEPIC model may overestimate crop yield in the regions where pest infestations are serious. Ignoring pest damage may be an important reason for the overestimation of yields in Brazil (see Table 1). Although EPIC has a generic pest component for simulating insect and disease damage and a weed competition component, they are difficult to apply on a global scale. In addition, for large countries, such as USA, China, and India, the GEPIC model should be calibrated and validated on a smaller than a national scale. Despite the small differences between simulated and statistical yields at the national level, spatial pattern of simulated wheat yields may not be consistent with the real spatial pattern. For example, the simulated national average yield in India is only 3.3% higher than the statistical national average yield in 2000. However, the grid simulation results show that in most areas of Rajasthan State in India, wheat yield was less than 1000 kg ha^{-1}, much lower than the reported yield of about 1700 kg ha^{-1} (Priya and Shibasaki, 2001). Therefore, for large countries it is more appropriate to calibrate and validate the GEPIC model based on provincial statistical data. An investigation at the sub-country level is underway.

Acknowledgements

This study was supported by the Swiss National Science Foundation (Project No: 205121–103600). We are grateful to Bill Dugas, Jeff Arnold, Jim Kiniry and Paul Dyke at the Blackland Research and Extension Center of USA for their valuable comments on the manuscript. We are also indebt to Peter Reichert and Karim Abbaspour at the Swiss Federal Institute of Aquatic Science and Technology (Eawag), who have shared many discussions with us throughout the preparation and writing of this paper. Last but not least, we thank two anonymous reviewers for their constructive comments on the earlier version of the manuscript.

References

Allan, J.A., 1998. Virtual water: a strategic resource – global solutions to regional deficits. Ground Water 36 (4), 545–546.

Angström, A., 1956. On the computation of global radiation from records of sunshine. Arkiv. Geof. 2, 471–479.

Baier, W., Robertson, G.W., 1965. Estimation of latent evaporation from simple weather observations. Can. J. Plant Sci. 45, 276–284.

Batjes, N.H. (Ed.), 1995. A homogenized soil data file for global environmental research: a subset of FAO. ISRIC and NRCS profiles (Version 1.0). Working Paper and Preprint 95/10b. International Soil Reference and Information Center, Wageningen, The Netherlands.

Bernardos, J.N., Viglizzo, E.F., Jouvet, V., Lertora, F.A., Pordomingo, A.J., Gid, F.D., 2001. The use of EPIC model to study the agroecological change during 93 years of farming transformation in the Argentine pampas. Agric. Syst. 69 (3), 215–234.

Bessembinder, J.J.E., Leffelaar, P.A., Dhindwal, A.S., Ponsioen, T.C., 2005. Which crop and which drop, and the scope for improvement of water productivity. Agric. Water Manage. 73 (2), 113–130.

Bierhuizen, J.F., Slayter, R.O., 1965. Effect of atmospheric concentration of water vapour and CO2 in determining transpiration–photosynthesis relationships of cotton leaves. Agric. Meteorol. 2, 259–270.

Chapagain, A.K., Hoekstra A.Y., 2004. Water footprints of nations. Value of Water Research Report Series No. 16, vols. 1–2, UNESCO-IHE, Delft, the Netherlands.

Chapagain, A.K., Hoekstra, A.Y., Savenije, H.H.G., 2006. Water saving through international trade of agricultural products. Hydrol. Earth Syst. Sci. 10 (3), 455–468.

Confalonieri, R., Bocchi, S., 2005. Evaluation of CropSyst for simulating the yield of flooded rice in northern Italy. Eur. J. Agron. 23, 315–326.

Curry, R.B., Peart, R.M., Jones, J.W., Boote, K.J., Auten, L.H., 1990. Simulation as a tool for analyzing crop response to climate change. Trans. ASAE 33 (3), 981–990.

Döll, P., Siebert, S., 2000. A digital global map of irrigated areas. ICID J. 49 (2), 55–66.

Dumesnil, D., 1993. EPIC user's guide-draft. USDA-ARS, Grassland, Soil and Water Research Laboratory, Temple, TX.

EROS Data Center, 1998. Global 30″ Digital Elevation Model (http://edcwww.cr.usgs.gov). Anonymous ftp access at edcftp.cr.usgs.gov.

FAO, 1990. Soil Units of the Soil Map of the World. FAO-UNESCO-ISRIC, Rome.

FAO, 1993. CLIMWAT for CROPWAT, a climatic database for irrigation planning and management by M. Smith. FAO Irrigation and Drainage Paper No. 49. Rome.

FAO, 2005a. FAO's information system on water and agriculture. Food and Agriculture Organization of the United Nations. Available on the World Wide Web: http://www.fao.org/ag/agl/aglw/aquastat/main/index.stm.

FAO, 2005b. FAO statistical database. Food and Agriculture Organization of the United Nations. Available on the World Wide Web: http://faostat.fao.org/.

FAO, 2005c. Review of global agricultural water use per country, crop water requirements. Food and Agriculture Organization of the United Nations, Rome, Italy. Available on the World Wide Web: http://www.fao.org/ag/agl/aglw/aquastat/water_use/index4.stm.

Fischer, G., 2005. Policy decision support for sustainable adaptation of China's agriculture to globalization (CHINAGRO). In: Policy Forum on China's Agriculture toward 2030. Beijing, China.

Fischer, G., van Velthuizen, H.T., Shah, M.M., Nachtergaele, F.O., 2002. Global agro-ecological assessment for agriculture in the 21st Century: methodology and results. International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria, Report RR-02-002.

Fraiture, C.D., Cai, X., Amarasinghe, U., Rosengrant, M., Molden, D., 2004. Does cereal trade save water? The impact of virtual water trade on global water use. Comprehensive Assessment Research Report No. 4, IWMI, Colombo, Sri Lanka.

Gassman, P.W., Williams, J.R., Benson, V.R., Izaurralde, R.C., Hauck, L.M., Jones, C.A., Altwood, J.D., Kiniry, J.R., Flowers, J.D., 2005. Historical development and applications of the EPIC and APEX models. Working Paper 05-WP-397. Center for Agricultural and Rural Development. Iowa State University. Iowa, US.

Gleason, B.E., Peterson, T.C., Groisman, P.Y., Easterling, D.R., Vose, R.S., Ezell, D.S., 2002. A new global daily temperature and precipitation data set. Presented at the 13th AMS Symposium On Global Change Studies, Orlando, FL, 13–17 January, 2002.

Hanna, S.R., 1988. Air quality evaluation and uncertainty. J. Air Pollut. Control Assoc. 38, 406.

Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Appl. Eng. Agric. 1, 96–99.

Hoekstra A.Y., Hung P.Q., 2002. Virtual water trade: A quantification of virtual water flows between nations in relation to international crop trade. Value of Water Research Report Series No. 11, UNESCO-IHE, Delft, the Netherlands.

Hoekstra, A.Y., Hung P.Q., 2003. Virtual water trade: a quantification of virtual water flows between nations in relation to international crop trade. In: Hoekstra, A.Y. (Ed.), Virtual Water Trade. Proceedings of The International Expert Meeting on Virtual Water Trade, 12-13 Dec, 2002, at UNESCO-IHE, Delft, the Netherlands, pp. 25–47.

Huang, B., Jiang, B., 2002. AVTOP: a full integration of TOPMODEL into GIS. Environ. Model. Software 17, 261–268.

Ines, A.V.M., Gupta, A.D., Loof, R., 2002. Application of GIS and crop growth models in estimating water productivity. Agric. Water Manage. 54, 205–225.

International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT), 1989. Decision Support System for Agrotechnology Transfer Version 2.1 (DSSAT V2. l). Honolulu: Dept. of Agronomy and Soil Science. College of Tropical Agriculture and Human Resources: University of Hawaii.

Isaaks, E.H., Srivastava, R.M., 1989. Applied Geostatistics. Oxford University Press, New York.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J., 2003. An overview of APSIM, a model designed for farming systems simulation. Eur. J. Agron. 18 (3–4), 267–288.

Kijne, J.W., Barker, R., Molden, D., 2003. Water productivity in Agriculture: limits and opportunities for improvement. CAB International, Wallingford, UK.

Liu, J., Zehnder, A.J.B., Yang, H., in press. Historical trends in China's virtual water trade. Water Int.

Mo, X., Liu, S., Lin, Z., Xu, Y., Xiang, Y., McVicar, T.R., 2005. Prediction of crop yield, water consumption and water use efficiency with a SVAT-crop growth model using remotely sensed data on the North China Plain. Ecol. Model 183, 301–322.

Molden, D., 1997. Accounting for water use and productivity. In: SWIM Paper 1, IIMI, Colombo.

Monsi, M., Saeki, T., 1953. Uber den Lichfaktor in den Pflanzengesellschaften und sein Bedeutung fur die Stoffproduktion. Jpn. J. Biotechnol. 14, 22–52.

Monteith, J.L., 1965. Evaporation and environment. The State and Movement of Water in Living Organisms. In: Proceedings of 19th Symposia of the Society for Experimental Biology. Cambridge University Press, London, UK, pp. 205–234.

Monteith, J.L., 1977. Climate and the efficiency of crop production in Britain. Philosophical Transactions of the Royal Society, London, pp. 277–294.

Monteith, J.L., 1996. The quest for balance in crop modeling. Agron. J. 88, 695–697.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models: Part I – A discussion of principles. J. Hydrol. 10, 282–290.

Oki, T., Sato, M., Kawamura, A., Miyake, M., Kanae, S., Musiake, K., 2003. Virtual water trade to Japan and in the world. In: Hoekstra, A.Y. (Ed.), Virtual Water Trade. Proceedings of The International Expert Meeting on Virtual Water Trade, 12–13 December 2002, at UNESCO-IHE, Delft, The Netherlands, pp. 221–235.

Penman, H.L., 1948. Natural evaporation from open, bare soil and grass. Proc. R. Soc. Lond. Ser. A 193, 120–145.

Priestley, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat flux on evaporation using large-scale parameters. Mon. Weather Rev. 100, 81–92.

Priya, S., Shibasaki, R., 2001. National spatial crop yield simulation using GIS-based crop production model. Ecol. Model. 135, 113–129.

Ramirez-Vallejo, J., Rogers, P., 2004. Virtual water flows and trade liberalization. Water Sci. Technol. 49, 25–32.

Rao, M.N., Waits, D.A., Neilsen, M.L., 2000. A GIS-based modeling approach for implementation of sustainable farm management practices. Environ. Model. Software 15 (8), 745–753.

Reed, B., 1997. Applications of the US geological survey's global land cover product. Acta Astronaut. 41 (4-10), 671–680.

Richardson, C.W., Nicks, A.D., 1990. Weather generator description. In: Sharpley, A.N., Williams, J.R. (Eds.), EPIC-Erosion Productivity Impact Calculator: I. Model Documentation. US Dept. Agric. Tech. Bull., p. 1768.

Ritchie, J.T., 1972. A model for predicting evaporation from a row crop with incomplete cover. Water Resour. Res. 8, 1204–1213.

Saxton, K.E., Rawls, W.J., Romberger, J.S., Papendick, R.I., 1986. Estimating generalized soil–water characteristics from texture. Soil Sci. Soc. Am. J. 50, 1031–1036.

Siebert, S., Döll. P., Hoogeveen, J., 2002, Global map of irrigated areas version 2.1, Center for Environmental Systems Research, University of Kassel, Germany/Food and Agriculture Organization of the United Nations, Rome, Italy.

Stöckle, C.O., Donatelli, M., Nelson, R.L., 2003. CropSyst, a cropping systems simulation model. Eur. J. Agron. 18 (3–4), 289–307.

Sui, D.Z., Maggio, R.C., 1999. Integrating GIS with hydrological modelling: practices, problems and prospects. Comput., Environ. Urban Syst. 23 (1), 33–51.

Tanner, C.B., Sinclair, T.R., 1983. Efficient water use in crop production: research or re-search? In: Taylor, H.M., Jordan, W.R., Sinclair, T.R. (Eds.), Limitations to Efficient Water Use in Crop Production. American Society of Agronomy, pp. 1–27.

Thornton, P.K., 1990. Using models to explore farming alternatives. Agrotechnol. Transf. 11, 1–9.

USGS – United States Geological Survey, 2000. HYDRO1k. Available on the World Wide Web: http://lpdaac.usgs.gov/gtopo30/hydro/.

Vossen, P., Rijks, D.A., 1995. Early crop yield assessment of the EU countries. The system implemented by the Joint Research Centre. Publication EUR 16318 EN of the Office for Official Publications of the EU, Luxembourg.

Wang, X., He, X., Williams, J.R., Izaurralde, R.C., Atwood, J.D., 2005. Sensitivity and uncertainty analyses of crop yields and soil organic carbon simulated with EPIC. Trans. ASAE 48 (3), 1041–1054.

Wichelns, D., 2001. The role of 'virtual water' in efforts to achieve food security and other national goals, with an example from Egypt. Agric. Water Manage. 49 (2), 131–151.

Willmott, C.J., 1982. Some comments on the evaluation of model performance. Bull. Am. Meteorol. Soc. 63 (11), 1309–1313.

Williams, J.R., 1995. The EPIC model. In: Singh, V.P. (Ed.), Computer Models of Watershed Hydrology. Water Resources Publisher, Colorado, USA, pp. 909–1000.

Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC crop growth model. Trans. ASAE 32, 497–511.

World Water Council, 2004. E-Conference Synthesis: Virtual Water Trade – Conscious Choices. WWC Publication No.2, March 2004.

Yang, H., Reichert, P., Abbaspour, K.C., Zehnder, A.J.B., 2003. A water resources threshold and its implications for food security. Environ. Sci. Technol. 37, 3048–3054.

Yang, H., Wang, L., Abbaspour, K.C., Zehnder, A.J.B., 2006. Virtual water trade: an assessment of water use efficiency in the international food trade. Hydrol. Earth Syst. Sci. 10 (3), 443–454.

Yang, H., Zehnder, A.J.B., 2002. Water endowments and virtual water trade. Gaia 4, 267–270.

Zhang, Y., Li, C., Zhou, X., Moore, B., 2002. A simulation model linking crop growth and soil biogeochemistry for sustainable agriculture. Ecol. Model. 151, 75–108.

Zwart, S.J., Bastiaanssen, W.G.M., 2004. Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize. Agric. Water Manage. 69, 115–133.