COMPARISON OF GLOBAL AGRICULTURAL MODELING RESULTS

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Abstract. Crop yield process models are commonly used to estimate the consequences of management practices and the effects of climate change at the field level. However, their applicability for modeling yields across regions larger regions and their skill at reproducing observed yields is an open question. Using weather data from satellites and weather stations, and global datasets of soil and management, we simulate yields for 6 major crops globally between 1970 and 2010 using two models, AquaCrop and DSSAT, and compare their results to reported yields. Correlations vary by country and by crop, from approximately .8 to -.5. Some of this range in crop model performance is explained by crop variety, data quality, and other natural, economic, and political features. We also quantify the ability of AquaCrop and DSSAT to simulate yields under past cycles of ENSO as a proxy for their performance under changes in climate.

Biophysical agricultural process models, such as DSSAT, APSIM, WOFOST, and AquaCrop attempt to predict agricultural outputs by modeling physical processes such as soil water balance, growing degree-day responses, and wilting conditions. They also incorporate the effects of management practices, such as irrigation, fertilizer application, and mulching. In many cases, these models represent a state of the art of available knowledge on the agricultural consequences of plant biology and management (Jame and Cutforth, 1996).

Although these models are described at the field level, they have an important potential for studies of regional and global processes like climate change and technological adoption. In some studies, simulated yields match observed yields closely, however agronomic studies typically calibrate their models on the same data used to test them (Schlenker and Roberts, 2009). In particular, the application of biophysical models to remote sensing data is a important area of active research (Delécolle et al., 1992, Rosenzweig et al., 2013).

In this paper, we study the current ability of two of these models, DSSAT and AquaCrop, to predict global historical yields using globally available datasets. In the first section, we describe our study design for running these models using 12 global datasets. In the second section, we analyze the simulation results, finding that their performance in this context varies widely, and is often low, and identify key factors that explain this variation. In the third section, we combine results from both DSSAT and AquaCrop to produce three additional estimates. We find that these generally out-perform both models. In the fourth section, we apply the models to ENSO cycles, to study how the models perform under ENSO as a proxy for global climate change,

1. Model and Inputs

The Decision Support System for Agrotechnology Transfer (DSSAT) is a advanced crop modeling system with 28 crop types, using CERES models for grains (Jones et al., 2003). A typical crop model contains over 100 parameters. AquaCrop, an extension of CROPWAT, was developed by FAO for water scarcity studies (Steduto et al., 2009). AquaCrop models contain about 70 parameters.

These models rely on detailed input data. We collected 15 global datasets, including weather station data, satellite data, and surveyed values. These are summarized in table 1.

Date Type	**Data Source**	**Scope**	**Resolution**	**AquaCrop**	**DSSAT**
Soil Texture	HWSD	Global	0.5’ × 0.5’	yes	yes[1]
Soil Profiles	WISE	Global	3404 profiles	no	yes
Soil Propeties	IGBP-DIS	Global	5’ × 5’	yes	no
Soil Moisture	CDAS-1	Global	112.5’ × 114.25’	yes	no
Precipitation	GLOBALSOD	Global	14 676 stations	yes[2]	yes[2]
Precipitation	GHCN	Global	33 147 stations	yes[2]	yes[2]
Precipitation	TRMM	Global	0.25° × 0.25°	yes[2]	yes[2]
Precipitation	CDAS-1	Global	1.875° × 1.904 128°	yes[2]	yes[2]
Temperature	CDAS-1	Global	1.875° × 1.904 128°	yes	yes
Evapotrans.	FAO	Global	0.5° × 0.5°	yes	no
Elevation	GLOBE	Global	0.5’ × 0.5’	yes[2]	yes
Crop Calendar	Sachs	Global	0.5” × 0.5”	yes	yes
Fertilizer	Potter	Global	0.5” × 0.5”	no	yes
Irrigation	MIRCA2000	Global	5’ × 5’	yes	yes
Harvested Area	SAGE	Global	5’ × 5’	no	no

Table 1. The datasets used as inputs for AquaCrop and DSSAT. More details on each are provided in the text.

1.1. Soil Characteristics.

Soil characteristics are used to model soil water balance, which determine water availability and wilting. The most detailed soil information we use is from in the WISE database (Batjes, 2009). Where WISE profiles are unavailable, we use soil texture data from the Harmonized World Soil Database (HWSD) (Nachtergaele and Batjes, 2012). Soil texture (in the form of gravel, sand, silt, and clay content, in both topsoil (0 to 30 cm) and subsoil (30 to 100 cm). These textures are translated into hydraulic

[1] WISE profiles are used if one exists within the feature rectangle. Otherwise, HWSD textures are used. If more than one WISE profile is within the feature, the profile closest to its centroid is used.

[2] Station precipitation is preferred to reanalysis data. The precipitation amount for each day is first filled in using the closest stations, out to a distance of .25° latitude or longitude away, or an elevation difference of 38.5m. Unavailable days are then filled in using TRMM data. Then stations out to 1° distant or an elevation difference of 77m are used. Finally, any remaining unavailable days are filled in using CDAS-1.

properties (e.g., field capacity and hydraulic conductivity) using the methods in Saxton et al. (1986). However, in many areas the HWSD is based on sparse data, so we include data from the IGBP-DIS Global Soil Data Task on wilting point and field capacity (Task, 2000) as an additional source for AquaCrop. The IGBP-DIS values are provided as an average over the top 100cm, in averaging the HWSD and IGBP-DIS results, we weigh the IGBP-DIS at 30% of the HWSD values in the topsoil and 70% of the HWSD values in the subsoil.

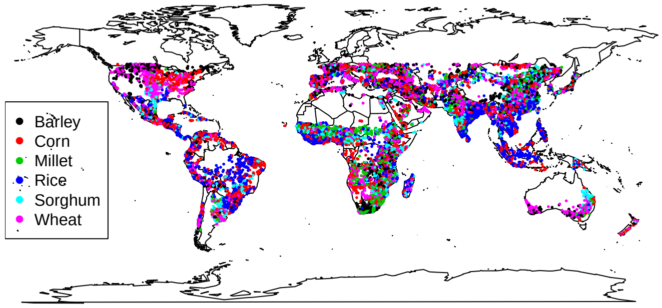
Finally, AquaCrop is initialized using measures of soil moisture at the beginning of the simulation. We use soil moisture from the NCEP/NCAR CDAS-1 dataset (Kalnay et al., 1996) at 0 to 10 cm and 10 to 200 cm.

1.2. **Weather Data.** The NCDC Global Surface Summary of Day station dataset (Husar et al., 1998) provides global coverage with 14 676 stations with particular density of stations in Western Europe, and Southeast Asia. These are nicely complemented by the Global Historical Climatology Network (GHCN) stations (Vose et al., 1992), which include over 30 000 stations, and have dense coverage in North America, eastern Europe, India, Brazil, and South Africa. We combine all of these stations to provide a clear representation of precipitation data.

Where no nearby station is available nearby, we use gridded reanalysis precipiation data. Precipitation data is provided by both TRMM 3B42 v6, starting Jan 1, 1988, and NCEP/NCAR CDAS-1 dataset from Jan 1, 1948. Station data is preferred to TRMM results if a station is closer than .25° latitude or longitude away, and less than an elevation difference of 38.5m. Station data is preferred to CDAS-1 results if a station is closer than 1° latitude or longitude away, and less than an elevation difference of 77m.

AquaCrop also relies on evapotranspiration data. The FAO GeoNetwork provides a monthly climatology evapotranspiration, prepared according to the FAO Penman-Monteith method (FAO, 2000).

1.3. **Management.** The most important management practices that are captured in process models are planting and harvesting dates, fertilizer application, and irrigation. All of these values are changing in time, but the datasets below are calibrated to the year 2000. Planting and harvesting dates, as well as harvested area by crop, are available at 5' resolution from Sacks et al. (2010). Manure and fertilizer application, in terms of nitrogen use, are avaiable from Potter et al. (2011) at a .5°. For generating model runs, we bin fertilizer into regions with application rates of 0 to 0.1 kg / Ha, 0.1 to 2 kg / Ha, 2 to 5 kg / Ha, 5 to 10 kg / Ha, 10 to 20 kg / Ha, 20 to 40 kg / Ha, 40 to 80 kg / Ha, 80 to 160 kg / Ha, and greater than 160kg / Ha. Fertilizer impacts are not calibrated for crop types in AquaCrop. Since nutrient limits in AquaCrop only result in a multiplicative change in yield, they are not used in that model. Finally, MIRCA2000 provides monthly portion irrigated vs. rainfed at 0.0833° resolution (Portmann et al., 2010). For constructing model



Crop	Locations	Countries
Barley	6611	91
Corn	8918	132
Millet	4199	85
Rice	8184	112
Sorghum	5184	115
Wheat	9497	103

FIGURE 1. **Left:** Simulation locations. The point drawing is randomized to give a sense of both density and range for each crop. **Right:** Summary statistics of simulation locations by crop.

runs, we allocate months as either irrigated or unirrigated, weighting each year collection to regenerate the total averages.

2. SIMULATIONS

We performed the tests using AquaCrop version 4.0 and DSSAT version 4.5. The following model configuration sets are used across all countries, as provided in the software packages:

Crop	**AquaCrop Model**	**DSSAT Model**
Barley	`Barley.CRO`	`BACER045.SPE`, IB0030 Maris Badger
Maize	`Maize.CRO`	`MZCER045.SPE`, IB0171 AG9010
Millet	`Tef.CRO`	`MLCER045.SPE`, IB0033 BJ104
Rice	`PaddyRice.CRO`	`RICER045.SPE`, IB0020 RD 23 (cal.)
Sorghum	`Sorghum.CRO`	`SGCER045.SPE`, IB0040 RS610
Wheat	`Wheat.CRO`	`WHCER045.SPE`, IB0488 NEWTON

The use of a single genotype across many geographic zones is explored in supplement 5.1.

Since crop process models simulate individual plots, we identify plots based on unique combinations of soil characteristics (HWSD soil type), irrigation (irrigated month schedule), and fertilizer management practices (binned nitrogen amount) within each country. We simulate yields for regions accounting for 90% of the planted area in each country. Field locations and summary statistics are shown in figure 1.

We simulate AquaCrop and DSSAT for each field location, with onlyweather conditions changing from year to year. In some cases, only either AquaCrop or DSSAT produces a valid result for a given field, due to their different input needs. We construct country-wide estimates of yields by taking an average of yields weighted by total planted area represented by the characteristics of that plot.

We then construct three stastical combinations of these estimates for comparison. The first statistical model, "Average", takes the average of the two estimates, on a country-wide basis. The second model, "Fitted", uses recorded country yields to estimate coefficients and an intercept for the two model results, according to,

$$y_{it} = \beta_{AquaCrop} y_{it}^{AquaCrop} + \beta_{DSSAT} y_{it}^{DSSAT} + \gamma_t + \epsilon_{it}$$

where y_{it} is the yield for country i in year t, and $\beta_{AquaCrop}$, β_{DSSAT} and γ_t (a year-specific intersept) are estimated by OLS. Finally, the third model, "Corrected", estimates generates yields using a series of estimated "corrections", each of which is a quadratic function of simulated yields specific to a country, soil type, irrigation schedule, or fertilizer quantity, as described in supplement 2.

We compare yields at a country-year level to recorded yields from FAO and the USDA Foreign Agricultural Service. The combination of both of these sources is described in supplement 1.

2.1. **Estimated and Recorded.** Table 2 shows the correlations for each combination of crop and model. The average model does not perform better in cases where the average correlation is negative. The corrected model out-performs all of the other models.

Crop	AquaCrop	DSSAT	Average	Fitted	Corrected
Barley	0.10	0.20	0.35	0.38	0.93
Maize	0.24	-0.19	0.22	0.25	0.90
Rice	-0.27	0.00	-0.13	0.26	0.85
Sorghum	0.14	-0.24	-0.02	0.36	0.86
Wheat	-0.15	0.05	-0.15	0.15	0.92

TABLE 2. Year-to-year correlations between modeled yields (combined as a weighted average) and country-wide recorded.

Figure 4 shows correlations by country, for each combination of crop and model.

AquaCrop performs well in northern latitudes, and particularly well with rice cultivation. However, Brazil and most of sub-Saharan Africa who low or negative correlation. Many of these are water stressed regions, where AquaCrop should do well.

DSSAT produces a wider variety of correlations at the field level than AquaCrop, but captures Africa almost as well as temperate regions. As management practice diverges from the year 2000 data, it seems to perform poorly with wheat, but well in most maize-growing regions.

The corrected method performs well in most regions on average, but as the management diverges from the year 2000 data, some regions perform very poorly. Within countries, the

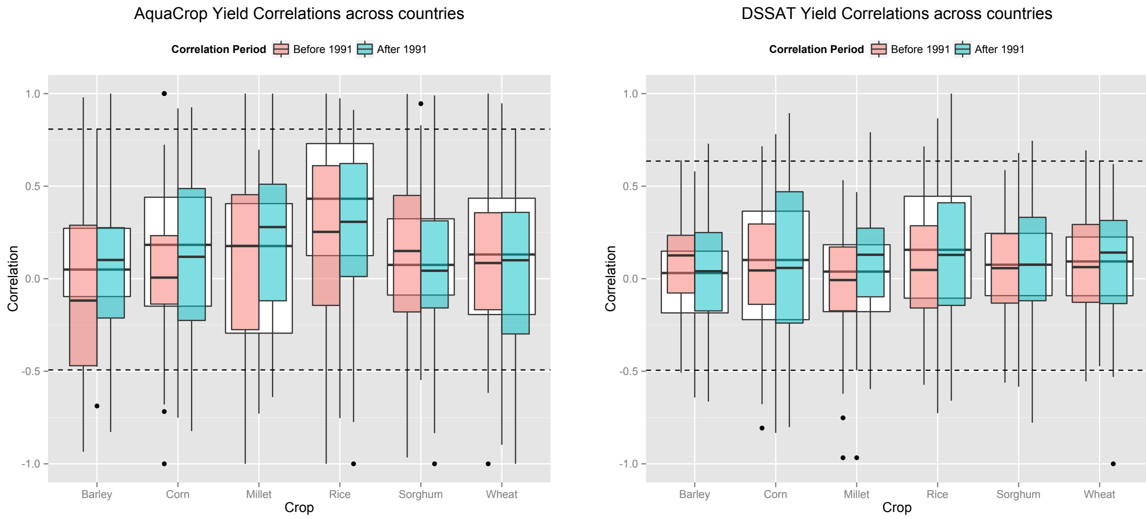


Figure 2. Correlations across countries and crops. Each box denotes the distribution of correlations across countries between predicted and recorded yields. White boxes include all years, while colored boxes are for 1970-1990 and 1991-2010. Horizontal lines show 90% confidence intervals across all correlations.

correlation is much more consistent for all fields within each country than for the field-based models.

2.2. **Explaining Variation.** We study the ability of four variables to explain the error observed.

Weather data quality: , using distance to the closest GHCN or GLOBALSOD weather station as a proxy.

Soil data quality: , using distance to the closest WISE soil profile as a proxy.

Weather variability: , using the average region size as a proxy.

Poor management data: , using the number of years before or after 2000, for which management data is provided.

We find that most error is explained only by unobserved features of the countries. Precipitation data quality is rarely a significant predictor of error and soil data quality is often inversely related to error (as our proxy for quality increases, error decreases). However, region size is almost always a significant predictor of error, suggesting that more locations are necessary to properly predict yields.

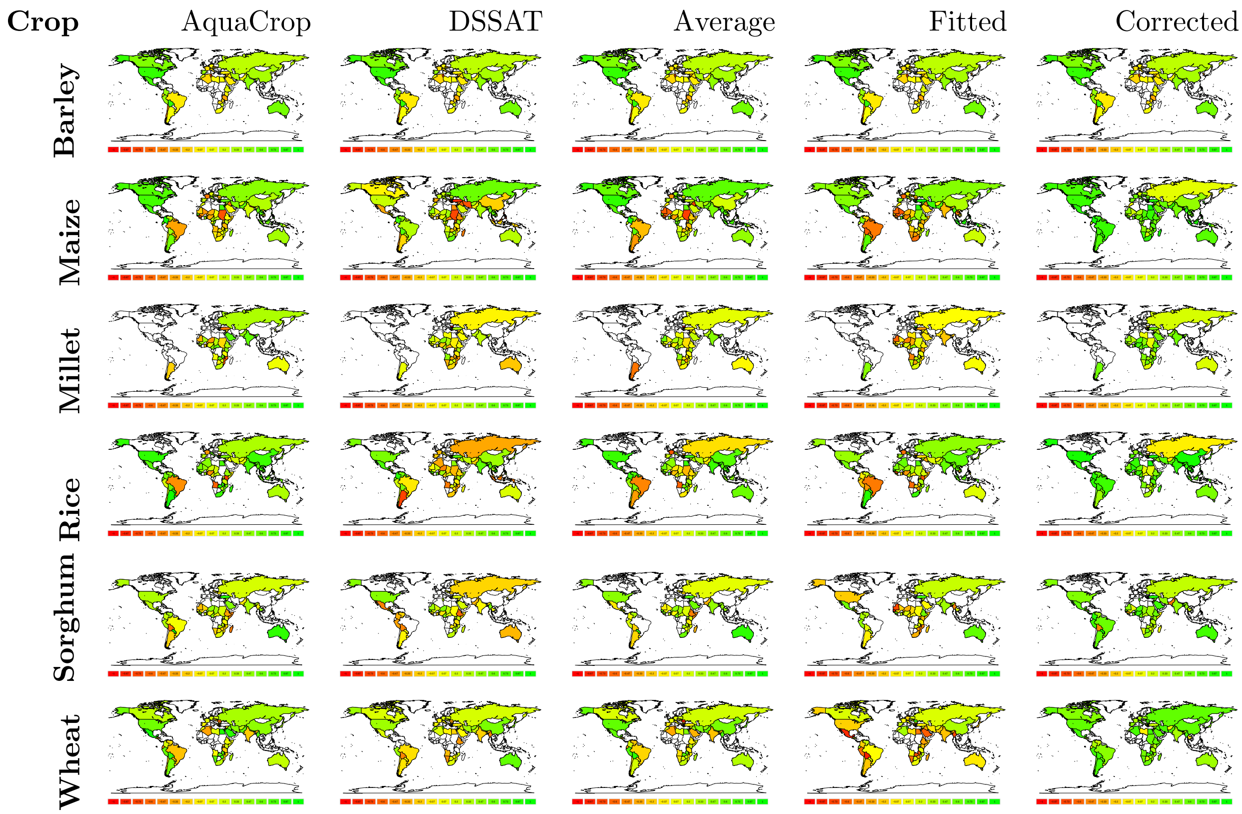


Figure 3. Correlations by country, for each combination of crop and model. Green denotes positive correlations, red denotes negative ones.

3. ENSO Terciles

We also quantify the ability of AquaCrop and DSSAT to simulate yields under past cycles of ENSO as a proxy for their performance under changes in climate.

We construct ENSO years using terciles of the ENSO 3.4 index. For years in each tercile, we calculate average yield, and the RMS error between observed country yields and simulated yields.

Recorded yields drop in both La Niña and El Niño years. This pattern is roughly reflected by AquaCrop and the Corrected model, but DSSAT has an increase of yields in La Niña years. The RMS errors are largest across all terciles for AquaCrop and smallest for DSSAT. However, both AquaCrop and DSSAT show largest errors for normal years, while this pattern is lost in the Corrected model.

	Barley	*Maize*	*Millet*
Region Count	$0.07\ (0.01)^{***}$	$0.41\ (0.33)$	$-0.01\ (0.01)$
Region Size	$0.00\ (0.00)^{***}$	$0.00\ (0.00)$	$0.00\ (0.00)$
Soil Distance	$0.19\ (0.09)^{*}$	$15.66\ (10.89)$	$-0.04\ (0.08)$
Precipitation Distance	$-0.13\ (0.11)$	$-0.05\ (0.10)$	$0.00\ (0.00)$
Year 2000 Difference	$0.08\ (0.02)^{***}$	$-0.14\ (0.05)^{**}$	$0.00\ (0.00)^{*}$
	Rice	*Sorghum*	*Wheat*
Region Count	$-0.02\ (0.01)^{*}$	$-0.19\ (0.06)^{**}$	$0.08\ (0.19)$
Region Size	$0.00\ (0.00)^{*}$	$0.00\ (0.00)$	$0.00\ (0.00)$
Soil Distance	$0.71\ (0.28)^{*}$	$-15.29\ (2.67)^{***}$	$-3.08\ (3.06)$
Precipitation Distance	$0.10\ (0.01)^{***}$	$0.06\ (0.08)$	$-0.07\ (0.06)$
Year 2000 Difference	$-0.01\ (0.01)$	$-0.03\ (0.04)$	$-0.10\ (0.03)^{**}$

(A) **AquaCrop Error Results:** Coefficients and standard errors ($^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$)

	Barley	*Maize*	*Millet*
Region Count	$-0.54\ (0.05)^{***}$	$0.50\ (0.06)^{***}$	$0.29\ (0.03)^{***}$
Region Size	$0.01\ (0.00)^{***}$	$0.00\ (0.00)^{***}$	$0.00\ (0.00)^{***}$
Soil Distance	$80.73\ (6.15)^{***}$	$-93.39\ (10.60)^{***}$	$-103.66\ (8.94)^{***}$
Precipitation Distance	$0.08\ (0.02)^{***}$	$-0.05\ (0.02)^{**}$	$0.02\ (0.01)^{*}$
Year 2000 Difference	$0.08\ (0.01)^{***}$	$-0.01\ (0.01)$	$-0.03\ (0.01)^{***}$
	Rice	*Sorghum*	*Wheat*
Region Count	$0.60\ (0.05)^{***}$	$0.09\ (0.04)$	$0.29\ (0.01)^{***}$
Region Size	$0.00\ (0.00)^{***}$	$0.00\ (0.00)^{*}$	$0.00\ (0.00)^{***}$
Soil Distance	$-118.89\ (10.05)^{***}$	$-35.50\ (17.61)^{*}$	$-161.21\ (6.83)^{***}$
Precipitation Distance	$0.01\ (0.01)$	$-0.01\ (0.03)$	$-0.02\ (0.01)$
Year 2000 Difference	$-0.01\ (0.01)^{*}$	$0.00\ (0.02)$	$0.09\ (0.01)^{***}$

(B) **DSSAT Error Results:** Coefficients and standard errors ($^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$)

	La Niña	Normal	El Niño	
Yield	−0.22%	0.75%	−0.31%	Recorded
	−0.8%	1.5%	0.2%	AquaCrop
	0.9%	0.3%	−2.1%	DSSAT
	−0.5%	0.4%	0.2%	Corrected
RMS	222%	228%	226%	AquaCrop
	26.7%	29.1%	27.5%	DSSAT
	77%	82%	83%	Corrected

TABLE 3. Globally, La Niña and El Niño years result in lower yields. AquaCrop and the corrected estimate roughly capture this change, but with huge relative RMS errors. DSSAT has much smaller errors, but shows an different ENSO signature. The large errors are expected, given the doubling of global yields of this period.

4. Future Work

The temperature data used in this study is notably weak. We use a low-resolution reanalysis product (CDAS-1). Future work could replace this with station temperature data or a higher resolution gridded dataset.

Currently only a monthly climatology is used for the evapotranspiration input for AquaCrop. The Penman-Monteith method provides a way to estimate evapotranspiration given temperature, humidity, solar radiation, and wind. Much of this data is available in gridded or station datasets.

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