Research Application Summary

Calibration and validation of AquaCrop model for maize in sub-humid and semi-arid regions of central highlands of Kenya

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Abstract

Farmers in the central highlands of Kenya have been experiencing declining crop yields due to low soil water availability caused by low and unreliable rainfall and poor water harvesting techniques. To increase crop yields, and reduce production risks, research on better use of available rainfall and the interactions between effects of climate, soil and field management on crop production is required. Simulation models, driven by daily climatic data, can be used to predict the impact of long-term climate variability on the probability of success of a range of crop, water and soil management strategies thus providing an opportunity of 'accelerated learning' compared with the traditional multi-location, multi-seasonal and multi-factorial field trials. We calibrated the crop water productivity model AquaCrop for maize and validated its performance over three growing season with contrasting rainfall patterns at a sub-humid and a semi-arid site in Central Kenya. The results showed high goodness of fit between observed and the simulated canopy cover with a model efficiency *(E)* of 0.82 in a sub-humid site and 0.81 in a semi-arid site. The grain and biomass yield simulation was better for the sub-humid site (E = 0.96 for short rains season and 0.88 for long rains season) than for the semi-arid site, though the fit was still acceptable for the latter. Soil water contents showed high correlations between the measured and the simulated values in 3 depth intervals (0-15, 15-25, 25-35 cm). AquaCrop's high reliability for the simulations of grain and biomass yield implies that, when properly calibrated, it can be used in developing strategies for improvement of field management decisions by small scale farmers in reducing crop production risks through ex-ante analyses of rainwater management and field operations options prior to implementation of the best bets.

Key words: AquaCrop, calibration, tropics

Résumé

Les agriculteurs de hauts plateaux du centre du Kenya ont connu une baisse des rendements des cultures due à la faible disponibilité en eau du sol causée par des pluies faibles et irrégulières et les mauvaises techniques de récolte de l'eau. Pour augmenter les rendements des cultures et réduire les risques de production, la recherche sur une meilleure utilisation des précipitations disponibles et les interactions entre les effets du climat, du sol et de gestion des champs sur la production agricole est nécessaire. Les modèles de simulation, conduits par les données climatiques journalières, peuvent être utilisés pour prédire l'impact de la variabilité à long terme du climat sur la probabilité du succès d'un ensemble de stratégies de gestion des cultures, de l'eau et du sol offrant ainsi la possibilité de «l'apprentissage accéléré» par rapport aux essais sur terrain multi-saisonniers, multi-factoriels et de multi-localisation traditionnels. Nous avons calibré le modèle de productivité de l'eau pour les cultures « AquaCrop » pour le maïs et validé sa performance sur trois saisons de croissance avec les modèles contrastants de pluviométrie sur un site sub-humide et un site semi-aride au centre du Kenya. Les résultats ont montré une grande concordance entre le couvert observé et le couvert simulé avec une efficacité du modèle (E) de 0,82 dans un site sub-humide et de 0,81 dans un site semi-aride. La simulation du rendement en grain et en biomasse était meilleure pour le site sub-humide (E = 0,96 pour la saison des courtes pluies et de 0,88 pour la saison des longues pluies) par rapport au site semi-aride, bien que l'ajustement était encore acceptable pour ce dernier. Les teneurs en eau du sol ont montré des fortes corrélations entre les valeurs mesurées et les valeurs simulées dans les 3 intervalles de profondeur (0-15, 15-25, 25-35 cm). Une grande fiabilité d' « AquaCrop » pour les simulations de rendement en grain et en biomasse implique que, lorsqu'il est correctement calibré, il peut être utilisé dans le développement des stratégies pour l'amélioration des décisions de gestion des champs par les petits agriculteurs dans la réduction des risques de production agricole à travers les analyses *ex-ante* de gestion des eaux de pluie et les options des opérations sur terrain préalables à la mise en œuvre des meilleurs enjeux.

Mots clés: AquaCrop, calibrage, tropiques

Background

In terms of the area under agricultural use and numbers of people sustaining their livelihoods from farming, the vast majority of smallholder farmers are found in tropical developing countries, often characterised by unreliable rainfall with recurrent floods, droughts and dry spells (Rockström, 2000). Per capita food availability in Sub-Saharan Africa (SSA), Kenya included, has declined over time, and the region suffers from the widespread food insecurity (Beintema and Stads, 2006). Apart from the fertility related factors, low water availability caused by low and/or erratic rainfall, low soil water holding capacity, poor/ lack of soil moisture conservation measures and excess runoff have been identified as serious constraints to agricultural productivity in this region. This corroborates the observation by UNESCO (2006) that agriculture sector faces a complex challenge: producing more food of better quality while using less water per unit of output; providing rural people with resources and opportunities to live a healthy and productive life; applying clean technologies that ensure environmental sustainability; and contributing in a productive way to the local and national economy. Furthermore, decisions by farmers on when to carryout various field management operations such as planting, weeding etc., given the erratic nature of rainfall, remain haphazard, as the basic understanding of the underlying mechanisms for successful crop production or failure coupled with erratic rainfall pattern in most tropical regions is weak. In order to increase crop yield and reduce crop production risks in the region, a focus on rainwater management options that target maximum retention of rain water within the root zone is required.

A host of management practices may be used to improve precipitation capture, reduce runoff and evaporation, and improve water use efficiency (Evett and Tolk, 2009). These management practices that increase infiltration and soil water holding capacity, and/or improve the ability of roots to extract more water from the soil profile could all potentially have positive impacts on agricultural water productivity. They also have a potential of mitigating rainfall fluctuations, and thereby increasing overall yield levels, stabilise yields over time and encourage the otherwise risk averse farmers to invest more in agriculture.

The most common way to test such options is through field experimentation/trials. Besides being expensive and time consuming, field experimentation is usually faced with many challenges such as high number of treatments, interaction effects and strong variations in treatment effects on crop yield spatially and temporally as a result of agro-climatic, field management and soil factors. In order to identify the options that lead to improved crop productivity and hence high returns to the farmers under prevailing set of circumstances requires repetition of such trials over several years or at several sites. This process is lengthy, time consuming and expensive. A less time and resource consuming alternative is the use of simulation models to predict the yield of different treatments for many growing seasons based on time series of meteorological data, soil physical and chemical properties, crop phenology and management characteristics. Simulation models, driven by daily climatic data, can be used to predict the impact of long-term climate variability on the probability of success of a range of crop, water and soil management strategies thus providing an opportunity of ‘accelerated learning’ compared with the more traditional multi-location, multi-seasonal and multi-factorial field trials (Twomlow *et al*., 2008). It can allow pre-evaluations of various options through a well-proven model to sharpen the field tests and to lower their overall costs (Whisler *et al*., 1986) and can also be used as decision support tools for system management. Optimum management practices, either strategic or tactic, such as planting date, cultivar selection, fertilization, or water and pesticides usage, can be assessed through proven models for making seasonal or within-season decisions (Boote *et al*., 1996). In other words, simulation allows easy investigation of management alternatives and the likely outcomes of choosing different management schemes (Evett and Tolk, 2009).

There are few crop growth models that have attempted to simulate crop growth under the contrasting environmental conditions as observed in the tropics (Gaiser *et al*., 2010). Given that no one universal model can exist in the field of agricultural science (Sinclair and Seligman, 1996), it is necessary to adapt system definition, simulated processes and model formalisations to specific environments or to new problems. This calls calibration for local climatic, soil and crop conditions using as minimum data as possible (Bhattacharya and Sastry, 1999). The objective of this study was therefore to calibrate the FAO water productivity model AquaCrop for maize and validate its performance under contrasting environmental conditions observed in the sub-humid and semi-arid climate of the tropics.

Methodology

Model description. AquaCrop simulates the attainable crop biomass and harvestable yield in response to the water available based on the relative yield versus relative water use paradigm (Steduto *et al*., 2009). AquaCrop allows to simulate a range of viable field management practices and facilitates decision making process both for researchers and the smallholder farmers. When well calibrated for a crop, the model is expected to be an effective tool even for novice users in aiding the development of water management strategies to improve production and save water (Hsiao *et al*., 2009). It allows rapid ex-ante analysis of complex combinations of soil, field management and climatic factors over time before evaluating the most promising combinations in the field. AquaCrop is based on Doorenbos and Kassam (1979) principles, where relative evapotranspiration is pivotal in calculating yield. It separates evapotranspiration into crop transpiration and soil evaporation, incorporating a simple canopy growth and senescence model as the basis for estimating transpiration and its separation from evaporation. Final yield is derived as a function of final biomass and the harvest index, while water stress effects are segregated into; canopy growth, canopy senescence, transpiration and harvest index (Steduto *et al*., 2009). The model strikes a balance between accuracy, simplicity, robustness, and ease of use, and is aimed at practical end users such as extension specialists, water managers, personnel of irrigation organizations, economists and policy specialists who use simple models for planning and scenario analysis (Hsiao *et al*., 2009).

Study Description

The field research was carried at two contrasting sites in Central Kenya (Fig. 1): Kiamaogo (add coordinates) in Tharaka Nithi County, Maara district, and Machang'a (add coordinates) in Embu County, Mbeere South district. The farmers in the region primarily rely on small-scale rainfed farming, which is mostly non-mechanized and involves little use of external inputs. Machang'a site lies at an altitude of 1106 metres a.s.l on the South-Eastern slopes of Mount Kenya in the Lower Midland Agro-ecological Zone 4 (LM4). Lower Midland 4 is a livestock-millet zone characterised by a short to very short cropping season. The zone is suitable for millet, common beans, cowpeas, mung beans, green grams, chick peas and dryland composite and hybrid maize varieties (Jaetzold *et al*., 2007). Mean annual temperature ranges from 20.7 to 22.5^{o}C with average annual rainfall ranging between 700 to 900 mm. The rainfall is bimodal with long rains (LR) from mid March to June and short rains (SR) from mid October to February, hence two cropping seasons per year. The soil of the experimental site is a Plinthic Cambisol (FAO and UNESCO, 1988). Although the area is more suitable for millet, cotton growing and livestock rearing (Jaetzold *et al*., 2007). The major crops grown by most households are maize (*Zea mays* L), cowpeas (*Vigna unguiculata*), pigeon peas (*Cajanus cajan*) and common beans (*Phaseolus vulgaris*).

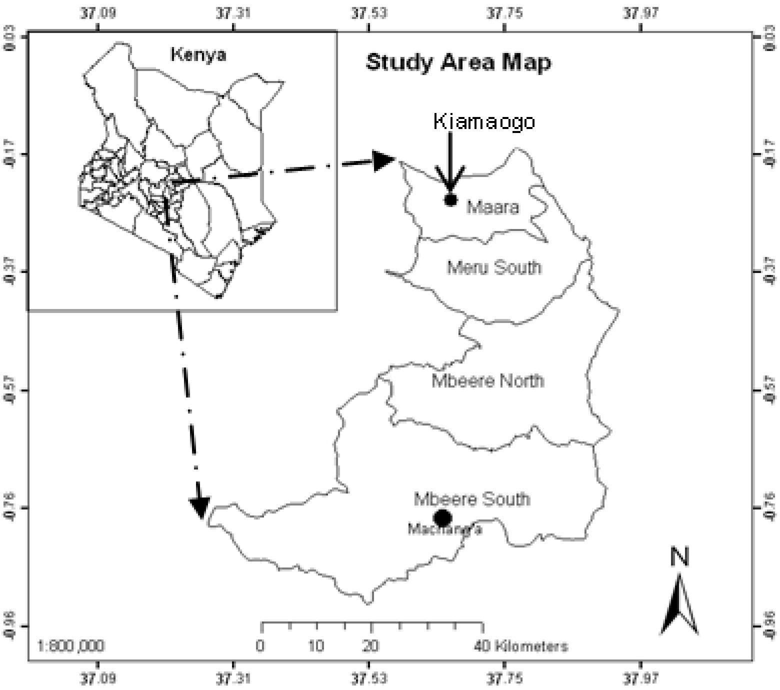

Figure 1. Location of the study sites.

Kiamaogo lies in the Upper Midland Agro-ecological Zone 3(UM3) on the eastern slopes of Mount Kenya at an altitude of 1500 m a.s.l. and has an annual mean temperature of 20^{o}C and total annual rainfall ranging from 1200 to 1400 mm. Major crops grown in UM3 are: beans (*Phaseolus vulgaris*), potatoes (*Solanum tuberosum*), sweet potatoes (*Ipomoea batatas*), cabbages (*Brassica oleracea*), kales (*Brassica oleracea*), tomatoes (*Solanum lycopersicum*), onions (*Allium cepa*) and maize (*Zea mays* L). The rainfall is bimodal with long rains (LR) from March to June and short rains (SR) from October to December. The soil type at the experimental field is a Humic Nitisol (FAO and UNESCO, 1988). It is a predominantly maize growing zone with smallholdings ranging from 0.1 to 2 ha with an average of 1.2 ha per household (Jaetzold *et al*., 2007).

Field trials. For the purpose of both model calibration and validation of AquaCrop, a field experiment with staggered planting dates was conducted at each site. Additional data were obtained from a water use efficiency (WUE) experiment carried side by side with the staggered planting trials during the same period. The staggered planting trial involved maize planting at three different dates for 3 consecutive seasons with the following treatments: 1) dry planting just before the rains and while the soils were dry, 2) wet planting after at least three days of continuous rain after onset or after a 20 mm storm, 3) late planting carried out 7 days after wet planting in Machang'a and 10 days after wet planting in Kiamaogo. Treatments were replicated thrice in a randomized complete block design, and plot size was 3 by 4 m for staggered planting and 6 by 4.5 for the WUE trial. Goat manure was spread before land preparation at a rate so as to supply 30 kg of the nitrogen per hectare, and incorporated during land preparation. Land preparation was done by hand hoeing to a depth of about 0.15 m. Inorganic fertilizers (NPK 23:23:0 and Triple Super Phosphate, TSP) were spot applied and thoroughly mixed with soil during planting at a rate of 60 kg N and 90 kg P ha^{-1}. Due to the difference in the agro-climatic conditions of the two sites, maize spacing varied. At Machang'a two seeds per hill per hill were planted with a spacing of 0.9 m between and 0.6 m within the rows giving a plant population of 37,037 ha^{-1}. In Kiamaogo two maize seeds per hill were planted with a spacing of 0.75 m between and 0.5 m within the rows resulting to a population density of 53,333 ha^{-1}. Weeding was done with a hoe when required to ensure clean fields throughout the seasons and pests were controlled when necessary following conventional best practices.

Measurements. Soil moisture contents were determined fortnightly using a Diviner 2000 capacitance sensor (Sentek Sensor Technologies, Stepney, South Australia) in a PVC access tube installed in the middle of selected representative plots. Crop parameters such as time from sowing to germination, full canopy cover, beginning and end of flowering and start of senescence, complete drying, and plant density at harvest were observed and recorded throughout the entire season. Other observations included maximum rooting depth (by observing root distribution in a profile pit) and plant population per hectare at planting based on spacing. Fraction of canopy cover was determined by taking digital photographs from pictures above the plants at midday for determination of canopy cover percentage. Above ground biomass yields were determined on dry weight basis after harvesting and sun drying until constant weight. Grain yield quantities were measured at 13.5% moisture content. Daily values of rainfall and minimum and maximum air temperature were recorded with an automatic weather station at each field.

AquaCrop Model Parameters

Climate data. The daily ETo was calculated with the Penman-Monteith equation as described in Allen *et al*. (1998), using the FAO ETo calculator (Version 3.1) with daily values of minimum, mean and maximum air temperature as inputs. The missing meteorological data were handled as follows; for wind speed, the ETo calculator default value for light to moderate winds was specified. The calculator handles missing humidity (e_a) data through estimation by assuming that the minimum air temperature (Tmin) is a good estimate for the mean dew point temperature (Tdew). For net radiation (R_n), an indicative default value of 0.16 for interior locations was chosen.

Soil data. Soil sampling was carried out horizon-wise from 0 to 1 m depth. Horizons were delineated based on homogeneity of colour, texture (feel method) and the general appearance. In the laboratory, soil texture (hydrometer method), organic carbon (Walkley black method) and Cation Exchange Capacity (CEC) were determined (Table 2) (Ryan *et al*., 2001). Saturated hydraulic conductivity and water content at saturation, field capacity and wilting point of individual soil horizons was estimated from soil texture and organic carbon content using pedo-transfer functions available in the hydraulic properties calculator (Saxton *et al*., 2006) (Table 1). For Machang'a, there was a restrictive plinthite at about 0.85 m depth and it was factored in the model's soil profile characteristics as a restrictive soil layer inhibiting root zone expansion at 0.8 m depth. Other model parameters were as follows: For Kiamaogo; Curve Number (CN) was 75, evaporable water from top layer (mm) was 10 mm, number of soil horizons were 4 and with no restrictive soil layer inhibiting root zone expansion. The fourth horizon was representative of the soil physical properties starting from 0.8 m and below (>0.8 m). For Machanga's site the CN was set to 85, evaporable water from top layer (mm) was 10 mm, the number of soil horizons were 5.

Crop data. The data used for calibration were from the 2009 long and short rains seasons of the staggered planting experiment in the two sites (Table 3). The two seasons were selected because of their unique attributes. The long rains season of 2009 was relatively dry while the short rains season was a wet and they both presented extreme agroclimatic scenarios. The staggered planting dates presented more possibilities and scenarios for simulation leading to enriched understanding of rainfall onset, planting date and rainfall cessation interactions and effect on both the observed and simulated yields.

Table 1. Hydraulic properties of the soils used as input to the AquaCrop Model.

Hor	Thickness (m)		Saturation (vol%)		Field capacity (vol%)		Wilting point (vol%)		K_{sat}[a] (mm/day)	
	Kiamaogo	Machang'a	Kiamaogo	Machang'a	Kiamaogo	Machang'a	Kiamaogo	Machang'a	Kiamaogo	Machang'a
1	0.2	0.14	51.6	42.1	42.5	32.7	29.5	21.9	44.4	50.4
2	0.2	0.14	52.7	45.1	43	39.4	29.3	27.5	53.3	11
3	0.4	0.3	46	45.2	36.2	40.5	18.3	28.7	66.5	6.2
4	1.5	0.22	46.2	45.5	36.5	35.8	18.5	18.3	64.8	64.3
5		0.2		39.3		21.3		13.4		129.5

[a] saturated hydraulic conductivity

Table 2. Soil texture and carbon content of the research sites.

Soil depth (m)		Carbon (%)		Sand (%)		Silt (%)		Clay (%)		Texture class	
Mach[a]	Kiam[b]	Mach	Kiam	Mach	Kiam	Mach	Kiam	Mach	Kiam	Mach	Kiam
0-0.14	0-0.2	0.5	1.1	52	14	12	36	36	50	SC[d]	C
0.14-0.28	0.2-0.4	0.3	0.5	42	4	12	20	46	76	C[e]	C
0.28-0.58	0.4-0.6	0.3	0.4	44	8	8	20	48	72	C	C
0.6-0.8	0.6-0.8	0.3	0.4	60	8	10	14	30	78	SCL[f]	C
0.80-1	0.8-1	0.3	0.8	68	6	10	16	22	78	SCL	C

[a] Kiamaogo site, [b] Machang'a site, [c] organic matter[d] sandy clay, [e] clay,[f] sandy clay loam.

Table 3. Conservative and calibrated user-specific crop parameters for maize in AquaCrop.

Conservative parameters (left unaltered)	Value	Units/Meaning
Base temperature	8.0	°C
Upper temperature	30.0	°C
Soil H_2O depletion factor, canopy expansion	0.02	Upper threshold (p-exp)
Soil H_2O depletion factor, canopy expansion	0.35	Lower threshold (p-exp)
Soil water depletion fraction for stomatal control	0.2	(*p* - sto) - Upper threshold
Soil water depletion factor for canopy senescence	0.3	(*p* - sen) - Upper threshold
Soil water depletion factor for pollination	0.8	(*p* - pol) - Upper threshold
Crop coefficient when canopy is complete (Kcb,x)	1.05	but prior to senescence
Coefficient of positive impact on HI	7.0	Vegetative growth
Coefficient of negative impact on HI	3.0	Stomatal closure
Allowable maximum increase of specified HI	15	%
H_2O productivity normalized for ETo & CO_2	33.7	gram/m^2 (WP*)
H_2O productivity normalized for ETo & CO_2 during yield formation	100	gram/m^2 (WP*)

User specific parameters (calibrated)	Kiamaogo	Machang'a	
Maximum effective rooting depth	0.85	0.80	(m)
Effect of canopy cover in late season	50	50	CC effect on soil evaporation
Soil surface covered by an individual seedling	6.5	6.5	At 90 % emergence (cm^2)
Number of plants per hectare	53,333	37,037	Ha^{-1}
Canopy growth coefficient (CGC):	0.1682	0.2213	per day CC increase
Maximum canopy cover (CCx)	0.88	0.89	(%) depends on plant spacing
Canopy decline coefficient (CDC):	0.1003	0.1169	per day CC decrease
Time from sowing to emergence	7	6	Calendar days
Time from sowing to maximum rooting depth	55	55	Calendar days
Time from sowing to start senescence	104	96	Calendar days
Time from sowing to maturity	130	107	Calendar days
Time from sowing to flowering	60	52	Calendar days
Length of the flowering stage	18	12	(days)
Building up of Harvest Index	65	50	From flowering (days)
Reference Harvest Index (HIo) (%)	48	48	%

The user-specific parameters and the general agronomic data and crop development were observed and recorded during the entire course of seasons. These included; planting dates, seedling emergence, duration of the various maize physiological periods from sowing date and harvesting dates (Table 3). Plant population was based on the recommended plant spacing for each site. Given that there were no obvious and significant maize variety differences recommended for each site in their growth and development, all varieties were treated uniformly within each site and differently between the two sites because of the differences in crop cycle lengths. Canopy cover development of the crop was monitored fortnightly by taking photographs and the shading effect/ground cover analysed using ERDAS imagine 9.1 image processing software. Percent shading was computed after image classification and the shaded proportion percentage was computed.

Statistical analysis. Model performance was evaluated using index of agreement (*d*) by Willmot (1984), root mean square error (RMSE) (Heng *et al*., 2009), the coefficient of efficiency (*E*) by Nash and Sutcliffe (1970) and the coefficient of determination (R^2). The RMSE (Eq. 1) represents a measure of the overall, or it is the mean value of O_i. mean, deviation between observed and simulated values, that is, a synthetic indicator of the absolute model uncertainty. It takes the same units of the variable being simulated. Values of mean residual and mean relative error close to zero indicate small differences between simulated and observed mean thus indicating little systematic deviation or bias in the entire data set hence the better the model's fit. Values of RMSE close to zero rather express precision and reliability of the simulation for observed estimation points.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \quad \text{.......................................} \quad (1)$$

where Si and Oi awerere the simulated and observed (measured) values as samples taken along the season (e.g., biomass and CC), or at the end of the season (e.g., grain yield), n is the number of observations, and O is the mean value of O_i

Efficiency *E* is defined as one minus the sum of the absolute squared differences between the predicted and observed values normalized by the variance of the observed values during the period under investigation. The range of *E* lies between 1.0 (perfect fit) and -∞. An efficiency of lower than zero indicates that the mean value of the observed would have been a better predictor than the model. The *E* (Equation. 2) expresses how much the overall deviation between observed and simulated values departs from the overall deviation between observed values (O_i) and their mean value ($\bar{O}$). The added value of this statistical indicator (*E*) as compared to RMSE, is in its ability to capture how well the model performs over the whole simulation span, for example, along the season. In other words, while RMSE does not distinguish between large deviations occurring in some part of the season and small deviations in other part of the season, *E* accounts for the different deviations, as they depart from (O_i –) along the season and expresses an efficiency of the model. The main weakness of *E* is due to the differences in the observed and simulated values are calculated as squared values leading to larger values being strongly overestimated while lower values are neglected

$$E = 1 - \left(\sum_{i=1}^{n}(O_i - S_i)^2 / \sum_{i=1}^{n}(O_i - \bar{O})^2\right) \quad \text{.......................... (2)}$$

To overcome the insensitivity of *E* and R^2 to differences in the observed and predicted means and variances index of agreement *d* (Willmot, 1981) was also determined (Equation 3)

$$d = 1 - \left(\sum_{i-1}^{n}(S_i - O_i)^2 / \sum_{i=1}^{n}\left(|S_i - \bar{O}| + |O_i - \bar{O}|\right)^2\right) \quad \text{......... (3)}$$

Coefficient of determination (R^2) estimates the combined dispersion against the single dispersion of the observed and simulated series. The range of R^2 lies between 0 and 1 which describes how much of the observed dispersion is explained by the simulation. A value of zero means no correlation at all whereas a value of 1 means that the dispersion of the simulated is equal to that of the observation. The fact that only the dispersion is quantified is one of the major drawbacks of R^2 if it is considered alone. A model which systematically over or under predicts all the time will still result in good R^2 values close to 1.0 even if all predictions were wrong (Equation 4) .

$$R^2 = \left(\sum_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S}) / \sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}\right)$$

.... (4)

AquaCrop calibration. The simulations were performed with AquaCrop version 3.1 Plus. We mainly focused on total biomass and grain yields, with some attention to canopy cover and soil moisture availability. Canopy cover development over time was considered in order to determine the initial canopy cover immediately after seedling emergence and the maximum canopy cover necessary as input parameters to the model. Further details on the nature of the experiments used on calibration are shown in Table 4, while canopy cover values are shown in Table 3.

The initial conservative parameters were chosen based on default values for the maize crop as calibrated by Hsiao *et al.* (2009). Soil fertility stress was not considered during simulation since blanket fertility management was applied throughout the experiments over the period under consideration. More focus was directed towards the water stress parameter. Through repeated simulation runs and output comparison (biomass and grain yields) of simulated versus observed yields, a set of values were arrived at for conservative parameters which seemed most appropriate and gave satisfactory results of situations and regions simulated (Table 3).

Model validation. For validation, data from two experiments were used (see the section on experiment descriptions). These experiments provided sufficient data especially due to the variations in planting dates and the replications in the two different agroclimatic regions were considered.

Results and Discussion

The results are presented and discussed by agroclimatic region/ sites (Kiamaogo and Machang'a). For each site, comparisons were made between simulated and measured values of the final grain and biomass yields, canopy cover and SWC at intervals over the growing season. For SWC, further analysis was carried out for the top 35 cm at three intervals of;0-0.15, 0.15-0.25 and 0.25-0.35 m depth (Table 5).

Canopy cover. The average observed CC plotted against the AquaCrop model simulation results under rain-fed conditions are shown in Figure 2. There was a remarkable match between the simulated and observed CC% in Machang'a with an *RMSE* of 14.28 CC%, *E* of 0.81, *d* of.99 and R^2 of 0.83 (Fig. 2a). Noticeable deviations between simulated and observed yields were at the beginning and at the end of the seasons. While 10.1% ground cover was observed 11 DAP, the AquaCrop simulated equivalence was 1% then. After about 25 DAP, AquaCrop simulation results still lagged by about 25.2 % behind the observed yields and it took the model considerable time to pick up at about 42 DAP. Observed yields peaked earlier attaining a higher maximum canopy cover of 88.5% compared to AquaCrop's 85 % by 53 DAP. Observed canopy senescence and its cover decline was slower and less for the observed compared to the simulated.

In Kiamaogo comparative analyses of the observed and simulated CC had an *RMSE* of 14.51 CC%, *E* of 0.82, *d* of.99 and R^2 of 0.81 (Fig. 2b). This highlights a comparatively good fit between the observed and the simulated results and the ability of AquaCrop to simulate canopy cover under sub-humid agroclimatic conditions. Generally, the simulated versus observed CC over time was comparable to that of Machang'a

Table 4. Field experiments for the calibration and validation of AquaCrop for maize at two contrasting sites in the Central Highlands of Kenya. The maize varieties in staggrered trial were H513, DH04, Pan 67, Duma 45 and DK3031 while for WUE trial it was H513 and DH04.

Year	Location	Experiment	Season	Sowing date	Season length	Rainfall (mm)
Calibration						
2009	Kiamaogo	Staggered	LR09	30th Mar	130	378
2009	Kiamaogo	Staggered	LR09	28th Mar	130	378
2009	Kiamaogo	Staggered	LR09	6th Apr	130	378
2009	Kiamaogo	Staggered	SR09	28th Oct	130	995
2009	Kiamaogo	Staggered	SR09	24th Oct	130	995
2009	Kiamaogo	Staggered	SR09	3rd Nov	130	995
2009	Machang'a	Staggered	LR09	28th Mar	107	208
2009	Machang'a	Staggered	LR09	12th Apr	107	208
2009	Machang'a	Staggered	LR09	21st Apr	107	208
2009	Machang'a	Staggered	SR09	6th Oct	107	482
2009	Machang'a	Staggered	SR09	21st Oct	107	482
2009	Machang'a	Staggered	SR09	30th Oct	107	482
Validation						
2010	Kiamaogo	Staggered	LR10	16th Mar	130	921
2010	Kiamaogo	Staggered	LR10	19th Mar	130	921
2010	Kiamaogo	Staggered	LR10	27th Mar	130	921
2010	Kiamaogo	Staggered	LR11	17th Mar	130	657
2010	Kiamaogo	Staggered	LR11	3rd Apr	130	657
2010	Kiamaogo	Staggered	LR11	24th Mar	130	657
2010	Kiamaogo	Staggered	SR10	30th Oct	130	347
2010	Kiamaogo	Staggered	SR10	1st Nov	130	347
2010	Kiamaogo	Staggered	SR10	7th Nov	130	347
2010	Machang'a	Staggered	LR10	25th Mar	107	469
2010	Machang'a	Staggered	LR10	22nd Mar	107	469
2010	Machang'a	Staggered	LR10	6th Apr	107	469
2010	Machang'a	Staggered	LR11	15th Mar	107	192
2010	Machang'a	Staggered	LR11	28th Apr	107	192
2010	Machang'a	Staggered	LR11	4th May	107	192
2010	Machang'a	Staggered	SR10	17th Oct	107	214
2010	Machang'a	Staggered	SR10	27th Oct	107	214
2010	Machang'a	Staggered	SR10	7th Nov	107	214
2009	Kiamaogo	WUE	LR09	31st Mar	130	378
2010	Kiamaogo	WUE	LR10	19th Mar	130	921
2011	Kiamaogo	WUE	LR11	24th Mar	130	657
2009	Kiamaogo	WUE	SR09	3rd Nov	130	995
2010	Kiamaogo	WUE	SR10	1st Nov	130	347
2009	Machang'a	WUE	LR09	28th Mar	107	208
2010	Machang'a	WUE	LR10	25th Mar	107	469
2011	Machang'a	WUE	LR11	4th May	107	192
2009	Machang'a	WUE	SR09	28th Oct	107	482
2010	Machang'a	WUE	SR10	21st Oct	107	214

Table 5. Goodness of fit analysis for the simulation of the soil water content (SWC) in 3 depth intervals with the calibrated AquaCrop model for Maize at Kiamaogo and Machang'a in three seasons.

Site	Season	RMSE (mm)	E	d	R
		0-0.15 m			
Kiamaogo	LR10	5.60	0.73	0.92	0.74
	LR11	5.52	0.50	0.87	0.70
	SR10	7.35	0.57	0.87	0.82
Machang'a	LR10	2.23	0.95	0.99	0.86
	LR11	6.38	-0.10	0.85	0.70
	SR10	3.18	0.81	0.96	0.83
		0.15-0.25 m			
Kiamaogo	LR10	6.40	0.38	0.87	0.69
	LR11	5.88	-0.01	0.80	0.61
	SR10	4.30	0.81	0.94	0.80
Machang'a	LR10	6.88	0.48	0.84	0.85
	LR11	12.54	-5.55	0.51	0.70
	SR10	9.32	-1.30	0.69	0.84
		0.25-0.35 m			
Kiamaogo	LR10	8.52	-0.24	0.77	0.74
	LR11	6.31	-0.84	0.75	0.75
	SR10	5.14	0.72	0.91	0.84
Machang'a	LR10	7.68	0.11	0.67	0.65
	LR11	14.10	-13.89	0.21	0.66
	SR10	13.29	-5.81	0.28	0.84

RMSE is the root mean squared error, E the Nash-Sutcliffe efficiency, d the Wilmot index of agreement, and R^2 is the coefficient of determination.

except that the time intervals between planting dates and the initial canopy development, maximum canopy and its duration and canopy senescence and decline was relatively longer (Fig. 2a). For instance, the maize crop attained 10.1% CC at 18 DAP while in Machang'a, the same was attained at 11 DAP. Another observation was at around 46 DAP when simulated surpassed the observed CC. Towards the end of the season, the observed versus the simulated difference was the highest compared to Machang'a site.

The observed lag by the model initially at Machang'a,s was probably due to the complex physiological interaction between the maize crop, the soil water content and the prevailing weather

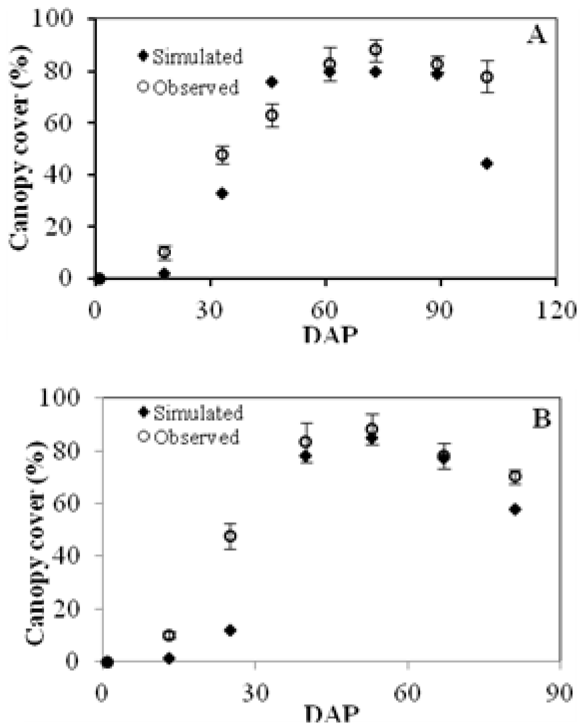

Figure 2. Observed and simulated canopy of maize as a function of days after planting (DAP) in the two study sites, Kiamaogo (A) and Machang'a (B) used for model calibration.

conditions which are probably not captured by the model. Based on the prevailing agro-ecological conditions of the region, the relatively high temperature influences the soil conditions. This might explain the early germination of maize and the vigorous growth and development when there was sufficient soil moisture. Kipkorir *et al*. (2009) explains such a scenario observed in their study as due to improved seedling vigour, resulting from a warmer seedbed, higher soil nitrogen levels and less water logging. Such external factors like soil and air temperature, though they affect crop growth, are not modelled since AquaCrop yet uses an empirical relationship.

The depressed CC growth observed in Kiamaogo was due to low water availability in the soil profile occasioned by prolonged dry speed during the period, given that leaf expansive growth is the most sensitive of plant processes to water stress and may be slowed when only a small fraction of the available water is depleted in the soil, that is, the upper threshold for the water stress coefficient of expansive growth (K_{sexp}) is reached at a low p value (Steduto *et al*., 2009). AquaCrop model did not capture the low water availability effect on the CC growth probably because it employs an exponential growth equation to simulate canopy development for the first half of the growth curve and the Ks and P values are conservative. Similar concerns of over-simplification have been be expressed regarding the stress response functions based on the fractional soil water depletion (p factors) by Hsiao *et al*. (2009). The approach employed by AquaCrop bypasses the process of root water uptake and transport to leaves, as well as the shoot water status, and instead links water stress in plant tissue directly to the total water content relative to the water holding capacity of the soil of the root zone.

The apparent lack of agreement between the simulated and observed CC towards the end of the season in both sites are explained by acceleration of canopy senescence occasioned by low water availability. Even though AquaCrop provides an option of improving canopy decline simulation through the growth period by adjusting CDC through water stress coefficient for acceleration of senescence (K_{ssen}). It calls for a compromise between better simulation of grain and biomass yields versus canopy development and duration. Green canopy cover and duration represent the source for transpiration and amount of water transpired translates into a proportional amount of biomass produced through water productivity relation in the conceptual equation at the core of the AquaCrop growth engine. In other words, the longer the canopy duration, the higher the harvestable portion of the biomass, and hence the grain yields, which is determined as Biomass × Harvest Index (Steduto *et al*., 2009).

Grain and biomass yield. Figure 3 (BL and BS) shows the 1:1 linear correlation graphs between observed and simulated of both dry final aboveground biomass and grain yields combined but separated into long and short rains seasons in Machang'a. Due to the low and erratic rainfall regimes in the region, crops failed in one of the two short rains seasons and two out of three during the long rains seasons and explains the zero values of grain yields in the graphs. The total biomasses were presented for all seasons. There was a good fit between the simulated aboveground biomass and grain yield agreed well with their corresponding observed data for all treatments during successful seasons. Long rains results had better fit (R^2=0.96) compared to short rains seasons (R^2=0.87). The wider spread of biomass yields in the short rains seasons was probably because of

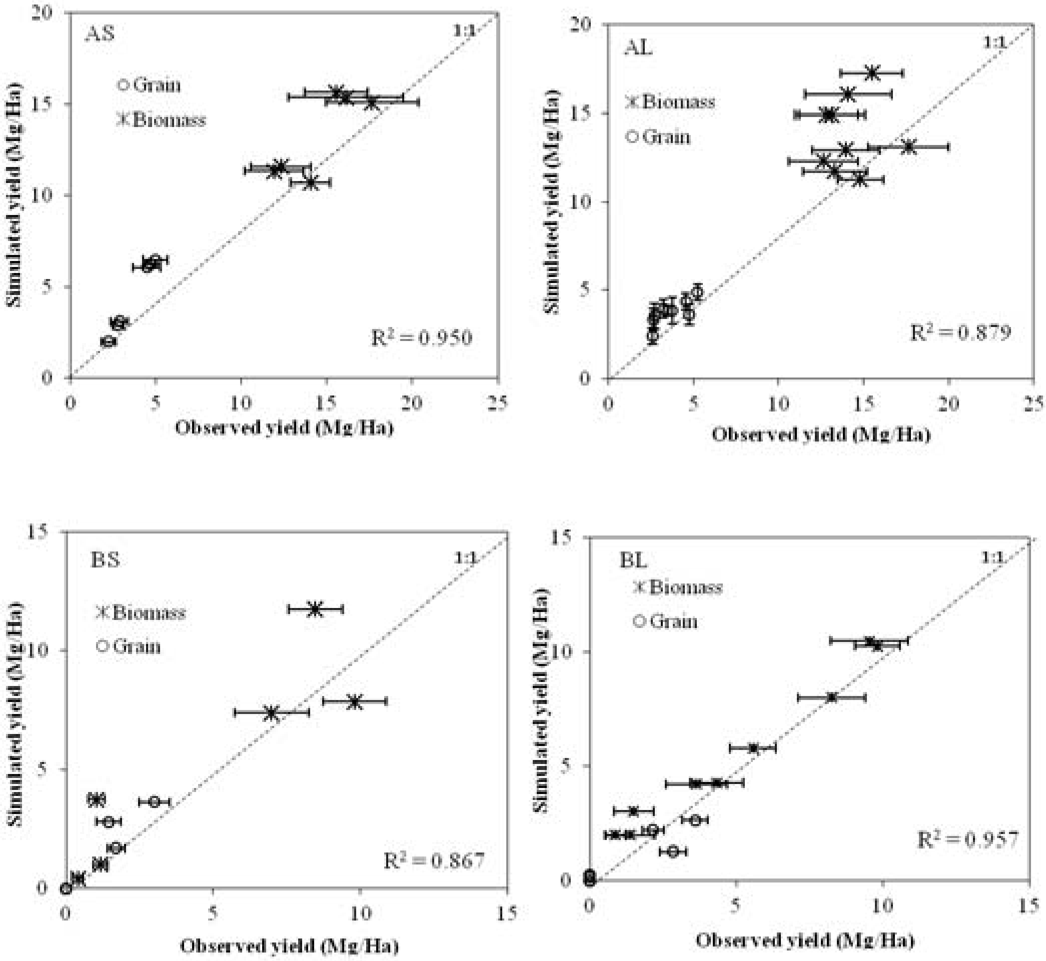

Figure 3. Simulated versus observed mean final dry aboveground biomass (asterisk like symbol) and grain yield (open circles) for Kiamaogo Long (AL, n=9) and short seasons (AS, n=6) and Machang'a Long (BL, n=9) and short seasons (BS, n=6) (— 1:1 line). R^2 are shown in individual graphs.

interaction between rainfall regime, soil physical properties and crop growth. The grain yields were slightly underestimated in the long rains season and the reverse was true for the short rains seasons.

The combined and observed and simulated aboveground biomass and grain yields of long and short rains seasons for Kiamaogo site are shown in Figure 3 (AL and AS) in a 1:1 linear correlation graphs. In the long rains season, AquaCrop grain yields simulation results were very close to the observed compared to the biomass yields. The seasonal variation was not apparent in both grains and biomass yields as there was no specific pattern or clustering of the scatter. Like in long rains seasons' results, grain yields were better simulated than the biomass during short rains season. Generally, the biomass yields were underestimated by AquaCrop compared to the observed. Comparatively, based on the combined R^2 for grain and biomass the model performed better during the short rains season than the long rains season. As observed in Table 1, the difference between the water content at permanent wilting point and field capacity of Machang'a's soils is narrow and hence relatively small variation in rainfall is bound to have bigger impact on the AWC. The simulation results confirmed the unique capability of AquaCrop in modelling under erratic rainfall regimens of rainfed agricultural production.

In the long rains season of Kiamaogo, observed variation in biomass yield can be attributed to other external factors prevailing under field conditions which are not captured by the model. These may include: farm operations such as weeding and the presence of weeds in the field which might have a direct bearing on water abstraction and the overall crop yield hence model performance. Heterogeneous soils and fertility dynamics in the field conditions cannot be easily controlled.

Just as observed by Hsiao *et al*. (2009), both seasons in Machang'a and the short rains seasons of Kiamaogo, the simulated biomass production tended to be higher than the measured values while in others they were low. This could have been the result of the using a constant water productivity (WP*) (Table 1) throughout the simulation exercise without alteration for different seasons. The WP* was not adjusted upward or downward given that it was considered as a conservatives parameter of AquaCrop. The decision was also informed by the findings of Hsiao *et al*. (2009) and Heng *et al*. (2009) who handled the WP* parameter in a similar way. There is also a chance of variation in WP* among maize varieties used.

Besides the use of constant WP* throughout the simulation, initial harvest index (HI) was set constant. Given the fact that the grain yields are derived directly as a factor from the total biomass yields, there is likely to be a compromise between over prediction or under-prediction of either grain yields or total biomass depending on the objective of simulation exercise. In this study, the focus leaned more on grain yields given its importance especially as a food and cash crop in the region. As observed by Todorovic *et al*. (2009) careful parameterization of crop growth parameters during the season might be particularly important in different agroclimatic scenarios of varying water stress conditions that should be examined for their peculiarity not only through a simple stress response function, based on the fractional soil water depletion, but also through the plant physiological responses that may vary during the crop development and growth. In turn, the intensity and duration of water stress could have different impacts on biomass growth and its partitioning into yield during each phase of the growing season (Todorovic *et al*., 2009).

Soil water content. The goodness of fit analysis of the SWC for the two sites are shown in Table 5. Given that soil moisture content was determined at 10 cm interval down to 1 m depth, it was possible to carry out comparative analysis of the simulated versus observed SWC. Due to the important role played by top 0.35 m of soil profile on crop growth and development, only this depth was considered in the analysis.

Generally, the simulated and observed goodness of fit based on different efficiency criteria SWC was high in 0-0.15 m depth followed by 0.15-0.25 m while 0.25-0.35 m was relatively low (Table 5). In the 0-0.15 m horizon, AquaCrop simulation results of LR10 were comparatively the best in both sites with an E of 0.73, d of 0.92 and R^2 of 0.74 in Kiamaogo site and in Machang'a the same season had an E, d and R^2 of 0.95, 0.99 and 0.86 respectively. In 0.15-0.25 m horizon, LR10, just like in upper horizon had a better fit between simulated and observed SWC compared to other seasons in Kiamaogo site while in Machang'a, SR10 seasons was the best (Table 5). In deeper profile under consideration, goodness of fit outcome between the seasons per site was directly the opposite of scenarios observed in the 0.15-0.25 m horizon (Table 5).

It is apparent that simulated and measured data agree rather well in all the horizons seasons and sites. The varied responses might be explained by the seasonal variation in the rainfall amounts and distributions (Table 4). The season of LR10 was particularly wet in both sites but the simulations results were good. This applied to all relatively wet seasons and especially for Kiamaogo site. In Machang'a, the goodness of fit was compromised by heterogeneity of soil physical and hence hydraulic properties within soil profile besides the dryer agroclimatic conditions in the region (Tables 1 and 2). It was also noted that, simulation results of SWC tended to be equal as the season progressed and soil moisture decreased in the profile. AquaCrop did not particularly segregate SWC based on planting time beyond the initial early periods of the season. Soil water content observed at a specific date tended to have no significant differences even though the planting dates were varied; hence it seems the model results rely more on crop parameters rather than the any other soil water dynamics beyond the *p* value.

The other reason especially for the observations in Machang'a site is the heterogeneity of K_{sat} within the different horizons in the soil (Table 1). This might have far reaching implications based on the assumption in AquaCrop that "the total drainage of the compartments above passes through the compartment below that has a drainage ability greater than or equal to that of the compartment above" (Raes *et al*., 2009), which might not necessarily be the case. By comparing drainage abilities and not water contents, the calculation procedure is independent of the soil layer, to which successive compartments may belong (Raes *et al*., 2009) but it might oversimplify the SWC of each horizon.

This might be the reason why most studies which have used AquaCrop in their studies keep the default settings for infiltration and drainage according to soil texture with no additional adjustment for the local soil. This is because the more critical testing of the model is for the water-limited conditions with very little prospect of runoff or drainage (Hsiao *et al*., 2009).

Conclusion

The underscores the potential use of calibrated AquaCrop model with a high degree of reliability in practical management, strategic planning estimation of yield production under varying climatic and agro-ecological conditions in the rainfed farming systems of the tropics. Its ability to utilize minimum and readily available data such as maximum and minimum temperature and rainfall and its user friendliness makes it a better choice as far as crop modelling is concerned. AquaCrop's high reliability for the simulations of grain and biomass yield implies that, when properly calibrated, it can be used in developing strategies for improvement of field management decisions by small scale farmers in reducing crop production risks through ex-ante analyses of rainwater management and field operations options prior to implementation of the best bets. As such, AquaCrop is recommended for applications under different agro-climatic conditions in the sub-Saharan Africa.

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