Chapter 1

Evaluation of the AquaCrop soil fertility management procedure

This chapter is based on:
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1.1 Introduction

Soil fertility exhaustion is widely acknowledged as a principal cause of low agricultural production in smallholder farming. The effects of soil fertility and the potential benefits of fertilizer application on crop production have traditionally been studied by means of experimental research. Unfortunately, field experiments tend to be laborious and time- and resource-consuming, and the results are often affected by the specific experimental set-up. For these reasons, present-day experimental research is often complemented with crop models, in order to study crop responses to soil fertility under various farming systems and environmental conditions (Myers, 2005). Crop models integrate different factors influencing crop production and contribute to the understanding of the interactions amongst these factors. Moreover, they enable very efficient long-term assessments to be made of numerous scenarios and fertility management strategies (Boote et al., 1996; Carberry et al., 2002) for both historical and future climatic conditions (Tubiello and Ewert, 2002).

Commonly used crop models, such as APSIM (Keating et al., 2003), CropSyst (Stöckle et al., 2003), DSSAT/CERES (Jones et al., 2003), STICS (Brisson et al., 2003) and WOFOST (Boogaard et al., 2014), typically make use of a nutrient-balance approach to consider the effects of soil fertility on crop production. Depending on the complexity of the model, environmental conditions, soil characteristics, the initial nutrient content of the soil, individual nutrient sources and their losses, and conversions of nutrients between different forms or ‘pools’ are taken into account in calculating the amounts of nutrients available to, or taken up by, the crop. In this way, crop productivity and growth processes can be related to the nutrient content of the soil, to nutrient uptake and to the nutrient content of specific plant organs. One of the disadvantages of such a detailed approach is the requirement for a vast input of data. Moreover, the nutrient-balances are mostly calculated for selected nutrients (often merely nitrogen), which are not always the nutrients that are the most limiting to crop growth and productivit(Probert and Keating, 2000; Probert, 2004; Brisson et al., 2003); in addition, the release of nutrients from organic fertilizers such as crop residues or manure is difficult to quantify but is nevertheless crucial for the estimation of the nutrient-balance (Probert and Dimes, 2004; Gijsman et al., 2002). Finally, the relationships between nutrients and crop production have mostly been developed for a specific crop type and hence the models are not widely applicable. These disadvantages clearly hamper the application of detailed, nutrient-balance-based crop models to smallholder farming systems in tropical and sub-tropical regions, where a wide variety of crops are grown (in rotation, or by intercropping), where organic fertilizers are the predominant soil fertility management strategy, and where other nutrients besides nitrogen (e.g. phosphorus) limit crop production (Delve et al., 2009; Whitbread et al., 2010).

An alternative to the nutrient-balance approach consists of modelling the effects of soil fertility on crop development and production in a semi-quantitative way. Such a semi-quantitative approach was implemented in AquaCrop (Hsiao et al., 2009; Steduto et al., 2009; Raes, 2009), the crop water productivity model developed by the Food and Agriculture Organization of the United Nations (FAO), and has been updated in the latest version, AquaCrop version 4.0 (Raes et al., 2012). In contrast to other models, nutrient cycles or balances are not considered explicitly in AquaCrop, but soil fertility stress is determined by its expected effects on crop biomass production. The calculation procedure does not distinguish between different nutrients and it is identical for all crops; only the calibration of the model is crop- and case-specific. Furthermore, AquaCrop integrates the effects of various production-limiting factors – including climatic factors, soil water stress, soil salinity stress and field management – with soil fertility stress. Within this integrated approach, between-stress interactions are taken into account, thereby allowing realistic yield simulations to be made.

In the present study, the semi-quantitative approach of AquaCrop (version 4.0) to the simulation of crop responses to soil fertility is described extensively for the first time and evaluated for different crops under diverse environmental and meteorological conditions. The study aims to evaluate the performance of AquaCrop’s fertility response algorithms in simulating not only final yield production, but also the soil water balance, canopy development, and dry above-ground biomass for various soil fertility levels, both in the presence and in the absence of soil water stress. By providing a reliable alternative to commonly used soil nutrient-balance approaches, the semi-quantitative approach will contribute to, rather than replace, the existing diversity of simulation approaches for crop responses to limited soil fertility. The semi-quantitative approach is particularly applicable in circumstances where detailed observations of soil nutrient conditions are unavailable.

1.2 Materials and methods

1.2.1 The semi-quantitative approach of AquaCrop

Instead of using a nutrient-balance, AquaCrop proposes a semi-quantitative assessment to determine the degree of stress that a crop experiences from nutrient deficiencies. This semi-quantitative measure corresponds to the maximum relative dry above-ground biomass (B_{rel}) that can be expected in a fertility-stressed environment with reference to stress-free conditions (Equation 1.1). B_{rel} ranges from 0%, corresponding to complete crop failure from nutrient deficiency, to 100%, indicating no nutrient stress.

$$B_{rel} = \frac{B_{stress}}{B_{ref}} \cdot 100 \tag{1.1}$$

where B_{rel} is the maximum relative dry above-ground biomass (%), B_{stress} is the total dry above-ground biomass at the end of the growing season in a field with soil fertility stress, and B_{ref} is the total dry above-ground biomass at the end of the growing season in a field without soil fertility stress. Both B_{stress} and B_{ref} are to be recorded in well watered fields (no soil water stress) and free of any other stress factors, such as weeds, pests, diseases and salinity.

Being a semi-quantitative input parameter, B_{rel} can be obtained easily. It is the maximum biomass that can be produced under the governing local conditions in a field that is only affected by soil fertility stress (the 'soil fertility stressed' field) in a good rainy year, or under irrigation when there is no water stress (B_{stress}). This biomass may be available from statistical reports or from indigenous farmer knowledge. The biomass is then expressed as a percentage of the biomass produced under stress-free conditions (B_{ref}), which can be obtained from nearby experimental fields, from published potential yields, or through the application of a full nutrient strip in one part of a farmer's field. In addition, model simulations can provide an estimation of the biomass for the local farming conditions under stress-free conditions (the 'reference' field).

When crop production is not affected by soil fertility stress, AquaCrop simulates crop productivity using a four-step process as discussed in Chapter 2 **??**.

First, green crop canopy cover (CC) is simulated. In a second step, crop transpiration (Tr) is simulated considering reference evapotranspiration (ET_0) and the simulated canopy cover. Next, crop transpiration is converted into dry above-ground biomass production (B). In a final step, crop biomass is converted to crop yield (Y) by means of the harvest index (HI). During this four-step simulation process, the model accounts for the effect of various abiotic stresses, including water stress, temperature stress, soil salinity stress and soil fertility stress (**??**).

In AquaCrop, the overall effect of soil fertility stress on crop production is simulated as the result of an integration of its effects on canopy cover development and biomass production. First, AquaCrop mimics the effect of soil fertility stress on the canopy cover, according to what can be observed in soil fertility stressed fields (Walburg et al., 1981; Albrizio and Steduto, 2005). For this reason, three adaptations to the canopy cover development are introduced (Figure 1.1): (i) reduced canopy expansion, and consequently slower canopy development; (ii) reduced CC_x, and hence a less dense canopy; and (iii) steady decline of the canopy cover once CC_x is reached at mid-season. Mimicking canopy cover development under soil fertility stress is a crucial feature of the semi-quantitative AquaCrop procedure because it enables a correct simulation to be made of transpiration and soil water balance. Secondly, based on observations from field experiments reported by Steduto and Albrizio (2005), the effect of soil fertility stress on daily biomass production is simulated by a reduction in WP^*. As the reservoir of soil nutrients gradually becomes depleted during crop development, the correction to WP^* gradually increases (therefore, WP^* itself is more strongly reduced) as more biomass is produced (Figure 1.2). This correction to WP^* was inspired by Geerts et al. (2008a) who reported, on the basis of experimental work with quinoa in the Bolivian Altiplano, that AquaCrop would more accurately represent the true situation if WP^* were reduced once a certain amount of biomass had been produced and nutrients had become limiting.

To simulate these four crop responses to soil fertility stress, AquaCrop uses four stress coefficients, i.e. for canopy expansion ($Ks_{exp,f}$), for maximum canopy cover (Ks_{CC_x}), for biomass water productivity (Ks_{WP}) and for canopy decline ($f_{CDecline}$). These stress coefficients range from 1 (no stress) to 0 (full stress). For every stress coefficient, a stress curve (Figure 1.3(a)) defines the relationship between the level of soil fertility stress and the reduction of the target crop parameter (canopy growth coefficient (cgc), CC_x, WP^* and CC, respectively) that is affected by soil fertility stress. The shape of the stress curve can be convex, concave or linear, according to the position of the curve's calibration point (Figure 1.3(a)). The calibration point is determined for each case through calibration of the parameters of the model. As mentioned above, even though the fertility stress simulation procedure is the same for different

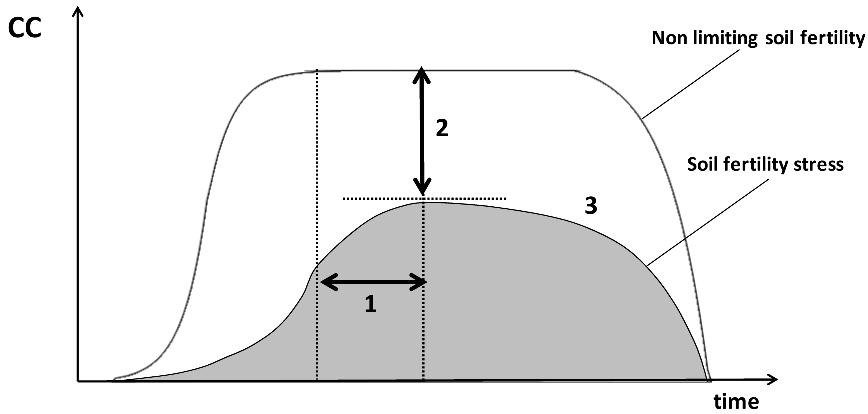

Figure 1.1: Soil fertility stress affects green canopy cover (CC) development by means of (1) a slower canopy development, (2) a less dense canopy and (3) a steady decline in canopy cover once the maximum is reached during mid-season.

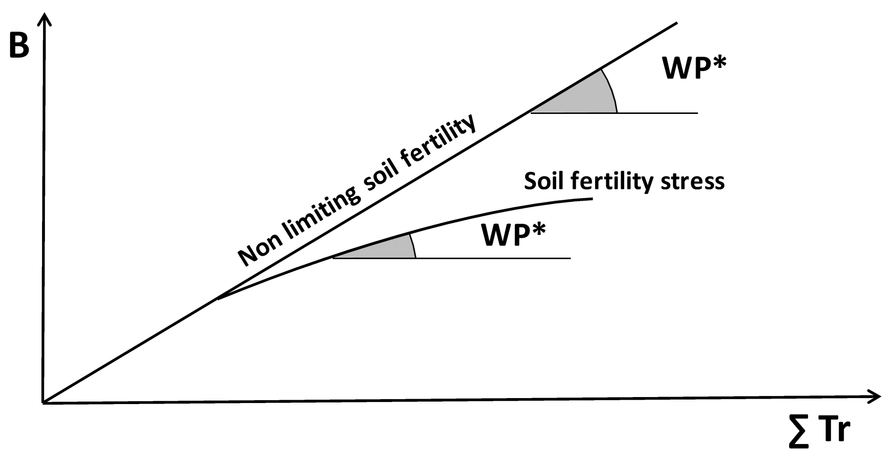

Figure 1.2: Soil fertility stress reduces biomass water productivity (WP^*) throughout the season as cumulative biomass (B) increases and the soil nutrient reservoir becomes depleted. The x-axis representing cumulative daily transpiration (ΣTr) could also been seen as an axis representing time.

crops, the crop response to soil fertility is specific to the crop type and to the environmental conditions under which the crop is cultivated, including climate and soil type. Therefore, the crop response to soil fertility stress cannot be described using conservative crop parameters (independent of location, crop cultivar or management practice) but requires calibration for each case.

To facilitate the calibration of the crop response to soil fertility stress, an automatic calibration procedure is incorporated in the latest AquaCrop software (version 4.0). This procedure requires field observations of CC_x and B_{rel} and a qualitative description of the observed canopy decline during the season for a 'soil fertility stressed' calibration field in comparison to a 'reference' field (no soil fertility stress). To avoid interference and interaction with other stress factors during calibration, both fields need to be free of soil water stress and salinity stress, as well as of diseases, weeds and pests. Based on the input of the field observations, the curves of the four soil fertility stress coefficients ($Ks_{exp,f}$, Ks_{CC_x}, Ks_{WP} and $f_{CDecline}$), i.e. the soil fertility stress relationships (Figure 1.3(a)), are automatically fixed by means of an iterative optimization algorithm. Next, the expected canopy development and reduction of biomass are calculated for every level of soil fertility stress between full stress and no stress, based on the four stress curves (Figure 1.3(a)) and assuming no water stress. This results in the determination of the relative biomass-soil fertility stress relation (Figure 1.3(b)). This relationship is not linear because (i) the shapes of the four stress curves are mostly non-linear, (ii) the shapes of the stress curves differ amongst the four stress coefficients, and (iii) the effect of soil fertility stress on WP^* increases when biomass increases. The AquaCrop reference manual version 4.0 (Raes et al., 2012) contains more information about the automatic calibration procedure.

Once the crop response to soil fertility stress is calibrated, crop production can be simulated for specified soil fertility levels under various environmental and management conditions. In order to perform a simulation, the user needs to specify the soil fertility level in terms of B_{rel} (ranging from 20 to 100%) or to select a class between 'non-limiting' and 'very poor' biomass production, which is linked to a default B_{rel} value. In the model, the user-specified input of B_{rel} is translated into a soil fertility stress level by means of the biomass – soil fertility stress relationship (Figure 1.3(b)). Next, this soil fertility stress level is linked to the corresponding stress coefficients so that the four target parameters are adapted accordingly. Additionally, AquaCrop accounts for other stresses affecting biomass production by making a dynamic adjustment of the soil fertility stress level at every time step. If, for example, soil water stress limits biomass production during time step i, the simulated B_{rel} during time step i will be lower than the B_{rel} that would be expected during that time step on the basis of soil fertility stress alone ($B_{rel,input}$). Consequently, AquaCrop will reduce the soil fertility stress during time step i+1 in such a way that

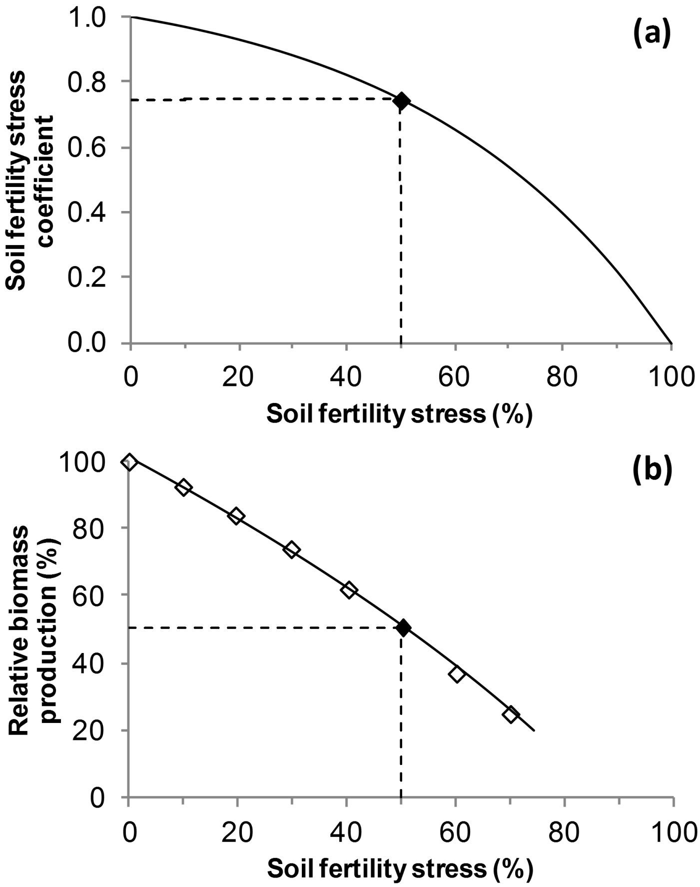

Figure 1.3: Four stress curves of the type shown in (a), which represent the relationships between soil fertility stress and the four soil fertility stress coefficients, determine the relationship between relative biomass production (B_{rel}) and soil fertility stress (b). The calibration point (black point) determines the shape of a stress curve.

$B_{rel,input}$ could theoretically still be reached at the end of the crop cycle. This dynamic adjustment is justified because it can be assumed that the limitation of biomass production during time step i leaves more nutrients in the soil.

1.2.2 Field experiments

The semi-quantitative AquaCrop approach was tested against: (i) three years of experimental data for fields of tef (*Eragrostis tef* (Zucc.) Trotter) in the drought-prone degraded highlands of Tigray in northern Ethiopia, (ii) two years of experimental data for fields of maize (*Zea mays* L.) and wheat (*Triticum aestivum* L.) in the humid plains of the central Terai in Nepal, and (iii) two years of experimental data for fields of quinoa (*Chenopodium quinoa* Willd.) in the semi-arid Bolivian Altiplano. Table 1.1 presents a summary of the environmental conditions at the experimental sites. All experiments were set up with a (factorial) randomized complete block design, with the water treatment as main factor and the soil fertility treatment as sub-factor (Table 1.1). In rainfed (RF) and deficit irrigated (DI) treatments, some degree of water stress was apparent, whereas in the fully irrigated (IR) treatment crops were maintained free of any water stress. Fertility treatments corresponded to applications of 0% (T0), 50% (T50), 100% (T100) and 150% (T150) of the (national) recommended fertilizer dose (see Table 1.1 for local recommendations). At all the experimental sites, the plots were regularly weeded and kept free from pests and diseases throughout the growing season. The following information was recorded: local daily weather data, soil water content in the root zone, the soil texture and physical characteristics, irrigation applications, fertilizer applications, crop development (green canopy cover development, monitored by overhead digital photographs), crop phenology (time of sowing, emergence, CC_x, flowering, senescence and maturity), effective rooting depth, intermediate and the final dry above-ground biomass, and the final grain yield. More detailed information on the set-up and data collection for the field experiments is described by Tsegay et al. (2012) for Ethiopia, by Shrestha et al. (2013a) for Nepal, and by Geerts et al. (2008b) for Bolivia.

Table 1.1: Three experimental sites with the experimental set up and environmental conditions (average climatic conditions according to New_LocClim (FAO, 2005)). Experiments were set up with a randomized complete block design (RCBD) or a factorial randomized complete block design (FRCBD). Water treatments consist of rainfed (RF), deficit irrigation (DI) and full irrigation (IR). Fertility treatments correspond to application of 0% (T0), 50% (T50), 100% (T100) and 150% (T150) of the (national) recommended fertilizer dose.

Experimental site	**Dejen**	**Maiquiha**	**Chitwan**	**Patacamaya**
Country	Ethiopia	Ethiopia	Nepal	Bolivia
Coordinates	13°20' N, 39°22' E	13°48' N, 39°27' E	27°36' N, 84°24' E	17°14' S, 67°55' W
Altitude (m a.s.l.)	2128	2078	160	3793
Environmental conditions				
Soil type	Loam, silty loam, sandy loam	Silty loam	Sandy loam	Silty loam
Aridity	Semi-arid	Semi-arid	Humid	Semi-arid
Mean annual rainfall (mm)	620	620	1870	403
Mean annual ET0 (mm)	1497	1497	1219	1208
Experimental set up				
Years	2008-2010	2009	2009-2011	2006/07 2009/10
Number of seasons	3	1	2	2
Design	FRCBD	FRCBD	RCBD/ FRCBD	FRCBD
Crops	tef	tef	wheat, maize	quinoa
Water treatments	RF, IR	RF, IR	RF, DI, IR	RF, DI, IR
Fertility treatments	T0, T50, T100*	T0, T50, T100*	T0, T100, T150*	T0, T50, T100*

* T0, T50, T100, T150: Application of 0%, 50%, 100% and 150% of the (national) recommended fertilizer dose

T100 tef: 60 kg/ha N and 26 kg/ha P on heavy soils and 40 kg/ha N and 26 kg/ha P on light soil (Ethiopian Agricultural Research Organization (EARO), 2002)

T100 maize: 120 kg/ha N, 60 kg/ha P, 40 kg/ha K (Ministry Of Agriculture and Co-operatives (MOAC), 2010)

T100 wheat: 100 kg/ha N, 50 kg/ha P, 25 kg/ha K (Ministry Of Agriculture and Co-operatives (MOAC), 2010)

T100 quinoa: 30 Mg/ha organic fertilizer (sheep manure) (Miranda et al., 2012)

1.2.3 Calibration and evaluation of the semi-quantitative AquaCrop procedure

As a starting point for the calibration of crop responses to soil fertility stress, the default crop parameters of AquaCrop version 4.0 (Raes et al., 2012) were used for all four crops. The non-conservative cultivar-specific crop parameters, describing the crop phenology, were fine-tuned to match the local cultivar and environmental conditions. The resulting crop files described canopy development, biomass production and yield under both optimal agronomic conditions and water stress, but not at this stage the crop responses to soil fertility stress.

The crop response to soil fertility stress was calibrated based on field observations during the rainy season of 2010 for tef, during the dry season of 2010/11 for maize and wheat, and during the growing season of 2009/10 for quinoa. Tef was only calibrated for one of the experimental sites (Dejen), because it was assumed that the soil fertility and environmental conditions for both sites would be similar, and that the crop would therefore respond identically to soil fertility stress at both sites. In the automatic calibration procedure (Table 1.2), observations of canopy cover development and of biomass for plots not experiencing water stress but undergoing full soil fertility stress (IR-T0) were compared to observations for plots undergoing neither water stress nor fertility stress (IR-T100 for Ethiopia and Bolivia and IR-T150 for Nepal). For the tef and quinoa experiments, the (national) recommended fertilizer dose (T100) was taken as the 'reference', because the T100 treatment relieved crops from fertility stress. In contrast, T100 cannot represent non-limiting soil fertility for the maize and wheat experiments in Nepal, because production increases for maize and wheat were observed with fertilizer doses that exceeded the national recommended dose. For this reason, T150 was used as the reference for the calibration of the maize and wheat responses to soil fertility stress in Nepal.

The calibrated crop response to soil fertility stress for each crop (Table 1.2) was evaluated with the remaining, independent field datasets covering the different experimental sites (for tef), the different growing seasons, and the various water and fertility treatments. The observed B_{rel} for the non-water stressed treatments was used as input, but no alterations to the calibrated crop responses (Table 1.2) were made; thus the biomass – soil fertility stress relation (Figure 1.3(b)) was applied as described in the calculation procedure above. For both calibration and evaluation, the environmental conditions at the experimental sites were used as the inputs for the AquaCrop model. The fit between the observed and simulated soil water content, canopy cover, biomass and yield was assessed by a combination of graphical displays (plots of simulated versus observed values) and three statistical indicators presented in Box **??**: R^2, RRMSE and EF. Model performance was qualified based on

Table 1.2: The relative dry above-ground biomass production (B_{rel}), maximum canopy cover (CC_x) and canopy decline in the season as observed for the soil fertility stressed calibration plots (IR-T0) of tef, maize, wheat and quinoa together with the resulting calibrated local effect of soil fertility stress on canopy development (canopy growth coefficient cgc, CC_x, canopy decline) and biomass water productivity (WP^*).

Crop		Tef	Maize	Wheat	Quinoa
Calibration location		Dejen	Chitwan	Chitwan	Patacamaya
Input for calibration					
B_{rel}	(%)	66	53	44	50
CC_x under soil fertility stress	(%)	66	52	50	44
Canopy decline	(-)	medium	medium	medium	medium
Results of calibration					
cgc reduction	(%)	15	15	39	36
CC_x reduction	(%)	19	31	44	41
Average canopy decline	(%/day)	0.78	0.85	0.28	0.19
WP^* reduction	(%)	19	31	50	19

RRMSE values following Jamieson et al. (1991). Special attention was paid to the performance of the model under conditions in which soil water stress coincided with soil fertility stress. For this purpose, the performance of the model was also evaluated using only the RF and DI plots.

1.3 Results

This section discusses the performance of the model in simulating crop responses to soil fertility stress, with a focus on the RRMSE values because they give a clear indication of the mean deviation of the simulation results obtained using the model, compared to the actual observations. Additionally, Table 1.3 (calibration) and Table 1.4 (evaluation) present the R^2 and EF values.

1.3.1 Calibration of the crop responses to soil fertility stress

Crops were calibrated for different local soil fertility stress conditions (Table 1.2). Soil fertility stress in the calibration fields was the highest for wheat (B_{rel} 44%) and the lowest for tef (B_{rel} 66%), with maize and quinoa being intermediate (B_{rel} 50-53%). The calibration results (Table 1.2) clearly show how the four crops in their specific environments responded very differently to the local nutrient limitations. For example, a soil fertility level B_{rel} of about 50% resulted in a greater reduction in WP^* and in canopy decline in maize than in quinoa. By contrast, the reduction in crop development and CC_x was greater in quinoa than in maize. The calibrated effect of soil fertility on CC and WP^* (Table 1.2) resulted in an acceptable simulation of SWC_r and of the overall development of CC and B throughout the crop cycle for the soil fertility stressed calibration plots (IR-T0) (Table 1.3). The model performed excellent in simulating SWC_r with RRMSE values below 10% for all crops. For CC and B, the model performance was more variable, with RRMSE values mostly above 10%. The model predicted CC with a mean deviation of about 16% for tef, but the deviation increased to 20-24% for wheat and maize. CC predictions could not be evaluated for quinoa, due to a lack of observations. With a RRMSE value of about 9%, the best prediction of B was obtained for maize, followed by tef and wheat, for which RRMSE values were 12 and 14% respectively. For quinoa, B was predicted with a RRMSE value of about 25%. Generally, the model calibration was most accurate (based on the RRMSE values for SWC_r, CC and B) for maize and tef, followed by wheat and quinoa.

Table 1.3: Relative root-mean-square error (RRMSE), Nash-Sutcliffe model efficiency (EF) and coefficient of determination (R^2) for n number of observationss of the soil water content in the root zone, canopy cover and dry above-ground biomass during the growing season of the soil fertility stressed calibration plots (IR-T0).

Parameter			Tef	Maize	Wheat	Quinoa
Soil water content	n	(-)	15	5	8	5
	RRMSE	(%)	5.6	2.6	6.7	9.6
	EF	(-)	0.74	0.85	0.81	0.97
	R^2	(-)	0.75	0.99	0.87	0.98
Canopy cover	n	(-)	12	6	9	-
	RRMSE	(%)	15.8	23.5	20.1	-
	EF	(-)	0.94	0.81	0.76	-
	R^2	(-)	0.97	0.91	0.87	-
B season	n	(-)	8	6	8	11
	RRMSE	(%)	11.9	9.3	14.2	25.2
	EF	(-)	0.94	0.98	0.94	0.92
	R^2	(-)	0.96	1	0.95	0.97

1.3.2 Evaluation of crop responses to soil fertility stress

The calibrated model performed well in simulating SWC_r, CC, B and Y for the remaining independent evaluation plots under different soil water stress levels (IR, DI and RF) and soil fertility stress levels (T0, T50 and T100 (only for Nepal)) (Table 1.4). The performance of the model in its simulation of CC was variable, with a RRMSE as high as 34% for maize, although lower

RRMSE values were obtained both for tef (23%) and for wheat (12%). For maize, this was probably a reflection of the relatively poor CC calibration (Table 1.3), whereas for wheat it reflected the good CC calibration. Despite the CC predictions, SWC_r was the most accurately predicted of all the parameters, with RRMSE values of between 6 and 13%. Together, the accuracy of the simulations of CC and SWC_r and the corresponding soil water stress levels determined the accuracy of prediction of B during the growing season and at maturity. Figure 1.4 illustrates that the effect of different soil fertility stress levels on the development of CC and B in a well-watered wheat field was well described by AquaCrop. The AquaCrop simulations clearly captured the slow canopy development, lower CC_x, early canopy decline and lower biomass production under different soil fertility levels as they were observed in the field. The development of B during the season, as well as the final value of B, was predicted most accurately for wheat, followed by maize; the final value of B was predicted with a RRMSE of only 4% for wheat, and of 12% for maize. For quinoa and tef, the mean deviations for the final B predictions were 18 and 24%, respectively. Finally, Y was one of the most accurately predicted parameters, second only to SWC_r. For maize, the prediction of yield was excellent, with a RRSME of only 7%. With RRMSE values of 10% for wheat, 16% for quinoa and 19% for tef, the model resulted in good final Y predictions for all crops. This is also illustrated in Fig. 5. In general, the model performed most accurately (based on the RRMSE values) for maize (for which it produced the best predictions for Y and SWC_r) and wheat (for which it produced the best predictions for B and CC), followed by quinoa and by tef.

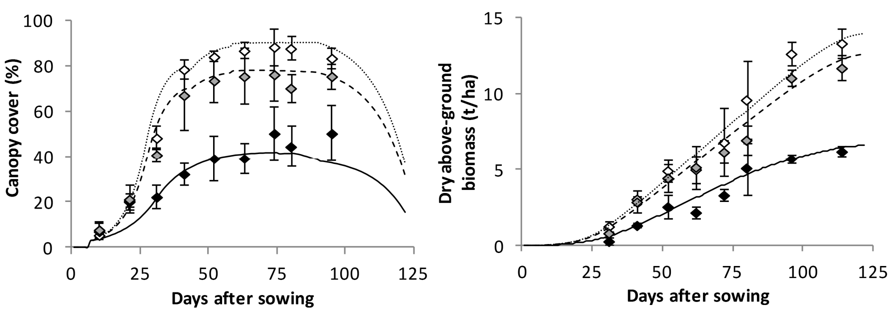

Figure 1.4: Simulated (lines) and observed (symbols) canopy cover (left) and dry above-ground biomass (right) of irrigated wheat in Chitwan during the season of 2010/11. Canopy development and biomass build-up are affected by the soil fertility level: non-limiting soil fertility T150 (dotted line, open symbol), full soil fertility stress T0 (full line, black symbol), and fertility treatment with 100% of the national recommended fertilizer dose T100 (dashed line, grey symbol). Error bars indicate ± standard deviation for three replications (n=3).

Table 1.4: Relative root-mean-square error (RRMSE), Nash-Sutcliffe model efficiency (EF) and coefficient of determination (R^2) for n number of observations of the soil water content in the root zone, canopy cover, dry above-ground biomass (B) during the season and at phenological maturity and the final grain yield of the evaluation plots with soil fertility stress (T0 and T50 for tef and quinoa, T0 and T100 for maize and wheat). The left-hand statistics include all water treatments (RF, DI and IR), while the right-hand statistics only include the plots with water stress (RF and DI).

			All water treatments (RF, DI, IR)				Water stressed treatments (RF, DI)			
Variable			Tef	Maize	Wheat	Quinoa	Tef	Maize	Wheat	Quinoa
Soil water content	n	(-)	189	39	60	15	98	26	40	10
	RRMSE	(%)	11	5.8	9.4	13.3	12.2	6.5	10.1	16.5
	EF	(-)	0.9	0.89	0.64	0.93	0.9	0.88	0.63	0.89
	R^2	(-)	0.9	0.89	0.9	0.93	0.9	0.91	0.91	0.89
Canopy cover	n	(-)	131	42	60	-	65	28	49	-
	RRMSE	(%)	22.7	34.2	6.7	-	26.8	38.1	12	-
	EF	(-)	0.9	0.74	0.93	-	0.89	0.68	0.93	-
	R^2	(-)	0.92	0.82	0.95	-	0.91	0.82	0.95	-
B season	n	(-)	96	39	51	43	50	26	34	30
	RRMSE	(%)	19.6	15.9	13.1	22.4	19.2	18.2	14.6	22.6
	EF	(-)	0.86	0.96	0.96	0.93	0.77	0.95	0.95	0.91
	R^2	(-)	0.88	0.97	0.96	0.95	0.87	0.96	0.95	0.95
B at maturity	n	(-)	15	6	6	13	8	4	4	10
	RRMSE	(%)	23.6	11.8	3.9	18.3	19.6	13.3	3.5	15.2
	EF	(-)	0.71	0.83	0.96	0.76	0.25	0.79	0.97	0.69
	R^2	(-)	0.77	0.95	0.96	0.91	0.82	0.97	0.98	0.87
Yield	n	(-)	15	6	6	13	8	4	4	10
	RRMSE	(%)	19.1	7.2	10.3	16.3	34	10.7	11.9	13
	EF	(-)	0.84	0.97	0.74	0.71	-0.5	0.96	0.73	0.84
	R^2	(-)	0.85	0.99	0.77	0.81	0.21	0.99	0.93	0.86

1.3.3 Performance of the model under combined soil fertility stress and water stress

When both soil fertility stress and water stress were prevalent, AquaCrop was still able to predict the evolution of SWC_r (Figure 1.6), CC (Figure 1.7) and B (Figure 1.8) accurately during the growing season. The statistics for the water stressed plots only (DI and RF) in Table 1.4 show that the fit is approximately as good as when all the water treatments (IR, DI and RF) are included. Compared to the evaluation for all the water treatments, the RRMSE values increased by only 0.7-3.2% for SWC_r, 0.1-4% for CC, and 0.2-2.3% for B, for the water stressed plots alone. For B, in the cases of tef and quinoa, the performance of the model at maturity was even better when only the water stressed conditions were taken into account (RRMSE decreased by 3-4%). The model predicted Y under combined water stress and soil fertility stress with a RRMSE of between 11 and 13% for maize, wheat and quinoa. The deviation only increased by 1.6% (wheat) and by 3.5% (maize), and for quinoa it even decreased (by about 3%). For tef, on the other hand, the predictions of Y

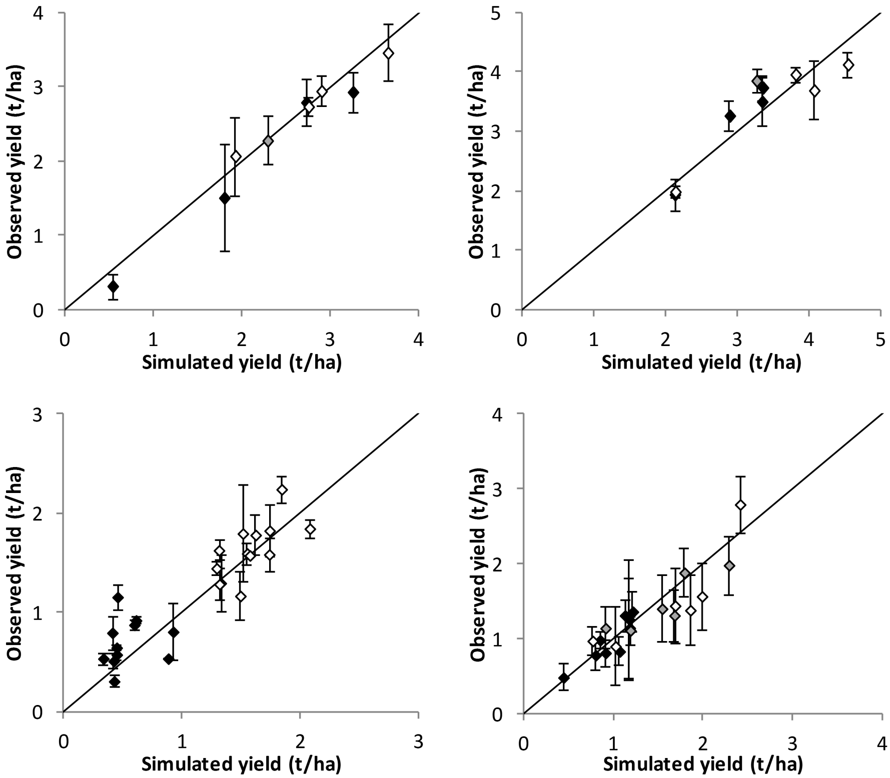

Figure 1.5: Observed versus simulated yield for maize (top left) and wheat (top right) in Nepal, for tef in Ethiopia (bottom left) and for quinoa in Bolivia (bottom right) for all simulated environmental conditions, soil fertility levels (T0, T50, T100 and T150) and water treatments (IR white symbols, DI grey symbols and RF black symbols). Error bars indicate ± standard deviation for three replications (n=3).

under combined soil water stress and soil fertility stress were rather poor. The RRMSE was as high as 34% and the correlation between the observed and the simulated values was insignificant. This may be due to inaccurate simulation of the effect of water stress on the harvest index. Finally, Figure 1.5 also shows how, with its semi-quantitative soil fertility approach, AquaCrop is able to predict values for grain production that range from as little as 0.5 t/ha to more than 4 t/ha as a result of the various climatic, agronomic and environmental conditions and from the combinations of soil fertility and soil water stress levels.

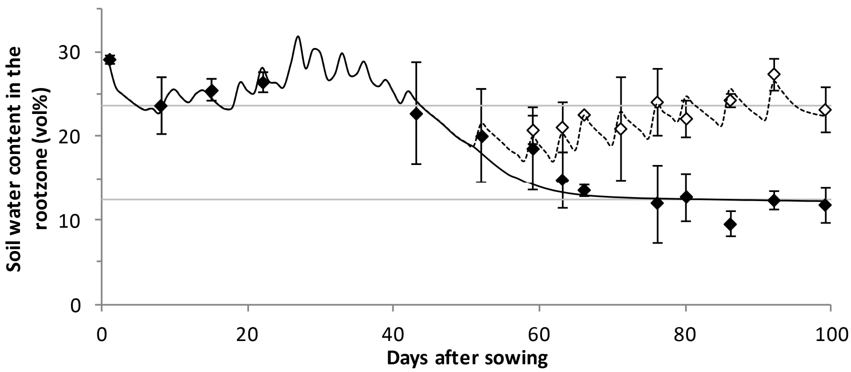

Figure 1.6: Simulated (lines) and observed (symbols) soil water content in the root zone for tef under soil fertility stress (T50) in Dejen, during the season of 2010. Both irrigated (IR, dotted line, open symbol) and rainfed (RF, full line, filled symbol) soil water content are well simulated. Horizontal grey lines indicate the soil water content at field capacity (top line) and permanent wilting point (bottom line). Error bars indicate ± standard deviation for three replications (n=3).

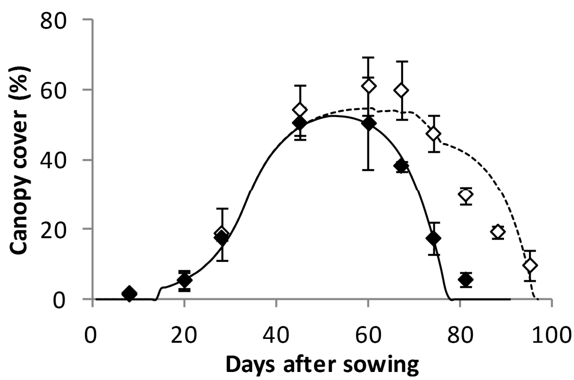

Figure 1.7: Simulated (lines) and observed (symbols) green canopy cover for tef under soil fertility stress (T0) in Maiquiha during the season of 2009. Both irrigated (IR, dotted line, open symbol) and rainfed (RF, full line, filled symbol) canopy cover development under soil fertility stress are well simulated. Error bars indicate ± standard deviation for three replications (n=3).

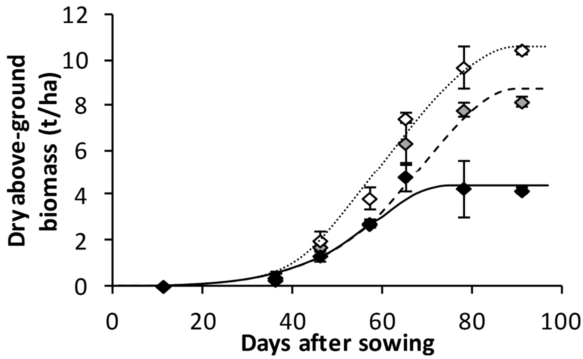

Figure 1.8: Simulated (lines) and observed (symbols) dry above-ground biomass for maize in Chitwan during the season of 2009/10. Irrigated (IR, dotted line, open symbol), deficit irrigated (DI, dashed line, grey symbol) and rainfed (RF, full line, black symbol) biomass production under soil fertility stress (T100) are all well simulated. Error bars indicate ± standard deviation for three replications (n=3).

1.4 Discussion

1.4.1 Performance of the semi-quantitative AquaCrop approach

Because the semi-quantitative AquaCrop procedure uses the relative biomass of a fertility-stressed field compared to that of a reference field (B_{rel}) as the input from which to determine the soil fertility stress coefficients, it appears obvious that the final biomass, and consequently the yield simulations, for fertility stressed fields match the observations that are made in the absence of water stress. Nevertheless, the present study has shown that the semi-quantitative AquaCrop soil fertility procedure provides realistic results; not only were the final biomass and the yield simulated with acceptable accuracy (RRMSE of 4-24% for B at maturity and 7-19% for Y), but the soil water content, canopy cover and biomass development during the growing season were all also simulated with satisfactory accuracy (RRMSE of 6-13% for SWC_r, 12-34% for CC and 13-22% for B) – and even for stress levels for which the model had not been calibrated. Moreover, it has been shown that AquaCrop can provide good indicative values for final biomass (RRMSE of 4-15%) and for yield (RRMSE of 11-13%) of maize, wheat and quinoa when crop production is affected by both soil fertility stress and soil water stress. In the case of tef, although biomass production was well simulated (RRMSE of 20%) under conditions of combined soil water stress and soil fertility stress, yield predictions were poor (RRMSE of 34%). Also Tsegay et al. (2012) noted, under conditions of non-limiting soil fertility, that AquaCrop performs less well in the estimation of tef yield under water-stressed conditions. Further calibration of the effects of water stress on the harvest index of tef might be necessary in order to improve yield predictions under water stressed conditions, both with and without soil fertility stress.

Notwithstanding its simplicity, the AquaCrop semi-quantitative approach performs as well as nutrient-balance-based models for the simulation of maize and wheat production under different levels of soil fertility stress and soil water stress. In evaluating simulations of wheat and maize production under different water and nitrogen treatments, Fang et al. (2008) found RRMSE values of 12% for biomass and 12-15% for yield with the CERES model, whereas Brisson et al. (2002) reported RRMSE values of 2-3% for biomass but 16-24% for yield using the STICS model; and Stöckle et al. (2003) reported RRMSE values between 8 and 14% for biomass and 8 and 32% for yield simulated with the CropSyst model. The APSIM model has been evaluated on a number of occasions for the simulation of more challenging situations such as, for example, the response of a crop to phosphorus or organic fertilizer. Micheni et al. (2004) and Kinyangi et al. (2004) obtained R^2 values of between 0.75 and 0.88 for the simulation of maize biomass production grown with organic fertilizer. Evaluating the simulation of maize production under different phosphorus and nitrogen supply levels, Fosu-Mensah et al. (2012) found RRMSE values of about 15% for yield and R^2 values for biomass of between 0.89 and 0.91 (corresponding to RMSE values of 0.661 - 0.780 t/ha). Finally, Delve et al. (2009), who studied the performance of maize grown under different phosphorus sources (manure versus fertilizer) and treatments (rate and frequency of application), found R^2 values of 0.83-0.88 for biomass (corresponding to RRSME values of at least 26%) and of 0.74-0.81 for yield. For maize and wheat, the performance statistics found in this study (Table 1.4) are clearly within the range of statistics reported for studies with nutrient-balance-based models. For tef and quinoa, the performance of the model cannot be compared to the performance of other crop models, since AquaCrop is currently the only crop model that has been calibrated to simulate crop production for these under-utilized crops (Geerts et al., 2009b; Tsegay et al., 2012).

It should also be noted that the present study evaluated the performance of AquaCrop's fertility response algorithms against observations that were obtained from on-farm experiments in relatively small plots. As such, problems such as lodging of the crop, damage to some of the plots, (partial) loss of samples due to technical problems and transport, and a limited sample size during the growing season could not be avoided. This inevitably led to deviations among replicates that were sometimes substantial, and this led to large standard deviations in the graphs presented. It can be expected that similar experiments conducted in a controlled environment of an experimental research station would yield an even better match between the observed and simulated values for soil water balance, canopy development, biomass production and yield.

1.4.2 Input and calibration requirements

The semi-quantitative approach of AquaCrop requires the user to specify the soil fertility level, expressed as the relative biomass (B_{rel}) that can be expected in a fertility-stressed field compared to that for a reference field in non-water-stressed conditions. The B_{rel} can readily be obtained from farmers, from experimental fields or from agricultural statistics relating to local crop production. The ease with which this input can be obtained makes the semi-quantitative AquaCrop approach user-friendly and accessible to users worldwide. Moreover, the approach integrates the effects of various soil nutrients (and not merely nitrogen) and mineralization processes without a requirement for vast amounts of input data, for initialization of the soil nutrient conditions, or for elaborate parametrization.

The AquaCrop model is applicable to different crops and environmental conditions, but the crop response to soil fertility stress is crop- and case-specific and consequently the model requires calibration in each case. The necessity for a case-specific calibration diminishes the practicability of the model for analyses on a large spatial scale, but in this respect AquaCrop is no different from models that make use of a nutrient-balance approach, which also need site-specific information (Gabrielle et al., 2002; Matthews and D.), 2002). Indeed, when crop production is being assessed over large areas, not only may various crops be being grown, but also the management, and the soil and nutrient conditions, may vary between different fields. Since each type of nutrient limitation affects canopy cover development and biomass in a different way, the crop response to soil fertility stress may differ amongst fields, even when the same crop is being grown. For example, a crop grown in a field where nitrogen is the most limiting nutrient will respond to the local soil fertility stress in a completely different way from a crop grown in a field where potassium is the most limiting nutrient. Fortunately, as this research shows, when simulations are run for different fields within the same area, in which the constraints on crop growth are similar, the calibrated crop response to soil fertility stress is quite robust. In the present study, for example, the response of tef to soil fertility stress was calibrated for one of the experimental sites (Dejen), but the model also performed well in simulating crop development and production at the other experimental site (Maiquiha). In another assessment using AquaCrop in Ethiopia, in which the barley yield gap was investigated at the district level, it was demonstrated that after calibrating the response of barley to soil fertility stress for one experimental site, AquaCrop could estimate with acceptable accuracy (R^2 of 0.84 for B and 0.87 for Y, RMSE 0.82 t/ha for B and 0.23 t/ha for Y) barley biomass and yield under soil fertility stress for other farmers' fields within the same district (Abrha, 2013). A case-or field-specific calibration should therefore be considered only if large soil, nutrient or management differences occur within the same area.

Clearly, crop- and case-specific calibration results in extra work, but the effort involved is limited. First of all, the calibration procedure for the model is automated and requires few input parameters, and these are easily obtainable. The required information for canopy cover development (CC_x and canopy cover decline) in a 'soil fertility stressed' calibration field can be easily obtained by means of visual estimates in the field or from digital photographs, and can be specified as an input by selecting a class ranging from 'very strong reduction' to 'close to reference, or small reduction'. Secondly, the calibration of the crop response to soil fertility stress is important mainly for a correct simulation of the soil water balance and canopy development, and less important for the assessment of crop biomass production under soil fertility stress, for which B_{rel} already gives an indication of the reduction of biomass (and consequently yield) due to soil fertility stress. The automated calibration aims to determine the relative contributions of all four effects (reduced CC expansion, reduction of CC_x, early CC decline, reduction of WP^*) to the overall effect of soil fertility on biomass production. This calibration step was introduced because the soil water content can be simulated more accurately by making a distinction between the soil fertility effect on WP^*, which does not directly affect the soil water balance and the three soil fertility effects on canopy cover development (reduced CC expansion, reduction of CC_x, early CC decline), which do affect the soil water balance, through their effect on transpiration. A reliable simulation of the soil water balance is of course indispensable for an accurate simulation of crop production (Aggarwal, 1995; Eitzinger et al., 2004), certainly in the AquaCrop model, which is based wholly on a water-driven growth module. Moreover, it allows the user to simulate the combined effect of soil fertility and water stress, which is a major strength of the AquaCrop model. Although very important for the simulation of the soil water balance, the calibration step is less important for the simulation of biomass production under soil fertility stress. Indeed, an indication of the local B_{rel} is sufficient to calculate the reduction of biomass (and consequently yield) that is due to soil fertility stress. For this reason, the calibration of the crop response to soil fertility should be seen more as a fine-tuning and estimation of the effect of soil fertility stress on canopy development and the soil water balance, rather than as a procedure that requires exact numbers and detailed information. This has also been illustrated by experimental data from Bolivia. Although data on canopy cover development were sparsely available, calibration nevertheless resulted in good predictions of biomass and yield.

1.4.3 Application of the model

After carrying out the calibration of the crop response to soil fertility stress, a user can apply the AquaCrop model to evaluate various soil fertility management strategies for the local environmental conditions, with respect to their effects on yield and crop water productivity. When conducted under different climatic conditions (wet versus normal or dry years), such a scenario analysis can help to develop best-practice guidelines for farmers, taking into account the interactions between variable climatic conditions and soil fertility management (Van Gaelen et al., 4/27/2014-5/2/2014). Moreover, the AquaCrop model accounts for the effect of elevated CO_2 on crop production (Vanuytrecht et al., 2011), so that fertility management strategies can be evaluated not just for historical or current climatic conditions, but for future climate scenarios as well.

On account of the lack of a dynamic soil nutrient-balance, however, the AquaCrop model is less suited to producing fertilizer recommendations. The model can reveal which soil fertility level optimizes crop (water) productivity, but it does not provide information on the amounts of nutrients that are required to attain this level of production. To establish fertilizer recommendations, the soil fertility level (B_{rel}) still has to be converted to the amounts of nutrients that are required to achieve the corresponding crop yield and consequently to the fertilizer dose that is required. Oyarmoi (2013) proposed that the concept of Nitrogen Agronomic Efficiency (NAE) could be used to define the nitrogen fertilizer dose based on the AquaCrop B_{rel}. However, further research based on experimental data is needed in order to evaluate the performance of this NAE-based approach.

Finally, it is clear that after analysing the agronomic benefits of different field management strategies using AquaCrop, a socio-economic analysis is indispensable. Following the examples of Garcia-Vila et al. (2009), Garcia-Vila and Fereres (2012) and Cusicanqui et al. (2013), who optimized irrigation management both from an agronomic and an economic point of view, it is clear that AquaCrop simulation results can be coupled to economic models so as to analyse the effect of the soil fertility management strategies on labour requirements and farmers' profits.

1.5 Conclusion

AquaCrop simulates the effect of soil fertility stress on crop production by making use of the relative biomass that can be expected in a fertility-stressed field compared to a reference field, as a measure for soil fertility stress. This semi-quantitative approach requires few input parameters, which are easily obtainable, and integrates the effects of various soil nutrients and mineralization processes. In the present study, it is shown that in spite of its simplicity, the procedure results in an accurate simulation of the soil water balance, crop development, biomass production and yield for several soil fertility levels, and for various crops at different locations, following case-specific calibration. Moreover, the procedure shows potential for application in dry conditions, because the model performed well under conditions of combined soil water stress and soil fertility stress. With its integrated soil fertility module, the AquaCrop model can be a powerful tool with which to investigate the impact of soil fertility management on local crop production for different crops, and with which to develop best-practice guidelines in locations where the acquisition of detailed field information on soil nutrients is difficult. Furthermore, the model can be used to explore existing yield gaps and their major causes, i.e. water stress, soil fertility stress and combinations of both.

Chapter 2

Development and evaluation of the AquaCrop weed management procedure

This chapter is based on:
Van Gaelen, H, Willems, P, Diels, J, and Raes, D (2016). Bridging rigorous assessment of water availability from field to catchment scale with a parsimonious agro-hydrological model. *Environmental Modelling & Software*, [submitted]

2.1 Introduction

Nowadays, studies on agricultural productivity rely increasingly on simulations models. Being more cost- and time-efficient, crop models offer an attractive supplement to field experiments. Crop models are not only used to estimate potential yield levels and investigate causes of yield gaps, but also to evaluate management strategies that can boost crop productivity and water use efficiency. Initially, most crop models were developed to simulate crop production at field scale for historical time series. However, model application has evolved towards large scale studies as well as prediction of future crop productivity.

While most crop models consider yield-limiting factors such as water stress and nutrient deficiencies, biotic factors such as weeds are often neglected. Notwithstanding, considerable yield losses due to weeds are not only faced by smallholder farmers in developing countries (FAO, 2009), but also occur in large-scale intensive cropping systems in developed countries (Swanton et al., 1993; Pimentel et al., 2000; Milberg and Hallgren, 2004). In addition, weeds transpire water and thereby reduce water availability to the crop. This unproductive water consumption is critical in drought-prone regions, where optimizing crop water productivity is a prerequisite for sustainable crop production.

To include the effect of weed infestation in simulation studies, one could apply empirical equations that predict crop yield losses based on variables such as weed density (Cousens, 1985), relative time of weed emergence (Cousens et al., 1987), relative leaf area (Kropff et al., 1995), and relative leaf cover of the weeds (Lotz et al., 1994). However, these empirical equations entirely rely on locally calibrated parameters, which hinder extrapolation to other weed species, crop species, locations, environmental conditions, and management practices (Kropff and Lotz, 1992; Murphy et al., 2002). Also, process-oriented, mechanistic simulation models such as ALMANAC (Kiniry et al., 1992), APSIM (Keating et al., 2003), CROPSIM (Chikoye et al., 1996) and INTERCOM (Kropff and van Laar, 1993) have been developed or extended to study crop-weed interactions. However, high requirements for input data, parameter calibration and validation, impede efficient application of these models for a wide range of environmental conditions and cropping systems (Weaver, 1996). Particularly in data-scarce regions, application of existing mechanistic simulation models is impractical.

The AquaCrop crop water productivity model (Hsiao et al., 2009; Steduto et al., 2009; Raes, 2009) was developed by the Food and Agriculture Organization of the United Nations (FAO) to estimate yield for herbaceous crops cultivated under various environmental conditions and management practices. Although the model is mechanistic by nature, simulated processes in the crop-soil system are largely simplified. Notwithstanding these simplifications, AquaCrop provides accurate productivity estimates based on a limited number of easily obtainable input variables and parameters. This makes the model practical to apply in data-scarce regions, as well as for studies on a regional scale (Lorite et al., 2013; Kim and Kaluarachchi, 2015). AquaCrop has been applied to assess irrigation and soil fertility management strategies (Geerts et al., 2009a, 2010; Shrestha et al., 2013b,a; Tsegay et al., 2015), but only recently a weed management module was developed for implementation in AquaCrop (test version 5.0). Like the AquaCrop model, this module was developed pursuing an optimal balance between model accuracy, robustness, transparency, and input requirements.

The current study discusses the new AquaCrop calculation algorithms for crop yield simulation in weed-infested fields. Moreover, the performance of the AquaCrop model to simulate the soil water content, canopy cover development and crop production in weed-infested fields is evaluated for two different grain crops grown in various environmental and agronomic conditions.

2.2 Materials and Methods

2.2.1 The AquaCrop model for weed-infested conditions

AquaCrop simulates crop productivity using a four-step process as discussed in Chapter 2 **??**. First, green crop canopy cover (CC) is simulated. In a second step, crop transpiration (Tr) is simulated considering reference evapotranspiration (ET_0) and the simulated canopy cover. Next, crop transpiration is converted into dry above-ground biomass production (B). In a final step, crop biomass is converted to crop yield (Y) by means of the harvest index (HI). Crop yield per unit of water evapotranspired (ET) is given by the ET crop water productivity (WP_{ET}). During this four-step simulation process, the model accounts for the effect of various abiotic stresses, including water stress, temperature stress, soil salinity stress and soil fertility stress (**??**).

When weed stress is considered, AquaCrop directly simulates crop canopy development as it is observed in a weed-infested field (CC_W, Figure 2.1). In addition, AquaCrop simulates canopy development of the crop-weed mixture (CC_{TOT}, Figure 2.1), which will be referred to hereafter as ‘total vegetation’. Simulation of total vegetation canopy cover is crucial since the denser canopy in weed-infested fields affects soil evaporation, transpiration and consequently water availability in the root zone and crop water productivity. In AquaCrop, total vegetation is represented by a theoretical crop with denser canopy cover, but otherwise identical characteristics to the crop growing in a weed-free field (CC_{WF}). Hence, crop characteristics such as phenology, rooting depth, growing cycle length and sensitivity to abiotic stresses are also applicable to the total vegetation. The denser canopy is reflected by both a higher initial (CC_0) and maximum canopy cover (CC_x). Due to this denser canopy and assumption of equal growing cycle length, the canopy decline rate of the total vegetation is also higher compared to the decline rate of the crop.

Simulation of both the total vegetation and crop canopy cover in weed-infested fields is completely determined by two user-specified inputs: (i) the weed infestation level or amount of weeds and (ii) the weed-induced increase of total canopy cover.

The weed infestation level is quantified by means of the relative leaf cover of weeds (RC, Equation 2.1) as defined by Lotz et al. (1994).

$$RC = \frac{WC}{CC_{TOT}} = \frac{WC}{WC + CC_W} \tag{2.1}$$

where RC is the relative leaf cover of weeds (m2/m2), WC is the area covered by weeds per unit ground area (m2/m2), CC_W is the area covered by the crop per unit ground area in a weed-infested field (m2/m2), and CC_{TOT} is the

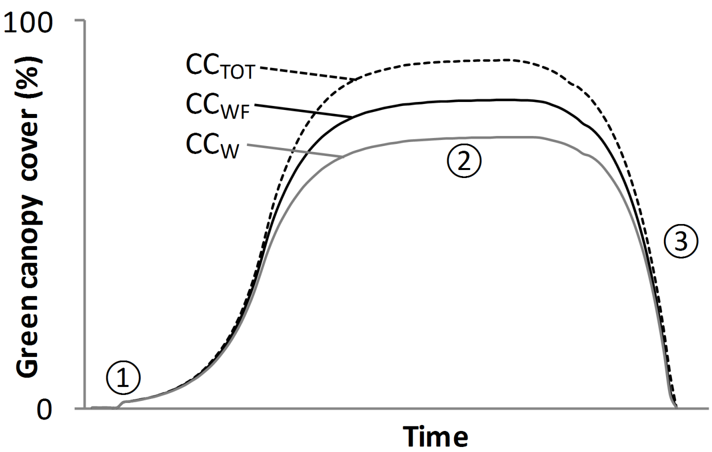

Figure 2.1: Weed infestation affects the simulated (1) initial canopy cover, (2) maximum canopy cover, and (3) canopy decline rate. As weeds take up empty space or suppress the crop, the crop canopy cover in weed-infested conditions (CC_W) is lower compared to weed-free conditions (CC_{WF}). Moreover, the canopy cover of the total vegetation (CC_{TOT}) is higher and has a faster decline compared to the crop canopy cover in weed-free conditions (CC_{WF}).

area covered by the total vegetation (crop-weed mixture) per unit ground area (m2/m2).

Relative weed cover is a multi-species canopy characteristic that varies during the growing season. Since the weed's share in leaf area at time of canopy closure is regarded as a good indicator of crop-weed competition (Kropff and Spitters, 1991), AquaCrop requires input of RC observed at the time maximum crop canopy cover is reached.

The weed-induced increase of total canopy cover (f_{weed}) is defined by Equation 2.2:

$$f_{weed} = \frac{CC_{x,TOT}}{CC_{x,WF}} \tag{2.2}$$

where f_{weed} is the weed-induced increase of total canopy cover (-), $CC_{x,TOT}$ is the maximum total vegetation canopy cover (m2/m2) and $CC_{x,WF}$ is the maximum crop canopy cover in weed-free conditions (m2/m2).

A large f_{weed} value indicates that weeds predominantly fill any empty gaps in the crop canopy cover, which results in a strong increase of the total canopy cover. A small f_{weed} value, on the other hand, indicates that weeds predominantly suppress crop growth by 'stealing' light. This results in a small increase in total canopy cover. Hence, for a certain weed infestation level (RC), differences in weed competitive abilities can result in different total vegetation canopy covers, and consequently different f_{weed} values. The AquaCrop user defines f_{weed} either directly or by specifying $CC_{x,TOT}$ for the selected weed infestation level and optimal growing conditions (no fertility, water or salinity stress). In addition, AquaCrop can automatically determine f_{weed} based on a user-specified canopy expansion factor (f_{shape}). This f_{shape} factor fixes the relation between the observed weed infestation level (RC) and the maximum total vegetation canopy cover ($CC_{x,TOT}$) for optimal growing conditions (Figure 2.2), and consequently represents the competitive ability of weeds to compete with the crop for light.

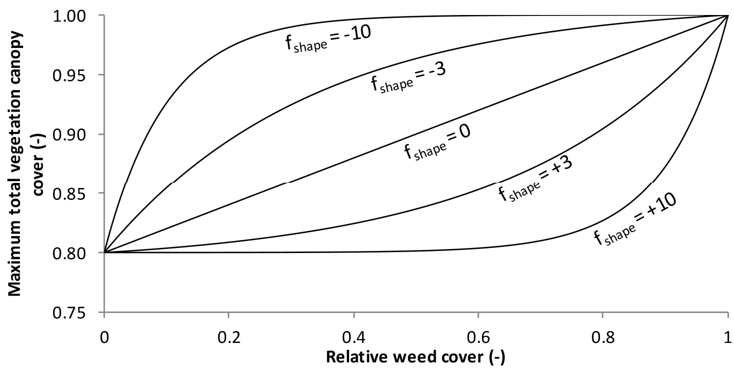

Figure 2.2: Relationship between maximum total vegetation canopy cover ($CC_{x,TOT}$) and relative cover of weeds (RC) is determined by the canopy expansion factor (f_{shape}). This example presents a crop with a maximum canopy cover ($CC_{x,WF}$) of 0.8 in weed-free conditions.

An AquaCrop simulation for weed-infested conditions starts by simulating total vegetation canopy cover (CC_{TOT}) by multiplying the crop canopy cover under weed-free conditions ($CC_{x,WF}$) with f_{weed}. Next, CC_{TOT} is corrected for water, soil fertility or soil salinity stress using the stress thresholds calibrated for the crop. Thereby it is assumed that weeds are equally as sensitive to those stresses than the crop. Subsequently, the crop canopy cover for weed-infested conditions (CC_W) is derived from CC_{TOT} based on RC (Equation 2.1). Finally, simulation of CC_W enables simulation of crop transpiration, crop biomass, crop yield and crop water productivity in weed-infested fields using the standard AquaCrop procedure (**??** to **??**).

Since weeds take up water and affect the soil water balance, AquaCrop calculates the soil water content in the root zone of a weed-infested field considering the total vegetation canopy cover. Evaporation and transpiration of the total vegetation are simulated considering the denser canopy of weed-infested versus weed-free fields (CC_{TOT} versus CC_{WF}). The simulated soil water content is used to correct the simulated crop and total vegetation canopy cover, crop transpiration and yield formation in a weed-infested field for water stress. It should be noted that increased water stress is the only mechanism through which weeds affect the harvest index in AquaCrop. An additional adjustment to the harvest index for weeds is not considered. Furthermore, weeds increase nutrient stress by 'stealing' crop nutrients. For that reason, the soil fertility level is adapted during simulation. In addition, a weed-induced increase of total canopy cover is no longer considered (f_{weed} is 1), since low soil fertility restricts total canopy cover development to the level that can be reached in weed-free conditions ($CC_{x,TOT}$ equals $CC_{x,WF}$).

2.2.2 Field experiments

The AquaCrop weed management algorithms were tested against two sets of experimental data (Table 2.1). The first set comprised data of four experiments conducted with barley (*Hordeum vulgare* L.) in the drought-prone, degraded highlands of Tigray in northern Ethiopia. The second set consisted of data from a field experiment with wheat (*Triticum aestivum* L.) conducted in semi-arid Wagga Wagga, Australia.

All experiments were setup with a split-plot design in which water treatment was the main factor and the weed treatment the sub-factor (Table 2.1). In S1 water treatments, crop development or production were affected by water stress, while crops did not suffer water stress in S0 treatments. Occurrence of water stress was caused by insufficient rainfall, inadequate irrigation, or the presence of a rainshelter. Since observed differences between water treatments were not significant for barley in all four experiments (Abrha, 2013), only one water treatment was retained for the current study (Table 2.1). In Dejen and Maiquiha, naturally occurring weeds were retained and weed treatments consisted of different hand weeding frequencies: no weeding, one time weeding at 21 days after emergence (only in 2009) and frequent weeding (at least three times). The majority of weed species were broad-leaved (e.g. *Scorpiurus muricatus*), but grasses (e.g. *Avena* sp., *Digitaria* sp.) and sedges (e.g. *Cyperus* sp.) were also present. In Mekelle, wild oat (*Avena fatua* L.) was sown together with barley at a proportion of 0%, 5%, 20% and 50% of the total amount of seeds. In Wagga Wagga, ryegrass (*Lolium rigidum* Gaud.) was sown aiming at a weed density of 250 plants/m2. At all experimental sites, the plots were kept free from pests, diseases and undesired weeds throughout the growing season. Moreover, all plots were kept at optimal fertility to ensure that neither crops nor weeds would suffer from nutrient stress. During the growing season observations of local daily weather, soil characteristics, irrigation and soil fertility management, soil water content, crop phenology, crop and weed canopy (leaf area index (LAI) or green canopy cover), dry above-ground crop biomass and crop yield, were recorded. Observations of the second data set were retrieved from the paper by Deen et al. (2003) or shared by those authors. Unfortunately, not all data could be retrieved; some observations of the weed-infested plots were missing (e.g. yield and soil water content) or observations were limited to average values without records of the deviation between replications. More detailed information on the experimental set-up and data collection is described by Deen et al. (2003) for wheat, and Abrha et al. (2012) and Abrha (2013) for barley.

Table 2.1: Experimental sites, setup and environmental conditions of the five experiments. Water treatments consist of absence (S0) or presence (S1) of water stress. Seasonal aridity indices represent the ratio of total rainfall to reference evapotranspiration (ET_0) during the growing season.

	Dataset 1				Dataset 2
Experimental site	Dejen	Dejen	Maiquiha	Mekelle	Wagga Wagga
Country	Ethiopia	Ethiopia	Ethiopia	Ethiopia	Australia
Coordinates	13°20’ N, 39°22’ E	13°20’ N, 39°22’ E	13°48’N, 39°27’E	13°28’ N, 39°29’ E	35°10’ S, 147°28’ E
Altitude (m a.s.l.)	2128	2128	2078	2212	200
Experimental setup					
Location	Farmer training centre	Farmer’s field	Farmer’s field	Research station	Research station
Season	2009	2010	2009	2010	1998
Sowing date	10/07/2009	13/07/2010	15/07/2009	15/07/2010	18/05/1998
Replications	3	3	3	3	5
Crop	Barley	Barley	Barley	Barley	Wheat
Weed species	Natural mix	Natural mix	Natural mix	Wild oat	Ryegrass
Water treatment(s)	S0	S0	S1	S0	S0,S1
Weed treatments	Hand weeding frequency: 0, 1, $\geq$3 times/season	Hand weeding frequency: 0, $\geq$3 times/season	Hand weeding frequency: 0, 1, $\geq$3 times/season	Weed seed proportion: 0, 5, 20, 50%	Weed density: 0, 250 plants/m2
Environmental conditions					
Soil type	Luvisol	Luvisol	Leptosol	Cambisol	Red-brown earth soil
Soil texture	Sandy loam to silt loam	Loam to silt loam	Silt loam	Sandy (clay) loam	Loam, silty clay
Seasonal rainfall (mm)	301	443	239	552	420 (S0) and 122 (S1)*
Seasonal ET_0 (mm)	324	280	367	285	353
Seasonal aridity index (-)	0.93	1.58	0.65	1.94	1.19 (S0) and 0.35 (S1)*

* Seasonal rainfall was affected by the presence of a rain shelter in the S1 treatment.

2.2.3 Model input

Observations of local climatic data, irrigation practices, soil characteristics and initial soil water content were used as inputs in a test version of AquaCrop 5.0. Simulations were conducted assuming non limiting soil fertility for all plots. Default crop parameters were used as a starting point; thereafter non-conservative crop parameters were adjusted to match the characteristics of the local cultivar and environment (Table 2.2). Crop developments stages were specified in growing degree days (GDD) to enable temperature dependent crop canopy development. Conservative crop parameters, which by definition are independent of cultivar, management and geographical location, were kept default, except for wheat. Since AquaCrop does not consider typical processes for winter crops such as vernalization, dormancy and cold acclimation, simulation of winter wheat development required adaptation of some conservative crop parameters (Table 2.2) following the example of Vanuytrecht (2013).

Table 2.2: Key crop parameters for barley and wheat grown at the experimental sites. Values that were changed from the default are presented in bold. * indicates the values for Mekelle.

		Barley	Wheat
Non-conservative parameters			
Initial canopy cover (CC_0)	%	2.70/**2.96***	**1.95**
Maximum canopy cover (CC_x)	%	80/**88***	**88**
Time to emergence	GDD	98	**80**
Time to start senescence	GDD	924	**710**
Total length of crop cycle	GDD	1296	**1401**
Maximum effective rooting depth	m	1.3	**1.2**
Conservative parameters			
Canopy growth coefficient (cgc)	%/GDD	0.9	**1.115**
Canopy decline coefficient (cdc)	%/GDD	0.6	0.400
Base temperature	°C	2	**4**
Upper temperature	°C	28	26
Minimum growing degrees required for full biomass production	°C/day	14	**10**
Normalized biomass water productivity (WP*)	g/m^2	15.0	**18.5**
Reference harvest index	%	33	48

Weed management inputs (RC and f_{weed}), listed in Table 2.3, were determined applying Equation 2.1 and Equation 2.2 to available CC_{WF}, CC_W and WC observations of well-watered plots at time of maximum crop canopy cover. For wheat experiments, LAI values were first converted to CC values using Equation 2.3 (Kropff and van Laar, 1993) with an extinction coefficient (k) of 0.6 and 0.5 for wheat and ryegrass respectively (Lantinga et al., 1999; Acevedo et al., 2002).

$$CC = 1 - exp\left(\sum_{i=1}^{n} k_i \cdot LAI_i\right) \tag{2.3}$$

where CC is the green canopy cover (m2/m2), k_i is the light extinction coefficient (-), and LAI_i the leaf area index (m2/m2) of species i as observed in a field with n species.

Since weed species were similar for all weed treatments of the same experiment, a single canopy expansion factor (f_{shape}) was selected for all treatments. The f_{shape} value was selected so that the resulting f_{weed} values, automatically determined by AquaCrop, approached the observed f_{weed} values well. Moreover, water availability in wheat plots affected the amount of weeds at time of canopy closure so that different RC values were selected for both water treatments.

Table 2.3: Weed treatments with selected AquaCrop weed management input: relative weed cover (RC) and weed-induced total canopy cover increase (f_{weed}) with corresponding canopy expansion factor (f_{shape}). Water treatments consist of absence (S0) or presence (S1) of water stress.

Experiment	**Water treatment**	**Weed treatment**	RC (%)	f_{shape} (%)	f_{weed} (%)
Dejen, 2009	S0	Weeding frequency (times/season)			
		≥3	0	-	-
		1	15	1	1.02
		0	50	1	1.10
Dejen, 2010	S0	Weeding frequency (times/season)			
		≥3	0	-	-
		0	13	-5.5	1.13
Maiquiha, 2009	S1	Weeding frequency (times/season)			
		≥3	0	-	-
		1	14	-1	1.05
		0	30	-1	1.10
Mekelle, 2010	S0	Weed seed proportion			
		0%	0	-	-
		5%	8	10	1.00
		20%	23	10	1.00
		50%	49	10	1.00
Wagga Wagga, 1998	S0	Weed density (plants/m2)			
		0	0	-	-
		250	20	-10	1.12
	S1	0	0	-	-
		250	15	-10	1.11

2.2.4 Model performance evaluation

The AquaCrop model was evaluated for its performance to simulate soil water content in the root zone, crop canopy cover, total vegetation canopy cover, crop biomass and crop yield both for weed-free and weed-infested conditions. Thereby observations of all experimental sites and water treatment, listed in Table 2.1, were included. Performance was assessed using graphical displays (plots of simulated versus observed values) and the four statistical indicators presented in Box **??**: R^2, RRMSE, EF and RME. Model performance was qualified based on RRMSE values following Jamieson et al. (1991).

2.3 Results

Two examples, presented in Figure 2.3, illustrate how AquaCrop simulates the effect of weed infestation on barley canopy and biomass development. The total vegetation canopy cover increased due to presence of weeds, while crop canopy cover reduced. As a consequence, less biomass was produced. Even though both experiments had a similar weed infestation level of about 50% (Table 2.3), the simulated weed-induced increase of total canopy cover was strong in the experiment of Dejen (2009), while it was negligible in Mekelle (2010). This was the results of selecting a different f_{weed} value (Table 2.3). Since the effect of weeds on crop canopy cover differed between both experiments, also the weed-induced reduction in biomass differed. The simulated decrease of crop final biomass due to a 50% RC was about 43% for Mekelle, but only 39% for Dejen. Also field observations indicated that due to the high crop sowing density in Mekelle there was almost no empty space in the canopy for weeds to occupy. While in Dejen only some weeds competed with the crop for light, all the weeds in Mekelle suppressed the crop by outcompeting it for light, thereby causing larger reduction in biomass and water productivity.

The goodness-of-fit statistics (Table 2.4) present the performance of AquaCrop to simulate different crop variables of both weed-free and weed-infested barley and wheat plots including all experimental sites and water treatments.

Table 2.4: Relative root-mean-square error (RRMSE), Nash-Sutcliffe model efficiency (EF) and coefficient of determination (R^2) for n number of observations of average soil water content in the root zone, crop canopy cover in weed-free conditions (CC_{WF}) or weed-infested conditions (CC_W), total vegetation canopy cover (CC_{TOT}), dry above-ground crop biomass (B) during the growing season and at phenological maturity, and crop yield in weed-free and weed-infested barley and wheat plots (all experimental sites and water treatments included). Dashes indicate that observations for performance assessment were unavailable.

		Weed free				**Weed infested**			
Crop	**Variable**	n (-)	rRMSE (%)	EF (-)	R^2 (-)	n (-)	rRMSE (%)	EF (-)	R^2 (-)
Barley	Soil water content	33	11.6	0.80	0.82	66	13.2	0.77	0.78
	CC_{WF}	36	22.8	0.90	0.90	-	-	-	-
	CC_{TOT}	-	-	-	-	73	22.3	0.90	0.90
	B season	26	21.2	0.85	0.88	52	23.7	0.83	0.87
	B at maturity	4	6.5	0.87	0.90	8	5.3	0.95	0.95
	Yield	4	11.5	0.67	0.88	8	25.3	0.18	0.85
Wheat	Soil water content	32	4.5	0.68	0.77	-	-	-	-
	CC_{WF} or CC_W	15	18.1	0.95	0.96	15	14.8	0.96	0.96
	CC_{TOT}	-	-	-	-	15	20.7	0.92	0.93
	B season	17	29.9	0.92	0.95	17	38.9	0.85	0.92

AquaCrop made fair predictions of barley canopy cover development and biomass build up during the growing season, as shown by the RRMSE values of between 21 to 24% (Table 2.4). Regardless of the fair biomass predictions during

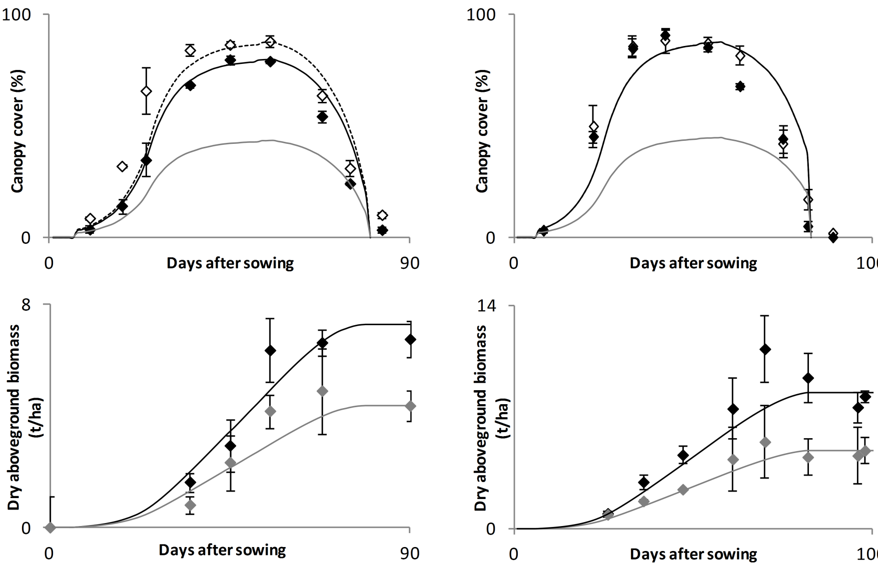

Figure 2.3: Simulated (lines) and observed (symbols) canopy cover (top) and dry aboveground biomass (bottom) in well-watered barley plots in Dejen 2009 (left) and Mekelle 2010 (right). Crop canopy cover and biomass are affected by the weed infestation level: weed-free (black) and weed-infested with a relative weed cover of about 50% (grey). The dashed line and open symbol present the total vegetation canopy cover in weed-infested conditions. Error bars indicate ± standard deviation for 3 replications.

the growing season, biomass at maturity was the most accurately predicted crop variable for both weed treatments (RRMSE values of 5-6 %). Moreover, AquaCrop made very good predictions of soil water content in the root zone (RRMSE of about 12-13%), despite only fair predictions of canopy cover and consequently transpiration. Furthermore, Table 2.4 illustrates that simulations were slightly less accurate for weed-infested barley plots compared to weed-free conditions. RRMSE values of weed-infested treatments were only 1.5-2.5% higher than weed-free treatments for soil water content and biomass. Predictions of barley biomass at maturity were even better than for weed-free conditions. Although final biomass was predicted excellent for all weed treatments, model performance decreased for grain yield depending on the weed treatment; barley yield predictions were very good for weed-free conditions (RRMSE of 12%), but only fair for weed-infested conditions (RRMSE of 25%). Figure 2.4 shows that yield was overestimated for all weed treatments, while biomass was predicted accurately. This indicates overestimation of the harvest index.

Simulation of the soil water content in the root zone of weed-free wheat plots was excellent, as indicated by the small RRMSE value of 4.5% (Table 2.4). However, because soil water content simulations were less good for the S0 treatment, EF

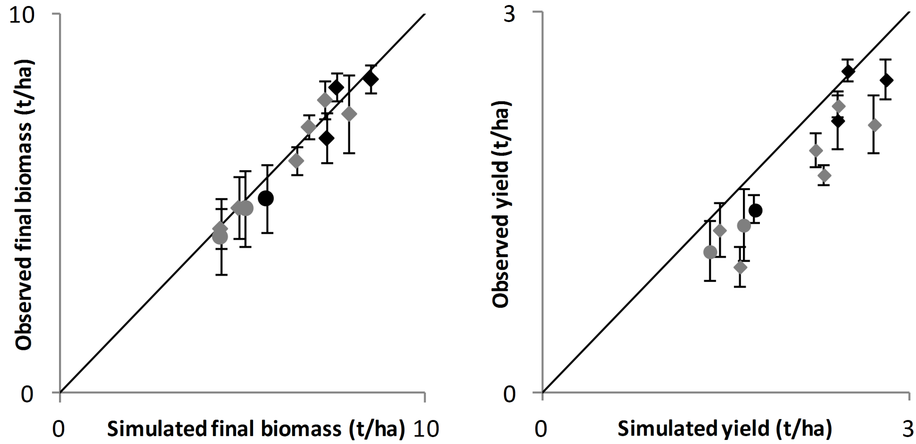

Figure 2.4: Observed versus simulated dry above-ground biomass at maturity (left) and grain yield (right) of barley grown in weed-free (black) and weed-infested (grey) plots with water stress (circle) or without water stress (diamond) at the three experimental sites in 2009 and 2010. Error bars indicate ± standard deviation for three replications.

and R^2 values were rather low. Unfortunately, observations of soil water content were not available for weed-infested fields. Furthermore, AquaCrop performed good for simulations of crop and total vegetation canopy cover, with RRMSE values between 15 and 21%. In contrast, performance was poor for simulation of crop biomass during the season. Figure 2.5 illustrates that AquaCrop was not able to capture the slow biomass build-up during winter, even though conservative crop parameters were altered to match the characteristics of winter wheat (Table 2.2). Introduction of weeds further decreased model performance. In weed-infested conditions, RRMSE values were 3-9% higher than in weed-free conditions. In spite of AquaCrop's limitations to accurately simulate biomass development, biomass at maturity was predicted very accurately with relative model errors as small as 1 to -2%. For both water treatments, final biomass in weed-free plots was underestimated, but overestimated for weed-infested plots.

2.4 Discussion

2.4.1 Model approach

Data availability is a major bottleneck for application of existing crop-weed competition models. In contrast, AquaCrop requires very few input variables and parameters that can be easily obtained. Simulation for weed-infested

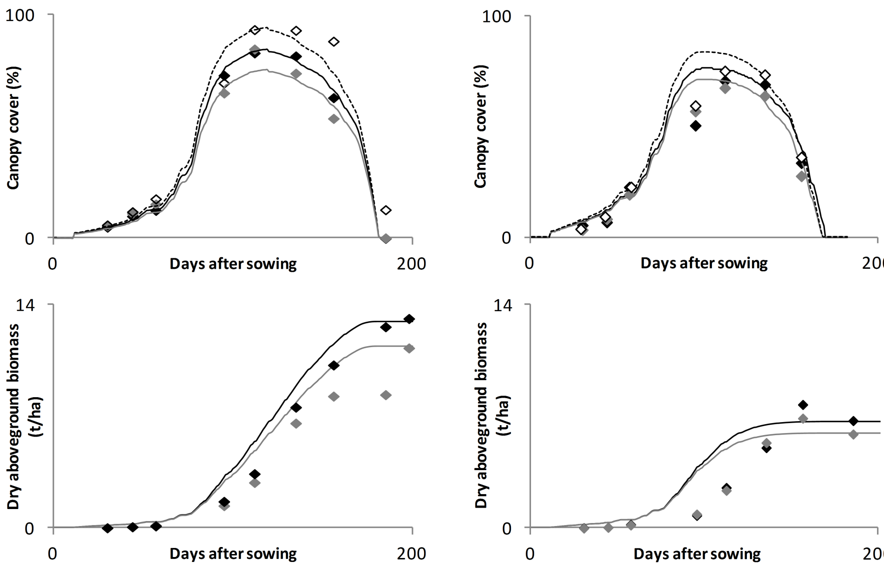

Figure 2.5: Simulated (lines) and observed (symbols) canopy cover (top) and dry above-ground biomass (bottom) in well-watered (left) and water-stressed (right) wheat plots in Wagga Wagga, 1998. Crop canopy cover and biomass are affected by the weed infestation level: weed-free (black) and weed-infested (grey) with a relative weed cover of about 20% for well- watered and 15% for water-stressed plots. The dashed line and open symbol present the total vegetation canopy cover in weed-infested conditions. Data points represent an average value over five replications. Error bars indicating the standard deviation were not available for the wheat dataset.

conditions requires only two additional inputs (RC and f_{weed}), which can be easily determined by analysing digital photographs or from remote sensing images (Lotz et al., 1994; Burgos-Artizzu et al., 2009). If such digital images are not available, one can also rely on visual estimates done in the field (Andújar et al., 2010). Since the two weed management inputs need to be specified for the weed mixture, knowledge of the exact weed species is not required. Moreover, this multiple-species approach is an important advantage, because competition by a single weed species is rarely encountered in farmers' fields.

AquaCrop relies completely on the input of relative weed cover to simulate partitioning of resources between crop and weeds. Light partitioning is by definition represented by RC. Water partitioning requires the total transpiration be divided into crop and weed transpiration based on total vegetation canopy cover and crop canopy cover. Since the latter are related through RC, partitioning of water is clearly determined by RC. Also, nutrient partitioning requires the soil fertility stress level to be adapted based on RC. One could argue that such an RC based approach neglects the competitive ability of weeds versus crop to obtain light, water and nutrients. Also, differences in sensitivity to scarcity of these resources seem to be neglected. However, this is not true since f_{weed} incorporates the competitive ability of crop and weed to obtain light. In addition, RC serves as a proxy for competitive ability and sensitivity to water and soil fertility stress. Also, Aldrich (1987) found light competition to be representative for total competition, since canopy size and structure is the result of competition for light, water and nutrients, as well as allelopathic interactions. Moreover, photosynthesis is not just involved in light competition, but also provides the energy for uptake of nutrients and water.

Furthermore, AquaCrop uses a static approach regarding weed infestation, as it uses a constant value of RC at time of maximum canopy cover to define the effect of weeds on crop canopy cover during the whole growing season. Such a static approach neglects the dynamics of weed cover, which can increase or decrease during the growing season depending on the competitive ability of crop versus weed. However, the absolute error made with this static approach is negligible at the beginning of the growing season, because canopy cover is still very small and little biomass is produced during the canopy expansion phase. In contrast, the error could be larger in mid-season, when crop canopy cover is large and most biomass is produced. Although the current study proved that good model results can be obtained with the static approach, future research should indicate whether RC dynamics in mid-season have a large impact on model results, and should be incorporated in the model.

Finally, it should be noted that AquaCrop's representation of the crop-weed vegetation as a single theoretical crop with the same growing cycle as the weed-free crop neglects possible differences between the crops' and weeds' growing cycles. Nevertheless, this simplification is valid both for late-emerging weeds, that cannot outgrow the crop, and for early-emerging weeds, which are removed during land preparation. Moreover, weeds with a life cycle similar to that of the crop will usually be the most successful competitors (Zimdahl, 2013) and consequently lead to major yield losses.

2.4.2 Model performance

AquaCrop performed well for simulated barley growth and production. This indicates that the selected crop parameters and inputs were a good representation of the local environment and cropping system. As the default crop parameters had been calibrated and validated by Abrha et al. (2012) for the same local barley variety grown in weed-free conditions, this is no surprise. Overestimation of yield indicated incorrect simulation of the harvest index, especially in weed-infested plots. This could be due to inaccurate settings of the barley water stress thresholds, or because AquaCrop disregards any direct effect of weeds on grain formation. Field experiments show that weeds can reduce barley grain yield by lowering the number of ear bearing tillers, number of grains per ear, and 1000-kernel weight (Wilson and Peters, 1982; Morishita and Thill, 1988). Introducing an RC-dependent stress coefficient that affects the harvest index, could improve model simulations. However, this would also lead to extra parameter uncertainty in the model.

Model performance to simulate wheat production was less good compared to barley, in particular for simulation of biomass during the growing season. It is expected that introduction of an extra stress coefficient to represent slow crop development because of low winter temperatures, as previously proposed by Vanuytrecht (2013), would significantly improve AquaCrop's performance for both weed-free and weed-infested winter wheat simulations. Despite the poor in-season biomass predictions, AquaCrop made excellent predictions of wheat biomass at maturity. In practice, final biomass, and not intermediate biomass, is most crucial to assess weed-induced yield losses.

Moreover, AquaCrop's performance for the wheat dataset was well within the performance range of four mechanistic crop-weed competition models (ALMANAC, APSIM, CROPSIM, INTERCOM) that were tested with the same dataset by Deen et al. (2003)(Box 2.1). However, this model performance comparison should be interpreted with care, as the AquaCrop approach is very different from mechanistic crop-weed competition models. The latter predict both crop and weed growth, partitioning of resources between crop and weed, and the resulting crop yield loss due to weeds. AquaCrop, on the other hand, uses input of the observed effect of weeds on crop canopy cover at time of canopy closure to simulate the effect of weeds on the soil water balance and crop production.

Finally, it should be noted that because of the experimental setup, the current study focused mainly on simulation of the outcome of crop-weed competition for light. Model performance for water competition was assessed based on the weed-infested, water-stressed treatments, which were only available for one of the barley experiments (Maiquiha 2009) and the wheat experiment. Although model performance proved very promising for these experiments, additional research including different water stress levels, ranging between low and very severe water stress, could further reveal to what extent AquaCrop can accurately capture the effect of weeds on soil water content and crop water availability. Furthermore, competition for nutrients was not considered in this study, because the soil fertility level was optimal in all experiments. Therefore, further evaluation of AquaCrop for weed-infested, soil-fertility-stressed fields remains necessary.

Box 2.1: Model comparison for simulation of weed-infested wheat fields

AquaCrop's performance to simulate wheat production for the experiment in Wagga Wagga (1998) was compared with the performance of ALMANAC, APSIM, CROPSIM and INTERCOM as reported by Deen et al. (2003). Simulated LAI values were converted to CC values using Equation 2.3 to enable model comparison. Models were compared based on the calculated RRMSE or RME in case of low number of observations.

In spite of AquaCrop's limitations to accurately simulate wheat development during winter, 2.4.2 shows that AquaCrop's performance to simulate crop canopy cover and biomass development was within the performance range of ALMANAC, APSIM, CROPSIM and INTERCOM. The five models covered a wide range from excellent to very poor performance, with RRMSE values of about 5 to 60%. AquaCrop simulations of crop canopy cover were most accurate of all models, apart from simulations for weed-free, water stressed conditions for which AquaCrop performed second best. In contrast, AquaCrop's performance was amongst the poorest for simulation of biomass during the season. Particularly in water-stressed conditions, RRMSE values revealed very poor model performance. Nevertheless, APSIM, CROPSIM, and INTERCOM performed even worse for some water or weed treatments.

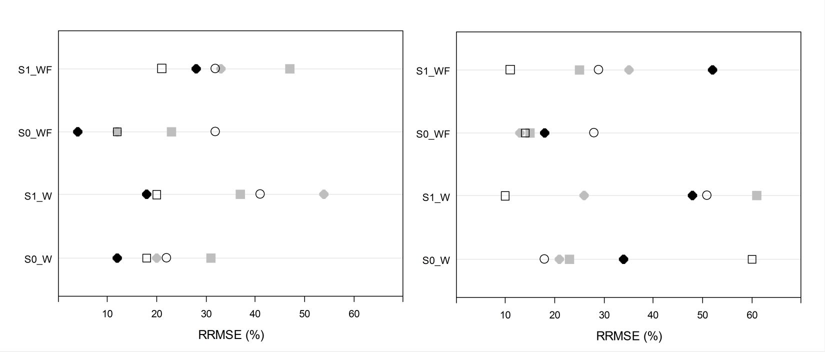

Figure 2.6: The relative root-mean-square error (RRMSE) for wheat canopy cover (left) and biomass during the growing season (right) varies between different models: AquaCrop (●), ALMANAC (●), APSIM(○), CROPSIM (■) and INTERCOM(□). Model performance also differs between water and weed treatments: absence (S0) or presence (S1) of water stress, weed-free (WF) or weed-infested (W).

Although biomass during the season was predicted rather poor, final biomass deviation (RME) was maximum 2% for AquaCrop (2.4.2). With these small deviations, AquaCrop was superior to all other models that had RME values as big as 27% or -25%. While the other models systematically overestimated (ALMANAC and INTERCOM) or underestimated (CROPSIM and APSIM) final biomass, AquaCrop did not show systematic deviation. Final biomass at maturity was slightly overestimated in weed-infested conditions, but underestimated in weed-free plots.

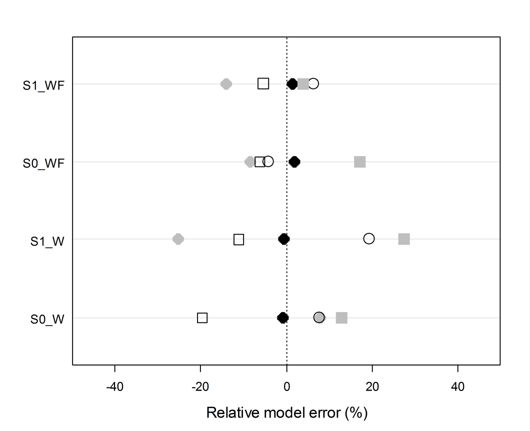

Figure 2.7: Deviation between simulated and observed biomass at maturity varies between different models: AquaCrop (●), ALMANAC (●), APSIM(○), CROPSIM (■) and INTERCOM(□). Model deviation also differs between water and weed treatments: absence (S0) or presence (S1) of water stress, weed-free (WF) or weed-infested (W).

2.4.3 Model application

Once properly calibrated to the local environment and cropping system, AquaCrop can be used to simulate crop growth, production and water productivity in weed-infested fields. Notwithstanding its simple approach, the new weed module is widely applicable. This was demonstrated by model evaluation for various experimental setups including different locations, soil types, climatic conditions, water treatments, crops, weed species and weed infestation levels. Furthermore, limited input and calibration requirements make AquaCrop applicable in data-scarce regions. If data are sparse, weed management inputs can even be specified in qualitative terms. A user can select one of the predefined RC classes, ranging between 'very poor' and 'perfect' weed management, or one of the predefined f_{weed} classes ranging between 'very weak' and 'very strong' weed-induced increase of total canopy cover. In addition, the transparent simulation procedure and user-friendly interface enable application by non-specialists.

Addition of weed infestation as a production- and water-limiting factor improves accuracy of yield predictions and yield gap analysis in weed-infested areas. Other potential model applications include investigation of tolerable weed infestation levels, as well as assessment of yield loss mitigation strategies such as changing sowing density or crop type. AquaCrop has the important advantage that weed infestation scenarios can be evaluated based on both simulated crop yield and crop water productivity. Assessing both these productivity indicators is vital in water scarce regions, where management decisions should be made in view of limited water availability.

Even though potential applications are numerous, the AquaCrop approach has limitations. The model can only support strategic management decisions, and cannot be used for assessment of tactical decisions. For example, model simulations can provide information on tolerable weed infestation levels, but can optimize neither pesticide dose nor timing of weed control operations. Moreover, the model cannot provide additional insights into the competition mechanisms. This would require a more detailed, process-based approach as adopted by other mechanistic models. Finally, it is clear that AquaCrop can support weed management decisions only from an agronomic point of view. However, by linking AquaCrop to an economic model, weed management can be optimized accounting for factors including labour and time requirement of weed control operations, prices of herbicides and prices of crop products. An example was set by Dunan et al. (1994) and Dunan et al. (1999) who optimized weed management based on both agronomic and economic aspects. Moreover, the linkage of AquaCrop to economic models has been demonstrated by Garcia-Vila et al. (2009), Garcia-Vila and Fereres (2012) and Cusicanqui et al. (2013).

2.5 Conclusions

The AquaCrop approach to simulate crop production in weed-infested fields proves to be a very intuitive approach that requires just two easily obtainable input variables: the relative leaf cover of weeds and weed-induced increase of total canopy cover. This makes the model applicable to all herbaceous crops grown in competition with any type or number of weeds. Despite its simple approach, AquaCrop performs good to simulate soil water content, crop development and crop production in weed-infested barley and wheat fields over a wide range of environmental and agronomic conditions. Further testing of the model remains necessary to assess model performance for weed-infested conditions combined with nutrient limitations or severe water stress. Because of its simple but accurate simulation procedure, wide applicability and low data requirements, AquaCrop is a practical tool to investigate the effect of weed infestation on crop production in data-scarce regions.

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