Soil–climate contribution to DNDC model uncertainty in simulating biomass accumulation under urban vegetable production on a Petroplinthic Cambisol in Tamale, Ghana

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Abstract

Crop yield simulation using the Denitrification–Decomposition (DNDC) model can help to understand key bottlenecks for improved nitrogen (N) use efficiency and estimate greenhouse gas (GHG) emissions in West African urban vegetable production. The DNDC model was successfully calibrated using high-resolution weather records, information on management practices and soils, and measured biomass accumulation and N uptake by amaranth (*Amaranthus* L.), jute mallow (*Corchorus olitorius* L.), lettuce (*Lactuca sativa* L.), and roselle (*Hibiscus sabdariffa* L.) for different input intensities (May 2014–November 2015) in urban vegetable production of Tamale (N-Ghana, West Africa). The root mean square error (RMSE) and relative error (E) values fell within the confidence interval (α 5%) of the measurements, and there was a high correlation (0.91 to 0.98) between measurements and predictions. However, the analysis of uncertainty and factor importance indicated that soil properties (pH, SOC, and clay content) and weather (precipitation) variability contributed highly to yield uncertainty of vegetable biomass.

Key words: carbon–nitrogen modelling / factor importance / horticulture / urban agriculture / West Africa

Accepted February 22, 2020

1 Introduction

Widespread land degradation in rural areas, job opportunities, and better educational and medical infrastructure in urban centres leads to rapidly increasing migration to West African cities (*Brinkmann* et al., 2012). As a consequence, the proportion of urban dwellers in West Africa grew 20-fold from 1950 to 2019, while the total population has increased five-fold (*United Nations*, 2019).

Due to strong local retail market connections, urban horticulture, as part of urban and peri-urban agriculture (UPA), plays an important direct (food provision) and indirect (contribution to household income) role in food security for local households. As elsewhere in sub-Saharan West Africa, UPA in Tamale (Northern Ghana) is characterized by the limited availability of water, high use of fertilizers and land scarcity (*Häring* et al., 2014; *Bellwood-Howard* et al., 2015). Due to the inherently low fertility of the predominantly heavily leached soils, high application rates of mineral fertilizers and organic soil amendments are frequently used to maximize marketable crop yields (*Bellwood-Howard* et al., 2015). However, application of uncontrolled amounts and quality of irrigation water and of mineral and organic fertilizers were shown to decrease water and nutrient use efficiency, which may lead to soil and groundwater pollution. It has been reported that in Bobo Dioulasso (Burkina Faso) up to 8% and 40% of the water supply in the dry and the rainy season, respectively, is drained away leading to total losses (application surplus) exceeding 2,000 kg N ha^{-1} y^{-1} (*Lompo* et al., 2012; *Sangare* et al., 2012). Under these conditions, annual gaseous emission losses may amount to 420 kg N ha^{-1} and 36 t C ha^{-1} (*Lompo* et al., 2012).

Previous research has shown the agronomic benefits of waste water and biochar application in UPA system of Tamale (*Werner* et al., 2018; *Akoto-Danso* et al., 2019a). Biochar application enhanced N-use efficiency on fertilized plots, while N surpluses were higher when the crops were irrigated with waste water (*Akoto-Danso* et al., 2019b). To better understand the nutrient dynamics in intensively managed UPA systems and to derive and test-implement sustainable management options, which minimize nutrient losses, further research is required. In this context, modelling can play a key role in understanding crop responses, especially in terms of yield potential and N utilization. It has to be understood that any such modelling efforts depend on the area of scientific interest such as assessing the effects of crop cultivars, and agro-ecological regions; the approaches adopted therefore depend on the complexity of the system (*Di Paola* et al., 2016).

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The Denitrification–Decomposition (DNDC) model was initially developed to simulate C and N turnover in US agricultural soils (*Li* et al., 1992a, 1992b). By using four agro-ecological drivers (basic climate, soil, vegetation, and anthropogenic activity), the DNDC model couples the soil–climate, plant growth and decomposition sub-models to calculate environmental variables, which can then be used to trace gaseous emission through denitrification, nitrification, and fermentation. Therefore, it may be a useful tool to understand the changes in soil C and greenhouse gas (GHG) emissions in UPA systems resulting from different management practices. However, to have a reliable estimate of these, biomass accumulation needs to be simulated correctly (*Li*, 2013).

Recently, the DNDC model has been used for a variety of crops in different agroecosystems and on a range of soils (*Ludwig* et al., 2011a; *Gilhespy* et al., 2014; *Zhang* et al., 2015). Testing of this model for crops grown under West African conditions is, however, still limited to N emissions from natural savannah ecosystems (*Grote* et al., 2009).

To assess the quality of modelling for a decision-making process, measuring uncertainties of the model is essential. This is especially important when determining how input variability propagates the uncertainty of the model output. The uncertainty analysis includes determining the contribution of each input parameters to model output uncertainty referred to as "factor importance"; this may be helpful to reduce model uncertainty. To fill the described knowledge gaps on N flows in West African UPA systems, the aims of this study were to (1) validate the DNDC model against measured biomass accumulation and N uptake data for different management intensities, which reflect the typical UPA vegetable production and (2) determine the uncertainty of vegetable biomass accumulation and the factor importance contribution to the modelled yield uncertainty.

2 Material and methods

2.1 Field experiment and sampling

Urban vegetable production was studied within the Urban Food[Plus] project (www.urbanfoodplus.org) within which a central field experiment was conducted in Tamale, N-Ghana (9°28′29N, 0°50′53W, 151 m asl) where average annual precipitation (2005–2015) is 1165 mm and air temperature averages 29°C (www.timeanddate.com). The experimental soil was classified as a Petroplinthic Cambisol (*Häring* et al., 2017). Prior to the study, the entire area was managed by one farmer and planted with rainfed maize (*Zea mays* L.).

At the site, a multi-factorial experiment with two fertilization levels (an unfertilized control and fertilization according to farmers' practices, FP) and two biochar levels (0 and 2 kg m^{-2} biochar addition) was established. The plots were irrigated with either clean or untreated waste water. There were two levels of irrigation (full, that is the typical irrigation quantity, and reduced, that is 2/3 of the full amount). The experiment was laid out in four blocks serving as replicates. Each block comprised four water quality and quantity levels as main-plots, which were split into sub-plots of four fertilization and biochar levels. The sub-plots (2 × 4 m) of 16 treatments in total were hand-hoed to a depth of 20 cm 2–3 days before planting/transplanting. During the experimental period (May 2014 to November 2015), a total of 11 crops were established and harvested. These comprised maize, cabbage (*Brassica oleracea* L.), amaranth (*Amaranthus cruentus*), lettuce (*Lactuca sativa* L.), jute mallow (*Corchorus olitorius* L.), and roselle (*Hibiscus sabdariffa* L.; Tab. 1; *Akoto-Danso* et al., 2019a, 2019b; *Werner* et al., 2019).

At the onset of the experiment, biochar (made from rice husks) treated plots received 2 kg biochar m^{-2}, which was hoed to a depth of 0–20 cm. NPK (15–15–15) was applied to all crops (200 to 563 kg ha^{-1}), except for jute mallow (April–May and June–July 2015), which received 247 and 256 kg ha^{-1} of urea, respectively (Tab. 1). All plots were irrigated with watering cans using either clean tap water or waste water from a military barrack (*Häring* et al., 2017). The nutrient concentration of the clean and waste irrigation water was determined weekly.

Yields (kg DM ha^{-1}) were determined by harvesting all aboveground biomass at maturity. To minimize edge effects, crop biomass from < 0.4 m of plot borders was discarded. The C and N concentration in the dry matter was determined by combustion using an elemental analyzer (Vario MAX CHN Elementar Analysensysteme GmbH, Hanau, Germany; *Akoto-Danso* et al., 2019a).

2.2 Model input

For our modelling tests, we used two years of cropping data (2014–2015), high-resolution weather records, and soil data (Tabs. 1 and 2). The weather data comprised minimum and maximum temperature (°C), precipitation (cm), wind speed (m s^{-1}), humidity (%), and solar radiation (MJ m^{-2} d^{-1}) measured at 20 min intervals of which daily means were used for modelling. Daily irrigation amount and the nutrient content of the irrigation water were combined in a fertigation file, which included Julian day, the quantity of irrigation water (cm), nitrogen (kg N ha^{-1}), phosphorus (kg P ha^{-1}) carried in the irrigation water, and the irrigation method. The parameters required to define crop growth in DNDC were obtained from the field experiment and literature (Tab. 3). The biomass fraction and C:N ratio of root, stem and leaves for each vegetable were derived from three control plots (1 × 1 m) in three farmer fields surrounding the experimental site. Crops were harvested at the same vegetative stage as in the experiment, except for maize and cabbage, for which the default data provided in the DNDC model were used. Biomass was calculated by harvesting all plant material (roots, stems, and leaves) and drying until weight constancy. To calibrate the model for new crops, we considered the pre-defined cotton (*Gossypium hirsutum* L.) growth parameters as a reference for roselle due to its similar growth habit (*Wester*, 1907), while for amaranth and jute mallow the pre-defined general vegetable growth information was used.

Table 1: Nutrient (kg ha^{-1}) and irrigation inputs (L m^{-2}) in the vegetable production systems in Tamale, Northern Ghana.[a]

Crop	1	2	3	4	5	6	7	8	9	10	11
	Maize	**Lettuce**	**Cabbage**	**Amaranth**	**Lettuce**	**Amaranth**	**Jute mallow**	**Jute mallow**	**Amaranth**	**Jute mallow**	**Roselle**
Planting date	09/05/2014	19/06/2014	26/07/2014	21/10/2014	15/12/2014	04/02/2015	24/04/2015	04/06/2015	25/07/2015	08/09/2015	20/10/2015
Harvesting date	08/06/2014	17/07/2014	06/10/2014	20/11/2014	01/02/2015	06/03/2015	25/05/2015	04/07/2015	28/08/2015	13/10/2015	25/11/2015
Tillage date	07/05/2014	17/06/2014	24/07/2014	19/10/2014	13/12/2014	02/02/2015	22/04/2015	02/06/2015	23/07/2015	06/09/2015	18/10/2015
Precipitation*	42	70	542	10	0	37	19	73	147	171	14
Fertilization date				04/11/2014	26/12/2014	14/02/2015	11/05/2015	22/06/2015		26/09/2015	01/11/2015
Fertilizer N	84.4	85.5	58.8	31.9	54.1	31.9	115.1	119.5	30.6	45.4	45.2
Fertilizer P	36.1	36.5	25.1	13.6	23.1	13.6	0.00	0.00	11.6	17.2	17.2
Full irrigation	198.0	339.6	204.9	242.0	431.8	176.0	200.8	160.9	38.5	8.3	264.0
Reduced irrigation	126.5	228.3	145.8	170.5	298.4	118.3	148.5	115.5	27.5	8.3	180.1
ww-N	30.8	52.9	19.3	32.7	172.0	55.0	86.9	91.2	15.0	2.3	55.0
ww-P	4.6	7.9	3.5	12.5	53.8	28.5	14.7	13.8	1.4	0.1	33.4
cw-N	0.5	0.9	0.5	1.7	3.0	1.2	1.1	0.5	0.1	0.0	1.3
cw-P	0.0	0.0	0.1	0.1	0.2	0.1	0.0	0.0	0.0	0.0	0.5

[a]N: nitrogen; P: phosphorus ; ww: waste water; cw: clean water; * precipitation is in mm.

Table 2: Selected climatic and soil input data for the DNDC model as calibrated in Tamale, N-Ghana.

Data	Value
Climatic data	
Latitude (°)	9.4329
N concentration in rainfall (mg N L^{-1})	0.3
Atmospheric background NH_3 concentration (μg N m^{-3})	0.06
Atmospheric background CO_2 concentration (ppm)	400
Soil data (0–20 cm)	
Soil texture	sandy loam
pH	5
Bulk density in g cm^{-3} (after biochar addition)	1.42 (1.40)
Clay fraction (0–1)	0.06
SOC in kg C kg^{-1} soil (after biochar addition)	0.0045 (0.0075)
Biochar fraction in SOC	0.4
Initial N concentration (mg N kg^{-1})	500 (NO_3^-) & 50 (NH_4^+)

2.3 Model calibration and validation

The DNDC model version 9.5 (www.dndc.sr.unh.edu) was calibrated against the biomass accumulation (kg C ha^{-1}) and N uptake (kg N ha^{-1}) of the control (unfertilized and no biochar addition) treatment with full clean water irrigation for the seven crops following the calibration instructions of *Li* (2013). Two crop growth parameters, the maximum potential biomass (kg C ha^{-1}) and thermal degree days (°C), were increased to match the field measurements. The crop biomass fraction and C:N ratio were adapted to measured field data.

To validate the model, biomass accumulation and N uptake were simulated across all treatments, excluding the control, using the default input values ("baseline scenario"), which were then compared to the measured values. The quality of the model validation was assessed using the root mean square error (RMSE), the relative error (E), and the correlation coefficients (*r*) based on Eqs. (1–3), respectively, between the measured and simulated values of all treatments. The statistical significance of the RMSE and E was tested by comparing model outputs to real harvest values obtained assuming a deviation corresponding to the 95% confidence interval of the measurements using Eq. (4) and Eq. (5) (*Smith* et al., 1997).

Table 3: Crop parameters for the DNDC model used to estimate vegetable yields in Tamale, Northern Ghana.

Parameters	Amaranth	Jute Mallow	Lettuce	Roselle
Maximum potential biomass for grain, leaves+stems and roots (kg C ha^{-1})	6000	3000	6000	5000
Grain, leaf, stem and root fractions of total biomass at maturity	0.1:0.5:0.3:0.1	0.1:0.5:0.3:0.1	0.1:0.6:0.2:0.1	0.1:0.6:0.2:0.1
C:N ratio for grain, leaves, stems and roots	10:20:25:25	10:9:13:25	11.5:8.5:10.5:12	10:14:40:40
Thermal degree days (°C)	2000	2000	2000	2000
Water demand (g water g^{-1} dry matter)	500	500	800	400
Optimum temperature (°C)	25	25	25	25

$$RMSE = \frac{100}{m}\sqrt{\sum_{i=1}^{n}\frac{(m_i - s_i)^2}{n}}, \tag{1}$$

$$E = \frac{100}{n}\sum_{i=1}^{n}\frac{m_i - s_i}{m_i}, \tag{2}$$

$$r = \frac{\sum_{i=1}^{n}(m_i - m)(s_i - s)}{\left[\sum_{i=1}^{n}(m_i - m)^2\right]^{\frac{1}{2}}\left[\sum_{i=1}^{n}(s_i - s)^2\right]^{\frac{1}{2}}}, \tag{3}$$

$$RMSE_{95\%} = \frac{100}{m}\sqrt{\sum_{i=1}^{n}\frac{\left[t_{(n-2)95\%}\times S_{e,i}\right]^2}{n}}, \tag{4}$$

$$E_{95\%} = \frac{100}{n}\sum_{i=1}^{n}\frac{\left[t_{(n-2)95\%}\times S_{e,i}\right]}{m_i}, \tag{5}$$

where m represents the mean of the measurement, n is the number of pairs, m_i is the i^{th} measurement of n, s_i is the i^{th} simulation of n, $s_{e,i}$ is the standard error of the measurements and $t_{(n-2)95\%}$ stands for the Student's t distribution with n – 2 degrees of freedom and a two-tailed P-value of 0.05. An accurate simulation is indicated by a smaller RMSE or E value. The correlation coefficient provides an assessment of how well the simulation shape matches the measurement shape (*Smith* et al., 1997).

2.4 Uncertainty and factor importance analysis

There were 400 annual combinations to be simulated using the Monte Carlo procedure built into the DNDC model to quantify the total uncertainty of the biomass accumulation as the result of input uncertainties during the 2-years cropping system (2014–2015) for each management practice. Five uncertainty input parameters of climate and soil were tested. These were temperature, precipitation, clay content, SOC, and pH, which were selected due to the high variability of the field measurements (Tab. 4).

The importance of each input parameter relative to the total uncertainty of biomass accumulation was expressed by the contribution index (c_i). To calculate this index, the Monte Carlo procedure was then re-simulated for the number input parameters assessed, for each simulation one input was held at its default value and the remaining inputs were varied within their defined range (i). The normalized standard deviation (c_i %) of each Monte Carlo simulation output was calculated using Eq. (6),

$$c_i = \frac{\sigma_g - \sigma_i}{\sum_{i=1}^{i_{max}}\sigma_g - \sigma_i}\times 100, \tag{6}$$

where σ_g is the normalized standard deviation in the total uncertainty and σ_i is the normalized standard deviation of the uncertainty as the result of variation in input i.

3 Results

3.1 Site simulation and model validation

Using the calibrated model, almost all the simulated biomass accumulation and N uptake for crops in each treatment fell within the measurement range, and they were also within the 95% confidence interval of the measurements (Tab. 5; Figs. 1–3). However, the DNDC model tended to underesti-

Table 4: Uncertainties of the inputs observed during the vegetable production in Tamale, Northern Ghana.

Parameters	Unit	Baseline	Std. deviation	Min	Max	Lower limit	Upper limit
Daily temperature	°C	29.1	0.27	28.9	29.3	–0.5	0.5
Daily precipitation	each day mm	2.1	0.5	1.7	2.5	–1	1
Clay	volume fraction	0.06	0.01	0.043	0.08	0.04	0.08
SOC	kg C kg^{-1} soil	0.0045	0.001	0.0027	0.0065	0.0025	0.0065
pH	unit pH	5	0.3	4.4	6	4	6

Table 5: Model goodness of fit between measured and simulated biomass accumulation and N uptake in vegetable production systems at Tamale, Northern Ghana.

Crops	Biomass accumulation					N uptake				
	RMSE	RMSE95%	E	E95%	*r*	RMSE	RMSE95%	E	E95%	*r*
Amaranth	24	24	5	23	0.91	25	25	15	28	0.94
Lettuce	26	32	17	30	0.95	22	32	8	29	0.95
Amaranth	15	21	–9	22	0.97	22	28	5	29	0.97
Jute mallow	15	16	–1	23	0.98	28	28	–4	30	0.91
Jute mallow	23	23	6	25	0.93	24	24	2	26	0.93
Jute mallow	21	51	12	42	0.94	26	59	–24	45	0.95
Roselle	18	19	4	20	0.96	17	17	9	16	0.96

mate yield and N uptake when clean water was applied. On the other hand, yield and N uptake was overestimated with waste water. The statistical analysis using the RMSE and E indicated that there was no significant bias between measured and simulated values (Tab. 5). The modelled values also showed a statistically significant correlation (r > 0.9) with their corresponding measured values (Tab. 5).

The simulation results showed that when waste water irrigation was increased from the reduced to the full rate, biomass accumulation and N uptake of all crops increased (Figs. 1–3) except for jute mallow cultivated from September to October 2015 (Fig. 3c, f). Especially for jute mallow, the effect of waste water irrigation on yield and N uptake was greater for the unfertilized than the fertilized treatments (Fig. 3a, b, d, e). The crop biomass harvested for the reduced and full rates of clean water irrigation were similar for all simulated crop yields and N uptake (Figs. 1–3). The increase in the simulated biomass accumulation and N uptake was driven by the input of N from waste water and mineral fertilizer with increases of up to 1800% and 500%, respectively. Irrigation with waste water of unfertilized amaranth, jute mallow and lettuce increased yields more than irrigation with clean water and mineral fertilization (Figs. 1–3). On the other hand, the simulated biomass accumulation and N uptake of roselle showed a greater response to mineral NPK fertilization than to waste water (Fig. 2b, d). The application of biochar increased biomass accumulation by a maximum of 30% and N uptake by a maximum of 7% (Figs. 1–3).

3.2 Uncertainty of biomass accumulation

The total uncertainty of modelled vegetable biomass, as predicted by the Monte Carlo simulations, varied across years and management practices. The mean of the total uncertainties varied between 1 and 39% relative to the baseline simulation. However, the baseline-simulated results were always

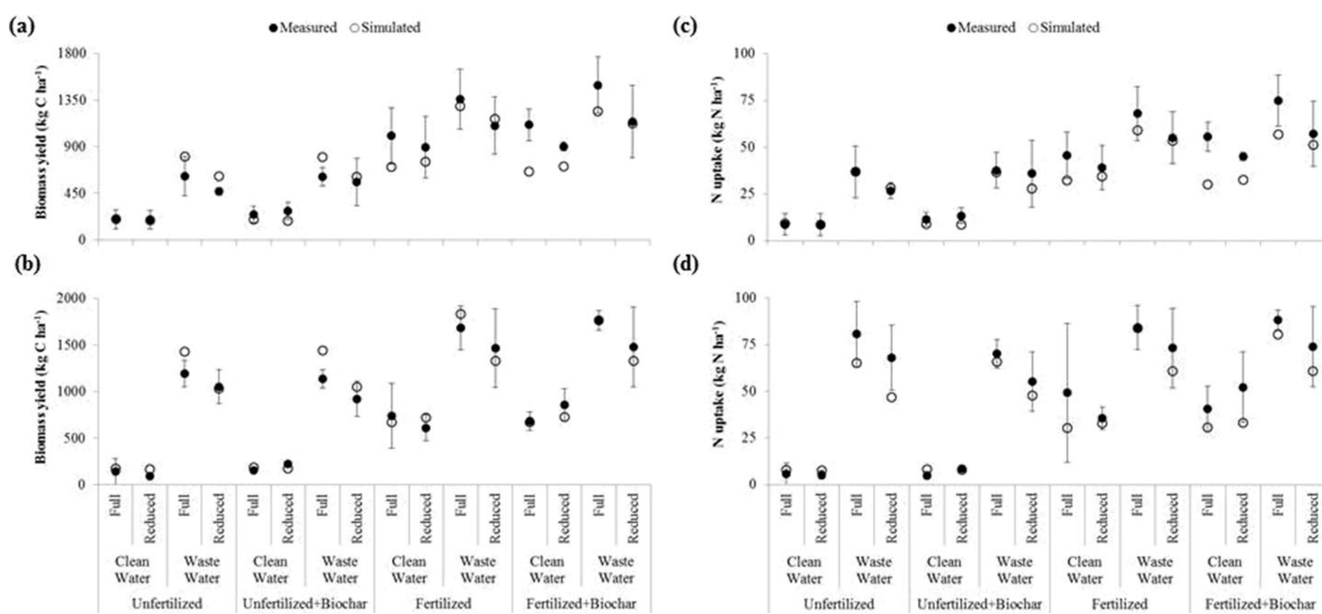

Figure 1: Simulated biomass accumulation and N uptake against field measured data (mean and standard deviations) of amaranth during the off-season growing period October–November 2014 (a, c) and February–March 2015 (b, d) under different management practices in an urban vegetable production system at Tamale, Northern Ghana.

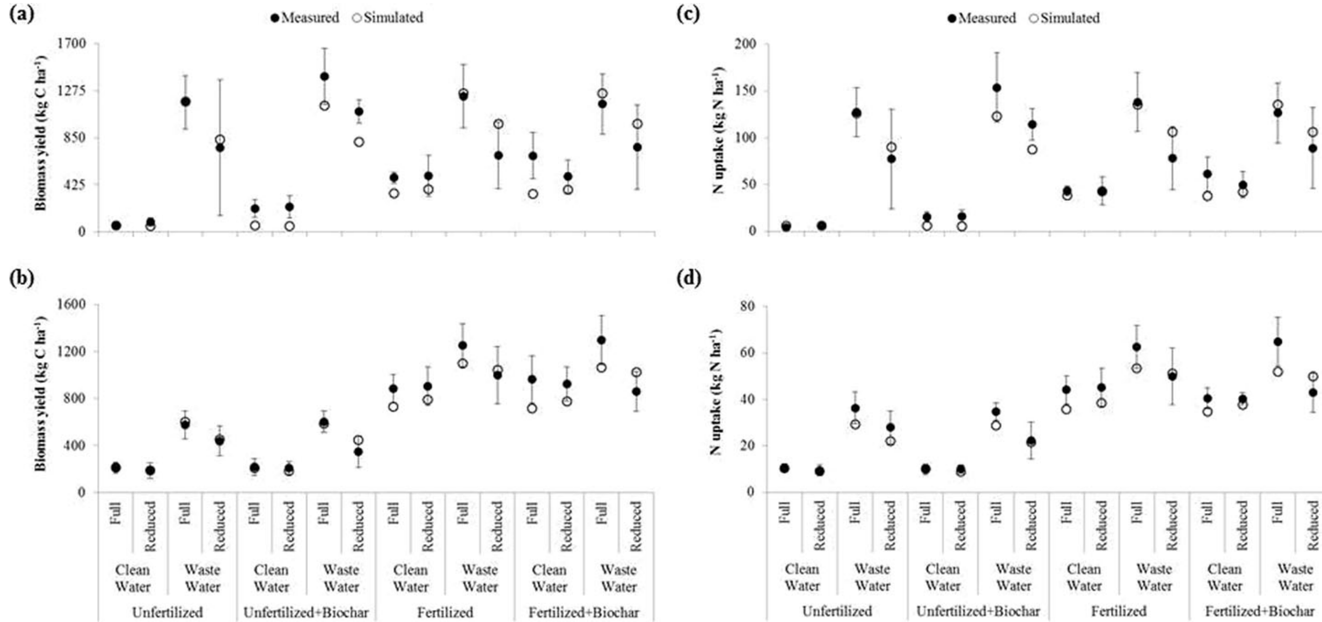

Figure 2: Simulated biomass accumulation and N uptake against field measured data (mean and standard deviations) of lettuce (a, c) and roselle (b, d) under different management practices in a simulated urban vegetable production system at Tamale, Northern Ghana.

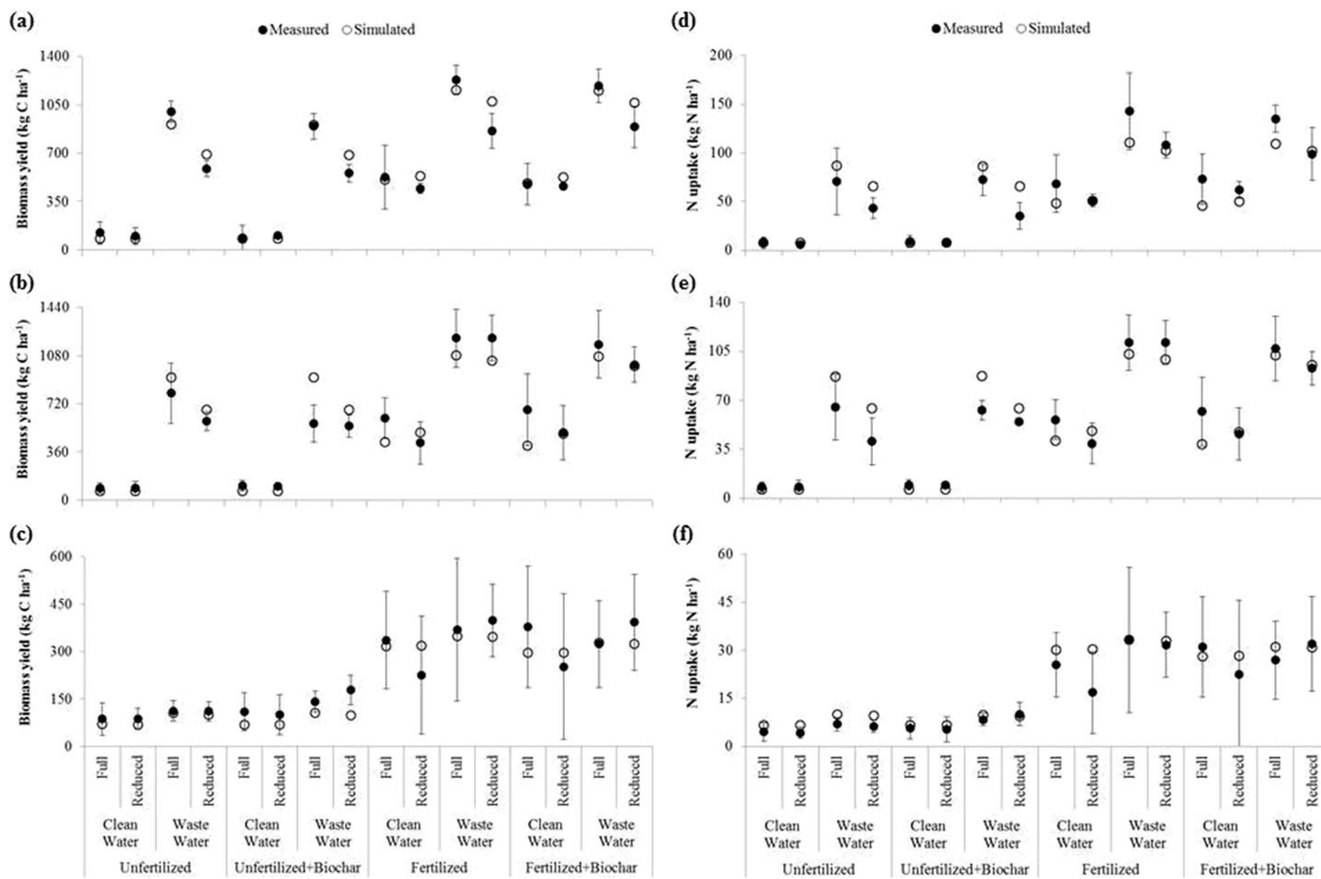

Figure 3: Simulated biomass accumulation and N uptake against field measured data (mean and standard deviations) of jute mallow the during growing period April–May 2015 (a, d), June–July 2015 (b, e) and September–October 2015 (c, f) under different management practices in an urban vegetable production system at Tamale, Northern Ghana.

within the range of the total uncertainty (Tab. 6). Total uncertainty of the simulated biomass accumulation was higher in 2014 than in 2015 for all treatments and was likely to have been influenced by the crop and the associated management and weather conditions (Tab. 1).

Table 6: Total uncertainty of modelled vegetable biomass accumulation for 2014–2015 under different management practices.

Treatments			2014					2015				
			Monte Carlo test			Baseline (b)	% difference (a – b)	Monte Carlo test			Baseline (b)	% difference (a – b)
			Variation	Mean (a)	S.D.			Variation	Mean (a)	S.D.		
Unfertilized (−Biochar)	Clean Water	Full	985–3367	2133	928	1463	31	622–1163	875	129	843	4
		Reduced	889–3349	2066	920	1445	30	578–1094	826	128	802.06	3
	Waste Water	Full	3912–5347	4570	392	4456	2	5547–6227	5866	147	5782.8	1
		Reduced	2977–4738	3923	521	3599	8	4079–4659	4361	138	4315.8	1
Unfertilized (+Biochar)	Clean Water	Full	832–3217	1758	844	1098	38	606–1137	873	135	836	4
		Reduced	729–3308	1739	859	1063	39	571–1121	827	135	797.98	4
	Waste Water	Full	3794–5057	4304	395	4104	5	5502–6162	5805	143	5729	1
		Reduced	2837–4521	3641	545	3336	8	4049–4629	4329	131	4285.7	1
Fertilized (−Biochar)	Clean Water	Full	2618–5246	4006	778	3546	11	3193–4342	3737	239	3568.1	5
		Reduced	3247–5403	4240	670	3742	12	3407–4682	3907	236	3762.6	4
	Waste Water	Full	4947–6624	5704	402	5484	4	7122–8546	7871	380	7501.3	5
		Reduced	4435–6485	5346	544	5211	3	5968–7306	6720	349	6413.6	5
Fertilized (+Biochar)	Clean Water	Full	2296–5023	3650	827	3056	16	3043–4323	3604	287	3424.6	5
		Reduced	2999–5135	3926	648	3460	12	3253–4547	3790	286	3656.5	4
	Waste Water	Full	4779–6432	5443	412	5263	3	6935–8420	7628	376	7329.3	4
		Reduced	4379–6113	5101	528	4667	9	5879–7279	6560	361	6248.2	5

3.3 Relative importance of model inputs for biomass accumulation

The relative contribution of five soil and climate input parameters to the total uncertainty of vegetable biomass accumulation was reflected in the contribution index, c_i (Fig. 4). A positive value of c_i indicated that changing a certain input factor increased total uncertainty and *vice versa*.

Across all management practices soil pH was the most important model input parameter determining uncertainty of biomass accumulation in the first year (2014); c_i varied between 84% and 147%. In the second year (2015), SOC was the main contributor (c_i = 86–104%) in the unfertilized treatments with clean water irrigation. On the other hand, for unfertilized plots with waste water irrigation, SOC and pH were equally important. The c_i order of the input parameters in 2015 showed different patterns in response to the fertilizer treatments under clean and waste water irrigation. Soil pH and clay content were the main contributors to total uncertainty for biomass accumulation under clean water irrigation. However, under waste water irrigation, soil pH and precipitation contributed more than the other parameters.

4 Discussion

After the initial calibration, the simulations of biomass and N uptake by the DNDC model were statistically valid for the studied leafy vegetables grown on the sandy soil of Tamale at different levels of N, biochar, and water quantity. The wide applicability of DNDC is well documented by previous studies of spring wheat (*Triticum aestivum* L.) on a sandy soil in Darmstadt, Germany (*Ludwig* et al., 2011b), and on silty clay, loam and clay loam soils in Eastern Canada (*Sansoulet* et al., 2014). Similarly, sorghum (*Sorghum bicolor* Moench.) production on a silty loam soil in Texas (*Dou* et al., 2014) and winter wheat–summer maize production in the North China Plain (*Zhang* et al., 2015, 2018; *Zhang* et al., 2017) and on the Southern Loess Plateau in China (*Chen* et al., 2015) have been successfully simulated by DNDC. The DNDC model has also been used to simulate yields under dif-

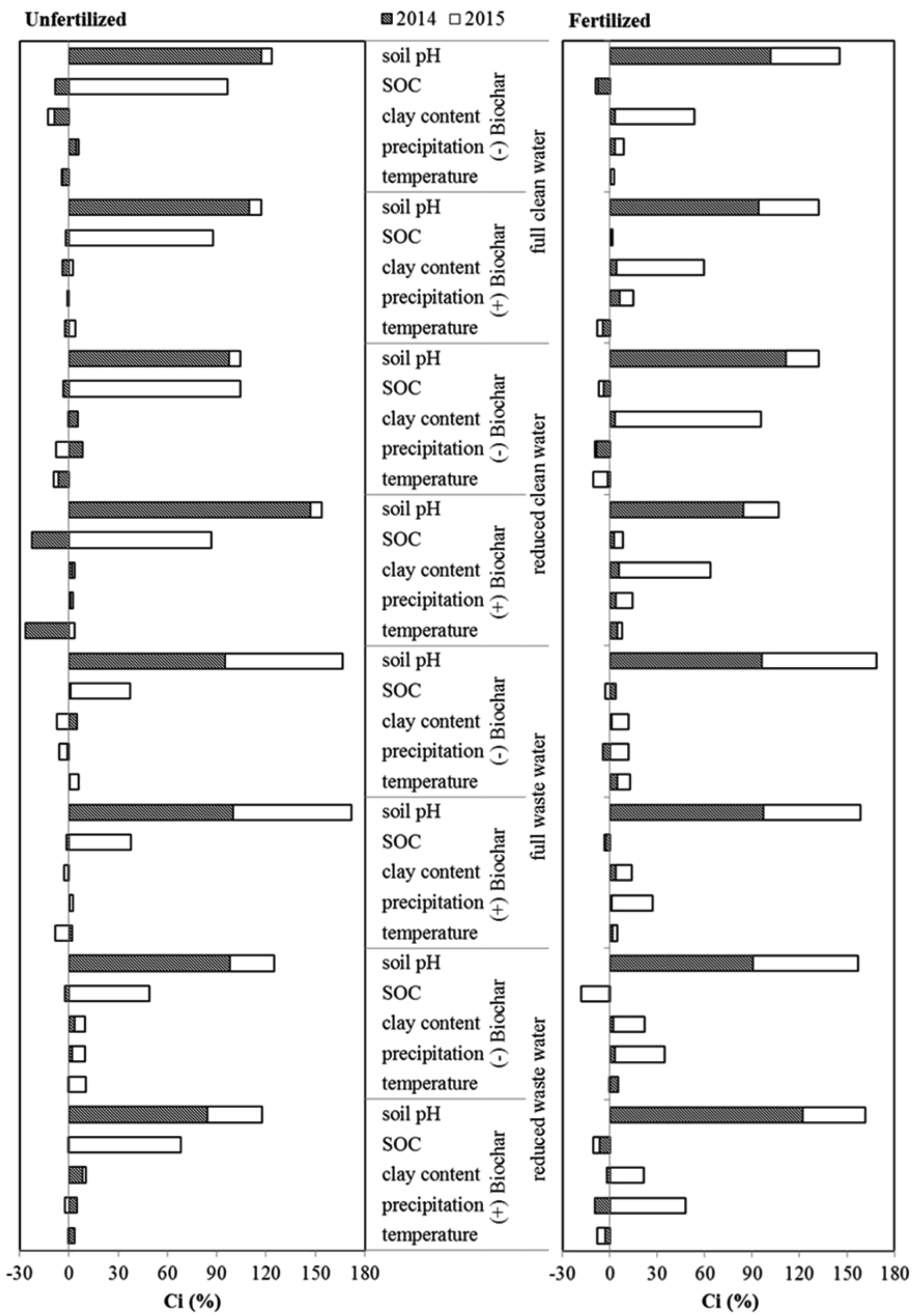

Figure 4: Contribution index (c_i) of each input factor to global uncertainty of vegetable yield 2014–2015 under different management practices in Tamale, Northern Ghana.

ferent biochar types in a sandy soil of Myanmar (*Kyaw*, 2015). The overestimated biomass accumulation under waste water treatment indicated that DNDC was more responsive to changing N inputs from irrigation water than to mineral fertilizer. This likely also reflected the yield limiting effects of nutrients other than N, particularly P, under the conditions of our study.

Nitrogen in mineral fertilizers or waste water increased biomass accumulation and N uptake more than increasing the quantity of irrigation water or the addition of biochar. This indicated that native soil N in Tamale was insufficient to promote high vegetable yields. The latter were rather robust to water deficit. A change in soil bulk density and SOC as a response to the addition of biochar had low short-term effects on biomass accumulation, especially for amaranth on the unfertilized soils during the February–March 2015 cultivation period. Although modelled effects were lacking, biochar may improve soil N uptake by crops under N limiting soil conditions (*Sarfraz* et al., 2017). Similarly, *Huang* et al. (2018) showed in a field experiment that biochar was able to increase soil N uptake in rice on a clay soil after a two-year application.

Sansoulet et al. (2014) reported that the predictions of biomass accumulation and N uptake for spring wheat in Eastern Canada under different N fertilization rates and rainfall deficit conditions were similar for DNDC, STICS (Simulateur mulTIdisciplinaire pour des Cultures Standard; *Brisson* et al., 2003), and DayCent (Daily version of CENTURY; *Parton* et al., 1998). However, under excessive rainfall, STICS was more effective than DNDC and DayCent in estimating N uptake, as the latter models lack functions to incorporate the effects of excess water on crop production (*Sansoulet* et al., 2014). On the other hand, DNDC tended to predict soil N better than DayCent and STICS (*Guest* et al., 2017). In long-term experiments with spring wheat in the Canadian prairies, DNDC and DayCent were effective in predicting crop yields and N_2O emissions. However, in DayCent the predictions of N_2O were mainly from the nitrification process, and they were evenly split between nitrification and denitrification in DNDC (*Grant* et al., 2016).

The DNDC model (v. 9.5) used in our study is the result of a series of modifications that have been made during the last 20 years. Main improvements were made in crop growth simulation and hydrological features (*Gilhespy* et al., 2014). As the calibrated DNDC model allowed to successfully estimate crop C and N for a range of farmer practices in Northern Ghana, it is a potentially useful tool to optimize the application of fertilizer and waste water in order to better predict crop yields, soil C, and GHG emissions.

However, if the model is used to drive decision support systems, understanding its measurement uncertainties is critical. The total uncertainty of vegetable biomass accumulation was derived from the propagation of uncertainty ranges of selected soil and climate parameters reflecting the variability under field condition. Our data show that the total uncertainty varied across different management practices and years. However, the input uncertainty was not the only reason for the uncertainty in the vegetable biomass accumulation, as the interaction between temporal site characteristics and management practices also contributed. Similar results were obtained when maize yield was modelled by the Agricultural Production Systems Simulator (APSIM) and the Lund-Potsdam-Jena managed Land (LPJmL) in West Africa (*Waha* et al., 2015).

5 Conclusions

The calibrated DNDC model predicted the biomass accumulation and N uptake of amaranth, jute mallow, lettuce, and roselle in response to different N inputs and irrigation water quantities as tested in our experiment in Northern Ghana with acceptable tolerance. In addition, the model is capable of simulating the effects of soil-applied biochar on crop production. This may also indicate potential model applications to estimate soil C and N stocks and emissions in order to develop more nutrient- and water-efficient vegetable production systems in the UPA of West Africa. The results indicated that the uncertainty associated with the variability in the soil and weather inputs differed between years and management practices. Soil pH, SOC, clay content, and precipitation were important contributors to total uncertainty, and it is thus important to have reliable data for these parameters. For predictive purposes, a better process-oriented understanding of uncertainty in these parameters would be of great help.

Acknowledgments

We thank the *German Federal Ministry of Education and Research* (*BMBF*) and the *German Federal Ministry for Economic Cooperation and Development* (*BMZ*) for funding the research of the *UrbanFood^{Plus}* project under the *GlobE-initiative* (*FKZ: 031A242-A*). We also thank the *Ministry of Research, Science, Technology and Higher Education* (*KEMENRISTEK-DIKTI*) of Indonesia for providing a PhD scholarship to the first author. We acknowledge *Dr. Ronald Kuehne* for constructive discussions on crop model simulation and the help of our field technicians and supporting farmers in Tamale and at the University for Development Studies (UDS) in Tamale for their support in data collection and setting up the field experiment. CFET's contribution to the work was supported by the *Scottish Government Strategic Research Programme*.

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