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ORIGINAL PAPER

Determining and managing maize yield gaps in Rwanda

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Abstract

Smallholder maize growers are experiencing significant yield gaps due to sub-optimal agricultural practices. Adequate agricultural inputs, particularly nutrient amendments and best management practices, are essential to reverse this trend. There is a need to understand the cause of variations in maize yield, provide reliable early estimates of yields, and make necessary recommendations for fertilizer applications. Maize yield prediction and estimates of yield gaps using objective and spatial analytical tools could provide accurate and objective information that underpin decision support. A study was conducted in Rwanda at Nyakiliba sector and Gashora sector located in Birunga and Central Bugesera agro-ecological zones, with the objectives of (1) determining factors influencing maize yield, (2) predicting maize yield (using the Normalized Difference Vegetation Index (NDVI) approach), and (3) assessing the maize yield gaps and the impact on food security. Maize grain yield was significantly higher at Nyakiliba (1.74 t ha^{-1}) than at Gashora (0.6 t ha^{-1}). NDVI values correlated positively with maize grain yield at both sites (R^2 = 0.50 to 0.65) and soil fertility indicators (R^2 = 0.55 to 0.70). Maize yield was highest at 40 kg P ha^{-1} and response to N fertilizer was adequately simulated at Nyakiliba (R^2 = 0.85, maximum yield 3.3 t ha^{-1}). Yield gap was 4.6 t ha^{-1} in Nyakiliba and 5.1 t ha^{-1} in Gashora. Soil variables were more important determinants of social class than family size. Knowledge that low nutrient inputs are a major cause of yield gaps in Rwanda should prioritize increasing the rate of fertilizer use in these agricultural systems.

Keywords Maize grain yield · Social classification · Prediction · Crop intensification

1 Introduction

The main goal of agricultural crop management in a country is to guarantee food resources for its population. At the global level, the challenge is to feed about 7 billion people, a number which will most likely double by year 2050 (Ray et al. 2013). Food security requires coordinated action of a cross section of stakeholders in the food production chain. Governments in collaboration with various stakeholders are investing constant efforts to assure current human needs and preserve land quality for future generations (Kayiranga 2006). The largest proportion of agricultural production in developing countries comes from smallholder farmers and projections indicate the trend is likely to remain the same for at least the next 30 years (Thornton and Herrero 2001).

In the case of Rwanda, efforts are invested in promoting the crop intensification programme with the aim of increasing agricultural productivity of high potential food crops (maize, rice, wheat, cassava, Irish potato, and beans) for ensuring food security and self-sufficiency (Kathiresan 2011). Farm inputs (improved seeds, amendment such as lime and fertilizers) are distributed to farmers through public-private partnerships and

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extension services together with improved agricultural practices. As a result, agricultural productivity has been growing in recent years, translating into improved food security and household income (Kathiresan 2012).

Despite tangible success in terms of total production of maize and an expansion in total cultivated area, which increased from 28,016 to 286,412 ha from 2007 to 2013, crop yields remain far lower than their yield potential (MINAGRI 2014). For example, maize yield increased from 0.72 t ha^{-1} in 2007 to 2.34 t ha^{-1} in 2013 against the potential yield of 5 t ha^{-1}. This yield gap may be due to several biotic and abiotic factors among which are pest and disease as well as nutrient deficiencies and climate change (FAO 2012).

Therefore, efforts meant for sustaining food production should target the farm and address all limiting factors associated with low productivity. In fact, performing seasonal yield assessment and building models for yield prediction can help to design mitigation strategies to avoid severe crop failures (Leng and Huang 2017).

Furthermore, numerous studies have recognized that plant development, stress, and yield capabilities are expressed in spectral reflectance from crop canopies and could be quantified using spectral vegetation indices such as the Normalized Difference Vegetation Index (NDVI) (Ahmad et al. 2014). The latter measures the amount of green vegetation in an area and is generally used to infer crop biomass and health over large areas where ground data are not available (Atzberger, 2013). At the time of maximum green leaf biomass development, NDVI has been shown to be highly correlated with final grain yield of cereals (Tucker et al. 1980) and can therefore be used to estimate in-season maize yield before harvesting while tracking factors undermining potential yield at farm level (Liu et al. 2012).

In Rwanda, NDVI-based studies integrating biotic, abiotic, and socio-economic factors that affect maize productivity are scanty and deserve focus. This study aimed at determining yield gap and devising appropriate strategies for managing maize yield gaps to ensure food security in Rwanda. Specifically, the study aimed at (1) characterizing farm-scale socio-economic and biophysical variables in relation to maize yield, (2) assessing the usefulness of the NDVI method for predicting maize yield and soil variable responses, and (3) estimating the maize yield gap and the impact on food security in relation to applied nutrients and other social variables.

2 Materials and methods

2.1 Characteristics of the study locations

The study was conducted in Bugesera and Rubavu districts as representatives of two contrasting agro-ecological (AEZ) zones of Rwanda (Fig. 1).

Bugesera district has a semi-arid climate with an annual rainfall of 850–1000 mm, characterized by a bimodal rainfall pattern with primary and secondary peaks in April and November, respectively. The region has a dry season lasting for 3 months and an average temperature of about 21 °C (Verdoodt and Ranst 2003). Soils in Bugesera are very weathered and dominated by humic and haplic Ferralsols.

Rubavu district has a sub-humid climate with an annual rainfall varying between 1300 and 1600 mm (Verdoodt and Ranst 2003), with a bimodal pattern of 2 major cropping seasons: the "long rains" from mid-February to mid-July (named season B) and a "short rainy" season from September to January (named season A). Soils in this area are typically Mollic Andosols (Verdoodt and Ranst 2003) and cropping is dominated by a mix of various commodities including maize, Irish potato, and bean, with predominance of the climbing types. Nyakiliba and Gashora sectors were, respectively, selected within these districts as representatives of maize-producing locations in 2015 and 2016 seasons. Biophysical characteristics, socio-economic indicators, and crop production systems of the research sites are reported in Table 1.

2.2 Methodology

The methodology applied a number of approaches and techniques to integrate various aspects that are critical to maize production. These approaches include a socio-economic survey and Normalized Difference Vegetation Index measurements coupled with remotely sensed and geo-information data. Process-based modelling of maize production was used to estimate yield gaps.

2.2.1 Survey

A survey was conducted in two contrasting regions, namely Bugesera district representing low altitude and low rains with frequent prolonged drought and Rubavu district, representing high altitude and rain intensity. The study sites were purposely chosen to reflect major contrasting cropland landscapes across Rwanda and therefore capture the large variability in terms of agricultural contexts under which Rwandan farmers operate. The two zones differ in terms of elevation, rainfall, temperatures, population size, and family structure.

The study targeted farmers in consolidated sites. To select representative farmers, a stratified sampling approach was applied. A field visit was organized with assistance of local leaders. In each district, three villages were randomly chosen and in each village three consolidated sites (upland, mid slope, and bottom land) were considered. The three villages were Kagako, Kiruhura, and Kagomasi in the Gashora sector and Bweza, Kibuye, and Kingoma in the Nyakiliba sector. In each village, three consolidated sites were selected. In each consolidated maize site, eight farmers having their plots in the same

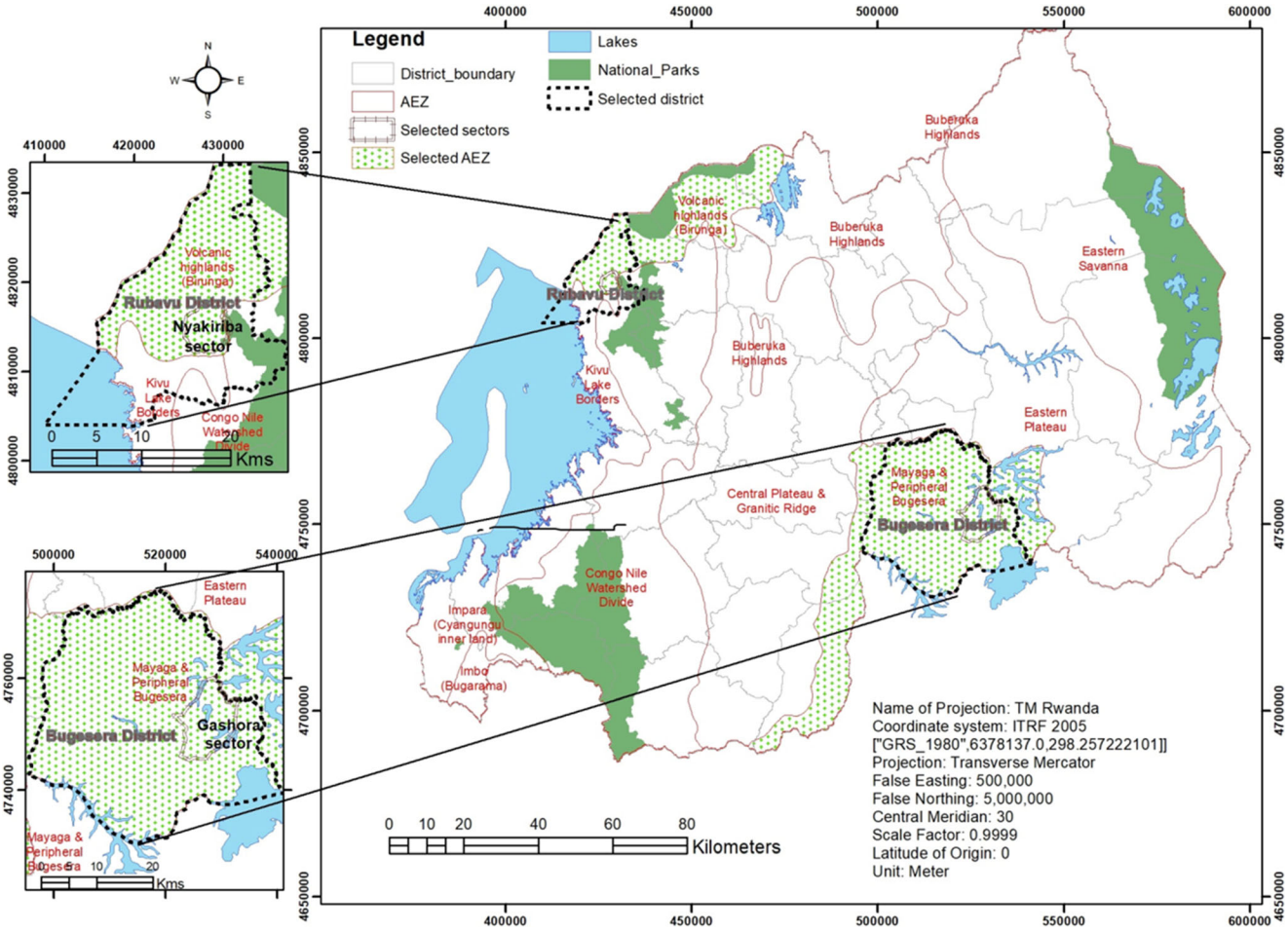

Fig. 1 Locations of Gashora and Nyakiliba, representing two contrasting agro-ecological zones

field were selected, making a total sample size of 144 farmers (2 districts × 3 villages × 3 consolidated sites × 8 farmers) across both districts. Primary data covering socio-economic and management practices were collected from a total sample of 144 farmers through semi-structured interviews.

2.2.2 Soil sampling and laboratory analysis

At the start of the experiment, soil samples for this study were collected from Gashora and Nyakiliba sectors, respectively. In one individual farm, 3 samples were collected (0–30-cm depth) and mixed up and one composite sample extracted, dried, and submitted to the laboratory for soil analysis. The soil analysis was done for chemical and physical characterization. The parameters analysed were pH_{H2O}, pH_{KCl}, soil organic carbon, nitrate, ammonium, available P, clay, silt, and sand soil particles. The pH value in soil water suspension and 1 M KCl solution was determined in a 1:2.5 ratio using a potentiometer equipped with a combined pH meter. Soil particle size analysis was done using the hydrometer method (Bouyoucos 1962). Nitrogen (nitrates, ammonium) was determined using the colorimetric method, while organic carbon was determined using the method outlined in Walkley and Black (1934). Available phosphorus was determined using the molybdenum blue method on a Bray-P No. 1 extract (Bray and Kurtz 1945).

2.2.3 Remotely sensed (NDVI measurement) and geo-information data

The optical sensor Green Seeker helped to measure NDVI spectral reflectance of maize leaves. The Green Seeker provides measurements for two wavelengths (c. 660 and 770 nm), enabling the calculation of the NDVI (Govaerts and Verhulst 2010). NDVI is computed by the following formula: NDVI = (NIR ref. − Red ref) / (NIR ref. + Red ref) (Gupta 2006). To understand the relationship existing between NDVI and final maize grain yield, we performed spatial statistical analysis of measured NDVIs and maize grain yield using Arc map 10.1 version. To explore correlation between maize grain yield and NDVI, we assumed that Yield = f (NDVI) (Eq. 1). NDVIs and maize grain yield (GY) measurements were subjected to regression analysis.

Table 1 Biophysical characteristics, socio-economic indicators, and crop production systems of the research sites, Nyakiliba and Gashora sectors, respectively

Variable	Units	Sites	
		Nyakiliba	Gashora
District		Rubavu	Bugesera
Agro-ecological zone		Birunga	Central Bugesera
[1]Altitude	m ASL	2041	1401
[2]Geographic coordinates	Degree	1° 55′ 09″ S, 29° 44′ 14″ E	2° 12′ 27″ S, 30° 14′ 37″ E
[3]Area	km^2	23.3	98.8
[4]Rainfall			
Total annual rainfall	mm	1500	900
Rain distribution			
Short rains		September to December	September to November
Long rains		February to May	February to May
[5]Soil texture (dominant)		Sandy loam	Sandy loam
[6]Temperature			
Annual mean	°C	20	26
Annual maximum	°C	25	30
Annual minimum	°C	9	21
[7]Population density (2012)	#inhab km^{-2}	1039 (Rubavu average pop. density)	280 (Bugesera average pop. density)
[8]Dominant cropping systems		Mostly intensive crops with predominance of Irish potatoes, beans, maize, bananas, sorghum, and vegetables	Mostly intensive crops with predominance of sweet potatoes, beans, maize, bananas, cassava, and soya beans

[1,2,5] Own data taken at field plot during study period (2015–2016); [3,4,8] DDP (district development plans for both Rubavu and Bugesera; [6] REMA (2018); [7] Rwanda statistical year book (2014)

2.2.4 Estimating maize yield gap and implication on food security

Experiments testing the response of maize to increasing N rates were installed at both Bugesera and Nyakiliba on farms in three villages per sector. The factorial experiment was run for two consecutive seasons: the short rain (SR) season 2015B (September 2015 to January 2016) and the long rain (LR) season in 2016A (February to May 2016). Plots of 20.25 m^2 (4.5-m length by 4.5-m width) were used and the experiment was laid out in a randomized complete block design (RCBD) with 4 treatments (4 N rates consisting of 0, 23, 46, and 92 kg N ha^{-1} as urea with a blanket application of 36 kg N and 40 kg P ha^{-1}as DAP). Maize (variety Pool 9A in Nyakiliba, PAN 691 in Bugesera) was established at 75 cm × 25 cm spacing between and within rows and thinned to one plant per hill. Plots were hand-weeded twice during the growing season.

The APSIM framework is a reputable, process-based, suite of one-dimensional daily crop, pasture, and tree models that can be linked in the software with livestock and farm-scale livelihood models. This framework has been successfully used internationally for simulating production under a range of crop, soil, climate, and management options for risk assessment in a wide range of production systems (Holzworth et al. 2018). The APSIM maize model is particularly suited to Rwanda, because it has a long history of use in development, testing, and use in East Africa (e.g. Smethurst et al. (2017)). The model was calibrated using data from the experimental control plots. Values of soil water contents used to set soil drainage parameters, namely lower and upper drained limits, were extracted from Ndoli et al. (2017) who measured soil moisture in the vicinity of our research area and in similar period. Measured soil carbon and N were used to initialize the model. Maize cultivars sown were not available in the model, but phenology and morphology parameters were approximated by simulating maize cultivar SC623. The parameter determining the cumulative temperature until the end of the juvenile period was set to 280 °C days in order to match the phenology observed during the experiment. The maximum number of kernels per maize ear was set to 504. Maize yield gaps were estimated by comparing measured experimental yield data with simulated yields using the APSIM Next Generation framework of models (Holzworth et al. 2018).

Grain fresh weight and grain moisture content (using a moisture meter) were measured and grain weight adjusted to 12% moisture. The simulations estimated (a) the response to N

fertilizer in presence of P fertilizer and (b) potential maize yield from hypothetically high N fertilizer rates that simulated yield with no N stress. Weather data were provided by the Rwanda Meteorology Agency. Management input variables, including sowing date, sowing density, fertilizer application, and fertilizer amount, were set according to each field experiment. The model was tuned to provide no water stress and a soil N supply that approximately reflected observed yields across the range of N fertilizer rates used. The yield gap was then assessed by subtracting measured maize yield from APSIM-predicted maize yield using the N fertilizer rate that eliminated N stress (simulated). The Nash-Sutcliffe modelling efficiency (NSE) and the root mean square error to standard deviation ratio (RSR) were used to evaluate model performance.

Yield gaps were also expressed in terms of food security indicators (amount of proteins and calories) for which the values of food energy and protein were derived using the average energy and protein content in maize estimated to be 342 kcal/100 g of energy and 9 g/100 g of protein on dry matter basis (Bucagu et al. 2014).

2.2.5 Discriminant analysis

Discriminant analysis (Statgraphics© software) was performed to investigate the extent to which descriptors (various qualitative and quantitative variables) could correctly classify maize yield, income, or social class. All dependent variables were defined as categorical variables.

2.3 Data analysis

The results were processed using SPSS 21 software for statistical analysis of baseline survey data (socio-economic). The results from soil chemical and physical analysis were compared using the GenStat ANOVA procedure. Predicted maize yield determined using the APSIM model was compared against the measured maize yield.

3 Results

3.1 Socio-economic characteristics

The results from the survey indicate that the average family size was 4 members per family in both sectors, but with a larger range from 1.5 to 10 in Gashora compared with 1.5 to 8 in Nyakiliba (Fig. 2). The family members comprise household heads, spouse, and children. The number of women headed households was higher in Gashora (52%) than in Nyakiliba (43%).

In the two study areas, most farmers surveyed had an average of 0.27 and 0.08 ha of land under maize cultivation in Gashora and Nyakiliba, respectively. These are individual maize plots merged with neighbouring plots but farmers retaining their land rights. Results indicate livestock ownership and distribution in both Gashora and Nyakiliba districts.

In Gashora, 69% of farmers own livestock. Among them, 19% of farmers own at least a cow, 4% a sheep, 28% at least a goat, 7% at least a hen, and 1% a pig. In Nyakiliba, 65% own either a small ruminant or a large livestock. Among them, 18% own a cow, 23% at least a goat, and 7% at least a hen. Some farmers have more than one type of livestock, e.g. a cow and goats (15%), and goats and pigs (7%) (Fig. 2). The estimated quantity of maize harvested largely varies from 50 to 2600 kg per household in both Nyakiliba and Gashora while the sold quantity of maize varies from 0 to 400 kg per household, representing 15% of total maize harvested.

3.2 Soil characteristics

Results of soil laboratory analysis are presented in Table 2. In both locations, soil pH was slightly acidic and falls in the range of 5.4 to 6.1 in Nyakiliba and 4.9 to 6.7 in Gashora. The values of N, available P, and OM significantly differed ($P < 0.001$) in the two locations. In Nyakiliba, nitrogen was 4.4 times higher in the Nyakiliba site (28.6 ppm) than in Gashora (6.36 ppm). Results show that the Nyakiliba sector had higher concentrations of soil organic carbon (2.81%) than Gashora (1.67%) (Table 2) but Gashora had higher concentration of available P (8.0 ppm) than Nyakiliba (3.0 ppm). Soil slope was classified as steep slope (> 30%) in 41% of cases in Gashora and 15% of cases in Nyakiliba. The soil texture was sandy loam in both study sites, with the presence of rocky material in some areas in Nyakiliba.

3.3 Management practices

In general, major agricultural practices conducted in maize-producing areas are ploughing, soil amendment, fertilizer application, weeding, integrated pest and disease management (IPM), and crop residue management. In Gashora, only a handful of farmers do an early ploughing and none in Nyakiliba, but all farmers plough once immediately before maize sowing. All farmers in both locations use organic fertilizers combined with mineral fertilizers. In Nyakiliba, all farmers practice maize plant thinning, while it is only done by a smaller percentage of farmers (11.1%) in Gashora. Weeding and pest and disease management are consistently done in both locations but few farmers recycle maize residues/stover (5.4%).

Management practices consisted of erosion control measures, mainly installation of ditches and terraces. In 2015 and 2016A cropping seasons, majority of farmers in Gashora cultivated beans while those in Nyakiliba cultivated beans in association with maize. The reason for the predominant crop mixing system in Gashora is linked with erratic weather conditions that prevail in the region and farmers strategizing for minimizing

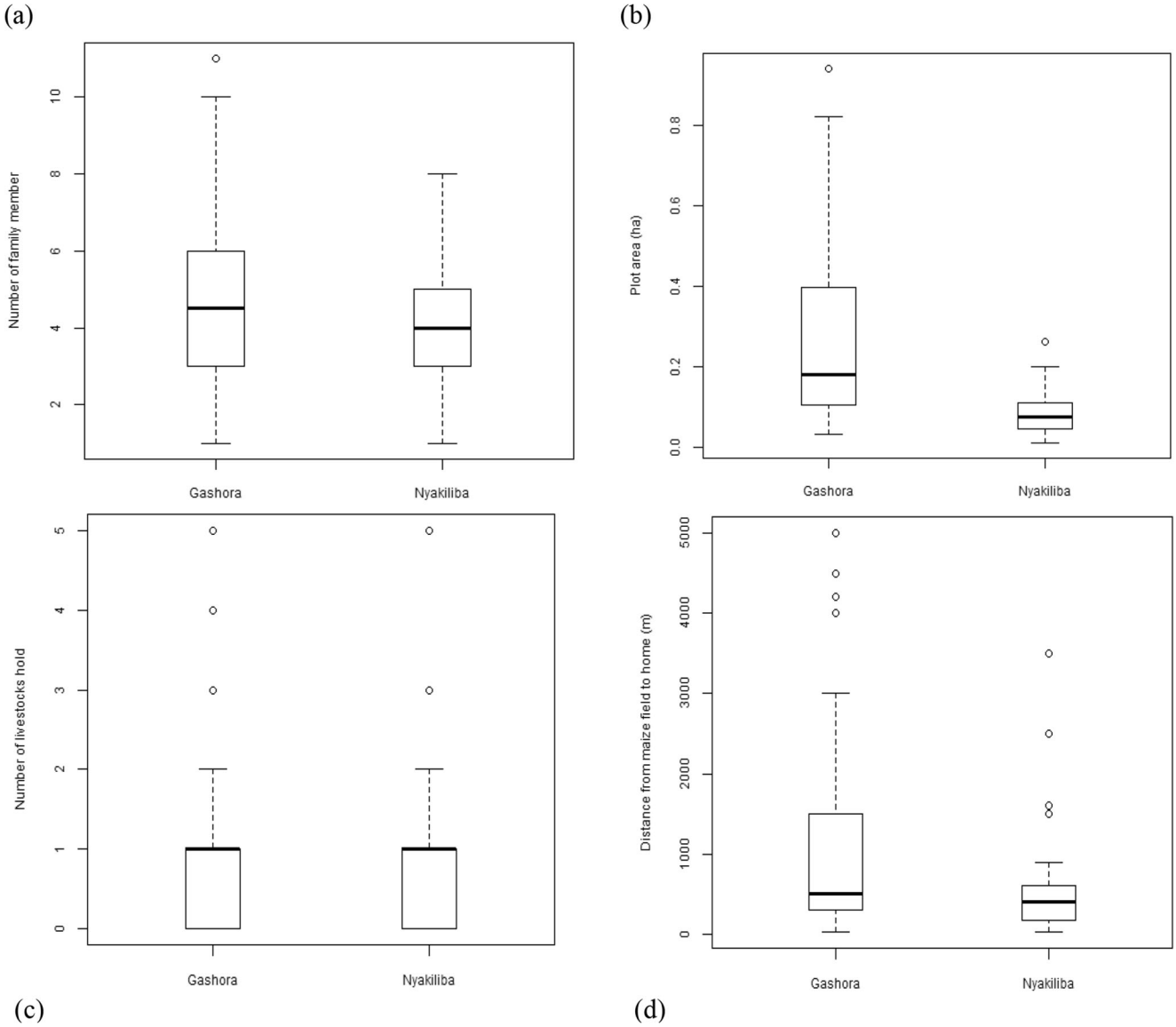

Fig. 2 **a**–**d** Major socio-economic characteristics in Gashora and Nyakiliba sectors

risks of food insecurity by practicing mixed cropping. This strategy, in the anticipation of a possible shortage of rain in the region, maximizes the chance of harvesting at least some beans, which have a short growth cycle.

3.4 Prediction of maize yield using the NDVI method

Correlation between NDVI and relative maize grain yield is illustrated in Fig. 3. The results indicated a significant ($P < 0.05$) and a positive and weak to moderate relationship between the relative maize yield and NDVI. In the cropping season 2015A, the coefficients of regression R^2 corresponded to 0.52 and 0.61 in Nyakiliba and Gashora, respectively, while in 2015B, the coefficients were 0.50 and 0.65 respectively in the mentioned sites. In all cases, maize yield increased with NDVI; however, the yield plateau reached at an NDVI of 0.8 beyond which no more yield increase was recorded (Fig. 3).

3.5 Relationship between NDVI and soil fertility parameters

Figure 4 illustrates the relationship between NDVI and soil fertility parameters. The results indicate positive linear relationships between NDVI and all measured soil parameters with R^2 values ranging from 55 to 70%. Correlation coefficients are much larger for Gashora than Nyakiliba except for NO_3-N. SOC explained about 67 and 55% of variation in NDVI in Nyakiliba and Gashora respectively; NO_3-N explained 69 and 70% of variation in NDVI in Nyakiliba and Gashora respectively while (NO_3-N + NH_4) explained 59 and

Table 2 Physical and chemical soil characteristics for Gashora and Nyakiliba sites

Chemical and physical properties	Unit	Nyakiliba			Gashora			Sign. difference levels
		Mean	Range	SE	Mean	Range	SE	
$pH_{(H2O)}$	-	5.85	0.66	0.032	5.91	1.66	0.07	NS
$pH_{(KCl)}$	-	5.41	0.64	0.032	5.38	1.95	0.08	NS
C	%	2.81	1.00	0.076	1.67	1.00	0.09	***
Org. matter	%	4.73	2.81	0.126	2.84	2.14	0.10	***
NH_4^+-N	ppm	5.93	4.38	0.226	0.71	3.09	0.22	***
NO_3^2-N	ppm	28.26	50.75	2.602	6.36	30.29	1.44	***
P avail.	ppm	3.00	6.00	0.287	8.00	25.00	0.96	***
Clay	%	7	0	1.49	21	16	0.58	***
Silt	%	29	2	0.72	14	18	0.72	***
Sand	%	64	2	1.24	65	6	0.43	NS
Texture class		Sandy loam			Sandy loam			

***Significant at $P < 0.0001$. *NS* no significant differences

69%. Phosphorus explained 60 and 63% of NDVI variation respectively in Nyakiliba and Gashora.

3.6 Maize grain yield and yield gap and implication on food security

Maize yield was affected by the main effect of P rate and interaction between N and P rates (Table 3). In Gashora, maize yield was the lowest in the absence of P and the highest with P applied at 40 kg ha^{-1} (1.08 t ha^{-1}) compared with the control. Interaction between N and P affected significantly maize yield at N applied at 10 and 20 kg ha^{-1} as compared with the control without fertilizers. N applied at 40 kg ha^{-1} combined with P at 92 kg ha^{-1} had the highest effect on maize yield (1.2 t ha^{-1}).

In Nyakiliba, maize response to P was much larger but with similar trend as in Gashora. Maize yield was the highest with 40 kg ha^{-1} (2.1 t ha^{-1}), significantly higher than the control without P. Interaction between N and P affected significantly maize yield at N applied at 10 and 20 kg ha^{-1} as compared with the control. N applied at 40 kg ha^{-1} combined with P at 92 kg ha^{-1} had the highest effect on maize yield (2.1 t ha^{-1}).

The response of maize grain yield to N fertilizer was adequately simulated at Nyakiliba in the presence of P fertilizer ($R^2 = 0.85$, maximum yield 3.5 t ha^{-1}), but the maximum rate of fertilizer used (92 kg N ha^{-1}) was simulated to be inadequate to maximize N-sufficient yield (8.1 t ha^{-1}, Fig. 5). Hence, at the highest rate of N fertilizer used, the yield gap was 4.6 t ha^{-1}, meaning farmers may be able to only produce 43% of the maximum maize yield. The gap was simulated to increase to 6.5 t ha^{-1} if no N fertilizer was applied, translating into 80% of total potential yield in the case of N-sufficient yield. The yield gap can be expected to be higher in the absence of P fertilizer, and higher rates of P and other fertilizers are likely to be needed to attain maximum grain yield. At Gashora, the observed response to N fertilizer could not be

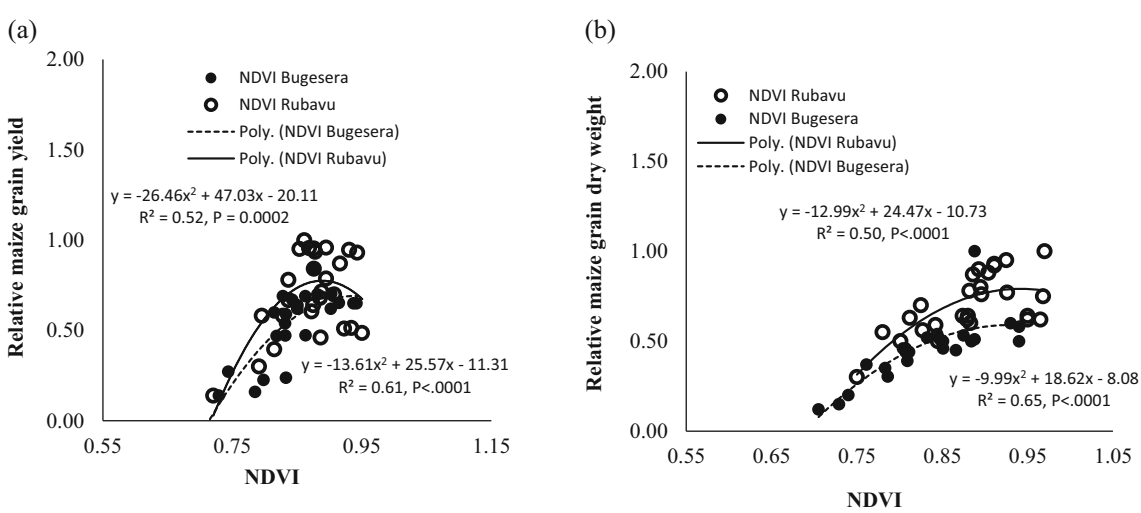

Fig. 3 Correlation between NDVI and relative maize grain yield during season 2015A (**a**) and season 2015B (**b**)

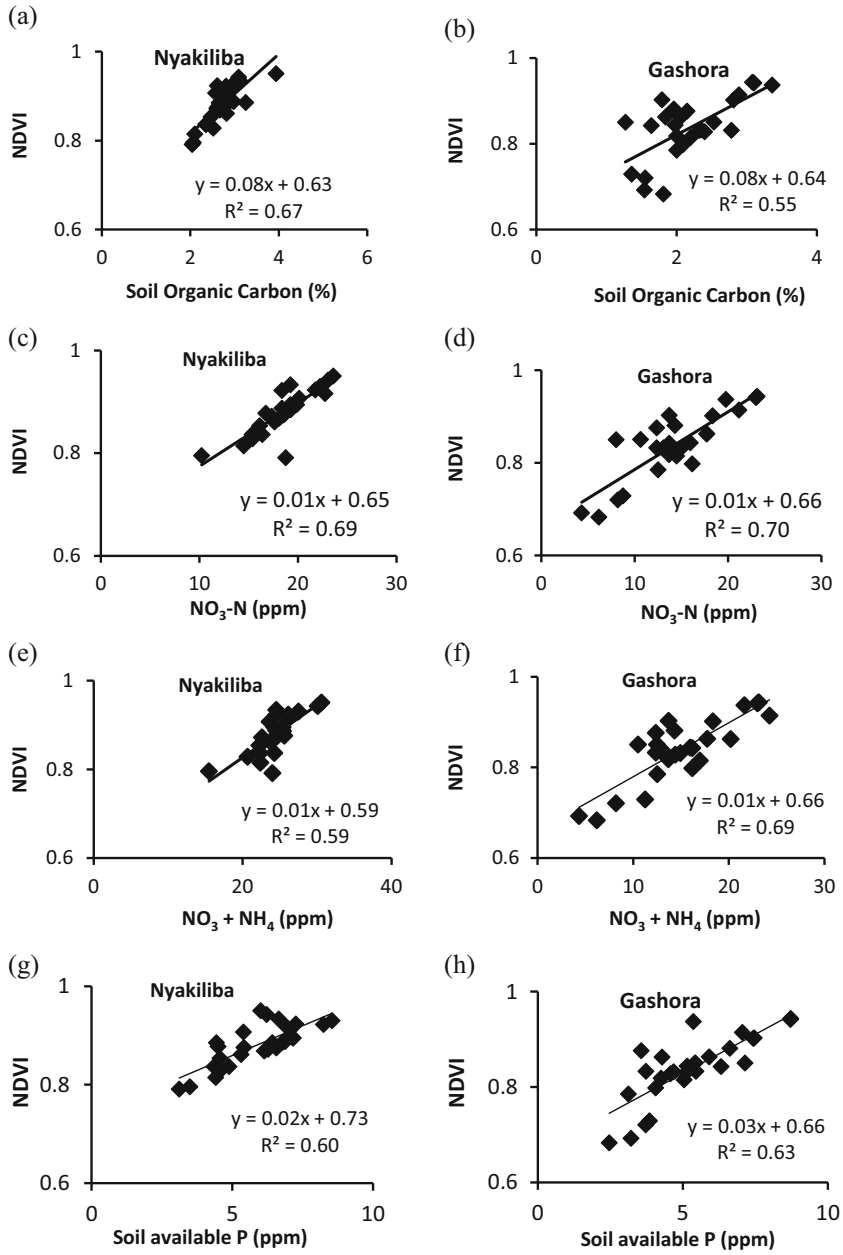

Fig. 4 **a**–**h** Relationship between field mean NDVI and soil fertility parameters

adequately simulated because simulated yields could not be reduced enough by limiting water and N supply alone in the APSIM model. Water and N-sufficient simulated yield at Gashora was 6.3 t ha^{-1}, which indicates a yield gap of at least 5.1 t ha^{-1}.

The level of maize yield gap in Nyakiliba and Gashora translates into 15,721 to 22,178 kcal ha^{-1} and 416 to 587 g of proteins under various N rates. Estimated monetary losses range from 1664 to 2348 USD on per hectare basis. In Gashora, the levels are respectively 17,442 kcal and 459 g of protein at 92 kg N ha^{-1} (Table 4).

3.7 Discriminant analyses for maize yield, income, and social class

A function for income category was significant, which correctly predicted 42% of cases. When maize yield, income, and soil factors were included, social category was correctly and significantly ($P < 0.01$) predicted in 74% of cases. Variables with large standardized coefficients that strongly predict social category were income > maize type > soil local name > soil texture (Table 5). The number of years the farm had been used, the number of livestock, the level of soil fertility, and

Table 3 Grain yield of maize as affected by the interaction effects of different levels of N and P fertilizer application in Gashora and Nyakiliba

Gashora					
	P levels (kg ha^{-1})				
N levels (kg ha^{-1})	**0**	**10**	**20**	**40**	**Average**
0	571.2	693.9	779.0	953.1	749.3
23	656.4	728.7	808.4	1080.5	818.5
46	658.1	733.8	812.6	1109.1	828.4
92	673.6	768.2	878.2	1201.6	880.4
Average	639.8	731.1	819.5	1086.1	819.1
P value (P)		< 0.001			
P value (N×P)		< 0.001			
SED (P)		102.7			
SED (N×P)		87.8			
Nyakiliba					
N levels (kg ha^{-1})	**0**	**10**	**20**	**40**	**Average**
0	1010.7	1667.3	1810.5	2077.2	1641.4
23	1168.7	1806.6	1812.5	2121.4	1727.3
46	1210.6	1820.9	1817.2	2191.6	1760.1
92	1215.0	1825.0	1817.4	2201.8	1764.8
Average	1151.2	1779.9	1814.4	2148.0	1723.4
P value (P)		< 0.001			
P value (N×P)		< 0.001			
SED (P)		265.7			
SED (N×P)		254.3			

the inter-row maize spacing were variables with the strongest predictability of farmer income (data not presented). Soil variables were more important determinants of social class than family size. On the other hand, family size had only a relative importance of 23% for maize production.

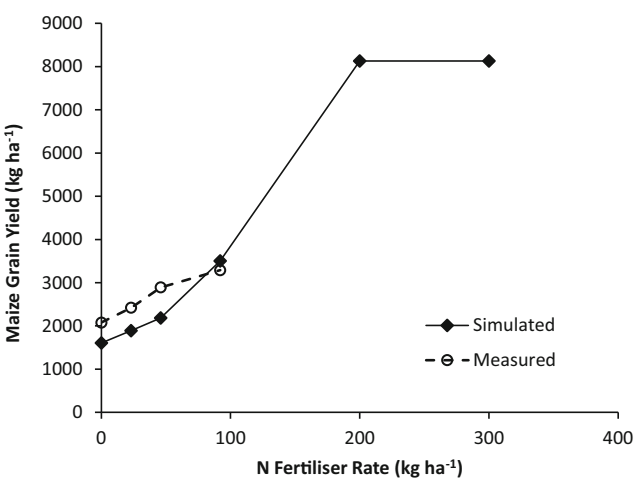

Fig. 5 Simulated and measured maize grain yield at Nyakiliba (Rubavu) in season B 2015

4 Discussion

The choice of contrasting locations (Nyakiliba and Gashora) lies in the fact they differ from each other, giving a broader representation of country's contexts of farmer cropping environment, climate, and soil type of Rwanda. Nyakiliba located in Birunga AEZ receiving sufficient rains and covered by Andosols (volcanic soils) and Gashora located in Central Plateau AEZ differ in terms of soil type and climatic conditions, resulting in higher maize productivity in Nyakiliba due to conducive climate (Table 1) and better soil fertility (Table 2). Both locations also differ in terms of social-economic aspects (family structure). These factors are known to significantly influence crop productivity in Africa (Bucagu et al. 2014). Efforts to reduce crop yield gap require identification of underlying factors that determine it at farm level and these are location specific (Tittonell et al. 2008; Van Ittersum et al. 2013; Beza et al. 2017).

4.1 Factors influencing maize yield gap

Our analysis looked at the extent to which biophysical and socio-economic factors predict maize production in the study sites (Table 5). The number of years the farm has been cultivated, the number of livestock holds, and the level of soil fertility seem to be major predictors of maize production on farm. Family size predicts about 23% of maize production. Maize inter-row spacing seems to also significantly influence maize production in both sites. In Gashora, farmers tend to adopt intercropping rather than a monocrop intensification programme, resulting in poor maize planting density and contributing to lesser maize yield. Maize yield was twice as high and the response of maize grain yield to fertilizer was much stronger in Nyakiliba compared with Gashora. This is attributed to the varying biophysical conditions, similarly to the trend observed by Sileshi et al. (2010). Yield gap determined at the global level, using a single crop model to simulate generic crop yields, indicated limitations in terms of comparison between countries (Van Ittersum et al. 2013). In Kenya, maize yield gap was attributed to varying soil and management decisions by farmers (Tittonell et al. 2008).

Maize yield differed significantly with P rates and interaction between N and P. The highest maize yield was obtained with P applied at rate of 40 kg ha^{-1} (Table 3). The level of maize yield gap in Nyakiliba translates into a substantial amount of 15,721 to 22,178 kcal ha^{-1} and 416 to 587 g of proteins under various N rates, respectively (Table 4). Estimated monetary losses range from 1664 to 2348 USD on per hectare and per year basis in Nyakiliba. In Gashora, the levels are respectively 17,442 kcal and 459 g of protein at 92 kg N ha^{-1}.

Based on the minimum calories and protein requirements of 0.8 g protein day^{-1} person^{-1} kg^{-1} body weight (for a body

Table 4 Estimated amount of calories, proteins, and monetary values corresponding to the levels of maize yield gaps at various N rates (kg ha^{-1})

Site	N rate	Yield gaps	Estimated calories	Estimated protein	Estimated* monetary value (USD)
Nyakiliba	(kg ha^{-1})	(kg ha^{-1})	(kcal ha^{-1})	(g ha^{-1})	
	0	6523	22,178.2	587.07	2348.28
	23	6241	21,219.4	561.69	2246.76
	46	5946	20,216.4	535.14	2140.56
	92	4624	15,721.6	416.16	1664.64

*Assuming 1 kg of maize grain cost 0.36 USD (exchange rate: BNR, 2016)

weight of 60 kg) and 2250 kcal person^{-1} day^{-1} (Trumbo et al. 2002), a single farmer would be in a position to cater for the basic food requirement of at least 8 more adult people in 1 day, if he/she manages to fill the maize yield gap on 1 ha of land in Nyakiliba. With about 5400 ha of estimated maize harvested area for Rubavu district (MINAGRI 2014), a scenario with maximized maize yield on a single hectare of maize area would translate into additional food production (i.e. for 15 adult people for 1 year) towards sustainable improvement in food security.

4.2 Use of NDVI in crop yield estimate and soil fertility response

Use of NDVI was introduced here to indicate a flexible method to determine farmer yield at any time during the course of the season and relate this to the soil fertility level. The study highlighted a positive relationship between sensed Normalized Difference Vegetation Index and field level yield (Fig. 3) and is in agreement with studies done by Teal et al. (2006), where a strong relationship was achieved between NDVI-measured indices using a Green Seeker sensor and maize grain yield. In the cropping season 2015A, the coefficients of regression R^2 corresponded to 0.52 and 0.61 in Nyakiliba and Gashora, while in 2015B, the coefficients were 0.50 and 0.65, respectively. The results of this study are also in line with the studies of Ray et al. (2003) and Gat et al. (2000). The NDVI has been shown to be highly correlated with the final grain yield of cereals around the time of maximum green leaf biomass development (Tucker et al. 1980).

The study indicated a moderate to strong relationship between NDVI and soil fertility parameters (Fig. 4) with R^2 values ranging from 55 to 70%. A strong relationship between NDVI and most soil nutrients, especially N and P, is a clear evidence of the contribution of the soil nutrients in explaining plant growth and development (Fig. 4). N and P are reported to be key limiting nutrients in sub-Saharan Africa (SSA) and particularly in the East African highlands (Shepherd et al. 1995; Kelly et al. 2002). The establishment of the relationship between NDVI (proxy of maize yield) and key soil nutrients could potentially offer possibilities of prediction of relative maize yield using simple linear regression relationship in the specific locations.

Table 5 Summary of discriminant functions

Attribute	Dependent variable			
	Maize yield category (t ha^{-1})	Maize yield category (t farm^{-1})	Income category (RWF)	Social category
Correctly predicted cases (%)	35	46	42	74
Probability level	0.07	< 0.01	< 0.01	< 0.01
Predictors	• ha of cultivated area • Organic fertilizer used • Number of seeds sown per hole	• Years of agriculture • % land cultivated • Number of livestock • Number of family members • Soil depth	• Organic fertilizer used • Number of seeds sown per hole • Spacing of inter-rows	• Soil colour • Soil texture • Soil depth • Soil local name • Erosion control • First plough • Organic fertilizer used • Maize yield (t ha^{-1}) • Maize yield (t farm^{-1}) • Maize type • Income

4.3 Use of APSIM model to predict maize yield

The APSIM model estimated maize yield gaps in Nyakiliba (Fig. 5). The approach compared the actual farmer yield with the attainable yield in the specific location. The average maize yield gap estimated in Nyakiliba (4.6 t ha^{-1}, 57% of total potential yield) was slightly higher compared with the records across the country of 3.03 t ha^{-1} (Niyitanga et al. 2015), but it was much larger in Gashora. The difference is due to the methodology used in the latter study. In this study, the yield gap was computed as the national average yield gap while the estimate from our study was done in a specific location with particular conditions. The level of yield gap was much larger in Gashora (5.1 t ha^{-1}), in the range of 80% of potential yield. The calculation of yield gaps may differ from one author to another due to the methodological approach used and also depending on the reference yield against which to compare the actual yield (Affholder et al. 2013; Tittonell et al. 2010). Niyitanga et al. (2015), computing from the differences between the potential yield and the actual farmer yield, estimated the gap in percentage for maize to be in the range of 60.7%. In the region, Tittonell et al. (2008) reported average maize (*Zea mays* L.) yield in Kenya to be around 25% of the water-limited yield.

5 Conclusion and recommendation

The present study aimed to assess the extent of maize yield gap and the factors that contribute to low maize yields in farmers' fields. A contribution of biophysical and socio-economic factors to maize yield gap was assessed in two districts, falling under two different agro-ecological zones in Northern and Southern parts of Rwanda. We show that the maize yield gap is explained by various factors associated with input nutrients and social-economic, and that the extent of yield gap is location specific. Both biophysical and social-economic factors may play explanatory roles. Addressing yield gap requires optimal use of inputs.

Use of NDVI indicates flexibility to predict maize yield in farmer fields in a specific location and correlates with major crop nutrient resources (N and P). The APSIM model was successfully used to determine the yield gap by measuring the difference between the potential maize yield and the actual farmer yield. The maize yield gap was estimated to be in the range of 57% in Nyakiliba where the response of maize grain yield to N fertilizer was adequately simulated and additional N inputs are required to reach the optimum of 4.6 t/ha. The increase of agricultural productivity in smallholder farms depends largely on the efficient use of available inputs. Supply of sufficient nutrients to plants is critical and their availability may heavily affect crop productivity. It is clear that applying correct soil nutrients and adequate management strategies will translate into subsequent additional food production towards sustainable improvements in food security and additional income for farmers. Yield gaps associated with particular farmer management strategies should therefore be monitored and further consideration be given to in-season predictions using NDVI. Such strategies could assist in addressing yield gaps (especially through nutrient management) in the context of crop intensification programme (CIP) and improve food security. By implementing these strategies, conditions are created to significantly raise productivity, reduce on-farm yield gaps and promote exports, and increase farm revenues. Efforts to develop objective-based approaches and methods aiming at reducing the crop yield gap should aim to supporting the research and extension services in the country. The country presents diversity in farming systems caused by differences in agro-ecological zones and socio-economic conditions that would determine the site-specific crop yield gap. The determination of yield gaps at the location level and associated factors is paramount in the efforts to increase on-farm productivity in the country.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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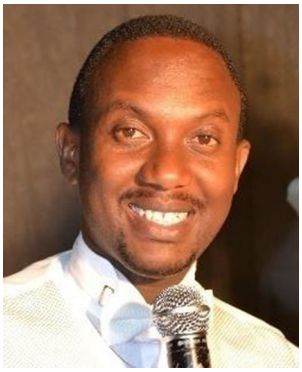

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