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Understanding the maize yield gap in Southern Malawi by integrating ground and remote-sensing data, models, and household surveys[1]

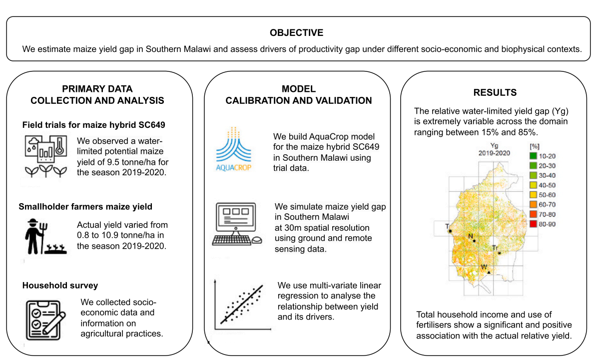
Daniela Anghileri [a,*], Tendai Polite Chibarabada [b], Agossou Gadedjisso-Tossou [c], Ailish Craig [a], Chengxiu Li [a,d], Yang Lu [a,e], Ellasy Gulule Chimimba [f], Oscar Kambombe [f], Frank Musa [g], Cosmo Ngongondo [f], Levis Eneya [f], Jean-Marie Kileshye Onema [h,i], Abdou Ali [c], Sosten Chiotha [j], Jadunandan Dash [a], Justin Sheffield [a]

[a] University of Southampton, Department of Geography and Environment, University Road, Southampton SO17 1BJ, United Kingdom
[b] Centre for Transformative Agricultural and Food Systems, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, P. Bag X01, Pietermaritzburg 3209, South Africa
[c] AGRHYMET, Regional Climate Centre for West Africa and the Sahel (RCC-WAS), 425 Boulevard de l'Université, BP 11011, Niamey, Niger
[d] Tsinghua University, Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies, Beijing 100084, China
[e] Sun Yat-sen University, School of Civil Engineering, Guangzhou 510275, China
[f] University of Malawi, School of Natural and Applied Sciences, P.O. Box 280, Zomba, Malawi
[g] University of Malawi, School of Humanities and Social Sciences, Chancellor College, P O BOX 280, Zomba, Malawi
[h] Université de Lubumbashi, Faculté Polytechnique, BP 1825, Lubumbashi, Democratic Republic of the Congo
[i] WaterNet Secretariat, North-West University, Mahikeng Campus, Private Bag X2046, Mmabato 2745, South Africa
[j] Leadership for Environment and Development (LEAD), P/Bag 7, Zomba, Malawi

HIGHLIGHTS

- We used a mixed-method approach to characterise households' maize yield gap and its drivers in Malawi.
- We surveyed characteristics of 70 smallholder households and observed farmers' maize yield between 0.8 and 10.9 t/ha.
- We obtained a water-limited maize yield of 9.5 t/ha for the season 2019–2020 in the trial site.
- Higher income and increased fertiliser application have the potential to close the yield gap.
- Our approach is valuable in identifying high-productive areas and differentiated policy interventions to close the yield gap.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Improving the productivity of smallholder farmers in sub-Saharan Africa is a key component in reducing poverty and increasing food security as crop production is a significant source of livelihood for the

* Corresponding author.
E-mail address: d.anghileri@soton.ac.uk (D. Anghileri).

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majority of the population. Still, crop yields show a huge variability in smallholder farming systems whose productivity is poorly measured and understood.
OBJECTIVE: In this work, we estimate maize (*Zea Mays*) yield gap in Southern Malawi (Phalombe district) and assess drivers of productivity gap under different socio-economic and biophysical contexts.
METHODS: We use a mixed-method approach which integrates multi-source datasets (including primary ground-truth data we collected in the maize growing season 2019–2020 and secondary remote-sensing data), empirical and process-based crop-growth models (AquaCrop) to calculate the water-limited yield gap. In addition, we analyse the relationship between the relative yield (defined as the actual yield observed at the farmers' plots normalised by the AquaCrop simulated water-limited potential yield) and possible socio-economic drivers which we collected through surveys administered to households iin the same season 2019–2020.
RESULTS AND CONCLUSIONS: We obtained a water-limited potential yield for the maize hybrid SC649 of 9.5 t/ha during the season 2019–2020 in the Malawian trial site. The observed actual yield at the households in the season 2019–2020 varied from 0.8 to 10.9 t/ha. The estimate of the yield gap ranged between 15% and 85% thus showing a large variability due to the high resolution, but low accuracy of the empirical model. Results suggest that with higher income and increased fertiliser application there is potential to increase the relative yield and that the marginal increase is spatially differentiated.
SIGNIFICANCE: Our spatially-explicit approach to yield-gap analysis is valuable in identifying high-productive areas and differentiated policy interventions aimed at closing the yield and income gaps for smallholder farmers.

1. Introduction

Improving the productivity of smallholder farmers is recognized as a key component of the effort to reduce global poverty and increase food security (Olasehinde-Williams et al., 2020; Waha et al., 2018). Staple crops including maize (*Zea Mays*) have been the focus of several studies and the target of multiple policy interventions around the globe. Over the past decades, maize productivity has more than doubled in Europe and the USA while other regions have observed modest increases. In sub-Saharan Africa (SSA), for example, maize productivity has increased only by 10% (Hoffmann et al., 2018; Tittonell and Giller, 2013). This has been attributed to low use of fertilisers, use of poor-quality seeds, water scarcity, lack of mechanization and irrigation, degraded soil quality, and increased frequency of droughts and variability in rainfall patterns (Hillocks, 2014; van Dijk et al., 2020; van Loon et al., 2019). Yield gap is a concept widely used to analyse the potential scope for raising smallholder farmers productivity (Hillocks, 2014; Sadras et al., 2015; Van Ittersum and Cassman, 2013). It represents the distance between the potential yield of a crop cultivar attainable when grown with water, nutrients, and biotic stresses successfully controlled, and the actual yield being achieved by farmers. The yield gap where there is no or poor irrigation infrastructure, such in most SSA, accounts for potential yield attainable in rainfed conditions, i.e., water-limited potential yield (Tittonell and Giller, 2013; Van Ittersum et al., 2013; Silva et al., 2017).

Previous attempts to estimate yield gaps in SSA (e.g. Assefa et al., 2020; Tamene et al., 2016; van Dijk et al., 2020; van Loon et al., 2019; van Bussel et al., 2015; Doré et al., 2008) are often based on agronomic analysis using primary data collection at farmers' fields or official yield statistics to estimate actual yield and controlled farm trials and/or crop modelling to estimate (water-limited) potential yield. The selection and combination of the above methodologies is context dependent and ultimately affects the uncertainty of the yield gap estimate (Maestrini et al., 2022). While official crop yield estimates based on farmers' self reported yield are known to be highly uncertain but relatively inexpensive to collect, primary data collection may be more accurate but very resource intensive, especially when large areas are investigated. Crop simulation models represent a significant milestone in understanding and predict agro-ecosystem performance (Boote et al., 2013; Jones et al., 2017), but their use is still limited by the need for data and specialist knowledge for parameterization, calibration and testing before they can be applied with confidence (Boote et al., 1996). Model calibration and testing is, in principle, required for any new crop environment and variety although, in practice, it may not be feasible due to lack of infrastructure and financial and human resources associated with collection of detailed phenological and growth analysis data (Hunt and Boote, 1998). In the case of SSA, for instance, crop models represent a major source of uncertainty as most of the their calibration and validation are done with data collected outside of SSA, thus considering a combination of environmental conditions and crop varieties that are not representative of the SSA context (Fraisse et al., 2001; Heng et al., 2009; Sima et al., 2020).

Approaches based solely on agronomic analyses, such the ones described above, may fail to understand the complexity of smallholder farming systems and the reasons underlying yield gaps. Mixed-method approaches combining agronomic analysis with socio-economic analysis are generally considered more appropriate to understand the complexity of the smallholder farming systems and the conditions underlying yield gaps (Mumo et al., 2018). Farmers surveys and interviews have been proven to be key in understanding smallholder farming systems because they can appropriately capture the heterogeneity of the landscape, small (on average) field size and diverse farming management practices which may lead to large variability in the actual yields observed at the household scale (Mumo et al., 2018). There is thus the need to estimate yield gaps and its possible drivers on scales that consider temporal and spatial granularity to characterise productivity at the field level and to have a better understanding of this variability over time and space as this may also inform meaningful and targeted interventions (Grassini et al., 2015; Hoffmann et al., 2018; Van Ittersum and Cassman, 2013; Affholder et al., 2013).

The aim of this paper is to quantify the yield gap of smallholder farming systems in Southern Malawi and understand its drivers. To this end, we use a mixed-method approach which integrates multi-source datasets (including primary ground-truth data we collected in the maize growing season 2019–2020 and secondary remote-sensing data), empirical (based on remote-sensing data), and process-based crop-growth models to calculate the water-limited yield gap at fine scale. In addition, we analyse the relationship between the yield gap and possible socio-economic drivers (e.g., labour, access to fertilisers, gender, farming practices) which we collected through surveys administered to households in three Extension Planning Areas (EPAs) in Southern Malawi (Phalombe district) in the same season 2019–2020. The novel contributions of the paper are: *i)* a mixed-method framework to assess yield gap and its potential drivers, *ii)* a parametrization of the AquaCrop model for simulating water-limited growth of the maize hybrid SC649, a medium maturing maize hybrid grown in most of Southern Africa, calibrated and validated using detailed crop-phenological data collected at field trials in Malawi and Zimbabwe, and *iii)* a better understanding of the socio-economic characteristics of smallholder farmers in Phalombe district, their farming practices, and yield-gap drivers.

Table 1
Main drivers identified in the surveyed literature and their impact on grain yield in rainfed smallholder farming in SSA (+ indicates directly proportional; − indicates inversely proportional;; +/− indicates context-dependent relationship).

Factor	Rel.	Interpretation	References	Additional remarks
Land availability	−	Labour and inputs may not increase accordingly because of limited capital.	Berre et al. (2017) and references therein; Dzanku et al., 2015; Owens et al. (2003); Frelat et al. (2016).	The relationship may be more complex, i.e., − for small land size and + for large land size (Dzanku et al., 2015).
Fertiliser	+	The right timing and amount of fertiliser usually guarantee higher yield.	Berre et al. (2017); Beza et al. (2017); Mueller et al. (2012); Rusinamhodzi et al. (2013).	The combined use of fertiliser and improved hybrid seeds may have a super-additive effect on actual yield (Dzanku et al. (2015) and references therein).
Weeding practices and herbicides	+	They decrease the weed-crop competition for water and nutrients.	Dzanku et al. (2015); Affholder et al. (2003); Doré et al. (1997).	The final impact may depend on other factors, e.g., capital availability to access the inputs and labour, stand density, soil fertility.
Walking distance home-field	+/−	Farmers may preferentially allocate fertiliser and labor to fields close to their home especially if this is where high-value crops are cultivated.	Berre et al. (2017); Tittonell et al. (2005).	
Off-farm activities	+	They may increase the capital available for investment in labour and inputs.	Assefa et al. (2020); Tamene et al. (2016); Berre et al. (2017).	
Farming experience	+/−	Farmers may take advantage from indigenous knowledge and previous management experience, but they may also be reluctant to adopt improved farming practices.	Tamene et al. (2016); Berre et al. (2017).	Farming experience tends to be correlated to farmer's age.
Education	+	It may increase the likelihood that farmers adopt new technologies.	Dzanku et al. (2015); Phiri et al. (2012).	
Improved hybrid seeds	+	Hybrid seeds usually guarantee higher yield and are more resistant to droughts and pests.	van Loon et al. (2019); Asiedu et al. (2007).	The final impact may depend on other factors, e.g., the combined use of fertiliser and herbicide or capital availability.
Soil fertility	+	Soil rich in nutrients usually guarantees higher yield.	van Loon et al. (2019); Affholder et al. (2013).	The actual impact may be context dependent and may vary across sites and seasons.
Gender (male)	+	Males and females may have unequal access to productive inputs, land size and productivity, and labour.	Van Vugt et al. (2017); Andersson Djurfeldt et al. (2019); Burke and Jayne (2021) and references therein.	Females tend to have less time to dedicate to farming because of traditional chore and family-care responsibilities.
Access to market	+	It allows farmers to buy inputs and sell outputs.	Affholder et al. (2013).	It generally correlates with the use of improved seeds which usually guarantee higher yield.
Labour	+	It allows for better and more timely agricultural management practices.	Kimhi (2006); Beshir et al. (2012); Silva et al. (2019).	The relationship may be more complex, i.e., + for relatively low levels and - for relatively high levels of labour (Dzanku et al., 2015).
Connection to agricultural Extension officers	+/−	It may enhance the impact of policies and uptake of new knowledge and technology.	Dzanku et al. (2015); Tamene et al. (2016); Owens et al. (2003).	
Livestock ownership	+	It may provide manure and animal labour.	Dzanku et al. (2015); Komarek and Msangi (2019).	

2. Smallholder farming systems in Southern Malawi

Malawi is one of the poorest countries in the world with 70% of the population living on less than USD 1.08 per day (Bhatti et al., 2021). Agriculture is the main economic sector in Malawi with smallholder farmers, operating under a low-input rainfed system, representing 90% of the sector (Tchale, 2009; Mthakati et al., 2012). The average size of smallholder farmer plots has decreased in time from between 0.5 and 2.5 ha in 2012 (Phiri et al., 2012) to approximately 0.32 ha in 2016 (Li et al., 2021). Maize is the dominant crop all over the country, but mostly in Southern Malawi which is also the most populated and cultivated region. Most of the population rely on farming for their subsistence. In fact, smallholder farmers directly consume over 60% of the maize they cultivate which represents approximately 54% of their caloric intake (Aragie et al., 2018; Minot, 2010).

Maize is grown during the rainy season from November to April. The sowing period ranges from mid November to the end of December, while the harvesting period ranges from the end of April to the end of July. The actual crop season depends on the individual farmers' agricultural practices and, mostly, on the onset of the rainy season which is impacted by the farm location, its altitude, and the local weather conditions. Malawi is among the most sensitive countries to climatic shocks in Southern Africa (Minot, 2010; Clay et al., 2003; Aragie et al., 2018). The whole country is prone to hydrometeorological hazards such as droughts or dry spells, but also localized floods (Anghileri et al., 2022; Sato et al., 2020). The Southern region is characterised by semi-arid conditions with average temperature equal to 25 °C and unimodal precipitation with annual average equal to 700 mm (Ngongondo et al., 2011). Interannual climate variability has increased in the last decades and it is expected to be further impacted by climate change, which, together with temperature increase, will impact particularly maize cultivation (Abramoff et al., 2023; Zhao et al., 2017).

Malawi has experienced several food crises (Hess and Syroka, 2005; Harrigan, 2008; Pourazar, 2017) and the number of severely food insecure people is steadily increasing (FAO, ACA, AUC, 2021). Actual maize yield is around 2 t/ha on average and it is considered largely smaller than what could be potentially achieved (Tchale, 2009; Mthakati et al., 2012). Cultivated soils have been depleted because of increased pressure on land and insufficient inputs (Tchale, 2009). Cropland expansion at the expense of forest has been used by farmers as a strategy to improve their productivity by cultivating more fertile soils. However, land scarcity and increased soil erosion demonstrate unsustainable cropland use in Malawi (Li et al., 2021). This is indeed a major concern within the country and policies have been implemented to promote agriculture intensification. Among those, the Agricultural Input Subsidy Programme has been likely the most successful one. The Programme introduced vouchers to smallholder farmers for buying fertilisers and improved hybrid seeds for maize production. It generally increased maize yields across the country (Dorward and Chirwa, 2011; Banik and Chasukwa, 2019) though there are varied results on its success (Matita et al., 2022).

Crop yield is generally characterised by large spatial and temporal variability in smallholder farming systems. Understanding the reasons behind this variability is extremely complex because there are a variety of agronomic and meteorological factors which interact with diverse agricultural practices and socio-economic conditions of smallholder farmers ultimately confounding the cause-effect relationships between productivity drivers and final yield (Affholder et al., 2003). To disentangle these relationships, understanding the specific context in the area of interest is key (Doré et al., 1997). We thus conducted a literature review, which is however not intended to be systematic, which is summarised in Table 1 and Fig. 1. Although this paper focuses on maize yield in Southern Malawi, we expanded our review to grain crop production (instead of maize only) in rainfed smallholder farming systems in Sub-Saharan Africa (instead of Malawi only) so as to enlarge the number of papers analysing the relationship between yield and its drivers. A complex picture emerges with multiple interactions between economical, social, and bio-physical factors. For most of the identified drivers, the literature is unanimous in identifying a (direct or inverse) proportional relationship to the yield, while for a few of them the relationship seems to be context dependent, suggesting that the mechanisms governing yield drivers are worth analysing to improve our understanding of the relationships one to another and to the yield.

3. Methodology

This study focuses on the Phalombe district located in Southern Malawi (Fig. 2). We used a mixed-method approach (Fig. 3) which includes: *i)* a biophysical analysis based on multi-source datasets (ground and remote sensed) and mathematical models to estimate the water-limited yield gap at fine scale and *ii)* a socio-economic analysis based on data collected through surveys administered to households in the three EPAs to understand the factors that drive maize yield. The next sections describe the primary data collection and modelling steps in detail while Table 2 summarises the dataset used in each modelling step.

3.1. Biophysical and socio-economic household data collection

We used the official yield data from the Ministry of Agriculture in Malawi to identify 3 EPAs that showed historically low, medium and high yields and which were, at the same time, accessible (in terms of distance one from another and street conditions, to ease the logistics of data collection). As a result, Naminjiwa, Tamani, and Waruma EPAs in Phalombe district (Fig. 2) were identified. Within these 3 EPAs, we selected a pool of possible plots using satellite high resolution images to ensure that they were spread across the EPAs, free from trees and characterised by an area not smaller than 30×30 m^2 (to ensure the comparison of the measured bio-physical variables with the remote sensing data used in the actual yield modelling, see Section 3.2). Finally, by visiting the plots on the ground, we removed plots where maize was not cultivated as main crop (i.e., at least on half of the plot area) to reduce the impact of maize competition with intercrops on the final yield. Using non-probability sampling, we then selected 150 farm plots and we recorded GPS coordinates of the four corners. The size of the plots resulting from this procedure ranged from 0.03 to 0.55 ha, with a mean value of 0.17 ha.

We collected in-situ data in all these plots across the maize growing season 2019–2020 (see Li et al. (2022) for more details). We also measured maize biomass and grain yield in late March 2020, simultaneously to the farmers' harvesting, on a subset of 70 plots (we could not complete the data collection in the remaining 80 plots due to logistical difficulties arisen by the COVID-19 pandemic). More precisely, we sampled three subplots of 1×2 m^2 in each plot where the grain was shelled from the cob and weighed. We then measured the grain moisture content using a grain moisture metre. The final maize grain yield data shown in this paper are presented with a correction for moisture content of 12%. We calculated the average of the three subplot measurements to represent the whole household plot.

In terms of socio-economic variables, we collected various pieces of information on the households characteristics and agricultural practices adopted in the same subset of 70 plots where we measured maize yield. The survey questionnaire was asked to the household heads and covered questions including socioeconomic, agricultural management practises and accessibility to inputs and information. We collected data about the characteristics of the household, such as householder head gender, age, education, marital status, years of experience in farming, household size and income from farm and off-farm activities. Additionally, we collected data on the farming practices, such as relative to the use of fertiliser, herbicide and pesticide, date of sowing and harvesting, maize seed type, number and type of intercrops, if any, labour involved into field preparation, sowing, and harvesting, pest and disease attacks, relationship with Extension Planning Officers and access to subsidies for seeds and

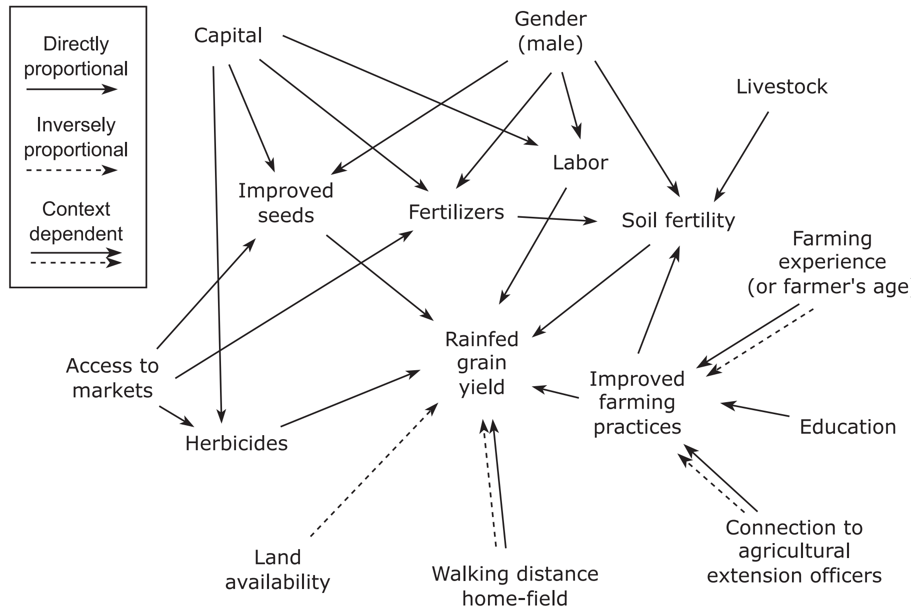

Fig. 1. Schematic representation of the relationship between the main drivers identified in the surveyed literature (see also Table 1) and actual grain yield in rainfed smallholder farming in SSA (own graphical representation of the surveyed literature).

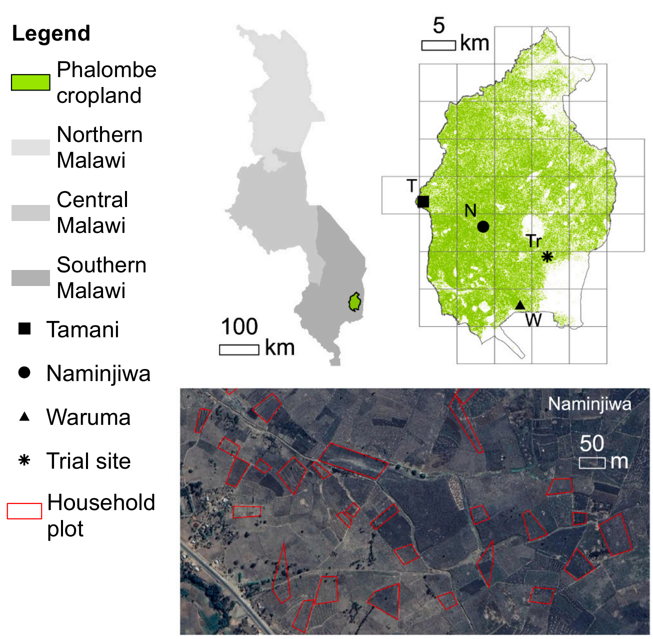

Fig. 2. Map of the Phalombe district in Southern Malawi and location of the three Extension Planning Areas (EPAs) of Naminjiwa (N), Tamani (T), and Waruma (W) and the field trial (Tr) where we collected bio-physical and socio-economic data. The picture on the bottom shows some of the household plots we analysed in Naminjiwa.

fertilisers.

3.2. Actual yield modelling

We considered two different estimates of actual yield at the farmers' fields. The first estimate, called hereafter *observed actual yield* $\left(Y_a^{Obs}\right)$, refers to the in-situ data we collected at the 70 farmer plots (see Section 3.1). The second estimate, called hereafter *RS-simulated actual yield* $\left(Y_a^{RS}\right)$, refers to the simulation of an empirical linear model calibrated using the observed actual yield and high-resolution remote sensing (RS) data (more precisely, we used the seasonal-peak red-edge vegetation index from Sentinel-2 as detailed in Li et al. (2022)). The use of this model allowed us to estimate the actual yield at 30×30 m^2 spatial resolution (and consequently the yield gap) in areas wider than the plots sampled in this work. Being mindful, however, that the empirical relationships between yield and RS-vegetation indexes are generally location specific (Bokusheva et al., 2016), we applied the model to the areas cultivated with maize (according to the World Bank Data Catalog 2019) in the Phalombe district only. There we could reasonably assume that the soil and water conditions and the agricultural practices did not change considerably from the sampled plots, eventually limiting the model extrapolation error. We refer the reader to Li et al. (2022) for the detailed description of the RS-data selection, model calibration and validation procedure, while we report the model performances in the three EPAs in Section 4.2 for the readers' convenience.

3.3. Potential yield modelling

3.3.1. AquaCrop model calibration using ground-truth data

We estimated the potential maize yield using AquaCrop, a crop growth model developed by the FAO to address food security and assess the effect of the environment and management on crop production (Steduto et al., 2009; Vanuytrecht et al., 2014). The model is water driven and simulates the attainable biomass and crop yield in response to water availability which is one of the major constraints in SSA (Raes et al., 2009; Steduto et al., 2009). It has successfully been adopted in several applications from climate change impact studies (Bird et al., 2016; Mabhaudhi et al., 2018; Gadédjisso-Tossou et al., 2018) to test agricultural and water management options to improve crop production (Bello and Walker, 2017), such as, e.g., irrigation systems (Araya et al., 2016; Jalil et al., 2020; Gadédjisso-Tossou et al., 2020). Thanks to its simple and generic structure, the model can be easily implemented for major crops using only precipitation, daily maximum and minimum temperature and reference evapotranspiration as forcing data, although usually requires some calibration for improving model accuracy for new environments and crop varieties (Heng et al., 2009). To this end, we conducted growth analysis field trials during the 2019–2020 cropping season in Zimbabwe and Malawi.

The field trial in Zimbabwe is located in the SeedCo Rattray Arnold Research Station (31°13′S; 17°40′E, 1341 m a.s.l.) and is characterised

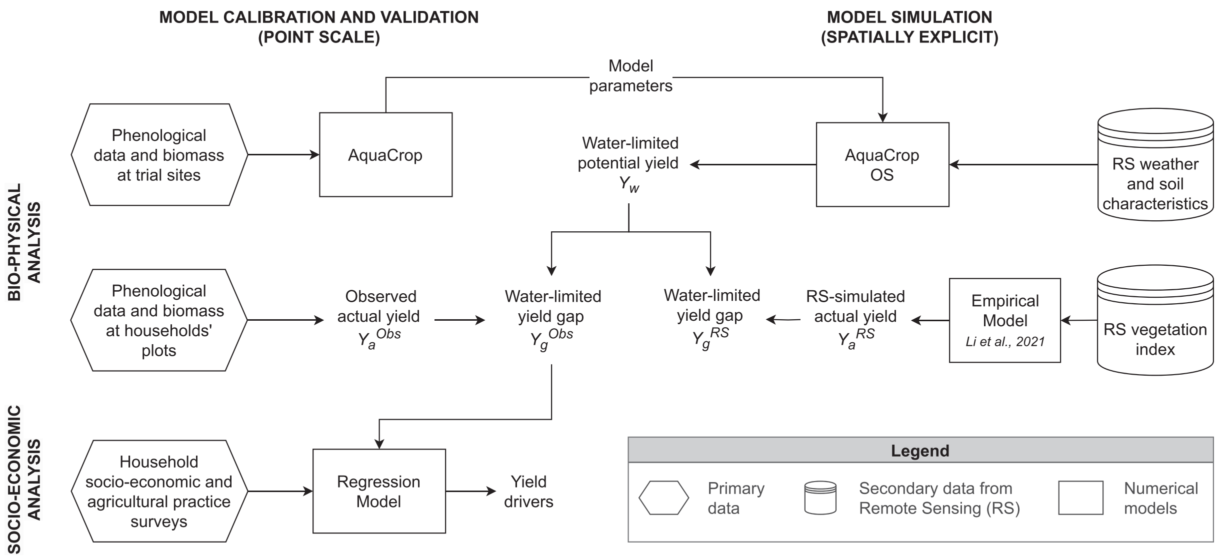

Fig. 3. Schematic representation of the mixed-method approach adopted in this study.

Table 2
Summary of the datasets used in this study.

Model calibration and validation (point scale)				
	Dataset	**Spatial resolution**	**Period**	**Source**
AquaCrop	Meteorology	Trial sites	2019–2020	Primary data collection
	Soil properties	Trial sites	2019–2020	Primary data collection
	Maize biomass	Trial sites	2019–2020	Primary data collection
Regression model	Socio-economic data	Household plots	2019–2020	Primary data collection
	Maize biomass	Household plots	2019–2020	Primary data collection

Model simulation (spatially explicit)				
	Dataset	**Spatial resolution**	**Period**	**Source**
AquaCrop OS	ERA5-Land	5×5 km^2 resampled	2010–2020	Muñoz-Sabater (2019)
	CHIRPS	5×5 km^2	2010–2020	Funk et al. (2015)
	SoilGrid	5×5 km^2 averaged	–	Hengl et al. (2017)
Empirical model	Sentinel-2 (VI)	30×30 m^2	2019–2020	Li et al. (2022)
	Official yield statistics	EPAs	2019–2020	Malawi Ministry of Agriculture

by reliable rainfall (between 750 and 1000 mm) from November to April and greyish brown sands and sandy loams. The field trial in Malawi is located in the Namijiwa Vocational Training Centre (15°45′S; 35°40′E, 766 m.a.s.l.) which is situated in Phalombe District (Fig. 2). We planted the maize hybrid SC649 (bred by SeedCo Ltd. and released in 2015), a medium maturing maize hybrid grown in most of Southern Africa, specifically Zimbabwe, South Africa, Malawi, Zambia and Mozambique with good yield and performance stability.[2] It is a relatively tall hybrid and places its cobs at slightly above 1.5 m. Compared to other medium maturing maize varieties, it produces up to 13 t/ha in high-potential environments, approximately 9 t/ha in medium-potential environments, and approximately 3 t/ha in low-potential environments. It is characterised by moderate drought-tolerance and tolerance to grey leaf spot and maize streak virus. We purposely selected this hybrid variety because, although smallholder farmers may use various seeds, it is well adapted to different niche environments and can be reasonably taken as a reference in our whole area of interest.

The field trial in Zimbabwe was 70×70 m^2 and in Malawi 40×38 m^2 and in both trials maize was grown under rainfed conditions and using the recommended plant population of 53,333 plants/ha. To ensure that there was no nutrition stress, we applied fertilisers based on the highest recommended rate by SeedCo for high-yielding varieties. Compound D (7–14-7) was applied at a rate of 600 kg/ha the day after planting and top dressing ammonium nitrate (34.5% N) was applied four weeks after emergence at 500 kg/ha. Trials were kept weed free through routine hand weeding. Crops were regularly monitored for early symptoms of diseases or insect attacks and would be controlled immediately to avoid yield losses. We routinely collected data during the growing season. The timing of key phenological events such as emergence, tasselling, silking, anthesis, senescence and maturity was monitored daily (in calendar days after planting). Above ground destructive sampling was conducted weekly and plants were air dried until there were no observed changes in total above ground biomass. Trials from Zimbabwe were used for model calibration while trials from Malawi were used for model validation.

[2] https://seedcogroup.com/products/sc-649-new

3.3.2. Experimental setting for the potential yield simulation in Phalombe

To facilitate the simulation of the potential yield in our spatial domain, i.e., the Phalombe district, we used an open-source version of AquaCrop, AquaCrop-OS v6.0 (Foster et al., 2017). The only difference between the FAO AquaCrop and AquaCrop-OS models is that AquaCrop-OS does not contain a soil fertility/salinity stress module. However, this difference does affect our analysis as we calibrated the model parameters accordingly, i.e., considering fertility stress-free conditions. More precisely, we adopted the following experimental setting. We simulated the water-limited potential yield for the maize hybrid SC649 (the one adopted in the controlled trial experiments) across the whole cropland in the Phalombe district. By using the crop parameters calibrated as described in Section 3.3.1, the simulation considers field management practices (as the ones performed at the trial fields) possibly leading to the highest production. The meteorological inputs consisted of daily time series of minimum and maximum temperature, total precipitation, and reference evapotranspiration. As there is no spatially-distributed ground data in the study area which would allow us to simulate the yield spatial variations, we used the remote sensing datasets CHIRPS and ERA5-Land. The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset is a quasi-global precipitation dataset which combines satellite and ground measurements with a spatial resolution of $5 \times 5\ \text{km}^2$ (Funk et al., 2015). With respect to other remote sensing precipitation datasets, CHIRPS has shown to be generally the most accurate in Africa (Gebrechorkos et al., 2018; Dinku et al., 2018). We used ERA5-Land data downloaded from the Copernicus Climate Change Service Climate Data Store (Muñoz-Sabater, 2019) as minimum and maximum temperature time series and to compute the reference evapotranspiration time series using the Priestly-Taylor equation. We acknowledge that the Penman-Monteith equation is considered the standard method to compute the reference evapotranspiration and it is recommended by the Food and Agriculture Organization (FAO) because it is physically based and explicitly incorporates both physiological and aerodynamic parameters (Allen et al., 1998; Sentelhas et al., 2010). The Priestly-Taylor equation is a simplified method where the aerodynamic term is replaced by an empirical coefficient. The impact of methods to compute the reference evapotranspiration has been shown to be different depending on climate, with drier climates showing usually larger differences (see e.g., Amatya et al., 1995; Xiaoying and Erda, 2005). The outputs of crop models (e.g., actual crop evapotranspiration and yield) can, however, show varying sensitivities when inputted with different estimates of reference evapotranspiration depending on climate, but also on the crop model and other settings used for the simulations (e.g., rainfed or irrigated simulation) which in turn determine the crop water-stress conditions (McAneney and Itier, 1996; Utset et al., 2004; Akumaga and Alderman, 2019). Section A.6 shows the result sensitivity to the method for computing the reference evapotranspiration used as input to our analysis. We resampled the ERA5-Land data using the nearest-neighbour resampling technique to downscale the time series from the original $10 \times 10\ \text{km}^2$ to the $5 \times 5\ \text{km}^2$ resolution of the CHIRPS dataset. For both datasets, we considered time series covering the period 2010–2020 to assess the yield variability associated with the weather variability in the last decade as well as to compute the yield gap in the season 2019–2020 when we conducted the household primary data collection. We considered variable maize planting and harvesting dates across the spatial domain to guarantee the maximum potential yield in each location. More specifically, we ran the model six times in each location setting the planting date at the beginning of each dekad in November and December (corresponding to the maximum time span recorded among the surveyed households, see Section 4.1) and we computed the final potential yield a posteriori as the maximum yield among the six experiments. In so doing, we accounted for the best rainfed-growing conditions as the planting and harvesting date were determined by the weather conditions at each location. Finally, we derived the soil properties from the SoilGrids dataset (Hengl et al., 2017) by considering the percentage of sand, clay and organic matter for six depth layers (i.e., 5, 10, 15, 30, 40, 100 cm). In this case, we resampled the data from the original spatial resolution, i.e., $250 \times 250\ \text{m}^2$, to $5 \times 5\ \text{km}^2$ using the mean.

3.4. Yield-gap drivers' identification

Data entry and cleaning occurred in Microsoft Excel, whilst we conducted the analysis in STATA 17. We computed descriptive statistics before the formal statistic analysis when we used multivariate linear regression to analyse the association between the relative observed actual yield, defined as observed actual yield normalised per water-limited potential yield (Y_a^{Obs}/Y_w and equal to $1 - Y_g^{Obs}$), which we used as dependent variable, and socio-economic household factors and agricultural management practises, which we used as independent variables. The relative yield represents a measure of the household farming performance with respect to what could be potentially achieved given the environment (i.e., weather and physical soil characteristics). This allowed us to discount the spatial variability of the bio-physical factors thus allowing us to compare low, medium, and high potential environments and isolate which socio-economic factors and farming practices significantly affected maize yields across them.

Although the household survey allowed us to understand many aspects of the households and their agricultural management practices (see Section 4.1), we selected a subset of information to analyse their relationship to relative yield. As the inclusion of too many independent variables compared to the sample size can result in a poorly predicting model (Austin and Steyerberg, 2015), we selected a subset of 7 independent variables to ensure a robust regression analysis and avoid overfitting (Table 3). The selection of the independent variables was informed by the literature review on grain yield limiting factors in SSA (Table 1 and Fig. 1) and exploring bivariate associations between the dependent and independent variables using correlation analysis and one-way ANOVA. We tested multicollinearity by computing the variance inflation factor (VIF) and excluding variables with VIF higher than 5 (Praveen and Sharma, 2020; Vittinghoff et al., 2005). The normality assumption of the independent variables was also tested and logarithmic transformation was adopted whenever needed (Table 3).

Table 3
Dependent and independent variables used in the regression analysis. Logarithmic transformation was performed as detailed in the last column.

Variable	Description	Base	Transf.
SeedType	Type of maize seed planted	Local	–
PestHerbUse	Use of pesticide and/or herbicide	No	–
TotalFert	Total fertiliser used for growing maize [kg/ha]	–	Log
Income	Household total income (from farm and off-farm activities) [MWK]	–	Log
FarmingExper	Experience in farming [year]	–	Log
HhSize	Household size (adults and children)	–	Log
Gender	Gender household head	Male	–
Y_a^{Obs}/Y_w	Relative observed actual yield [–]	–	Log

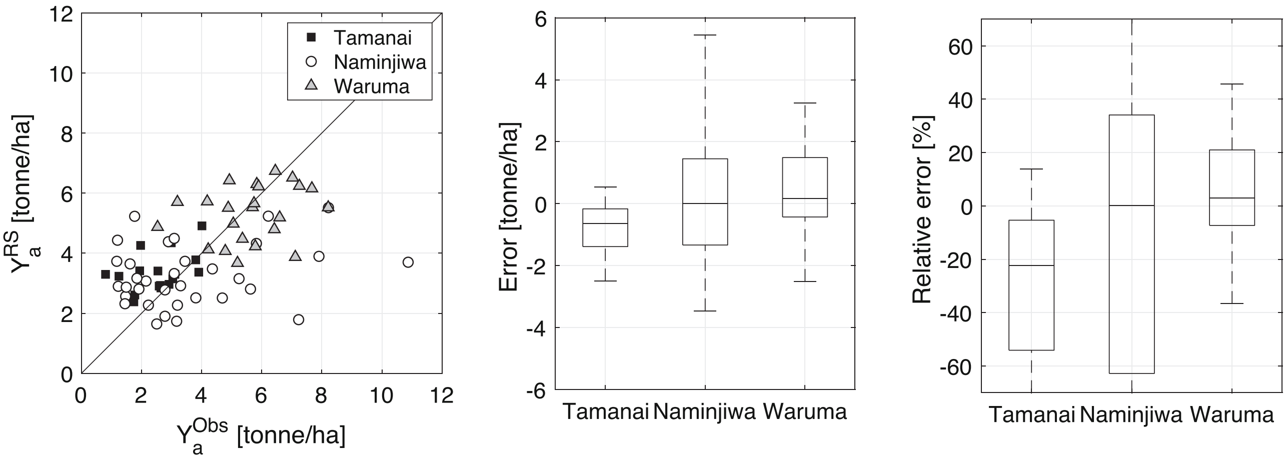

Fig. 4. Comparison between the actual yield estimated (Y_a^{Obs}) at the farmer's fields in the three EPAs during the season 2019–2020 and the actual yield estimated using the remote sensing data (Y_a^{RS}). The model error is defined as $Y_a^{Obs} - Y_a^{RS}$ and the relative error as $(Y_a^{Obs} - Y_a^{RS})/Y_a^{Obs}$.

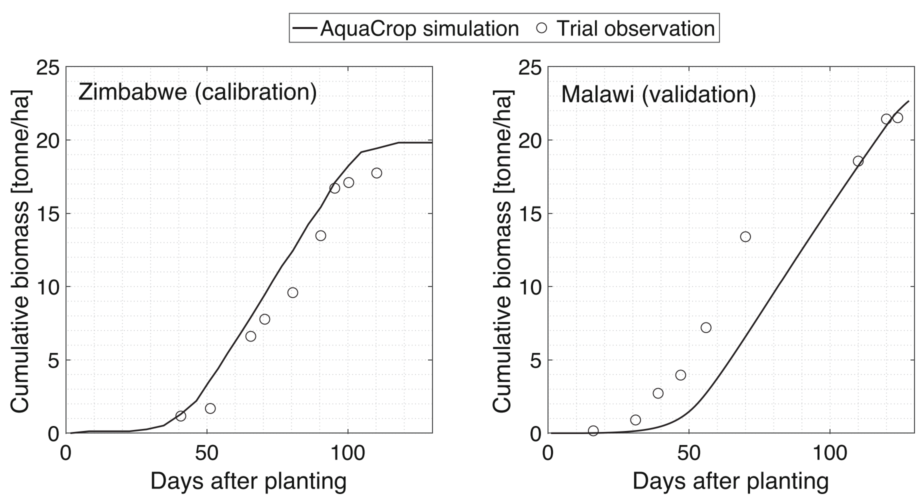

Fig. 5. Comparison of total maize cumulative biomass simulated by AquaCrop and observed in the trial experiment in Zimbabwe (left) and Malawi (right) corresponding to model calibration and validation respectively.

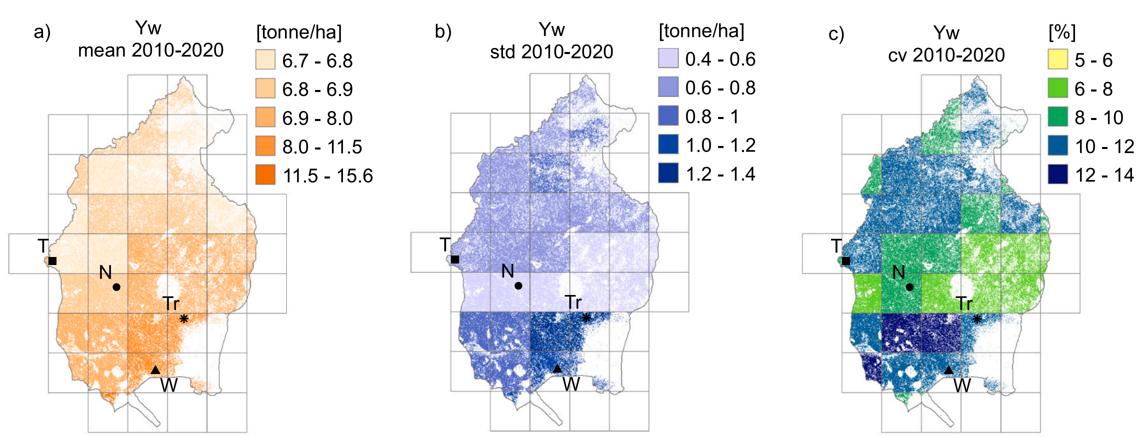

Fig. 6. Spatial map of (AquaCropOS-simulated) water-limited potential yield (Y_w) across Phalombe at 5×5 km^2: a) mean, b) standard deviation, and c) coefficient of variation computed over the period 2010–2020. Results are shown over cropland only.

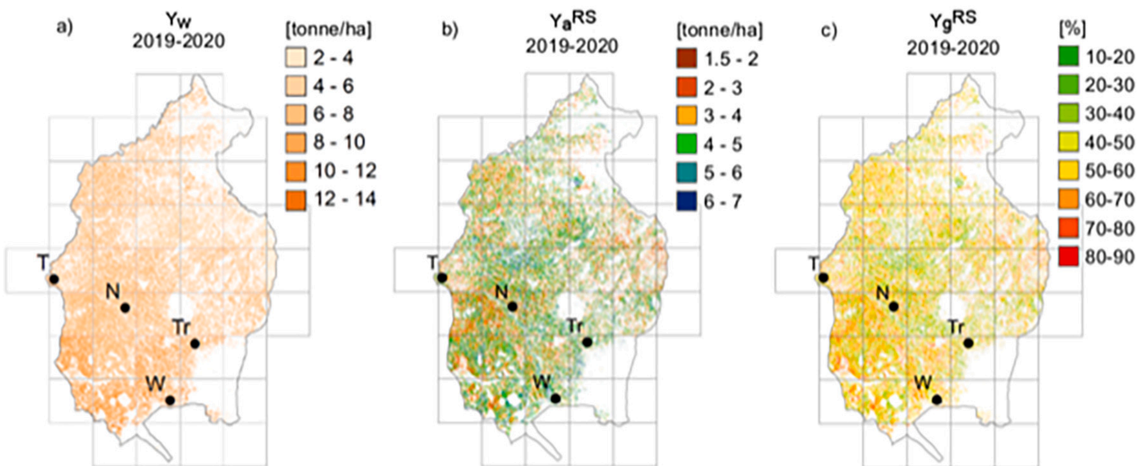

Fig. 7. Spatial maps of: a) AquaCropOS-simulated water-limited potential yield Y_w, b) RS-simulated actual yield Y_a^{RS}, and c) relative yield gap Y_g^{RS} for the cropland cultivated with maize in the season 2019–2020 across the Phalombe district.

4. Results

4.1. Household characteristics and farming practices

Table 5 summarises the main characteristics of the surveyed households. The average household size was 5.4 people including adults and children, the gender of the household head was almost equally split into male (54.3%) and female (45.7%). The household head was on average 41.5 years old with 19 years farming experience. The farm activity was the only source of income for 55.7% of the households. Of the remaining, farm activity still represented at least half of the income in 48.4% of the households. The average farm size was 1.72 ha, but with high variability (coefficient of variation equal to 1.07). The main form of land tenure was "Customary" (72.6%) of which 86.3% of farmers inherited. Maize was the main cultivated crop although 57% of the farmers practised intercropping with pigeon peas, sorghum, millet, soya, sunflower and groundnut (see also Li et al., 2023; Mdee et al., 2019, for more details on intercropping practices in the area). Approximately 48% of the households planted hybrid maize seeds, while the remaining 51.4% planted local varieties. All the households employed family manual labour for the land preparation, planting and harvesting and only 15.7% employed additional paid casual labour. The growing season showed a large spatial variability within the period October–May because of the combination of different personal choices and weather variability. In particular, farmers decided to plant after the first rain (63.9%) or when the soil was considered to be wet enough (20.5%) and to harvest when maize dried fully (55.7%) or because they experience theft (28.5%). About 81% of total harvest was kept for consumption within the household and the remaining was sold. Farming practices included application of fertiliser in 93% of the cases (among which almost 60% purchased the fertiliser with personal finances and 30% via subsidies), pesticide or herbicide in 50% of the cases. Almost 93% of the maize fields experienced pest attack (fall army worm, locust and termite) mainly between 2 and 4 weeks after planting.

4.2. Observed and RS-simulated actual yield

The observed actual yield $\left(Y_a^{Obs}\right)$ at the 70 households in the season 2019–2020 varied from 0.8 to 10.9 t/ha with lower yields observed in

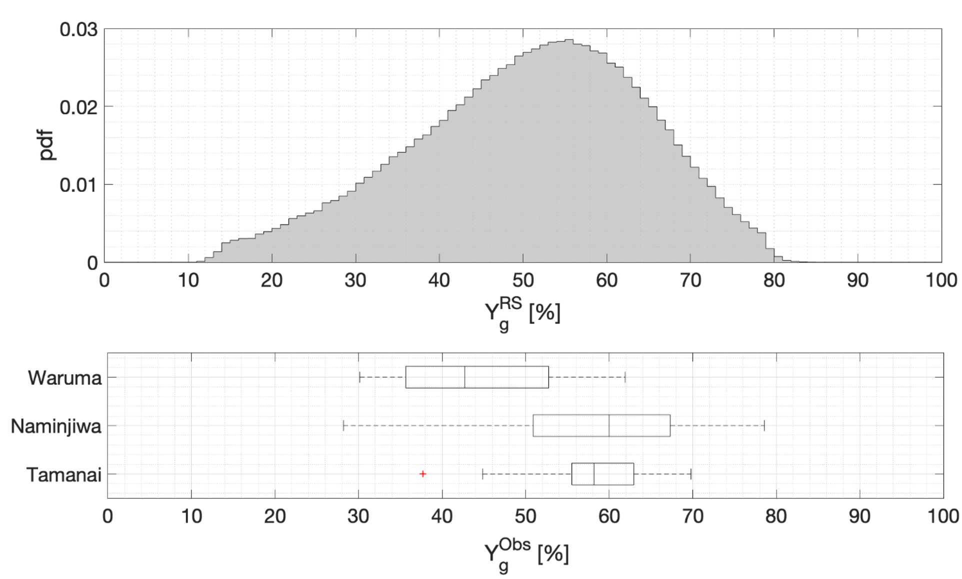

Fig. 8. Empirical probability distribution function (pdf) of the water-limited yield gap $\left(Y_g\right)$ estimated across the Phalombe district (top panel). Boxplot of the water-limited yield gap $\left(Y_g\right)$ estimated for the sampled household plots in the three EPAs (bottom panel).

Table 4
Regression results. Legend ***: p<0.01; **: p<0.05; *: p<0.1.

Variable	Coefficient	Std. err.	t	$P > \|t\|$	Beta
SeedType					
Local	0	(base)			
Hybrid	0.025	0.05	0.50	0.62	0.054
PestHerbUse					
No	0	(base)			
Yes	−0.082	0.053	−1.55	0.127	−0.175
Gender					
Male	0	(base)			
Female	−0.014	0.051	−0.28	0.782	−0.030
TotalFert	0.123	0.045	2.72	0.008 ***	0.305
Income	0.071	0.033	2.14	0.036 **	0.238
FarmingExper	0.093	0.078	1.19	0.239	0.135
HhSize	0.214	0.160	1.33	0.187	0.154
constant	−1.171	0.196	−5.95	0.000 ***	

Tamani and higher yields observed in Waruma. Fig. 4 compares the observed and RS-simulated actual yield $\left(Y_a^{RS}\right)$. Although the model fairly reproduced the observed actual yield, it showed a tendency towards overestimating the lowest yields and underestimating the highest yields. The absolute model error was generally within ±2 t/ha which however corresponded to large relative errors (between −60% and 40%) especially in low-yield EPAs, i.e., Tamanai and parts of Naminjiwa. We used the 2020 official EPA yield data, accessed through the Ministry of Agriculture in Malawi, for the validation of the model outside the calibration spatial domain, i.e., the sampled households. As detailed in Li et al. (2022), the RS-simulated yield was comparable to the official data, although with a tendency towards overestimation between 24% for Naminjiwa and Waruma and 54% for Tamani. Because the relative errors computed at the household level and EPA level were comparable, we could assume that the model estimated on the household plots could be applied to the neighbouring areas with a similar precision (i.e., the extrapolation error was negligible).

4.3. Water-limited potential yield simulated via AquaCrop

Fig. 5 shows the results of the calibration of the AquaCrop model using the data collected at the field trial in Zimbabwe and Malawi, which were used for the calibration and validation of the model respectively. The cumulative biomass was well reproduced by the model both in calibration (coefficient of determination - R2 = 0.98, root mean squared error - RMSE = 1.58 t/ha, mean absolute relative error - MARE = 0.22) and validation (R2 = 0.92, RMSE = 3 t/ha, MARE = 0.5).

We thus used the model parameters (Table 7 in Section A.5) to simulate the water-limited potential yield (Y_w) over the period 2010–2020 using AquaCrop-OS across Phalombe. The mean potential yield varied between 6.7 t/ha in the northern cells and 15.6 t/ha in the southern cells (Fig. 6a). Figs. 6b and c show that the cells with higher mean yield had generally higher yield variability, which ranged between 1 and 1.4 t/ha. This analysis shows that the Phalombe district comprises diverse environments for the maize hybrid SC649 from medium-low to high potential environments. These are due to the combinations of soil characteristics and meteorological variability within the district (as all the other simulation settings were constant across both the spatial and temporal domain) as detailed in Section A.2.

4.4. Yield gap quantification in the season 2019–2020

Fig. 7 shows the spatial maps of (AquaCropOS-simulated) water-limited potential yield Y_w, RS-simulated actual yield Y_a^{RS}, and the relative water-limited yield gap, defined as $Y_g^{RS} = \left(Y_w - Y_a^{RS}\right)/Y_w$, computed across the cropland cultivated with maize in the season 2019–2020 in Phalombe. The water-limited potential yield Y_w ranged between 5 and 13 t/ha with the highest yields located in the southern part of the district which received higher precipitation volumes in the 2019–2020 season with respect to other parts of the district. The RS-simulated actual yield Y_a^{RS} ranged between 1.5 and 7 t/ha. The spatial variability of Y_a^{RS} was higher than the spatial variability of Y_w because the model had a finer spatial resolution (i.e, 30×30 m^2 versus 5×5 km^2) and represented more diverse combinations of productivity factors (see Section 4.1). Still, some spatial clusters of (relatively) low and high Y_a^{RS} appeared throughout the spatial domain. The relative yield gap Y_g^{RS} ranged from 10 to 90% and shows spatial patterns very similar to Y_a^{RS} (which was expected because of the large difference in spatial resolution between the models adopted to estimate the potential and actual yield). Fig. 8 shows the empirical probability distribution function of the relative yield gap Y_g^{RS} and, as a reference, the relative yield gap Y_g^{Obs} estimated for the sampled fields in the three EPAs. The distribution was slightly left skewed and had a median value of 51.8%.

4.5. Socio-economic and biophysical factors driving yield gap

The 7 independent variables selected to ensure a robust regression analysis and avoid overfitting (Table 3) included 3 categorical variables (type of maize seed planted, use of pesticide and/or herbicide, and gender of the household head) and 4 continuous variables (amount of total fertiliser used, household total income, experience in farming, and household size). All the selected variables had a VIF below 5, thus, the data was free of multicollinearity (Table 6). Table 4 shows the result of the regression analysis and includes the standardised beta for easier interpretation. The linear regression had a significant F-test (0.0013) meaning that the linear regression provided a better fit to the data than a model that contained no independent variables. The model adjusted R2 was equal to 0.229 meaning that 23% of the variance in the relative observed actual yield could be explained by the independent variables included in the model. The overall regression model was also significant.

Of the 7 independent variables, two had a significant association with the relative observed actual yield: the total amount of fertiliser and the household income. Both were positively associated with relative maize yield. A unit increase in total fertiliser was associated with a 0.31 unit increase in the relative observed actual yield, holding other independent variables at constant. Meanwhile, an increase in income by one unit was associated with a 0.24 unit increase in the relative observed actual yield. Although the associations of the remaining independent variables were not significant, the results would suggest larger household sizes, more years of farming experience and using a hybrid seed were associated with higher relative yields. Similarly, female headed households and using pesticides was associated with lower relative yields.

5. Discussion

5.1. Bio-physical analysis

The water-limited potential yield we obtained for the season 2019–2020 in the Malawian trial site was on average 9.5 t/ha. The potential yield attainable locally by the farmers, computed as the 95*th* percentile of the observed actual yield was 7.9 t/ha when computed on the entire dataset and 8.1 t/ha when considering data collected in Naminjiwa and Waruma only, which are closer to the trial site (see Fig. 2). The water-limited potential yield we simulated in the decade 2010–2020 across the entire Phalombe district was quite variable and ranged between approximately 5 and 13 t/ha. At the trial site in the season 2019–2020, the simulated yield was 8.7 t/ha which slightly underestimated the observed yield. This small difference is probably due to the uncertainty of the remote sensing weather. In fact, CHIRPS precipitation is slightly smaller than the precipitation recorded at the station in the trial site, i.e., 675 and 870 mm respectively.

The relative yield gap is strictly dependent on the reference used to compute it, i.e., the water-limited potential yield. We refer the reader to Appendix A.3 for a comparison of the yield-gap values obtained when using different definitions of potential yield. We also refer the reader to Appendix A.6 for the results obtained when computing the reference evapotranspiration using the Penman-Monteith method. There we acknowledge that the choice of the method for computing the reference evapotranspiration has an impact on the results of our analysis, particularly in some areas (e.g., in Naminjiwa), but we also show that the main conclusions and policy implications are not impacted. In this work, we decided to use the spatially-distributed yield we simulated using AquaCrop-OS to account for the biophysical differences related to soil composition and weather across the domain. In so doing, we could assume that the differences in yield gap across the Phalombe district were due to socio-economic and agricultural practices only. The relative water-limited yield gap was extremely varying across the domain ranging between approximately 15% and 85% (Fig. 7c and Fig. 8). This range is generally wider than in other works in SSA. Water limited yield gaps in smallholder farmers of Ghana ranged between 3.8 and 13.6 t/ha (67 to 84%) (van Loon et al., 2019). In central Malawi, attainable yields considered as 95th percentile were 8.4 t/ha while average farmer yields were 4.1 t/ha suggesting yield gaps of approximately 5.3 t/ha (<50%) (Tamene et al., 2016). In five districts of Ethiopia, water limited yield gaps ranged from 1.6 t/ha (15%) to 7.8 t/ha (73%) depending on the farming system (Assefa et al., 2020). Comparable yield gap ranges (28 to 65%) were also observed in the central Rift Valley of Ethiopia, but with high interannual variability (CV = 36%) (Kassie et al., 2014). The wider variability simulated in our work is a combination of the fine spatial resolution (i.e., 30×30 m^2) and the spatially-variable potential yield used as the reference to compute the relative yield gap. Indeed, considering a spatially-distributed estimate of the water-limited potential yield allows for a better characterization of the extremes of the yield gap distribution (see Fig. 8) which may be important to identify the best and worst performing areas. This result suggests that it is important whenever possible to consider spatially-distributed and high-resolution distribution of the yield. In this respect, it would be interesting to explore in future works the effect of the intra-cell distribution of the soil characteristics on yield.

Explaining yield gaps in a quantitative manner using the theoretical framework presented in Fig. 3 is particularly complex due to the number of interacting and confounding factors embedded in the estimate of the (potential and actual) yield and requires the application of a combination of approaches. A first limitation of our study is that our data collection spanned one growing season only. This did not allow us to capture any time variability associated with maize yield that may affect management decisions, pest and disease outbreaks, etc. This should be taken into account when interpreting the results and calls for more long-term studies to better understand the dynamic relationships between maize yield gap and its drivers. We acknowledge that, although the performance of the AquaCrop model is very accurate, the simulation of the potential yield Y_w assumes that the maize hybrid SC649 is cultivated everywhere in the Phalombe district, while, in reality, smallholder farmers plant a variety of seeds. We also highlight that we observed large relative errors (between −60% and 40%) in the empirical model we used to estimate the spatially-distributed actual yield Y_a^{RS}. We underscore that further analysis would be needed to test whether the model accuracy in reproducing actual yield still holds outside from the calibration range both spatially (i.e., outside of the range observed in the sampled plots) and temporally (i.e., outside of the range observed during the season 2019/2020).

The large scale simulation of yield gap still presents many challenges which call for better knowledge of the agricultural systems, and improvement in the modelling tools (especially if based on remote sensing inputs and empirical relationships). Physically based models proved to be more accurate in our case, but it has to be noted that we collected in-situ data to calibrate the AquaCrop model. This required resources and efforts that are not always affordable. For this reason, we believe that sharing primary agronomic data and calibrated models within the scientific community is key to improve the yield estimate and better understand the yield gap. Our results highlight how the water-limited potential simulated by AquaCrop is very sensitive to the precipitation input (a fact that is well known in the literature, see e.g. van Bussel et al. (2015)) and that a good estimate of the precipitation is key to precisely assessing the potential yield. This highlights as well a limitation of our study, i.e., the unavailability of accurate spatially-distributed ground precipitation data, which is however common across SSA.

5.2. Socio-economic analysis

Our results are generally aligned with the literature. The significant and positive association of income and yield has been recognized in other works (e.g. Assefa et al., 2020). Higher income is believed to increase the household budget spent on inputs and hiring extra labour to facilitate timely farming management activities (Tamene et al., 2016). Many works in the literature highlight, in particular, the role of off-farm activities which have been shown to represent an important part of livelihoods in systems with high labour (Berre et al., 2017). In our analysis, however, only the total income was positively associated with relative yield. We did not observe improvement in the model when distinguishing between farm and off-farm activities (not shown). The significant and positive association of the use of fertiliser with relative yield which we found in our dataset is reported in other works as well (van Loon et al., 2019; Pasley et al., 2019).

Although not significant, the relationships we observed between the remaining variables and the relative yield are as expected from the literature. The effect of maize seed type suggested that the use of hybrid seeds was associated with higher relative yield than using local seeds. Also Assefa et al. (2020) and van Loon et al. (2019) claim that using improved maize seed varieties contributed to increasing the yield in Ethiopia and Ghana, respectively. More farming experience and larger household sizes were associated with higher relative yields. Female farmers were associated with lower relative yields than male farmers. The only unexpected result concerned the use of pesticides and herbicides which was associated with a reduction of relative yield. Although not significant, this result is in contrast to the literature and may be worth exploring further. For example, asking the household head about the timing and amount of application or measuring stand density and soil fertility may clarify how and why herbicides are used. In fact, low fertility or low stand density, leading to low leaf area index (LAI) and low rate of radiation interception by the crop, may favour weed infestation and need for herbicide use to avoid a complete failure of the crop, while highly fertile and densely sown plots with high yields may not need herbicide at all (see, e.g., Affholder et al. (2003)).

This study is unique as at each household we collected crop yield data and household characteristics data allowing comparisons to be made between the two. Nevertheless, the socio-economic analysis has a number of limitations that must be acknowledged. Data collection did not employ probability sampling so the findings between the relative maize yield and the household socioeconomic factors or agricultural practices can not be generalised beyond the field sites (Sharma, 2017; Groves Jr. et al., 2011). Although of a relative small size, our sample of 70 did, however, allow us for formal statistical testing, although it limited the number of independent variables that could be included in the regression model. Explaining yield gaps (quantitatively) is extremely complex because of a variety of interacting and confounding factors, especially in environments that can not be controlled (such as farmers fields in contrast to trials and model-based simulations) (Silva et al., 2017; Doré et al., 2008). Statistical correlations should thus be taken with care as it may result in false identification of crop growth factors (see Doré et al. (1997) for some examples). Silva et al. (2017), for example, underline that by simulating crop growth models one assumes a maximisation of crop yield which may be not aligned with the actual farmers' preferences and habits. For example, farmers hardly perform the recommended fertiliser applications because of accessibility issues (e.g., capital constraints), preferences in minimising the risk of yield loss in case of wrong fertiliser application, and/or social and community habits (such as sharing fertilisers and herbicides with neighbours).

5.3. Policy implications

Our study suggests several recommendations for policy design and emphasis for closing the gap between actual and potential yield gaps. The simulated water-limited maize yield suggests the presence of some high potential and low potential areas within the Palombe district, which are likely the result of climate and soils. Our study shows positive correlation between relative yield and use of fertiliser. However, results of the survey showed unequal access to fertiliser with some farmers not applying fertilisers, some receiving them through subsidies, and some purchasing them with their own money. Consultation with Key Informants vis-a-vis government extension agents revealed also that, despite government subsidy program has enhanced availability of inorganic fertiliser to farmers, the actual benefits of fertiliser use may be lower than expected due to farmers behaviour. For example, the actual amount of fertiliser applied per unit area tends to be lower than the suggested amount because households having access to the subsidy program tend to share the fertilisers with households not having access to it. We refer the reader to Craig et al. (2022) for an overview of resource sharing in Southern Malawi and its relationship to farmers' social capital and food security. The current success of the Agricultural Input Support Programme has shown varied results (Matita et al., 2022) also due to the recent increase in the price of fertilisers which has prevented some of the poorest households from purchasing inputs even if subsidized (Craig et al., 2023). In this respect, our spatially-explicit approach may become even more valuable in identifying areas where fertiliser-subsidy policies may be more efficient. In fact, areas with low potential yields and high relative yields (i.e, where actual yields are close to potential yields) are not likely to benefit from fertiliser-subsidy policies as much as areas with low relative yields. Furthermore, among these last ones, areas with low potential yield may indicate low-return-to-input hotspots where additional policy interventions (e.g., promotion of weather-based crop insurances, see Anghileri et al. (2022)) may be needed as the crop-failure risk may become unaffordable to farmers even if fertiliser are subsidized. The differentiation of fertiliser application by yield potential may also contribute to reducing the detrimental effects of over application of fertilisers on soil health and ecosystems (John and Babu, 2021; Pingali, 2012). In this study, female farmers were associated with lower yields than male farmers. It was not clear whether this was due to limited resource access by women or lack of experience of women farmers compared to male farmers. There is need for gender sensitive policies that empower females also taking into account other cultural roles women have. While this study only considered women as a minority group, the same policies should seek to include other minority groups that may not have been highlighted in this study. Farming experience was also associated with higher relative yields which highlights the importance of training of farmers and targeted efforts to less experienced farmers. Higher relative yields were also associated with higher income implying that closing income gap maybe part of the solution to closing yield gap. The focus of various policies has been on assisting farmers with inputs but there may be the need to address the deep root of low incomes to give farmers financial freedom to acquire inputs.

6. Conclusions

Improving the productivity of smallholder farmers is thought to be a key component of the effort to reduce global poverty and increase food security. However, the productivity of most smallholder farmers in Sub-Saharan Africa remains poorly measured and understood. Our work makes a contribution towards collecting ground-truth data in Southern Malawi on household maize yields, socio-economic conditions, and agricultural practices and understanding how bio-physical and socio-economic variables are connected to potential and actual maize yield. Results suggest that with higher income and increased fertiliser application there is potential to increase actual yields and that the marginal increase is spatially differentiated. Our spatially-explicit approach to yield-gap analysis is thus valuable in identifying high-productive areas and differentiated policy interventions aimed at closing the yield and income gaps for smallholder farmers. Future works should aim at validating the framework on a larger dataset both spatially and temporally (i.e., outside of the range observed during the season 2019/2020 in the sampled plots) and at improving the accuracy of the empirical model used to estimate the actual yield from remote-sensing data.

CRediT authorship contribution statement

Daniela Anghileri: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Tendai Polite Chibarabada:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Agossou Gadedjisso-Tossou:** Software, Validation, Writing – original draft, Writing – review & editing, Data curation, Formal analysis, Investigation, Methodology. **Ailish Craig:** Data curation, Formal analysis, Investigation, Writing – review & editing, Methodology, Software, Validation, Writing – original draft. **Chengxiu Li:** Conceptualization, Data curation, Formal analysis, Investigation, Software, Validation, Writing – original draft, Writing – review & editing. **Yang Lu:** Data curation, Formal analysis, Investigation, Software, Validation, Writing – original draft. **Ellasy Gulule Chimimba:** Data curation, Writing – review & editing. **Oscar Kambombe:** Data curation, Writing – review & editing. **Frank Musa:** Data curation, Supervision, Writing – review & editing. **Cosmo Ngongondo:** Supervision, Writing – review & editing, Resources. **Levis Eneya:** Resources, Supervision, Writing – review & editing. **Jean-Marie Kileshye Onema:** Conceptualization, Resources, Supervision, Writing – review & editing. **Abdou Ali:** Methodology, Supervision, Writing – review & editing. **Sosten Chiotha:** Supervision, Writing – review & editing. **Jadunandan Dash:** Methodology, Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing. **Justin Sheffield:** Supervision, Writing – original draft, Writing – review & editing, Conceptualization, Funding acquisition, Methodology, Project administration.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2024.103962.

References

Abramoff, R.Z., Ciais, P., Zhu, P., Hasegawa, T., Wakatsuki, H., Makowski, D., 2023. Adaptation strategies strongly reduce the future impacts of climate change on simulated crop yields. Earth's Future 11, e2022EF003190. URL: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022EF003190, doi:10.1029/2022EF003190, arXiv:https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2022EF003190. e2022EF003190 2022EF003190.

Affholder, F., Scopel, E., Madeira Neto, J., Capillon, A., 2003. Diagnosis of the productivity gap using a crop model. Methodology and case study of small-scale maize production in Central Brazil. Agronomie 23, 305–325. https://doi.org/10.1051/agro:2003004.

Affholder, F., Poeydebat, C., Corbeels, M., Scopel, E., Tittonell, P., 2013. The yield gap of major food crops in family agriculture in the tropics: assessment and analysis through field surveys and modelling. Field Crop Res. 143, 106–118. https://doi.org/10.1016/J.FCR.2012.10.021.

Akumaga, U., Alderman, P.D., 2019. Comparison of penman-monteith and priestley-Taylor evapotranspiration methods for crop modeling in Oklahoma. Agron. J. 111, 1171–1180. URL: https://acsess.onlinelibrary.wiley.com/doi/abs/10.2134/agronj2018.10.0694, doi:https://doi.org/10.2134/agronj2018.10.0694, arXiv:https://acsess.onlinelibrary.wiley.com/doi/pdf/10.2134/agronj2018.10.0694.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., et al., 1998. Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-fao Irrigation and Drainage Paper 56, 300. Fao, Rome, p. D05109.

Amatya, D.M., Skaggs, R.W., Gregory, J.D., 1995. Comparison of methods for estimating ref-et. J. Irrig. Drain. Eng. 121, 427–435. https://doi.org/10.1061/(ASCE)0733-9437(1995)121:6(427).

Andersson Djurfeldt, A., Djurfeldt, G., Hillbom, E., Isinika, A.C., Joshua, M.D.K., Kaleng'a, W.C., Kalindi, A., Msuya, E., Mulwafu, W., Wamulume, M., 2019. Is there such a thing as sustainable agricultural intensification in smallholder-based farming in sub-Saharan Africa? Understanding yield differences in relation to gender in Malawi, Tanzania and Zambia. http://mc.manuscriptcentral.com/rdsr, 6, pp. 62–75. URL: https://www.tandfonline.com/doi/abs/10.1080/21665095.2019.1593048, doi:https://doi.org/10.1080/21665095.2019.1593048.

Anghileri, D., Bozzini, V., Molnar, P., Sheffield, J., 2022. Comparison of hydrological and vegetation remote sensing datasets as proxies for rainfed maize yield in Malawi. Agric. Water Manag. 262, 107375 https://doi.org/10.1016/J.AGWAT.2021.107375.

Aragie, E., Pauw, K., Pernechele, V., 2018. Achieving food security and industrial development in Malawi: are export restrictions the solution? World Dev. 108, 1–15. URL: https://linkinghub.elsevier.com/retrieve/pii/S0305750X18301025.

Araya, A., Kisekka, I., Holman, J., 2016. Evaluating deficit irrigation management strategies for grain sorghum using AquaCrop. Irrig. Sci. 34, 465–481. URL: https://link.springer.com/article/10.1007/s00271-016-0515-7. https://doi.org/10.1007/S00271-016-0515-7/TABLES/10.

Asiedu, E., Asante, R., Sallah, P., Baduon, A., Avah, E., 2007. Effects of farmers' seed source on maize seed quality and crop productivity. Ghana J. Agricult. Sci. 40, 105–111.

Assefa, B.T., Chamberlin, J., Reidsma, P., Silva, J.V., van Ittersum, M.K., 2020. Unravelling the variability and causes of smallholder maize yield gaps in Ethiopia. Food Secur. 12, 83–103. URL: https://link.springer.com/article/10.1007/s12571-019-00981-4.

Austin, P.C., Steyerberg, E.W., 2015. The number of subjects per variable required in linear regression analyses. J. Clin. Epidemiol. 68, 627–636. URL: https://www.sciencedirect.com/science/article/pii/S0895435615000141. https://doi.org/10.1016/j.jclinepi.2014.12.014.

Banik, D., Chasukwa, M., 2019. The politics of hunger in an sdg era: food policy in Malawi. Food Ethics 4, 189–206. URL: doi:10.1007/s41055-019-00055-3. https://doi.org/10.1007/s41055-019-00055-3.

Bello, Z.A., Walker, S., 2017. Evaluating AquaCrop model for simulating production of amaranthus (amaranthus cruentus) a leafy vegetable, under irrigation and rainfed conditions. Agric. For. Meteorol. 247, 300–310. https://doi.org/10.1016/J.AGRFORMET.2017.08.003.

Berre, D., Corbeels, M., Rusinamhodzi, L., Mutenje, M., Thierfelder, C., Lopez-Ridaura, S., 2017. Thinking beyond agronomic yield gap: smallholder farm efficiency under contrasted livelihood strategies in Malawi. Field Crop Res. 214, 113–122. https://doi.org/10.1016/J.FCR.2017.08.026.

Beshir, H., Emana, B., Kassa, B., Haji, J., 2012. Economic efficiency of mixed crop-livestock production system in the north eastern highlands of Ethiopia: the stochastic frontier approach. J. Agricult. Econ. Develop. 1, 10–20.

Beza, E., Silva, J.V., Kooistra, L., Reidsma, P., 2017. Review of yield gap explaining factors and opportunities for alternative data collection approaches. Eur. J. Agron. 82, 206–222. URL: https://www.sciencedirect.com/science/article/pii/S1161030116301290, doi:10.1016/j.eja.2016.06.016. farming systems analysis and design for sustainable intensification: new methods and assessments.

Bhatti, M.A., Godfrey, S.S., Ip, R.H., Kachiwala, C., Hovdhaugen, H., Banda, L.J., Limuwa, M., Wynn, P.C., Ådnøy, T., Eik, L.O., 2021. Diversity of sources of income for smallholder farming communities in Malawi: importance for improved livelihood. Sustainability 13. https://doi.org/10.3390/SU13179599. Page 9599 13, 9599. URL: https://www.mdpi.com/2071-1050/13/17/9599/htm https://www.mdpi.com/2071-1050/13/17/9599.

Bird, D.N., Benabdallah, S., Gouda, N., Hummel, F., Koeberl, J., La Jeunesse, I., Meyer, S., Prettenthaler, F., Soddu, A., Woess-Gallasch, S., 2016. Modelling climate change impacts on and adaptation strategies for agriculture in Sardinia and Tunisia using AquaCrop and value-at-risk. Sci. Total Environ. 543, 1019–1027. https://doi.org/10.1016/J.SCITOTENV.2015.07.035.

Bokusheva, R., Kogan, F., Vitkovskaya, I., Conradt, S., Batyrbayeva, M., 2016. Satellite-based vegetation health indices as a criteria for insuring against drought-related yield losses. Agric. For. Meteorol. 220, 200–206. URL: https://linkinghub.elsevier.com/retrieve/pii/S0168192316300016.

Boote, K.J., Jones, J.W., Pickering, N.B., 1996. Potential uses and limitations of crop models. Agron. J. 88, 704–716. URL: https://onlinelibrary.wiley.com/doi/full/10.2134/agronj1996.00021962008800050005xhttps://onlinelibrary.wiley.com/doi/abs/10.2134/agronj1996.00021962008800050005xhttps://acsess.onlinelibrary.wiley.com/doi/10.2134/agronj1996.00021962008800050005x.

Boote, K.J., Jones, J.W., White, J.W., Asseng, S., Lizaso, J.I., 2013. Putting mechanisms into crop production models. Plant Cell Environ. 36, 1658–1672. URL: https://onlinelibrary.wiley.com/doi/full/10.1111/pce.12119 https://onlinelibrary.wiley.com/doi/abs/10.1111/pce.12119 https://onlinelibrary.wiley.com/doi/10.1111/pce.12119. https://doi.org/10.1111/PCE.12119.

Burke, W.J., Jayne, T.S., 2021. Disparate access to quality land and fertilizers explain Malawi's gender yield gap. Food Policy 100, 102002. https://doi.org/10.1016/J.FOODPOL.2020.102002.

Clay, E., Bohn, L., de Armas, E.B., Kabambe, S., Tchale, H., 2003. Malawi and Southern Africa: Climatic Variability and Economic Performance. Technical Report 7. World Bank Group, Washington, D.C.. URL: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/391461468774612214/malawi-and-southern-africa-climatic-variability-and-economic-performance.

Craig, A., Hutton, C.W., Sheffield, J., 2022. Social capital typologies and sustainable development: spatial patterns in the central and southern regions of Malawi. Sustainability 14. https://doi.org/10.3390/su14159374. URL: https://www.mdpi.com/2071-1050/14/15/9374.

Craig, A., Hutton, C., Musa, F.B., Sheffield, J., 2023. Bonding, bridging and linking social capital combinations for food access; a gendered case study exploring temporal differences in southern Malawi. J. Rural. Stud. 101, 103039. URL: https://www.sciencedirect.com/science/article/pii/S0743016723001055.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., Ceccato, P., 2018. Validation of the CHIRPS satellite rainfall estimates over eastern Africa. Q. J. R. Meteorol. Soc. 144, 292–312. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/qj.3244. https://doi.org/10.1002/qj.3244.

Doré, T., Sebillotte, M., Meynard, J., 1997. A diagnostic method for assessing regional variations in crop yield. Agric. Syst. 54, 169–188. URL: https://www.sciencedirect.com/science/article/pii/S0308521X96000844. https://doi.org/10.1016/S0308-521X(96)00084-4.

Doré, T., Clermont-Dauphin, C., Crozat, Y., David, C., Jeuffroy, M.H., Loyce, C., Makowski, D., Malézieux, E., Meynard, J.M., Valantin-Morison, M., 2008. Methodological progress in on-farm regional agronomic diagnosis. a review. Agron. Sustain. Dev. 28, 151–161.

Dorward, A., Chirwa, E., 2011. The Malawi agricultural input subsidy programme: 2005/06 to 2008/09. Int. J. Agric. Sustain. 9, 232–247. https://doi.org/10.3763/ijas.2010.0567.

Dzanku, F.M., Jirström, M., Marstorp, H., 2015. Yield gap-based poverty gaps in rural Sub-Saharan Africa. World Dev. 67, 336–362. https://doi.org/10.1016/J.WORLDDEV.2014.10.030.

FAO, ACA, AUC, 2021. Regional overview of food security and nutrition 2021, Africa statistics and trends. In: Technical Report. Food and Agriculture Organization of the

United Nations (FAO), the United Nations Economic Commission for Africa (ECA) or African Union Commission (AUC). Accra, Ghana. https://doi.org/10.4060/cb7496en.

Foster, T., Brozović, N., Butler, A.P., Neale, C.M., Raes, D., Steduto, P., Fereres, E., Hsiao, T.C., 2017. AquaCrop-OS: an open source version of FAO's crop water productivity model. Agric. Water Manag. 181, 18–22. https://doi.org/10.1016/J.AGWAT.2016.11.015.

Fraisse, C.W., Sudduth, K.A., Kitchen, N.R., 2001. Calibration of the ceres–maize model for simulating site–specific crop development and yield on claypan soils. Appl. Eng. Agric. 17 https://doi.org/10.13031/2013.6453.

Frelat, R., Lopez-Ridaura, S., Giller, K.E., Herrero, M., Douxchamps, S., Andersson Djurfeldt, A., Erenstein, O., Henderson, B., Kassie, M., Paul, B.K., Rigolot, C., Ritzema, R.S., Rodriguez, D., van Asten, P.J.A., van Wijk, M.T., 2016. Drivers of household food availability in sub-saharan africa based on big data from small farms. Proc. Natl. Acad. Sci. 113, 458–463. URL: https://www.pnas.org/doi/abs/10.1073/pnas.1518384112. https://doi.org/10.1073/pnas.1518384112.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J., 2015. The climate hazards infrared precipitation with stations - a new environmental record for monitoring extremes. Sci. Data 2, 150066. URL: http://www.nature.com/articles/sdata201566. https://doi.org/10.1038/sdata.2015.66.

Gadédjisso-Tossou, A., Avellán, T., Schütze, N., 2018. Potential of deficit and supplemental irrigation under climate variability in northern Togo, west africa. Water 10. https://doi.org/10.3390/w10121803. URL: https://www.mdpi.com/2073-4441/10/12/1803.

Gadédjisso-Tossou, A., Avellán, T., Schütze, N., 2020. Impact of irrigation strategies on maize (zea mays l.) production in the savannah region of northern Togo (west africa). WaterSA 46. https://doi.org/10.17159/wsa/2020.v46.i1.7894. URL: https://watersa.net/article/view/7894.

Gebrechorkos, S.H., Hülsmann, S., Bernhofer, C., 2018. Evaluation of multiple climate data sources for managing environmental resources in East Africa. Hydrol. Earth Syst. Sci. 22, 4547–4564. URL: https://hess.copernicus.org/articles/22/4547/2018/.

Grassini, P., van Bussel, L.G., Van Wart, J., Wolf, J., Claessens, L., Yang, H., Boogaard, H., de Groot, H., van Ittersum, M.K., Cassman, K.G., 2015. How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. Field Crop Res. 177, 49–63. https://doi.org/10.1016/J.FCR.2015.03.004.

Groves Jr., R.M., F.F.J, Couper, M.P., Lepkowski, J.M., Singer, E., Tourangeau, R., 2011. Survey Methodology. John Wiley & Sons.

Harrigan, J., 2008. Food insecurity, poverty and the Malawian starter pack: fresh start or false start? Food Policy 33, 237–249. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306919207000528.

Heng, L.K., Hsiao, T., Evett, S., Howell, T., Steduto, P., 2009. Validating the FAO AquaCrop model for irrigated and water deficient field maize. Agron. J. 101, 488–498. URL: https://onlinelibrary.wiley.com/doi/full/10.2134/agronj2008.0029xshttps://onlinelibrary.wiley.com/doi/abs/10.2134/agronj2008.0029xshttps://acsess.onlinelibrary.wiley.com/doi/10.2134/agronj2008.0029xs.

Hengl, T., De Jesus, J.M., Heuvelink, G.B., Gonzalez, M.R., Kilibarda, M., Blagotić, A., Shangguan, W., Wright, M.N., Geng, X., Bauer-Marschallinger, B., Guevara, M.A., Vargas, R., MacMillan, R.A., Batjes, N.H., Leenaars, J.G., Ribeiro, E., Wheeler, I., Mantel, S., Kempen, B., 2017. SoilGrids250m: global gridded soil information based on machine learning. PLoS One 12, e0169748. URL: https://research.wur.nl/en/publications/soilgrids250m-global-gridded-soil-information-based-on-machine-le.

Hess, U., Syroka, J., 2005. Weather-Based Insurance in Southern Africa -the Case of Malawi. Technical Report, The World Bank.

Hillocks, R.J., 2014. Addressing the Yield Gap in Sub-Saharan Africa, 43, 85–90. URL: https://journals.sagepub.com/doi/abs/10.5367/oa.2014.0163?casa_token=gCv40vrdz0kAAAAA%3AxT5oPL6Uma2OPQL_Gjj3r6zjSk75RXEmR4qm3pVJsienX_gRD7Ysok0sa2AvmTZlwPOPReekxdtl. https://doi.org/10.5367/OA.2014.0163.

Hoffmann, M.P., Isselstein, J., Rötter, R.P., Kayser, M., 2018. Nitrogen management in crop rotations after the break-up of grassland: insights from modelling. Agric. Ecosyst. Environ. 259, 28–44. https://doi.org/10.1016/j.agee.2018.02.009.

Hunt, L.A., Boote, K.J., 1998. Data for model operation, calibration, and evaluation. In: Hoogenboom, T.G.Y., Gerritand, T.P.K. (Eds.), Understanding Options for Agricultural Production. Springer, Netherlands, Dordrecht, pp. 9–39.

Jalil, A., Akhtar, F., Awan, U.K., 2020. Evaluation of the AquaCrop model for winter wheat under different irrigation optimization strategies at the downstream Kabul River basin of Afghanistan. Agric. Water Manag. 240, 106321 https://doi.org/10.1016/J.AGWAT.2020.106321.

John, D.A., Babu, G.R., 2021. Lessons from the aftermaths of green revolution on food system and health. Front. Sustain. Food Syst. 5 https://doi.org/10.3389/fsufs.2021.644559.

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., Keating, B.A., Munoz-Carpena, R., Porter, C.H., Rosenzweig, C., Wheeler, T.R., 2017. Brief history of agricultural systems modeling. Agric. Syst. 155, 240–254. https://doi.org/10.1016/j.agsy.2016.05.014.

Kassie, M., Jaleta, M., Mattei, A., 2014. Evaluating the impact of improved maize varieties on food security in Rural Tanzania: evidence from a continuous treatment approach. Food Secur. 6, 217–230. URL: https://link.springer.com/article/10.1007/s12571-014-0332-x.

Kimhi, A., 2006. Plot size and maize productivity in Zambia: is there an inverse relationship? Agric. Econ. 35, 1–9. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1574-0862.2006.00133.x.

Komarek, A.M., Msangi, S., 2019. Effect of changes in population density and crop productivity on farm households in Malawi. Agric. Econ. 50, 615–628. URL: https://onlinelibrary.wiley.com/doi/full/10.1111/agec.12513 https://onlinelibrary.wiley.com/doi/abs/10.1111/agec.12513 https://onlinelibrary.wiley.com/doi/10.1111/agec.12513. https://doi.org/10.1111/AGEC.12513.

Li, C., Kandel, M., Anghileri, D., Oloo, F., Kambombe, O., Chibarabada, T.P., Ngongondo, C., Sheffield, J., Dash, J., 2021. Recent changes in cropland area and productivity indicate unsustainable cropland expansion in Malawi. Environ. Res. Lett. 16, 084052. URL: https://iopscience.iop.org/article/10.1088/1748-9326/ac162a https://iopscience.iop.org/article/10.1088/1748-9326/ac162a/meta.

Li, C., Chimimba, E.G., Kambombe, O., Brown, L.A., Chibarabada, T.P., Lu, Y., Anghileri, D., Ngongondo, C., Sheffield, J., Dash, J., 2022. Maize yield estimation in intercropped smallholder fields using satellite data in southern Malawi. Remote Sens. 14, 2458. URL: https://www.mdpi.com/2072-4292/14/10/2458.

Li, C., Kambombe, O., Gulule Chimimba, E., Fawcett, D., Brown, L.A., Yu, L., Gadédjisso-Tossou, A., Dash, J., 2023. Limited environmental and yield benefits of intercropping practices in smallholder fields: evidence from multi-source data. Field Crop Res. 299, 108974. URL: https://www.sciencedirect.com/science/article/pii/S0378429023001673.

Mabhaudhi, T., Chibarabada, T.P., Chimonyo, V.G.P., Modi, A.T., 2018. Modelling climate change impact: a case of bambara groundnut (Vigna subterranea). Phys. Chem. Earth, Parts A/B/C 105, 25–31. https://doi.org/10.1016/J.PCE.2018.01.003.

Maestrini, B., Mimić, G., van Oort, P.A., Jindo, K., Brdar, S., Athanasiadis, I.N., van Evert, F.K., 2022. Mixing process-based and data-driven approaches in yield prediction. Eur. J. Agron. 139, 126569. URL: https://linkinghub.elsevier.com/retrieve/pii/S1161030122001174.

Matita, M., Chiwaula, L., Wadonda Chirwa, E., Mazalale, J., Walls, H., 2022. Subsidizing improved legume seeds for increased household dietary diversity: evidence from Malawi's farm input subsidy programme with implications for addressing malnutrition in all its forms. Food Policy 113, 102309. URL: https://www.sciencedirect.com/science/article/pii/S0306919222000859, doi:https://doi.org/10.1016/j.foodpol.2022.102309. Role of policy in reducing malnutrition in sub-Saharan Africa.

McAneney, K., Itier, B., 1996. Operational limits to the priestley-Taylor formula. Irrig. Sci. 17, 37–43.

Mdee, A., Manda, S., Dedaa, A., Djurfeldt, A., 2019. A Political Economy of Inclusive Agricultural Intensification Zambia Country Report. Technical Report. University of Leeds, Leeds.

Minot, N., 2010. Staple Food Prices in Malawi.

Mthakati, A.P.R., Chilonda, P., Manyamba, C., 2012. Challenges and opportunities for raising agricultural productivity in Malawi. Int. J. Agric. For. 2, 210–224. URL: http://article.sapub.org/pdf/10.5923.j.ijaf.20120205.04.pdf.

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254–257. URL: doi:10.1038/nature11420. https://doi.org/10.1038/nature11420.

Mumo, L., Yu, J., Fang, K., 2018. Assessing impacts of seasonal climate variability on maize yield in Kenya. Int. J. Plant Prod. 12, 297–307. URL: doi:10.1007/s42106-018-0027-x. https://doi.org/10.1007/s42106-018-0027-x.

Muñoz-Sabater, J., 2019. ERA5-Land hourly data from 1981 to present. Technical Report. Copernicus Climate Change Service (C3S) Climate Data Store (CDS).

Ngongondo, C., Xu, C.Y., Gottschalk, L., Alemaw, B., 2011. Evaluation of spatial and temporal characteristics of rainfall in Malawi: a case of data scarce region. Theor. Appl. Climatol. 106, 79–93. URL: http://link.springer.com/10.1007/s00704-011-0413-0.

Olasehinde-Williams, G., Adedoyin, F.F., Bekun, F.V., 2020. Pathway to achieving sustainable food security in sub-saharan africa: the role of agricultural mechanization. J. Labor Soc. 23, 349–366. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/wusa.12483, doi:https://doi.org/10.1111/wusa.12483, arXiv: https://onlinelibrary.wiley.com/doi/pdf/10.1111/wusa.12483.

Owens, T., Hoddinott, J., Kinsey, B., 2003. The impact of agricultural extension on farm production in resettlement areas of Zimbabwe. Econ. Dev. Cult. Chang. 51, 337–357.

Pasley, H.R., Cairns, J.E., Camberato, J.J., Vyn, T.J., 2019. Nitrogen fertilizer rate increases plant uptake and soil availability of essential nutrients in continuous maize production in Kenya and Zimbabwe. Nutr. Cycl. Agroecosyst. 115, 373–389. URL: doi:10.1007/s10705-019-10016-1. https://doi.org/10.1007/s10705-019-10016-1.

Phiri, M.A.R., Chilonda, P., Manyamba, C., 2012. Challenges and opportunities for raising agricultural productivity in Malawi. Int. J. Agricult. Forest. 2, 210–224. https://doi.org/10.5923/J.IJAF.20120205.04.

Pingali, P.L., 2012. Green revolution: impacts, limits, and the path ahead. Proc. Natl. Acad. Sci. 109, 12302–12308. URL: https://www.pnas.org/doi/abs/10.1073/pnas.0912953109.

Pourazar, E., 2017. Spaces of Vulnerability and Areas Prone to Natural Disaster and Crisis in Six SADC Countries. Technical Report, International Organization for Migration (IOM). URL: https://www.preventionweb.net/publications/view/55595.

Praveen, B., Sharma, P., 2020. Climate change and its impacts on Indian agriculture: an econometric analysis. J. Public Aff. 20, e1972. URL: https://onlinelibrary.wiley.com/doi/full/10.1002/pa.1972https://onlinelibrary.wiley.com/doi/abs/10.1002/pa.1972https://onlinelibrary.wiley.com/doi/10.1002/pa.1972.

Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: II. Main algorithms and software description. Agron. J. 101, 438–447. URL: https://onlinelibrary.wiley.com/doi/full/10.2134/agronj2008.0140shttps://onlinelibrary.wiley.com/doi/abs/10.2134/agronj2008.0140shttps://acsess.onlinelibrary.wiley.com/doi/10.2134/agronj2008.0140s.

Rusinamhodzi, L., Corbeels, M., Zingore, S., Nyamangara, J., Giller, K.E., 2013. Pushing the envelope? Maize production intensification and the role of cattle manure in recovery of degraded soils in smallholder farming areas of Zimbabwe. Field Crop Res. 147, 40–53. URL: https://www.sciencedirect.com/science/article/pii/S037842901300097X.

Sadras, V., Cassman, K., Grassini, P., Bastiaanssen, W., Laborte, A., Milne, A., Sileshi, G., Steduto, P., 2015. Yield gap analysis of field crops: Methods and case studies. Technical Report. FAO Water Reports No. 41. Rome, Italy. URL: https://digitalcommons.unl.edu/wffdocs/87.

Sato, G.J., Joshua, M.K., Ngongondo, C., Chipungu, F., Malidadi, C., Monjerezi, M., 2020. Evaluation of Different Tillage Systems for Improved Agricultural Production in Drought-Prone Areas of Malawi. Springer International Publishing, pp. 157–167. https://doi.org/10.1007/978-3-030-31543-6_12.

Sentelhas, P.C., Gillespie, T.J., Santos, E.A., 2010. Evaluation of fao penman–monteith and alternative methods for estimating reference evapotranspiration with missing data in southern Ontario, Canada. Agric. Water Manag. 97, 635–644. URL: https://www.sciencedirect.com/science/article/pii/S0378377409003436.

Sharma, G., 2017. Pros and cons of different sampling techniques. Int. J. Appl. Res. 3, 749–752. URL: https://www.allresearchjournal.com/archives/2017/vol3issue7/PartK/3-7-69-542.pdf.

Silva, J.V., Reidsma, P., Laborte, A.G., van Ittersum, M.K., 2017. Explaining rice yields and yield gaps in Central Luzon, Philippines: an application of stochastic frontier analysis and crop modelling. Eur. J. Agron. 82, 223–241. https://doi.org/10.1016/J.EJA.2016.06.017.

Silva, J.V., Baudron, F., Reidsma, P., Giller, K.E., 2019. Is labour a major determinant of yield gaps in sub-saharan africa? A study of cereal-based production systems in southern Ethiopia. Agric. Syst. 174, 39–51. URL: https://www.sciencedirect.com/science/article/pii/S0308521X18306711.

Sima, M.W., Fang, Q.X., Qi, Z., Yu, Q., 2020. Direct assimilation of measured soil water content in root zone water quality model calibration for deficit-irrigated maize. Agron. J. 112, 844–860. URL: https://onlinelibrary.wiley.com/doi/full/10.1002/agj2.20088https://onlinelibrary.wiley.com/doi/abs/10.1002/agj2.20088https://acsess.onlinelibrary.wiley.com/doi/10.1002/agj2.20088.

Steduto, P., Hsiao, T.C., Raes, D., Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: I. Concepts and underlying principles. Agron. J. 101, 426–437. URL: https://onlinelibrary.wiley.com/doi/full/10.2134/agronj2008.0139shttps://onlinelibrary.wiley.com/doi/abs/10.2134/agronj2008.0139shttps://acsess.onlinelibrary.wiley.com/doi/10.2134/agronj2008.0139s.

Tamene, L., Mponela, P., Ndengu, G., Kihara, J., 2016. Assessment of maize yield gap and major determinant factors between smallholder farmers in the Dedza district of Malawi. Nutr. Cycl. Agroecosyst. 105, 291–308. URL: https://link.springer.com/article/10.1007/s10705-015-9692-7.

Tchale, H., 2009. The efficiency of smallholder agriculture in Malawi. AFJARE 3.

Tittonell, P., Giller, K.E., 2013. When yield gaps are poverty traps: the paradigm of ecological intensification in African smallholder agriculture. Field Crop Res. 143, 76–90. https://doi.org/10.1016/J.FCR.2012.10.007.

Tittonell, P., Vanlauwe, B., Leffelaar, P.A., Shepherd, K.D., Giller, K.E., 2005. Exploring diversity in soil fertility management of smallholder farms in western Kenya: ii. Within-farm variability in resource allocation, nutrient flows and soil fertility status. Agric. Ecosyst. Environ. 110, 166–184. URL: https://www.sciencedirect.com/science/article/pii/S0167880905001544.

Utset, A., Farré, I., Martìnez-Cob, A., Cavero, J., 2004. Comparing penman-monteith and priestley-Taylor approaches as reference-evapotranspiration inputs for modeling maize water-use under mediterranean conditions. Agric. Water Manag. 66, 205–219. URL: https://www.sciencedirect.com/science/article/pii/S0378377403003184.

van Bussel, L.G.J., Grassini, P., Van Wart, J., Wolf, J., Claessens, L., Yang, H., Boogaard, H., de Groot, H., Saito, K., Cassman, K.G., van Ittersum, M.K., 2015. From field to atlas: upscaling of location-specific yield gap estimates. Field Crop Res. 177, 98–108. URL: https://www.sciencedirect.com/science/article/pii/S0378429015000878.

van Dijk, M., Morley, T., van Loon, M., Reidsma, P., Tesfaye, K., van Ittersum, M.K., 2020. Reducing the maize yield gap in Ethiopia: decomposition and policy simulation. Agric. Syst. 183, 102828 https://doi.org/10.1016/J.AGSY.2020.102828.

Van Ittersum, M.K., Cassman, K.G., 2013. Yield gap analysis—rationale, methods and applications—introduction to the special issue. Field Crop Res. 143, 1–3. https://doi.org/10.1016/J.FCR.2012.12.012.

Van Ittersum, M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Yield gap analysis with local to global relevance—a review. Field Crop Res. 143, 4–17. https://doi.org/10.1016/J.FCR.2012.09.009.

van Loon, M.P., Adjei-Nsiah, S., Descheemaeker, K., Akotsen-Mensah, C., van Dijk, M., Morley, T., van Ittersum, M.K., Reidsma, P., 2019. Can yield variability be explained? Integrated assessment of maize yield gaps across smallholders in Ghana. Field Crop Res. 236, 132–144. https://doi.org/10.1016/J.FCR.2019.03.022.

Van Vugt, D., Franke, A.C., Giller, K.E., 2017. Participatory research to close the soybean yield gap on smallholder farms in Malawi. Exp. Agric. 53, 396–415. URL: https://www.cambridge.org/core/journals/experimental-agriculture/article/participatory-research-to-close-the-soybean-yield-gap-on-smallholder-farms-in-malawi/015101C4D9B6BBD166542910530EB4E2.

Vanuytrecht, E., Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., Heng, L.K., Garcia Vila, M., Mejias Moreno, P., 2014. AquaCrop: FAO's crop water productivity and yield response model. Environ. Model. Softw. 62, 351–360. https://doi.org/10.1016/J.ENVSOFT.2014.08.005.

Vittinghoff, E., Glidden, D.V., Shiboski, S.C., McCulloch, C.E., 2005. Regression Methods in Biostatistics: Linear, Logistic, Survival, and Repeated Measures Models. Springer, US. https://doi.org/10.1007/b138825. URL: http://link.springer.com/10.1007/978-1-4614-1353-0.

Waha, K., van Wijk, M.T., Fritz, S., See, L., Thornton, P.K., Wichern, J., Herrero, M., 2018. Agricultural diversification as an important strategy for achieving food security in africa. Glob. Chang. Biol. 24, 3390–3400. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14158, doi:https://doi.org/10.1111/gcb.14158, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcb.14158.

Xiaoying, L., Erda, L., 2005. Performance of the priestley-Taylor equation in the semiarid climate of North China. Agric. Water Manag. 71, 1–17. URL: https://www.sciencedirect.com/science/article/pii/S0378377404001817.

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D.B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P., Durand, J.L., Elliott, J., Ewert, F., Janssens, I.A., Li, T., Lin, E., Liu, Q., Martre, P., Müller, C., Peng, S., Peñuelas, J., Ruane, A.C., Wallach, D., Wang, T., Wu, D., Liu, Z., Zhu, Y., Zhu, Z., Asseng, S., 2017. Temperature increase reduces global yields of major crops in four independent estimates. Proc. Natl. Acad. Sci. 114, 9326–9331. URL: https://www.pnas.org/doi/abs/10.1073/pnas.1701762114, doi:https://doi.org/10.1073/pnas.1701762114, arXiv:https://www.pnas.org/doi/pdf/10.1073/pnas.1701762114.