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Impact of climate change on farms in smallholder farming systems: Yield impacts, economic implications and distributional effects

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ABSTRACT

The impact of climate change on farms can be determined by factors such as local climatic changes, farm physical environment, the type of crops grown, and household socio-economic characteristics that limit or increase adaptability to climate change. The current study assesses the impacts of climate and socio-economic changes on smallholder farms in two districts of Ethiopia representing different agro-ecology in a major agricultural region. For this purpose, observed farm production data, simulated yield under climate change and socio-economic scenarios were used. The aim was to produce information that facilitates an understanding of the unequal economic implications of climate change on farms. To this end, the study applied the Tradeoff Analysis for Multi-Dimensional impact assessment (TOA-MD) economic simulation model in combination with the AquaCrop yield simulation model. The findings on climate change impact towards 2030 highlight the uneven implications of climate change on farms and the role that agro-ecology and future socio-economic development scenarios play in determining climate change impact. It is found that, under the climate projections we considered crops such as *tef*, barley and wheat are found to benefit from the projected climate change in cool regions. In warm regions, *tef* and wheat are projected to be negatively affected whereas maize would benefit. The proportion of farms that are negatively affected by climate change ranged between 51% and 78% in warm regions under different scenarios; in cool regions, the proportion of negatively affected farms ranged between 10% and 22%. The implications of climate change are found to vary under various socio-economic scenarios, in which positive socio-economic scenarios considerably reduced the proportion of negatively affected farms. The economic implications of climate change also found to differ among farms within agro-ecology because of differences in land allocation to various crops that have different sensitivity to climate change, and due to other farm differences. Thus, the study shows the importance of using farm and site-specific production and climate data to reveal variabilities in climate change impact. It also provides evidence on the relevance of accounting for agro-ecology and crop differences as well as consideration of potential socio-economic changes. Overall, the results suggest that appropriate agricultural interventions that recognize location and crop differences are essential to minimize climate change impact.

1. Introduction

Climate change is one of the biggest challenges the world faces today posing a threat to many populations around the globe. Studies indicate that in many regions of the world agriculture will be affected by climate change, limiting food production and threatening food security (Tai et al., 2014; Wheeler and Braun, 2013). Sub-Saharan African countries are among the most vulnerable to climate change having warm climate and lower socio-economic status that limits their capacity to adapt to the rapidly growing climate change effects (Ringler et al., 2010). As smallholder farmers in these countries continue to face an increasing threat from climate change, a growing body of literature is investigating to understand the potential impacts of climate change on the agriculture of this region. Findings from previous impact studies have indicated that agriculture will by and large be negatively affected in this region due to climate change (Schlenker and Lobell, 2010; Knox et al., 2012); for example mean yield changes of up to −22% have been found in some crops (Schlenker and Lobell, 2010). However, most previous studies have either focused on assessing climate change impact on yield of individual crops (e.g., Abraha and Savage, 2006; Jones and Thornton, 2003) or used aggregate models to assess economic impact (Claessens et al., 2012).

Assessing climate change impact on individual crops alone does not provide enough information for an understanding of the overall

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economic implications in systems where farms often simultaneously produce crops with varying degrees of sensitivity to climate change. Furthermore, as individual crop yield assessments mainly focus on evaluating the yield performance of crops in relation to future climatic conditions, other relevant socio-economic conditions that may change in the future are little considered in such studies. On the other hand, aggregate economic models do not adequately represent the heterogeneity in farming systems and conceal variability, which is of paramount importance to effective policy intervention. In previous climate change (Rao et al., 2015; Zubair et al., 2015) and technology (Suri, 2011) impact assessment studies in smallholder farming systems, a considerable amount of heterogeneity in terms of impact has been observed across households, which can be attributed to the spatial variability of the farms' physical environment, production activity and other household characteristics (Antle, 2011). This essential heterogeneity in agricultural systems (Antle et al., 2014) is not adequately represented in earlier studies, though currently, studies that recognize the differential effects of climate change are emerging (e.g., Claessens et al., 2012; Rao et al., 2015). Overall, climate change impact studies that represent the direct yield response of the various crops grown by farms alongside future socio-economic changes and agro-ecological differences may provide useful information in understanding the overall implications of climate change.

In this study, we applied the Tradeoff Analysis for Multi-Dimensional impact assessment (TOA-MD) framework in combination with the AquaCrop yield simulation model to assess the economic impact of climate change in a typical smallholder farming population in Ethiopia using local and farm-specific data. To this end, the current study characterizes the economic returns of farms under baseline and future climatic conditions, and socio-economic settings using observed and simulated crop yield data in combination with socio-economic scenarios. We carry out the assessment for two study areas representing two different agro-ecologies in a major agricultural production region. This study contributes to an understanding of the distributional economic implications of climate change representative of mixed-crop farming systems characterized by heterogeneous farm and household characteristics.

In the remaining part of this paper, Section 2 discusses conceptual issues and approaches of climate change impact assessment. Section 3 explains the materials and methods used in the study followed by results and discussion in Section 4. Finally, the conclusion and policy implication is presented in Section 5.

2. Climate change impact: conceptual issues and approaches

Climate change affects crop productivity primarily due to the effects of temperature, rainfall and CO_2 on crop physiological activities and phenological development (Lobell and Gourdji, 2012). It can also impair crop production by altering pest incidence and plant-pest interaction (Juroszek and Tiedemann, 2013).

However, several factors can determine the direction and magnitude of climate change impact on farms. First, as climate change manifests itself in different ways across locations, the impact may likewise vary depending on the specific local climatic changes. Secondly, even when areas experience a similar degree of climatic changes, the consequences will be detrimental, for example, in regions where temperatures are already near to physiological maxima (Gornall et al., 2010). Another important aspect is that different crops do not respond to climate change in the same way owing to variation in their sensitivity to temperature, rainfall and CO_2 changes (Gornall et al., 2010). The impacts of climate change may also vary from place to place and farm to farm due to differences in the capacity of agricultural systems and farms to adapt to climate change (Smit and Wandel, 2006).

Farms in smallholder farming systems vary in terms of composition and intensity of production activity, household characteristics, use of agricultural technology and farm physical environment. This variation has an important implication for climate change impact. In environmental and other technological impact assessments, it is thus essential to recognize farm heterogeneity in such systems (Antle, 2011). Another important aspect in climate change impact assessment is the socio-economic condition within which future agriculture is expected to work (Antle et al., 2014). Potential changes, for example, in agricultural price and cost variables and changes in land holdings that may happen in the future due to changes in various sectors of the economy, or changes in demand and supply, need to be taken into consideration in climate change impact assessment studies.

Past studies have assessed the impact of climate change on agriculture mainly using process-based crop models (Thornton et al., 2009; Abraha and Savage, 2006), statistical models (Lobell and Burke, 2010) or the Ricardian approach (Mendelsohn et al., 1994). Process-based crop models assess the impact of climate change on yield based on the relationship governing productivity as a function of climate, soil and management. The statistical model approach is based on historical relationship between crop yield data and weather data (Lobell and Burke, 2010). The Ricardian approach measures economic impact by examining the relationship between land values or farm revenue, and a set of climatic and other variables from cross sectional data (Mendelsohn et al., 1994). Process-based crop-yield simulation has good potential to predict the direct impact of climate change on yield provided the minimum standards for data selection and quality are met. The statistical approach is deemed to provide an alternative when detailed field data is lacking to calibrate process-based crop models (Lobell and Burke, 2010). However, the problem of collinearity among predictor variables such as between rainfall and temperature variables is among the major concerns in the use of the statistical approach (Lobell and Burke, 2010). The Ricardian approach has been significant for its ability to implicitly control for actual farmers' adaptation (Mendelsohn et al., 1994). However, its failure to consider issues such as carbon fertilization effects and future changes in price has been a concern (Mendelsohn and Dinar, 2009; Cline, 1996).

A more recently introduced TOA-MD economic simulation model provides a useful framework; particularly for agricultural systems in which farms involve in multiple agricultural activities composed of various crops, livestock and off-farm activity (Claessens et al., 2012). The model also allows an easy incorporation and simulation of the impact of future socio-economic changes in the analysis. Combined with crop yield simulation models and socio-economic scenarios, the approach provides a relevant framework by which climate change impact can be assessed accounting for crop and farm differences and future socio-economic settings. The TOA-MD model approach and how it is applied in the current study is discussed in detail in Section 3.3.1.

3. Materials and methods

3.1. Study area

The study is conducted on smallholder farmers in the Welmera and Dugda districts of Ethiopia. In Ethiopia, agriculture is the main livelihood for more than 80% of the population contributing over 40% of the gross domestic product (GDP). The GDP growth has shown a close link with rainfall variation in the past indicating the ties between climate conditions and the agriculture based economy (World Bank, 2006). Long term meteorological records show that the country has experienced climatic changes in the past decades (Tadege, 2007). The country features diverse agro-ecology and topography and this study assesses climate change impact in two study areas representing two agro-ecologies as described below.

The Welmera district is located in central Ethiopia, covering an area of 809 km^2 at a mean altitude of about 2527 m above sea level, and had a total population of 83,823 in 2007 (CSA, 2010). The annual rainfall for the area varied between 729 mm and 1301 mm with a mean of 1038 mm during the past four decades. The average maximum and minimum temperatures during this period were about 22 °C and 6 °C, respectively. Small-scale subsistence crop-livestock mixed farming system is the common agricultural practice. Farmers grow a mix of crops such as wheat, *tef* and barley in the area. Crop production is mainly rain-fed, low-input and the use of mechanized agriculture is rare. In addition to farming, some farmers participate in non-agricultural income activities.

The Dugda district is located in the central rift valley area of Ethiopia, covering an area of 959.5 km^2 at a mean altitude of about 1700 m above sea level, and had a total population of 144,910 in 2007 (CSA, 2010). The annual rainfall of the area varies between 511 mm and 1130 mm with a mean of 771 mm over the past four decades. The mean maximum and minimum temperatures are 27 °C and 14 °C, respectively. The dominant farming system in the area is small scale mixed crop-livestock. Food crops such as maize, wheat, and *tef* are commonly grown as rain-fed systems. Some households earn additional income from non-agricultural activities.

3.2. Farm survey data

The farm data used in this study is from a household-level interview conducted during November 2012 to February 2013 in the two districts. Farm-level production data on the various agricultural activities and household socio-economic information are collected including (i) information on land allocation for each major crop grown, and (ii) input-output information for each crop activity i.e., information on input use and yield. Respondents were randomly selected households from six peasant associations (the lowest administrative unit) located in the two districts. In total, 200 households in Welmera and 100 households in Dugda were interviewed. The analysis in this paper included 179 households from the Welmera district and 90 households from the Dugda district that provided information relevant for this analysis. Additional relevant production data required for the analysis were obtained from the central statistical agency archives and district agricultural offices. These data include average unit price of crop products and inputs representative of the study period and districts (CSA, 2013).

3.3. Methods

The current study assesses the economic implications of climate change in association to agricultural activities on major crops in the study districts. The major crop activities considered in the Welmera district are *tef*, wheat, and barley; in Dugda the major crops are *tef*, wheat and maize. We analyze the economic impact of climate change on farms in the study area by comparing the returns of production systems under different climate and socio-economic scenarios. To represent production systems in future periods more realistically, the current study focuses on the near-term effects of climate change centered at 2030. The TOA-MD model (Antle and Valdivia, 2011) in combination with the AquaCrop yield simulation model is used for the analysis. In the next section, we provide a detailed explanation of the TOA-MD model. The AquaCrop modeling is explained under Section 3.3.3.

3.3.1. The TOA-MD model

In the TOA-MD simulation model approach, *"a farmer at site s using a production system h (defined as a combination of technology, climate and socio-economic setting) earns per-hectare returns each period equal to* $V_t = V_t(s,h)$. *Over T time periods, production system h provides a discounted net return of:*

$V(s,h) = \sum_{t=1}^{T} \delta_t v_t(s,h)$ *where* δ_t *is the relevant discount factor*" (Claessens et al., 2012 p. 89)

When one or more of the components (for example climate) of the production system within which the farm operates changes, the associated expected net return may change. Defining $\omega = V(s,h_1) - V(s,h_2)$, where h_2 and h_1 respectively, represent a production system with and without the change at site *s*, a negative ω indicates a gain from h_2 whereas a positive ω represents a loss. Because of variation in physical and socio-economic conditions such as farm size, land quality, and household characteristics e.g., farming experiences and household size, the expected net returns of a system associated with each site are spatially distributed (Antle, 2011). Accordingly, ω is also spatially distributed with density function $\varphi(\omega)$ and the proportion of farms that lose returns less than or equal to *a* can be estimated as (Antle, 2011):

$$r(a, h_1, h_2) = 100\int_{-\infty}^{a} \varphi(\omega, h_1, h_2) d\omega$$

In the current study, we use the TOA-MD model to assess the impact of climate change and socio-economic scenarios on farm returns by comparing farm returns of baseline production system (h_1) against production system with climate and socio-economic change (h_2). For this, the returns of the crop production activities under the baseline production system are estimated from the production input-output and socio-economic data collected from household surveys in the study area and other relevant secondary sources. The expected returns of crop production under climate and socio-economic change are estimated by using outputs from crop yield simulations and using socio-economic scenarios. Detailed descriptions of the TOA-MD model parametrization process for both production systems are provided in the following section.

3.3.2. Characterization of the baseline production system

We first stratified the farm population in each study area into two farm groups based on whether farms are located in villages officially recognized to have irrigation access. We assumed that, due to differences in irrigation access, land holdings and land allocations for major crop activities may vary between the two groups; potentially leading to differences in climate change impact. Thus, stratification can enable us to understand potential climate change impact differences on the two groups. In addition, stratification into sub-populations based on the appropriate factor improves the normality assumption made about the distribution of net returns and outcome variables in the TOA-MD model (Antle, 2011). Stratification is only for the purpose of unravelling potential differences in landholding and crop allocations, otherwise all the major crops under consideration are produced under rain-fed system in the main cropping season. Farms use irrigation to produce vegetables in small areas during the dry season.

After stratification, the relevant model parameters for each group are then estimated. The summary is presented in Table 1. Values for farm size, off-farm income, allocated area, and yield for each crop are all estimated from the household-level survey data. Input costs are estimated based on farm data on the amount of input applied by farmers and the district-level average unit input price information from agricultural offices reported for the year under consideration. The net returns are calculated as total return minus variable costs of seed, fertilizers, and chemicals. The average prices representative of each study area and study period as reported by the central statistical agency were used to value total return. Farmers in the area depend almost entirely on family labor, and because farmers are not in the habit of recording time spent on farming activities it is often challenging to obtain a reliable estimation of labor costs. As a result, labor cost is excluded in the net return calculation. The problem of inclusion of labor costs has been reported in other studies too (Kurukulasuriya and Mendelsohn, 2008). Fixed costs in smallholder production systems are a small portion of the total cost and as it is not expected to change significantly between systems in the near future, excluding this from net return estimation will not bias the final output.

3.3.3. Characterization of the production system under climate and socio-economic changes

The expected net returns of the production systems under climate and socio-economic changes are estimated by integrating the outputs of yield simulation and socio-economic scenarios. In this, farm net returns for each crop activity are calculated based on expected yields

Table 1
Data used in the TOA-MD model to characterize baseline production systems.

District	Farm groups	Farm size (ha)	Off-farm income (birr)	Crop activity	Area (ha)	Yield (kg ha^{-1})	Net return (birr ha^{-1})
Welmera ($N = 179$)	In villages with irrigation access	1.45 (1.1)	383 (1418)	*Tef*	0.41 (0.31)	1151 (714)	8532 (6612)
				Wheat	0.44 (0.30)	1532 (1086)	5395 (6173)
				Barley	0.07 (0.14)	1199 (737)	2246 (3514)
	In villages with no irrigation access	1.46 (1.2)	1518 (3687)	*Tef*	0.47 (0.56)	1400 (1063)	10,188 (10203)
				Wheat	0.50 (0.50)	1963 (1578)	6615 (9785)
				Barley	0.25 (0.36)	1820 (1381)	4432 (7561)
Dugda ($N = 90$)	In villages with irrigation access	1.34 (1.3)	846 (2524)	*Tef*	0.26 (0.29)	1229 (510)	15,343 (6979)
				Wheat	0.31 (0.30)	2004 (857)	10,865 (5432)
				Maize	0.79 (0.70)	3866 (2061)	17,134 (9250)
	In villages with no irrigation access	2.23 (0.9)	896 (2689)	*Tef*	1.32 (0.57)	875 (256)	9873 (3501)
				Wheat	0.47 (0.44)	1655 (543)	8862 (4007)
				Maize	0.49 (0.40)	1791 (962)	7750 (4632)

Birr is the unit of currency in Ethiopia
The values in parenthesis are standard deviations
All crops under consideration are produced under rain-fed system. The grouping of farms under villages with and without irrigation access is for the purpose of identifying potential differences in landholdings and crop allocations.

of each crop under climate change and expected changes on socio-economic settings such as prices and input costs. In the next two sub-sections we explain how we estimated yield and socio-economic changes.

3.3.3.1. Yield under climate change. The AquaCrop model is applied to simulate yield under climate change. The AquaCrop model simulates daily biomass production and final yield of crops in relation to water use and agronomic management (Vanuytrecht et al., 2014a). The model has been validated and applied including in studies that have assessed the impact of climate change on different crops (Muluneh et al., 2014); the impact of adaptation strategies under climate change (Bird et al., 2016) and to investigate the uncertainty associated with using different climate models (Vanuytrecht et al., 2014b). The studies show that the model is a valuable tool in predicting yield, particularly in areas under limited water environments such as most parts of Ethiopia. To simulate yield, AquaCrop requires input data on rainfall, temperature, reference evapotranspiration (ET_0), CO_2 concentration, soil data, crop parameters and management data. Details of the concepts of the model and the simulation process can be found in Steduto et al. (2009) and Raes et al. (2009).

The model has been calibrated and validated for crops such as wheat, maize, barley, *tef* and others under various environmental conditions, and the model provides starting values and recommendations of crop parameters obtained from calibration/validation exercises (Raes et al., 2012). The crop parameters used in this study are adopted from previous calibration and validation exercises of the AquaCrop model conducted under Ethiopian conditions and elsewhere (Abreha et al., 2012; Tsegay et al., 2012; Biazin and Stroosnijder, 2012). We used the AquaCrop default crop parameters provided by the model for *tef*, barley and wheat crops; the default crop parameters of AquaCrop for *tef* and barley are from calibrations under Ethiopian conditions. For maize, we modified the default crop parameters following the crop parameters recommended by the study of Biazin and Stroosnijder (2012) conducted in Ethiopia.

Daily data on rainfall, maximum- and minimum temperature, and solar radiation required in the yield simulation process were obtained from the web version of the stochastic weather-generating tool MarkSimGCM (http://gisweb.ciat.cgiar.org/MarkSimGCM/). The comparison of MarkSimGCM simulations with historical data from various climatic locations (Jones and Thornton, 2013) including for sites in Ethiopia (Muluneh et al., 2014) has shown reasonably accurate simulation potential of MarkSimGCM. Two sets of climate data i.e., one for a baseline period and one for a future period were generated for a representative site in each district. For the baseline period, daily weather data in each site was generated for 30 replicates (different weather years) (Jones and Thornton, 2003). For the future period, daily weather data is generated for the period 2020–2049 for two representative concentration pathways (RCPs[1]); the very low forcing level concentration pathway RCP 2.6, and the very high forcing level concentration pathway RCP 8.5 (van Vuuren et al., 2011) from an ensemble of 17 global circulation models. The period 2020–2049 is used to represent the climate and yield of 2030. The outputs of the weather generation process are presented in Appendix 1.

Reference evapotranspiration (ET_0) is computed by the Penman-Moneith method using an ET_0 calculator incorporated in the AquaCrop model using minimum- and maximum temperature and solar radiation data. The CO_2 concentration value used for the baseline period is the mean annual measured at Mauna Loa observatory station and for the future period, the RCP2.6 and RCP8.5 concentration values are used as provided by the AquaCrop model. The dominant soil texture conditions in the study areas, i.e., clay loam in Welmera and sandy loam in Dugda are used as input for the simulation (Hengsdijk and Jans, 2006; Tangka et al., 2002). The common rain-fed cropping system and the model default management condition (i.e., optimum soil fertility) is considered.

Simulation is carried out for the baseline and future periods using the local crop calendar obtained from the FAO crop calendar global dataset and available at http://www.fao.org/agriculture/seed/cropcalendar/welcome.do. The simulated yield for 2030 is represented by calculating the average yield of the 2020–2049 time period. The simulated yield for the baseline period is represented by calculating the average yield of the 30 baseline weather years. Finally, the yield under climate change at each farm is calculated as follows:

Yield under climate change at each farm = [((mean simulated yield under baseline climate) − (mean simulated under climate change)) / (mean simulated yield under baseline climate)] ∗ farm observed yield

By using the farm observed yield instead of direct AquaCrop simulation output to approximate future yield, we assume to implicitly introduce possible spatial variation in yield that arises from site-specific and household-specific differences into the TOA-MD model.

On a separate analysis, this study has made validation of the AquaCrop model for the study area based on correlation analysis for AquaCrop simulated yield, and available local yield statistics (available at the next higher administrative unit to the district i.e., zone level) for each crop. Yield simulation for the validation process is carried out using historical climate data in the period 1995–2009 observed at meteorological stations in or nearby the study districts. The climate data is obtained from meteorological agency of Ethiopia and an agricultural research institute. The outputs are presented on Appendix 2. The correlations were positive and statistically significant at the 5% significance

[1] The RCPs are a set of four future greenhouse gas concentration pathways used by general circulation models and are identified by how much radiative forcing level they lead to by the end of the century (van Vuuren et al., 2011).

level for all the cases except *tef* and wheat in Dugda that showed non-significant positive correlation. Overall, the correlations suggest the potential of the AquaCrop model to represent yield trends in the areas as a function of the local climate in most cases.

3.3.3.2. Socio-economic changes. The impact of climate change is sensitive to the interaction of many biophysical and socio-economic factors (Wiebe et al., 2015). It is thus relevant to include this dimension in climate change impact assessment studies. The future socio-economic scenarios assumed in our study are estimated from scenarios developed based on the concepts of representative agricultural pathways (RAPs)[2] for a country with comparable socio-economic conditions. We benefit from the work of Claessens et al. (2012) that provides two alternative parametric socio-economic scenarios for Kenya. There are similarities in the development of the smallholder sector as well as in the macro-economic policies and structural changes of Kenya and Ethiopia. For example, with regard to market development for agricultural products, the market liberalization for maize in both countries shows more or less similar trends (Aylward et al., 2015; Wangia et al., 2002). Also, the economic contribution of the agriculture sector in the two countries shows similar trend in recent years. Cereal yield, for example, show similar level and trend in both countries. Agriculture in the two countries faces many similar constraints; for example, access to credit and access to input and output markets are big issues for the farms. Considering these similarities and the recent efforts made by the two governments to pursue regional integration to promote economic development (proclamation no 836/2014, Ethiopia), and the Ethiopian government's effort to join the World Trade organization (WTO), it can be expected that the socio-economic conditions and institutional settings of the agricultural sector in both countries will be comparable in the future. Therefore, the RAPs developed for Kenya are considered to be applicable for our study region that is more or less affected by similar socio-economic conditions and market infrastructure.

One of the RAPs refers to a future with positive economic growth characterized by infrastructure development, policy changes and non-agricultural sector developments, whereas the second refers to a future with low economic growth characterized by higher population growth, poor agricultural policies and low infrastructure development (Claessens et al., 2012). Table 2 shows the parametric socio-economic scenarios developed for 2030 consistent with the two RAPs. Claessens et al. (2012) provides price and cost scenarios for maize; in the current study we extrapolate the scenarios to the other cereals considered in our analysis. The parametric socio-economic scenarios are based on RAPs that made assumptions on, among other factors, non-agricultural sector developments, associated off-farm income and farm size changes. Therefore, to be consistent with these assumptions we added off-farm incomes into our farm income analysis in the TOA-MD model.

Table 2
Socio-economic changes (expressed as percent of the baseline period (100%)) assumed in the TOA-MD model.
Source: Adapted from Claessens et al. (2012).

	RAP1 (positive economic development)	RAP2 (low economic development)
Cereals price	130	100
Cereals cost	90	110
Farm size	120	80
Off-farm income	150	100

RAP = Representative Agricultural Pathway

4. Results and discussion

4.1. Yield response to climate change

The simulated changes in mean yield relative to the baseline period are presented in Fig. 1. Detailed output of the yield simulation process is presented in Appendix 3. The simulated changes in yield vary between locations, among crops and representative concentration pathways. The variation in simulated yield change between locations is considerable.

In Welmera, the yield of all crops increased in both representative concentration pathways at varying magnitudes. In highland Welmera, it is likely that the projected increase in rainfall in the month of July coupled with an increase in temperature (Appendix 1) during the growing period, have resulted in overall positive yield impact. Increasing temperature in highland areas is generally believed to potentially enhance crop productivity where cooler temperatures currently constrain plant productivity (Thornton et al., 2015).

In Dugda, *tef* and wheat yield declined while maize yield increased in both concentration pathways. Yield decline in *tef* and wheat is mainly induced by water stress as a result of an extended dry period during the growing period of future climate. As Dugda is already located in a warmer zone that receives less rainfall, an increase in temperature coupled with decreased rainfall, particularly in the month of August, has most likely contributed to major yield losses in *tef* and wheat. Studies have found that successive dry spells during critical growing stage of *tef* such as flowering can lead to sever yield reduction (Araya et al., 2011). The dry spells have not coincided with maize critical growing stages as maize is planted earlier. On the other hand, the rainfall increase in May coupled with temperature increases may have created conducive environment for maize performance.

In addition to rainfall and temperature effects, the AquaCrop model also represents the effects of rising CO_2 concentrations. Therefore, the simulated changes in yield are attributed to the combined effects of change in climate variables as well as CO_2 effects. In general, C_3 plants are believed to respond positively to the direct CO_2 fertilization effects (Boote et al., 2011). However, C4 plants have also been found to improve their water use efficiency particularly in areas with limited water availability in response to elevated CO_2 level (Leakey, 2009). The AquaCrop model also makes adjustments to elevated CO_2 accordingly (Raes et al., 2012).

Overall yield simulation results from the two agro-ecologies suggest that the combined effect of a slight increase in rainfall, an increase in temperature and CO_2 fertilization effect will result in yield increase in areas characterized by relatively less limiting current rainfall and lower temperatures. However, the impact of a likely further increase in temperature or a change in rainfall pattern and distribution in mid-term period or the end of century will have to be determined in future studies. On the other hand, the combined effect of a rainfall decrease and an increase in temperature in the middle of the growing season can be detrimental for some crops in areas characterized by limited current rainfall and warmer temperatures.

Considering previous studies, Jones and Thornton (2003) have predicted localized substantial yield increases in maize particularly in highland areas (up to 100%), and in some areas dramatic decreases in 2055 in Ethiopia. A study by Muluneh et al. (2014) that considered impact for mid-term and end of century periods also indicated agro-climate-specific yield changes for maize that ranged from plus 59% to minus 46%; the same study predicted an increase in yield of up to 40% for wheat crops in the humid zone of the central rift valley of Ethiopia. The findings of Kassie et al. (2015) study conducted in Ethiopia shows that maize yield will decrease in 2050s under the climate projection they

[2] "Representative agricultural pathways (RAPs) are plausible qualitative story-lines for future socio-economic settings that can be translated into model parameters such as farm and household size, prices and cost of production and policy" (Claessens et al., 2012 p. 88). The RAPs are being developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP) to facilitate climate change impact assessment studies that are in joint context with the emission and socio-economic scenario assumptions in climate models (Rosenzweig et al., 2013). RAPs are based on assumptions made in "population growth, income growth and technology changes as well as trade, investment, energy and agricultural policy" (Rosenzweig et al., 2013 p. 174).

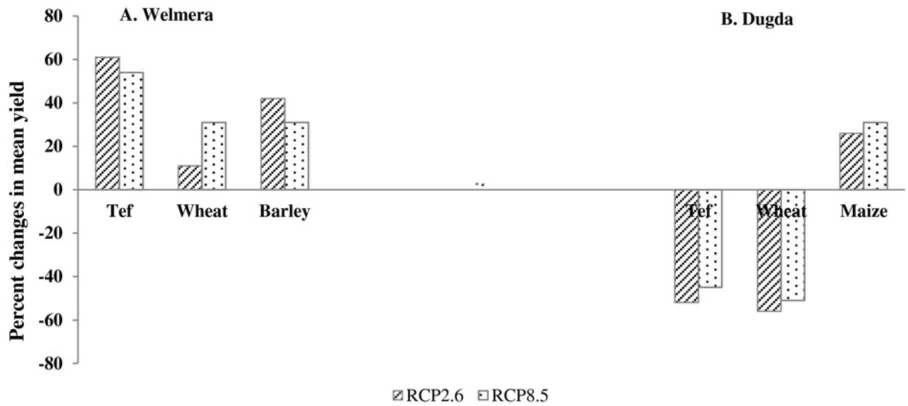

Fig. 1. Simulated percent changes in mean yield in 2030 relative to the baseline period in (A) Welmera and (B) Dugda districts under the two climate emission pathways.

considered. A further study that has assessed the manner in which climate change spatially affects crop production in Ethiopia has shown shifts in land suitability with net losses in land area suitable for cereal production (Evangelista et al., 2013). The study by Abreha et al. (2012) that has investigated the impact of hypothetical climate and CO_2 scenarios on maize in South-Africa finds doubling of CO_2 concentration alone, and the combined effect of doubling of CO_2, and temperature and rainfall increases of 2 °C and 10% respectively, all increase maize yield. Other studies from Sub-Saharan Africa also show substantial spatial variability and crop-specific yield responses to climate change (Thornton et al., 2009). A study by Ringler et al. (2010) also indicates how heterogeneous the impact of climate change is across crops and agro-ecological zones.

4.2. Economic implications of climate and socio-economic changes

The results of the TOA-MD model analysis are presented in Fig. 2 and Table 3. Fig. 2 illustrates the distributional impacts of climate change on farm populations in the two districts representing two different agro-ecologies. The point at which the curve crosses the x-axis shows the proportion of farms that are positively impacted with zero or negative loss (i.e., benefit). The results are presented for the analysis of the sensitivity of the baseline production system to climate change (i.e., the performance of the baseline production system under the two RCPs retaining current socio-economic conditions) and for a combination of the two RCPs and the two RAPs scenarios.

The graph in Fig. 2 reveals that in all the scenarios, the impact of climate change on farms is found to be non-uniform; a distribution of impact is observed in the population of both districts. The differential impacts of climate change among farms may have arisen because of differences in the crop allocation, physical environment, or household characteristics. These differences are represented in the model in terms of variation in farm crop yield (which is the result of physical environment and household characteristics among other things) as well as land allocation for the different crop activity among farms. The proportion of farms that are negatively impacted by climate change varied considerably between the socio-economic scenarios. The proportion of farms that are negatively impacted is higher for low economic development scenarios, followed by scenarios without socio-economic changes and with positive economic development, respectively.

Comparison of the proportion of negatively affected farms between the positive and low economic growth scenarios suggests the extent to which climate change results in negative impacts on the wider population when coupled with low economic development. Additionally, the findings indicate that the proportion of farms that are negatively affected by climate and socio-economic changes is much higher in the warmer Dugda than in Welmera in all the scenarios considered. This proportion ranges from about 10% to 22% in the Welmera district. The proportion of negatively affected farms in Dugda ranges from 51% to 78%.

Table 3 summarizes the results on the percent of negatively affected farms and associated net losses per farm separately for each farm group. Additionally, net losses per farm and net losses as a percent of mean net farm returns in the baseline system (from the major crops and off-farm income) are presented in the table. As can be seen from the table, for the Welmera district, the net loss per farm associated with the different scenarios is negative in all the cases in both farm groups suggesting a net positive impact. The difference in impact between farm groups is low in Welmera. Given the similarities in land allocations between the two

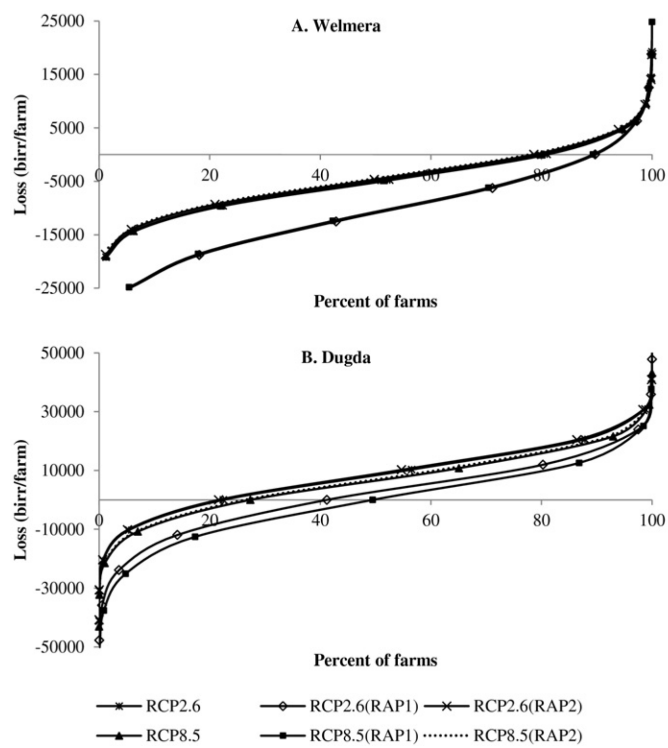

Fig. 2. The expected impact of climate and socio-economic changes on (A) Welmera & (B) Dugda farm populations by 2030. RCP2.6 = the impact of RCP2.6 climate change projection alone without consideration of socio-economic changes. RCP8.5 = the impact of RCP8.5 climate change projection alone without consideration of socio-economic changes. RCP2.6 (RAP1) = the combined effects of RCP2.6 climate change projection and RAP1 socio-economic scenario. RCP8.5 (RAP1) = the combined effects of RCP8.5 climate change projection and RAP1 socio-economic scenario. RCP2.6 (RAP2) = the combined effects of RCP2.6 climate change projection and RAP2 socio-economic scenario. RCP8.5 (RAP2) = the combined effects of RCP2.6 climate change projection and RAP2 socio-economic scenario.

Table 3
Impact of climate and socio-economic changes on farms.

Scenario	Welmera			Dugda		
	In villages with irrigation access	In villages with no irrigation access	Total	In villages with irrigation access	In villages with no irrigation access	Total
Percent of negatively affected farms						
RCP2.6	14	24	19	63	92	78
RCP2.6(RAP1)	6	14	10	42	76	59
RCP2.6(RAP2)	17	26	21	64	93	78
RCP8.5	16	24	20	58	88	73
RCP8.5(RAP1)	7	15	11	37	64	51
RCP8.5(RAP2)	19	26	12	58	89	74
Net loss per farm in birr						
RCP2.6	−4193	−5455	−4822	4140	10,978	6707
RCP2.6(RAP1)	−8358	−9995	−9174	−3196	5278	−15
RCP2.6(RAP2)	−3748	−4900	−4319	4418	11,439	7053
RCP8.5	−3970	−5342	−4653	2384	9034	4880
RCP8.5(RAP1)	−8111	−9814	−8960	−5433	2721	−2376
RCP8.5(RAP2)	−3484	−4622	−4051	2662	9507	5231
Net loss as a percent of mean net farm returns in baseline system						
RCP2.6	−74	−60	−66	16	46	27
RCP2.6(RAP1)	−133	−88	−104	−12	22	−0.06
RCP2.6(RAP2)	−66	−55	−60	17	48	28
RCP8.5	−70	−59	−63	10	38	19
RCP8.5(RAP1)	−130	−87	−102	−21	11	−9
RCP8.5(RAP2)	−67	−54	−59	10	40	21

RCP = representative concentration pathway
RAP1 = representative agricultural pathway with positive economic development
RAP2 = representative agricultural pathway with low economic development
NB: negative net loss indicates benefit

farming groups in the district, the results are as expected. The impact variation between the two groups in Welmera is assumed to be mainly due to differences in off-farm income levels. Therefore, we assume the stratification has helped to show this difference. In Dugda, the majority of the farm population in both farm groups would be negatively impacted in most of the scenarios. The net impact is mixed, revealing negative net losses linked to the positive economic scenarios in the farm groups with irrigation access. In most cases, impact is found to vary substantially between the two farm groups. This variation may have arisen mainly due to differences in farm size and land allocations in the two farm groups. The farms which are found in villages with no irrigation access allocate more of their land to *tef* and wheat production, which has resulted in higher negative impacts.

It follows that, in general the results suggest that, even in the near-term period in which climatic changes are expected to be relatively small, there are many farmers that would be negatively affected. The results also suggest that climate change may have more negative effects in warmer regions. As could be expected, the impact of climate change was minimized in positive economic development scenarios showing the role that socio-economic improvement can play in reducing vulnerability of farms in developing countries. At least for the period 2030, the positive economic growth scenario that projects increase in farm size and price coupled with a decrease in input costs, can partly offset the negative impact of climate change for some farms.

Other studies from the region report similar substantial negative impacts of climate change on smallholder farmers (Deressa and Hassan, 2009; Kabubo-Mariara and Karanja, 2007). The uneven distribution of impact observed between study districts representing different agro-ecology is in line with Deressa and Hassan's (2009) findings. Kurukulasuriya (2006) also shows warmer areas to be affected more seriously. This is consistent with our findings.

For a better understanding of the findings in this paper, it is important to discuss the main assumption made both in the crop and economic models. As indicated in the yield simulation section, the crop yield simulation has taken into consideration the fertilization effects of CO_2 that may have compensated some of the yield losses from climate change. However, potential yield loss due to increasing biotic stresses such as pest and disease in a changing climate (Boote et al., 2011) are not represented in the yield simulation model. In our representation of yield in the future in the economic model, we have not included the potential yield growth that can be associated with technological development. Given the near-term time period we analyzed, and the observed low rate of technological access and adoption in the study region, we do not expect the growth factor of technological development to be significant. Another issue is that temporal variation in management, and potential changes in farmland allocation for the various crops as a result of climate change was not considered in our study.

As is often the case in future climate change impact studies, potential uncertainties associated with climate models, crop models, CO_2 fertilization effects and future socio-economic scenarios also apply in this study. In the current study, climate data from the ensemble of multi-models, two emission scenarios, and two representative agricultural pathways were used to assess impact and show a range of probable future changes in yield and socio-economic conditions under the different assumptions made. Another important aspect is that, it is often the case that most studies, including the current one, do not include the effects of extreme climatic events that are believed to have far more detrimental impacts than gradual climate change. This is because climate models have limited potential in terms of predicting the future occurrence of these events. Therefore, it is relevant to consider potential damages from extreme events when evaluating the overall impact of climate change for mitigation and adaptation policy interventions.

5. Conclusion and policy implications

The study assessed the expected impacts of climate and socio-economic changes on farm populations in two districts of Ethiopia representing different agro-ecology. The approach combined assessing the direct impacts of climate change on crop yields and the associated economic implications. The findings on climate change impact towards 2030 highlighted the uneven implications of climate change on farms and the role agro-ecology and future socio-economic developments play in determining climate change impact. The study also shows that the use of farm and site-specific production and climate data is relevant to revealing variabilities in climate change impact. The findings provide useful information to policy-makers in reaching informed decisions on adaptive and preventive actions both on the local and global scale.

For policy makers, the findings suggested that unless appropriate measures are taken the livelihoods of many farmers, particularly in warm regions, might be threatened even in the near-term. The results also suggest that the realization of a positive economic development in a national development plan has the potential to reduce the negative impact. Climate-sensitive agricultural technology development particularly related to crops sensitive to the projected climate change can reduce impact. From the crop simulation output, one may suggest switching crops as one climate change adaptation option. However, nutritional aspects must be taken into consideration in policy interventions. As these are smallholder farmers who often produce for their own consumption, growing only a few types of crops that are less affected by climate change could have negative nutritional impacts. Therefore, climate related interventions should place emphasis on increasing productivity as well as be nutrition sensitive. If farmers opt to switch to crops less sensitive to local climatic changes and become less diversified due to absence of other adaptation options, policy-makers need to consider improving market integration. Another important aspect is, in smallholder farming systems it is the local production, which is more relevant for food security than national or regional level productivity. Thus, policies which aim to address food security concerns should be informed by locally specific climate change impact assessments instead of merely depending on aggregate level information that hide local variability. Finally, we suggest that future studies that evaluate plausible adaptation methods could increase insight in understanding the scope of potentially reducing impact through adaptation.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.agsy.2016.12.006.

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