Modelling agricultural biodiversity and land allocation in a general equilibrium framework.

The case of maize and wheat in Ethiopia.

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Abstract

Although the adoption of modern varieties typically showed to have positive effect on crop productivity (Cassman, 1999), it is also true that the progressive use of modern hybrid species can reduce the number of traditional varieties and lead to a dramatic decline of inter and intra crop genetic diversity (Tilman et al., 2002; Jarvis et al., 2011). This reduction has a negative impact on agriculture's resilience to climatic shocks and there is a large evidence showing that agricultural biological diversity can significantly contribute to increase agriculture's capacity to adapt to climate change and reduce farmers' risk exposure (Di Falco and Chavas, 2009; Bellon, 2004; Jarvis et al., 2008. In addition, crop biodiversity is a key element for the functioning of ecological systems and generates benefits in terms of ecosystem services (Narloch et al., 2011). Thus, the question of whether we should foster the use of modern species or preserve the heterogeneity of crops arises. Answering such question is even more important for developing countries where agriculture represents a large part of their value added and a significant share of farmers still produce using traditional cultivation techniques preserving diversity. Previous research on economic modeling of climate change analyzing the impacts on agriculture did not explicitly consider the role of crop biodiversity as a potential adaptation factor that can mitigate the economic consequences of climate change impacts.

The objective of this study is to fill this gap and provide a preliminary analysis for the Ethiopian economy on the links between crop diversity and climate change using a Computable General Equilibrium (CGE) methodology. The CGE model used is based on the Gtap 9 database (Aguiar et al. 2016) and employs a recursive dynamic version of the gtap-e model (Burniaux and Truong 2002, McDougall and Golub 2007). The Gtap database and model have been modified to take into account the different characteristics of the given crop sector distinguishing between production with modern and traditional varieties. In this revised model, it is assumed that, for each crop, the modern and traditional industries produce the same commodity (i.e. there are two industries for one commodity such as maize) which is sold in the

market at the same price. This assumption is justified by the impossibility to distinguish the two products by consumers.

The study will focus on maize and wheat crops that are relevant sectors of the Ethiopian agriculture in terms of crop diversity (i.e. the share of traditional industries is significant) and are affected by climate change through both direct and indirect pathways. The CGE analysis will be used also to explore the propagation of shocks in the system and the international spillovers of economic consequences, to emphasize sectoral specificities and highlight particular vulnerabilities.

The CGE analysis is supported by an econometric analysis aiming to estimate the crop productivity differential between the traditional and the modern varieties. To this end, the study utilizes the Ethiopian LSMA-ISA 2013-2014 survey of the World-Bank. The estimation approach is based on an endogenous switching regression model which allows obtaining differentiated parameters of the impact of socio-economic characteristics, national policies and agro-geological factors on both the type of varieties. In particular, the analysis also evaluates the effect of climatic shocks on the productivity of both the categories of crops thereby highlighting, *ceteris paribus*, their respective resilience. Such estimated impacts are used to calibrate the CGE model and simulate a climate change impact scenario on national agricultural production for Ethiopia.

Keywords: *genetic diversity, land use modeling, agricultural economics, endogenous switching, computable general equilibrium, ethiopia.*

JEL codes: Q12, Q17, Q24, Q57, C61, C68

1. Introduction

Since the 1970s agricultural economists developed several models to demonstrate the economic benefit of increasing crop productivity using modern varieties bred by professional plant breeders, that supported the green revolution and the intensification of production practices (Byerlee and Traxler, 1995; Morris and Lopez-Pereira, 1999; Alston et al. 2000; Heisey et al. 2002, Everson and Gollin, 2003). Several studies underlines how the rationale for the use of traditional varieties on farmers' fields goes beyond the conservation of crop genetic diversity. Numerous reasons exist for smallholder farm households to continue growing traditional crop varieties even in presence of widely available modern ones and agricultural development (Smale et al. 2001, Jarvis et al. 2011). Traditional crop varieties have a specific capacity to adapt to marginal or specific agricultural ecosystems (Barry et al, 2007), in particular where heterogeneous environments are present (Bisht et al, 2007) also because of their capacity to manage specific pest and disease, reducing the need for external inputs (Thurston et al., 1999; Zhu et al., 2000; Trutmann et al., 1996; Finckh et al. 2003; Jarvis et al., 2007a). They can also adapt to rainfall variability and variable soil types (Bellon and Taylor, 1993, Duc et al, 2010) acting as insurance against environmental risks (Sawadogo,2005 Bhandari, 2009), which is a particularly interesting feature in a context of climate change. Looking from a market perspective, traditional varieties resulted able to meet changing market demands (Smale, 2006; Vandermeer, 1995; Brush and Meng, 1998; Gauchan and Smale, 2007), social and economic characteristics of the household such as adult labor availability or distance to the market (Gauchan et al., 2005; Fu et al., 2006; Benin et al., 2006; Van Dusen, 2006; Bela et al., 2006) and cultural and religious needs (Rana et al., 2008; Nabban, 1989; Tuxill et al., 2009). Studies on dietary and nutritional values of traditional varieties are also emerging (Johns and Sthapit, 2004, Belanger et al. 2008) and are providing evidence of the role that agricultural biodiversity could have in future availability of nutritious and diverse food, particularly in areas with poor market linkages. Crop varietal diversity can also provide several ecosystem services (Hajjar et al. 2008) that in many cases are at the base of agro ecological systems and allow to reduce the use of fertilizers and pesticides (Di Falco and Perrings, 2007) and reduce the need to buy new seeds each year resulting in significant production cost reduction. Clearly all these rationale are not present in the same time and in all locations. Regmi et al. (2015) underline how the links between biodiversity, ecosystem services and food security vary across scales and are strongly influenced by socio-economic drivers of agricultural systems.

At the same time, no economic models include crop diversity as an explicit component linking it to an economy-wide framework that take into account relationships between markets (e.g. general equilibrium structure). The aim of this work is to include crop diversity in a CGE modeling framework using information on the diffusion of traditional and modern varieties in Ethiopia and to assess the economic impact of the use of traditional varieties on farmers' fields.

The research proceeds along the following steps:

- Modify the theoretical structure of the standard Gtap CGE model to take into account crop diversity and tailor the data structure to an appropriate sectoral and regional detail differentiating between traditional and improved varieties.
- Build reference social economic scenario "without climate change impacts" that will serve as counterfactual against which to assess the indirect economic impacts of climate change.
- Perform the econometric analysis to estimate the climate change impacts on both traditional and improved wheat and maize yield.
- Perform the climate change impact simulations and assess the related economic consequences.

The paper is structured according to these three main lines: section 2 provides a review of the Ethiopian agricultural context; section 3 describes both the econometric and theoretical modelling framework; section 4 introduces the scenarios run with the model; section 5 discusses the results and section 6 briefly highlights the main findings.

2. The context: Agriculture in Ethiopia

Ethiopia highland is the center of genetic diversity for a number of important crop species (Vavilov, 1951). Durum wheat is among the most diversified crop species in Ethiopia accounting for about 12% of the national genebanks holdings (Mengistu et al, 2016). Ethiopian highlands are, as other highlands locations, highly dissected terrain where humans dedicated to agriculture for very long period of time, allowing crop species to be subjected to varying microclimates and agricultural conditions. This process of crop cultivation over the millennia leads to an high crop species diversity (Egziabher 1991; Zimmer 1992). Ethiopia is often used as an example of the nexus between climate, agriculture and food shortage due to climate variability, particularly drought, land fragmentation and high population, especially in the highlands area where very long periods of agricultural occupation exists (Unruh, 2004).

Even if the share of population living below poverty line in Ethiopia decreased from 45,5% in 1995/96 to 29,6% in 2010/11 (CSA, 2011), food security remain a key challenge for Ethiopian Government as differences between rural and urban households have increased. The vast majority of the population lives in rural areas (85%) and depends on agriculture for its livelihoods. The agricultural sector contributes in 2014 to 42% of a GDP with a growth rate of 89% between 2009 and 2015.

Ethiopian farmers are mostly small scale producers, with lands between 5 and 2 hectares (WB, 2014) on which different types of agricultural activities (crop production, livestock etc.) are performed in a semi-subsistence agriculture where farmers relay on own factors to produce for own consumption, with a possibility of engaging in the product and factor markets outside the household (Aragie & McDonald, 2014). The CSA underline how over 95% of the annual gross total agricultural output is generated by this type of farms. Large and medium commercial famrs, more orietated to profit, represent the other 5%. The two subsectors, identified by the CSA, clarly differ in term of farm management practices and decision-making processes. However both farm types make a large use of traditional varieties.

Teff, maize and wheat are the main crops of Ethiopian agriculture. Increasing yields of those crops is key to increase food security across households in Ethiopia (Benson et al. 2014) as productivity of cereals is low in both modern and traditional varieties, with an average of 2,21 t/ha between 2010 and 2014. This is due to several conditions such as land degradation, small farm size, recurrent drought and poor farm technology.

Maize and Wheat are the two crops that have an higher contribution in term of calories uptake in the diet of Ethiopian households, with a contribution of 29% of calories intake from cereals coming from maize and 21% from wheat (FAO, 2013, Berhane er al. 2011). Even if maize is the crop with higher share of area devoted to the cultivation of modern varieties (21%) traditional varieties are still dominating the seed system.

Significant research efforts has gone into developing widely adapted hybrid varieties of maize and wheat for Ethiopia, starting from exogenous genetic material with the aim of improving yields and tolerate stress with narrow genetic bases (Jemanesh et al. 2013, Mengistu et al. 2016, Beyee et al. 2016). However, the limited adoption of modern farm varieties shows some limitation.

3. Modelling Framework

3.1 The Econometric framework

3.1.1 The model

The Endogenous switching regression (ESR) analyses the binary decision to adopt a modern crop variety (MV), and the implications it has on crop productivity in a two-stage framework. The use of the ESR to evaluate the technology adoption in agriculture is quite diffused (Alene and Manyong, 2007; Noltze et al., 2013; Abdulai and Huffman, 2014; Cavatassi et al., 2011; Coromaldi et al., 2015). In fact, the adoption decision, in a context of cross sectional analysis and without a randomized controlled experiment, might suffer of sample selection and endogeneity biases. Sample selection bias refers to the case where the decision to adopt is observed only by a restricted, non-random sample. The adoption status may be endogenous when the decision to adopt or not adopt is correlated with unobservable factors that affect the outcome variables, i.e. the maize and wheat production. The failure to control for this correlation yields an estimated downward biased adoption effect on outcomes. These factors are unknown to researchers, but accounted for in farmers' expectations, affecting both the decision to adopt and the outcome variables. Moreover, since the outcome gap between adopters and non-adopters is assumed to be systematic, two different outcome equations are estimated in the ESR. The covariates are assumed to have different impacts on the two groups of farmers while a pooled sample would have considered the difference between groups as just intercept shifters. Therefore, with an ESR model, endogeneity and sample-selection (Hausman, 1978; Heckman, 1979) are both taken into account.

The econometric specification is as follows:

(1) $\delta^{*} = \alpha'\left(y_{MV} - y_{LL}\right) + z'\gamma + \varepsilon$

(2) $\begin{cases} \delta = 0\ if \quad \delta^* \leq 0 \\ \delta = 1\ if \quad \delta^* > 0 \end{cases}$

Equations (1) and (2) are the specification of a probit model for the dichotomous adoption decision (criterion function) in the first stage (Maddala, 1983). δ^* is the latent variable that determines if a farmer is a MV adopter or not, and is based on the farmers' expectations regarding the relative performance of the new technology in respect to the Local landraces (LL), expressed in terms of an outcome variable *y*; δ^* is not observable but we observe δ, which is the MV adoption dummy; z' is a vector of covariates that are relevant for the adoption decisions; α and γ are unknown parameters vectors to be estimated and ε is a random disturbance term with zero mean and σ^2 variance.

Equation 3 and 4 represent the regime equations, in the second stage, that we observe conditional to adoption decisions made at the first stage:

(3) $y_{LL} = \varphi'\beta_{LL} + \eta\ if\ \delta = 0$

(4) $y_{MV} = \varphi'\beta_{MV} + \epsilon\ if\ \delta = 1,$

where φ' is a vector of covariates that affects *y* and may overlap with z', but with the caution, for the model identification purpose, to have at least one instrument in the criterion equation that is not in the regime equations; β_{MV} and β_{LL} are vectors of parameters to be estimated, ϵ and η are random disturbances terms with zero mean and σ_ϵ^2 and σ_η^2 variance. The covariance matrix is:

(5) $\Sigma(\varepsilon, \epsilon, \eta) = \begin{vmatrix} \sigma_\epsilon^2 & \sigma_{\eta\varepsilon} & \sigma_{\epsilon\varepsilon} \\ \sigma_{\eta\varepsilon} & \sigma_\eta^2 & \sigma_{\eta\varepsilon} \\ \sigma_{\epsilon\varepsilon} & \sigma_{\eta\varepsilon} & \sigma_\varepsilon^2 \end{vmatrix},$

where σ_ε equals 1 since α and γ are estimable only up to a scale factor (Greene, 2008). Moreover, $\sigma_{\eta\varepsilon} = 0$ because it is not possible to observe adoption and non-adoption outcomes contemporary (Maddala and Nelson, 1975). Estimation of the covariance terms can provide a test for the endogeneity through the significance of the following correlation coefficients:

(6) $\rho_{\epsilon\varepsilon}=\sigma_{\epsilon\varepsilon}/\sigma_\epsilon\sigma_\varepsilon,\ \rho_{\eta\varepsilon} = \sigma_{\eta\varepsilon}/\sigma_\eta\sigma_\varepsilon$

These correlations have also an economic interpretation that will be explained in the description of results. The expected values of the truncated errors are equal to:

(7) $E(\eta|\delta = 0) = -\sigma_{\eta\varepsilon}\lambda_\eta = -\sigma_{\eta\varepsilon}\frac{f\left(\frac{\xi}{\sigma_\varepsilon}\right)}{1-F\left(\frac{\xi}{\sigma_\varepsilon}\right)}$

(8) $E(\epsilon|\delta = 1) = \sigma_{\epsilon\varepsilon}\lambda_\epsilon = \sigma_{\epsilon\varepsilon}\frac{f\left(\frac{\xi}{\sigma_\varepsilon}\right)}{F\left(\frac{\xi}{\sigma_\varepsilon}\right)}$

where λ_ϵ and λ_η are the Inverse Mill Ratios estimated at $\xi = \alpha'(y_{MV} - y_{LL}) + z'\gamma$ and f and F are, respectively, the density and the cumulative distribution function.

As explained in Lokshin and Sajaia (2004), the ESR can efficiently be estimated with the full information maximum likelihood (FIML) approach, ensuring the simultaneous estimation of the probit model and regime equations with consistent standard error.

3.1.1.2 Treatment effect

The conditional expectations from the ESR can be used to estimate the average treatment effects (ATE) of the counterfactual scenario for both the groups. Expectations conditional to adoption decision are estimated as follows (Di Falco et al., 2011):

(9) $E(y_{MV}|\delta = 1) = \varphi'\beta_{MV} + \sigma_{\epsilon\varepsilon}\lambda_{\epsilon}$

(10) $E(y_{LL}|\delta = 1) = \varphi'\beta_{LL} + \sigma_{\eta\varepsilon}\lambda_{\epsilon}$

(11) $E(y_{MV}|\delta = 0) = \varphi'\beta_{MV} + \sigma_{\epsilon\varepsilon}\lambda_{\eta}$

(12) $E(y_{LL}|\delta = 0) = \varphi'\beta_{LL} + \sigma_{\eta\varepsilon}\lambda_{\eta}$.

Equations (9) and (12) are the actual outcome expectations conditional to the adoption status chosen by farmers. These represent the expected outcome of MVs adopters when they adopt and the non-adopters outcome when they do not adopt. Equations (10) and (11) evaluate the outcomes in the counterfactual case that adopters did not adopt and that non-adopters adopted thereby providing a measure of the relative performance of the status for which the farmer has opted. Thus, the ATE of adoption on adopters (TT) and the ATE of adoption on non-adopters (TU) are equal to:

(13) $TT = E(y_{MV}|\delta = 1) - E(y_{LL}|\delta = 1) = \varphi'(\beta_{MV} - \beta_{LL}) + (\sigma_{\epsilon\varepsilon -}\sigma_{\eta\varepsilon})\lambda_{\epsilon}$,

(14) $TU = E(y_{MV}|\delta = 0) - E(y_{LL}|\delta = 0) = \varphi'(\beta_{MV} - \beta_{LL}) + (\sigma_{\epsilon\varepsilon -}\sigma_{\eta\varepsilon})\lambda_{\epsilon}$.

3.1.1.3. Data description

We use data from 2013 LSMS-ISA nationally representative survey in Ethiopia, gathered by the World Bank. Information on rural household and plot cultivation characteristics, inputs use, availability of extension services and agro-climatic characteristics were collected over the planting and harvesting seasons. The survey also recorded geo-referenced enumeration area level data that allows to merge plot level data with monthly local rainfall and temperature from the NOAA and the European center for medium range weather forecast.

Considering data limitation for some of the covariates utilized, the final sample consists of 2617 plots that cultivate maize and 1230 that cultivate wheat.

Descriptive data with statistical significance test on equality of means between modern varieties adopters and non-adopters are reported in Table 1. The percentage of modern varieties adopters for maize is equal to the 23.79%, while in the case of wheat it equals the 11.62%.

The outcome variable is the yield expressed in kilograms per hectare. We can see that for both the crops, the modern varieties outperform the traditional ones on average. In particular, the mean maize yield of non-adopters is equal to

1930 kilograms per hectare, while for adopters is equal to around 2450 kg/ha. The differential is larger for wheat where we observe a yield of 1500 and 2500 kg/ha for the non-adopters and adopters, respectively.

A set of covariates including socio-economic characteristics, geographic and climatic elements, soil and agro-stresses, agricultural inputs use and an instrumental variable of advice on seed use are considered according to literature (Di Falco et al, 2011; Bryan er al, 2013; Teklewold et al., 2013; Noltze et al., 2013; Shiferaw et al., 2014; Coromaldi et al., 2015).

Table 1

	Description	MAIZE		WHEAT	
		Non-adopters (76.21%)	Adopters (23.79%)	Non-adopters (88.38%)	Adopters (11.62%)
		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
yield	Yield, kg per ha	1960.534***	2447.107***	1527.137***	2489.327***
		(2485.098)	(2275.476)	(1641.606)	(2775.496)
sex_head	sex_head (1=female)	0.205*	0.172*	0.180*	0.245*
		(0.404)	(0.377)	(0.384)	(0.431)
edu_15_60	Education level of member between 15 and 60 years	0.799***	0.946***	1.028***	1.360***
		(1.147)	(1.239)	(1.228)	(1.638)
hh_size	Household size	6.004**	6.239**	6.174	6.343
		(2.354)	(2.314)	(2.237)	(2.338)
Temperature	Annual Mean Temperature (°C)	19.962***	18.338***	16.266***	17.065***
		(2.738)	(1.993)	(2.293)	(1.597)
Rainfall	Annual Precipitation (mm)	1099.979***	1335.909***	1128.448***	1027.007***
		(381.727)	(314.684)	(323.516)	(433.095)
dist_market	HH Distance in (KMs) to Nearest Market	69.047***	50.901***	68.316***	48.220***
		(55.238)	(40.411)	(45.509)	(40.998)
Drought	Drought experience	0.074***	0.027***	0.089***	0.259***
		(0.262)	(0.163)	(0.285)	(0.439)
S	Shannon index	2.365	2.298	2.151	2.042
		(1.412)	(1.545)	(1.438)	(1.313)
aez2	ssa_aez09==Tropic-warm/subhumid	0.044***	0.003***	0.537***	0.392***
		(0.204)	(0.057)	(0.499)	(0.49)
aez3	ssa_aez09==Tropic-cool/semiarid	0.365***	0.085***	0.177	0.126
		(0.481)	(0.279)	(0.382)	(0.333)
aez4	ssa_aez09==Tropic-cool/subhumid	0.398***	0.734***		
		(0.49)	(0.442)		
aez5	ssa_aez09==Tropic-cool/humid	0.140*	0.169*		
		(0.347)	(0.375)		
fert_ha	Kilograms of fert per ha	80.364***	319.339***	133.461***	205.220***
		(315.462)	(618.056)	(214.492)	(235.042)
labour1_ha	Men days of labour1 per ha	603.296	517.699	297.142	336.663
		(1537.8)	(1034.51)	(685.195)	(708.043)
agri_land	Percent agriculture within approx 1 km buffer	29.839***	33.326***	31.039*	34.119*
		(19.384)	(15.34)	(19.757)	(21.636)
Income_class_2	Consumption quintile== 2	0.2	0.201	0.186	0.147
		(0.4)	(0.401)	(0.389)	(0.355)
Income_class_3	Consumption quintile == 3	0.185	0.185	0.204	0.231
		(0.388)	(0.388)	(0.403)	(0.423)
Income_class_4	Consumption quintile == 4	0.199	0.215	0.211	0.245
		(0.399)	(0.411)	(0.408)	(0.431)
Income_class_5	Consumption quintile == 5	0.185	0.189	0.214	0.238
		(0.388)	(0.392)	(0.41)	(0.427)
slope_parcel	weighted mean slope of plot	11.867***	8.881***	14.429***	10.614***
		(10.38)	(9.45)	(12.447)	(9.642)
anti_erosion	Anti erosion measures	0.645	0.64	0.79	0.783
		(0.479)	(0.48)	(0.407)	(0.414)
land_fair	land== fair	0.347*	0.308*	0.34	0.287
		(0.476)	(0.462)	(0.474)	(0.454)
land_poor	land== poor	0.272***	0.551***	0.336	0.343
		(0.445)	(0.498)	(0.473)	(0.476)
MV_advice	Received advice on seeds	0.056***	0.803***	0.046***	0.825***
		(0.229)	(0.398)	(0.209)	(0.381)

Standard deviations in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

3.1.2 Results

Table 2 illustrates the results of the ESR model, which is estimated at plot level using the FIML approach with a log-log functional form. Estimation of the criterion equation are shown in columns (1) and (4) for the maize and wheat, respectively. In columns (2) and (3) we report the maize yield function of non-adopters and adopters of modern varieties. The same are reported in column (5) and (6) for the wheat.

Overall, from the criterion equations we see that the instrument we utilized for identifying our model, the fact that farmers received advice on the type of seed to utilize, is highly significant in explaining the adoption decision on their plots by farmers. Also it is interesting to note that, with the exception of the distance from the agricultural market that has a negative impact on the probability of adopting a modern variety, the other socio-economic variables are not significant drivers of such decision. Nevertheless, being in top quintile of income is a characteristic that enhances the chance to adopt.

We are here interested in the climatic variables and how they impact on the yield. Our results highlights the following findings: an increase in temperature has a significant negative impact on the maize yield of non-adopters thereby determining a reduction in productivity of the 6% for a 1% of the increase in temperature. The temperature, instead, has not significant impact on the adopters yield.

On the contrary, we see that the yield of wheat benefits of higher temperature and this is true for both the adopters and the non-adopters, but the marginal effect is significantly higher for the adopters. In fact, an increase of 1% of temperature produce 1.3% increase of wheat yield of non-adopters against a 12% increase of adopters.

Lastly, also should be underlined the effect of the crop diversification on yield. The Shannon index shows an opposite impact on the non-adopters and adopters. While it sustain the productivity of non-adopters in both the case of maize and wheat, it reduces the yield of adopters (just for maize) confirming as the diversification can be a risk minimization strategy for marginalized farmers that heavily rely on traditional agriculture, while the adoption of modern varieties to let the productivity at plot level highly responsive require a strategy of intensification and monocropping.

Table 2: Endogenous Switching regression on Maize and Wheat Cultivation

	Maize			Wheat		
	(1)	(2)	(3)	(4)	(5)	(6)
	Regime	Non-adopters	Adopters	Regime	Non-adopters	Adopters
1) Socio-economic						
sex_head	-0.261*	-0.087	-0.159	-0.026	0.006	0.547
	(0.117)	(0.108)	(0.088)	(0.195)	(0.085)	(0.292)
edu_15_60	0.081	0.069	0.040**	0.062	-0.065	-0.081
	(0.088)	(0.086)	(0.023)	(0.146)	(0.061)	(0.185)
hh_size	-0.017	-0.134	0.082	0.033	0.024	-0.009
	(0.113)	(0.099)	(0.085)	(0.035)	(0.015)	(0.049)
dist_market	-0.095*	-0.0829	-0.0672	-0.076***	-0.014	-0.022
	(0.057)	(0.0556)	(0.0449)	(0.011)	(0.045)	(0.153)
Income_class_2	0.110	0.155	0.112	0.005	0.160	-0.274
	(0.140)	(0.129)	(0.102)	(0.274)	(0.104)	(0.380)
Income_class_3	0.195	-0.030	0.212*	-0.066	0.327**	0.451
	(0.143)	(0.134)	(0.106)	(0.257)	(0.103)	(0.349)
Income_class_4	0.226*	0.107	0.253*	0.035	0.411***	0.116
	(0.141)	(0.133)	(0.106)	(0.266)	(0.103)	(0.361)
Income_class_5	0.379***	0.245	0.215*	0.357**	0.300**	0.194
	(0.146)	(0.140)	(0.108)	(0.172)	(0.105)	(0.368)
2) Agricultural inputs						
fert_ha	0.271***	0.039	0.085***	0.176***	0.069***	0.012
	(0.017)	(0.022)	(0.020)	(0.043)	(0.013)	(0.078)
labour1_ha	0.0615	0.178***	0.139***	0.016	0.107***	0.319***
	(0.038)	(0.034)	(0.028)	(0.067)	(0.028)	(0.081)
agri_land	0.037	0.071	0.053	0.116	0.028	-0.096
	(0.051)	(0.039)	(0.052)	(0.078)	(0.029)	(0.099)
Shannon	-0.007	0.0527*	-0.0643**	0.103	0.036*	-0.018
	(0.031)	(0.0316)	(0.0228)	(0.055)	(0.022)	(0.084)
3) Agro-ecological						
slope_parcel	0.027	-0.115*	-0.098*	-0.080	-0.006	-0.125
	(0.060)	(0.053)	(0.045)	(0.087)	(0.037)	(0.127)
Land_fair	0.338**	0.091	-0.233*	-0.076	0.168*	0.246
	(0.126)	(0.104)	(0.108)	(0.195)	(0.081)	(0.248)
Land_poor	0.794***	-0.030	-0.386***	0.249	-0.411***	0.010
	(0.133)	(0.125)	(0.110)	(0.219)	(0.093)	(0.284)
slope_parcel	0.027	-0.115*	-0.098*	-0.080	-0.006	-0.125
	(0.060)	(0.053)	(0.045)	(0.087)	(0.037)	(0.127)
Drought	0.086	-0.276	-0.099	0.427	-0.078	0.259
	(0.202)	(0.163)	(0.210)	(0.219)	(0.115)	(0.269)
aez2	-0.145	0.903**	1.721*	-0.819**	0.323**	1.568***
	(0.498)	(0.302)	(0.766)	(0.297)	(0.114)	(0.459)
aez3	0.240	1.607***	0.473	-0.649	0.0216	1.443*
	(0.442)	(0.275)	(0.556)	(0.370)	(0.143)	(0.601)
aez4	0.996**	1.609***	0.757			
	(0.468)	(0.291)	(0.558)			
aez5	0.972**	1.814***	0.775			
	(0.497)	(0.333)	(0.602)			
4) Climatic						
Temperature	-6.281***	**-6.183*****	**-1.122**	7.356*	**1.345****	**12.201***
	(1.679)	(0.143)	(1.588)	(3.523)	(0.653)	(5.375)
Temperature_sq	1.041***	1.068***	2.100	-1.278*	**-0.232****	**-2.151***
	(0.283)	(0.240)	(2.692)	(0.618)	(0.114)	(0.943)
Rainfall	-0.042	2.337	3.076	-1.845***	4.271	0.362
	(3.136)	(2.949)	(2.852)	(0.882)	(4.356)	(1.296)
Rainfall_sq	0.010	-0.123	-0.246	1.367*	-0.344	-0.156
	(0.227)	(0.216)	(0.204)	(0.634)	(0.311)	(0.928)
5) Instrument						
Seeds_Advice	1.996***			2.534***		
	(0.091)			(0.161)		
cons	90.86***	83.45***	11.45	-46.33	-26.52	-163.2
	(23.85)	(21.94)	(21.34)	(61.70)	(18.04)	(91.47)
sigma		0.602***	-0.260***		0.021	0.083
		(0.016)	(0.028)		(0.021)	(0.059)
rho		-0.216*	0.085		-0.132	-0.089
		(0.089)	(0.081)		(0.103)	(0.187)
N	2617			1230		
chi2_c	4.855			1.640		

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.2 CGE Model description

3.2.1 General Overview

Since the end of the '90s CGE models have been increasingly used to study the economic implication of climate change impacts and mitigation (see e.g.: Deke et al., 2001; Darwin and Tol, 2001; Bosello et al., 2006, 2007; Bohringer et al., 2009; Aaheim et al., 2010; Eboli et al., 2010; Roson and Van der Mensbruegghe, 2010; Ciscar et al., 2011, 2013; Orecchia et al., 2013; Dellink et al., 2014). They are multi-country multi sector model whose main strength is the ability to capture endogenous demand and supply reactions to climate shocks transmitted through changes in relative prices.

For the purpose of this exercise, we use a modified version of the GTAP-E model (McDougall and Golub 2009) with endogenous dynamics for capital accumulation. The calibration year is 2011, data come from the GTAP9 database (Narayanan et al. 2015) and the simulation time is 2012-2050.

As standard in CGE models, this modified version of the GTAP-E model makes use of the Walrasian perfect competition paradigm to simulate market adjustment processes. A representative consumer in each region receives income, defined as the service value of national primary factors (natural resources, land, labor, and capital). Capital and labor are perfectly mobile domestically, but immobile internationally. The income is used to finance three classes of expenditure: aggregate household consumption, public consumption, and savings (Figure 1). The expenditure shares are generally fixed, as the top-level utility function has a Cobb-Douglas specification.

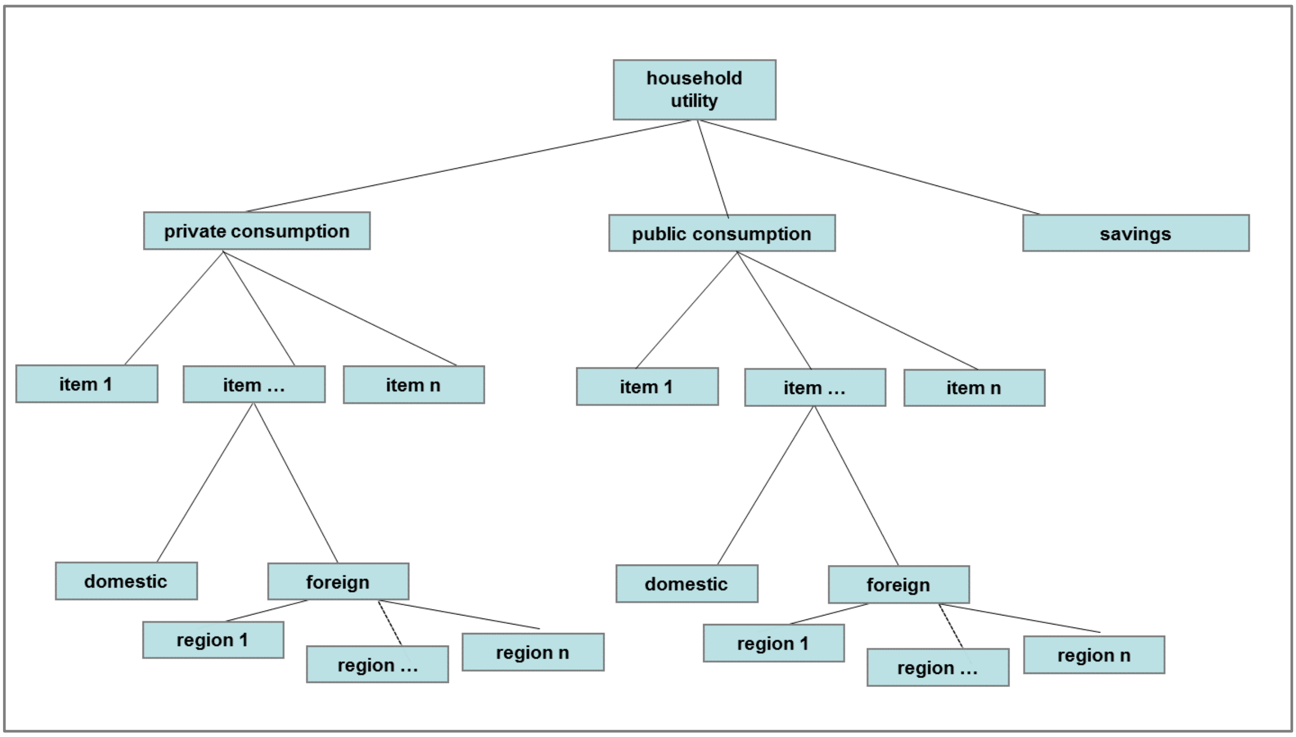


Figure 1 – Demand structure

Public consumption is split in a series of alternative consumption items, also according to a Cobb-Douglas specification. However, almost all expenditure is actually concentrated in one specific industry: public services. In a lower nest public consumption is split in a series of alternative composite Armington aggregates. These postulate the imperfect substitutability across domestic and imported commodities. Private consumption is analogously split in a series of alternative consumption items. However, the functional specification used at this level is the Constant Difference in Elasticities form: a non-homothetic function, which is used to account for possible differences in income elasticities for the various consumption goods.

Industries are modeled through representative firms, minimizing production costs while taking prices as given. In turn, output prices are given by average production costs. Production functions are specified via a series of nested constant elasticity of substitution (CES) functions. Domestic and foreign inputs are imperfect substitutes, according to the "Armington" assumption.

All sectors use primary factors such as labour and capital-energy, and intermediate inputs. In some sectors (fossil fuel extraction industries and fishery), primary factors include natural resources (e.g., fossil fuels or fish) and land. The nested production structure depicted in Figure 2 is the same across all sectors, and diversity in production processes as well as technologies is captured through sector-specific productivity and substitution elasticity parameters.

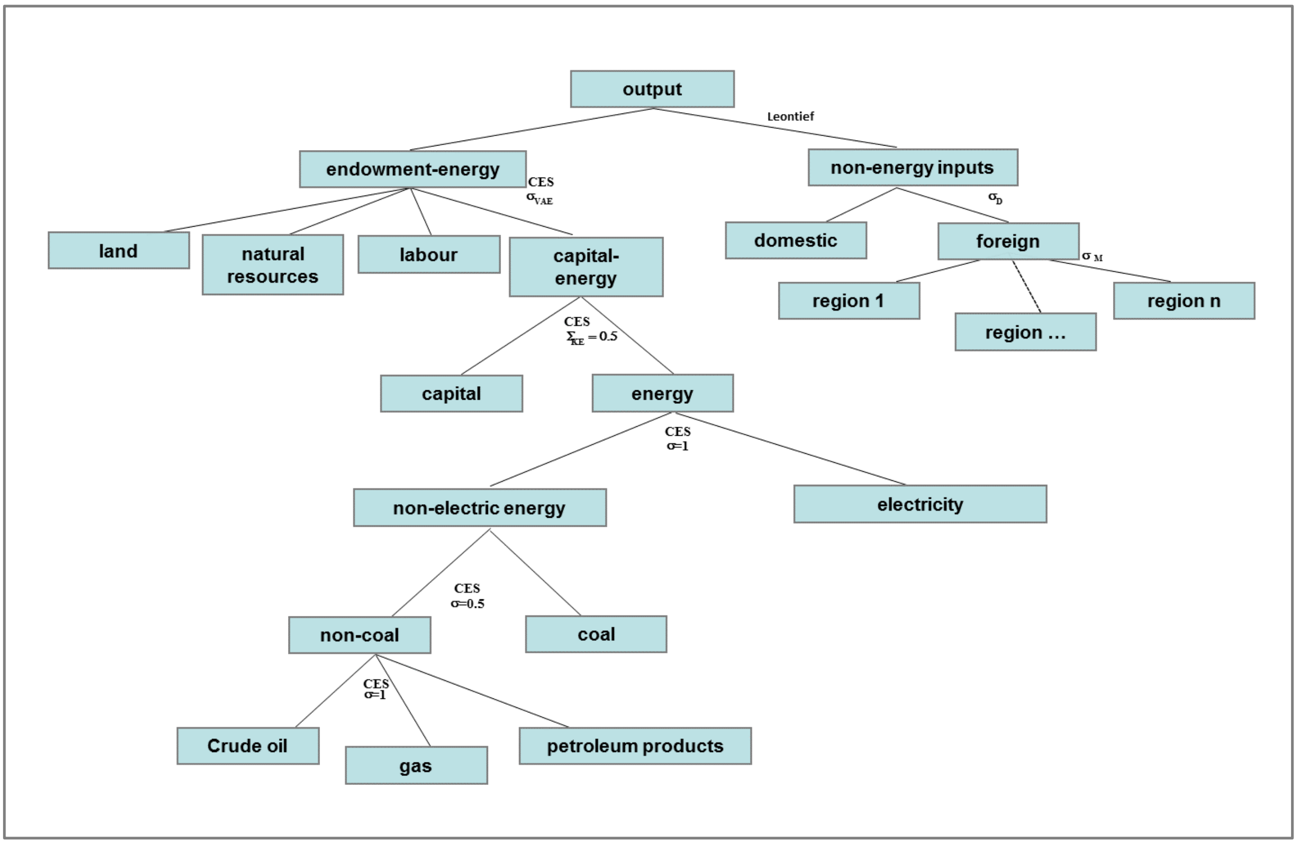


Figure 2 – Supply structure

The dynamics of the model rely on the idea of "recursiveness" where a sequence of static equilibria are connected by the process of capital accumulation. Capital growth is standard along exogenous growth theory models and follows:

$$Ke_r = I_r + (1-\delta)\, Kb_r \tag{1}$$

where Ke_r is the "end of period" capital stock, Kb_r is the "beginning of period" capital stock, δ is capital depreciation and I_r is endogenous investment.

Sources of world investments are savings from households. Allocation of investments across regions follows Pant (2007) and is given by

$$I_r = \varphi_r RGDP_r\, e^{[(\rho_r(R_r^E - R^W))]} \tag{2}$$

where RGDP is real GDP, ρ_r and φ_r are given parameters, R_r^E and R^W are the expected rate of return to capital in region r and the world rate of return to capital respectively.

Investment is internationally mobile: savings from all regions are pooled and then investment is allocated so as to achieve equality of expected rates of return to capital. As a result, savings and investments are equalized at the world, but not at the regional, level. Because of accounting identities, any financial imbalance mirrors a trade deficit or surplus in each region.

Technological progress, governing both productivity of factors and their substitutability is exogenous. Energy efficiency is represented by a Hicks-neutral autonomous and exogenous energy-efficiency improvement function.

3.2.2 Crop diversity

The original Gtap-E model is significantly modified to introduce crop industries by different level of crop diversity (and differentiate between traditional and improved varieties). First we used the SplitCom (Horridge, 2005) software to single out the maize sector from the original Gtap sector GRO "Cereal grains nec". To perform this split we used the share of maize in original Gtap gro sector in total production (around 36%). At this step we maintain for both sectors(the new maize sector and the gro sector without maize named "Other cereals") the same cost-structure of the original sector. Then we sequentially split each crop industry to obtain two distinct industries of traditional and improved production. Here we characterize the production structure of the new sectors using information on the shares of traditional and improved industries in the sales, costs, and trade items of each crop industry. Table 2 presents the split of the database according to the information obtained from the Ethiopian LSMA-ISA 2013-2014 survey of the World-Bank.

Table 2 - Agricultural area allocation (%), production (%) and input share (%), by crop species and variety

Crop	**Production (% of total production)**		**Area (% of total land)**		**Labour (% of crop labour)**		**Chemical fertilizers (% of crop fertilizers)**	
	Trad	Imp	Trad	Imp	Trad	Imp	Trad	Imp
Maize*	0.605	0.395	0.750	0.251	0.662	0.338	0.234	0.767
Rice	0.938	0.063	0.824	0.177	0.928	0.072	0.541	0.459
Wheat	0.909	0.091	0.910	0.090	0.883	0.117	0.873	0.127
Other cereals	0.981	0.020	0.973	0.027	0.980	0.020	0.970	0.030
Vegetables and fruits	0.981	0.020	0.992	0.009	0.992	0.008	0.989	0.011
Oil seeds	0.992	0.009	0.995	0.006	0.993	0.007	0.969	0.031
Sugar cane, sugar beet	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
Plant-based fibers	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
Other crops	0.994	0.006	0.993	0.008	0.983	0.017	0.921	0.079

*share of maize in original Gtap gro sector: Area=0.274, Production=0.358

The procedure followed to split the database is based on some assumptions. First we assumed that the traditional and modern products are homogeneous. Homogeneity implies that there are two industries that produce the same crop commodity. Using the example of maize, this means that the price of traditional and modern maize are the same. The second assumption regards the price of inputs which we assume to be the same for the two new sectors. This implies that the price of the seeds is the same for Modern and Traditional industries. Finally, we modified the input-output ratio for Traditional and Modern production according to the Ethiopian LSMA-ISA 2013-2014 survey of the World-Bank. All these assumptions imply that the cost shares for each input used are different in the two industries. For example, the cost share of land in the traditional wheat industry is different from the cost share of land in the modern wheat industry. Crop genetic diversity is an implicit input embodied in the traditional land. Higher revenues due to crop diversity will be reflected in the land rent.

To allow the production of a single homogeneous commodity by two different industries we followed the modelling approach used by Taheripour et al. (2013) and we introduced the following equations:

$$pi_{traditional_j} = pi_{improved_j} = ps_j, for\ all\ j\ \in set\ of\ crop\ commodities \tag{1}$$

$$pi_j = \sum_{k \in top\_comm}^{k} S_{jk}\ pf_{jk}\ \ for\ all\ j\ \in set\ of\ crop\ commodities \tag{2}$$

$$qf_{jk} = qi_j - \epsilon\left(pf_{jk} - pi_j\right) for\ all\ k\ \in top_{comm} and\ all\ j\ \in set\ of\ crop\ commodities \tag{3}$$

$$qo_c = \sum_{w\ \in\ traditional,improved} Shr_{cw}\ qi_{cw}\ for\ all\ c\ \in set\ of\ crop\ commodities \tag{4}$$

Where *pi* and *qi* represent percent changes in the price and quantity of *j* at the industry level and *ps* and *qo* represent their corresponding percentage changes at the commodity market level (where there is no distinction about the method of production). The variables *qf* and *pf* stand for percentage changes in price and quantities of inputs used for crop production at the industry level. Finally, S_{jk} represents the cost share of input *k* in industry *j*, ε is the elasticity of substitution among intermediate inputs and Shr_{cw} is the share of crop c supply by diversification type w.

Equation 1 ensures that traditional and improved industries which produce the same crop (e.g., wheat) will receive the same price and that the prices at the industry and commodity levels are the same. Equation 2 is the zero profit condition for each crop industry. Equation 3 represents the demand for intermediate input k in crop industry j, and finally, Equation 4 ensures market clearing condition for each crop.

We also adjust the land supply structure to allow for competition among the different agricultural sectors and among traditional and modern agriculture in particular. The land supply tree is presented in Figure 3. As shown in this figure the top level allocates land among forest and agriculture. The second level of the new structure allocates agriculture between grazing and cropland categories. The third level allocates land between traditional and modern cropping activities. Finally, the lower level of the new tree governs the supplies of traditional and modern areas among the traditional and modern cropping activities. Elasticity of substitution between Traditional and Improved varieties has been estimated and is equal to 1.98. To our knowledge, this is the first attempt to provide an estimate of this elasticity and no other study exists to compare this result.

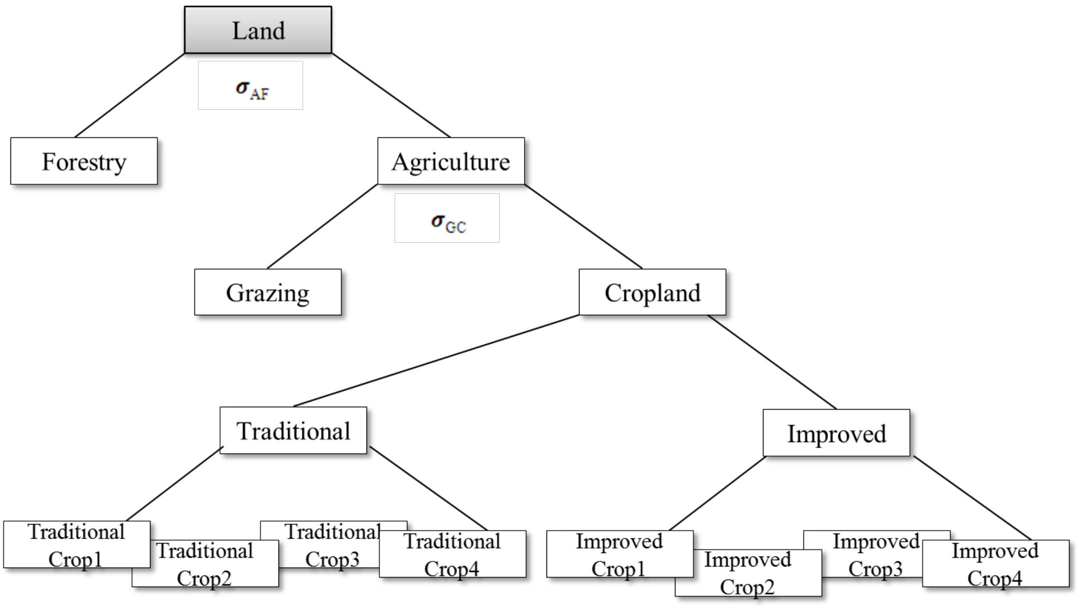


Figure 3 – Land supply

4. The scenarios

The simulation scenario matrix is summarized by Table 3. We run a no climate change scenario and then we add the climate shocks for Wheat and Maize differentiated between Traditional and Improved varieties. In this scenario only the Ethiopian economic system is hit by (positive or negative) climate change shocks. The simulations make use of the estimates obtained from the endogenous switching regression model presented in the previous section.

Table 3 – Scenario Matrix

1 - Baseline SSP2 – standard market driven adaptation	2 - Wheat and Maize crops impact scenario RCP 4.5 – standard market driven adaptation

4.1 The benchmark construction process

Table 4 presents the regional and sectoral detail used in the simulation. Given the focus of our study, the emphasis is put on the primary sector with nine agricultural products. Similarly, country aggregation has been decided in order to single out the most important trading partners of Ethiopia.

Table 4 - Sectoral and regional detail of the model

Regions	Commodities	Industries
Ethiopia	Rice	Rice Traditional
SSA (Sub-saharan Africa)	Wheat	Rice Improved
Oceania (Australia, New Zealand)		Wheat Traditional
China	Maize	Wheat Improved
Asia		Maize Traditional
SEAsia	Cereal grains nec	Maize Improved
SouthAsia	Vegetables, fruits, nuts	Other Cereals Traditional
USA	Oil Seeds	Other Cereals Improved
Rest of North America	Sugar cane, sugar beet	Vegetables and fruits Traditional
Latin America	Plant-based fibers	Vegetables and fruits Improved
	Crops nec	Oil Seeds Traditional
European Union 28	Timber	Oil Seeds Improved
Russia	Livestock and Meat Products	Sugar cane & sugar beet Traditional
Middle East and North Africa	Coal	Sugar cane & sugar beet Improved
Rest of the World	Oil	Plant-based fibers Traditional
Rest of the World	Gas	Plant-based fibers Improved
	Petroleum Products	Other crops Traditional
	Electricity	Other crops Improved
	Processed Food	Timber
	Textiles and Clothing	Livestock and Meat Products
	Chemicals	Coal
	Light Manufacturing	Oil
	Heavy Manufacturing	Gas
	Transport and Communication	Petroleum Products
	Other Services	Electricity
		Processed Food
		Textiles and Clothing
		Chemicals

	Light Manufacturing
	Heavy Manufacturing
	Transport and Communication
	Other Services

Data are from the GTAP 9 database whose base year is 2011. For the 2013-2050 period, the simulation horizon, we calibrate the model using information from the SSP2 scenario (O'Neil et al 2012)[1].

Figure 4 reports the % macro-sectoral composition of Ethiopia value added as reported by the World bank (WDI, 2016)[2] in 2013 and what calibrated with the model. The matching between the two is almost perfect, featuring the agricultural, industrial and services macro-sectors contributing the 44.9%, 11.9% and 43.2% to total value added respectively.

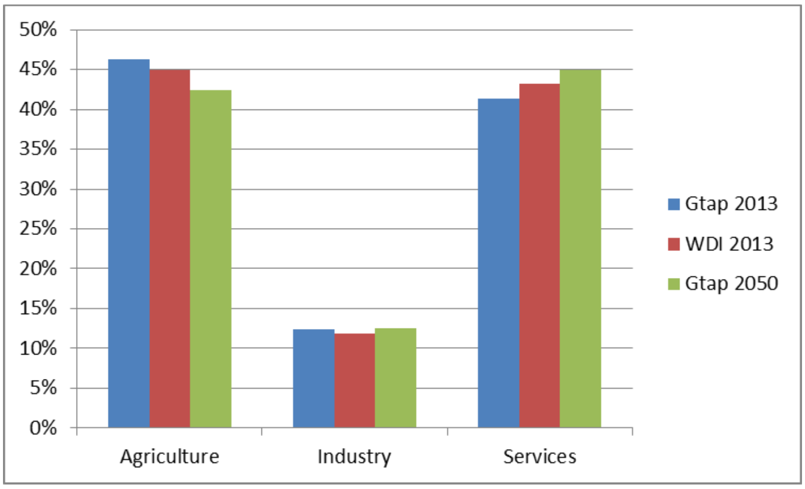


Figure 4 - (%) shares of sectoral Value Added in Ethiopia

Figure 9 reports the share of exports and imports of Ethiopia per trading partner in 2013. Differently from the sectoral composition of value added, these have not been calibrated, as international trade flows in a CGE model are very difficult to control. Furthermore, in CGE models with global coverage, and GTAP 9 database makes no exception, bilateral import-export flows tend to diverge sometimes non marginally from national statistics. This is due to the

[1] The Shared Socioeconomic Pathways (SSPs) are part of a new framework that the climate change research community has adopted to facilitate the integrated analysis of future climate impacts, vulnerabilities, adaptation, and mitigation. They are built around a matrix that combines climate forcing on one axis (as represented by the Representative Forcing Pathways) and socio-economic conditions on the other. Together, these two axes describe situations in which mitigation, adaptation and residual climate damage can be evaluated (for more information visit: https://secure.iiasa.ac.at/web-apps/ene/SspDb/static/download/ssp_suplementary%20text.pdf. SSP2 represent the "Middle of the Road" scenario. It is a world where trends typical of recent decades continue, with some progress towards achieving development goals, reductions in resource and energy intensity at historic rates, and slowly decreasing fossil fuel dependency. Development of low-income countries proceeds unevenly, with some countries making relatively good progress while others are left behind. SSP2 is conceived as a scenario posing intermediate challenges to both mitigation and adaptation.

[2] Last Update 21-Dec-2016.

difficulty to match bilateral multi-national data that are often incomplete or based upon quite different accounting/statistical criteria. What reported in Figure 9 are thus endogenous outputs of the model.

Anyway they replicate reasonably well the patterns of Ethiopian international trade, featuring Europe, South Asia, the Rest of Sub Saharan Africa aggregate as the major destination markets. Imports are sourced primarily from USA and Russia.

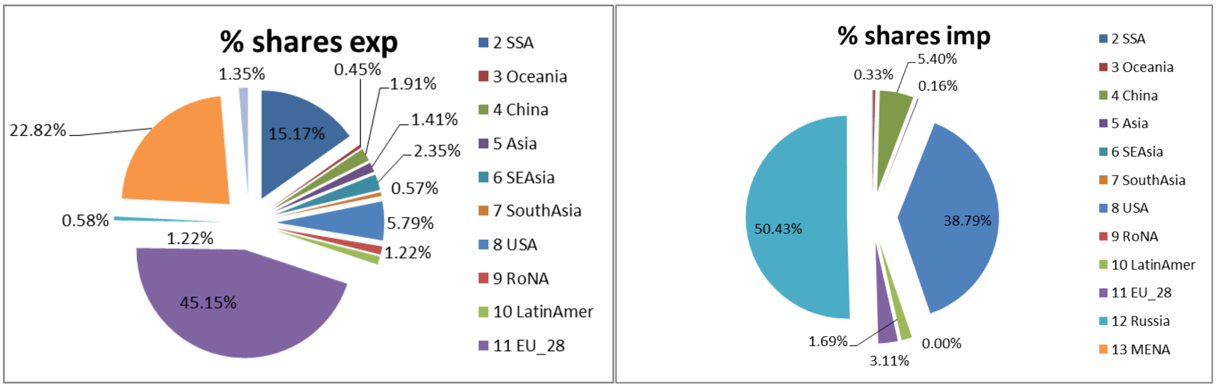


Figure 5 - (%) Maize and Wheat shares of export and import by trading partner in 2013

It is worth noticing that wheat represents almost 80% of all cereal imports while its share of exports is very small.

Ethiopian GDP and population growth rates in SSP2 coinciding with those featured by the model are reported in Figure 6.

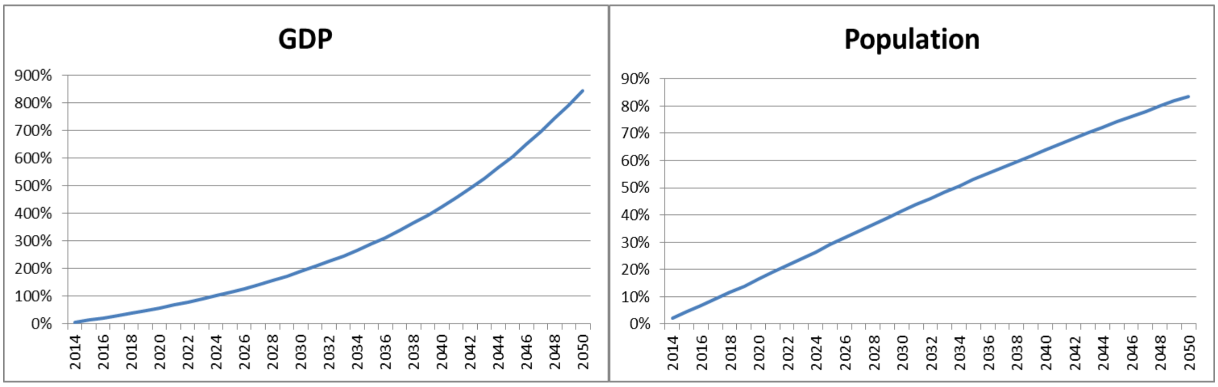


Figure 6 - Ethiopia GDP (left) and population (right) % growth rates 2014-2050

Both GDP and population are projected to increase significantly in SSP2 scenario highlighting for Ethiopia a GDP increase of nearly 900% in 2050 wrt the 2013 levels. Population as well, is projected to increase around 90% between 2014 and 2050 in SSP2.

Going back to Figure 4, it can be noticed that the composition of macro sectoral value added (that in the SSPs projections is left free to vary endogenously) remains quite stable until mid-century, with a slight increase of the weight of the industrial and services sector.

By 2050 international trade depicts a tendency to reallocate import export flows toward the fast growing developing countries. In particular Ethiopia is expected to increase its imports share from Russia and that of exports towards South Asia.

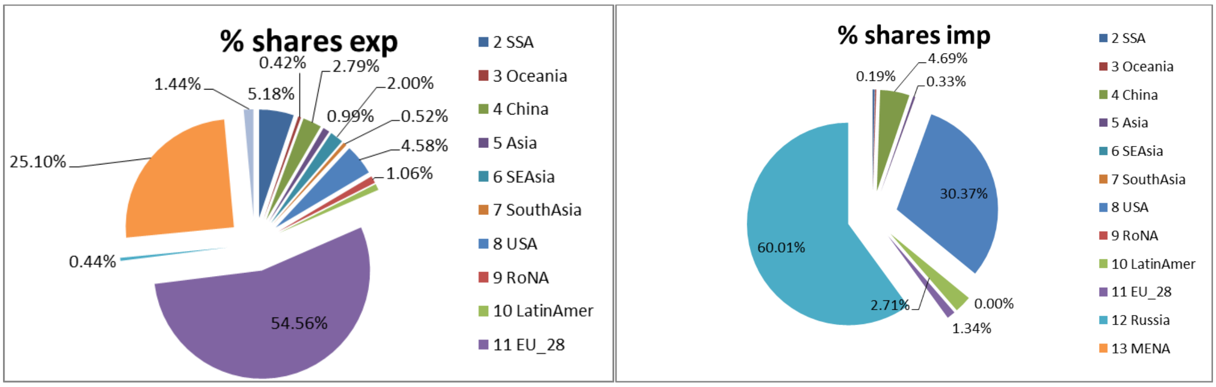


Figure 7 - (%) Maize and Wheat shares of export and import by trading partner in 2050

Agricultural production is expected to significantly increase along the period considered. In particular, wheat production is expected to increase by 800% while maize to reach a 6-fold increase with respect to 2013 (Figure 8).

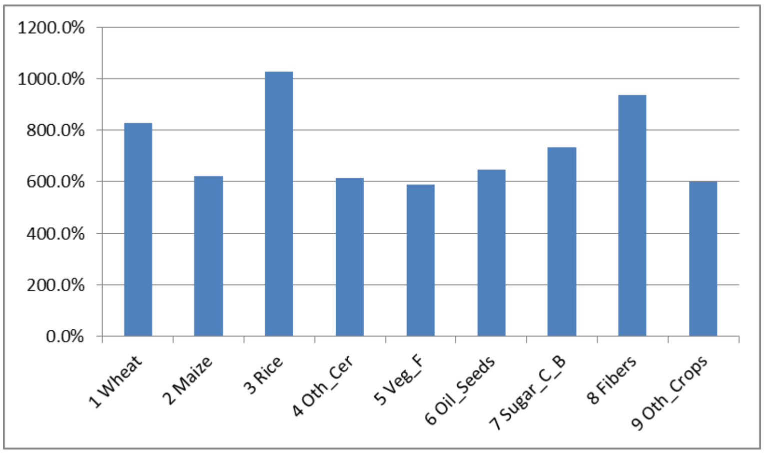


Figure 8 – Change in Output wrt 2013 in agricultural sectors in 2050

In terms of land allocation, the evolution for the two crops is similar between 2013 and 2050 with improved land increasing their share on total land (Figure 9).

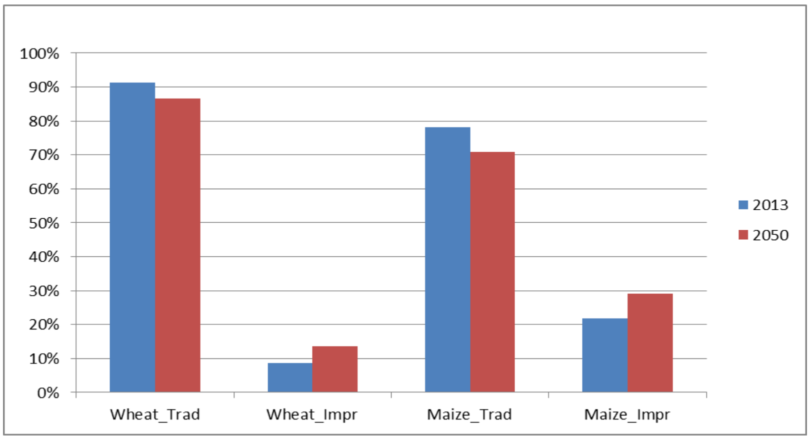


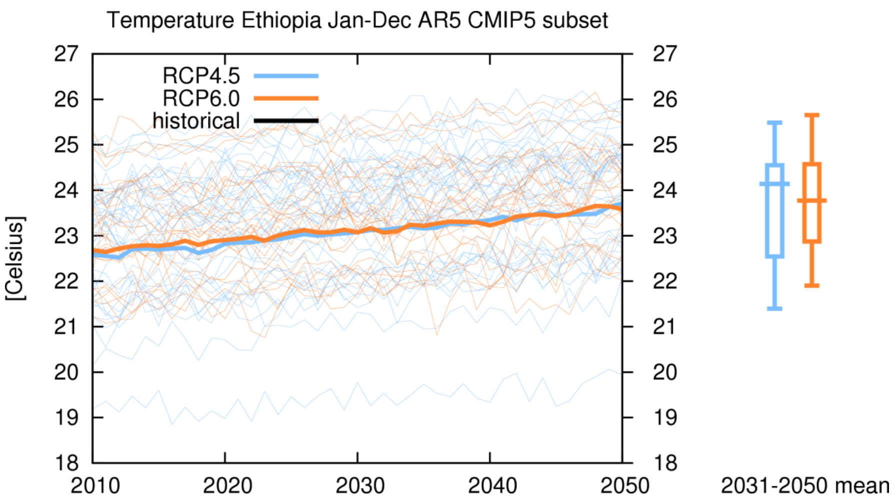
Figure 9 – Share of Traditional and Improved varieties in total land demand in 2013 and 2050

5. Results

5.1 Climate change impacts scenario

The secondo scenario will compare the performance of traditional and modern varieties in a context of climate change in Ethiopia.

Having defined the social economic reference, it is necessary to define the climate change scenarios producing the impacts to be analyzed. According to Riahi et al. (2016) up to 2050, SSP2 scenario is consistent with both high and low representative concentration pathways (RCP 4.5 and RCP6.0) and the associate temperature increases are rather similar (Figure 10). Thus, one temperature increase of +1 °C wrt 2010-13 period is considered.



Source: KNI Climate explorer http://climexp.knmi.nl

Figure 10 – Temperature projections for Ethiopia in RCP4.5 and 6.0

According to the econometric model presented in the paragraph 3.1, for maize traditional an increase in temperature of 1% determines a reduction in productivity of the 6%. The temperature, instead, has not significant impact on maize improved yield. On the contrary, we see that the yield of wheat benefits of higher temperature and this is true for both the adopters and the non-adopters, but the marginal effect is significantly higher for the adopters. In fact, an increase of 1% of temperature produce 1.3% increase of wheat yield of traditional land against a 12% increase of improved land. According to RCP 4.5 and 6.0, Ethiopia will experience a 5.8% increase in average temperature going from 22.6 °C to 23.9 C°. This implies a reduction of land yield for maize traditional of 40.3% and an increase of 7.0% and 71.4% for wheat traditional and wheat improved varieties respectively. These shocks have been linearized along the 2013-2050 horizon and introduced into the model as productivity percentage shifts for the "Wheat and Maize crops impact scenario". They are added to the reference scenario where agricultural productivity increases in each period based on average performances of the agricultural sector between 2001-2013. This latter information is based on the WDI 2016.
Results show that compared to the baseline, wheat output is increased by 10.6% while that of maize is decreased by 1.0%. This yields positive gains in agriculture (+0.5% wrt Baseline) and the chemicals sector (+4.3%) due to the increased use of fertilizers particularly from the improved industries.

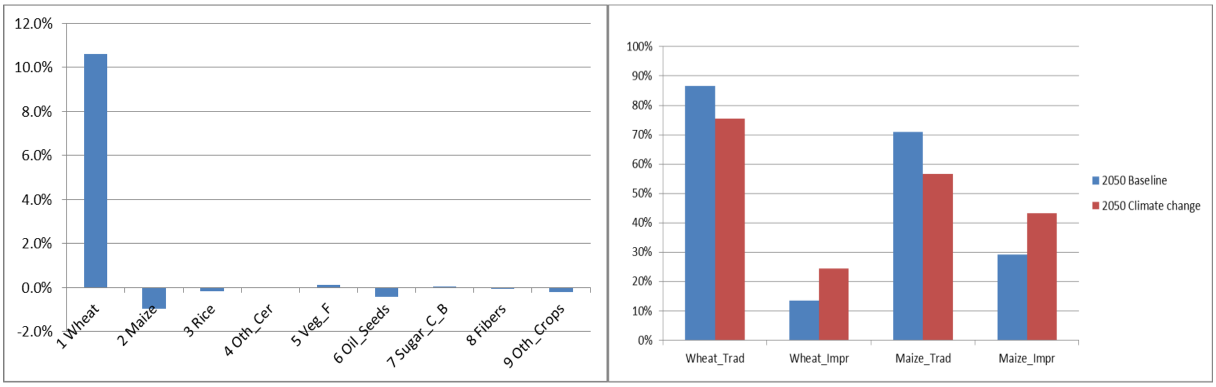


Figure 11 - Change in Output wrt Baseline scenario in agricultural sectors in 2050 (left) and Share of Traditional and Improved varieties in total land demand in 2050 under climate change impacts (right)

The effects on total GDP are negligible but negative. Real GDP shows a 0.03% reduction compared to baseline in 2050 induced by the contraction in the maize sector and that in the industry and services. Among GDP components, exports show the largest contraction (-0.63% compared to baseline).
The imports of wheat are significantly reduced (-25.6%) while the exports more than doubled thereby further benefiting the balance of trade. The composition of international trade shows a tendency to relocate exports to the rest of Sub Saharan Africa (SSA) and towards other small-scale importers (Figure 12). The composition of imports remain quite stable if compared to those of the baseline.

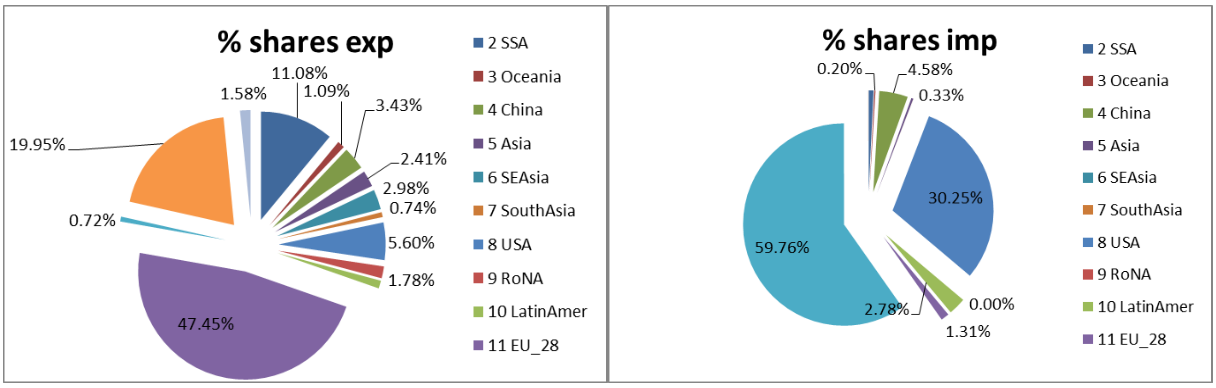


Figure 12 - (%) Maize and Wheat shares of export and import by trading partner in 2050 under Climate Change.

6. Conclusions

The climatic shocks determine a recomposition in the use of inputs and primary factors relatively to the baseline. Due to the negative productivity shift, the traditional maize sector shows a decline in production and as a consequence also a reduction of primary factors demand particularly labour. This determines an increase of the land share relatively to other factors in valued added composition. On the contrary, due to the positive impact the improved wheat sector increase its demand of primary factors, particularly its labour demand inducing a slight upward pressure on wages (+0.5% for all sectors) and a consequent migration of those employed in other sectors (industry and services). All this dynamics lead to a recomposition of land allocation in favour of wheat and maize improved varieties.

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