The Distributional and Multi-Sectoral Impacts of Rainfall Shocks: Evidence from Computable General Equilibrium Modelling for the Awash basin, Ethiopia

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Abstract

This paper presents an analysis of the multi-sectoral and distributional economic impacts of rainfall shocks in the Awash river basin in Ethiopia. Using novel disaggregated data on crop production, we estimate the direct impacts of rainfall shocks on agriculture and then use a Computable General Equilibrium model to simulate how these rainfall shocks propagate through the wider economy of the basin under three different climate change scenarios. The basin's economy and expanding agricultural sector are highly vulnerable to the impacts of rainfall shocks. A rainfall decrease scenario could lead to a 5% decline in the basin's GDP, with agricultural GDP standing to drop by as much as 10%. All sectors benefit from greater rainfall amounts. Distributional impacts depend on income group, with poor households accruing greater benefits relative to non-poor households under a scenario of additional rainfall and suffering proportionally lower income losses under a scenario of rainfall decrease.

Keywords: computable general equilibrium, Ethiopia, rainfall variability, agricultural shocks, climate change in Sub-Saharan Africa, poverty

1. Introduction

Understanding the impact of hydro-climatic factors on the economy informs the design of agricultural and water polices. It has important implications for the economic appraisal of investments in the water sector vis-à-vis investments in other sectors, quantifying if and how unmanaged hydro-climatic variables lead to unfavorable economic outcomes. In the face of climate change and increasing water demands, this understanding also informs adaptation decisions and is increasingly being integrated into investment decision-making.

For over a decade, scholars have highlighted the regional and global economic impacts of hydro-climatic variables on economies, recognizing for instance that factors such as rainfall variability and drought affect economic outcomes at multiple scales ranging from national economic production (Barrios et al., 2010; Grey and Sadoff, 2007; Sadoff et al., 2015; Hall et al., 2014; Garrick and Hall, 2014) to household wealth and income dynamics (Dercon, 2004; Coulter et al, 2010; Barrett and Santos, 2014). Despite recognition of the importance of hydro-climatic variables in influencing economies and perpetuating poverty traps, there still remains much to be studied in terms of the mechanisms by which these variables influence different economic sectors and how the impacts are distributed through society and different income groups.

This paper follows this line of work and aims to quantify the multi-sectoral and distributional impacts of rainfall shocks in the Awash River basin, Ethiopia. This analysis has implications for informing adaptation strategies in the Awash basin and, more broadly, for understanding current and future vulnerabilities to climatic factors in areas such as Sub-Saharan Africa where rainfed agriculture is dominant.

The paper is structured as follows. Section 2 reviews the motivating evidence for this study and articulates the main contributions. Section 3 presents the background to the study area and Section 4 presents the data and the analytical framework used to investigate the linkages between economic activities and rainfall and extremes at the river basin scale. In Section 5 the results are presented and in Section 6 the limitations are discussed. Section 7 presents conclusions from the study and suggests areas for future research.

2. Motivating Evidence and Contribution

The question of climate's role (both rainfall and temperature) in influencing the economy has challenged thinkers for several decades and is of increasing relevance to assessments of the economic impacts of climate change (Hsiang, 2016; Carlton and Hsiang, 2016). In the case of rainfall, studies examining its role in influencing economic outcomes have ranged from econometric analyses at the global scale (Brown and Lall, 2006; Brown et al., 2013) to household level surveys (Dercon and Christiaensen, 2007; Coulter et al., 2010). Overall, studies have found that rainfall variability and extremes have a significant effect on both household welfare and national economic output, especially in agricultural-based economies (Shiferaw et al., 2014).

Given the natural relationship between agricultural production and rainfall, it is not surprising that in agricultural-dependent economies where most agriculture is rainfed, variations in rainfall can cause significant economic impacts. However, this intuition may be difficult to test in practice, because high resolution data on agricultural production and rainfall are often lacking and because it is difficult to estimate how direct impacts, especially on the agricultural sector, are transmitted through other sectors of the economy.

Early work in the economics literature used production function approaches to establish a relationship between hydro-climatic variables and agricultural output and then simulate the impacts of changing climate conditions (Adams, 1989; Dell, 2014). More recently, studies have used panel methods to estimate the impact of climatic factors on agricultural production. Most of these studies have focused on the role of temperature, such as Deressa and Hassan (2009) who showed how increasing temperatures would reduce crop revenue in Ethiopia or Schlenker and Lobell (2010) who demonstrated that higher temperatures lead to lower agricultural yields in Sub Saharan Africa. Other studies have examined the role of climate variability and extreme weather events in influencing crop production at local (Rowhani et al., 2011) and global scales (Lesk et al., 2016), quantifying the extent to which crop yields are sensitive to both intra- and inter-seasonal changes in temperature, precipitation, and drought occurrence. Panel data analysis has also been used to examine farmer responses to changes in rainfall variables, for instance by examining how rainfall variability in Ethiopia impacts fertilizer use (Alem et al., 2000) or food crop choices (Bezabih and Di Falco, 2012), or the impacts of rainfall shocks on agroecosystem productivity (Di Falco and Chavas, 2008).

Beyond analysis of the agricultural sector, econometric analyses using panel data have been employed to investigate the impacts of long-term hydro-climatic fluctuations and extremes on national economies. Examples include Barrios et al (2010) who showed that higher rainfall is associated with faster economic growth in Sub-Saharan Africa, Brown and Lall (2006) who established a statistically significant relationship between greater rainfall variability and lower per capita GDP, Brown et al. (2011) who demonstrated negative impacts of droughts on GDP per capita growth and Brown et al. (2013) who found that rainfall extremes (i.e., droughts and floods) have a negative influence on GDP growth. Recent work by Sadoff et al. (2015) has used for the first-time surface runoff to test its impact on national economies, finding that it has a negative impact on economic growth at the global level.

Building on empirical estimates of the direct effects of rainfall on economic outcomes, scholars have also investigated the economy-wide impact of water-related variables, especially rainfall variability and availability. These analyses have relied on Computable General Equilibrium (CGE) models to show the impact of rainfall on economies at various scales under historical climate variability and also under climate change. Pauw et al. (2011) combined a crop loss model with a CGE model to estimate the impacts of rainfall extremes on Malawi's economy. Strzepek et al. (2008) used a CGE model to look at variability in water supply and model the economic value of reduced variability following the construction of the High Aswan dam in Egypt. Other applications of CGE models to assess the indirect impacts of water-related variables include Berrittella et al. (2007), who investigated the role of water resources and scarcity in international trade, Roson and Damania (2016), who explored the macroeconomic impact of future water scarcity and alternative water allocation strategies, Brouwer et al. (2008), who modelled the direct and indirect impacts of water quality improvements on the economy of the Netherlands, and Carrera et al. (2015), who assessed the impacts of extreme events (flood shocks) in Northern Italy.

In the context of Ethiopia, analysts have emphasized the vulnerability of the agricultural sector to climate change (Deressa et al, 2008) and found evidence of the linkages between economic outcomes and rainfall variability (Grey and Sadoff, 2007). Revisiting the Grey and Sadoff (2007) analysis with a longer data series, Conway and Schipper (2011) found a weaker relationship between rainfall and GDP, but still emphasized the sensitivity of Ethiopia's economy to major droughts and argued that evidence of the relationship between wet and dry extremes and the economy is essential to assess the significance of future climate change. Following a similar line of work, Deressa (2007) investigated the economic impact of climate on Ethiopia's agriculture and found that increasing temperature and decreasing rainfall have negative impacts on farmers' net revenues. Bewket (2009) identified strong correlations between cereal production and rainfall in the Amhara region and similar conclusions were reached by Alemayehu and Bewket (2016) for the central highlands.

Despite this growing body of work, there remain some unanswered questions of scholarly and policy relevance. First, most studies have typically focused on country-level assessments, without diagnosing the distributional and multi-sectoral impacts of rainfall shocks at the river basin scale. Although country-level assessments provide valuable information to focus policy-makers' attention on the issue, the most interesting variations in economic variables of relevance for decision-making are often observed at regional rather than national scales (Henderson et al, 2012), and for different sectors and income groups. Second, as noted by Brown et al. (2013), most analyses to date have relied on spatially averaged rainfall data, which introduces systematic biases in the results by smoothing out variability and extremes.

To address these gaps and contribute to the existing literature on the impacts of hydro-climatic variability and climate change at different scales, this study analyses the multi-sectoral and distributional impacts of rainfall shocks in the Awash basin, Ethiopia. First, the direct impacts of rainfall shocks on crop production are quantified. To avoid bias due to rainfall averaging, spatially disaggregated rainfall data are used to estimate the effects of positive and negative rainfall anomalies on agricultural production at the administrative zone level. Second, a CGE model is used to quantify how these shocks are transmitted through the economy under three different climate scenarios. This allows us to quantify the potential economic impacts of climate change-induced variations in rainfall. Using a CGE model also allows us to compute the indirect impacts of rainfall shocks for different income groups, providing an understanding of the distributional implications of rainfall shocks.

3. Background

The Awash River basin, spanning 23 administrative zones, covers 10% of Ethiopia's area and hosts about 17% of its population. In aggregate, the water available for use (including surface water and groundwater) of the Awash river basin meets existing demand, with 4.9 billion m^3 available per year on average compared to an average annual demand of 2.8 billion m^3 (Tiruneh et al., 2013). However, this availability is highly variable both temporally and spatially. Most rainfall occurs between July and September and water availability during the dry season is on average 28% lower than in the rainy season (Bekele et al., 2016). The lower reaches of the Awash receive on average 27% to 45% of the rain that falls in the upstream basin areas and also experience greater variability, as shown in Figure 1.

The high spatial and temporal variability makes it difficult (and therefore economically costly) for actors in the basin to plan investments that take advantage of the water when it is available. Furthermore, recurrent extreme wet and dry weather events challenge economic activities in the basin. The large portion of rural poor engaged in rainfed agriculture in the drought-prone marginal lands located in the middle and lower reaches of the basin suffer greatly from recurring drought, which often make populations reliant on international food assistance for survival (Edossa et al, 2010).

The Awash Basin's economy is dominated by the agricultural and services sectors, with the latter prevailing in the large urban center of Addis Ababa. Agriculture dominates water use (about 89% of total water use in the basin) and is expected to continue to be the basis for economic growth in the coming years (Tiruneh et al., 2013). Crop production in particular is a major component of the basin's economy and has seen rapid growth in recent years, with the value of output expanding by 7.9% per year in real terms between 2004 and 2014. Data collected for this study shows that as of 2012, the total irrigated area of the basin is less than 2% of the total area under cultivation.

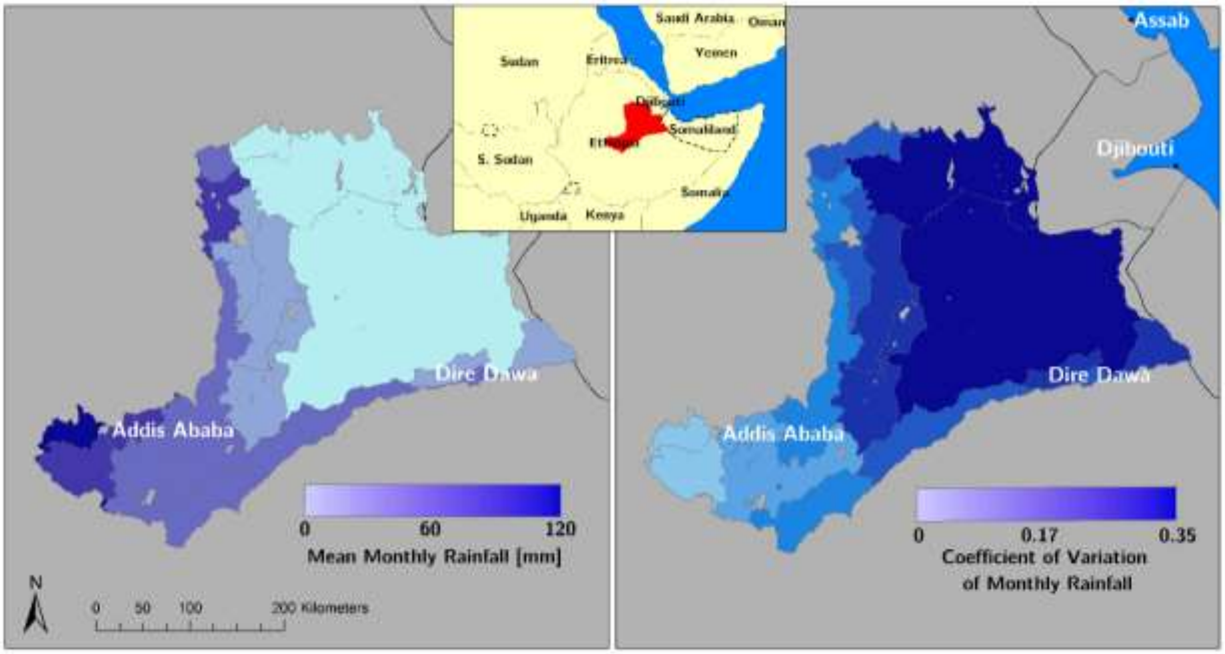

Figure 1. Mean (left panel) and coefficient of variation (right panel) of monthly rainfall by administrative zone in the Awash basin (1979-2015). Rainfall data from the Global Precipitation Climatology Centre (Schneider et al., 2011).

4. Data and Methods

4.1. Data

4.1.1. Crop Production

We examine the effect of rainfall shocks on crop production in the different administrative zones of the Awash basin. A panel of crop production for each zone for multiple crops from 2004 to 2014 was constructed using data from the Central Statistical Agency (CSA) annual surveys of private peasant holdings and of commercial farms (large and medium commercial farm surveys). The crops contained in CSA's records considered in this study are barley, cereals, chat, coffee, cotton, fruits, hops, maize, pulses, oilseeds, pulses, sorghum, sugarcane, vegetables, and wheat. Zonal level prices of these items from the CSA were included to produce data on monetary values and to construct price deflators that help intertemporal comparisons.

4.1.2. Rainfall

The rainfall data used in this study were obtained from the Global Precipitation Climatology Centre (GPCC) (Schneider et al., 2011). These are rainfall time series of monthly rainfall totals from 1979 to 2015 on a 0.5x0.5 degrees grid (approximately 55 km x 55 km). The gridded rainfall data were assigned to each administrative zone in the Awash basin using proportional assignment, meaning that the rainfall value assigned to each administrative zone is the average of the grid cells' values intersecting it weighted by the fraction of the administrative zone covered by each grid cell.

The gridded datasets were analyzed to obtain information on the occurrence of extreme weather events. A number of different metrics have been proposed in the literature to define flood and drought events based on rainfall time series (Keyantash and Dracup, 2002). In this study, the weighted anomaly standardized precipitation index (WASP) was used to define drought. This index was selected because it has been widely applied in previous studies exploring the relationship between rainfall and runoff variables and economic activities (Brown et al, 2013; Brown et al., 2011; Sadoff et al., 2015).

The WASP index calculates deviations in monthly rainfall from its long-term mean and then sums those anomalies weighted by the average contribution of each month to the annual total (Brown et al., 2011; Lyon and Barnston, 2005):

$$WASP_N = \sum_{i=1}^{N} \left(\frac{P_i - \bar{P}_i}{\sigma_i} \right) \cdot \left(\frac{\bar{P}_i}{\bar{P}_A} \right) \qquad (1)$$

Where P_i is the observed rainfall for month i and $\bar{P}_i$ is the long-term average rainfall for month i, σ_i is the standard deviation of monthly rainfall for the month in question and $\bar{P}_A$ is the mean annual rainfall. N indicates the number of months over which the index is calculated. Following Brown et al. (2011), N was set to 12 to capture annual rainfall anomalies. WASP values less than or equal to -1 indicate the occurrence of a drought D (Brown et al., 2011; Sadoff et al., 2015).

Floods were identified using the peak-over-threshold approach (e.g., Katz et al., 2002), which defines all rainfall values above a predefined threshold level as floods. The threshold was set to the monthly values 90th percentile for each zone. While this offers an index capable of identifying periods with extremely wet conditions, floods can occur over time spans much shorter than can be captured using monthly data, so it is important to recognize that the index remains relatively crude. Given the lack of sub-monthly rainfall data or data on flood events, this is the most practical way to try to identify flood events or, at least, periods with extended higher than average rainfall.

To drive the CGE analysis and estimate economy-wide impacts under climate change, three rainfall scenarios were developed using output from the CMIP5 (Climate Model Intercomparison Project). The main rationale behind these scenarios is to identify rainfall projections which allow for a 'what if' analysis of the implications of changes in rainfall on the economy of the Awash basin. These are not meant to be predictive rainfall projections, they are meant to be representative projections of plausible changes in rainfall in the Awash basin, spanning the primary dimensions along which changing rainfall conditions might affect economic outcomes. All scenarios comprise four years long monthly rainfall time series. The characteristics of the three scenarios and the data and model sources used to generate them are described in Table 1.

Table 1. Climate scenarios used in the Computable General Equilibrium analysis with a brief description of their characteristics and the sources used to generate the rainfall time series. [rcp: representative concentration pathway].

Scenario	Description	Source (Climate model, scenario and time slice)
Rainfall decrease	A modest decrease (about 5% compared to long-term averages) in rainfall throughout the basin, relatively evenly distributed throughout the year	rcp 85 HadGEM2-ES r1i1p1 (2090/01 to 2094/12)
Rainfall increase	A modest increase in rainfall (about 5% compared to long-term averages) throughout the basin, relatively evenly distributed throughout the year	rcp 45 CNRM-CM5 r1i1p1 (2025/01 to 2029/12)
Spatial redistribution	A modest decrease in rainfall in the upper reaches of the basin, accompanied by an increase in rainfall in the lower reaches of the basin	rcp 45 CESM1-CAM5 r1i1p1 (2025/01 to 2029/12)

4.2. Methods

4.2.1. Productivity Shocks Using Regression

In the panel analysis, monthly rainfall, flood, and drought events are matched to crop production by crop type for each administrative zone during the period 2004-2014. Summary statistics for these variables are presented in Appendix A. The regression model estimates crop production for each crop type as a function of rainfall *r* for each month *m*, occurrence of a drought *D* and a flood *F*. To account for the productivity changes registered in the basin between 2004 and 2014, we also include a linear time trend *T*. Using the panel of rainfall, extreme weather events and crop production we estimate the following:

$$Y_{i,t} = c + \sum_{m} \alpha_m r_{m_{i,t}} + \beta \cdot T + \gamma \cdot D_{i,t} + \xi F_{i,t} + \epsilon_{i,t} \tag{2}$$

where administrative zones are indexed by *i* and years by *t*. *Y* is the production for each crop, *c* is a constant term, and $\epsilon_{i,t}$ is the error term that captures variation in crop production unexplained by the other variables. This econometric specification was in part dictated by the CGE model's structure, which requires changes in productivity as an input rather than value. Additionally, while output value, or production multiplied by price, is an important measure of economic impact, its relationship to rainfall is complicated due to the extra variable of price. It is not clear how price might change with respect to rainfall, because it depends on a wide variety of other factors such as international market conditions and output in other sectors.

By analyzing different crops separately, we are able to account for the fact that crops might respond differently to rainfall, as some crops require less water or require it at different times during the year. Including flood *F* and drought *D* events in the regression allows for extreme weather events to be controlled in all specifications and avoid biases due to temporal averaging of rainfall. Data limitations mean that there are insufficient degrees of freedom to allow the relationship between water availability and output to vary in each of the 23 administrative zones. Zonal fixed effects were considered, but tests failed to show statistically significant differences between zones in the basin, and so were excluded from the analysis for parsimony.

4.2.2. From Regression Results to CGE Input

The estimated direct impacts on crop production were used as the starting point to compute the multi-sectoral and distributional impacts of rainfall shocks with the CGE model. In our application of the model, we are interested in computing the overall impact, in equilibrium, of productivity changes in agriculture induced by rainfall shocks on multiple sectors and income groups. To compute this impact the following steps were followed:

1. Estimate the elasticity of crop production to rainfall shocks. This was accomplished by employing a log-log format whereby regression coefficients from the panel analysis are interpreted as elasticities.
2. Compute productivity shock in agriculture. For each climate change scenario in Table 1, the percentage productivity shock in agriculture was computed using the crop elasticities estimated in step 1 and an assumption about how these shocks relate to livestock production. Due to the lack of data on livestock production, livestock impacts were estimated by taking an average of the sorghum and maize impacts within each zone, weighted by the relative share of production for the two crops in the relevant zone. In doing this, livestock production is assumed to track these two staple crops, which were chosen because they are often used as feed for livestock (FAO, 2006).
3. Apply productivity shocks to baseline levels of production. The percentage productivity shocks were applied to the baseline levels of production, defined as the economic performance (either GDP or income) observed during the period 2011-2015.
4. Run CGE model. The levels of production modified with the productivity shocks were inserted in the CGE model to evaluate the multi-sectoral and distributional impacts of rainfall shocks for each year during the period 2011-2015.

This process hinges on using observed variability (estimated in step 1) to make projections of what might happen outside the bounds of that observed variability. The econometric model examines direct effects within a relatively narrow band of variability, in which rainfall availability is often the binding constraint. Because there are other factors including adaptive responses to extreme conditions that are either unobservable or unable to be modelled due to the data constraints discussed in Section 5, using regression estimates alone will not account for the presence of these factors that might become binding with sufficient deviation in rainfall. That may then overstate the true impact of rainfall shocks. In order to prevent such an overstatement, the impacts were censored to be no more than 20% growth or 30% decline in any year at the individual level. These numbers were chosen to be consistent with the maximum changes observed in the historical economic data. However, in doing so, the true impacts on production of the climatic scenarios may be understated, meaning that the estimates presented here are considered conservative.

4.2.3. Multi-sectoral and Distributional Impacts using CGE Modelling

This study uses a recursive dynamic CGE model, which is an extension of the International Food Policy Research Institute (IFPRI)'s standard static model (Lofgren et al., 2002; World Bank, 2008) widely applied to study climate change impacts on Ethiopia's economy (e.g., World Bank, 2008; Arndt et al., 2011; Robinson et al., 2012; Gebreegziabher et al., 2015). A CGE model is a representation of the interactions between producers and consumers in the economy. It tracks the selling of goods from households to firms, the selling of factor services from households to firms and the investment expenditure arising from household savings (Yu et al., 2013).

The CGE model takes as inputs factor endowments (amount of labor, land, and capital), sector productivity and updated country-specific data on production and consumption. The outputs of the CGE model include production by sector, income by household group and other which are not examined in this study (international trade, public accounts). More details on the CGE model used in this study are provided in Appendix B.

The values of the variables and parameters in the CGE model are drawn from the 2009/10 updated version of the 2005/06 Ethiopian Social Accounting Matrix (SAM) constructed by the Ethiopian Development Research Institute (EDRI, 2009). This SAM is a representation of all the transactions and transfers between agents in Ethiopia. It records all economic transactions taking place in a given year, for multiple sectors, representative households, and commodities amongst other factors.

The Ethiopian Social Accounting Matrix (SAM) is a comprehensive, economy-wide data framework, representing the economy of the nation and also consistent with macro- to micro-accounting framework based on Ethiopia's national accounts, the 2004/05 Household Income, Consumption, and Expenditure Survey (HICES) and other data. The SAM is disaggregated into 113-activities (i.e., 77 in Agriculture, 24 in industry, 11 in service, and a mining sector), 64-commodities, 16-factors, 13-households, and 17-tax (8 indirect commodity taxes and 9 direct taxes) accounts. The SAM also has government, saving-investment, inventory, and rest of the world accounts to capture all income and expenditure flows.

Households are disaggregated into poor and non-poor according to their income compared to the absolute poverty lines for 2009 and 2010, which are approximately 2590 birr per year (EDRI, 2009). Following the Ethiopian SAM, households are further categorized into five types: (i) highland cereal producing areas, (ii) highland other crops producing areas, (iii) drought prone areas, (iv) pastoral areas and, (v) urban areas (EDRI, 2009). The urban and highland cereal and other crops producing households are mostly located in the upper reaches of the basin to the south-west, whilst pastoralists and drought prone households are mostly located in the downstream part (north-east) of the basin.

Although the CGE and SAM represent the whole economy of Ethiopia, their application to estimate results at the basin level is justified for the following reasons. First, the productivity shocks inserted in the CGE model are generated using basin-level data only and are weighted using the share of agricultural commodities produced in the basin. Second, the basin accounts for about 30% of Ethiopia's GDP and contains all the five household types included in the Ethiopian SAM. Third, they are the best and only available mathematical tools to study the economic response to rainfall shocks and climate change in this basin.

5. Results

5.1. Direct Impacts on Crop Production

We first present the direct impacts of rainfall shocks on crop production and then show how these impacts are transmitted through the basin's economy and for different sectors and income groups. The estimated coefficients for each crop and month are presented in Table 2 and they suggest significant responses of crop production to rainfall, with impacts depending on the season, the type of crop and the occurrence of extreme events. Regression diagnostics, including tests for normality, misspecification, and multicollinearity, suggest that our regression model is well specified (see Appendix C).

Table 2. Regression coefficients by crop. *, ** and * indicate significance at the 0.01, 0.05, and 0.1 levels respectively.**

	Rainfall													Extreme event		
Crop Type	Annual change in production (trend variable)	January	February	March	April	May	June	July	August	September	October	November	December	Flood Indicator	Drought Indicator	Constant
Chat	-6173.2	-2259.9**	230.2	-591.0	854.7*	78.4	92.9	-483.6***	94.7	368.7*	1093.6***	708.2**	-153.5	-127323	-29690.8	12400000
Coffee	-1316.4*	67.9	254.9***	3.2	38.3	63.5***	-48.5	-61.7**	-31.6	61.1**	324.5***	437.5***	88.4	-62572.1***	-77864.9***	2623877*
Cotton	6992.2	-23.9	-375.5*	376.4	-365.8	-31.7	-340.2	173.0	-278.6	-11.9	338.9	-184.9	-638.0*	138389.7*	-68320.9	-13900000
Fruit	4052.9	647.9	333.5**	327.4	-33.9	84.1*	-64.6	-24.0	-64.2	36.2	529.3***	932.4**	158.6	-130002***	-202061***	-8130089
Barley	18112.4	5471.2	1865.7	-840.1	213.2	723.0	502.6	1313.9	1180.1	49.6	2904.2*	4011.2	4229.7*	-862148**	-1314542**	-36800000
Maize	33854.9	4645.6	1967.7	1020.6	502.8	1891.1**	4872.6***	-1466.8	-1035.7	1238.4	6283.7**	8391.6***	4542.8*	-1296638**	1470011	-68000000
Sorghum	-30722	-8178.5*	619.2	-3804.1	4459.1**	1161.0	-4002.2***	762.0	2966.7**	1769.6	8851.8***	9429.4***	-1949.6	-611047	-528243	60800000
Teff	77644.3***	3948.6	-536.3	-966.7	-347.5	736.1	4559.4***	2908.1**	1728.0	-1025.6	-361.8	468.8	4283.7*	-653947	3036354	-156000000***
Wheat	45285.7	17785.1**	6374.4**	4263.8	-1388.5	1806.8*	937.3	491.4	957.4	173.1	7027.7**	10209.7**	4874.7	-2319072***	-60217.8	-91400000
Hops	1792.9***	148.3*	-65.5*	-49.5	63.4*	-28.3*	26.8	90.4**	-8.9	19.9	-21.9	-31.2	-15.9	-1056.8	88007.3	-3597995***
Oilseeds	-1033.7	995.3	941.3*	-318.5	241.7	300.1***	304.8	-166.9	76.6	223.4	1470.8***	1076.2**	787.0	-210079*	-437613**	1963214
Other Cereals	-1115.7**	116.1	157.9**	-41.8	28.5	27.6*	-109.5***	103.5***	-2.4	16.83	152.9**	265.0***	65.2	-44812.2*	-54733	2215645**
Pulses	41725.8***	4636.6	311.2	-620.7	63.2	568.9	-313.9	2276.8**	1857.9*	-545.2	1581.7	1193.8	1598.6	-671002**	1373913	-83900000***
Sugarcane	203321.1	13428.4	-1649.0	18104.3	-11092.9	-103.8	5385.5	-12420.1	7517.2	-2211.7	7270.7	-6473.5	-10549.9	-3128590	-3299997	-406000000
Vegetables	13475.9***	1885.2***	57.2	1020.6***	-119.5	249.3**	875.3***	-233.6*	14.2	33.8	323.9	1601.9***	1197.0***	-253954***	62263.2	-27000000***

Production of several crops, including fruits, cereals (wheat, sorghum, maize) and oilseeds, shows a strong positive relationship with additional rainfall during the harvest (October to November). Additional rainfall is also beneficial in April and May-June for sorghum and maize respectively, suggesting potential benefits of additional water availability during the sowing period for these two crops. Teff shows a positive relation with rainfall availability in June and July, again highlighting the potential benefits of extra water availability during the time of sowing. As found in Alemayehu and Bewket (2016), additional rainfall in August has a positive impact on crops including wheat, teff, sorghum and barley (Table 2). Some crops, including cotton and barley are less sensitive to additional rainfall amounts, only showing statistically significant impacts at greater levels of significance (Table 2).

The occurrence of extreme events impacts crop production. Coffee, fruit, and barley show a statistically significant negative relationship with both floods and droughts. Flood events negatively influence production of maize, wheat, pulses, and vegetables, whilst oilseeds production suffers largely due to droughts. Physical mechanisms that could account for the negative effect of flood events include water-logging of poorly drained fields or crop damage following heavy downpours (WFP, 2014).

Our econometric results show surprisingly a positive, albeit not statistically significant, effect of droughts on some crops (see maize, teff and hops for instance). This result is explained by bearing in mind that the regression outputs include both the physical effects and the decision effects of extreme events. Based on perceived water availability, farmers may change what, where, when or how much they plant. Using our framework, we are not able to differentiate between lower crop output due to crop loss/failure to grow fully or due to farmers' decision to substitute to other, more profitable crops. Our focus on crop production offers a partial picture of the full impacts of extreme weather conditions on agriculture, as these impacts may be affected by changes in harvested area and cropping intensity not considered here.

5.2. Economy-wide and Multi-Sectoral Impacts

To assess the economy-wide impacts of rainfall shocks in agriculture, we run the CGE model under the three different climate scenarios described in Section 4. The economy-wide impacts of the three climate scenarios are presented in Figure 2, which shows the deviation in basin GDP from the baseline, defined as the economic performance observed in the basin during the period

2011-2015. The economy of the basin is vulnerable to changing rainfall patterns as represented in our climate scenarios. All scenarios apart from the rainfall increase scenario entail significant decreases in the GDP of the basin with respect to the 2011-2015 baseline, underscoring the economy's sensitivity to rainfall shocks and extreme weather events beyond the agricultural sector. Under a rainfall decrease scenario, the basin's economy could decline by almost 5%, which is not unreasonable given that during the 1984-1985 drought Ethiopia's GDP dropped by about 10% (World Bank, 2008).

Our analysis suggests that under a scenario of decreasing rainfall availability in the upstream part of the basin (Scenario 3: Spatial Redistribution), the entire basin's GDP would suffer. This can be explained by considering that some of the most productive agriculture in the basin takes place in the upstream highlands of the basin, where higher levels of rainfall are also recorded. Rainfall reductions in these areas could have significant negative impacts on the basin's economy. A modest rainfall increase (about 5%) throughout the basin (Scenario 2: Rainfall increase) could potentially benefit the economy of the basin. This is not surprising given the extent of rainfed agriculture in the Awash and it parallels findings from other climate change impact studies for Ethiopia (e.g., Deressa, 2009).

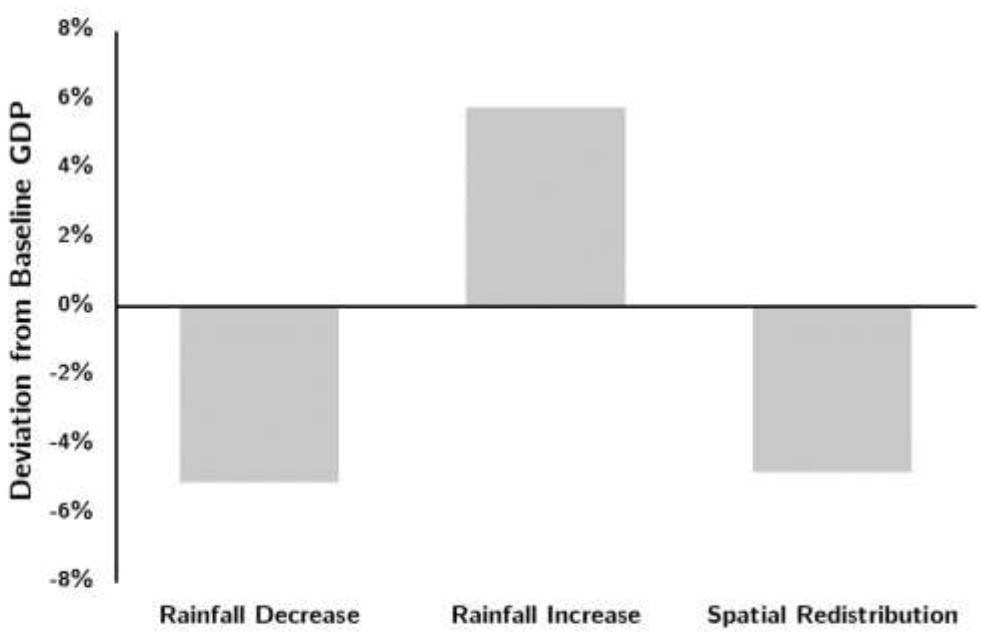

Figure 2. Macroeconomic impacts of three different climate scenarios measured as deviations from the baseline GDP (2011-2015).

The CGE model results also show the response of sectoral output under the alternative climate scenarios. Figure 3 presents the percentage change from the baseline in output by sector. Unsurprisingly, the impacts on agriculture are the largest in all three scenarios and are always negative except under a wetter climate.

The impacts on the industrial and services sectors are more heterogenous. Under the rainfall increase scenario, the industrial sector production increases by less than 1%. However, industry’s production increases by about 5% under the spatial redistribution scenario. The rainfall shocks affect relative prices and incomes, triggering endogenous adaptation responses by farmers, producers, and consumers (Robinson et al., 2013), which could explain the positive impacts observed for the industrial sector under some scenarios. When agricultural production goes down due to lower rainfall, the wages that industry pays to workers can decrease in real terms due to decreased opportunity costs, lowering the costs of production and leading to minor increases in overall industrial productivity as observed in the Spatial Redistribution scenario.

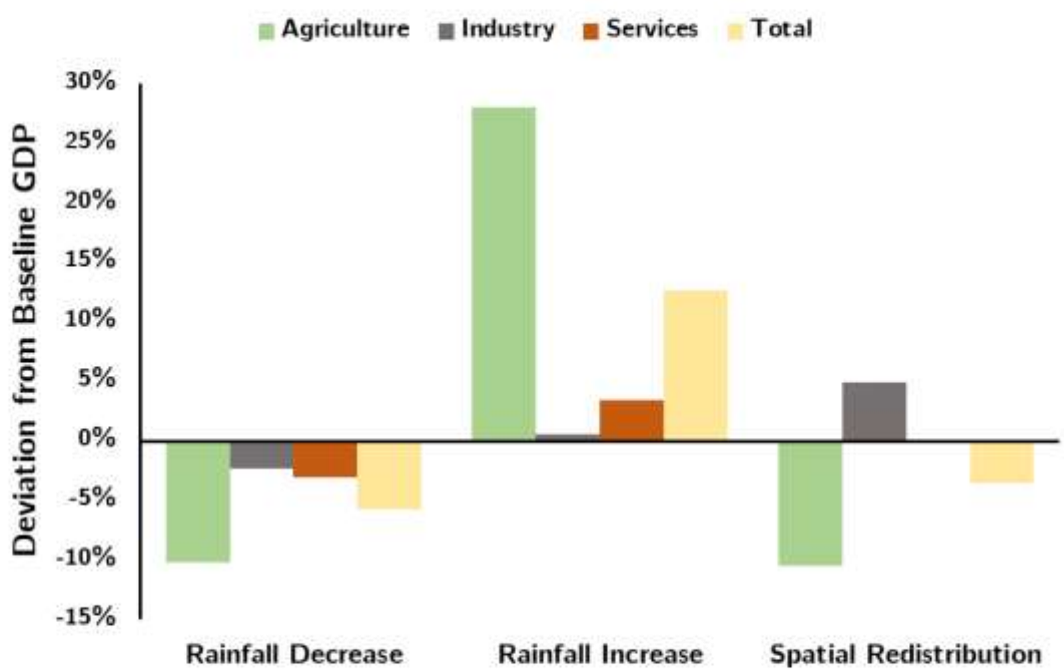

Figure 3. Macroeconomic impacts by sector of three different climate scenarios measured as deviations from the baseline GDP (2011-2015).

5.3. Distributional Impacts

The CGE simulations were also used to explore the distributional implications of rainfall shocks. Figure 4 shows the cumulative impacts on household incomes for two income groups (poor and non-poor) and for different household types. Results show that impacts depend on household income and type, with urban and highland producers (mostly located in the upper reaches of the basin) and pastoralists (mostly located in the downstream areas) households suffering the greatest impact under scenarios of rainfall decrease and spatial redistribution. The large impact on urban households can be explained by considering the higher food prices following rainfall shocks, as also noted by Gebreegziabher et al. (2015).

Under the rainfall reduction scenario, the CGE results show that poor households located in the drought prone areas and in cereal cultivated highlands may benefit from rainfall shocks. This effect may be due to the different crops that these groups tend to farm and consume. The poor in these two household types do better because the cereals and legumes on which they rely are more resilient to rainfall shocks than other water sensitive crops, such as vegetables, and assets, such as livestock, which make up a larger part of a high-income household's earnings and diet. Shocks in the agricultural sector might raise the price of some crops, which are mostly grown by poor households in the highlands and drought prone areas (e.g., legumes) and which, although less profitable during normal rainfall years, become profitable during low rainfall years because they are more drought-resistant. This can account for the increases in the income of some of the poor households shown in Figure 4 and moves some of the production into the industrial sector (see Figure 3).

Under a scenario of rainfall increase, all income categories benefit from greater rainfall amounts, with poor households accruing greater benefits relative to non-poor households. The positive effect of additional rainfall is also visible in the results for the 'spatial redistribution' scenario, where rainfall increases in the lower reaches of the basin (pastoralist areas) lead to positive economic impacts and rainfall decreases in the upper reaches lead to negative economic impacts (highland areas). These results suggest that adaptation in agriculture, for instance in the form of soil and conservation technologies (Evans et al., 2012; Kato et al., 2011), institution-building to plan for water allocation (Mosello et al., 2015), increases in irrigated area (Calzadilla et al.,

2013) and sustainable intensification (Gilmont and Antonelli, 2012; Grafton et al., 2015), could offset some of the negative impacts caused by changes in rainfall patterns due to climate change.

The CGE results reflect the limitations of the SAM, which fails to capture the multiple ways that farmers and consumers change their behavior under different circumstances and only accounts for marketed goods. The poor might suffer less in terms of proportional income losses, but they certainly suffer more in terms of adjustment costs (e.g., sale of livestock, loss of school time, child marriage) which cannot be quantified in the CGE analysis (Robinson et al., 2013).

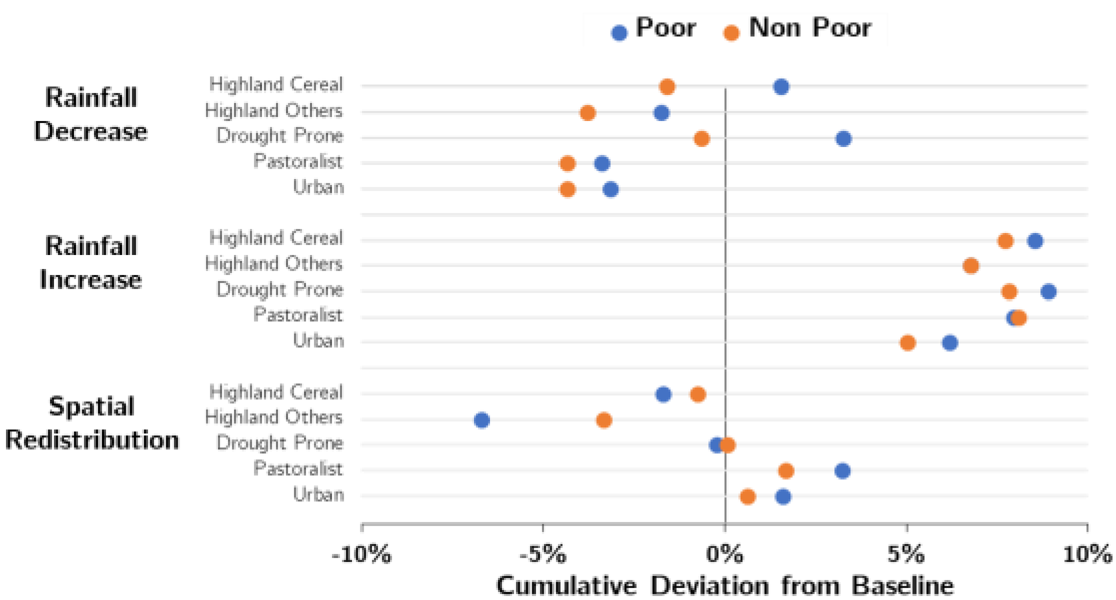

Figure 4. Five Year cumulative impacts on household incomes for different climate scenarios measured as deviations from the income in the baseline period (2011-2015). Poor and non-poor categories are established based on their annual income according to the absolute poverty lines for 2009 and 2010, which are 2590 birr per year.

6. Discussion

This study presents new evidence of the direct impacts of rainfall shocks on agriculture and of the indirect impacts of these shocks on the wider economy of the Awash basin. The methodological framework developed in this study is of relevance to other river basins around the world especially in regions like Sub-Saharan Africa where rainfed agriculture is dominant (IWMI, 2010). Our analysis highlighted several ongoing challenges for research seeking to quantify the impacts of hydro-climatic variables on economic outcomes for multiple sectors and income groups.

First, data reliability and availability remain an issue. We could not validate our crop production estimates against other sources of data, thus we are left with uncertainty over consistency of collection methods and presence of other sources of variability (e.g., pests or soil erosion phenomena occurring in different administrative zones within the basin) masking rainfall effects (e.g., Conway and Schipper, 2011). To deal with the lack of data on livestock production we had to assume it to be related to sorghum and maize. Although this is a reasonable assumption given these crops' use as fodder, direct accounts of livestock production would provide more robust data for the analysis. In future work, bottom-up crop models such as APSIM (McCown et al., 1996) could be used to validate the crop production estimates and expand the analysis to project crop water needs in the future (e.g., Grafton et al. 2017).

We used state-of-the-art rainfall estimates and accounted for spatial and temporal variation in rainfall patterns, though we did not investigate how different rainfall estimates affect our results. As we move towards improved data collection on rainfall and crop water requirements based on remote sensing (Garcia et al., 2016) and improved process-based modelling of crop response to rainfall patterns (Vanutrecht et al., 2014; Ewert et al., 2015), these datasets will provide new information to validate the type of analysis presented here and inform water management decisions at the basin scale.

A third set of limitations arises from the estimation of the wider economic and distributional implications of rainfall shocks. The CGE model assumes that households and firms have the capacity to rapidly respond to changes. In practice, this is rarely the case as firms and households may struggle due to financial or other constraints to respond to rainfall shocks. Standard CGE models cannot be used to simulate the human costs of these adjustments nor can they be used to estimate impacts on non-market goods. This consideration is particularly relevant when trying to quantify impacts on poor households, which rely more on non-market goods sensitive to rainfall patterns –such as domestic labor to collect water– and impacts on health or food security which might arise from rainfall shocks. The relative impacts also need to consider that poor households are more likely to resort to “distress sales” of assets, including livestock, during drought, reducing their ability to adapt to future shocks (Shiferaw et al. 2014). Furthermore, our CGE model results are likely to present an overall underestimation of impacts because production adjusts to shocks in one sector by switching factors of production to other sectors. In reality, these adjustments may not happen making multi-sectoral impacts larger than what was estimated here.

A fourth limitation comes from our focus on rainfall shocks, which makes our estimates of climate-related economic vulnerabilities conservative. The estimated impacts for the four scenarios only reflect economic impacts mediated through rainfall shocks on agricultural production. This means that we do not quantify all the possible mechanisms by which climatic factors may affect economic outcomes in the basin. The findings of this study could be complemented with data on direct economic losses related to hydro-climatic events on multiple economic sectors (e.g., Carrera et al., 2015; You and Ringler, 2010), on the effects of green water availability and variability (water stored in soils) on rainfed agriculture (Kummu et al. 2014) and on the effects of higher temperature on crop production. This would allow for a more comprehensive assessment of the effects of climatic changes and of failure to adapt to these changes on the economy of the Awash basin. Our results are conservative also because we do not quantify the impact that rainfall shocks have on willingness to invest and returns on investments.

Finally, there are limitations linked to our methodological choices, which were dictated by data and model availability. The regression results presented in Section 5 are bound by the extremes in the observed data, which do not necessarily include the most extreme historical events which may have occurred in the basin but for which we could not find matching economic data (e.g., the 1983-1985 drought). Furthermore, in order to use the regression results in the CGE analysis we had to assume that the crop production shocks are time invariant, which may not be the case under climate change. This limitation is linked to the recognition that as climate change materializes, threshold effects and nonlinearities in the ways in which crops respond to rainfall may occur.

7. Conclusion

This study has quantified the distributional and multi-sectoral impacts of rainfall shocks in the Awash basin, Ethiopia. Panel data analysis of novel disaggregated data on crop production was used to assess the direct impacts of rainfall shocks on agriculture. Building on these empirical results, a CGE model was used to simulate how these impacts propagate through the basin’s economy under three different climate scenarios.

Given the dominance of rainfed agriculture in the basin (covering around 98% of total cropland as of 2012), changes in rainfall patterns due to climate change can severely compromise economic activities in the basin. Under a rainfall decrease climate scenario, basin-wide GDP would drop by 5% compared to current GDP, with the agricultural sector losing as much as 10% and the services and industrial sectors losing about 3%. Conversely under a scenario of increased rainfall, the basin's GDP could show potential increases in the range of 5% to 10% compared to current GDP. This highlights how additional water availability could foster agricultural production and have positive ramifications on the economy of the whole basin.

All income categories benefit from greater rainfall amounts. Poor households show the greatest increase in income relative to non-poor households under a rainfall increase scenario. Under a rainfall decrease scenario, most households suffer income losses, with non-poor households suffering more in relative terms. Under this scenario some poor households located in the drought prone areas and in the highland cereal cultivating areas show an increase in incomes, an effect that may be due to the different crops that these groups tend to farm and consume.

This study demonstrates the additional information gained by estimating the distributional and multi-sectoral impacts of rainfall shocks at the local level, at the same time highlighting the data-related challenges linked with finer scales. Future work should focus on collecting more empirical evidence on economic and water-related variables—such as data on livestock production and estimates of the direct impacts of and adjustment costs to rainfall shocks on the manufacturing sector and different income groups—and on the adaptation options available to address climate-related vulnerability across the basin.

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Appendix A

This appendix presents summary statistics for the crop production (Table A1) and rainfall data (Table A2) used in the regression.

Table A1. Summary statistics for production (in quintal) by crop type average across administrative zones in the Awash basin (2004-2015).

Variable	Mean	Std. Dev.	Min	Max
Other cereals	13,553	26,458	-	294,905
Chat	47,576	133,962	-	979,389
Coffee	10,674	25,938	-	172,402
Cotton	17,791	120,447	-	1,251,661
Fruits	31,988	66,413	-	685,153
Barley	367,410	546,965	-	2,539,189
Maize	569,694	824,738	-	3,894,270
Sorghum	674,522	880,303	-	3,730,086
Teff	662,449	884,438	-	3,861,619
Wheat	670,572	1,078,072	-	7,383,871
Hops	7,378	15,992	-	117,291
Oilseeds	71,576	122,728	-	716,748
Pulses	465,112	573,383	-	2,141,646
Sugarcane	357,672	3,933,832	-	59,800,000
Vegetable	82,512	124,162	-	705,176

Table 3. Summary statistics for monthly rainfall (in mm) and drought and flood indicators (dimensionless) averaged across administrative zones in the Awash basin (2004-2015).

Variable	Mean	Std. Dev.	Min	Max
January rainfall	13.988	14.155	0.000	53.900
February rainfall	21.617	31.124	0.000	128.000
March rainfall	48.209	29.072	0.000	145.000
April rainfall	73.720	39.042	0.044	191.000
May rainfall	114.775	117.521	0.014	578.000
June rainfall	72.159	51.447	0.016	219.000
July rainfall	187.794	81.827	0.167	383.000
August rainfall	203.252	73.411	17.200	419.592

September rainfall	119.328	72.241	0.972	489.000
October rainfall	45.960	30.010	0.000	114.888
November rainfall	21.627	23.960	0.029	102.000
December rainfall	9.229	14.676	0.000	89.500
Flood indicator	0.111	0.107	0.000	0.417
Drought indicator	0.004	0.031	0.000	0.250

Appendix B

This study uses a recursive dynamic extension version of the standard CGE model of the International Food Policy Research Institute (IFPRI) as documented in Diao et al. (2011) and Thurlow (2008). The model simulates the functioning of the economy as a whole and tracks detailed transmission mechanisms (mainly through backward and forward linkages) of a given shock in the economy.

The dynamic CGE model considers the full effect of policy and non-policy changes in one period throughout the subsequent periods. The model is formulated as a set of simultaneous linear and non-linear equations, which define the behavior of economic agents, as well as the economic environment in which these agents operate. This environment is described by market equilibrium conditions, macroeconomic balances, and dynamic updating equations.

Producers can substitute between domestically sold and exported commodities based on constant elasticity of transformation (CET) function, which distinguishes between exported and domestic goods, and by doing so, captures any time or quality differences between the two products (Lofgren, 2001). Furthermore, the model includes three macro-economic balances OR CLOSURES for government account balance, external account balance, and savings-investment account. In order to bring about equilibrium in the various macro accounts these closure rules represent important assumptions on the way institutions operate in the economy and can substantively influence the results of the model. Closure rules are chosen due to their appropriateness in the Ethiopian context. For the current account, it is assumed that the level of foreign savings is fixed and exchange rate is flexible. This implies that during shortage of foreign savings the real exchange rate adjusts by simultaneously reducing spending on imports and increasing earnings from export in order to maintain a fixed level of foreign borrowing. In the government account, the tax rates are held constant and government savings are flexible implying the government finances its deficit through borrowing and constrained in raising taxes to cover additional public spending. Savings-driven investment closure is adopted in which investment adjusts endogenously to the availability of loanable funds, and the savings rates of domestic institutions are fixed to ensure that savings equals investment spending in equilibrium. The consumer price index is chosen as the numéraire such that all prices in the model are relative to the weighted unit price of households' initial consumption bundle. The model is also homogenous of degree zero in prices, implying that a doubling of all prices does not alter the real allocation of resources (Diao et al, 2011).

As is briefly described above, this general equilibrium modeling involves the interactions of different actors in the economy including the activities that are linked to government income through value added and sales taxes; the households that supply and determine the level of factors of production and have implications on their income and subsequent level of direct income tax; and the level of imports which not only have implications on import duty but also on level of import tax , import VAT, and sales tax on domestically sold imported commodities; and the level of government transfer from the rest of the world. This general equilibrium analysis calibrates the effects of rainfall shocks on the economy of the Awash basin through total factor productivity (tfp). For this, we rely on estimations/parameters from a separate partial equilibrium analysis that is described above. While the partial equilibrium estimates the productivity elasticities due to climate variables, the GAMS/CGE thoroughly looks at interactions of the entire economy that have implications on major macro variables. Therefore, possible impacts of the rainfall shocks on major national accounts and productivity levels would be profoundly examined. We would be able to discern the effects of the changes in economic conditions on individual sectors of the economy. In addition, the recursive dynamic nature of our model implies that the behavior of its agents is based on adaptive expectations when faced with difficult circumstances, rather than on the forward-looking expectations that underlie inter-temporal optimization models. The model specifications were adapted from Thurlow (2008) and Lofgren et al (2002) and can be obtained from the corresponding author.

Appendix C

Regression diagnostics were run to check for normality, misspecification, and multicollinearity in the data. To check for normality, the quantiles of the variables were compared with the quantiles of a normal distribution. The Ramsey RESET test was applied to check for misspecification and the variance inflation factor was applied to check for multicollinearity. All tests show that the regression model is well specified and does not suffer from non-normality nor multicollinearity. Heteroscedasticity robust standard errors are used in the estimation. Results for these tests can be obtained from the corresponding author.

To check for stationarity, we apply the Harris and Tzavalis (1999) test. The test's null hypothesis is that the time series variables have a unit-root (i.e., are non-stationary) against an alternative where the variables are stationary. The test is designed for datasets which have a short temporal span, which is the case for our data which only span 5 years. The results from the unit root tests, including time trends, are shown in table A3.

Table B1. Results from the Harris-Tzavalis unit root test.

Dependent variables		
Variable	**Z Statistics**	**P – Value**
Chat	-5.8235	0.0000
Coffee	-6.9240	0.0000
Cotton	-7.1352	0.0000
Fruits	-10.5179	0.0000
Barley	-6.1699	0.0000

Maize	-7.5870	0.0000
Sorghum	-4.1650	0.0000
Teff	-2.7134	0.0000
Wheat	-1.4014	0.0000
Hops	-10.5721	0.0000
Oilseeds	-7.1738	0.0000
Other cereals	-8.5530	0.0000
Pulses	-6.0815	0.0000
Sugarcane	-14.0250	0.0000
Vegetable	-6.7963	0.0000
Independent variables		
Variable	**Z Statistics**	**P – Value**
January	-10.8872	0.0000
February	-9.0277	0.0000
March	-5.9884	0.0000
April	-7.4327	0.0000
May	-9.9355	0.0000
June	-11.4783	0.0000
July	-6.8600	0.0000
August	-4.8693	0.0000
September	-9.0702	0.0000
October	-3.5365	0.0000
November	-10.0436	0.0000
December	-9.3680	0.0000

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