Revisiting Development Strategy Under Climate Uncertainty: Case Study Of Malawi

by
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Abstract

This paper scrutinizes the effectiveness of agriculture-led development as compared to non-agriculture-led development strategies, under the perspective of climate-induced economic uncertainty. Utilizing Malawi as a case study, we introduce the application of Stochastic Dominance (SD) analysis, a tool from decision analysis theory, for comparing these two strategies in the context of weather/climate-affected variability in crop yields. Our findings suggest that an agriculture-led development strategy consistently surpasses a non-agriculture-led approach in poverty and undernourishment outcomes across almost all possible weather/climate scenarios. This underscores that, despite an escalating exposure of the entire economy to weather/climate uncertainty, agriculture-led development remains an optimal strategy to alleviate poverty and undernourishment in Malawi. The study further endorses the broader use of SD analysis in policy planning studies, promoting its potential to integrate risk and uncertainty into contemporary policymaking.

Keywords: climate uncertainty; development strategy; structural transformation; CGE modeling.

JEL classification: D58, C68, Q54, O20.

1. Introduction

Due to its higher poverty-growth linkages of agricultural sectors compared to non-agricultural, traditional development economics typically endorse agriculture-led development in Sub-Saharan Africa (SSA) (see, e.g. Diao et al., 2010; Valdes and Foster, 2010; Klasen and Reimers, 2017). However, considering agriculture's high climate sensitivity and growing acknowledgment of uncertain future climates, it becomes crucial to integrate climate-related uncertainty into the discourse of comparing two development strategies.

Climate change is a growing concern, particularly due to its projected negative impact on agriculture - a sector that is crucial to the economies of many Sub-Saharan African (SSA) countries. Numerous studies have analyzed the potential consequences of various climate change scenarios on economic outcomes in SSA, with more recent works acknowledging the uncertain nature of future weather/climate projections and quantifying the associated economic uncertainty. For instance, Arndt and Thurlow (2014), Arndt et al. (2014), and Siddig et al. (2020) provide valuable insights into the climate-related economic uncertainty in Mozambique, Malawi, and Sudan respectively. Despite this, a comparison of alternative development scenarios in the context of their climate-driven uncertain outcomes has not been adequately considered. In this context, this paper proposes the use of Stochastic Dominance (SD) analysis from decision theory to conduct such a comparison.

SD analysis aims to rank competing options by comparing their Cumulative Distribution Functions (CDF) that characterize their uncertainty (Levy, 1992). Although used extensively in finance, to our knowledge, SD analysis has not yet been adopted in policy planning models. Thus, this paper's demonstration of SD analysis to compare uncertainties of agriculture versus non-agriculture-led development strategies is one of the pioneering efforts in facilitating policy decisions under uncertainty.

As a case study, we use Malawi - a poor country with an agriculture-centric economy particularly prone to climatic shocks (WB 2016, 2018). These circumstances serve as a perfect setting to revisit the narrative of prioritizing agriculture-led development, and we examine the impact of weather/climate-related crop productivity uncertainty on the country's two hypothetical development scenarios: intensive growth in the Agrifood System (AFS) sectors and intensive growth outside AFS (NAFS).

To model weather/climate uncertainty, we integrate distributions of climate shocks into a Computable General Equilibrium (CGE) model. We employ available weather/climate-associated yield distribution estimates for key Malawian crops by Thomas et al. (2022b) and construct a complete set of weather/climate-associated uncertainty scenarios for the entire crop sector. We then feed them into the CGE model of Malawi and its auxiliary poverty and undernourishment microsimulation modules, where weather/climate-associated yield scenarios are combined with the AFS and NAFS development scenarios. Finally, we execute post-simulation estimations to construct empirical CDFs of outcome variables and use SD analysis to compare the two development strategies.

Our findings reveal that despite being more vulnerable to weather/climate shocks and having lower and more uncertain GDP levels, the AFS strategy almost certainly outperforms NAFS in terms of poverty reduction. This is true in the short term (the 2020s), and it is preserved for 99.85% of possible weather/climate scenarios in the long term (the 2040s). Furthermore, AFS univocally outperforms NAFS in terms of better undernourishment levels across all possible climate/weather scenarios.

However, two crucial caveats are necessary. First, due to the absence of comparable data for other sectors, we model weather/climate-related productivity variation of crop sectors only. Second, we assume that crop sectors will absorb weather/climate-associated productivity shocks without any adaptation measures. These factors imply that we probably overestimate the relative uncertainty of the AFS strategy. Yet, even under these circumstances, AFS outperforms NAFS for almost all possible weather/climate scenarios, suggesting a clear advantage of prioritizing an agriculture-led development path for Malawi.

More broadly, this approach of comparing uncertain competing options can be applied in numerous other policy planning studies. Regardless of the sources of uncertainty (climate, demography, world markets, etc.), many projections involve uncertainty that is rarely considered in policymaking (for a detailed overview, see Marinacci, 2015; Manski, 2011, 2018). Therefore, our use of the elements of SD theory expands a set of methods to account for the risk and uncertainty in modern policymaking (for additional methods that incorporate risk and uncertainty into policy planning models, see, for example, Ziesmer et al., 2023; Mukashov, 2023).

The remainder of this paper is organized as follows: Section 2 presents a contextual overview of the Malawian economy and its vulnerability to climate shocks. Section 3 describes the modeling framework. Section 4 discusses the results, and Section 5 concludes.

2. Overview of the Malawian economy

Similar to other SSA countries, the Malawian economy is experiencing a slow structural transformation, with the non-agricultural economy slowly increasing its importance. The agricultural GDP and employment shares, as well as the share of the rural population, slightly declined over the last 30 years, with the primary recipient of the rural exodus being the urban service sector (Table 1a-c). At the same time, the change is slow, and, similar to other less developed SSA countries, Malawi is experiencing problems in generating stable growth and structural transformation. In particular, the country is characterized by relatively volatile GDP growth (Table 1d) that can be attributed to macroeconomic and political instability, and adverse climatic shocks (WB 2018). As a result, Malawi remains one of the poorest countries in the world, with very low per capita GDP and consumption levels as well as high poverty and undernourishment (Table 2b). Primary agriculture, despite constituting about a quarter of GDP, employs 62.39 % of the labor force (Table 1a-b), and most of the country's population are smallholder subsistence farmers (WB 2018). Furthermore, the country remains mostly rural (Table 1c), with the urban population being relatively better off than rural residents (Table 2b).

Table 1: Overview of structural transformation of the Malawian economy

a. Sectoral GDP shares

Sector	1991	2019
Agriculture, forestry, and fishing	26.79	23.54
Industry (inc. construction)	21.44	19.80
Manufacturing	18.68	12.55
Services	51.76	56.65
Total	100.00	100.00

Source: own calculations based on World Bank World Development Indicators (WDI) database (World Bank, 2023).

b. Employment shares (ILO estimates)

Sector	1991	2019
Agriculture, forestry, and fishing	76.10	62.39
Industry (inc. construction)	7.40	7.78
Services	16.51	29.83

c. Population shares

	1991	2019
Rural	88.11	82.83
Urban	11.89	17.17

Source: own calculations based on WB WDI 2023

d. Decomposition of real GDP growth by component, selected periods.

	1980-1994	1995-2002	2003-2010	2011-2015
GDP growth	0.90	2.85	6.25	3.82
Contribution of				
(1) Total factor productivity	-1.46	2.14	2.59	1.55
(2) Physical capital	0.69	0.07	1.09	0.24
(3) Labor	1.68	0.63	2.57	2.03

Source: WB 2018.

Table 2: Status quo summary of the Malawian economy

a. Activities, 2019

	Value added share, 2019
Agriculture, forestry, and fishing	24.31
of which crops	20.43
Mining	0.78
Manufacturing	12.28
of which agro-processing	9.11
Utilities	3.26
Construction	3.41
Private services	52.99
of which trade and transport	18.38
Public administration	2.97

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b. Households, 2019

GDP per capita, USD	584.36
Survey consumption per capita (USD)	
National	292.70
Urban	530.76
Rural	248.70
Poverty (% of population) *	
National	70.1
Urban	33.4
Rural	76.9
Prevalence of undernourishment (% of population) **	
National	17.6
Urban	9.1
Rural	19.2

Notes: * Henceforth, we refer to poverty as the proportion of the population living below the international poverty line of 2.15 USD per person per day (using 2017's Purchasing Power Parity).
** Henceforth, we refer to undernourishment as the portion of the population that consumes below the minimum energy requirement norms defined by the Food & Agriculture Organization (FAO).

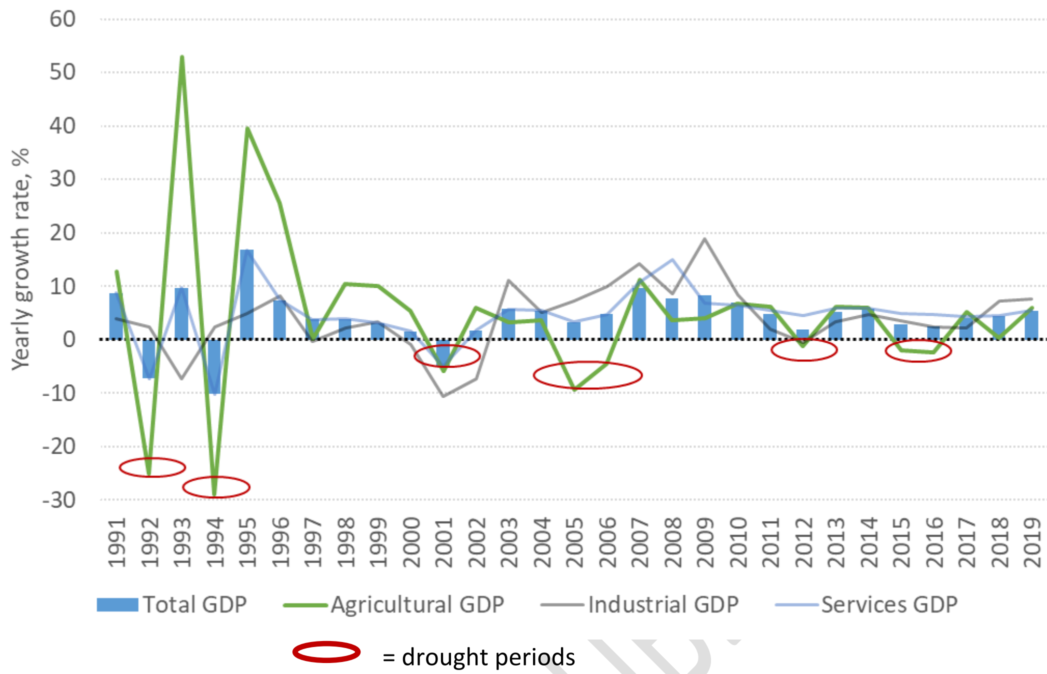
Source: own calculations based on constructed SAM, household survey (Malawi Government, 2020), and World Bank WDI database (World Bank, 2023).

Despite past and existing difficulties, the Malawian government launched an ambitious "Malawi 2063" development strategy that declares the achievement of lower-middle-income status by 2030 and upper-middle-income status by 2063 as its targets (WB 2021). As a means of achieving these goals, the government distinguishes three development pillars: agricultural productivity and commercialization, industrialization, and urbanization (including the development of tourism). The formulated strategy envisions a twin shift from subsistence to commercial agriculture and from a predominantly rural to an urbanized service and industry-driven economy (WB 2021).

In light of historically weak governance and the lack of the country's own funds to implement its development programs (WB 2021), the development of all sectors at once seems unrealistic. In this context, our goal is to shed light on the country's most important priority trade-offs and provide a comprehensive comparison between the AFS and NAFS strategies that take into account one of the key uncertainty factors in Malawi – climatic shocks.

Historically, mostly rain-fed Malawian agriculture was particularly prone to climatic shocks such as droughts and demonstrated very high volatility (Figure 1). Since 2000, the country experienced four major droughts (2005, 2012, 2015, and 2016), and, these droughts had severe impacts on the entire Malawian economy. For instance, according to WB (2016), the 2015/2016 El Nino-induced droughts led to a reduction in total GDP growth of around 2.2 percentage points, making Malawi one of the worst-impacted countries in the region. At the same time, as a result of lower production, the country experienced a dramatic rise in the price of staple crops like maize, which had a devastating impact on both the rural poor and urban poor (WB 2016, 2018).

Figure 1: Historical volatility of sectoral GDP



Source: Own elaborations based on the World Bank WDI database (World Bank, 2023).

3. Modeling Malawian development under climate uncertainty

3.1 Integrating weather/climate crop productivity uncertainty information into the CGE model of Malawi

Thomas et al. (2022a, 2022b) model the weather/climate-driven crop productivity uncertainty in 10 countries of Southern Africa. The authors use a combination of a large ensemble of climate models[1], historical data on an inter-annual variation in temperature and precipitation, and employ crop modeling (and emulation) methods in combination with Gaussian quadrature sampling and provide a yearly distributional estimate of the climate-driven productivity uncertainty for key crops in the region (maize, drybeans, groundnuts, soybeans, and sorghum). Then, for each crop, the authors compare the dynamics of yield distributions in the short term (2020s) and compare them with respective yield distributions in the long term (2040s and 2060s). The authors find that for many crops and countries, both medians and left tails (5th percentiles) decrease, meaning that

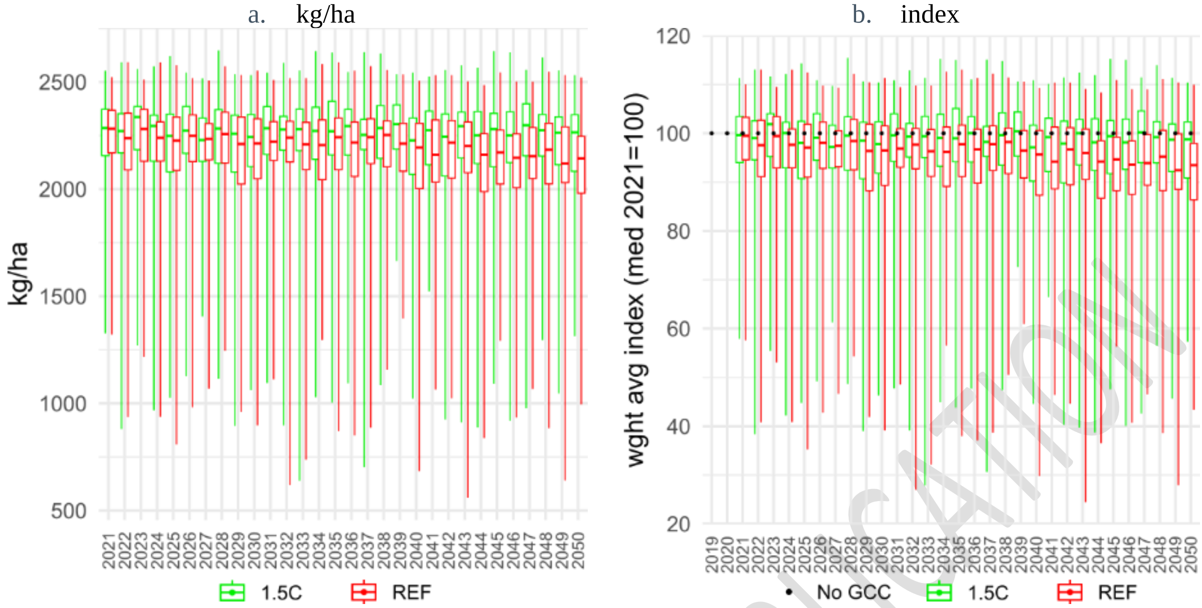
[1] Coupled Model Intercomparison Project (CIMP) 5. See Thomas et al. (2022a, 2022b) for details.

in addition to average yields decline, one can expect an amplification of severity (or increased frequency) of rare low-yield events such as 1 in 20 years droughts.

We use these Thomas et al. (2022a, 2022b) estimates as a starting point for our climate-associated yield variation scenarios for Malawi. Figure 2a represents the example of maize yield distribution estimates by Thomas et al. (2022b) (in kg per hectare, similar estimates are available for drybeans, groundnuts, soybeans, and sorghum). For the sake of parsimony, in this paper, we focus on two polar cases of global climate change scenarios considered by Thomas et al. (2022b) - an 'optimistic' scenario (1.5C) that assumes global warming is kept to 1.5°C above pre-industrial levels, and a 'pessimistic' scenario (REF) that assumes no explicit climate mitigation policies are implemented anywhere in the world. Figure 2a then represents the estimated dynamics of maize yield distribution for every climate and year (each year and climate have a sample of possible 455 weathers, each of which has its own probability).

Figure 2: Climate-associated yield uncertainty of maize (yearly boxplots)

a. kg/ha b. index



Note: No GCC= No Global Climate Change (compared to the median of 2021).
Source: Own elaborations based on Thomas et al. (2022b).

Given the requirements of our CGE model, we cannot use yield scenarios defined by Thomas et al. (2022b) per se. To properly define scenario inputs for our Malawian CGE model, we have to conduct several preprocessing steps.

First, unlike Thomas et al. (2022b), our CGE model reflects that the Total Factor Productivity (TFP) of activities can increase over the years. In this context, we decide to adopt Thomas et al. (2022b) scenarios in *relative terms*. To do so, we create a hypothetical No GCC (No Global Climate Change) scenario that corresponds to the weighted average median yields of the initial year for which weather/climate yields are available (2021). No GCC scenario then serves us as a reference (as if there is no weather/climate-driven variation), and we normalize to it the kg per hectare estimates originally defined in Thomas et al. (2022b) (Figure 2b).

Second, given data and modeling restrictions, Thomas et al. (2022b) provide estimates for six key crops only (Table 3a). Therefore, to properly reflect weather/climate-driven productivity variation of the entire crop sector, we need to impute the climate-driven yield variability for remaining crops (Table 3b). In doing so, we use FAO estimations on historical yields in Malawi and apply regression methods (a detailed explanation is given in Appendix A1).

Table 3: Imputation of weather/climate-driven productivity variation of Malawian crops

a. Subsectors with available scenarios

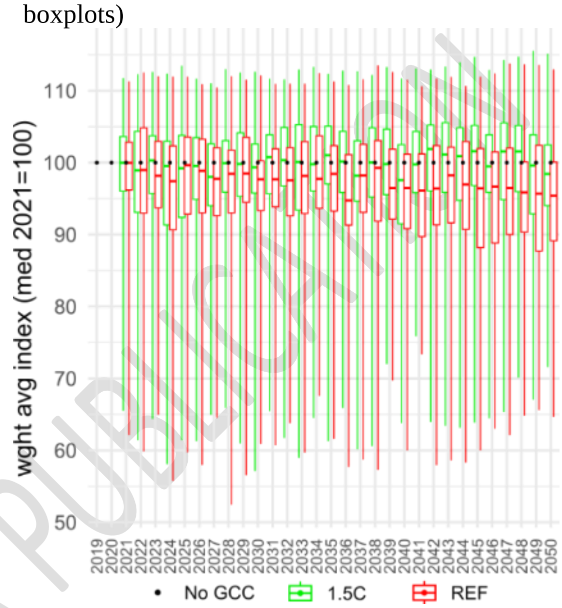
Thomas et al. (2022b)	SAM long	SAM short	Value-added %
Maize	Maize	amaiz	33.67
Drybeans	Pulses	apuls	10.12
Groundnuts	Groundnuts	agnut	5.50
Soybeans	Other oilseeds	aoils	1.81
Sorghum	Sorghum	asorg	0.92
	Total		52.02

b. Subsectors with imputed scenarios

SAM long	SAM short	Value-added %
Rice	arice	4.43
Cassava	acass	5.11
Irish potatoes	aipot	2.03
Sweet potatoes	aspot	3.87
Leafy vegetables	Aleaf	13.85
Other vegetables	Avege	5.38
Sugarcane	Asugr	2.49
Tobacco	Atoba	1.98
Cotton and fibers	Acott	0.25
Nuts	Anuts	0.40
Bananas	Abana	1.97
Plantains	Aplan	0.65
Other fruits	Afrui	4.13
Leaf tea	ateal	1.03
Coffee	acoff	0.18
Other crops	aocrp	0.24
Total		47.98

Source: own calculations based on constructed SAM.

c. Weather/climate-associated yield uncertainty of the entire crop sector (weighted average index, yearly boxplots)



Note: Estimated percentiles (decadal averages)

Decade	Scenario	5th	median	95th
2020s	1.5C	79.11	99.46	107.71
2040s	1.5C	80.57	100.59	109.19
2020s	REF	77.49	98.54	107.66
2040s	REF	76.71	96.42	107.17

Then, even before referring to the CGE modeling, the obtained information on the yield uncertainty of the remaining crops allows us to conduct the first-level analysis of the severity of climate change in Malawi. In particular, assuming constant value-added shares, yearly yield distributions of each crop can be used to construct a yearly weather/climate-associated yield uncertainty of the entire crop sector (Table 3c). In this context, it is worth noting that under less severe climate scenario 1.5C, the aggregate performance of the entire crop sector in Malawi on average is expected to be moderately affected by weather/climate-driven factors (as evidenced by almost the same percentiles in the 2020s and 2040s). However, the impact of the climate can be expected to be more pronounced under a more severe scenario REF, whose both median and 5th percentiles in the 2040s are considerably lower than in the 2020s. Given that the 95th percentile almost does not change, we can conclude that weather/climate-associated productivity uncertainty in Malawi increases over time, and this increase can be primarily attributed to the increased probability of low-yield events such as droughts.

3.2 Design of CGE simulations

As a modeling basis, we use the standard recursive-dynamic CGE model of the International Food Policy Research Institute (IFPRI) and its satellite poverty and undernourishment microsimulation modules. As corresponding data inputs, we use constructed national SAM for the 2019 and 2019/2020 household survey (Malawi Government, 2020). Given the space constraints of this paper, in what follows, we briefly outline key aspects of the model and specific arrangements we make to simulate Malawi's development under weather/climate uncertainty.

Core CGE. The IFPRI CGE model allows for a macroeconomically consistent representation of economic linkages between activities, households, and the rest of the world, and its completely endogenized prices for products and factors (land, labor, capital) reflect resource competition on all levels. Given these advantages, the model is a workhorse tool that is routinely used to simulate country-level economy-wide adjustments in response to various scenarios, including climate change studies (e.g. Arndt and Thurlow, 2014, Arndt et al. 2014 and Siddig et al., 2020).

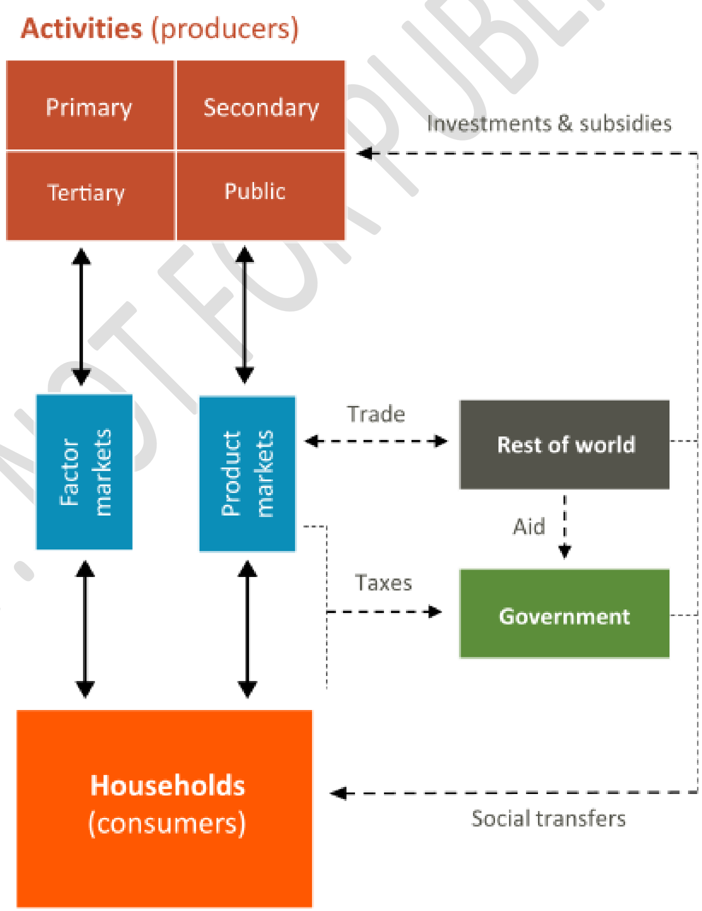
A brief description of the standard IFPRI CGE CGE model tailored to the case of Malawi is presented in Table 4.

Table 4. Specification of the Malawian CGE model

a. Functional forms (long-term simulations)

Block	Category	Form/closure (endogenous variables)
Activities	Value-added	Constant Elasticity of Substitution (CES)
	Intermediate	Leontief
	Top nest	Leontief
Trade	Import	CES
	Export	Constant Elasticity of Transformation (CET)
Households	Consumption	Linear Expenditure System (LES)
Closures	Numeraire	The Consumer Price Index is fixed (domestic producers' price level is flexible)
	Rest of the World	the current account balance and world market prices are given exogenously (exchange rate
	Government	Fixed government tax rates; (dis)savings adjust to available net revenues;
	Savings/Investment	balanced investment-driven closure (SI-5, see Lofgren et al., 2002 for details)
	Factors	Labor and land: fully employed and mobile; Capital: 'putty clay';

b. Scheme of the flows in the CGE model



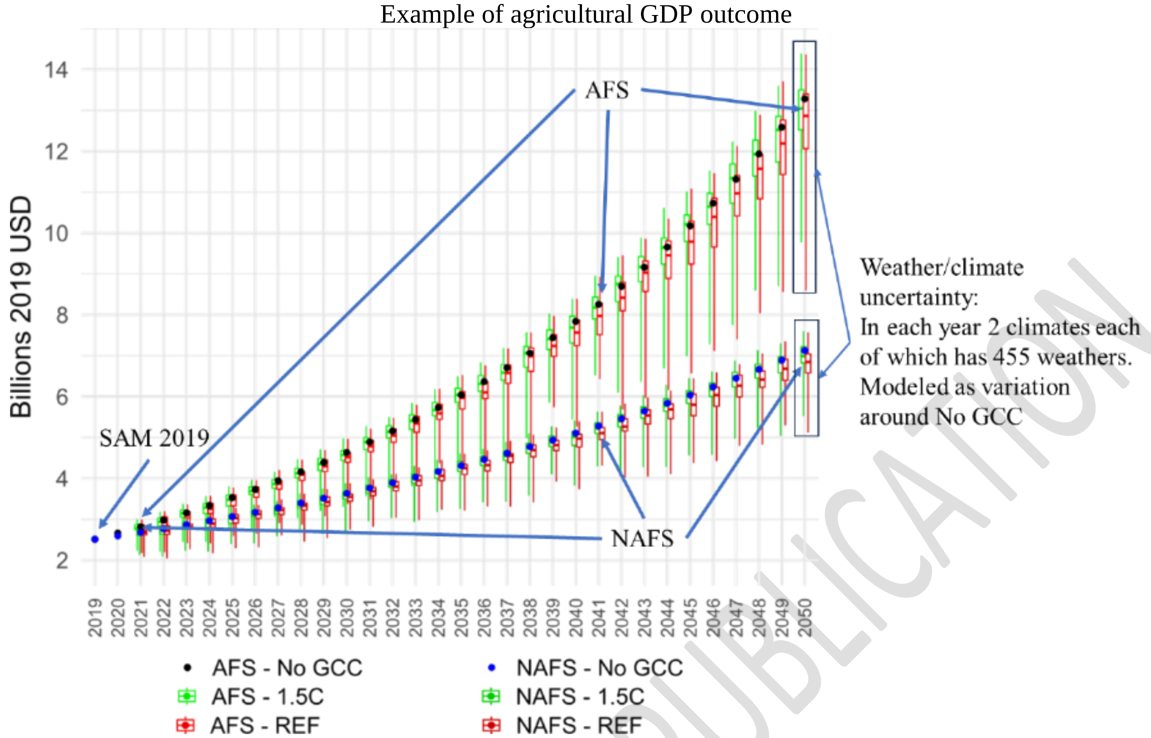
Source: own elaborations.
Note: the detailed statements of the equations can be found in Lofgren et al. (2002), and Diao and Thurlow (2012); the description of satellite poverty and undernourishment microsimulation modules can be found in Pauw and Thurlow (2011).

Base year SAM[2]**.** The constructed Malawian SAM[3] is used as primary data input to the Malawian CGE model. The SAM utilizes the latest available information and reflects the detailed snapshot of the flows across the Malawian economy for the year 2019 (which accordingly, becomes the base/start year of our simulations). In particular, our SAM consists of 203 accounts, of which 82 are activities, 83 are commodities, 13 are primary factors (labor, capital, and land), and 15 are households.

The general design of simulations. Figure 3 represents a schematical representation of our model simulations' design. Most importantly, it is necessary to make an explicit distinction between long-term development strategy scenarios and weather/climate crop productivity scenarios. The development strategy block, besides the implicit Business-As-Usual (BAU) scenario[4], consists of two intensive development scenarios: development via AFS sectors versus development via NAFS sectors. In this context, it should be noted that we do not use the standard counterfactual approach often met in CGE analysis (where outcomes of the baseline scenario serve as a reference). Instead, we focus on absolute levels and each of the development scenarios is modeled as uncertain (and the driver of the uncertainty is weather/climate-driven variation of crop productivity).

[2] A detailed explanation of context-relevant SAM data concept can be found in Pyatt and Round (1985) and Breisinger et al. (2009).
[3] The constructed SAM is available from the authors upon request.
[4] Given the space constraints of the paper, we omit the BAU scenario from the discussion.

Figure 3: Design of model simulations
Example of agricultural GDP outcome



Source: own elaborations.

Development scenarios. We select 2050 as our simulation horizon and focus on average outcome levels achieved in the decades of the 2020s and the 2040s (referred to as short and long terms respectively). Given our focus on the outcome levels and long-term simulation horizon, the specification of real GDP growth components plays an essential role, and in what follows, we describe the respective CGE model parameters (exogenously specified growth of primary factors and TFP in the dynamic component of the model).

(Implicit) BAU development scenario. In the context of mediocre and volatile past performance (see Table 1d), as well as concerns expressed in the Systematic Country Diagnostic report by the World Bank (2018) regarding Malawi's future economic development, we assume that under the BAU scenario, the country will grow at approximately 1 % per annum (p.a.) per

capita, and the GDP growth components will be distributed as follows: TFP: 1 % p.a. (across all sectors); Labor (and land): 2 p.a.; Capital: 2% p.a.[5].

Intensive development scenarios. Then, instead of BAU economywide TFP growth of 1% p.a., our intensive development scenarios assume weighted average (economywide) TFP growth of 2% p.a. Then, the difference between the two alternative scenarios is the sectoral distribution of the additional TFP growth. In particular, under the AFS scenario, we assume that the additional 1% of economywide TFP growth is achieved via the sectors associated with agriculture (uniform distribution across primary agriculture, agro-processing, and food services (e.g. hotels and restaurants)). Alternatively, under the NAFS scenario, we assume that the TFP boost is achieved via the sectors associated with (other) industrial and service sectors (except public administration). Then, because of the different means of achieving similar economy-wide TFP growth, the two scenarios can be compared across the dimensions of their varying outcomes[6]. In particular, Figure 3 which explains our simulation design, demonstrates that the two scenarios are significantly different in terms of agricultural GDP levels.

Weather/climate uncertainty. The weather/climate crop productivity uncertainty block consists of 455 yearly weather scenarios for each of the two climate change scenarios. Importantly, we assume that in the long term, the reallocation of factors in the economy follows the long-term fundamental factors as if there is no climate/weather-associated uncertainty (No GCC scenario in Figure 3). Then, weather/climate uncertainty is modeled as a possible variation around this No GCC long-term development trajectory. In particular, we assume that land in the long adjusts according to the long-term fundamentals, but in the short term (yearly variation),

[5] Under the balanced investment-driven closure 5 (see Lofgren et al., 2002 for details) and "putty clay" assumption for new capital allocation (the distribution of new capital (generated by the total investment of the previous year) depends on relative rents (sectors with higher rents receive more capital increase, see Diao and Thurlow (2012) for more details.

[6] The strong implicit assumption is that in Malawi the technological development is homogenous across all sectors, and that sectors of the same size for the same budget will get the same TFP increase.

land is immobile across agricultural activities. In other words, we assume that the land is (re)allocated in line with long-term rents and short-term weather/climate fluctuations do not affect this fundamental adjustment process.

Post-simulation imputation of uncompleted simulations. Finally, it should be noted that in some instances our specified CGE model and its implementation in General Algebraic Modeling System (GAMS) cannot find a (feasible) numeric solution. Most of the time the model's inability to find the solution is associated with the magnitude of negative yield shocks of particular crops. For example, in some years most extreme scenarios originally defined by Thomas et al. (2022b) assume more than 90% yield reduction of soybeans. To accommodate these shocks, our specified CGE model has to look for numerical solutions in the unfeasible domain[7]. In this context, to avoid truncation of the distributions in the domain of unsolved cases (depending on the year, reaches ca. 1% of weather scenarios), we decided to impute these missing/unsolvable simulations. In doing so, we use the following approach: 1. For each year and climate scenario, we select the lowest 25 percentile of complete cases 2. We (linearly) regress outcome variables on the weighted average crop weather/climate index of complete cases (the explanatory power of this simple CGE emulator, depending on the year, scenario, and the outcome variable, varies from R sq. = 0.64 to R. sq. 0.95). 3. We project outcomes of the unsolved simulations using their weighted average crop climate/weather index (for the unsolved year) and estimated relationship.

We suppose that this ad-hoc approach is sufficient to conduct *the comparison* of the complete distributions of our outcome variables associated with the AFS and NAFS strategies. At the same time, it should be emphasized that this imputation approach might be insufficient/inappropriate if the behavior of the economic system under the extreme case

[7] E.g., turn the value-added activity price of the affected crop sector negative.

scenarios itself becomes a goal of a study (in this case, one would require a completely different modeling approach which is beyond the focus of this study).

4. Simulation results: climate uncertainty does not change the narrative

Given our focus on key developmental aspects of agriculture versus non-agriculture in the context of Malawi's development agenda, we present the results associated with three key outcome variables - real per capita GDP, poverty, and undernourishment rates. These results are depicted in Figures 4-6. The first subfigures (a) display yearly dynamics over time (boxplots for each climate and year), and the second subfigures (b) represent the SD analysis of outcomes in the 2020s and 2040s (CDFs of average decadal levels for each development strategy and climate).

It should be noted that we use the term 'stochastic dominance' to refer exclusively to first-order stochastic dominance. By its definition, first-order stochastic dominance of X over Y means that X must have at least as high a probability of reaching a particular outcome as Y for any given realization of an uncertainty scenario (for more details, refer to Levy, 1992). In our context, 'stochastic dominance' implies that strategy X yields a better outcome than strategy Y, with 'better', depending on the context, meaning higher outcomes (e.g., per capita GDP) or lower outcomes (e.g., poverty levels).

Most crucially, the NAFS strategy is associated with higher GDP per capita levels. Under the assumption of constant weather/climate (No GCC, Figure 4a), NAFS gradually outperforms the AFS and by 2050, the difference reaches 15.81%. This is primarily because NAFS sectors have more substantial downstream economy-wide linkages than AFS, and their increased productivity has many indirect benefits. For instance, enhanced productivity of crucial industrial intermediates as well as trade and transport means that all sectors of the economy benefit from increased production and lower prices. Similarly, enhanced productivity and lower prices of

NAFS investment sectors (e.g., construction) particularly benefit capital accumulation, resulting in higher GDP levels in the long term.

Incorporating climate-associated uncertainty into the comparison does not alter the GDP per capita ranking of the two options. As evident from Figure 4b, both NAFS climate trajectories (dashed lines) stochastically dominate their AFS counterparts (solid lines). In the 2020s, the differences are marginal (depending on the weather and climate, in the 2020s NAFS outperforms AFS by only 0%-0.51%); however, by the 2040s, the difference significantly widens and, depending on the weather and climate, reaches 10.01%-13.70%.

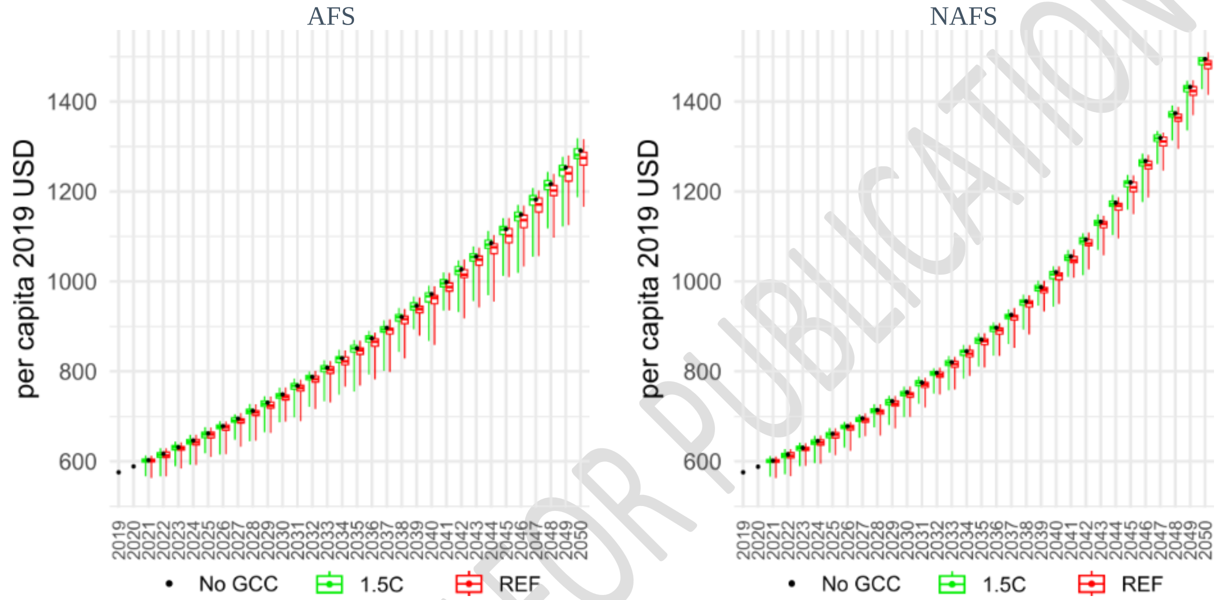
At the same time, it should be noted that AFS uncertainty is higher than that of NAFS. Under the AFS strategy, the GDP difference between the most and least favorable weather/climate scenarios (min-max variation) for AFS by 2050 reaches 13.06%, which is substantially higher than the min-max variation of only 7.18% under NAFS. This is because the strategies have different impacts on the economic weights of the crop sector, which is the driving force of the weather/climate uncertainty in our simulations. Specifically, the NAFS strategy over the years reduces the share of the crop sector (from 20.43% of GDP in 2019 to 12.51% in 2050), while AFS increases the share of the crop sector (from 20.43% of GDP in 2019 to 26.13% in 2050). As a result, the two strategies have varying exposure to weather/climate uncertainty, with the NAFS strategy being more inert than AFS. In this context, it's worth noting that although the variation between the two climate scenarios within the same development scenario, in general, is marginal (1.5C versus REF), AFS and NAFS have important differences. In particular, although in both AFS and NAFS, the 1.5C scenario is always better than its REF counterparts (Figure 4b), AFS is characterized by a higher climate sensitivity. Depending on the weather scenario, in the 2020s, the difference between 1.5C and REF under AFS development varies from 0% to -0.5%

(compared to 0%-0.4% for NAFS), and by the 2040s, it increases to -0.3% to -3.1% (compared to -0.1% to -1.8 % for NAFS).

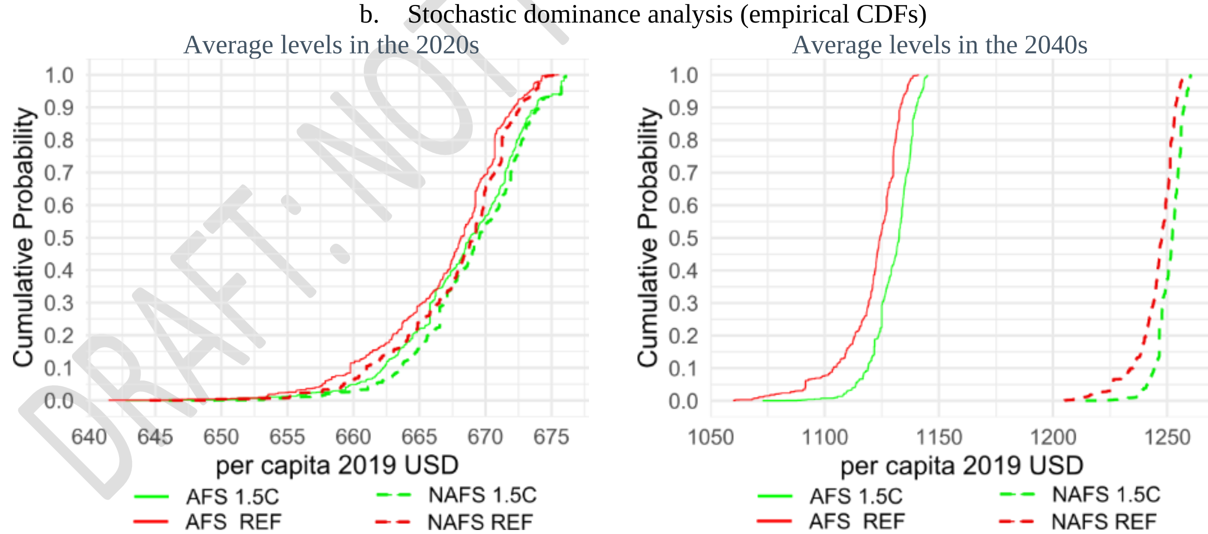
In conclusion, it can be stated that NAFS is characterized by higher and more certain GDP per capita outcomes.

Figure 4: Simulation results: GDP per capita

a. Level dynamics over the years



b. Stochastic dominance analysis (empirical CDFs)



Source: Own estimations.

National poverty headcount rate (Figure 5)

Despite the high dependence between GDP and household disposable income, poverty results do not repeat patterns observed in GDP per capita outcomes, and AFS tends to outperform

NAFS. In particular, assuming constant weather/climate (No GCC, Figure 5a), AFS is constantly better than NAFS, and by 2050, the share of the poor population under AFS is 2.75 % lower than under NAFS (equivalent to additional 910 thousand Malawians pulled out of poverty). Similar to other studies (e.g. Diao et al., 2010, Valdes and Foster, 2010; Klasen and Reimers, 2017) this difference can be primarily attributed to deeper pro-poor linkages of agriculture. In the context of our CGE model, the difference between the two strategies can be attributed to the following factors. 1. Increased TFP of agricultural sectors directly raises the incomes of rural farmers, who are the poorest in Malawi 2. Increased production leads to cheaper prices which particularly benefit the poor, both urban and rural 3. Increased TFP of AFS sectors means that AFS sectors require less labor, enabling the agricultural labor force to shift to urban sectors where their labor is the most needed. In other words, increased TFP of AFS has a more pronounced effect on the structural transformation than NAFS (for more details, see Rodrick 2015).

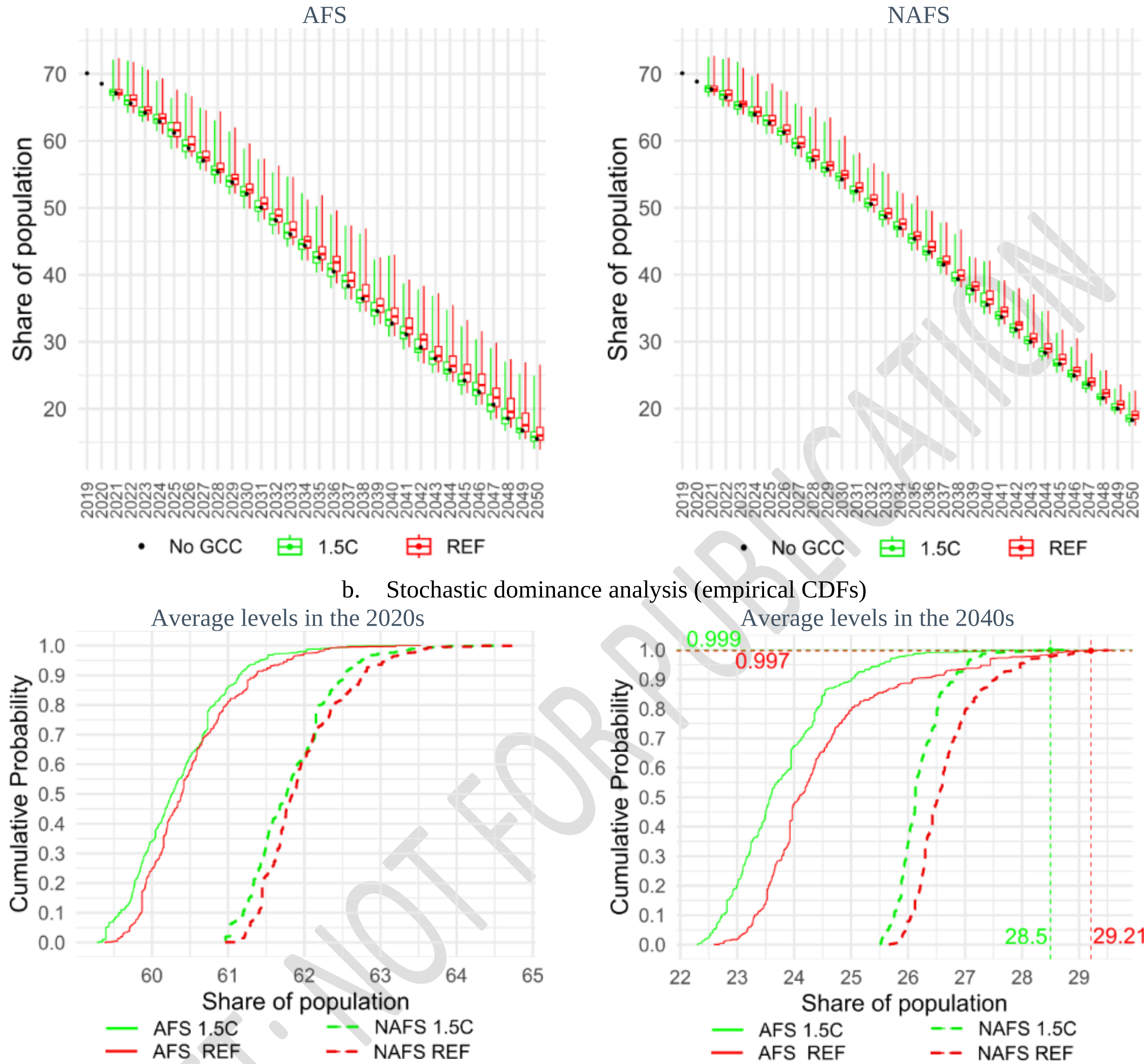
Introducing weather/climate-associated uncertainty into the comparison complicates the picture. As the share of crop sectors is growing with time under the AFS strategy, the economy is becoming more exposed to weather/climate uncertainty and poverty results are becoming more uncertain. The effect is particularly pronounced in the long term. By 2050, under the most favorable weather/climate conditions, the poverty rate of AFS can reach 13.83%, and under the worst weather/climate scenario, the poverty rate can be at 26.6% (see Figure 5a, AFS). This range is much wider than NAFS, which ranges from 22.68% under the worst and 17.36% under the best weather/climate (Figure 5a, NAFS).

At the same time, the SD analysis of decadal averages (Figure 5b) reveals further important details. Particularly, in the 2020s, AFS is characterized by robustly lower poverty rates than NAFS across all possible weathers (solid versus dashed in left Figure 5b). By the 2040s, as AFS is becoming more exposed to weather/climate shocks, and the magnitude of the shocks themselves is becoming more severe (see Section 3.2), AFS is no longer robustly superior to NAFS (solid versus dashed counterparts in right Figure 5b). However, it's important to emphasize that NAFS CDFs intersect AFS CDFs at the very extreme worst-case scenarios. Specifically, under the 1.5C scenario, AFS intersects NAFS at a 0.999 cumulative probability, and under the REF scenario, the intersection is at a 0.997 cumulative probability. Assuming both 1.5C and REF climate scenarios are equally possible, we can calculate an average of 0.9985 cumulative probability and conclude that for 99.85% of possible weather/climate scenarios, AFS will have lower poverty levels than NAFS. In other words, NAFS can outperform AFS in terms of poverty reduction only under 0.15% of all weather/climate scenarios that assume extremely low crop yields. At the same time, it should be emphasized that the distance between the two strategies increases with the weather scenarios getting more favorable. In particular, in the 2040s, under the worst 5% weathers (cumulative probability=0.95), the difference between AFS and NAFS is 1.53% for the 1.5C climate and only 0.25% for the REF climate; for median weather (cumulative probability=0.5), the difference between AFS and NAFS reaches 2.55% for 1.5C and 2.04 % for REF climates; under the most favorable weather (cumulative probability=0), difference reaches 3.21% and 2.91% for 1.5C and REF respectively. In other words, the rate of AFS outperformance of NAFS depends on climate/weather conditions, and the further weather/climate will be from negative extremes, the better will be the AFS's outperformance.

In conclusion, it can be stated that AFS is characterized by lower poverty levels than NAFS for almost all weather/climate scenarios.

Figure 5: National poverty headcount rate

a. Level dynamics over the years



Source: Own estimations.

National undernourishment headcount rate (Figure 6).

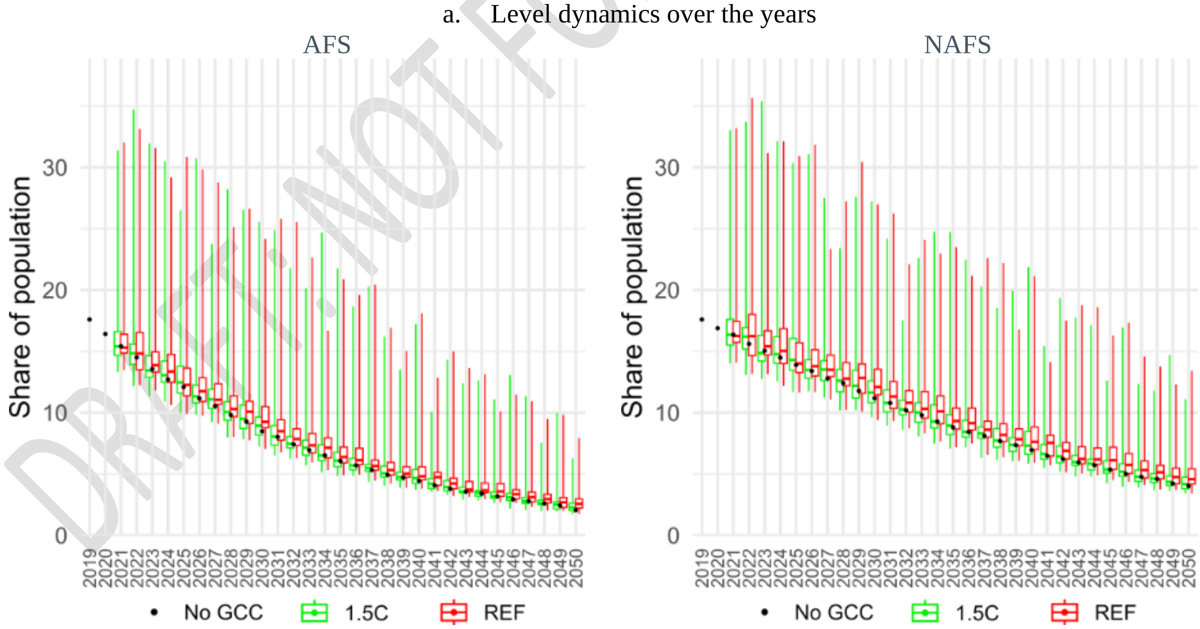
AFS unequivocally NAFS in terms of better undernourishment results (with or without weather/climate uncertainty, both in the short and long term). This is mostly because increased TFP in AFS sectors leads to increased domestic production and a consequent decrease in food prices, which improves food accessibility. As a consequence, the rise in calorie intake among undernourished households is much higher under the AFS strategy compared to NAFS (where food consumption primarily increases due to increased incomes). The decline in undernourishment rates under the AFS is so significant that the escalating severity of climate/weather scenarios is not sufficient to notably affect its undernourishment levels. Thus, both in the short and long term, AFS is robustly superior (stochastically dominant) to NAFS.

Furthermore, it is noteworthy that the distance between respective CDFs is relatively constant for all decades and scenarios except for REF in the 2040s (Figure 6b). Deterioration of NAFS undernourishment levels under more severe weathers of the REF scenario in the 2040s becomes particularly pronounced, and under 5% of the most extreme REF weathers, NAFS can have two times more undernourished levels than its AFS counterpart (Figure 6, right, cumulative distribution >0.95).

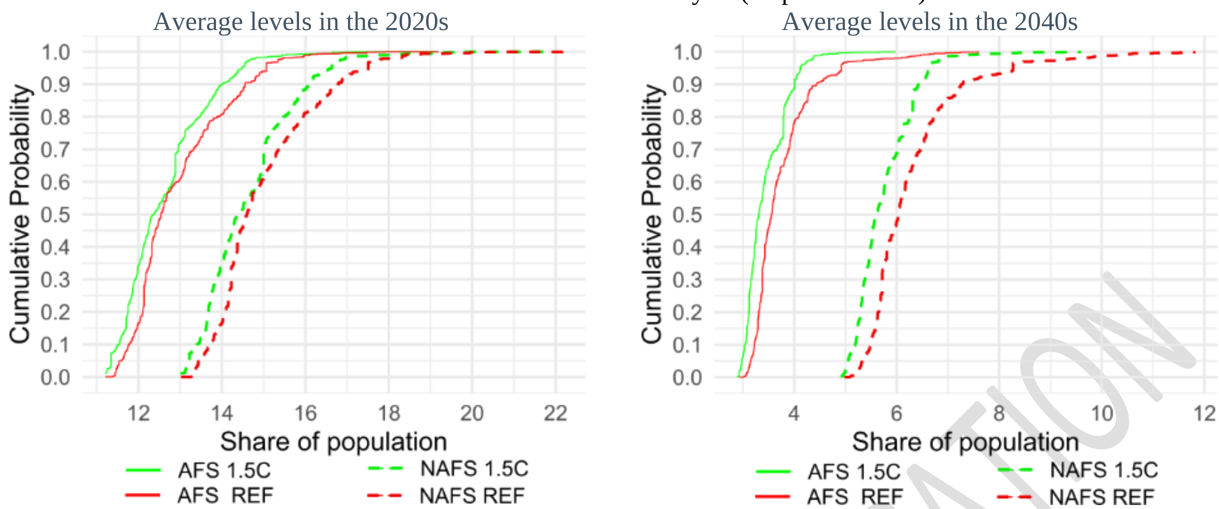
In summary, it can be concluded that for 100% of potential weather/climate scenarios, AFS will yield lower undernourishment levels than NAFS, and under very negative weather/climate scenarios, the superiority of AFS can be highly significant.

Figure 6: National undernourishment headcount rate

a. Level dynamics over the years



b. Stochastic dominance analysis (empirical CDFs)



Source: Own estimations.

5. Conclusion

Our study has employed an innovative approach to comparing two potential development strategies in the context of uncertain climate projections for Malawi, a country heavily reliant on its climate-sensitive agricultural sector. Specifically, we used elements of SD theory to examine the uncertainties associated with AFS and NAFS growth strategies driven by weather/climate crop yield variation.

We demonstrate that despite the higher weather/climate-associated economic uncertainty, the AFS development trajectory leads to lower poverty rates and decreased levels of undernourishment (exhibiting stochastic dominance across almost all weather and climate scenarios). It is crucial to note that we model variation of weather/climate-related productivity of crop sectors only and we do not consider potentially buffering climate adaptation measures within agriculture itself. This means that overall, we probably overestimate the relative uncertainty of AFS versus NAFS. However, even with that, AFS outperforms NAFS in terms of both poverty and undernourishment reduction. In the context of the multifaceted vision of the 'Malawi 2063' national development plan, which equally emphasizes the development of agriculture, industrialization, and services (World Bank 2021), our findings thus underscore the clear benefits of prioritizing an agriculture-led development path for Malawi, even without climate adaptation measures.

In light of these findings, it becomes essential to pursue further deeper-level research and consider trade-off aspects of climate adaptation options within agriculture. Several micro-level studies have already begun to investigate specific aspects of various climate adaptation strategies within Malawi's agricultural sector. For example, Amadu et al. (2020a) developed a typology of farm-level Climate-Smart Agriculture practices in southern Malawi, and Amadu et al. (2020b) analyzed the effects of climate-smart agricultural aid investment on maize yields. Sitko et al. (2021) used household-level data and analyzed climate-adaptive agricultural practices in the context of households' risk perception leverage through receiving food aid. At the same time, such studies, while offering valuable insights based on ex-post micro-level empirical evidence on certain climate adaptation methods in agriculture, cannot fully reflect a complete picture of policy trade-offs. A relevant example is the study by Warnatzsch and Reay (2020), who used a crop model to highlight how the uncertainty about future precipitation is associated with maladaptation risk for maize cultivars in Malawi. The authors stressed the need for more reliable precipitation projections for proper decision-making. However, given the inherent uncertainty of weather and climate scenarios themselves, the emergence of 'robust precipitation projections' is doubtful. In this context, our suggested methodology of comparing uncertain competing options via the means of SD can be extended and used in these kinds of deeper-level studies.

References

Amadu, Festus O., Paul E. McNamara, and Daniel C. Miller. 2020. "Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi." *World Development* (Elsevier BV) 126: 104692. doi:10.1016/j.worlddev.2019.104692.

Amadu, Festus O., Paul E. McNamara, and Daniel C. Miller. 2020. "Yield effects of climate-smart agriculture aid investment in southern Malawi." *Food Policy* (Elsevier BV) 92: 101869. doi:10.1016/j.foodpol.2020.101869.

Arndt, C., A. Schlosser, K. Strzepek, and J. Thurlow. 2014. "Climate Change and Economic Growth Prospects for Malawi: An Uncertainty Approach." *Journal of African Economies* (Oxford University Press (OUP)) 23: ii83–ii107. doi:10.1093/jae/eju013.

Arndt, Channing, and James Thurlow. 2014. "Climate uncertainty and economic development: evaluating the case of Mozambique to 2050." *Climatic Change* (Springer Science and Business Media LLC) 130: 63–75. doi:10.1007/s10584-014-1294-x.

Breisinger, C., M. Thomas, and J. Thurlow. 2009. *Social accounting matrices and multiplier analysis An Introduction with Exercises.* International Food Policy Research Institute. doi:10.2499/9780896297838fsp5.

Diao, Xinshen, and James Thurlow. 2012. "A recursive dynamic computable general equilibrium model." Chap. 2 in *Strategies and priorities for African agriculture : economywide perspectives from country studies*, edited by Xinishen Diao, James Thurlow, Samuel Benin and Shenggen Fan, 17-50. International Food Policy Research Institute. doi:10.2499/9780896291959.

Diao, Xinshen, Peter Hazell, and James Thurlow. 2010. "The Role of Agriculture in African Development." *World Development* (Elsevier BV) 38: 1375–1383. doi:10.1016/j.worlddev.2009.06.011.

Dubčáková, Renáta. 2010. "Eureqa: software review." *Genetic Programming and Evolvable Machines* (Springer Science and Business Media LLC) 12: 173–178. doi:10.1007/s10710-010-9124-z.

FAO. 2023. "FAO stat." Database, Food and Agriculture Organization. http://www.fao.org/faostat/en/#home. Accessed Date: January 31, 2023

Klasen, Stephan, and Malte Reimers. 2017. "Looking at Pro-Poor Growth from an Agricultural Perspective." *World Development* (Elsevier BV) 90: 147–168. doi:10.1016/j.worlddev.2016.09.003.

Levy, Haim. 1992. "Stochastic Dominance and Expected Utility: Survey and Analysis." *Management Science* (INFORMS) 38: 555–593. http://www.jstor.org/stable/2632436.

Löfgren, Hans, Rebecca Lee Harris, and Sherman Robinson. 2002. "A Standard Computable General Equilibrium (CGE) Model in GAMS." Microcomputers in Policy Research 5, International Food Policy Research Institute. http://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/74845/filename/74846.pdf.

Manski, Charles F. 2018. "Communicating uncertainty in policy analysis." *Proceedings of the National Academy of Sciences* (Proceedings of the National Academy of Sciences) 116: 7634–7641. doi:10.1073/pnas.1722389115.

Manski, Charles F. 2011. "Policy Analysis with Incredible Certitude." *The Economic Journal* (Oxford University Press (OUP)) 121: F261–F289. doi:10.1111/j.1468-0297.2011.02457.x.

Marinacci, Massimo. 2015. "MODEL UNCERTAINTY." *Journal of the European Economic Association* (Oxford University Press (OUP)) 13: 1022–1100. doi:10.1111/jeea.12164.

Mukashov, A. 2023. "Parameter uncertainty in policy planning models: Using portfolio management methods to choose optimal policies under world market volatility." *Economic Analysis and Policy* (Elsevier BV) 77: 187–202. doi:10.1016/j.eap.2022.11.007.

Pauw, Karl, and James Thurlow. 2011. "Agricultural growth, poverty, and nutrition in Tanzania." *Food Policy* (Elsevier BV) 36: 795–804. doi:10.1016/j.foodpol.2011.09.002.

Pyatt, Graham, and Jeffrey I. Round. 1985. *Social accounting matrices : a basis for planning.* Washington, D.C., U.S.A: World Bank.

Schmidt, Michael, and Hod Lipson. 2009. "Symbolic Regression of Implicit Equations." In *Genetic Programming Theory and Practice VII*, 73–85. Springer US. doi:10.1007/978-1-4419-1626-6_5.

Siddig, Khalid, Davit Stepanyan, Manfred Wiebelt, Harald Grethe, and Tingju Zhu. 2020. "Climate change and agriculture in the Sudan: Impact pathways beyond changes in mean rainfall and temperature." *Ecological Economics* (Elsevier BV) 169: 106566. doi:10.1016/j.ecolecon.2019.106566.

Sitko, Nicholas J., Antonio Scognamillo, and Giulia Malevolti. 2021. "Does receiving food aid influence the adoption of climate-adaptive agricultural practices? Evidence from Ethiopia and Malawi." *Food Policy* (Elsevier BV) 102: 102041. doi:10.1016/j.foodpol.2021.102041.

Thomas, Timothy S., C. Adam Schlosser, Kenneth Strzepek, Richard D. Robertson, and Channing Arndt. 2022. "Using a Large Climate Ensemble to Assess the Frequency and Intensity of Future Extreme Climate Events in Southern Africa." *Frontiers in Climate* (Frontiers Media SA) 4. doi:10.3389/fclim.2022.787721.

Thomas, Timothy S., Richard D. Robertson, Kenneth Strzepek, and Channing Arndt. 2022. "Extreme Events and Production Shocks for Key Crops in Southern Africa Under Climate Change." *Frontiers in Climate* (Frontiers Media SA) 4. doi:10.3389/fclim.2022.787582.

Valdés, Alberto, and William Foster. 2010. "Reflections on the Role of Agriculture in Pro-Poor Growth." *World Development* (Elsevier BV) 38: 1362–1374. doi:10.1016/j.worlddev.2010.06.003.

Warnatzsch, Erika A., and David S. Reay. 2020. "Assessing climate change projections and impacts on Central Malawi's maize yield: The risk of maladaptation." *Science of The Total Environment* (Elsevier BV) 711: 134845. doi:10.1016/j.scitotenv.2019.134845.

WB. 2021. "COUNTRY PARTNERSHIP FRAMEWORK FOR THE REPUBLIC OF MALAWI FOR THE PERIOD FY21-FY25." Tech. rep., World Bank. doi:https://doi.org/10.1596/35513.

WB. 2016. "El Nino Drought in SADC: Economic Impacts and Potential Mitigation Solutions." techreport, World Bank.

WB. 2018. "Malawi Systematic Country Diagnostic: Breaking the Cycle of Low Growth and Slow Poverty Reduction." Report, World Bank, Malawi Country Team, Africa Region. doi:https://doi.org/10.1596/31131.

WB. 2023. "World Development Indicators." Database. https://databank.worldbank.org/source/world-development-indicators. Accessed Date: January 31, 2023

Ziesmer, Johannes, Ding Jin, Askar Mukashov, and Christian Henning. 2023. "Integrating fundamental model uncertainty in policy analysis." *Socio-Economic Planning Sciences* (Elsevier BV) 87: 101591. doi:10.1016/j.seps.2023.101591.

A1: Imputation of the climate-driven yield variability of missing crops

Thomas et al. (2022b) provide estimates of weather/climate-associated crop yield variation scenarios for five key crops: maize, drybeans, groundnuts, soybeans, and sorghum. To impute the climate-driven yield variability for remaining crops, we use FAO estimations on historical yields in Malawi (FAO 2023) and utilize the following conventions:

1. We use the 2003-2020 historical range (for many crops data before 2003 doesn't exist)
2. Our SAM has aggregated accounts for certain groups of crops (e.g. vegetables). To approximate these crops, instead of using weighted averages, we select the FAO crops with the most consistent and reliable data. For instance, as a proxy for yield variation of vegetables, we select FAO data on green peas (other vegetables such as tomatoes, have data consistency problems).
3. We are focused on weather/climate factors. In this context, we filter out linear trends from FAO yield estimates and assume that historical yield variation around the linear trend was driven by weather/climate factors;
4. Similar to crops for which Thomas et al. (2022b) provide estimates, we normalize the yields and use relative indices (100 reflects that zero impact of weather/climate factors; the yield was on the trend).
5. Because our goal is to specify climate-driven yield variability for remaining crops (and not make any fundamental inferences), we are focused only on prediction accuracy (R squared). In this context, we utilize the automated software Eureqa (for a brief review, see Dubcakova, 2010) and Schmidt and Libson, 2009) and run (full) quadratic polynomial regressions where endogenous variables are missing crops and covariates are maize, drybeans, groundnuts, soybeans, and sorghum. As a result, we select the following regressions:

Table A1: Imputation formulas of missing crops

CGE	FAO	R^2	Formula/note
crice	Rice	0.85	crice = 3.67 + 0.59*coils + 0.27*csorg + 0.12*cmaiz
ccass	Cassava, fresh	0.62	ccass = 98.53 + 0.0026*cgnut^2 - 0.25*coils
cipot	Potatoes	0.64	cipot = 51.95 + 0.49*coils
ctoba	Unmanufactured tobacco	0.75	ctoba = 39.51 + 0.61*cgnut
cplan	Plantains and cooking bananas	0.66	cplan = 80.21 + 1.40*csorg + 1.07e-6*csorg^2*coils^2 - 0.009*csorg*coils - 0.0001*coils*csorg^2
cnuts	Other nuts n.e.c.	0.63	cnuts = 114.70 + 0.11*csorg + 0.10*cmaiz + 0.0028*cpuls^2 - 0.48*cpuls - 0.0012*csorg*puls - 0.0003*cmaiz^2
cleaf	Cabbages	0.55	cleaf = 215.46 + 0.287*cpuls + 0.19*csorg + 0.03*cmaiz*cgnut - 2.87*cgnut - 0.006*cmaiz*cpuls - 0.01*cmaiz^2
cvege	Peas, green	0.81	cvege = 85.12+ 0.66*coils + 0.04*csorg*cgnut + 0.003*cpuls*cgnut - 2.29*csorg - 0.009*cgnut^2 - 0.0002*csorg*cgnut^2
ccott	Seed cotton, unginned	0.74	ccott = 227.25 + 0.0008*csorg*coils^2 - 0.05*coils^2 - 0.0004*coils*csorg^2
cfrui	Other fruits, n.e.c.	0.53	cfrui = 99.86 + 0.02*coils + 0.0002*cgnut^2 - 0.001*cmaiz - 0.01*cgnut - 0.0002*cgnut*coils
cocrp	Other stimulant, spice and aromatic crops, n.e.c.	0.76	cocrp = 81.10 + 0.05*csorg + 0.0003*cpuls + 0.004*cpuls*coils + 4.13e-5*csorg*cgnut*coils - 2.94e-5*cpuls*csorg^2 - 4.06e-5*cgnut*coils^2
csugr	Sugar cane	-	FAO data problems - use cocrp formula
cteal	Tea leaves	-	FAO data problems - use cocrp formula
ccoff	Coffee, green	-	FAO data problems - use cocrp formula
cbana	Bananas	-	FAO data problems - use cplan formula
cspot	Sweet potatoes	-	FAO data problems - use cipot formula

Source: own elaborations.