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Integrating climate prediction and regionalization into an agro-economic model to guide agricultural planning

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Abstract
Advanced skill in seasonal climate prediction coupled with sectoral decision models can provide decision makers with opportunities to benefit or reduce unnecessary losses. Such approaches are particularly beneficial to rainfed agriculture, the livelihood choice for the majority of the world's poor population, for which yields are highly sensitive to climate conditions. However, a notable gap still exists between scientific communities producing predictions and the end users who may actually realize the benefits. In this study, an interdisciplinary approach connecting climate prediction to agricultural planning is adopted to address this gap. An *ex ante* evaluation of seasonal precipitation prediction is assessed using an agro-economic equilibrium model to simulate Ethiopia's national economy, accounting for interannual climate variability and prediction-guided agricultural responses. Given the high spatial variability in Ethiopian precipitation, delineation of homogeneous climatic regions (i.e., regionalization) is also considered in addition to growing season precipitation prediction. The model provides perspectives across various economic indices (e.g., gross domestic product, calorie consumption, and poverty rate) at aggregated (national) and disaggregated (zonal) scales. Model results illustrate the key influence of climate on the Ethiopian economy, and prospects for positive net benefits under a prediction-guided agricultural planning (e.g., reallocation of crop types) strategy, as compared with static business-as-usual agricultural practices.

1 Introduction

Climate plays a critical role in agriculture, effecting planting dates; investment decisions such as seeds, fertilizer, and insurance procurement; and in-season management. Advanced skill in seasonal

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climate prediction coupled with sectoral decision models can provide decision makers with opportunities to benefit or reduce unnecessary losses. Such approaches are particularly beneficial to rainfed agriculture, the livelihood choice for the majority of the world's poor population, for which yields are highly sensitive to climate conditions. Literature exploring how climate variability influences agriculture surveys and interviews characterizing farmer perspectives, and implementation and outcomes demonstrate the demand for climate prediction and its substantial potential benefit to agriculture and the whole economy (e.g., Alexandrov and Hoogenboom 2000; Palosuo et al. 2011; Patt et al. 2005; Roncoli 2006; Roncoli et al. 2009; Semenov and Porter 1995). However, a notable gap still exists between scientific communities producing predictions and the end users who may actually realize the benefits. Factors such as predictions being too general, communication failure, lack of governmental or institutional support, little access to information, low capacity to respond, and data scarcity have constrained the widespread application and uptake of seasonal prediction information, particularly for smallholder farmers in less-developed countries (Broad and Agrawala 2000; Hansen 2002; Hansen et al. 2011).

An interdisciplinary approach connecting climate prediction to agricultural planning may help to fill this gap, particularly when the information is tailored and communicated in a manner relevant to decision makers. An *ex ante* evaluation of a coupled prediction system can indicate a quantitative measurement of expected sectoral benefits given a range of potential response strategies—a more agricultural-centric image than purely climate predictions alone. An *ex ante* evaluation of seasonal prediction may also be beneficial beyond providing actionable information to users by broadly drawing attention to smallholder farmers and institutions, and subsequently supporting mobilization of funds and strategic planning in times of expected risk and need. Additionally, it can guide policy and decision makers in resource allocation based on simulated net benefits specific to varying stakeholder priorities (Meza et al. 2008; Thornton 2006). Thus, institutional processes could become more supportive of seasonal prediction, alleviating key factors that impede successful applications.

A number of studies explore the expected economic value of seasonal climate forecasts on agricultural systems at varying scales; a summary of relevant literature can be found in Meza et al. (2008). Many studies focus on the value of El Niño Southern Oscillation (ENSO)–based forecasts (e.g., Adams et al. 2003; Hammer et al. 1996; Letson et al. 2005; Marshall et al. 1996; Messina et al. 1999; Solow et al. 1998), while only a few investigate the value of seasonal precipitation predictions and none addresses country-level outcomes (Jones et al. 2000; Katz et al. 1987; Mjelde et al. 1988; Wilks and Murphy 1986). Although the majority of studies focus on rainfed crops, they all emphasize intensification of modern technology (e.g., fertilizer, pesticide, degree of mechanization) and commercial agriculture in general; subsistence agriculture is consistently omitted (Meza et al. 2008).

In this study, an *ex ante* evaluation of seasonal precipitation prediction is assessed using an agro-economic equilibrium model to simulate Ethiopia's national economy, accounting for interannual climate variability and prediction-guided agricultural responses. Given the high spatial variability in Ethiopian precipitation, climate regionalization information is also considered in addition to growing season precipitation prediction. The model provides perspectives across various economic indices (e.g., gross domestic product, calorie consumption, poverty rate) at aggregated (national) and disaggregated (zonal) scales. Agricultural production, particularly the dominant subsistence farming, is explicitly modeled in this study. With 80% of the population living in rural areas and engaged in farming, there is a high susceptibility to the impacts of climate variability (Dixon and Segerson 1999; Hansen 2002; Oram 1989). This motivates an innovative means of evaluating predictive information, which can serve as a foundation for communication, decision-making, and strategic planning.

2 Methods

The Ethiopian economy-wide multi-market model (EMM; Diao and Pratt 2007), originally developed by the International Food Policy Research Institute (IFPRI), is modified to (1) simulate the zonal to country-level economy with a dynamic (varying) climate and (2) evaluate climate prediction and regionalization (Zhang et al. 2016; Zhang et al. 2018) by comparing various economic outputs (GDP, food consumption, and poverty) for prediction-guided agricultural responses versus baseline (business as usual) agricultural planning.

2.1 Ethiopia's economy-wide multi-market model

The EMM (Diao and Pratt 2007) is an economy-wide, multi-market model with two aggregated sectors representing industry and service and a detailed structure of the agricultural sector, including 32 agricultural commodities (both crops and livestock). However, it does not explicitly model the backward and forward linkages between the two non-agricultural sectors and the agricultural sector (Supplementary Materials). The model is built on 56 administrative zones with available data. Supply and demand are modeled at the zonal (administrative) level to capture producer responses to the market. Agricultural supply is a function of yield and area, where yield is affected by climate factors. The zonal level demand functions reflect consumer's demand for each commodity given its market price and per capita income. Price elasticity, including own-price and cross-price elasticities, and income elasticity vary by zone and by commodity given income levels and consumption patterns. Per capita income is endogenously determined by dividing production revenue by population, allowing supply and demand to be linked at the zonal level. The EMM is benefit-only—intermediate inputs and their costs are omitted; thus, producer price is adjusted to represent the value added. Consequently, the aggregation of zonal supply at its value-added price equals the gross domestic product (GDP), differentiated as agricultural and non-agricultural GDP. Other output variables such as poverty rate and calories per capita per day are also calculated given zonal income levels and food consumption.

Multi-market linkages are established based on zonal price margins and national central market prices in Addis Ababa. The price margins between markets are determined according to the distance of each zone to Addis Ababa, representing the basic transportation costs. Food surplus zones (supply exceeds demand) face a lower commodity price than at the central market, with the difference being the marketing margins at equilibrium. Food deficit zones, in contrast, endure higher prices equal to the price at the central market plus the transportation costs. The model also captures international imports and exports with the assumption that the domestic and international commodities are perfect substitutes but distinguished by transportation and other market costs. For example, if the supply of maize decreases along with an increasing domestic price, the import of maize from other countries is only profitable when the domestic price exceeds the import parity price plus any transaction costs. Similarly, the domestic price of one commodity has to be low enough to trigger export. Consequently, the aggregated supply and demand of each commodity reach equilibrium at the national level.

The model is calibrated for the base year 2003, using data from national household surveys, agricultural sample surveys, geographic information system, and other national and regional data (Supplementary Materials). More detailed information about the EMM can be found in Diao and Pratt (2007).

2.2 Incorporating climate variability into the EMM (baseline)

Climate yield factors (CYFs; Block et al. 2008) represent the overall effect of climate on crop yield, based on the Yield Response to Water (Doorenbos and Kassam 1979), and Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements (Allen et al. 1998). The CYFs are calculated through a process-based crop growth model (Supplementary Materials). The model is particularly useful when water is the limiting factor (as in our study region) with highly varied spatial-temporal rainfall patterns and predominantly rainfed subsistence agriculture. The CYF for six staple crops in Ethiopia are modeled, including teff, maize, wheat, sorghum, millet, and barley.

CYF calculation takes gridded monthly climate data as inputs including elevation, cloud cover, temperature, diurnal temperature range, vapor pressure, and wind from the University of East Anglia's Climate Research Unit (CRU) (Harris et al. 2014). Reference evapotranspiration (ET_0) calculations based on these data are performed using the Penman-Monteith method (Allen et al. 1998). Consequently, each grid cell has a unique ET_0 value for each month in each year from 1983 to 2011. Potential crop evapotranspiration (ETC) for each crop in each grid cell is subsequently obtained by multiplying ET_0 by a crop-specific empirical constant, *Ks*. Gridded monthly precipitation observations from the National Metrology Agency (NMA) of Ethiopia (Dinku et al. 2014) and CRU (Harris et al. 2014) and soil data from the FAO Digital Soil Map of the World (FAO-UNESCO 1988) are used to obtain actual evapotranspiration (ETA) through a soil-water balance model (Allen et al. 1998). The CYF is then determined according to the ratio of ETA over ETC and a crop's sensitivity to limited water availability using *Ky*, a crop-specific empirical constant, where higher values indicate greater sensitivity to water scarcity (Eq. 1). Low ETA/ETC ratios and high sensitivity to water stress (*Ky*) produce relatively low CYF values, indicating a greater overall impact on crop yield due to water scarcity. The specific equation is provided below:

$$\mathrm{CYF} = 1 - Ky \cdot \left(1 - \frac{\mathrm{ETA}}{\mathrm{ETC}}\right) \tag{1}$$

CYF values range from 0 to 1. A CYF = 1 implies that yields are not limited by water stress, although limitation by other factors such as pests, soil fertility, and management skills is still possible. A CYF = 0.9 indicates a 90% yield based on water availability. A CYF = 0 indicates crop failure. Note that the calculation is performed for each crop stage—vegetative, flowering, yield formation, and harvest—spanning different months given varying *Ks* and *Ky* values. The lowest CYF across all stages in one annual cycle is retained as the final CYF; thus, each grid cell has one CYF value for each crop in each year.

Since the EMM operates at a zonal level, the gridded CYF values are converted to zonal values by overlaying zonal boundaries on the gridded region and calculating the area-weighted average of CYF in each zone.

In this study, the CYF values in each year are used to incorporate dynamic climate variability into the EMM, calibrated to the base year 2003, to create the baseline outputs (Fig. 1). As all other inputs are held constant, whereas climate variability is the only changing factor in the system, the baseline outputs reflect the economic influence due to climate variability only. Year-to-year effects are not carried over; thus, each year is an independent experiment without accounting for growth in population, crop area, etc.

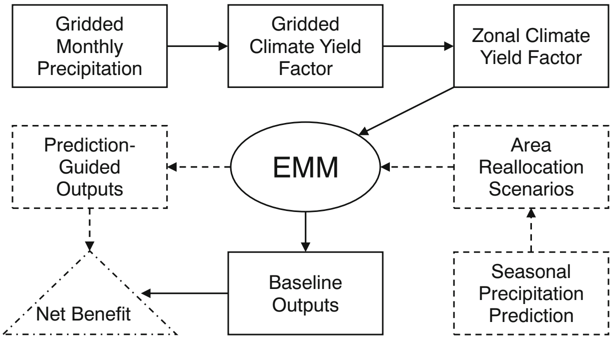

Fig. 1 Methodological flow chart. Solid lines indicate baseline simulation steps and dashed lines indicate prediction-based steps

Spatial average CYF values for the five staple crops (barley and sorghum are almost identical) illustrate that maize is the most sensitive to water stress and also has the largest year-to-year variability (Fig. 2). The lowest spatial average CYF for maize occurs in 2002, a notorious drought year in Ethiopia, with a value below 0.5, indicating expected yields of less than 50% of no water-limited conditions. In years with above-normal precipitations, the spatial average CYF values for maize range from 0.65 to 0.7 (zonal level CYF values range from near 0 to 1). In contrast to maize, teff is less sensitive to drought, illustrated by high CYF values ranging from 0.74 to 0.87 (Fig. 2).

2.3 Integrating seasonal prediction and regionalization

A regional-average seasonal prediction of June to September (JJAS) precipitation, representing the main rainy season and crop growing period in western Ethiopia, spanning 29 years (1983–2011) (Zhang et al. 2018) is applied here. Western Ethiopia is the dominant agricultural production region with 84.0% of the total population. The GDP and agricultural GDP in

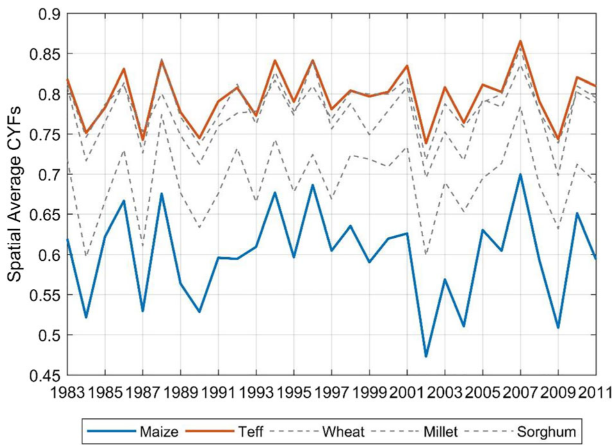

Fig. 2 Spatial average zonal climate yield factor (CYF) values over all 56 zones for five staple crops (color should be used for this figure in print)

western Ethiopia are 84.7% and 86.9% of the national GDP and agricultural GDP, respectively. A categorical prediction of above-normal, near-normal, and below-normal intervals is implemented to represent relatively wet, average, and relatively dry conditions. Intervals are selected such that one-third of the historical observations fall into each category. This categorical prediction format is consistent with the current operational seasonal forecasts issued by NMA in Ethiopia (Korecha and Sorteberg 2013). To account for the high spatial variability of JJAS seasonal precipitation in western Ethiopia, regionalization is provided with eight clusters considered homogeneous in precipitation (Fig. 3; Zhang et al. 2016). Zones that fall into the same cluster are likely to share the same climate conditions and therefore behave similarly in terms of expected net benefits. Zones that fall into one or more clusters are assigned to the cluster in which the greatest percent of its area falls. Overall, maize and teff represent approximately 20% and 16% of all agricultural land in Ethiopia, respectively. Agricultural land in western Ethiopia accounts for more than 90% of total country-wide agricultural land; maize and teff represent approximately 15% and 21% of the total agricultural land in the region. They are distinct from each other in terms of their sensitivity to water stress—maize is more vulnerable to water stress, while teff can maintain higher yields under such conditions. However, maize typically has a much higher yield per unit of planting area than teff under ideal climate conditions, although maize is often sold for a lower price. Overall, the economic value, which is a product of yield and price, per unit of planting area, is higher for maize than that for teff under such climate conditions. Thus, maize may be more desirable

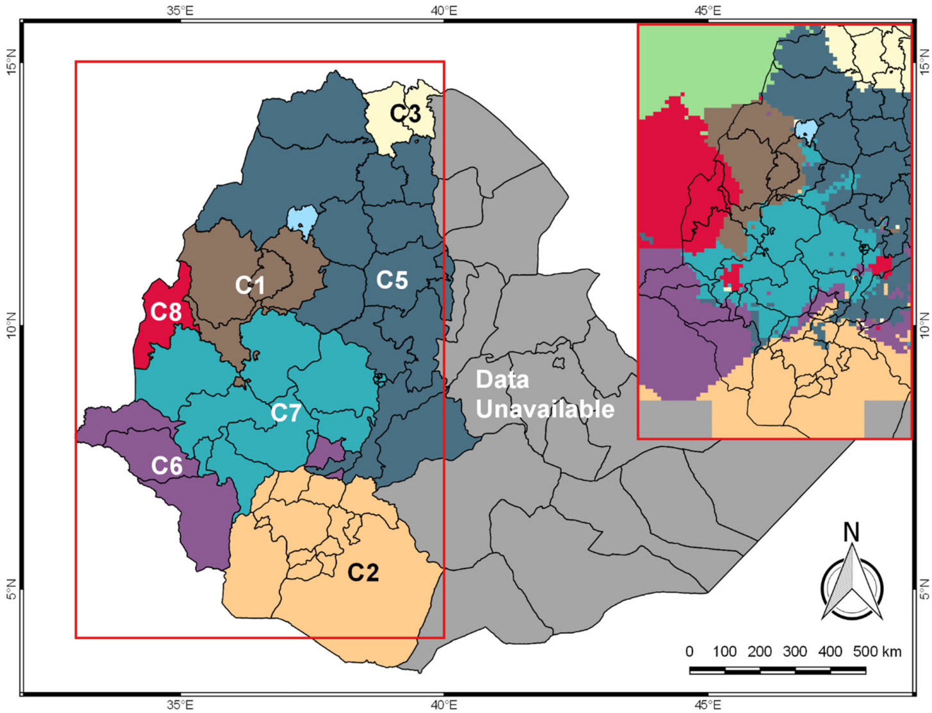

Fig. 3 Ethiopian administrative zones outlined in black and eight climate clusters in color used in the EMM (adapted from Zhang et al. 2016). Zones without sufficient climate regionalization information are marked in gray, labeled as "data unavailable" (color should be used for this figure in print)

for above-normal precipitation conditions, while teff may be more valuable in years when maize yields are likely to be reduced. In addition, maize and teff occupy 22.9% and 13.1% of the total per capita calorie consumption per day on average, respectively, which are among the top three crops with the highest calorie consumption (maize, wheat, and teff). To test the sensitivity of reallocating maize to teff or vice versa, a range of land reallocation (5%, 10%… to 95%) is explored. The total area devoted to these two crops remains unchanged from the baseline and only includes crop areas where precipitation is the major factor affecting the yield (excludes areas applying irrigation, fertilizer, pesticide, improve seeds, etc.). Further, if benefits in excess of the baseline (net benefits) accrue under reallocation strategies and are correlated with precipitation conditions, a skillful seasonal prediction may help prescribe the proper shift in crop reallocation, applied either equivalently across all zones in western Ethiopia or individually by zone.

Hence, a series of land reallocation strategies was implemented into the EMM to understand possible net benefits under different precipitation conditions. Seasonal precipitation predictions and regionalization were then applied to guide land reallocation strategies across zones, aiming to accrue positive net benefits given the predicted precipitation conditions and associated reallocation strategies. The prediction-guided land reallocation strategies were implemented into the EMM again under the actual climate to estimate benefits, which were subsequently compared with baseline for net benefit (Fig. 1).

2.4 Reallocation scenarios

Three scenarios are compared in this work:

(1) Baseline: a "business as usual" strategy with no year-to-year reallocation between teff and maize. However, cropland allocation can vary by year based on climate variability.
(2) Uniform reallocation: reallocation between teff and maize applied uniformly across all zones.
(3) Zonal reallocation: reallocation between teff and maize applied independently by zone.

Predictions, allowing farmers the opportunities to take pre-season alternative actions, are applied to prescribe reallocation strategies for scenarios (2) and (3), either from teff to maize or maize to teff (following Fig. 1). For scenario (3), zonal-level reallocation is determined based on cluster-level regionalization (Zhang et al. 2016) and allows unique strategies by zones.

3 Results

3.1 Baseline scenario

National GDP is strongly positively correlated with JJAS total precipitation (corr. = 0.68, $p < 0.0001$; Table 1). Note that all GDP values here refer to real GDP, based on prices in the base year (2003). Agricultural GDP, which is a large portion of total GDP, and grain (staple crops) GDP have similarly high correlations with precipitation (corr. = 0.68 and 0.69, respectively, both $p < 0.0001$; Table 1). Unsurprisingly, in years with high JJAS

Table 1 Pearson correlation coefficients between spatial average JJAS total precipitation in western Ethiopia and various economic indicators at country level over 1983–2011

	GDP	Agricultural GDP	Grain GDP	Calorie per capita per day	Poor population	Price of maize	Price of teff	Import of wheat
Corr. with precipitation	0.679***	0.684***	0.686***	0.637**	−0.728***	−0.563*	−0.228	−0.690***

* $p < .05$, ** $p < .0005$, and *** $p < .0001$ under two-tailed t test

precipitation, the total supply of commodities and GDP is higher due to preferable climate conditions. Across the years explored, total GDP can vary by as much as 0.72 billion USD, fully attributable to climate variability (mainly precipitation reduction), ceteris paribus (Fig. 4).

Total calories per capita per day also show a strong and positive correlation with JJAS total precipitation (corr. = 0.64, $p < 0.0005$; Table 1), indicating that above-normal precipitation conditions result in more food and higher consumption. This applies to both food deficit and surplus zones in general, though some spatial variability exists. Deficit zones have a lower level of calorie consumption than surplus zones, with a mean difference of 212 calories (Cal) per capita per day.

The number of poor people falling under the nationally defined poverty line (Diao et al. 2005) is even more strongly correlated with precipitation than GDP and calories per capita per day (corr. = − 0.73, $p < 0.0001$; Table 1). Poverty rates in rural areas reach 55% in 1987 and 2002, approximately 10% higher than the poverty rates in years with sufficient precipitation (e.g., 2007). As expected, urban poverty rates, ranging from 24 to 30%, are much lower than rural rates. The variability of poverty rates in urban zones is also lower than that in rural zones, as the poverty rate in urban zones is less affected by climate conditions. The total poverty rate is close to the rural poverty rate due to the large proportion of the population living in rural areas.

3.2 Uniform reallocation scenario

Uniformly reallocating across zones from teff to maize generates a positive change in GDP compared with the baseline in most years with above-normal precipitations, and

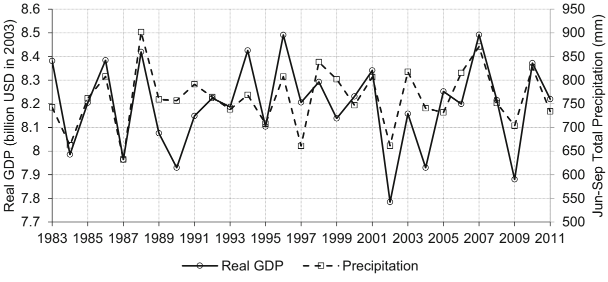

Fig. 4 National real GDP and spatial average JJAS total precipitation in western Ethiopia for simulated years

moderate to negative change in GDP for near- and below-normal precipitations (Fig. 5a). Thus, reallocation from teff to maize appears warranted under above-normal precipitations only. Interestingly, when reallocating from maize to teff, no positive change in GDP is apparent under any precipitation conditions (Fig. 5b). While spatial variability could play a role—there may be positive changes in some zones as investigated in the next scenario—it appears that teff has already reached a saturation point relative to maize. Thus, aggregated across all zones, the current allocation of teff and maize appears suboptimal in some years.

The seasonal precipitation prediction model forecasts seven of the 29 years to be above normal (Fig. 6), when reallocating from teff to maize appears beneficial. Five of these years are actually above normal based on observations (1996, 1998, 2003, 2007, and 2010); the two missed are near-normal years (1989 and 1994). Additionally, five above-normal years are missed by the prediction model (1986, 1988, 1991, 1999, and

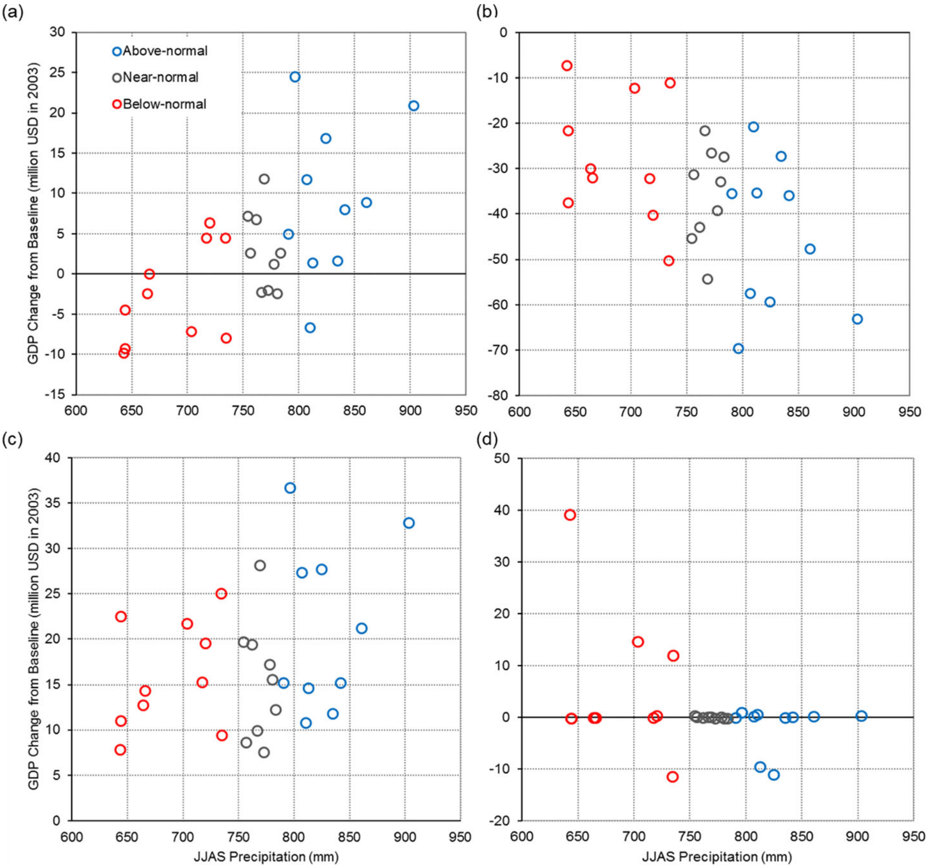

Fig. 5 Real GDP change (difference between reallocation scenario and baseline scenario) for all years under *uniform* reallocations from teff to maize (**a**) and from maize to teff (**b**), and under *zonal* reallocations from teff to maize (**c**) and from maize to teff (**d**), averaged over all area reallocation percentages (5%, 10%… 95%). Above-normal, near-normal, and below-normal refer to precipitation conditions (color should be used for this figure in print)

2001). Thus, teff is reallocated to maize for the seven years with predicted above-normal precipitation conditions across the full range of reallocating percentages.

As a result, average positive change in GDP from the baseline occurs in five of the seven years; the two exceptions are 2003 and 1989, when the GDP decreases by 6.7 and 2.5 million USD on average, respectively (Fig. 7a), even though 2003 is actually an above-normal year. This is mainly attributable to heterogeneous distribution of precipitation across zones and zones with large maize areas actually receiving less precipitation than average, even though the spatially aggregated precipitation is high in 2003. Even reallocating a small fraction of teff to maize in 2003 (5%) results in a 0.22 million USD reduction in GDP (Fig. 7b). In 1989, although the average net benefit over all the reallocation percentages tested is negative, the highest net benefit reaches 0.34 million USD under a reallocation percentage of 15% teff to maize (Fig. 7b). In other predicted above-normal years, larger reallocation percentages generally result in larger positive changes in GDP, ranging from 9.9 to 27.3 million USD per year. However, the incremental increase in GDP change gradually decreases, as the increments become relatively small at 60% reallocation, where a 7.7 million USD increase in GDP is achieved (Fig. 7b). For the above-normal years which the prediction model missed, the average potential gain in GDP ranges from 1.4 to 24.5 million USD, including 1986 when the average gain would have reached the highest among all years (Fig. 7a).

The average calories per capita per day for the above-normal predicted years also increase from the baseline up to a maximum of 95 additional Cal (Fig. 8a). Calories from teff consumption decrease gradually due to lower supply and increasing domestic price; however, the calorie change becomes relatively constant at approximately −50 Cal as teff starts to be imported from other countries[1] (Fig. 9). In 2003, the import quantity of teff is the lowest among the above-normal years predicted, mainly due to a lower level of GDP in that year which in turn constrains the domestic food demand.

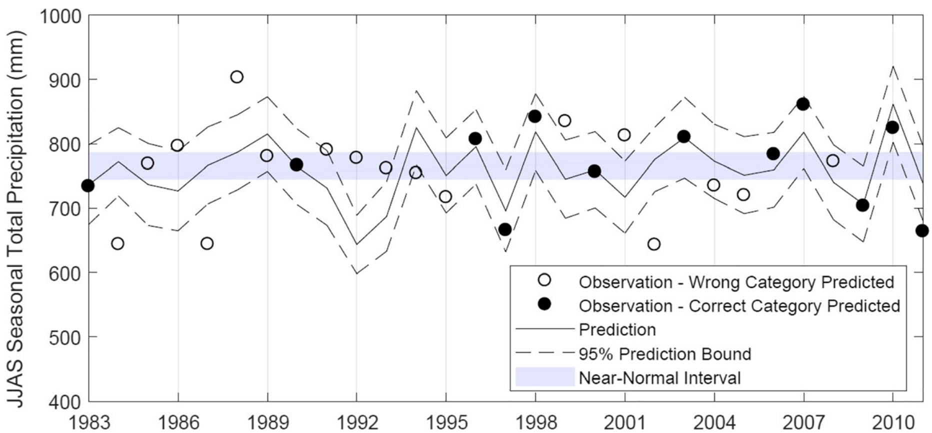

Fig. 6 Seasonal prediction of JJAS precipitation average over the western Ethiopia region, 1983–2011

[1] Ethiopia produces the most teff in the world. Eritrea, India, the USA, Australia, and Netherland also produce teff. There is no teff import in the 2003 baseline and historically no known teff imports into Ethiopia. The import of teff is triggered when 55% or more of the teff area is reallocated to maize, which is a modeling possibility, but realistically less likely given the importance of this grain to Ethiopia.

The change in poor population and poverty rate outcomes is notably different than GDP and calories. Instead of best conditions occurring at large reallocation percentages, they occur near 25% reallocation: 73,000 reductions in rural poor population, 5000 reductions in urban poor population, and 0.12% reduction in overall poverty rate. At higher reallocation percentages, the rural poverty actually increases, although urban poverty decreases, with an overall net increase (Fig. 10a). This highlights the uneven welfare distribution given the uniform national level reallocation policy considered.

3.3 Zonal reallocation scenario

By investigating outcomes at the cluster level, clusters associated with positive change in GDP are identified respectively for reallocations from teff to maize and from maize to teff. Zones that belong to those clusters are selected for reallocation. Consequently, reallocation from teff to maize is applied to zones in clusters 2, 3, 6, 7, and 8, and reallocation from maize to teff is applied to zones in cluster 1 (Fig. 3).

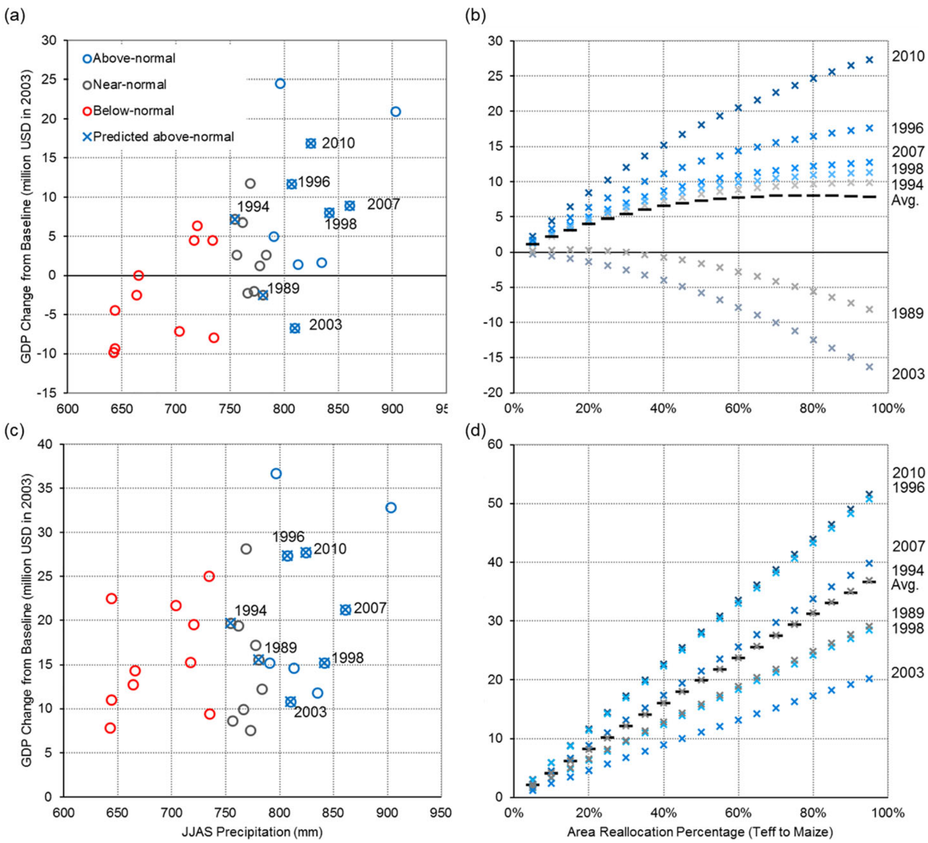

Fig. 7 Real GDP change (difference between reallocation scenario and baseline scenario) under *uniform* reallocations from teff to maize averaged over reallocating percentages (**a**) and for each reallocating percentage (**b**), respectively, and under *zonal* reallocations from teff to maize averaged over reallocating percentages (**c**) and for each reallocating percentage (**d**), respectively. Years predicted as above-normal are marked with crosses (color should be used for this figure in print)

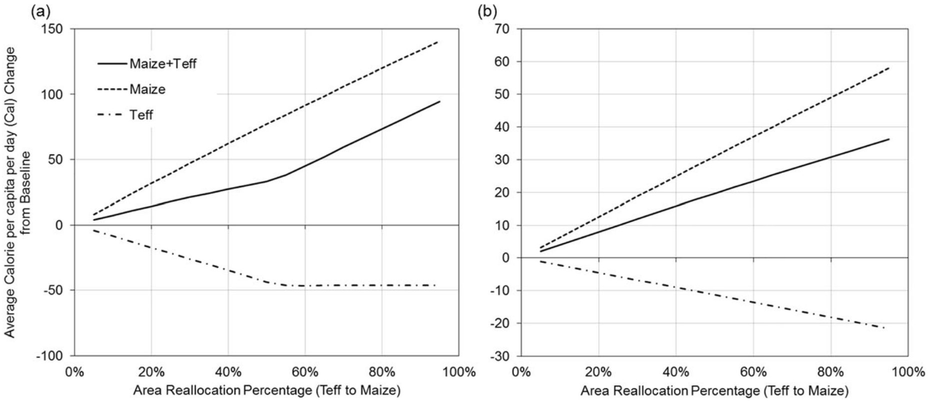

Fig. 8 Calorie per capita per day (Cal) change (difference between reallocation scenario and baseline scenario) averaged over predicted above-normal years under *uniform* reallocations (**a**) and under *zonal* reallocations (**b**) from teff to maize for each area reallocation percentage

Under the zonal reallocation scenario for teff to maize, the average changes in GDP are positive for all years (Fig. 5c) in contrast to the mixed positive and negative outcomes under the uniform reallocation scenario (Fig. 5a). However, both scenarios illustrate an increase in GDP change as precipitation increases. As for the zonal reallocations from maize to teff, positive changes in GDP are noticeable in three below-normal years (Fig. 5d), in contrast to negative net benefits in all years under the uniform reallocation scenario (Fig. 5b). The highest positive change in GDP (39.2 million USD) is associated with the driest year of 2002. In other years, the changes in GDP appear to be rather random, with most years illustrating little to no change regardless of the precipitation conditions (Fig. 5d).

Therefore, zonal reallocations from teff to maize are applied for the same set of predicted above-normal years as in the uniform reallocation scenario. The average change in GDP over the predicted above-normal years reaches 19.7 million USD per year (Fig. 7c), which is more

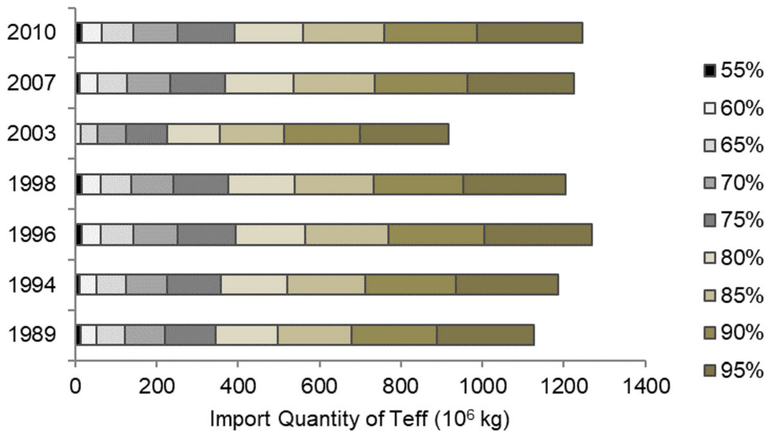

Fig. 9 Quantity of teff imported under *uniform* reallocations from teff to maize for each predicted above-normal year and each reallocation percentage. Note that teff is imported for large (> 50%) reallocation percentages only (color should be used for this figure in print)

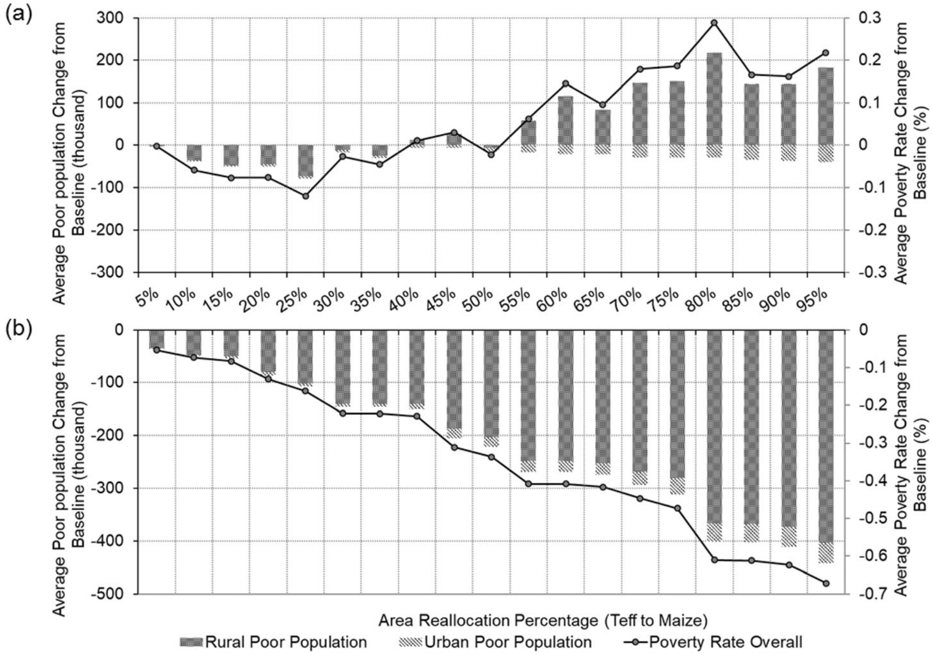

Fig. 10 Change in poor population (rural and urban) and poverty rate (difference between reallocation scenario and baseline scenario) over predicted above-normal years under *uniform* reallocations (**a**) and under *zonal* reallocations (**b**)

than three times that under the uniform reallocation scenario (6.2 million USD per year; Fig. 7a). The positive change in GDP increases with increasing area reallocation percentage, and the trend is relatively linear with the highest positive change in GDP (36.6 million USD) occurring at the largest reallocation percentage of 95% (Fig. 7d).

The calorie consumption per capital also increases with increasing reallocation percentage (Fig. 8b). The average change in calorie consumption from maize and teff over the predicted above-normal years is approximately 36 Cal at 95% reallocation, which is lower than the value under the uniform reallocation scenario (95 Cal; Fig. 8a). The reallocation from teff to maize in a subset of zones did not trigger the import of teff to meet domestic demand.

Considering the change in poor population averaged over the predicted above-normal years, both rural and urban poor populations decline for all reallocation percentages. The total poor population continues to decrease at higher reallocation percentages; however, the rate of decrease is not constant with the steepest decrease occurring at 30%, 55%, and 80% (Fig. 10b).

4 Conclusions and discussions

In this study, climate variability is imposed on an agro-economic model to simulate its impacts on Ethiopia's economy. Distinguishing from traditional partial equilibrium multi-market models, our model includes a service and industry sector in addition to a detailed agriculture sector to simulate the impact of climate variability on GDP, consumption, and poverty. Climate clearly plays an important role in Ethiopia's economy with poverty rate being the most sensitive to total precipitation in the main rainy season. This is consistent with findings in Diao and Pratt (2007) that growth in staple crops contributes strongly to poverty reduction. With high rainfall variability in the productive agricultural region in western Ethiopia, the spatial variance of crop production and therefore food security and economic well-being is high. As a result, spatially explicit climate prediction becomes valuable for predicting crop yields and further demands a spatially disaggregated agro-economic model to better inform adaptation strategies. Such disaggregated models allow for adaptation strategies at regional or zonal levels that may support increasing benefits, as illustrated in this study, and also enables evaluation of outcomes across disaggregated regions for comprehensive policy-making.

Block et al. (2008) also implement variable climate into the EMM and compare with economic outputs based on static (average) climate conditions. They illustrate that Ethiopia can be highly, and potentially be adversely, affected by variable climate, based on projections of future economy using stochastic variable climate sampled from the historical period and projected model parameters. In contrast, this study utilizes historical climate observations for the simulation periods to evaluate the impact of climate variability, holding all other parameters constant. In addition, we articulate the potential value of climate predictions (not just the impact of variable climate) by addressing adaptive responses and alternative actions given the prediction. In this study, land reallocation between crops is the adaptive response demonstrated, leveraging the spatially disaggregated seasonal precipitation prediction, to investigate potential net benefits compared with a baseline (no forecast) approach. This framework can easily be applied to alternative adaptive responses or prediction sources. For instance, predictions from general circulation models (GCM) and climate forecast systems could also be integrated and should be explored further; however, previous research (Zhang et al. 2018) indicates that the statistical prediction model used in this study is superior to dynamical predictions and is thus expected to result in higher net benefits.

In this study, in the seven years with predicted above-normal precipitation, reallocating from teff to maize uniformly across zones results in an average of 6.2 million USD (at 2003 prices) additional profits. Calorie consumption also increases, indicating that in above-normal precipitation years, both the maize value and its calories are higher than teff per unit of planting area. However, poverty rate does not monotonically decrease with increasing GDP, revealing an uneven distribution of welfare. Reallocation at the zonal level leads to additional positive change in GDP, which increases to an average of 19.7 million USD over the same set of predicted above-normal years. Additionally, zonal reallocations result in a continuous fall in poverty rates as the reallocation percentage increases. Calorie consumption is however lower under zonal reallocations than that under uniform reallocations. The resultant net benefits are based on predicted precipitation conditions, although there is still potential to achieve higher benefits by further improving prediction skill. Applying perfect prediction (observations), additional profits increase to 92.0 million USD under uniform reallocation and 213.6 million USD under zonal reallocation, compared with 6.2 and 19.7 million USD when actual predictions are used.

It is also worth noting that high reallocation percentages may not be realistic, considering access and availability of seeds and its significant effect on price fluctuation. Additional analysis is required from a social-economic perspective to further guide policy in response to climate prediction and associated agricultural land reallocation. This study provides an initial effort in reducing the gap between the scientific community and policy makers by converting climate predictions into expected economic outcomes for consideration by decision makers.

The evaluation of net benefits attributable to prediction and regionalization in this study is restricted to a single adaptation strategy. Although reallocating between maize and teff is considered a realistic adaptation strategy, as in general, there is evidence that areas growing teff also grow maize across different agro-ecological systems (AES) (Tessema and Simane 2019), particularly in the midland, wetland, and lowland AES, where both maize and teff are plentiful and rotated from year to year (e.g., Gizaw et al. 2018); reallocation between crops other than maize and teff and dynamic reallocation (i.e., reallocation percentages change annually) based on probabilistic seasonal climate forecasts could be explored. Additional scenarios with modern agricultural technologies (fertilizer, improved seed) applied according to predictions may also warrant investigation. Given the demonstrated spatial heterogeneity, addressing such scenarios at the zonal level could potentially further increase expected benefits. Categorical precipitation prediction intervals could also be individualized at the zonal level to better prescribe reallocation.

The purpose of this study is not to optimize the value of using prediction and regionalization, rather to present an innovative way to evaluate the benefit of climate prediction information using economic indices at national and zonal levels. Such analysis can provide a foundation for communication, decision and policy-making, and strategic planning.

In addition, although the EMM model captures the detailed agricultural sector in Ethiopia, it does not specifically include all aspects related to food security, including governmental policies and international food aid. These external policies may have some effect on farmers' decision-making and potentially enhance overall benefits, which is desirable but may dampen the effect of capturing climate variability through prediction and subsequent adaptation strategies. Additionally, labor migration is not captured in the model. This may affect household income and expenditure patterns; however, the effects on agricultural production are likely minor compared with the effects of climate variability. Finally, there has been increasing awareness of land degradation and soil erosion due to unsustainable farming practices; these also are not included in the model but may warrant further attention particularly if environmental conditions become critical constraints in agricultural production in the future.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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