SDGs under the climate change threat: an impact assessment in the agricultural sector

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L. Campagnolo, Junior Researcher Fondazione ENI Enrico Mattei (FEEM)
M. Davide, PhD candidate, Fondazione ENI Enrico Mattei (FEEM) and Cà Foscari University
E. Delpiazzo, Junior Researcher at Fondazione ENI Enrico Mattei (FEEM) and Post-Doc at Centro Euro-Mediterraneo per il Cambiamento Climatico (CMCC) Fondazione
elisa.delpiazzo@feem.it
(+39) 041.2700.456
Isola di San Giorgio Maggiore, 8
Venice IT-30124

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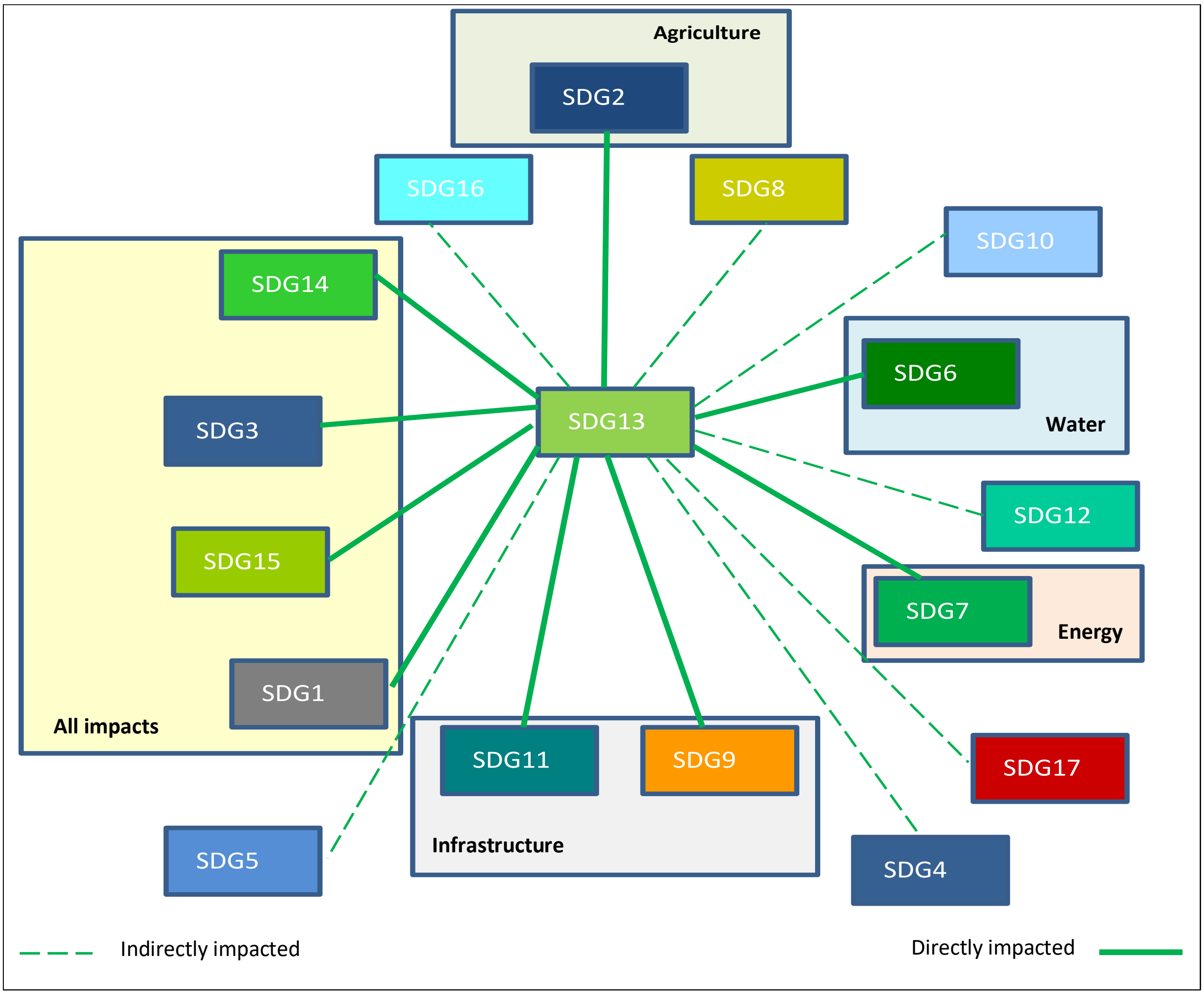
1. Introduction

In September 2015, the adoption of the Sustainable Development Goals (SDGs) by the United Nations defined broad and ambitious development targets for both developed and developing countries encompassing all sustainability dimensions (economic, social, and environmental) and designing the pathway towards an inclusive green growth. The architecture of the system supposes each goal is linked to the others integrated into a broader framework and mutually reinforcing (UNA-UK, 2016). An example of this synergic structure is goal 13 "Climate Action", a cross-cutting element among SDGs. Climate change will pose serious risks for human and natural systems, hindering the already arduous way toward SDGs. It is not only a further direct threat to goal 13 but climate change has a relevant direct or indirect effect on the other SDGs too. While some of them are directly and generally affected by failing in meeting SDG13, some others are directly related to sector- specific impacts (i.e. SDG2 is related to impacts on the agricultural sector; SDG6 impacts on the water sector). However there is a number of SDGs which are indirectly impacted by climate change, such as SDG4 "Education". Education facilities could be vulnerable infrastructures to climate-related disasters, increasing pressure to take children out of school (figure 1).

As climate change impacts will not be evenly distributed within regions and across regions, it will represent one more obstacle in the fulfillment of goal 10 "reduce inequality" as well, since poor people and developing countries will likely be affected more than the others by global warming side-effects due to their higher vulnerability and the lack of resources to invest in precautionary adaptation (Wright *at al*., 2015) introducing a likely gap both in "between" and "within" inequality.

In the definition of adaptation policies, the prerequisite is to quantify the heterogeneity of climate change impacts across regions for1modeling funds and better direct them to the more impacted areas. Moreover, It is important not only taking into account the economic costs of climate change impacts, but also a broader set of indicators, ranging from poverty and malnutrition prevalence to healthy life expectancy, since it impacts not only the economic sphere but also the social one.

Figure 1: Interactions of SDG13 and other SDGs



This paper will offer an ex-ante assessment of climate change impacts on the global pathway towards achieving SDGs supposing a failure in reaching goal 13. The presentation will shed some light on the possible costs of climate change impacts in the agricultural sector overcoming the usual analyses that stops to a mere economic assessment and highlighting how and at which extent shocks may affect all sustainability spheres, demonstrating a cascade mechanism among SDGs.

Our analysis relies on a recursive-dynamic Computable General Equilibrium (hereby CGE) model developed and enriched with indicators representative of each SDG. CGE models have a flexible structure, and can capture trade-offs and higher-order implications across sectors and countries that follow a shock or a policy. These models are suited to assess the performance of economic and some environmental indicators.

The CGE model has been further developed relying on the empirical literature and directly estimating the relations between indicators and endogenous variables of the model. Our framework considers 28 indicators covering 16 SDGs.

The paper is structured as follows. Section 2 summarizes literature review of climate change impacts on the agricultural sector, considering both CGE applications and other modeling tools used in the framework of SDGs. Section 3 deals with the methodology used in this paper with a brief description of the CGE model and the empirical estimation section. Section 4 reviews the scenarios and the input data for the analysis. Section 5 describes the main results both in 2030 and in 2050 to give a longer term perspective on what could happened to SDGs if SDG 13 is not met. Finally, section 6 concludes.

2. Literature review

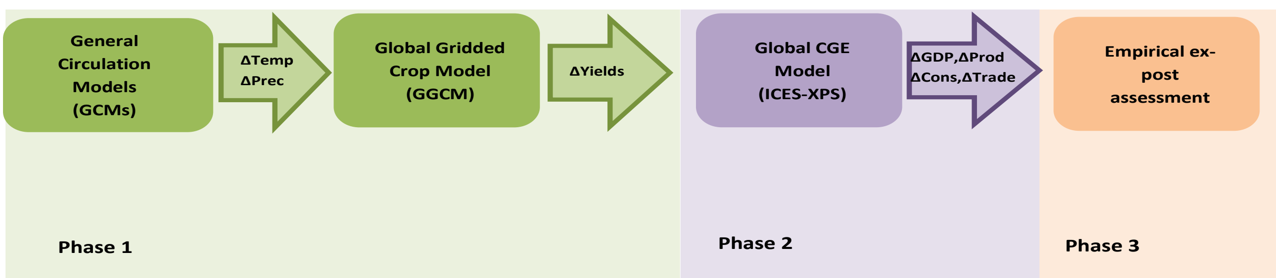
The vulnerability of the agricultural sector to both climate change and variability is well established in the literature. The general consensus is that changes in temperature and precipitation will cause changes in land and water regimes that will consequently affect agricultural productivity. Research has also shown that, specifically in tropical regions, impacts on agricultural productivity are expected to be particularly detrimental because of the presence of most of the poorest countries. Their vulnerability is particularly likely to be acute in light of technological, resource, and institutional constraints. Given the range of warming predicted by the scientific community, regional and local variation in impacts on the agricultural production is likely to be high. However, scholars predict tropical regions will face both a reduction in agricultural yields (Rosenzweig *et al*., 2002) and a rise in poverty levels as livelihood opportunities for many engaged in the agricultural sector become increasingly susceptible to expected climate pressures (Ahmed *et al*., 2009; Hertel *et al*., 2010; Jacoby *et al*., 2011; Skoufias *et al*., 2011). In contrast, climate change is also expected to result in some beneficial effects, particularly in temperate regions (Intergovernmental Panel on Climate Change, 2014). The lengthening of growing seasons, carbon fertilization effects, and improved conditions for crop growth are forecast to stimulate gains in agricultural productivity in high-latitude regions, such as in northern China and many parts of northern America and Europe (Nechifor and Winning, 2017). As a result, experts predict a spatial shift of crops and agricultural practices away from the tropics toward the temperate and polar regions (IPCC, 2014). Consequently, the expected impacts of climate change on the agricultural sector have prompted concern over the magnitude of future global food production (IPCC, 2014).

Numerous factors shape and drive the agricultural sector: market fluctuations, changes in domestic and international agricultural policies (such as subsidies, incentives, tariffs, credit facilities, and insurance), management practices, terms of trade, the type and availability of technology and extension, land-use regulations and biophysical characteristics (availability of water resources, soil quality, carrying capacity, and pests and diseases). Given its intrinsic link to natural resources, agricultural production is also at the mercy of uncertainties driven by climate variation, including extreme events such as flooding (Chang *et al*., 2015) and drought (Pauw *et al*., 2011). Climate change, considered as long-term changes in mean temperature or precipitation normal, has gradually been recognized as an additional factor which will have a significant weight on the form, scale, spatial and temporal impact on agricultural productivity. Because the agricultural sector is related to other factors which are more economic and political than physical and natural, the effect of climate change on the agricultural sector is mainly analyzed using CGE models (for a comprehensive review see Elbehri and Burnfisher, 2015). Because of their structure, they are suitable instruments to analyze the interaction of physical and climate impacts with economic variables. They mostly focus on welfare effects of yield changes at the global level (Moore *et al*. 2016) or in a single-country framework (Lofgren *et al.*, 2010, for Mozambique); or poverty effects at the single country level (Ahmed *et al*., 2011a for Tanzania;); some of them consider, instead, the role of trade as an adaptation tool (Ahmed *et al*., 2011b; Valenzuela and Anderson, 2011).

3. Methodology

This analysis complements the CGE model with an empirical ex-post quantification of indicators and finally SDGs. Figure 1 summarizes the main steps of the methodology applied.

Figure 2: Modeling chain of this analysis



3.1. Phase 1

Phase 1 summarizes the input data phase of our work.

Global climate models, or general circulation models (hereby GCMs), are numerical models that apply physical, chemical and biological principles to simulate the interaction of the atmosphere, oceans, land surface, snow, ice and permafrost in determining the earth's climate. GCMs have been applied to project the responses of the climate variables (mainly changes in temperature and precipitation) to increased greenhouse gas (GHG) emissions in the atmosphere. The fitted relationships are then used to simulate the effects of alternative climate-forcing scenarios (representative concentration pathways, hereby RCPs) that describe various levels of human-induced GHG emissions. Their results describe projected changes in climate over the this century or more, including changes in temperature, rainfall and atmospheric pressure. GCMs describe climate changes over relatively large spatial and temporal scales.
In this work we consider climate data from five different GCMs: GFDL-ESM2M (Dunne *et al*., 2013), HADGEM2-ES (Jones *et al*., 2011), IPSL -CM5A-LR (Dufresne *et al*., 2013), MIROC-ESM (Watanabe *et al*., 2011) and NorESM (Bentsen *et al*., 2013). To address the uncertainty in climate predictions, we use for each GCM two alternative RCPs (RCP8.5 and RCP2.6[1]).

These physical changes due to climate change affect crop yields and agricultural production. They are then passed into global gridded crop models (hereby GGCMs), which simulate the resulting crop production according to changes in temperature and precipitation (Rosenzweig *et al*., 2014). The crop model used for this study are the Lund–Potsdam–Jena managed Land Dynamic Global Vegetation and Water Balance Model (LPJmL) (Bondeau *et al*., 2007). It focuses on water and temperature stress, whereas other models consider specific heat and nitrogen stresses. On the other hand, this GGCM takes into account all crops: maize, millet, rice, wheat, sunflower, rapeseed, soybean, cassava, ground nuts, sugar beet and sugar cane. In our simulation we consider scenarios with CO_2 fertilization as well.

These input data are taken from the ISI-MIP database and project (Rosenzweig *et al*., 2014; Warszawski *et al*., 2014; Schellnhuber *et al*., 2014).

3.2. Phase 2

At this stage, the quantitative projections of GGCMs are translated into an economic variable which could be shocked in the CGE model. The change in crop yields is considered as a change in land productivity in the agricultural sector. CGE models are widely used in assessing the economic impacts of climate change because of their structure. Indeed, they are economy-wide models and include the economic interactions of a country's producers, consumers, investors, government and trade partners. The starting point is an equilibrium state, described as a set of price and quantities which satisfy all agents. This means that nobody wants to change supply and demand. But the climate shock perturbs this equilibrium, thus economic agents responses to a price signal: producers adjusts their production towards commodities with higher relative prices and consumers shift their consumption towards cheaper commodities (i.e. price and income effect). The models solves for a new vector of equilibrium prices and a new vector of equilibrium quantities.

Specifically, in this analysis we use a global CGE model, called ICES-XPS (Delpiazzo *et al*., 2017) based on the GTAP model (Corong *et al*., 2017), which covers the whole World. Each country is connected to the other through two channels: trade and investments. Moreover, it is a recursive dynamic model, thus it considers a series of equilibria (in 1-year steps) over the period 2007-2040, incorporating the adjustment pathway of the economies respect to the climate change impacts and other exogenous trends, such as population growth or economic development (i.e. productivity

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[1] RCP2.6 represents an average global warming increase of 1.0°C (the lowest case), while RCP8.5 considers an average global warming increase between 2.0°C (in the first half of the 21^{st} century) and 3.7°C (in the second half). For a comprehensive review of RCPs, see Collins *et al.* (2013).

trends)[2]. These exogenous trends are consistent with the Shared Socioeconomic Pathway 5 (O'Neill *et al.*, 2014)[3].

Up to this phase, the methodology is quite standard and reviewed in Nelson *et al*. (2014), and Elbehri and Burnfisher (2015).

3.3. Phase 3

In this phase, the economic outcomes of the CGE model are used to derive SDG indicators[4]. According to the methodology established in the APPS project (Campagnolo and Davide, forthcoming), the economic values are used as independent variables in several out of sample econometric regressions. As we focus on agriculture, we consider the directly affected SDG indicators, such as poverty, inequality, and malnutrition. For each of them, we run an in sample regression on historical data and relying on empirical literature on the topic. Furthermore, the estimated coefficients are then used in the out of sample regressions together with figures stemming from the CGE model.

a) Poverty

Based on Lofgren *et al.* (2013) and Hilderink *et al.* (2009) as well as on the empirical literature on the topic, we run a panel regression in order to understand the link between the measure of poverty prevalence (Poverty headcount ratio at 2005$1.25 a day), the average income per capita (GDP PPP2005 per capita) and the indicator of unequal distribution of income (Palma ratio). Furthermore, we included a country fixed effect.

$$ln\left(POV_{i,t}\right) = \boldsymbol{\beta_0} - \mathbf{2.26} * ln\left(GDPPPPpc_{i,t}\right) + \mathbf{0.22} * ln\left(Palma_{i,t}\right) + \varepsilon_{i,t} \qquad (1)$$

In order to account for heteroskedasticity and autocorrelation that characterise our panel, we use a linear regression model with robust standard errors, including a first order correlation within each panel. The data source is the World Development Indicator database (World Bank, 2016); the panel considers 99 countries, both developed and developing, in the period 1990-2013.

b) Inequality

As a measure of within-country inequality we consider the Palma ratio, which is formally defined as "the ratio of the richest 10 % income over the income of poorest 40% of the population".

The share of GDP detained by the richest 10% of the population and that owned by the poorest 40% are our dependent variables given their key role in the computation of Palma ratio, adopted in this paper as the measure of inequality within a country. As explanatory variables, we consider some macroeconomic variables drawn from World Development Indicator database and World Governance Indicators (World Bank, 2016), which are consistent with the literature, characterized by an appropriate country and year coverage and directly linkable to endogenous variables in our CGE model. We ran two independent regressions with the following specification:

$$\begin{aligned} ln\left(y_{i,t}^{low40}\right) = {} & \beta_0^{low40} + \mathbf{0.02} * ln\left(PEduExpsh_{i,t-1}\right) + \mathbf{0.12} * ln\left(AgriVAsh_{i,t-1}\right) + \mathbf{0.20} \\ & * ln\left(IndVAsh_{i,t-1}\right) + \mathbf{0.03} * CorruptCtrl_{i,t} - \mathbf{0.003}\, ln\left(Unempl_{i,t-1}\right) + \mathbf{0.02} \\ & * d_{c_{i_{i,t}}} + t^{low40} + \varepsilon_{i,t}^{low40} \end{aligned} \qquad (2)$$

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[2] On the other side we identify single country models and static models. The former consider specifically a country context losing the general effect on the World economy (i.e. Arndt *et al*., 2010) ; the latter, instead, compare the starting equilibrium with the post-shock equilibrium in a comparative static analysis. It lacks in describing the adjustment path.

[3] SSP5 is characterized by relatively rapid economic development, and slower population growth. Energy demand is high and most of it is met with carbon-based fuels. Investments in alternative energy technologies are low.

[4] See Appendix 1 to have a complete picture of indicators in each SDG according to the APPS framework.

$$ln(y_{i,t}^{high10}) = \beta_0^{high10} - \mathbf{0.02} * ln(PEduExpsh_{i,t-1}) - \mathbf{0.09} * ln(AgriVAsh_{i,t-1}) - \mathbf{0.13} * ln(IndVAsh_{i,t-1}) - \mathbf{0.02} * CorruptCtrl_{i,t} + \mathbf{0.002}\, ln(Unempl_{i,t-1}) + \mathbf{0.002} * d_{c_{i_{i,t}}} + t^{high10} + \varepsilon_{i,t}^{lhigh10}$$

where $y_{i,t}^{low40}$ and $y_{i,t}^{high10}$ are the shares of GDP owned by the poorest 40% and the richest 10% of the population. The explanatory variables are: the share of Public Education Expenditure ($PEduExp\_sh$), the sectoral composition of the Value Added (VA), i.e. the share of VA from agriculture ($AgriVA\_sh$), and industry ($IndVA\_sh$); an indicator on corruption control perception ($CorruptCtrl$), the unemployment rate ($Unempl$), and a dummy distinguishing whether the dependent variable derives from a consumption or income distribution[5] (d_c_i). In addition, we included a time trend (t) and country fixed effects. Also in this case, we use a linear regression model with panel corrected standard errors accounting for heteroskedasticity.

c) Malnutrition

Undernourishment indicator is based on an empirical analysis of data drawn from the UN database, which covers data from 1990 to 2012 for 132 countries.

$$Undern\_prev_{i,t} = \boldsymbol{\beta_0} - \mathbf{3.14} * \boldsymbol{ln}(GDPPPPpc_{i,t-1}) - \mathbf{7.68} * ln(Agri\_prod\_pc_{i,t-1}) - \mathbf{0.03} * Urb_{sh_{i,t-1}} - \mathbf{0.12} * Ind\_VA_{\boldsymbol{i,t-1}} + \mathbf{0.93} * Palma_{i,t-1} + \boldsymbol{\varepsilon_{i,t}} \quad (3)$$

In this regression, the independent variable ($Undern\_prev$) is explained through the average income per capita ($GDPPPPpc_{i,t-1}$), the agricultural production ($Agri\_prod\_pc_{i,t-1}$), the share of urban population ($Urb_{sh_{i,t-1}}$), the share of VA from the industry sector ($\mathrm{Ind\_VA}_{i,t-1}$) and the Palma ratio ($Palma_{i,t-1}$). All these explanatory variables are considered respect to the previous year.

4. Scenarios set up

4.1. Aggregation of ICES-XPS

As ICES-XPS has a global geographical coverage and it is based on GTAP database v.8 (Narayanan *et al*., 2012), we need to specify and aggregation for countries and sectors, especially related to the agricultural sectors. Indeed, we need a mapping between the crops in LPJmL model and the productive agricultural sectors in ICES-XPS. Table 1 summarizes the aggregation of the agricultural sectors and the mapping between the two models.

Table 1: Agricultural mapping between LPJmL model and ICES-XPS

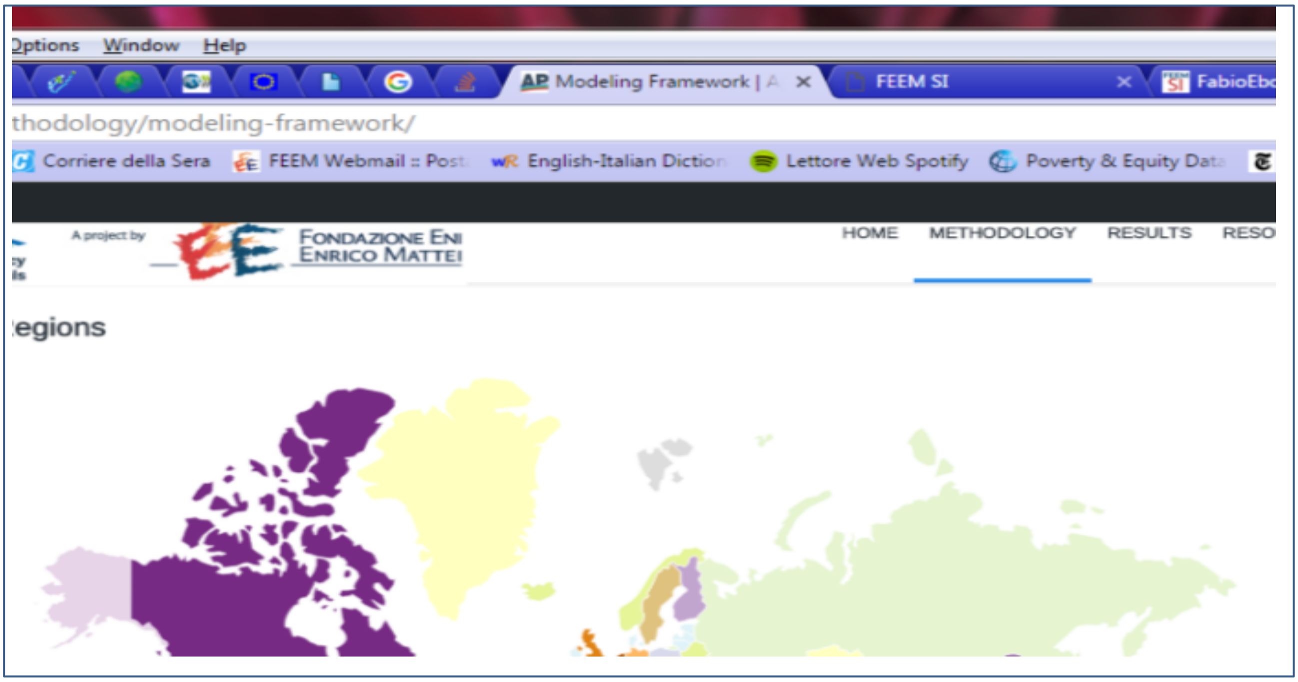
ICES-XPS	GTAP	LPJmL
Rice	Paddy rice	Rice
Wheat	Wheat	Wheat
Othgrains	Cereal grains	Maize, millet
Othseeds	Oil seeds	Rapeseed, soybeans
Sugar	Sugar cane, sugar beet	Sugar cane, sugar beet
Othcrops	Vegetables, fruit, nuts Plant-based fibers Crops nec	--

Source: ICES-XPS

Respect to countries, the World is divided into 45 countries and/or regions, as depicted in the figure below.

[5] The dummy variable (d_c_i) assumes value 1 when the dependent variable derives from a consumption distribution, value 0 in the case of income distribution. Following Alvaredo and Gasparini (2015), we included this dummy in order to account for the wedge between income and consumption-based inequality measures.

Figure 3: Geographical aggregation in the ICES-XPS CGE model



Source: APPS website (http://www.feemsdgs.org/methodology/modeling-framework)

4.2. Scenarios

This analysis is based on a comparison of different scenarios.

1) Reference scenario (no CC). In this case we assume no Climate Change but only socio-economic development. This means using targets for GDP growth and population growth rate consistent with SSP5. Fossil fuel prices instead are calibrated according to the Witch model projections. As each GCM has its own trend in crop yield production in the historical period 1971-2005, we have differentiated reference scenarios according to land productivity in the agricultural productive sectors[6].

2) Climate Change scenarios (with CC). Because of the high uncertainty regarding future projections of climate change impacts in the agricultural sector, we try to capture this uncertainty in the Climate Change scenarios. Therefore, assuming a constant GGCM (i.e. LPJmL) we assume uncertainty in terms of GCMs and RCPs. So, "with CC" scenarios are entries of a 10- cell matrix (GCMs x RCPs).

4.3. Input data

Appendix 2 summarizes the land productivity for each crop according to RCP. On the *y*-axis there are land productivities in 2040 in levels.

Considering land productivity used to cultivate **rice**, on average it increases more in RCP8.5 than in RCP2.6 in 2040 (17.8% and 4.6%, respectively). This is the case of China, the biggest rice producer in 2007 (27% of World rice production). There is no evident change in land productivity among "no CC" and "with CC" scenarios; however, in the latter case there is an increase in uncertainty among CGMs, and a low increase in productivity in RCP8.5 (i.e. 1.85%). Generally, in "with CC" scenarios there is a more pronounced increase in land productivity in USA (10.4% in RCP2.6 and 14.5% in RCP8.5), Peru (2.0% in RCP2.6 and 11.8% in RCP8.5), Poland, Russia (48.0% in RCP2.6 and 82.4% in RCP8.5) and Turkey (3.9% in RCP2.6 and 12.5% in RCP8.5),

[6] They are calculated as a mobile average of the historical data and projected in the future.

although they count for nearly 2% of World rice production in the base year. The higher productivity in Poland is meaningless because of the null production of rice in this country.

On the other hand, South Korea, Italy and Spain has the highest decreases (they count 7% of rice production all together). In RCP2.6 they loss 16.9% on average while in RCP8.5 it is 12.8%.

Land productivity for **wheat** production has the highest uncertainty among GCMs, especially in the EU region, where Benelux, France and Germany decrease their productivity, while Italy and UK has nearly stable ones in level but with a higher dispersions among models. The EU region produces 27% of total wheat production in the base year, thus uncertainty is relative important in terms of wheat supply. South Korea, Canada, and China has moderate increases in productivity ranging between 2.5% (South Korea, RCP2.6) and 14.3% (Canada, RCP8.5).

On the other hand Egypt, Venezuela, Argentina and USA show a drop in productivity in 2040. The reduction in Egypt is particularly evident in both RCPs with a loss in productivity respect to 2040 “no CC” of more than 40%.

The total effect seems to have slight positive consequences, because productivity increases in countries with the highest production (15% with respect to 12%, respectively).

Land productivity for **other grains** production reduces in Africa, between 10% and 11%, (except Ethiopia and South Africa) and central EU (i.e. Benelux, France, Germany, UK). There is a generalized increase (between 57% and 70% on average) in land productivity in the American continent (only exception Chile), in Northern and Eastern EU countries (i.e. Czech Republic, Finland, Poland), Russia, Turkey, Italy and Spain. This means a likely shift towards America in other grains production and in cooler regions of Europe.

In the case of productivity for **oil seeds**, in “with CC” scenarios, there is a generalized reduction in uncertainty among GCMs and on average the reduction is more evident in RCP2.6 where the man value is -2.3%. On the other hand, in RCP8.5 although most countries have decreases in land productivity, at the global level we have a slight increase by 1%.

For **sugar**, land productivity increases in the Asian regions with the lowest increase in India (18% of sugar total production in 2007). While in the USA there is a drop in productivity, most of the American continent faces an increase (higher in RCP8.5 than in RCP2.6). In the African continent the most evident feature is the high uncertainty among models which increases in the “with CC” scenarios. Kenya, Uganda and South Africa are exceptions in the content with increasing productivity in the “with CC” scenarios, however they count for a very small fraction of sugar production in 2007. Land productivity for **other crops** production is not shocked in the “with CC” scenario.

5. Results

In this section we summarize the main findings of phase 2 and 3 of our work. Firstly, we will present the losses in “with CC” scenarios with respect to “no CC” in terms of GDP and looking at crop production. They are standard results for a CGE model. Then, we use the CGE outcomes to derive indicators and analyze how they move because of climate change impacts in the agricultural sector.

Figure 4 depicts a global picture of GDP losses in 2040 “with CC” with respect to 2040 “no CC”.

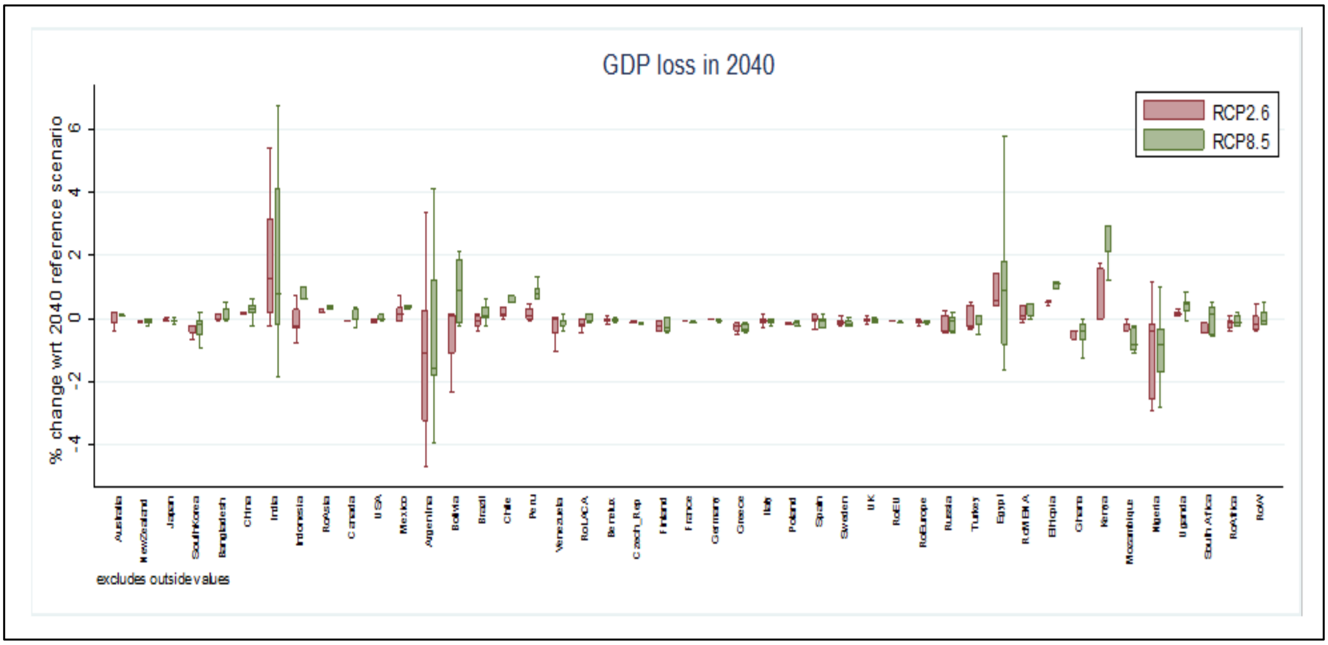
In terms of model uncertainty, on average, RCP8.5 shows a lower agreement on GDP effects than RCP2.6. It is evident in the cases of India, Argentina, Bolivia, Egypt, Kenya and Nigeria. Only Bolivia and Kenya show an evident improvement in GDP in RCP8.5, while in the other cases there is an overlapping of the two RCPs. Despite India, which has a GDP growth between 3% and 4%, GDP increases in other countries are lower than 2%. Moreover, European countries seem to be quite unaffected by climate change impacts in the agricultural production.

Asian countries face a moderate increase in GDP (generally lower than 1%) with the exceptions of South Korea (losses in both RCPs) and Indonesia (loss in RCP2.6).

American continent is evidently divided into Northern and Southern part. In the North, gains in GDP are very small with a differentiated pattern between countries and RCPs; indeed, while the USA has improvements in RCP2.6 the situation reverses for Canada and Mexico with better performances in RCP8.5.

While in North Africa all countries observe increases in GDP in “whit CC” scenarios, central and south Africa have differentiated results; Central Eastern Africa (Ethiopia, Kenya, Uganda) gains from climate change while Central Western countries (Ghana and Nigeria) lose.

Figure 4: Percentage GDP losses in 2040 wrt 2040 reference



Source: ICES-XPS results

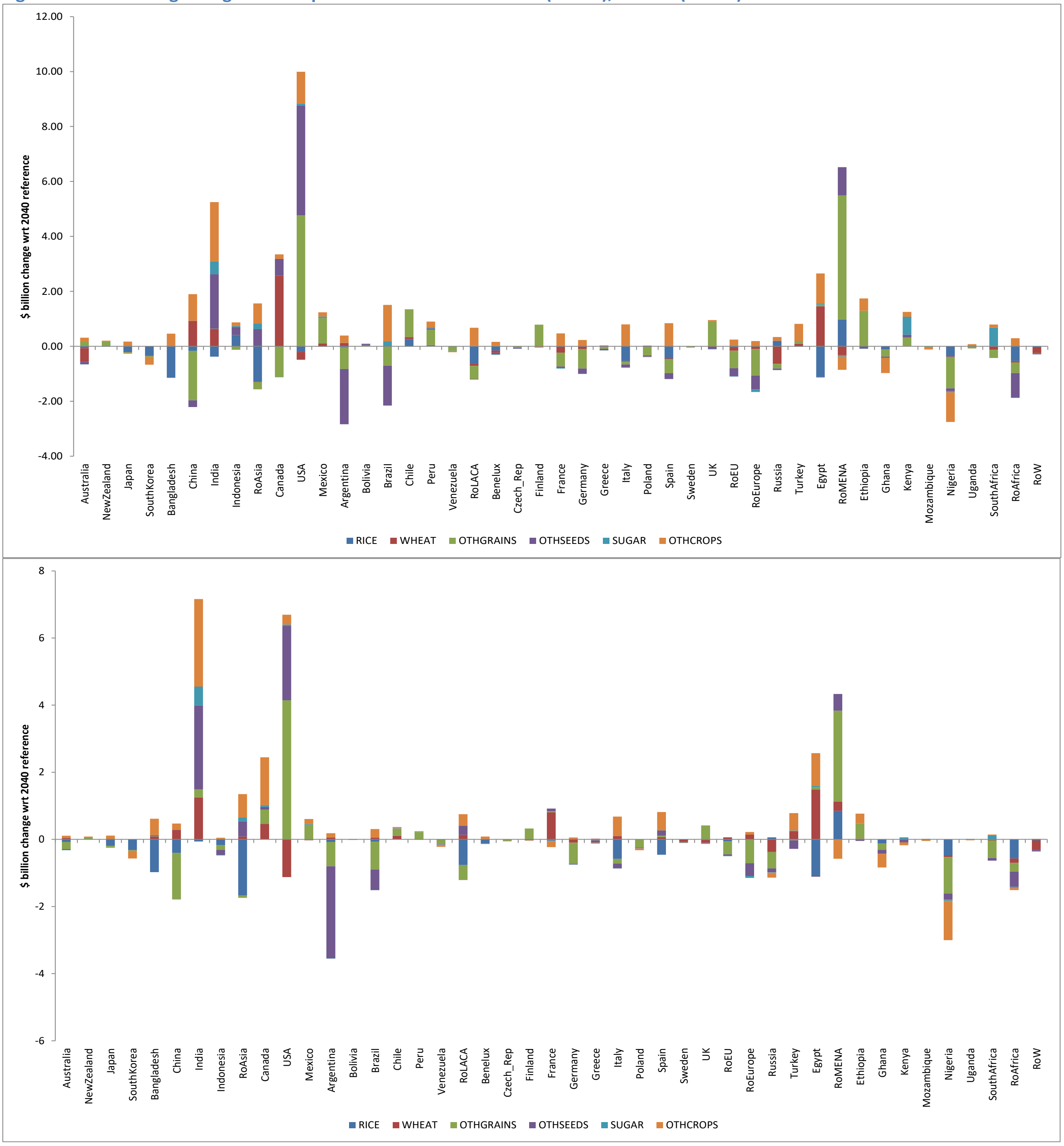
Figure 5 shows the change in agricultural production and the component for each crop according to RCPs.

In RCP8.5 the US, India, Rest of MENA and Egypt increase their agricultural production between 2 USD billion and 9 USD billion. However, their improvements have different main contributors, in terms of crops. Thus, if for the US and Rest of MENA the production mainly increases for other grains, India benefits from other seeds production increase and Egypt from wheat production. Generally, the most negatively affected countries are in Africa, with Nigeria, Rest of Africa and Ghana losing more than 1 USD billion. However, some other losers are outside the African continent as Argentina and Rest of Europe.

Finally, China is not as impacted as other countries because controversial effects at the crop level. Indeed, as it experiences an increase in other crops and wheat production, these gains are completely counterbalanced by a dramatic loss in other grains (nearly 2 USD billion). The Chinese final outcome is a reduction in agricultural production of only 0.3 USD billion.

Considering RCP2.6 we note no difference in terms of which countries increase (or reduce) their production but there is only a change in magnitude of the final effect. More precisely, there is a generalized reduction where in RCP8.5 agricultural production increases and higher losses. The most representative case is the one of the US. Although it continues to face an increase in production, it is nearly 4 USD billion lower than in RCP8.5. This is caused mainly by a reduction in wheat and other seeds production. The same happens for Argentina, which is one of the loser even in RCP8.5 but in this case its loss in production in nearly 3.4 USD billion. The only exception is India. While it gains in RCP8.5, its increase in production is even higher in RCP2.6, passing from 4.9 USD billion to more than 7 USD billion in 2040.

Figure 5: Mean change in agricultural production between RCP8.5 (above), RCP2.6 (below) and 2040 reference



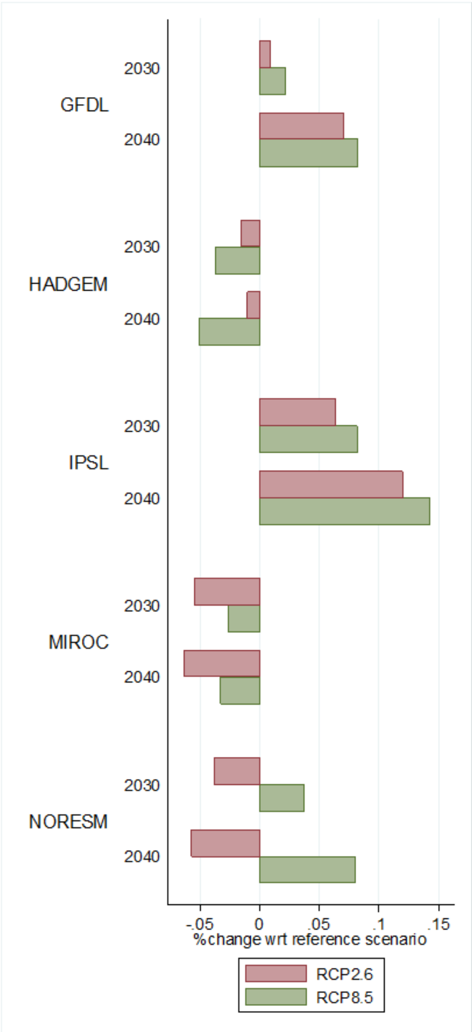
Source: ICES-XPS results

Now we present the main results for indicators described in section 3.3.

a) Poverty

Figure 6 depicts how the poverty indicator moves between 2030 and 2040 in the “with CC” scenario respect to the “no CC” scenario. According to GFDL an IPSL poverty should increase in 2030 and in 2040, with an average percentage change near 1%. Conversely, HADGEM and MIROC-ESM show a reduction in poverty, around 0.05%. However, while in the former model RCP8.5 has a lower reduction in poverty, in the latter case RCP2.6 is better. NorESM, instead, has a controversial result as poverty increases in RCP8.5 (0.08% in 2040) and lowers in RCP2.6 (-0.05% in 2040).

Figure 6: Poverty indicator percentage changes in 2030 and 2040 respect to reference scenario



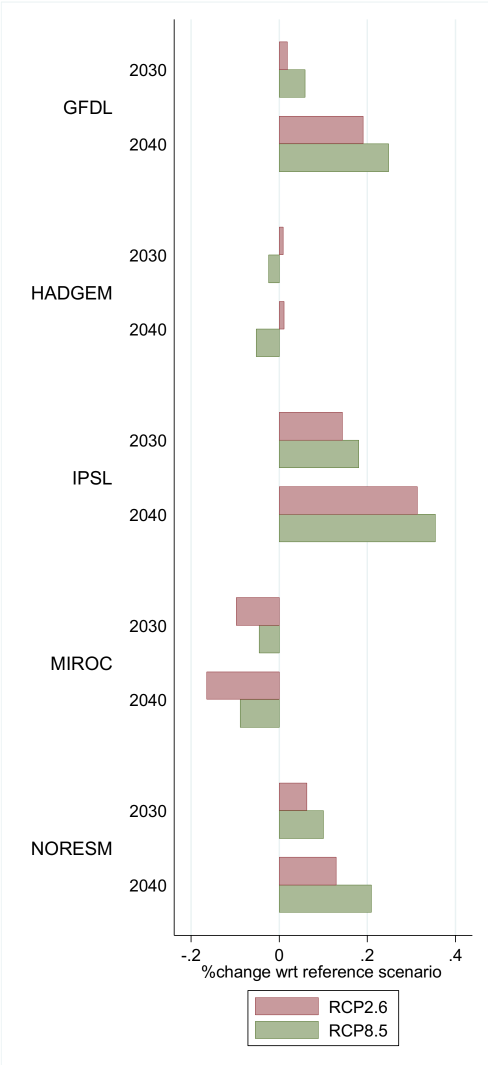
Source: Regressions results

Appendix 3 summarizes the outcome for countries with a poverty rate higher than 3% in 2030. Looking at country details poverty declines in Nigeria with a reduction on average of 0.2 million people in both RCPs in 2030, conversely, in India poverty rises slightly (0.01 million people) in both RCPs. Other countries results are centered around zero, with visible differences (lower than 0.1 million) in Rest of Africa and Rest of Asia. In 2040, instead, differences increase across countries. Nigeria still lowers its poverty but less than in 2030 (0.1 million of new poverty respect to 2030). In RCP8.5 India increases its poverty in RCP2.6, with a higher level of uncertainty as well. More evident but in the same direction are the changes in poverty for Rest of Africa and Rest of Asia. Finally, Bangladesh and China have no relevant changes between 2030 and 2040.

b) Inequality

Figure 7 depicts how inequality evolves in 2030 and 2040 according to different GCMs and in both RCPs. Most GCMs suggest an increase in within-country inequality at the world level (+0.2%), that is higher in RCP8.5 than in RCP2.6. However, MIROC-ESM outcomes show a reverse finding with declining inequality, especially in RCP2.6. HADGEM, instead, has a borderline outcome, close to zero, but differentiated according to RCP. Thus, in RCP2.6 inequality is slightly increasing but stable between 2030 and 2040, while in RCP8.5 it declines marginally in the same period.

Figure 7: Within-country inequality percentage changes in 2030 and 2040 respect to reference scenario



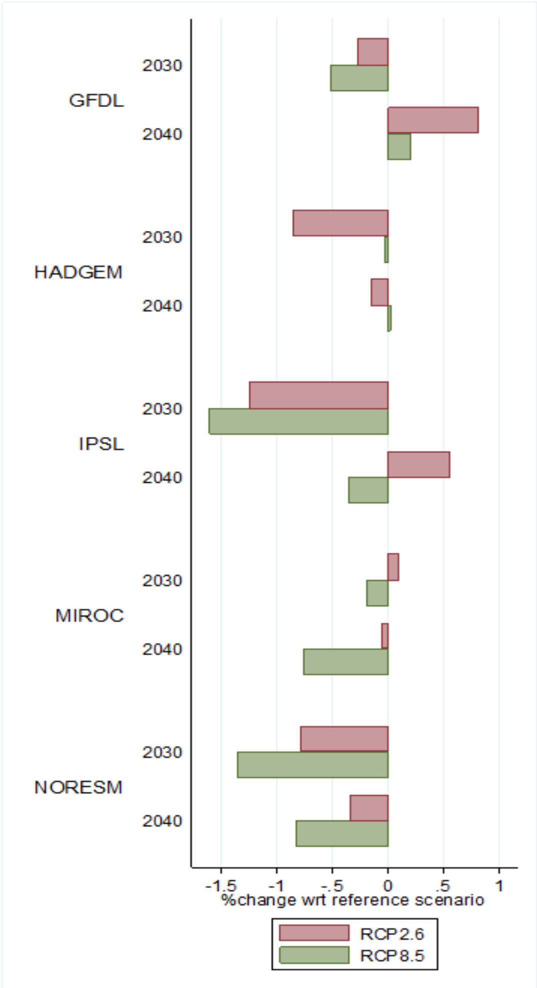
Source: Regressions results

At the country level (see appendix 4), Bangladesh reduces more its within inequality between 2030 and 2040 in both RCPs; Kenya, instead, shows an drop in inequality in RCP8.5 comparing 2030 and 2040, while in RCP2.6 it has an unclear result as it is centered around zero. Similarly, Ethiopia increases its inequality in the short run (up to 2030) but it declines afterwards respect to the "no CC" scenario. Conversely, Indonesia increases its inequality in both RCPs. Finally, Nigeria reduces inequality in both RCPs but it lowers the GCMs uncertainty as well.

c) Malnutrition

Figure 8 shows at the World level the undernourishment rate differentiating among GCMs and RCPs. In general, in 2030 all models suggest a reduction in malnutrition (except MIROC-ESM in RCP2.6) while in 2040 the results are different for GFDL and IPSL. While in most cases the reduction in 2030 reduces in 2040 but it maintains a positive effect on malnutrition, in GFDL there is an opposite outcome, as in both RCPs malnutrition increases; in IPSL the increase in malnutrition is evident in RCP2.6. In RCP2.6 malnutrition lowers from 1.25% (IPSL) to 0.27% (GFDL) in 2030; this means a reduction between 3.9 and 0.8 million people. In the same time period, RCP8.5 seems to be more positive in its outcomes with a reduction in undernourishment reaching 4.9 million people (IPSL). In 2040, instead, the reduction in malnutrition slows with an average increase in undernourished people between 2.1 million people (RCP2.6) and 1.8 million people (RCP8.5).

Figure 8: Malnutrition percentage changes in 2030 and 2040 respect to reference scenario



Source: Regressions results

Appendix 5 presents the national details for malnutrition for countries exceeding 5% rate of malnutrition in 2030, to compare whether in the longer run (2040) there are changes and in which direction. In details, in 2030 mostly affected countries are Asian; although Indonesia increasing its undernourishment indicator (RCP2.6), the other countries reduces them in both RCPs. Bangladesh and India have higher inequality in 2040, however it does not exceed the "no CC" scenario. Indonesia has a similar result in 2040 as well. African countries show different trends: Ethiopia and Kenya have lower undernourishment rates in 2040, while the other ones (i.e. Mozambique, Rest of Africa, Uganda) increase but lower than 0.5%.

6. Conclusions

This paper offers a worldwide assessment of the influence of climate change on agriculture production and their effects on country economies under 5 different GCMs and 2 RCPs scenarios that capture the uncertainty in future climate and yield projections. Furthermore, our analysis goes beyond the usual economic impact assessment describing the consequences of climate change on three social indicators, namely poverty, inequality and malnutrition that are strongly related to agricultural production. Despite the negligible impact of climate change on GDP, we observe that under a sustainable development perspective encompassing other dimensions beyond GDP, not achieving SDG 13 (Paris agreement) has several drawbacks. The within-country inequality worsens under RCP8.5 (no stabilized emission path) compared to RCP2.6 (stabilized emission path, +3° in 2100), poverty rate increases as well as malnutrition prevalence,

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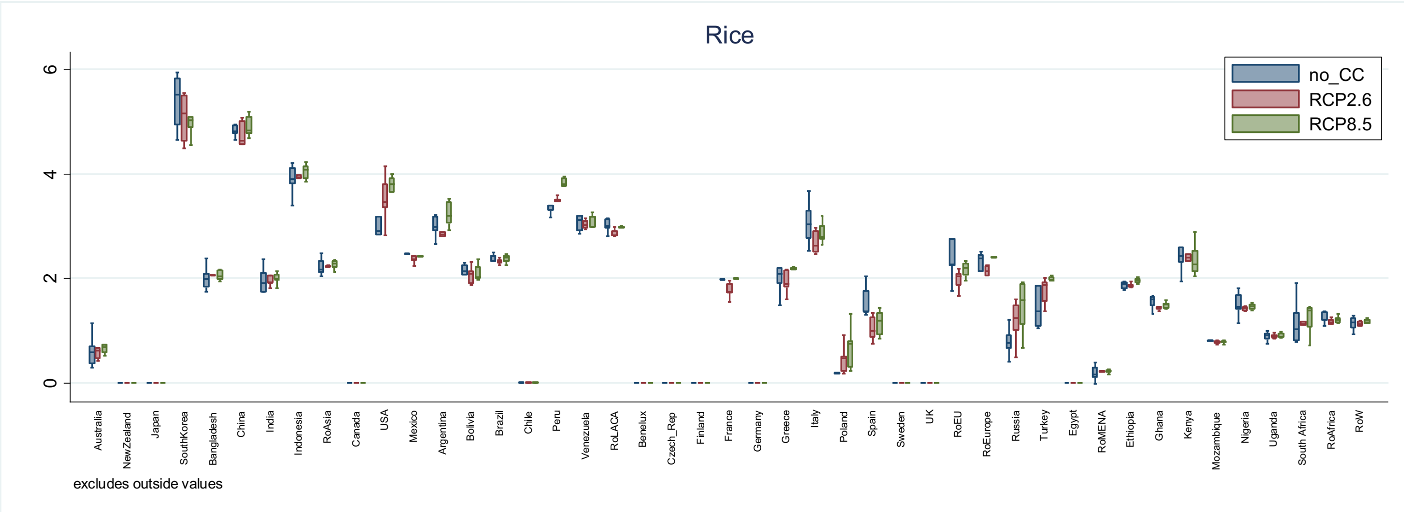
Appendix 1: SDG targets and APPS indicators

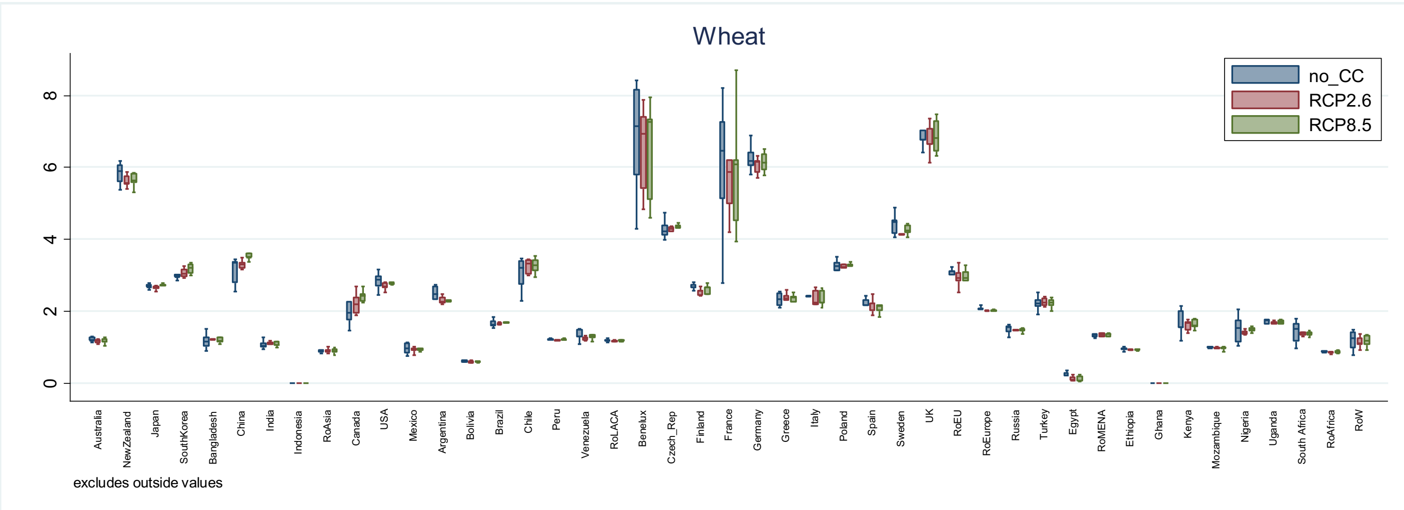
UN SDG	APPS indicators	SDG targets
1. NO POVERTY	**Poverty headcount ratio at \$1.25 a day (PPP2005) (% of population)**	1.1 By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than \$1.25 a day
2. ZERO HUNGER	**Prevalence of undernourishment (% of population)**	2.1 By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round
3. GOOD HEALTH AND WELL-BEING	**Physician density (per 1,000 people)**	3.c Substantially increase health financing and the recruitment, development, training and retention of the health workforce in developing countries, especially in least developed countries and small island developing States.
	Healthy Life Expectancy (HALE) at birth (years)	n/a
4. QUALITY EDUCATION	**Youth literacy rate (% of population 15-24 years)**	4.6 By 2030, ensure that all youth and a substantial proportion of adults, both men and women, achieve literacy and numeracy
5. GENDER EQUALITY	**n/a**	n/a
6. CLEAN WATER AND SANITATION	**Annual freshwater withdrawals, total (% of internal renewable water)**	6.4 By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity
7. AFFORDABLE AND CLEAN ENERGY	**Access to electricity (% of total population)**	7.1 By 2030, ensure universal access to affordable, reliable and modern energy services
	Renewable electricity (% in total electricity output)	7.2 By 2030, increase substantially the share of renewable energy in the global energy mix
	Primary energy intensity (J / \$PPP2011)	7.3 By 2030, double the global rate of improvement in energy efficiency
8. DECENT WORK AND ECONOMIC GROWTH	**GDP per capita growth rate (%)**	8.1 Sustain per capita economic growth in accordance with national circumstances and, in particular, at least 7 per cent gross domestic product growth per annum in the least developed countries
	GDP per person employed (\$ PPP2011)	8.5 By 2030, achieve full and productive employment and decent work for all women and men, including for young people and persons with disabilities, and equal pay for work of equal value
	Employment to population ratio (%)	n/a
9. INDUSTRY, INNOVATION AND INFRASTRUCTURE	**Manufacturing value added (% GDP)**	9.2 Promote inclusive and sustainable industrialization and, by 2030, significantly raise industry's share of employment and gross domestic product, in line with national circumstances, and double its share in least developed countries
	Total energy and industry-related GHG emissions over sectoral value added (t of CO_2eq/\$PPP2011)	9.4 By 2030, upgrade infrastructure and retrofit industries to make them sustainable, with increased resource-use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes, with all countries taking action in accordance with their respective capabilities.
10. REDUCED INEQUALITIES	**Palma ratio**	10.1 By 2030, progressively achieve and sustain income growth of the bottom 40 per cent of the population at a rate higher than the national average
11. SUSTAINABLE CITIES AND COMMUNITIES	**PM2.5 pollution, mean annual exposure (micrograms per cubic meter)**	11.6 By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management
	CO_2 intensity of residential and transport sectors (t of CO_2eq/ton of oil equivalent energy use)	n/a

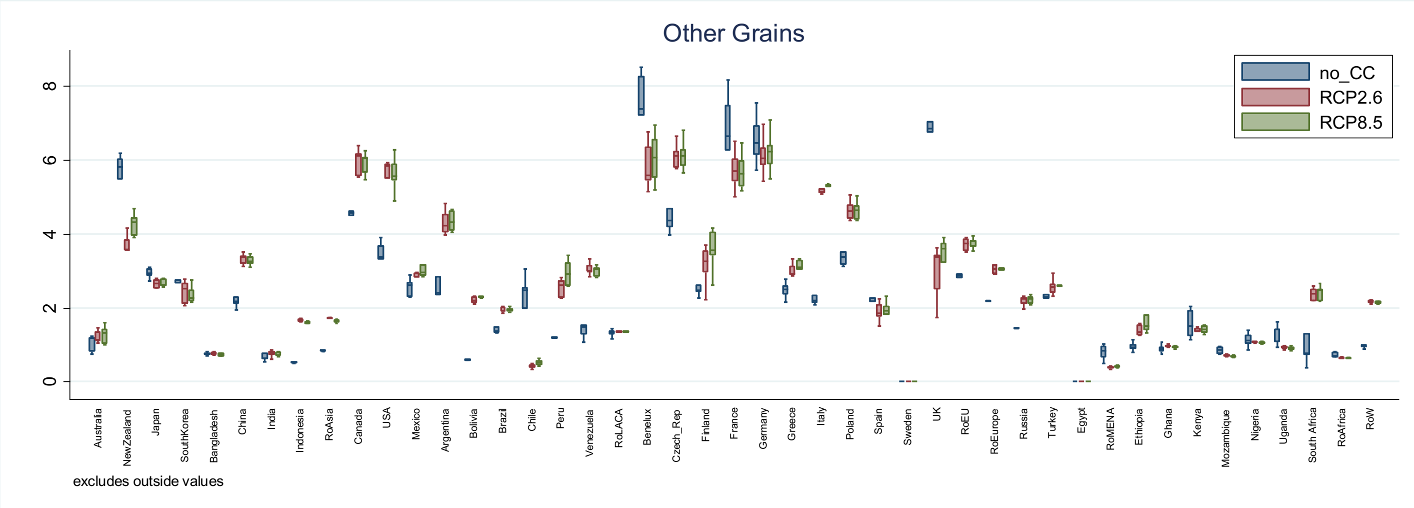
UN SDG	APPS indicators	SDG targets
12. RESPONSIBLE CONSUMPTION AND PRODUCTION	**Material productivity ($PPP2011/Kg)**	12.2 By 2030, achieve the sustainable management and efficient use of natural resources
13. CLIMATE ACTION	**Net GHG emissions from agriculture, forestry and other land use (AFOLU) sectors per square meter of forest and agricultural land (t of CO2e / sq. m)**	n/a
	Compliance to Conditional INDCs	13.2, Integrate climate change measures into national policies, strategies and planning
	Gap from equitable and sustainable GHG emissions per capita in 2030 (t CO2eq)	15.5 Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity, and, by 2020, protect and prevent the extinction of threatened species
14. LIFE BELOW WATER	**Marine protected areas (% of territorial waters)**	14.5 By 2020, conserve at least 10 per cent of coastal and marine areas, consistent with national and international law and based on the best available scientific information
15. LIFE ON LAND	**Terrestrial protected areas (% of total land area)**	15.1 By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and dry lands, in line with obligations under international agreements
	Forest area (% of land area)	15.2 By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally
	Endangered and vulnerable (animals and plants) species (% of total species)	15.5 Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity, and, by 2020, protect and prevent the extinction of threatened species
16. PEACE, JUSTICE AND STRONG INSTITUTIONS	**Corruption Perception Index**	16.5 Substantially reduce corruption and bribery in all their forms
17. PARTNERSHIPS FOR THE GOALS	**Central government gross debt (% of GDP)**	17.4 Assist developing countries in attaining long-term debt sustainability through coordinated policies aimed at fostering debt financing, debt relief and debt restructuring, as appropriate, and address the external debt of highly indebted poor countries to reduce debt distress
	Research and Development (R&D) expenditure (% of GDP)	17.6 Enhance North-South, South-South and triangular regional and international cooperation on and access to science, technology and innovation and enhance knowledge sharing on mutually agreed terms, including through improved coordination among existing mechanisms, in particular at the United Nations level, and through a global technology facilitation mechanism when agreed upon

Source: APPS website (http://www.feemsdgs.org/methodology/screening-selection-of-indicators/)

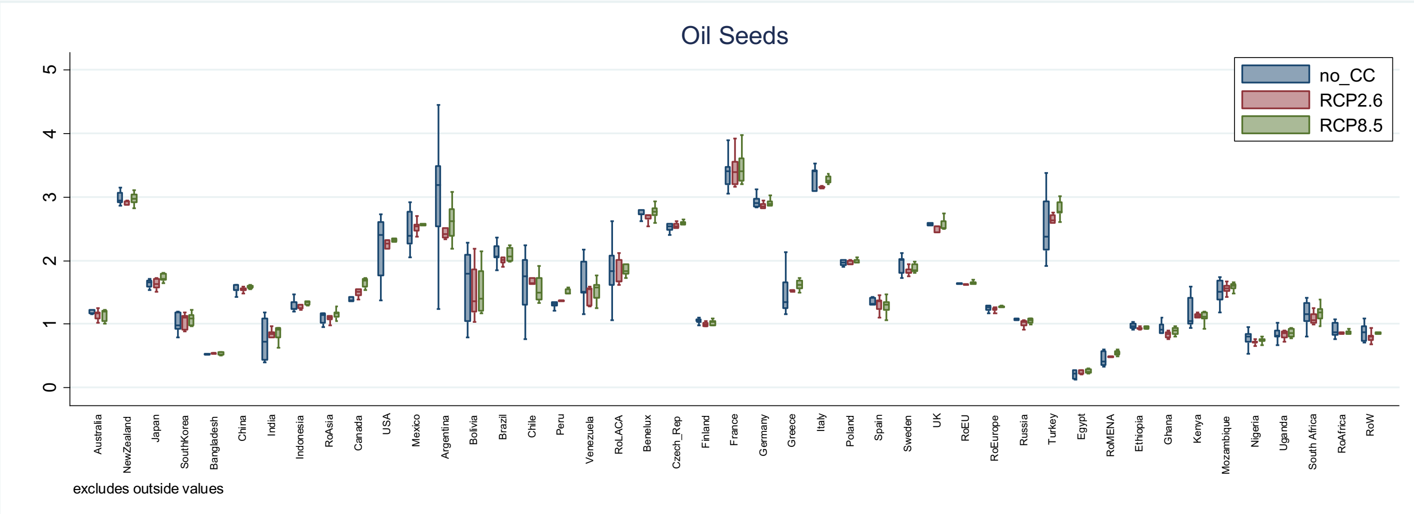
Appendix 2: Land productivity changes in "noCC" and "with CC" according to RCP



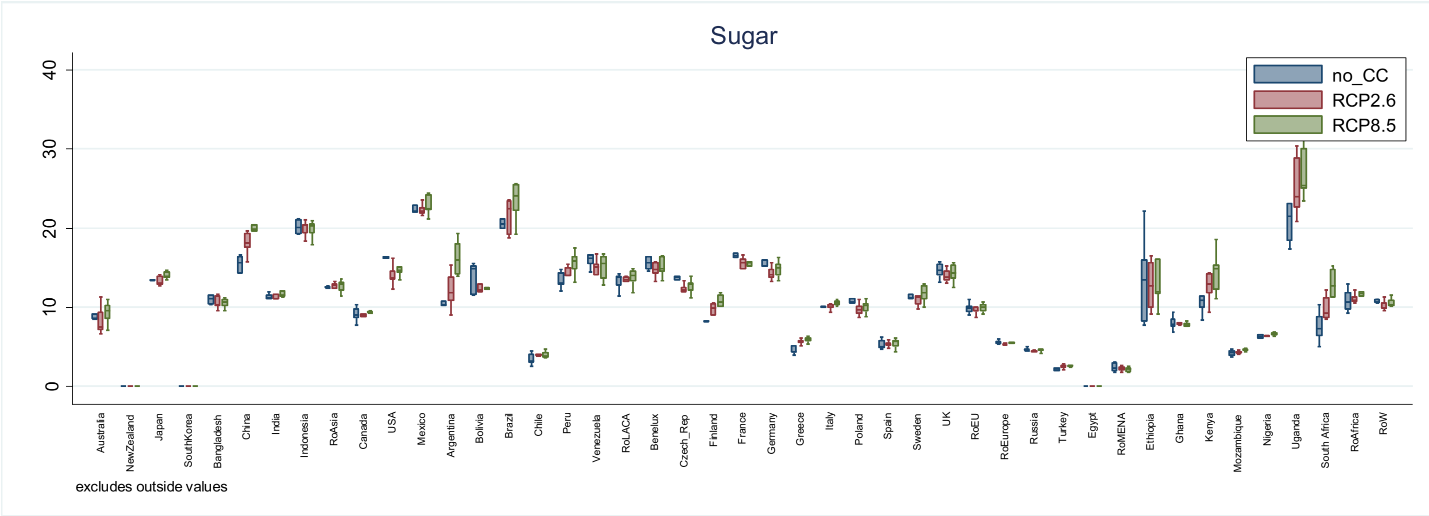




Other Grains
no_CC
RCP2.6
RCP8.5
0
2
4
6
8
Australia
NewZealand
Japan
SouthKorea
Bangladesh
China
India
Indonesia
RoAsia
Canada
USA
Mexico
Argentina
Bolivia
Brazil
Chile
Peru
Venezuela
RoLACA
Benelux
Czech_Rep
Finland
France
Germany
Greece
Italy
Poland
Spain
Sweden
UK
RoEU
RoEurope
Russia
Turkey
Egypt
RoMENA
Ethiopia
Ghana
Kenya
Mozambique
Nigeria
Uganda
South Africa
RoAfrica
RoW
excludes outside values

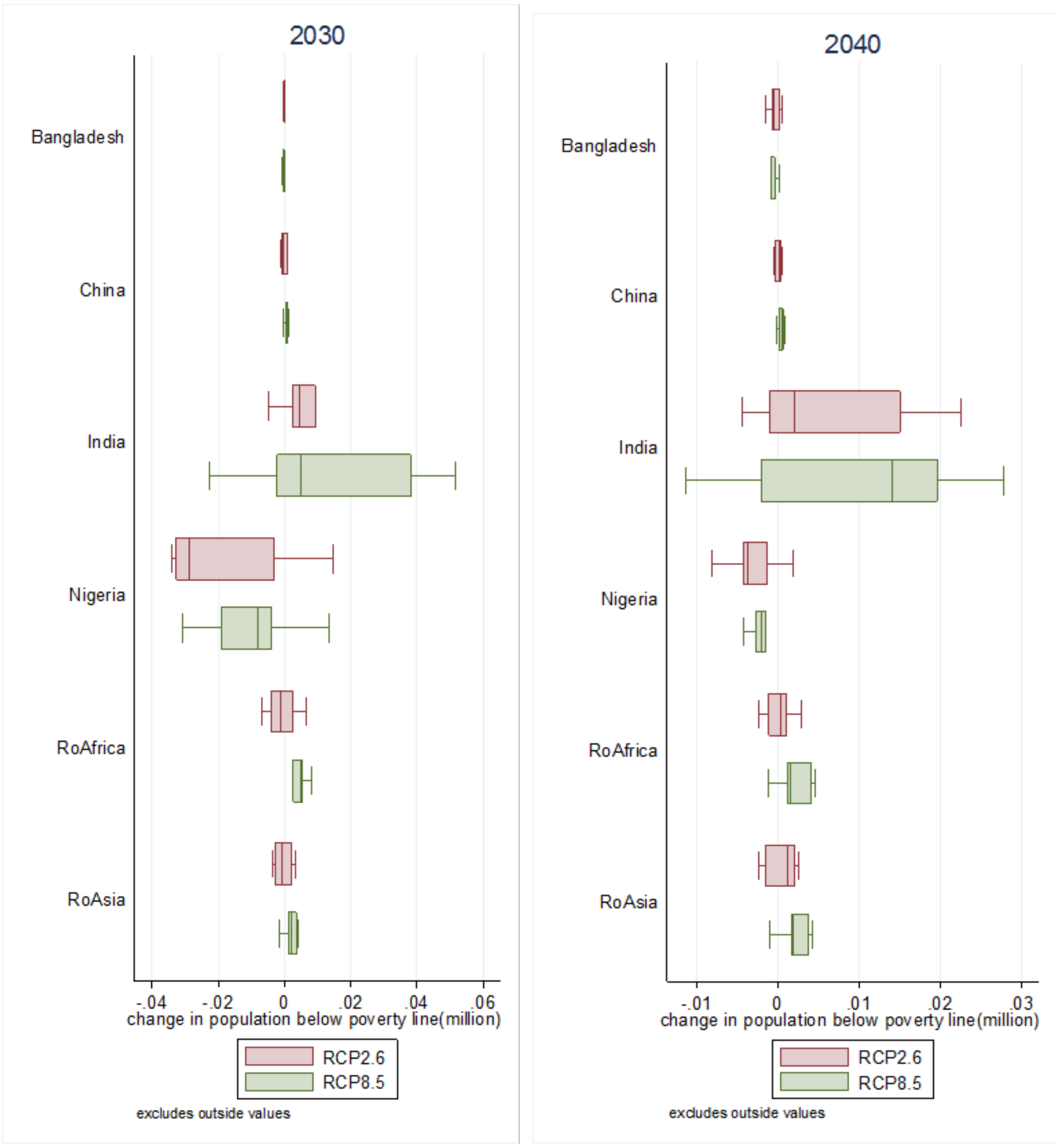


Oil Seeds
no_CC
RCP2.6
RCP8.5
0
1
2
3
4
5
Australia
NewZealand
Japan
SouthKorea
Bangladesh
China
India
Indonesia
RoAsia
Canada
USA
Mexico
Argentina
Bolivia
Brazil
Chile
Peru
Venezuela
RoLACA
Benelux
Czech_Rep
Finland
France
Germany
Greece
Italy
Poland
Spain
Sweden
UK
RoEU
RoEurope
Russia
Turkey
Egypt
RoMENA
Ethiopia
Ghana
Kenya
Mozambique
Nigeria
Uganda
South Africa
RoAfrica
RoW
excludes outside values

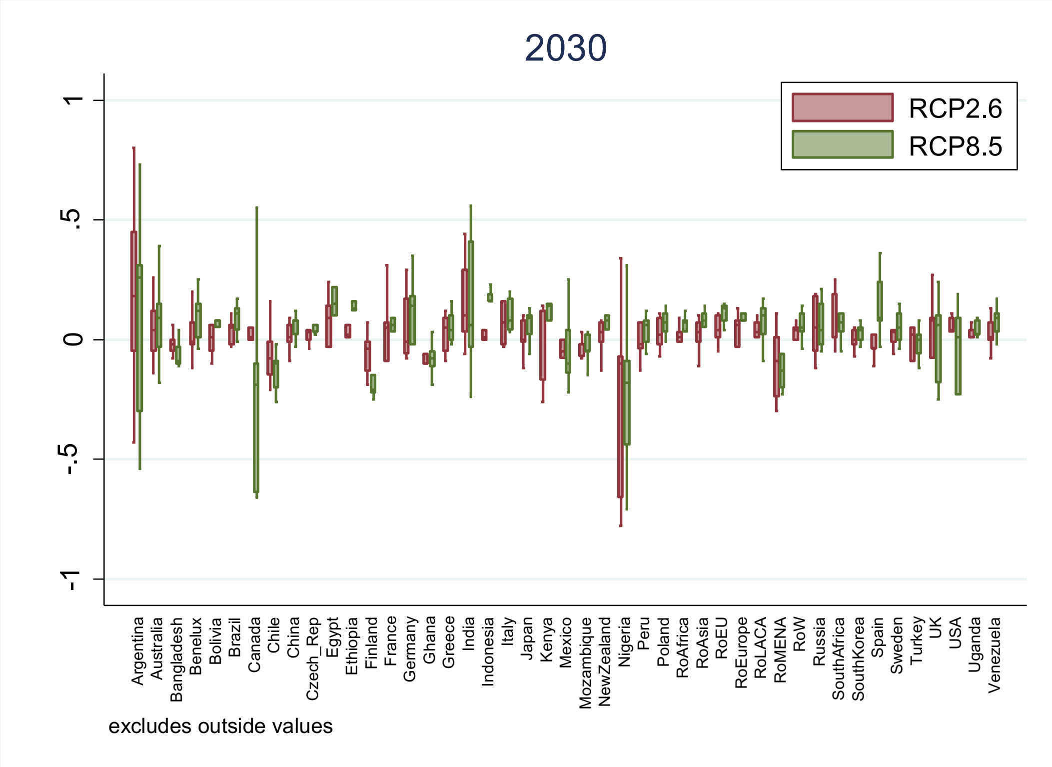


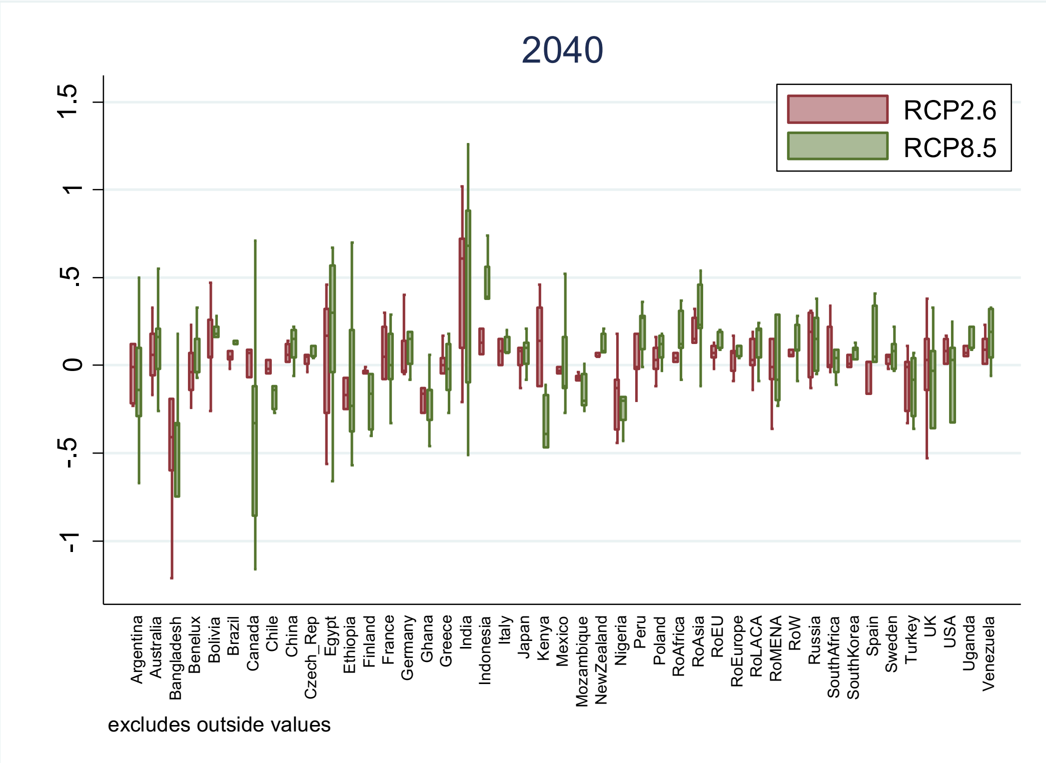
Source: authors' calculations

Appendix 3: Poverty indicator by country in 2030 (left) and 2040 (right)



Appendix 4: Inequality indicator changes by country in 2030 (above) and 2040 (below)





Appendix 5: Undernourishment indicators changes by country in 2030 (left) and 2040 (right)