Climate Change, Comparative Advantage and the Water Capability to Produce Agricultural Goods

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Abstract

This article analyzes how climate change influences the capabilities to export agricultural goods and the specialization of nations (e.g., comparative advantages) by altering farmers' capability to use available water. Our main contribution is methodological since we present the first attempt to link precisely the micro-determinants of production to the macro-determinants governing the specialization of countries. We use a rich set of data both locally (at the crop level analyzing thousand fields that cover the Earth's surface) and at the global level (analyzing bilaterally the international trade of nations). At the local level, we estimate the elasticity of production to the thermal and hydrologic conditions (including blue and green water as well as groundwater storage) along with fixed effects (at country-product and at the crop level) to control for omitted variables. At the global level, we use the predicted value of these elasticities to compute an indicator of the water capability to export agricultural goods, which is then used in a trade gravity equation to control for trade costs that also shape the specialization of countries. From these estimates, we finally build an indicator of comparative advantage in agricultural goods and analyze how these relative advantages are affected by climate change in 2050. We present unexpected results at first sight, that are however in line with the Ricardian theory, such as cases where a deterioration of the local conditions to produce a good does not prevent an improvement in the comparative advantage to produce it (representing 32.51% of cases in our simulation), or the reverse, when the improvement of the local conditions happens simultaneously with a deterioration of the comparative advantages (representing 18.16% of cases in our simulation).

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1 Introduction

Climate change will have a myriad of effects on the productions of agricultural goods (IPCC (2007)). The most obvious, is that by deteriorating the natural conditions of plant growth, it will lead to less production. A more subtle consequence is that climate change will affect differently the relative costs of production of different crops (Costinot et al., 2016). Then, apparently unexpected results can arise, such as the production of goods that are not fully adapted to the new climate but which are possible because climate change will have even worse consequences on other outputs in this country

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relatively to what occurs elsewhere, leading producers to focus their investments and resources on these less affected agricultural products. In case of a positive shock, the same mechanism holds, not all the favoured products by climate change are going to be produced, but only those with the lowest relative costs of production in comparison with foreigner competitors. This is at least what can be expected in a globalized world according to the theory of comparative advantage of Ricardo (1817): the specialization of countries is based on a comparison of their relative productivity differences. In this paper, we analyze to what extent the utilization of an essential factor of production, water, explains the specialization of countries on different agricultural products. Then, we study how climate change, by affecting this resource, can destabilize the current comparative advantages of all the countries in the world.[1]

We define the water capability to produce as all the conditions related to water that enable to grow a plant. We thus build an indicator that includes the availability of all sources of water (such as river's runoff, groundwater and precipitation), taking into account the water use competition between the different crops (as well as the competition with municipal and industrial consumption). We also consider the climatic constraints that impact the efficiency of the available water in the production of agricultural goods. Indeed the evapotranspiration of plants (depending of their location), and the temperature requirement of each crops determine whether there is enough water to sustain production.[2] Finally, we build an indicator that measures the cost of using water for a particular crop relatively to all other production that are possible according to the climate and hydrologic conditions.

We focus on this water capability to produce, for two reasons.The first and the most obvious is that the utilization of water is an essential component of the agricultural production and thus worth of interest regarding the essential role of agriculture for human development.[3] The second reason is that many researches have been done by hydrologists and agronomists on water, enabling to have an accurate measure of the current water capability to produce at a very disaggregated spatial level and for different agricultural products all over the world. We then build an indicator of water capability at the scale of a 30 arc-minute worldwide grid or approximately 55 kilometers at the equator. This spatial disaggregation at the grid scale, which is then finer than a regional or even a communal scale, is important to observe where the specialization of countries comes from. Hence our detailed analysis enables to locate the development and crisis related to water for the production of agricultural inside each country. Furthermore, the product disaggregation of the water capability to produce different goods is also critical for our research question, because it enables to determine the water productivity of a location for *all* agricultural activities, and not just those in which it is currently employed. This allows to study how different lands can be converted to develop new types of products in front of climate change.

Why does it matter to take into account international trade in this analysis of the effect of climate change? After all, why exchange is so important, and not only internal food production? As stated earlier, from the theoretical framework from which the current analysis is based, namely the comparative advantage of Ricardo (1817), it is the process of international exchange that drives the specialization of nations. Such an emphasis on the importance of trade integration to explain the

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[1] We focus here on how climate change by increasing water scarcity has a significant negative effect on agriculture production and then specialization. Obviously, climate change also affects agriculture via other channels, for instance, by enhancing the probability of floods, it would equally damage crops (e.g. Bronstert, 2003; Su, 2020). We do not consider here the effects of climate change on flooding, which would require a different analysis that is left for future research.

[2] More concretely, data on precipitation, runoff and evapotranspiration come from the AQUAMAPS data of the FAO, which are merged with data of the Global Agro-ecological Zones v3.0 (GAEZ) to take into account the thermal regime (including the crop suitability of the local thermal regime), the soil quality, the terrain slope, the share of land covered with building and other natural coverage (lake, forest or ice). These variables are then used to explain the agriculture production (available from MIRCA2000) to build our new indicator of the local water capability to produce agricultural goods.

[3] According to Bairoch (1973) and to a more recent literature in economic growth (see Ashraf and Galor, 2011) successful productivity growth in agriculture has been the source of early structural transformation leading to industrialization, urbanization and development in most of today's high income countries.

specialization of nations is not solely at the heart of the modern Ricardian theory (e.g. Eaton and Kortum (2002), Costinot et al. (2012)) but it is a common feature of all analysis in international economics.[4] Moreover the relative cost of production inside a country is not enough to determine its specialization, international trade costs also matter. For instance, the relative productivity advantage due to water in one country, can be outweighted by the high trade costs to export agricultural goods from this country (relatively to other countries). In brief, locational (dis)advantage also explains the specialization of nations. From that stand point, it would be illusive to analyze the specialization of countries without taking into account international trade. In this paper, we use international trade flows, to measure trade costs (via a trade gravity equation) and then to reveal the comparative advantage of countries (via the Balassa (1965) index, aptly named the Revealed Comparative Advantage index, hereafter RCA).[5] Then, by studying how climate change affects the water capability to export agricultural goods, we are able to predict how the agricultural RCA can evolve.[6] Furthermore, by considering the implications for the world development, analyzing climate change in an open economy also enables to study the conditions under which international trade can mitigate the consequences of climate change via agricultural reallocation of production between countries.

Our findings concerning the production of agricultural goods measure the importance of the thermal and hydrologic conditions and the essential role of groundwater storage. Indeed, our estimates show that having insufficient renewable water resources available to fulfill the needs of plants may induce a minimum loss of capability to produce agricultural goods by approximately 4%. Yet, such a loss may be attenuated by pumping water from the underground as we find that an increase of groundwater stock by 1% could potentially help to increase this capability by approximately 0.03% in the localities with insufficient renewable water resources. When simulating the effects of climate change, we find that 64.2% of agricultural lands may experience a decrease in their capabilities to produce. The most vulnerable countries to climate change will likely bear the most of these negative changes with a total loss of almost 17% of agricultural lands.[7] Regarding the international trade of agricultural products, we find that the water elasticity to export[8] is the smallest for the most vulnerable countries. This finding that exports of the most vulnerable countries are less sensitive to the water conditions seems to be a good new, indicating a specialization in the production of goods that are less intensive in water. However, these specializations seem to be insufficient to cope with climate change as we find that these countries could experience a drop of their exports by 14 % partly due from a strong decrease in their capabilities to use water for producing agricultural goods at the local level (-17 %) and partly due to a relatively low access to international markets (less than 10% of global trade in 2050).[9] This indicates a relative increase in the cost to produce agricultural goods and an increase in the marginalization of these countries to the world exchange. This may be particularly problematic for the development of these countries where exports of agricultural goods may have spillover effects in terms of productivity and explain the agricultural-demand-led industrialization (Adelman, 1995; De Pineres, 1999; Bustos

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[4] In the neo-classical analysis of comparative advantage based on factor endowments (the Heckscher-Ohlin model), openness leads countries to specialize their production in goods that use the most intensively the most aboundant factor. According to the new theories of trade, openness fosters a specialization in the production of goods which have the largest domestic market (the so-called home market effect, see Costinot et al. (2019)) or drives the resource toward the most productive firms (Melitz, 2003).

[5] The RCA is an index used in international economics for calculating the relative advantage or disadvantage of a certain country in a certain class of goods as evidenced by trade flows. See French (2017) who shows why this index is appropriate to uncover countries' fundamental patterns of comparative advantage.

[6] In what follows, we often use the term "comparative advantage" instead of "revealed comparative advantage" or "RCA" because it is more telling and convenient but all our analysis of comparative advantages is based on the RCA.

[7] In our analysis, we distinguish 4 group of countries depending upon their vulnerability to climate change (using an index developped by the FERDI).

[8] The water elasticity of trade is a measure of how sensitive the export from one country to another is to its water capability to produce agricultural goods. The term "strong elasticity" means that changes in the water capability to produce have a relatively strong effect on exports.

[9] We also present a substantial reallocation of production at the benefit of the less vulnerable countries that could experience a rise of their export by around +72% (with a strong increase of their comparative advantages: +59.5% on average) despite a drop of their average capabilities to use water for producing agricultural goods at the local level.

et al., 2016).[10]

Therefore, our analysis going from the micro geographical scale of the crop to the macro analysis of countries specialization enables to determine where the deterioration of the local conditions could lead to a deterioration of the comparative advantages (e.g. for cassava in Africa), as well as the reverse, namely the identification of locations where the improvement of the local conditions could lead to an improvement of the comparative advantages (this represents approximately half of the cases). We also present less intuitive results, such as cases where the deterioration of the local conditions to produce a good leads to an improvement in the comparative advantages to trade it (representing 32.5 % of cases, e.g. potatoes in the mediteranean countries), or when the improvement in the conditions to produce a good leads to a deterioration of the comparative advantages to trade it (representing 18.2 % of cases, e.g. rice in India).

Our analysis is related to different fields. Our concept of the water capability to produce agricultural goods is related to an emerging array of research on the link between water scarcity and the supply of crops. For instance, Vallino et al. (2020) propose to use an indicator of management of domestic and transboundary water resources to approximate the economic water scarcity and show that this indicator explains the agricultural productivity of countries. Interestingly they find that their indicator is not always associated to high country's income or to the hydrological water scarcity. Rosa et al. (2020) also propose an indicator of agricultural economic water scarcity, defined as the lack of irrigation due to limited institutional and economic capacity. They identify agricultural economic water scarce lands where investments in sustainable irrigation have the possibility to increase food production (e.g. in Sub-Saharan Africa). In comparison, our study does not analyze the role of institutions and governance of water, but better captures the hydrologic constraints and physical opportunities to produce agricutural goods.

Hydrologists have also developed models of the determinants of agricultural production linked to the water availability at the local level, such as the LPJmL (Lund-Potsdam-Jena managed Land, developed by Bondeau et al. (2007)), a dynamic global vegetation model designed to simulate vegetation composition and distribution for natural and agricultural ecosystems. However, such type of models have not only the major drawback of being very difficult to handle due to the complexity of the computation,[11] but also often failed to analyze the economic consequences such as the impact of the economic water scarcity of the agricultural specialization of nations. Economists on the other side, investigate in details how comparative advantages evolve (Costinot et al., 2016, Coniglio et al., 2021), but neglect the detailed hydrological information at the local level to understand the role of water in the production of agricultural goods. For instance, Murphy (2009) and Afkhami et al. (2018) capture the availability of water with annual runoffs and groundwater recharges in the exporting country. These indicators are problematic because the sole water endowment aggregated at the country level is misleading as some regions inside a nation can have sufficient water resources but not the temperatures or soil quality required to produce.[12] Our value added is thus to propose an indicator richer than the one used by economists, but simpler and more transparent than those presented by hydrologists in order to understand how the specialization of nations in different agricultural goods.

Our contribution can also be discussed at the light of a large literature on virtual water trade,

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[10] There are many researches and debates on the conditions under which exports of agricultural goods stimulate growth. Bustos et al. (2016), for instance, show the introduction of genetically engineered soybean seeds in Brazil in the context of a high level of trade openess has led to industrial growth in this country because this new technology was strongly labor-saving.

[11] The use of these models are challenging for non-hydrologist scientists who may consider them as "black boxes". Furthermore, these models also turn-out to be sometimes inadequate for economic studies as key parameters are generally estimated through country fixed effects (which induces major concerns about endogeneity bias when this indicator is used as an explanatory variable in a regression that also introduces fixed effects).

[12] In fact, authors implicitly assume that a surplus of water in one location can be transferred to another part of country where water is missing, but unlike other types of production factors such as capital, water resources cannot always be moved easily from a water-abundant region where production is not possible to a water-scarce one where other conditions to produce are located.

which measured the volume of water used in production of goods that are traded at the global level. Debaere (2014) finds that relatively water abundant countries export more water intensive products. Delbourg and Dinar (2020) demonstrate that arid countries use trade in order to alleviate their problem of water scarcity. They also show that some countries with abundant factors (land and labor) use water with less efficiency. A lively debate has however being at the center of this literature, since numerous authors have found opposite results, such as the fact that some water scarce countries actually export water-intensive crops (and vice versa).[13] Vallino et al. (2021) improve these analyses by weighting the global virtual water trade with a new composite water scarcity index that combines physical and economic water scarcity. They find that almost half of water volumes traded comes from countries that are worse-off than their partners regarding their composite water scarcity and their economic wealth. While this literature considers that governance, institutions and economic development at the local level can explain the conflict between the comparative (dis)advantage of countries and their specialization in agricultural goods, we pursue another explanation by considering that the unequal access to international markets for exporters from different countries can contradict the comparative advantage defined at the local/national level. By considering this, our article proposes a new contribution to the literature on the interaction between specialization and trade costs. To date, the most significant findings in this literature have been theoretical. Venables and Limao (2002) first propose a theoretical model to demonstrate that the equilibrium pattern of specialization involves a trade-off between comparative production costs and comparative transport costs.[14] Deardorff (2014) also shows that this trade-off matters and develops a concept of "local comparative advantage" (defined as autarky prices in comparison to nearby countries) to explain the specialization of countries. While some empirical analysis have been done from these theoretical foundations (e.g. Harrigan, 2010), we propose here a new methodology to reconciliate the local comparative advantage (linked to water) to international trade costs in order to determine the comparative advantage at the national level.

Finally, the consequence of climate change on agricultural trade have been at the core of many studies in the last decade (Huang et al. (2011), Costinot et al. (2016), Gouel and Laborde (2021)). The conclusion is optimistic, international trade can mitigate the consequences of climate change via agricultural reallocation of production inside and between nations. Climate change will also induce yield changes and large price movements fostering incentive to adjustments. In comparison with this literature, we propose a very different methodology which is based on estimations and not on numerical simulations of Computable General Equilibrium models (CGE). We also provide a new analysis of the hydrological conditions at the source of the comparative advantage of nations. Our results also differ and are less optimistic, for example, we present many cases where the reallocation of production inside nations fails to sustain the comparative advantage of countries.

The reminding part of this article includes the following sections. In Section 2, data on precipitation, runoff, groundwater storage, evapotranspiration and the thermal regime are used to explain the agricultural production at the local level. Then, the predicted values of this estimation are at the basis of our new indicator of the local water capability to produce agricultural goods. In Section 3, this indicator is used to explain bilateral trade between countries.[15] We also study how this water

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[13] See Fraiture et al. (2004) and Kumar and Singh (2005) for early critical analyses of virtual water trade. See also Ramirez-Vallejo and Rogers (2004) who show that virtual water trade flows are independent of water resource endowments in contradiction with one standard theory of international trade (the Heckscher-Ohlin Theory). Verma et al. (2009) quantify and critically analyze inter-state virtual water flows in India. Han et al. (2021) show that virtual water trade intensifies the water scarcity in Northwest China.

[14] The literature called "the New Economy Geography" summarized in Fujita et al. (2001) and Candau (2008) has analyzed how increasing returns and transport costs interact to explain the agglomeration of activities, and then indirectly explains how trade costs affect the trade patterns, however few analysis have been done on comparative advantage (see however Ricci, 1999).

[15] Trade decisions are obviously complex and not completely determined by changes in production patterns, they depend on prices, policies, and changes occurring in other nations. To take into account all these elements, and then to isolate the role of our water variable, we use the best practice in the literature of international trade (see Head and Mayer (2014) for a survey), that consists to explain trade flows via a gravity equation with bilateral fixed effects to control for all the bilateral relationships between partners (e.g. trade agreements), country effects and product effects that control

capability to produce agricultural goods influences differently the exports of different groups of countries distinguished by their degree of vulnerability to climate disruption (and endowment in capital). In Section 4, we build an index of the revealed comparative advantage that takes into account this variable of water and all the determinants of trade (including trade costs). All this analysis enables to follow the effect of climate change on water conditions at the local level, and then on production and trade to analyze the specialization of countries. Finally, Section 5 concludes with some avenues for future research.

2 Agricultural production and water at the crop level, a world analysis

The agricultural production depends on water but obviously depends on many other determinants, that need to be taken into account to isolate the productive effect of water on agricultural specialization. Some determinants are related to water and are often defined at the micro-spatial level (e.g. at the crop level where the water is available). Other determinants that depend, for instance, on the agricultural technology and/or on the global market access of producers are defined at the national and/or even at the international level. Our analysis is thus divided in two parts. In this section we lead a substantial investigation at the crop level to measure all the micro-constraints encounter by agricultural to produce. These micro-level constraints refer to the *capability* of producers to transform the available water resources into agricultural goods at the local level, they depend on temperature, soil quality, and so on. At this micro-spatial level we measure the relative costs of using water for a particular product relatively to all other products that can be produced (namely in the spirit of the Ricardian theory of comparative advantage). In the next section, we use a trade gravity equation to capture all the determinants that limit the *capability* to export. Among these constraints, trade costs between countries,[16] and differences in technology are taken into account.

2.1 Supply of crop at the micro-geographical level

To infer the impact of local water availability upon the capabilities to grow different type of crops, it is possible to follow a rich literature[17] that defines the behavioral rules of farmers regarding the crop acreage choice subject to agronomic and climatic constraints. On that matter, different models have been proposed such as multicrop production models with multinomial logit acreage shares presented in Carpentier and Letort (2013) or the Ricardian model of trade in Costinot et al. (2016). However, we do not use a formal model from this literature, as we aim to develop an indicator that does not depend on the expected gross margins per hectare of crop, on the price of the good produced or on the intermediate goods used. Our aim is to determine the supply of crops related to water that depends on natural determinants such as precipitations, the surface of waters, groundwaters and the water requirement of the different crops. This point matters to alleviate an endogenous bias in our empirical investigation (due to reverse causality between production and export). Indeed since our indicator is used to explain exports, we need an index that is not based on the current production choice of farmers but on a hypothetical choice based on the water endowment of locations. In other words, we do not compute an indicator on the types of products that *are produced* at a location l (depending of prices, fertilizers and so on), but rather on the types of products that *could be* produced in l given various exogenous conditions. In that respect, our work is based upon the idea of capabilities to transform the available natural resources into valuable goods given local natural constraints that can be traded on the international markets.

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for the competitiveness of exporters, demand effects, and changes occuring in other nations (what's the literature called the "multilateral resistances").

[16] These trade costs, that can be decomposed in four components, called "the four Ts" by Spulber (2007), are transaction costs (due to customs, business practices, and legal environments), tariff and non-tariff trade barriers (including environmental regulation and anti-dumping practices), transport costs and time costs.

[17] See Carpentier et al. (2015) for a literature review.

Furthermore, we follow the core principle of these aforementioned models by analyzing the *relative* capability to produce agricultural goods instead of an *absolute* value. Thus, similar to Carpentier and Letort (2013) or Costinot et al. (2016), we define our local capability to use water for producing a specific crop in comparison to the capabilities to use water to produce other crops and/or to fullfil non-agricultural needs.

Formally, we divide the world into gridded cells of 30 arc-minutes each representing localities l in which farmers can grow multiple crops, indexed by k. The categorization of these crops will follow the international nomenclature of the Harmonized Commodity Description and Coding Systems (called HS4 later in the text).[18] In such a setting, the heterogeneity of farmers comes from the fact that farmland does not match the cells such that multiple farmers may be within each locality l and the farmland of one farmer may overlays multiple localities. In that respect, different behaviors may arise within each locality leading to a certain diversity of crop acreage in l.

Following Carpentier et al. (2015), local constraints to grow a given crop k in locality l can be decomposed into two broad categories: the *land use choice* variables and the *acreage choice* variables.
The land use choice describes the individual choice to produce agricultural production in a given locality. Among the variables that determine this choice, there are, for instance, the soil quality, the thermal regime, the hydrologic conditions. These variables are important determinants of the average productivity of land for agricultural use in the broad sense. They are also useful to define localities l where agricultural production is not possible for any type of crop k. This last point is particularly important once we consider climate change, since the land use choice to produce agricultural goods can be hindered by a deterioration of these variables (IPCC, 2007).

Acreage choice describes the choice of farmers to produce a particular good among the different types of crop k that can be grown in each locality l. This choice depends on a vector of variables, hereafter denoted C_l^k, that are defined at the crop level, such as the crop specific suitability of hydrologic conditions and of the thermal regime at the cell level. In other words, this vector of variables encompasses all the agronomic factors that affect directly the capability of farmers to use water for agricultural production which will be more precisely define in the next section. This choice is also done by a comparative analysis: the incentive to produce a particular product depends on its suitability to the natural conditions compared to the suitability of all other goods that can be produced under these conditions ($\sum_k C_l^k$) (Carpentier and Letort, 2013; Costinot et al., 2016). This choice also depends on the alternative uses of water (namely water not used for the agricultural production), that reduce the water available to grow the crop k (Flörke et al. (2018)). These alternative uses (e.g. water for consumption in cities) are denoted W_l^{mun}. The higher W_l^{mun}, the smaller the share of a field l allocated to any given crop k that can benefit from water, and then the smaller the production at this location. To summarize, we aim to capture here the relative cost to use water for a particular k in comparison with other use of water (agricultural and non-agricultural).

We combine these elements[19] to build an indicator of the production of a given crop k in locality l, L_l^k, that may be interpreted as a measure of the *local water capability to produce agricultural goods* such as:

$$L_l^k = Land\,Use_l \times \underbrace{\frac{C_l^k}{W_l^{mun} + \sum_k C_l^k}}_{Acreage\ Choice} \tag{1}$$

This expression (1) takes a similar form than the one presented in Costinot et al. (2016) (Equation 8) where farmers allocate their fixed land inputs to multiple crops with land share assigned to each

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[18] A list of all products we consider in our analysis can be found in table (4) in the Appendix and a detailed explanation of these different classification can be found at http://www.fao.org/statistics/standards/en/

[19] See the data section 2.2 where we further expand the explanation and computation of these different variables.

crop being somewhat proportional to its relative productivity. Here, we solely substitute the concept of productivity by the one of capability.

2.2 Data and Empirical Strategy

In this section, we present the data and the different steps necessary to build our indicator of the local water capability to produce agricultural goods in the next section. Since this involve a complex methodology, we breakdown the procedure into two different steps which are dedicated to the vector of variables C_l^k where we first present the data and computation used to define each variable included in C_l^k and in the second step, we estimate the weight of each of this variable through a structural estimate of equation (1) allowing us to build a set of values C_l^k for each locality l and crop k.

2.2.1 Data and Computation of the Variables in C_l^k

The vector of variables that define the acreage choice concerning C_l^k is defined hereafter.

The crop specific thermal regime (T_l^k) is the temperature constraint factor from the Global Agro-ecological Zones v3.0 (GAEZ) to define the suitability of each cell l for growing any specific crop k. Here, the monthly profile is not necessary as the variable given by GAEZ already accounts for the adequation of temperatures in the growing period of each crop. This variable is expressed in percentage and thus ranges from 0 to 1 (where 0 implies the thermal regime of the locality l being unsuitable for the crop k and 1, the locality l being perfectly suitable for growing the crop k).

The crop specific suitability of local renewable hydrologic supplies (RW_l^k) is computed as the monthly average of the ratio between the local renewable water availability and the local crop water requirement. On the one hand, the local renewable water availability in locality l for each month m is the sum of soil moisture defined as R_{lm}^{SM} (data taken from the C3S Soil Moisture developed within ESA's Climate Change Initiative Soil Moisture Project), surface water runoff defined as R_{lm}^{SR} (data taken from the "Global Composite Runoff Fields", CSRC-UNH and GRDC, 2002) and groundwater recharge defined as R_l^{GR} (data taken from the "Groundwater Resources of the World", WHYMAP GWR). Finally, since ground and surface water resources can be interconnected, the simple sum may induce some double counts. To avoid that, we follow the FAO guidelines (FAO (2003)) to calculate a common water variable at the local level (CW_l) that will be subtracted from the calculation to avoid the double counting of the amount of water available in each cell l. On the other hand, the crop specific water needs (defined as D_{lm}^k) can be approximated by the evapotranspiration in each cell l for the month m and the crop k using the monthly potential evapotranspiration from the "Global map of monthly reference evapotranspiration", AQUAMAPS-FAO which is multiplied by a crop coefficient given in the Chapter 6 of Allen et al. (1998) (for each crop, we build a "Kc curve" which calculates the amount of water required depending of the growing stage of the plant, allowing to calculate an accurate monthly water requirement for agricultural production). More formally, $D_{lm}^k = c^k \times PET_{lm}$ with c^k, the crop coefficient for k and PET_{lm}, the potential evapotranspiration in l for the month m. Thus, the computation of RW_l^k is as follow:

$$RW_l^k = \frac{1}{M_l^k} \sum_m \left[\frac{1}{D_{lm}^k} \left(R_{lm}^{SM} + R_{lm}^{SR} + \frac{R_l^{GR} - CW_l}{M_l^k} \right) \right]$$

Where M_l^k is the number of months of the growing period of the crop k in locality l. We divide the adjusted groundwater recharge by this variable because data are only on annual basis such that we transform these yearly values into monthly ones with the assumption that farmers may capture the full yearly recharge to use it during the sole growing period.[20] Interpretation of RW_l^k is relatively straightforward: if $RW_l^k < 1$, the amount of renewable water in locality l is insufficient to fulfill the needs of the crop k but if $RW_l^k \geq 1$, then the crop k in locality l is not limited by water resources.

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[20] We are thankfull to the anonymous referee for pointing out this aspect.

The supplemental quantity of non-renewable water (NRW_l^k) is defined as underground non-renewable water that can be used by farmers in case of insufficient renewable water. The groundwater storage, noted R_l^{GS} is taken from the study of Gleeson et al. (2015) who estimate the volume and the spatial distribution of modern groundwater storage with several methods. We choose to use the method that matches recharge and water table in our calculation (we also test with another method that matches recharge and porosity and found only very marginal changes). We then assume that this water storage is only used when the renewable water in locality l is insufficient to fulfill the needs of crop k (pumping non-renewable underground being often costlier than the surface water, this resource is generally used in last resort, Siebert and Döll (2010); Wada et al. (2012)). In that respect,

$$NRW_l^k = \begin{cases} R_l^{GS} & if\ RW_l^k < 1 \\ 0 & otherwise \end{cases}$$

2.2.2 Estimation of the Variables in C_l^k

We estimate a Log-linearization of Equation (1) that takes the following form:

$$\ln\left(L_l^k\right) = c_L + \underbrace{\hat{\theta}_T \ln\left(T_l^k\right) + \hat{\theta}_{RW} \ln\left(RW_l^k\right) + 1_{\left\{RW_l^k<1\right\}}\left[\hat{\theta}_{NRW} \ln\left(R_l^{GS}\right) + \hat{\eta}\right]}_{\ln C_l^k} + \underbrace{f_l}_{\ln \frac{land\,use_l}{W_l^{mun} + \sum_k C_l^k}} + f_o^k + \varepsilon_l^k \tag{2}$$

where the variables that define C_l^k (namely T_l^k, RW_l^k and R_l^{GS}) are introduced additively. Following Morais et al. (2018), we add a locality fixed effect, noted f_l that captures all variables of the land use choice of Equation (1) and of the crop independant variables in the acreage choice (more formally, $f_l = \ln[land\,use_l/\left(W_l^{mun} + \bar{C}_l\right)]$) and we also add a second set of fixed effect at the country-product level (named f_o^k) intended to capture the macroeconomic effects (national policies, international trade, ...).[21]

The coefficient $\hat{\theta}_T$, $\hat{\theta}_{RW}$ and $\hat{\theta}_{NRW}$ represent the estimated elasticities of the crop thermal regime suitability, the crop suitability of local renewable hydrologic supplies and the supplemental quantity of non-renewable water respectively. When $\hat{\theta}_T$ ($\hat{\theta}_{RW}$) is higher, the supply is more sensitive to changes in the thermal regime (renewable water available). The indicator variable $1_{\left\{RW_l^k<1\right\}}$ takes the value 1 if the quantity of renewable water is insufficient to fulfill the need of the crop k ($RW_l^k < 1$) and is factorized with the groundwater storage (R_l^{GS}) to correspond to the variable NRW_l^k. Finally, the estimated parameter $\hat{\eta}$ captures potential heterogeneity of $\hat{\theta}_{RW}$ in localities with a low quantity of renewable water supplies (as such, this coefficient is also factorized with the indicator variable $1_{\left\{RW_l^k<1\right\}}$). Table (1) presents estimates of coefficients $\hat{\theta}_T$, $\hat{\theta}_{RW}$, $\hat{\theta}_{NRW}$ and $\hat{\eta}$ from the Equation (2).

Column (1) explains the production of agricultural goods by considering the thermal and hydrologic conditions, the groundwater storage and our indicator of Insufficient Renewable Water Resources, herefater denoted IRWR. Thermal and hydrological conditions have the expected sign and the groundwater variable has a positive significant effect in locations where the renewable water resources are insufficient (0,2362=0.296-0.0598). The lack of controls in this estimation is however problematic due to the bias of omitted variables. Column (2) introduces locality fixed effects and presents similar results notably concerning the suitability of the thermal regime and of water conditions.[22] Surprisingly, the IRWR

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[21] These fixed effects are only used to control the estimation and are not used in the calculation in the rest of the computation.

[22] The effect of groundwater storage is not estimated (and the interaction of this variable with IRWR is no longer significant) due to the colinearity with fixed effects that are defined at the same locality level.

Table 1: Micro-geographical Level Capabilities Estimations

	(1) Production	(2) Production	(3) Production
Thermal Regime Suitability	0.763^{***}	1.123^{***}	0.863^{***}
- θ_T	(0.0251)	(0.0208)	(0.0358)
Renewable Water Suitability	0.148^{***}	0.283^{***}	0.0203^{**}
- θ_{RW}	(0.00707)	(0.00984)	(0.00884)
Groundwater	-0.0598^{***}		
- $\log(\mathrm{R}_l^{Gs})$	(0.00569)		
Insufficient Renewable Water Res.	-0.218^{***}	0.0899^{***}	-0.0399^{*}
- η	(0.0287)	(0.0342)	(0.0224)
Insufficient Renewable Water Res. × Groundwater	0.296^{***}	0.000812	0.0261^{***}
- θ_{NRW}	(0.00911)	(0.0122)	(0.00789)
Constant	0.0230	-0.0152	0.0322^{***}
	(0.0171)	(0.0115)	(0.00836)
Localities FE	No	Yes	Yes
Country-Product FE	No	No	Yes
Observations	256378	255446	255336
Log-Likelihood	-678966.2	-602176.6	-483199.0
R2 ajusted	0.0120	0.366	0.748

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

variable has a positive effect which may come from the lack of control regarding the specialization of agricultural producers. To address this issue, we add country-product fixed effects in Column (3). The positive effect of groundwater on production in locations where there is not enough renewable water is confirmed (see the coefficient of the interaction between groundwater and IRWR), indicating that farmers rely on this non-renewable water resource when necessary. Quite logically, locations with not enough renewable water and without groundwater are negatively affected, we indeed observed that the IRWR variable alone has now the expected negative sign, showing that places with relatively low quantity of water have a significant tendancy to produce less. We also observe that the coefficient of hydrologic condition is smaller than in the previous estimation, indicating that the bias of omitted variables is now partly corrected. Comparing the estimated coefficients of thermal regime suitability with the one of renewable water suitability, we can see that the former is much larger than the latter (0.863 for the thermal suitability and 0.0203 for the renewable water suitability). This difference can be partly explained by the difference in magnitude of the two variables (the thermal suitability is bounded to 1 but not the renewable water suitability) but also validates the core idea that the capability to use water at the local level matter a lot to produce. This also implies that taking only water resources available at the national level as many researches in economics have done (e.g. Debaere, 2014) does not allow to account for heterogeneous thermal regime inside countries. Putting differently, using the water endowments at national level largely overestimate the potential to effectively use this water for producing agricultural goods. Since the explanatory power of this last estimation is much higher than the previous ones ($R^2\ adj = 0.75$), we consider that the model is sufficiently controled for a various range of external effects and we use these estimated parameters in the rest of the paper. Obviously, this approach using fixed-effects is valid for obtaining the mean value of these elasticities but does not take into account that these elasticities are likely to be non-linear and location specific.

2.3 Indicator

This section presents the computation our indicator L_l^k from Equation (1) using the set of values C_l^k estimated in the previous step in combination with the $Land\,Use_l$ and W_l^{mun} variables.

Using the previous estimates, we can now compute the explicit form of C_l^k as:

$$C_l^k = \left(T_l^k\right)^{\hat{\theta}_T} \left(RW_l^k\right)^{\hat{\theta}_{RW}} \exp\left\{1_{\{RW_l^k<1\}} \left[\hat{\theta}_{NRW} \ln\left(R_l^{Gs}\right) + \hat{\eta}\right]\right\}$$

Introducing this expression in Equation (1) gives then:

$$\hat{L}_l^k = Land\,Use_l \times \frac{\left(T_l^k\right)^{\hat{\theta}_T} \left(RW_l^k\right)^{\hat{\theta}_{RW}} \exp\left\{1_{\{RW_l^k<1\}} \left[\hat{\theta}_{NRW} \ln\left(R_l^{Gs}\right) + \hat{\eta}\right]\right\}}{W_l^{mun} + \sum_k \left\{\left(T_l^k\right)^{\hat{\theta}_T} \left(RW_l^k\right)^{\hat{\theta}_{RW}} \exp\left\{1_{\{RW_l^k<1\}} \left[\hat{\theta}_{NRW} \ln\left(R_l^{Gs}\right) + \hat{\eta}\right]\right\}\right\}} \tag{3}$$

Concerning the water demand for municipal and industrial uses, W_l^{mun}, we use the country average municipal and industrial water consumption per capita (data taken from AQUASTAT of the FAO)[23] multiplied by the population density per square kilometer of the location l (given by the SEDAC). Using the population density instead of population count allows to convert to the same unit as the other variables (cubic-meter per surface area). We then compute the ratio between this water demand and the yearly surface river runoff in locality l defined as $R_l^S = \sum_m R_{lm}^S$ (data taken from the "Global Composite Runoff Fields", CSRC-UNH and GRDC, 2002).

To take into account determinants of the land use choice, $Land\,Use_l$, presented in (3), we consider the following multiplicative form:

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[23] We do not have these informations for some countries in our data, we thus decide to fill in missing values by the world average (testing for different method of fill in values does not change significatively the results).

$$Land\,Use_l = A_l S_l \bar{T}_l \bar{W}_l \tag{4}$$

where A_l is the area of each locality. These values are directly taken from the Socioeconomic Data and Applications Center (SEDAC) which account for the reduced area of cells along the coast lines (the delimitation of each cell being arbitrary, it often overlaps with seas and oceans for cells along the coast lines). The unit of this variable is in km^2.

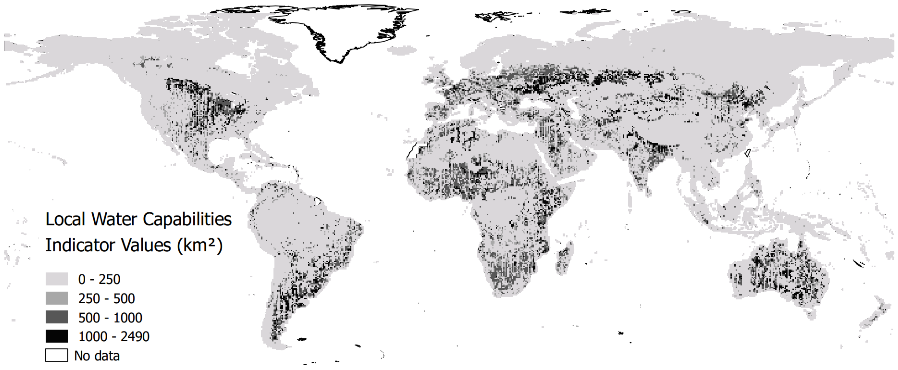
S_l represents the suitability of land for agricultural production. This variable is built from the multiplicative combination of four variables given by the Global Agro-ecological Zones v3.0: the soil quality (s_l^{soil}), the terrain slope (s_l^{slope}), the share of the land covered with buildings (s_l^{built}) and if other natural coverage (such as lake, forest or ice) limit the development of agricultural production (s_l^{land}). All of these four variables have values ranging from 0 (unsuitable) to 1 (perfectly suitable) and the calculation is: $S_l = s_l^{soil} \times s_l^{slope} \times s_l^{built} \times s_l^{land}$ (if one of the four variables equals to 0, then S_l also equals to 0).

To measure the mean value of local thermal regime suitability, $\bar{T}_l$, we compute the average value of the crop specific temperature constraint factors (T_l^k) to define a general thermal regime suitability of each cell l irrespective of any specific crop k. The initial value given by GAEZ ranges between 0 (unsuitable) and 1 (perfectly suitable), thus the average value that we use here also ranges between 0 and 1 with identical interpretation.

Finally, to approximate the mean value of local hydrologic condition suitability, $\bar{W}_l$, we compute the average value of the crop specific suitability of local renewable hydrologic supplies (RW_l^k) and restrict the limit definition of this average value from 0 to 1 (any average value superior to 1 implies that renewable water is sufficient to fulfill the need for at least one crop).

By inserting (4) in (3), we get our indicator, $\hat{L}_l^k$. The following map depicts the value of this indicator all around the world (to represent this variable with an unique figure, we compute the sum over the product k of our indicator or more formally: $L_l = \sum_k L_l^k$).

Figure 1: Predicted local water capability to produce agricultural goods (in km^2)



After aggregating at the country level, this variable is used in the next section to estimate the impact of water resources on the agricultural trade. We used the third column of the estimation to compute the indicator.

3 The Water Capability to Export

As stated earlier, the macro-level capability is defined by the different constraints, typically trade costs, which limit the potential trade of agricultural goods and influence the specialization of countries. In particular, Venables and Limao (2002) and Deardorff (2014) have presented theoretical models in which the comparative advantage of production can be reverted by a comparative disadvantage in trade costs. Harrigan (2010), while working on a different subject (comparative advantage and the cost of shipping goods by airplanes), finds empirical evidences of this result. To link our measure of the local capacity to produce, which represents a local comparative advantage, to the macro-level that takes into account trade costs, we propose to undertake two further steps. The first one is to aggregate our indicator of water from the cells level to the country level. For the sake of simplicity, we take the sum of our indicator $\hat{L}_l^k$ at the country level o : $\hat{L}_o^k = \sum_l \hat{L}_l^k$ with $l \in o$. Similarly, we compute for the importer side as $\hat{L}_d^k = \sum_l \hat{L}_l^k$ with $l \in d$. These values are computed for the years around 2000's because all the data required are not available on a more recent period. The second step is to estimate the bilateral trade frictions using a gravity equation. We take the average bilateral trade flows from the origin, i.e. the exporter o, to the destination, namely the importer d, for the product k over the time period from 1995 to 2005, noted X_{od}^k . The equation to be estimated is thus:

$$X_{od}^k = \exp\left\{c + \lambda_o \ln\left(\hat{L}_o^k\right) + \lambda_d \ln\left(\hat{L}_d^k\right) + \delta_d + \delta_{od} + \delta_o + \delta^k + \varepsilon_{od}^k\right\} \tag{5}$$

We control for the bilateral frictions, importer, exporter and product characteristics with fixed effects, respectively noted δ_{od}, δ_d, δ_o and δ^k. Adding an exporter fixed effect allows to control for the capital stock and thus, the capability to mitigate the unfavorable natural conditions for growing crops in a country through technology. These individual fixed effects (exporter fixed effects δ_o, but also importer fixed effects δ_d) enables to take into account all the multilateral trade resistances,[24] the difference in agricultural technologies (δ_o) and in demand size (δ_d) between countries that influence bilateral trade flows (see (Head and Mayer, 2014) for theoretical models that lead to this so called 'structural' gravity equations). Finally the two-way fixed effects δ_{od}, capture trade costs between countries.

Taking into account this rich set of fixed effects enables to get an unbiased estimate of λ_o and λ_d. The elasticities estimated, $\hat{\lambda}_o$ and $\hat{\lambda}_d$, represents the sensitivity of export to the water capacity to produce in o ($\hat{L}_o^k$) and in d ($\hat{L}_d^k$), purged to all other variables defined at the origin of the flow, at the destination, or both.

The main coefficient of interest is λ_o. We expect that exporter with a high level of water capacity to produce goods k (relatively to other goods), $\hat{L}_o^k$, are going to export these goods more than other countries, but however not to all destinations, and in particular not to countries with good water capacity to produce them, $\hat{L}_d^k$. In other terms, we expect that $\hat{\lambda}_o > 0$ and $\hat{\lambda}_d < 0$.

One drawback of this estimation is that it is implicitly assumed that the trade elasticity of water is homogeneous across space, which is questionable. To take into account the fact that countries may react differently to change in their endowment of water, we estimate again this gravity equation by dividing up our whole set of countries into four categories $n = \{1, 2, 3, 4\}$ in order to estimate these trade elasticities for different types of countries. Such groups of countries are delineated according to their vulnerability to climate change (this is more precisely detailed in the next section).The new estimation is given by:

$$X_{od}^k = \exp\left\{c + \lambda_o \ln\left(\hat{L}_o^k\right) + \sum_{n=1}^{4} \lambda_o^n 1_{\{o \subset n\}} \ln\left(\hat{L}_o^k\right) + \lambda_d \ln\left(\hat{L}_d^k\right) + \delta_d + \delta_{od} + \delta_o + \delta^k + \varepsilon_{od}^k\right\} \tag{6}$$

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[24] Multilateral trade resistances may be understood by considering them as a price index of all the goods that are consumed/imported in one country. This price index in a country d depends on the trade costs between the partner o and d, but also of all other trade costs of goods that are imported in d from other countries. Thus a change in trade costs from these external countries (external in a sense that they are external to the bilateral trade considered between o and d), can have an effect on the exchange between o and d by modifying the price index. These resistances are sometimes called "third country effects".

where the variable $1_{\{o \subset n\}}$ is an indicator variable taking the value one if the country o is in the group n and zero otherwise. We consider several indicators to split our sample that are related to the level of capital endowment in different countries, to the readiness of countries to climate change and to the vulnerability of countries to climate disruption. For each indicator (described in the data section), interpretation of elasticities is for any category n: $\lambda_o + \lambda_o^n$.

To deal with zero trade flows and problems of heteroskedasticity we follow a large strand of the literature by assuming that the distribution of the errors are of a Poisson type (hence, the exponential form of the equation) and for that reason we use the PPML estimator.[25]

3.1 Data at the Macro-Geographical Level

At the macro-geographical level, we use classical trade data for the gravity estimations in addition to the less classical specification of dividing the country set into categories. We focus our estimation on a large subset of 114 countries and a total of 30 products (at the 4 digit of the Harmonized Commodity Description and Coding Systems, called HS4) including major crops such as rice, maize.

Trade data (X_{od}^k) comes from the "Base pour l'Analyse du Commerce International" (named BACI) developed by CEPII (Gaulier and Zignago (2010)). It contains annual bilateral flows on the period 1995-2017 highly disaggregated for an important number of countries. It covers more than 5000 products and 200 countries. This dataset is appealing for the estimation of gravity equation because authors have been employed an approach to reconcile the original data (COMTRADE database of the United Nations Statistics Division) where the information between imports and exports for a same flow can be different. This procedure allows to correct some errors and to obtain reliable data. It is important to note that we do two modifications to these data. The first one relates to South Africa which encompasses in BACI the trade flows of Namibi, Botswana, Lesotho and Swaziland in addition to the South Africa country. As it is not possible to delineate trade flows from each of these countries, we combine the five countries in one and perform the estimates on this group of countries. The second modification relates to exports products from prior imports which cannot be separate from the exports of products from production within countries (e.g. Finland exporting a substantial amount of coffee while not being able to produce it). We attempt to reduce the biases by setting trade flows to zero when the exporter country cannot produce the good (when $\hat{L_o^k} = 0$ then $X_{od}^k = 0$).

The four categories are defined as quartils based upon an indicator of physical vulnerability to climate change built by Feindouno et al. (2020). This indicator, called Physical Vulnerability to Climate Change Index (PVCCI) is an index of exogenous vulnerability, namely not influenced by the present policy of the countries concerned. It takes into account the risk of flooding from the rise of sea level, the risk of increasing aridity, the risk of increasing recurrent shocks (storms and typhoons). This indicator is computed for 191 countries and the score obtained is between 0 and 100. The higher is the score, the more vulnerable is the country. To define our four categories, we simply break down the whole set of countries into four equal parts with the category 4 being 25th percent of the countries with the highest value of vulnerability while the category 1 gathers the 25th percent of countries with the lowest value. The following map shows the countries with their respective category.

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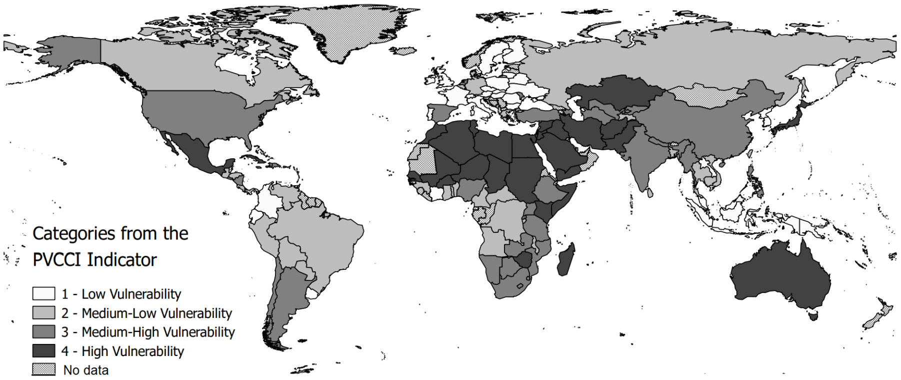
[25] This estimator is the most used in the literature. See Santos Silva and Tenreyro (2006) and Head and Mayer (2014) for a discussion. Our estimations need substantial fixed-effects (bilateral, importer, exporter and product), the PPML command in Stata leads to estimations which are very long. To overcome this problem, we use a recent Stata module to implement Pseudo Poisson Maximum Likelihood including multiple high-dimensional fixed-effects, called ppmlhdfe developed by Correia et al. (2019). The speed of estimations can be explain by two elements. Firstly, the using of iterative reweighted least square algorithm allows to reduce the dimensionality problem. Secondly, this command uses the advantage of reghdfe command allowing to reduce some computations which are performed once and so it is not necessary to perform these computations for each iteration.

Figure 2: Map Depicting Countries according to the index of physical vulnerability (PVCCI)



In the empirical exercise below, we also consider a different categorization of countries based on Readiness indicator which is a sub indicator of the ND-GAIN from the University of Notre Dame (Notre Dame Global Adaptation Initiative, Chen et al., 2015). This indicator is a measure of the ability of countries to leverage investments to adaptation actions, which includes economic factors, governance and social readiness. We used an additional indicator for the estimations: the Gross Capital Formation per capita (the list of country by category is available in Appendix). It is important to point out that the country classification of these two last categorizations (Readiness and Capital) are different from the categorization PVCCI. In the Readiness categorization, the first category corresponds to the 25 percent of countries least prepared to adapt to climate change (while the fourth category is the 25 percent of countries the most prepared to adapt to climate change), and in the Capital categorization, the first category corresponds to the 25 percent of countries with the lowest level of Gross Capital Formation per capita (while the fourth category corresponds to the 25 percent of countries with the highest level of Gross Capital Formation per capita).[26]

3.2 The Elasticity of the Water Capability to Export

We study here the water determinants of bilateral trade as presented in Equation (5). Our indicator of water capability to produce a product k in countries o, significantly explains the exports of these products toward all the partners d on average (Column 1, Table (2)). However a high level of water capability at the destination countries d seems to reduce these exports (Column 2). In other terms, our estimation shows that a high capability to produce in d makes the demand less dependant of the supply of agricultural goods coming from outside. Finally, by considering how bilateral trade is explained both by the water capability to produce of the exporter and of the importer, we confirm these results (Column 3). This contributes to account for the importance of good water conditions to sustain the international trade of agricultural goods.

To evaluate the performance of our measure of water to explain the exportation of agricultural goods, we compare our results with those obtained with a more classical indicator of water endowment, the Total Renewable Water Resources, hereafter TRWR (see for instance Debaere (2014), Fracasso (2014)or Afkhami et al. (2018)). This indicator is computed on both exporter and importer side from the total renewable water resources (which include rainfalls, runoffs and groundwaters) at the country level divided by the country population (in order to get the water availability per capita) and multiplied by a sectoral water intensity. This computation gives a variable at the country-product dimension (we use here exactly the methodology and the data of Debaere (2014)).[27] In comparison

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[26] Data and replication codes are available at https://data.mendeley.com/datasets/s468kpnvx8/1

[27] The methodology is to log-transform the total amount of renewable water resources per capita of a country and multiply this log-value by a water sectoral intensity.

with our approach, water intensities are not directly related to evapotranspirations, temperatures or crop coefficients such that any changes in those variables, for instance due to climate changes, implies a problematic discrepancies between the value of water intensities and the real water needs of crops. Maybe in reason of this lack of accuracy, or in reason of a problem of endogeneity, this indicator performs poorly as demonstrated by the next table. More precisely, the last three columns in Table (2) present the previous estimation with the TRWR respectively for the exporter, the importer and both. Signs are the reverse of what can be expected (negative for exporter and positive for importer), which is, to say the least, a dubious result.

Two reasons may explain the difference between our results and those obtained with the TRWR. The first one is that our indicator is more accurate than the TRWR because it takes into account many local factors at the grid level that explain whether the endowment of water is used or not.[28] A second explanation is that the estimation using the TRWR represents an application of the absolute advantage to have a high endowment of water, but it well known from Ricardo (1817) to Eaton and Kortum (2002) that what matters to explain exports is the relative advantage of production and not the absolute one. Our indicator is based on this idea, since it measures the water capability to produce a product k relatively to the water capability to produce all other products (see the denominator of Equation 3), which may explain why our results are in line with what is expected (in theory at least).

These first results give the average effect of water on trade by treating the heterogeneity of our sample thanks to fixed effects. However, to take into account the heterogeneity of the utilization of water to exports agricultural goods in different countries, we estimate the gravity equation again by dispatching the different countries according to their endowment in capital per capita (Gross Capital Formation on population) and to their physical vulnerability to climate change.

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[28] In many locations l inside a country, one can have an endowment of water that cannot be used to produce a product k due for instance to thermal conditions. In that case, our variable T_l^k equals zero and thus the water located in l is not taken into account for the production of these goods. In contrast, many indicators defined at the national level, such as the TRWR, take into account the total endowment of water, including these unusable waters, and thus over-estimate the amount of water that is really available.

Table 2: Gravity Equation Regression by Group

	(1) Flow	(2) Flow	(3) Flow	(4) Flow	(5) Flow	(6) Flow
Exp. Water Indic.	0.820***		0.771***			
	(0.0349)		(0.0434)			
Imp. Water Indic.		-0.130***	-0.111***			
		(0.0133)	(0.0161)			
Exp. TRWR				-0.529***		-0.408***
				(0.130)		(0.126)
Imp. TRWR					0.0497	0.0582
					(0.117)	(0.120)
Constant	3.007***	11.06***	3.550***	10.62***	10.27***	9.882***
	(0.301)	(0.0771)	(0.357)	(0.201)	(0.124)	(0.214)
Importer FE	No	Yes	Yes	No	Yes	Yes
Exporter FE	Yes	No	Yes	Yes	No	Yes
Product FE	No	No	Yes	No	No	Yes
Bilateral FE	Yes	Yes	Yes	Yes	Yes	Yes
Imp-Prod. FE	Yes	No	No	Yes	No	No
Exp-Prod. FE	No	Yes	No	No	Yes	No
Observations	237492	186138	243570	192122	185342	195690
Log-Likelihood	-78668697.0	-47922720.2	-124321307.8	-100437177.4	-51527888.7	-148510393.8
Pseudo R2	0.829	0.890	0.730	0.776	0.884	0.670

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependant variable is the mean of bilateral flows between 1995 and 2005.

Table (3) provides the main results of the estimation with different categorizations.

Table 3: Gravity Equation Regression by Group (Vulnerability Indicator)

	(1) PVCCI	(2) Capital	(3) Readiness
Exp. Water Indic.	1.061***	0.419***	0.386***
	(0.0954)	(0.0683)	(0.0801)
Exp. Indic=2 × Exp. Water Indic.	-0.0540	0.00473	0.237**
	(0.131)	(0.0873)	(0.108)
Exp. Indic=3 × Exp. Water Indic.	-0.364***	0.264	0.159
	(0.100)	(0.216)	(0.151)
Exp. Indic=4 × Exp. Water Indic.	-0.591***	0.560***	0.551***
	(0.194)	(0.0928)	(0.0932)
Imp. Water Indic.	-0.113***	-0.112***	-0.112***
	(0.0162)	(0.0166)	(0.0162)
Constant	3.279***	3.142***	3.492***
	(0.334)	(0.457)	(0.328)
Importer FE	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes
Product FE	Yes	Yes	Yes
Bilateral FE	Yes	Yes	Yes
Importer-Product FE	No	No	No
Exporter-Product FE	No	No	No
Observations	243570	236520	243570
Log-Likelihood	-123488348.8	-122326321.7	-123165063.3
Pseudo R2	0.732	0.733	0.733

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In all specifications, the dependent variable is the mean of bilateral flows between 1995 and 2005.

The capital indicator is Gross Capital Formation per inhabitant.

The Exp. Indic is different for each columns and is indicated in the header of column (PVCCI, Readiness, and Capital).

A general result is that our water capability to export indicator is significant and positive in almost all specifications, implying that water do impact the ability to trade water intensive products. Looking at the Colomn (1), we also find from these estimates that the more vulnerable the countries are, the less they export. However, the effect of water on exports is decreasing with the level of vulnerability. Countries that are the less vulnerable have a trade water elasticity of 1.083 (Group 1 and 2), while countries with intermediate of vulnerability (Group 3) have an elasticity of 0.721 (=1.083-0.362), and finally in countries with the worst score (Group 4), the effect is equal to 0.484 (=1.083-0.599). Obviously, the explanations behind the results obtained for vulnerable and not vulnerable countries differ. The most vulnerable countries are maybe less dependent on water conditions in reason of their specialization in products that are less water intensive. The high coefficient obtained for the less vulnerable countries (Group 1 and 2) may reflect that among these countries, there are some high income countries that in reason of their technology, export more agricultural goods than other countries. We verify this result in Column (2) where we distinguish countries along their capital endowment (Gross Capital Formation on population). The indicator of readiness (Column (3)), which measures the ability of countries to leverage investments to adaptation actions, is relatively different but confirms the results obtained so far. For instance, exporters from countries with the lowest level of readiness are also less sensitive to their water conditions (0.703=0.385+0.318) than countries with the highest level of readiness (0.999=0.385+0.606), confirming the hypothesis that these countries are already specialized in water intensive goods.

4 Illustrative Application: Forecasting the Effects of Climate Changes on the Water Comparative Advantage

In the previous section, the gravity equation enables to distinguish the determinants of trade flows that depend on water to other determinants defined at the macro level (e.g. trade costs). This offers the possibility to analyze how climate change by affecting this water capability can affect the international trade of nations and the specialization of countries *via* the formula of the Revealed Comparative Advantage (RCA) of Balassa (1965). Finally, we analyze how climate change by affecting the water capability to produce affects these RCAs.

4.1 Methodology

To update our indicator of water capability to produce with the potential variations of climatic variables following climate change, we take several key variable's predictions from multiple sources which is based on the specific scenario A2 from the model 3 of the Hadley centre, UK Meteorological Office (see the data section for more details) but we do not change the logic of calculation as expressed in Section 2.[29] In that respect, we compute a new local capability indicator based upon these forecast values of climatic variables for the years around 2050, noted $\widehat{L}^k_{l,t}$. The changing variables composing this indicator are also denoted with the lowerscript t' which are the temperatures $T^k_{l,t'}$, the water resources $R_{lm,t'}$, the pseudo-demand for water by crops $D^k_{lm,t'}$ and the demand of water for municipal and industrial uses $W^{mun}_{l,t'}$ (the methods and data for computing these new variables for the years 2050's are presented more deeply in the Section 4.2). The computation of $\widehat{L}^k_{l,t'}$ is thus as follow:

$$\widehat{L}^k_{l,t'} = A_l S_l \bar{T}_{l,t'} \bar{W}_{l,t'} \frac{\left(T^k_{l,t'}\right)^{\hat{\theta}_T} \left(RW^k_{l,t'}\right)^{\hat{\theta}_{RW}} \exp\left\{1_{\{RW^k_l<1\}}\left[\hat{\theta}_{NRW}\ln\left(R^{Gs}_l\right)+\hat{\eta}\right]\right\}}{W^{mun}_{l,t'} + \sum_k \left[\left(T^k_{l,t'}\right)^{\hat{\theta}_T} \left(RW^k_{l,t'}\right)^{\hat{\theta}_{RW}} \exp\left\{1_{\{RW^k_l<1\}}\left[\hat{\theta}_{NRW}\ln\left(R^{Gs}_l\right)+\hat{\eta}\right]\right\}\right]} \tag{7}$$

From this indicator of local water capability in 2050, we can compute the future trade flows of agricultural goods by using the elasticities $\hat{\lambda}_o$, $\hat{\lambda}^n_o$, $\hat{\lambda}_d$ and the fixed effects $\hat{\delta}_{od}$, $\hat{\delta}_o$, $\hat{\delta}_d$ and $\hat{\delta}^k$ estimated from the specification using the categorization from the PVCCI (Column 1 of Table 3) in the previous section. We assume that the trade elasticities of water capability to export are constant over time between the 2000's and the simulations in the 2050's (where we are using these elasticities to compute new trade flows).[30] This is a strong assumption but to date, there is no research allowing to determine how climate change is going to affect this trade elasticity in the 2050's. We thus get the predicted trade $\widehat{X}^k_{od,t'}$ by the following equation:

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[29] However, we need to drop one country with this simulation (the Serbia-Montenegro) as data are not available.

[30] While this *ceteris paribus* analysis, may be justified for some variables, for instance, the effect of distance on trade has been surprisingly stable for the past fifty years (see Disdier and Head, 2008), there are obviously many determinants of trade that are going to change by 2050.

$$\widehat{X}^k_{od,t'} = \exp\left\{\hat{c} + \hat{\lambda}_o \ln\left(L^{\hat{k}}_{o,t'}\right) + \sum_{n=1}^{4} \hat{\lambda}^n_o 1_{\{o \subset n\}} \ln\left(L^{\hat{k}}_{o,t'}\right) + \hat{\lambda}_d \ln\left(L^{\hat{k}}_{d,t'}\right) + \hat{\delta}_d + \hat{\delta}_{od} + \hat{\delta}_o + \hat{\delta}^k\right\} \quad (8)$$

It may be interesting to observe that in addition to the variables of the water capability to produce agricultural goods (representing here a local comparative advantage), we have bilateral fixed effects that capture the relative difference in trade costs between countries. Our calculation of this predicted value of trade is thus in the spirit of the theoretical literature on specialization and trade costs which emphasizes that the advantage in the cost of production can be contradicted by a bad market access (Venables and Limao, 2002; Deardorff, 2014).

A comparison between the country international trade simulated in the 2050's ($X^k_{o,t'} = \sum_d \widehat{X}^k_{od,t'}$) and the country predicted trade in the 2000's shows that both values are closely correlated (with a correlation coefficient of 0.95) with 50% of trade flows which are decreasing and 12.5% of trade flows that are reduced by half.

Turning to the computation of the comparative advantages, we use the Balassa's revealed comparative advantages (Balassa (1965)) :

$$\widehat{RCA}^k_{o,t} = \frac{\widehat{X}^k_{o,t}}{\sum_o \widehat{X}^k_{o,t}} / \frac{\sum_k \widehat{X}^k_{o,t}}{\sum_o \sum_k \widehat{X}^k_{o,t}} \quad (9)$$

Where $\widehat{X}^k_{o,t} = \sum_d \widehat{X}^k_{od,t}$, with $t = 2000,\ 2050$.

By using the predicted value of exports, the advantage of this computation is that we take into account all the determinants of trade that are captured by the gravity equation, including differences in productivity between countries (exporter fixed effects) and products (product fixed effects) or specific bilateral relationship due to distance or to political links (bilateral fixed effects). This matters because the water capability to produce should be somewhat weighted by all other variables that explain trade to compute its impact. One drawback of this approach is that these RCAs are based on the initial linear regression of agricultural production (Equation 2), then by not taking into account in our indicator of water capability that the elasticities of production are not linear with respect to water resources (e.g. that reducing the water resources is likely to reduce crop suitability more in water-scarce parts of the world than in water-rich parts of the world) we make a strong assumption that may influence our result on RCA. Not reported here, we have however led several sensitive tests by taking different elasticities for different types of countries according to their level of water resources and we have found that our results on RCAs are very similar to those presented in this section[31].

4.2 Data for Simulating Trade in the 2050's

To recompute our indicator for 2050, we use different data sources. To keep a certain consistency within these new datasets of predicted values for the years 2050's, we use data from the climate model 3 from Hadley centre, UK Meteorological Office. Regarding the scenario, we consider the SRES (Special Report on Emissions Scenarios) A2 scenario as defined by the Intergovernmental panel on Climate Change (IPCC).[32] This scenario depicts an heterogeneous world with increasing demographic rate of

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[31] The sensitive tests are available in the supplementary analysis at https://github.com/fcandau/Water-Comparative-Advantage

[32] It exists four scenarios (A1, A2, B1 and B2) each of these are based are three main features: population predictions, economic development as well as structural and technological changes. The scenarios of the A's category focus on economic development (with a difference about globalisation development (A1) and regional development (A2)). The scenarios of the B's category focus on less environmental (with a difference in the im-

the population, with significant differences growth rates of GDP per capita and technological changes between regions of the world. The use of this scenario is interesting because it allows to apprehend the consequences of inaction: few decisions are taken regarding climate change. We enumerate new sources for each variable (spatial and volumetric units stay unchanged for simulations).

The crop specific suitability of local renewable hydrologic supplies ($RW^k_{l,t'}$): part of the variable is re-computed to account for the change in 2050 using exactly the same methodology as for the computation of the crop specific suitability of local renewable hydrologic supplies in the 2000's. For the renewable water resources available: the soil moisture (R^{SM}_{lm}) and surface water runoffs (R^{SR}_{lm}) are both predicted from the future precipitation ($R^P_{lm,t'}$) taken from the Climate Change, Agriculture and Food Security[33] (CCAFS). We keep the same distribution of these precipitations within each basin. For the crop requirement ($D^k_{lm,t'}$), we compute the monthly potential evapotranspiration with two methods in using the predicted monthly temperatures. For both method, SPEI package (Vicente-Serrano et al. (2010); Beguería et al. (2014)) of R software has been used. This package allows several methods of calculation of evapotranspiration according to the available climatic data. We base on the Hargreaves (1994) equation which requires the minimum and maximum temperatures as well as latitude (this variable is used as proxy for the mean external radiation).[34]

The supplemental quantity of non-renewable water ($NRW^k_{l,t'}$): we do not compute new value for the groundwater storage (R^{Gs}_l) because this would implies to predict the rate of extraction over the years from the 2000's to the 2050's which would add a lot of complexities. However, we re-compute the indicator variable $1_{\left\{RW^k_{l,t}<1\right\}}$ (taking the value 1 for localities that suffer from insufficient renewable water resources and 0 otherwise). Thus, we use the updated variable $RW^k_{l,t'}$ as explained above and calculate a new indicator variable $1_{\left\{RW^k_{l,t'}<1\right\}}$ for the year 2050 that will account for localities with insufficient renewable water in 2050.

The water demand for municipal and industrial uses ($W^{mun}_{l,t'}$): this variable is based on three parts : municipal, industrial water consumption and the density of population. It doesn't exist data about the future water consumption for industrial and municipal purposes. Morethan, the estimation is complicated. So we conserve these data. But it exists data about the projections of population for 2050. This part is very important, because the scenario used, as explained previously, is based on important increasing in population. The projections of population for 2050 data come from the same source as previous population data, that is, from SEDAC.

The thermal regime ($T^k_{l,t'}$): as previously, we use the temperature constraint factor for 2050 from the Global Agro-ecological Zones v3.0 to define the suitability of each cell l for growing any specific crop k. As explained above, we take data obtained with the climate model 3 and scenario SRES A2 for consistency reason between data used in the indicator.

The suitability of land (S_l): given the impossibility to obtain data about this indicator, we assumed no changes and reused the same data. This hypothesis is obviously strong and in particular regarding forests (think to deforestation in the Amazon, and elsewhere in the world), but predicting forest change and management is such a significant work, that we follow the literature in international economics by postponing this task to a future work (see also Gouel and Laborde (2021)).

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plementation of global climate measures (B1) and regional measures (B2)). For more details about different SRES scenarios, please read the Special Report on Emissions Scenarios from IPCC at the following web link : https://www.ipcc.ch/site/assets/uploads/2018/03/emissions_scenarios-1.pdf

[33] http://ccafs-climate.org/data_spatial_downscaling/

[34] We compute potential evapotranspiration as Thornthwaite (1948) equation for which the computation used the monthly mean temperatures and used proxy from the literature for the rest of variables (we use the predicted mean temperatures which are describe below) and latitude. The both method lead to similar results for the evapotranspiration.

4.3 Results

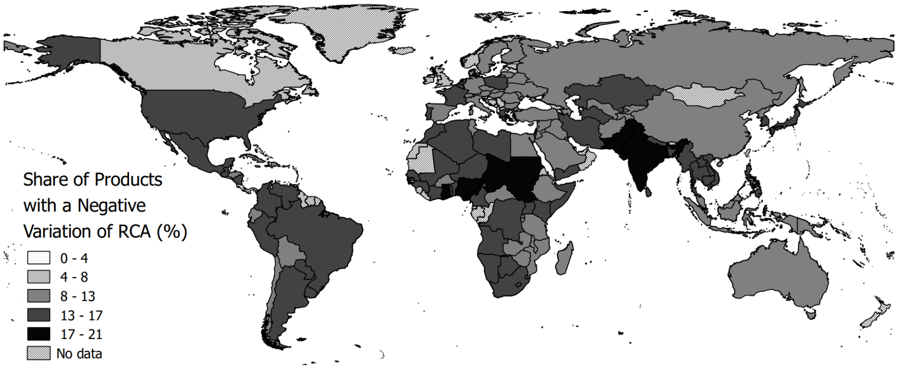
4.3.1 Export Flows and Specialization

Based on computable general equilibrium models (see Dellink et al. (2017), Gouel and Laborde (2021)), a standard results that developed countries generally gain in term of agricultural export from climate changes in comparison to developing countries, mainly because they are better prepared to mitigate the disruptive effects of climate changes (due to technologies and capital) and because the global raising temperature will induce a more favorable climate for number of crop varieties in these countries (at least those located southern of the Capricorn Tropic and northern of the Cancer Tropic). Our results based on the variation of exports (see Appendix 7) confirm these analysis. According to our computation (and then assumptions) countries which are the less vulnerable to climate change (in Group 1 and 2) register an increase in their total exports (e.g. Canada, France, Germany, but also Peru and to a lesser extent Russia). In contrast many countries in Africa and in the Middle East experience a sharp decrease in their exports (such as Egypt, Yemen, Libya and Senegal). Many of these countries are considered among the most vulnerable to climate change in the PVCCI index (category 4 in our estimations), all of them are ranging from the 24th to 38th country the most vulnerable.

While these effects on exports are already known, the consequence of climate change on the comparative advantages of nations remains a very active line of research with no definitive conclusion (see the discussion in the Introduction). To provide the most exhaustive presentation of our results on RCA, which is made difficult by the high number of countries and products, we present in Appendix 7 the revealed comparative advantages with the predictions for the years 2000's against the simulations for the years 2050's for different crops. The overall picture is that, in general, RCA are not radically modified by the climate change in 2050. However such a general conclusion does not hold for all countries and products.

To illustrate the losses of competitiveness in the agricultural production at the country level, Figure (3) presents the share of product with a strong negative variation in RCA. These results show that in several vulnerables countries the decrease in export is linked to a decrease in comparative advantage (e.g. in Africa), but the most interesting result of this Figure (3) is that even in countries where the total volume of exports is not affected (or even improved), a loss of comparative advantage is also at play due to climate change (for instance in Belgium, France, Finland, India or Peru).

Figure 3: Share of Product with a Negative Variation of RCA



4.3.2 Comparative Advantage at local-level

A major interest of our methodology is to go within countries to uncover the local variations at the roots of the comparative advantage changes. In the following maps, we depicts the local changes from the 2000's to the 2050's for a selected number of countries and products. This enables to document a somewhat strong heterogeneity within countries with substantial spatial reallocation of production.

More precisely, we report in different maps (namely Figure (5) and Figure (4) for the USA and Europe, Figure (6) for Asia, Figure (7) for Africa, and Figure (8) for South-America) how the RCA has evolved between 2000 and 2050. In each map this result is matched with the variation of the local capability to produce a good k on the territory l in the country o. Because we cannot present this analysis for all products, we chose idiosyncratically some commodities, among which maize, wheat, coffee, soya beans and potatoes to illustrate our finding for different part of the world. Four situations are studied:

- A deterioration of the local conditions to produce a good but an improvement in the comparative advantages to trade it (country in green with localities in red triangle shaped symbols).

This result that bad conditions to produce a good can lead to an increase of its exports may seem puzzling, but it is not and can be explained by an environment that becomes even more hostile (costly) to other productions. This mechanism is at the heart of the theory of comparative advantage that concerns relative costs of production. Such a case occurs in Europe for the production of potatoes, for instance, in Ukraine, Romania and Hungary (see Figure (4)). Adaptation by farmers in this production is an example on how the negative effects of global warming can be mitigated and at the source of new comparative advantages.

Another mechanism that explains these opposite variations between RCA and the local water resources is the spatial reallocation of production. Indeed, the losses in one part of the country can be more than compensated by an improvement in another place of the country, leading this country to develop an advantage. This is typically what could occur in the USA for the production of wheat and meslin (see Figure (5)) which are going to become harder to produce in 2050 in the West and in the East of the Corn Belt but easier in its center leading to improve the yields of this crop.

Figure 4: Variation of Local Comparative Advantage in Europe for several products

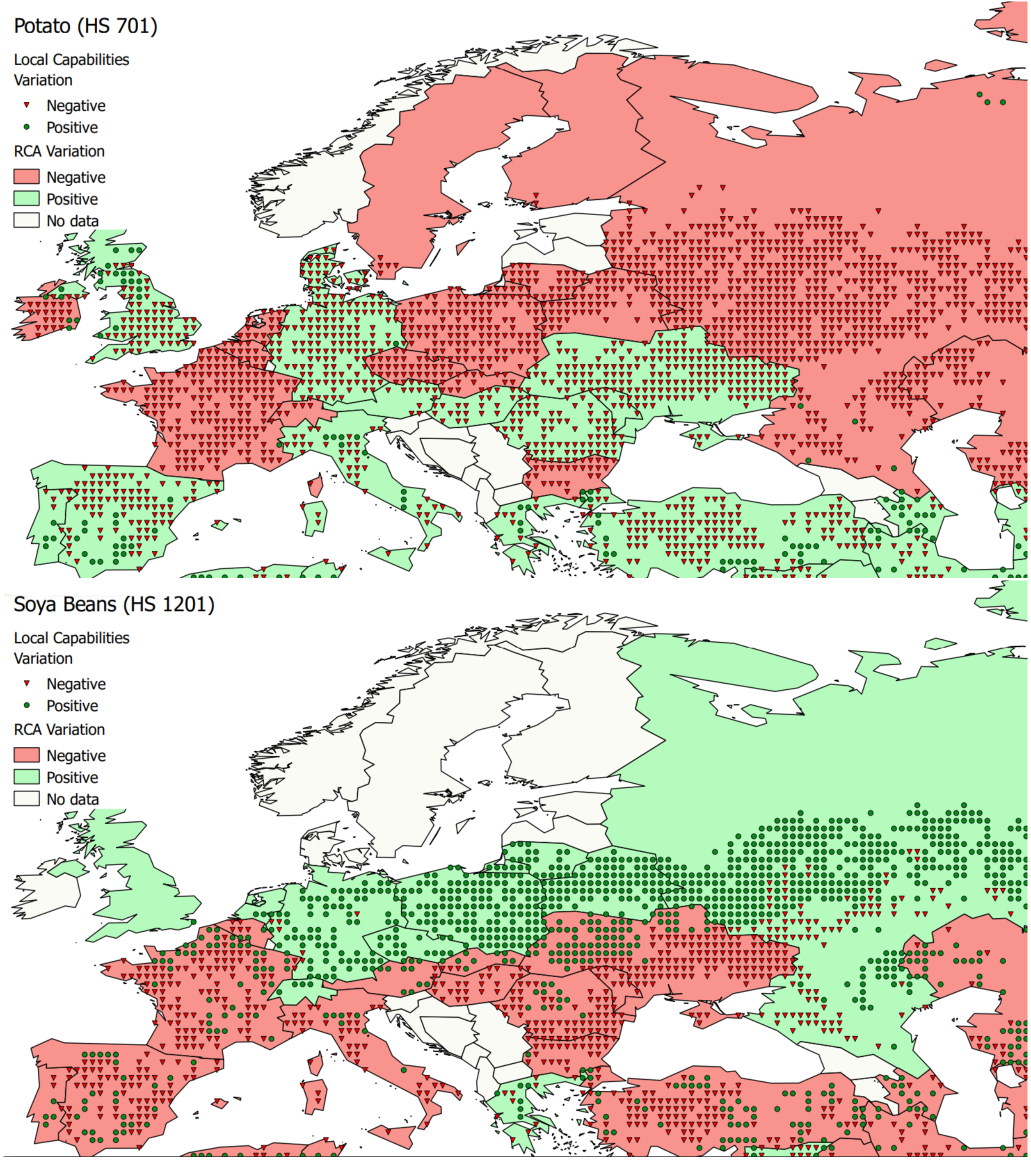
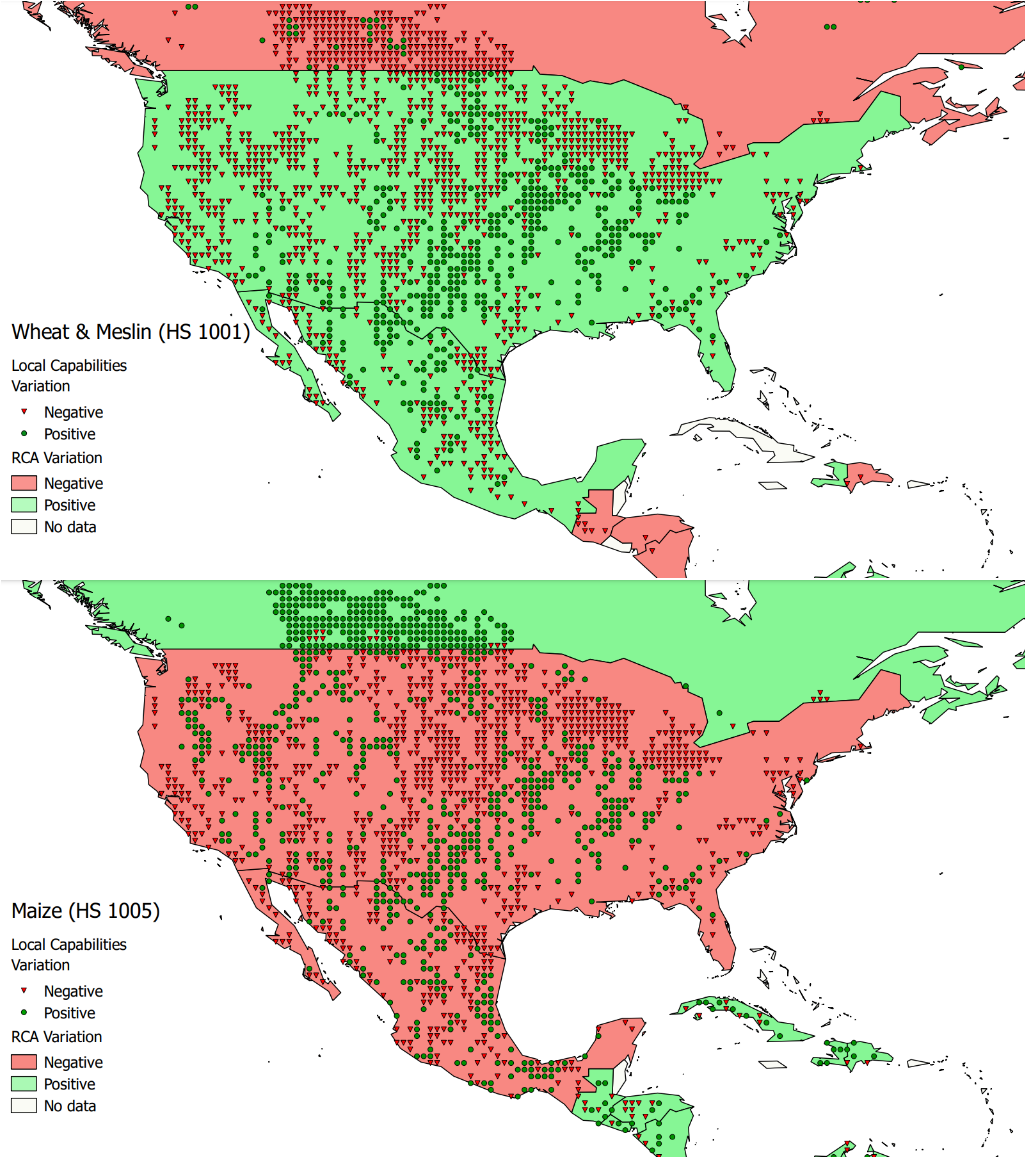


Figure 5: Variation of Local Comparative Advantage in North America for several products



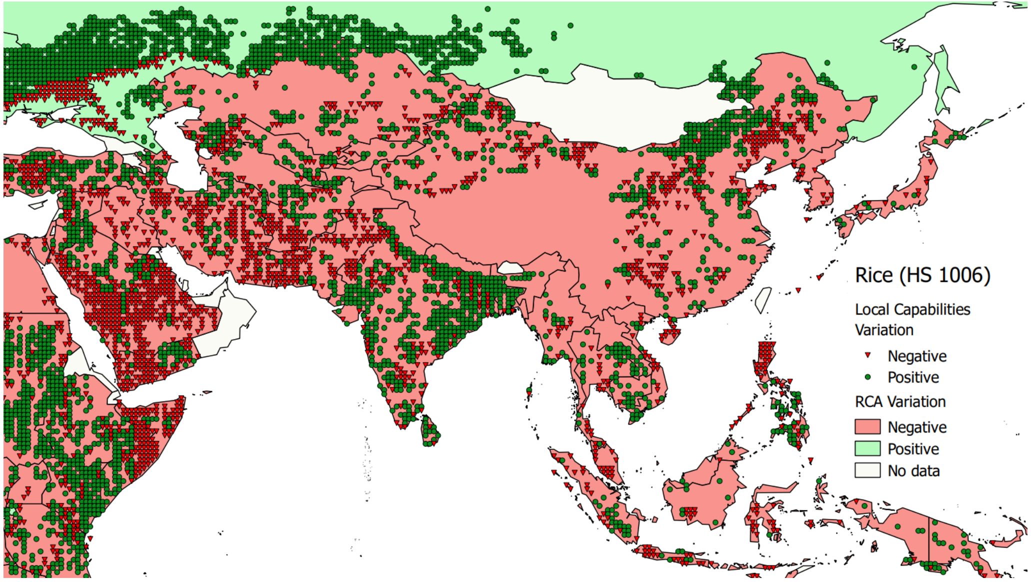
- An improvement in the conditions to produce a good but a deterioration of the comparative advantages to trade it (country in red with localities in green circle shaped symbols).

This case turns the previous one on its head but follows the same reasoning. Despite an improvement in the water capability to export a good, the comparative advantage in this production is reduced because other goods are even more adapted to the new local conditions. The production of maize in the core of the Corn Belt in the U.S. follows this pattern. This production that is water intensive may find a more profitable substitute due to climate change (e.g. wheat).

In Asia, many countries could suffer a decrease in their comparative advantages for rice despite an increase in local capabilities in many places (see Figure (6)). For example, our simulations suggest that India will see a widespread increase in local capability for rice production but these changes are not enough to prevent a loss in term of RCA.

In South-America, the production of soya beans is in a similar situation of a decreasing RCA despite an improvement of the hydrological conditions for this crop (see Figure (8)).

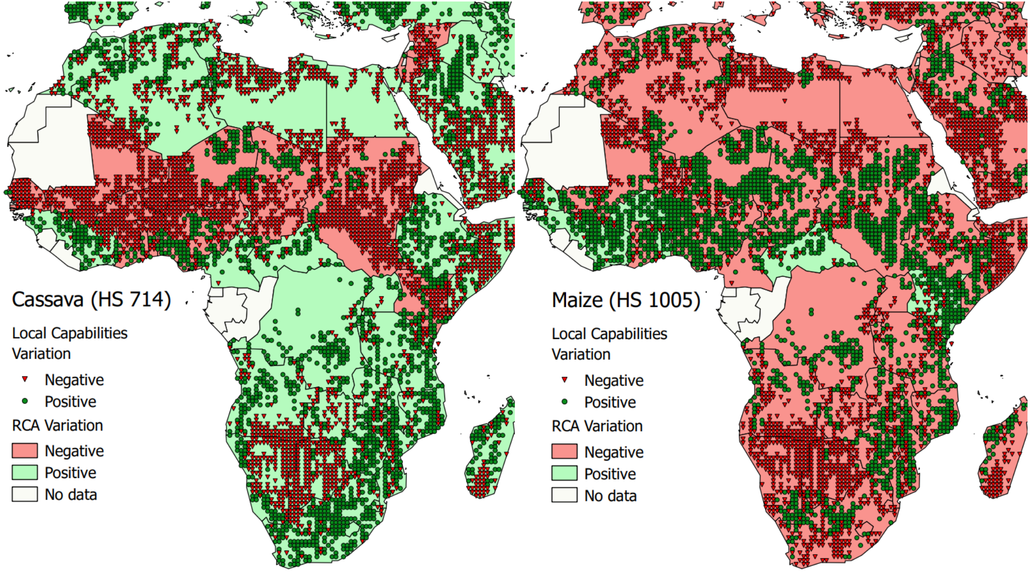
Figure 6: Variation of Local Comparative Advantage in Asia for Rice



- A deterioration of the local conditions leads to a deterioration of the comparative advantages (country in red with localities in red triangle shaped symbols).

This situation is more intuitive, when climate change deteriorates the conditions to produce a good over all the country, then the comparative advantage to produce this good is negatively affected. The decline in the RCA of soya beans in France and in Spain is an example (see Figure (4)). Similarly the production of cassava (or manioc) between the Equator and the Tropic of Cancer, could be much more difficult due to climate change in Africa, reducing the comparative advantages of many countries to produce this good (see Figure (7)). In some countries, such as in Ghana or Nigeria, there are some possibilities to relocate this production, but even with this spatial reallocation, the decline of the RCA in cassava seems inevitable. Yet, only countries along the Equator may be affected by a negative variation of their RCAs since countries in the Maghreb and South of the Equator may gain some comparative advantages in cassava. However, almost all countries in Africa may experience a decrease of their comparative advantage for the maize often due to strong decrease of local capabilities (despite some localities having still a gain in local capability).

Figure 7: Variation of Local Comparative Advantage in Africa for Manioc and Maize

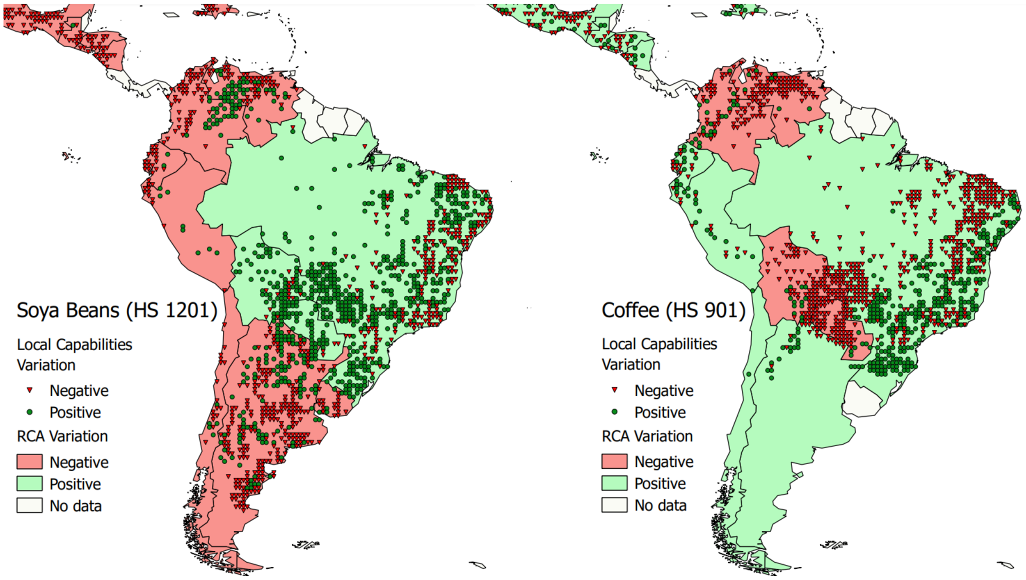


- An improvement in the conditions to produce a good leading to an improvement of comparative advantage (country in green with localities in green circle shaped symbols).

Improvement of RCA are obviously also due to an increase in the local water capability to export. For instance, in South Africa, the improvement in the local capabilities to produce cassava there (and in other african countries such as Ivory Coast, Cameroon, Mozambique and Tanzania) insure an increase in RCA (see Figure (7)). In Angola, the predicted strengthening of the comparative advantage of exporting cassava is due to an increase in the local water capability to produce this good in the center of this country (that compensates the losses along its southern border).

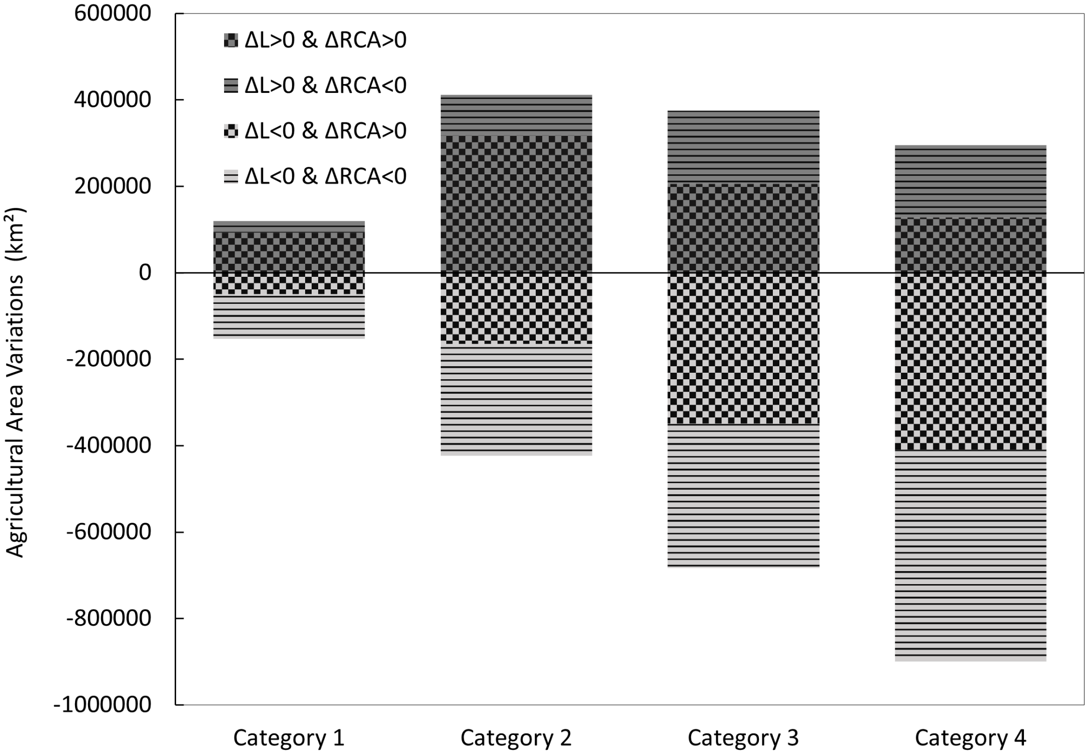
Considering now coffee and soya beans in the South American continent (see Figure (8)), it is interesting to observe that among the main traditional exporters of Coffee (Columbia, Venezuela and Brazil), our simulations suggest that only Brazil will improve its comparative advantage. This improvement is associated to a reallocation of the local capabilities to produce this coffee toward the southern part of the country.

Figure 8: Variation of Local Comparative Advantage in South America for Coffee and Soya Beans



In Figure (9), we present the evolution between the micro-level (local capabilities) and the macro-level (RCA) by distinguishing countries according to their level of vulnerability. We find that countries with a high vulnerability to climate change have the lowest share of localities with a simultaneous increase in water capabilities and in RCA. We also find that these vulnerable countries could suffer from a strong decrease in their local capabilities (a 26.61% drop of the agricultural area) often related to a decrease in RCA.

Figure 9: Variation of Local Capabilities and RCA



5 Conclusion

As it has been pointed out by Costinot et al. (2016), the effect of climate on the comparative advantages of nations remains an open question. Once we control for capital, labour and institution, at the source of the agricultural comparative advantages of nations lies the water resources, on which climate change will have substancial impact. In this article, we use rich micro-level data on hydrological conditions in order to approximate the water capability of nations to produce agricultural goods. We then estimate the agricultural trade elasticity of water for different types of countries differenciated according to their vulnerability to climate change. Based on these estimates, we compute the revealed comparative advantages of nations for a vast number of crops, and finally we analyze how these advantages have evolved with climate change.

Then, from these three steps that go from the production, to exports and comparative advantages, we find several results. First, we find that groundwater sustains the production of goods that suffers of the insufficiency of renewable water resources. Since a part of these groundwater are non-renewables, this poses a particular challenge in front of climate change. Second, the physical vulnerability to climate change is already detrimental for exports, however agricultural exports from vulnerable countries could be less sensitive to water conditions than those from other countries. Vulnerable countries may be more specialized in the production of agricultural goods that are less intensive in water. Our simulation shows a general resilience of the comparative advantages of nations but also reveals significant changes within countries and for different sectors. At the local scale, these changes may have dramatic consequences for farmers which call policy makers to implement mitigation strategies in territories under water pressure. While in some countries climate change leads to a deterioration of important agricultural production without alternative solution (e.g. Coffee in Argentina), there are also places where crops of substitution remains available (e.g. maize in the USA).

The limitations of our studies are obviously numerous. Our indicator of local capabilities takes into account the climatic conditions under which a good can be produced, and not the real behavior of farmers. There is no certainty that the possibilities of new productions are going to be taken into account by farmers in 2050. Consequently, the improvement in trade, and implicitly the capability of producers to adapt their production, is certainly overestimated in the northern hemisphere.[35] Similarly, the forecasted value of trade flows only evolves in our model in reason of the relative costs to produce different goods under climate change, and takes as given the technology and the possible change in the demand of consumers. Our results may also be sensitive to some specific assumptions, for instance, by lumping together the elasticity of crop production to water for all countries, we do not take into account the non-linearity of these elasticities at the local level that certainly drive partially changes in RCAs because they affect the relative changes in crop production.

Finally, our analysis does not pay enough attention to how the water resources is shared. Our computation at the national level is simply the sum of the indicator computed at the local level, which is a too simple manner to take into account the political and hydrological dynamics of the localities within countries. A better implementation of the local institutions upon which rely most of the water allocation can be particularly helpful in devising a more accurate indicator of water availability.

In that respect, this article is an only first step toward a deeper analysis into the relationship between the effective water endowment and the international trade of agricultural goods in the wake of climate change.

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[35] However, the advantage of this strategy is that in vulnerable countries our indicator is certainly more realistic since it presents the physiological constraints of ecosystems to produce particular crops.

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6 Appendix

HS4 Code	Entitled of HS4
701	Potatoes
702	Tomatoes
703	Onions, shallots, garlic, leeks and other alliaceous vegetables
706	Carrots, turnips, salad beetroot, salsify, celeriac, radishes and similar edible roots
709	Other Vegetables
713	Leguminous Vegetables
714	Manioc, arrowroot, salep, Jerusalem artichokes, sweet potatoes and similar roots and tubers with high starch or inulin content
801	Nuts, coconuts, Brazil nuts and cashew nuts
803	Bananas, including plantains
805	Citrus fruit
806	Grapes
901	Coffee
902	Tea
1001	Wheat and meslin
1002	Rye
1004	Oats
1005	Maize
1006	Rice
1007	Sorghum
1008	Buckwheat, millet and canary seeds
1201	Soya beans
1202	Groundnuts
1205	Rape or colza seeds
1206	Sunflower seeds
1207	Oil seeds and oleaginous fruits
1211	Plants and parts of plants (including seeds and fruits), of a kind used primarily, in perfumery, in pharmacy or for insecticidal, fungicidal or similar purposes
1212	Locust beans, seaweeds and other algae, sugar beet, sugar cane, fresh, chilled, frozen or dried, whether or not ground;fruit stones, kernels and other vegetable products (including unroasted chicory roots) used primarily for human consumption
1214	Swedes, mangolds, fodder roots, hay, lucerne (alfalfa), clover, sainfoin, forage kale, lupines, vetches and similar forage products
1801	Cocoa beans
2401	Tobacco
5201	Cotton
5301	Flax

Table 4: List of HS4 Products

Table 5: Countries included in category 1 for each variable

Vulnerability Indicator	Capital per inhabitant Indicator	Readiness Indicator
Austria	Bangladesh	Afghanistan
Belarus	Burkina Faso	Angola
Bulgaria	Burundi	Bangladesh
Colombia	Cambodia	Burkina Faso
Cote d'Ivoire	Central African Republic	Burundi
Czech Republic	Chad	Cameroon
Ecuador	Congo, DRC	Central African Republic
Finland	Cote d'Ivoire	Chad
France	El Salvador	Congo, DRC
Hungary	Ethiopia	Cote d'Ivoire
Indonesia	Guinea	Cuba
Ireland	Kenya	Guinea
Italy	Madagascar	Haiti
Laos	Malawi	India
Lithuania	Mali	Libya
Malaysia	Mozambique	Myanmar
North Korea	Myanmar	Niger
Papua New Guinea	Nepal	Nigeria
Poland	Niger	North Korea
Portugal	Nigeria	Pakistan
Romania	Rwanda	Rwanda
Slovakia	Sudan	Somalia
South Korea	Tanzania	Sudan
Sweden	Togo	Tajikistan
Switzerland	Uganda	Turkmenistan
Ukraine	Yemen	Uzbekistan
United Kingdom	Zimbabwe	Venezuela
Uruguay		Zimbabwe

Table 6: Countries included in category 2 for each variable

Vulnerability Indicator	Capital per inhabitant Indicator	Readiness Indicator
Angola	Azerbaijan	Algeria
Bangladesh	Benin	Azerbaijan
Belgium	Bolivia	Bolivia
Benin	Bulgaria	Brazil
Bolivia	Cameroon	Cambodia
Brazil	China	China
Burundi	Egypt	Colombia
Cambodia	Ghana	Ecuador
Cameroon	Guatemala	Ethiopia
Canada	Haiti	Guatemala
Central African Republic	Honduras	Honduras
Congo, DRC	India	Indonesia
Denmark	Indonesia	Iran
Germany	Iraq	Iraq
Ghana	Kyrgyzstan	Kenya
Greece	Laos	Laos
Guatemala	Moldova	Madagascar
Guinea	Nicaragua	Malawi
Honduras	Pakistan	Mali
Malawi	Philippines	Mozambique
Paraguay	Senegal	Nicaragua
Peru	Sri Lanka	Papua New Guinea
Russia	Syria	Paraguay
Sri Lanka	Tajikistan	Senegal
Tajikistan	Uzbekistan	Tanzania
Thailand	Vietnam	Togo
Togo	Zambia	Uganda
Venezuela		Ukraine
Vietnam		Yemen

Table 7: Countries included in category 3 for each variable

Vulnerability Indicator	Capital per inhabitant Indicator	Readiness Indicator
Argentina	Algeria	Argentina
Azerbaijan	Angola	Belarus
Chile	Belarus	Benin
China	Brazil	Bulgaria
Dominican Republic	Chile	Dominican Republic
El Salvador	Colombia	Egypt
Ethiopia	Dominican Republic	El Salvador
Haiti	Ecuador	Ghana
India	Iran	Jordan
Kyrgyzstan	Jordan	Kazakhstan
Moldova	Kazakhstan	Kyrgyzstan
Mozambique	Lithuania	Mexico
Myanmar	Malaysia	Moldova
Nepal	Mexico	Morocco
Netherlands	Morocco	Nepal
Nicaragua	Paraguay	Peru
Nigeria	Peru	Philippines
Philippines	Poland	Romania
Rwanda	Romania	Russia
South Africa	South Africa	Saudi Arabia
Spain	Thailand	South Africa
Tanzania	Tunisia	Sri Lanka
Turkey	Turkey	Syria
Turkmenistan	Turkmenistan	Tunisia
Uganda	Ukraine	Turkey
United States	Uruguay	Uruguay
Uzbekistan	Venezuela	Vietnam
Zambia		Zambia

Table 8: Countries included in category 4 for each variable

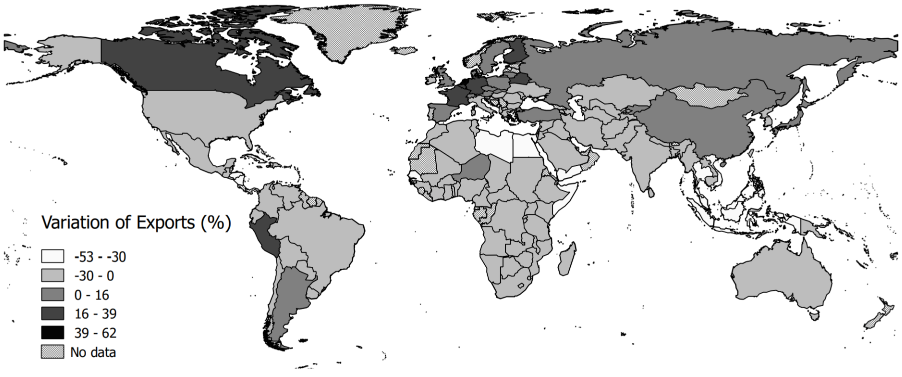
Vulnerability Indicator	Capital per inhabitant Indicator	Readiness Indicator
Afghanistan	Argentina	Australia
Algeria	Australia	Austria
Australia	Austria	Belgium
Burkina Faso	Belgium	Canada
Chad	Canada	Chile
Cuba	Czech Republic	Czech Republic
Egypt	Denmark	Denmark
Iran	Finland	Finland
Iraq	France	France
Israel	Germany	Germany
Japan	Greece	Greece
Jordan	Hungary	Hungary
Kazakhstan	Ireland	Ireland
Kenya	Israel	Israel
Libya	Italy	Italy
Madagascar	Japan	Japan
Mali	Netherlands	Lithuania
Mexico	Portugal	Malaysia
Morocco	Russia	Netherlands
Niger	Saudi Arabia	Poland
Pakistan	Slovakia	Portugal
Saudi Arabia	South Korea	Slovakia
Senegal	Spain	South Korea
Somalia	Sweden	Spain
Sudan	Switzerland	Sweden
Syria	United Kingdom	Switzerland
Tunisia	United States	Thailand
Yemen		United Kingdom
Zimbabwe		United States

7 Appendix

7.1 Export flows

Generally speaking, world trade of agricultural product may decrease by 3.49 % with a relatively clear delineation between northern and southern countries (+ 0.88 % for the North and -13.27 % in the South) as depicted in the Figure (10). Some notable exceptions arise with the USA that decrease their exports by 7 % while Peru, Argentina and Niger increase their export by 32.18 %, 0.37 % and 4.54 % respectively. Looking by continent, North America may see their export increase by 13.78 % largely driven by the Canada (+ 28.4 %) followed by Europe with an increase of 7.66 %. All other continents may see a drop of their exports with Oceania, Asia and Africa experiencing the most important decrease (-24.57 %, -17.04 % and -14.59 % respectively) while the South and Central America may be the least affected with a drop of 12.21 % of their exports.

Figure 10: Variation of Total Exports by Country



A clear pattern emerges when looking at the variation of trade depending on the vulnerability to climate change. Indeed, the least vunerable countries may experience the smallest drop of trade with a decrease of 1.8 % of export (with only 17 countries over 28 having a negative variation of trade), followed by the medium-low vulnerability and medium-high vulnerability countries (with a respective drop of 3.5 % and 7.7 %). Finally, the most vulnerable countries may suffer from the largest drop of export with a decrease of 14 % with 26 countries over 29 experiencing a decrease of exports.

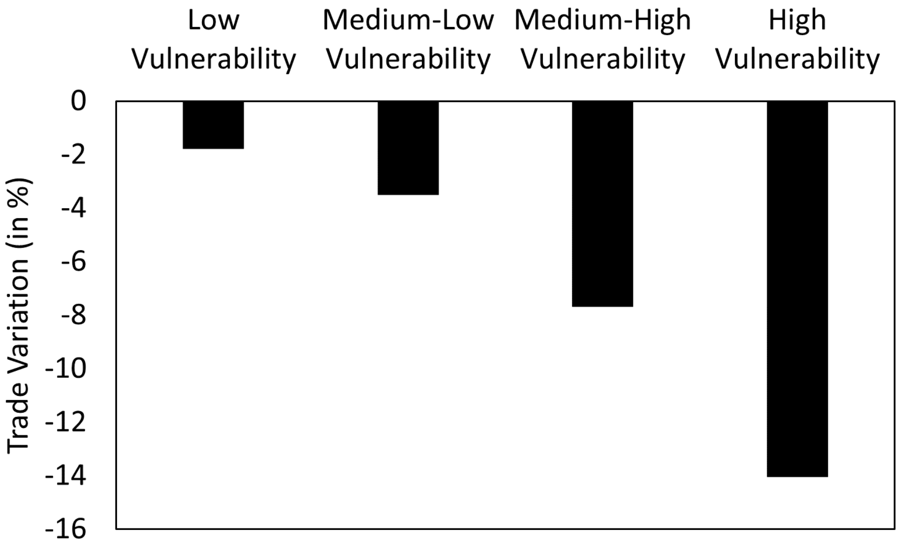


Figure 11: Trade Variation by Category of Vulnerability to Climate Changes

These results are complementary to a large literature, mainly based on computable general equilibrium (see Dellink et al. (2017), Gouel and Laborde (2021)), showing that developed countries generally gain in term of agricultural export from climate changes in comparison to developing countries. Two mechanisms are certainly at play. Firstly, developed countries are better prepared to mitigate the disruptive effects of climate changes than developing countries. Second, it is well aknowledge that the global raising temperature will induce a more favorable climate for number of crop varieties southern of the Capricorn Tropic and northern of the Cancer Tropic. Therefore, it is relatively intuitive to understand such results with developed countries being apparently better off while developing countries being worse off from climate change.

7.2 How RCA could change in 2050?

We present here the revealed comparative advantages concerning the predictions for the years 2000's (horizontal axis) against the simulations for the years 2050's (vertical axis) for six crops, namely maize, wheat, manioc, potatoes, tomatoes and citrus. The 45° line represents a situation where the RCA has not changed over the period. Countries below this line have faced a decrease in their comparative advantages (this does not mean that these countries have initially a strong comparative advantage on the product studied) and *vice-versa*. We also differenciate the four categories of countries based on the PVCCI index to derive some more accurate trends. For many products, the conclusion of the literature seems well verified, many countries have their RCA clustered around the 45° line, indicating few changes in their specializations due to climate change.

However, such a general conclusion does not hold for all countries and products. Some exceptions exist as we can see for citrus product, some countries move away from the 45° line which are countries mainly considered as more vulnerable to climate change (Mexico, Australia, Kenya, ...). Even if Figure (12) depicts an average tendency of small change, we can note some difference in function of products. For maize, the majority of countries are close to the line but have a slightly negative impact on the RCA and we can note the reverse situation in the case of Manioc.

Figure 12: Comparison of Revealed Comparative Advantages between the 2000's and the 2050's

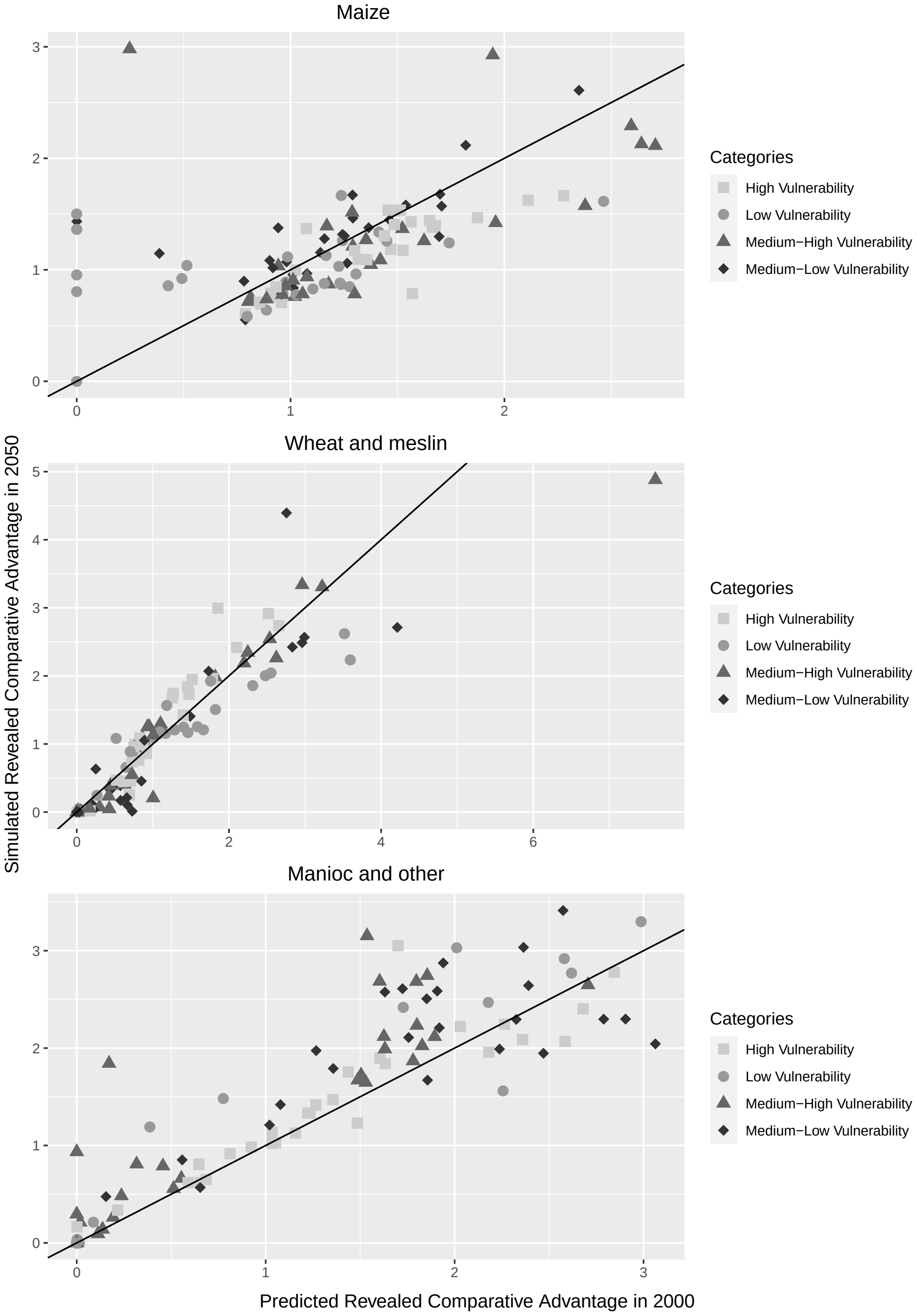
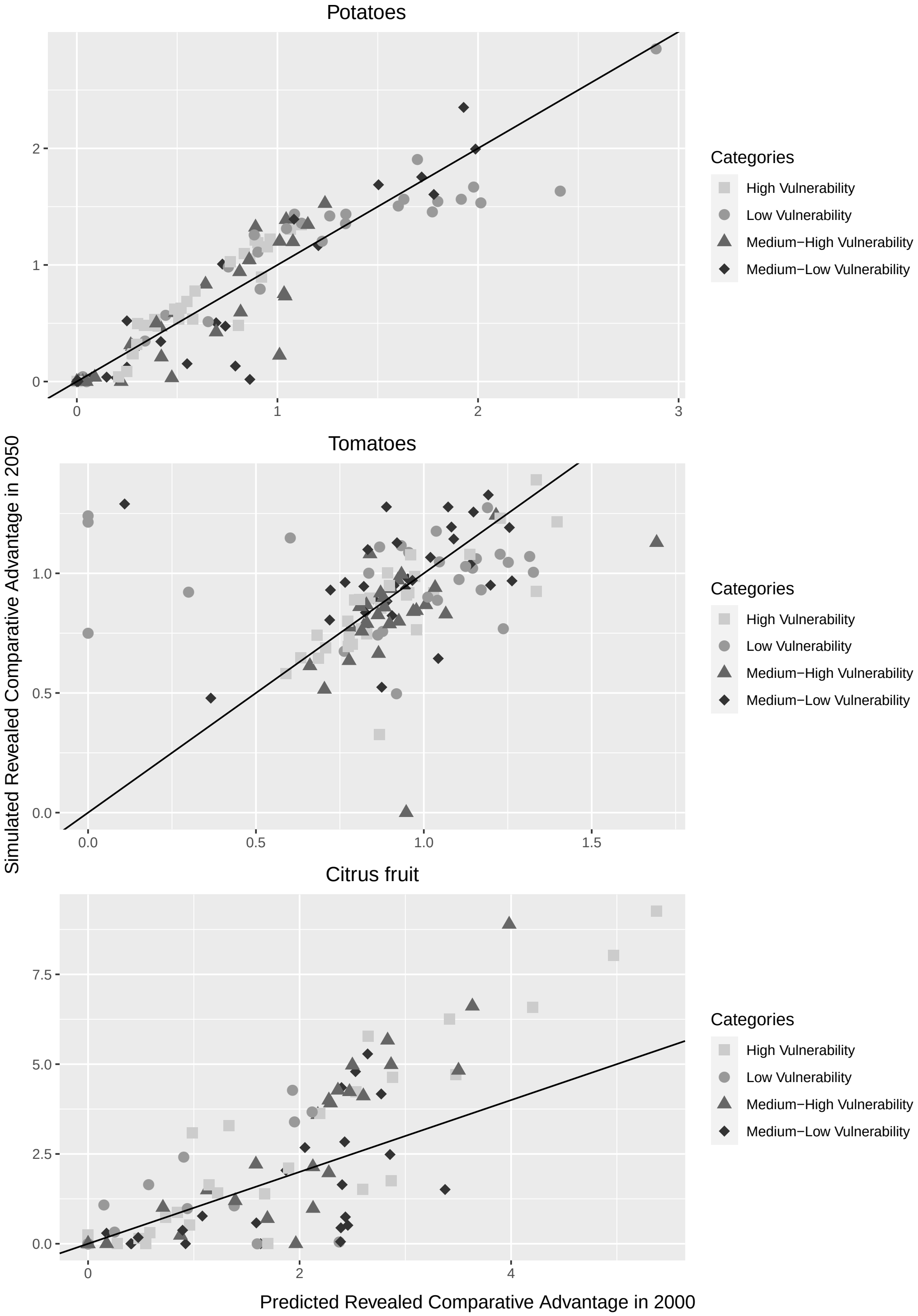


Figure 13: Comparison of Revealed Comparative Advantages between the 2000's and the 2050's



Not reported here to save space,[36] we have also reproduced this analysis for all the products of our database, namely for 24 additional crops. We found the same general trend of small changes around

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[36] These results are however available on request.

the 45° line, but with however some interesting rise and fall of RCAs such as a loss of specialization in sunflower seeds in Russia, manioc in South-Africa, vegetables in Mexico or flax in Canada and a potential improvement in grapes for Italy (and for African countries such as in Uganda and Ethiopia), groundnuts for Kenya and tobacco for Poland among many other results. All these results are obviously conditioned by the assumptions done in this paper.