Agro-climatic environment heterogeneity and productivity convergence

May 30, 2024

Abstract

This study proposes an alternative approach for studying the role of countries' weather differences on agriculture productivity changes. As weather is beyond the control of farmers, we model weather differences by defining time-dependent output-specific agro-climatic environments. These environments condition countries' production process and technology, and indirectly impact their productivity gains. Building on a tailored database for 91 countries, we study productivity changes between 1961 and 2015. This represents a unique opportunity to analyse productivity changes for many countries over a long period. From a theoretical perspective, we define new output-specific indexes for productivity change and convergence between and within agro-climatic environments and decompose them into several parts. Another distinguishing feature of our approach is to rely on a non-parametric estimation method. We find that agro-climatic environment heterogeneity has a clear impact on productivity change and convergence, that depends on the outputs and evolves. Overall, our results show that productivity change is positive and productivity convergence occurs, both mainly due to technological change. Next, path dependence is observed for efficiency convergence but not for technological convergence. Finally, we cannot confirm that there are technology spillovers.

Keywords: agriculture productivity; weather; environment gap; convergence.

JEL codes: O30; D24; O47.

1 Introduction

Much efforts have been and are continuing to be made to understand the role of weather in productivity changes and differences across countries in the agriculture sector.[1] Two main reasons for this scientific interest are that, first, productivity has been recognized as an important source of output growth over the past half-century for the agriculture sector (IPCC, 2014; USDA/ERS, 2019), and, second, agriculture is probably the most impacted sector by climate change (Liu et al., 2014). Two topical questions, relevant to agriculture policy in general, are, how weather affects the productivity convergence/divergence process and how it impacts the productivity sources across countries over time.

While there is an important number of empirical studies about the role of weather in productivity changes and differences, there exists a considerable disagreement about the sign and magnitude of potential impacts (Mendelsohn et al., 1994; Darwin, 1999; Schlenker et al., 2006; Kelly et al., 2005; Timmins, 2006; Ashenfelter and Storchmann, 2006; Deschenes and Greenstone, 2007). Different reasons can explain this disagreement. First, there is no doubt that weather impacts agriculture outcomes – such as yield, land value, profit, efficiency, and productivity – it is perhaps not so clear through which channel(s). Next, the relationship between agriculture outcomes and weather is often seen as nonlinear, asymmetric, and dynamic. Also, unlike other production factors (e.g. labour, tractor, fertiliser), the weather is beyond the farmers' control. Finally, weather creates endogeneity as it does not cause outcomes (Gollin, 2010). All in all, these concerns imply that proposing an economic model considering weather factors is a challenging task.

When productivity change is the main interest, two main strategies have been employed in practice to incorporate weather factors. One is to measure productivity ignoring weather variables, but rather use them in a second-stage econometric analysis as explanatory variables of productivity differences or when decomposing productivity changes (Ball et al. 2004; O'Donnell et al., 2008; O'Donnell, 2010, 2012; Ayinde et al., 2011; Key and Sneeringer, 2014; Zhong et al., 2019). A second strategy is to incorporate weather factors in the production process as inputs or as factors impacting inefficiency. Next, productivity change is decomposed or econometric analyses are used (Mukherjee et al., 2013; Key and Sneeringer, 2014; Nelson et al., 2014; Qi et al., 2015; Njuki and Bravo-Ureta, 2015; Lachaud et al., 2017; Wang et al., 2017; Njuki et al., 2018; Chambers and Pieralli, 2020). The second approach seems to be more popular over time in light of the increasing number of works,

[1] A non-exhaustive list of recent works is Cermeño et al. (2003), Gutierrez and Gutierrez (2003), Johnson et al. (2006), Ayinde et al. (2011), Eberhardt and Teal (2013), Mukherjee et al. (2013), Villavicencio et al. (2013), Dell et al. (2014), Key and Sneeringer (2014), Nelson et al. (2014), Wang and McPhail (2014), Qi et al. (2015), Lachaud et al. (2017), Liang et al. (2017), Wang et al. (2017), Eberhardt and Vollrath (2018), Njuki et al. (2018), Ortiz-Bobea et al. (2018), Sabasi and Shumway (2018), Zhong et al. (2019), Chambers and Pieralli (2020), and Rahman and Anik (2020).

even if it is not so clear whether it is better to incorporate weather factors directly, i.e. as inputs, or as indirectly, i.e. through inefficiency, impacting the outcomes.

In this paper, we take weather differences into account by defining time-dependent output-specific agro-climatic environments. These agro-climatic environments regroup countries that have similar weather features and thus share a common unobserved environment conditioning their production process and technology. Weather differences are, in a sense, used as a proxy variable to define different environments. From an economic point of view, countries in similar agro-climatic environments have comparative advantages while technology transfer and spillover failures are observed when the environments are different. This approach avoids asking how weather impacts productivity and what is the best economic modelling; it rather recognizes its impact at a more general level by defining environments that may evolve and that are different for each output.

Building on our time-dependent output-specific agro-climatic environments and a tailored database for 91 countries, we study productivity changes between 1961 and 2015. This represents a unique opportunity to analyse productivity changes for many countries over a long period. From a theoretical perspective, we define new output-specific indexes for productivity change in our agro-climatic environmental heterogeneity context and decompose them into several parts. A particular focus is given to productivity convergence for the agriculture outputs, and its sources, between and within agro-climatic zones. While productivity convergence has been studied before (mainly across countries: Schimmelpfennig and Thirtle, 1999; Rae and Hertel, 2000; Rao and Coelli, 2004 Coelli and Rao, 2005; Rezitis, 2010; Baráth and Fertő, 2017), this represents the first attempt to empirically evaluate such phenomenon in an agro-climatic environment context.

The rest of the paper is structured as follows. In Section 2, we present and describe our data. We explain how we construct our time-dependent output-specific agro-climatic environments and the indexes in Section 3. In Section 4, we explain our non-parametric estimation method. We give the main results of our empirical analysis in Section 5, and conclude in Section 6.

2 Data sources and descriptive statistics

We use a recent database for 91 countries from 1961 to 2015 compiled by O'Donnell and Peyrache (2019).[2] This represents a unique opportunity to analyse agriculture productivity changes for many countries over a long period. To avoid making our empirical analysis on two points in time only (e.g. the initial and final year: 1961 and 2015), we choose to base our investigation on time intervals. Interval lengths have to be properly selected to capture

[2]Data is not freely available but there is a free report: https://doi.org/10.61145/GSUZ1506.

long-term effects (the climatological normal period is around 30 years) and to reduce the impact of possible abnormal results of a specific year. In light of these arguments, we select two 15-years intervals: 1961–1975 and 2001–2015.[3]

O'Donnell and Peyrache (2019) have combined several reliable sources, such as FAOSTAT, ILOSTAT, APO, to create their database as such long-term data are not freely and easily available. Moreover, there are sometimes potential consistency issues and missing data for some variables. They have used econometric and frontier methods to clean their data sources. They obtained data for two outputs: crops and livestock; and four inputs: land, labour, fertilizers, and tractors. These outputs and inputs are used in most of the empirical studies on agriculture (see the references in the Introduction). We highlight that only aggregated level inputs and outputs are available in the database as it is the case in most well-known databases such as FAOSTAT, ILOSTAT, APO.

An advantage of our methodology is that we do not have to aggregate the inputs and the outputs; we, rather, use data as disaggregated as possible. We provide, in Table 1, the average values for the outputs and inputs for our two intervals as well as the (average) growth. Note that outputs and inputs have been centred and rescaled such that they are unit-free.

Table 1: Input and output descriptive statistics

interval	crops	livestock	land	labour	fertilisers	tractors
1961-1975	5,339,662	2,999,430	37,874	22,424	556,601	142,069
2001-2015	14,453,998	8,006,520	40,629	32,778	1,775,191	293,207
growth	187.76%	175.28%	7.78%	47.10%	232.07%	145.96%

A first observation is that all outputs and inputs have raised between 1961–1975 and 2001–2015. Similar positive growth for the crops and livestock, with an increase of 187.76% and 175.28%, respectively, are observed, while, for the inputs, it is another story with more variabilities in the changes. The land input has grown by almost 8% while fertiliser use has more than tripled. Between these two extreme changes, we find tractors, often used as a proxy for capital, that have more than doubled, and labour that has increased by a little bit more than 47% over the period. Agriculture seems becoming more capital and fertiliser-intensive over time. Overall, on a descriptive basis, when comparing changes in outputs and inputs, we could say that productivity gains are present.

O'Donnell and Peyrache (2019) split countries into four agro-climatic zones (wet temperate, dry temperate, wet tropical/subtropical, and dry tropical/subtropical) and four geographical regions (Africa, the Americas, Asia, and Europe). While the latter has less

[3] Three remarks have to be made. First, data between 1976 and 2000 will be used in the estimation process (see Section 3.1). Second, these two intervals exclude the potential impacts of the mid-1970s oil shocks. Last, in a different context, Chambers and Pieralli (2020) also make use of a 15-years interval.

interest for us, the former will be used to define our time-dependent output-specific agro-climatic environments.[4] For each year and output, we consider that there is a different agro-climatic environment in each zone. The repartition of the countries per zone is illustrated in Figure 1, and interesting descriptive statistics for the zones are given in Tables 2 and 3 to contextualize our empirical study.[5] Note that these additional data will be used to investigate productivity convergence differences in Section 4.4.

Figure 1: Climate-zone environments

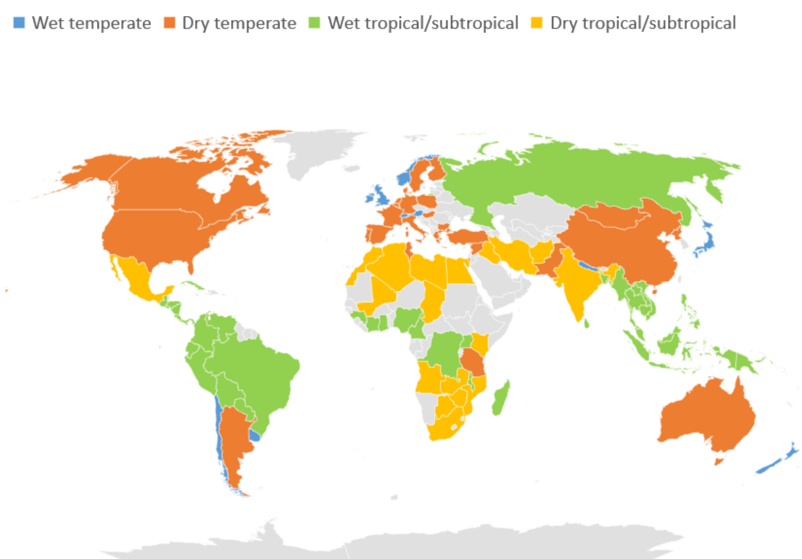


Table 2: Area and population descriptive statistics per agro-climatic zones

zone	countries	areas	population		
			1961-1975	2001-2015	growth
wet temperate	12.09%	2.35%	21,308,644	28,579,953	44.54%
dry temperate	29.67%	41.46%	53,207,219	87,393,761	65.52%
wet tropical/subtropical	38.46%	36.94%	21,624,228	46,173,145	147.19%
dry tropical/subtropical	19.78%	19.26%	42,273,289	98,783,269	176.79%

The largest zone is the dry temperate zone that contains one country over three. The smallest one is the wet temperate zone with a bit more than one country over ten. The population has grown more importantly in the wet and dry tropical and subtropical zones and is higher in the dry temperate and dry tropical/subtropical zones. Unsurprisingly, agriculture to GDP shares have importantly decreased in all zones, but the share of agriculture

[4]See Kottek et al. (2006) for more detail about classifying countries into climate zones.

[5]Countries in white in Figure 1 are those for which data are not observed in O'Donnell and Peyrache (2019). Data for Tables 2 and 3 are retrieved for the World Bank Database.

Table 3: Trade descriptive statistics per agro-climatic zones

zone	agriculture to GDP (share)		
	1961-1975	2001-2015	growth
wet temperate	24.51%	5.32%	-63.16%
dry temperate	19.25%	6.17%	-55.18%
wet tropical/subtropical	29.14%	15.85%	-52.94%
dry tropical/subtropical	25.36%	14.57%	-44.17%
zone	**agriculture exports (USD)**		
	1961-1975	2001-2015	growth
wet temperate	189,668,578	1,981,956,632	2224.30%
dry temperate	527,806,102	4,255,953,114	980.61%
wet tropical/subtropical	107,100,316	1,242,729,402	2064.76%
dry tropical/subtropical	152,990,528	519,793,219	1470.22%
zone	**agriculture imports (USD)**		
	1961-1975	2001-2015	growth
wet temperate	596,141,801	3,032,597,209	642.09%
dry temperate	549,680,825	5,008,677,716	1183.14%
wet tropical/subtropical	17,075,195	595,852,257	3196.30%
dry tropical/subtropical	71,367,663	777,550,576	1139.90%

to GDP remains higher in the wet and dry tropical/subtropical zones. At the same time, the importance of agriculture trade has importantly raised in all zones. We highlight the greater growth in the wet tropical/subtropical zone for both the exports and imports, while it is the dry temperate zone that presents the higher import and export levels. We continue the description of our sample with the descriptive statistics for the outputs and inputs per zone in Table 4.

In terms of quantities, the dry temperate zone is the most important producer of both crops and livestock. This zone has the largest land, fertiliser, and tractor uses, while it is the dry tropical/subtropical zone that has the highest labour use (this is true only in 2001-2015). Greater output increases occur in the dry and wet tropical/subtropical zones while a smaller one happens in the wet temperate zone. All inputs increase, in different proportions, in all zones except the land and labour inputs that decrease in the wet temperate zone. We also note the important increase in the use of fertilisers in all zones except in the wet temperate zone where it is the tractor input that raises the most. This means that this zone is more capital-intensive over time. Moreover, the land input increases by around 10% in the dry and wet tropical/subtropical zones. Finally, we point out the less important positive change in the labour inputs in comparison with the other inputs in all zones. All in all, climate zones are heterogeneous in terms of their input use.

Table 4: Input and output descriptive statistics per climate zones

interval	crops	livestock	land	labour	fertilisers	tractors
wet temperate zone						
1961-1975	2,343,265	2,739,086	8,187	7,583	526,101	117,292
2001-2015	3,182,317	4,709,697	7,246	6,181	567,887	325,469
growth	57.59%	119.31%	-12.84%	-27.06%	37.01%	293.49%
dry temperate						
1961-1975	10,265,454	6,982,833	70,891	34,094	1,410,135	402,026
2001-2015	25,741,105	16,648,461	72,220	39,852	3,630,774	623,030
growth	245.72%	198.02%	1.47%	15.83%	341.72%	124.76%
wet tropical/subtropical zone						
1961-1975	2,821,405	761,212	17,487	13,293	90,589	9,149
2001-2015	9,608,543	3,497,957	23,009	21,784	792,397	48,041
growth	288.77%	241.97%	11.80%	40.68%	449.16%	138.77%
dry tropical/subtropical zone						
1961-1975	4,678,717	1,535,520	46,132	31,746	201,077	25,736
2001-2015	13,833,309	5,824,984	47,904	59,800	1,640,605	255,469
growth	299.13%	261.41%	9.92%	64.95%	536.16%	193.39%

3 Methodology

We posit that we observe a sample of countries, partitioned into K distinct agro-climatic environments, during T time periods. For each country i, we observe its input-output combination $(\mathbf{x}_{it}, \mathbf{y}_{it})$ for every period t. As a preliminary step, we explain how we model technology heterogeneity between outputs and over time. Next, we explain how we measure the impact of the agro-climatic environment heterogeneity on agriculture productivity. After, we define our productivity and convergence indexes and show how they can be decomposed. Finally, we explain how to compute the indexes.

Our approach is directly related to three important streams of research in agriculture economics. First, recent works have revealed the most important role of weather differences in explaining countries' technology heterogeneity (Johnson et al., 2006; Vollrath, 2011; Eberhardt and Teal, 2013; Eberhardt and Vollrath, 2018). These works have shown that technology heterogeneity across countries cannot be ignored as was the case in important initial studies (Hayami and Ruttan, 1970; Craig et al., 1997; Martin and Mitra, 2002). In practice, an econometric model with country-specific technology heterogeneity that does not vary over time is used. We believe that this approach is too extreme especially when dealing with long-term empirical analyses as is the case in this paper. Next, this approach does not recognize that technology diffusion is possible for countries with similar weather features. We indeed may expect that countries with similar weather factors tend to have similar technologies through technology spillover and diffusion. Finally, we believe that a fair analysis should take the best points of comparison inside each environment, instead of overall points.

Second, several works have recognized the importance of environment heterogeneity using the level of development (Hayami and Ruttan, 1985; Cermeño et al., 2003; Gutierrez and Gutierrez, 2003; O'Donnell et al., 2008) or geographical criteria (Coelli and Rao, 2005; Zhuo et al., 2008; Jiang and Sharp, 2015; Alem et al., 2016; Rahma et al., 2019). A problem with these approaches is the lack of economic foundation. While it is often argued that economic development or geographical distance are powerful determinants of the magnitude of economic exchange between countries, they are certainly not good proxies for climatic differences. Instead, weather conditions are directly related to such differences and thus represent a better proxy.

Third, it is difficult to believe that a similar technology is used for each output (e.g. crops vs. livestock). Several recent works have incorporated output-specific technology heterogeneity in their economic or econometric modelling (Lobell and Field, 2007; Schlenker et al., 2008; Seo and Mendelsohn, 2008; Vollrath, 2011; Eberhardt and Teal, 2013; Qi et al., 2015; Asante et al., 2017). Moreover, it is also difficult to believe that weather impacts similarly each output (Myers et al., 2014; McCarl and Hertel 2018). Putting this differently, we need time-dependent agro-climatic environments that are output-specific.

Whatever the chosen approach, a functional form has to be selected for the production process. As this is challenging, non-parametric approaches have gained popularity for agriculture empirical studies (Fulginiti and Perrin, 1997; Nin et al., 2003; Sharma et al., 2011; O'Donnell, 2012; Khan et al., 2015; Zhang et al., 2019; Chambers and Pieralli, 2020; Xu et al., 2020). A main advantage of the non-parametric approach is to avoid making a functional assumption for the production process, which is not insidious. Moreover, even when convincing arguments are found to support a specific functional form, a weakness of the parametric approach is the important number of parameters. Also, empirical evidence has shown that the agriculture production process may be too complex to be captured by methods focusing on the first (or second) moment, making econometric regressions not applicable. Finally, in the context of environment heterogeneity, this problem becomes even more complex since several production functions have to be specified.

All in all, our approach, while connected to previous works offers the following advantages: no functional forms have to be specified, technological change is possible, output-specific technology heterogeneities are modelled, technology spillover and diffusion are taken into consideration, and the weather is not modelled as an input.

3.1 Agriculture environment heterogeneities

The starting points of our modelling are, on the one hand, the definition of time-varying output-specific production functions and, on the other hand, the existence of inefficiency behaviours implying potential productivity gains. First, we acknowledge that each agricultural output (e.g. crops and livestock) can be produced using a different technology.[6] Nevertheless, this does not necessarily imply that the output-specific production processes are not connected since, generally, inputs are jointly used to produce outputs to benefit from economies of scale and scope (Panzar and Willig, 1981).[7] Next, we recognize that technology may change over time. While technology progress is possible, we believe, however, that technology degradation is impossible in a macroeconomic agriculture context (Henderson and Russell, 2005; Chambers and Pieralli, 2020; Walheer, 2021). Considering that option would imply that technological implosion is possible over time. Finally, we acknowledge that countries may present inefficient behaviour in their ability to convert inputs to outputs (Debreu, 1951; Farrell, 1957). Such inefficient components may explain why actual outputs differ from potential ones reflecting the existence of potential productivity gains. All in all, we obtain for every output j and country i at time t the following production process:

$$y_{ijt} = f_{jt}(\mathbf{x}_{it}) \times u_{ijt}(\mathbf{x}_{it}). \tag{1}$$

In words, $f_{jt}(\mathbf{x}_{it})$ is the time-varying output-specific production function for output j at time t, and therefore represents the potential output.[8] The distance between actual and potential outputs is captured by $u_{ijt}(\mathbf{x}_{it})$, which can be interpreted as an (in)efficiency component reflecting the inability to properly convert inputs into outputs using a certain technology. When potential output exceeds actual one, $u_{ijt}(\mathbf{x}_{it}) < 1$, revealing an inefficiency behaviour and thus a potential productivity gain. $u_{ijt}(\mathbf{x}_{it})$=1, therefore, is the benchmark situation when actual and potential outputs are equal. In practice, both $f_{jt}(\mathbf{x}_{it})$ and $u_{ijt}(\mathbf{x}_{it})$ are unobserved. Finally, note that it might be surprising that no error term appears in (1), this will be discussed in Section 3.3.

Besides inefficiency, a distinguishing feature of our approach is that we recognize the impact of agro-climatic environment heterogeneities on the (in)ability of the countries to reach their potential productivity gain. Agro-climatic environment heterogeneities put a

[6]This option has recently gained attention in the economic and operations research literature in various contexts (Fernandez, et al., 2002, 2005; Ferreira and Steel, 2007; Cherchye et al., 2015, 2016; Walheer, 2016, 2021; He and Walheer, 2020).

[7]Allocating inputs to output production processes is possible if needed (Cherchye et al., 2015; Walheer, 2017). If suffices to replace $\mathbf{x}_{it}$ by $\mathbf{x}_{ijt}$ in (1) where $\mathbf{x}_{ijt}$ refers to the input vector used to produce output j.

[8]y_{ijt} is our notation for the jth entry of the output vector $\mathbf{y}_{it}$. Note that when all outputs are produced with the same technology, we obtain that $y_{ijt} = f_t(\mathbf{x}_{it}) \times u_{ijt}(\mathbf{x}_{it})$, and if we add that the technology is fixed over time, we have that $y_{ijt} = f(\mathbf{x}_{it}) \times u_{ijt}(\mathbf{x}_{it})$. These cases, while rather restrictive, are the most used settings in the literature (see the Introduction).

constraint by conditioning the production processes and, thus, restrict the potential productivity gains. It turns out that, when considering agro-climatic environmental heterogeneities, production functions are environment-specific and potential productivity gains are less important.[9] Formally, we obtain for every output j and country i in environment k at time t:

$$y_{ijt} = f^k_{jt}(\mathbf{x}_{it}) \times u^k_{ijt}(\mathbf{x}_{it}). \tag{2}$$

$$f^k_{jt}(\mathbf{x}_{it}) \leq f_{jt}(\mathbf{x}_{it}). \tag{3}$$

The first equation reflects what is happening in each agro-climatic environment while the second equation captures the impact of agro-climatic environment heterogeneities on the potential productivity gains. $f^k_{jt}(\mathbf{x}_{it})$ and $u^k_{ijt}(\mathbf{x}_{it})$ have to be interpreted as $f_{jt}(\mathbf{x}_{it})$ and $u_{ijt}(\mathbf{x}_{it})$, but when agro-climatic environment heterogeneity is considered. It turns out that $f_{jt}(\mathbf{x}_{it})$ defines the maximal potential value for output j at time t; that is, it captures the best practice situation. We may therefore see $f_{jt}(\mathbf{x}_{it})$ as an overall or world-level production function. In a similar vein, $u_{ijt}(\mathbf{x}_{it})$ represents the minimal (in)efficiency value that can be achieved for output j at time t.

To capture the impact of the agro-climatic environment heterogeneity on potential productivity gain, we suggest comparing our two previous potential output measurements $f^k_{jt}(\mathbf{x}_{it})$ and $f_{jt}(\mathbf{x}_{it})$ using a simple ratio.[10] Formally, it is given for output j and country i for group k and time t as follows:

$$f^k_{jt}(\mathbf{x}_{it}) = f_{jt}(\mathbf{x}_{it}) \times g^k_{ijt}(\mathbf{x}_{it}). \tag{4}$$

$g^k_{ijt}(\mathbf{x}_{it})$ has to be understood as a measurement of the agro-climatic environment heterogeneity gap. It is the distance between the potential output of group k and the world counterpart. When $g^k_{ijt}(\mathbf{x}_{it}) = 1$, it reflects that agro-climatic environment heterogeneity has no impact on potential productivity gain. When it is not the case, i.e. $g^k_{ijt}(\mathbf{x}_{it}) < 1$ implying $f^k_{jt}(\mathbf{x}_{it}) < f_{jt}(\mathbf{x}_{it})$, agro-climatic environment heterogeneity puts a restriction on potential productivity gain. An important aspect is how such agro-climatic environmental heterogeneity evolves. We point out that $g^k_{ijt}(\mathbf{x}_{it})$ can alternatively be fully defined in terms

[9]Note that, in this paper, the number of environments does not change over time. Such an option is fairly easy to consider in our modelling (see e.g. Walheer, 2023).

[10]Another option is to use a difference: $f^k_{jt}(\mathbf{x}_{it}) - f_{jt}(\mathbf{x}_{it})$. The ratio, popularized by Battese and Rao (2002), is preferred for several reasons such as it is unit-free, easy to interpret, and to measure over time. It is fairly easy to adapt the indexes in Section 2 to a different version of the agro-climatic environment heterogeneity gap.

of the inefficiency components (using (1) and (2)):

$$g_{ijt}^{k}(\mathbf{x}_{it}) = \frac{f_{jt}^{k}(\mathbf{x}_{it})}{f_{jt}(\mathbf{x}_{it})} = \frac{u_{ijt}(\mathbf{x}_{it})}{u_{ijt}^{k}(\mathbf{x}_{it})}. \tag{5}$$

This rewriting will be useful when defining the indexes in Section 3.2. By combining the definition of the environment gap with our initial definition of the production process in (1) and (2), we obtain a useful alternative definition of the output-specific technologies:

$$y_{ijt} = f_{jt}(\mathbf{x}_{it}) \times g_{ijt}^{k}(\mathbf{x}_{it}) \times u_{ijt}^{k}(\mathbf{x}_{it}). \tag{6}$$

This version highlights the impact of agro-climatic environment heterogeneity on the inability of countries to obtain potential productivity gains, i.e. making y_{ijt} closer to $f_{jt}(\mathbf{x}_{it})$ by reducing their inefficient behaviour. This is exactly the dynamic we want to capture over time in the next section.

3.2 Agriculture productivity change and convergence

Without loss of generality, let us assume that we would like to quantify the countries' agriculture productivity changes between a base and current time periods; labelled b and c, respectively. To do so, we rely on the Malmquist productivity index (MI) introduced by Caves et al. (1982). This index has been used by many scholars in agriculture empirical studies (Fulginiti and Perrin, 1997; Galanopoulos et al., 2004; Coelli and Rao, 2005; Chambers and Pieralli, 2020; Pan et al., 2021). A desirable feature of the Malmquist is that no price data are needed. A shortcoming is that it is not transitive meaning that it is not appropriate when dealing with multiple periods. As our objective is to compare productivity change between two intervals, this undesirable feature has less impact in our case. Given the specificities of our modelling – output-specific production functions and agro-climatic environment heterogeneity – we want to define an index for each output while taking environment heterogeneity into account.

Our first step is to define indexes for productivity changes at the world level. This represents our benchmark productivity change that countries might attempt if agro-climatic environment heterogeneity has no impact. Putting it differently, these indexes relate to potential productivity changes. The next step is therefore to relate such index to actual productivity change to understand the impact of agro-climatic environment heterogeneity over time. In particular, we define the MI to compare the productivity behaviour of country

i for output j between time b and c as follows:

$$MI_j(\mathbf{x}_{ib}, \mathbf{x}_{ic}) = \left[\frac{u_{ijb}(\mathbf{x}_{ic})}{u_{ijb}(\mathbf{x}_{ib})} \times \frac{u_{ijc}(\mathbf{x}_{ic})}{u_{ijc}(\mathbf{x}_{ib})}\right]^{1/2}. \tag{7}$$

An index larger (smaller) than unity implies a productivity progression (regression) for output j of country i between periods b and c. When the index is one, it represents the performance statu quo. We highlight that the MI is defined as a geometric average of two path-dependent indexes as there are two ways to evaluate productivity between periods b and c: one with respect to technology at time b $\left(\frac{u_{ijb}(\mathbf{x}_{ic})}{u_{ijb}(\mathbf{x}_{ib})}\right)$ and another when time c is chosen as the referent time period $\left(\frac{u_{ijc}(\mathbf{x}_{ic})}{u_{ijc}(\mathbf{x}_{ib})}\right)$. Such geometric average procedure is known as the Fisher ideal decomposition (Caves et al., 1982) and overcomes the path dependence.[11]

A major advantage of the MI is that it can be straightforwardly decomposed into several components allowing us to better understand the sources of productivity improvement/reduction. Several decompositions have been suggested (Balk, 2004), while the most popular, as suggested by Färe et al. (1994), decomposes the MI into efficiency and technological change components. It is defined as follows:

$$MI_j(\mathbf{x}_{bi}, \mathbf{x}_{ic}) = EC_j(\mathbf{x}_{ib}, \mathbf{x}_{ic}) \times TC_j(\mathbf{x}_{ib}, \mathbf{x}_{ic}),$$

where

$$\begin{aligned} EC_j(\mathbf{x}_{ib}, \mathbf{x}_{ic}) &= \frac{u_{ijc}(\mathbf{x}_{ic})}{u_{ijb}(\mathbf{x}_{ib})}, \\ TC_j(\mathbf{x}_{ib}, \mathbf{x}_{ic}) &= \left[\frac{u_{ijb}(\mathbf{x}_{ib})}{u_{ijc}(\mathbf{x}_{ib})} \times \frac{u_{ijb}(\mathbf{x}_{ic})}{u_{ijc}(\mathbf{x}_{ic})}\right]^{1/2}. \end{aligned} \tag{8}$$

These two components have to be interpreted in a similar manner to the MI: a value larger (smaller) than unity implies an efficiency/technological progression (regression) for output j of country i between periods b and c. The technological change gives us a measure of the movement of the technical frontier, i.e. the production possibilities, and the efficiency change tells us how countries have moved with respect to the technical frontiers.

Indexes defined before relating to a situation where agro-climatic environmental heterogeneity has no impact on the productivity changes; that is they reflect potential productivity changes. Now, we define actual productivity change when agro-climatic environmental heterogeneity is taken into account. Such heterogeneity represents therefore a constraint or

[11] Note that the MI can alternatively be fully defined using the potential outputs. Indeed, as pointed out in (5), ratios of inefficiency terms are equal to ratio of potential outputs; for example, $\frac{u_{ijb}(\mathbf{x}_{ic})}{u_{ijb}(\mathbf{x}_{ib})} = \frac{y_{ijb}/f_{jb}(\mathbf{x}_{ic})}{y_{ijb}/f_{jb}(\mathbf{x}_{ib})} = \frac{f_{jb}(\mathbf{x}_{ib})}{f_{jb}(\mathbf{x}_{ic})}$.

a limit to productivity change. The next step, developed hereafter, is thus to compare both perspectives. To define the heterogeneity-dependent productivity indexes, it suffices to use the corresponding (in)efficiency terms, defined in (3), in the indexes in (7) and its decomposition in (8) defined before. We obtain the following:

$$\begin{aligned} MI_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic}) &= \left[\frac{u_{ijb}^k(\mathbf{x}_{ic})}{u_{ijb}^k(\mathbf{x}_{ib})} \times \frac{u_{ijc}^k(\mathbf{x}_{ic})}{u_{ijc}^k(\mathbf{x}_{ib})}\right]^{1/2}, \\ EC_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic}) &= \frac{u_{ijc}^k(\mathbf{x}_{ic})}{u_{ijb}^k(\mathbf{x}_{ib})}, \\ TC_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic}) &= \left[\frac{u_{ijb}^k(\mathbf{x}_{ib})}{u_{ijc}^k(\mathbf{x}_{ib})} \times \frac{u_{ijb}^k(\mathbf{x}_{ic})}{u_{ijc}^k(\mathbf{x}_{ic})}\right]^{1/2}. \end{aligned} \tag{9}$$

These indexes have to be interpreted as before but in each group k: an index larger (smaller) than unity implies a progression (regression) for output j of country i in group k between periods b and c. They therefore capture what is happening inside each group. In other words, these indexes may be seen as intra-productivity change indexes.

We have now everything we need to define our notion of the agriculture productivity convergence index. Such indexes are designed to capture the impact of agro-climatic environment heterogeneity over time by comparing potential to actual productivity change indexes. That is, they model inter-productivity changes and, thus, measure convergence. It is given for output j of country i in group k between b and c as follows:

$$PCI_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic}) = \frac{MI_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic})}{MI_j(\mathbf{x}_{ib},\mathbf{x}_{ic})}. \tag{10}$$

When $PCI_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic})$ is larger than unity, it reveals that productivity change is larger in group k than for the world. That is, agro-climatic environment heterogeneity has less impact over time on the ability to convert potential productivity gains. Productivity convergence is therefore observed. An index smaller than unity implies the opposite: productivity change is smaller in group k than for the world, agro-climatic environment heterogeneity has more impact over time, and productivity divergence is observed. Interestingly, we can rewrite the index using our definition of agro-climatic environment heterogeneity gap in (5) as follows:

$$PCI_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic}) = \left[\frac{g_{jb}^k(\mathbf{x}_{ic})}{g_{jb}^k(\mathbf{x}_{ib})} \times \frac{g_{jc}^k(\mathbf{x}_{ic})}{g_{jc}^k(\mathbf{x}_{ib})}\right]^{1/2}. \tag{11}$$

$PCI_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic})$ is therefore itself a Malmquist-type index for the agro-climatic environment heterogeneity gap. When $PCI_j^k(\mathbf{x}_{ib},\mathbf{x}_{ic})$ is larger than unity, it reveals that the agro-climatic environment heterogeneity gap increases making the impact greater over time. As for any MI, the index can be decomposed into two components as follows:

$$
\begin{aligned}
PCI_j^k(\mathbf{x}_{ib}, \mathbf{x}_{ic}) &= ECI_j^k(\mathbf{x}_{ib}, \mathbf{x}_{ic}) \times TCI_j^k(\mathbf{x}_{ib}, \mathbf{x}_{ic}),\\
ECI_j^k(\mathbf{x}_{ib}, \mathbf{x}_{ic}) &= \frac{g_{jc}^k(\mathbf{x}_{ic})}{g_b^k(\mathbf{x}_{ib})},\\
TCI_j^k(\mathbf{x}_{ib}, \mathbf{x}_{ic}) &= \left[\frac{g_b^k(\mathbf{x}_{ib})}{g_c^k(\mathbf{x}_{ib})} \times \frac{g_b^k(\mathbf{x}_{ic})}{g_c^k(\mathbf{x}_{ic})}\right]^{1/2}.
\end{aligned} \tag{12}
$$

The decomposition allows us to investigate converge for the (in)efficiency behaviour and the technological change. Such decomposition is of particular interest as it gives the opportunity to better understand the reasons for the productivity convergence process.

3.3 Estimation

In this last part of the methodology section, we discuss the practical computation of the indexes. We follow a non-parametric spirit by making as less assumptions as possible about the countries' production processes. To do so, we use a well-known linear programming technique: Data Envelopment Analysis (DEA) introduced by Charnes et al. (1972). Without loss of generally, let us consider that we observe n_k countries in each zone k.[12]

A first observation is that all the indexes defined before depend on (in)efficiency scores and thus on potential outputs. It is sufficient to evaluate four potential outputs (at period b, at period c, a counterfactual at period b, and another at period c) to obtain all the indexes. Nevertheless, we have to distinguish two cases: indexes defined in each agro-climatic environment and those defined at the world level. To obtain the former, we can define a simple linear programming that can be used to compute the four potential outputs.[13] For example, the counterfactual potential output at period b, i.e. at time b with respect to

[12]Note that, in this paper, the number of countries in each environment is different but it does not change over time. Such an option is fairly easy to consider in our modelling (see e.g. Walheer, 2023).

[13]To obtain the other potential outputs, it suffices to replace the outputs-inputs in (13) by the desired values. Use y_{sjb}, $\mathbf{x}_{ib}$, and $\mathbf{x}_{sb}$ to obtain the potential output at time b; use y_{sjc}, $\mathbf{x}_{ic}$, and $\mathbf{x}_{sc}$ to obtain the potential output at time c; and use y_{sjb}, $\mathbf{x}_{ic}$, and $\mathbf{x}_{sc}$ to obtain the counterfactual potential output at time c, i.e. at time c with respect to technology at time b.

technology at time c, is given for output j of a particular country i in group k as follows:

$$
\begin{aligned}
f^k_{jc}(\mathbf{x}_{ib}) = \max_{\forall s,t:\lambda_{st}\geq 0; y\geq 0} & \; y \\
\text{(C-1)}\; & y \leq \sum_{t=1}^{c}\sum_{s=1}^{n_k}\lambda_{st}y_{sjt}, \\
\text{(C-2)}\; & \mathbf{x}_{ib} \geq \sum_{t=1}^{c}\sum_{s=1}^{n_k}\lambda_{st}\mathbf{x}_{st}, \\
\text{(C-3)}\; & \sum_{t=1}^{c}\sum_{s=1}^{n_k}\lambda_{st} = 1.
\end{aligned}
\tag{13}
$$

The linear programming is non-parametric as no functional form is selected for the output-specific production functions. To avoid a trivial result, some assumptions are implicitly made about the technology in (13): it is assumed that the production functions are monotone, quasi-concave, and satisfy variable returns-to-scale. Such assumptions are standard in economics and used in many empirical contexts. Making such assumptions is weaker than relying on a parametric specification for the production functions. Another specificity of the linear programming in (13) is that it includes all available observations at a certain period when computing the potential outputs (this is captured by the first sum in the three constraints). Intuitively, this is a way to take what has happened in the past into account. Such practice is known as a sequential approach and avoids technology degradation (Henderson and Russell, 2005; Chambers and Pieralli, 2020; Walheer, 2021).

Next, to be fair, we remark that a disadvantage of using linear programming is that measurement errors and potential outliers are ignored. To mitigate this shortcut, we adopt the well-known order-m estimator to compute the potential outputs (Daraio and Simar, 2007). The basic principle is to compute expected potential outputs obtained with random sub-samples of m peers.[14] That is, (13) is computed for each sub-sample and the expected potential output is simply the arithmetic average of the sub-sample potential outputs.

To obtain the four potential outputs at the world level, we can not follow a similar procedure as it will not guarantee that (3) is correct. As discussed before, the world's potential outputs represent the best practice. To capture this spirit, we define the potential output j of a particular country i at time b with respect to technology at time c as follows:

$$
f_{jc}(\mathbf{x}_{ib}) = max_{k\in\{1,\ldots,K\}}\left\{f^k_{jc}(\mathbf{x}_{ib})\right\}. \tag{14}
$$

The max procedure guarantees that the world-level outputs are always greater or equal

[14] Practically, the sampling procedure is repeated B times to obtain the expected potential output. In this study, we set $B = 1,000$, and $m = 10$ or 20 or 30 depending on the size of the group.

to the agro-climatic environment-specific counterparts. Moreover, such procedure implies that world technology is defined as the envelopment of the agro-climatic environment technologies, highlighting the best practice spirit of the world-level potential outputs. At this point, we highlight that such envelopment is non-convex making (14) a more conservative measurement than when using a linear programming with pooled country-level observations (Walheer, 2018; Kerstens et al., 2019).

4 Results

As an initial step, we present the results for the environment gaps and the potential outputs This allows us to statistically verify the existence of agro-climatic environment heterogeneity and investigate what is happening inside and between zones. Next, we present our results for our different indexes. Following the three types of indexes defined in the methodological section, we present the results in three steps. First, we start by presenting our productivity results at the world level. This represents, as explained before, the best-case scenario. Next, we investigate intra-productivity change by looking at what is happening in each agro-climatic environment. Finally, the productivity convergence indexes are used to describe inter-productivity changes.

4.1 Environment gaps and potential outputs

We give the results for the decomposition of the outputs into three parts – potential output, environment gap, and (in)efficiency – between 1961-1975 and 2001-2015 in Table 6.[15] This allows us to, first, quantify the difference between actual and potential outputs, and, second, to measure the impact of the agro-climatic environment heterogeneity empirically. Generally speaking, while the efficiency level differs across zones, there is a decrease in the efficiency behaviour in each zone. The most efficient zone in livestock production is the wet temperate one. It is more difficult to come to such a conclusion for the crops as the efficiency levels are comparable over zones. Next, the impact of environment heterogeneity is observed as average gaps are lower than one. We note that the best practice for the crops is due to the wet tropical/subtropical zone whilst it is due to the dry temperate zone for the livestock.

To formally verify the impact of agro-climatic environment heterogeneity on the inability of countries to obtain potential productivity gain, we make use of an ANOVA test.[16] The $p-$values, displayed in the first part of Table 10 in Appendix A, confirm the impact for both

[15] In practice, potential outputs are computed for every year in each interval and the averages are computed at the interval level.

[16] H_0: environment gap averages are equal over zones, i.e. agro-climatic environment heterogeneity has no (relative) impact on potential outputs. Note that similar results are obtained using the Kruskal–Wallis test in place of ANOVA.

Table 5: Agro-climatic zone efficiency

interval	crops			livestock		
	potential output $f(\mathbf{x})$	environment gap $g^k(\mathbf{x})$	efficiency $u^k(\mathbf{x})$	potential output $f(\mathbf{x})$	environment gap $g^k(\mathbf{x})$	efficiency $u^k(\mathbf{x})$
wet temperate zone						
1961-1975	2,680,591	0.71	0.87	2,594,976	0.96	0.95
2001-2015	4,497,465	0.74	0.71	4,390,750	0.70	0.93
dry temperate zone						
1961-1975	12,405,857	0.95	0.83	5,544,878	0.98	0.79
2001-2015	32,648,318	0.94	0.79	11,038,019	0.99	0.66
wet tropical/subtropical zone						
1961-1975	5,742,560	1.00	0.86	594,306	0.78	0.78
2001-2015	17,215,570	0.99	0.82	2,565,927	0.91	0.73
dry tropical/subtropical zone						
1961-1975	6,345,247	0.62	0.81	1,177,988	0.76	0.77
2001-2015	17,988,018	0.61	0.85	4,445,359	0.79	0.76

outputs and time intervals. Once the impact has been demonstrated, the next step is to investigate how it evolves. The best scenario would be that environment gaps increase over time implying less impact of agro-climatic environment heterogeneity. We see in Table 6 that this is not the case for each zone and output. Environment gaps have indeed positively changed for the livestock in all zones except for the wet temperate zone, and the crops in the wet temperate zone. Also, the amplitude varies over zones and outputs. To statistically verify these changes, we again rely on an ANOVA test.[17] The $p-$values, given in the second part of Table 10 in Appendix A, confirm the negative change for the wet temperate zone and the positive change for the wet tropical/subtropical zone for the livestock. For the other zones, environment gaps seem stable over time.

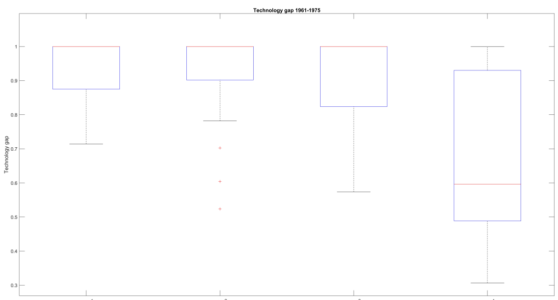
Although the averages in Table 6 give us a quick answer regarding the impact of the agro-climatic environment heterogeneity, we prefer to complete our investigation by showing the box plots of the environment gaps in Figure 2. There, we see that environmental gaps depend on the zones, outputs, and intervals. The best results are observed for the livestock in 1961–1975. The dry temperate and wet tropical/subtropical zones present, overall, better results. We rely on Kolmogorov-Smirnov's test to verify how the environment gap distributions have evolved over time.[18] The $p-$values, presented in the last part of Table 10 in Appendix A, support the changes observed with the averages. This means that the

[17] H_0: environment gap averages are equal over time, i.e. agro-climatic environment heterogeneity has not changed over time. Note that similar results are obtained using the Kruskal–Wallis test.

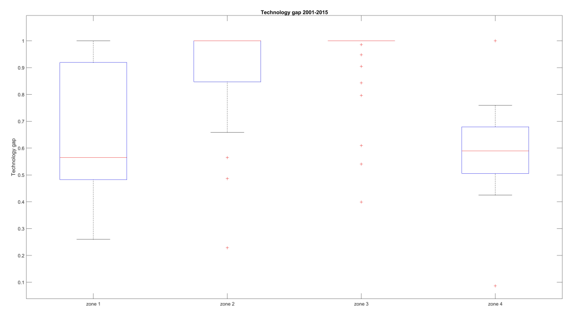
[18] H_0: environment gap distributions are equal over time, i.e. agro-climatic environment heterogeneity has not changed over time. Note that similar results are obtained using the Kuiper's test.

impact of agro-climatic environment heterogeneity on the inability of countries to obtain potential productivity gain remains true over time. This aspect can thus not be ignored when studying agriculture productivity change.

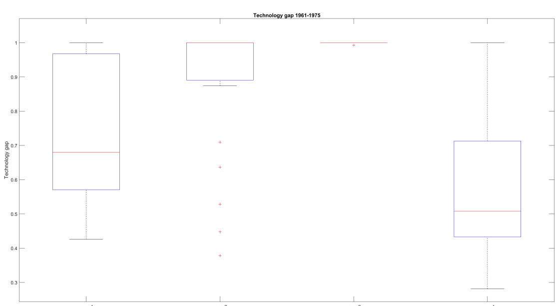
Figure 2: Agro-climatic zone environment gap 1961-1975 against 2001-2015



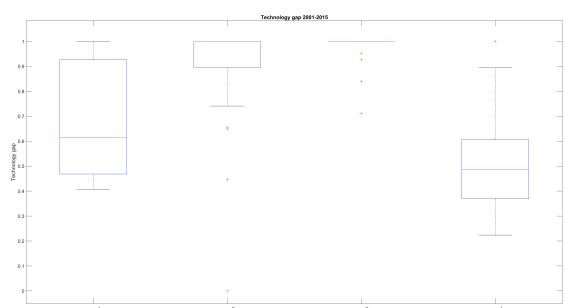
(a) Livestock: 1961-1975



(b) Livestock: 2001-2015



(c) Crops: 1961-1975



(d) Crops: 2001-2015

4.2 World productivity changes

In Table 6, we give the averages and standard deviations for the productivity changes and its two components, efficiency and technological changes, between 1961-1975 and 2001-2015.[19] Overall, there are important productivity changes for the crops and livestock, both mainly due to a positive technological change. Note that the productivity change of livestock is smaller due to a negative efficiency change and a smaller technological change. Also, efficiency change is slightly positive for the crops. A negative efficiency change accompanied by a positive technological change highlights that some countries are pushing the technical frontier while others lag. Finally, more disparities are observed for the crops in terms

[19] In practice, indexes are computed for each pair of years (1961 and 2001, 1962 and 2002, etc.) and the average is computed over the pairs.

of productivity change, while variability is comparable to efficiency change. To formally verify these findings, we make use of two Student tests. The first one checks whether improvement is indeed verified while the second one tests the average difference between crops and livestock.[20] The $p-$values of these tests, given in Table 10 in Appendix A, confirm that productivity and technological changes are positive for both outputs and that crops better perform than livestock in the three dimensions.

Table 6: World agriculture productivity

dimension	statistics	crops	livestock
productivity change	average	1.7700	1.6386
	std	1.3042	0.8591
efficiency change	average	1.0336	0.9258
	std	0.6840	0.6905
technological change	average	1.7506	1.6386
	std	0.7785	0.5909

To better explain the empirical findings based on the averages and standard deviations, we plot the distributions for the productivity changes and its two components in Figure 3. An important finding is the presence of multiple modes for the distributions. This highlights the presence of groups of countries: some pushing the technical frontier and benefiting from efficiency gain and others lagging. An important related question, that we will answer in the next Section, is which groups define the best practice and which groups are lagging. Two peaks are observed for the livestock productivity change and its decomposition. Several peaks are observed for the technological change for the crops, while it is less clear for the efficiency and productivity changes.

To verify these facts more reliably, we make use of the calibrated Silverman's (1981) test for multimodality designed to verify the existence of several modes for a distribution.[21] We can reject the null hypothesis for both the crops and the livestock output (see Table 10 in Appendix A) confirming our initial observation of the existence of several modes for the technological change. For the efficiency and productivity changes, we do not have evidence of the existence of several modes (all $p-$values in Table 10 in Appendix A are larger than 5%).

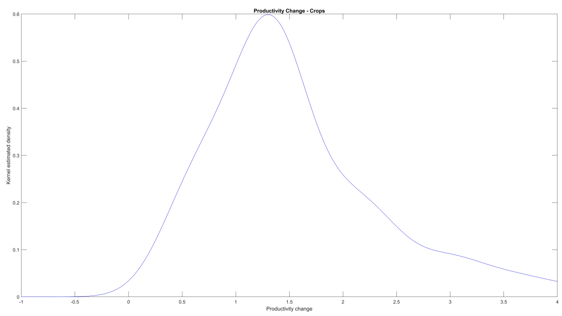
Finally, we compare our results to those when agro-climatic heterogeneity is not assumed. In that case, productivity change is evaluated when pooling all countries together.[22]

[20] The alternative hypotheses are stated as H_1 the average is larger than unity and H_1 the crops average is different than the livestock average, respectively.

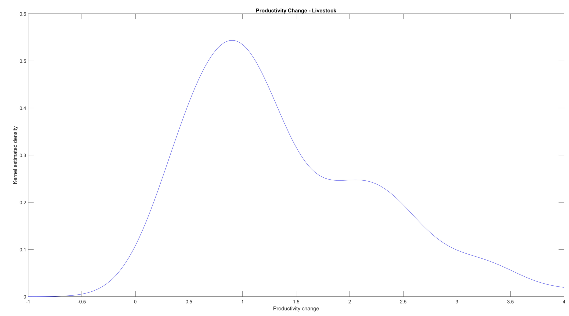
[21] H_0: the distribution has one mode. In practice, it is advised to use the bootstrapped version according to Hall and York (2001).

[22] From a practical point of view, the linear programming in (13) can still be used but countries are pooled together.

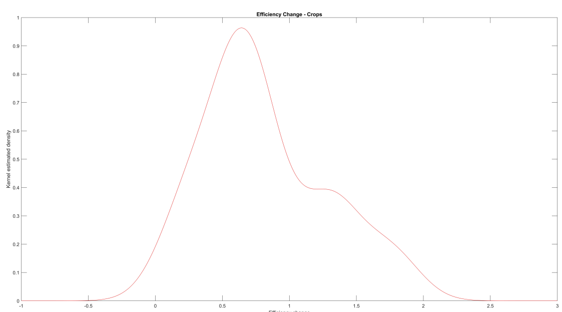
Figure 3: World agriculture productivity change 1961-1975 against 2001-2015



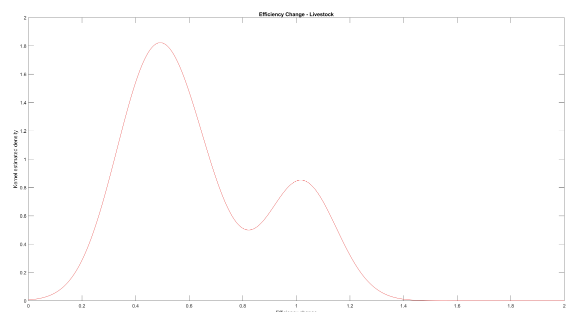
(a) Crops - productivity change



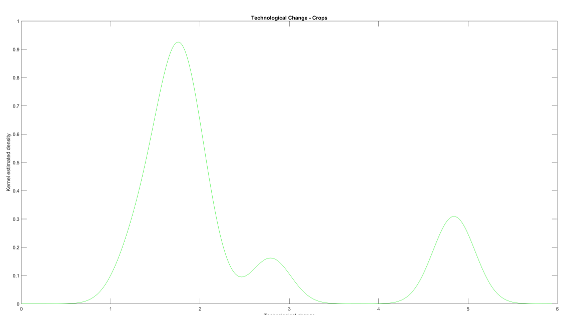
(b) Livestock - productivity change



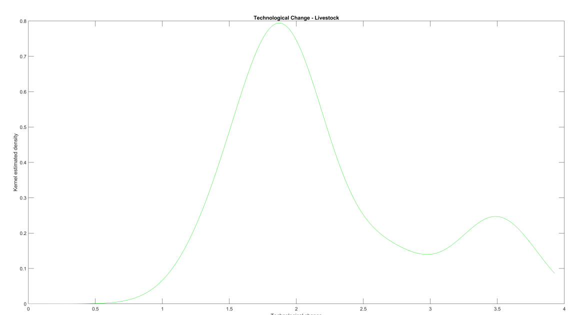
(c) Crops - efficiency change



(d) Livestock - efficiency change



(e) Crops - technological change



(f) Livestock - technological change

Results are given in Table 12 and Figure 10 in Appendix B. Overall, averages are smaller when ignoring agro-climatic environment heterogeneity implying a downward bias. In terms of volatility, standard deviations are different but no clear rankings appear. Finally, the productivity change distributions, while different, present similar shapes. Overall, this comparison gives us more arguments to continue with our agro-climatic environment heterogeneity modelling.

4.3 Intra-productivity changes

Building on our previous result of the existence of agro-climatic environments, we continue our investigation by presenting the results per agro-climatic zone. Averages and standard deviations for the productivity changes and their decomposition are given in Table 7. Accompanied graphical representations are displayed in Figure 4.[23] The superiority of the crops in the three dimensions is not observed for all zones. Important positive productivity changes are observed for both outputs but the amplitude varies across agro-climatic zones. In all cases, technological change is the main reason for such productivity change. The most important productivity change for the crops is observed in the wet temperate zone, while it is in the dry tropical/subtropical zone for the livestock. In the former case, it seems to be due to a group of countries that have obtained more important efficiency improvements. Efficiency change is, on average, negative in the wet temperate zone for both outputs and positive in the wet tropical/subtropical zone for both outputs. Also, we observe a more positive important efficiency change for the livestock in the dry temperate zone. Finally, most of the distributions seem to be unimodal appealing to similar changes in each agro-climatic group.

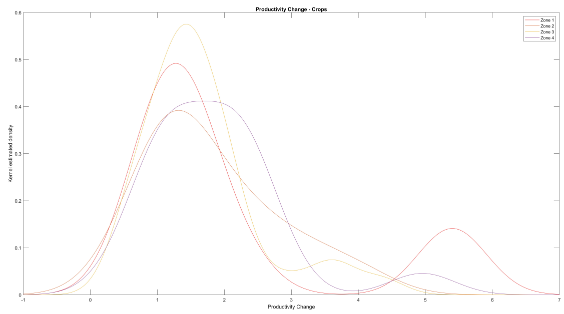
To confirm statically these results, we again perform the two Student tests used before for the world-level analysis. We complete these two tests by an ANOVA test verifying that the changes are different across zones. All empirical findings are confirmed by the $p-$values of the tests available in Table 10 in Appendix A. For the modes, Silverman's test confirms that all distributions present one mode except the productivity change distribution in the wet temperate zone. At this point, we highlight that the technological change distributions have one mode in each zone (this was not the case at the world level) meaning that countries in each agro-climatic zone follow a common technology improvement path. This goes again in favour of the existence of agro-climatic heterogeneity in the world.

[23]For better readability, we denote the wet temperate zone, dry temperate zone, wet tropical/subtropical zone, and et tropical/subtropical zone as zone 1, 2, 3, and 4 in Figures in this paper.

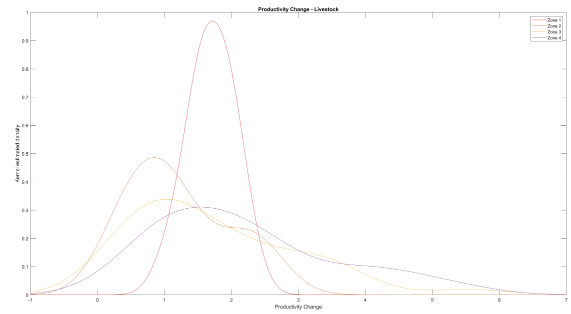
Table 7: Agro-climatic zone agriculture productivity change

dimension	statistics	crops	livestock
wet temperate zone			
productivity change	average	2.0743	1.7030
	std	1.6944	0.3253
efficiency change	average	0.7946	0.9461
	std	0.2578	0.1117
technological change	average	2.5546	1.7980
	std	1.7145	0.2611
dry temperate zone			
productivity change	average	1.7766	1.4872
	std	0.9635	1.5802
efficiency change	average	0.9510	1.4756
	std	0.6031	4.0464
technological change	average	2.0134	1.8767
	std	0.9984	0.7374
wet tropical/subtropical zone			
productivity change	average	1.6440	1.7403
	std	0.8687	1.2248
efficiency change	average	1.0411	0.9712
	std	0.4693	0.5114
technological change	average	1.5461	1.7005
	std	0.2233	0.5909
dry tropical/subtropical zone			
productivity change	average	1.8601	2.1833
	std	0.9993	1.3190
efficiency change	average	1.0507	1.1897
	std	0.3788	0.6200
technological change	average	1.7419	1.7968
	std	0.4748	0.5446

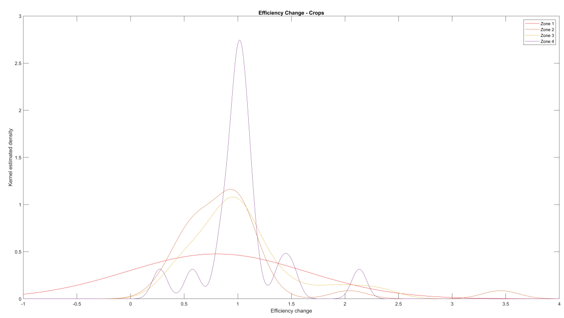
Figure 4: Agro-climatic zone agriculture productivity change 1961-1975 against 2001-2015



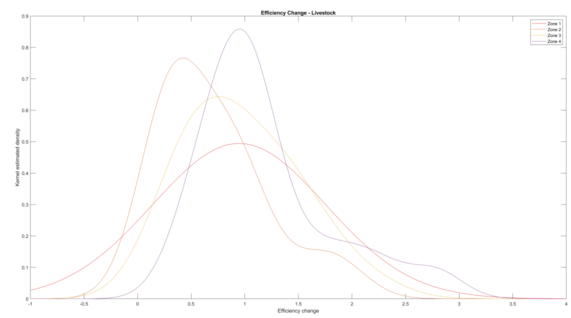
(a) Crops - productivity change



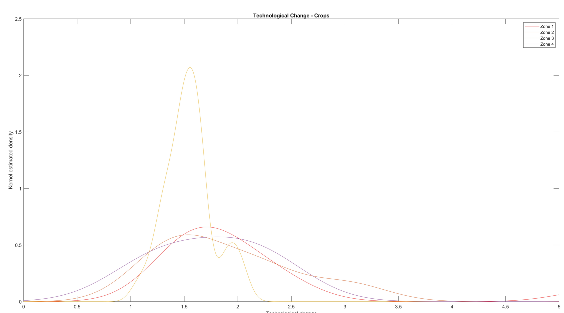
(b) Livestock - productivity change



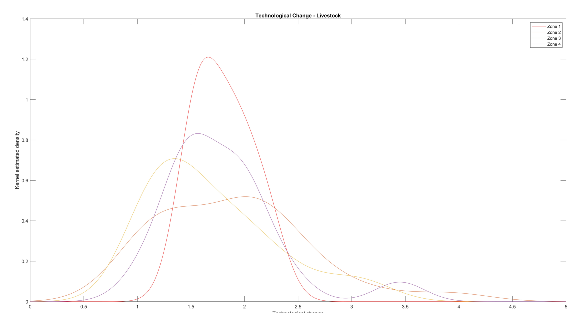
(c) Crops - efficiency change



(d) Livestock - efficiency change



(e) Crops - technological change



(f) Livestock - technological change

4.4 Inter-productivity changes

We are now in a position to investigate productivity, efficiency, and technology convergence between agro-climatic zones. To do so, we rely on our convergence index described in Section 3.2. As a reminder, we recall that a value larger than unity implies a convergence, while a value less than one indicates a divergence. Averages and standard deviations are given in Table 8 and the distributions are shown in Figure 5. Productivity convergence is observed everywhere except for the crops in the dry temperate zone (as the average index is smaller than one in that case). When productivity convergence is observed for the crops, this is due to both technological and efficiency convergence. In the dry temperate zone, the productivity divergence is also due to both efficiency and technological divergence. For the livestock, there is an efficiency convergence in all zones but technological convergence is only observed in two zones; wet and dry tropical/subtropical zones. This means that efficiency convergence is larger than technological divergence in the dry and wet temperate zones resulting in a productivity convergence pattern. Using the Student tests and the ANOVA test, we are in a position to statistically confirm these initial findings. Indeed, all $p-$values in Table 11 in Appendix A go in the direction of our initial observations. A last point is whether a common convergence path is observed in each agro-climatic zone. The $p-$values of the Silverman's test, available in Table 11 in Appendix A, show that all distributions for the productivity and efficiency changes are unimodal. This holds also true for the technological changes with the dry temperate zone being the only exception.

Now that productivity convergence is established, we want to know more about the convergence process. First, we want to see whether technology convergence is more important for countries more impacted by the agro-climatic environment heterogeneity (i.e. with smaller environment gaps)? Next, we test the existence of a similar pattern for the (in)efficiency behaviour: is efficiency convergence more important for countries presenting a more inefficient behaviour? Putting this differently, we ask the question of the existence of path-dependence for the technology and efficiency dimensions (Aghion et al., 2016; Tsekouras et al., 2016; He and Walheer, 2019), i.e. are future paths based on past states?

To answer the first question, we perform a linear regression of the technology convergence index against the environment gaps.[24] We do the same for the efficiency convergence and the efficiency score to answer the second question. Results are given in Figures 6 and 7; there, we also give the slope coefficients and the associated $t-$statistics. The first result is that all slope coefficients are significant. We see that countries with a smaller environment gap, i.e. those more impacted by the agro-climatic environment heterogeneity, have, on average, a higher technology convergence index. That is, these countries caught up over time. Note that the slope coefficient is larger for the livestock. For the efficiency convergence, it is another story as the slope coefficient is positive: countries with more inefficiency behaviour have, on average, lesser efficiency convergence indexes. It implies the presence of a path-dependence for the (in)efficiency behaviour: countries less (more) efficient tend to become more (less) efficient over time.

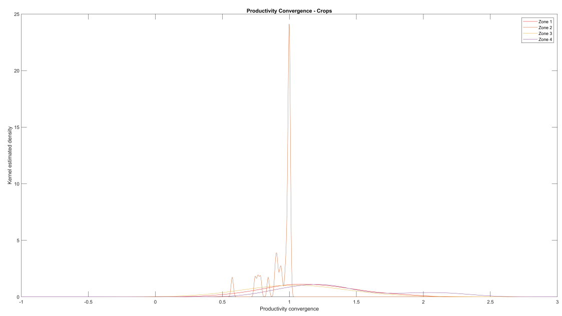
Another interesting aspect is how agro-climatic environments impact each other. Putting

[24] GLS is used as estimation method to correct for potential econometric issues such as heteroscedasticity, and Simar and Wilson's (2007) procedure is adopted to correct for potential bias in the indexes.

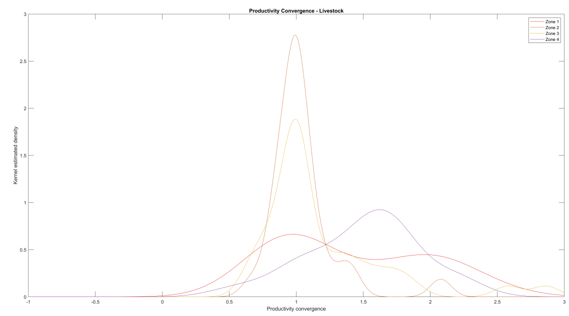
Table 8: Agro-climatic zone agriculture productivity convergence

dimension	statistics	crops	livestock
wet temperate zone			
productivity convergence	average	1.1623	1.4071
	std	2.6367	0.5665
efficiency convergence	average	1.1659	1.6575
	std	0.4712	0.5964
technological convergence	average	1.0552	0.8644
	std	1.2798	0.2217
dry temperate zone			
productivity convergence	average	0.9339	1.0482
	std	1.1268	0.2584
efficiency convergence	average	0.9790	1.1533
	std	0.8165	0.6672
technological convergence	average	0.9556	0.9706
	std	0.9597	0.1615
wet tropical/subtropical zone			
productivity convergence	average	1.0578	1.1942
	std	0.7344	0.4845
efficiency convergence	average	1.0205	1.0033
	std	0.4354	0.2351
technological convergence	average	1.0338	1.1778
	std	0.1862	0.2983
dry tropical/subtropical zone			
productivity convergence	average	1.4010	2.1051
	std	1.2134	2.604
efficiency convergence	average	1.2251	1.4664
	std	0.9508	1.6855
technological convergence	average	1.3019	1.4242
	std	0.2107	0.2732

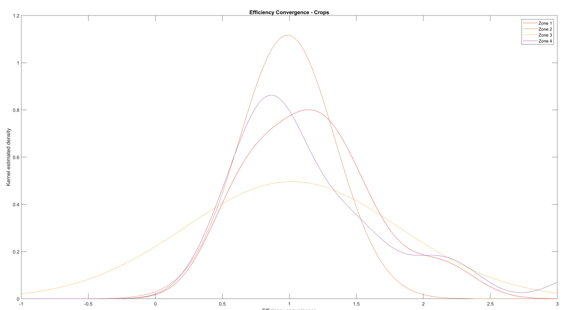
Figure 5: World agriculture productivity convergence 1961-1975 against 2001-2015



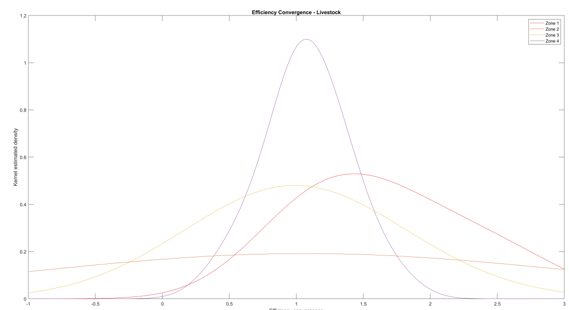
(a) Crops - productivity change



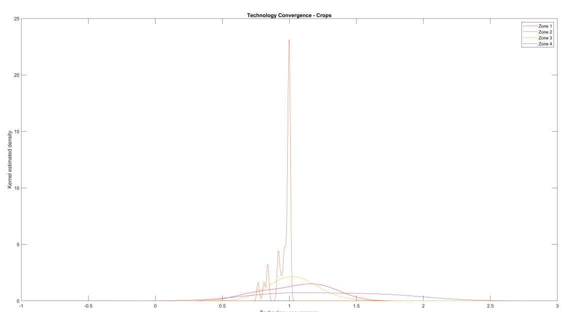
(b) Livestock - productivity change



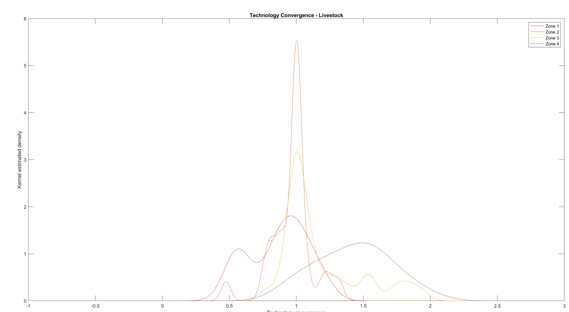
(c) Crops - efficiency change



(d) Livestock - efficiency change

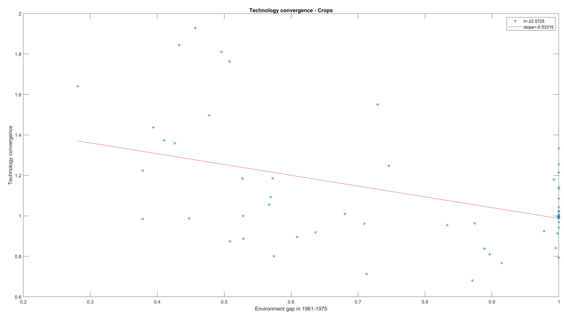


(e) Crops - technological change

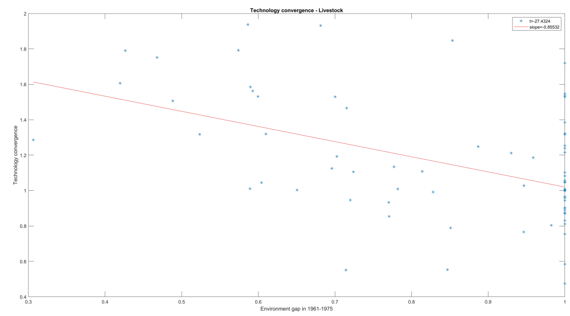


(f) Livestock - technological change

Figure 6: Technology convergence regressions

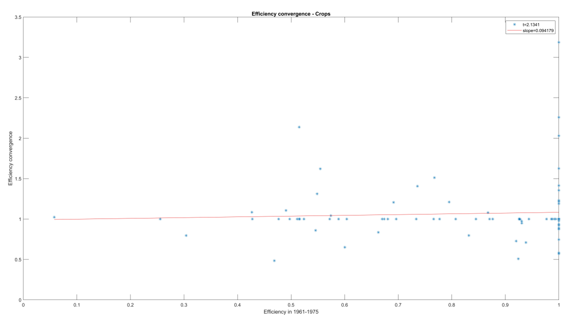


(a) Crops - technological convergence regression

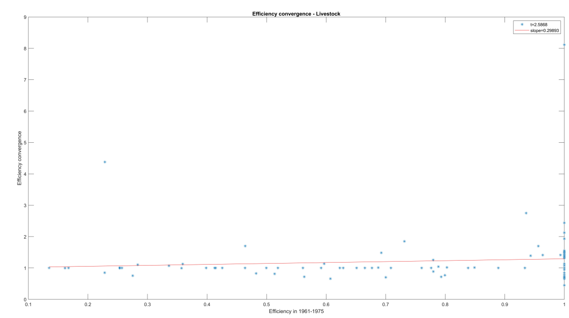


(b) Livestock - technological convergence regression

Figure 7: Efficiency convergence regressions

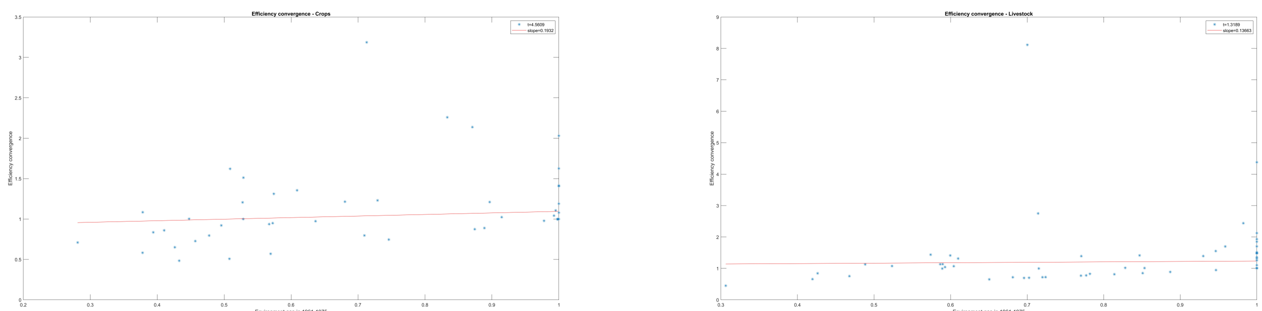


(a) Crops - efficiency convergence regression



(b) Livestock - efficiency convergence regression this differently, we are interested in the possible presence of spillovers across zones (Arzaghi Henderson, 2008; Tsekouras et al., 2016; He and Walheer, 2020). We distinguish two kinds of spillover: incoming and outgoing. The former refers to the situation where countries with higher efficiency scores present a larger technology convergence index. In that case, the world technology benefits from their best practice. The latter occurs when countries less impacted by the agro-climatic environment heterogeneity are becoming more efficient over time. If this is the case, those countries benefit from the world's best practices. As done before, we perform two linear regressions. For the incoming spillover, we regress the efficiency convergence index on the 1961-1975 environment gap average. We proceed in a similar vein for the outgoing spillover by regressing the technology convergence index on the 1961-1975 efficiency score average. Figures 8 and 9 provide the scatter points with the fitted lines, the slope coefficients, and the associated $t-$stats. We can only confirm the existence of incoming spillover for the crops as $t-$stats are too small in all other cases. This highlights that technology and best practice transfers are difficult due to agro-climatic environment heterogeneity.

Figure 8: Incoming spillover regressions



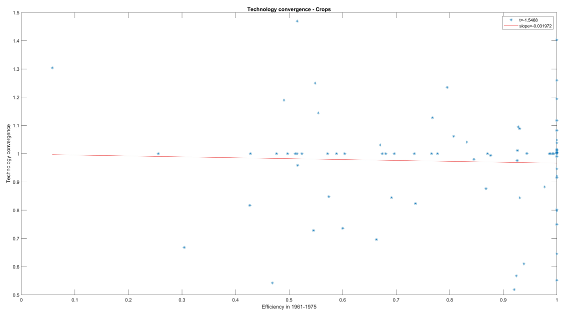
(a) Crops - incoming spillover

(b) Livestock - incoming spillover

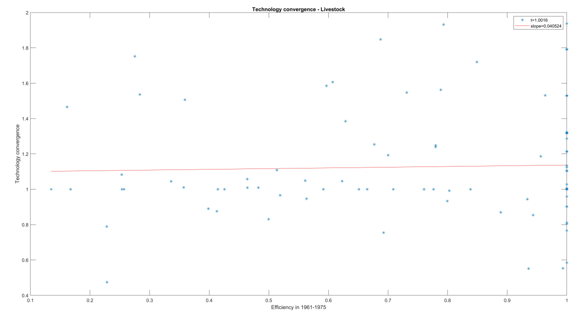
All in all, the last couple of regressions have tried to come up with more clues about the convergence process.[25] Some interesting lessons can be learned from these extra analyses. First, technological convergence is not path-dependent while efficiency convergence is. This means that technological convergence occurs more often for countries that are lagging. It is the opposite of efficiency change. Next, neither incoming spillovers nor outgoing spillovers

[25]Note that we have even verified whether economic and pollution conditions are related to productivity convergence. We consider both the initial values and the growths of three economic indicators –agriculture to GDP share, agriculture exports, and agriculture imports – and one pollution indicator – greenhouse gas emissions. Correlation coefficients with the associated $p-$values are provided in Table 13 in Appendix C. All correlation coefficients are insignificant indicating that the productivity convergence process is not related to economic or pollution conditions. A similar finding is correct for the efficiency and technological convergences.

Figure 9: Outgoing spillover regressions



(a) Crops - outgoing spillover



(b) Livestock - outgoing spillover

are observed indicating the difficulty of technology transfer due to agro-climatic environment heterogeneity.

5 Conclusion

Agriculture is probably the most impacted sector by climate change while productivity is recognized as an important source of output growth over the past half-century for that sector. Both facts probably explain the large number of empirical studies about the role of weather in productivity changes and differences across countries in the agriculture sector. In this paper, we suggest an alternative approach by defining time-dependent output-specific agro-climatic environments. These agro-climatic environments reflect that weather is beyond the control of producers by conditioning countries' production processes and technology and indirectly impacting their productivity gains. This approach avoids asking how weather impacts productivity and what is the best economic modelling. It rather recognizes its impact at a more general level by defining environments that may evolve and that are different for each output.

From a theoretical perspective, we define new output-specific indexes for productivity change in an agro-climatic environment heterogeneity context and decompose them into several parts. A particular focus is given to productivity convergence for the agriculture outputs, and its sources, between and within agro-climate zones. While productivity convergence has been studied before, this represents the first attempt to empirically evaluate such a phenomenon in an agro-climate environment context. Nevertheless, our approach is directly related to three important streams of research in agriculture economics: technology heterogeneity between groups of countries, environment heterogeneity using the level of development, and output technology heterogeneity. Finally, a last distinguishing feature of our approach is to rely on a non-parametric estimation method avoiding making a functional assumption for the production processes.

Building on a tailored database for 91 countries, we study productivity changes for the 1961–2015 period. This represents a unique opportunity to analyse productivity changes for many countries over a long period. We find that agro-climatic environment heterogeneity has a clear impact on productivity change and convergence that depends on the outputs and evolves. Productivity change, mainly due to technological change, is positive for all outputs. Productivity convergence occurs mainly due to technology convergence but is not related to output convergence. Technology convergence is not path-dependent while efficiency convergence is. Moreover, technology transfers do not occur as spillovers are not observed.

While our approach offers several advantages: no functional forms have to be specified, technological change is possible, output-specific technology heterogeneities are modelled, technology spillover and diffusion are taken into consideration, and the weather is not modelled as an input; it also ignores heterogeneities inside the countries and across individual crops and animal products. When such data are available, the methodology developed in the paper can be extended to include those features.

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Appendix A

Table 9: $p-$values for the environment gaps

interval / zone	crops	livestock
ANOVA		
1961-1975	0.0285	0.0115
2001-2015	0.0234	0.0340
ANOVA		
wet temperate	0.6425	0.0131
dry temperate	0.4016	0.7806
wet tropical/subtropical	0.1517	0.0003
dry tropical/subtropical	0.5476	0.5681
Kolmogorov-Smirnov		
wet temperate	0.6589	0.7273
dry temperate	0.9607	0.6969
wet tropical/subtropical	0.6128	0.8848
dry tropical/subtropical	0.3738	0.5749

Table 10: $p-$values for the productivity change distributions

world / zone	Silverman		Student (> 1)		Student ($\neq$)	ANOVA	
	crops	livestock	crops	livestock		crops	livestock
Productivity change							
world	0.6541	0.2547	0.0001	0.0001	0.0021	–	–
wet temperate	0.0082	0.8019	0.0001	0.0001	0.0245	0.0001	0.0001
dry temperate	0.4564	0.5125	0.0001	0.0001	0.0010		
wet tropical/subtropical	0.6872	0.7465	0.0001	0.0001	0.1215		
dry tropical/subtropical	0.3588	0.3983	0.0001	0.0001	0.0001		
Efficiency change							
world	0.1541	0.0705	0.0541	0.8531	0.0051	–	–
wet temperate	0.6927	0.8798	0.6478	0.5478	0.0011	0.0001	0.0001
dry temperate	0.7392	0.6549	0.4789	0.0001	0.0001		
wet tropical/subtropical	0.4785	0.7144	0.0879	0.6598	0.0457		
dry tropical/subtropical	0.2473	0.6894	0.0978	0.0414	0.011		
Technological change							
world	0.0011	0.0008	0.0001	0.0001	0.0645	–	–
wet temperate	0.6284	0.8654	0.0001	0.0001	0.0001	0.0001	0.0001
dry temperate	0.7838	0.7469	0.8471	0.0001	0.0022		
wet tropical/subtropical	0.7395	0.9001	0.0001	0.0001	0.0454		
dry tropical/subtropical	0.8217	0.7896	0.0001	0.0001	0.3247		

Table 11: $p-$values for the productivity convergence distributions

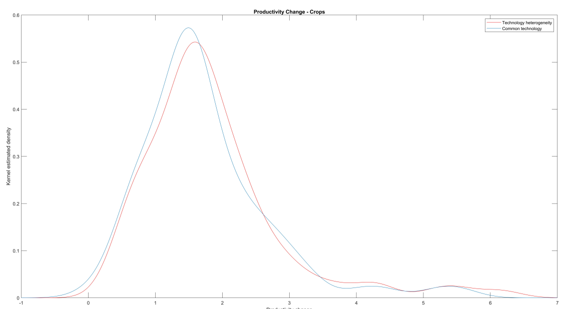
world / zone	Silverman		Student (> 1)		Student ($\neq$)	ANOVA	
	crops	livestock	crops	livestock		crops	livestock
Productivity convergence							
wet temperate	0.8965	0.2722	0.0001	0.0001	0.0001	0.0001	0.0001
dry temperate	0.7895	0.3458	0.6879	0.2457	0.4578		
wet tropical/subtropical	0.6598	0.2748	0.0001	0.0001	0.0001		
dry tropical/subtropical	0.2487	0.5878	0.0001	0.0001	0.0001		
Efficiency convergence							
wet temperate	0.7898	0.8798	0.0001	0.0001	0.0001	0.0001	0.0001
dry temperate	0.8475	0.9194	0.7891	0.0001	0.0001		
wet tropical/subtropical	0.6898	0.4578	0.2485	0.3258	0.5213		
dry tropical/subtropical	0.8435	0.7624	0.0001	0.0001	0.0001		
Technological convergence							
wet temperate	0.8424	0.0914	0.0001	0.8951	0.0001	0.0001	0.0001
dry temperate	0.3274	0.0214	0.4598	0.6279	0.0878		
wet tropical/subtropical	0.6897	0.0878	0.3481	0.0001	0.0111		
dry tropical/subtropical	0.8458	0.6587	0.0001	0.0001	0.0001		

Appendix B

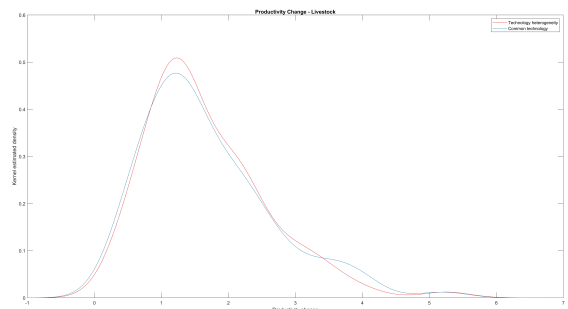
Table 12: World agriculture productivity with no environment heterogeneity

dimension	statistics	crops	livestock
productivity change	average	1.6600	1.4107
	std	1.0140	0.8776
efficiency change	average	1.0149	0.9476
	std	0.6168	0.7215
technological change	average	1.6993	1.6176
	std	0.7641	0.5740

Figure 10: Productivity change distributions with no environment heterogeneity



(a) Crops - productivity change



(b) Livestock - productivity change

Appendix C

Table 13: Economic and pollution condition correlation coefficients

indicator	time	statistics	crops			livestock		
			prod	eff	tech	prod	eff	tech
agriculture to GDP	1961-1975	coeff	0.1931	0.0496	0.0818	0.2047	0.1969	0.0913
		$p-$value	0.0667	0.6404	0.4410	0.0516	0.0614	0.3892
	growth	coeff	0.1840	0.0722	0.0785	0.0810	0.0280	0.1428
		$p-$value	0.0808	0.4963	0.4595	0.4454	0.7925	0.1768
agriculture exports	1961-1975	coeff	-0.0840	-0.0378	-0.0729	-0.0491	-0.0691	-0.0019
		$p-$value	0.4288	0.7221	0.4921	0.6439	0.5152	0.9857
	growth	coeff	-0.0018	-0.0395	-0.0014	0.0759	0.0227	0.1040
		$p-$value	0.9864	0.7101	0.9891	0.4744	0.8305	0.3267
agriculture imports	1961-1975	coeff	-0.0215	0.0889	-0.1605	-0.0046	0.0602	-0.1390
		$p-$value	0.8395	0.4021	0.1286	0.9653	0.5708	0.1890
	growth	coeff	-0.1022	-0.1201	-0.0197	0.0114	-0.0573	0.1006
		$p-$value	0.3350	0.2566	0.8531	0.9148	0.5898	0.3428
greenhouse gases	1961-1975	coeff	0.0509	-0.0337	0.1301	0.0074	0.0019	0.0264
		$p-$value	0.6320	0.7511	0.2192	0.9448	0.9859	0.8036
	growth	coeff	-0.0331	-0.0640	0.0104	-0.0190	-0.0273	-0.0881
		$p-$value	0.7555	0.5467	0.9219	0.8579	0.7973	0.4062