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Abstract

This study provides an economic method to identify the impact of changes in stochastic (climatic) and non-stochastic (farm managed) inputs on the production of a representative sample of French field crop farms between 1990 and 2015. This economic decomposition method specifically attributes output changes to the impact of soil characteristics, climatic variables, non-stochastic farm managed inputs, and technological adaptation change. We quantify these impacts by decomposing product changes over time via Luenberger-type indicators, through a second-order flexible parametric technology estimation. We identify large disruptive effects due to climatic variables, especially since the beginning of this century.

1 Introduction

Humans rely on agricultural products for their food. Agricultural production relies on soil, climate, agricultural inputs, and farmers' knowledge. An obvious sector of human activity which has close relationship with climate is agriculture. A changed climate, in turn, could either be detrimental or beneficial to agricultural outcomes. If it is true that climate has been changing, an estimation of climatic inputs' impacts on agriculture free of restrictive assumptions is key to understanding a strategy towards a sustainable future.

The importance of climatic and soil inputs has been recently reconsidered in agricultural production. However, despite a growing interest on the impact of weather on French agriculture, the impacts of temperature, precipitation, and soil conditions on French field crop output remain imperfectly understood. Most recent empirical economic knowledge (Moore and Lobell, 2014, 2015) is based on the effects of regionally aggregated outputs or regionally aggregated inputs, including aggregated summary measures of temperature and precipitation. These two studies show that increased temperature over the growing season decreases maize and wheat yields but does not significantly decrease economic profits across countries in the EU. The responses depend on the length of horizon in the analysis.

A reason of concern is that the quantification of the impact of climatic factors on agricultural production has been conducted mainly with somewhat restrictive regression methods that, potentially, impose undesirable assumptions on the obtained results. The functional forms used in analyzing the response of crops to climatic variables have been very often quite restrictive (e.g. Cobb-Douglas), not considering interactions between farm managed inputs and between inputs and climatic variables. Moreover, most functional forms of these types may assume that inputs can be substituted at unreasonably high rates one for the other.

Contrary to most of the literature until now, we allow in this study interaction between inputs and between rainfall and inputs, by adopting a second-order flexible functional form to represent the technology. At the same time, we characterize flexibly, via a step-function, the distribution of thermal-time exposure in a certain location. In addition and for the first time considering the thermal-time exposure in the climate change econometrics literature, we recognize the different impact, on the plant metabolic system, of the heat received either during the day or during the night at different temperature ranges. These details allow the identification of remarkable disruptive effects of weather variability on French field crop production.

The literature on the impact of climate change on human activities has recently rapidly increased. Economists have considered evaluating the impact of climate change from different perspectives. A review of an extensive and increasing literature on identifying empirically the effects of climate change is in Dell et al. (2014). Their review shows that older cross-sectional estimates of the impact of climate change were correlating agricultural output and climate to simulate the impact of climate change (Adams, 1989). Earlier cross-sectional estimates have then been replaced by econometric panel estimates. Among others, Deschênes and Greenstone (2007) and Schlenker and Roberts (2009) have treated different ranges of precipitation and temperature, along the whole growing season, as additively separable inputs. Deschênes and Greenstone (2007) estimate the impacts of climatic variables in a profit maximizing context and project future impacts, along different climate scenarios, to produce estimates of climate change damages. Schlenker and Roberts (2009) estimate sensitivities to climate by correlating yields of different separate crops with climatic variables. These estimates result in elasticities which, projected in the future with climate change scenarios, produce damage estimates. Ortiz-Bobea and Just (2013) further demonstrated, thanks to an agronomic insight, that precipitation and temperature are not additively separable inputs along the entire growing season. For that reason, Ortiz-Bobea and Just (2013) treat precipitation and temperature variables from different months as different inputs, implying that they have different production impacts. Lobell et al. (2011) estimate effects of climate on global crop yield productivity via a regression framework.

In Europe the impact of climate change on agriculture has been less studied in a non-Ricardian regression framework. Moore and Lobell (2014) estimate crop yield response to climate change in Europe at a regionally aggregated level in a regression framework. In another paper, Moore and Lobell (2015) evaluate the impact on long-term yield trends in response to climate change with regionally aggregated (NUTS 3) European data. Both of these studies use aggregate means of temperature and rainfall to capture the climatic effects. Ay et al. (2014) propose a model to study the impact of climate change on land use and biodiversity outcomes. Most recent study (Gammans et al., 2017), directly related to the present research, does not consider farm input management in the estimates of the impact of climatic variables on French wheat and barley production.

This study goes beyond the current literature by taking, on one hand, into account farm managed inputs and including more refined climatic data on French agriculture. On the other hand, we use the methods derived from the production economics literature to identify responses to changing soil and climatic characteristics. We devise an economic method to account for soil, farm, and climatic inputs' change and we apply this method to a large representative sample of French field crop farmers.

If Ortiz-Bobea and Just (2013) treat precipitation and temperature variables from different months as different inputs, our intuition goes further. The precipitation enters the production technology in a non-separable manner, because it is disaggregated monthly and it is interacted with the other inputs. The thermal-time exposure is included flexibly via two series of step-functions depending on the time of the day in which the heat occurs, either during nighttime or daytime. Moreover, we consider separately the impact of dynamically changing soil fertility on production.

We justify the consideration of changing weather circadian rhythms because climate change has had an asymmetric impact on the levels of temperatures during nighttime and daytime (Easterling et al., 1997). In particular, climate change analyses and forecasts show an increase in the minimum temperatures higher than the increase in maximum temperatures. This is not usually captured in climate change studies if one considers a mean daily or monthly temperature or accumulated sums of growing degree days during specific periods.

Biologists (Cumming and Wagner, 1968; Kulshrestha et al., 2013; McClung, 2006) have shown that plants have the highest peak of enzymes (such as invertase), necessary for growth, during the early hours of the day, approximately when the minimum temperatures are recorded. Nozue et al. (2007) show that high gene transcription levels in *Arabidopsis thaliana*, regulated by the circadian clock, and protein accumulation in the dark promote plant growth at the end of the night. Again on seedlings of *Arabidopsis thaliana*, Nusinow et al. (2011) confirmed that the circadian clock is linked to hypocotyl growth and that maximal growth occurs at dawn.

The aggregation to a daily amount of thermal power (e.g. in growing degree days) does not take this potentially differential effect into account and may result in erroneous conclusions. In specific, the analysis proposed here hints to a negative impact on crop growth of night warming due to climate change. In other words, usually a negative impact on crop growth is measurable for increases in average daily temperatures and associated to high extreme heat temperatures. However, most of that increase may have occurred during the night. This type of diurnal cycle effect, which is very well known to plant physiologists, has been almost ignored until now in the climate change economics literature. There are some notable exceptions among which is the work by Welch et al. (2010) and the literature cited therein.

We decompose the impact of temperature on agricultural outcomes by considering not only the distinction between growing degree hours accumulated in a certain growing season of the year, but also whether the heat has been accumulated either during the day or during the night. In the following, we estimate the technology by including separately the daytime and nighttime thermal exposures for each location. Further research is devoted to a more specific treatment of the differences arising from this novel type of estimation. Additionally, we consider changes in the amount of precipitation and in the amount of soil carbon and soil pH on the production process.

To identify these empirical components, this study proposes an economic generalized decomposition method that, with second-order flexible functional forms, can attribute portions of product changes to different groups of farm managed inputs, climatic variables, and soil characteristics. We estimate the impacts of the different components by characterizing the production technology of a representative sample of French field crop farmers between 1990 and 2015 via parametric econometric methods. We assume that producers are output maximizers with a second-order flexible technology and different farm-specific technological adaptation quadratic paths.

This article proposes to study the impact of soil and weather variability on French agricultural production between 1990 and 2015 because France has observed in the 20th century an increase in temperature 30% higher than elsewhere in the world (ONERC, Paris 2009). Moreover, France is one of the largest agricultural producers in Europe especially for wheat, barley, and maize. These crops are potentially some of the most highly affected by climatic factors and their future change.

2 Methodology

The present contribution extends to a directional distance function context the methods developed by Färe et al. (1994) and Kumar and Russell (2002). These methods (Malmquist, 1953; Caves et al., 1982; Färe et al., 1994) are typically used to decompose changes in productivity and profitability among different decision making units. However, the methodological extensions developed here for directional distance functions (Chambers et al., 1996) have not yet been applied to the analysis of the importance of climatic variables.

The usual agricultural technology is augmented, in this study, to include soil characteristics and weather stochastic inputs, in addition to non-stochastic farm managed inputs and technological adaptation. The method attributes output changes over time to different components. Apart from the quantification of output effects due to environmental factors, this attribution is critical from the policy perspective because resource-constrained policy interventions need to be focused on most critical production drivers. For example, if the climatic factor is one of the most important drivers determining output variability, one may consider unimportant subsidizing farmers steadily over years but develop safety nets to be activated in climatically difficult years.

Let $\mathbf{y} \in \mathbb{R}_+^P$ denote multiple outputs, $\mathbf{x} \in \mathbb{R}_+^Q$ denote the farm managed inputs, $\mathbf{c} \in \mathbb{R}_+^W$ denote climatic inputs, $\mathbf{s} \in \mathbb{R}_+^S$ denote soil inputs, and t denote time. The multi-input multi-output technology set $N \subset \mathbb{R}_+^{Q+W+1+S+P}$ is defined as:

$$N = \{(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, \mathbf{y}) \in \mathbb{R}_+^{Q+W+1+S+P} : (\mathbf{x}, \mathbf{c}, t, \mathbf{s}) \text{ can be used by farms to produce } \mathbf{y}\}. \quad (1)$$

Define the directional output distance function by:

$$\vec{D}_O(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, \mathbf{y}; \mathbf{0}^{Q+W+1+S+P}, g_{\mathbf{y}}) = \sup\{\phi : (\mathbf{x}, \mathbf{c}, t, \mathbf{s}, \mathbf{y} + \phi g_{\mathbf{y}}) \in N\}. \quad (2)$$

Because of the non-negativity of the directional output distance function for any of the points in the interior of the technology, one can write:

$$v_i = \vec{D}_O(\mathbf{x}_i, \mathbf{c}_i, t_i, \mathbf{s}_i, \mathbf{y}_i; \mathbf{0}^{Q+W+1+S}, g_{\mathbf{y}}) + \epsilon_i \quad (3)$$

where v_i is a positive random error variable and ϵ_i is a double-sided random error term.

Exploiting the translation property of the directional output distance function as shown in Guarda et al. (2013), it is possible to write:

$$\vec{D}_O(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, \mathbf{y} + \lambda g_{\mathbf{y}}; \mathbf{0}^{Q+W+1+S}, g_{\mathbf{y}}) = \vec{D}_O(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, \mathbf{y}; \mathbf{0}^{Q+W+1+S}, g_{\mathbf{y}}) - \lambda, \ \lambda \in \mathbb{R} \quad (4)$$

or, equivalently, by substituting (3) into (4) and rearranging terms:

$$-\lambda = \vec{D}_O(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, \mathbf{y} + \lambda g_{\mathbf{y}}; \mathbf{0}^{Q+W+1+S}, g_{\mathbf{y}}) - v + \epsilon. \quad (5)$$

We then assume $\lambda = -y_1$ and use as numeraire for output y_1 a standard unit number $g_{y_1} = 1$. At the same time, we set the other output numeraire entries to null $g_{y_2} = \cdots = g_{y_P} = 0$. It is then possible to substitute numerically for λ in (5) and obtain a maximum output frontier for output y_1, which is also econometrically easily estimable:

$$y_1 = \vec{D}_O(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, 0, y_2, \ldots, y_P) - v_i + \epsilon_i \quad (6)$$

The function $\vec{D}_O(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, 0, y_2, \ldots, y_P)$ is interpretable as a maximum output y_1 expressed, thanks to the common numeraire vector of the directional distance, in the same units as y_1, with distance from observed output measured by v_i.

One could potentially have different frontiers for the different outputs. However, in this study we concentrate on the case of specialized farmers where the average field crop monetary value of output (among all years of presence in the data) represents more than 75% of the total output value. For this reason, in the following, we simplify the treatment by only considering output y_1 in the technology. Consequently, the function $\vec{D}_O(\mathbf{x}, \mathbf{c}, t, \mathbf{s}, 0, y_2, \ldots, y_P)$, where $y_2 = \cdots = y_P = 0$, can be rewritten by means of a function $f : \mathbb{R}_+^{Q+W+1+S} \to \mathbb{R}_+$. We omit the numerical index to identify the unique output y to obtain:

$$y = f(\mathbf{x}, \mathbf{c}, t, \mathbf{s}) - v + \epsilon. \quad (7)$$

In the following, we adapt and extend the methods contained in Kumar and Russell (2002), Färe et al. (1994) and Henderson and Russell (2005) to attribute production differences to specific components. The production difference between two time periods 1 and 0 can be decomposed as:

$$y_1 - y_0 = f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) - v_1 + v_0 + \epsilon_1 - \epsilon_0 \quad (8)$$

Even though this is not necessarily the case generally, in this study we consider the numbers 0 and 1 to represent two subsequent periods. This representation implies that, in the following, we will consider chain-linked indicators. To simplify the treatment, we focus the explanation of the decomposition on the first two terms of the right-hand side of the equation (8). The other difference of terms $-v_1 + v_0$ measures the difference in heterogeneity of each farm and their potential infrastructural differences, not associated with the passing of time t.

Different decompositions of the first two right-hand terms of (8) are possible. To illustrate, first sum and subtract $f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1)$, $f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0)$ and $f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0)$ to obtain

$$\begin{aligned}
f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) &= f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) \\
+ f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) &+ f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0).
\end{aligned} \quad (9)$$

The first of the differences on the right-hand side of (9) is an indicator of change in maximum output due to time $f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1)$. The second term is instead an indicator of change in maximum output due to soil $f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0)$. The third element is an indicator of change in maximum output due to climatic inputs $f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0)$. The fourth element is an indicator of change in maximum output due to input change $f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0)$. However, it is also possible to decompose the same terms of (8) by summing and subtracting $f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1)$, $f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1)$, and $f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1)$. This obtains:

$$\begin{aligned}
f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) &= f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) \\
+ f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1) &+ f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) + f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0)
\end{aligned} \quad (10)$$

The first of the terms on the right-hand side of (10) is an indicator of change in maximum output due to input change $f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1)$. The second of the terms is an indicator of change in maximum output related to change in climatic conditions $f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1)$, while the third term is an indicator of change due to the passing of time $f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1)$. The fourth term is an indicator measuring the change in maximum output due to difference in soil characteristics $f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0)$.

In these decompositions, unless one assumes special types of separability, the indicators corresponding to the change in the same elements, e.g. the climatic inputs, are different in the two decompositions: $f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0)$ and $f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1)$. This difference implies that the attribution of portions of output change to different groups of inputs is not unequivocal and it changes depending on the decomposition path chosen. Considering the number of all possible combinations of four changing elements, there are twenty-four possible paths to decomposing the first two right-hand side terms of (8).

This problem is well-known in the production economics literature as the *path dependency* problem. To illustrate the path dependency issue, one can consider figure 1, where only one farm managed input x and one climatic variable c can vary. Different paths can be chosen to decompose the difference between $g(x_1, c_1)$ and $g(x_0, c_0)$, where $g : \mathbb{R}^2_+ \to \mathbb{R}_+$ is a function similar to f in the previous treatment. Different paths attribute different measures to changes in x and c. One can determine different paths by changing the variables in different orders. One path is to move from point $g(x_1, c_1)$ to point $g(x_1, c_0)$, and then to point $g(x_0, c_0)$ (first path). Another possible path is to move from point $g(x_1, c_1)$, first to point $g(x_0, c_1)$, and then to point $g(x_0, c_0)$ (second path). The problem of path dependency arises because, as in this example in the picture, the portions of the change from $g(x_1, c_1)$ to $g(x_0, c_0)$ attributed to each component are different, depending on the path followed. One could attribute more or less importance to one factor or the other, depending on the path followed. This indeterminacy, in other terms, means that either the natural environmental factor c or the farm managed input x could be considered as the critical driver of the output difference, depending on the path followed.

A workable alternative that avoids this arbitrariness is to follow Caves et al. (1982), Färe et al. (1994), Kumar and Russell (2002), and Henderson and Russell (2005) and rely on an additive counterpart of a "Fisher ideal index" that takes an arithmetic average of the two possible decomposition paths.

In our additive decomposition, the path dependency problem is solved by taking the arithmetic mean of the twelve actually different possible paths obtaining a decomposition á la Luenberger. Consequently, the resulting input change effect is as follows:

$$\begin{aligned}
X\Delta(\mathbf{x}_1, \mathbf{x}_0; t, \mathbf{c}, \mathbf{s}) = \big(& f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_1) + f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_0)\big) * 1/12.
\end{aligned}$$

The weather change effect is represented by

$$\begin{aligned}
C\Delta(\mathbf{c}_1, \mathbf{c}_0; \mathbf{x}, t, \mathbf{s}) = \big(& f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_1) + f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_1) + f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) \\
&+ f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_0) - f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) \\
&+ f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_1)\big) * 1/12.
\end{aligned}$$

The soil change effect is

$$\begin{aligned}
S\Delta(\mathbf{s}_1, \mathbf{s}_0; \mathbf{x}, t, \mathbf{c}) = \big(& f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) \\
&+ f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_0) \\
&+ f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_0)\big) * 1/12.
\end{aligned}$$

Finally, the technological adaptation change effect is

$$\begin{aligned}
T\Delta(t_1, t_0; \mathbf{x}, \mathbf{c}, \mathbf{s}) = \big(& f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) + f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_1) + f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_1) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) + f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_0) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_0, t_1, \mathbf{s}_0) - f(\mathbf{x}_1, \mathbf{c}_0, t_0, \mathbf{s}_0) + f(\mathbf{x}_0, \mathbf{c}_1, t_1, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_1, t_0, \mathbf{s}_0) \\
&+ f(\mathbf{x}_1, \mathbf{c}_1, t_1, \mathbf{s}_1) - f(\mathbf{x}_1, \mathbf{c}_1, t_0, \mathbf{s}_1) + f(\mathbf{x}_0, \mathbf{c}_0, t_1, \mathbf{s}_0) - f(\mathbf{x}_0, \mathbf{c}_0, t_0, \mathbf{s}_0)\big) * 1/12. \qquad (11)
\end{aligned}$$

The final decomposition divides the change between maximum outputs into the sum of arithmetic means of a technological adaptation change effect ($T\Delta(t_1, t_0; \mathbf{x}, \mathbf{c}, \mathbf{s})$), of a farm managed inputs change effect ($X\Delta(\mathbf{x}_1, \mathbf{x}_0; t, \mathbf{c}, \mathbf{s})$), of a climatic inputs change effect ($C\Delta(\mathbf{c}_1, \mathbf{c}_0; \mathbf{x}, t, \mathbf{s})$), and of a soil change effect ($S\Delta(s_1, s_0; \mathbf{x}, \mathbf{c}, t)$), in addition to a farm heterogeneity effect ($-v_1 + v_0$) and an error effect ($\epsilon_1 - \epsilon_0$):

$$y_1 - y_0 = T\Delta(t_1, t_0; \mathbf{x}, \mathbf{c}, \mathbf{s}) + X\Delta(\mathbf{x}_1, \mathbf{x}_0; t, \mathbf{c}, \mathbf{s}) + C\Delta(\mathbf{c}_1, \mathbf{c}_0; \mathbf{x}, t, \mathbf{s}) + S\Delta(\mathbf{s}_1, \mathbf{s}_0; \mathbf{x}, t, \mathbf{c}) - v_1 + v_0 + \epsilon_1 - \epsilon_0. \tag{12}$$

To have an idea of how these changes relate to the changes in maximum output quantities, we calculate percentage change differences by dividing the absolute changes by the output in base period 0.

Given the translation property, the directional output distance function in (6) is nothing else than the representation of a maximum output function. Inspired by Cornwell et al. (1990), we parameterize econometrically the maximum output function as a second-order flexible quadratic functional form with farm-specific quadratic time trends that represent how the farm-specific quadratic technological adaptation evolves over time:

$$\begin{aligned} y_{1it} &= \sum_{q=1}^{Q} b_q x_{qit} + \sum_{u=1}^{S} b_u s_{uit} + \sum_{w=2}^{W} b_w c_{wit} + \frac{1}{2}\sum_{q=1}^{Q}\sum_{q'=1}^{Q} b_{qq'} x_{qit} x_{q'it} + \frac{1}{2}\sum_{u=1}^{S}\sum_{u'=1}^{S} b_{uu'} s_{uit} s_{u'it} \\ &+ \frac{1}{2}\sum_{w=2}^{W}\sum_{w'=1}^{W} b_{ww'} c_{wit} c_{w'it} + \sum_{q=1}^{Q}\sum_{w=2}^{W} b_{qw} x_{qit} c_{wit} + \sum_{q=1}^{Q}\sum_{u=1}^{S} b_{qu} x_{qit} s_{uit} + \sum_{u=1}^{S}\sum_{w=2}^{W} b_{uw} s_{uit} c_{wit} \\ &+ \sum_{s=1}^{4} \sum_{r=4,9,14,19,24,29,34,39,44} b_{1rd} c_{1r_{\pm 2}dit} + \sum_{s=1}^{4} \sum_{r=4,9,14,19,24,29,34,39,44} b_{1rn} c_{1r_{\pm 2}nit} + \epsilon_{it} + v_{0Di} + \alpha_{it} \end{aligned} \tag{13}$$

where y_{1it} is the level of output, $c_{1r_{\pm 2}dit}$ is the level of thermal time (TT) that is accumulated during the day from sunrise to sunset, between $r-2$ degrees and $r+2$ degrees Celsius in each season s, $c_{1r_{\pm 2}nit}$ is the level of corresponding thermal time that is accumulated during the night from sunset to sunrise in each season s, and c_{wit} with $w = 2, \ldots, W$ represent the rainfall accumulated in each farm in the 12 different calendar months. In estimating our main model, we include a second-order flexible functional form of the interactions between inputs to show the importance of input interactions on the maximum output function. Moreover, ϵ_{it} is a double-sided random error term, v_{0Di} is a farm specific factor representing structural farm heterogeneity associated with the model and α_{it} represents time-varying farm-specific technological adaptation trends (i.e. farm-specific quadratic technological trends): $\alpha_{it} = \alpha_{1i}t + \alpha_{2i}t^2$.

3 Data

We use an unbalanced panel data set of French field crop farms from the Farm Accountancy Data Network (FADN), observed between 1990 and 2015.[1] The data from the FADN contain accountancy data for representative commercial farms from a stratified, rotating sample. Because we are interested in looking at the impact, over time, of changes in climatic variates year-to-year, we preserve only the farms who have no year gaps in observations along the period of analysis. Among these farms, we maintain only the farms that have at least three quarters of their output from field crop production on average in all the years of presence in the sample.[2] The resulting data contains 2953 French field crop farms with a total of 25892 observations, with approximately 9 years of data on average per farm.

Summary statistics of inputs and output used in the analysis are in tables (1)-(4). We use a parsimonious one-output technology with multiple inputs. As farm managed inputs, we consider unpaid labor (expressed in Annual Working Units, in full time equivalent), utilized land area (in hectares, ha), and an aggregate intermediate input index including all other inputs. Both the aggregate intermediate input and output values are deflated with aggregate price indexes derived either from EUROSTAT (for the inputs) or from the National Institute of Statistics and Economic Studies (INSEE, for the outputs) with base period 2010. Aggregate price indexes have been constructed for each farm and are Lowe price indexes, where the required fixed weights shares are farm-specific average (over time) input and output category shares.

Farms have quite a large extension in terms of land with an average 124 hectares (ha) but require only 1.2 units of unpaid labor per year on average. However, large variations in the data are present with some farms utilizing as little as approximately 5 ha and some as much as 700 ha. A similar large variation is true for the input and output implicit quantities.

We match these data with a series of different environmental data sources. In particular, we consider soil properties measured in the GIS SOL data base in France[3]. We take aggregate observed data in France between 1990 and 2015 at the department (NUTS 3) level. The

[1] Farm Accountancy Data Network (FADN) 2018. We gratefully acknowledge the usage of the data obtained from Directorate-General for Agricultural and Rural Development (DG AGRI) C.3 Unit. The confidential data used are accessible through specific authorization from the European Commission. More information is available at http://ec.europa.eu/agriculture/rica/.

[2] Field crop product, in this case, is understood to contain all measured output from cereals, protein crops, potatoes, sugar beet, oil-seed crops, and industrial crops. In the names of the variables from the FADN standard results this corresponds to: se140+se145+se150+se155+se160+se165.

[3] We acknowledge the usage of public data from the GIS SOL database available online at https://webapps.gissol.fr/geosol/.

points are grouped in different periods of five years in the database: between 1990 and 1994, 1995 and 1999, 2000 and 2004, and 2005 and 2009. Among those averages we interpolate linearly.

As critical soil properties we consider soil organic carbon concentration (in g Kg^{-1}) and soil pH. Soil organic carbon concentration is usually considered as a proxy for soil structure and fertility. It varies but only in the long run; it helps the structure of the soil and enhances its water-holding capacity (Brady and Weil, 2008). Soil organic carbon concentration is transformed to obtain tons of carbon per hectare utilized in each farm.

Soil pH is also a fundamental variable because it enables conditions in the soil conducive to stable and reliable plant growth. If the average pH in the period observed is around 7.3, the observations vary between acidic soils below 5.9 and very basic ones above 8.3. The effect of more or less acidic soils on specific plants is different depending on the field crop considered, on crop cultivars, and on organic carbon concentration. Acidity of the soil neighboring plant roots is fundamental for nutrients' uptake.

The climatic inputs are obtained from the Gridded Agro-Meteorological Data in Europe database of Agri4Cast of the Joint Research Centre of the European Union[4], which is a gridded dataset with a regular grid resolution of 25km*25km. All gridded variables represent grid points inside the borders of French NUTS 3 regions, which are the smallest administrative units at which the FADN data are identifiable in the historical sample we obtained. For example, let one consider the department of Dordogne in Figure (2) where hypothetically a farm (small red circle) is surrounded by the gridded data points (the gray dots). Because we do not have the specific position of farmers in the corresponding NUTS 3 region, we overimpose different crop masks for each year for field crops from the European Union Joint Research Centre and calculate a weighted average of all points in each region (gray dots) for the climatic variables of interest, with crop areas cultivated as weights. We allocate these weighted averages at the regional level to all farms in that NUTS 3 region.

From the data provided in the Agri4Cast database, we use daily minimum and maximum temperature (in degree Celsius) and daily precipitation (in mm). For each of the days of the year, we reconstruct the hours of exposure of each grid location point to a certain temperature, by interpolating the minimum and the maximum with a sinusoid curve between minimum and maximum and with an exponential decay between maximum and minimum.[5] For each degree Celsius interval (e.g. 1-2, 2-3, etc. until 45), we reconstruct how many hours

[4]We acknowledge the JRC dataset from the European Commission Joint Research Centre (http://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx).

[5]For interpolating hourly the minima and maxima and to recover the sunset and sunrise times at different grid point locations, we use the R package chillR https://CRAN.R-project.org/package=chillR.

in the day crops have been exposed to that temperature, in a certain grid location. We then transform these thermal exposure hours in thermal exposure days and sum all thermal time (to which a certain location has been exposed to) in blocks of five degrees each, from 4 until 44°C. All thermal time (TT) is defined to be the accumulated time a certain location has been exposed to a temperature from half the unit before to half more than the unit. This means for example that the TT for 2°C is all the accumulated time a place has been exposed to temperature in the range between 1.5 and 2.5. In this manner, the defined intervals utilized in the estimation cover 5 degrees each. For example, the interval at 4°C aggregates all time a region has been exposed to temperature between 1.5 and 6.5°C. In other words, we sum all thermal time between 1.5 and 6.5°C, between 6.5°C and 11.5°C, between 11.5°C and 16.5°C, and so on until 46.5°C.[6] We do not consider directly deep freezing. In this exercise we do not sum TT exposure below 1.5°C. However, because the recorded temperature is modeled at $2m$ height, the temperature on the ground can be lower than reported and actually freeze, especially in clear nights with low wind. In this way, we capture the negative effects of potentially light frosts, which are most important for crop growth, especially during Spring.

Recognizing that temperature inputs are different depending on the season of occurrence, we approximate 4 simplified seasons. The first represents winter and goes between the beginning of the year and end of February. The second season represents spring and goes from March (revitalization of the dormant plants in the soil, especially wheat) until 31st of May. The third season covers approximately the Summer time going from June until the end of September and the fourth season covers the Autumn (October to December).

Finally, the contribution of this paper is, additionally, in realizing that not only the exposure to a certain temperature is a different input for plant growth depending on the timing during the growing season and on the temperature range, but also depending on the time of the day in which it occurs. This is why we aggregate the thermal time separately for the night hours and for the daily hours of each grid location.

Typical plants used in French agricultural fields, such as C3 and C4 plants, have specific circadian rhythms and perform different vital functions during the night and the day. While during the day plants typically photosynthesize and create starches and sugars, during the night plants typically distribute sugars to the cells where need to be metabolized and utilized for respiration and for building plant structure. The highest peaks of plant growth thanks to enzymes catalyzing metabolic functions (Cumming and Wagner, 1968; Kulshrestha et al., 2013; McClung, 2006) or thanks to protein accumulation and circadian clock (Nozue et al.,

[6]Some regions have been exposed to the highest temperature in the last bin only during Summer months. We considered as maximum temperature of the distribution 46.5 but, in fact, temperatures were registered only until 45°C.

2007) are typically attained around the end of the night, approximately when minimum temperatures are measured.

For the precipitation we aggregate daily values to monthly aggregates and multiply these by the extension of the farms to get a total amount of water as an input to our production function. The final precipitation amounts depend on the land extension used in each farm in each year.

4 Results

The results at the national level, averaged over the years, are depicted in Figure (3). The results are weighted to be representative at the national level with yearly farm sampling weights, changing every year in the FADN sample. The index of total output change has been increasingly fluctuating, especially after the turn of the century. If one observes Figure (3), after the first year (1991) of recovery from a hard drought hit in 1990, and two consecutively negative years (1992 and 1993), average output has, substantially, grown uninterruptedly until the late 1990s.

After the year 2000, variations in growth rates increasingly larger than in the previous period, alternating above and below zero, are observed. The years after 2008 are especially marked by large and sudden variations. The most striking result in this graph is that, after 2008, total output change variability is not explained by large variations in inputs or technological adaptation and, only in part, by weather, as it was the case in the years 1992-1999. On the contrary, fluctuations in aggregate output follow, most prominently, weather patterns. Particularly after the year 2000, the bulk of aggregate average output change is almost completely mimicked by the weather effect, except in some particular cases. The variability of the output change in the years thereafter (2008-2015) is strikingly almost precisely replicating the weather-related effect.

While more positive than negative variability is observed in the first twenty years of the period analyzed (until 2010), in the last five years the draws are much deeper than the peaks. After the 2011 deep (-20.2%), there is only a 7.4% peak the year after, signaling only a partial recovery. The other draw in 2013 (-14.05%) has only been recovered by a 11.4% positive effect in 2014. All these numbers are obtained by weighted averaging the percentage effects. If one were not to use the weights given to each farm, the numbers would be slightly less negative. This means that the most hit farms in the sample represent also more farms in reality.[7]

[7] The 2011 deep would be a negative -16.7% average climatic variables' effect, while 2013 would result in a negative -10.8% and in 2009 the climatic effect would be even more positive with a +18.9%.

The absolute changes in the right half of Table (5) are sample-weighted averages of absolute changes. The relative percentage changes in the left half of Table (5) are directly calculated on the right half weighted averages of absolute changes. If one looks at Table (5), the input effect has been positive in 60% of the years, with a period average (1991-2015) of 0.45%. In the period before 2000 an average input change of approximately 0.56% on average indicates a positive contribution of inputs to output change. After 2000, that number is just equal to 0.39%. However, this small difference masks a period of sustained increases averaging 1% after the year 2006, and a period of sluggishness starting between 2000 and 2006 (average 2000-2006 is -0.5%).

While in the period up to 1997, the soil effect has had some negative years with an average of -0.1%, and from 1998 until 2002 slightly positive (+0.1%), after 2003 the soil effect has had a slightly negative trend with consecutive negative change numbers between 2003 and 2015 (average since 2003 is -0.04%). At this level of analysis, one could speculate that there has been some degree of substitution in this last period between inputs and soils, evidenced by increases in the input component mirrored by a slight worsening of the soil component.

On average, over the period, the aggregate technological adaptation effect has been positive with a yearly 0.9% increase. The aggregate technological adaptation effects averaged per year have almost always been positive in the model (exceptions are 1991, 1992), with high figures in the early years and slightly decreasing until 2008 (0.9% averaged from 1991 until 2008), and then lower figures but increasing again in the second period (0.8% averaged from 2009 until 2015). This effect has also been remarkably stable with low variability (standard deviation only 0.0083).

Even if it is true that a part of the behavior in the total output changes depicted in Figure (3) is due to the input and the time effects and very little to the soil effect, it is also true that most reproduced variability in the total output changes comes from the variability in the weather events' indicator. This component is one of the most important of the decomposition. The standard deviation of the weather indicator change is 0.0612 over the period, while the same figure for the total output change is 0.0808. This means the weather effect is almost as variable as output change.

Overall, the weather indicator contributes only slightly positively, if averaged over the period (average +0.33%). However, this masks large jumps both toward negative and positive values. The weather indicator is quite volatile over the years, with clear draws in 1993 (-7.4%), 2001 (-7.6%), 2003 (-3.9%), 2011 (-13.9%), and 2013 (-8.25%). Draws are usually contrasted by peaks in subsequent years, such as in 2005 (7.85%), in 2009 (15.5%), or in 2012 (5.3%).

All the draws evidenced here are connected to climatic extreme events at the national level, especially (but not only) during the Spring time, such as extreme droughts or extended cold weather. This sensitivity to Spring weather is to be expected as most cereals planted in France have their vegetative and maturity stages during Spring. For this reason the growing conditions during Spring are most relevant for the wellness of the cereal crops. Moreover, a portion of the utilized agricultural area is also used for Summer crops, such as maize, protein or industrial crops, which may be more affected by heat during late Spring or Summer. In some cases, for example in 2003, the impact of the drought in July and August has been clearly stronger on Summer crops such as protein crops or maize. Some oil-seed crops, such as rapeseed, are more resistant to heat than other protein crops. An explanation of some climatic extremes occurred in France during the most climatically eventful years will be offered when presenting the farm-level results, at the district level, in a later subsection.

In terms of aggregate yearly averages over the whole period, looking at absolute changes in output, regardless of whether positive or negative, 58.5% of the variation is explained by the climatic variables change, 22% is explained by input change, 18% by changes in technological adaptation change, and, approximately, 1.5% is due to soil change variation. Depending on the years, the importance of each component is different. The variations of weighted (absolute) percentage averages, in different years, are presented in Figure (4), where we associate proportional areas in the chart to the components of change along different years. It is clear, at first sight, how the variability of output has been increasingly due to climatic variables' changes, over the years and, especially, since the beginning of this century.

4.1 Counterfactual Aggregate Farm Analysis

The relative amounts in national yearly averages are fundamental to understand the components' importance and their variability. These averages match closely how absolute changes develop. However, they only hint at how absolute quantities develop. In Figure (5), we first show how absolute changes match closely the relative output changes presented in the previous section, by creating counterfactual averages of absolute changes. Second, in Figure (6) we will present the absolute average quantities and analyze the behavior of French field crop production in the period 1990-2015.

We construct counterfactual average absolute changes in Figure (5), starting from soil change (thin-dotted line) and adding successively technological adaptation change (to obtain the long-dashed line), adding technological adaptation and farm managed inputs' change (to obtain the short-dashed line), and, finally, technological adaptation, farm managed inputs' change, and climatic events (dash-dotted line), to obtain a very close approximation to the real average output changes occurred among field crop producers in France (solid line).

The short-dashed line represents the output changes without changes relative to weather variables. This line really represents what the absolute output changes would have been if weather variables had not changed over time. One could hazard to say that the production path would have been almost monotonous without weather variability. The changes are strongly exacerbated by weather variables. These changes resemble closely the relative percentage changes in output, especially in more recent years.

We then aggregate the absolute effects starting from the absolute averages at the farm level up to the national level. We create in this manner a series of absolute average counterfactuals to show that the determinant factor in shaping the distribution is clearly the change brought by the climatic variables' effect.[8]

The changes in weighted absolute quantities are constructed in Figure (6) and are very instructive about the way French field crop production developed. In this Figure (6), we reconstruct, step by step, the absolute weighted averaged quantities in French field crop production, summing the decomposed changes to the average output. We begin with the initial period average output (y_0) and successively sum the soil effect (to obtain the thin-dotted line), the soil and technological adaptation change effect (to obtain the long-dashed line), the soil, technological adaptation change and inputs' change (to obtain the short-dashed line), and, finally, all previous changes plus the climatic events' effects (to obtain the dash-dotted line), which is almost identical to the real total output quantities (solid line, y_1).

Two results are particularly striking. The first is that the effects of climatic events have generally helped during the first decade (1991-1999, except for 1993), while they have been dramatically and increasingly negative in the last five years of the period (2011-2015). The second striking result for the observer of Figure (6) is that representative aggregate average output of field crop producers has substantially stagnated from 1999 until 2008. Moreover, during this period of sluggish output (1999-2008),[9] climatic variables' effects have been less dramatic but have still driven most of the variability in average output. Large negative climatic extreme events have occurred in 2001 and 2003.

One could consider different portions of data corresponding to specific regions to analyze separately the effects and to identify the impact of climatic events on agricultural output change. However, here we limited our analysis to the national counterfactual experiment.

National yearly results are important to gauge a general tendency for different years, but

[8]Errors contribute to yearly averages approximately 1.3%, which is very small compared to the other changes.

[9]This sluggish period of production may, in part, be due to environmental set-aside policies enacted after 2005.

more diversified results are obtainable from regional and farm level analyses. In the next sections, the results of the decomposition analysis will be interpreted, in sequential order, both at the regional and at the farm level.

4.2 Regional averages

We consider the variability across regions in Figure (7) and in Tables (6)-(8). Figure (7) depicts the regional (NUTS 3) sample-weighted averages of the indexes at the farm level. This visualization highlights the values of the component changes and it shows the differences between regions.

In the top-left map of Figure (7), we see the input effect regional averages, while, in the top-right map, the technological adaptation change effects are presented. In Tables (6)-(8), the weighted regional averages of the input effects are very different depending on the region, with some regions showing an average negative input effect of more than 20% and some regions arriving at positive averages above 10%. Only 28 regions present negative averages, while the others are positive. Among the positive results there are the majority of the breadbasket regions of France (Picardie, Champagne-Ardenne, Ile de France, Alsace, big parts of Centre and Franche-Comté, Lorraine, and Bourgogne) and the Departments of Finistère, Morbihan, Loire-Atlantique, Vendée, Haute-Garonne, and Ariège. These territories have a majority of highly mechanized farms with high levels of invested capital and a high usage of intermediate inputs, such as pesticides and fertilizers.

The regional averages of the technological adaptation effects are similar, slightly more stable than the input effects, and are positive in approximately four fifths of the regions (in 63 out of 78 regions). However, there are special cases, both positive and negative in Tables (6)-(8). On the positive side, three Departments have values exceeding 15%: one is Haute-Savoie with 32.3% and the other is Var with 20.7%; the region of Hautes-Alpes arrives at slightly more than 16.3% technical adaptation change on average. On the other hand, there are exceptional departments showing large negative numbers. For example, the Creuse department shows a negative effect of -6.7%. Other two examples include Dordogne (-4.9%) and Morbihan (-4.4%), who also present negative values. These are large variations in technological change adaptation implying an increasing divergence in technological trends between regions, motivations of which deserve separate further research.

On the lower level, we clearly observe regional patterns with spatial clusters in the soil effect levels. We see in Tables (6)-(8) that, in this case, the averages are, generally, much smaller, with extremes between -2% and +2.5%. It is clear that the changes are much smaller than in other components of the decomposition but it is interesting to notice that best soil effects are regionally concentrated where more acidic soils are (e.g. Bretagne, Basse Normandie, Aquitaine, and part of Auvergne, Franche-Comté, and Lorraine). Coincidentally, some of these regions (Bretagne, Auvergne, Franche-Comté) are also regions with very high soil carbon concentration. On the contrary, most negative soil effects are where more basic soils are present (e.g. Charentes, Nord-Pas de Calais, Picardie, Champagne-Ardenne, Herault, Vaucluse, Bouches de Rhône, Alpes de Haute Provence, and Hautes Alpes). One could speculate that, in part, these resulting positive effects are potentially due to the dominating presence in these regions of crops that require moderately acidic soils to thrive (e.g. pea, turnip, soybean, sunflower, corn, potato). On the other hand, soil fertility, as proxied by the soil carbon, is equally important for plant health and could be the dominating factor.

These soil-weighted average effects hide extremes, which are large, both positive and negative, visible in Tables (6)-(8). Some of the most positive are from regions of France with different soil characteristics: a 2.46% average in the Doubs department (with a moderately acidic soil, around 6.2-6.5 pH, but high soil carbon concentration), the Loire-Atlantique department with a 2.4% average (with a moderately acidic soil, 6.2-6.5 pH, and optimal soil carbon concentration), and 2% in the Finistère department (with an acidic soil but high soil carbon concentration).

The most negative regional average soil effect comes from the Vaucluse department, with a -1.9%, where relatively basic soils are reported (8.22 pH) and portions of territory present very low soil carbon concentration. This is really interesting because it confirms the perception that many field crops, except for some of the cereals, are better adapted to thrive in moderately acidic soils, with relatively high amounts of soil carbon, proxying for soil fertility. Moreover, in recent years, also some wheat cultivars have been bred to be more resistant to more acidic soils.

The final piece of the puzzle is the average regional effect of climatic extreme events. The regional averages, visible in Tables (6)-(8), are very much concentrated between -7% and +7%. It is very interesting to notice that the weather effect regional averages, in general, are very moderate. The large variations of effects highlighted in the previous subsection are indeed mitigated. Not surprisingly, extreme weather variations from one year to another compensate over time in regional averages, especially if both bad and good years alternate in a regular fashion. This alternation has been less regular in the more recent years with larger negative draws than positive peaks.

The worst regional average effects in Tables (6)-(8) are registered in Haute-Savoie (-23.3%), in Creuse (-7.2%), and in Var (-6.8%). These negative numbers diminish the positive technological trends registered in Haute-Savoie and Var. Very positive average regional effects for climatic events are registered, instead, in Hautes-Alpes (+52%) and in Vaucluse

(+7.3%). While Vaucluse has a large positive technological trend of approximately 4% and a largely positive input effect (+7.3%) with a decidedly negative soil effect (-1.9%), Hautes-Alpes has negative input (-18.9%) and soil (-0.5%) effect, but a positive technological adaptation (+16.3%) change effects.[10]

From the analysis of the yearly and regional averages, it is clear that some effects are more clearly heterogeneous spatially and stable over time, such as the soil effects, while some effects are both temporally and spatially diverse, such as the weather effects. It is for this reason that in the next section the analysis will be done at the farm level, presenting, for confidentiality reasons, farm effects aggregated at the most disaggregated level possible for specific years.

4.3 Bumper crop or dearth: the farm level analysis

For the purpose of summarizing the main findings, in the previous subsections we disregarded the farm level detail at which the estimations have been done. Firstly, we neglected the regional differences and analyzed only year-on-year variability. Secondly, we neglected the year-on-year variability and analyzed the regional average differences. In this subsection, we go deeper and analyze both temporal and spatially disaggregated variability by concentrating on the results at the farm level.

For confidentiality reasons, we represent at the lowest possible level of regional aggregation (French NUTS 3 regional maps) yearly weighted averages of components of output change, for each farm. One can look at the results by considering both inter-annual and inter-regional variability.

In the following, we focus our attention on some of the years that have marked French climatology during the study period: 2001, 2003, 2009, 2011, and 2013. The results are presented, in chronological order, in Figures (8)-(12). Among the worst years for droughts on French agriculture are 2003 and 2011.[11] In addition, 2001 and 2013 are remembered for very wet conditions during Spring time, with rainfall exceeding the normal by more than

[10] The analysis at the regional level averages has been repeated without the climatic variables. The results for the inputs' effects and technological adaptation effects obtained when excluding the climatic variables are very similar to the effects obtained when including the climatic variables. On the contrary, the soil effects obtained are very different and compensate with a negative result the effects that are, in reality, due to climatic variables. In the version of the results with climatic variables, the Southwest shows a negative climatic effect but, when excluding the climatic variables, the soil variables in this region absorb part of the negative results in a typical problem of omitted variable bias.

[11] For most of the explanations on weather events in the following paragraphs, to ascertain the weather effects observed, we draw on a variety of information sources among which the ones generously provided by Meteo France and by Guillaume Séchet on http://www.meteo-paris.com/.

50% and 30%, respectively. As an example of a good year from a climatic point of view, the year 2009 is presented. In specific years, which will be introduced chronologically, the climatology had specific effects on crop growth.

Unfortunately, some of these years are remembered as the worst in French climatology and negative records are broken always more often in recent years. One may notice that the years proposed for further scrutiny all occurred since the beginning of this century: in this period, the climatic factors caused dramatic fluctuations in agricultural output.

The decomposition effects calculated for year 2001 are presented in Figure (8). The effect of inputs' change on output shows negative results especially in the breadbasket region of France and towards Bretagne. However, the provinces of Bretagne, Pays de la Loire, Basse and Haute Normandie have positive technological adaptation change and positive soil effects. The effect of the climatic variables is instead widespread strongly negative, especially in the Northern part of the country.

This negativity in climatic variables' effect between 2001 and 2000 is explained by large flooding in Spring in the Northern portion of the country, for the whole April and a good portion of May. Then a late frost occurred over France on June 4th, which swept cereal cultures, especially in the Northern part of the country. The result in the total output change is generally negative for the Northern part of the country and negative in some parts of the Southwest.

The decomposition effects calculated for year 2003 are presented in Figure (9). While the inputs' effect, the technological adaptation change and the soil effects do not have clear regional patterns, the weather effect is negative and regionalized in a band that goes from the Southwest to the Northeast diagonally, with increasing negative effects towards the Southwest. This regionalization is due to a variety of climatic reasons, especially extreme heat during periods of July and August, which hit strongly during that Summer. Large part of the Summer crops, such as sunflower, rapeseed, and maize, are grown in the areas where strong negative effects are reported due to climatic variables.

The annual average anomaly in 2003 on Metropolitan France was +1.3°C on the normal 1971-2000. Repeated droughts occurred in June and July culminating in the August *canicule* (heat wave). Many sites in France have exceeded 40°C maximum temperature in the first half of August. Minimum temperatures were also abnormally high. This extreme phenomenon was due to an air blockage that prevented the hot air from moving away and from circulating freely out of France. In 2003, the temperatures were, in some seasons, above average by 2 or 3°C. Moreover, there was a very warm March and a late frost on April 8-10 to partially stress the winter crops.

The decomposition effects calculated for year 2009 are presented in Figure (10). The soil change effect is quite stable and similar to previous years in different regions. While the technological adaptation change and inputs' change effects are more variable and, in some portions of France, more negative than in other years, the effects of climatic variability are extremely positive across most France. The positiveness of the climatic variables' effect is explainable by the timing of weather events occurred especially in the Spring and Summer of 2009.

The year 2009 had a strong winter with precipitations, both rain and snow in January and February, with average temperature lower than the climate normal. April started with snow but ended with episodes of heat very important for the germination of field crops. Heat and storms (with an isolated hail episode) occur at the end of May. Heat and storms follow one another with a slightly hotter May, June, and July period than the climate normal, and slightly wetter June and July. Since mid-July until mid-August, the heat is pervasive around all France. This period is, however, supported by slightly heavier rains than normal. Isolated storms in the South appear at the end of August and September.

The effects in the breadbasket regions of France and Poitou-Charentes are decidedly positive on output change. The higher humidity in some of the Summer months compensates the slightly positive deviation of the temperature from the climate normal. There is growing evidence (Chambers and Pieralli, 2017; Ortiz-Bobea et al., 2018) that higher rainfall, coupled with higher temperature, is beneficial to crop growth. Even though these studies do not distinguish necessarily the timing of the climatic events, it is most probably during vegetative stages that the incremental heat and rainfall are most important. For 2009, the mean rainfall all over France is lower than the normal for August and September. This non-excessive humidity has the additional positive effect of not allowing pests to grow during maturity stages.

Some of the years in the last five years of the study period, could almost be labeled climatic disasters. The year 2011 surpassed 2003 and broke the record for the hottest year, on average, on metropolitan France since 1900, with a +1.5°C anomaly on the normal 1971-2000. The results of the decomposition for this year are in Figure (11).

While the soil effects are similar between 2009 and 2011, the climatic variables in year 2011 show disastrous effects on French field crop farming. This very negative effect is due to terrible conditions, especially during the Spring time. The Spring 2011 has appeared, at that time, as the hottest (+3°C over the normal) on record in Metropolitan France and the Spring with the highest insolation. For these reasons, this period of the year was strongly affected by a widespread and long drought that had, at the end of May, more than 60 departments rationing water usage.

This drought affecting the Spring and part of the Summer had its origins in the Winter between beginning of year and mid-February. Around mid-March, the weather was very difficult in the South but the drought protracted through March and the first half of April, especially in the North half of France. The first ten days of April were very hot with a water deficit of up to half of the normal in the North. This is the most critical moment because cereals should be germinating but, reportedly, they were not. The South was less hit by this phenomenon in the early Spring but received hail at the end of April.

The month of April 2011 was the driest in a century. Episodes of frost came in early May to weaken the only germinated cereals and heat and drought started again for the rest of May, which was also very dry. Morning frosts came again at the end of May in some of the most important agricultural regions of France, such as Picardie, Champagne, and the Northwest.

The Summer 2011 was also very erratic. In June, episodes of strong rains and hail occurred again, together with heat coming from Northern Africa and above normal temperatures ending the month of June. July was very rainy until mid-August, then heat and storms alternated until the end of October. This weather appears very erratic and, in some cases, some events are occurring in critical moments of the germinative and vegetative growth stages of the plant. The prolonged drought and consequent soil moisture deficit in Spring, originating from low rainfall in the Winter, and the late frosts until end of May seem to have made the difference in 2011.

Finally, the effects of climatic variables for year 2013, together with the other decomposition effects are in Figure (12). The inputs and technological adaptation change effects have been less positive in 2013 than in 2011. At the same time, the soil effects have been similar while the negative weather effects appear less marked but robustly negative. However, the causes of the negative effects for the climatic variables in 2013 are different to those of 2011.

In 2013, the north half of France is kept under snow and cold almost until beginning of April, especially above the Loire river. Apart from Corse, the cold extends with frosting temperatures until the end of April, in this way preventing heat beneficial for crops to set in. Additionally, in May, big phenomena of flooding, frost and extended rains disrupt critical moments of an already delayed plant growth, during important phenological stages for crop outcomes. Storms and hail episodes in June destroy portions of French cultures.

Summer (July, August and September) weather is very hot, but strong storms with time-concentrated large amounts of water alternate to above-normal heat and episodes of hail (tennis ball size), which are dangerous for growing crops (especially maize, oil-seeds, and protein crops). If, on one hand, the prolonged cold weather during Spring has affected cereals like maize and barley more, the heat and storms during Summer have impacted more maize, oil-seed, and protein crops.

The climatic variables' effects are also more volatile year-on-year and changes are observed not only over the years but also between Departments in different years. The variation between Departments in different years is key to understanding the challenges that climatic variability poses to farms in different Departments.

We take into account in particular two representative Departments: one is Saône-et-Loire and the other is Haute-Garonne. Saône-et-Loire, located in the east of France, is the second largest Department in France per utilized agricultural area with more than half a million hectares. Cereals and forage make up more than 80% of the hectares of agricultural land available in the Department, with oil-seeds covering slightly more than 10% (Chambre d'agriculture Saone-et-Loire, 2018). Even though only a minimal amount of land is occupied by vineyards, its share of the agricultural added value is around 27%. In addition to wine production, breeding of suckling cows and dairy production represent around a third of the agricultural value added in Saône-et-Loire.

The second Department is Haute-Garonne. Situated in the South of France, this is the Department surrounding the city of Toulouse. With more than a third of a million hectares of area in agriculture, involved in large-scale farming, this is the first Department in France for extension of wheat. Other cultures include hemp fiber (second Department in France) and sunflower and soybeans (third Department in France).

In the farm results in Table (6) aggregated for confidentiality reasons at the Department level, Saône-et-Loire (FR263) has one of the highest positive technological adaptation change effect on output, a relatively small negative climatic variables' effect and a modestly negative inputs' change effect. However, the Department has suffered large negative extreme effects from climatic events. On one hand, the region was one of the most hit Departments in 2003 when the climatic variables' effect contributed with a staggering -26.6% to the output change between 2002 and 2003. In 2009, the Department was blessed with great weather and the estimated weather effect was +16.4%. However, after that year, the Department has recorded major negative climatic events effects in two of the years in the last five of the study period: -10.3% in 2011 and -6.6% in 2013. Additionally, together with small negative soil effects and large negative technological adaptation change effects from 2010 until 2013, this four-year period eroded approximately 8% of the weighted average Departmental output of 2009.

Haute-Garonne (FR623) in Table (7) instead shows, at the Departmental weighted average level, a positive climatic events' effect (around 1.78%), with positive input (+3.63%) and positive technological change effects (+1.67%). The soil effect is negligible to the third decimal digit at the Departmental average. However, also this Department suffered extremes. In 2003 the Department suffered a -32.32% decrease due to extreme climatic events and it recovered brilliantly in 2004 (21.34%) and 2005 (31.12%). On the contrary, when it was hit again in the double digits in 2013 with a drop of -27.41%, it only recovered partially the year after (23.12%).

One observes in these estimates a lower resilience of regional farming systems in later years with respect to previous periods. This may be due to potentially increasing agricultural crop specialization in some agricultural departments. This increasing specialization may make agriculture more vulnerable to climatic extremes, as also found in Ortiz-Bobea et al. (2018).

5 Conclusions

This article is important because it devises a new economic methodology to decompose output changes from one period to another in different components. From a theoretical point of view, this decomposition methodology is general and can be applied to any context where a production technology is estimated. Some effects may become trivial in the case of only first-order flexible functional approximations to the technology.

The method does not require specific assumptions on the separability of certain inputs to identify the drivers of output changes. Moreover, the type of flexible technology used can be changed to be more or less flexible, without changing the generic economic method proposed. With the same method, one could also think of estimating the components' changes nonparametrically via linear programming.

The quadratic interactions between inputs allow to model input substitutions or complementarities. One could also potentially refine the theoretical method and use more complex decompositions to disentangle contributions to output of specific inputs or even of other outputs (if multiple outputs were important for the characterization of the technology).

From an empirical point of view, this article identifies the contributions of soil, technological adaptation change, farm managed inputs, and climatic variables to changes in agricultural field crop output in France between 1990 and 2015. The proposed method includes the possibility of a farm-specific heterogeneous quadratic technological trend and heterogeneity, allowing for identification of different technological adaptation paths for each farm. The study period is marked by a staggering presence of strong effects due to climatic variables, especially since the beginning of the 21^{st} century.

The variability in agricultural field crop outputs observed in yearly averages in the period 1990-2015 is mainly due to climatic variables (58.5% of the variation on average), followed by changes in inputs (22% of variation), technological adaptation (18% of variation), and soil characteristics change (1.5% of variation). The already important portion of variability due to changes in climatic variables increases dramatically going from the period before to the period after 2000. The model represents very precisely the year-to-year variability of observed output changes in field crop production in France.

This article also shows the variability among different regions spatially. The variation however, especially in the largest year-to-year variable driver, which is the weather expressed by the climatic variables, is strongly muted by regional averaging. The spatial patterns, when averaging regionally, are most marked in soil characteristics. Soils with regionally averaged best contributions to output change are shown to be more acidic and with higher soil carbon concentration.

Some of the effects on output change from most difficult years of French climatology in the period 2000-2015 are captured correctly by the method. Climatic variables show either positive or negative impacts depending on the year analyzed. Some climatic events, such as persistent heatwaves and droughts or extended cold periods during Spring or Summer, cause disruptive effects on French field crop agricultural output. For example, the impacts of the 2003 and 2011 abnormal Spring and Summer heat together with the impacts of excessive rains (for 2001 and 2013) or extended cold (for 2013) on the variation of field crop output are correctly identified.

These conclusions are nonetheless only valid for this sample and for these technology assumptions. This is only a first step in reconsidering the impact of climatic inputs and soils at a disaggregated farm level, with a simple but general economic methodology. This general economic methodology can be applied to disentangle not only short-term changes in production but also, more generally, long-term effects by redefining appropriately the time 0 and time 1 of reference. For example, one could measure the impacts of climate change by considering long-term differences from a climate normal. The long-term climatic effect would be measured as the effect originated from the difference between the average temperature in the 30 years, a climate normal (defined as a common t_0), and each of the years in the period considered (to be defined as t_1). This example shows the flexibility of the methodology derived in this article and helps in imagining a series of different contributions dedicated to exploiting this methodology.

Finally, considering the importance of long panels in the evaluation of climatic inputs' importance, this study is only an approximation to the results obtainable if longer data series were available. Once these data were to become available, an even more precise study would be possible.

6 Figures

Figure (1) Graphical representation of the problem of path dependency

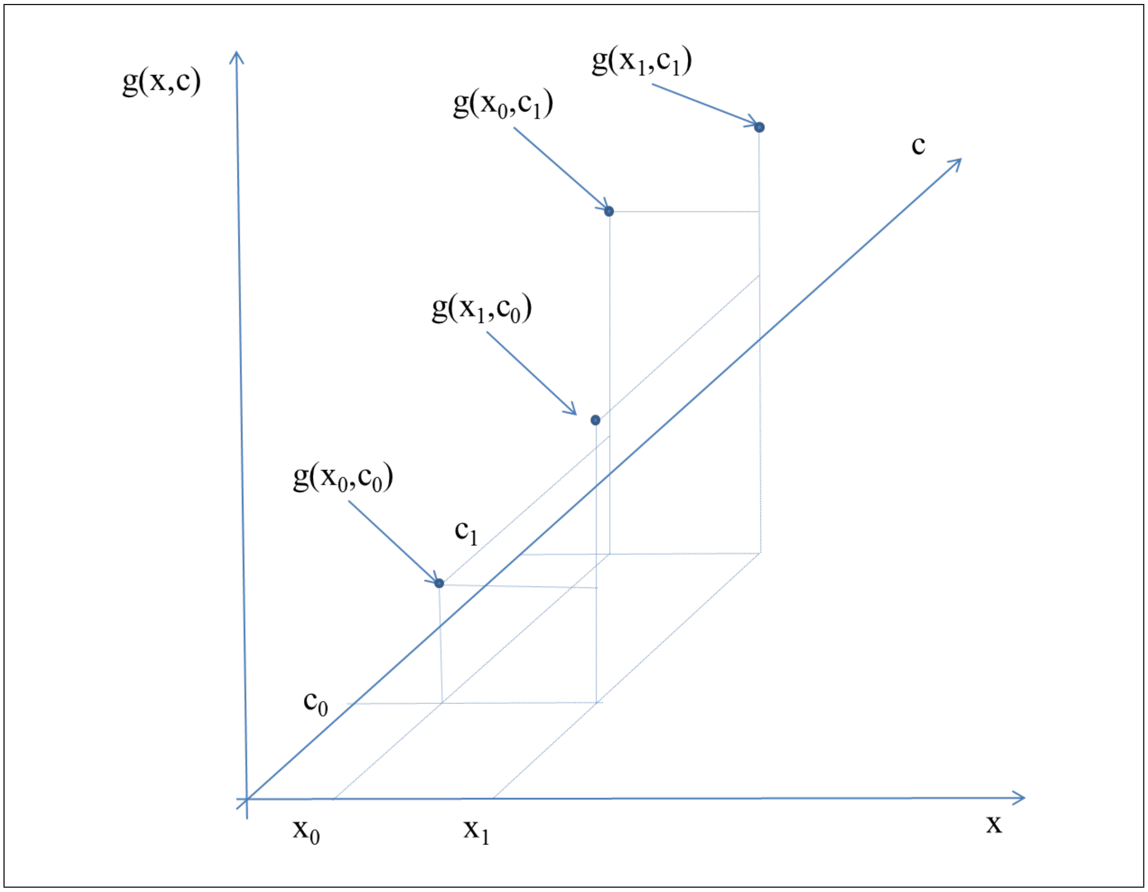


Figure (2) Graphical representation of the spatial aggregation problem faced with a farmer and different grid points where climatic information is present, French Dordogne NUTS 3 region

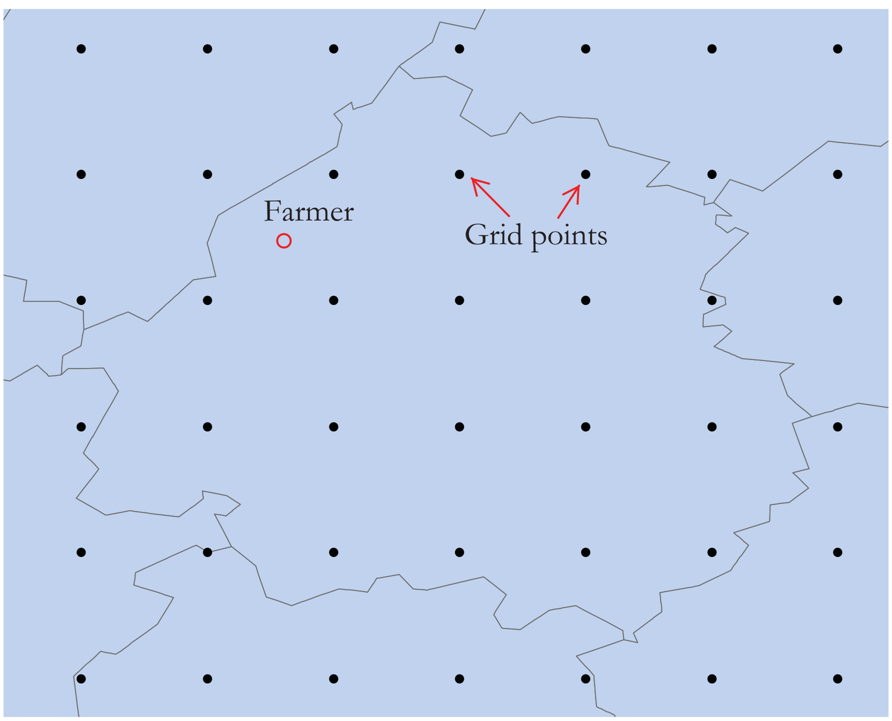


Figure (3) Sample-weighted yearly averages of components of output change decomposition into soil, weather, farm managed inputs, and technical adaptation change, France, 1990-2015

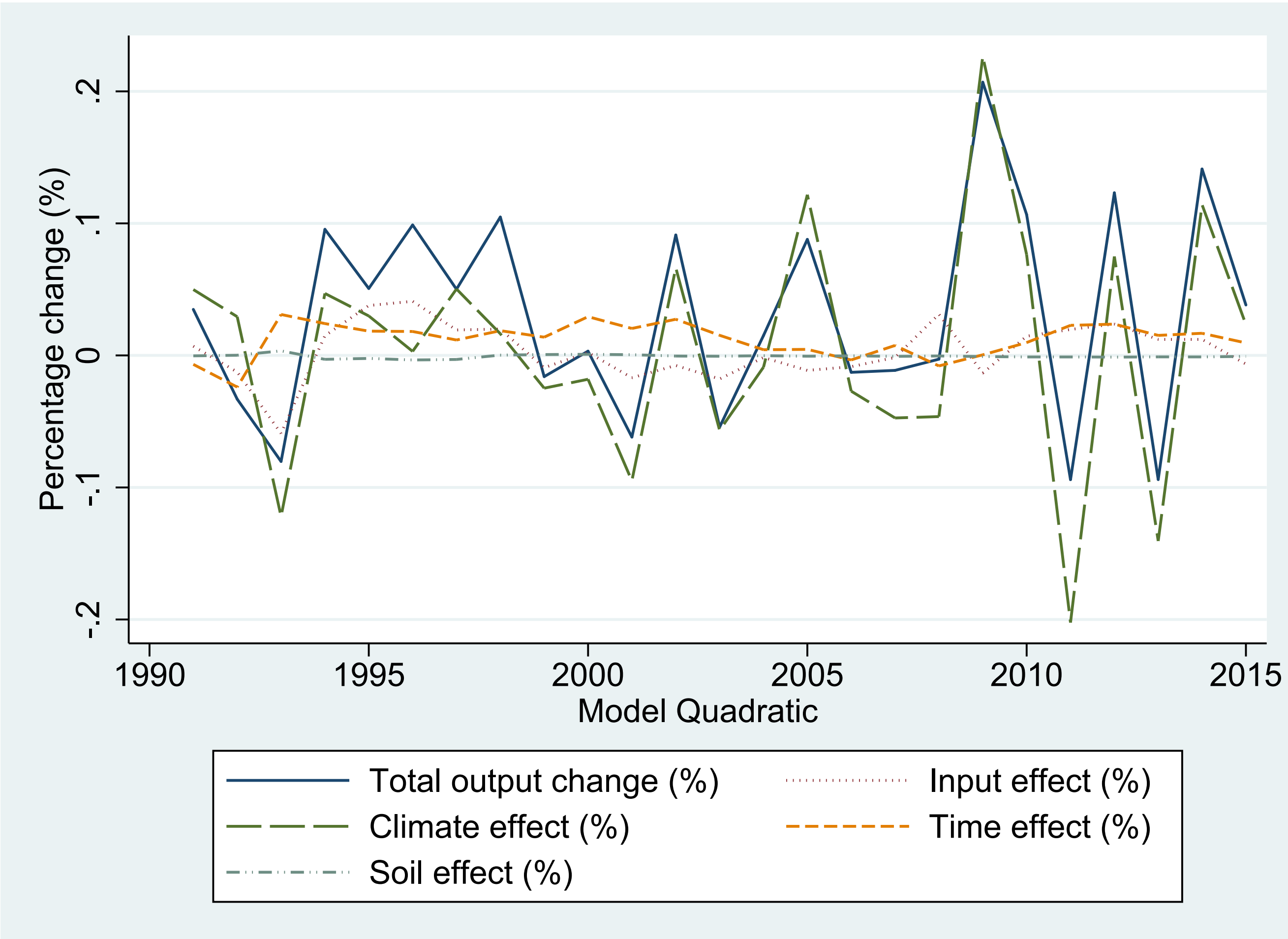


Figure (4) Percentages of yearly average decompositions of absolute field crop output change due to soil, weather, farm managed inputs, and technical adaptation change, France, 1990-2015

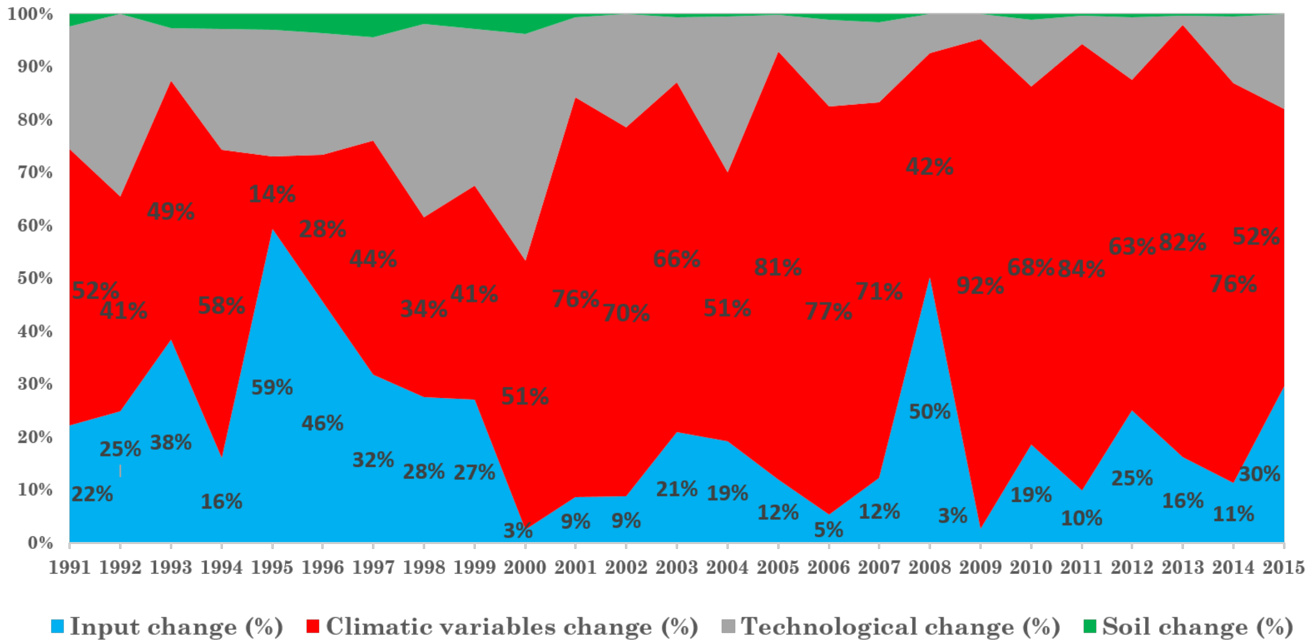


Figure (5) Sample-weighted yearly averages of absolute output changes in counterfactual yearly averages of 1) soil change, 2) soil and technical change, 3) soil, technical, input change, 4) soil, technical, input and climatic events change, France, 1990-2015

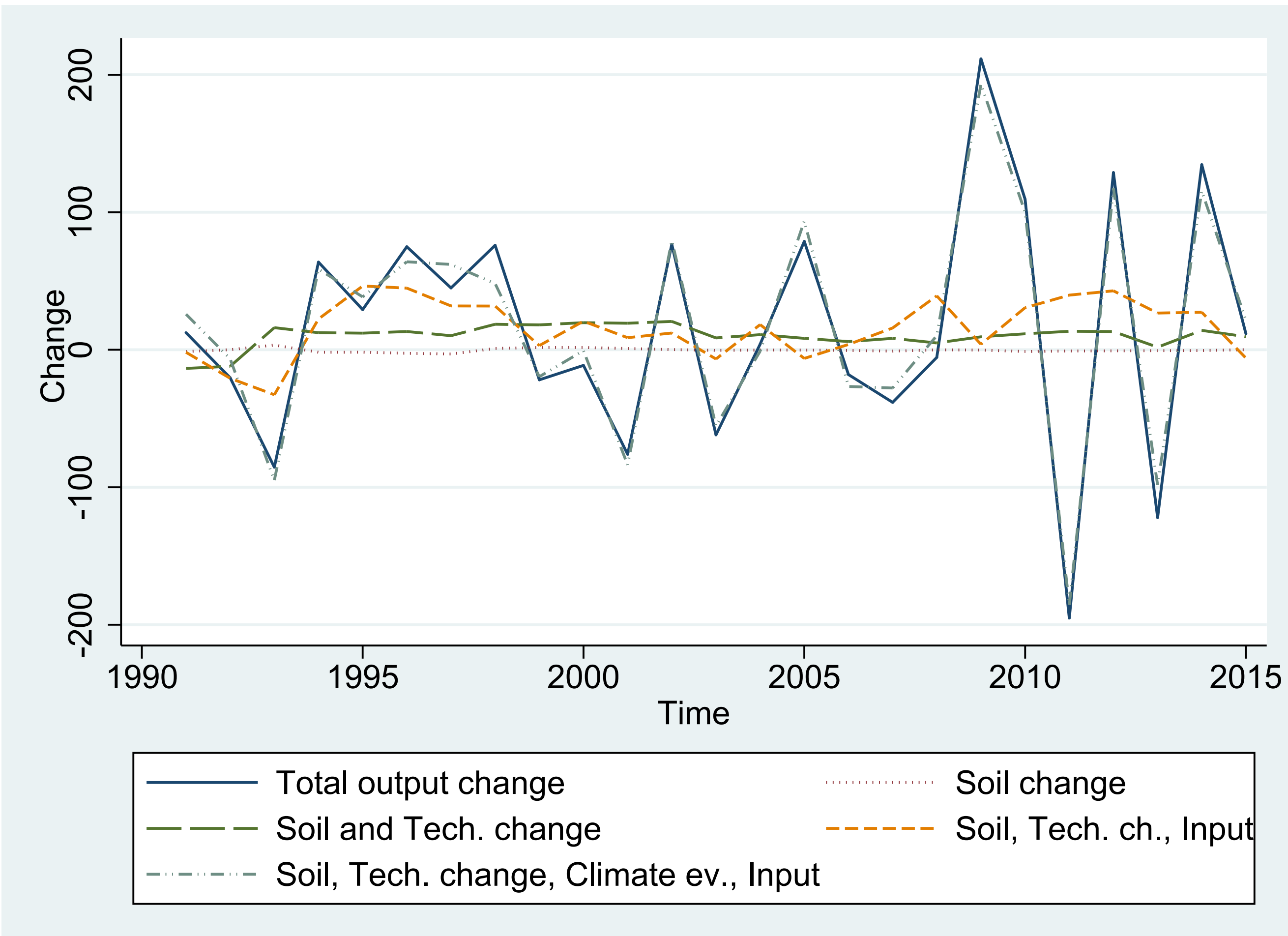


Figure (6) Yearly weighted averages of components of output decomposition into counterfactual yearly averages of 1) soil effect, 2) soil and technical effect, 3) soil, technical, input effect, 4) soil, technical, input and climatic events effect, France, 1990-2015

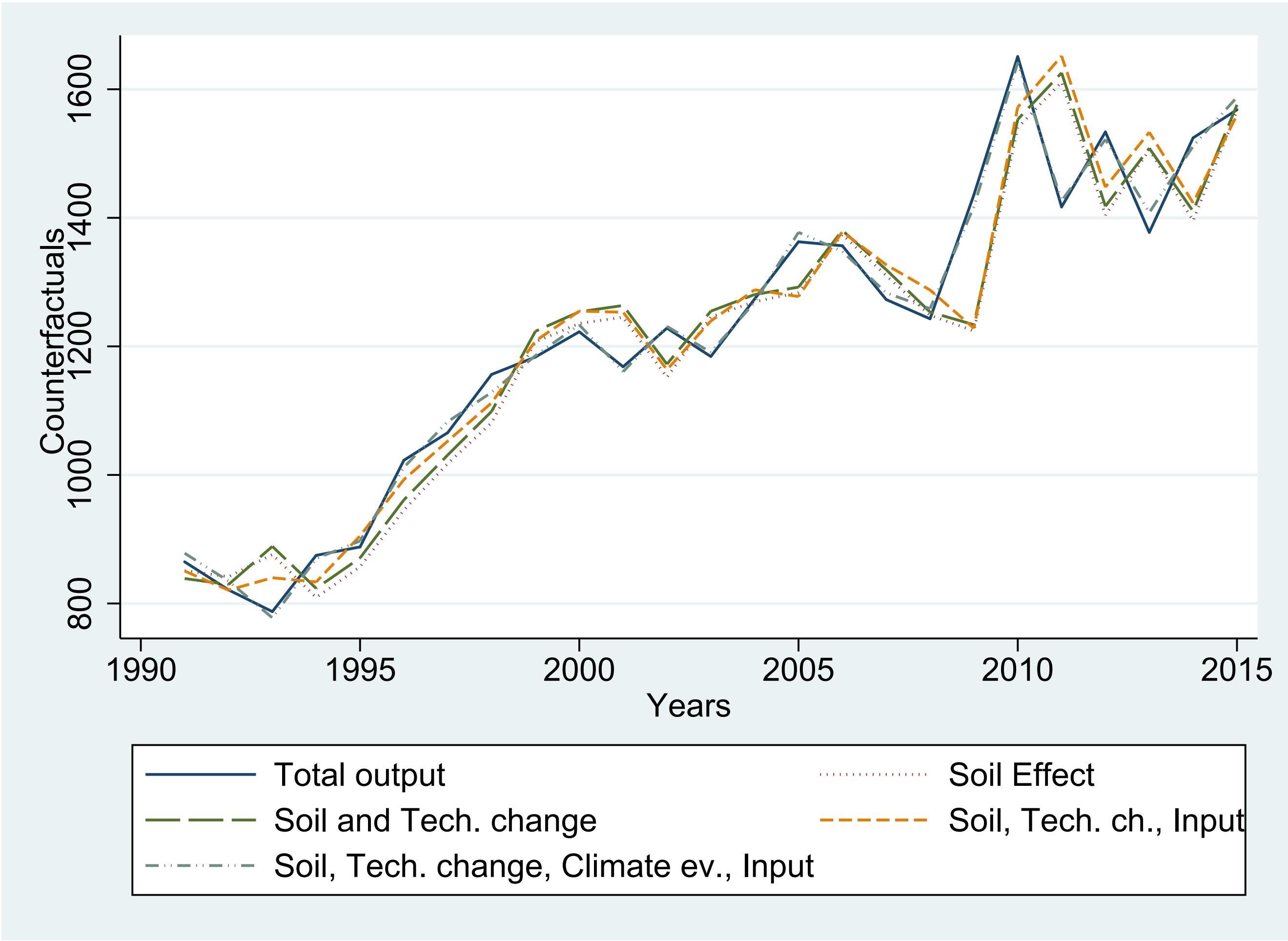


Figure (7) Regional (NUTS 3) averages of components of output change decomposition into input, technical change, soil, and weather, France, 1990-2015

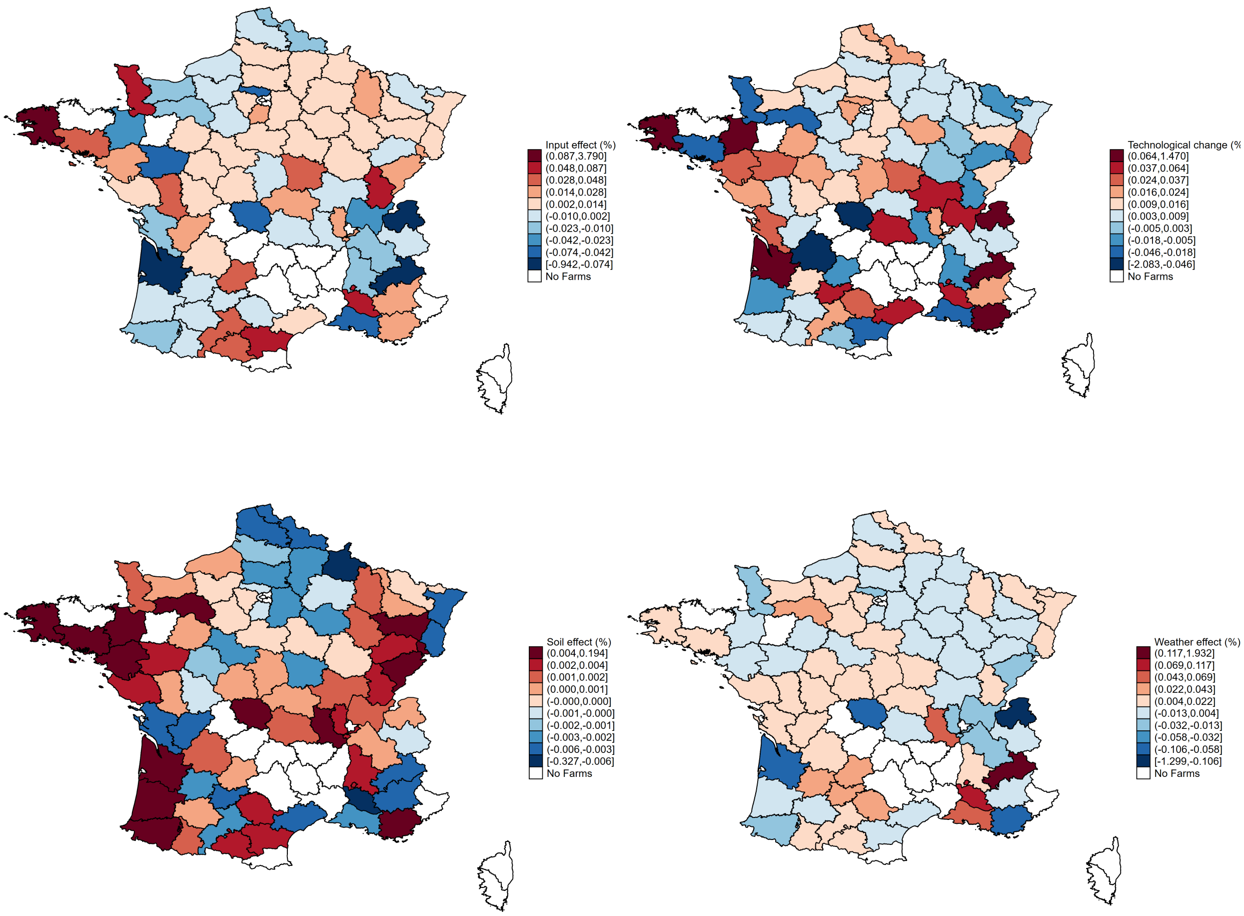


Figure (8) Graphical representation of the decomposition of output change averages in NUTS 3 between 2001 and 2000

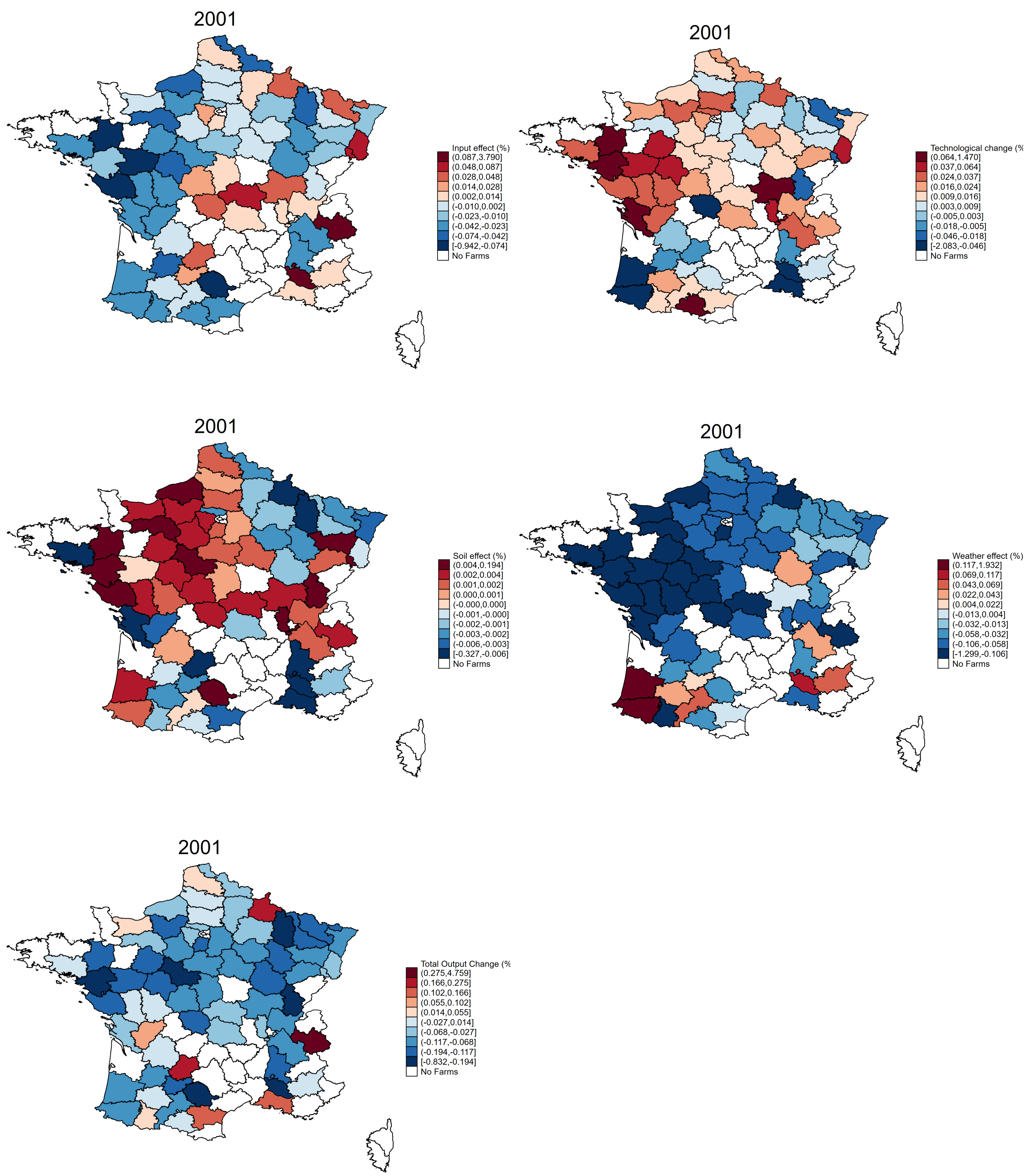


Figure (9) Graphical representation of the decomposition of output change averages in NUTS 3 between 2003 and 2002

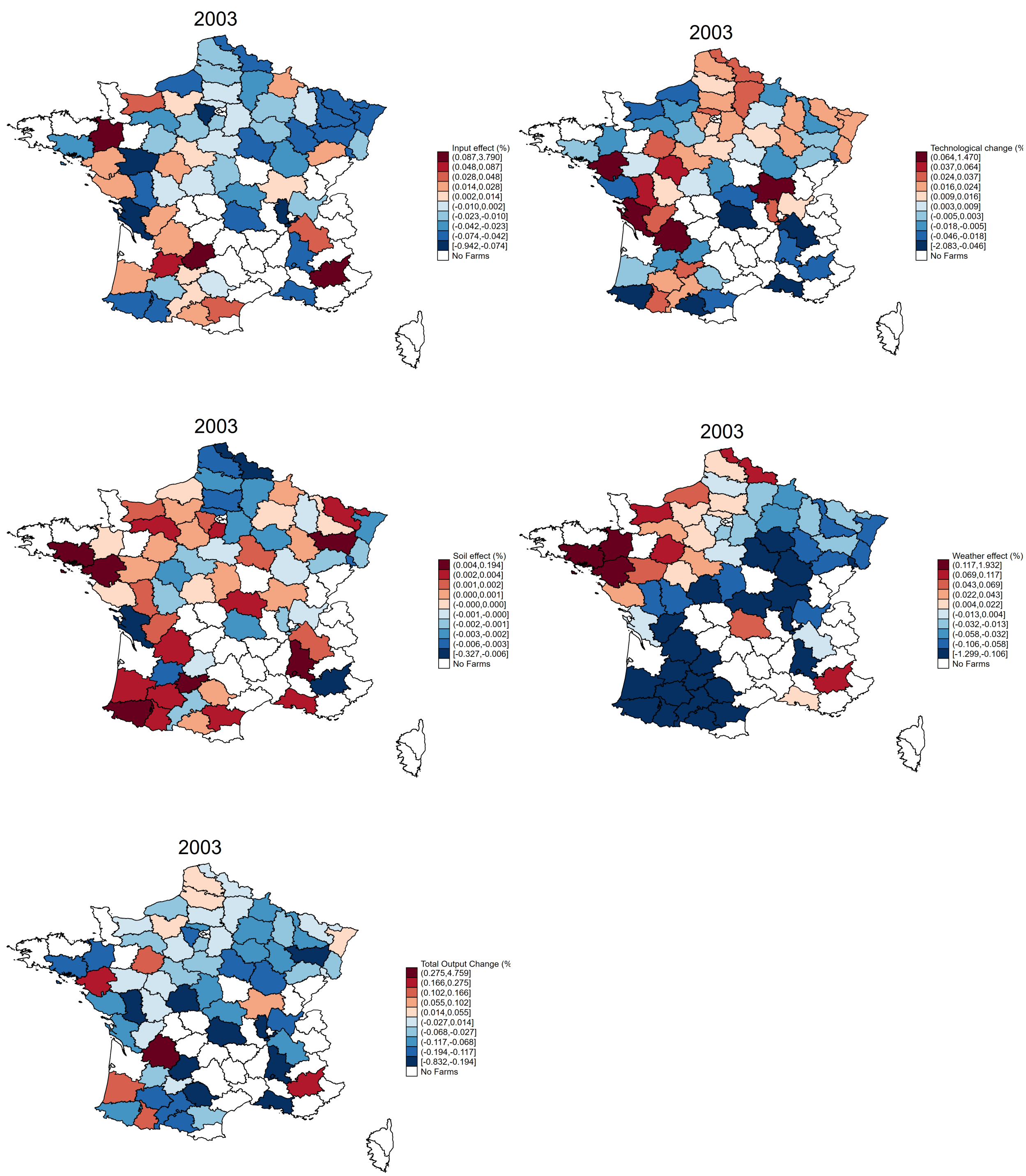


Figure (10) Graphical representation of the decomposition of output change averages in NUTS 3 between 2009 and 2008

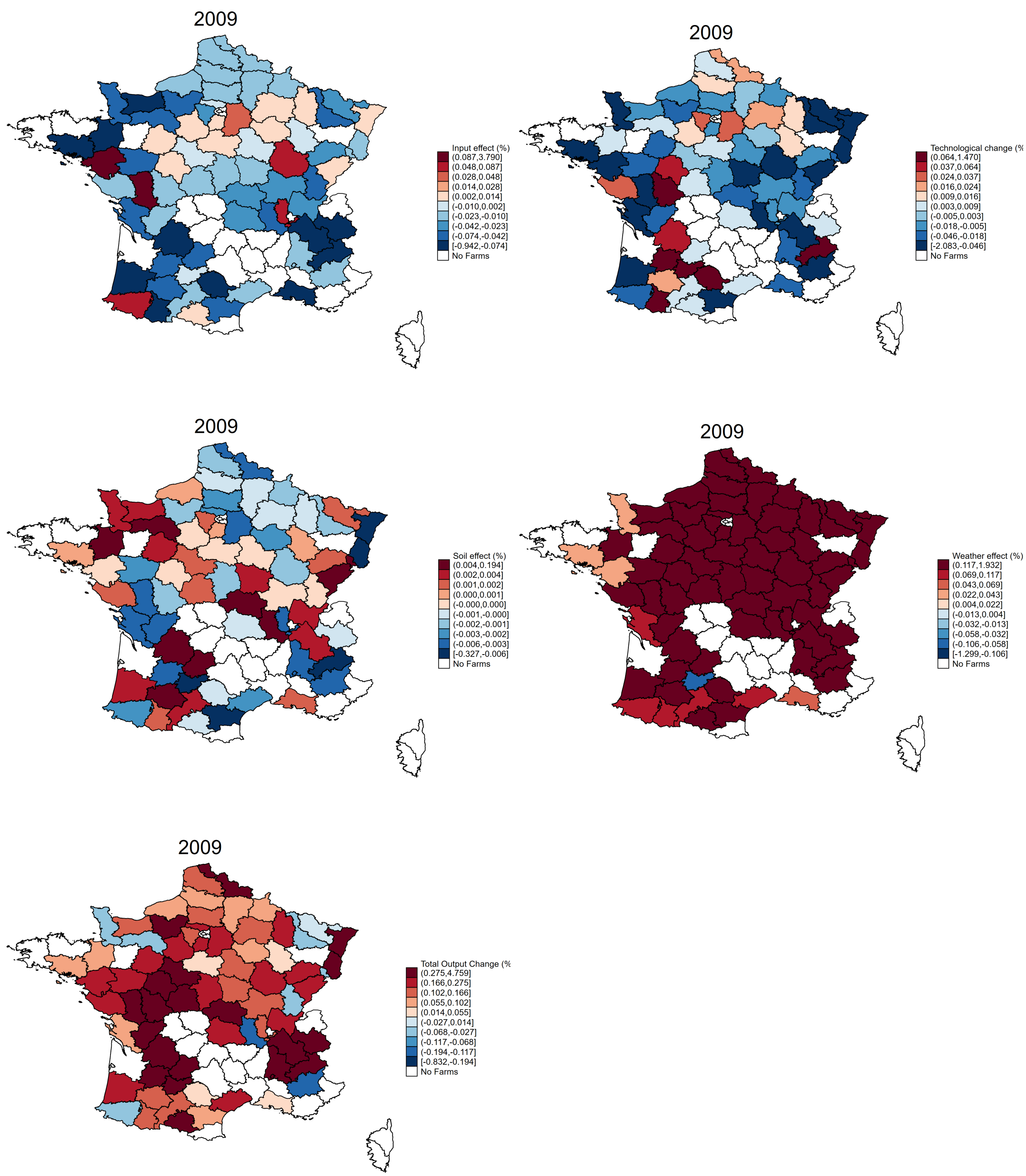


Figure (11) Graphical representation of the decomposition of output change averages in NUTS 3 between 2011 and 2010

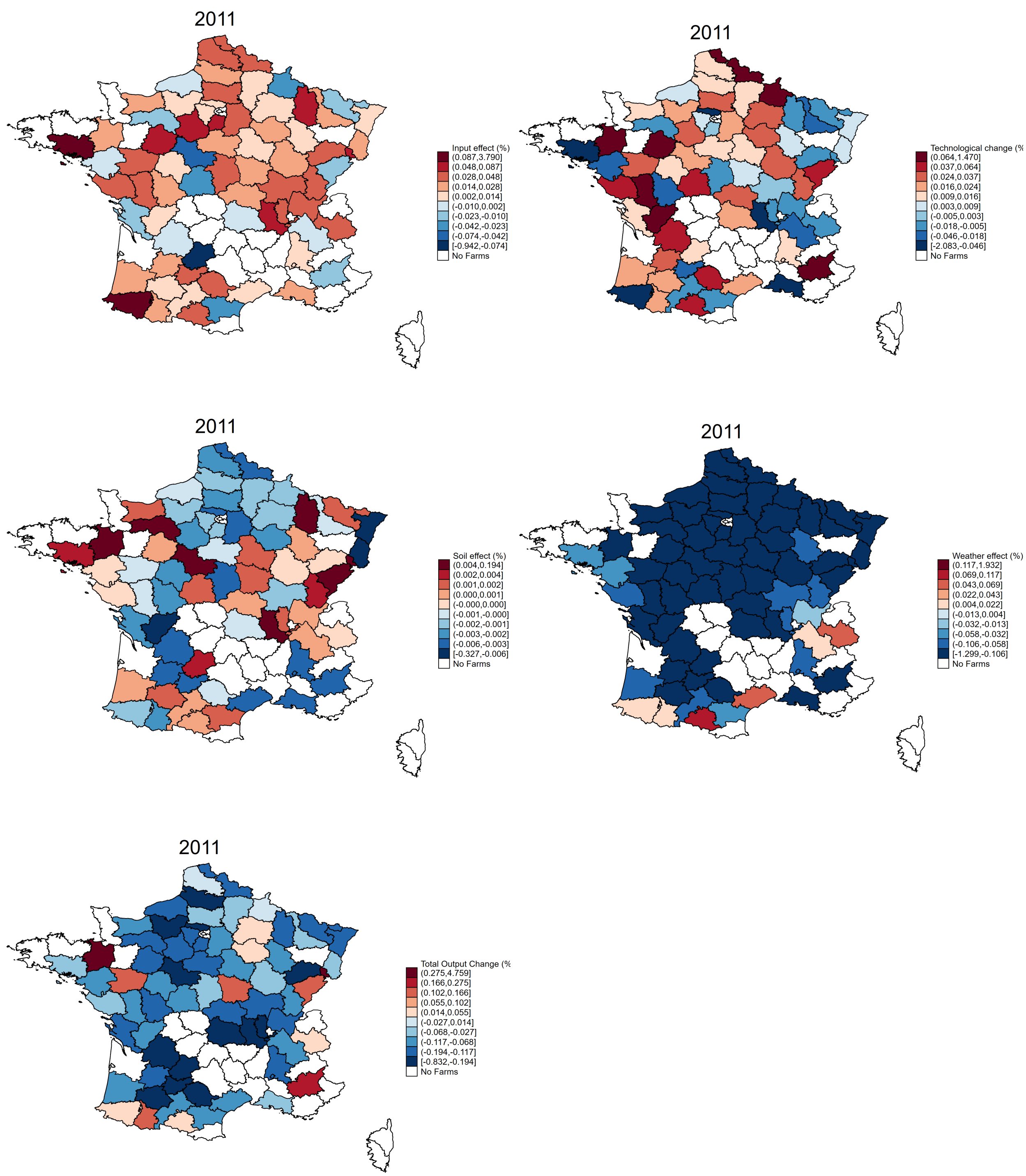
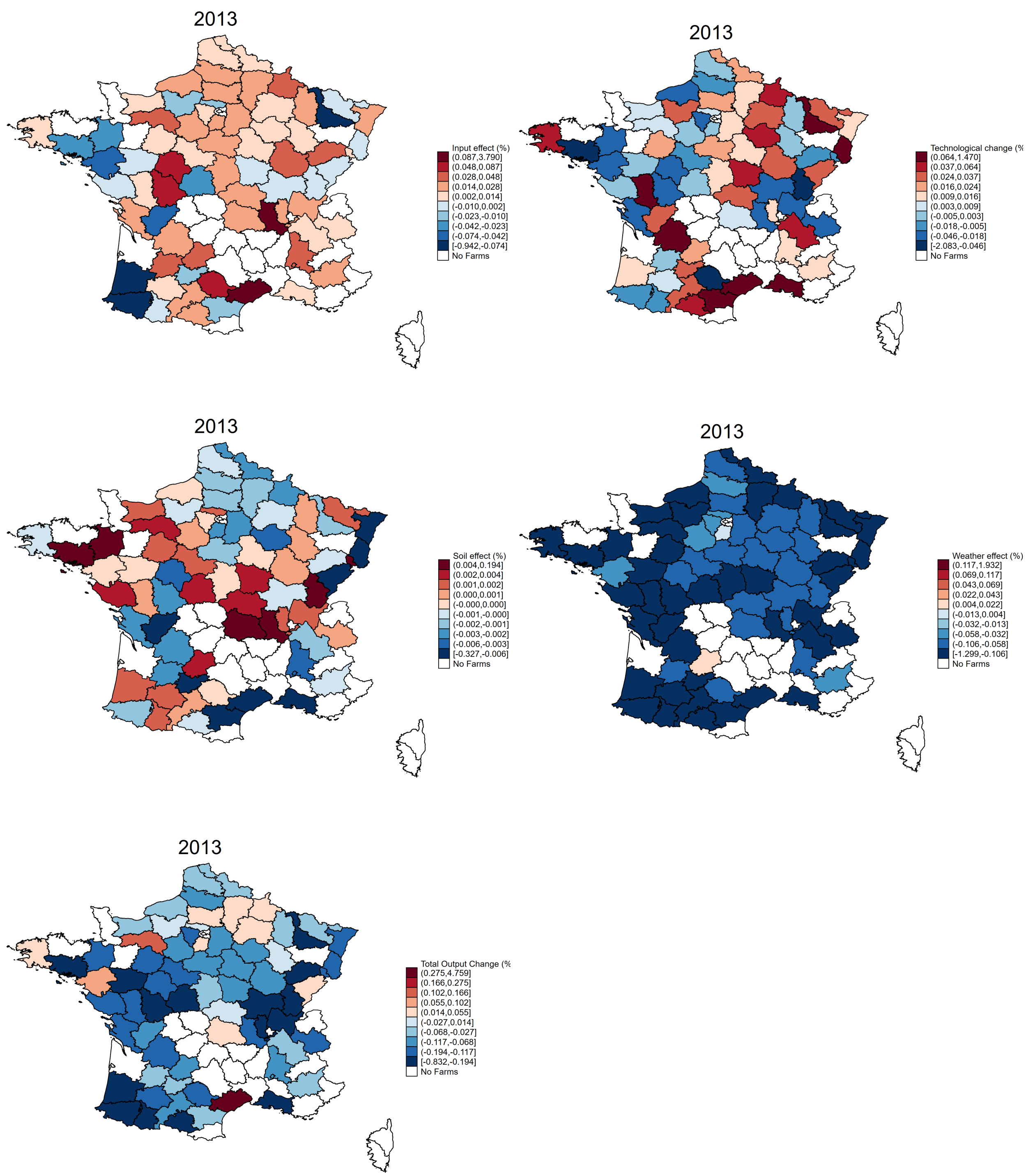


Figure (12) Graphical representation of the decomposition of output change averages in NUTS 3 between 2013 and 2012



7 Tables

Table (1) Summary statistics of inputs, output, soil-quality physical characteristics, and precipitation

	Mean	**St.dev.**	**Minimum**	**Maximum**
Output (Implicit quantities)	1462.595	962.551		
Labor (A.W.U.)	1.269	0.501		
Land (ha)	124.775	71.270		
Other Inputs (Implicit quantities)	1714.682	1062.453		
Total Rainfall (month 01 of year)	67 262.170	57 208.220	336.761	866 292
Total Rainfall (month 02 of year)	59 310.150	52 203.780	57.756	828 701.800
Total Rainfall (month 03 of year)	55 896.550	54 734.640	3.114	813 858.300
Total Rainfall (month 04 of year)	68 159.060	63 514.480	51.676	754 492.900
Total Rainfall (month 05 of year)	76 792.210	60 017.570	573.168	832 868
Total Rainfall (month 06 of year)	71 106.090	58 914.670	448.165	982 489.600
Total Rainfall (month 07 of year)	75 069.960	63 398.230	332.545	1 093 341
Total Rainfall (month 08 of year)	74 345.470	66 152.020	404.634	1 299 900
Total Rainfall (month 09 of year)	70 404.310	60 925.870	369.056	1 068 565
Total Rainfall (month 10 of year)	85 033.060	68 222.150	976.709	1 109 921
Total Rainfall (month 11 of year)	84 296.710	70 473.510	397.041	863 904.200
Total Rainfall (month 12 of year)	84 377.310	69 529.800	861.729	997 308.400
S.O. Carbon (Tons in first 10 cm)	1800.858	1167.004	75.687	13 405.270
pH	7.346	0.489	5.870	8.328
Observations	25 892			

Table (2) Summary statistics of thermal time exposure (night only)

	Mean	**St.dev.**	**Minimum**	**Maximum**
TT (Spring night 4 plus and minus 2°C)	12.418	2.399	3.832	21.549
TT (Summer night 4 plus and minus 2°C)	0.758	0.674	0	4.502
TT (Winter night 4 plus and minus 2°C)	17.303	3.776	4.060	28.458
TT (Autumn night 4 plus and minus 2°C)	14.397	3.034	5.546	25.195
TT (Spring night 9 plus and minus 2°C)	16.541	2.057	11.124	27.579
TT (Summer night 9 plus and minus 2°C)	8.769	3.202	0.027	19.394
TT (Winter night 9 plus and minus 2°C)	19.103	5.038	8.500	33.453
TT (Autumn night 9 plus and minus 2°C)	7.784	4.162	0	25.124
TT (Spring night 14 plus and minus 2°C)	6.843	2.482	1.521	16.644
TT (Summer night 14 plus and minus 2°C)	23.003	3.157	7.017	32.986
TT (Winter night 14 plus and minus 2°C)	7.838	3.430	0.777	25.251
TT (Autumn night 14 plus and minus 2°C)	0.373	0.576	0	5.447
TT (Spring night 19 plus and minus 2°C)	0.882	0.656	0	5.027
TT (Summer night 19 plus and minus 2°C)	12.476	4.528	2.694	30.214
TT (Winter night 19 plus and minus 2°C)	0.839	1.044	0	8.399
TT (Autumn night 19 plus and minus 2°C)	0.001	0.010	0	0.231
TT (Spring night 24 plus and minus 2°C)	0.029	0.052	0	0.510
TT (Summer night 24 plus and minus 2°C)	1.892	1.784	0	16.796
TT (Winter night 24 plus and minus 2°C)	0.022	0.065	0	0.882
TT (Autumn night 24 plus and minus 2°C)	3.120×10^{-6}	0.000	0	0.004
TT (Spring night 29 plus and minus 2°C)	9.470×10^{-6}	0.000	0	0.022
TT (Summer night 29 plus and minus 2°C)	0.094	0.192	0	2.870
TT (Winter night 29 plus and minus 2°C)	0.000	0.000	0	0.015
TT (Autumn night 29 plus and minus 2°C)	0	0	0	0
TT (Spring night 34 plus and minus 2°C)	0	0	0	0
TT (Summer night 34 plus and minus 2°C)	0.000	0.003	0	0.083
Observations	25 892			

Table (3) Summary statistics of thermal time exposure (day only)

	Mean	**St.dev.**	**Minimum**	**Maximum**
TT (Spring day 4 plus and minus 2°C)	4.484	1.905	0.419	12.724
TT (Summer day 4 plus and minus 2°C)	0.131	0.129	0	0.936
TT (Winter day 4 plus and minus 2°C)	7.141	2.308	0.638	14.388
TT (Autumn day 4 plus and minus 2°C)	7.907	2.309	1.853	15.795
TT (Spring day 9 plus and minus 2°C)	14.104	3.499	4.153	26.331
TT (Summer day 9 plus and minus 2°C)	2.258	1.098	0	6.572
TT (Winter day 9 plus and minus 2°C)	12.093	2.709	4.767	18.781
TT (Autumn day 9 plus and minus 2°C)	8.752	2.824	1.083	18.153
TT (Spring day 14 plus and minus 2°C)	17.961	2.399	11.645	29.564
TT (Summer day 14 plus and minus 2°C)	13.644	4.826	1.161	29.117
TT (Winter day 14 plus and minus 2°C)	10.052	2.934	3.792	26.141
TT (Autumn day 14 plus and minus 2°C)	2.461	2.107	0	11.850
TT (Spring day 19 plus and minus 2°C)	10.355	3.083	1.404	22.647
TT (Summer day 19 plus and minus 2°C)	28.609	5.354	8.382	47.252
TT (Winter day 19 plus and minus 2°C)	3.948	2.208	0.091	12.653
TT (Autumn day 19 plus and minus 2°C)	0.148	0.343	0	3.608
TT (Spring day 24 plus and minus 2°C)	3.549	1.945	0.087	12.261
TT (Summer day 24 plus and minus 2°C)	20.745	4.280	4.743	33.773
TT (Winter day 24 plus and minus 2°C)	0.763	1.015	0	6.433
TT (Autumn day 24 plus and minus 2°C)	0.004	0.032	0	0.662
TT (Spring day 29 plus and minus 2°C)	0.416	0.494	0	3.713
TT (Summer day 29 plus and minus 2°C)	8.180	4.182	0.120	29.894
TT (Winter day 29 plus and minus 2°C)	0.042	0.140	0	1.724
TT (Autumn day 29 plus and minus 2°C)	0.000	0.001	0	0.055
TT (Spring day 34 plus and minus 2°C)	0.007	0.044	0	0.699
TT (Summer day 34 plus and minus 2°C)	1.348	1.402	0	16.151
TT (Winter day 34 plus and minus 2°C)	0.000	0.003	0	0.127
TT (Autumn day 34 plus and minus 2°C)	0	0	0	0
TT (Spring day 39 plus and minus 2°C)	0	0	0	0
TT (Summer day 39 plus and minus 2°C)	0.085	0.321	0	3.940
Observations 25892				

Table (4) Summary statistics of thermal time exposure (day only)

	Mean	**St.dev.**	**Minimum**	**Maximum**
TT (Winter day 39 plus and minus 2°C)	0	0	0	0
TT (Autumn day 39 plus and minus 2°C)	0	0	0	0
TT (Spring day 44 plus and minus 2°C)	0	0	0	0
TT (Summer day 44 plus and minus 2°C)	0.000	0.001	0	0.049
TT (Winter day 44 plus and minus 2°C)	0	0	0	0
TT (Autumn day 44 plus and minus 2°C)	0	0	0	0
Observations 25892				

Table (5) Averages of decomposition results by year

Year	Output change (%)	XΔ (%)	CΔ (%)	TΔ (%)	SΔ (%)	Output (i.q.)	XΔ	CΔ	TΔ	SΔ
1990						858.2936				
1991	0.0207	0.0137	0.0323	-0.0143	-0.0015	876.0623	11.7161	27.7041	-12.2535	-1.3203
1992	-0.0436	-0.0100	0.0162	-0.0138	0.0001	837.8638	-8.7358	14.2308	-12.0899	0.0459
1993	-0.0671	-0.0582	-0.0744	0.0151	0.0041	781.6266	-48.7849	-62.3350	12.6583	3.3990
1994	0.1529	0.0127	0.0465	0.0182	-0.0023	901.1098	9.9605	36.3093	14.2308	-1.8311
1995	0.0184	0.0381	-0.0088	0.0154	-0.0020	917.7222	34.3125	-7.9281	13.8578	-1.7962
1996	0.1408	0.0344	0.0208	0.0173	-0.0028	1046.9170	31.5870	19.1316	15.8435	-2.5998
1997	0.0471	0.0207	0.0288	0.0127	-0.0030	1096.2700	21.6478	30.1986	13.3112	-3.0976
1998	0.0786	0.0121	0.0149	0.0161	0.0009	1182.4100	13.2453	16.3308	17.5980	0.9327
1999	0.0090	-0.0128	-0.0191	0.0139	0.0014	1192.9940	-15.0805	-22.6342	16.4345	1.6624
2000	0.0206	0.0009	-0.0179	0.0151	0.0014	1217.5270	1.0714	-21.3836	18.0280	1.6475
2001	-0.0305	-0.0086	-0.0759	0.0151	0.0007	1180.4150	-10.4814	-92.4461	18.3647	0.8985
2002	0.0453	-0.0071	0.0569	0.0173	0.0001	1233.8720	-8.4381	67.2199	20.4660	0.1368
2003	-0.0453	-0.0124	-0.0394	0.0073	-0.0004	1178.0010	-15.3131	-48.6635	9.0558	-0.4751
2004	0.0803	0.0062	-0.0164	0.0095	-0.0002	1272.5920	7.2942	-19.3579	11.2089	-0.2295
2005	0.0676	-0.0115	0.0785	0.0067	-0.0002	1358.6780	-14.6267	99.8808	8.5531	-0.2486
2006	-0.0445	-0.0015	-0.0225	0.0047	-0.0004	1298.2670	-2.0968	-30.5268	6.4181	-0.4854
2007	-0.0561	0.0058	-0.0336	0.0071	-0.0008	1225.3900	7.5549	-43.6509	9.2703	-1.0018
2008	-0.0026	0.0280	-0.0236	0.0041	-0.0001	1222.1660	34.2712	-28.9462	5.0189	-0.0860
2009	0.1527	-0.0045	0.1549	0.0079	-0.0002	1408.8350	-5.5015	189.2865	9.6539	-0.2327
2010	0.1553	0.0135	0.0493	0.0091	-0.0009	1627.6800	19.0127	69.4603	12.8571	-1.2677
2011	-0.1416	0.0161	-0.1386	0.0088	-0.0006	1397.2420	26.2800	-225.5942	14.3628	-0.9185
2012	0.0842	0.0212	0.0533	0.0100	-0.0006	1514.8390	29.6316	74.4624	14.0125	-0.7890
2013	-0.0907	0.0164	-0.0825	0.0017	-0.0004	1377.3700	24.8089	-124.9824	2.5243	-0.6518
2014	0.1067	0.0096	0.0640	0.0106	-0.0004	1524.3970	13.1976	88.1306	14.6584	-0.5865
2015	0.0287	-0.0102	0.0181	0.0062	0.0000	1568.1390	-15.5733	27.5795	9.4330	0.0248

Table (6) Averages of decomposition results by region, part a

Region	Output (%)	XΔ (%)	CΔ (%)	TΔ (%)	SΔ (%)	Output (i.q.)	XΔ	CΔ	TΔ	SΔ
Seine-et-Marne	0.0222	0.0037	0.0042	0.0092	-0.0022	1339.2080	10.6637	0.6413	14.7757	-2.2980
Yvelines	0.0461	0.0085	0.0050	0.0179	0.0002	1933.3550	26.8611	2.9684	35.8273	0.4946
Essonne	0.0303	0.0183	-0.0050	0.0082	-0.0004	1606.8850	16.8775	-3.6801	16.1470	0.3482
Val-d'Oise	-0.0299	-0.0444	-0.0178	0.0187	-0.0005	905.2146	-18.6846	-8.3634	5.8319	-0.3451
Ardennes	0.0144	0.0088	0.0006	0.0050	-0.0075	788.8511	3.8055	-0.8670	2.7964	-3.4881
Aube	0.0283	0.0056	-0.0030	0.0174	-0.0019	1089.4070	5.4796	-3.0772	18.0343	-1.2568
Marne	0.0154	0.0040	0.0013	0.0072	-0.0005	1759.1270	5.3113	2.0300	13.7706	-0.3528
Haute-Marne	0.0139	0.0058	0.0037	0.0005	0.0011	1184.2590	5.0805	3.0482	-5.2498	1.7829
Aisne	0.0151	0.0031	0.0014	0.0088	-0.0019	1748.2790	3.6246	-1.3151	12.2885	-1.3192
Oise	0.0280	0.0040	0.0007	0.0129	-0.0019	1263.4060	5.2007	0.2291	11.3865	-1.3823
Somme	0.0352	0.0075	0.0054	0.0091	-0.0015	2285.6630	16.7015	9.9222	14.1703	-1.7789
Eure	0.0167	-0.0050	0.0084	0.0046	-0.0001	1564.7550	-4.1734	-0.0645	5.8367	0.5777
Seine-Maritime	0.0236	-0.0083	0.0013	0.0133	0.0010	1358.1790	2.9725	2.3178	16.3794	0.4068
Cher	0.0321	-0.0004	0.0065	0.0168	0.0008	1569.0510	-0.1055	2.4471	16.8998	1.0168
Eure-et-Loir	0.0293	0.0015	0.0082	0.0083	-0.0001	1358.7200	3.7490	2.6843	13.1274	0.1789
Indre	0.0440	0.0089	0.0123	0.0095	0.0004	986.3963	4.0380	3.6080	11.5193	0.3953
Indre-et-Loire	0.0506	0.0128	0.0057	0.0185	-0.0011	1059.0570	9.2753	1.7168	20.0108	-0.8206
Loir-et-Cher	0.0306	0.0036	0.0011	0.0084	-0.0016	1131.3620	0.9925	-5.6676	10.6125	-1.1254
Loiret	0.0278	0.0036	0.0088	0.0147	-0.0003	1393.9420	5.2782	3.2569	8.4056	-0.1710
Calvados	0.0279	-0.0109	0.0136	0.0118	0.0003	1190.9740	-0.6926	7.5066	12.3378	1.1834
Manche	0.2713	0.0633	-0.0236	-0.0231	0.0016	1051.9170	26.8763	-10.7433	-21.0199	1.4621
Orne	-0.0121	-0.0172	0.0285	-0.0364	0.0044	1206.8660	-18.9582	7.1088	-17.7637	4.3987
Côte-d'Or	0.0328	0.0126	-0.0008	0.0026	-0.0001	1261.5060	7.4381	-2.5579	-0.7873	1.0116

Table (7) Averages of decomposition results by region, part b

Region	Output (%)	XΔ (%)	CΔ (%)	TΔ (%)	SΔ (%)	Output (i.q.)	XΔ	CΔ	TΔ	SΔ
Nièvre	0.0917	0.0358	0.0137	0.0268	-0.0019	1001.1900	28.6267	17.4343	16.9483	-2.5925
Saône-et-Loire	0.0361	-0.0033	-0.0076	0.0479	0.0019	1241.6420	28.9724	-5.1852	16.7855	-0.3409
Yonne	0.0220	0.0024	0.0001	0.0079	-0.0002	1392.0360	7.7177	-0.9717	5.0764	-1.0545
Nord	0.0269	-0.0104	0.0191	0.0162	-0.0045	1026.1810	-0.8410	4.6891	11.9383	-2.3241
Pas-de-Calais	0.0243	0.0015	0.0033	0.0136	-0.0036	1442.5940	8.3130	1.9530	12.7855	-2.1382
Meurthe-et-Moselle	0.0131	0.0056	0.0027	0.0091	0.0003	1305.0050	5.5291	1.9007	3.8460	1.8619
Meuse	0.0392	0.0165	0.0073	0.0030	0.0010	1824.8240	19.5092	5.0650	3.5197	2.5712
Moselle	0.0301	0.0012	0.0071	-0.0082	0.0002	1940.5210	11.1607	2.9956	7.8944	-0.4845
Vosges	0.0461	0.0142	-0.0113	0.0103	0.0125	1704.7190	16.6858	-31.2100	32.5724	25.1439
Bas-Rhin	0.0148	0.0051	0.0071	0.0074	-0.0054	824.6365	4.7915	-0.4986	8.0430	-2.8281
Haut-Rhin	0.0401	0.0077	0.0141	0.0295	-0.0038	969.0281	8.1104	2.0974	8.9711	-1.6767
Doubs	0.0509	0.0222	-0.0153	0.0119	0.0246	1231.5650	17.2237	-9.7866	-9.1239	48.3921
Jura	0.1032	0.0773	0.0155	-0.0171	0.0035	829.4898	46.9898	-0.3415	-16.2380	4.0920
Haute-Saône	0.0122	-0.0027	-0.0019	-0.0072	0.0036	1306.4750	-4.3255	-8.2400	-2.1013	3.1865
Territoire-de-Belfort	0.0208	0.0265	-0.0178	-0.0215	0.0124	445.5884	3.9556	-5.1471	-5.5193	4.3649
Loire-Atlantique	0.1021	0.0238	-0.0031	0.0290	0.0238	528.1487	11.1201	-4.1173	-6.6826	4.0241
Maine-et-Loire	-0.0080	-0.0418	-0.0130	0.0300	0.0029	637.8271	-10.0875	-5.9005	10.0828	0.9054
Sarthe	0.0355	0.0064	0.0005	0.0193	0.0003	495.1287	2.0792	-2.0255	2.1138	0.2894
Vendée	0.0499	0.0049	0.0045	0.0194	0.0039	1492.3110	3.9566	3.5643	31.3954	4.6928
Finistère	0.2203	0.1131	0.0103	0.0768	0.0199	1093.5160	63.7151	16.1386	66.9856	12.8611
Ille-et-Vilaine	0.0470	-0.0316	-0.0115	0.0951	0.0098	364.4022	-6.4106	-1.1827	13.6052	3.3230
Morbihan	0.0329	0.0440	0.0153	-0.0447	0.0076	1904.4340	24.3887	-7.3150	43.7996	9.3008
Charente	0.0474	0.0167	0.0044	0.0089	-0.0044	645.5519	10.7951	2.0355	5.3096	-0.8324
Charente-Maritime	0.0064	-0.0229	0.0141	0.0362	-0.0047	854.6346	-12.8448	3.4503	8.7837	-1.9879

Table (8) Averages of decomposition results by region, part c

Region	Output (%)	XΔ (%)	CΔ (%)	TΔ (%)	SΔ (%)	Output (i.q.)	XΔ	CΔ	TΔ	SΔ
Deux-Sèvres	0.0796	0.0372	0.0212	0.0071	0.0008	809.9582	28.2692	12.0281	14.6629	0.9047
Vienne	0.0556	0.0139	0.0082	0.0126	-0.0005	1048.9490	20.2281	-2.2614	9.7022	-1.8696
Dordogne	0.0516	0.0033	0.0174	-0.0493	0.0019	463.9592	-2.6342	5.7549	-9.3669	0.5731
Gironde	-0.1132	-0.1589	-0.0687	0.0897	0.0142	3221.8230	74.6798	-29.9669	98.6731	-14.8120
Landes	0.0224	-0.0076	-0.0043	-0.0091	0.0053	939.5547	-11.2934	6.3213	-0.6067	2.5059
Lot-et-Garonne	0.0414	-0.0050	0.0401	0.0149	-0.0026	1228.5520	22.6589	24.3069	15.9102	-1.8822
Pyrénées-Atl.	0.0129	-0.0124	-0.0145	0.0065	0.0076	383.0779	-4.0051	-7.8004	6.0897	2.0624
Ariège	0.0312	0.0310	0.0093	0.0017	0.0024	1017.7830	11.9204	-2.7756	9.7448	1.8389
Haute-Garonne	0.0671	0.0363	0.0178	0.0167	-0.0019	836.6864	13.9816	0.6326	12.1075	-1.0575
Gers	0.0258	-0.0017	0.0037	0.0061	0.0008	691.6694	-0.2332	-2.3180	5.9149	1.3540
Lot	0.1223	0.0378	0.0293	-0.0127	0.0008	845.9260	23.6103	16.8599	-7.3474	0.3996
Hautes-Pyrénées	0.0266	-0.0010	0.0076	0.0088	0.0021	922.0903	3.1362	5.2612	5.8377	1.3512
Tarn	0.0716	-0.0095	0.0300	0.0308	0.0034	508.0580	-3.1583	4.1223	6.3151	0.8720
Tarn-et-Garonne	0.1022	-0.0030	0.0236	0.0483	-0.0041	661.3116	1.1329	6.4755	22.0530	-1.9591
Creuse	-0.1772	-0.0425	-0.0726	-0.0668	0.0047	731.4625	-29.6606	-61.1211	-53.2057	3.7845
Ain	0.0141	-0.0275	-0.0138	0.0554	0.0014	697.7513	-2.7762	-7.1697	13.0499	0.5949
Drôme	0.0004	-0.0140	0.0164	-0.0067	0.0031	847.3658	-0.1379	4.0672	3.2621	0.0584
Isère	0.0188	-0.0111	-0.0220	0.0090	0.0009	756.1443	-0.1628	-8.0492	7.3082	0.6894
Loire	0.0223	-0.0040	0.0487	-0.0097	0.0153	555.6411	-1.0536	24.8022	-14.1409	8.7601
Rhône	0.0231	0.0195	-0.0180	0.0193	0.0037	689.6610	11.5323	-12.6734	10.1008	1.9489
Haute-Savoie	0.0311	0.0016	0.0033	0.0036	-0.0004	692.4947	-0.2109	-5.2794	6.0467	-0.0589
Savoie	-0.0125	-0.2282	-0.2330	0.3234	0.0007	182.9934	-41.7680	-39.6390	52.1838	0.1925
Allier	0.0639	0.0166	0.0193	0.0036	0.0006	1259.0910	17.8743	1.8483	13.0495	1.0157
Puy-de-Dôme	0.0288	0.0015	-0.0094	0.0431	0.0012	825.3568	-0.6937	-3.3328	12.1883	0.2266
Aude	0.0833	0.0497	-0.0017	-0.0248	0.0044	1000.3460	21.9183	-1.9601	-7.4032	0.8977
Hérault	0.0677	0.0103	-0.0110	0.0536	-0.0037	2247.9370	0.1724	-12.5227	34.7971	-7.3388
Alpes-de-Haute-Prov.	0.0386	0.0198	-0.0115	0.0217	-0.0035	934.0237	12.6372	-7.1558	10.0389	-2.3552
Hautes-Alpes	0.4282	-0.1886	0.5207	0.1630	-0.0049	236.1465	-39.3092	94.8830	31.0931	-1.4024
Bouches-du-Rhône	-0.0285	-0.0536	0.0440	-0.0321	-0.0020	1239.3320	-40.8390	19.1087	-18.3782	-0.4044
Var	0.1749	0.0284	-0.0683	0.2073	0.0075	795.8802	31.7270	-33.6607	91.6440	5.6694
Vaucluse	0.1458	0.0736	0.0731	0.0377	-0.0193	552.0210	44.5986	14.2042	-5.7187	-8.9631

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