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ANALYSIS

An assessment of the distributional impacts of autonomous adaptation to climate change from European agriculture

Maxime Ollier [a,b,c,*], Pierre-Alain Jayet [b], Pierre Humblot [b]

[a] Agricultural and Resources Economics, Institute of Natural Resource Sciences, Zürich University of Applied Sciences (ZHAW), CH-8820, Wädenswil, Switzerland
[b] Université Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics, 91120, Palaiseau, France
[c] Climate Economics Chair, Paris-Dauphine University, Paris, France

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ABSTRACT

Farmers facing a durable change in climate conditions may autonomously adapt through the intensive margin, the extensive margin, or through the adoption of new practices. Based on a coupling between a microeconomic model of European agriculture (AROPAj) and a crop model (STICS), this article investigates the potential distributional impacts of farm-level autonomous adaptation to climate change within the European Union (EU-27). Considering the representative concentration pathway (RCP) 4.5 of the second report on emission scenario of the fifth assessment report (SRES AR5), we implement two levels of autonomous adaptation for farmers, and three time horizons. The results indicate that *ceteris paribus*, climate change may lead in terms of social welfare to a slightly worse situation in the middle term and a slightly better situation in the long term with respect to the present. However, the ranking of agents in the distribution is importantly impacted. Our Shapley inequality decomposition shows that income inequality is largely explained by the region and type of farming. Climate change barely affects the marginal contribution of these two characteristics to overall income inequality.

1. Introduction

As agriculture is highly exposed to climate, the sector is expected to suffer important economic losses from climate change (IPCC, 2022). Nevertheless, IPCC (2022) highlight the existence of various agricultural adaptation options (e.g., agricultural diversification, agroforestry, irrigation expansion) quite efficient in reducing climate impacts in a 1.5 °C warming world. The impacts of climate change on agricultural production can be softened by farmers' autonomous adaptation. This adaptation, also known as *private adaptation* in the literature (Mendelsohn, 2000), concerns adaptation actions that farmers may take at their level from both the intensive margin (e.g., a change in input demand) and the extensive margin (e.g., a change in crop choice) but also from the adoption of new practices (e.g., agroforestry), more suitable to a change in climate conditions.

The present article addresses two main issues. First, it investigates the potential distributional impacts of farm-level autonomous adaptation to climate change on European farmers' income. To the best of our knowledge, this paper is the first attempt to assess the distributional effects of farms autonomous adaptation to climate change. Second, it seeks to quantify the marginal contribution of the main individual characteristics to overall farmers' income inequality, and to analyze how these contributions vary when farmers autonomously adapt to climate change.

European agriculture provides an interesting field for our question for several reasons. The production of European agriculture is highly diverse and important (418 billion euros in 2019)[1] and may be substantially affected by climate change (Van Passel et al., 2017). Meanwhile, European Union (EU) has always included in the goals of the Common Agricultural Policy (CAP) to *ensure a fair standard of living to the agricultural community* (European Community, 1957) and more recently stated that CAP *should contain a more equitably distributed first pillar* (European Commission, 2010), therefore, the European authorities may be concerned by the potential distributional consequences of the adaptation of farmers to climate change.

* Corresponding author at: Agricultural and Resources Economics, Institute of Natural Resource Sciences, Zürich University of Applied Sciences (ZHAW), CH-8820, Wädenswil, Switzerland.

E-mail addresses: maxime.ollier@zhaw.ch (M. Ollier), pierre-alain.jayet@inrae.fr (P.-A. Jayet), pierrot.humblot@gmail.com (P. Humblot).

[1] European agriculture is the world's leading producer. Source: Eurostat.

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This study builds on several streams of the literature. It borrows from the extensive literature on the measurement of inequality by a Lorenz-consistent criterion (Aaberge, 2001). In particular, we employ generalized Lorenz curves (Shorrocks, 1983) for ranking farmers' income distribution[2] and delta Lorenz curves (Ferreira et al., 2018) for analyzing income changes across the distribution. The study also relates to the inequality-decomposition literature (Bourguignon, 1979; Shorrocks, 1980) by adapting a framework based on the Shapley (1953) value, developed in Chantreuil et al. (2019, 2020).

The impacts of climate change have given rise to an important body of literature in environmental economics (see, e.g., Dell et al. (2014) for a review). In agriculture, studies have analyzed the effect of climate on various economic outcomes such as land value (Mendelsohn et al., 1994) or profit (Deschênes and Greenstone, 2007) but also across various regions in America (Seo and Mendelsohn, 2008; Schlenker and Roberts, 2009), Europe (Van Passel et al., 2017), or Asia (Zhang et al., 2017; Hossain et al., 2019). Recent examples highlight adaptative behaviors and quantify gains from adaptation (Aragón et al., 2021; Iqbal and Aziz, 2022). The topic of income inequality within farmers has been widely examined (Finger and El Benni, 2014), particularly in Europe, in relation to the CAP (Allanson, 2008; Hanson, 2021; Piet and Desjeux, 2021).

Our modeling approach broadly refers to the literature quantifying the effect of adaptation to climate change using crop simulation models and assuming some incremental adaptations (see e.g. Challinor et al. (2014) for a meta-analysis). In particular, we rely on a coupling between a supply-side microeconomic model of European agriculture (AROPAj) and a crop model (STICS). Two levels of farmers' autonomous adaptation to climate change are simulated. For *weak adaptation*, by modifying yield response functions, climate change shifts the optimal quantity of inputs and farmers can adapt through adjustments in the intensive and/or the extensive margin. However, crops remain the same as initially. For *strong adaptation*, farmers have in addition the possibility of changing the sowing date, or the crop variety. AROPAj has the main advantage of providing EU-27 aggregate results while covering an important diversity in terms of type of farming, region, and economic size. Our study must be considered as an analysis of the effects of a change in climate variables on the European agricultural sector *ceteris paribus*, rather than a prospective – or forecasting – exercise of the future state of the European agricultural system.

Our contribution to the literature is twofold. First, we provide an estimate of the potential distributional consequences of farmers' autonomous adaptation to climate change. Our findings indicate that all other things being equal, climate change could in the middle run worsen the situation compared to the present one in terms of aggregate welfare. This is due to (i) a reduction in income share for bottom quantiles and (ii) a decrease in total income. However, in the long-term horizon, climate change may lead to a preferable situation in terms of aggregate welfare, due to (i) an income share quite stable for bottom quantiles and (ii) an increase in total income. We also show that the ranking of farmers in the distribution is significantly affected.

As a second contribution, we identify the two main drivers – i.e., region and type of farming – of farmers' income inequality. We show that these two individual characteristics contribute approximately 73% to overall farmers' income inequality. We find the region to be an even more determinant characteristic than the type of farming to explain this inequality. Our results also indicate that climate change slightly impacts the marginal contribution of these two attributes to farmers' income inequality.

[2] Atkinson (1970) formally demonstrates that an ordering of income distributions with Lorenz curves is equivalent to an ordering of aggregate social welfare. Shorrocks (1983) extended the result for ranking distributions with different means.

The remainder of the article is structured as follows. Section 2 presents the modeling framework, the data and the inequality-decomposition framework. Section 3 depicts our aggregate and distributional results of farm-scale autonomous adaptation to climate change within the European agricultural sector. It also presents the results of our income inequality decomposition. Our findings are discussed in Section 4. Section 5 concludes.

2. Modeling strategy

Our assessment of the potential distributional impacts of European farm-level autonomous adaptation to climate change relies on a soft coupling between a microeconomic supply-side model of the European agricultural sector (AROPAj) and a crop model (STICS). Yield response functions, obtained from STICS for various climate and soil characteristics, are incorporated into production factors from AROPAj. This modeling framework has already been used to quantify the environmental and economic impacts (e.g., production, land use, irrigation water) of climate change on agriculture (Leclère et al., 2013; Lungarska and Chakir, 2018; Barberis et al., 2020).[3]

An overview of the modeling framework is presented in 1.

In this section devoted to methods and data, we first introduce the models, AROPAj and STICS. Second, we present the climate scenario and the two levels of adaptation. Third, we describe the construction of income and the inequality-decomposition framework.

2.1. A microeconomic model of the EU agricultural supply

The microeconomic model AROPAj (Jayet et al., 2023) depicts the annual economic behavior of a set of European representative farmers in terms of farmland allocation (crops, pastures, and grasslands) and livestock management (animal numbers and feeding). The model includes various agricultural productions in terms of crops[4] (i.e., 24 major European crops, permanent and temporary grassland) and animal husbandry (i.e., dairy and non-dairy cattle, sheep, goats, swine, poultry).

The economic behavior of each representative farmer is modeled with a static, mixed integer linear-programming model. Each farmer is assumed to maximize its gross margin[5] subject to technical (e.g. required crop rotations, nitrogen and water needs for associated crop yields, animal feeding requirements for milk or meat production) and economic (e.g. CAP payments, environmental policies) constraints. Farmers, assumed to be price-takers, are entirely independent one from another. It should also be noted that the herd size is bounded into a ±15% range.

The representative farm results from a clustering procedure of actual surveyed farms from the European farm accountancy data network (EU-FADN). FADN provides general farm economic data, costs and prices, as well as crop and livestock yields. Farms are clustered along (i) type of farming (FADN classification TF14 Grouping[6]), (ii) the proportion of irrigated areas, (iii) economic size (9 categories), and (iv) location:

[3] The modeling strategy originates from Godard et al. (2008) and has been extended by Leclère et al. (2013) to assess the autonomous adaptation of European farms to climate change. Humblot et al. (2017) present a theoretical framework for generating water–nitrogen yield response functions at the plot scale, then employed in bio-economic farm models. Originally implemented for maize in two French regions, yield response functions have been extended for 9 major crops to all France Barberis et al. (2020). In the present article, we expand the extraction of yield response functions of these 9 crops to EU.

[4] Permanent crops (e.g., orchards, vineyards), horticulture and market gardening are not modeled.

[5] The gross margin is defined as the difference between farm's profit minus variable costs.

[6] The classification can be found at https://ec.europa.eu/agriculture/rica/detailtf_en.cfm?TF=TF14&Version=13185.

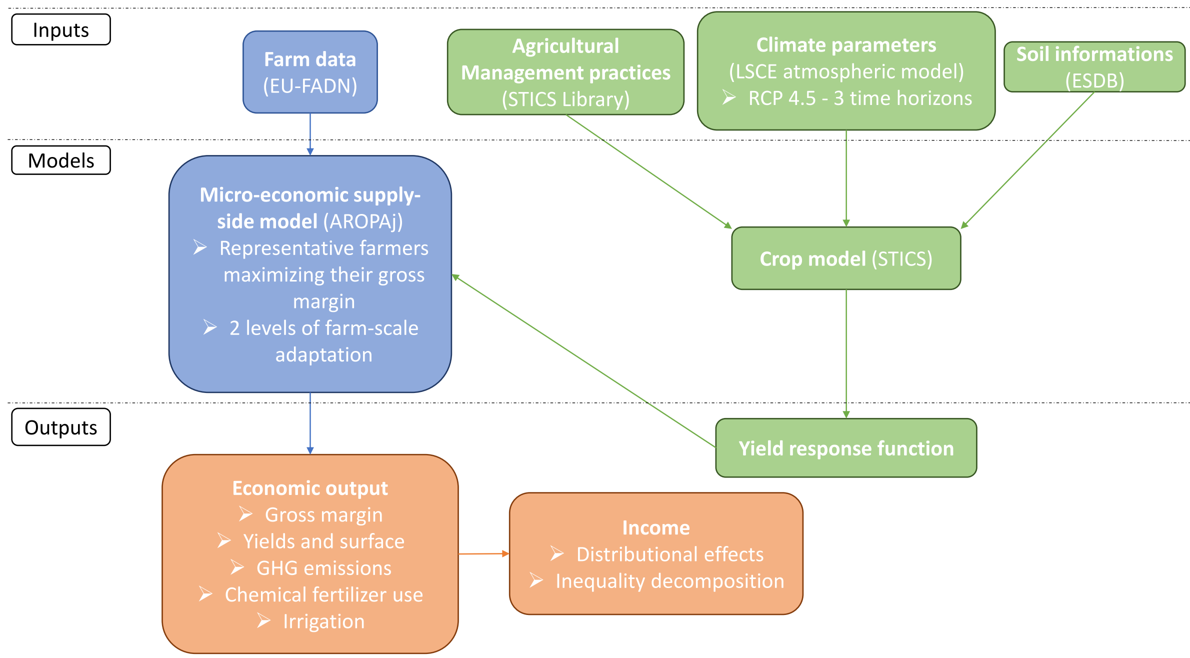

Fig. 1. Overview of the modeling framework.

region and altitude (3 thresholds; 0, 300, and 600 meters above sea level). The clustering procedure allows us to comply with the FADN privacy policy while improving AROPAj computing time. EU-FADN year 2012 provides data for 70,000 farms (representing 3.766 million European farms) clustered into 1993 representative farms, across 133 regions.

Model outcomes include farms' gross margin, input consumption (i.e., irrigation water and nitrogen fertilizers), animal products, crops yield and surface, and various environmental outputs, for instance greenhouse gas (GHG) emissions.

2.2. A crop model providing yield response functions

The microeconomic model of European agriculture is sharpened by substituting a function that links inputs and yields at the plot scale. The main reason for incorporating dose–response functions into AROPAj production factors is to overcome the lack of exhaustivity of the EU-FADN. EU-FADN does not allow us to estimate yield functions for a large diversity of contexts in terms of crops and farming systems. The crop model STICS simulates the soil–atmosphere–crop system applied to a wide range of crops and pedo-climatic conditions (Brisson et al., 2003). For a given representative farm and a given crop, it provides a yield function associated with inputs in (i) nitrogen fertilizers and (ii) water. STICS crop model requires (i) climate parameters, acquired from the *Laboratoire des sciences du climat et de l'environnement* (LSCE) atmospheric model, (ii) soil information, gathered from the European Soil Database (ESDB) (Panagos et al., 2012), and (iii) data on agricultural management practices (provided by the STICS library). It should be noted that the substitution of yield response functions from STICS to AROPAj input-yield points turns the structure of AROPAj non-linear. Thus, the optimization solving problem is in two stages. First, the gross margin is maximized for each unit of area of a crop and for each farm type. Second, the STICS yields are replaced in the linear optimization problem. Note also that the use of yield response functions allows us to come through the estimation of input prices.

In summary, STICS generates yield response functions for a specific crop under specific pedoclimatic conditions and calibrates nitrogen–water-yield relationships for crops present in a given AROPAj farm group.

2.3. Time horizons for climate change and autonomous adaptation

The climate scenario implemented in this study is the representative concentration pathway (RCP) 4.5. This climate scenario is then translated into weather variables by the LSCE atmospheric model, available at the scale of a regular grid with a mesh size of 0.11°—approximately 12.5 km. In the present paper, we use an early version of the model IPSL-CM5 A from LSCE.[7] This model is among the models that find the biggest positive change in average and extreme precipitation (Sillmann et al., 2017) and also among the models finding the biggest positive change in temperature (Forster et al., 2013). For example, Forster et al. (2013) show a +3.3 °C temperature change since preindustrial for the RCP 4.5 scenario of IPSL-CM5 A, whereas the average for this type of model is at +2.5 °C for this scenario. As a farm type is localized by a region and an altitude, weather variables are averaged for each region and altitude level, so at most three values per region for a weather variable. In order to quantify the European farm-level autonomous adaptation to climate change, we compute three time horizons. The present horizon is the representative climatic year for the period 2006–2035. The middle-term (resp. the long-term) horizon is the representative climatic year for the period 2041–2070 (resp. 2071–2100).[8]

We simulate two levels of autonomous adaptation for farmers. In the *weak adaptation* level, farmers may adapt to a change in weather conditions through the extensive–e.g. a change in crop allocation–and the intensive–e.g. a change in input demand–margins. Farms only adapt through crops initially present in their farm type (calibrated on the 2012 EU-FADN). In the *strong adaptation* level, farmers can in addition adapt through the adoption of crop varieties more suitable to the new weather conditions or through a change in the sowing date. Thus, the two levels of adaptation should be considered separately from one another. Within a type of adaptation, we compare simulation results of future horizons with simulation results of the present horizon to

[7] Information on the model can be found here: https://www.drias-climat.fr/document/Doc_DRIAS_database_IPSL2014-IPSL-CM4_WRF.pdf.

[8] A note on the method used for the choice of a representative climatic year over a 30-year period is given in Appendix A.

assess the impact of climate change on the distribution of farmers' income. In this respect, the present horizon with weak (respectively strong) adaptation is often used as a baseline for comparing future horizons with weak (respectively strong) adaptation. None of the two levels of adaptation take into account a possible improvement in plant genomics to create new varieties more resistant to heat and/or water stress. However, autonomous adaptation remains quite important and realistic in this work.

2.4. Farmers' income and active population

Several difficulties lie in estimating an appropriate income for farmers. First, the economic outcome from the model AROPAj is the gross margin. Thus, to get closer to a measure of disposable income, we remove wages paid from the gross margin.

Second, there are possibly several unpaid workers by farms. EU-FADN data gives the amount of unpaid workers in a full-time equivalent annual workforce unit (AWU). The 3.766 million European farms represent 4.967 million unpaid farmers. It corresponds to about 1.32 unpaid AWU on average per farm, from 0.04 to 6 unpaid AWU per farm. We perform an income per unpaid AWU to analyze the income inequality per individual. This is the estimation of the farmers' income in Piet and Desjeux (2021). Note that we present some results taking a per farm basis in Appendix F.

Third, when using farms' accounting data, a share of incomes is negative. This is clearly an issue when conducting distributional analysis, as negative incomes make it difficult to draw social welfare implications (Atkinson, 1970) and unclear to interpret delta Lorenz curves (Ferreira et al., 2018). Several authors suggest an alternative Gini index to include negative values (Chen et al., 1982; Raffinetti et al., 2014), particularly used in agriculture, where the presence of negative income is not rare (Allanson, 2008; Deppermann et al., 2014). However, when including negative incomes, a Gini index must be seen as a measure of variability rather than a concentration measure (De Battisti et al., 2019). Therefore, according to Ravallion (2017), De Battisti et al. (2019) and Piet and Desjeux (2021), we chose to eliminate negative incomes from the analysis. Our distributional analysis concerns 4.702 million unpaid AWU (94.3% of the initial sample) in the *weak adaptation* level, and 4.731 million unpaid AWU and (95.7% of the initial sample) in the *strong adaptation* level. We provide a focus on negative incomes in Appendix C, showing their (i) regional location and (ii) type of farming. Negative incomes are mainly located in some Eastern regions such as Romania and Bulgaria but also in Western regions like Brittany, the Netherlands, Catalonia. In terms of type of farming, negative incomes are principally animal farmers (e.g., specialist pigs, poultry, various granivore). Combining this information, we may think that an important share of negative incomes comes from off-land farmers.

2.5. Inequality-decomposition framework

Following Chantreuil and Lebon (2015) and Chantreuil et al. (2019), we consider a set of farmers N such that $N := \{1, \dots, i, \dots, n\}$ with $n \geq 2$, and a set of income sources $M := \{1, \dots, j, \dots, m\}$ with $m \geq 2$. We denote by S a coalition of income sources and by $\mathcal{M}$ the set of possible coalitions. A situation $x := [x_i^j]$ where $x_i^j \geq 0$ represents each income sources j received by the farmer i. Therefore, x can be seen as a matrix $n \times m$ where the row i represents the income source received by farmer i, and the column j is the distribution of the source j between farmers n. The distribution of source j is given by $x^j := (x_1^j, \dots, x_n^j)$. The aggregate distribution is $X := \sum_{j \in M} x^j$ and the average income is $\mu(X) := \frac{1}{n} \sum_{j \in M} x^j$. In the same way, the aggregate distribution of the sources included in S is $X^S := \sum_{j \in S} x^j$ and the associated average income is $\mu(X^S) := \frac{1}{n} \sum_{j \in S} x^j$. The distribution of farmers' income according to income sources taking into account is such that

$$\Psi(S) = \left(\sum_{j \in S} x_1^j + \mu(X^{\setminus S}), \dots, \sum_{j \in S} x_n^j + \mu(X^{\setminus S}) \right) \text{ for all } S \in \mathcal{M} \text{ and } S \neq \emptyset \quad (1)$$

The contribution of a source j to overall income inequality is then given by the Shapley formula:

$$Sh_j = \sum_{S \subset \mathcal{M}, j \in S} \frac{(s-1)!(m-s)!}{m!} \cdot [G(\Psi(S)) - G(\Psi(S - \{j\}))] \quad (2)$$

where G is the Gini inequality index.

In our application, income distribution $\Psi(S)$ is defined for a population in which the farmer's income is linked to three characteristics—i.e., region, type of farming, and a third variable that includes all other individual characteristics. We consider these three dimensions of farmer status as different sources of income. Farmers' income (y) is then decomposed by region (ω) and type of farming (σ) (Chantreuil and Lebon, 2015; Chantreuil et al., 2020). This decomposition implies writing the income of a farmer (i) as the sum of three elements:

$$y_i = \overline{y}_{\omega_i} + (\overline{y}_{\omega_i,\sigma_i} - \overline{y}_{\omega_i}) + (y_i - \overline{y}_{\omega_i,\sigma_i}) \quad (3)$$

or

$$y_i = \overline{y}_{\sigma_i} + (\overline{y}_{\omega_i,\sigma_i} - \overline{y}_{\sigma_i}) + (y_i - \overline{y}_{\omega_i,\sigma_i}) \quad (4)$$

where in Eq. (3) (respectively Eq. (4)), the income y can be expressed as the sum of (i) the average farmer's income in the region (respectively, type of farming) considered: $\overline{y}_{\omega_i}$ (respectively, $\overline{y}_{\sigma_i}$), (ii) the difference between this average income and the average farmer's income of the type of farming in the same region: $(\overline{y}_{\omega_i,\sigma_i} - \overline{y}_{\omega_i})$ (respectively, $(\overline{y}_{\omega_i,\sigma_i} - \overline{y}_{\sigma_i})$), and (iii) an individual part associated with unobserved characteristics (r): $(y_i - \overline{y}_{\omega_i,\sigma_i})$. The two possible decomposition orders are presented because there is *a priori* no reason to choose an order over another (Chantreuil et al., 2020). We obtain three distributions (i.e., region, type of farming, and residuals), the sum of which allows us to meet the distribution of farmers' income. We can then apply the Shapley formula to a Gini index of different distributions where an individual characteristic can take either its exact or average value to determine the contribution of a characteristic $j = \{\omega, \sigma, r\}$ to overall income inequality.

3. Results

In this section, we first provide aggregate results. We then go further into the distributional analysis. We end the section by delivering our findings in terms of region and type of farming, and by assessing their contribution to farmers' income inequality.

3.1. Aggregate results

Table 1 presents aggregate results in terms of crops (corn and wheat), inputs (fertilizers and irrigation), GHG emissions, and income for the levels *weak* and *strong adaptation* and for three time horizons. For both *weak* and *strong adaptation* levels, production (wheat and corn) and total income decrease in the middle-term horizon with respect to the present, −6.2% (respectively −8.5%) for *weak* (resp. *strong*) *adaptation* level. Income then increases in the long-term horizon with respect to the present, +2.6% (respectively +2.0%) for *weak* (resp. *strong*) *adaptation* level.

In the *weak adaptation* level, the model computes 67.714 million tons of corn and 140.022 million tons of wheat for the present, which is quite close to the actual production (i.e., for the period 2010–2020, the European Commission recorded on average 67 million tons of corn

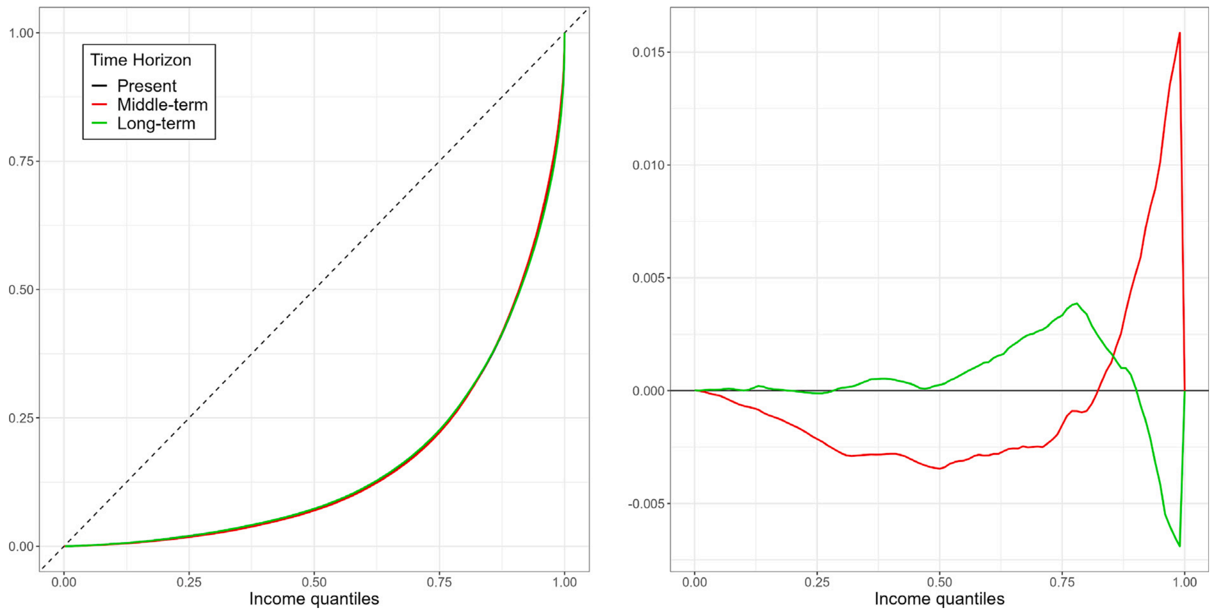

Fig. 2. Distribution of farmers' income for *weak adaptation* level. Left: Lorenz curves. Right: Delta Lorenz curves with respect to the present time horizon.

Table 1
Aggregate results for studied sample (4.702 million unpaid AWU for *weak adaptation* vs. 4.731 million unpaid AWU for *strong adaptation*) for crop production (corn & wheat), input consumption (mineral fertilizers & irrigation water), GHG emissions, and income.

		Unit	Present	Middle-term	Long-term
Weak Adaptation	Corn	10^3 t	67,714	47,821	72,192
	Wheat	10^3 t	140,022	129,888	150,619
	Fertilizers	10^3 t	42,124	39,201	44,416
	Irrigation	10^3 m^3	4,710,097	4,931,883	5,063,983
	GHG emissions	10^3 tCO_2eq	349,328	345,950	353,266
	Income	10^6 €	170,932	160,168	175,365
Strong Adaptation	Corn	10^3 t	103,941	73,848	111,550
	Wheat	10^3 t	169,924	158,427	173,531
	Fertilizers	10^3 t	49,746	47,921	48,898
	Irrigation	10^3 m^3	6,301,973	7,036,939	5,771,647
	GHG emissions	10^3 tCO_2eq	353,635	353,031	352,558
	Income	10^6 €	193,456	176,977	197,284

and 125 million tons of wheat per year[9]). It should be noted that the increase in income and production in the long-term horizon is accompanied by an increase in water (+7.5%) and mineral fertilizers (+5.4%) consumption, and GHG emissions (+1.1%).

In the *strong adaptation* level, expected more optimistic than the *weak adaptation* level, income and crop production are higher, even in the present horizon.[10] Input consumption and GHG emissions are also higher than in the *weak adaptation* level. However, one may notice that input demand could decrease in the long-term horizon with respect to the present, due to the adoption of less input-consuming varieties.

3.2. Distributional analysis

Fig. 2 illustrates per unpaid AWU farmers' income Lorenz curves (left) and delta Lorenz curves with respect to the present horizon (right) for *weak adaptation*. Delta Lorenz curves (Ferreira et al., 2018) show the change in cumulative share of income across quantiles. Lorenz curves are quite close: the Gini index is equal to 0.681 in present and middle-term horizons, and 0.680 in the long-term horizon. However, the delta Lorenz curves show that, in the middle-term horizon, the bottom 50% of incomes (i.e., incomes below the fifth decile) reduce their income share in total income. However, an inversion of the red curve in the fifth decile shows that almost the top 50% of incomes (i.e., incomes above the fifth decile) increase their income share in total income. It should be noted that the middle run is also detrimental for very high incomes. In the long-term horizon, the income share seems quite stable (compared to the present time horizon) for the bottom 50% of incomes, then increases for the upper middle incomes and decreases for the top 20% of incomes.

Fig. 3 illustrates per unpaid AWU farmers' income Lorenz curves (left) and delta Lorenz curves compared to the present (right) for *strong adaptation*. Lorenz curves are quite close in this level of adaptation too. The Gini index is equal to 0.674 in the present, 0.680 in the middle term, and 0.674 in the long term. Delta Lorenz curves are quite similar to the *weak adaptation* level. They show that, in the middle-term horizon, the bottom 50% of incomes reduce their income share in total income, while the top 50% of incomes increase their income share. In the long-term horizon, the income share seems quite stable for the lowest 50% of incomes, then increases for upper middle incomes and decreases for the top 20% of incomes. Note that the very high incomes (i.e., the top 1% of incomes) reduce (respectively increase) their income share in the middle-term (respectively long-term) horizon. We present in Appendix D the regional location of farms within income deciles. Low incomes are mainly located in the East (e.g., Romania, Bulgaria, Poland). These regions experience a decline in income in the middle term horizon, so this could explain the increase in income inequality. Central and western Europe, where high incomes are principally located, are less touched in the short run. In the long term, the gain in income for Eastern region, where a large share of low incomes is located, may explain the positive result in terms of income inequality.

[9] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agricultural_production_-_crops.

[10] Even if the magnitude is globally respected, results on production within the *strong adaptation* scenario are slightly more important than what is currently observed, for the present horizon. This could be due to a change in the crop variety from what is initially present for the calibration model.

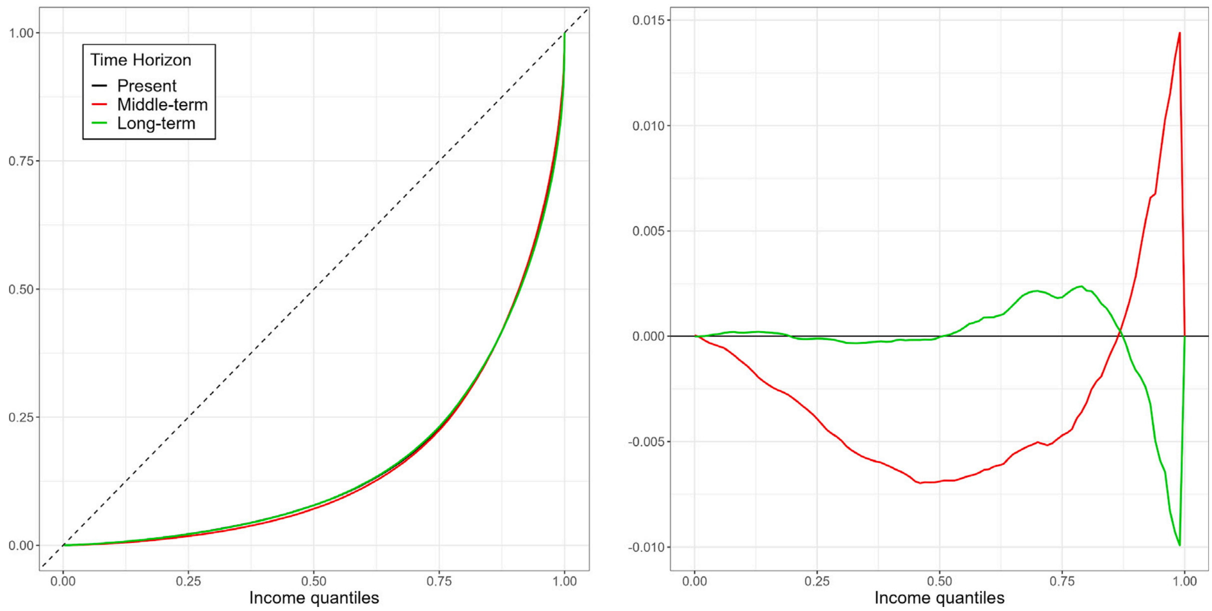

Fig. 3. Distribution of farmers' income for *strong adaptation* level. Left: Lorenz curves. Right: Delta Lorenz curves with respect to the present time horizon.

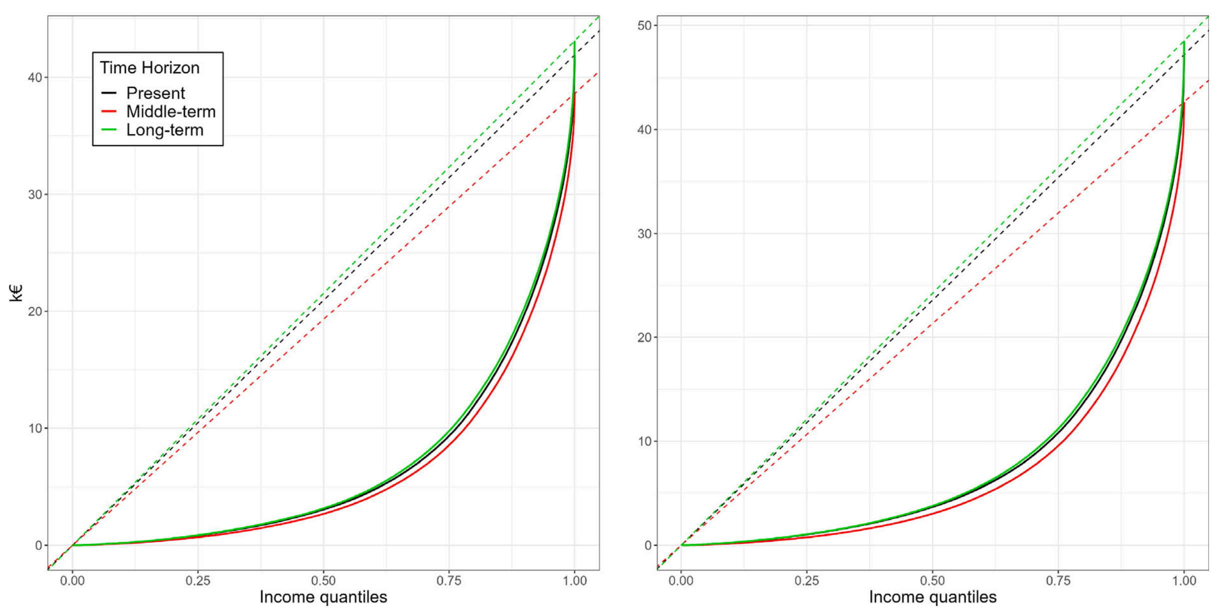

Fig. 4. Generalized Lorenz curves of farmers' income. Left: Weak adaptation. Right: Strong adaptation.

Fig. 4 presents the per unpaid AWU farmers' income generalized Lorenz curves (Shorrocks, 1983) for *weak* and *strong adaptation* levels, for three time horizons.[11] For the two levels of adaptation, the generalized Lorenz curve of income lies entirely below the present generalized Lorenz curve in the middle-term horizon. This result may be explained both by (i) a decrease in income share for bottom quantiles and (ii) a decrease in total income. Then in the long run, the curve lies entirely above the present, for weak and strong adaptation. This can be explained both by (i) a constant income share for bottom quantiles and (ii) an increase in total income.

In terms of aggregate social welfare,[12] climate change (under RCP 4.5 scenario) may lead to (i) a worse situation in the middle run and (ii) a preferable situation in the long run with respect to the present situation.

3.3. Reranking effects

Now we study the potential reranking effects (i.e., the shift of individual places in the distribution). Fig. 5 shows future income (in the middle-term and in the long-term horizon) with respect to present income, for both adaptation levels. For both middle and long-term horizons, future income is quite close to income in the present horizon.

[11] The generalized Lorenz curve is constructed by scaling up the Lorenz curve by the mean of the distribution: $GL(F(x)) = \mu L(F(x))$, with μ the mean of the distribution and F the cumulative distribution function.

[12] The generalized Lorenz dominance is equivalent to a second-order stochastic dominance (Shorrocks, 1983; Thistle, 1989).

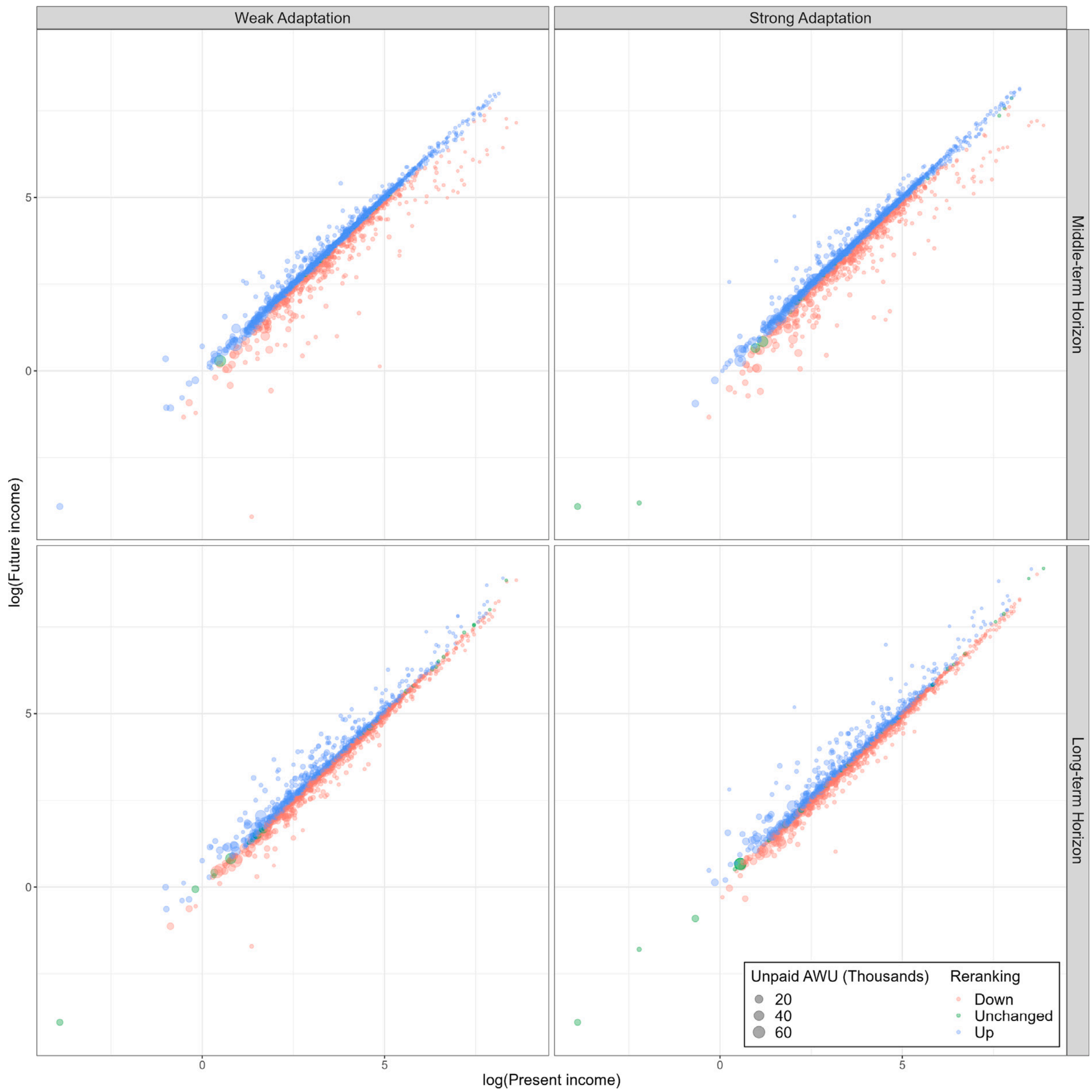

Fig. 5. Future income with respect to present income (in logs). Top left: Middle-term horizon and weak adaptation, Top right: Middle-term horizon and strong adaptation, Bottom left: Long-term horizon and weak adaptation, Bottom right: Long-term horizon and strong adaptation.

Note that there are coherently more incomes that decrease with respect to present income in the middle-term than in the long-term horizon.

The distributional effects of autonomous adaptation are slightly pronounced, but there is an important share of the population that changes its place in the distribution. For both levels of adaptation and for both middle and long-term horizons, only 3% (from 1.5% to 4.3%) of the population on average maintain their position in the distribution with respect to the present horizon. Approximately on average 50.3% (respectively 46.7%) of the population experience an increase (resp. a decrease) in their rank in the distribution.

What are the marginal contributions of the main individual farmers' characteristics to income inequality? How do these contributions vary when farms autonomously adapt to climate change? To investigate these questions, we apply the inequality-decomposition framework based on the Shapley value (Shapley, 1953) introduced by Chantreuil and Trannoy (2013) to farmers' income. The method aims at assessing the marginal contribution of an individual characteristic to overall inequality (Chantreuil et al., 2019).

3.4. Regional and type of farming income

Fig. 6 depicts the average regional income per unpaid AWU for the present and for *weak* and *strong adaptation* levels. It also presents how the average regional income varies in future horizons with respect to the present for the two levels of adaptation. It shows an important variability among regions. The regions with the highest average income are concentrated in northern Europe, for example, the north of France, Germany, the Netherlands, and Denmark. It should be noted that per unpaid AWU average income is particularly high in eastern Germany and the Czech Republic, with approximately 200 thousand euros.[13] It is possibly related to the existence of former sovkhozes (Johan Swinnen, 2009). In the middle-term horizon, the mean income decreases in most regions with respect to the present, for example, in Mediterranean

[13] In the case of the Czech Republic, 13,300 farms are sharing 3.3 million Ha, hence a farm is 245 Ha on average. Very large farms where the owner is working on the farm explain these important incomes.

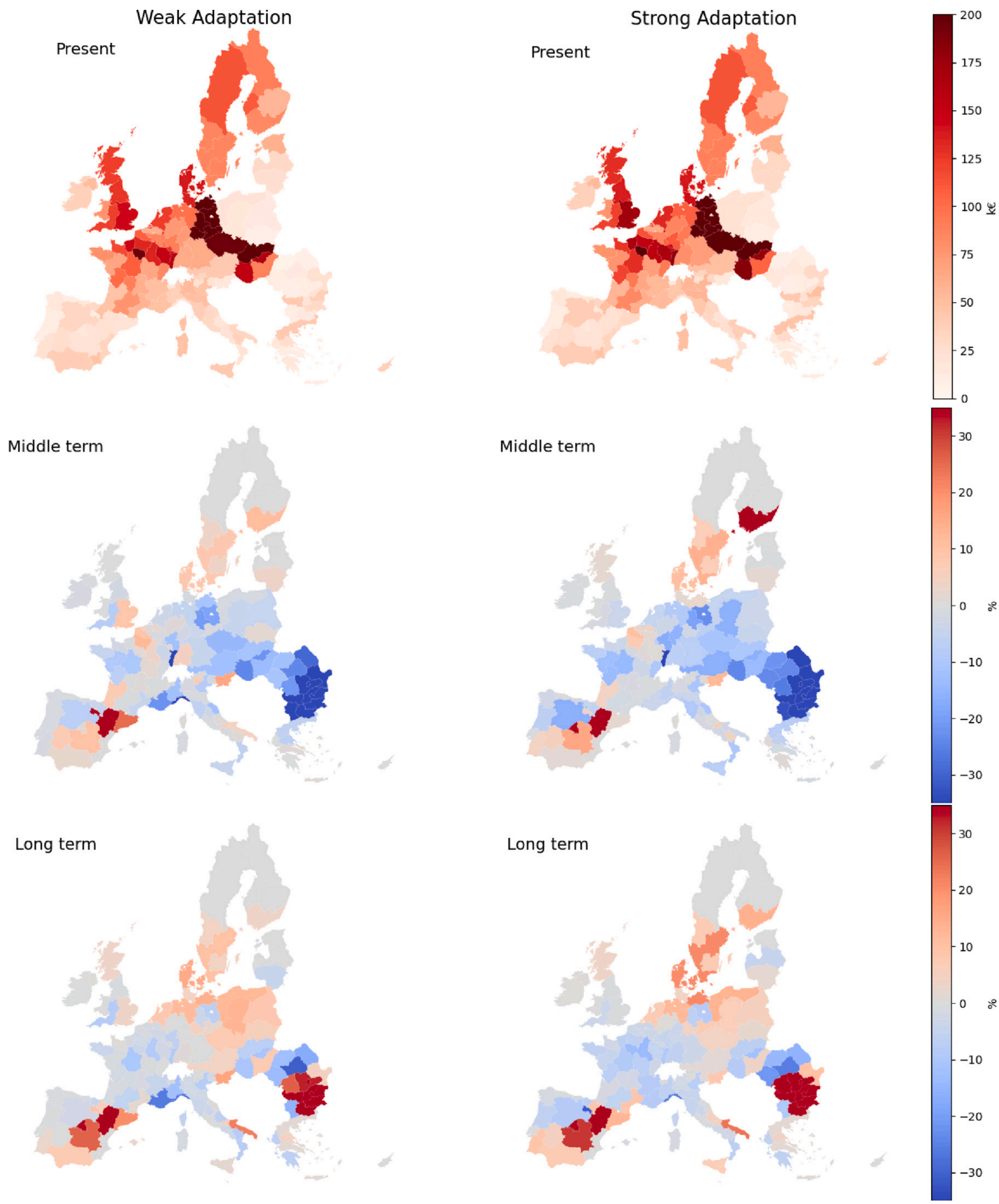

Fig. 6. Average regional per unpaid AWU farmers' income (10^3€) for the present horizon and for weak (top left) and strong (top right) adaptation. Regional income variation with respect to the present (%) for weak adaptation and in the middle-term horizon (middle left) and in the long-term horizon (bottom left). Regional income variation with respect to the present (%) for strong adaptation and in the middle-term horizon (middle right) and in the long-term horizon (bottom right).

regions or eastern European countries. It should be noted that mean income increases in some regions, among them Denmark and Scandinavia. On the long-term horizon, most regions experience an increase in average income with respect to the present horizon. For example, mean income increases in countries in eastern Europe (approximately +35%) and in several German, Danish, and Scandinavian regions (approx. +20%). Various French regions experience a slight reduction in mean income. Appendix E depicts the yields by region for major crops (corn and wheat). Several regions in Eastern Europe are enduring a strong reduction in corn and wheat yields (e.g., Romania) in the short-term horizon with respect to present, before experiencing an increase in the long run. This could constitute a potential channel for explaining the income distributional impacts.

Table 2 presents the average income per unpaid AWU by type of farming for the present and for *weak* and *strong adaptation*. It also shows the variation in the average income by type of farming for future horizons with respect to the present. For both *weak* and *strong adaptation*, the reduction in mean income concerns all types of farming in the middle-term horizon with respect to the present. This loss is quite marked for crop producers, for example −15% (resp. −16%) for specialist cereals in the *weak* (resp. the strong) *adaptation* level. This loss in mean income is less marked for livestock farmers: it is

Table 2
Present average per unpaid AWU farmers' income (10^3 €) by type of farming for weak and strong adaptation. Average per unpaid AWU farmers' income variation for middle and long-term horizons with respect to the present (%) by type of farming and for weak and strong adaptation. Note: Only the main European types of farming (at least 80,000 unpaid AWU) are presented. See Appendix B for an exhaustive list of the computed types of farming.

	Type of farming	Present	Middle-term	Long-term
Weak Adaptation	Specialist cereals, oilseeds and protein crops	73.5	−14.7%	+5.2%
	General field cropping	40.9	−4.2%	+6.1%
	Specialist dairying	50.2	−1.4%	+0.0%
	Specialist cattle — rearing and fattening	24.9	−0.4%	+0.8%
	Cattle — dairying, rearing and fattening combined	29.9	−4.0%	−1.0%
	Sheep, goats and other grazing livestock	18.2	−4.4%	−2.2%
	Mixed cropping	13	−6.9%	+5.4%
	Mixed livestock, mainly grazing livestock	8.6	−9.3%	+7.0%
	Field crops — grazing livestock combined	47.3	−5.5%	+2.1%
	Various crops and livestock combined	8.6	−9.3%	+11.6%
Strong Adaptation	Specialist cereals, oilseeds and protein crops	87.9	−16.7%	+6.1%
	General field cropping	50.4	−8.1%	+2.8%
	Specialist dairying	52	−2.3%	−0.4%
	Specialist cattle — rearing and fattening	25.9	−1.2%	+0.8%
	Cattle — dairying, rearing and fattening combined	31.6	−5.7%	−1.6%
	Sheep, goats and other grazing livestock	19.2	−6.8%	−3.1%
	Mixed cropping	16.3	−12.9%	+2.5%
	Mixed livestock, mainly grazing livestock	10.2	−15.7%	+4.9%
	Field crops — grazing livestock combined	54.8	−8.2%	+0.2%
	Various crops and livestock combined	11.1	−13.5%	+8.1%

Table 3
Shapley decompositions of per unpaid AWU farmers' income Gini index for three time horizons. Note: The two decomposition orders are presented, when starting the decomposition by region (order ω) and when starting the decomposition by type of farming (order σ).

	Time Horizon	Present		Middle-term		Long-term	
	Decomposition start	ω	σ	ω	σ	ω	σ
Weak Adaptation	Region (ω)	45.3%	50.2%	47.6%	51.9%	44.3%	49.7%
	Type of farming (σ)	27.5%	22.2%	26.8%	22.1%	27.9%	22.3%
	Residual (r)	27.2%	27.6%	25.6%	26.0%	27.8%	28.0%
	Gini index	0.6805		0.6814		0.6796	
Strong Adaptation	Region (ω)	44.9%	49.1%	47.9%	51.0%	43.5%	48.3%
	Type of farming (σ)	26.9%	22.5%	26.0%	22.4%	27.7%	22.8%
	Residual (r)	28.2%	28.4%	26.1%	26.6%	28.8%	28.9%
	Gini index	0.6740		0.6796		0.6743	

on average −1.7% for specialist dairying for both adaptation levels. In the long-term horizon, average income increases for most types of farming with respect to the present. This increase is more pronounced for crop producers, for instance approximately +6% on average for both adaptation levels. Generally, we can see that crop producers' average income is more sensitive to climate change than livestock producers' average income, which is quite stable over the different time horizons.

3.5. Decomposition results

Table 3 illustrates the Shapley decomposition of farmers' income inequality for *weak* and *strong adaptation* levels and for present, middle-term and long-term time horizons.

The region and the type of farming contribute significantly to overall income inequality of farmers. Whatever the order of decomposition, the level of adaptation, or the time horizon, these two characteristics explain 71.1 to 74.4% of overall farmers' income inequality. The region seems to be the individual attribute that contributes the most to the income inequality of farmers (43.5–51.0%), whereas the type of farming explains 22.1 to 27.9% of income inequality. The contribution of farmers' region and type of farming is quite similar for all time horizons. Climate change slightly alters the marginal contribution of these two individual attributes to overall income inequality. It increases the contribution of the region in the middle-term horizon and reduces it in the long-term horizon.

4. Discussion

In this section, we first discuss the consistency of our results with respect to the literature. Second, we debate our positive findings in the long-term horizon. Third, we highlight several limitations of this study.

Our results are broadly in line with the existing literature. The majority of studies assessing climate change impacts on European agriculture globally identifies positive effects on agricultural production or revenues (Iglesias et al., 2011; Van Passel et al., 2017). These studies also find that Mediterranean regions may suffer from climate change, whereas regions from northern Europe could benefit from it. It should be noted that the increase in the use of irrigation and chemical fertilizer in the *weak adaptation* level is consistent with Iglesias et al. (2011) mentioning this increase in production and inputs, which can, in turn, have unwanted environmental consequences. Furthermore, working in European agriculture, Vaitkeviciute (2018) finds that climate change can have negative impacts in the middle term and positive impacts in the long term. In a meta-analysis, Challinor et al. (2014) highlight that crop yields may increase from 7 to 15% under climate change with adaptation, quite close to our results (about +7% for corn and +5% for wheat, on average for both adaptation levels).

The positive findings of this study regarding farmers autonomous adaptation to climate change in the long term may be nuanced on certain points. First of all, the climate scenario used in this study (RCP 4.5) is quite optimistic. This climate scenario implies an ambitious global GHG emission mitigation policy, as overall emissions start to decrease in the mid-21st century. Therefore, by the end of the 21st century, the CO_{2eq} concentration is expected to stabilize at about 650 ppm and the global mean surface air temperature will increase by 1.8 °C (from 1.1 °C to 2.6 °C). For the *weak adaptation* level, the better situation in the long-term horizon than in the present horizon in terms of social welfare is accompanied by an increase in the demand for mineral fertilizers. This increase may cause additional environmental pollution – e.g. eutrophication, GHG emissions – and degrade aggregate welfare in turn. We also note a serious increase in irrigation water consumption, which could lead to possible pressure on the resource. The slight increase in GHG emissions naturally arises the question of combining GHG emission mitigation policies with adaptation to climate change. Does the implementation of an ambitious climate policy within European agriculture constrain the adaptation options available for farmers? How does it affect the long-term positive distributional consequences of autonomous adaptation? For the *strong adaptation* level, in the long-term horizon we also obtain positive economic results, and a decrease in input (i.e., water and mineral fertilizers) consumption. It should be noted that this adaptation level, by enabling farmers to procure varieties more suitable for their environment, is optimistic by construction. As a consequence of this important adaptation option, the *strong adaptation* level overestimates the European production in the present horizon. Our positive findings may also be nuanced by other dimensions of climate change that we do not account for in this study. For instance, climate change could cause an increase – or an apparition – of plant disease affecting crop yields. Climate change also certainly increases the frequency of extreme weather events, such as droughts and floods (IPCC, 2014) that may have an important effect on agricultural production. Nevertheless, the climate model we use in this study (i.e., IPSL-CM5 A) is among the models giving the most important change in temperature and precipitation for scenario RCP 4.5 (Forster et al., 2013; Sillmann et al., 2017). As temperature is arguably the most important climatic variable explaining climate change impacts within agriculture (Challinor et al., 2014), we may imagine changes within European farmers to be less pronounced with climate models that perform a lighter change in warming and precipitations. For example, we mention that climate change effect on crop yield could be a potential channel for explaining the distributional impacts (see Appendix E). Lobell and Field (2007) find that an additional degree Celsius may decrease crop yield by 5.4% for wheat, and by 8.3% for corn. However, they show that precipitation trends have only minor effects on yields.

Among the limitations and hypotheses underlying our study, we insist on some biotechnical and economic elements. The first type of limitation refers to the characteristics of our modeling framework. The findings of this work strongly rely on the crop yields computed by the STICS crop model. Among the crop simulation models able to perform under various climate, soil and management practices parameters, STICS is a well evaluated model (Palosuo et al., 2011; Rötter et al., 2012). However, the model has been found to slightly overestimate crop yields. It should also be noted that we do not consider any technical progress which would be quite uneasy to transform in biophysical and economic information requested to feed the model. Particularly, plant breeding will certainly help to obtain crops that better suit a different climate. Concerning the autonomous adaptation at the farm scale, our analysis is based on an assumption of behavior on the part of the producers who adapt to the weather conditions as sketched by the climate models. Other usual limits refer to the overall economic environment that would be expected in the future, for example in terms of agricultural prices, which are exogenous and kept unchanged in our simulations. Thus, we do not account for a possible change in input or output prices, due e.g., to climate change or to a change in eating habits. We also consider the structure of farms to be unchangeable. We maintain the original typology (i.e. constant number of representative farms, constant farms agricultural surface). The evolving structure of farms challenges this type of model, shifting the problem towards structural and dynamic aspects, out of the scope of our modeling approach. As far as we know, it is particularly difficult to deal with this in other quantitative agro-economic models. A similar remark can be made for the land use, where capturing the dynamic facets of the land market proves to be especially challenging. On the one hand, these assumptions allow us to assess the autonomous adaptation of European farmers to climate change *all other things being equal*. As we keep the agricultural population constant over different time horizons, we are able to quantify the distributional effects. On the other hand, this prevents us from capturing indirect effects. By modifying agricultural yields, climate change could obviously impact agricultural goods prices, and thus, farms structure.

5. Conclusion

Relying on a soft coupling between a crop model and a microeconomic model of European agricultural supply, we inform the distributional impacts of EU-27 farm-level autonomous adaptation to climate change. In addition, we provide a farmers' income inequality decomposition. It allows us to identify and quantify the contribution of main farms' characteristics to overall income inequality and how they vary under climate change.

Our findings indicate that *ceteris paribus*, climate change may lead, in terms of social welfare, to a hardly worse situation (with respect to the present) in the middle-term horizon. This result can be explained by (i) a decrease in income share for bottom quantiles and (ii) a decrease in total income. However, in the long run, climate change could lead to slightly a better situation, due to (i) a constant income share for bottom quantiles and (ii) an increase in average income. Even if the income distribution is not substantially affected, our results suggest that nearly half of the agents represented in the model could see their individual situation deteriorate, which will necessarily challenge public decision-makers. We also assess the marginal contribution of two major individual characteristics – i.e. region and type of farming – to overall income inequality. These two attributes substantially contribute to farmers' income inequality (approximately 73%). The region seems to be the most determinant characteristic. Our results show that climate change slightly influences the region and type of farming contribution to income inequality.

This work could be extended in several directions. First, the analysis could concern other regions. The distributional impacts of climate change may be different where agriculture is differently structured. One could also be interested in studying the distributional impacts of climate change on other economic sectors. Second, it could consider other sides of climate change, such as the increase in the frequency of extreme weather events or the appearance of crop diseases. Third, it could be of major interest to study the interaction of adaptation to climate change with GHG emission mitigation policies, within European agriculture. How could agricultural GHG mitigation policies impact the distributional effects of adaptation to climate change within the European agricultural system? The microeconomic model used in this work could help disentangle this question.

CRediT authorship contribution statement

Maxime Ollier: Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization. **Pierre-Alain Jayet:** Writing – review & editing, Supervision, Methodology. **Pierre Humblot:** Software.

Declaration of competing interest

We disclose the data used in this article. We declare no conflict of interest.

Data availability

Data and code will be available in a supplementary material.

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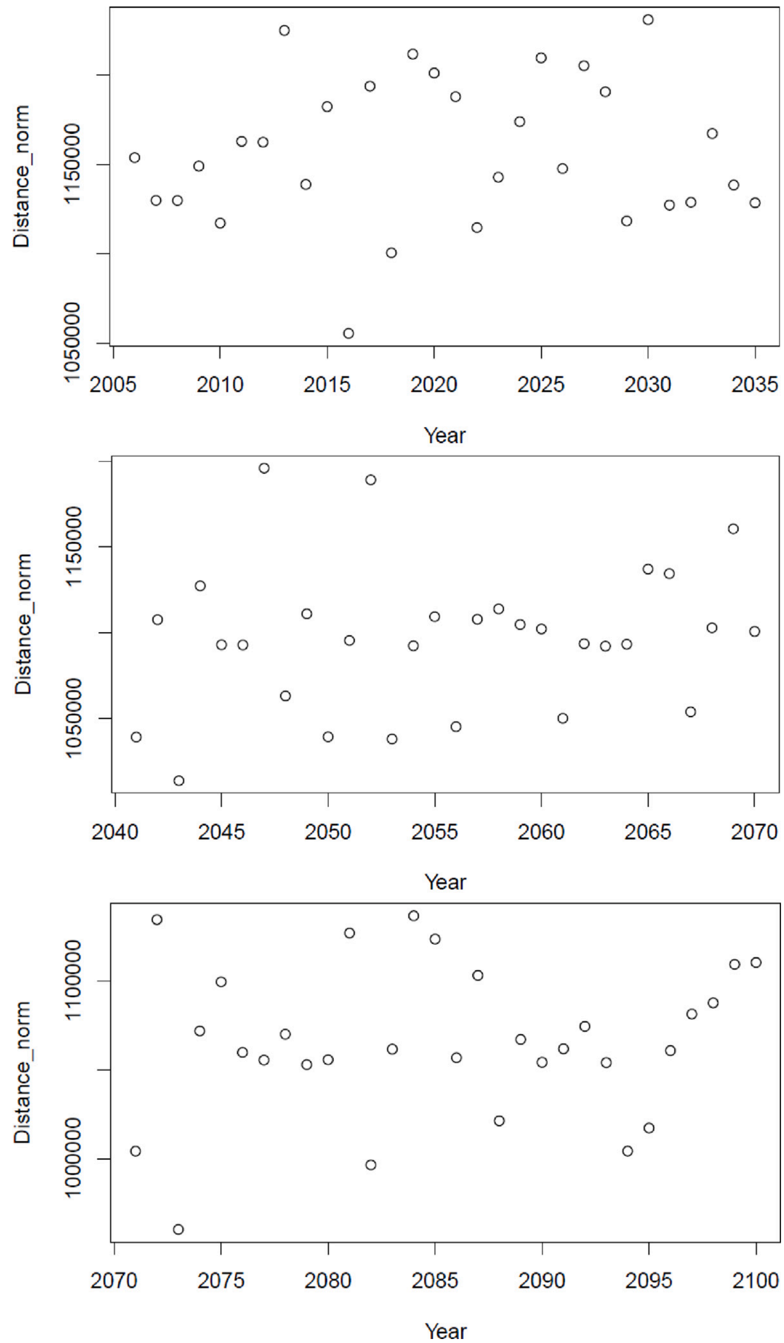

Fig. A.7. Normalized distance between year observations and average values for periods 2006–2035, 2041–2070, and 2071–2100.

Appendix A. Modeling strategy

For selecting a representative year over a 30-year period, we measure the distance between each year's observations and the average values for the period. Each distance is calculated for the days of the year, and the FADN region and altitude class intersection (indexed by n). The variables considered are indexed by k. Therefore, we compare the matrix with average values (M), and the matrix with annual observations for the year i (A_i) as follows:

$$Distance_i = \sum_{j=1}^{n} \sum_{l=1}^{k} (M - A_i)^2 \tag{A.1}$$

Since the units of the climate variables and their variability are different, we calculate the distance with the variables normalized by their mean annual values over the 30-year period (avg), as follows (see Fig. A.7):

$$Normalized\ distance_i = \sum_{j=1}^{n} \sum_{l=1}^{k} \left(\frac{M - A_i}{avg} \right)^2 \tag{A.2}$$

Following the results obtained with normalized distance, the year 2016 is the best choice to represent the climate in the beginning of the 21st century (period 2006–2035), and the year 2073 is the best choice to represent the climate in the late 21st century (period 2071–2100).

Appendix B. Classification of types of farming

Table B.4
Types of farming covered with the model.

Specialist cereals, oilseeds, protein crops
General field cropping
Specialist dairying
Specialist cattle — rearing and fattening
Cattle — dairying, rearing and fattening combined
Sheep, goats and other grazing livestock
Specialist pigs
Specialist poultry
Various granivore combined
Mixed cropping
Mixed livestock, mainly grazing livestock
Mixed livestock, mainly granivores
Field crops — grazing livestock combined
Various crops and livestock combined

Appendix C. Negative incomes

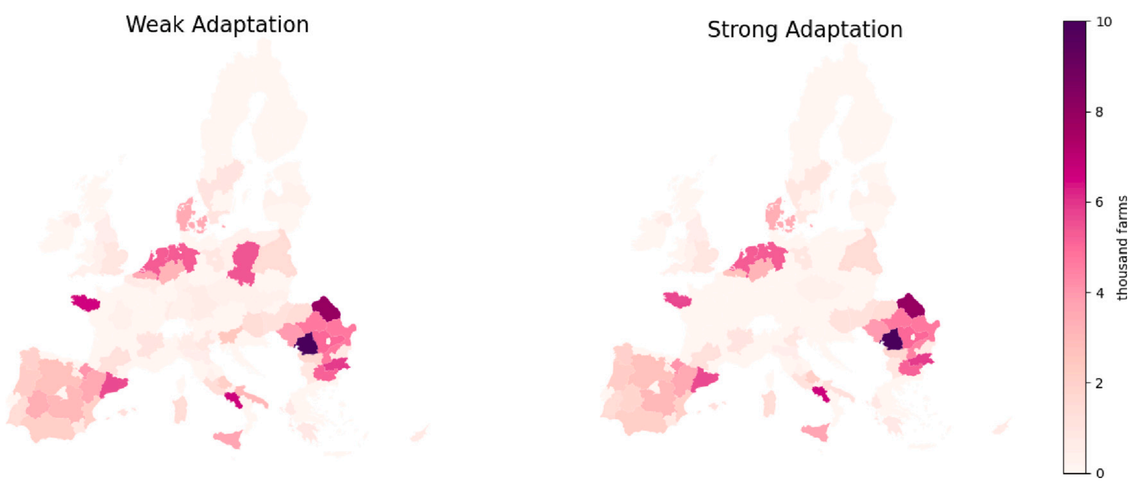

Fig. C.8. Regional number of farms (10^3) with negative incomes in at least one of the three time horizons for *weak* and *strong adaptation* levels.

Table C.5
Number of farms (10^3) with negative incomes in at least one of the three time horizons for *weak* and *strong adaptation* levels by type of farming.

Type of farming	Weak adaptation	Strong adaptation
Specialist cereals, oilseeds, protein crops	6.6	6.4
General field cropping	12.1	9.3
Combination of general, mixed field cropping and grazing livestock	5.7	5.7
Specialist pigs	5.6	4.8
Specialist pigs and poultry	22.4	18.8
Specialist pigs, poultry, and various granivore	44.7	43.1
Specialist pigs, poultry, various granivore, and mixed livestock, mainly granivores	5.8	5.8
Specialist pigs, poultry, various granivore, mixed livestock, mainly granivores, and various crops and livestock combined	18.3	17.7
Mixed cropping	12.3	10.7
Mixed livestock, mainly granivores, and various crops and livestock combined	6.6	5.0
Field crops — grazing livestock combined	9.3	9.3

Appendix D. Income deciles

Fig. D.9. Regional location of farms per unpaid AWU income deciles in the *weak adaptation* scenario.

Appendix E. Regional yields

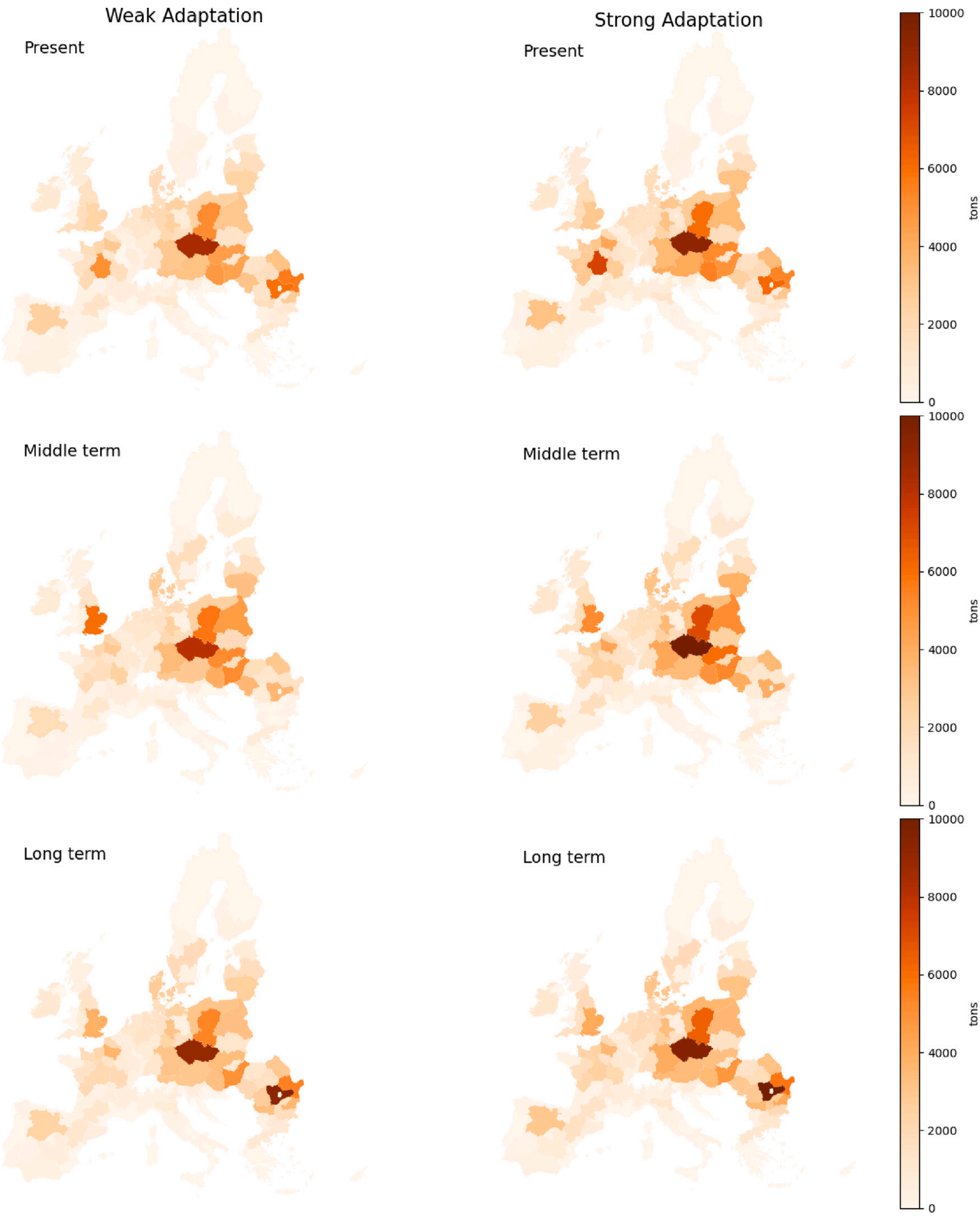

Fig. E.10. Total wheat regional yield (tons) for the three time horizons and for *weak* and *strong adaptation*.

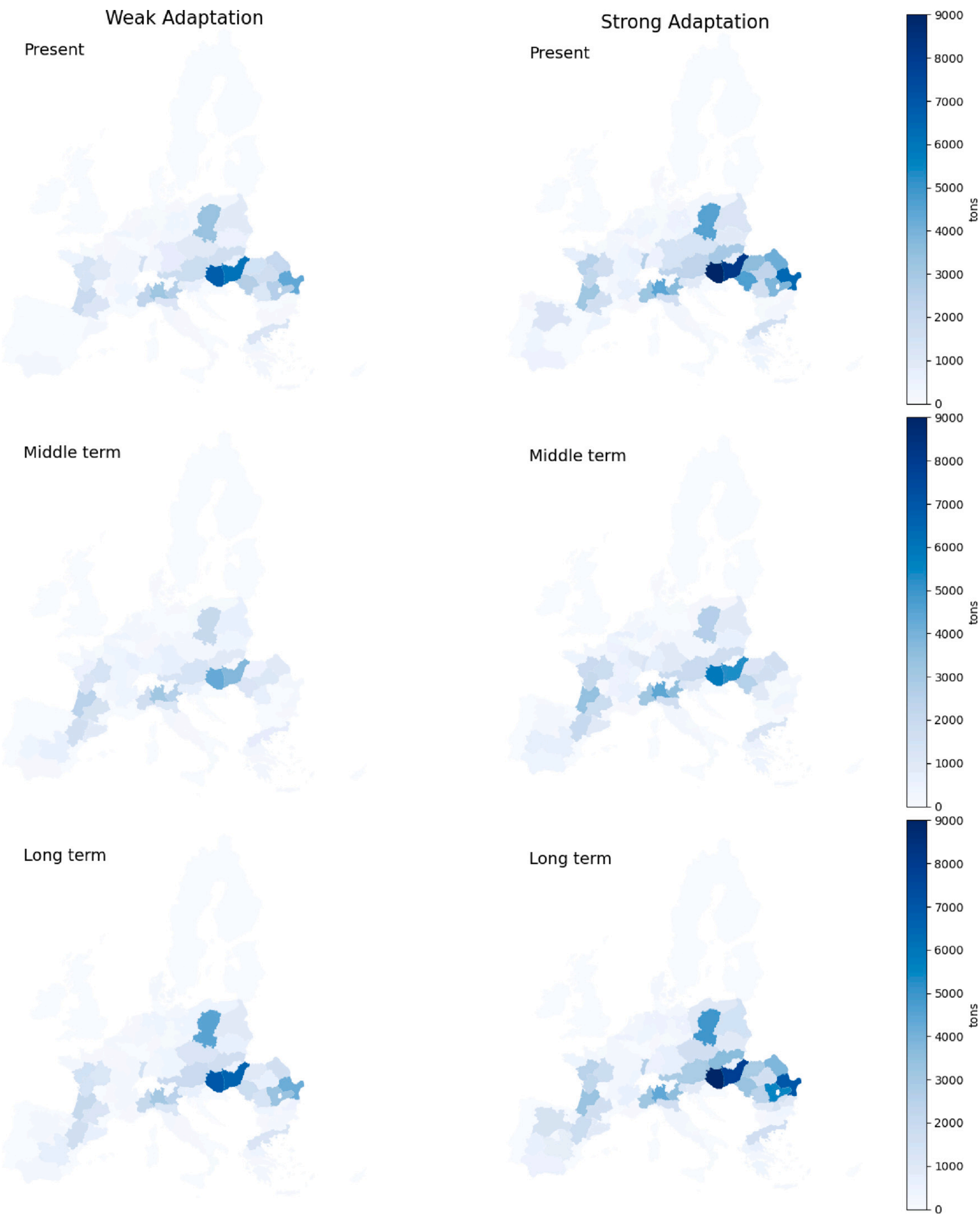

Fig. E.11. Total corn regional yield (tons) for the three time horizons and for *weak* and *strong adaptation*.

Appendix F. Gini index

Table F.6
Gini index for per unpaid AWU and per farm income, for *weak* and *strong adaptation* levels, and for three time horizons.

	Income	Present	Middle-term	Long-term
Weak Adaptation	Per unpaid AWU	0.6805	0.6814	0.6796
	Per farm	0.6907	0.6931	0.6885
Strong Adaptation	Per unpaid AWU	0.6740	0.6796	0.6743
	Per farm	0.6840	0.6907	0.6817

Appendix G. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108221.

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