Does Land Consolidation Increase Vulnerability to Climate Change? Evidence from French Agriculture*

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Abstract

This paper investigates the consequences of land consolidation on agriculture's vulnerability to extreme temperatures. Combining quasi-weekly satellite data on land productivity with farm-level cadastral data, we show that while highly consolidated land provides the majority of the country's food production, it suffers disproportionately from extreme weather events. We find that a key driver of resilience is the negative relation between land consolidation and biological diversity, which helps buffering the adverse effects of heat-shocks. This implies a trade-off between productivity and resilience, which becomes critical as heat-shocks grow stronger and more frequent.

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1 Introduction

Does farmland consolidation make agriculture more or less vulnerable to climate change? The productivity gains from land consolidation and modern agriculture are well documented (Adamopoulos and Restuccia, 2014; Foster and Rosenzweig, 2022). Yet far less is understood in economics about how these structural changes may interact with increasing climate risks. The rise of industrial agriculture has played a crucial role in providing sufficient nutrition for the world's population, with one defining feature being the consolidation of land ownership, leading to larger farm sizes and higher land inequality. This trend is consistent with the presence of large economies of scale in a price taking market. However, it has also led to intensive farming practices, increased crop specialization, and reduced ecological diversity. The agro-biology literature provides evidence that the latter two may be key to moderating adverse climate shocks (Renard and Tilman, 2019). A better understanding of the relationship between land distribution and climate resilience is critical for food security. And while the existing literature has focused on forecasting the damage caused by climate change and adaptation through technology (Vogel et al., 2019; Moscona and Sastry, 2023; Bilal and Känzig, 2024), it has not addressed whether climate shocks are more detrimental to primary production when productive allocation is highly concentrated

This paper empirically investigates these questions by linking yearly land ownership and utilization records with high-frequency plant growth observations in France. We measure land consolidation through geo-referenced cadastral data, providing detailed information on agricultural plots, including their shape, size, precise location, and crop composition. This dataset allows us to construct detailed yearly estimates of farmland concentration, such as Gini coefficients and average farm sizes at a granular level, alongside estimates of crop diversity with over 200 species categorized at the plot-level. To complement this, we incorporate satellite imagery from NASA, which estimates biomass production across the entire French territory, and can be analyzed to focus specifically on the productivity of food-producing farms. These satellite-based estimates, adjusted for factors such as cloud coverage, provide land productivity measurements at a $500m^2$ resolution every eight days, allowing for precise tracking of growth dynamics. Productivity is measured through Gross Primary Productivity (GPP)—a widely used biological metric that reflects biomass production per unit area. GPP captures carbon content rather than economic value, making it distinct from market-based yield measures.[1] Additionally, we integrate temperature data from Météo France's SAFRAN physical model, enabling us to account for the impact of weather conditions. We define temperature shocks using the local threshold where agricultural productivity begins to decline, taking into account the nonlinear relationship between yield and temperature. These treatment thresholds are established by calculating the weighted average of crop-specific thresholds within a given area, based on the yearly crop composition. Together, these data sources allow us to create a 7 year panel with observations at the weekly level for an arbitrary geographic area.

Our results reveal a nuanced relationship between land consolidation, productivity, and resilience. We begin by confirming the established inverse relationship between farm

[1] While GPP is always proportional to yields, it does not directly correspond to market prices, as it primarily measures carbon content rather than economic value. This allows us to focus on produced quantities without needing to disentangle price effects, which emphasies food security rather than profit maximization.

size and productivity, where higher land consolidation results in lower per-square-meter yields. We then expand this by showing how these productivity differences grow sharper across the temperature spectrum. We find that under extreme temperatures, larger, more consolidated farms suffer sharper productivity declines compared to smaller, diversified ones. Despite their labor efficiency, consolidated farms prove more vulnerable to thermal stress, suggesting that their capacity to withstand climate extremes is diminished. This finding, robust to a range of controls, underscores the trade-offs between efficiency and resilience, with significant implications given that yearly aggregate agricultural output in France is dominated by regions with high Gini coefficients and large farms.

In our preferred specification, we estimate that farms in the first quartile of land Gini lose around 3.9% of their production for every additional degree above the threshold, while those in the fourth quartile lose 6.4% of their weekly production, on average. We estimate average treatment effects for crossing the threshold with a Gini inter-quartile range between -5 to -7 percentage points. The significantly sharper productivity declines seen in highly consolidated land under extreme heat underline the importance of the productivity-resilience trade-off. We illustrate this by augmenting the simple supply model with a biodiversity parameter that is positively correlated with crop resilience but also positively correlated with costs. Farmers' (and policy makers') optimal production decisions then become more nuanced in a world with increased climate risk.

We then investigate whether biological diversity levels explain the differential impacts of heat shocks across varying degrees of land consolidation. Two types of mechanisms emerge from the biology literature. The first is portfolio mechanisms, which relate to crop diversification both within and between crop types (Abson, Fraser, and Benton, 2013; Renard and Tilman, 2019). A diversified crop portfolio spreads risk across species with varied heat tolerances, genetic traits, and growth strategies. This approach enhances resilience by ensuring that even if one crop struggles under extreme conditions, others may still thrive due to different heat responses or genetic resistance to stress. Our analysis shows that lower crop diversity in highly consolidated areas explains part of the variation in treatment effects across the consolidation spectrum. The second type of mechanism is ecosystem services, which are linked to the presence of natural and semi-natural areas (Kremen and Miles, 2012; Tamburini et al., 2020). These areas, often diminished in more consolidated land, play a critical role in enhancing crop resilience by providing key ecological functions—such as temperature regulation, refuge for pollinators, water retention, soil erosion control, and pest management. Our findings indicate that ecosystem services help explain much of the differential effects observed across the quantiles of Gini and farm size, underscoring their importance in sustaining agricultural resilience in the face of climate shocks.

In sum, we find that land inequality and natural diversity can be thought of as different faces of a coin, one side being the political economy that accounts for institutional factors and productive decisions, while the other accounts for both biological and portfolio mechanisms. And although our data show a very strong inverse relationship between the two, consistent with market incentives, it is non-deterministic. Individual producers and policy makers are free to chose to diversify their production considering climatic risks.

The European Union has implemented a set of policies promoting agro-ecology, which involves leveraging biodiversity to reduce greenhouse gas emissions while sustaining production. This concept is integral to the European Green Deal and recent Common Agricultural Policy reforms. In France, agro-ecology has been a legal objective since 2014, supported by major initiatives like France Relance and Ecophyto. Although agro-ecological investments are typically framed as a way to mitigate the causes of climate change while preserving biodiversity, they are seldom recognized for their potential to address the consequences of climate change. Our findings highlight the dual strategic value of such investments.

Our findings contribute to two strands of literature: climate change adaptation and the inverse relationship between farm size and productivity (IFSP). We expand on existing research by providing empirical evidence that crop diversification, especially when combined with seminatural areas, enhances agricultural resilience to extreme temperatures, making it an effective means of adaptation. This perspective bridges insights from biology with the complexities of property rights and economic decision-making, underscoring the technical and political challenges of implementing diversification policies. Furthermore, we contribute to the IFSP literature by showing that this relationship is not solely determined by farm-level factors but also influenced by broader ecosystem dynamics. We also extend this framework to include temperature effects, highlighting how climate variations interact with farm size and productivity.

The remainder of this paper is structured as follows. Section 2 summarises related strands of literature, as well as our contribution to them. Section 3 presents our simple supply function model, which serves as a theoretical framework for our empirical analysis. In section 4, we quickly describe data sources, definitions, concentration indices, and our heat-shock variable. Section 5 presents the stylized facts, results, and robustness checks of our empirical analysis, examining the relationship between land inequality, diversity, and agricultural productivity. Section 6, discusses and concludes on our findings, their implications for policy and for future research.

2 Related literature

This study intersects with two strands of the literature. First, the emerging literature on adaptation to global warming, which aims at preparing our productive systems to looming extreme weather events, with a special focus on agriculture. Second, it contributes to the literature on the inverse relationship between farm size and productivity, a century old puzzle to which we bring new insights.

2.1 Adaptation to climate change

The adaptation to climate change has been a focal point of recent research, exploring both mitigation strategies and the challenges posed by extreme weather. However, most findings from this body of work paint a rather grim picture, revealing limited signs of effective adaptation.

Burke and Emerick (2016) study historical data on U.S. agricultural production, highlighting the scarce evidence of farmers' adaptation. The authors find that long-run adjustments have done little to mitigate the short-run impacts of extreme heat on corn yields, despite the clear detrimental effects of extreme temperatures on yields. Expanding beyond the agricultural sector in the U.S., Burke, Zahid, et al. (2024) examine various outcomes—such as crop yields, mortality, and economic activity—in regions including the U.S., Europe, and Brazil. They conclude that while some areas show reduced sensitivity to climate change, the majority of outcomes studied do not exhibit significant adaptation, indicating that existing strategies have not effectively mitigated climate-related damage. Some studies even find counterproductive responses, such as Aragón, Oteiza, and Rud (2021), while studying Peruvian subsistence farmers. The authors reveal that increased input use in response to extreme heat, particularly land intensification, paradoxically exacerbates yield reductions in the longer run.

Some studies offer slightly more encouraging, albeit limited findings. Moscona and Sastry (2023) investigate the potential for directed innovation and demonstrate the significant, though incomplete, role of technological change in adapting to global warming in U.S. agriculture. Their research shows that directed innovation has offset approximately 20% of potential losses in U.S. agriculture due to damaging climate trends since 1960, with projections suggesting that innovation could offset 13-16% of the projected damage by 2100. Although promising, these results depend on continued innovation and adaptation efforts. In a more theoretical perspective, Costinot, Donaldson, and Smith (2016) emphasize the role of comparative advantage in international markets, suggesting that the effects of climate change on yields could be mitigated through a strategic reshuffling of production and trade patterns, given the geographical heterogeneity in climate change impacts.

A subgroup of this literature also addresses how diversification strategies –in a broad sense– can help subsistence farmers in developing countries maintain revenues under extreme weather. Although these studies do not directly examine land concentration or natural diversity at the scale of our analysis, they provide valuable insights into the resilience benefits of diversification. For instance, Valdivia, Dunn, and Jetté (1996), Di Falco and Chavas (2009), Birthal and Hazrana (2019), and Seo (2010) investigate how crop diversification serves as a protective mechanism for subsistence farmers facing climatic shocks. While their primary focus is on indivudal revenue preservation, their findings indirectly support the broader idea that increased biodiversity can enhance agricultural resilience.

These studies highlight the need for strategies that consider both the immediate and long-term implications of climate change. To this literature, our paper provides evidence on how diversification strategies, both at the individual or collective level, could become an effective coping mechanism to improve the resilience of agricultural productivity, resonating with findings from biology (Tamburini et al., 2020; Beillouin et al., 2021). Additionally, our paper shows how closely intertwined diversity patterns are to property rights, suggesting that diversification policies could not only pose technical problems, but also political ones.

2.2 Farm size and productivity

The relationship between farm size and productivity has long intrigued economists, beginning with the observation that smaller farms often report higher yields per square meter than larger ones within a given country. This inverse relationship, first noted by Chayanov (1926) in Russia and later expanded upon by Sen (1962) in India, has been confirmed across various settings throughout the last century in both developed and developing countries, challenging traditional economic models that assume constant returns to scale in agriculture (Sen, 1962; Berry, Cline, et al., 1979). This phenomenon, known as the Inverse Farm Size-Productivity (IFSP) relationship, has fueled debates about the potential benefits of land redistribution, arguing that smaller farms could potentially lead to higher productivity (Cornia, 1985).

Three leading conjectures have emerged as potential explanations for relation. The first suggests that market imperfections –such as those in labor and insurance markets, alongside moral hazard– might drive this pattern (Sen, 1962; Feder, 1985; Barrett, 1996). For example, Sen (1962) argued that surplus labor in developing economies leads to family labor being underpaid compared to market wages, meaning that smaller farms, which rely more heavily on family labor, achieve higher yields. The second explanation considers omitted variables, particularly land quality, which might inversely correlate with farm size, as argued by Bhalla and Roy (1988) and Benjamin (1995). The third explanation posits that measurement error, particularly in how farm size and output are recorded, could be negatively correlated with farm size, thus producing the observed inverse relationship (Lamb, 2003). However the evidence doesn't fully support any of these explanations. While these conjectures offer plausible mechanisms, empirical studies often struggle to consistently validate them across different contexts. The persistence of the IFSP remains puzzling, suggesting that other, less explored factors might be at play (Barrett, Bellemare, and Hou, 2010).

Recent research by Foster and Rosenzweig (2022) provides a more nuanced understanding, highlighting that while larger farms tend to exhibit decreased land productivity, they actually benefit from significantly increased labor productivity. This explains why large farms make economic sense, as the IFSP primarily holds for land productivity rather than total productivity. Their work highlights a U-shaped relationship, where small farms initially show higher productivity due to inefficiencies and market failures at larger scales. However, as farms expand, the adoption of capital-intensive technologies dramatically boosts labor productivity, eventually leading to overall higher productivity.

Our research, using granular and comprehensive data from a country with a mature and large agricultural sector, also finds evidence of the IFSP, in terms of land productivity, which remains largely unexplained. One of our key contributions to this literature is to bring new evidence on its mechanisms by adopting a new perspective. Instead of focusing solely on individual productive units, we take a more comprehensive view, considering what happens outside these farms as well. By adopting an ecosystem perspective, we reveal how biodiversity, particularly the presence of semi-natural areas contributes to increased land productivity.

Our results can be interpreted as an examination of the IFSP curve through a temperature dimension. We observe a consistent differential in land productivity that becomes even more pronounced in the presence of extreme temperatures. This suggests that the benefits of biological diversity and the presence of seminatural contribute to the IFSP, playing a critical role in normal times, and even more so under conditions of heat stress.

3 A simple model of agricultural production

This section presents a simple supply model to illustrate how land concentration and diversity affect the resilience of agricultural production to climate change. The model takes into account economies of scale and costs as a function of biodiversity. It first shows how farmers face rational incentives to specialise and consolidate land. We then add a parameter that connects biodiversity and weather shocks. The simple model provides a starting point for why higher land inequality is positively correlated to profits in normal times, but that there is a trade-off with resilience to adverse climate shocks.

3.1 Setup

Consider an agricultural production function with land (L), capital (K) and the acreage of land allocated to biodiversity (D) as inputs with contraint $L > D$.

$$Y = AL^{\alpha}K^{\beta}D^{\psi} \qquad ; \qquad \Pi = Y - C(Y) \tag{1}$$

Farmers have equal access to technology, credit markets (both captured in A) and are price takers. Ignoring climatic shocks, farmers maximise profits (Π) by optimizing over land, capital and plot biodiversity. Prices are normalized to one, and the cost function $C(Y)$ is composed of two parts: fixed costs $F(L, K, D)$ and variable costs $c(L, K, D)$ that increase with output Y and exhibit economies of scale.

$$AC(Y) = \frac{C(Y)}{Y} = \frac{F(L, K, D)}{Y} + \frac{c(L, K, D)}{Y} \tag{2}$$

Both fixed and variable costs are twice differentiable and increasing in all arguments. The cost function exhibits strong economies of scale in land since initial fixed costs are high and variable costs relatively low.

This implies the long-run optimal choices of inputs. The first order condition for profit maximisation with respect to L and D is equivalent to cost minimization. The farmer's problem is to minimize average costs which leads to equating marginal products of both inputs to their marginal costs,

$$\min_{L,D} \frac{C(Y)}{Y} \qquad \longrightarrow \qquad \frac{Y'_L}{Y'_D} = \frac{C'_L}{C'_D} \tag{3}$$

Because initial investment costs in land are high but have low variable costs, C'_L is relatively flat. Clearly this allows farmers to push production higher to a point where marginal product, Y'_L is close to zero, creating a long-run incentive to increase plot size.

3.2 Optimal biodiversity

For ease of exposition, we normalize captital $K = 1$.[2] The first order conditions with respect to L and D are,

$$\alpha A L^{(\alpha-1)} D^{\psi} - \frac{\partial C(Y)}{\partial L} = 0$$

$$\psi A L^{\alpha} D^{(\psi-1)} - \frac{dC(Y)}{dD} = 0$$

Combining, we can solve for the optimal level of biodiversity that farmers set for their agricultural land,

$$D^{*} = \frac{\psi Y L}{\frac{dC(Y)}{dD} - \alpha Y} \tag{4}$$

It is increasing in biodiversity's elasticity with production and declining in its marginal cost. Where,

$$\frac{dC(Y)}{dD} = \frac{\partial C(Y)}{\partial D} + \frac{\partial C(Y)}{\partial L}\frac{dL}{dD}$$

The marginal cost entails a direct cost related to increased crop diversity (first term on the right), but also the *opportunity cost* of allocating a higher proportion of land to non harvestable plant growth (second term).

The optimal level of biodiversity is determined by a trade-off between its positive direct effect on productivity and the cost of increasing crop diversity and foregoing revenue that could be generated if all a plot's land was utilized for commercial production.

3.3 Extreme weather effects

We now introduce a scaling fucntion, $h(T, D)$, to account for the effects of temperature T on productivity:

$$Y = A L^{\alpha} D^{\psi} h(T, D) \quad ; \quad \Pi = Y - C(Y, D)$$

where $h(T, D)$ takes the following form:

$$h(T, D) = -\lambda(T - T_0) * (1 - D^{\theta})$$

in which T_0 represents a threshold temperature above which plant growth is hampered (e.g., 30°C). $\lambda > 0$ is a parameter reflecting the sensitivity of crops to temperature, and $\theta > 0$ captures the moderating effects of biodiversity on temperature contribution to production. This function is positive in T and largest at low increments of temperature

[2]Our empirical strategy allows for this assumption because we can control for yearly changing in all unobserved inputs.

increases until it crosses the threshold where it becomes negative. Its slope is negative and determined by θ. Higher θ, implies a smaller positive effect of temperature increases below the threshold, but also smaller adverse effects above the threshold.

Optimal D now can now be expressed as,

$$D^* = \frac{\psi Y h}{\frac{dC(Y)}{dD} - \frac{\partial h}{\partial D}} \tag{5}$$

While minimizing biodiversity will increase yields in normal times, it also increases the vulnerability of their production to climate extremes.

In an environment where $T > T_0$ occurs more and more frequently the marginal benefit from crop diversity in mitigating these shocks increases. Farmers are now faced with a more complex optimization problem: maximizing profits while balancing the cost-saving benefits of low diversity against its risk-reducing benefits.

4 Data, Tools, and Definitions

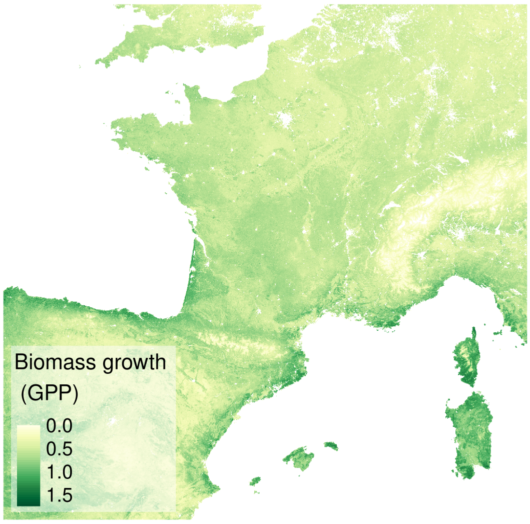
This section describes the three major data sources used in our empirical analysis: satellite imagery, agricultural cadastre records, and weather estimates. We also quickly review methods used to construct concentration measures of both farmland and biological diversity, as well as the definition of temperature shocks used in our empirical assessment. Figure 1 displays data samples, the following subsections elaborate on each source individually.

4.1 Productivity data

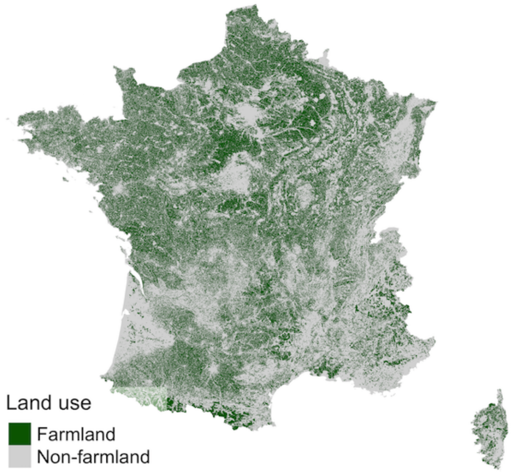
Satellites can detect photosynthesis, the fundamental process of plant growth. Some plant cells –usually leaf-cells– use the sun's energy to split CO_2 molecules around them in two parts. They keep carbon (C), which is mixed with other matter to build their own mass; and they release oxygen (O_2) back into the air as a byproduct. Such process leaves an invisible fluorescent signature track, which some satellites can measure. That is the case of the Terra satellite, thanks to the MODIS remote sensing device, launched on board of the satellite by NASA in 2000. It measures the gross primary productivity (GPP) of plants, which is a generic measure of biomass production around the globe, gross of plant respiration. Cloud-coverage adjusted measures of cumulative production are provided by Running and Zhao (2019) at a quasi-weekly frequency. We use their estimates, which come in a 500m x 500m grid, expressed as kilos of carbon per square meter. Figure 1a showcases total cummulated production for a given year, with each pixel representing a data point.

One of our first concerns is to determine how our productivity measure is relevant to what the economics field understands as land productivity or yield. GPP is proportional to yield but cannot be directly converted to economic yield. To do so, we would need specific GPP-to-yield conversion factors for each crop. As an example, Table 1 displays conversion factors between satellite estimates of GPP and actual agricultural yield of

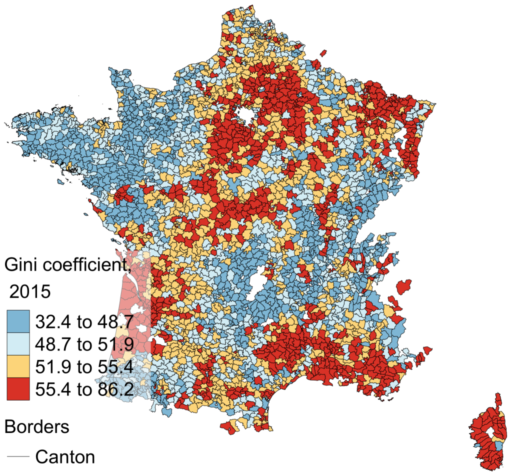
Figure 1 – Main inputs: high definition geo-located information



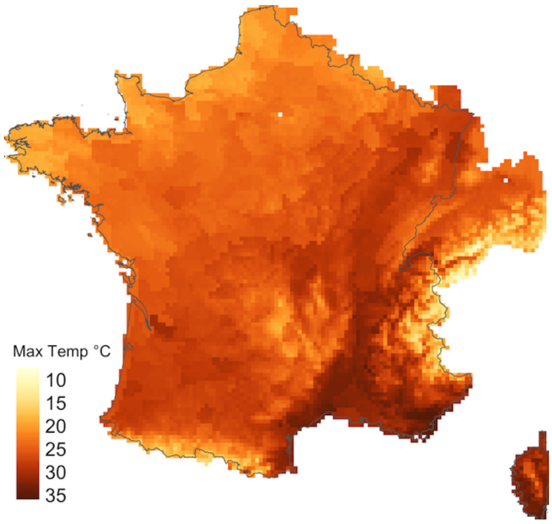
(a) Yearly land productivity, 2021



(b) Exhaustive farm information



(c) Land Gini coefficient



(d) Midsummer max. temperatures (ºC)

Notes. Panels 1a: satellite data cover the whole national territory, allowing for high-frequency measurements of land productivity. Panel 1b: cadastral information precisely locates all farms in the French territory with exhaustive information on crop allocation. Panel 1c: showcases one of our benchmark farmland concentration measures, based on the cadastral data and aggregated to the canton level. Panel 1d: displays daily maximum temperatures as measured in our weather data, estimated by the main weather data provider in the country.

crops in the context of a study in Montana, USA. The study combines observations taken at ground level with remote-sensing observations from our same source. Unfortunately, these are still uncommon and we do not have the capacity to build such estimates for hundreds of crops in a nationwide study. However, this is not problematic to our goal, which is to measure variations in productivity at extreme weather events. Since we can localise crops precisely thanks to the cadastral data described further, controlling for crop composition becomes an easy task. Working with a generic measure of biomass lets us refer to the physical production of plants without having to deal with price effects or price differentials, yet it prevents us from stamping an accurate price tag to our measurements.

Table 1 – GPP to Yield conversion factors, examples

Crop	Factor
Alfalfa	0.55
Barley	0.42
Maize	0.44
Durum wheat	0.22
Peas	0.28
Spring wheat	0.24
Winter wheat	0.35

Notes. By He et al. (2018) for annual yield of staple crops in Montana, USA

To isolate the part of the GPP layer that is relevant to our subject of study, we use exhaustive cadastral information to extract the slices of data that overlap with productive farmland, avoiding the contamination of our estimates with forest productivity, for instance. Figure A.1 provides a visual representation of such overlap. The cadastral data is described in more detail in the following subsection.

4.2 Cadastral data

Almost all French farmers must declare information on land use to the national authority, including the exact crop allocation within agricultural plots (figure 1b). Such declaration is necessary for them to receive annual subsidies from the European Union's Common Agricultural Policy. We obtain the administrative data from the Graphic Parcel Register dataset (RPG, for its acronym in French) provided jointly by the National Geographic Institute (IGN) and the Services and Payment Agency (ASP) of France. For every year the dataset reports the precise location of each exploitation, with detailed information of land use. We use the data between 2015-2021 for our analysis, despite the series starting five years earlier, because previous years contain information only on the dominant crop within plots instead of an exhaustive declaration. The only farmers that are excluded from the database are subject to some selective denominations of winemaking which don't benefit from subsidies.

Appendix A.1 provides an appreciation of the granularity of the cadastral data. In the background layer, one can notice productivity measurements coming at a coarser resolution, which explains why individual farm analysis is not possible with this data. The unit of observation of the cadastral data are productive agricultural plots controlled by a single person or entity, regardless of whether they control more than one, since they are recorded with a different id. As a consequence, our land inequality estimates probably represent a lower bound of land consolidation.

We use cadastral information to estimate farmland concentration in both terms of land inequality and biological diversity. The construction of these indices is explained further in this section.

4.3 Concentration measures

To analyze resilience to heatwaves across various dimensions of land concentration, we aggregate data at the level of French administrative divisions. The most granular administrative unit available is the *commune* or municipality. However, due to the extensive size of many farms, which often span multiple communes, we employ the next level of aggregation, *cantons*, as our primary unit of analysis. Cantons, although originally established for electoral purposes, provide a more practical scale for our study, dividing the French territory into over 3,500 distinct areas. This aggregation allows us to analyze weather conditions, farmland productivity, and other relevant variables within each canton at quasi-weekly frequency.

Land consolidation within these cantons is quantified using several measures, primarily the Gini coefficient (figure 1c), which provides an indication of land concentration. To calculate the Gini coefficient, agricultural fields are ranked by their surface size. From this ranking, we construct a Lorenz curve and apply the standard formula to estimate the Gini coefficient. In addition, we also calculate the average farm size within each canton as an alternative measure of land consolidation. This additional metric yields very similar results. Other measures, such as the coefficient of variation and the standard deviation of logarithms, were also computed; however, they align closely with the Gini coefficient.

Inter- and intra-crop diversity are assessed by treating each crop as a distinct unit within the canton. For this, we use a simple count of crop types as well as the Herfindahl-Hirschman Index, a commonly used measure of market concentration. The index is calculated as the sum of the squares of the market shares of each crop, where higher values indicate greater concentration. This index captures both the dominance of certain crops and the overall diversity of agricultural production.

In addition to examining crop diversity through simple counts and concentration indices, we explore the concept of crop diversity as portfolio diversification. For this purpose, we adopt the diversification ratio (D) as defined by Choueifaty and Coignard (2008). This ratio is calibrated using two decades of historical data on national crop yields. The diversification ratio is the ratio of the weighted average variance (WAV) to the overall portfolio variance (OPV). The WAV captures the variance within individual crop yields, while the OPV accounts for how these variances syncronize, incorporating their covariances. A higher diversification ratio indicates that the crop composition planted minimizes covariance among crops, signifying greater diversification. Further technical details on the calculation and calibration of the diversification ratio are provided in appendix A.2.

To account for the presence of semi-natural areas, we measure their size as a percentage of the total farmland within each canton, where farmland excludes all semi-natural areas. In rare instances where semi-natural areas exceed the farmland area, this percentage can exceed 100%, highlighting regions where semi-natural landscapes –excluding fully natural areas like forests– are particularly prevalent. Semi natural areas mostly include prairies, which are untreated long grass fields often held to preserve biodiversity, field edges with semi-natural local vegetation and bosquets, which are blocks of trees planted within or next to crop fields for the same purpose.

4.4 Weather data

Weather estimates are sourced from *Météo-France*, the official national provider of such data. We focus on three key meteorological variables: daily maximum temperatures (figure 1d), humidity, and precipitation. These variables, originally collected several times a day, are aggregated to a quasi-weekly frequency to align with agricultural production measures, which are aggregated over 8-day intervals.

The dataset is produced using the SAFRAN-ISBA model, which integrates ground-based observations and prediction models for spatial interpolation across climatologically homogeneous zones. This system produces a 8km grid with a battery of weather variables. A significant advantage of this approach is its reliance on physical models for spatial interpolation, which offers superior accuracy compared to simpler techniques such as kriging or inverse distance weighting. We also prefer it over laser measurements from the Terra satellite, since they can be blocked by cloud coverage. Since covered days are not reported in raw datasets, averages tends to report warmer temperatures. In contrast, physical models used by Météo-France are not affected by this, providing a more reliable ground for our analysis.

4.5 Defining temperature shocks

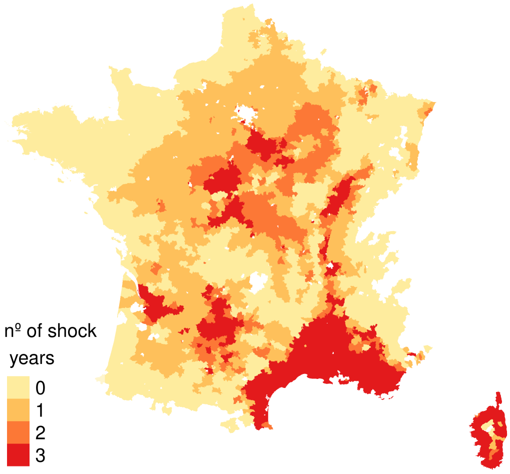
Different species of plants have different climatic requirements, and they vary with the course of development phases. Spring and summer wheat, two major staple crops in French agriculture, are a good example. Winter wheat has very specific requirements at early stages of growth. During a phase called vernalization, the plant requires a period between one and two months of cold temperatures (0-5ºC) that are absolutely necessary to reach the next phase. During that period, temperatures as low as 6ºC could arguably be called thermal shocks, but not for spring wheat, which does not endure vernalization. Since we expect the impact of thermal shocks to be more visible at the extremes, we focus on climatic requirements during summer-spring seasons. During that part of the year, both spring and winter wheat go through phases known as flowering (anthesis) and grain-filling, which are directly relevant to the ultimate cereal yield, which is our object of study. The temperature requirements at that stage are similar for both kinds, winter wheat suffers at temperatures beyond 33ºC, while spring wheat starts suffering at 32ºC. Yet the temperature is higher for the sunflower, at 35ºC, and lower for alfalfa, at 30ºC, for instance (see table 2).

To take into account the presence of a variety of crops ($c = 1, 2, 3, \ldots, N$), we define the threshold T_A for treatment in area A as the mean value of crop-specific temperature thresholds T_c, during spring-summer, weighted by the area's crop composition $w_{A,c}$, as a share of surface.

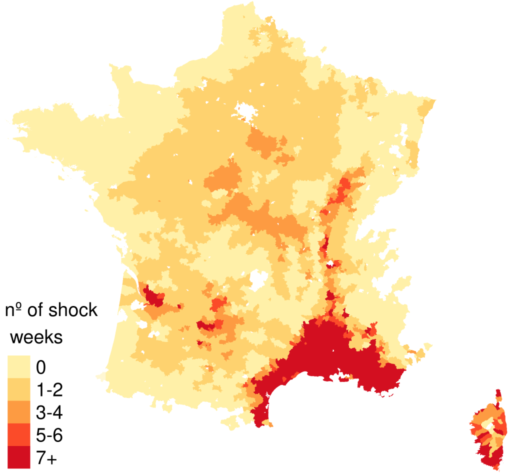
$$T_A = \sum_{c=1}^{N} T_c * w_{A,c} \tag{6}$$

In practice, finding crop-specific estimates of critical temperatures at that level of precision is not an easy task. Not only the actual estimation of such thresholds is subject to variations in methods, including issues such as controlling for other weather variables

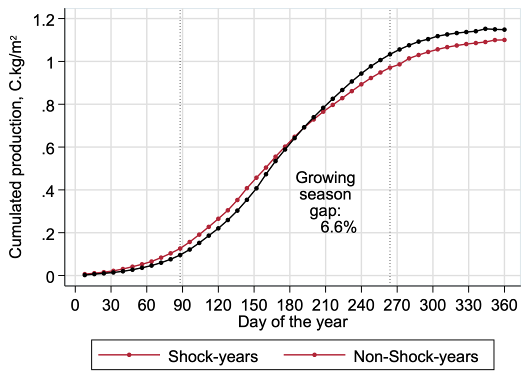
Figure 2 – The spatial distribution of heatshocks



(a) Years with at least one shock



(b) Total number of heatshocks



(c) Average loss under heat-shocks

Note. Figures 2a and 2b present the distribution of heat shocks across France from 2015 to 2021, based on weather data from Météo France. Heat shocks, or treatments, are defined as periods where the maximum daily temperature averaged over eight days exceeds the threshold outlined in Equation 6. This threshold varies by region, accounting for local crop composition (see figure A.2). Figure 2c includes canton fixed effects. Shock years contain at least one occurrence within the year, as defined in section 4.5. Own estimates based on data from Running and Zhao (2019) and Météo France.

or the choice of functions for modelling, but they can also vary in their geographical and chronological dimension. We thus use estimates from French specific data or lab experiments in first priority when they are available, which is the case for many staple crops like wheat, corn, barley, rapeseeds, alfalfa and sunflower. Otherwise, we use data from research papers produced using data from other countries, which is the case for soybeans, for instance, where we use estimates from the United States (Schlenker and Roberts, 2009). For areas that are not covered by any of the options above, including pasture zones, we define the threshold at 30ºC, which is chosen arbitrarily as a value where the downward trend is clearly identifiable (see appendix A.3).

Figures 2a and 2b illustrate the distribution of heat-shocks across the French territory between 2015 and 2021. The shocks are broadly dispersed across most regions, though certain areas, particularly along the coastline and in mountainous regions, are never impacted due to their more temperate climates. Over the seven-year study period, most regions

Table 2 – Crop-specific maximum temperatures

Crop	Max. temp (ºC)	Land share	Cumulative	Reference
Winter wheat	32	34.5	34.5	Gammans et al. (2017)
Corn/Maize	32	17.4	51.9	Hawkins et al. (2013)
Winter barley	33	7.4	59.3	Gammans et al. (2017)
Rapeseed	27	6.1	65.4	Pollowick and Sawhney (1988)
Sunflower	35	4.3	69.8	Rondanini et al. (2003)
Grapevine	30	3.6	73.3	Imputed
Spring barley	32	3.3	76.6	Gammans et al. (2017)
Alfalfa	30	2.8	79.5	Murata et al. (1965)
Beetroot	30	2.6	82.1	Imputed
Potato	30	1.1	83.2	Imputed
Soybean	30	1.0	84.1	Schlenker and Roberts (2009)
Spring wheat	33	0.2	84.3	Gammans et al. (2017)
Other (<1%)	30	15.6	100.0	Imputed

Notes. Compiled by the authors based on Cadastral data and references.

experience at least one heat-shock, with a maximum of three shock-years recorded for any given canton. Notably, some areas, especially along the southern Mediterranean coast, can experience multiple shocks within a single year, signalling more intense and prolonged exposure to heat. On average, land productivity is lower during shock-years, as 6.6% of the yield is lost by the end of the growth season. Figure 2c shows that the effects are long-lasting and determinant to yearly production.

5 Results

This section presents our findings. We first explore the relationship between land consolidation productivity and aggregate food production in France. We then examine consolidation's moderating effects under heat stress. We then assess candidate mechanisms that influence resilience in agricultural systems and are correlated with land inequality.

5.1 Land productivity and land consolidation

We begin our analysis by examining the relationship between land consolidation and primary productivity across French agricultural cantons. Our panel tracks land configuration and productivity at the canton level over time, allowing us to exploit within-area variation in land consolidation while controlling for crop composition and fixed effects at the geographic level.

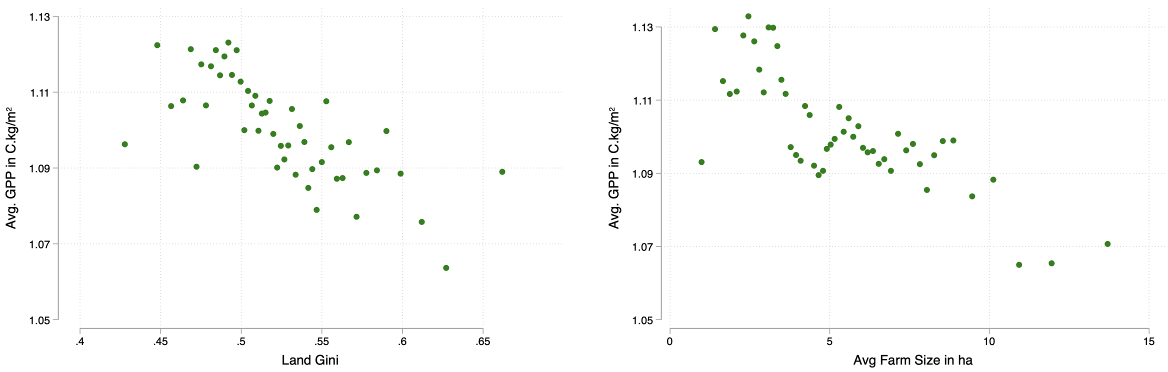
Panel A of Table 3 presents our initial findings: there is a significant inverse correlation between land consolidation, as measured by the land Gini coefficient or the average farm size, and land productivity, measured by cumulative gross primary productivity (GPP) at the end of the year. Specifically, we find that a one-point increase in the Gini coefficient (on a 100-point scale) is associated with a 0.0015 kg/m^2 decrease in productivity—a

Table 3 – Average yearly land productivity, GPP (C.kg/m^2)

	Land Gini			Farm Size		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Consolidation	-0.0088***	-0.0027***	-0.0015***	-0.0104***	-0.0036***	-0.0030***
	(0.0007)	(0.0005)	(0.0004)	(0.0019)	(0.0008)	(0.0006)
Constant	1.5625***	1.2450***	1.1809***	1.1596***	1.1209***	1.1176***
	(0.0388)	(0.0268)	(0.0198)	(0.0111)	(0.0045)	(0.0036)
Panel B:						
mean 1st quantile (ref)	1.179***	1.126***	1.112***	1.152***	1.122***	1.120***
	(0.006)	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)
2nd quantile	-0.067***	-0.016***	-0.003	-0.016**	-0.017***	-0.022***
	(0.008)	(0.005)	(0.004)	(0.008)	(0.006)	(0.005)
3rd quantile	-0.111***	-0.039***	-0.016***	-0.065***	-0.024***	-0.023***
	(0.007)	(0.006)	(0.004)	(0.007)	(0.007)	(0.006)
4th quantile	-0.138***	-0.049***	-0.023***	-0.122***	-0.043***	-0.034***
	(0.008)	(0.006)	(0.005)	(0.007)	(0.008)	(0.007)
p-val equal effects	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.13	0.71	0.81	0.10	0.70	0.81
N	17373	17352	17352	17449	17434	17434
(Geo x Year) FEs		✓	✓		✓	✓
Crop types			✓			✓

Notes. The dependent variable is the total primary production within the farmland of each canton per year. Panel A presents the linear relationship between the continuous measures of Gini and farm size. Panel B presents the results non-parametrically with indicator variables for each quantile. Standard errors are clustered at the canton. * $p < .1$, ** $p < .05$, *** $p < .01$.

Figure 3 – Average yearly land productivity, GPP (C.kg/m^2)



(a) Gini (b) Farm size

Notes. 50 quantile spaced bins conditional on geography x year FEs and crop composition.

decline equivalent to 3% of a standard deviation (0.05). These results persist even after controlling for crop composition and fixed effects.

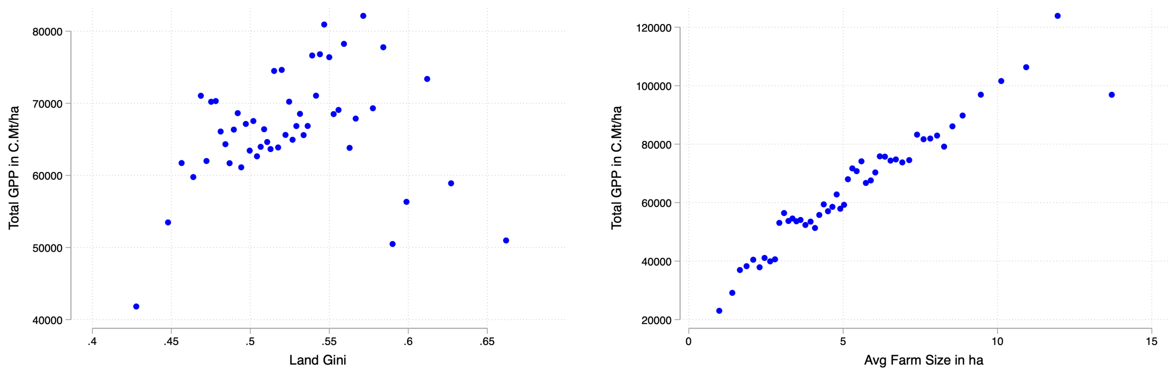
To further explore this relationship, Panel B of Table 3 and Figure 3 display the results non-parametrically, dividing the land consolidation measures into quartiles. The visualization of the conditional expectation function confirms the negative association between land consolidation and productivity across both measures.

Table 4 – Total agricultural GPP v. consolidation, GPP (C.Mt/ha) × Surface (ha.)

	Land Gini			Farm Size		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Consolidation	468**	202	-44	4885***	3905***	3495***
	(194)	(233)	(234)	(701)	(872)	(753)
Constant	41705***	55752***	68606***	38469***	44049***	46357***
	(10073)	(12284)	(12386)	(3781)	(4806)	(4181)
Panel B:						
mean 1st quantile (ref)	59326***	60979***	63558***	42181***	43193***	47498***
	(1619)	(1816)	(1826)	(1239)	(1868)	(1844)
2nd quantile	6364***	5349**	2364	14875***	12631***	9394***
	(2341)	(2297)	(2263)	(1963)	(2314)	(2237)
3rd quantile	12942***	10568***	6460**	31820***	29254***	23178***
	(2594)	(2655)	(2619)	(2147)	(2879)	(2804)
4th quantile	8903***	5762*	2071	48971***	49890***	41928***
	(2776)	(3083)	(3050)	(2564)	(3639)	(3502)
p-val equal effects	0.000	0.001	0.085	0.000	0.000	0.000
R-squared	0.01	0.27	0.33	0.14	0.34	0.37
N	17373	17352	17352	17449	17434	17434
(Geo x Year) FEs		✓	✓		✓	✓
Crop types			✓			✓

Notes. The dependent variable is the total primary production within the farmland of each canton per year multiplied by the farm surface area and expressed in megatons per hectare. Panel A presents the linear relationship between the continuous measures of Gini and farm size. Panel B presents the results non-parametrically with indicator variables for each quantile. Standard errors are clustered at the canton. * $p < .1$, ** $p < .05$, *** $p < .01$.

Figure 4 – Total agricultural GPP v. consolidation (GPP (C.Mt/ha) × Surface (ha))



(a) Gini (b) Farm size

Notes. 50 quantile spaced bins conditional on geography x year FEs and crop composition.

However, when we adjust our metric to account for the total agricultural volume—by multiplying cumulative yearly GPP by the average surface area covered by farms—the relationship with land consolidation reverses. Table 4 and Figure 4 illustrate this shift, revealing a U-shaped relationship between land Gini and total agricultural output. This non-linear pattern helps explain why the linear estimate presented in column 3 of Panel A appears insignificant. Although higher land consolidation is associated with lower average land productivity, the majority of agricultural output still comes from more consolidated lands, supporting the notion that agricultural production is efficiently allocated to the most efficient producers.

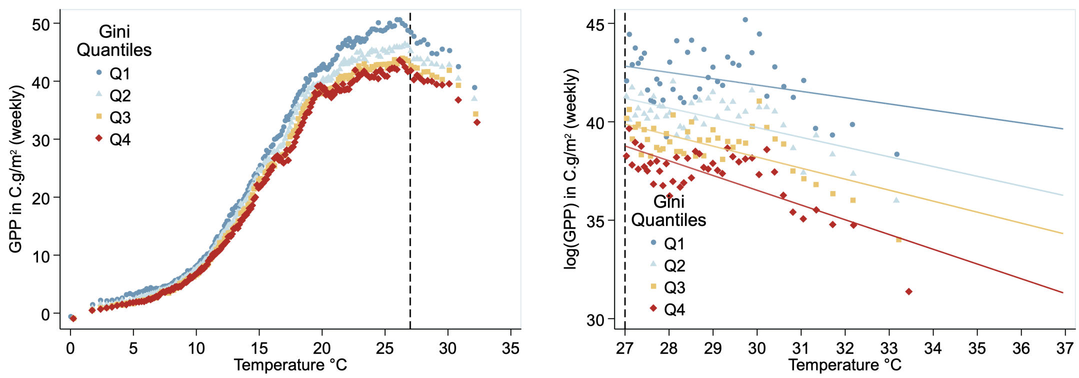
5.2 Temperature and productivity

The implications of differences in underlying land productivity and food supply are particularly important when considering the impact of temperature shocks. Given that a substantial portion of our food supply originates from highly consolidated land, understanding how these areas respond to temperature fluctuations is crucial.

We now explore the effect of temperature on productivity over land consolidation. Given the weekly variation in temperatures and productivity, we can now isolate the variation within cantons each year by conditioning on canton-by-year fixed effects. Identification of any differential effect of temperature shocks now relies on the assumption that more and less consolidated agricultural land would have had similar productivity trends in absence of a shock. Indeed, land consolidation can be correlated with a range of factors that correlated with productivity responses to temperature variation. This includes, but is not limited to, differences in production inputs, crop composition, local soil quality and product/labor market conditions. Including canton-year fixed effects allows us to not only control for any fixed differences in canton characteristics, but also any changes in the baseline characteristics each year.

We first plot weekly gross primary productivity (GPP) against temperature by land Gini quantiles.

Figure 5 – Weekly GPP v. temperature over land Gini quantiles



(a) All temperatures (b) Above minimum threshold

Notes. Bins selected using Cattaneo et al. (2024). The bottom panel overlays a linear fit on the selected bins. The vertical dashed line indicates 27ºC, the minimum threshold for treatment in table 2.

Figure 5a, the results are consistent with our earlier findings: more consolidated land exhibits lower productivity across the entire temperature gradient. This negative association, observed at the cumulative yearly level is driven by stable differences over

Table 5 – Weekly log(GPP) over land inequality

	All	>wgt. threshold
	(1)	(2)
Temp. 1st quantile (ref)	0.14101***	-0.03867***
	(0.00084)	(0.00728)
Temp. x 2nd quantile	-0.00323***	-0.00429
	(0.00117)	(0.00928)
Temp. x 3rd quantile	-0.00471***	-0.02384***
	(0.00121)	(0.00847)
Temp. x 4th quantile	-0.00594***	-0.02578***
	(0.00135)	(0.00779)
R-squared	0.74	0.57
N	795944	6976
(Panel unit x Year) FEs	✓	✓

Notes. The dependent variable is the log of weekly GPP. Standard errors are clustered at the canton level. * $p < .1$, ** $p < .05$, *** $p < .01$.

the temperature gradient. Figure 5b focuses on temperatures exceeding the minimum weighted shock threshold, providing a more granular view of how extreme temperatures affect productivity. Here, the productivity drop is sharper for more consolidated land, highlighting the vulnerability of these areas to extreme heat.

Table 5 provides magnitudes of the associations and inference. A one-degree increase in temperature results in a 14% decline in GPP, with the impact being slightly lower for more consolidated lands over all temperatures. However, when temperatures exceed the damage threshold, the productivity drop becomes more pronounced, with a 3.8% decline in the first Gini quartile compared to a 6.4% decline in the fourth quartile. Translated into levels, the lowest Gini quartile loses 1.23 grams of biomass weekly for every degree of heat above the threshold, while the top quartile loses 1.96 grams.

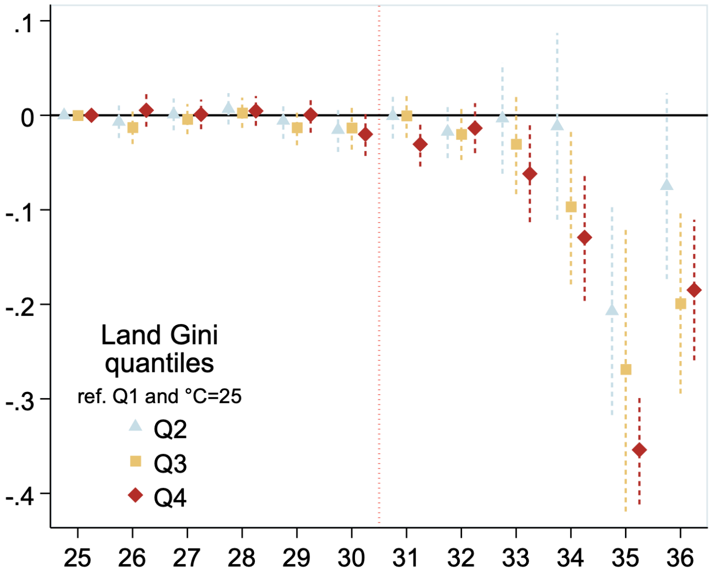
These OLS estimates assume a linear relationship and the binned data does not allow for a test of the parallel trends assumption in response to temperature.

We now compare differential responses to temperature bins non-parametrically by interacting dummies for each (rounded) temperature integer with our land consolidation indicators using the first quantile as the comparison group.

$$\begin{aligned} \log(GPP)_{ijt} = q_1 + &\left(\sum_{j>25} 1(Temp = j)_{ijt} + \sum_{q \neq 1} \beta_{qj} (1(Temp = j)_{ijt} \times q_i) \right) \\ &+ \sum_t (c_i \times year_t + year_t) + c_i + e_{ij} \end{aligned} \tag{7}$$

in which q represents indicators for the quartile of the Gini in the initial year, while $1(Temp = j)_{ij}$ indicates that canton i experienced temperature j in a given week. c and $year$ are canton and year fixed effects and e a normally distributed error term with mean

Figure 6 – Impacts over temperatures on weekly log(GPP)



Notes. Quantile indicators are interacted with indicators for each temperature (rounded to an integer). The comparison group is the impact on the first Gini quantile at 25°C. Vertical lines correspond to 95% confidence intervals. Standard errors are clustered at the canton level.

0. The coefficients $\beta_{2j}, \beta_{3j}, \beta_{4j}$ thus capture the differential response to temperature j compared to the the least consolidated land at 25°C, q_1.

The event study graph in Figure 6 presents the estimates of β_{qj}'s using weeks restricted to 25°C or above. We see no substantial differences between the conoslidation quantiles until we cross the minimum of the the weighted threshold. We then start to see the emergence of the gradient apparent in Figure 5b with some relatively striking numbers. At 33°C the most consolidated land experiences a 6% higher drop in weekly productivity compared to the least consolidated land. At 35°C, this difference grows to -35%. This analysis reveals that the returns to solar energy are significantly lower in areas with higher land inequality and that this difference is exacerbated under extreme temperatures.

5.3 Average treatment effects of shocks

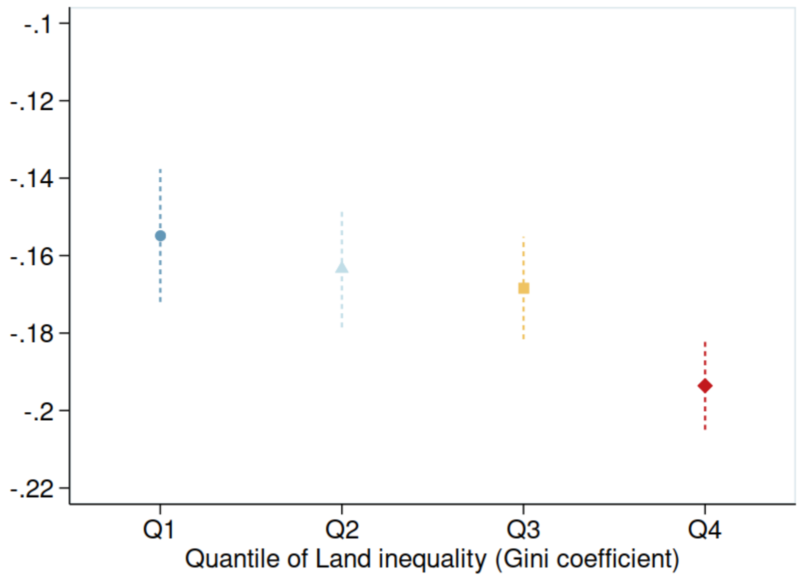
We now estimate average treatment effects of crossing the weighted threshold on average weekly GPP using difference in differences with the weekly time dimension. This allows us to compare potential differences in the effect of the shock over land consolidation dynamically. We start with a simple two-way fixed effect (TWFE) estimator in which we again isolate within canton-year variation over a high-frequency time dimension: the 8-day intervals of temperature and productivity measures which we will call "week" w indexed by k. We focus this analysis on the weeks during the height of the growth season in June and July and where extreme heat shocks are becoming more frequent.

$$log(GPP)_{ikt} = c + \beta_1 D_{iwt} + \sum_{q>1} \beta_q (D_{iwt} \times q_i) + \sum_k w_k + \sum_t (c_i \times year_t + year_t) + c_i + u_{ikt} \tag{8}$$

In this model D is the weighted shock indicator, q are quantile dummies and w are week of year fixed effects. The coefficients β_2, β_3 and β_4 capture the differential effect of the shock over land consolidation quantiles compared to the least consolidated, β_1.

The average treatment effects are presented for each quantile in Figure 7 allong with the p-value of the test that the effects are jointly equal for all quantiles.

Figure 7 – Averate treatment effect of heatshock in summer months, log(GPP) by quartile

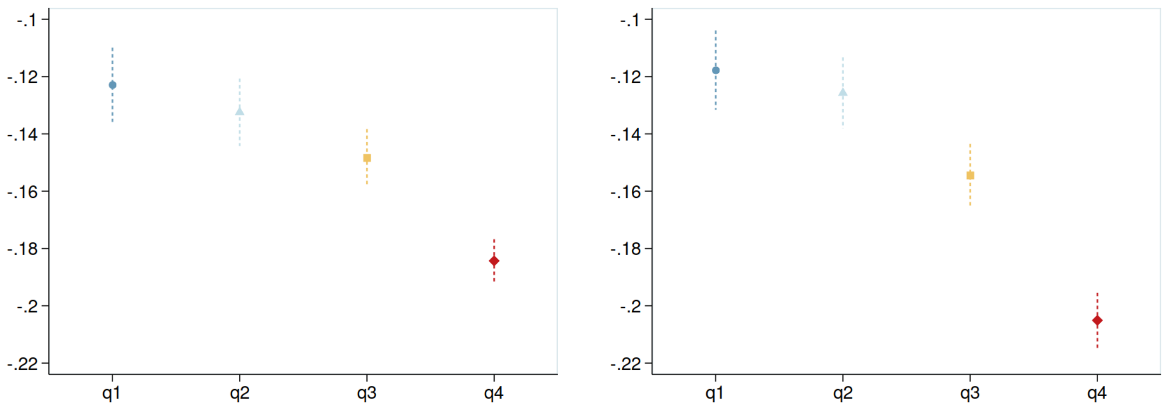


Notes. Estimates of shock impacts by quantile from equation 8. Vertical lines correspond to 95% confidence intervals. Standard errors are clustered at the canton-year level.

The estimated effects are consistent with the previous results using continuous or discrete changes in temperature above the threshold and we easily reject the null that the shock's effect is equal.

Because certain cantons are treated during different weeks within a year, it is important to test the robustness of this result to the possibility of some (i, w) are improperly weighted leading to biased estimates. The recent literature on difference in difference estimators show that TWFE estimators may be biased in the presence of treatment effect heterogeneity over time. This is due to the negative weighting issues studied by De Chaisemartin and d'Haultfoeuille, 2020. They show that issues arise because the estimator is a weighted average of many (i, w) cell-level Average Treatment Effect (ATE), some of which some may compare newly treated units to those that have already be treated. In the presence of negative weights, the estimated effects and tests for the parallel trends assumption should use only "clean" control groups: never treated units within the year/not-yet-treated units. Using the diagnostic tools developed by (De Chaisemartin and d'Haultfoeuille, 2020) we find that some (i, w) cell ATEs receive a negative weight, but the proportion is reassuringly small: 9.4%, or 385 out of 4080 ATEs.

Figure 8 – Heterogeneity-robust difference-in-differences estimates



(a) Never and not yet treated as controls

(b) Never treated as controls

Notes. Estimates applying the heterogeneity-robust difference-in-differences algorithm in De Chaisemartin and d'Haultfoeuille, 2020 using not-yet-treated and never treated as controls (a) and on never treated (b). Vertical lines correspond to 95% confidence intervals. Standard errors clustered at the canton-year level.

Comparing estimates between Figures 7 and 8 we see that they are highly comparable. Overall, the shock's effect is slightly smaller for the first quantiles, but the gradient becomes even steeper using the DiD heterogeneity robust estimator.

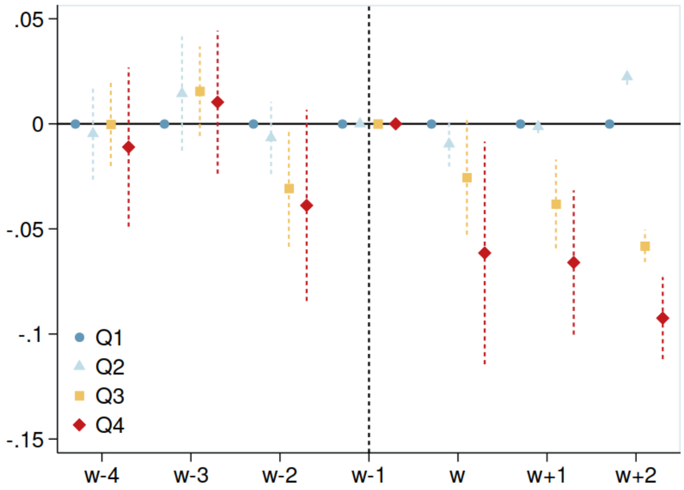
We now examine the dynamic effects as differences off the effect on the least consolidated land in Figure 9. We see that in the weeks before the shock different levels of land consolidation trend similarly. We then see in the week of the shock a dramatic differential impact in the week of and those that follow the extreme heat shock: quantile 3 experiences between 2.5 and 5 percentage point higher losses than quantile 1, while quantile 4 experiences between 6 and 9 percentage point higher productivity losses.

5.4 Mechanisms

To better understand the underlying mechanisms through which land consolidation and other factors influence the impact of temperature shocks on agricultural productivity, we examine how various correlates interact with these shocks.

The first set of results, illustrated in Figure 10, shows the relationship between land consolidation variables and GPP under shock conditions. We find that a 10% increase in the Gini coefficient magnifies the negative effect of a temperature shock by an average of 1.8%. This indicates that higher land inequality exacerbates the detrimental impact of climate shocks on productivity. Interestingly, while crop diversity shows little moderation, the presence of semi-natural areas plays a much more significant role. When controlling for all covariates the effect of the Gini coefficient becomes statistically insignificant, suggesting that semi-natural could be the mechanism behind the measured effect of land consolidation on resilience.

Figure 9 – Dynamic heterogeneity robust estimates of differential effect over consolidation



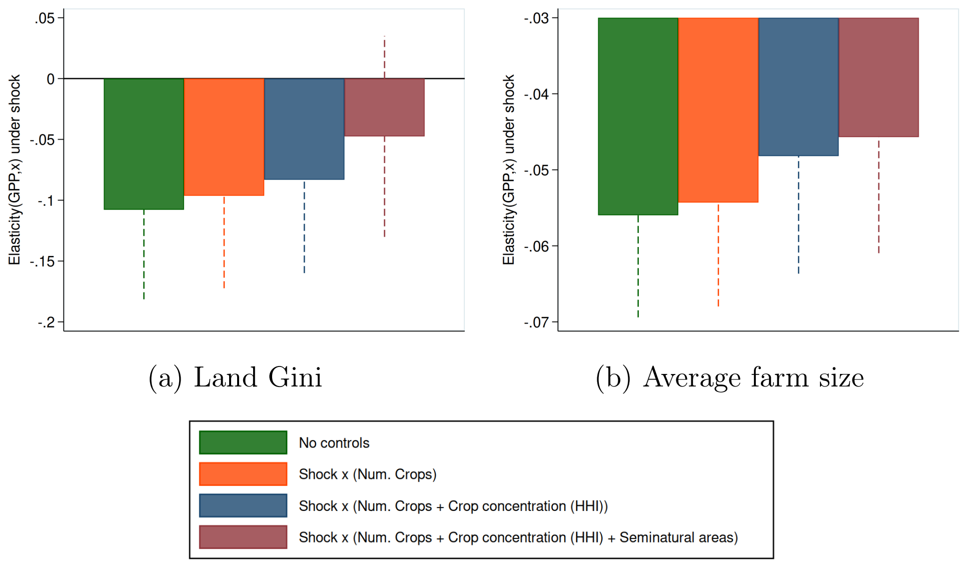
Notes. Estimates of differential impacts from -4 to + 3 weeks applying the heterogeneity-robust difference-in-differences algorithm in De Chaisemartin and d'Haultfoeuille, 2020 using not-yet-treated and never treated as controls. Quantile 1 and the week before the shock are the reference levels. Vertical lines correspond to 95% confidence intervals. Standard errors clustered at the canton-year level.

Further analysis, depicted in Figure 11, examines the differential impacts of temperature shocks across land consolidation measures, split by the median exposure to semi-natural areas. The gradients observed in previous sections remain present but the effects are significantly lower and flatter for farms that are more exposed to semi-natural areas. This implies that semi-natural areas act as a protective factor, reducing the vulnerability of agricultural systems to extreme temperature events. In regions with higher exposure to these ecosystems, the productivity declines associated with land consolidation and farm size are less pronounced. Conversely, the absence or reduced exposure to semi-natural areas worsens the outcomes under heat stress, which suggests that lower natural biodiversity makes agricultural systems more vulnerable to climate shocks. This relationship likely serves as a critical mechanism underlying the observed effects of land consolidation.

The processes through which semi-natural areas mitigate the impacts of temperature shocks are described in the biology literature. These ecosystems can enhance resilience through several biological factors:

- Pollination: Heatwaves often decimate pollinator populations, on which most crops depend to produce the edible parts of crops. Semi-natural areas serve as habitats for a variety of pollinators and offer them refuge during extreme heat, thus sustaining pollination services even under stressful conditions.
- Water Retention: Semi-natural environments support below-ground biodiversity, including complex root systems, fungi, and insects, which enhance water retention and help crops endure periods of extreme weather by maintaining soil moisture levels.
- Regulating Bio-Aggressors: Biodiversity within semi-natural areas effectively regulates pests through barrier effects, as well as pull and push strategies, thereby reducing crop damage and loss during periods of environmental stress.

Figure 10 – Correlates of land consolidation and heat-shocks



(a) Land Gini

(b) Average farm size

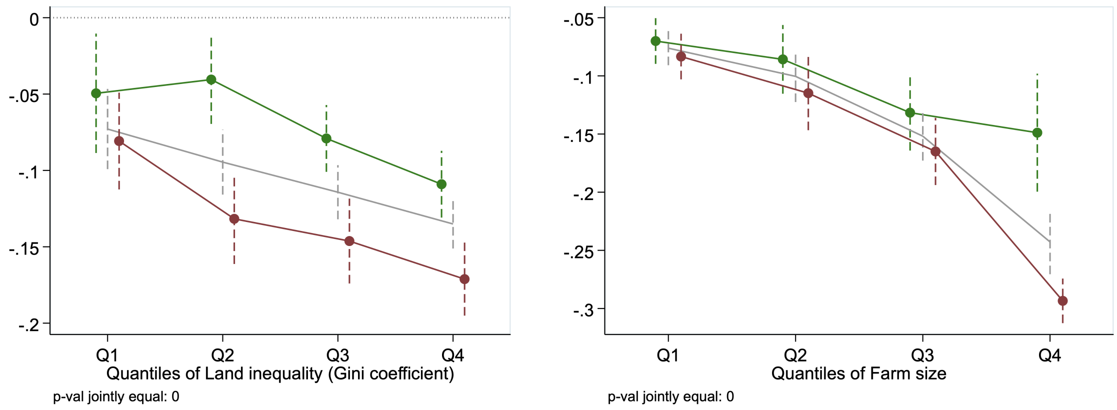
Notes. Estimates of the elasticity of GPP to land Ginis and average farm sizes under heatshocks. Vertical lines correspond to 95% confidence intervals. Standard errors are clustered at the canton-year level.

In our analysis, we also explored various dimensions of diversity, such as inter- and intra-species diversity within and across farms, measured through crop counts and Herfindahl-Hirschman indices. We additionally considered crop configuration, by controlling for crop shares. However, it is the presence of semi-natural areas that consistently emerges as a significant moderator of climate impacts, overshadowing the effects of crop diversity alone.

These mechanisms do not operate exclusively under heat stress; they also explain the productivity differences observed in normal times. This insight brings new evidence to the longstanding literature on the inverse relationship between farm size and productivity. Such ecological factors were largely overlooked by this century-old literature and are likely part of the omitted variables that have puzzled economists. Smaller farms, which tend to coexist with other small farms in low inequality areas, are more likely to be surrounded by semi-natural vegetation, such as buffer strips (the vegetation between plots) or *prairies*. In France, prairies are a particularly relevant example of this semi-natural vegetation –these communal lands are traditionally kept untouched and serve as intentional biodiversity reservoirs. This spatial arrangement has broader implications for land use and property rights. In regions with high land consolidation, there are stronger incentives and fewer barriers to land grabs, which often lead to the conversion of semi-natural vegetation into more consolidated, less diverse agricultural fields. The incentive structures in these highly consolidated areas favor land appropriation.

These findings align with our broader argument that land inequality and natural diversity are two sides of the same coin, reflecting both the political economy of land use and the biological mechanisms that sustain productivity. However, the interaction between these factors is non-deterministic, as producers have some discretion in how they manage

Figure 11 – Splits by median of semi-natural areas within quantiles



(a) Gini quartiles

(b) Farm size quartiles

Notes. Estimates of shock impacts by quantile above and below the median level of Seminatural surface (as a percentage of total farmland). Vertical lines correspond to 95% confidence intervals. Standard errors are clustered at the canton-year level.

their lands, particularly in response to climatic risks. While land consolidation might be economically rational under normal conditions due to economies of scale, our results indicate that it can reduce resilience to climate variability, particularly in the absence of semi-natural ecosystems. This nuanced trade-off between productivity and resilience underscores the importance of considering ecological diversity as an effective tool in adapting to climate change.

6 Conclusion

This paper demonstrates that land consolidation amplifies the negative effects of heatwaves on agricultural productivity in France. Using a combination of high-resolution satellite imagery and cadastral data, our analysis reveals that more concentrated areas exhibit lower productivity, particularly under extreme heat conditions, compared to less concentrated regions. This finding suggests a fundamental trade-off between the economies of scale achieved through land consolidation and the increased vulnerability to climate shocks that consolidation imposes.

We have shown that the presence of semi-natural areas plays an important role in mitigating the adverse effects of temperature shocks, highlighting the relevance of maintaining biodiversity in agricultural landscapes. While crop diversification also contributes to resilience, it is the ecological functions provided by semi-natural areas—such as pollination, water retention, and pest regulation—that offer the most significant buffering effects. Our results thus extend the traditional literature on farm size and productivity by integrating the biological and temperature dimensions, showing that the inverse relationship between farm size and productivity is magnified in the presence of extreme weather.

These findings have several policy implications. Current European agricultural policy, with its emphasis on agroecology and biodiversity preservation, appears to be on the right track in promoting both sustainability and resilience. Our results suggest that policies encouraging the preservation of semi-natural areas, as well as promoting a more equitable distribution of farmland, will be critical in enhancing the resilience of agricultural systems to the increasing frequency and severity of climate-related shocks. Furthermore, our work underscores the importance of recognising the ties between land inequality and natural diversity, both influenced by and influencing broader economic and ecological systems.

Looking forward, future research should explore the dynamics of land consolidation and agricultural resilience in other contexts, including different geographical regions and types of crops in more detail. While our study has focused on the immediate impacts of temperature shocks on productivity, understanding the long-term effects of climate change on agricultural systems, particularly in relation to shifts in property rights and land use, remains an essential area for further investigation. By deepening our understanding of these relationships, we can better design policies to foster resilient and sustainable agricultural landscapes in the face of an uncertain climate future.

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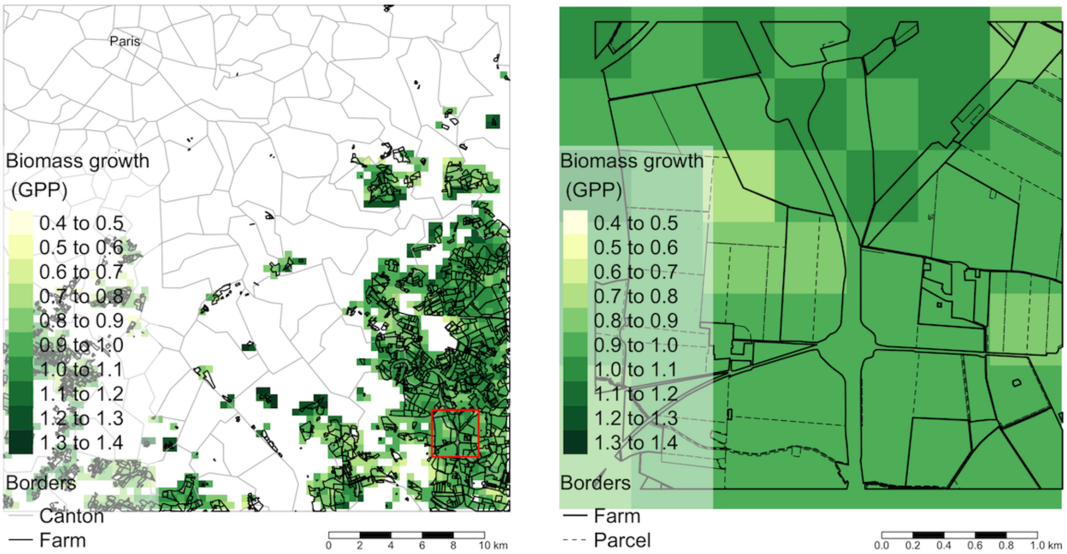
A Appendix

A.1 Sample visualizations of cadastral data

Figure A.1 – Sample visualisation of cadastral data and GPP overlay



(a) A closer look (b) High-resolution

Note. This figure overlays snapshots of French cadastral data and our estimates of plant productivity (GPP). French cadastral data precisely locates all farms operating in the national territory (panel 1b). Our analysis aggregates data at the cantonal level, which are represented by grey borders in panel A.1a. Panel A.1b showcases a randomly selected group of farms, with high-resultion data on crop composition within farms. Authors' elaboration based on the *Registre Parcellaire Graphique* (RPG) of 2021.

A.2 The diversification of a crop portfolio

In our financial analogy, we draw upon the foundational principles of modern portfolio theory, pioneered by Markowitz (1952). This theory operates on a simple premise: for a given level of risk, higher yields are always preferable. Here, expected yields are represented by the expected value of a variable, while risk is quantified through its variance. A diversified portfolio is a means to mitigate risk. By diversifying our assets, or in this case, crops, we aim to reduce the overall level of risk. This is achieved by selecting assets with uncorrelated yields, or even better, yields that are negatively correlated.

To quantify diversification we use the diversification ratio (D) defined in Choueifaty and Coignard (2008). It is the ratio of the weighted average variance (WAV) divided by the overall portfolio variance (OPV), which considers not just the variances of the individual components but also how they move together, which is captured by their covariances. The numerator and the denominator of this ratio can differ due to the diversification effect. When assets in a portfolio are uncorrelated or negatively correlated, total portfolio variance can be lower than what one would expect from simply adding up the individual risks (after weighting them). In such case, the ratio would be above unity. Hence, a large ratio denotes a large diversification effect.

$$D = \frac{WAV}{OPV} \tag{A.1}$$

Weighted Average Variance refers to the sum of the individual variances σ_i of the portfolio components (crops, in our case) multiplied by their weights squared w_i. It represents what the portfolio's variance would be if the components were not correlated at all (i.e., if their performances were completely independent of each other). In a case with n crops, it is defined as follows.

$$WAV = \sum_{i=1}^{n} (w_i^2 * \sigma_i^2) \tag{A.2}$$

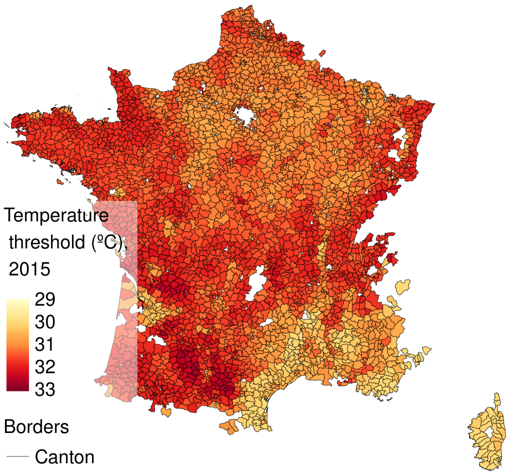
Overall Portfolio Variance is calculated by considering both the variances of the individual assets and the covariances between each pair of components i and j.

$$OPV = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j Cov(i, j) \tag{A.3}$$

A negative covariance between two assets means that when the productivity of one asset goes up, the return of the other tends to go down, and vice versa. This inverse relationship can significantly reduce the overall volatility of a portfolio because the negative performance of one asset can be offset by the positive performance of another. Essentially, when one asset is experiencing a downturn, another may be performing well, stabilizing the portfolio's overall performance. Very low covariance indicates that the returns on two assets have very little or no predictable relationship. While not as impactful as negative covariance in terms of reducing volatility, low covariance still contributes to diversification because the assets' returns do not move in tandem. This means that fluctuations in one asset will have a minimal impact on another, leading to more stable overall portfolio performance compared to if the assets were highly correlated.

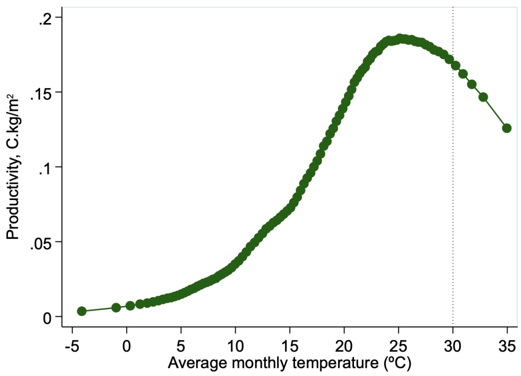
A.3 Land productivity vs. temperatures

Figure A.2 – Treatment thresholds



Note. The map presents the spatial distribution of treatment thresholds across France, reflecting region-specific temperature limits based on the local crop composition. Treatment thresholds are calculated as weighted averages of the maximum temperature tolerances for different crops, as outlined in Equation 6. These thresholds account for the distinct thermal requirements in spring/summer. Crops for which temperature data is unavailable, such as pasture zones or other uncommon crops, a default threshold of 30ºC is applied (see figure A.3).

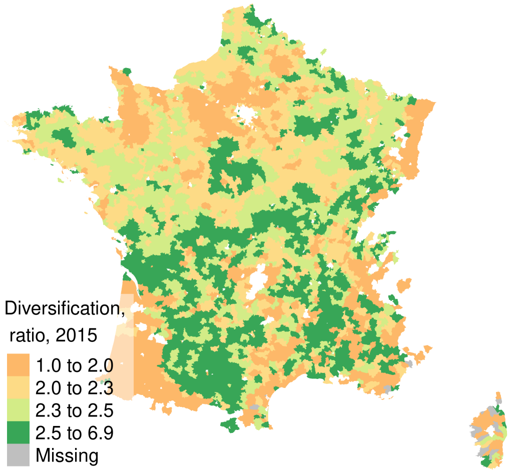
Figure A.3 – Land productivity vs. monthly temperatures based on satellite data, 2000-2020



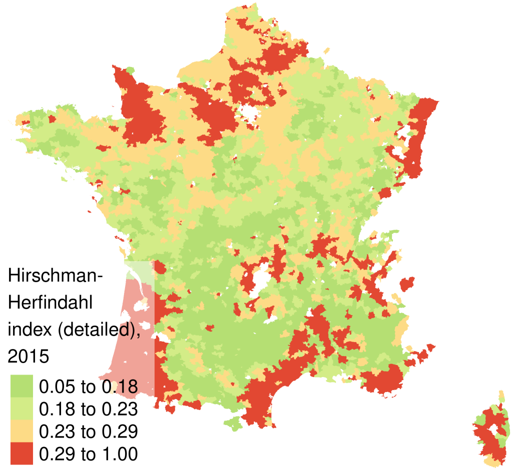
Notes. Own estimates based on data from MODIS sensor (Running and Zhao, 2019). Binned scatterplot, with canton-level observations. Displays average monthly farmland productivity in 100 equally sized groups, at corresponding temperature ranges.

A.4 The spatial distribution of heterogeinity variables

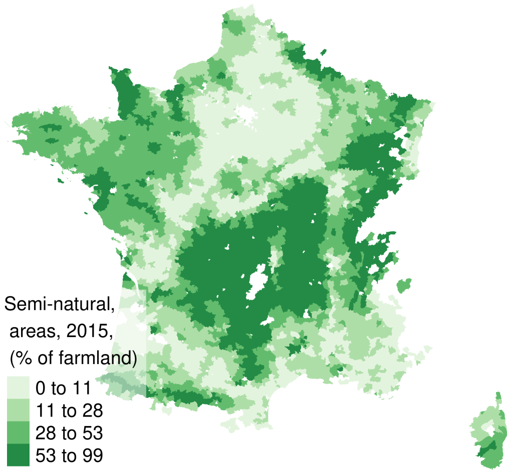
Figure A.4 – Different dimensions of diversity at the canton level



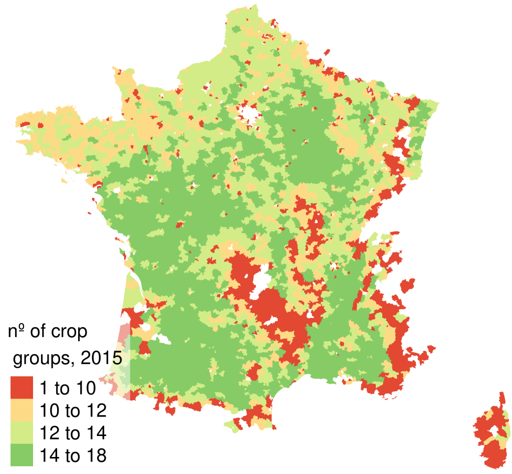
(a) The diversification ratio



(b) The crop concentration index



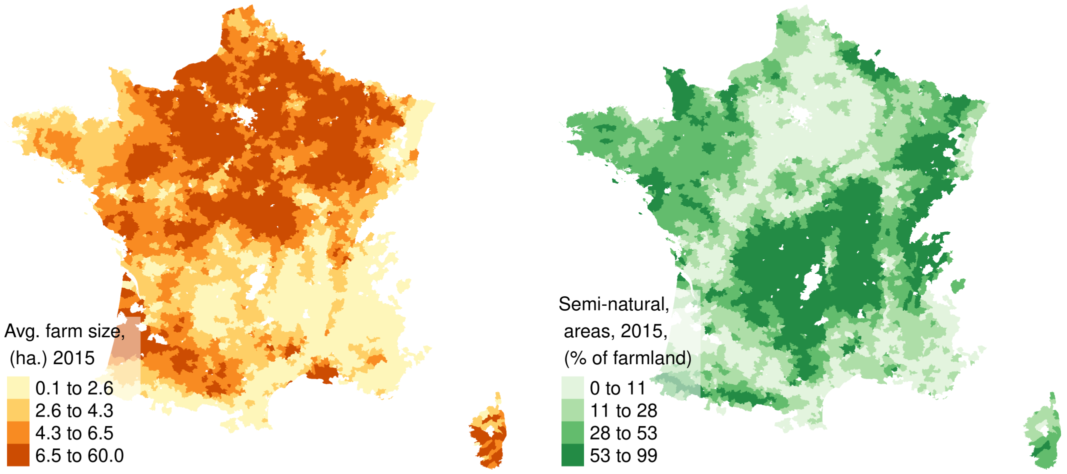
(c) The presence of semi-natural areas



(d) Counting crop groups

Note. Authors' elaboration based on the *Registre Parcellaire Graphique* (RPG) of 2015.

Figure A.5 – The correlation between consolidation and semi-natural areas



(a) Average farm size (b) Semi-natural areas

Note. Authors' elaboration based on the *Registre Parcellaire Graphique* (RPG) of 2015.

Contents