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

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Agricultural resilience in focus

Industrialization and structural shifts in XXth century:

- ↗ Big productivity gains, sustaining a soaring world population (Green revolution)
- Emergence of larger farm sizes and increased land inequality
- ↘ Intensive farming, increased crop specialization, and reduced ecological diversity

Agroecological Insights from Biology:

- Lower ecological diversity may reduce resilience to climate shocks (Renard and Tilman, 2019)

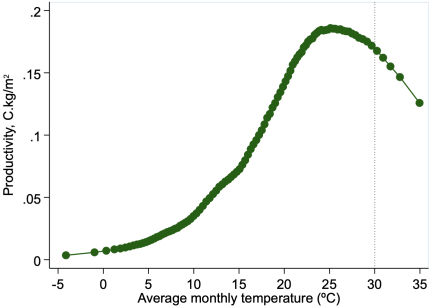
Key Question:

- Does farmland consolidation make agriculture more or less vulnerable to climate change?

Our contribution

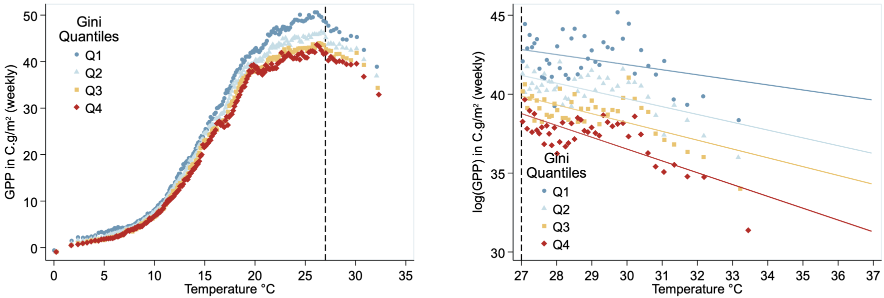
Examining how structural shifts in land ownership impact the resilience of our economic system, e.g., food security

The non-linear relation of temperature and productivity



Notes. Monthly productivity vs. temperature (2000-2021). Binned scatter plot in centiles of observations, no controls. Using Running and Zhao, 2019, Wan, Hook, and Hulley, 2021, and French cantons.

The essence of our measured heterogeneity



(a) Productivity vs. all temperatures

(b) Zoom to high temperatures

Notes: Bins selected using Cattaneo et al. (2024). Right panel overlays a linear fit on the selected bins. Vertical dashed line indicates 27ºC, the minimum threshold for treatment.

Results preview: the productivity–resilience trade-off

Temperature Effects:

- Productivity gaps widen along the temperature gradient
- Farms in the lowest land Gini quartile lose $\approx 3.9\%$ of production per extra degree above a the damage threshold, while the highest quartile lose $\approx 6.4\%$

Insights on the concentration of production:

- Production is mostly clustered in highly consolidated farmland
- Higher consolidation associated with lower per-square-meter plant growth, conditional on land and crop composition

A data-driven strategy

Comprehensive sources:

- Geo-referenced agricultural cadastre across metropolitan France
- Satellite measures on biomass production - NASA, 500m^2 res.
- Temperature estimates from Météo France's SAFRAN model

Key Empirical Measures:

- Land concentration: Gini coeffs. and average farm sizes
- Crop diversity: assessed with over 200 categories at the plot level
- Temperature shocks: based on crop-specific thresholds

Panel Design:

- Construction of a seven-year panel with weekly observations (8-days period) at canton level ($\approx$ 4000)

Mechanisms driving heterogeneity (1/2)

Farm size distribution:

- Land Gini correlates with the nº and proportion of large farms (intensive agricultural practices)

Role of ecological services:

- Natural areas enhance crop resilience through temperature regulation, pollinator refuge, water retention, soil erosion control, and pest management (Kremen and Miles, 2012; Tamburini et al., 2020)
- Exposure to natural or semi-natural areas explains more than half the heterogeneity in temperature shock effects

Mechanisms driving heterogeneity (2/2)

Limited role of crop diversification:

- Portfolio mechanisms related to crop diversification (Abson, Fraser, and Benton, 2013; Renard and Tilman, 2019) play a much smaller role in mitigating the heterogeneous impacts

In the paper (not presented today):

- We show how the current CAP transfers generate disincentives in the allocation of land to biodiversity enhancing purposes

Contributing to the Economics of climate change

Climate change on agricultural productivity

- Advances in forecasting damage and coping strategies, but limited contributions on our topic
- Negative impacts on productivity: extreme weather events (Lobell and Field, 2007; Schlenker and Roberts, 2009). Compound shocks (Haqiqi et al., 2021). Overall production (Dell, Jones, and Olken, 2012)
- Positive impacts on productivity: the CO_2 fertilisation effect (Taylor and Schlenker, 2021)
- Long term predictions and technological adaptantions: Predictions (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Michael Hanemann, and Fisher, 2005; Burke and Emerick, 2016)
- Techonolgical adaptations (Moscona and Sastry, 2023)

Other related literature

Farms consolidation and productivity

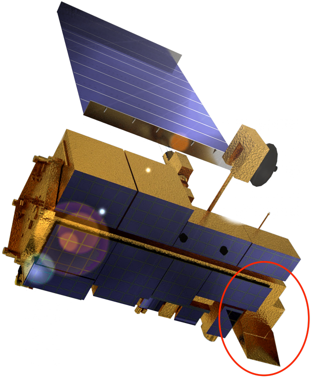
- Convergence towards higher farmland consolidation with development (due to increased labour productivity) (Eastwood, Lipton, and Newell, 2010; Frankema, 2010; Adamopoulos and Restuccia, 2014; Lowder, Sánchez, and Bertini, 2021). Explains most of cross-country differences in productivity levels, average farm sizes, and in farmland distributions

Biology literature

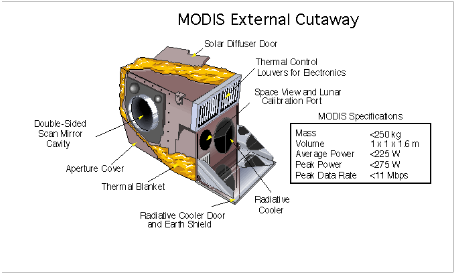
- Strong links and clear mechanisms between diversity and resilience in both natural and agricultural ecosystems (Cadotte, Cardinale, and Oakley, 2008; Kremen and Miles, 2012; Duffy, Godwin, and Cardinale, 2017; Renard and Tilman, 2019).

Data and definitions

Measurements from the sky: in orbit since 2000



Terra spacecraft model



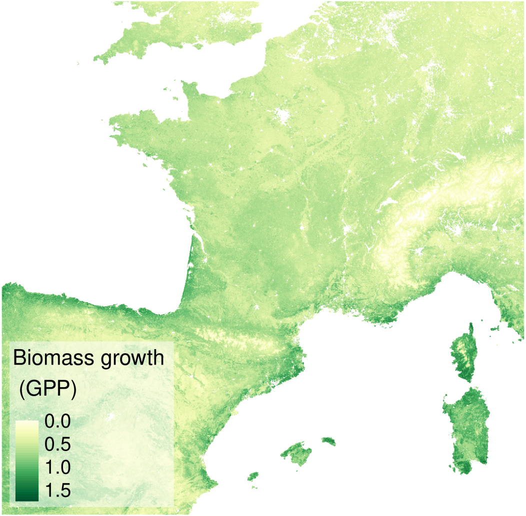
MODIS sensor

Measurements from the sky: main variable

Gross Primary Productivity (GPP)

- Measures the growth of biomass every 8-days in $C.kg/m^2$
- Based on fluorescence from photosynthesis
- Resolution: 0.5km pixels
- Credits to Running and Zhao (2019)

Cumulated 2021 GPP at 500m resolution



Can we convert GPP into yield?

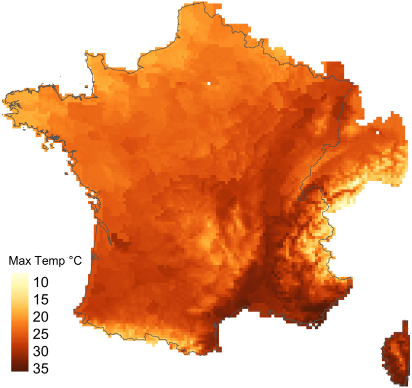
Examples of GPP to Yield conversion factors

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): annual yield of staple crops in Montana, USA

- Possible in theory, but not enough information at our scale
- GPP measures biomass production through carbon content, being proportional to yields but not reflecting market prices.
- Focuses on physical output and food security, no price effects

Temperature estimates from the SAFRAN physical model (ºC)



Temperature on a random summer day, Météo France hourly data

Temperature shocks

The non-linear relation of temperature and productivity

- More light is beneficial for plants in normal times (photosynthesis), but there are limits
- Schlenker and Roberts, 2009 find a nonlinear relation with crop-dependent turning points: corn (29ºC), soybean (30ºC) and cotton (32ºC) in the US

Critical temperatures by crop in spring/summer

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

Note. Compiled by the authors

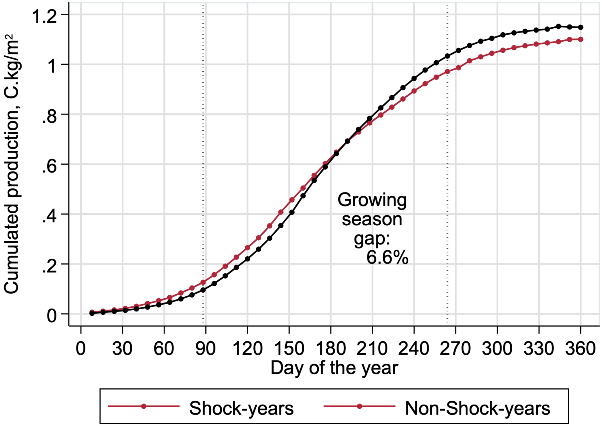
Defining a threshold for heatwaves

- **Critical temperature for treatment** in canton c for year t is

$$T_{c,t} = \sum_{i=1}^{N} T_i * A_{i,c,t}$$

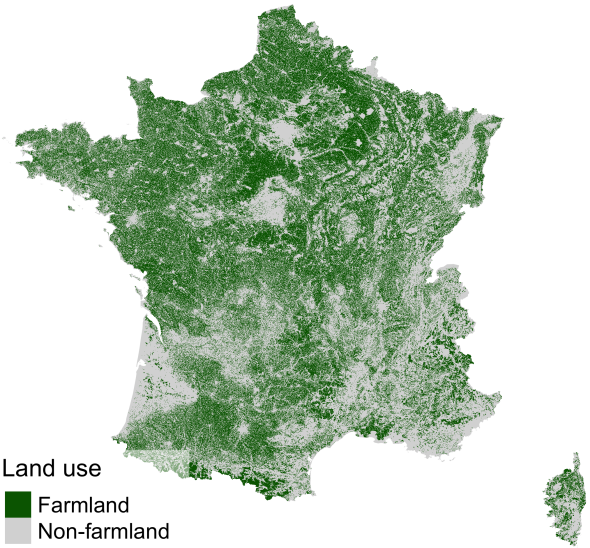
- The average critical temperature of crop i (T_i) weighted by its land share ($A_{i,c,t}$)

The average loss under heatshocks

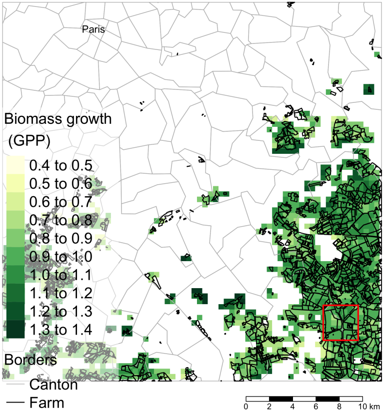


Measurements from the land

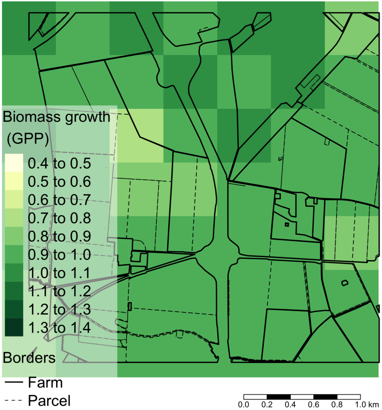
Exhaustive farm information



Overlapping cadastral data and GPP (Zoom-in)



Farms near Paris



High resolution

Measurements from the land: main variables

Cantonal crop diversity:

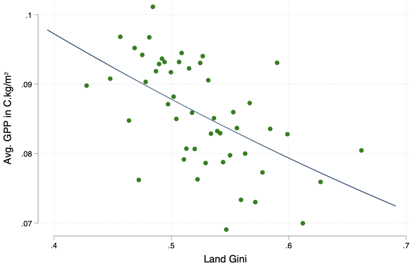
- Data on crop-mixes within farm borders
- Crop level, independent of ownership
- Broader categories (28) or detailed (150+)
- We build a Herdindahl-Hirschman index on concentration

Cantonal Land Inequality:

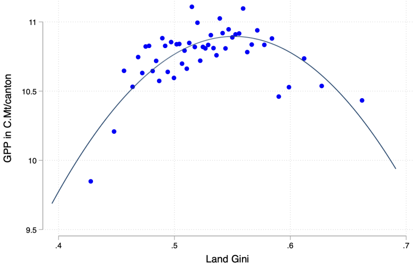
- Uses georeferenced information on farm borders
- Farm level $\neq$ owner level

Results

Productivity and land consolidation



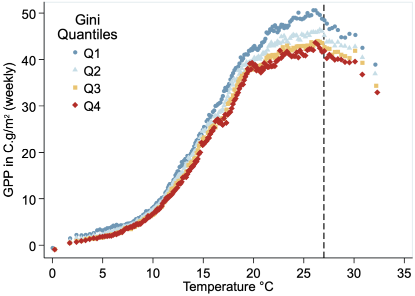
(a) Average productivity per square meter (*GPP*)



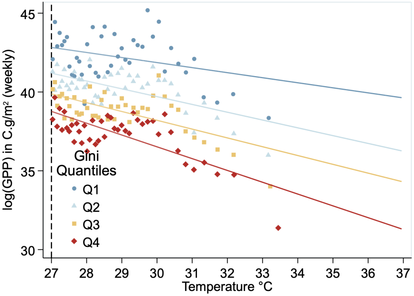
(b) Total yearly production ($GPP \times m^2$)

Notes. 50 quantile spaced bins, conditional on AR × Year FEs and crop composition. A substantial share of our food supply originates from highly consolidated land, understanding how these areas respond to temperature shocks is crucial.

Productivity vs. temperature (by land Gini)



(a) All temperatures



(b) Above minimum threshold

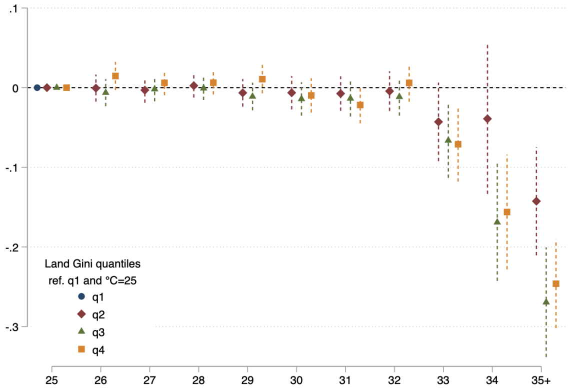
Notes: Bins selected using Cattaneo et al. (2024). Right panel overlays a linear fit on the selected bins. Vertical dashed line indicates 27ºC, the minimum threshold for treatment.

Differential temperature effects on productivity

$$\log(GPP)_{ijt} = a + \left(\sum_{j>25} (Temp = j)_{ijt} + \sum_{q \neq 1} \beta_{qj} \Big((Temp = j)_{ijt} \times_i \Big) \right) + \sum_t \Big(c_i \times year_t + year_t \Big) + c_i + e_{ij} \tag{1}$$

- Dependent variable: log of GPP in canton i, for temperature j at time t
- $(Temp = j)_{ijt}$ equals 1 when the temperature is j (with $j > 25$)
- β_{qj} captures how the response to temperature varies across land Gini quartiles q_i (ref. q_1)
- We include canton (c_i) and year ($year_t$) fixed effects, e_{ij} is the error term

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 indicate 95% confidence intervals. S.E. clustered at canton level.

Heterogeneous impacts of heat shocks (1/3)

$$\log(GPP)_{ikt} = a + \beta_1 D_{iwt} + \sum_{q>1} \beta_q \Big(D_{iwt} \times q_i \Big) + \sum_k w_k + \sum_t \Big(c_i \times year_t + year_t \Big) + c_i + u_{ikt} \tag{2}$$

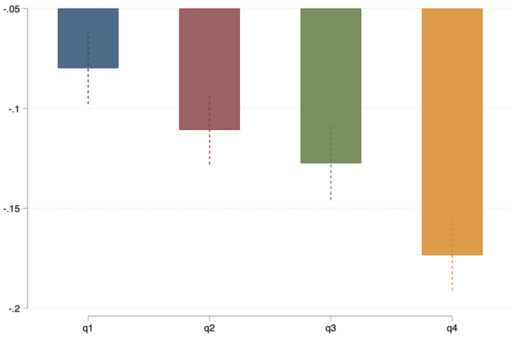
- [TWFE:] $\log(GPP)_{ikt}$ is the log of GPP for canton i, week k, in year t
- D_{iwt} is a **weighted heat shock** indicator (crop-specific threshold)
- The interaction terms $D_{iwt} \times q_i$ allow the impact of the shock to vary across land consolidation quantiles (ref. Q1)
- $\sum_k w_k$ includes week-of-year fixed effects while $\sum_t (c_i \times year_t + year_t)$ and c_i capture the **interaction of canton and year fixed effects**. u_{ikt} is the error term

Heterogeneous impacts of heat shocks (2/3)

	log(GPP)
	(1)
Panel (a): ATE by quantile	
q1	-0.080***
	(0.009)
q2	-0.111***
	(0.009)
q3	-0.127***
	(0.009)
q4	-0.174***
	(0.009)
Panel (b): log-log	
log(Gini) x Shock	-0.275***
	(0.056)
R-squared	0.22
N	277968
(Canton x Year) FEs	✓

Notes. Heat shock ATEs by quantile of the land Gini (panel a) and by log of land Gini. SE are clustered at the canton level.

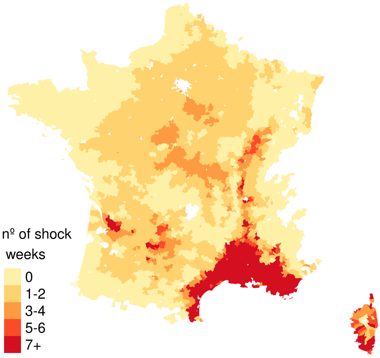
Heterogeneous impacts of heat shocks (3/3)



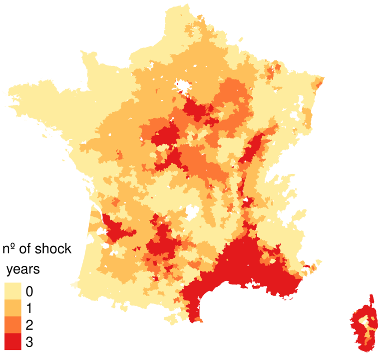
Notes: Estimates of shock impacts by quartile. Vertical lines represent 95% confidence intervals. S.E. are clustered at the canton-year level.

- Cantons can be treated in different weeks within a year, so we need to adress "dirty controls" (De Chaisemartin and d'Haultfoeuille, 2020)

Defining clean control groups for the DiD strategy



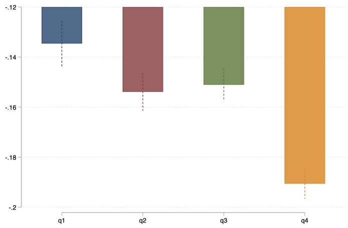
Treatment weeks



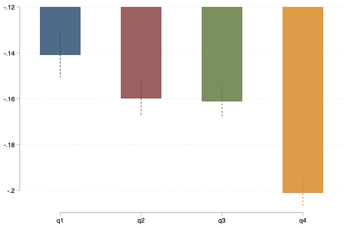
Treatment years

Notes. The figure displays the spatial distribution of heat shocks across the whole period.

Heterogeneity-robust difference-in-differences



(a) Never and not yet treated

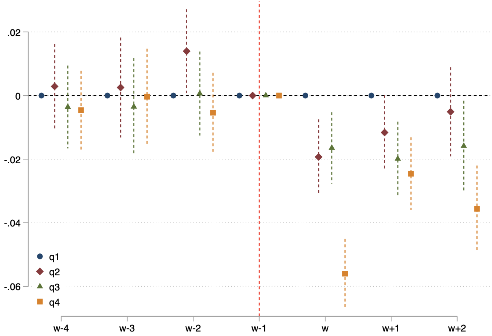


(b) Never treated

Notes: Estimates applying the heterogeneity-robust difference-in-differences alternative control groups (using not-yet-treated and never treated cantons). Vertical lines indicate 95% CI. SE clustered at the canton-year level.

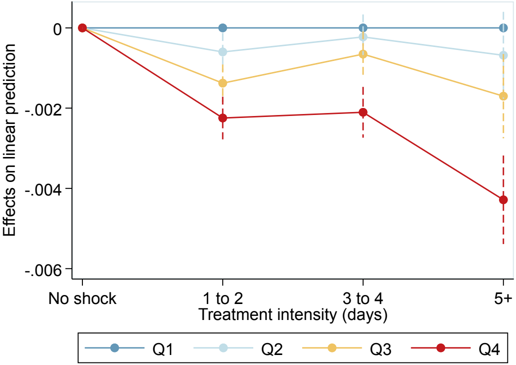
- The gradient becomes even steeper using the DiD heterogeneity robust estimator

Dynamic heterogeneity robust estimates



Notes: Differential impacts from -4 to +3 weeks, using the heterogeneity-robust DiD estimator. Quantile 1 and the week before the shock are the reference levels. Vertical lines indicate 95% CI. SE clustered at the canton-year level.

Testing treatment intensity in days



Notes: Quantile indicators are interacted with treatment at various intensity levels. SE are clustered at the canton level.

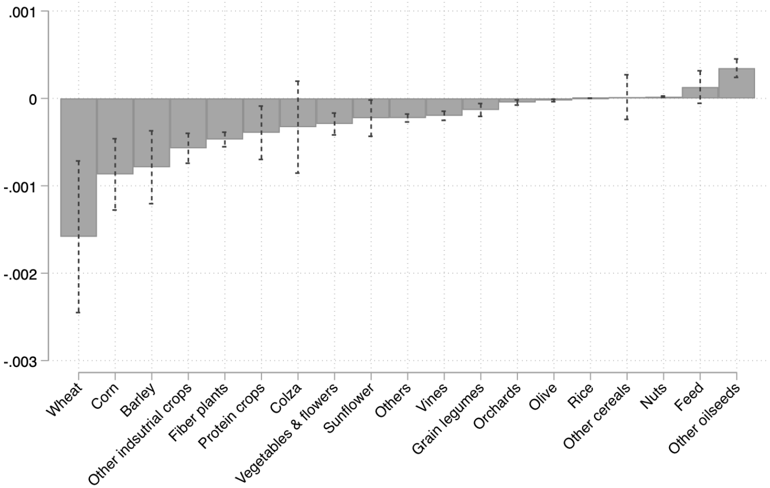
Mechanisms

Elasticity of farm size and land Gini

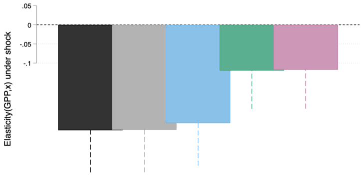
	$log E(N_{Small})$ (1)	$log E(N_{Medium})$ (2)	$log E(N_{Large})$ (3)	$log E(N_{Super})$ (4)
log(Gini)	1.084***	-0.312	3.349***	4.824***
	(0.277)	(0.208)	(0.485)	(0.784)
Mean Number	527.95	705.96	5.90	0.93
N	796128	796128	720641	428728
(AR x Year) FEs	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓

Notes. Elasticity estimates from a Poisson regression of the number of each type of farm in a canton on the log of the land Gini. Standard errors are clustered at the canton. * $p < .1$, ** $p < .05$, *** $p < .01$.

Crop × heat shock interactions



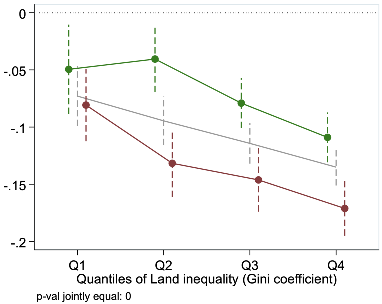
Correlates of land consolidation and heat-shocks



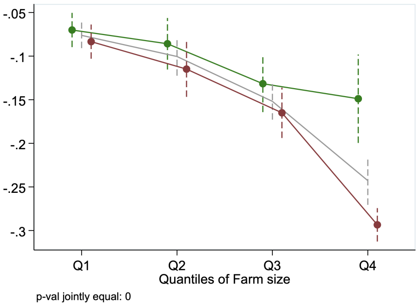
(a) Land Gini

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

Splits by median of semi-natural areas



(a) Gini quartiles



(b) Farm size quartiles

Notes: Estimates of shock impacts by quantile above and below the median level of semi-natural surface (as a percentage of total farmland). Vertical lines denote 95% confidence intervals. S.E. are clustered at the canton-year level.

Concluding remarks

Summary of Findings:

- Higher land inequality increases vulnerability to climate shocks
- Ecological mechanisms, especially the presence of semi-natural areas, buffer the impact (pollination, water retention, and bioagressor regulation)
- Crop diversification alone has limited potential to mitigate vulnerability

Policy Implications:

- Promoting agroecological practices not only prevents the causes of climate change, but also helps with its consequences
- Current agricultural policy frameworks (CAP, Ecophyto, Farm to Fork) should improve incentivizes on biodiversity conservation in mega farms

Future research

Expanding the scope of this project:

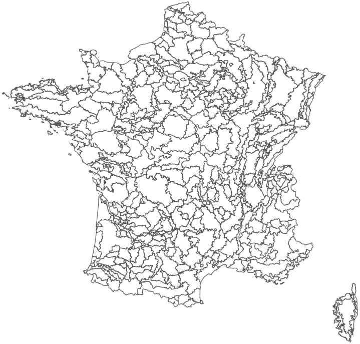
- Explore the interaction of land inequality with other climate events (e.g., drought, floods)
- Measure positive and negative externalities
- Expand the geographical horizon (USA)

Adding a historical dimension:

- Extend analysis to historical data to study famines, their consequences and reaction (1840s)

Appendix

Controlling for “Agricultural Regions” (AR)



- Limited within-canton variation over time in terms of consolidation
- AR group areas in 432 categories with homogenous agricultural practices, independent of administrative boundaries.
- We include AR $\times$ Year FE to reflect differences driven solely by variation between cantons within AR-year pairs.

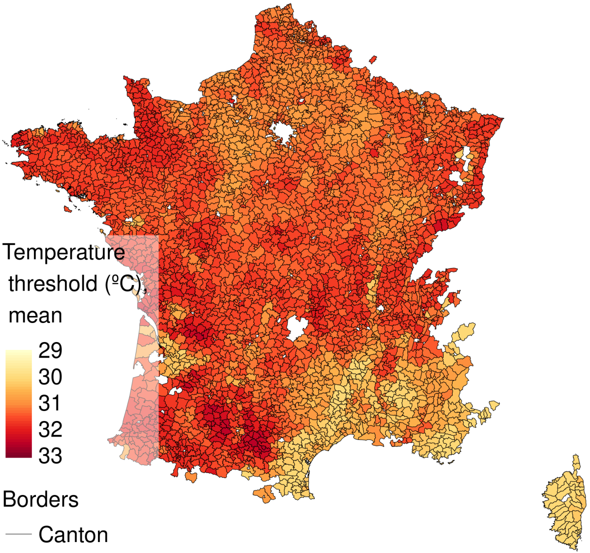
Appendix: Higher concentration corresponds to more mega-farms

Table: Land composition by farm class

		Small farm		Medium farm		Large farm		Very large farm	
Variable	Quantile	Mean	sd	Mean	sd	Mean	sd	Mean	sd
Crop count	1	12.5	(11.1)	70.8	(24.4)	5.9	(9.5)	10.8	(23.1)
	2	12.3	(10.2)	77.1	(17.7)	5.1	(6.1)	5.5	(14.6)
	3	11.4	(9.6)	81.3	(12.7)	4.8	(5.3)	2.5	(8.0)
	4	11.9	(9.5)	81.6	(11.4)	4.4	(5.1)	2.1	(6.5)
	5	11.4	(8.8)	82.4	(11.2)	4.2	(5.1)	2.0	(6.0)
Land Gini	1	12.9	(11.4)	85.5	(11.4)	1.4	(3.1)	0.2	(3.1)
	2	11.9	(9.9)	85.1	(9.0)	2.6	(3.4)	0.4	(2.2)
	3	11.9	(9.7)	83.7	(8.3)	3.9	(4.5)	0.6	(1.4)
	4	11.8	(9.2)	80.7	(8.8)	6.0	(6.4)	1.5	(3.4)
	5	11.1	(9.0)	57.7	(22.9)	10.6	(8.8)	20.5	(25.0)

Notes. Standard classification: small ($<$ 2ha), medium (2-50ha), large (50-100ha), and very large ($>$ 100ha). Farms

Average temperature threshold distribution

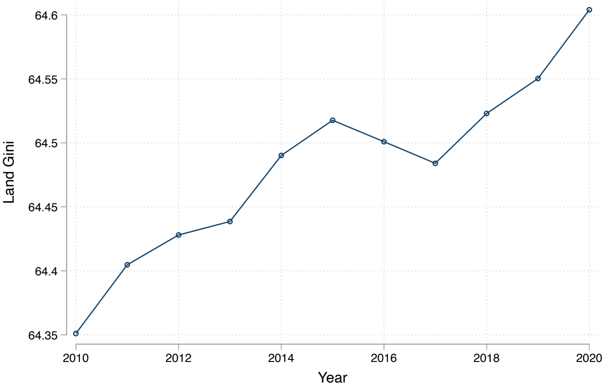


Productivity vs. land consolidation (2/2)

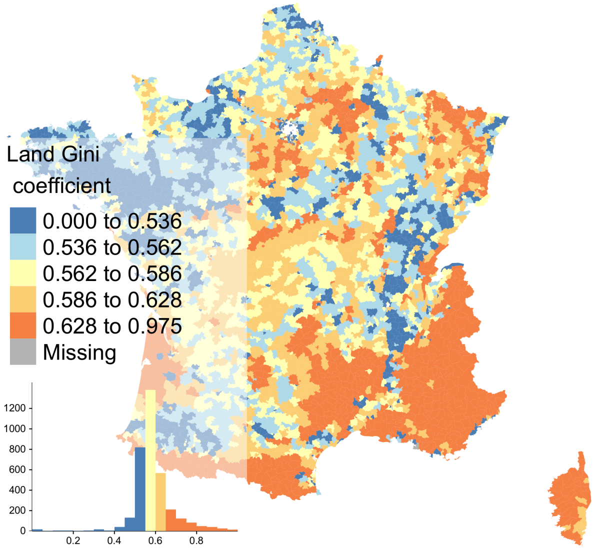
	(1)	(2)	(3)
Panel A:			
Land Gini	-0.0080***	-0.0015***	-0.0007**
	(0.0006)	(0.0004)	(0.0003)
Constant	0.5078***	0.1650***	0.1238***
	(0.0332)	(0.0196)	(0.0170)
Panel B:			
2nd quantile	-0.059***	-0.011***	-0.003
	(0.007)	(0.004)	(0.003)
3rd quantile	-0.098***	-0.019***	-0.007**
	(0.006)	(0.004)	(0.003)
4th quantile	-0.125***	-0.026***	-0.010**
	(0.007)	(0.005)	(0.004)
Mean 1st quantile	0.157	0.156	0.156
p-val equal means	0.000	0.000	0.065
R-squared	0.13	0.84	0.89
N	17373	16938	16938
(AR x Year) FEs		✓	✓
Crop types			✓

Notes. The dependent variable is the yearly cumulative GPP on farmland (C.kg/m2) for each canton. Panel A presents the linear relationship. Panel B presents the results non-parametrically. SE are clustered at the canton level.

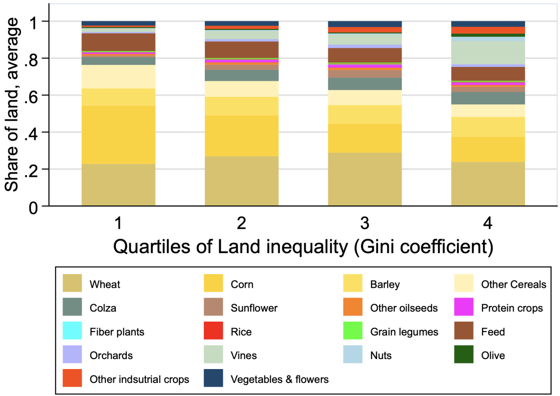
Appendix: Consistent trend with census



Appendix: Map of Gini coefficients, latest year



Appendix: Crop composition by fractile



Crop composition by Gini

Appendix: Agricultural area by canton (%)