Adaptation of agriculture to climate change: some econometric insights

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15 May 2024

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Outline

Agriculture and climate change

- Agriculture interacts with climate in two significant ways :
  1. It accounts for nearly a quarter of global greenhouse gas emissions and thus must contribute to mitigation efforts $\rightarrow$ Mitigation
  2. Agriculture is heavily impacted by climate change, posing challenges to food production and security $\rightarrow$ Adaptation
- Mitigation : requires a coordinated international effort to reduce greenhouse emissions
- Adaptation : a local issue but the increasing globalization of agricultural markets involves actors beyond the boundaries $\rightarrow$ Food security of the farm.
- A comprehensive understanding of the connection between global warming and agricultural production is essential for policymakers to anticipate issues related to food security.

Agriculture in COP Negotiations

- Agriculture was not initially a focal point in COP negotiations until COP21 in 2015.
- The signing of the Paris Agreement during COP21 in 2015 introduced food security as a crucial principle, bringing agriculture into the COP agenda.
- COP 23, held in Bonn in 2017, marked a pivotal moment in agricultural negotiations under the UNFCCC.

⇒ Creation of The Koronivia Joint Work that aims to **develop strategies for assessing adaptation**, co-benefits, and resilience in agriculture, crucial for sustainable food production in a changing climate.

COP 23 : A Turning Point for Agriculture

- The Koronivia Joint Work on Agriculture emerged as a key outcome, offering a fresh perspective on addressing climate change impacts on agriculture and global food security.
  - Agriculture's reliance on climate underscores the urgency of mitigating climate change effects to safeguard natural resources vital for agricultural sustainability.
  - While temperature increases may occasionally benefit crop yields, the overall impact of climate change on agriculture tends to be negative, compounded by challenges in water availability and extreme weather events.

$\Rightarrow$ Measuring the impacts of climate change in agriculture remains problematic despite the growing literature on this topic (Huang and Sim, 2018).

Introduction

- Early studies in natural science used crop simulation models to evaluate climate change impacts on plant growth by modifying biophysical processes like photosynthesis or photorespiration (Asseng et al., 2015)
- While these direct impacts on plant growth are expected to reduce yields, farmers are anticipated to adapt their practices to new climatic conditions.
- Economic literature has extensively investigated farmers' adaptation (Mendelssohn and Dinar, 2009) :
  1. crop simulation models (Ciscar et al., 2011);
  2. Computable General Equilibrium (CGE) models (Nelson et al., 2014);
  3. **Ricardian approach** : cross-sectional analyses of land values (Mendelsohn et al., 1994);
  4. **Weather panel approach** : analysis of net revenues across weather (Deschênes and Greenstone, 2007) or yield (Lobell et al., 2011).

⇒ The last two approaches are the most frequently found in econometric literature

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Adaptation

- "*Adaptation to climate change in human systems is the process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities*" (IPCC, 2014).
- Assessing the potential impacts of climate change on agriculture require considering how farmers would adapt to a new climate.
- Not accounting for adaptation would overstate potential damages or under appreciate potential opportunities.
- Private farmer adaptation refer to adjustments of production choices to maximize profit in response to changes in climate or weather fluctuations, holding prices and technology fixed.
- Potential adaptation strategies : changes in input use, tilling practices, planting dates, crop mix,...

Weather and climate

- Weather is a random variable representing the state of the atmosphere. Example : the value of the average temperature in Paris today.
- Climate refers to the moments of the probability distribution of that random variable. Example : long-term average of temperature in May in France (1993-2023)
- Climatologists (and economists by extension) refer to “climatology” as the 30-year average of a weather variable
- “climate change” is the change in the long-term distribution of weather conditions at a given location.

General econometric models of agricultural adaptation

- Economic Theory :
  - Farmers adapt their economic decisions to meteorological variations (short-term adaptation) and climate change (long-term adaptation).
- Econometric Model :
  - Agricultural profitability = f(economic variables, climate/weather variables, other variables) + error term
- Possible Specifications :
  - Agricultural profitability : Yield, Land prices, Profit/income
  - Structural model or reduced form
  - Panel data, cross-sectional, spatial autocorrelation
  - Choice of climate/weather variables : GDD, KDD, growing season/off-season, linear/non-linear impact
- two main approaches
  - Ricardian approach : long-run adjustments to climate change
  - Weather-panel approaches : within-season short-run responses to weather fluctuations

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Ricardian approach

- Mendelsohn et al. (1994) proposed to assess the impacts of climate change on agriculture by regressing land prices on climate conditions
  - Birth of the "**Ricardian approach**"
  - Proposed as a response to the "production-function" approach
  - Land prices reflect the discounted sum of future rents once all potential adaptation strategies have been implemented (e.g changes in capital or crop allocation)

    $\rightarrow$ internalize the productivity shocks in the long run
  - Provides the *long-term value* of climate
  - Appealing result of potentially beneficial impacts of climate change

Ricardian approach

- The hedonic model supposes that farmers are revenue maximizing and produce the exact supply required to satisfy demand, in conditions of both perfect competition and long run equilibrium.
- Consequently, the price of farmland is equal to the expected present net value of the future stream of income derived from the land

$$V_{LE} = \int_0^\infty p_L(E)e^{-rt}dt = \int_0^\infty [P_{q_i}q_i(x_i, E) - R_{x_i}x_i]e^{-rt}dt, \qquad (1)$$

- Assuming that farmers choose the production technology and the combination of inputs x_i that maximize their net revenues, given the characteristics of the farm and the market prices in equation (1), then in equation (1) q_i and x_i are determined to maximize V_{LE} for any given combination of the exogenous variables.

Ricardian approach

- The resulting profit maximizing outcome is a reduced form model, which examines how V_{LE} is affected by the set of exogenous variables : climate variables C, and a vector of the soil quality variables S

$$V_{LE} = f(C, S, Z) \tag{2}$$

  where the functional form of $f(.)$ is, a priori, unknown.

- The standard linear Ricardian model is written as :

$$V_{LE} = \beta_0 + C_i\beta_1 + S_i\beta_2 + Z_i\beta_3 + u_i, \tag{3}$$

  where u is the error term.

- The functional form of the Ricardian model can be written in different ways : the equation can be linear, semi-logarithmic or log-log.

Ricardian approach

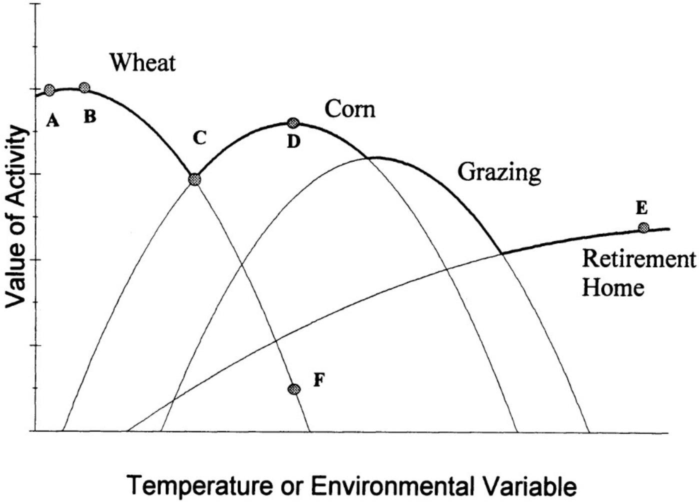

Figure – Ricardian approach v.s. production-function approach (*Source :* Mendelsohn et al., 1994)

Ricardian approach

- The Ricardian analysis is a **cross-sectional** hedonic pricing analysis exploiting differences in farmland prices and climates across regions/individuals
  - Farmland prices reflect specialization to the right “climate-adapted” agricultural activity
  - *Spatial heterogeneity* in climate provides nice opportunity to assess the impact of future climate conditions (“*space for time substitution*")
- Applied in + than 250 studies and 50 countries (Mendelsohn and Massetti, 2017). Some consistent results across studies :
  - Beneficial effects of hotter spring and autumn temperatures but harmful effects of hotter summer and winter temperatures (Mendelsohn et al., 1994; Van Passel et al., 2017)
  - Climate change will be slightly beneficial for agriculture in US and Europe (Mendelsohn and Massetti, 2017)

Ricardian approach : extensions and weaknesses

- Extensions
  - endogenous land and adjustment cost (Timmins, 2006)
  - irrigation (Schlenker et al., 2005)
  - Spatial error dependance (Schlenker et al., 2006),
  - pooled and random-effect (Massetti and Mendelsohn, 2011; Fezzi and Bateman, 2015)
  - spatial panel (Vaitkeviciute et al., 2019)
- Main weakness : **omitted variable biases** (Deschênes and Greenstone, 2007)
  - *Unobserved characteristics* that may be correlated with climate (e.g. soil quality, altitude, slope, population density...) could bias the estimates
  - Such controls are usually introduced in Ricardian analyses but often result in *measurement errors* (e.g. due to spatial scale mismatch)
  - For example, Ortiz-Bobea (2020) suggested that non-farm pressures lead to biases in recent Ricardian estimates

The weather-panel approach

- The weather approach exploits year-to-year weather fluctuations to estimate its impacts on year-to-year yields/revenues/profits deviations, usually using reduced-form equation :

$$z_{it} = \beta' \mathbf{w}_{it} + FE_i + FE_t + \varepsilon^z_{it}$$

  with z_{it} ={yields; revenues; profits}, $\mathbf{w}_{it}$ =weather during the growing season (usually April-September) and β =vector of estimates
- β is interpreted as the impacts of weather on farmers' outcomes, once farmers have undertaken adaptation
- More robust and precise estimates than the Ricardian analysis (Deschênes and Greenstone, 2007)

The weather-panel approach

- The weather approach assumes that there is adaptation but, actually, there has been limited efforts to identify real adaptation strategies in the literature
  - Some studies on the adoption of specific practices (Di Falco and Veronesi, 2013; Tambet and Stopnitzky, 2019)...
  - ... but outside the weather approach framework (Sesmero et al., 2018)...
  - ... or failing to statistically measure the induced impacts on crop yields (Aragón et al., 2021; Cui and Xie, 2021; Jagnani et al., 2021), despite accounting for explicit growing seasons adjustments (planting dates, input adjustments)
- Does β capture impacts of real adaptations ?
- Is β really different from what find studies using crop simulation models ?

The weather-panel approach

- Deschênes and Greenstone (2007) proposed to introduce individual fixed effects $\rightarrow$ regressing **profit** deviations ($\pi_{it} - \bar{\pi}_i$) on **weather** deviations ($w_{it} - \bar{w}_i$) $\rightarrow$ referred to as the “panel approach" in the literature
  - Many debates to understand whether the two methods provide similar information (e.g. Merel and Gammans, 2021)...
  - ... but the current consensus is that the “panel approach" provides the *short-term value* of climate, which is theoretically lower than the *long-term value* of climate
  - Relates both to the distinction of weather/climate (draw v.s. distribution) and to the imposed implicit constraints (e.g. fixed crop allocation)

The weather-panel approach

- The weather approach assumes that there is adaptation but, actually, there has been limited efforts to identify real adaptation strategies in the literature
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2 contributions to the literature

Journal of Environmental Economics and Management 119 (2023) 102822

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

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The impact of climate change on agriculture: A repeat-Ricardian analysis

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Figure – Contribution to the Ricardian approach

Received: 11 January 2022 | Accepted: 9 June 2023

DOI: 10.1111/ajae.12420

ARTICLE

Structural identification of weather impacts on crop yields: Disentangling agronomic from adaptation effects

François Bareille | Raja Chakir

Figure – Contribution to the weather-panel approach

Contributions 1

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The impact of climate change on agriculture: A repeat-Ricardian analysis

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Figure – Contribution to the Ricardian approach

Objective of the paper Bareille and Chakir (2023)

New method for the estimation of Ricardian models

Using plot-level repeat-sale data, we investigate how differences in farmland prices across plots are explained by differences in climate conditions between two sale dates.

- Our **"repeat-Ricardian" analysis** consists in the introduction of a **plot fixed effect** into a standard Ricardian analysis
- Exploitation of spatial AND temporal heterogeneity in climate and land prices
- It combines the advantages of both methods :
  - account for long-term adaptation thanks to the use of farmland prices (as in standard Ricardian analysis)...
  - ... while controlling for confounding omitted variables with individual (plot) fixed effects (as in the panel approach)

Empirical models - Pooled Ricardian models

- A pooled Ricardian model can be written as :

$$\log(P^{l}_{ijt}) = \alpha + \boldsymbol{\theta}'\mathbf{C}_{jt} + \boldsymbol{\beta}'\mathbf{N}_i + \boldsymbol{\gamma}'\mathbf{N}_j + \boldsymbol{\delta}'\mathbf{N}_{jt} + \epsilon_{ijt}, \quad (4)$$

- P^{l}_{ijt} : price of plot i in municipality j and year t
- $\mathbf{C}_{jt}$: vector of climate variables in j and t
- $\mathbf{N}_i$: vector of plot i's time-invariant characteristics (plot size here)
- $\mathbf{N}_j$: vector of the time-invariant characteristics of the municipality j where i is located (here, average altitude, slope and soil conditions)
- $\mathbf{N}_{jt}$: vector of time-varying variables (here, population density) for j in t

Empirical models - Pooled Ricardian models

- A pooled Ricardian model can be written as :

$$\log(P^{l}_{ijt}) = \alpha + \boldsymbol{\theta}'\mathbf{C}_{jt} + \boldsymbol{\beta}'\mathbf{N}_{i} + \boldsymbol{\gamma}'\mathbf{N}_{j} + \boldsymbol{\delta}'\mathbf{N}_{jt} + \epsilon_{ijt},$$

- Based on Massetti and Mendelsohn (2011), we estimate four different pooled Ricardian models :
- Model 1 : No control variables, no year dummies
- Model 2 : Control variables, no year dummies
- Model 3 : No control variables, with year dummies
- **Model 4 :** Control variables, with year dummies

Empirical models - Pooled Ricardian models

- A pooled Ricardian model can be written as :

$$\log(P^{l}_{ijt}) = \alpha + \boldsymbol{\theta}'\mathbf{C}_{jt} + \boldsymbol{\beta}'\mathbf{N}_{i} + \boldsymbol{\gamma}'\mathbf{N}_{j} + \boldsymbol{\delta}'\mathbf{N}_{jt} + \epsilon_{ijt},$$

- Problem : control variables $\mathbf{N}_j$ (altitude, slope and soil conditions) are very heterogeneous within a municipality (Ay, 2021)
  $\rightarrow$ cor($\mathbf{N}_j$,$\mathbf{N}^0_i$) $<< 1$
- Problem of measurement errors
- Omitted variable biases remain
- Luckily, $\mathbf{N}^0_i$ is constant over time

Empirical models - Repeat-Ricardian models

- A Ricardian model with plot fixed effects can be written as :

$$\log(P^{l}_{ijt}) = \alpha + \boldsymbol{\theta}'\mathbf{C}_{jt} + \boldsymbol{\beta}'\mathbf{N}_{i} + \boldsymbol{\gamma}'\mathbf{N}_{j} + \boldsymbol{\delta}'\mathbf{N}_{jt} + FE_{i} + \zeta_{ijt}, \qquad (5)$$

where FE_i are the plot fixed effects that capture all the time-invariant unobserved factors of plot i.

Empirical models - Repeat-Ricardian models

- The repeat-Ricardian analysis consists of removing these time-invariant factors by estimating :

$$\log(P^l_{ijt}) - \log(\bar{P}^l_{ij}) = \alpha - \alpha\boldsymbol{\theta}'(\mathbf{C}_{jt} - \bar{\mathbf{C}}_j) + \beta'(\mathbf{N}_i - \bar{\mathbf{N}}_i) + \gamma'(\mathbf{N}_j - \bar{\mathbf{N}}_j) + \boldsymbol{\delta}'(\mathbf{N}_{jt} - \bar{\mathbf{N}}_j) + (FE_i - \bar{FE}_i) + \zeta_{ijt} \quad (6)$$

- Or simply :

$$\log(P^l_{ijt}) - \log(\bar{P}^l_{ij}) = \boldsymbol{\theta}'(\mathbf{C}_{jt} - \bar{\mathbf{C}}_j) + \boldsymbol{\delta}'(\mathbf{N}_{jt} - \bar{\mathbf{N}}_j) + \mu_{ijt} \quad (7)$$

- Model 1 : No control variables, no year dummies
- Model 2 : Control variables, no year dummies
- Model 3 : No control variables, with year dummies
- Model 4 : Control variables, with year dummies

Farmland prices data 1/2

- We use individual data on farmland transactions from the PERVAL database
  - Exhaustive information about all real estate transactions that have occurred in France (except for the *Ile de France* region) since 1996
  - Distinguishes between houses, flats, farmland and forests.
  - Information on prices, characteristics of the properties, location at the municipality level and transaction date
- Different type of database from most Ricardian studies who use aggregated information (county or departmental levels) from annual land surveys (Mendelsohn et al., 1994; Ortiz-Bobea, 2020)
- No aggregation bias (Fezzi and Bateman, 2015)
- No “declarative" bias (Bigelow et al., 2020)

Farmland prices data 2/2

- 660,755 farmland transactions over the 1996-2019 period
- **Repeat-Ricardian analysis :** purchase of the sample of French plots that have been sold ***exactly* twice** between 1996 and 2019 and that maintained a similar area between the two sale dates
  - 4,494 plots (i.e. 8,988 transactions or 1.36% of all French farmland plots that were sold during our study period)
  - After outlier removal, the final sample consists of 4,307 observations (8,614 transactions)

Climate data 1/2

- We use the daily weather information since 1959 from the SAFRAN database provided by *Météo France* to compute climate conditions
- This database uses historical daily measurements for the 8,604 French stations, which are spatialized by *Météo France* at the 8×8 km^2 SAFRAN grid squares (9,892 grid squares for the whole France).
- The choice of climate variables is an important empirical challenge in the Ricardian literature
  - Long-term average temperatures and precipitation for the four seasons (Mendelsohn and Massetti, 2017)
  - Cumulative degree days over the growing season in addition to the four-seasons (Ortiz-Bobea, 2020)

$\Longrightarrow$ **four-seasons ricardian** have been identified as being superior to degree-days Ricardian models (Massetti et al., 2016) or two-seasons Ricardian models (Vaitkeviciute et al., 2019).

Climate data 2/2

- In line with the literature, we estimate **four-seasons ricardian model**
- We define climate by the set of seasonal climatologies on temperature (°C/day) and precipitation (cm/month)
- We compute the climatologies as 30-year averages of temperatures and precipitation between $t-30$ and $t-1$
    - Spring is defined as March-May (respectively June-August, September-November and December-February for summer, autumn and winter)
- For example, climate in 1996 (resp. 2019) is measured as the averages of annual weather conditions between 1966 and 1995 (resp. between 1989 and 2018).
- The heterogeneity of the climate conditions for our initial and final periods thus relies on 23 years, 1989-1995 being common to the two periods.

Aggregated summary statistics

Table – Summary statistics for the plots in the repeat-sale samples (N=8,614)

Levels	Mean	S.D.	Min	Q1	Median	Q3	Max
Farmland price (€/ha)	9,132.69	16,505.61	0.54	2,549.81	4,214.23	8,251.14	273,583.22
log(farmland price) (€/ha)	8.48	1.04	-0.62	7.84	8.34	9.02	12.52
Year of transaction	2008	6.73	1996	2003	2008	2014	2019
Farmland area (ha)	2.99	4.79	0.01	0.50	1.29	3.27	105.17
Spring temperature (°C/day)	10.05	1.62	-0.78	9.20	9.83	10.87	14.48
Summer temperature (°C/day)	18.03	2.27	0.07	16.69	17.89	19.24	23.57
Autumn temperature (°C/day)	11.44	1.69	0.04	10.52	11.26	12.34	16.40
Winter temperature (°C/day)	4.50	1.67	-4.96	3.43	4.46	5.78	9.02
Spring precipitation (cm/month)	6.64	1.46	0.04	5.74	6.40	7.16	14.40
Summer precipitation (cm/month)	5.86	1.70	0.04	4.96	5.83	6.63	16.40
Autumn precipitation (cm/month)	8.13	1.82	0.04	6.84	7.86	9.21	22.77
Winter precipitation (cm/month)	7.13	1.92	0.03	5.83	6.88	8.22	17.51
Municipal population density (inhabitants/km^2)	103.53	210.11	0.83	25.63	48.79	102.48	4767.22
Altitude (m)	190.76	212.50	1.00	69.27	135.42	225.52	2,217.23
Slope (%)	2.61	3.68	0.00	0.88	2.61	2.79	39.23
Soil (category 1)	0.12	0.25	0.00	0.00	0.00	0.05	1.00
Soil (category 2)	0.43	0.40	0.00	0.00	0.33	0.86	1.00
Soil (category 3)	0.35	0.40	0.00	0.00	0.10	0.75	1.00
Soil (category 4)	0.10	0.25	0.00	0.00	0.00	0.00	1.00

Aggregated summary statistics

Table – Summary statistics for the plots in the repeat-sale samples, expressed in differences between the two sale dates (N=8,614)

Differences between t_2 and t_1	Mean	S.D.	Min	Q1	Median	Q3	Max
Farmland price (€/ha)	2,621.18	9,936.48	-103,389.66	-82.37	721.55	2,598.78	154,876.42
log(farmland price) (€/ha)	0.27	0.62	-9.18	-0.02	0.18	0.51	4.10
Spring temperature (°C/day)	0.31	0.27	-0.06	0.08	0.23	0.46	1.47
Summer temperature (°C/day)	0.25	0.23	-0.13	0.07	0.18	0.36	1.41
Autumn temperature (°C/day)	0.17	0.19	-0.52	0.03	0.11	0.27	1.02
Winter temperature (°C/day)	0.10	0.18	-0.92	-0.02	0.06	0.19	1.25
Spring precipitation (cm/month)	-0.04	0.26	-1.45	-0.18	-0.03	0.11	1.11
Summer precipitation (cm/month)	0.12	0.27	-1.25	-0.04	0.08	0.25	1.33
Autumn precipitation (cm/month)	0.09	0.32	-1.08	-0.11	0.05	0.24	2.31
Winter precipitation (cm/month)	0.01	0.36	-2.56	-0.15	0.01	0.17	1.77
Municipal population density (inhabitants/km^2)	4.77	15.96	-139.51	-0.03	1.29	5.53	409.01

Heterogeneous changes in climate across France

The standard Ricardian analysis uses differences over space of climatologies *in levels*

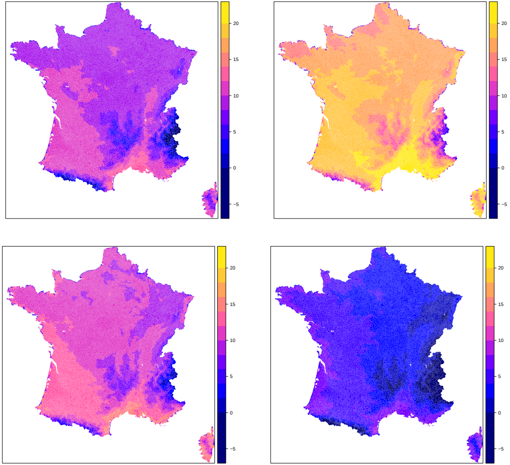

Figure – Seasonal temperatures for the 1966-1995 period in France in (a)

Heterogeneous changes in climate across France

- The repeat-Ricardian analysis exploits differences over space of *changes* in climatologies

Table – Climate change across French municipalities between 1996 and 2019 (N=36,486)

	Mean	S.D.	Min	Max		Mean	S.D.	Min	Max
Temperature (°C/day)					**Precipitation (cm/month)**				
Spring 1996	9.18	1.62	-3.40	13.6	Spring 1996	6.95	1.69	0.01	16.8
Spring 2019	10.24	1.67	-2.50	14.40	Spring 2019	6.82	1.71	0.01	15.50
Spring change 1996-2019	1.06	0.23	0.00	2.16	*Spring change 1996-2019*	-0.13	0.32	-1.70	1.27
Summer 1996	17.39	2.00	0.01	22.70	Summer 1996	6.32	1.78	0.01	15.90
Summer 2019	18.34	2.11	0.01	23.80	Summer 2019	6.53	1.77	0.01	16.30
Summer change 1996-2019	0.95	0.26	0.00	2.40	*Summer change 1996-2019*	0.21	0.38	-1.60	1.73
Autumn 1996	10.73	1.70	0.01	16.50	Autumn 1996	7.87	2.10	0.01	24.10
Autumn 2019	11.16	1.74	0.01	17.10	Autumn 2019	8.17	2.36	0.01	29.80
Autumn change 1996-2019	0.43	0.30	-0.96	1.41	*Autumn change 1996-2019*	0.31	0.57	-1.00	5.74
Winter 1996	3.67	1.82	-6.8	9.39	Winter 1996	7.01	2.03	0.01	17.90
Winter 2019	4.09	1.76	-6.6	9.78	Winter 2019	7.04	1.97	0.01	19.50
Winter change 1996-2019	0.42	0.30	-1.10	1.58	*Winter change 1996-2019*	0.03	0.66	-3.10	2.11

Heterogeneous changes in climate across France

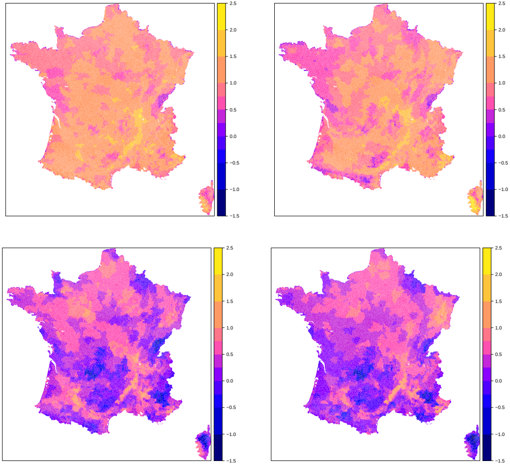

Figure – Changes in seasonal temperatures from 1996 (1966-1995 averages) to 2019 (1989-2018 averages) in (a) Spring, (b) Summer, (c) Autumn and (d) Winter.

Heterogeneous changes in climate across France

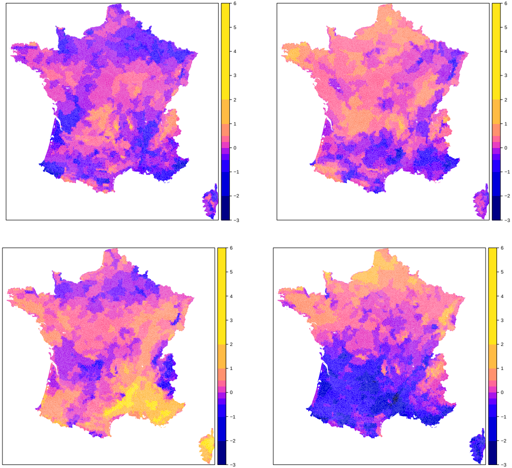

Figure – Changes in seasonal precipitation from 1996 (1966-1995 averages) to 2019 (1989-2018 averages) in (a) Spring, (b) Summer, (c) Autumn and (d) Winter.

Heterogeneous changes in farmland prices across France

- Representative of the general population (no evidence of selection bias)

Table – Summary statistics on transactions for the repeat-sales sample and the general population

	Repeat-sales (N=8,614)			All sales (N=660,755)			
	Mean	S.D.	Median	Mean	S.D.	Median	*t*-value
Area (ha)	2.99	4.79	1.29	3.23	7.36	1.02	3.02 ***
Price (€)	14,130	23,007	6,238	14,025	50,760	5,000	0.59
Price (€/ha)	9,133	16,506	4,214	10,434	16,366	3,278	0.74
Annual price variation (%/year)	15.76	39.53	4.74	-	-	-	-
Years between two sales	6.58	5.43	5.00	-	-	-	-

Prices are expressed in 1996 real prices. Annual price variation represents the farmland price variation
*between the two sale dates. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.*

Heterogeneous changes in farmland prices across France

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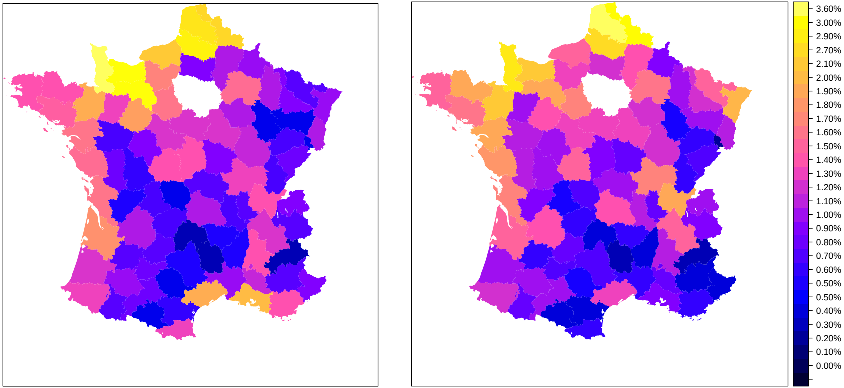

Figure – Distribution of the observed transactions in (a) the repeat sales sample and (b) the general population.

Heterogeneous changes in farmland prices across France

- The standard (pooled) Ricardian analysis exploits spatial differences in farmland prices (*in levels*)

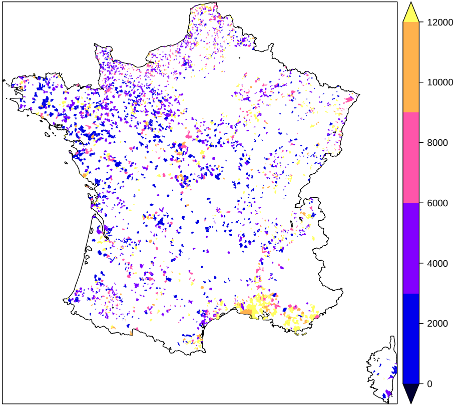

Figure – Farmland prices in the repeat-sales sample

Heterogeneous changes in climate and price across France

The repeat-Ricardian analysis exploits spatial differences of *changes* in farmland prices

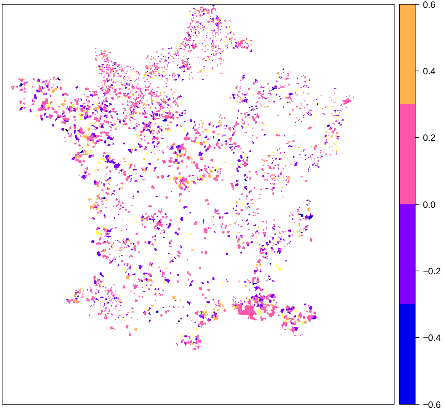

Figure – Annual price variation between the two sale dates in the repeat-sales sample.

Estimation Results

	Dependent variable : log(price)							
	Pooled Ricardian				**Repeat-Ricardian**			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Temperature (C/day)								
Spring	0.28 ***	0.26 ***	0.08	-0.22 *	0.36 ***	0.36 ***	0.34 **	0.35 **
	(0.07)	(0.08)	(0.09)	(0.13)	(0.13)	(0.13)	(0.14)	(0.14)
Summer	-0.19 ***	-0.17 **	-0.09	0.08	0.26 *	0.26 **	0.25 *	0.25 *
	(0.06)	(0.06)	(0.08)	(0.10)	(0.14)	(0.13)	(0.15)	(0.15)
Autumn	0.26 **	0.25 **	0.28 **	0.21 *	0.15 *	0.15 *	0.12	0.13
	(0.10)	(0.09)	(0.14)	(0.13)	(0.09)	(0.09)	(0.09)	(0.09)
Winter	-0.27 ***	-0.26 ***	-0.20*	-0.10	-0.22 ***	-0.23 ***	-0.19 **	-0.20 **
	(0.09)	(0.09)	(0.11)	(0.12)	(0.08)	(0.08)	(0.08)	(0.09)
Precipitations (cm/month)								
Spring	-0.18 ***	-0.18 ***	-0.17 ***	-0.11 ***	0.00	0.00	-0.02	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Summer	0.01	0.01	0.01	0.00	0.10 **	0.10 *	0.11 *	0.10 *
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)
Autumn	0.14 ***	0.10 ***	0.11 ***	0.08 ***	0.03	0.04	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Winter	-0.09 ***	-0.06 **	-0.09 ***	-0.08 ***	0.07 *	0.07 *	0.06	0.06
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Number of observations	8,614	8,614	8,614	8,614	8,614	8,614	8,614	8,614
Time invariant plot controls		Yes		Yes				
Time invariant municipal controls		Yes		Yes				
Time variant municipal controls		Yes		Yes		Yes		Yes
Annual dummies			Yes	Yes			Yes	Yes
Plot fixed effects					Yes	Yes	Yes	Yes
Adjusted R2	0.09	0.14	0.10	0.16	0.14	0.14	0.14	0.14

*Climatologies are computed using 30-year averages. Plot controls solely include plot size. Time invariant municipal controls include average altitude and soil conditions. Time variant municipal controls solely include population density. Standard errors are indicated within brackets and account for spatial correlation of disturbances. *, ** and *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.*

Estimation Results - Implications

- Evidences that **omitted variable bias** is important in standard Ricardian analysis
  - Instability of pooled estimates to the introduction of controls and dummies
  - Several estimates are statistically different between the pooled and repeat-Ricardian analyses
- Particularly true for **summer temperatures**. Looking at Models 1, an additional 1°C/day in summer affect land prices such that :
  - Pooled Ricardian estimates : *reduction* from -834 to -2,636€/ha
  - Repeat-Ricardian estimates : *increase* of between 271 and 4,477€/ha

Estimation Results - Implications 2/2

- Farmers benefit from warmer summer temperatures in the long term. Why?
  - Switch towards high-value crops that benefit from warm summers, such as fruit productions (vineyards or orchards) in France
  - Consistent with the potential role of plot fixed effects :
    - Orchards and vineyards need particular topological and soil conditions (e.g. arid hillside), which may be correlated to climate conditions
    - Plot fixed effects free the estimates from these confounding characteristics

Estimation Results - Robustness analyses

- The functional form could be mispecified Table
  - Mendelsohn et al. (1994) used linear Ricardian models
  - Schlenker et al. (2005) showed that log-linear models better fit farmland values
  - Massetti and Mendelsohn (2011) showed that log-quadratic Ricardian models are particularly suited when climate varies a lot between locations
- Length-definition of climate Table
  - The repeat-sales occurred within less than 23 years
  - The climatologies measured on 30-year averages use weather conditions from similar years for the two sale years (at least 30-23=7 common years)
  - As in Schlenker et al. (2006), Burke and Emerick (2016) or Hsiang (2016), we provide robustness checks using shorter length-definitions of climate
- Distinction of observations based on the length between two sale dates Table
  - 1 and 5 years (53.06% of the whole sample)
  - 6 and 10 years (23.80% of the whole sample)
  - 11 and 23 years (23.14% of the whole sample)

Estimation Results - Heterogeneity analyses

- The role of irrigation (Schlenker et al., 2005) Table
  - Distinction of irrigated and rainfed farmlands based on the 2010 Agricultural Census
  - Irrigated farmland if more than 20% of the departmental UAA is irrigated (978 transactions in total)
  - All other transactions (7,636) are considered to be part of the rainfed sample
- The role of initial climates Table
  - Distinction between Continental, Mediterranean, Mountain and Oceanic climates Figure

Simulations of Climate Change Impacts

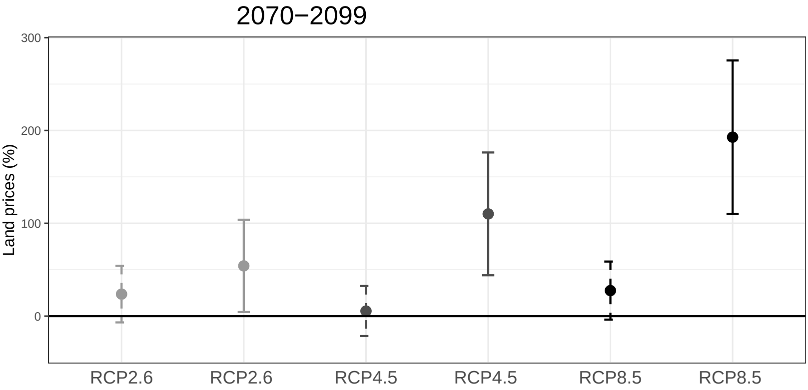

Figure – Climate change impacts on farmland prices in 2070-2099 (in % of farmland prices from 1996-2019). *Dots represent point estimates and whiskers show the 95% confidence interval. The dashed lines correspond to pooled Ricardian models. The solid lines indicate repeat-Ricardian models. All estimates come from Ricardian models with control variables and annual*

Simulations of Climate Change Impacts

Table – Climate change impacts on farmland prices under various scenarios and time horizons using pooled Ricardian and Repeat-Ricardian estimates.

2070-2099	Mean	S.D.	Min	Q1	Median	Q3	Max	$1 - \frac{\hat{\text{Impacts}}_{\text{Pooled}}}{\hat{\text{Impacts}}_{\text{Repeat}}}$
RCP2.6								
Pooled Ricardian	0.24	0.15	-0.85	0.19	0.27	0.33	0.70	-
Repeat-Ricardian	0.54	0.25	-0.14	0.36	0.54	0.73	1.80	0.56
RCP4.5								
Pooled Ricardian	0.06	0.14	-0.90	-0.01	0.06	0.13	0.51	-
Repeat-Ricardian	1.10	0.33	0.01	0.87	1.10	1.34	2.63	0.95
RCP8.5								
Pooled Ricardian	0.28	0.16	-1.33	0.22	0.30	0.36	0.82	-
Repeat-Ricardian	1.93	0.42	0.01	1.69	1.96	2.21	3.62	0.85

- Assuming constant French UAA, pooled Ricardian analysis **underestimates** by between **72 and 374 billion euros** the benefits of climate change
- But repeat-Ricardian estimates are more likely to be correct for small deviations compared to historical climates (probably correct for RCP2.6... but less for RCP8.5)

Conclusion 1

- New methodology to correct for omitted variable bias in the Ricardian analysis : **the repeat-Ricardian analysis**
  - Combine the advantages of the Ricardian analysis (Mendelsohn et al., 1994) with the techniques of panel econometrics (Deschênes and Greenstone, 2007)
- Different results between pooled and repeat-Ricardian analyses :
  - Pooled Ricardian estimates indicate similar results to those usually found in the Ricardian literature (e.g. negative impacts of summer temperatures)
  - Repeat-Ricardian estimates indicate positive impacts of summer temperatures
  - Instability of the pooled Ricardian estimates underline omitted variable biases
  - Repeat-Ricardian estimates are stable and robust to several empirical choices
- Simulations suggest that the omitted variables lead to an underestimation of the impacts of climate change on agriculture by between **56% and 95%**.

Contribution 2

Received: 11 January 2022 | Accepted: 9 June 2023

DOI: 10.1111/ajae.12420

ARTICLE

Structural identification of weather impacts on crop yields: Disentangling agronomic from adaptation effects

François Bareille | Raja Chakir

Figure – Contribution to the weather-panel approach

Main Objectives of the paper Bareille and Chakir (2024)

- Our main objective is to properly model and estimate the consequences of farmers' adaptation on crop yields
- We propose a structural model derived from a profit-maximizing farmer program that allows us to simultaneously and separately measure :
  - (i) the direct impacts of weather change on crop yields, independently of farmers' adaptation (referred to as *agronomic impacts*),
  - (ii) the farmers' response to weather change through modifications in practices (what the literature usually calls *adaptation*), and
  - (iii) the consequences of these adaptations on crop yields (called *adaptation impacts*).
- We build our identification strategy on the standards of the yield-weather-panel approach, exploiting farm-specific weather deviations from farm averages to explain our dependent variables (Blanc and Schlenker, 2017).

Main Objectives

- We check whether the usual reduced-form models give similar results to our structural model (grounded on microeconomic theory).
- We verify whether the usual reduced-form estimates from the yield-weather-panel literature do really account for the "indirect" weather impacts resulting from farmers' adaptation – that have been only assumed so far – on top of the "direct" weather impacts on plant growth (that have been documented by agronomic studies).
- We verify whether the yield-weather-panel literature is really more appropriate than former crop simulation models at measuring weather impacts on crop yields.

Main Objectives

- We investigate how farmers adjust pesticide and fertilizer applications to weather conditions during the growing season.
- Indeed, given that crop allocation can be considered as fixed during the growing season, fertilizer and pesticide applications remain the only possible adaptation strategy for farmers at that time (at least in rain fed regions).
- There are several reasons for presuming that farmers adjust their input applications to weather changes within the growing season.
  - The agronomic literature indicates that higher temperatures and precipitation increase pest pressure (Rosenzweig et al., 2001; Bailey, 2004), possibly leading farmers to use more pesticides in these conditions.
  - Weather changes can also influence input applications by affecting input productivity (Xia and Wan, 2008; Kaminski et al., 2013).

Main Objectives

- Our structural model proposes a channel linking weather changes to
  - (i) changes in fertilizer and pesticide productivity, which translates into
  - (ii) changes in fertilizer and pesticide applications, ultimately allowing us to identify
  - (iii) changes in crop yields (i.e. the adaptation impacts).
- The identification of these within-season adaptation impacts on top of the measure of the total impacts allows us to measure, by difference, the agronomic impacts.

Farmers' program during the growing season

- Consider a risk-neutral farmer i growing J crops whose objective is to maximize their profit in year t according to the set of weather conditions during the growing season (noted $\mathbf{w}_{i,t}$) and to the set of input and output prices

Disentangling Marginal Weather Impacts

- To explicitly represent the effects of farmers' adaptation on crop yields, we examine here how farmers respond to marginal weather changes and how these changes translate into crop yields.
- Assuming no effects on input and output prices, we can disaggregate a marginal change in the z^{th} element of $\mathbf{w}_{i,t}$ (noted $\mathbf{w}_{i,t}^{(z)}$, e.g. the average temperature during the growing season) on $\pi_{i,j,t}$ as follows :
width=totalheight=keepaspectratio

$$\frac{\mathrm{d}\pi_{i,j,t}}{\mathrm{d}\mathbf{w}_{i,t}^{(z)}} = E(p_{i,j,t}^{y}) \underbrace{\frac{\partial f_j(\mathbf{x}_{i,j,t}^{*}(\mathbf{w}_{i,t}); \mathbf{w}_{i,t})}{\partial \mathbf{w}_{i,t}^{(z)}}}_{\text{Total impact on yields}} - \mathbf{p}_{i,t}^{\mathbf{x}}{}' \underbrace{\frac{\partial \mathbf{x}_{i,j,t}^{*}(\mathbf{w}_{i,t})}{\partial \mathbf{w}_{i,t}^{(z)}}}_{\text{Input adjustments}} . \quad (8)$$

Relation (8) states that a marginal weather change affects the crop-specific profit through both an effect on yields and an effect on input applications. The effect on input applications comes from the fact that farmers re-optimize input applications under new weather conditions.

Disentangling Marginal Weather Impacts

- These input adjustments affect crop yields through $f_j(\mathbf{x}_{i,j,t};\mathbf{w}_{i,t})$ and, importantly, add to the initial shock of the marginal weather change on plant growth, together forming the "total weather impact".
- The yield-weather-panel literature typically measures this total impact when regressing crop yields on weather conditions, without distinguishing the two effects.
- We can, however, theoretically distinguish them by disaggregating the total weather impact as :

$$\underbrace{\frac{\partial f_j(\mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t});\mathbf{w}_{i,t})}{\partial \mathbf{w}^{(z)}_{i,t}}}_{\text{Total impact}} = \underbrace{\frac{\partial f_j(\bar{\mathbf{x}}^*_{i,j,t}(\bar{\mathbf{w}}_i);\mathbf{w}_{i,t})}{\partial \mathbf{w}^{(z)}_{i,t}}}_{\text{Agronomic impact}} + \underbrace{\frac{\partial \mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t})}{\partial \mathbf{w}^{(z)}_{i,t}}' \frac{\partial f_j(\mathbf{x}^*_{i,j,t}(\mathbf{w}_{i,t});\mathbf{w}_{i,t})}{\partial \mathbf{x}_{i,j,t}}}_{\text{Adaptation impact}}, \tag{9}$$

Conceptual framework

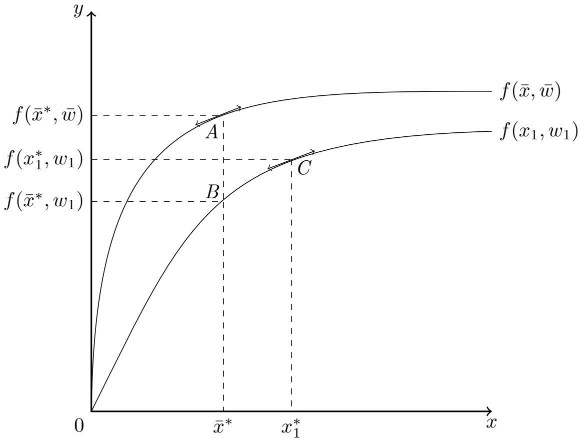

Figure – Decomposition of the weather effects on crop yields.

Structural modeling

- We assume quadratic relationships between crop yields and fertilizers ($k = 1$) and pesticides ($k = 2$), represented by :

$$y_{i,j,t} = \boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) - \frac{1}{2}\sum_{k=1}^{2}\sum_{l=1}^{2}\gamma^{-1}_{j,k,l}(\mathbf{w}_{i,t})[\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t}) - x_{i,j,k,t}][\boldsymbol{\beta}_{j,l}(\mathbf{w}_{i,t}) - x_{i,j,l,t}], \quad (10)$$

  where $\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$, $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$, and $\gamma_{j,k,l}(\mathbf{w}_{i,t})$ are sets of crop-specific parameters.

- This specification, proposed by Femenia and Letort (2016), allows explicit representation of technical changes in the production function. We define the symmetric 2×2 matrix $\Gamma_j(\mathbf{w}_{i,t}) \equiv [\gamma^{-1}_{j,k,l}(\mathbf{w}_{i,t})]$ to arrange technical shifters. The parameters $\boldsymbol{\alpha}_j(\mathbf{w}_{i,t})$ and $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$ have agronomic interpretations, while the productivity of inputs depends on various factors including input requirements and technical shifters.

Structural model.

- The formulation of our structural model explicitly represents the set of optimal decisions of farmers under the particular technology and weather conditions, and the consequences of these decisions on crop yields.
- The optimal demand function for input k on crop j :

$$x^*_{i,j,k,t} = \beta_{j,k}(\mathbf{w}_{i,t}) - \frac{p^x_{k,t}\gamma^{-1}_{j,k}(\mathbf{w}_{i,t}) + p^x_{l,t}\gamma^{-1}_{j,1,2}(\mathbf{w}_{i,t})}{E(p^y_{i,j,t})(\gamma^{-1}_{j,1,1}(\mathbf{w}_{i,t})\gamma^{-1}_{j,2,2}(\mathbf{w}_{i,t}) - \gamma^{-2}_{j,1,2}(\mathbf{w}_{i,t}))}, \qquad (11)$$

with $k \neq l$. Relation (11) indicates that weather affects the optimal applications of input k through the sets of parameters $\beta_{j,k}(\mathbf{w}_{i,t})$ and $\gamma^{-1}_{j,k,l}(\mathbf{w}_{i,t})$. [1]

Structural model.

- We can then obtain the consequences of these optimal input applications by reinserting them into relation (10). This leads to the optimal yield for crop j :

$$y^*_{i,j,t} = \boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) - \frac{1}{2}\frac{(p^x_{1,t})^2\gamma^{-1}_{j,1,1}(\mathbf{w}_{i,t}) + (p^x_{2,t})^2\gamma^{-1}_{j,2,2}(\mathbf{w}_{i,t}) + 2p^x_{1,t}p^x_{2,t}\gamma^{-1}_{j,1,2}(\mathbf{w}_{i,t})}{(E(p^y_{i,j,t}))^2(\gamma^{-1}_{j,1,1}(\mathbf{w}_{i,t})\gamma^{-1}_{j,2,2}(\mathbf{w}_{i,t}) - \gamma^{-2}_{j,1,2}(\mathbf{w}_{i,t}))}. \quad (12)$$

Relation (12) indicates that weather affects the optimal yields only through the parameters $\boldsymbol{\alpha}_{j,k}(\mathbf{w}_{i,t})$ and $\gamma^{-1}_{j,k,l}(\mathbf{w}_{i,t})$, but not through $\boldsymbol{\beta}_{j,k}(\mathbf{w}_{i,t})$.

Structural model.

- Overall, our structural model consists of one yield equation (relation (12)) and two input demand equations (relation (11) for fertilizers and pesticides) for each crop $j \in \mathbb{J}$.
- The parameters $\gamma_{j,k,l}^{-1}(\mathbf{w}_{i,t})$ are thus shared between the yield and input demand functions of the structural model (Pope and Just, 2003).

Econometric Strategy : reduced form

- Our econometric strategy consists of comparing the estimated weather impacts on crop yields using reduced-form and structural models for wheat ($j = 1$), barley ($j = 2$) and rapeseed ($j = 3$).
- As a benchmark, we estimate the relationship between crop yields and weather conditions during the growing season using a reduced-form model in the spirit of the yield-weather-panel literature.
- We specify for each crop a quadratic relationship with both average temperature and total precipitation during the growing season, conditionally on farm fixed effects :

$$y_{i,j,t} = \psi_j^T T_{i,t} + \psi_j^{T^2} T_{i,t}^2 + \psi_j^P P_{i,t} + \psi_j^{P^2} P_{i,t}^2 + \vartheta_{i,j}^y + \varepsilon_{i,j,t}^y, \tag{13}$$

with $\vartheta_{i,j}^y$ the farm fixed effect, $\boldsymbol{\psi}_j(\mathbf{w}_{i,t})$ the set of parameters of interest and $\varepsilon_{i,j,t}^y$ the remaining error terms that are assumed to have white noise characteristics. The farm fixed effects capture the heterogeneous farm-specific time-invariant drivers of crop yields such as soil quality. The effects captured by $\boldsymbol{\psi}_j(\mathbf{w}_{i,t})$ are the total impacts of weather conditions during the growing season on crop yields. We estimate relation (13) using ordinary least squares (OLS).

Econometric Strategy : Structural estimation.

- We estimate the structural model consisting of relations (11) and (12) for each crop. Specifically, we estimate for crop j the following system :

$$\begin{cases} y_{i,j,t} = \boldsymbol{\alpha}_j(\mathbf{w}_{i,t}) - \boldsymbol{\delta}_{j,1,1}(\mathbf{w}_{i,t})\frac{(p^x_{1,t})^2}{2(E(p^y_{i,j,t}))^2} - \boldsymbol{\delta}_{j,2,2}(\mathbf{w}_{i,t})\frac{(p^x_{2,t})^2}{2(E(p^y_{i,j,t}))^2} - \boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})\frac{p^x_{1,t}p^x_{2,t}}{(E(p^y_{i,j,t}))^2} \\ x_{i,j,1,t} = \boldsymbol{\beta}_{j,1}(\mathbf{w}_{i,t}) - \boldsymbol{\delta}_{j,1,1}(\mathbf{w}_{i,t})\frac{p^x_{1,t}}{E(p^y_{i,j,t})} - \boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})\frac{p^x_{2,t}}{E(p^y_{i,j,t})} + \omega^x_{i,j,1} + \mu^x_{i,j,1,t}, \\ x_{i,j,2,t} = \boldsymbol{\beta}_{j,2}(\mathbf{w}_{i,t}) - \boldsymbol{\delta}_{j,2,2}(\mathbf{w}_{i,t})\frac{p^x_{2,t}}{E(p^y_{i,j,t})} - \boldsymbol{\delta}_{j,1,2}(\mathbf{w}_{i,t})\frac{p^x_{1,t}}{E(p^y_{i,j,t})} + \omega^x_{i,j,2} + \mu^x_{i,j,2,t}, \end{cases}$$

  with $\omega^y_{i,j}$ and $\omega^x_{i,j,k}$ the farm fixed effects, $\mu^x_{i,j,k,t}$ and $\mu^y_{i,j,t}$ the remaining error terms with white noise properties and $\boldsymbol{\delta}_{j,k,l}(\mathbf{w}_{i,t}) = \frac{\gamma^{-1}_{j,k,l}(\mathbf{w}_{i,t})}{\boldsymbol{\gamma}^{-1}_{j,1,1}(\mathbf{w}_{i,t})\boldsymbol{\gamma}^{-1}_{j,2,2}(\mathbf{w}_{i,t})-\boldsymbol{\gamma}^{-2}_{j,1,2}(\mathbf{w}_{i,t})}$ $\forall\{k;l\} \in \{1;2\}^2$.

- Given the potential correlation between the error terms of the system equations in relation (14), we estimate the structural models using estimators from seemingly unrelated equations (SUR).

Data

- Our primary data is an unbalanced panel of farms located in the French department of *Meuse* observed between 2006 and 2012. The panel is composed of 296 crop farms remaining in the database for an average of 3.73 years, constituting 1,104 farm$\times$year observations in total.
- *Meuse* is a rainfed agricultural department (NUTS3 region) located in north east France and specialized in crop production.
- The agriculture in *Meuse* is representative of the agriculture in north east France (and the *Paris Basin* in general), which is mainly orientated towards cereals and industrial crops and where farmers use intensive cropping practices. Together, the farms of our sample occupy 31.09% of the whole useful agricultural area of *Meuse*.
- All the farms in our sample grow wheat, barley and rapeseed, which together occupy an average of 79.17% of farmers' arable area.
- The database originates from the Meuse Management Center local accounting agency (*Centre de Gestion de la Meuse*).
- One of the main interests of using this farm-level dataset is that we can access detailed accounting information *per crop*. On top of information on

Weather variables.

- We use historical daily weather information for the whole period from *Météo France*.
- Before computing our weather variables, we first reconstruct the distribution of temperature within each day using a sine interpolation between minimal and maximal daily temperatures, *à la* Schlenker and Roberts (2009).
- We then compute the average temperature during the growing season as the average of the reconstructed temperature distribution between February 1^{st} and July 31^{th}.
- This method provides better approximation of the average temperatures over the growing season than alternative methods relying on daily or monthly temperature averages only.
- One can interpret our measure of average temperatures as the accumulated temperatures (i.e. sum of beneficial and killing degree days) divided by the number of days during the growing season.
- We compute the total precipitation during the growing season as the sum of observed precipitation between February 1^{st} and July 31^{th}.

Summary Statistics.

- We use an accounting agency database provided by the *Centre de Gestion de la Meuse* and observed weather from *Météo France* to build an unbalanced panel of 296 farms (3.96 years on average) from 2006 to 2012 (N*T=1104).

	Mean	**S.D.**	**Min**	**Max**
Average temperature (C)	12.65	0.64	11.17	14.18
Total precipitation (mm)	408.81	109.72	198.10	591.27
Wheat yield (100kg/ha)	70.88	10.49	31.49	106.96
Barley yield (100kg/ha)	64.30	11.10	20.00	90.76
Rapeseed yield (100kg/ha)	33.59	6.60	7.96	50.26
Wheat price (€/100kg)	16.49	3.49	3.82	28.32
Barley price (€/100kg)	14.63	3.61	6.55	30.82
Rapeseed price (€/100kg)	35.05	6.32	11.93	63.81
Fertilizer applications for wheat (constant €/ha)	123.04	28.14	3.79	210.16
Fertilizer applications for barley (constant €/ha)	106.85	25.00	3.15	211.05
Fertilizer applications for rapeseed (constant €/ha)	122.30	29.81	3.55	247.84
Pesticide applications for wheat (constant €/ha)	160.10	44.25	8.45	377.63
Pesticide applications for barley (constant €/ha)	152.51	45.69	34.13	392.07
Pesticide applications for rapeseed (constant €/ha)	220.88	52.25	63.24	423.47
Fertilizer price (index)	1.17	0.21	0.91	1.51
Pesticide price (index)	0.98	0.03	0.94	1.01

Estimation Results

Table – Reduced-form and structural estimates of weather elasticities on crop yields.

	Reduced-form			Structural		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Temperature	0.57 ***	-0.67 ***	1.00 ***	0.53 ***	-0.63 ***	1.02 ***
	(0.09)	(0.11)	(0.12)	(0.09)	(0.11)	(0.12)
Precipitation	0.03 ***	0.03 **	0.00	0.03 **	0.02	-0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)

NOTE. Elasticites are computed at sample mean values. Below each estimate we report in brackets the standard errors obtained with the delta method. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

Table – Weather elasticities on input applications.

	Temperature			Precipitation		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Fertilizers	1.02 ***	1.34 ***	0.61 ***	0.10 **	0.02	0.20 ***
	(0.19)	(0.23)	(0.24)	(0.04)	(0.04)	(0.04)
Pesticides	-0.39 **	0.30	-0.19	0.11 **	0.09 **	-0.24 ***
	(0.20)	(0.27)	(0.20)	(0.04)	(0.04)	(0.03)

NOTE. Elasticites are computed at sample mean values. Below each estimate we report in brackets the standard errors obtained with the delta method. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.

Table – Weather elasticities on crop yields : total, agronomic and adaptation effects.

	Temperature			Precipitation		
	Wheat	**Barley**	**Rapeseed**	**Wheat**	**Barley**	**Rapeseed**
Total	0.53 ***	-0.63 ***	1.02 ***	0.03 **	0.02	-0.00
	(0.09)	(0.11)	(0.12)	(0.01)	(0.01)	(0.02)
Agronomic effects	0.22 **	-0.84 ***	0.89 ***	-0.01	0.02	-0.02
	(0.09)	(0.11)	(0.12)	(0.01)	(0.01)	(0.02)
Adaptation effects	0.31 ***	0.21 ***	0.12 ***	0.04 ***	0.00	0.02 **
	(0.02)	(0.03)	(0.02)	(0.01)	(0.00)	(0.01)

- 1% increase in temperature during the growing season increases wheat yields by 0.53% : the total effects is due to the cumulative effects of a beneficial agronomic effect of 0.22% and a beneficial adaptation effect of 0.31%.
- 2/3 of the positive effect of temperature on wheat yields thus comes from the farmers' response to higher temperatures

⇒ Farmers substantially increase fertilizer applications in response to higher temperatures, for only a small reduction in pesticides

Projections of the impacts of warmer temperatures

	Wheat			Barley			Rapeseed		
	+1C	**+2C**	**+3C**	**+1C**	**+2C**	**+3C**	**+1C**	**+2C**	**+3C**
	A. 2006-2012 Averages								
Initial yields (100 kg/ha)	70.88	70.88	70.88	64.30	64.30	64.30	33.59	33.59	33.59
	B. Reduced-form Estimates								
Changes in yields (100 kg/ha)	-1.61 ***	-12.84 ***	-33.68 ***	-8.63 ***	-27.70 ***	-57.19 ***	-0.48	-7.23 ***	-20.27 ***
	(0.59)	(2.01)	(4.50)	(0.62)	(2.13)	(4.77)	(0.37)	(1.25)	(2.79)
	C. Structural Estimates								
Changes in yields (100 kg/ha)	-1.18 *	-10.66 ***	-28.42 ***	-8.36 ***	-27.03 ***	-55.99 ***	-0.36	-6.83 ***	-19.41 ***
	(0.63)	(2.11)	(4.69)	(0.68)	(2.25)	(4.96)	(0.38)	(1.29)	(2.86)
Agronomic effects	-3.72 ***	-22.31 ***	-55.30 ***	-11.16 ***	-37.65 ***	-79.54 ***	-0.44	-8.95 ***	-25.52 ***
	(1.02)	(3.54)	(7.77)	(1.23)	(3.99)	(8.56)	(0.77)	(2.44)	(5.14)
Adaptation effects	2.53 ***	11.66 ***	26.88 ***	2.80 ***	10.63 **	23.55 ***	0.08	2.13	6.11
	(0.73)	(3.73)	(8.67)	(0.62)	(3.98)	(9.31)	(0.10)	(2.15)	(5.31)

- Negative impacts of warmer temperatures in both RF and SF.
- Agronomic impacts of warmer temperatures are negative
- Farmers' adaptation allows to offset part of these negative direct impacts.

$\longrightarrow$ Adaptation effects are sizable and positive.

Conclusion 2 : important insights

1. Reduced-form and structural approaches provide similar estimates of the total impacts of weather conditions on crop yields.
2. Farmers do adjust their input applications in response to weather changes.
    1. increase in fertilizer applications when temperatures increase
    2. less precisely estimated weather impacts on pesticide applications
3. Adaptation impacts offset by one quarter to two thirds the agronomic impacts of non-marginal increases in temperature, with heterogeneous effects depending on the crops and temperature increases considered.
4. The usual yield-weather-panel approach does account for the consequences of farmers' adaptation for crop yields (on top of the direct impacts on plant growth).

Table of Contents

General Conclusion

- The estimation of the impact of climate change on agriculture has been the subject of extensive research for over three decades.
- Although the economic literature rapidly developed around the Ricardian and weather-panel approaches, our recent work demonstrates that conceptual improvements to both approaches are still possible and desirable.
- We contribute to a growing body of methodological advances aimed at taking appropriate account of the effects of agricultural adaptation (e.g., Burke and Emerick, 2016 ; Mérel and Gammans, 2021).
- Further efforts are required in this direction, in particular to gain a more comprehensive understanding of the impact of climate change on agricultural abandonment (i.e., the highest level of adaptation possible by definition).

Ongoing projects

- FAST ANR Project (2021-2027) : How farmers adapt their pesticide purshases to weather variations udring the growing season ?
- Project Cland (2017-2027) : water, climate change and growth
- Europpean project LAMASUS (2022-2026) : Land use adaptation to climate change at the EU level
- Project ANR ACCLIMATE (2023-2026) : role of land markets in land use adaptation in France
- Project INRAE WWR (2023-2025) : Multiple agricultural risks induced by high winter temperatures

Thank you for your attention!!
any questions?
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Bibliographie I

Aragón, F. M., Oteiza, F., and Rud, J. P. (2021). Climate change and agriculture : Subsistence farmers' response to extreme heat. *American Economic Journal : Economic Policy*, 13(1) :1–35.

Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., Kimball, B. A., Ottman, M. J., Wall, G., White, J. W., et al. (2015). Rising temperatures reduce global wheat production. *Nature climate change*, 5(2) :143–147.

Ay, J.-S. (2021). The informational content of geographical indications. *American Journal of Agricultural Economics*, 103(2) :523–542.

Bailey, S. W. (2004). Climate change and decreasing herbicide persistence. *Pest Management Science*, 60(2) :158–162.

Bareille, F. and Chakir, R. (2023). The impact of climate change on agriculture : A repeat-ricardian analysis. *Journal of Environmental Economics and Management*, 119 :Forthcoming.

Bareille, F. and Chakir, R. (2024). Structural identification of weather impacts on crop yields : Disentangling agronomic from adaptation effects. *American Journal of Agricultural Economics*, 106(3) :989–1019.

Bibliographie II

Bigelow, D. P., Ifft, J., and Kuethe, T. (2020). Following the market ? hedonic farmland valuation using sales prices versus self-reported values. *Land Economics*, 96(3) :418–440.

Blanc, E. and Schlenker, W. (2017). The use of panel models in assessments of climate impacts on agriculture. *Review of Environmental Economics and Policy*, 11(2) :258–279.

Boussemart, J.-P., Leleu, H., and Ojo, O. (2011). Could society's willingness to reduce pesticide use be aligned with farmers' economic self-interest ? *Ecological Economics*, 70(10) :1797–1804.

Burke, M. and Emerick, K. (2016). Adaptation to climate change : Evidence from us agriculture. *American Economic Journal : Economic Policy*, 8(3) :106–40.

Carpentier, A. and Letort, E. (2012). Accounting for heterogeneity in multicrop micro-econometric models : implications for variable input demand modeling. *American Journal of Agricultural Economics*, 94(1) :209–224.

Chakir, R. and Thomas, A. (2022). Unintended consequences of environmental policies : the case of set-aside and agricultural intensification. *Environmental Modeling & Assessment*, 27 :363–384.

Bibliographie III

Ciscar, J.-C., Iglesias, A., Feyen, L., Szab, L., Van Regemorter, D., Amelung, B., Nicholls, R., Watkiss, P., Christensen, O. B., Dankers, R., Garrote, L., Goodess, C. M., Hunt, A., Moreno, A., Richards, J., and Soria, A. (2011). Physical and economic consequences of climate change in europe. *Proceedings of the National Academy of Sciences*, 108(7) :2678–2683.

Cui, X. and Xie, W. (2021). Adapting agriculture to climate change through growing season adjustments : Evidence from corn in china. *American Journal of Agricultural Economics, Online first.* :1–24.

Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change : evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1) :354–385.

Di Falco, S. and Veronesi, M. (2013). How can african agriculture adapt to climate change ? a counterfactual analysis from ethiopia. *Land Economics*, 89(4) :743–766.

Femenia, F. and Letort, E. (2016). How to significantly reduce pesticide use : An empirical evaluation of the impacts of pesticide taxation associated with a change in cropping practice. *Ecological Economics*, 125 :27–37.

Fezzi, C. and Bateman, I. (2015). The impact of climate change on agriculture : Nonlinear effects and aggregation bias in ricardian models of farmland values. *Journal of the Association of Environmental and Resource Economists*, 2(1) :57–92.

Bibliographie IV

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, 8 :43–75.

Huang, K. and Sim, N. (2018). Why do the econometric-based studies on the effect of warming on agriculture disagree ? a meta-analysis. *Oxford Economic Papers*, 70(2) :392–416.

IPCC (2014). Climate change 2014 impacts, adaptation, and vulnerability. *IPCC report*.

Jagnani, M., Barrett, C. B., Liu, Y., and You, L. (2021). Within-season producer response to warmer temperatures : Defensive investments by kenyan farmers. *The Economic Journal*, 131(633) :392–419.

Joly, D., Brossard, T., Cardot, H., Cavailhes, J., Hilal, M., and Wavresky, P. (2010). Les types de climats en france, une construction spatiale. *Cybergeo : European Journal of Geography*.

Kaminski, J., Kan, I., and Fleischer, A. (2013). A structural land-use analysis of agricultural adaptation to climate change : a proactive approach. *American Journal of Agricultural Economics*, 95(1) :70–93.

Koutchadé, O. P., Carpentier, A., and Femenia, F. (2018). Modeling heterogeneous farm responses to european union biofuel support with a random parameter multicrop model. *American Journal of Agricultural Economics*, 100(2) :434–455.

Bibliographie V

Lobell, D. B., Schlenker, W., and Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, pages 616–620.

Massetti, E. and Mendelsohn, R. (2011). Estimating ricardian models with panel data. *Climate Change Economics*, 2(04) :301–319.

Massetti, E., Mendelsohn, R., and Chonabayashi, S. (2016). How well do degree days over the growing season capture the effect of climate on farmland values ? *Energy Economics*, 60 :144–150.

Mendelsohn, R., Nordhaus, W. D., and Shaw, D. (1994). The impact of global warming on agriculture : a ricardian analysis. *American Economic Review*, pages 753–771.

Mendelsohn, R. O. and Massetti, E. (2017). The use of cross-sectional analysis to measure climate impacts on agriculture : theory and evidence. *Review of Environmental Economics and Policy*, 11(2) :280–298.

Mendelssohn, R. and Dinar, A. (2009). Climate change and agriculture : An economic analysis of global impacts, adaptation and distributional effects (new horizons in environmental economics)'. *Publisher (s) : Edward Elgar Publishing Ltd, Publication date : 2009*.

Merel, P. and Gammans, M. (2021). Climate econometrics : Can the panel approach account for long-run adaptation ? *American Journal of Agricultural Economics*, 103(4) :1207–1238.

Bibliographie VI

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., Elliott, J., Fujimori, S., Hasegawa, T., Heyhoe, E., et al. (2014). Climate change effects on agriculture : Economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences*, 111(9) :3274–3279.

Ortiz-Bobea, A. (2020). The role of nonfarm influences in ricardian estimates of climate change impacts on us agriculture. *American Journal of Agricultural Economics*, 102(3) :934–959.

Pope, R. D. and Just, R. E. (2003). Distinguishing errors in measurement from errors in optimization. *American Journal of Agricultural Economics*, 85(2) :348–358.

Rosenzweig, C., Iglesius, A., Yang, X.-B., Epstein, P. R., and Chivian, E. (2001). Climate change and extreme weather events-implications for food production, plant diseases, and pests. *Global Change & Human Health*, 2(2) :90.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2005). Will us agriculture really benefit from global warming ? accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1) :395–406.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2006). The impact of global warming on us agriculture : an econometric analysis of optimal growing conditions. *Review of Economics and Statistics*, 88(1) :113–125.

Bibliographie VII

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37) :15594–15598.

Sesmero, J., Ricker-Gilbert, J., and Cook, A. (2018). How do african farm households respond to changes in current and past weather patterns ? a structural panel data analysis from malawi. *American Journal of Agricultural Economics*, 100(1) :115–144.

Tambet, H. and Stopnitzky, Y. (2019). Climate adaptation and conservation agriculture among peruvian farmers. *American Journal of Agricultural Economics*.

Timmins, C. (2006). Endogenous land use and the ricardian valuation of climate change. *Environmental and Resource Economics*, 33(1) :119–142.

Vaitkeviciute, J., Chakir, R., and Van Passel, S. (2019). Climate variable choice in ricardian studies of european agriculture. *Revue économique*, 70(3) :375–401.

Van Passel, S., Massetti, E., and Mendelsohn, R. (2017). A ricardian analysis of the impact of climate change on european agriculture. *Environmental and Resource Economics*, 67(4) :725–760.

Xia, J. and Wan, S. (2008). Global response patterns of terrestrial plant species to nitrogen addition. *New Phytologist*, 179(2) :428–439.

Estimation Results

Table – Marginal values of seasonal climatologies for log-linear and log-quadratic Ricardian models in the Pooled and Repeat-Ricardian analyses Back

	Dependent variable : log(price)							
	Pooled Ricardian				Repeat-Ricardian			
	Linear		Quadratic		Linear		Quadratic	
	Model 2	Model 4	Model 2	Model 4	Model 2	Model 4	Model 2	Model 4
Temperature (C/day)								
Spring	0.26 ***	-0.22 *	0.02	-0.51 ***	0.36 ***	0.35 **	0.29 **	0.30 **
	(0.08)	(0.13)	(0.09)	(0.14)	(0.13)	(0.14)	(0.14)	(0.14)
Summer	-0.17 **	0.08	-0.06	0.17	0.26 **	0.25 *	0.33 **	0.33 **
	(0.06)	(0.10)	(0.07)	(0.11)	(0.13)	(0.15)	(0.15)	(0.15)
Autumn	0.25 **	0.21 *	0.47 ***	0.58 ***	0.15 *	0.13	0.14	0.14
	(0.09)	(0.13)	(0.10)	(0.14)	(0.09)	(0.09)	(0.09)	(0.09)
Winter	-0.26 ***	-0.10	-0.34 ***	-0.29 ***	-0.23 ***	-0.20 **	-0.14 *	-0.14 **
	(0.09)	(0.12)	(0.08)	(0.11)	(0.08)	(0.09)	(0.08)	(0.07)
Precipitations (cm/month)								
Spring	-0.18 ***	-0.11 ***	-0.27 ***	-0.16 ***	0.00	-0.02	0.01	0.00
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
Summer	0.01	0.00	0.07 *	0.04	0.10 *	0.10 *	0.10 *	0.10 *
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Autumn	0.10 ***	0.08 ***	0.06 ***	0.02	0.04	0.03	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Winter	-0.06 **	-0.08 ***	0.01	-0.01	0.07 *	0.06	0.02	0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Number of observations	8,614	8,614	8,614	8,614	8,614	8,614	8,614	8,614
Time invariant plot controls	Yes	Yes	Yes	Yes				
Time invariant municipal controls	Yes	Yes	Yes	Yes				
Time variant municipal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual dummies		Yes		Yes		Yes		Yes
Plot fixed effects					Yes	Yes	Yes	Yes

Estimation Results

Table – Repeat-Ricardian estimates with alternative climate definitions

Back

	Dependent variable : log(price)				
	30 years	**20 years**	**15 years**	**10 years**	**5 years**
Temperature (C/day)					
Spring	0.35 **	0.38 ***	0.19 ***	0.13 *	0.04
	(0.14)	(0.11)	(0.06)	(0.08)	(0.03)
Summer	0.25 *	0.21 *	0.34 ***	0.05	-0.05
	(0.15)	(0.12)	(0.07)	(0.05)	(0.04)
Autumn	0.13	0.19 ***	0.22 ***	0.38 ***	0.35 ***
	(0.09)	(0.06)	(0.06)	(0.05)	(0.04)
Winter	-0.20 **	-0.22 ***	-0.20 ***	-0.11 ***	-0.01
	(0.09)	(0.07)	(0.05)	(0.04)	(0.02)
Precipitations (cm/month)					
Spring	-0.02	0.09 **	0.06 *	0.02	0.00
	(0.04)	(0.04)	(0.03)	(0.02)	(0.01)
Summer	0.10 *	0.06 *	0.07 ***	0.01	-0.00
	(0.05)	(0.03)	(0.02)	(0.02)	(0.01)
Autumn	0.03	0.06 **	0.04 **	0.00	-0.03 ***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Winter	0.06	0.03	-0.02	0.00	-0.02 ***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)
Number of observations	8,614	8,614	8,614	8,614	8,614
Time variant municipal controls	Yes	Yes	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.14	0.14	0.13	0.13	0.13

Climatologies are computed for different periods. Time invariant municipal controls solely include

Estimation Results

Table – Repeat-Ricardian estimates for sub-samples differing according to the length of time between two sale dates Back

	Dependent variable : log(price)			
	All	**1-5 years**	**6-10 years**	**≥11 years**
Temperature (C/day)				
Spring	0.35 **	1.09 ***	0.48 *	-0.21
	(0.14)	(0.27)	(0.26)	(0.21)
Summer	0.25 *	0.44 *	0.15	0.37 *
	(0.15)	(0.27)	(0.28)	(0.20)
Autumn	0.13	0.05	0.06	0.01
	(0.09)	(0.18)	(0.20)	(0.15)
Winter	-0.20 **	-0.43 ***	-0.18	0.09
	(0.09)	(0.16)	(0.19)	(0.15)
Precipitations (cm/month)				
Spring	-0.02	-0.05	-0.09	-0.04
	(0.04)	(0.09)	(0.00)	(0.07)
Summer	0.10 *	0.12	0.28 ***	-0.01
	(0.05)	(0.11)	(0.09)	(0.09)
Autumn	0.03	-0.13	0.02	0.09
	(0.04)	(0.08)	(0.07)	(0.06)
Winter	0.06	0.09	-0.11	0.09
	(0.04)	(0.08)	(0.07)	(0.06)
Number of observations	8,614	4,520	2,068	2,026
Time variant municipal controls	Yes	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes	Yes
Adjusted R2	0.14	0.09	0.17	0.24

Climatologies are computed using 30-year averages. Time invariant municipal controls

Estimation Results

Table – Repeat-Ricardian estimates in irrigated and rainfed departments

Back

	Dependent variable : log(price)		
	All	**Irrigated departments**	**Rainfed departments**
Temperature (C/day)			
Spring	0.35 **	0.18	0.37 **
	(0.14)	(0.38)	(0.12)
Summer	0.25 *	-0.15	0.28 *
	(0.15)	(0.47)	(0.15)
Autumn	0.13	0.72 **	0.11
	(0.09)	(0.32)	(0.10)
Winter	-0.20 **	-0.31	-0.18 **
	(0.09)	(0.24)	(0.09)
Precipitations (cm/month)			
Spring	-0.02	0.18	-0.03
	(0.04)	(0.19)	(0.05)
Summer	0.10 *	0.46 **	0.04
	(0.05)	(0.19)	(0.06)
Autumn	0.03	0.00	0.04
	(0.04)	(0.12)	(0.04)
Winter	0.06	-0.48 ***	0.09 **
	(0.04)	(0.15)	(0.04)
Number of observations	8,614	978	7,636
Time variant municipal controls	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes
Adjusted R2	0.14	0.08	0.15

Estimates are computed using log-linear Ricardian models. Plots are classified into two sub-samples accord-

Estimation Results

Table – Repeat-Ricardian estimates in different climates Back

	Dependent variable : log(price)				
	All	**Continental**	**Oceanic**	**Mediterranean**	**Mountain**
Temperature (C/day)					
Spring	0.35 **	0.62 **	0.90 ***	-0.47	0.00
	(0.14)	(0.24)	(0.25)	(0.47)	(0.40)
Summer	0.25 *	-0.25	-0.17	1.49 ***	0.39
	(0.15)	(0.25)	(0.24)	(0.51)	(0.46)
Autumn	0.13	0.06	-0.05	-0.27	0.42 *
	(0.09)	(0.16)	(0.15)	(0.36)	(0.23)
Winter	-0.20 **	0.04	-0.42 ***	-0.18	-0.01
	(0.09)	(0.13)	(0.15)	(0.24)	(0.26)
Precipitations (cm/month)					
Spring	-0.02	0.18 **	-0.15 **	0.24	0.34 **
	(0.04)	(0.09)	(0.07)	(0.15)	(0.15)
Summer	0.10 *	0.13	0.05	0.12	-0.19
	(0.05)	(0.10)	(0.08)	(0.22)	(0.16)
Autumn	0.03	-0.07	-0.02	-0.02	-0.16
	(0.04)	(0.08)	(0.06)	(0.11)	(0.13)
Winter	0.06	-0.04	0.25 ***	-0.12	-0.03
	(0.04)	(0.07)	(0.07)	(0.10)	(0.19)
Number of observations	8,614	2,904	3,604	1,098	1,008
Time variant municipal controls	Yes	Yes	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.14	0.14	0.20	0.13	0.08

Estimates are computed using log-linear Ricardian model. Plots are classified into four sub-samples according to their initial climate. Climatologies are computed using 30-year averages. Time invariant municipal cont-

Estimation Results

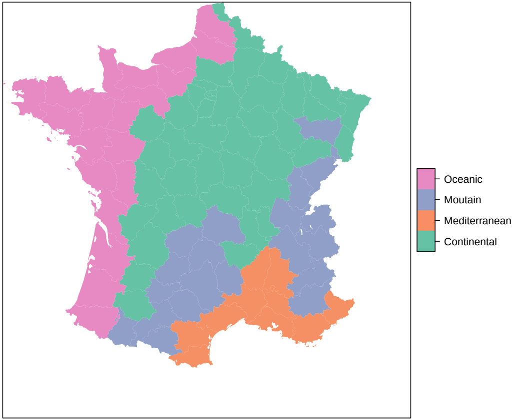

Figure – The diversity of French climates (Source : authors based on Joly et al., 2010). Back

Simulations of Climate Change Impacts

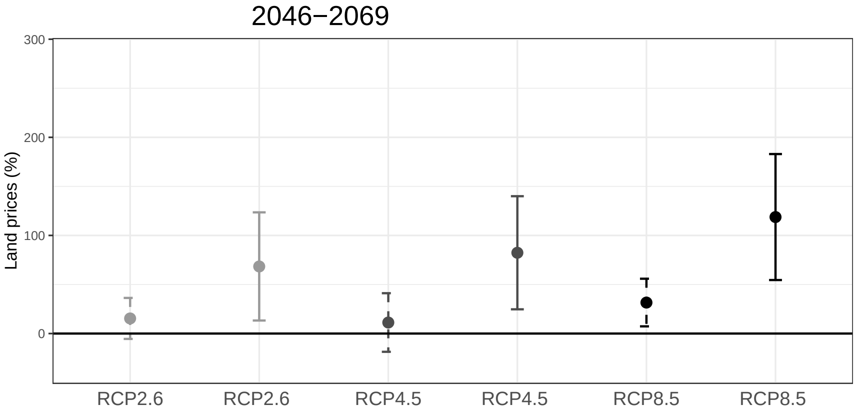

Figure – Climate change impacts on farmland prices for various scenarios in 2046-2069. *Dots represent point estimates and whiskers show the 95% confidence interval. The dashed lines correspond to pooled Ricardian models. The solid lines indicate repeat-Ricardian models. All estimates come from Ricardian models with control variables and annual*

Data

- We define climate by the set of seasonal climatologies on temperature (°C/day) and precipitation (cm/month)
- We compute the climatologies as 30-year averages of temperatures and precipitation between $t - 30$ and $t - 1$, using daily weather information for the 8,602 French stations since 1959 from the SAFRAN database (provided by *Météo France*)
  - Spring is defined as March-May (respectively June-August, September-November and December-February for summer, autumn and winter)

Data

- The repeat-Ricardian analysis exploits differences over space of *changes* in climatologies

Table – Climate change across French municipalities between 1996 and 2019 (N=36,486)

	Mean	S.D.	Min	Max		Mean	S.D.	Min	Max
Temperature (°C/day)					**Precipitation (cm/month)**				
Spring 1996	9.18	1.62	-3.40	13.6	Spring 1996	6.95	1.69	0.01	16.8
Spring 2019	10.24	1.67	-2.50	14.40	Spring 2019	6.82	1.71	0.01	15.50
Spring change 1996-2019	1.06	0.23	0.00	2.16	*Spring change 1996-2019*	-0.13	0.32	-1.70	1.27
Summer 1996	17.39	2.00	0.01	22.70	Summer 1996	6.32	1.78	0.01	15.90
Summer 2019	18.34	2.11	0.01	23.80	Summer 2019	6.53	1.77	0.01	16.30
Summer change 1996-2019	0.95	0.26	0.00	2.40	*Summer change 1996-2019*	0.21	0.38	-1.60	1.73
Autumn 1996	10.73	1.70	0.01	16.50	Autumn 1996	7.87	2.10	0.01	24.10
Autumn 2019	11.16	1.74	0.01	17.10	Autumn 2019	8.17	2.36	0.01	29.80
Autumn change 1996-2019	0.43	0.30	-0.96	1.41	*Autumn change 1996-2019*	0.31	0.57	-1.00	5.74
Winter 1996	3.67	1.82	-6.8	9.39	Winter 1996	7.01	2.03	0.01	17.90
Winter 2019	4.09	1.76	-6.6	9.78	Winter 2019	7.04	1.97	0.01	19.50
Winter change 1996-2019	0.42	0.30	-1.10	1.58	*Winter change 1996-2019*	0.03	0.66	-3.10	2.11

Data

- Representative of the general population (no evidence of selection bias) Back

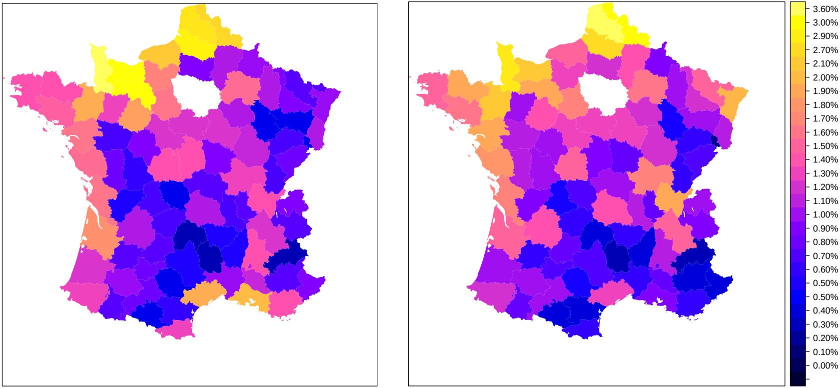

Figure – Distribution of the observed transactions in (a) the repeat sales sample and (b) the general population.

Data

Table – Summary statistics for the plots in the repeat-sale samples, expressed in differences between the two sale dates (N=8,614)

Differences between t_2 and t_1	Mean	S.D.	Min	Q1	Median	Q3	Max
Farmland price (€/ha)	2,621.18	9,936.48	-103,389.66	-82.37	721.55	2,598.78	154,876.42
log(farmland price) (€/ha)	0.27	0.62	-9.18	-0.02	0.18	0.51	4.10
Spring temperature (°C/day)	0.31	0.27	-0.06	0.08	0.23	0.46	1.47
Summer temperature (°C/day)	0.25	0.23	-0.13	0.07	0.18	0.36	1.41
Autumn temperature (°C/day)	0.17	0.19	-0.52	0.03	0.11	0.27	1.02
Winter temperature (°C/day)	0.10	0.18	-0.92	-0.02	0.06	0.19	1.25
Spring precipitation (cm/month)	-0.04	0.26	-1.45	-0.18	-0.03	0.11	1.11
Summer precipitation (cm/month)	0.12	0.27	-1.25	-0.04	0.08	0.25	1.33
Autumn precipitation (cm/month)	0.09	0.32	-1.08	-0.11	0.05	0.24	2.31
Winter precipitation (cm/month)	0.01	0.36	-2.56	-0.15	0.01	0.17	1.77
Municipal population density (inhabitants/km^2)	4.77	15.96	-139.51	-0.03	1.29	5.53	409.01