Assessing the benefits of irrigation: The case of Southern France vineyards

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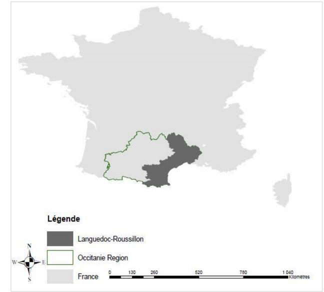
Motivations

Agriculture worldwide is threatened by climate change. Specifically, the **decrease of water resource availability** combined with **increasing water needs** is a key challenge in many rain fed areas, where irrigation appears as a straightforward adaptation option. The production of vine is no exception to the impacts of climate change: droughts and thermal stress are impacting vine yields and quality, thus changing vine growing conditions.

In the Languedoc Roussillon wine production basin, while grape has been long cultivated without irrigation, numerous irrigation networks have been deployed to face an increasing water stress. The main arguments for these projects are to maintain a quantitative and qualitative production in face of increasing international competition.



This work aims to **highlight the impact of irrigation access on vine producing estates, and to understand the mechanisms explaining those impacts**. Has irrigation "only" allowed a maintenance of yields and revenues, i.e. strict adaptation to climate change, or more (intensification), or did this strategy have other indirect effects, such as crop diversification, change in the type of production / quality ?

Case study

The Languedoc-Roussillon, first wine growing area of France, accounts for more than 245 000 hectares of vine.
It is characterized by a strong diversity of vine growing estates, which differ in size, in the production's labels, in the type of structure, in their economic strategy and results.

In response to an increasing water stress, several farms in the region have been equipped with irrigation in the last decade: more than 22700 hectares between 2010 and 2020 (+115%).
30% of winegrowers are irrigated in the area.

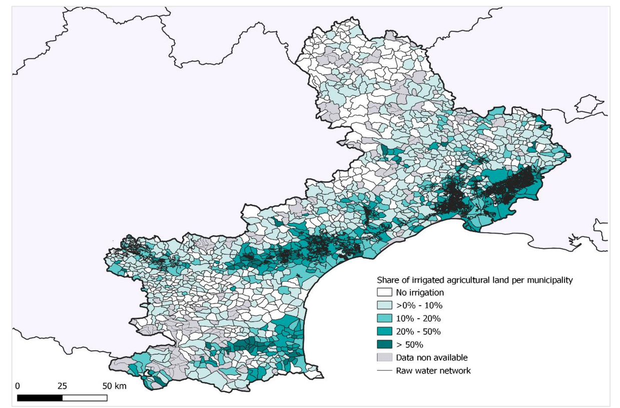


Figure 1: Share of irrigated land per municipality and Aquadomitia's water network in Languedoc Roussillon (2020).
Source of the data: Agricultural census, BRL (Own elaboration)

A higher gross revenue per hectare observed for irrigated vines

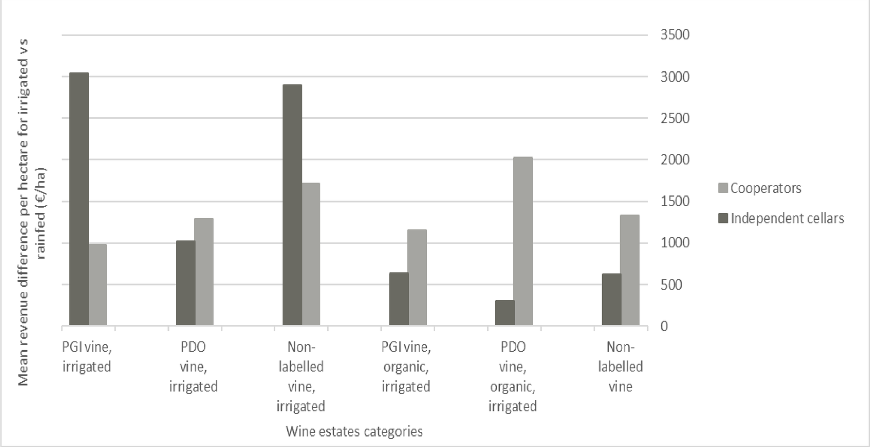


Figure 2: Estimation of the difference in mean revenues per hectare per wine activity: advantage of irrigation alternative over rainfed.

As a first descriptive approach, we use a linear regression model to regress Rj the revenue of farms on the cropped area x_i (of N different crop types $i \in [1, \mathrm{N}]$), and thus estimate the revenue per unit of land $(p_i . yi)$.

$$Rj = \sum_{i=1}^{n} (p_i . y_i) . x_i$$

In N, we include the three vine labels (PDO, PGI, non-labelled), other crops, organic and non organic, irrigated and rainfed.

➔ On average, irrigated plots are more productive than rainfed.

Methodology

This analysis brings two main methodological challenges:

1- The endogeneity issue

For an estate i, we want to measure the effect of irrigation on the income, comparing the two potential incomes with irrigation (Yi^1) and without irrigation (Yi^0).

➔ Need to identify a proper counterfactual: non-irrigated farms that are comparable with irrigated ones.

➔ Irrigation has been developed in areas with higher production potential or where access to water is less expensive: not exogenous.

2 - A continuous treatment

Adoption of irrigation is not a binary treatment: a farm can implement irrigation system on from 0 to 100% of its plots.

On average, 25% of farm land is irrigated within farms.

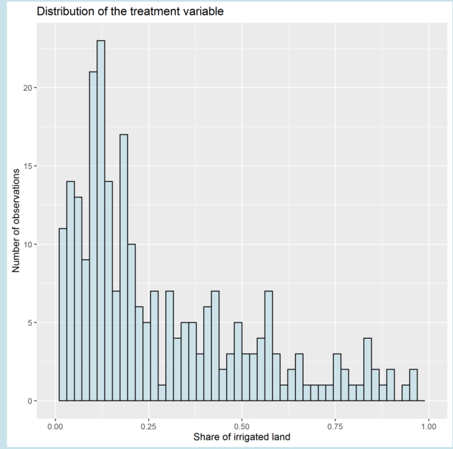


Figure 3: Distribution of the treatment variable

Regarding this setting, we rely on the Generalized Propensity Score approach developed by Hirano & Imbens (2004), which is based on dose-response functions.
In our case, the "dose" is the **share of irrigated land over total farm's land** and the "response" is **annual farm's revenue per hectare**.
This empirical approach follows three steps:

i. Estimate the global propensity score, relying on the assumption of a normal distribution of the treatment given the covariates.

$$G(t_i)|X_i \sim N\{h(\alpha X_i), \sigma^2\}$$

With $G(t_i)$ being the transformation of our treatment variable (irrigation intensity), X_i the covariates, $h(\alpha X_i)$ a function of covariates

$$\widehat{GPS}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp\left[-\frac{1}{2\hat{\sigma}^2}\{G(T_i) - h(\hat{\alpha}, X_i)\}\right]$$

ii. Estimate the conditional expectation of gross revenue per hectare (Yi) given the treatment (Ti) and the global propensity score (GPSi), including all second-order moments

$$E(Y_i|T_i, GPS_i) = \beta_1 + \beta_2 T_i + \beta_3 T_i^2 + \beta_4 GPS_i + \beta_5 GPS_i^2 + \beta_6 T_i GPS_i$$

iii. Finally, estimate the dose-response function at each level of treatment t : $E\{\overline{Y(t)}\}$.

Data

We use three main sources of data that are merged together at farm level:

Source	Level	Variables
The wine register 2013-2021	Farm level	*Wine production per type of label (PDO, PGI), type of wine producer*
The agricultural census 2010, 2020	Farm level	*Farm size, cropped land, irrigated land, organic production, economic size*
Fiscal declaration data 2016-2021	Farm level	*Gross revenue, gross margin*
Météo France data 2016-2021	Municipal level	*Rainfall-ETP, No. Of days with average T>25°C, Tmax, Tmoy.*

Merged & cleaned =1087 obs.

Results and discussion

Modelling the conditional distribution of the treatment given the covariates

Covariates must include pre-treatment variables that affect the treatment assignment and the outcome. We consider the following variables:

- Pedoclimatic zones (5 zones)
- Organic labelling of farm in 2010.
- Main labelling of farm's production
- Type of farms: cooperators, independent cellars or mixed
- Farm size in 2010
- Economic size (small/medium/large, based on standard gross output).

Table 1: Determinants of irrigation intensity: parameter estimates, standard error and significance level

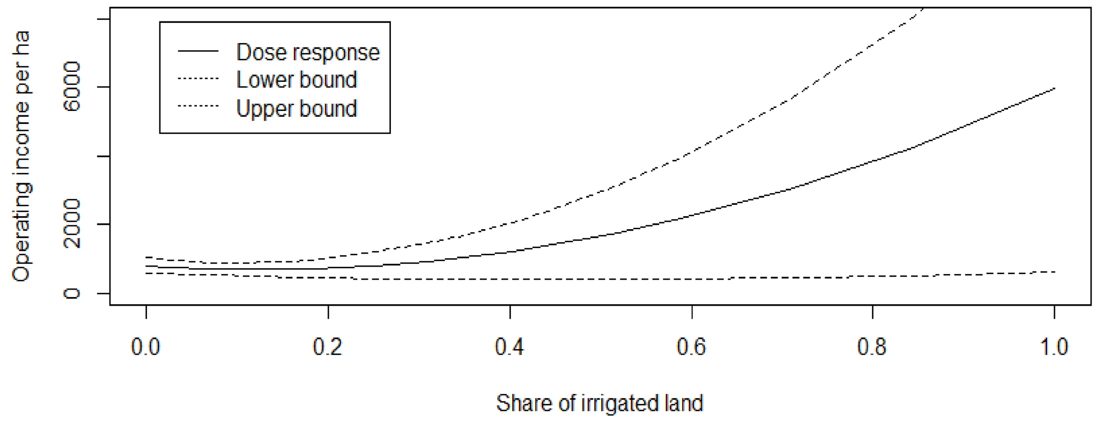
	Estimates	*std. Error*
(Intercept)	0.03 *	0.01
Pedoclimatic zone 2	-0.05 *	0.02
Pedoclimatic zone 3	-0.05 ***	0.01
Pedoclimatic zone 4	0.05 **	0.02
Pedoclimatic zone 5	-0.05	0.10
Organic farmic in 2010 (1)	-0.01	0.02
Main label: PGI (>70% of production)	0.06 ***	0.01
Main label: non-labelled (>70% of production)	0.10 **	0.04
Main label: mix of labels	0.03 *	0.01
Type of farm: independent cellar	0.01	0.01
Type of farm: mixed	-0.02	0.02
Farm size 2010	-0.01	0.01
Economic size: medium	0.01	0.01
Economic size: small	0.01	0.03
Observations	1087	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Estimation of the treatment effect

The figure below reports the average effect, i.e the level of gross revenue per ha with respect to irrigation level. Overall, a higher level of irrigation is associated with a bigger increase in the gross revenue per hectare.

Figure 4: Average effect of irrigation on operating income per ha (2020) – Preliminary results



Note that the lower and upper confidence bounds are very large as we tend to 100% irrigation level: this is probably due to a low number of observations in the sample and strong heterogeneity in this group (>50% irrigated land).

Discussion

This work proposes an application of the generalized propensity score approach to estimate the impact of irrigation on farm's revenue. Analyzing the average effect, but also the marginal effect of irrigation will bring interesting insights from a public policy point of view.

Moreover, we would like to be able to estimate dose-response functions for different types of farms, to evaluate heterogeneous treatment effects in different groups (regarding size, structure, etc.). In addition, the same type of analysis could be ran on yield data, to further investigate the determinants of farms revenue.
Within the Talanoa project (Graveline et al. 2023), the results of this work will feed discussions on future adaptation scenarios, and allow to calibrate mathematical programming models.

References:

- Hirano, K. and Imbens, G. W. (2004). The propensity score with continuous treatments. Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives 226164: 73–84
- Graveline et al. (2023). Combining Modelling and Participation to Build Agricultural Adaptation Strategies in Water Stressed Territories (Poster also presented at this conference)

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