Weather shocks and pesticide purchases

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Abstract

Climate change is likely to affect pest distribution and to consequently modify pest damage to agriculture. This paper investigates whether farmers adapt their pesticide use to cope with these new conditions. Using a unique, exhaustive dataset detailing pesticide purchases per zip code in France between 2014 and 2019, we econometrically explain pesticide purchases by weather conditions during the growing season, conditionally on zip code fixed effects and regional time trends. Our estimates indicate that farmers' pesticide purchases increase with contemporaneous temperature and precipitation. Because our analyses suggest limited year-to-year pesticide storage, we interpret these estimates as causal weather impacts on pesticide use. We find that farmers adjust more their use of fungicides and herbicides than those of insecticides. Our preferred estimates indicate that a +1% temperature increase during the growing season leads to use additional +1.70% fungicides, +1.72% herbicides, and +0.37% insecticides. The impacts of intermediate temperatures on pesticide use are weakly positive, while extreme temperature impacts are strongly negative. We document heterogeneous weather impacts across seasons and locations. Simulations of the impacts of a RCP4.5 climate change scenario show that French farmers would increase by 11% their use of fungicides and herbicides, while keeping their use of insecticides at 2014-2019 averages.

Keywords: adaptation, climate change, crop protection, weather.

JEL Codes: Q12, Q53, Q54

1 Introduction

Pests reduce crop yields by about a third worldwide (Oerke, 2006). As such, they represent a serious threat to global food security. Therefore, protecting crops from pest damage is a critical aspect of farmers' job. Among the possible strategies to limit pest pressure, pesticide application is now favoured by most farmers over the world (Tang et al., 2021). Although pesticides have helped farmers to increase crop yields and generate higher agricultural incomes (Popp et al., 2013), their use often imposes external costs to society (Le Goffe, 2000). Scientific evidence has indeed accumulated to demonstrate negative impacts of pesticides on farmers' health (Alavanja et al., 2003) and biodiversity degradation (Beketov et al., 2013), but also potential negative impacts on food and water consumers' health (see Baudry et al., 2018; Dias et al., 2023, respectively). In light of this evidence, policymakers from most countries seek to regulate pesticide use (de Vries and Hanley, 2016; Finger et al., 2017). For example, as part of the Farm-to-Fork strategy announced in 2020, the European Commission aimed to halve pesticide use by 2030 compared to 2020 levels (Schebesta and Candel, 2020).[1] While already ambitious, these objectives may be even harder to achieve in the context of climate change (IPPC, 2021). Indeed, because climate change is likely to affect the spatial distribution of pests and diseases (Chen et al., 2011; Deutsch et al., 2018), but also to cause pests to occur earlier in the growing season (Musolin, 2007), rational farmers are expected to adapt their pesticide use to new climatic conditions.

This paper aims to examine whether such adaptation behavior can be observed in recent years. Using pesticide purchase to approximate pesticide use, our objective is to identify econometrically how French farmers adjusted their pesticide use according to weather conditions during the growing season. To achieve this, we use an original, exhaustive database detailing purchased quantities of all active substances used as pesticides in France between 2014 and 2019 at the zip code level (representing an average area of about 9 km $\times$ 9 km).[2] Using classification of active substances, we aggregate these purchases into three categories (insecticides, herbicides and fungicides), and separately run our econometric estimations for each. To our knowledge, this database is one of the most detailed covering pesticide purchases anywhere in the world, in particular with regard to its

[1] Several European countries have already tried to implement policies to reduce pesticide use (Skevas et al., 2013). In the particular case of France, the national action plan established in 2008 targeted a reduction of pesticide use by 50% in 2013. However, these policies failed as pesticide use actually increased by 5% in the period. The revised French national action plan established in 2016 had similar objectives, with limited evidence of success so far.

[2] The zip code is an administrative unit intended to facilitate mail distribution by identifying the post office which ensures delivery to recipients. The 35,300 French municipalities are grouped into 6,300 zip codes.

spatial resolution. Its utilization has thus the potential to provide original quantitative insights on how farmers adapt to weather shocks through pesticide use.

There are several reasons to suspect why farmers would adjust their pesticide use to changing weather conditions. The agronomic literature brings two main elements. First, weather affects the temporal and spatial distribution of pests. For example, higher temperature and humidity create favorable conditions for the growth of fungi, weeds and insects (Patterson et al., 1999; Delcour et al., 2015; Deutsch et al., 2018; IPPC, 2021; Yu et al., 2022). This intensifies the competition between pests and crops, leading rational farmers to use more pesticides. However, beyond a certain threshold, pesticide use may typically become less suitable, as higher temperature and rainfall can actually decrease pest occurrence (Patterson et al., 1999; Delcour et al., 2015). Second, it is well known from agronomists that weather affects pesticide productivity (Delcour et al., 2015). For example, higher temperature and humidity increase the volatilization of pesticides and accelerate the degradation of their chemical components (Patterson et al., 1999; Bloomfield et al., 2006; Delcour et al., 2015). As another illustration, pests tend to develop resistance to pesticides as temperature rises (Patterson et al., 1999; Delcour et al., 2015; Pu et al., 2020). Higher precipitation can also increase pesticide runoffs (Bloomfield et al., 2006; Delcour et al., 2015). In these three examples, weather conditions modify pesticide productivity, which leads rational farmers to adjust their pesticide use accordingly (by reducing it in the above-mentioned examples).[3]

Following the standards of the literature examining weather impacts on agricultural outcomes (Blanc and Schlenker, 2017), our methodology exploits abnormal deviations in weather conditions during the growing season to explain abnormal deviations in pesticide purchases. Our preferred analysis consists of a reduced-form estimation of the annual purchases of pesticides in the zip code by linear and quadratic terms of average temperatures and precipitation during the growing season, conditionally on zip code fixed effects and regional time trends. According to the literature, such estimates represent plausibly causal impacts of weather conditions on pesticide purchases. Because our analyses reveal limited evidence of pesticide storage behaviors from one year to another, we interpret these estimates as causal impacts on pesticide use (rather than just purchases). In line with previous studies, we test the sensitivity of our results to several alternative empirical specifications and sub-samples. Finally, we also investigate the non-linearity of the farmers' responses to temperature changes using flexible functional forms inspired by Schlenker and Roberts (2009).

[3]It is worth noting that the pesticide manufacturers themselves provide instructions on the appropriate weather conditions to apply pesticides. For example, pesticide manufacturers recommend that glyphosate should ideally be applied at temperatures not exceeding 28°C (Dias et al., 2023).

All our estimates suggest that farmers adjust their pesticide use in response to weather shocks during the growing season. However, they adjust differently for insecticides, herbicides and fungicides. Our preferred estimates indicate that a one percent increase in temperature during the growing season leads farmers to use additional +1.70% of fungicides, +1.72% of herbicides, but only +0.37% of insecticides. This suggests that growth of fungi and weeds – and related damage – are more affected by weather conditions than insects abundance. These findings align with agronomic knowledge and remain robust to the vast majority of our sensitivity analyses. In particular, because we identify very limited responses of total agricultural area and crop allocations to weather changes, these estimates likely reflect true responses at the intensive margins (or, at least, their lower bound estimates). Heterogeneity analyses reveal that our preferred estimates for fungicide and herbicide use are primarily driven by weather shocks occurring during spring, in the first half of the growing season. In contrast, insecticide use responds more strongly to weather shocks in summer. Although weather impacts are larger during the growing season, we observe small but significant effects of weather conditions outside the growing season. Additional heterogeneity analyses reveal that zip codes specialized towards cereal and oilseed crops exhibit higher sensitivity to weather shocks compared to other regions. Finally, our more flexible analyses on the non-linear effect of temperature show that pesticide use weakly increases with moderate and warm temperatures but strongly decreases with extreme temperatures. The relationship between temperature and pesticide use actually looks like a sharp "piecewise linear" function in the spirit of Schlenker and Roberts (2009), with a maximum at about 33°C for all pesticide types (or slightly less for herbicides). This sharp piecewise relationship between temperature and pesticide use significantly differs from those for precipitation, which exhibits a smoother concave relationship.

By investigating whether French farmers adapt their pesticide use to within-season weather conditions, we contribute to two bodies of literature. In the one hand, we contribute to the recent economic literature on the measurement of farmers' short-term adaptation to climate change, such as changes in planting date or double cropping (Kawasaki, 2019; Cui and Xie, 2022; Amare and Balana, 2023). To our knowledge, only Jagnani et al. (2021) and **?** have studied pesticide application as a particular adaptation strategy. Based on household-level data, the two studies found that farmers are indeed likely to adjust their pesticide applications in response to weather changes, even if most of their estimates are small or non-significant. We extend the results of Jagnani et al. (2021) and **?** in several aspects, thanks to the addition of three elements related to the quality of our data. First, our original database allows us to categorize pesticide use depending on their specific targets, providing accurate separated measurements of fungicide, herbicide and insecticide purchases. Through this classification, we uncover heterogeneous weather impacts on the use of different pesticide types, which remain otherwise obscured when analyzing aggregate pesticide use (as conducted in the aforementioned studies). Second, we account for the *within-day* temperature variation on top of average temperatures, which allows us to distinguish heterogeneous impacts of temperature across the distribution. In line with this addition, our results indeed suggest that pesticide use is deferentially affected by moderate and extreme temperatures. Finally, our study is likely to have higher external validity than Jagnani et al. (2021) or **?** as we account for *all* French farmers' purchase, and not only for surveyed households in a sample of villages or in a particular region (as in the aforementioned studies). Overall, we find much stronger farmers' pesticide use responses to weather shocks than in **?** – by a factor about five.[4]

In the other hand, we contribute to the more interdisciplinary literature on the drivers of pesticide applications, such as prices and policies (Femenia and Letort, 2016; Finger et al., 2017), agricultural specialization (Wuepper et al., 2023) or landscape structure (Chaplin-Kramer et al., 2011). In particular, given the dependency of pest abundance to weather, some papers have already investigated how pesticide use and purchase are driven by weather conditions. For example, Chen and McCarl (2001) explained crop-specific pesticide purchase *aggregated at the US state level*, and found that they increase with temperature and precipitation. Still at the US state level, Rhodes and McCarl (2020) found however that these effects are actually highly dependant on the pesticide category and the targeted crop. At more detailed spatial resolutions, Larsen and McComb (2021) and Möhring et al. (2022) explain farmers' insecticide applications in US counties and Swiss fields respectively, and both found that extreme temperatures decrease farmers' insecticide applications. We contribute to this literature by using detailed, exhaustive data on all active substances purchased by farmers at the zip code level in France. To our knowledge, our study is the first to investigate the role of weather on the use of all pesticide categories at such a detailed spatial resolution. Our results are thus less likely to exhibit aggregation bias (Fezzi and Bateman, 2015; Damania et al., 2020). Doing so, we notably confirm the results of Larsen and McComb (2021) and Möhring et al. (2022) that extreme temperature has strong negative impacts on insecticide use, but extend this striking result to fungicides and herbicides.

The paper is organized as follows. Section 2 details the data and the summary statistics. Section 3 presents the econometric strategy. Section 4 describes the estimation results. Section 5 simulates the impacts of climate change on pesticide use in France. Section 6 discusses and concludes.

[4] Clear comparison with Jagnani et al. (2021) is difficult given that their variables to measure temperature differs from ours, and that they do not report results for rainfall.

2 Data sources and summary statistics

This article relies on a collection of pesticide, weather and general agricultural data. We proceed hereafter to a presentation of the main data sources and variables of interest.

2.1 Data sources

Pesticides data. We use pesticide purchase data from the "*Banque Nationale des Ventes de produits phytopharmaceutiques par les Distributeurs agréés*" (BNVD). This database was created by the French government in 2009 to monitor the new French pesticide taxation scheme *"Redevances pour Pollutions Diffuses"* introduced in December 2006 within the framework of the French law on water and aquatic environments. Based on pesticide distributors' declarations of annual purchases, local water agencies compile information on all pesticide products and active substances in the BNVD for the whole of France.[5]

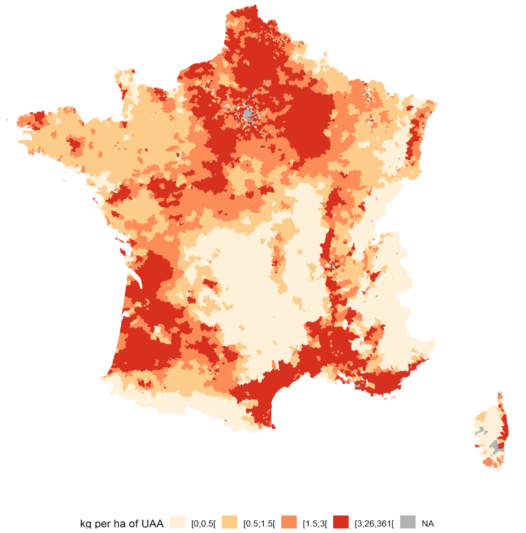
For the purpose of our analysis, we use the latest BNVD version from 2014 to 2019.[6] Specifically, it provides information about the quantities of pesticide purchased by products and by active substances for each year and each zip code in France. Using open data from the E-Phy catalog for pesticides produced by the French National Agency for Food, Environmental and Job Health Safety (ANSES), we classify all pesticides into the different pesticide categories, namely *insecticides*, *herbicides*, *fungicides* and *others*. This last category includes pesticides as diverse as rodenticides, molluscicides, plant growth regulators, pesticides combined with fertilizers, etc., which together account for less than 5% of total purchases (see Section 2.2.). Since products are made up of several active substances that may differ in function, we choose to measure the different pesticide categories by directly summing the quantities of active substances purchased (in kilograms). We thus avoid questions related to the effectiveness and toxicity of the different active substances (Möhring et al., 2020), and focus only on the *quantity* of pesticide purchased.

Figure 1 displays the average quantity of pesticide purchased per category over the period 2014-2019. Figure 1 clearly shows spatially-distinct production areas where pesticide purchases are quite heterogeneous. In particular, it illustrates the fact that farmers purchase few pesticides in mountain areas (Alpes, Jura, Massif central, Pyrenees and Vosges) and, to a lesser extent, in north-west France, where agricultural production is mainly oriented towards livestock activities

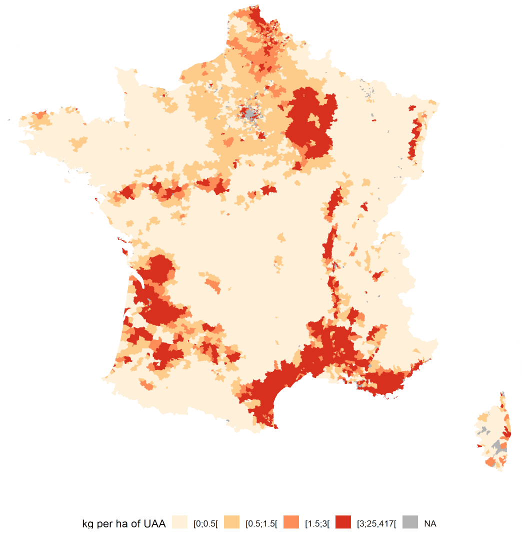
[5]While the first version of the BNVD detailed quantities of pesticides *sold by pesticide distributors* at the departmental level (corresponding on average to 6,000 km^2, i.e. about one to three US counties), since 2013, the second version details the pesticide *purchased by buyers* at the zip code level (corresponding on average to 86 km^2).

[6]We dropped 2013 data due to reporting issues following the change between the two BNVD versions.

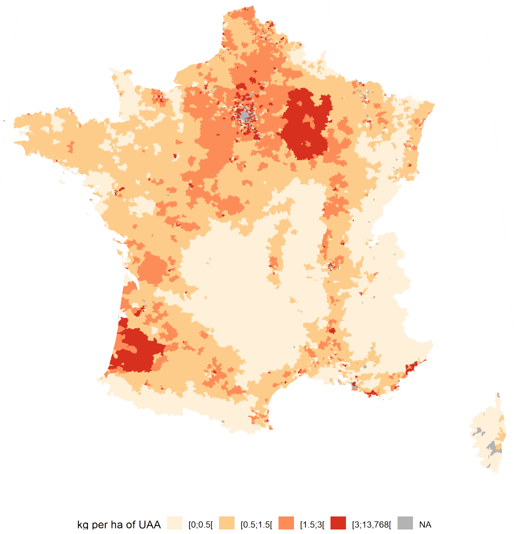
(grassland and production of other forage requires less pesticides than crops; see Urruty et al., 2016, for example). By comparison, specialist wine-producing areas (Bordeaux, Champagne, Provence, Loire valley, Alsace and Rhône valley) seem to use much greater quantities of pesticides, particularly fungicides (which include copper use against mildew for example).



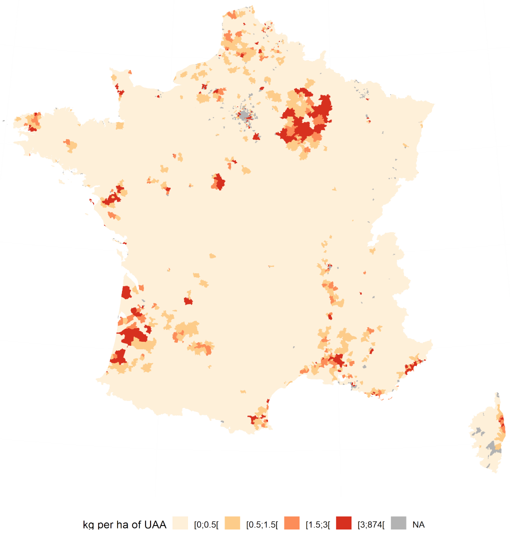
a) All Active Substances



b) Fungicides



c) Herbicides



d) Insecticides

Figure 1: 2014-2019 average purchase of active substances by pesticide category. NOTE. The figures display the average purchase of pesticides between 2014 and 2019 by zip code for each pesticide category, as indicated in the BNVD. We report the pesticide purchases on total useful agricultural area.

The BNVD is not the only database worldwide to provide exhaustive information on pesticide use or purchase. However, it is one of the few to provide such information at the substance level. To the best of our knowledge, the only other database to provide exhaustive information for all active substances is the California Pesticide Information Portal, for which information is available for pesticide *use* at the zip code level (instead of pesticide *purchase* as in the BNVD).[7] The BNVD offers a significant advantage over the California Pesticide Information Portal since our data is provided at a much finer scale. Indeed, with the average area of a zip code in California being 414 km^2, our database is actually five times finer (to recall, a zip code represents an average area of about 81 km^2).[8] This enables us to merge highly detailed and disaggregated pesticide data with comparably disaggregated weather data (see paragraph below), and thus abstract from potential aggregation biases (Fezzi and Bateman, 2015; Damania et al., 2020).

Weather data. We collected the weather information using observed daily weather conditions provided by *Météo France* for the whole period on a grid of 8 km x 8 km (called *SAFRAN* units). The information includes the minimum and maximum daily temperature as well as the daily quantity of rainfall. Using these information, we recompute the average temperature within the growing season – from March 1st to August 31th – using the reconstructed temperature distribution *à la* Schlenker and Roberts (2009), where temperature distribution within each day is approximated using a sine interpolation between minimal and maximal daily temperatures.[9] We attributed these weather information at the zip code level using overlapping GIS coordinates, weighting by grid overlapping areas. Figure 2 presents the average daily temperature and the cumulative precipitation during the growing season. It shows that temperatures are the warmest in the south of France, in particular around the Mediterranean basin and that rainfall is the highest in mountain areas.

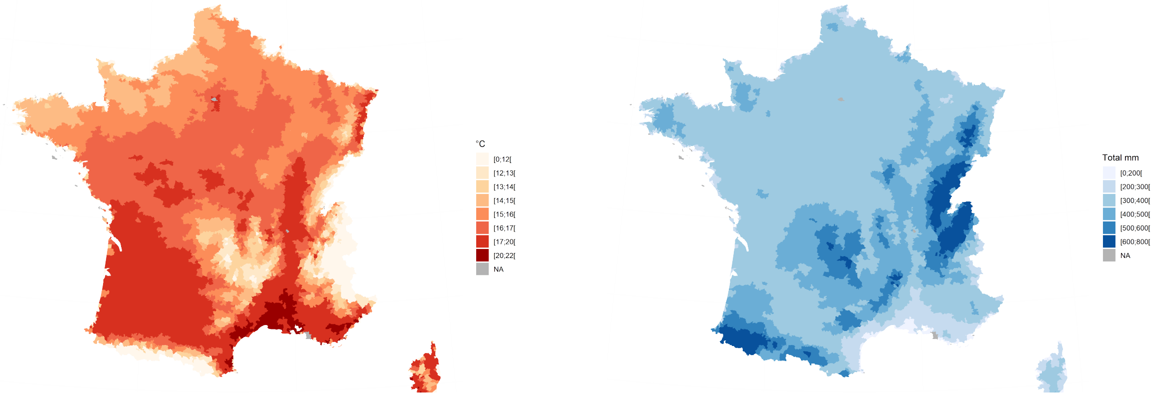
Land use data. To complete our analysis, we need annual land use data that could be aggregated at the zip code level to compute total useful agricultural area (UAA) per zip code. Detailed land-use data are also useful to analyse the heterogeneity of our results regarding zip code agricultural specialization.

We use land use data from the *Registre Parcellaire Graphique* (RPG), provided by the *Institut National de l'Information Géographique et Forestière* (National Institute of Geographic and Forestry

[7]Another well documented database is the one administered by the Danish Ministry of Environment and Food (Kudsk et al., 2018), where Danish farmers have to upload an extract of their spray records online. While available at the farm level, the issue of the Danish database is that the information is declarative and concerns only the biggest users of pesticides (farms with less than 10 ha are exempted from declaration). The recorded information is thus not exhaustive and may additionally suffer from declarative biases.

[8]Note that information on pesticide use in California is sometimes available at the field level (Larsen et al., 2021). However, this concerns only some rare counties and, in most cases, the information is only available on aggregated at the zip code level.

[9]As explained in Section 3 and with the objective to investigate the nonlinearities between pesticide purchases and temperature distribution, we notably recompute the cumulative temperature that usually benefit crops within the growing season (termed as growing degree days and noted GDD_0^{33}, for temperature falling between 0°C and 33°C), and the cumulative temperature that usually harmed crops (termed as harmful degree days and noted HDD_{33}^{∞}, for temperature higher than 33°C).



a) Temperature b) Precipitation

Figure 2: Average weather conditions during the growing season (March 1st to August 31th) between 2014 and 2019. NOTE. The missing value corresponds to zip codes having missing data for 2014-2019. For zip codes with missing data for one to four years, we calculated a moving average of temperature and precipitation.

Information). The RPG data are the most detailed land use data for agriculture in Europe, available for 28 crops at the plot level. These data come from farmers' declaration within the framework of the Common Agricultural Policy (CAP). Indeed, to benefit from CAP subsidies, farmers have to declare the crop produced on each plot. We aggregate these data at the zip code level for each of the 28 crop categories (in hectares), before grouping them into eight main crop categories, namely cereals, corn, oil and protein crops, temporary grasslands and fallow land, permanent grasslands, fruits, vineyards and other crops (the last category including vegetables and several industrial crops).[10] We compute the UAA as the sum of areas for the eight categories.

Figure 3 displays the dominant agricultural use by zip code. Agriculture in France is mainly orientated towards cereals and other industrial crops in the Paris basin. Interestingly, the areas that are mainly covered by vineyards are also those where the purchase of pesticides were the highest (Figure 1), in line with the common agronomic observation that vineyards are among the most pesticide-intensive crops (Agreste, 2020). The remaining parts of France are mainly covered by grasslands, highlighting the specialization towards livestock and milk production and, thus, the low pesticide purchase in these areas (Figure 1).

[10] Some farmers do not receive any subsidy from the CAP, thus some areas could be missing. This mainly concerns fruit and vegetable producers (including winegrowers) who, despite being located on smaller areas than crop and mixed farms, use pesticides more intensively (Urruty et al., 2016). To complete the RPG, we thus compile the data with those constructed by Lardot et al. (2021) to reproduce the departmental annual agricultural official statistics from the French Ministry of Agriculture. After addition, the aggregated missing areas represented about 6% of the total UAA on average.

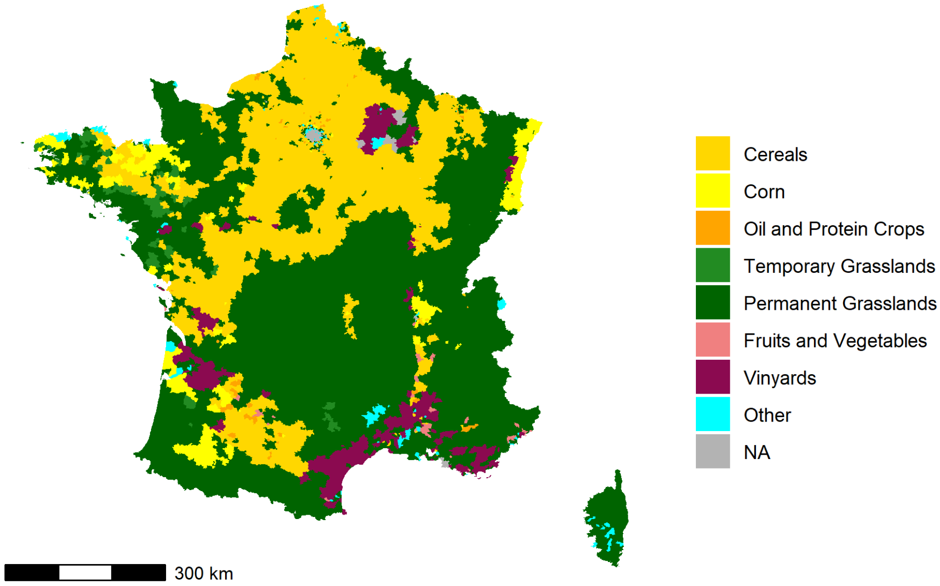


Figure 3: Average main agricultural use by zip code in 2014-2019. NOTE. The displayed values represent the dominant agricultural use in the zip code.

2.2 Summary statistics

Data on weather conditions and land uses are merged with pesticide data, which leads to a balanced panel of 5,848 zip codes observed between 2014 and 2019, representing 97% of all zip codes in mainland France.[11] After removing all zip codes for which less than 10% of the area is under agriculture, those from Corsica and overseas territories, we obtain a balanced panel of 5,014 zip codes between 2014-2019, representing about 97% of the total UAA of mainland France. In some zip codes, the BNVD indicates no purchases of pesticides. These figures may actually be misleading as the BNVD does not include observations protected by the statistical secret.[12] Such zip codes with at least one year with null observation represent a small share of the sample. Specifically, they represent 1.17% of the zip codes for the total pesticide purchases, 3.72% for fungicides, 1.60% for herbicides and 4.28% for insecticides. The remaining zip codes that we use in our preferred analyses are those that present non missing values in Figures A1, A2 and A3 presented in the Appendices.

Table 1 presents the summary statistics of pesticide purchases and weather conditions in our sample. It shows that more than 50% of pesticide use relates to fungicides. This statistic is interesting as most scientific studies and media coverage about pesticides relates to herbicide and

[11] The missing observations relate to zip codes that are not filled in the BNVD, partly due to the absence of any pesticide purchase in some zip codes, but also because of some administrative burdens that have changed between 2014 and 2019 in some parts of western France.

[12] According to French legislation, statistical secret applies since there are less than three buyers within the zip codes, or if a single farm represents more than 85% of the total zip-code purchases.

insecticide use (e.g. Larsen and McComb, 2021; Möhring et al., 2022). In particular, insecticides are much less used than other pesticides as they only represent 9% of total purchases. Their use is also much more spatially heterogeneous than that of other pesticides, as shown in Figure 1 or as expressed by the variation coefficient of insecticide use (6.86≈1.92/0.28, which is three to seven times greater than those of fungicides and herbicides respectively). In particular, herbicide use, which represents about 33% of all pesticides applied, presents a much lower heterogeneity. This is particularly noticeable in Figure 1, where herbicide purchases are more homogeneously spatially distributed than fungicide and insecticide purchases (the latter being particularly used in wine-producing regions, but not much elsewhere). In other words, farmers' application of herbicides seem much more systematic than for the two other pesticide types. Their purchases are thus less likely to be explained by weather conditions.

Table 1: Summary Statistics (N=29,166)

Variable	**Mean**	**S.D.**	**Min**	**Q1**	**Median**	**Q3**	**Max**	**Zip codes with one null observation**
Total Pesticides (kg/ha)	2.98	5.48	0	0.54	1.46	3.18	150.68	1.15%
Fungicides (kg/ha)	1.51	4.16	0	0.09	0.30	0.95	108.45	3.70%
Herbicides (kg/ha)	0.99	1.05	0	0.31	0.77	1.37	36.90	1.58%
Insecticides (kg/ha)	0.28	1.92	0	0.02	0.05	0.13	111.27	4.26%
Other active substances (kg/ha)	0.17	0.28	0	0.02	0.17	0.22	8.17	11.19%
Average temperature (°C)	16.18	1.94	8.71	15.07	16.13	17.27	21.85	–
Growing degree days (GDD_0^{33})	2,964.26	347.11	1,602.57	2,767.98	2,959.58	3,161.73	3,924.88	–
Harmfull degree days (HDD_{33}^{∞})	11.98	13.99	0	2.15	7.95	16.25	121.84	–
Total precipitation (mm)	382.75	117.10	68.57	305.90	367.70	440.51	1,079.14	–
UAA (ha)	5,802.65	5,637.83	38.03	1,294.49	3,966.46	8,826.31	48,057.52	–

Note. The figures provide the summary statistics of our sample on which we performed our preferred analyses. The last column displays the share of observations with at least one null observation (includes true zeros and observations deleted due to statistical secret).

Looking at the independent variables, Table 1 indicates that weather conditions during the growing season are also heterogeneous, but in overall terms less than pesticide purchases. For example, the coefficients of variation of average temperature and total precipitation are both much smaller than one. Only HDD has a coefficient of variation comparable to those of pesticide purchases. Finally, note that the zip codes are also heterogeneous with respect to their UAA (coefficient of variation equals to about $0.97 \approx 5{,}637.83/5{,}802.75$), explaining why we weight the observations by their UAA when estimating the different models (see Section 3).

Based on these data, the purpose of our econometric strategy – see Section 3 – is to explain annual deviations in pesticide purchases at the zip code level compared to their averages over the period (Figure 1) by similar deviations in weather conditions (Figure 2). Figures A1, A2 and A3 in the Appendices show such annual deviations over the period for all zip codes. Our typical estimation consists in explaining the annual deviations in pesticide purchases (Figure A1) as a function of annual weather deviations (Figures A2 and A3) and regional time trends. These figures highlight the great amount of remaining variations after controlling for location-specific averages. We use these sources of heterogeneity as primary sources for identification. We provide the details of our econometric strategy in the following section.

3 Methods

The previous section shows that pesticide purchases and weather are largely heterogeneous over space. These elements could reflect strong relationship between pesticide use and weather, but could simply reflects the role of other spatially-varying factors that we do not observe. A simple cross-sectional regression of pesticide purchases on weather conditions would thus suffer from potential omitted variable bias. To deal with this issue, our econometric approach consists in exploiting plausibly exogenous location-specific deviations from location-specific averages, for both the dependent and independent variables, such that the effects of unobserved spatially-varying but time-invariant factors would be purged from the analysis. We present hereafter two main approaches to account for the weather effects on pesticide use. The first aims to capture the impacts of average weather conditions during the growing season. The second aims to further investigate potential non-linearities between pesticide use and the whole temperature distribution during the growing season.

3.1 Average weather during the growing season

Preferred specification. Following the standards of the literature on the measurement of weather impacts on economic outcomes (Blanc and Schlenker, 2017), our preferred specification consists of explaining farmers' pesticide purchase in zip code i in year t as a quadratic function of average weather conditions during the growing season, conditionally on zip code fixed effects and time trends for each region r. We write this model as:

$$\log(X^k_{i(r),t}) = \beta^k_1 \bar{T}_{i(r),t} + \beta^k_2 \bar{T}^2_{i(r),t} + \beta^k_3 \bar{P}_{i(r),t} + \beta^k_4 \bar{P}^2_{i(r),t} + \nu^k_{i(r)} + \mu^k_r(t) + \varepsilon^k_{i(r),t}, \tag{1}$$

where $X^k_{i(r),t}$ is the purchase of pesticides of type k ($k \in \{1,2,3\}$ for fungicides, herbicides and insecticides respectively) in zip code i and year t, $\bar{T}_{i(r),t}$ is the average temperature during the growing season in year t and zip code i, $\bar{P}_{i(r),t}$ is the total amount of precipitation that fell during the growing season of year t in zip code i, $\boldsymbol{\beta}^k$ is the set of parameters of interest, $\nu^k_{i(r)}$ is the zip code fixed effect, $\mu^k_r(t)$ is regional time trend and $\varepsilon^k_{i(r),t}$ is the remaining error. We estimate this model using weighted least square (WLS), weighting observations by their UAA corrected for permanent grassland and fallow land, on which we assume that farmers do not apply any pesticides. According to the literature (Dell et al., 2014), the obtained estimates can be interpreted as causal impacts of contemporaneous weather conditions on pesticide purchases.

A common challenge in the literature assessing weather impacts on economic outcomes is to deal with the spatial dependence between the observations. This potentially high degree of spatial dependence is notably due to the natural autocorrelation of weather variables across space, but also to those occurring in other potential drivers of pesticide use (e.g. the extent of cooperatives, extension services and agri-environmental schemes in the surrounding area). A particular issue is that measurement error in weather variables is notably likely to be highly correlated across space (Ortiz-Bobea et al., 2021). These spatially-autocorrelated elements would result into smaller estimated standard errors than they truly are. A standard practice in the literature to correct the estimations for spatial dependence is to cluster the standard errors *à la* Conley (1999). Specifically, the Conley's correction relies on a kernel that weighs the elements of the covariance matrix based on the spatial distance between observations, decreasing from one for null distances to zero for distances above a threshold (Ortiz-Bobea et al., 2021). We proceed similarly in this paper, specifying a threshold of 25 kilometers beyond which we assume no spatial autocorrelation between the observations.

As displayed in equation (1), our baseline estimations include individual fixed effects and regional time trends. The individual fixed effects capture all the time-invariant characteristics at the zip code level – such as soil conditions – that are heterogeneous across space but that may be correlated with pesticide purchases and climate (and *a fortiori* weather). This is important as zip codes often specialize towards specific types of farming, with some growing crops that are particularly sensitive to pests (such as cereals) while others specialize in more resistant crops. This is particularly common in mountain and other marginal areas, where farmers mostly specialize in livestock activities (see Figure 3). The consequence is that farmers' intrinsic needs for pesticides varies between zip codes, regardless of weather conditions.[13] The inclusion of zip code fixed effects controls for such time-invariant characteristics. Specifically, it allows us to exploit plausibly exogenous location-specific deviations in pesticide purchase and weather from their location-specific

[13] In other words, pesticide purchases displayed in Figure 1 may reflect the role of farm specialization rather than long-term average weather conditions (ti.e., climate conditions; see Dell et al., 2014).

averages to estimate our parameters of interest. Similarly, the inclusion of regional time trends allows us to control for the potential effect of changes in agricultural practices, prices or policies that would influence pesticide purchase at the regional level (Fisher et al., 2012). The inclusion of regional time trends allows us to capture all common trends at the national or regional levels that are likely to affect pesticide purchase and that could be correlated with tendency changes in weather.

Another strategy to capture all common time shocks that are likely to affect pesticide purchase and that could be correlated with weather would be to include time fixed effects. However, fixed effects in two dimensions may over-purge the true "signal" from weather, leaving mainly "noise" for the estimation (Kropko and Kubinec, 2020), such that the obtained estimates may be affected by attenuation biases due to measurement errors in weather variables. By comparison, regional time trends leave more "signals" for the estimation (Fisher et al., 2012). To further investigate this issue, we test the sensitivity of our results to the use of two-way fixed effects (TWFE) specification in Section 4.3. Specifically, we show that, in most cases, our TWFE estimates present similar signs to those obtained with our preferred specification but turn non-significantly non-null.[14]

Dependent variable. The nature of the dependent variable in equation (1) calls for several comments. First, it is expressed in kilograms per hectare of UAA *corrected for permanent grassland and fallow land*. As explained before, we assume that farmers do not apply pesticides on such lands. This assumption is supported by agronomic studies (Aubertot et al., 2005; Urruty et al., 2016). The rational behind this assumption is that permanent grassland and fallow land are fairly less productive than other agricultural lands, such that the costs of pesticide purchases and applications would exceed their benefits (i.e. the prevented damages on permanent grasslands and fallows). Rational farmers would thus not apply pesticides on permanent grasslands and fallow lands, which nevertheless represent together 36.2% of the whole UAA (see Section 2). As a sensitivity analysis, we re-estimate equation (1) reporting pesticide purchases on the whole UAA (instead of those adjusted for permanent grassland and fallow land) and show that our results are robust.

Second, equation (1) shows that the dependent variable is expressed in logarithm. Such logarithmic transformation allows us to linearize the distribution of pesticide purchase (which is right-skewed otherwise, see Section 2). The problem with this transformation is that we have to drop the null observations, which may bias our estimates. As shown in Section 2, this concerns less than 5% of the observations for all pesticide types (about 1% when we aggregate all pesticide types),

[14] As shown in Section 4.3, our TWFE estimates are in fact sensibly reduced towards zero, overall confirming the presence of attenuation biases with TWFE estimations.

such that the issue may not be of primary importance. However, to further investigate this issue, we change the logarithmic transformation to use the inverse hyperbolic sine transformation of our dependent variable instead. The interest of the inverse hyperbolic sine transformation is that it nicely approximates the natural logarithm while accounting for null values (Aihounton and Henningsen, 2021). On top of this sensitivity analysis, we also test the sensitivity of our results taking a simple linear form for the pesticide purchases. These analyses show that our results are robust to these alternative choices.

Third, equation (1) indicates that we estimate successively the purchases of fungicides, herbicides and insecticides. Indeed, as there is no *a priori* reason to think that the changes in abundance of fungi, weeds and insects induced by weather changes will be similar (IPPC, 2021), it is likely that the use of fungicides, herbicides and insecticides may react differently to similar weather conditions.[15] In other words, it is likely that the parameters of interests $\boldsymbol{\beta}^k$ are different among pesticide types. These successive estimates allow us to investigate the differentiated impacts of similar weather conditions on use of different pesticide types. On top of these specific models per pesticide type, we also estimate a similar model than equation (1) but with an aggregated measure of pesticide purchase ($X_{i(r),t}$) as dependent variable. The estimates obtained with these aggregated pesticide use are notably interesting to compare our results with those obtained in studies that do not differentiate between different pesticide types (e.g. Jagnani et al., 2021; **?**), and detect potential aggregation biases.

Approximating pesticide use by pesticide purchase. The estimation of equation (1) relies on the major assumption that farmers adjust their pesticide purchase to contemporaneous weather conditions and that the amount of purchased pesticides precisely corresponds to the used amount.[16] We believe this assumption is reasonable for two reasons.

In the one hand, we assume that farmers behave rationally. This means that we assume that they use pesticides until the cost of the last unit of pesticide is equal to the productivity of that

[15]Because the other types of pesticides (the residuals of the aggregate pesticide purchases) are mainly growth inhibitors and generic pesticides that do not target any specific pests, we do not investigate the impacts of weather conditions on these other types of pesticide. As shown in Section 2, these other active substances are fairly marginal compared to fungicides, herbicides and insecticides, representing about 5% of the aggregate on average.

[16]In line with this first assumption, we further assume that pesticides are applied in the same zip code in which the purchase are recorded. This allows us to link pesticide purchase in the BNVD to weather conditions observed in the buyer's zip code area. To test the sensitivity of our results to this assumption, we re-estimate equation (1) by aggregating the observations at higher spatial scales. Specifically, we aggregate the observations either (i) at the *Petite Region Agricole* level (literally the "small agricultural region), an administrative area of a size of about 30 km × 30 km (i.e. about 10 times larger than the zip code level) or (ii) at the *department* level, an administrative area of a size of about 75 km × 75 km (i.e. about 70 times larger than the zip code level). As displayed in Section 4.3, our results are robust to these aggregation, and suggest that there are no much pesticide applications outside of the zip codes of the buyers' headquarters.

unit. For constant prices, an increase in pest pressure induces an increase in pesticide use and thus of pesticide purchase (as long as pesticides present decreasing returns, which they do; see Delcour et al., 2015, for example). Because pest pressure responds to weather conditions (IPPC, 2021), rational farmers are thus suspected to adjust their use and purchase of pesticides accordingly.

In the other hand, pesticide purchase is a reasonable approximation of pesticide use as long as we assume that farmers do not store pesticides from one year to another (or only in fixed quantities). There are several reasons to believe that changes in pesticide inventories are limited between years. First, it is not recommended to store more pesticides than those expected to be used within the year due to potentially high toxicity and perishable nature of the active substances (FAO, 1996). Second, storage of pesticide is not free. Farmers need to cover costs for space, rent and surveillance of pesticides. Third, French farmers are authorized to send back unused pesticides to their pesticide retailers. This enables them to pay only for the quantity of pesticides actually used. If this is not mandatory, there is no reason for a rational farmer to conserve such unused pesticides, at least as long as storage costs are higher than transaction costs. Fourth, storing pesticides would be rational only if farmers expect an increase in pesticide prices in following years. However, compared to other agricultural inputs, pesticide prices tend to be fairly stable.[17] Hence, given the non-null costs of storage and the stability of pesticide prices, rational farmer would not store pesticides in large quantities during a particular year, *unless they anticipate the prohibition of a specific product.*[18] Finally, there is no reason to believe that farmers within zip codes behave similarly in terms of storage. Since we work at the aggregate zip code level, we can assume that variations in storage and removal practices within the zip code would overall offset each other.

Despite all these reasons, we acknowledge that we cannot formally test whether farmers' storage behavior would bias our estimates $\hat{\beta}^k$. To directly test for this issue would require that we observe the stocks of pesticides, which we do not. The best we can do to address this concern is to provide indirect evidence using lagged pesticide purchases. Specifically, we perform two sensitivity analyses with this strategy in mind. In the first, we explain two-years moving averages of pesticide purchases by contemporaneous weather conditions during the growing season. In other words, we replace the dependent variable in equation (1) by the average of contemporaneous and one-time lagged pesticide purchases (i.e. to replace $\log(X^k_{i(r),t})$ by $\log(0.5 \times X^k_{i(r),t} + 0.5 \times X^k_{i(r),t-1})$). The intuition for this model is to consider that purchases from last year can be directly used in the next calendar

[17]The French monthly pesticide price index did not change by more than 2.0% in the 2014-2019 period compared to the average of the period (see https://www.insee.fr/fr/statistiques/serie/010539050).

[18]To test the sensitivity of our results to this possibility, we re-estimate equation (1) in Section 4.3, excluding officially banned pesticides in the period and, as a precautionary measure, glyphosate (whose ban has been heavily discussed among French and European policymakers in the period of our study), and show our results are robust.

year in response to contemporaneous weather changes. If storage behavior is not an issue for our preferred estimations, then the estimates obtained with this sensitivity analysis should be half of those obtained with our preferred model in magnitude. We show that this is the case in Section 4.3. In the second, we estimate a dynamic panel model that includes lagged pesticide purchase as an additional predictor of current pesticide purchase.[19] Such a specification allows us to test whether abnormally high past purchase reduces contemporaneous purchase and whether it changes the weather estimates accordingly. In other words, it enables us to examine whether storage alters our preferred estimates. If storage behavior is not an issue for our preferred estimations, then the estimates obtained with this sensitivity analysis should be of similar magnitude than those estimated with our preferred model. We show that this is the case in Section 4.3.

Weather elasticities. For the sake of clarity, we report in Section 4 the weather elasticities of pesticide purchases on top of the estimated parameters of interest $\hat{\boldsymbol{\beta}}^k$. Reporting weather elasticities allows us to compare the estimated impacts at the average points, without putting too much emphasis on the non-linearities in the relationships between pesticide use and weather conditions – such non-linearities are typically further explored using another method (see Section 3.2). Taking as illustrative example the case of temperatures, the temperature elasticities are recomputed from equation (1) as:

$$\xi_T^k = (\hat{\beta}_1^k + 2\hat{\beta}_2^k \bar{T})\bar{T}, \tag{2}$$

where ξ_T^k is the temperature elasticity of pesticide use of type k , $\hat{\beta}_1^k$ and $\hat{\beta}_2^k$ are the estimates obtained with the WLS estimation of equation (1), and $\bar{T}$ is the average temperature during the growing season within the sample.

These elasticities provide the marginal effects for a deviation of one percentage from the average temperature and precipitation conditions in the zip code. Because the model is nonlinear, these marginal effects may vary with large changes from the average sample value. In order to learn how our model responds to nonmarginal changes in temperature and precipitation (changes that typically occur with climate change), we additionally simulate in Section 5 the consequences of predicted climate outcomes in 2050 on pesticide use. For this purpose, we specifically use the average projections of ALADIN (*Aire Limitée Adaptation dynamique Développement InterNational*) regional climate model from Météo-France's *Centre National de Recherches Météorologiques* for

[19]This addition of such a new regressor comes with specific estimation issues. Appendix A2 presents in details the estimated equation and the econometric solutions to overcome these issues.

France between 2050 and 2055. The beginning of Section 5 provides further details on these data and on how these simulations are carried out.

3.2 Non-linear impacts of temperature

A potential issue with our preferred specification in equation (1) is that using the average temperature across the entire growing season could mask the true temperature response. This is because the same average temperature value could result from two very different growing seasons: one with little temperature variation and the other with significant variation. Even if the average temperature is the same, the year with greater variations entails greater exposure to extreme heat and cold, which could considerably impact pest pressure and, consequently, pesticide use. To identify potential nonlinearities and breakpoints in the relationship between temperature and pesticide use, we adopt a flexible modeling approach inspired by Schlenker and Roberts (2009). The model takes the form:

$$\log(X^k_{i(r),t}) = \int_{\underline{\mathrm{h}}}^{\bar{h}} f^k(h)\phi_{i(r),t}(h)dh + \eta^k_1 \bar{P}_{i(r),t} + \eta^k_2 \bar{P}^2_{i(r),t} + \nu^k_{i(r)} + \mu^k_r(t) + \varepsilon^k_{i(r),t}, \tag{3}$$

where $\phi_{i(r),t}(\cdot)$ is the reconstructed distribution of temperature in zip code i and year t, $\underline{\mathrm{h}}$ and $\bar{h}$ are respectively the observed lower and upper temperatures within the growing season, and $f^k(h)$ is a function linking the temperature distribution and use of pesticides of type k. The reconstructed distribution of temperature is first recalculated within each day using a sine interpolation between minimal and maximal daily temperatures and then summed over the whole growing season (from March 1st to August 31st). Following Schlenker and Roberts (2009), we consider three types of functional form $f^k(\cdot)$ in equation (3). We present these non-linear specifications in Appendix A3. The other elements in equation (3) are similar to those in equation (1). In particular, we estimate equation (3) by WLS, weighting the observations by their adjusted UAA.

4 Results

In this section, we first examine how the average weather conditions during the growing season affect pesticide purchases (Section 4.1). We then provide indirect evidence suggesting that changes in pesticide purchases likely represent changes in pesticide use (Section 4.2). We then provide evidence on the robustness of our results (Section 4.3). We then turn to heterogeneity analyses with respect to the differential effects of the seasons across the year and of the agricultural specialization of the zip codes (Section 4.4). Finally, we investigate the possibility for large non-linear temperature impacts on pesticide use, beyond the average temperature effects (Section 4.6).

4.1 Average weather during the growing season

Preferred estimates. Table A1 in the Appendices presents the WLS estimates of equation (1) obtained for fungicide, herbicide and insecticide use, as well as aggregated pesticide use. Using these estimates and the formula in equation (2), we recompute the elasticities of pesticide use with respect to weather conditions at the average point (see Table 1 for the average point description).[20] Table 2 displays these elasticities. It shows that a one-percent increase in average temperature leads to the use of about 1.66% more pesticides in aggregated. This effect appears to be mainly driven by fungicide and herbicide use, which respectively increase by 1.70% and 1.72% for a one-percent increase in average temperature. Insecticide use is much less affected by temperature, with an estimated elasticity of 0.37, and overall less precisely identified. Regarding rainfall impacts, Table 2 indicates that a one percent increase in rainfall raises the aggregated use of pesticide by 0.37%. Here, fungicide use seems to drive the overall effect. Indeed, fungicide use increases by 0.53% for a one percent precipitation increase, that is about two times more than herbicide and insecticide use (estimated elasticities of about 0.25 for both).

Table 2: Weather elasticities of pesticide purchase

	All pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	1.657***	1.704***	1.718***	0.368**
	(0.144)	(0.229)	(0.130)	(0.181)
Total Precipitation	0.365***	0.526***	0.254***	0.250***
	(0.026)	(0.043)	(0.024)	(0.039)

NOTE. The table displays the elasticities of the impact of average weather conditions during the growing season on pesticide use. The elasticities are computed at sample mean values using the WLS estimates and equation (2). The standard errors are clustered at the zip code leveland corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and displayed in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

Interestingly, Table 2 seems to suggest no aggregation bias when taking aggregated pesticide purchases as dependent variable. Indeed, weighting the weather elasticities of specific pesticide

[20] As presented in Section 2, the temperature elasticities correspond to the impacts of an increase of 0.16°C on pesticide purchases at the sample mean value. An issue with such elasticities is that temperature measurement unit is not sensitive (Hsiang, 2016). To be clear, a one percent increase in temperature would have been different if we measured temperature with Fahrenheit or Kelvin degrees. As such, the display of temperature elasticities is not standard in the literature, even if sometimes reported (e.g. **?**). The precipitation elasticities correspond here to the impacts of a +3.83mm precipitation increase on pesticide purchases. Such precipitation elasticities do not suffer from similar drawbacks than those for temperature.

type by their share in the total purchases (see Table 1) indicates aggregated elasticities of 1.57 for temperature and 0.40 for precipitation,[21] that is with less than 10% difference with those directly measured in Table 2. This is an important result given that most research on the relationship between weather and pesticide use relies on aggregate measurements of pesticide use (e.g. Jagnani et al., 2021; **?**). These previous studies thus likely provide consistent estimates of the sensitivity of aggregated pesticide use to weather conditions.

More detailed analyses on the form of the relationships between pesticide purchase and weather conditions indicates rather linear relationship for temperature but concave relationship for rainfall. Indeed, the estimates displayed in Table A1 indicate a non-significant non-linear curvature at the average point in the case of temperature, but a statistically significant positive concave relationship for rainfall. In the first case, this suggests that farmers apply more pesticide in a constant manner for marginal temperature increases around the average point. In the second, this indicates that farmers increasingly use pesticides as rainfall increases, up to a threshold for which their use decreases. For example, farmers use more of (aggregated) pesticides up to 865 mm of total rainfall during the growing season. The threshold is much lower for fungicides (809 mm) and insecticides (698 mm), but a bit higher for herbicides (899 mm).

Consistency with the literature. Our analyses above indicate that (i) farmers apply more pesticides as temperature or rainfall increase, (ii) among all types of pesticide, uses of herbicides and fungicides are the most sensitive to contemporaneous weather conditions and (iii) there is a concave relationship between rainfall and pesticide use, but rather a linear relationship for temperature. These findings are consistent with the agronomic literature. Indeed, this literature indicates on the one hand that higher temperature and humidity increase pest pressure (e.g. Delcour et al., 2015; Yu et al., 2022), which would lead rational farmers to use more pesticides. Our results thus align with this insight. Because weather elasticities are greater for fungicides and herbicides, our results suggest in particular that fungi and weed abundance respond much more to weather conditions than insects, which would make sense given the greater complexity of the growth of the latter (Delcour et al., 2015). Another explanation brought by the agronomic literature that could explain our results is that runoffs from crops to the environment reduce pesticide productivity (Bloomfield et al., 2006). As such, typical rational farmers would reduce their pesticide uses under these conditions. This is what we identify in Table 2. On top of these effects, the agronomic literature also documents that high temperatures decrease pesticide productivity (Delcour et al., 2015), which

[21] Such aggregated number are recomputed ex post using information from Tables 1 and 2. In the case of temperature for example, we obtain the figure as $(1.704{\times}1.51{+}1.718{\times}0.99{+}0.368{\times}0.28)/(1.51{+}0.99{+}0.28)$.

would decrease pesticide use. However, these thresholds appear at much higher temperatures than those surrounding the average point (e.g. Möhring et al., 2022), which is consistent with our results. We investigate in Section 4.6 such non-linearities at higher temperatures.

Our results are rather in line with the remaining of the economic literature. For example, our results for both temperature and precipitation are consistent with those of Chen and McCarl (2001) on US agriculture, even if they conducted their analysis at a coarser spatial resolution and consequently obtained higher estimates than ours. For example, they estimated that a one-percent increase in rainfall raises pesticide expenditures by 2.8%, an effect about eight times ours. These larger effects suggest aggregation biases related to the choice of large spatial resolutions, which is usually indicated in the literature as a source of aggregation bias (e.g. Fezzi and Bateman, 2015; Damania et al., 2020).[22] Consistently with this reasoning, our results indicate larger weather impacts that those estimated on microeconomic household-level data (e.g. Jagnani et al., 2021; **?**). Indeed, both Jagnani et al. (2021) and **?** find significantly positive temperature impacts on pesticide uses, but to a much smaller extent than those estimated here. If Jagnani et al. (2021) do not report their results for rainfall, **?** indicate also smaller impacts of precipitation on pesticide use than those we find in this study – by a factor about five. Once again, this is consistent with the role of potential aggregation biases induced by the choice of a greater spatial unit in our case (zip code vs. household level). Overall, our results illustrate the properties of our pesticide data, which stands as a nice trade-off between (i) usual exhaustive data measuring pesticide purchase at larger spatial areas than ours and (ii) usual microeconomic household-level data which are not exhaustive but based on a limited sample of the whole population.

4.2 Are pesticide purchases a good proxy of their use?

Our results suggest that farmers purchase more pesticides in response to higher temperature and precipitation. These results are consistent with the literature in agronomy and economics. Our main empirical strength compared to these studies is that we are able to map exhaustive and fine-grained observed data on pesticides, at a scale of about 9 km $\times$ 9 km, with similarly spatially-detailed weather data at a scale of about 8 km $\times$ 8 km. A fit at such a detailed spatial resolution allows us to exploit a large and precise amount of information for identification. However, one threat to identification is that, while interpreted as if they were pesticide use, our dependent variables fundamentally represent purchases. To investigate whether results reflect more purchase behaviors

[22] As explained before, they however likely not reflect aggregation bias due to the use of aggregated pesticide purchase as dependent variable (Fadhuile et al., 2016), as we find similar weather impacts on aggregated pesticide use than on the recomputed weighted pesticide-specific sum.

than use ones, this section reports estimates from regressions with various modifications regarding the spatial and temporal dimensions.

Spatial mismatch. One possible threat to a causal interpretation of our regression design pertains to the potential disparity between the buyers' location and the location where the purchased pesticides are actually used. In other words, a potential issue relates to whether all of the pesticide purchases linked to a zip code are indeed used in the same zip code, or within areas located in other zip codes. To test for this possibility, we aggregate our observations measured at the zip code level to higher spatial scales. In the first case, we aggregate the purchases at the *petite région agricole* (PRA), a spatial aggregation unit representing an area of about 30 km $\times$ 30 km, i.e. about 10 times larger than the zip code level. In the second, we aggregate the purchases at the department (DEP), an even larger area, with a size of about 75 km $\times$ 75 km, i.e. about 70 times larger than the zip code level. Table A2 in the Appendices present the obtained estimates. Table 3 displays the recomputed elasticities. Our results remain the same overall.[23] The single difference with Table 2 is that the precipitation elasticities of pesticide use go towards zero when observations are aggregated at the departmental level (but remain positive). This indicates a potential bias induced by the aggregation of rainfall at a too broad spatial scale (Damania et al., 2020).

Table 3: Weather elasticities of pesticide use at aggregated geographical scales

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	PANEL A. AGGREGATION AT *PETITE RÉGION AGRICOLE* LEVEL			
Average Temperature	1.377***	1.452***	1.518***	0.478***
	(0.229)	(0.377)	(0.199)	(0.292)
Total Precipitation	0.382***	0.591***	0.273***	0.349***
	(0.031)	(0.052)	(0.027)	(0.059)
	PANEL B. AGGREGATION AT *DEPARTMENT* LEVEL			
Average Temperature	1.370***	1.055***	1.679***	0.733**
	(0.188)	(0.280)	(0.175)	(0.335)
Total Precipitation	0.021**	0.019	0.021**	0.025*
	(0.010)	(0.013)	(0.009)	(0.015)

NOTE. Elasticities are computed at sample mean values using WLS estimates and equation (2). The standard errors are clustered at the adapted geographical scaleand corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and displayed in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

[23] We consistently find that farmers purchase additional pesticides for higher temperature and precipitation. In particular, the elasticities at the PRA level are statistically equal to those at the zip code level. These findings indicate that no significant pesticide use is likely to occur beyond the zip codes where the buyers are located.

Temporal mismatch. As explained in Section 3, we approximate pesticide use by pesticide purchase but acknowledge that such an assumption may be incorrect if farmers store pesticides from one year to the next. We examine this issue by (i) excluding banned pesticides and glyphosate (Appendix A6 displays the obtained estimates), (ii) averaging the purchases over two consecutive years (see Appendix A7) and (iii) estimating a dynamic panel model (see Appendix A8). The recomputed elasticities are displayed in Table 4. Results from panels A. and B. suggest that the exclusion of banned active substance or glyphosate does not affect our preferred estimates, which remain statistically equal with those in Table 2. This suggests that farmers do not massively store pesticides in response to announced or planned bans. Panel C. provides estimates that are equal to half of those displayed in our preferred analyses in Table 2. As explained in Section 3, this suggests that farmers do not store pesticides from one year to another. Finally, panel D. indicates that the estimates of the dynamic model are sometimes statistically smaller than those in our preferred analyses (Table 2). The maximum difference with our preferred estimates amounts to approximately 20%. In particular, all estimates consistently display positive values, confirming that farmers tend to use more pesticides in response to higher temperature and precipitation levels, even when they have made substantial pesticide purchases in the previous year. Consequently, the dynamic model suggests that any potential storage behavior, if present, has negligible effects on the estimation of our parameters of interest.

All the results presented in this section indicate that farmers' storage behavior does not significantly impact our results. Therefore, we can consider that our dependent variable – that fundamentally represent pesticide purchases – is a reliable approximation of pesticide use.

4.3 Robustness checks

Our results show that pesticide use is positively affected by temperature and precipitation during the growing season, and that the nature of the relationship with weather differs with the type of pesticide used. If we provide first evidence that pesticide purchases likely reflect pesticide use, these results may still remain sensitive to some of our empirical choices. To ensure their robustness, we conduct several tests with alternative empirical specifications regarding (i) the inclusion of time fixed effects (see Appendix A9), (ii) the use of pesticide purchase applied to the whole UAA as dependent variable, including permanent grasslands and fallows (see Appendix A10), (iii) the use of the entire sample, including urban and mountain zip codes (see Appendix A11) and (iv) the change of functional form, either using the inverse hyperbolic sine or linear transformations (see Appendices A12 and A13 respectively).

Table 4: Weather elasticities of pesticide use with alternative assumptions regarding storage

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	PANEL A. NO BANNED ACTIVE SUBSTANCE			
Average Temperature	1.647***	1.683***	1.705***	0.368***
	(0.144)	(0.228)	(0.130)	(0.181)
Total Precipitation	0.364***	0.523***	0.251***	0.250***
	(0.026)	(0.043)	(0.024)	(0.039)
	PANEL B. NO GLYPHOSATE			
Average Temperature	1.513***	-	1.737***	-
	(0.153)		(0.134)	
Total Precipitation	0.321***	-	0.135***	-
	(0.029)		(0.027)	
	PANEL C. TWO-YEARS MOVING AVERAGES			
Average Temperature	0.694***	0.677***	0.548***	0.171
	(0.063)	(0.090)	(0.066)	(0.111)
Total Precipitation	0.149***	0.166***	0.105***	0.143***
	(0.013)	(0.020)	(0.014)	(0.032)
	PANEL D. DYNAMIC MODEL *À LA* ARELLANO AND BOND (1991)			
Average Temperature	1.239***	0.762***	1.180***	0.165***
	(0.046)	(0.044)	(0.037)	(0.030)
Total Precipitation	0.387***	0.353***	0.265***	0.072***
	(0.009)	(0.010)	(0.007)	(0.008)

NOTE. Elasticities are computed at sample mean values using equation (2). Underlying estimates in panels A. to C. are obtained using weighted least squares. Underlying estimates in panel D. are obtained using GMM (see Appendix A2 for additional details on the GMM estimation). The standard errors are clustered at the zip code level and corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

Figure 4 provides a summary of the estimated weather elasticities of pesticide use with our robustness analyses. It demonstrates the robustness of our main findings to these alternative choices. Indeed, our sensitivity analyses replicate the results obtained in Section 4.1 for all specifications except one. The exception arises when employing time fixed effects instead of regional time trends. Although we confirm the sign of most relationships, several TWFE results become statistically non-significant. As mentioned in Section 3, this may be related to the fact that TWFE leaves too little signal for identification (Fisher et al., 2012; Kropko and Kubinec, 2020).[24] Our TWFE results support this phenomenon, as most TWFE estimates seem affected by exacerbated attenuation biases.

[24] More precisely, the argument in Fisher et al. (2012) is that the state-by-year fixed effects may absorb useful variation. One could thus wonder whether the argument applies for standard TWFE. We believe it is the case since our data represents roughly two times the size of an average US state only. The level of remaining variation after adjusting for year effects is likely roughly the same.

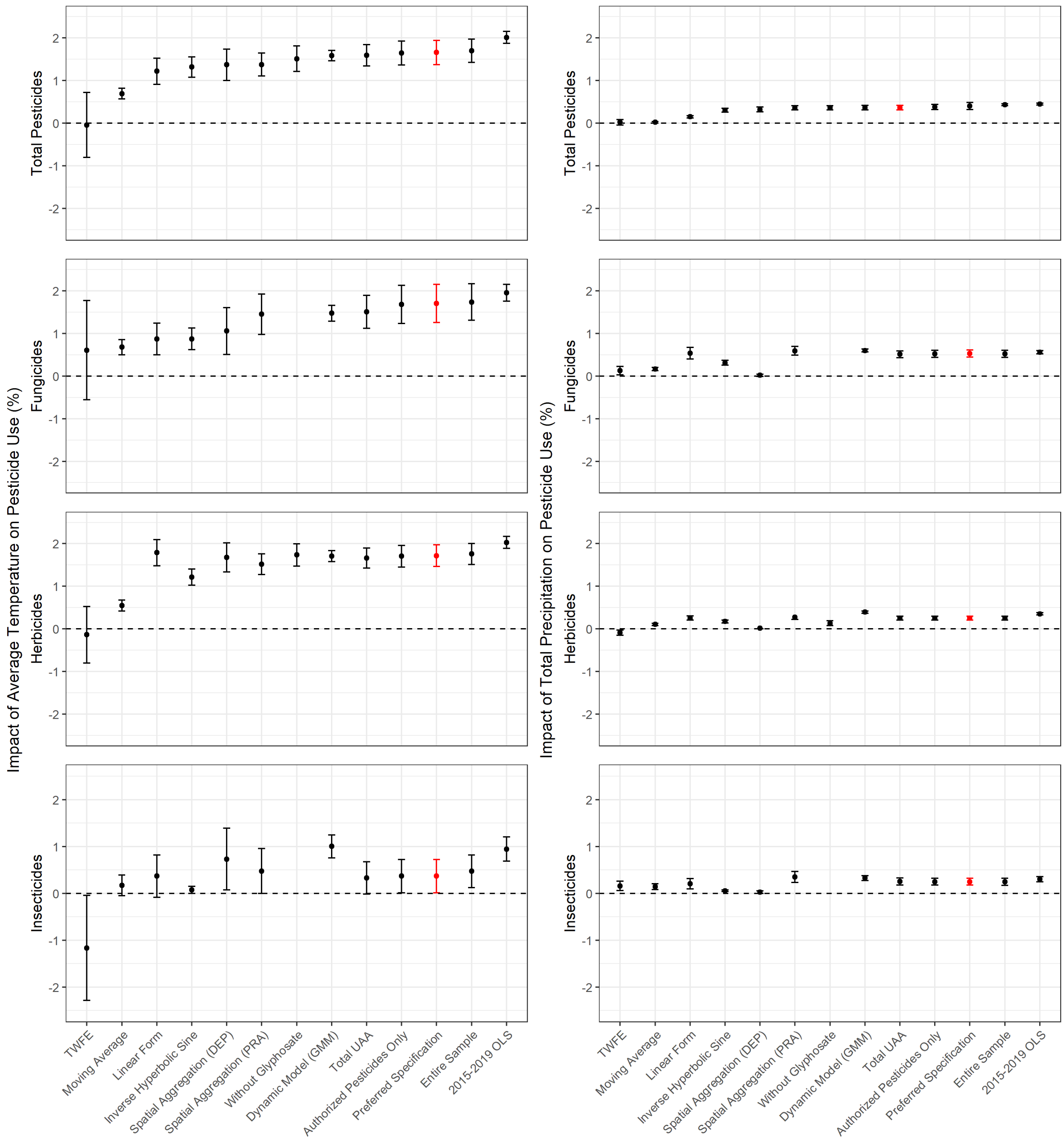


Figure 4: Comparison of impacts of average temperatures and total precipitation on pesticide use with alternative empirical choices. NOTE. The graph displays recomputed elasticities of average temperature and total precipitation on pesticide use at sample mean value using the alternative empirical choices. The estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). The bars displays 95% confidence intervals. The red figures represent the estimates obtained our preferred analysis, as displayed in Section 4.1.

Figure 4 shows that, compared to the temperature impacts, the effects of rainfall are much more precisely estimated. Also, they exhibit greater stability regardless of changes in specifications. These phenomenon likely reflect the higher spatial heterogeneity of precipitation compared to temperature (Damania et al., 2020). Specifically, differently incorporating spatial considerations in our various sensitivity analyses has minimal impacts on the obtained elasticities.

4.4 Heterogeneous weather effects

In this section, we present several analyses that explore potential heterogeneities in the weather impacts on pesticide use within our entire dataset. We examine two types of heterogeneous effects related to (i) differential weather impacts depending on the seasons and (ii) differential weather impacts depending on the agricultural specialization of the zip codes.

Differential weather impacts within time. If farmers adjust their pesticide use within the growing season in response to changes in weather conditions, their responses may vary across different periods of the year. There are at least two reasons that could explain these heterogeneous weather impacts over time. First, crops may exhibit varying levels of sensitivity to pests at different stages of growth. Second, the influence of weather on pest density itself may depend on the period of year. To investigate these effects, we conduct a revised analysis similar to our preferred approach, but focusing on seasonal effects. Each season is defined as a three-month period (e.g. March 1st to May 31th for spring), for which we compute average temperature and total precipitation.[25] Table A17 in the Appendices displays the obtained estimates for such an additional analysis. Table 5 hereafter presents the recomputed elasticities.

The findings presented in Table 5 indicate that our preferred elasticities, as displayed in Section 4.1, seem heavily influenced by weather conditions during spring, in the first half of the growing season. This result aligns closely with the findings of Jagnani et al. (2021), who showed that Kenyan farmers primarily adjust their pesticide applications in response to weather changes during the first half of the growing season. This pattern holds true not only for overall pesticide use, but also for use of fungicides and herbicides. This result either suggests that crops are predominantly sensitive to pest damages during spring, or that the growth of fungi and weeds is primarily influenced by weather conditions at that time. This latter explanation is consistent with agronomic insights, which indicate that fungi and weeds tend to emerge in the early stages of the growing season when

[25] Compared to our preferred analysis, we thus divide the growing season in two stages of similar length (92 days), and additionally considered pre and post growing periods (winter and autumn respectively).

Table 5: Weather elasticities of pesticide use across seasons

	Total Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	Panel A. December-February			
Average Temperature	0.087***	0.160***	0.062	-0.038
	(0.050)	(0.080)	(0.045)	(0.030)
Total Precipitation	0.123***	0.159***	0.124***	-0.003
	(0.025)	(0.038)	(0.022)	(0.041)
	Panel B. March-May			
Average Temperature	1.177***	1.598***	1.003***	-0.230
	(0.151)	(0.231)	(0.151)	(0.257)
Total Precipitation	0.203***	0.336***	0.125***	0.144***
	(0.029)	(0.043)	(0.026)	(0.037)
	Panel C. June-August			
Average Temperature	-0.098	-0.352	0.258	0.622
	(0.283)	(0.453)	(0.248)	(0.394)
Total Precipitation	0.059**	0.051	0.072***	0.194***
	(0.023)	(0.032)	(0.035)	(0.022)
	Panel D. September-November			
Average Temperature	-0.396***	-0.414**	-0.425***	-0.358
	(0.154)	(0.242)	(0.138)	(0.261)
Total Precipitation	-0.098***	-0.121***	-0.082***	-0.066**
	(0.020)	(0.026)	(0.022)	(0.029)

Note. Elasticities are computed at sample mean values using WLS estimates and equation (2). The standard errors are clustered at the zip code level and corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01. Average temperature and precipitation from December to February are 8.5°C and 203.8mm respecitvely. They are of 11.6°C and 198.7 mm for March to May, 20.3°C and 179.6mm for June to August and 13.08°C and 222.0 mm for September to November.

temperature and humidity levels are optimal for their development (Patterson et al., 1999; Delcour et al., 2015). By comparison, Table 5 indicates that insecticide use is primarily influenced by weather conditions during summer (the effect is statistically significant at the 15% level). This result either implies that insect growth is particularly sensitive to weather conditions during summer, or that crops are primarily vulnerable to insect damage at that time.

Table 5 not only displays heterogeneous weather impacts within the growing season but also reveals that weather conditions outside the growing season have an effect on pesticide purchases. Specifically, we find that warmer and wetter winters lead to higher pesticide use. This result aligns with agronomic insights, as dry and cold winters hinder pest growth (Delcour et al., 2015), thus reducing the need for farmers to apply pesticides. Although the weather impacts during winter exhibit similar signs to those observed during spring, their magnitude is significantly smaller (about ten times less important).

Finally, Table 5 reveals clear negative impacts of warmer and wetter autumns on pesticide use. This result starkly contrasts with the weather impacts observed in other seasons. For instance, we observe that a one-percent increase in autumn temperature leads to a 0.40% decrease in pesticide use for all pesticide types, whereas temperature increase tends to increase pesticide use in all the other seasons. These contrasting results likely stem from the fact that only specific types of crops are cultivated in autumn. In France, for instance, most arable crops are typically harvested by that time, leaving only a few remaining crops such as fruits and vineyards to protect. It is plausible that our results reflect that these particular crops are not subject to the same types of pest damages. To test this hypothesis, we further explore the role of agricultural specialization in the subsequent analysis.

Differential weather impacts across agriculture types. All French regions are not specialized into the same productions. As such, they do not present the same agricultural practices and, thus, may not use pesticides in similar ways (see Figure 1 or Urruty et al., 2016). In particular, regions specialized in different agriculture types may differently adjust their pesticide use to similar weather shocks (Chen and McCarl, 2001; Rhodes and McCarl, 2020). To test for these potential heterogeneous effects, we divide our sample according to the farming specialization in each zip code and re-perform our benchmark analysis (see Table A18 in Appendices). Table 6 presents the recomputed elasticities of pesticide use with respect to temperature and precipitation during the growing season for the different agricultural specialization considered.

Table 6 provides several insights. First, zip codes specialized in cereals and oilseed crops represent about 52% of our sample, implying that they are likely to drive the overall findings. Indeed, we find that pesticide use increases in this sub-sample when temperature and precipitation during the growing season increase (see panel A. of Table 6), as in the remaining of the paper. The difference stands with the amplitudes of the estimated effects. In this sample, a one-percent increase in temperature increases aggregated pesticide use by 2.21%, which is a more substantial effect than that for the whole sample. Similarly, a one percent increase in precipitation increase aggregated pesticide use by 0.43%. For fungicide and herbicide use too, the effect of temperature and precipitation is consistently at least 150 to 200% larger than for the whole sample. Comparing these results to the other panels of Table 6 show that zip codes specialized in cereals and oilseed crops are actually the most sensitive to weather shocks.

Second, our preferred results also closely align with the findings obtained for zip codes specialized in forage crops and pastures (see Panel B. of Table 6). This is probably explained by the fact that zip

Table 6: Weather elasticities of pesticide use according to the agricultural specialization of the zip codes

	Total Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	Panel A. Cereal and Oilseed Crops			
Average Temperature	2.214***	2.621***	2.254***	0.024
	(0.209)	(0.177)	(0.325)	(0.206)
Total Precipitation	0.428***	0.701***	0.301***	0.259***
	(0.041)	(0.034)	(0.062)	(0.047)
Average use (kg/ha)	3.591	1.274	1.722	0.314
	Panel B. Feedcrops and Pasture			
Average Temperature	1.115***	0.884***	1.135***	0.807***
	(0.153)	(0.151)	(0.282)	(0.300)
Total Precipitation	0.334***	0.374***	0.253*	0.244
	(0.126)	(0.134)	(0.150)	(0.492)
Avg. use (kg/ha)	2.525	1.311	0.832	0.313
	Panel C. Fruits and affiliated			
Average Temperature	1.541**	-0.624	0.418	3.280**
	(0.720)	(0.598)	(0.533)	(1.272)
Total Precipitation	0.154***	0.259***	0.201***	0.008
	(0.047)	(0.038)	(0.034)	(0.090)
Avg. use (kg/ha)	16.216	7.791	1.468	6.643
	Panel D. Vineyards			
Average Temperature	-0.660*	-0.869***	0.087	1.670**
	(0.366)	(0.290)	(0.373)	(0.821)
Total Precipitation	0.420***	0.432***	0.262***	0.373***
	(0.022)	(0.040)	(0.024)	(0.124)
Avg. use (kg/ha)	17.274	14.715	1.574	0.474

Note. Elasticities are computed at sample mean values usingWLS estimates and equation (2). The standard errors are clustered at the zip code level and corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01. Cereal and Oilseed Crops include wheat, barley and maize, rape, sunflower, oilseeds, protein crops and pulses. Feedcrops and Pasture encompasses fodder and temporary grasslands. Fruit and Affiliated encompasses orchards, nuts, olive trees, rice, vegetables and sugarcane.The average temperature and precipitation in zip codes specialized in Cereals and oilseeds crops are 16.2 °C and 356 mm respectively; 15.8 °C and 427 mm in zip codes specialized in feedcrops and pasture; 17.9 °C and 298 mm in zip codes specialized in fruits and 19.9 °C and 291mm in zip codes specialized in vineyards.

codes specialized in forage crops and pastures represent 42% of all our observations. Consequently, our preferred estimates in Section 4.1 fall in between the estimates obtained in panels A. and B. Here, a one-percent increase in temperature typically leads zip codes specialized in forage crops and pasture to an approximately one-percent increase in pesticide use across all types, while a one-percent increase in precipitation results in an approximate 0.3% increase. In other words, zip codes specialized in forage crops and pastures exhibit about half the level of sensitivity to similar weather variations compared to those specialized in cereals and oilseed crops.

Finally looking at the estimates obtained for zip codes specialized in fruit production or vineyards (see Panels C. and D. of Table 6), the results are fairly consistent with those obtained for the other regions, at least for rainfall. However, the estimates obtained for temperature are noteworthy different compared to the remaining of the paper. Specifically, we observe negative or null effects of temperature on the use of fungicides and herbicides in zip codes specialized in fruit production or vineyards. This outcome aligns well with the results identified in Table 5 regarding the weather impacts in autumn, when these crops are the main remaining ones being harvested. In particular, we find that zip codes specialized in vineyards, which make up approximately 4% of our overall sample, actually respond to higher temperatures by reducing their purchases of fungicides. Additionally, it is interesting to note that zip codes specialized in fruit production or vineyards exhibit much greater adjustments in their insecticide use in response to temperature compared to the rest of the sample. This suggests that insecticide use primarily responds much more to weather changes on fruit production and vineyards than on other crops. This notably suggests that fruits and vineyards are more sensitive to insect damages, or that farmers have greater incentives to protect them as they are significantly more profitable compared to other crops. Because fruit productions use ten to twenty times more insecticides than other zip codes (see Table 6), these results actually suggest that the use of insecticides in France is primarily influenced by temperature shocks in zip codes specialized in fruit production.[26]

4.5 Ruling out alternative mechanisms

Results so far suggest that French farmers adjust their pesticide purchases to deal with greater temperature and precipitation. Given the lack of evidence suggesting that farmers store pesticides from one year to another, we interpreted these results as adjustment of pesticide applications in response to changes in pest pressure. In other words, we assumed that farmers respond to weather changes by adjusting them at the *intensive margin* only. This explanation could however be threaten by two possible mechanisms. First, farmers could adjust to weather changes at the extensive margin by changing their crop allocations (Graveline and Mérel, 2014; Cui, 2020). As such,

[26]One possible explanation for these distinct outcomes in the zip codes specialized in fruits and vineyards is that they are located in warmer regions compared to zip codes specialized in more conventional crops. As shown in Table 6, zip codes specialized in vineyards are for instance located in areas that are three to four degrees Celsius warmer than the average zip code in our sample. These latter findings may thus not solely be attributed to agricultural specialization, but rather to potential non-linear impacts of temperature on pesticide use. We further examine this possibility in Section 4.6.

because crops do not necessarily rely on the same pesticide intensity (see Table 6), crop allocation changes could mechanically modify overall pesticide use, ultimately introducing composition issue in the measurement of our dependent variable in equation (1). Second, farmers could also respond to weather changes by adjusting at the super-extensive margin (Graveline and Mérel, 2014; Cui, 2020), by either increasing farmland or abandoning land no longer suitable for production. In this latter case, variations in our dependent variable from equation (1) would not solely come from adjustments of the numerator (pesticide purchases), but also from changes in the denominator (adjusted UAA). In either case, our previous interpretations of our estimates may not be entirely supported as they could encompass several mechanisms. Because we cannot formally test whether farmers respond to weather changes at the intensive margin only, our approach aims to quantify the extent of the extensive and super-extensive margins in order to rule out potential confounding effects of these alternative mechanisms on our estimates of interest. We investigate these issues hereafter.

Formally, we re-estimate equation (1) by changing our dependent variable, conserving all the other estimation elements. As a first step, we consider the yearly adjusted UAA by zip code as our new dependent variable. The results from this estimation allow us to test whether farmers adapt at the super-extensive margin. In particular, results indicating that adjusted UAA *reduces* in response to higher temperature or precipitation would challenge the validity of our results suggesting that hotter or wetter growing seasons increase pesticide use, as they can indeed reflect the effect of a reduction in adjusted UAA instead of a true intensive margin response. As a second step, we investigate whether farmers adjust at the extensive margin by estimating the impacts of weather on the shares of major agricultural uses within the zip codes. Evidence suggesting adaptation at the extensive margin may alter the interpretation of our results, in particular if we see that farmers respond to hotter or wetter growing season by shifting their crop allocations towards more pesticide-intensive crops (such as fruits or vineyards; see Table 6). Table 7 displays the results obtained from such complementary estimations.

On the one hand, results from the first column of Table 7 indicate that the total adjusted area devoted to agriculture is not sensitive to temperature changes. This suggests that French farmers do not adapt at the super-extensive margin as a response to short term temperature deviations from averages. Because this indicates constant denominator in the estimation of equation (1), this result goes in favor of our previous interpretations that farmers mainly adjust their pesticide purchases at the intensive margin. Results for the response at the extensive margin also supports this interpretation (Table 7). Indeed, results from other columns of Table 7 suggest minor changes

Table 7: Weather elasticities of agricultural areas

	Super-extensive	**Extensive**			
	Adjusted UAA	**Cereals**	**Feedcrops**	**Fruits**	**Vineyards**
Average Temperature	0.049	0.006	0.034***	-0.070***	0.046***
	(0.036)	(0.004)	(0.003)	(0.020)	(0.013)
Total Precipitation	0.029***	0.002*	0.003***	0.007*	0.006***
	(0.011)	(0.001)	(0.001)	(0.004)	(0.002)

NOTE. Elasticities are computed at sample mean values using WLS estimates and equation (2) with alternative dependent variables (see column names). The standard errors are clustered at the zip code level and corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01. Cereals include wheat, barley and maize, rape, sunflower, oilseeds, protein crops and pulses. Feedcrops encompasses fodder and temporary grasslands. Fruits encompass orchards, nuts, olive trees, rice, vegetables and sugarcane.

of crop allocations in response to higher temperature. For example, the share of cereals – which constitute almost 50% of total UAA in average – is not sensitive to temperature variations. Actually, farmers primarily respond to higher temperature by slightly decreasing the share of fruits – one of the most pesticide-intensive crop; see Table 6 – and replacing it by narrower expansions of vineyard and feedcrops. Given that these two latter crops consume equally or less pesticides by area unit than fruits (see Table 6), this means that the changes in crop allocations induced by higher temperatures would actually conduct farmers to use *less pesticides* on average. In other words, the extensive margin effect in response to higher temperatures would lead farmers to decrease pesticide use. This goes *against* our previous estimates, which are all significantly positive (see Table A1 for example). Given the mixed results on the adaptation at the extensive and super-extensive margins induced by higher temperature, we believe that our previous temperature estimates do reflect farmers' adjustment at the intensive margin. More precisely, they actually reflect the *lower bound* of the farmers' intensive margin response to higher temperature in terms of pesticide use.

On the other hand, Table 7 indicates that farmers do adapt at the super-extensive margin in response to higher precipitation. This means that the denominator in equation (1) is not constant, and that we cannot solely attribute our previous estimates to adjustment at the intensive margin. That being said, we find that farmers *extend* their adjusted UAA in response to wetter growing seasons. This implies that, if farmers did not additionally react at the intensive margin, our previous estimates would have been negative. Yet, because our estimates are positive (see Table A1 for example), this implies that the numerator have increased more than the denominator in response to higher precipitation. In other words, our previous estimates do reflect the overall positive impact of intensive margin responses to greater rainfall. Taking into account the reverse effects of the super-extensive margin response, this means that our previous estimates actually reflect the *lower bound* of the farmers' intensive margin responses to greater precipitation in terms of pesticide use. The results at the extensive margin in the right-hand columns of Table 7 are more ambiguous. They do not reflect strong crop allocation changes, with all crop shares slightly increasing in response to higher precipitation (about ten times smaller in amplitude than those highlighted for temperature). Because these effects are small and only slightly significant (two of these effects are not statistically different from zero at 5%), we believe that these effects are of minor importance for the present debates. At least, they do not reflect any shifting from pesticide-extensive crops towards pesticide-intensive crops. In other words, our preferred precipitation estimates should not suffer from any strong composition effects.

All together, the results from Table 7 suggest that adaptation mechanisms at the extensive and super-extensive margins are, at best, limited and go, in any case, in the opposite directions than the signs of our preferred estimates. In other words, these additional results support our previous interpretations that our preferred estimates actually reflect intensive margin responses to weather changes. They actually likely reflect lower estimates of such intensive margin responses.

4.6 Non-linear temperature impacts

Now that we have presented robust results using average temperatures during the growing season (and that we provide elements suggesting that these results do reflect intensive margin responses), we turn to the presentation of the non-linear impact estimates. Previous analyses already reported consistent non-linear concave effects of rainfall on pesticide use (see Table A1 in the Appendices for example). We further investigate the non-linear effects of temperature within the growing season by estimating equation (3) using three functional forms (step-wise functions, 9^{th}-order polynomial functions and bins; see Appendix A3). Figure 5 presents the estimated impacts of the whole temperature distribution during the growing season on pesticide use with these functional forms.[27]

Figure 5 reveals that the response of pesticide use to temperature varies across its entire distribution. They consistently demonstrate, for all pesticide types, that moderate temperatures have a slightly linear positive effect on pesticide use, but that exposure to extreme temperatures strongly reduces pesticide use.[28] Such linear responses for moderate temperatures are consistent with that identified in Section 4.1. However, we have not previously identified such a negative relationship

[27]Table A19 in the Appendices presents the estimates of the step-wise functions. The estimates for the other functional forms are not reported but available from the authors by request.

[28]Since using TWFE affects the estimated results in the previous model, we also re-estimate the non-linear models using year fixed effects instead of regional time trends. Appendix **??** presents the robustness of these results.

for very high temperature. This suggest that the concave effect of temperature is actually identified far away from the average. We examine these relationships in more detail here.[29]

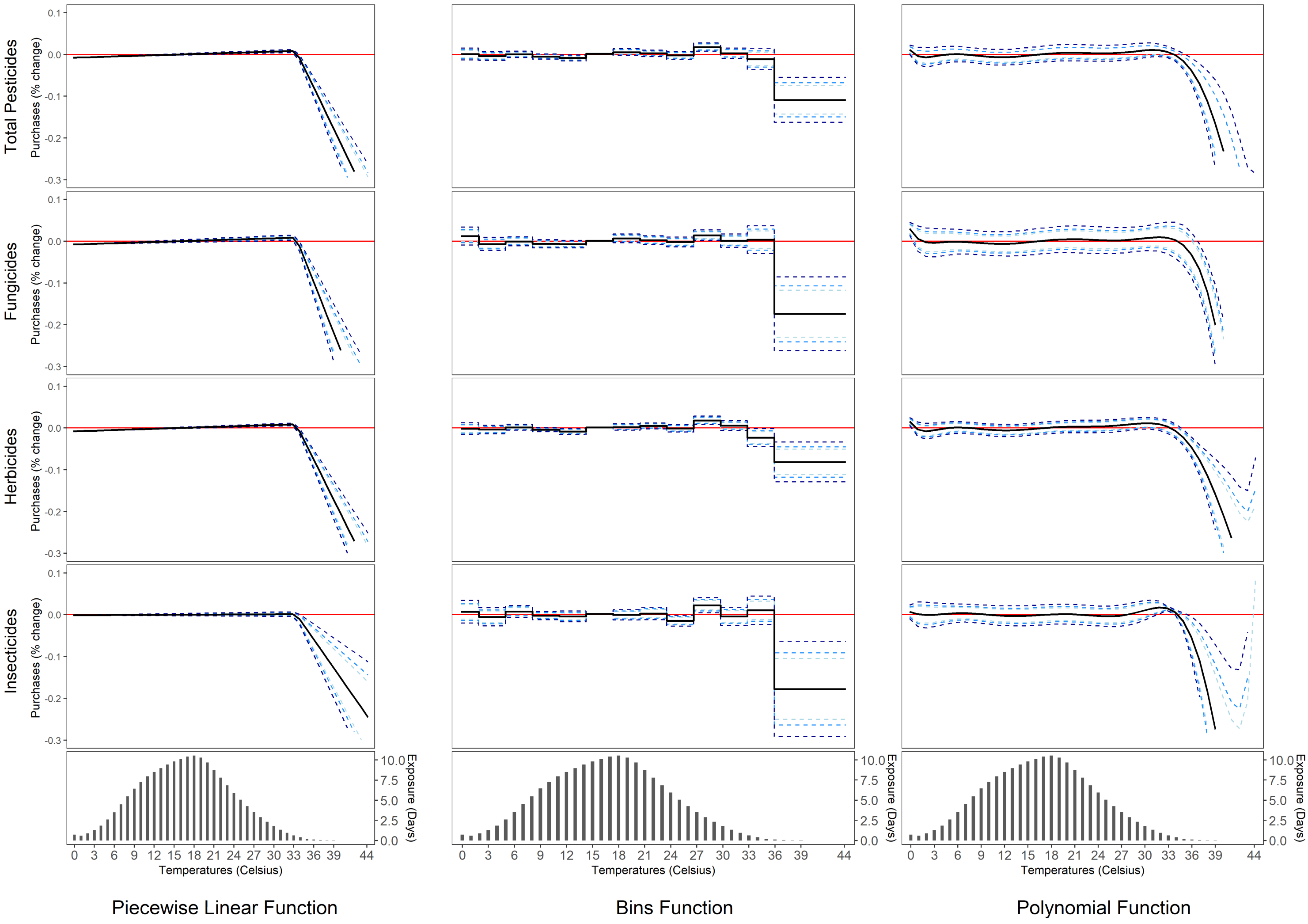


Figure 5: Impacts of temperature distribution on pesticide use during the growing season. Note. Graphs display changes in pesticide purchase in kg/ha if crops are exposed for one day to a particular 1°C temperature interval where we sum the fraction of a day during which temperatures fall within each interval. The 90%, 95% and 99% confidence bands (from light to dark blue) are adjusted for spatial correlation using the Conley spatially-robust correction. Curves are centered so that the exposure-weighted impact is zero. Histograms at the bottom of each graph display the average temperature exposure among all zip codes.

Figure 5 indicates that exposure to temperatures up to about 25°C seems to have marginal impacts on use of all pesticide types. The relationship between temperature and pesticide use is indeed weakly increasing from 8°C up to this threshold for all pesticide types, with most effects not distinguishable from zero. This is only for temperature higher than 25°C that uses significantly increase. For example, a one additional day of exposure to 27 to 30°C would increase aggregated

[29]The effect of precipitation on pesticide use remains robust using the step-wise, bins and polynomial functions (see for example Table A19 in the Appendices.

pesticide use by about 2% relative to average exposure to 16 to 18°C (reference bin). The bins and polynomial functions then clearly show a negative influence of extreme temperatures on use of all pesticide types. For example, one additional day of exposure to temperatures above 33°C would decrease fungicide use by 10 to 25% depending on the functional form and confidence interval used. Our findings are similar regarding herbicide use, which start to be negatively affected by temperatures above 30°C. One additional day of exposure to temperatures above 30°C would decrease herbicide use by 5 to 15%. Even though they are less precisely estimated, insecticide use are also negatively affected by temperatures above 33°C.

These results are consistent with agronomic insights and with the economic literature. Indeed, pests start to develop as temperatures warm, but extreme events deteriorate weed and fungi growth conditions and damage insect populations (Deutsch et al., 2018; Delcour et al., 2015; Patterson et al., 1999). Our results on insecticide use are particularly consistent with Möhring et al. (2022) and Larsen and McComb (2021) who both found a negative relationship between extreme temperature and insecticide use. They are also close to Rhodes and McCarl (2020), who find that a high number of hot days (33°C and above) have a negative impact on insecticide purchase on soybeans and winter wheat. We further expand on the aforementioned findings by demonstrating that the adverse effects of extreme temperatures not only apply to insecticide uses, but also apply to those of fungicides and herbicides.

While these negative impacts of extreme temperature events on pesticide use are strong and significant, it is essential to weight these results by their very low frequency in our sample (see the observed temperature distribution in Figure 5). This raises the question of whether the more frequent occurrence of extreme temperature events associated with climate change will have an overall negative impact on future pesticide usage. We explore these potential future effects in the following section.

5 Simulations of climate change impacts

In this Section, we use our previous estimates to roughly project future pesticide use under upcoming climate conditions. Specifically, we multiply our preferred estimates by the difference of average temperature and precipitation conditions during the growing season between 2014 and 2019 and those between 2050 and 2055 – as projected by climatic models – assuming all other factors to be constant.[30] As information of future temperature and precipitation conditions, we use the spatially-explicit projections from the ALADIN climate model of Météo-France to project tailored future conditions for each zip code within our sample.[31] Specifically, we use the ALADIN projections under medium emission pathways scenario (RCP 4.5 scenario). Such climate projections indicate an overall warming of the temperatures and a rarefaction of average precipitation during the growing season. In this particular scenario, the temperature in France is expected to rise in average by 1.41°C and precipitation to reduce on average by 30mm (see Appendix A17). The results of projections of future pesticide use are displayed in Figure 6 and Table 8.

Figure 6 shows the tailored projections of pesticide use in 2050-2055 compared to 2014-2019 averages, when using our preferred estimates presented in Section 4.1. It shows that farmers in different regions will react differently to the heterogeneous weather changes. In particular, the south-eastern part of France stands out among the other French regions. Total pesticide purchases will increase in this particular region by up to 35%, about three times more than in the other parts of France. This large increase seems particularly driven by the farmers' responses in terms of fungicide and herbicide use. Indeed, if fungicide and herbicide use seem to increase in most location, it particularly surge in this area. By comparison, Figure 6 shows that insecticide use in this region will respond very heterogeneously to future climate conditions, with some locations increasing insecticide use by up to 15%, while others might decrease insecticide use by up to 35%.

Panel A. of Table 8 sums up the overall climate effects displayed in Figure 6 (see columns "Avg. Temp."). Panels B. and C. respectively decompose the total climate change impacts into those attributed to temperature and those attributed to precipitation. On top of the results using our preferred estimates relying on average temperature (see Section 4.1), Table 8 also displays the results with the step-wise function parameters reported in Section 4.6 on the non-linear impacts of the cumulative temperature during the growing season (see columns "Cum. Temp." in Table 8). Table 8 indicates a clear picture. According to our preferred approach, French farmers would adapt to warmer temperatures by increasing their aggregated pesticide use by an average additional 11% for a RCP4.5 climate change scenario (Panel A.). This aggregate increases is actually driven by the farmers' responses in terms of herbicide and fungicide uses, which would also increase by an average 11% for a RCP4.5 climate change scenario (between +8 to +14% with a 95%

[30]We notably assume constant crop allocation and UAA. If results from Section 4.5 indicate that farmers adjust their total agricultural area and crop allocations to weather changes in the growing seasons, these adaptation patterns are rather limited and our estimates mostly reflect intensive margin responses (see Section 4.5).

[31]The projections of climate change provided in ALADIN have the unique advantage of being tailored at the same 8 km × 8 km *SAFRAN* unit than the historical weather conditions than we used elsewhere in the paper. Note that we specifically use the projections provided by the ALADIN63 module, which draws on the same methods than those applied to obtain the historical weather data used in this paper.

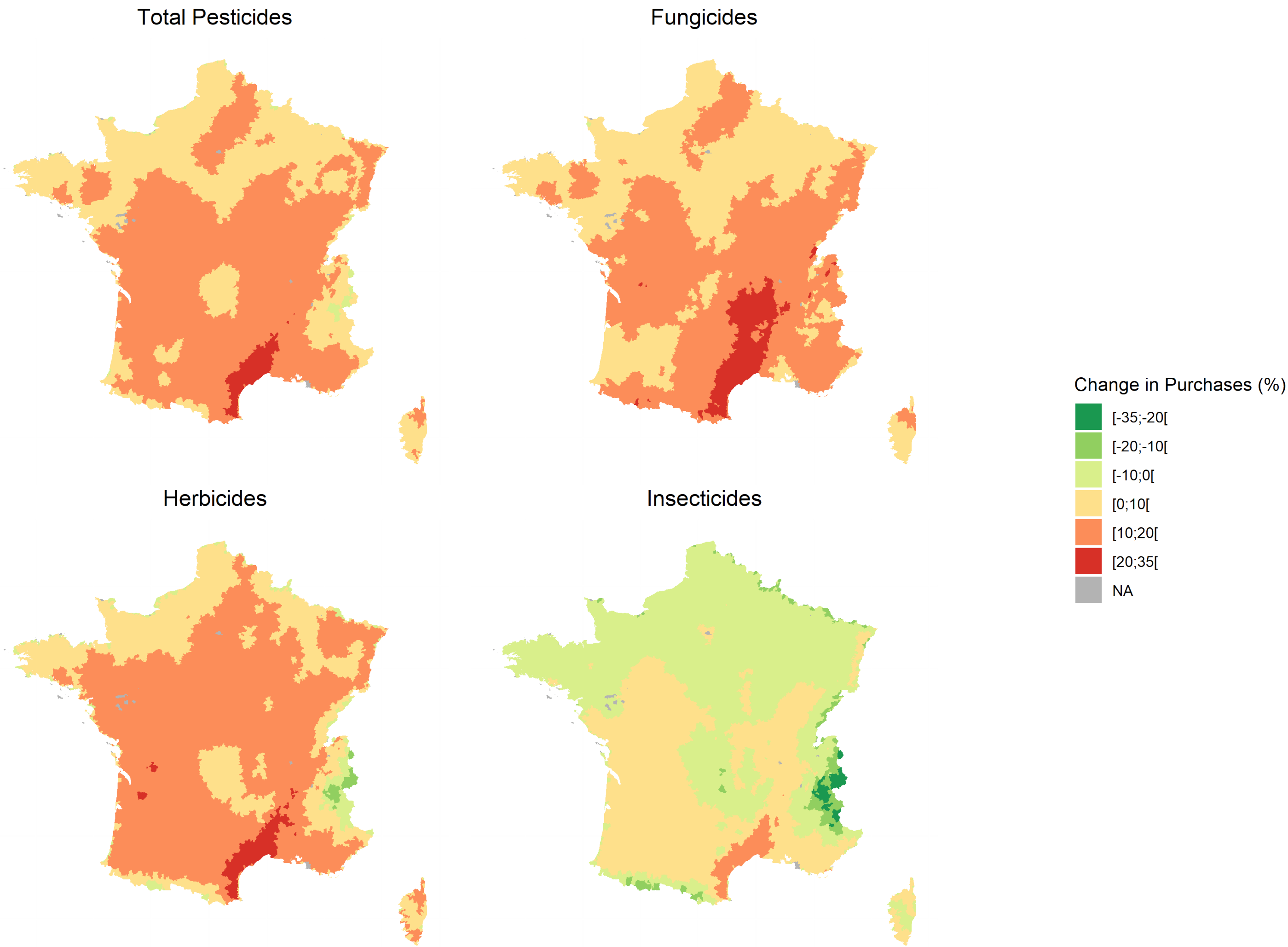


Figure 6: Pesticide use projections in 2050 under RCP4.5 climate change scenario. NOTE. Graphs display estimated changes in pesticide purchase in kg/ha if crops are exposed to hypothetical changes in temperature and precipitation during the growing season (from March 1^{st} to August 31^{th}) according to our preferred estimates and to the information provided by the ALADIN climatic model for the RCP 4.5 emission pathways scenario between 2050 and 2055. In this scenario, average temperature in France is projected to increase by 1.75°C (S.D. = 0.27°C), while average precipitation is projected to be reduced by 30mm (S.D. = 44mm).

confidence interval), while maintaining their insecticide use at average 2014-2019 levels. These effects are overall driven by the impacts of warmer temperatures. Indeed, Table 8 indicates that higher temperatures projected in the RCP4.5 scenario would increase total pesticide, fungicide and herbicide uses by about 13 to 15% (Panel B.), while precipitation changes would reduce them by about 2 to 4% (Panel C.). By comparison, the overall impact of this climate scenario on insecticides is null. This is because the small negative effects of precipitation changes on pesticide use are offset by corresponding small – but non-significant – temperature impacts. While slightly smaller in magnitude, these results are consistent when using the coefficients of the step-wise function of cumulative temperature (see columns "Cum. Temp." in Table 8). As such, the more frequent extreme heat events under RCP4.5 climate change scenario only offset a marginal part of the impacts of higher moderate temperatures.

Table 8: Projections of changes in pesticide use in 2050 under RCP4.5 climate change scenario, average effects in France (in percentages of initial use)

	Total Pesticides		**Fungicides**		**Herbicides**		**Insecticides**	
	Avg. Temp.	Cum. Temp.	Avg. Temp.	Cum. Temp.	Avg. Temp.	Cum. Temp.	Avg. Temp.	Cum. Temp.
	Panel A. Total impacts							
Changes in use (%)	11.074***	7.839***	11.028***	6.236***	11.549***	9.150**	-0.384	-1.720
	(1.761)	(1.447)	(3.760)	(2.261)	(1.680)	(2.164)	(2.943)	(2.164)
	Panel B. Temperature impacts							
Changes in use (%)	13.847***	9.720***	15.012***	9.078***	13.482***	10.261***	1.479	-0.414
	(2.133)	(1.411)	(3.760)	(2.334)	(1.680)	(1.273)	(2.942)	(2.113)
	Panel C. Precipitation impacts							
Changes in use (%)	-2.774***	-1.881***	-3.984***	-2.842***	-1.933***	-1.110**	-1.863***	-1.306**
	(0.448)	(0.468)	(0.635)	(0.616)	(0.438)	(0.461)	(0.899)	(0.598)

Note. The figures indicate the percentage changes in pesticide use under hypothetical increases in temperature and precipitation during the growing season (from March 1st to August 31th) using our preferred estimates and average RCP4.5 ALADIN projections between 2050 and 2055. Specifically, average temperature in France in this scenario is projected to increase by 1.75°C (S.D. = 0.27°C), while average precipitation is projected to be reduced by 30mm (S.D. = 44mm). Standard errors are corrected for spatial correlation using Conley (1999) and shown in brackets.

Overall, the projections presented in Figure 6 and Table 8 suggest that French farmers are expected to respond to future climate conditions of RCP4.5 scenario by 2050. This response involves an increased use of fungicides and herbicides, while maintaining the current use of insecticides. The amplified use of these chemical inputs is primarily concentrated in the southeastern region of France, specifically around the Mediterranean basin. It is important to note that the selection of this climate scenario is not intended to provide an accurate forecast of the actual pesticide outcomes in 2050. Rather, it serves the purpose of demonstrating the projected implications of our model based on a plausible climate scenario.

6 Concluding remarks

A recent and abundant literature has measured the effects of abnormal weather shocks on abnormal crop yield deviations to assess the impacts of climate change on future crop production *implicitly accounting for farmers' adaptation* (Schlenker and Roberts, 2009; Blanc and Schlenker, 2017). However, efforts to explicitly measure these adaptation behaviors have been limited in practice. This paper proposes measurements of such adaptation behaviors by focusing on pesticide use as an illustrative case. Using a novel, original and exhaustive dataset of purchase of all active substances in France, we show that farmers do react to contemporaneous temperature and precipitation changes by adjusting their pesticide use. In particular, we find that farmers react to similar weather shocks by adjusting much more their use of fungicides and herbicides than those of insecticides. Our preferred estimates indicate that a one percent increase in temperature during the growing season leads farmers to use additional +1.70% of fungicides, +1.72% of herbicides, but only +0.37% of insecticides. These results are robust to many sensitivity analyses. In particular, we show that our dependent variables – that are fundamentally data on pesticide purchases – likely represent pesticide use. Additional analyses indicate that our preferred estimates are largely driven by weather changes during spring, at the time when farmers apply pesticides, and that zip codes specialized in cereals and oilseed crops are much more sensitive to weather shocks than other regions. We also identify non-linear, concave effects, which appears close to the sample average for precipitation, but far from this point for temperature.

All our results are identified thanks to fine-grained weather shocks on spatially detailed pesticide use per pesticide types. Therefore, our results are less sensitive to aggregation biases related to the use of coarse spatial scales (Fezzi and Bateman, 2015; Damania et al., 2020). To our knowledge, we are the first to perform this kind of econometric assessment of weather impacts on pesticide use at such a detailed resolution (about 9 km $\times$ 9 km). In an attempt to summarize all our results, we show that French farmers are likely to increase aggregated pesticide use by about 15% on average by 2050 in response to a RCP4.5 climate change scenario. In details, we find that they would increase their use of herbicides and fungicides by 11%, while maintaining their insecticide use at 2014-2019 averages.

Our results are valuable for the ongoing debates among French stakeholders and policymakers about the possibility of quickly reducing pesticide applications after the introduction of the European Commission's Farm-to-Fork plan (Bareille and Gohin, 2020; Schebesta and Candel, 2020). In particular, our results indicate that climate change is expected to strengthen the incentives for farmers to use pesticides. Thus, achieving the ambitious goal of reducing pesticide use by half in Europe by 2030 will be even more challenging in the context of climate change. To successfully reduce pesticide use in the future, policymakers need to account for farmers' adaptation behaviors and adjust their policy instruments accordingly. Moreover, while most public attention and research has so far been focused on the impacts of insecticides on health and the environment, our study reveals that insecticide use is projected to remain stable in the future, but that fungicide and herbicide applications are likely to increase. Therefore, further research is required to determine the external costs that these two types of pesticide impose to society.

This paper presents some limitations that should be acknowledged. First, the identified impacts are only short-term effects and further research is necessary to identify long-term adjustments to climate change. Such long-term adaptation strategies could relate, for example, to changes in cropping areas (Cui, 2020; Bareille and Chakir, 2023), or to expansion of the total agricultural area (Graveline and Mérel, 2014). While we provide evidence that our estimates should not be really affected by these adaptation mechanisms at the extensive and super-extensive margins in the short term (see Section 4.5), such elements may affect farmers' pesticide use decisions in the longer run (Di Falco et al., 2012). An additional limitation is that we have not considered the potential combined effect of temperature and precipitation on pesticide use, despite they may be important for agricultural production (Fezzi and Bateman, 2015). Finally, our analysis does not address the toxicity and efficacy of the different active substances (Möhring et al., 2020), which however impose different external costs to society. The inclusion of such elements is necessary to improve the predictions of future pesticide use under new climate conditions and, *in fine*, improve our assessments of the costs associated with climate change.

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Appendices

A1 Data and summary statistics

Figures A1, A2 and A3 show annual deviations of pesticide use, temperature and precipitation compared to their average over the period in our final sample (after excluding for potential outliers; see Section 2.2). Figure A1 shows for example that 2018 was a particular year for pesticide purchases, with most areas specialized in cereals and oilseed crops in the Parisian basin purchasing most pesticide this particular year (see Figure 3). Our identification strategy relies on the exploitation of such particular events, by explaining abnormal deviations in pesticide purchases from location-specific averages by abnormal deviations in weather conditions. For example, Figure A2 indicates that these regions have experimented greater temperature than the remaining of France in 2018. *Ceteris paribus*, our estimates are thus likely to positively link pesticide use to temperature.

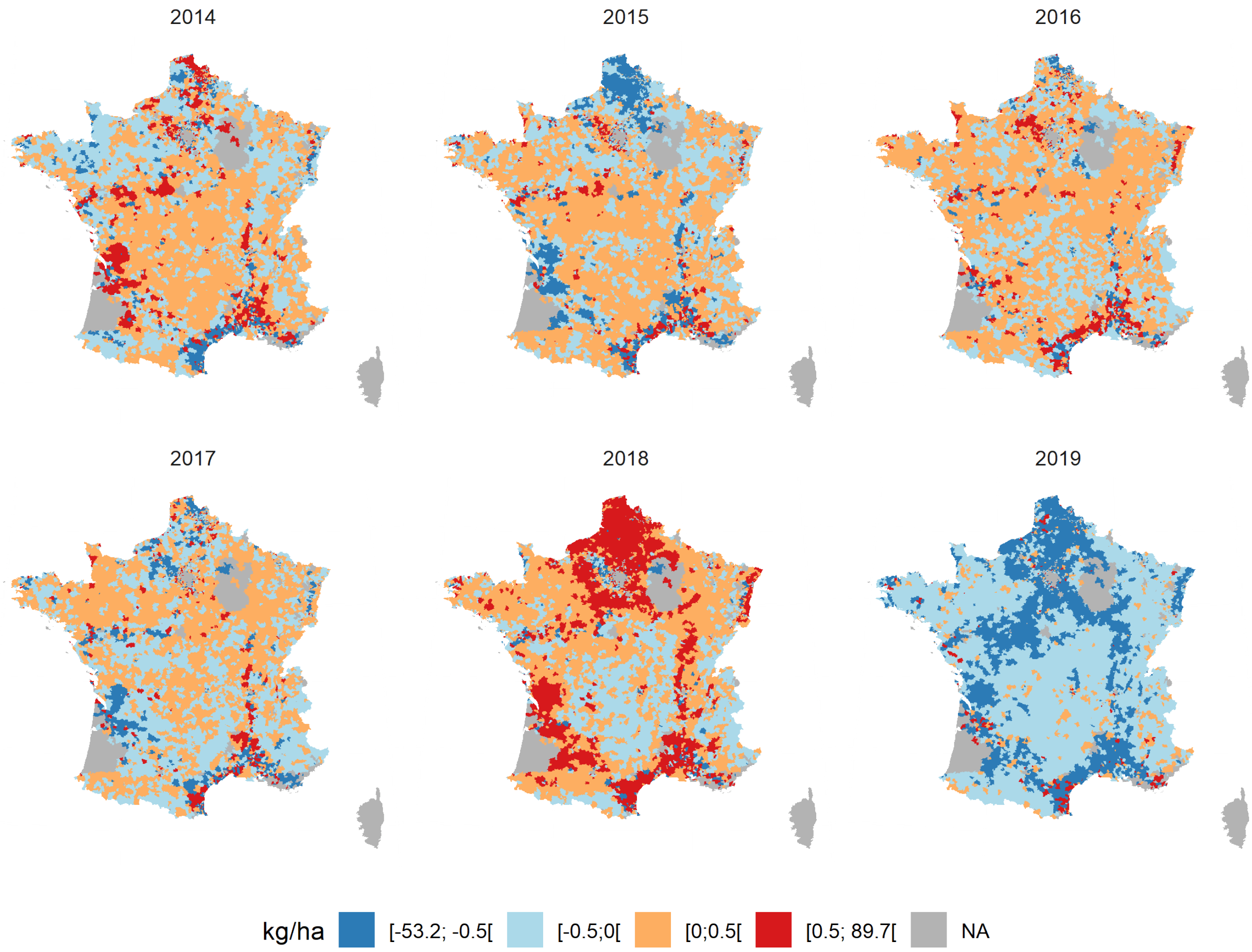


Figure A1: Annual pesticide purchase differences from 2014-2019 average. Note. The Figure displays annual deviations of pesticide purchase from location-specific averages over the 2014-2019 period.

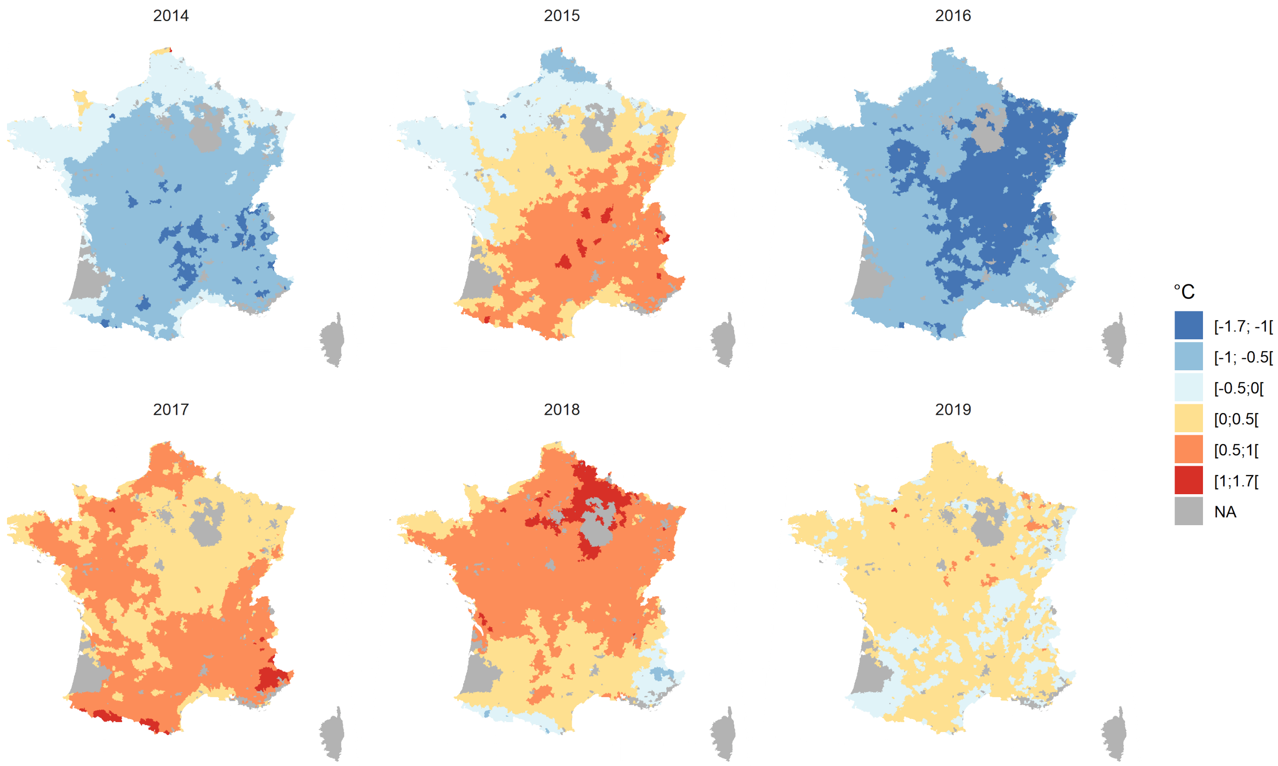


Figure A2: Annual temperature differences from 2014-2019 average. NOTE. The Figure displays annual deviations of temperature during the growing season (from March 1^{st} to August 31^{th}) from location-specific averages over the 2014-2019 period.

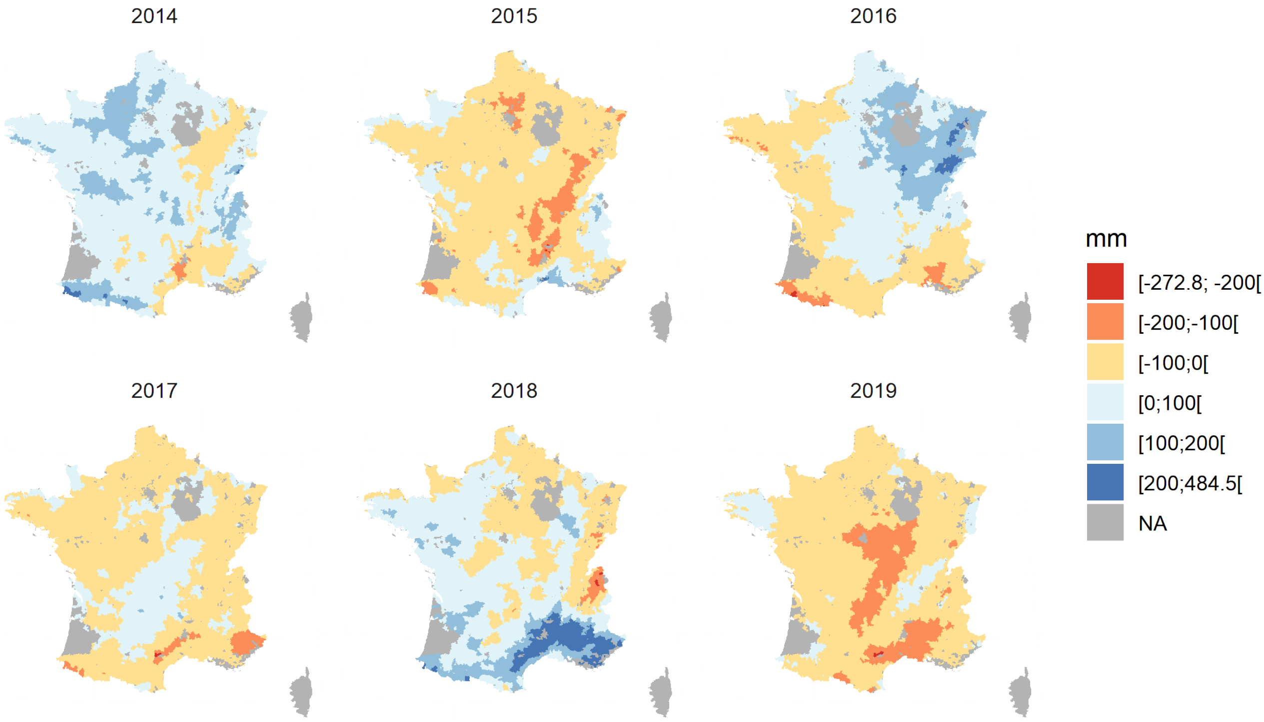


Figure A3: Annual precipitation differences from 2014-2019 average. NOTE. The Figure displays annual deviations of precipitation during the growing season (from March 1^{st} to August 31^{th}) from location-specific averages over the 2014-2019 period.

A2 Methods – Dynamic Panel Model

To further check whether farmers store pesticides or not, we estimate a dynamic panel model using equation (4):

$$\log(X^k_{i(r),t}) = \gamma^k \log(X^k_{i(r),t-1}) + \delta^k_1 \bar{T}_{i(r),t} + \delta^k_1 \bar{T}^2_{i(r),t} + \delta^k_3 \bar{P}_{i(r),t} + \delta^k_4 \bar{P}^2_{i(r),t} + \nu_{i(r)} + \mu_r(t) + \varepsilon^k_{i(r),t}, \tag{4}$$

where $X^k_{i(r),t-1}$ is the lagged pesticide purchase in zip code i and γ^k is the associated coefficient. If farmers store pesticides, and if the storage behavior is correlated with weather conditions, the estimation of equation (1) would lead to biased parameters $\hat{\boldsymbol{\beta}}^k$. In this case, the addition of the lagged dependent variable as an additional predictor as in equation (4) would remove such bias. In particular, if farmers store pesticides one year from another, γ^k should be negative, as farmers need to buy less pesticide than they actually need. The set of estimates $\hat{\boldsymbol{\delta}}^k$ is then free from the bias induced by storage.

We estimate equation (4) using Arellano and Bond (1991)'s procedure. In the presence of fixed effects, demeaning $X^k_{i(r),t-1}$ creates a correlation between the transformed lagged dependent variable and the transformed error term. One method is to use first difference instead to get rid of the individual effect. There is still correlation between the lagged value of the dependent variable and the lagged error term, but it is now possible to instrument $X^k_{i(r),t} - X^k_{i(r),t-1}$ with $X^k_{i,t-2}$. Arellano and Bond (1991) shows that the General Method of Moment (GMM) is a more efficient estimator than two stage least squares if the residuals are not serially correlated.

A3 Methods – Non-linear impacts of temperature

We present here the three types of functional form $f^k(\cdot)$ that we use for the estimation of equation (3) in Section 3. The three specifications are inspired from Schlenker and Roberts (2009).

First, we express $f^k(h)$ as a step-function for temperature with three-degree bins over the growing season. The step-function counts the number of days of the growing season between steps of three degrees Celsius of the reconstructed temperature distribution, such that: $\int_{\underline{h}}^{\bar{h}} f^k(h)\phi_{i(r),t}(h)dh = \sum_{h=\min(\mathbf{T})}^{\max(\mathbf{T})} \psi_d[\phi_{i(r),t}(h+3) - \phi_{i(r),t}(h)]$, where $\min(\mathbf{T})$ and $\max(\mathbf{T})$ are respectively the minimum and maximum temperatures observed during the growing season in the whole sample.

Second, we follow the literature and make the usual distinction between beneficial growing degree days (GDD) and harmful degree days (HDD). Indeed, one important modelling insight from Schlenker and Roberts (2009) is that growing degree days can be used to specify such a piece-wise linear relationship for temperature, which in overall terms provides a similar relationship to the step-wise function (and is easier to estimate). Formally, we compute beneficial growing degree days as $GDD_{i(r),t} = \int_{T_{base}}^{T_{max}} \min\{T - T_{base}, T_{max} - T_{base}\}\phi_{i(r),t}(T)\,dT$ with T_{base} the limit above which we start accounting for temperature, T_{max} the limit above which we stop accounting for temperature and $\phi_{i(r),t}(T)$ the reconstructed distribution of temperature during the growing season. Similarly, we compute harmful degree days as $HDD_{i(r),t} = \int_{T_{max}}^{\infty}(T - T_{max})\phi_{i(r),t}(T)\,dT$. Schlenker and Roberts (2009) clearly identified the threshold above which temperature starts reducing yields due to heat stress (29°C-33°C depending on areas), the definition of the threshold T_{max} that would have a negative impact on pest abundance has not been studied in the literature to our knowledge. In our case, we try using all possible thresholds T_{base} and T_{max} and pick those with the best fit.

Finally, the last specification assumes that $f^k(\cdot)$ is an 8^{th} order Chebychev polynomial of the form $f(h) = \sum_{j=1}^{8} \omega_j T_j(h)$, where $T_j(h)$ is the j^{th} order Chebyshev polynomial. Such a specification should allow us to estimate smoother relationships between temperatures and pesticide use.

A4 Results – Baseline estimates

Table A1 presents the WLS estimates of equations (1) obtained for fungicide, herbicide and insecticide use, as well as aggregated pesticide use when using our preferred estimates (obtained with individual fixed effects and regional time trends.

Table A1: Impacts of average weather conditions during the growing season on pesticide use

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	0.004	0.144	-0.146*	-0.252
	(0.120)	(0.220)	(0.085)	(0.171)
Squared Average Temperature	0.003	-0.001	0.008**	0.008*
	(0.004)	(0.007)	(0.003)	(0.005)
Total Precipitation	0.002***	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000***	-0.000***	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Regional Time Trends	Yes	Yes	Yes	Yes
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Adjusted R^2	0.962	0.947	0.958	0.886
Number of observations	28,824	28,080	28,698	27,918

Note. The figures report the WLS estimates of weather conditions during the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare (applied to the adjuted UAA, corrected for the area under permanent grasslands and fallows). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using Conley's (1999) correction and are reported in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A5 Sensitivity analysis – Spatial aggregation

Table A2 presents the WLS estimates of equations (1) obtained for all pesticide types when we aggregate the data at the PRA and department levels. The estimates remain very close to our preferred estimates in Table A1.

Table A2: Impacts of average weather conditions during the growing season on pesticide use using the aggregated data at the PRA and department level

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	Panel A. Aggregation at *petite région agricole* level			
Average Temperature	0.017	0.247*	-0.082	-0.276***
	(0.081)	(0.140)	(0.079)	(0.104)
Squared Average Temperature	0.002	-0.005	0.005**	0.009***
	(0.003)	(0.004)	(0.002)	(0.003)
Total Precipitation	0.002***	0.002***	0.001***	0.001
	(0.000)	(0.001)	(0.000)	(0.0006)
Squared Total Precipitation	-0.000***	-0.000**	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Regional Time Trends	Yes	Yes	Yes	Yes
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Adjusted R^2	0.977	0.971	0.978	0.931
Number of observations	3,930	3,912	3,930	3,924
	Panel B. Aggregation at *department* level			
Average Temperature	-0.063	0.061	-0.130	-0.233
	(0.120)	(0.155)	(0.114)	(0.205)
Squared Average Temperature	0.005	0.0002	0.007**	0.009
	(0.004)	(0.005)	(0.003)	(0.006)
Total Precipitation	0.010**	0.009	0.010**	0.011*
	(0.005)	(0.006)	(0.004)	(0.006)
Squared Total Precipitation	-0.0004**	-0.0003	-0.0004**	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Regional Time Trends	Yes	Yes	Yes	Yes
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Adjusted R^2	0.957	0.963	0.959	0.923
Number of observations	540	540	540	540

Note. The figures report the WLS estimates of weather conditions during the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare (applied to the adjusted UAA, corrected for the area under permanent grasslands and fallows). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using Conley's (1999) correction and are reported in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A6 Sensitivity analysis – Banned Pesticides and glyphosate.

Table A3 presents the weather elasticities of pesticide use when removing banned pesticides (announced or hinted). Table ?? presents the recomputed elasticities. Specifically, columns 1 to 4 of Table A3 present the estimates of the average growing season temperature and precipitation on pesticide use where we restrict our sample to pesticides that remained authorized during the entire period. Some active substances (N=24) have indeed been banned, which may induce farmers to buy more pesticide to store them for future use. Even though glyphosate had not been formally suspended, the ongoing debate about a future ban could also have led farmers to stock products containing this active substance. We also present our results for total pesticides and herbicides without glyphosate in Columns 5 and 6 of both tables.

Our results are consistent with our main specification, confirming that farmers' anticipation of bans affecting active substances is not a major issue in our study. They confirm the non-linear effect of temperature on fungicide use and the non-linear effect of rainfall on each type of pesticide. The elasticities are also of similar sign and magnitude as with our preferred specification. Looking at herbicide use without glyphosate, elasticities are lower than when only banned active substances are excluded, confirming the widespread use of this active substance.

Table A3: Impacts of average weather conditions during the growing season on pesticide use, excluding banned pesticides and glyphosate

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**	**All Pesticides**	**Herbicides**
	NO BANNED ACTIVE SUBSTANCE				NO GLYPHOSATE	
Average Temperature	0.006	0.157	-0.144*	-0.252	-0.088	-0.243***
	(0.120)	(0.219)	(0.085)	(0.171)	(0.156)	(0.095)
Squared Average Temperature	0.003	-0.002	0.008***	0.008*	0.006	0.011***
	(0.004)	(0.007)	(0.003)	(0.003)	(0.005)	(0.003)
Total Precipitation	0.002***	0.003***	0.001***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000***	-0.000***	-0.000*	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	No	No	No	No	No	No
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.962	0.948	0.957	0.886	0.961	0.959
Number of observations	28,824	28,080	28,698	27,918	28,800	28,578

NOTE. The figures report the WLS estimates of weather conditions during the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare (related to adjusted UAA, corrected for the area under permanent grasslands and fallows). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using the Conley (1999) correction and are shown in brackets.

A7 Sensitivity analysis – Temporal aggregation

Table A4 presents the estimates for the average temperature and total precipitation using the sum of contemporaneous and one-time lagged pesticide purchases as dependent variable. Compared to our preferred analysis, the form of the relationships between pesticide use and weather conditions change for both temperature and average. In case of temperature, the relation turns from a positive and linear relationship towards a positive concave one. One the contrary, the relation between pesticide use and precipitation turns from a positive concave relationship towards a positive and linear one.

Table A4: Impacts of average weather conditions during the growing season using using two years moving average of pesticide purchase

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperatures	0.120**	0.204**	0.113**	0.031
	(0.050)	(0.087)	(0.056)	(0.088)
Squared Average Temperatures	-0.002	-0.005*	-0.002	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Total Precipitation	0.000*	0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	No	No	No	No
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes
Adjusted R^2	0.984	0.978	0.984	0.934
Number of observations	24,020	23,400	23,915	23,265

NOTE. The figures report the WLS estimates of weather conditions during the growing season on the log transformation of two years moving average of pesticide use expressed in kilograms per hectare (applied to the adjusted UAA, corrected for the area under permanent grasslands and fallows). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using Conley's (1999) correction and are reported in brackets.

A8 Sensitivity analysis – Dynamic panel model

Table A5 presents the estimates for the average temperature and total precipitation using the dynamic panel model (Arellano and Bond, 1991) presented in equation 4 in appendix A2. Table **??** shows the recomputed elasticities. The coefficient of the lagged pesticide variable are negative, as expected, but close to zero. Elasticities all show that an increase in average temperature and precipitation positively influences each type of pesticide use, which confirm that storage is not a major issue in our study.

A possible issue with the estimation of equation (4) is that we drop the first year of the panel, we cannot weight the observations by their corrected UAA, and we can not use Conley's (1999) correction. We thus compare the $\hat{\boldsymbol{\delta}}^k$ obtained with the estimation of equation (4) to the $\hat{\boldsymbol{\beta}}^k$ obtained with the OLS estimation of equation (1) after dropping the first year of the panel. The existence of a bias due to storage of pesticide from one year to another would be indicated by differences between $\hat{\boldsymbol{\delta}}^k$ and $\hat{\boldsymbol{\beta}}^k$. We present the recomputed elasticities from this comparable OLS model in Table A6. We obtain elasticities that are similar and which confirm results from our preferred specification.

Table A5: Dynamic impacts of average weather conditions during the growing season on pesticide use using Arellano and Bond (1991)

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Lagged Pesticides	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Average Temperature	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Average Temperature	0.002***	0.001***	0.002***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Precipitation	0.002***	0.002***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trend	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No

NOTE. The figures report the GMM estimates of weather conditions for the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare related to adjusted UAA (corrected for the area under permanent grasslands and fallows). Standard errors are reported in brackets.

Table A6: Weather elasticities of pesticide use obtained with the OLS model on 2015-2019

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	1.554***	1.045***	1.391***	0.179***
	(0.048)	(0.045)	(0.039)	(0.032)
Total Precipitation	0.363***	0.328***	0.234***	0.064***
	(0.009)	(0.009)	(0.007)	(0.008)

NOTE. Elasticities are computed at sample mean values using WLS estimates with equation (2) for the period 2015-2019. Underlying estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A9 Sensitivity analysis – TWFE

Tables A7 presents the estimates of temperature and precipitation during the growing season on pesticide use using time fixed effects instead on regional time trends in equation (1). Tables A8 presents the recomputed elasticities. Our results are consistent with our main specification. They confirm the non-linear effect of precipitation on pesticide use. Temperature has a non-significant concave effect on pesticide use with year fixed effects. The elasticities are lower and less precisely estimated for all types of pesticide, and sometimes of opposite sign. For example, the effect of precipitation on herbicide use is of opposite sign (significant at the 5% statistical level).

Table A7: Impacts of average weather conditions during the growing season using TWFE

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperatures	0.114	0.261	0.019	-0.043
	(0.120)	(0.228)	(0.085)	(0.190)
Squared Average Temperatures	-0.004	-0.007	-0.001	-0.001
	(0.003)	(0.007)	(0.003)	(0.005)
Total Precipitation	0.001*	0.001***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trends	No	No	No	No
Adjusted R^2	0.967	0.950	0.962	0.883
Number of observations	28,824	28,080	28,698	27,918

NOTE. The figures report the TWFE estimates of weather conditions during the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare (applied to the adjusted UAA, corrected for the area under permanent grassland and fallow). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using Conley's (1999) correction and are reported in brackets.

Table A8: Elasticities of the impact of average weather conditions during the growing season on pesticide use using TWFE

	All pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	-0.042	0.608	-0.137	-1.164**
	(0.390)	(0.593)	(0.340)	(0.573)
Total Precipitation	0.021	0.126***	-0.088***	0.159***
	(0.032)	(0.050)	(0.030)	(0.051)

NOTE. Elasticities are computed at sample mean values using TWFE estimates and equation (2). The standard errors are clustered at the zip code leveland corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and displayed in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A10 Sensitivity analysis – Total useful agricultural area

Table A9 presents the estimates of the growing season average temperature and precipitation using as dependent variable pesticide use divided by total UAA (instead of the UAA adjusted for permanent grasslands and fallows; see Section 3). Table A10 presents the recomputed elasticities. The results are again close to those obtained with our main specification. They confirm the non-linear effect of temperature on fungicide and the non-linear effect of rainfall on each type of pesticide. The elasticities also have similar signs and magnitudes to the main specification.

Table A9: Impacts of average weather conditions during the growing season on pesticide use related to the whole UAA

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	-0.77	0.076	-0.210***	-0.357**
	(0.096)	(0.180)	(0.075)	(0.161)
Squared Average Temperature	0.005*	0.001	0.010***	0.012**
	(0.003)	(0.005)	(0.002)	(0.005)
Total Precipitation	0.001***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000**	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	No	No	No	No
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes
Adjusted R^2	0.967	0.955	0.962	0.900
Number of observations	28,824	28,080	28,698	27,918

NOTE. The figures report the WLS estimates of weather conditions during the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare (related to the entire UAA, including fallow and grassland). Estimates are weighted by the zip code UAA. Standard errors account for spatial correlation using the Conley (1999) correction and are shown in brackets.

Table A10: Elasticities of the impact of average weather conditions during the growing season on pesticide use related to the whole UAA

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	1.594***	1.506***	1.662***	0.329*
	(0.127)	(0.196)	(0.121)	(0.176)
Total Precipitation	0.360***	0.510***	0.251***	0.253***
	(0.026)	(0.041)	(0.024)	(0.040)

NOTE. Elasticities are computed at sample mean values using WLS estimates and equation (2). The standard errors are clustered at the zip code level and corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A11 Sensitivity analysis – All zip codes

Tables A11, A12 present the estimates of the average growing season temperature and precipitation using the entire sample, including zip codes with less than 10% of UAA. The results are again close to those obtained with our preferred specification. They confirm the non-linear effect of temperature on fungicide use and the non linear effect of rainfall on each pesticide type. The elasticities also have similar signs and magnitudes to the main specification.

Table A11: Impacts of average weather conditions during the growing season using our basic WLS specification with all zip codes.

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	0.004	0.141	0.140*	-0.272
	(0.119)	(0.218)	(0.084)	(0.170)
Squared Average Temperature	0.003	-0.001	0.008***	0.009*
	(0.004)	(0.007)	(0.003)	(0.005)
Total Precipitation	0.002***	0.003***	0.001*	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000***	-0.000**	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	No	No	No	No
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes
Adjusted R^2	0.960	0.947	0.956	0.883
Number of observations	31,786	30,507	31,512	30,390

NOTE.The figures report the WLS estimates of weather conditions for the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare related to adjusted UAA (corrected for the area under permanent grasslands and fallows). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using Conley's (1999) correction and are reported in brackets.

Table A12: Elasticities of the impact of average weather conditions during the growing season on pesticide use using our basic WLS specification with all zip codes

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	1.701***	1.735***	1.757***	0.471***
	(0.140)	(0.219)	(0.127)	(0.177)
Total Precipitation	0.361***	0.519***	0.253***	0.249***
	(0.026)	(0.042)	(0.023)	(0.038)

NOTE. Elasticities are computed at sample mean values using WLS estimates and equation (2). The standard errors are clustered at the zip code leveland corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and displayed in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A12 Sensitivity analysis – Inverse hyperbolic sine, including zip codes with no pesticide purchases

Tables A13 and A14 present the WLS estimates and recomputed weather elasticities using pesticide purchases expressed under the hyperbolic sine transformation – instead of the logarithm transformation – as the dependent variable. The interest of such a transformation is that it allows to include zip codes with null pesticide purchases (something that we cannot in our preferred analysis with the logarithmic transformation). The results are similar to those obtained with our main specification using the logarithmic transformation of pesticide purchases.

Table A13: Impacts of average weather conditions during the growing season on pesticide use obtained with the hyperbolic sine transformation

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	0.060	0.139***	0.020	-0.018
	(0.049)	(0.049)	(0.040)	(0.015)
Squared Average Temperature	0.001	-0.003*	0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Total Precipitation	0.002***	0.002***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000**	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	No	No	No	No
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes
Adjusted R^2	0.940	0.950	0.902	0.762
Number of observations	29,160	29,160	29,160	29,160

NOTE. The figures report the WLS estimates of weather conditions during the growing season on the hyperbolic sine transformation of pesticide use expressed in kilograms per hectare (related to the adjusted UAA, excluding fallow and grassland). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using the Conley (1999) correction and are shown in brackets.

Table A14: Elasticities of the impact of average weather conditions during the growing season on pesticide use obtained with hyperbolic sine transformation

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	1.318***	0.873***	1.216***	0.073*
	(0.121)	(0.130)	(0.096)	(0.038)
Total Precipitation	0.303***	0.312***	0.174***	0.055***
	(0.024)	(0.028)	(0.018)	(0.009)

NOTE. Elasticities are computed at sample mean values using WLS estimates and adjusted equation (2) for the inverse hyperbolic sine transformation. The standard errors are clustered at the zip code level and corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A13 Sensitivity analysis – Linear form

Tables A15 and A16 present the WLS estimates and recomputed weather elasticities using pesticide use in linear form as the dependent variable. The interest of such a linear transformation is that it allows to include zip codes with null pesticide purchases (something that we cannot in our preferred analysis with the logarithmic transformation). The results are similar to those obtained with our main specification using the logarithmic transformation of pesticide use. They confirm the positive concave effect of rainfall on each type of pesticide. The elasticities are overall similar to those obtained in Table 2.

Table A15: Impacts of average weather conditions during the growing season on pesticide use in linear form

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	0.701**	0.629***	0.067	-0.030
	(0.294)	(0.200)	(0.078)	(0.036)
Squared Average Temperature	-0.013	-0.016***	0.002	0.001
	(0.009)	(0.006)	(0.002)	(0.001)
Total Precipitation	0.009***	0.006***	0.002***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Squared Total Precipitation	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	No	No	No	No
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes
Adjusted R^2	0.837	0.870	0.830	0.640
Number of observations	29,160	29,160	29,160	29,160

NOTE. The figures report the estimates of weather conditions during the growing season on pesticide use expressed in kilograms per hectare (related to adjusted UAA, corrected for area under permanent grasslands and fallows). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using the Conley (1999) correction and are shown in brackets.

Table A16: Weather elasticities of pesticide use obtained using linear form

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Average Temperature	1.218**	0.868**	1.789***	0.368*
	(0.156)	(0.190)	(0.157)	(0.230)
Total Precipitation	0.404**	0.537***	0.256***	0.208***
	(0.042)	(0.069)	(0.027)	(0.056)

NOTE. Elasticities are computed at sample mean values using WLS estimates and adjusted equation (2) for the linear transformation. The standard errors are clustered at the zip code level and corrected for spatial dependence using the Conley spatially-robust correction. Standard errors are computed using the delta method and shown in brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

A14 Heterogeneity analysis – Within the growing season

Table A17 presents the estimates for the average temperature and total precipitation across seasons. Parameters from the WLS analysis confirms the non-linear precipitation effects.

Table A17: Impacts of average weather conditions on pesticide use during the two stages of the growing season, pre season and post season

	Total Pesticides	Fungicides	Herbicides	Insecticides
	A. December-February (Pre-season)			
Average Temperature	-0.044**	-0.037	-0.069***	-0.046
	(0.019)	(0.030)	(0.016)	(0.034)
Squared Average Temperature	0.003***	0.003**	0.004***	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Total Precipitation	0.001***	0.001***	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	B. March-May			
Average Temperature	0.178***	0.290**	0.055	-0.208
	(0.068)	(0.128)	(0.058)	(0.152)
Squared Average Temperature	-0.003	-0.007	0.001	0.008
	(0.003)	(0.005)	(0.003)	(0.006)
Total Precipitation	0.001***	0.003***	0.001***	0.001***
	(0.000)	(0.001)	(0.00)	(0.000)
Squared Total Precipitation	-0.000**	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
	C. June-August			
Average Temperature	-0.231**	-0.296*	0.196**	0.386*
	(0.092)	(0.179)	(0.081)	(0.208)
Squared Average Temperature	0.006***	0.007*	0.005***	-0.009*
	(0.002)	(0.004)	(0.002)	(0.005)
Total Precipitation	0.001**	0.001	0.001***	0.001*
	(0.000)	(0.001)	(0.000)	(0.001)
Squared Total Precipitation	-0.000	-0.000	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	D. September-November (Post-season)			
Average Temperature	-0.099	-0.217**	-0.025	0.175
	(0.078)	(0.097)	(0.077)	(0.116)
Squared Average Temperature	0.003	0.007**	-0.000	-0.008*
	(0.003)	(0.003)	(0.003)	(0.004)
Total Precipitation	-0.001***	-0.001***	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	0.000***	0.000***	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trend	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No o
Adjusted R^2	0.968	0.949	0.965	0.889
Number of observations	29,429	28,536	29,285	28,374

NOTE. The figures report the weighted least square estimates of weather conditions for the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare related to adjusted UAA (corrected for area under permanent grassland and fallow). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using the Conley (1999)'s correction and are shown in brackets.

A15 Heterogeneity analysis – Across types of agriculture

Table A18 presents the WLS estimates of the average temperature and precipitation during the growing season on pesticide use according to farm specialization of the zip codes. We confirm the non-linear effect of rainfall on each type of pesticide and each type of agricultural specialization.

Table A18: Impacts of average weather conditions during the growing season on pesticide purchase according to farm specialization

	Total Pesticides	**Fungicides**	**Herbicides**	**Insecticides**	**Total Pesticides**	**Fungicides**	**Herbicides**	**Insecticides**
	Cereal and Oiseed Crops				**Feedcrops and Pasture**			
Average Temperature	0.315*	0.632***	0.196	-0.257	-0.026	0.069	-0.201**	-0.311
	(0.162)	(0.234)	(0.141)	(0.158)	(0.155)	(0.323)	(0.091)	(0.246)
Squared Average Temperature	-0.005	-0.014**	-0.002	0.008*	0.003	-0.000	0.009***	0.011
	(0.005	(0.007)	(0.004)	(0.004)	(0.005	(0.010)	(0.003)	(0.007)
Total Precipitation	0.003***	0.005***	0.002***	0.001	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Squared Total Precipitation	-0.000***	-0.000***	-0.000***	-0.000	-0.000*	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average use (kg/ha)	3.580	1.259	1.714	0.309	2.472	1.221	0.810	0.290
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No	No	No	No
Adjusted R^2	0.863	0.895	0.783	0.760	0.964	0.939	0.959	0.889
Number of observations	15,216	15,060	15,180	15,006	12.042	11.466	11.952	11.346
	Fruit and affiliated				**Wine production**			
Average Temperature	0.621***	-0.003	0.064	1.13***	-0.081	-0.218	0.605***	0.998
	(0.230)	(0.271)	(0.387)	(0.428)	(0.261)	(0.267)	(0.228)	(0.644)
Squared Average Temperature	-0.015**	-0.001	0.001	-0.026**	0.001	0.005	-0.016***	-0.024
	(0.006)	(0.007)	(0.010)	(0.011)	(0.007)	(0.007)	(0.006)	(0.016)
Total Precipitation	0.001***	0.001***	0.001***	0.000	0.003***	0.003***	0.002***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)
Squared Total Precipitation	-0.000**	0.000***	-0.000***	-0.000	-0.000**	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average use (kg/ha)	15.58	7.18	1.41	6.38	17.27	14.71	1.57	0.47
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.948	0.952	0.934	0.908	0.741	0.737	0.777	0.655
Number of observations	294	282	294	294	1,272	1,272	1,272	1,272

NOTE. The figures report the WLS estimates of weather conditions during the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare related to adjusted UAA (corrected for area under permanent grasslands and fallows). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using the Conley (1999) correction and are shown in brackets.

A16 Non-Linear impacts of temperature

Table A19 shows estimates of the non-linear effects of temperature on pesticide use using step-wise functions, with marginal effects reported in Figure 5 of Section 4. Additional growing degree days from 0 to 33°C have a positive but weak effect on each type of pesticide use, while additional degree days from 33°C have a negative effect on each type of pesticide use. We confirm the non-linear effect of precipitation on each type of pesticide.

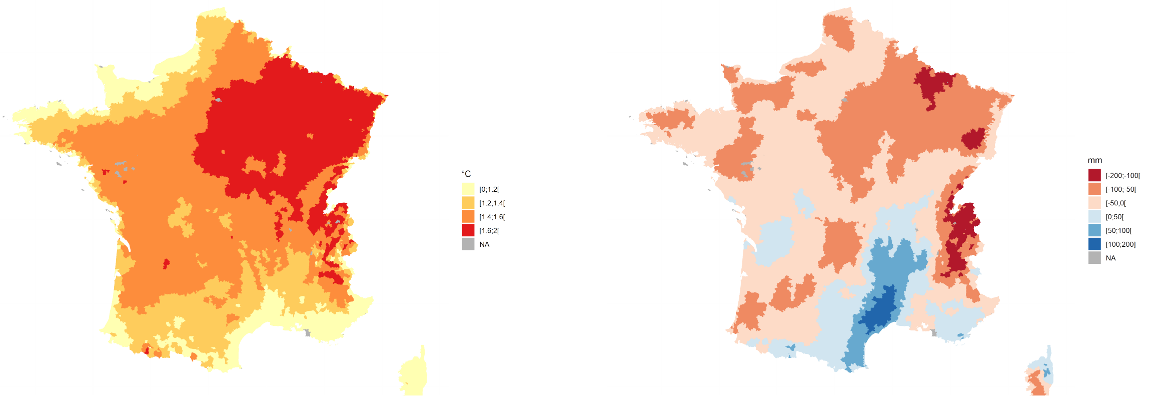
Table A19: Non Linear impacts of temperature during the growing season on pesticide use using step-wise functions

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
Beneficial Degree Days	0.001***	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Killing Degree Days	-0.034***	-0.042***	-0.033***	-0.024***
	(0.003)	(0.004)	(0.003)	(0.005)
Total Precipitation	0.001***	0.002***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared Total Precipitation	-0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Zip-Code Fixed Effects	Yes	Yes	Yes	Yes
Regional Time Trend	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Adjusted R^2	0.963	0.949	0.959	0.887
Number of observations	28,824	28,080	28,698	27,918

NOTE. The figures report the estimates of weather conditions during the growing season on the log transformation of pesticide purchases expressed in kilograms per hectare related to adjusted UAA (corected for the area under permanent grassland and fallow). Estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). Standard errors account for spatial correlation using the Conley (1999) correction and are shown in brackets.

A17 Simulations – temperature and precipitation conditions in 2050

Figure A4 presents the average daily temperature and the cumulative precipitation during the growing season (from March 1st to August 31th) between 2050 and 2055 using the information provided by the ALADIN climatic model for the RCP 4.5 emission pathways scenario. It shows that temperature will increase over the whole of France, notably in the eastern parts. By comparison, precipitation changes are much more heterogeneous, with most locations that will experience a decrease of rainfall, but regions in the south-east, along the Rhone basin, will experience large increase in precipitation.



a) Temperature b) Precipitation

Figure A4: Projected temperature and precipitation conditions during the growing season (March 1st to August 31th) in 2050. NOTE. The Figure displays average temperature and precipitation conditions between 2050 and 2055 using the projections of RCP 4.5 emission pathway as predicted by the ALADIN climate model of Météo-France. The missing value corresponds to zip codes having missing data for 2014-2019. For zip codes with missing data for one to four years, we calculated a moving average of temperature and precipitation.