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Abstract

This paper investigates whether farmers adapt their pesticide use to cope with weather shocks. Using a unique, exhaustive dataset detailing all active substance purchases per zip code in France between 2014 and 2019, we econometrically explain pesticide purchase deviations by weather shocks. We identify heterogeneous weather impacts across pesticide types, seasons and locations. Because our analyses suggest limited year-to-year pesticide storage and farmers' adaptation along other margins, we interpret our estimates as true weather impacts on pesticide use. Our preferred estimates suggest that, *ceteris paribus*, farmers increase pesticide use by 7%-15% in 2050 under a RCP4.5 climate change scenario.

Keywords: adaptation, climate change, crop protection, weather, within-season adjustments.

JEL Codes: Q12, Q53, Q54

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1 Introduction

Pests constitute a serious threat to global food security, reducing crop yields by about a third worldwide (Oerke, 2006). Protecting crops from pest damage is thus a critical aspect of farmers' job. Among the possible strategies to limit pest pressure, pesticide use is now favoured by most farmers throughout the world (Wuepper et al., 2023). Although pesticides have helped increase crop yields and farmers' incomes, their use often results in external costs to society (Dias et al., 2023). Scientific evidence highlights negative impacts of pesticides on farmers' health (Alavanja et al., 2003) and biodiversity (Beketov et al., 2013), but also potentially on consumers' health (Baudry et al., 2018; Calzada et al., 2023; Dias et al., 2023; Fletcher and Noghanibehambari, 2023). In light of this evidence, policymakers from most countries seek to regulate pesticide use (Finger et al., 2017). For example, the Farm to Fork and Biodiversity Strategies aim to halve both the use of and risk from chemical pesticides by 2030 in the EU (Schebesta and Candel, 2020). While already ambitious, these objectives may be even harder to achieve in the context of climate change (IPPC, 2021). Indeed, because climate change will affect the spatial distribution of pests and diseases (Deutsch et al., 2018), but also stimulate pests to occur earlier in the growing season (Delcour et al., 2015), rational farmers are expected to adapt their pesticide use to new climate conditions.

This paper examines whether such short-term adaptation behavior have already occurred in recent years, using temporary weather deviations from averages – i.e. "weather shocks" – to infer plausible climate change impacts. Specifically, our objective is to econometrically identify how farmers adjust their pesticide use to weather shocks. To achieve this, we approximate pesticide use by their purchase and use an original, exhaustive database detailing purchased quantities of *all* active substances used as pesticides in France between 2014 and 2019 at the level of buyers' *zip code*. Using classification of active substances, we aggregate these purchases into three categories (insecticides, herbicides and fungicides), and separately run our 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 fine spatial resolution (a French zip code typically represents an area of about 9 km $\times$ 9 km). It enables us to provide original quantitative insights into how farmers adapt their crop practices to weather shocks, with little concern for potential aggregation biases (Fezzi and Bateman, 2015; Damania et al., 2020).

There are several reasons why farmers might adjust their pesticide use to weather shocks. The agronomic literature provides at least three elements. First, weather affects the temporal and spatial distribution of pests (IPPC, 2021). Weather shocks can thus modify pest pressure and related damage to agriculture (Kawasaki, 2023). Second, weather affects pesticide efficacy (Delcour et al., 2015). As such, weather shocks are likely to affect the quantity of pesticide necessary to reduce pest damage. Third, weather affects crop yields through modifications of numerous biophysical processes governing plant growth (Asseng et al., 2015). That is, weather shocks can directly impact farmers' attainable crop yields, changing the implicit value of the production to protect and, ultimately, farmers' pesticide applications.

Following the standards of the literature examining weather impacts on agricultural outcomes (Blanc and Schlenker, 2017), our methodology exploits plausibly exogenous weather shocks to explain abnormal deviations in pesticide purchases. Our preferred specification is a reduced-form estimation of annual pesticide purchases by farmers in the zip code by linear and quadratic terms of average temperature and precipitation during the growing season, conditional on zip code fixed effects and regional time trends. According to the literature, such estimates represent plausible causal impacts of weather on pesticide purchases (Blanc and Schlenker, 2017). We test the robustness of these estimates to several alternative empirical specifications, sub-samples and alternative mechanisms. We also investigate the non-linearity of the farmers' responses to temperature using more flexible functional forms inspired by Schlenker and Roberts (2009).

All of our results show that farmers adjust their pesticide use in response to weather shocks. However, they adjust insecticides, herbicides and fungicides differently. Our preferred estimates using average temperature during the growing season indicate that a one percent temperature increase leads farmers to purchase an additional +1.70% of fungicides, +1.72% of herbicides, but only +0.37% of insecticides. Because our analyses suggest limited year-to-year pesticide storage and farmers' adaptation along other margins,[1] we interpret these estimates as causal impacts of weather on pesticide use at the intensive margin (rather than just purchases).[2] These findings align with agronomic knowledge and remain robust to our numerous sensitivity analyses. Heterogeneity analyses reveal that our preferred estimates for fungicides and herbicides are primarily driven by weather shocks occurring during spring, in the first half of the growing season. They also show that zip codes specializing in cereals exhibit higher sensitivity to weather shocks than others. We also document heterogeneous weather impacts depending on pesticide toxicity, with the farmers' use of the most harmful herbicides and insecticides responding more to weather shocks than less damaging ones. Finally, our more flexible analyses show that pesticide use weakly increases with moderate temperatures but strongly decreases with extreme heat. This sharp piece-wise relationship between temperature and pesticide use significantly differs from that for precipitation, which exhibits a smoother concave relationship.

By investigating whether French farmers adjust their pesticide use to weather shocks, we contribute to three bodies of literature. On the one hand, we contribute to the recent economic literature exploiting weather shocks to assess 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 Bareille and Chakir (2023) have studied pesticide use as a particular adaptation strategy in this context. Based on individual-level data, the two studies found that farmers are indeed likely to adjust their pesticide applications in response to weather shocks, even if most of their estimates are small or non-significant. We extend their results in several aspects, thanks to three elements related to the quality of our data. First, we can distinguish pesticides depending on their targets to separately measure fungicide, herbicide and insecticide purchases. Through this classification, we uncover heterogeneous weather impacts

[1] Specifically, we exclude the idea that our estimates could reflect changes in total agricultural area or in crop allocation towards pesticide-intensive crops. Using Graveline and Mérel (2014)'s vocabulary, our estimates do not encompass adaptation mechanisms at the extensive or super-extensive margins, on top of those at the intensive margin.

[2] They specifically represent the combined effects of weather on pest pressure, pesticide efficacy and attainable yields.

on the use of different pesticide categories, which remain otherwise obscured when analyzing aggregate pesticide use (as in the aforementioned studies). Second, we account for the whole *within-day* temperature distribution on top of averages, which allows us to distinguish heterogeneous temperature impacts across the distribution. Finally, our study is likely to have higher external validity than those of Jagnani et al. (2021) and Bareille and Chakir (2023), as we account for *all* French farmers' purchases, and not only for surveyed households in a sample of villages or in a particular region. Overall, we find stronger farmers' pesticide use responses to weather shocks than in Bareille and Chakir (2023) – by a factor of about five.[3]

On the other hand, we contribute to the more interdisciplinary literature on the drivers of pesticide use, such as landscape structure (Larsen and McComb, 2021), agricultural specialization (Wuepper et al., 2023) or prices and policies (Femenia and Letort, 2016; Finger et al., 2017). In particular, given the dependency of pest abundance on temperature and precipitation, some papers have already investigated how pesticide use and purchase evolve with weather. For example, Chen and McCarl (2001) found that crop-specific pesticide purchases *aggregated at the US state level* increase with temperature and precipitation. Still at the US state level, Rhodes and McCarl (2020) found 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) explained farmers' insecticide applications in US counties and Swiss fields respectively, and both found that extreme temperatures decrease farmers' insecticide applications. We add to these studies by using detailed and exhaustive data on *all* active substances purchased by farmers (not only insecticides), measured at a fine-grained spatial resolution. In this manner, we notably confirm the results of Larsen and McComb (2021) and Möhring et al. (2022) that extreme heat has strong negative impacts on insecticide use, but extend this striking result to fungicides and herbicides.

Finally, we contribute to the narrower literature on the indirect impacts of climate change adaptation on environmental and health outcomes. Specifically, we find that farmers' short-term adaptation to higher temperatures would lead them to use more pesticides, and in particular the most hazardous ones. We thus join the small number of papers documenting negative impacts of farmers' adaptation on environmental outcomes (Fezzi et al., 2015; Hashida and Lewis, 2019; Bayramoglu et al., 2020), and extend these results to human health. To our knowledge, we are the first to document potential negative *indirect* impacts of climate change on health via farmers' adaptation (through pesticide use in particular), extending the previous works that estimated the direct impacts of climate change on human health (Deschenes, 2014; Barreca et al., 2016; Hu and Li, 2019; Carleton et al., 2022).

The paper is organized as follows. Section 2 presents our conceptual framework. Section 3 details the data. Section 4 presents the econometric strategy. Section 5 describes the estimation results. Section 6 simulates the impacts of climate change on pesticide use in France. Section 7 discusses and concludes.

[3] Clear comparison with Jagnani et al. (2021) is difficult given that their temperature measurement variables differ from ours, and that they do not report results for precipitation.

2 Conceptual framework: linking pesticide use and weather

This section explores how and why farmers' pesticide use is likely to be affected by weather shocks. Formally, we assume that risk-neutral rational farmers determine the optimal application of pesticides by solving the following program:

$$x^*(w, z) = \text{argmax}_x\{p^y f(x; w, z) - p^x x\}, \tag{1}$$

where p^y and p^x are respectively the output and input prices (supposed constant), and where $f(x; w, z)$ is the production function depending on three variables, namely pesticide applications x, weather w and pest pressure z. The production function respects the usual non-negative, non-decreasing, linearly homogeneous and concave relationship with x. We assume that the production function is non-negative and linearly homogeneous with w, and that it is non-negative, decreasing and linearly homogeneous with z. The solution of program (1) is the optimal pesticide application for particular values of w and z, given the netput prices. This level x^* is obtained when the last unit of applied pesticide generates as much revenue in terms of pest damage reduction as it costs.

Drawing on the literature that considers pesticides as damage-reducing inputs (e.g. Lichtenberg and Zilberman, 1986; Kuosmanen et al., 2006; Böcker et al., 2019), we assume the following specification for the production function:

$$f(x; w, z) = [1 - z(w) \times [1 - h(x, w)]] \times y^a(w), \tag{2}$$

where $y^a(w)$ and $h(x, w)$ are respectively the attainable yield and pesticide efficacy functions. For the sake of clarity, we assume that the attainable yields depend on weather *only* – one can actually think of $y^a(w)$ as the maximal yield under w, that encompasses all weather-adjusted optimal cropping practices (Bareille and Chakir, 2023; Kawasaki, 2023). The attainable yield function is non-negative and linearly homogeneous with w. Similarly, we assume that the pest pressure $z(w)$ is a non-negative function of weather only, and that the pesticide efficacy $h(x, w)$ function is non-negative, linearly homogeneous with both pesticide applications x and weather w, and increasing with x. We normalize the function $z(w)$, taking the null value when there is no pest and the value one when pest pressure is at its maximum – which, according to equation (2), leads to null production. We similarly normalize $h(x, w)$ such that it takes the null value when no pesticide is applied, and the value one when the quantity of applied pesticides eliminates all pests – the production recovers its attainable yield $y^a(w)$ in the latter case.

Equations (1) and (2) clearly indicate that the function of optimal pesticide applications actually depends on weather only (for given prices). Specifically, it depends on weather via three channels, namely the weather impacts on (i) pest pressure, (ii) pesticide efficacy and (iii) attainable yields. To highlight how these channels respond to weather, we derive, around the optimum, the production function with respect to weather hereafter. Formally, we have:

$$\frac{\partial f(\cdot)}{\partial w} = -\underbrace{z_w(w)[1-h(x^*,w)]y^a(w)}_{\text{Change in pest pressure}} + \underbrace{z(w)h_w(x^*,w)y^a(w)}_{\text{Change in pesticide efficacy}} + \underbrace{[1-z(w)[1-h(x^*,w)]]y^a_w(w)}_{\text{Change in crop yields}}, \quad (3)$$

where the subscript w indicates the derivatives of the alternative functions with respect to weather. Together with equation (1), equation (3) makes it clear that, because production depends on these three channels, the optimal level of pesticides depends in a complex way on weather. Although only described in theory here, these three channels of weather impacts are indeed documented *in situ*.

First, there are many natural science studies indicating that weather affects pest pressure (see Delcour et al., 2015, for a literature review). For example, it is usually found that higher temperature and humidity during the growing season improve the conditions for the development of weeds, fungi and insects (Delcour et al., 2015; Deutsch et al., 2018; IPPC, 2021; Yu et al., 2022). In other words, the literature does document weather impacts on pest pressure (as indicated in equation (3)), with higher temperature and humidity supposedly increasing fungi, weed and insect pressures at the margin (Kawasaki, 2023).

Second, several studies empirically document weather impacts on pesticide efficacy (Delcour et al., 2015). One reason is that high temperatures increase the volatilization of pesticides and accelerate the degradation of their chemical components (Bloomfield et al., 2006). Pests also tend to develop pesticide resistance as temperatures rise (Patterson et al., 1999). Another reason is that greater precipitation increases runoff and pesticide leaching, ultimately reducing pesticide efficacy (Bloomfield et al., 2006). As indicated together by equations (1) and (3), these weather impacts on pesticide efficacy lead rational farmers to adjust their pesticide use (Bareille and Chakir, 2023). In this context, pesticide manufacturers themselves provide instructions on the appropriate weather conditions to apply pesticides (UIPP, 2011). For example, they recommend that glyphosate should ideally be applied at temperatures not exceeding 28°C (Dias et al., 2023).

Finally, there is a large literature documenting weather impacts on crop yields during the growing season (Schlenker and Roberts, 2009). The reason is that plant growth depends on several biophysical processes that are governed by temperature and precipitation, such as photosynthesis and photorespiration (Asseng et al., 2015). This translates into net changes in observed crop yields, that are at least partly independent of farmers' adaptation in terms of cropping practices (Bareille and Chakir, 2023). In other words, this means that there are weather impacts on attainable yields, as theoretically indicated in equation (3). Kawasaki (2023) shows that these weather impacts are mostly independent of induced changes in pest pressure.

To sum up, rational farmers' pesticide applications are expected to vary with weather because of its combined effects on pest pressure, pesticide efficacy and attainable yields. While this narrative is theoretically and empirically supported, we are not able to formally demonstrate it in its entirety in this paper. Indeed, although we observe both weather and pesticide applications – or, rather, pesticide purchases – at the zip code level, we lack precise spatial data for both pest pressure and crop yields. As such, we can only identify total weather impacts on pesticide purchases (combining the three channels of weather impacts together).

3 Data

This article relies on a set of longitudinal data covering pesticide, weather and general agricultural information for France from 2014 to 2019. We present our main data sources and variables of interest hereafter.

3.1 Data sources

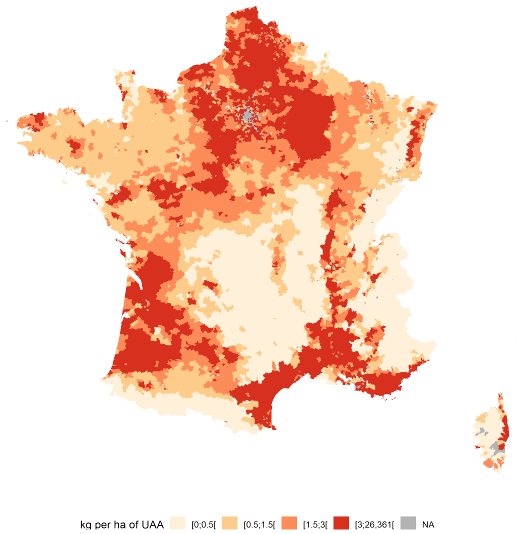
Pesticides data. We use pesticide purchase data from the *Banque Nationale des Ventes de produits phytopharmaceutiques par les Distributeurs agréés* (BNVD). This database was created by the French government in 2009 to monitor the new French pesticide taxation scheme *"Redevances pour Pollutions Diffuses"*, scheme introduced in December 2006 to notably implement differentiated tax rates on pesticides depending on their toxicity.[4] The BNVD is fed by public authorities based on exhaustive pesticide distributors' declarations of all pesticide products annually purchased in France.[5]

For the purpose of our analysis, we use the latest BNVD version from 2014 to 2019 that informs about the annual quantities of pesticides purchased at the *buyers' zip code level*. Using data from the E-Phy catalog produced by the French National Agency for Food, Environmental and Job Health Safety, 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 3.2.). Since products are made up of several active substances that may differ in function, we measure the different pesticide categories by summing the quantities of active substances purchased. We develop an additional analysis in Section 5.4 where we distinguish the pesticides according to their toxicity.

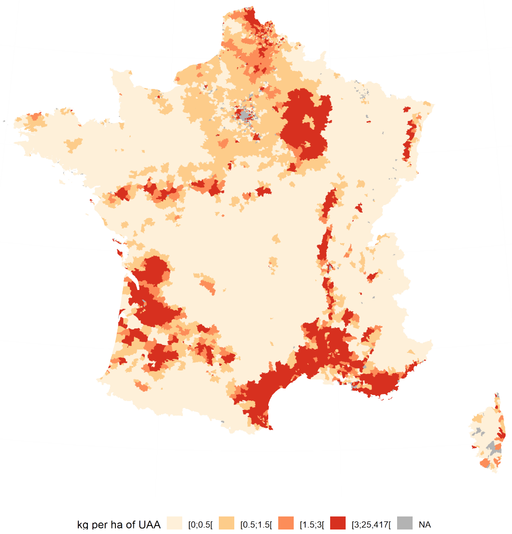
Figure 1 shows the average quantity of pesticide purchased per category over the period 2014-2019. It clearly shows spatially-distinct production areas where pesticide purchases are quite heterogeneous. In particular, it illustrates the fact that farmers purchase few pesticides in mountain areas (Alps, Jura, Massif Central, Pyrenees and Vosges) and, to a lesser extent, in north-west France, where agricultural production is mainly oriented towards livestock activities (grasslands and production of other forage crops requires fewer 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) use much greater quantities of pesticides, particularly fungicides (including copper used to combat mildew for example).

[4] The BNVD classifies the toxicity of the alternative substances following the European Chemicals Agency's classification (more details are available at https://echa.europa.eu/regulations/clp/understanding-clp), specifically distinguishing the (i) substances with highest potential risks for human health, from (ii) those with highest potential risk for the environment and (iii) those with the lowest risks. Substances classified as "potentially hazardous for human health" and "potentially hazardous for the environment" have been respectively taxed at €5.1/kg and €2/kg since 2011. Other (less toxic) substances were not taxed within this scheme.

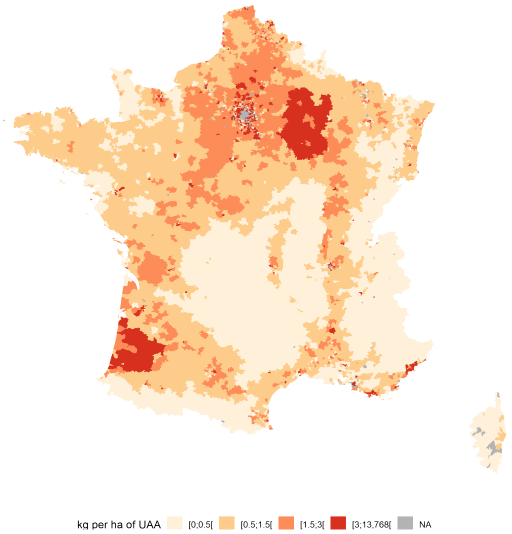
[5] While the first version of the BNVD detailed quantities of pesticides *sold by pesticide distributors* at the departmental level (corresponding on average to 6,000 km^2, i.e. about one to three US counties), since 2013, the second version details the pesticides *purchased by buyers* at the buyers' zip code level (corresponding on average to 86 km^2). Specifically, 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. We dropped 2013 data due to reporting issues following the change between the two BNVD versions.



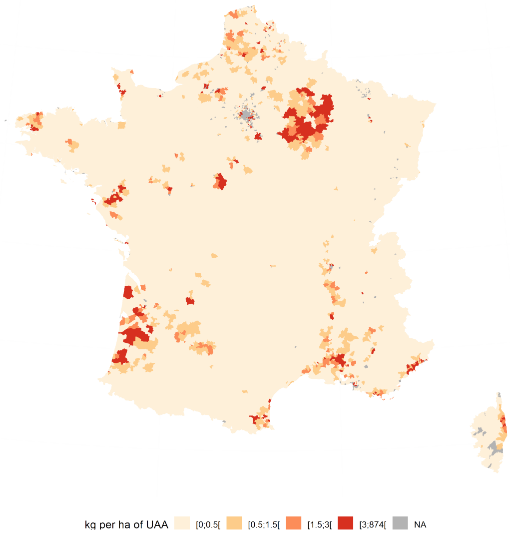
a) All Active Substances



b) Fungicides



c) Herbicides



d) Insecticides

Figure 1: Average pesticide purchases between 2014 and 2019. 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 divide the pesticide purchases by the total useful agricultural area in each zip code.

At this point in the paper, it should be noted that purchased pesticides could differ from pesticides actually used. There is unfortunately no annual data on detailed pesticide use at a fine-grain resolution in France. The best available resolution for such data is the regional level – there are thirteen regions in mainland France, each approximately representing an area covered by 500 zip codes. Produced by the French Institute of Statistics, the agricultural economic accounts (AEAs) provide such data on regional pesticide use. We take advantage of this information to verify whether aggregated pesticide purchases at the regional level are correlated to pesticide use. Table A1 in the online Appendices shows the result of the regression of regionally aggregated pesticide purchases (from the BNVD) on regional pesticide use (from the AEAs) between 2014 and 2019, conditionally on region and year fixed effects. It clearly indicates that pesticide purchases are indeed positively correlated to pesticide use (significant at the statistical threshold of 99%).

The BNVD is not the only database worldwide to provide exhaustive information on pesticide use or purchase (Mesnage et al., 2021). However, it is one of the few to provide such data at the *active 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 (CPIP), for which information is available for pesticide *use* at the zip code level (instead of pesticide *purchase* as in the BNVD).[6] The BNVD offers a significant advantage over the CPIP 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 86 km^2 in France).[7] 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). Note that there are also several databases that provide information on pesticide use per crop (e.g., Rhodes and McCarl, 2020; Jagnani et al., 2021; Bareille and Chakir, 2023), but the data are often aggregated for all pesticide categories. Once again, the BNVD stands out from most of the other databases by the quality of its spatial resolution and the details of all purchases at the *active substance level*.

Weather data. We collected weather data using daily conditions provided by *Météo France* for the whole period on a grid of 8 km $\times$ 8 km (called *SAFRAN* units). The data includes the minimum and maximum daily temperature as well as the daily quantity of precipitation. From these data, we recompute the average temperature within the growing season – from March 1$^{\text{st}}$ to August 31$^{\text{th}}$ – using the reconstructed temperature distribution *à la* Schlenker and Roberts (2009), where the daily temperature distribution is approximated using a sine interpolation between minimal and maximal temperatures.[8] We attributed these data at the zip code level using overlapping GIS coordinates, weighting by grid overlapping areas.

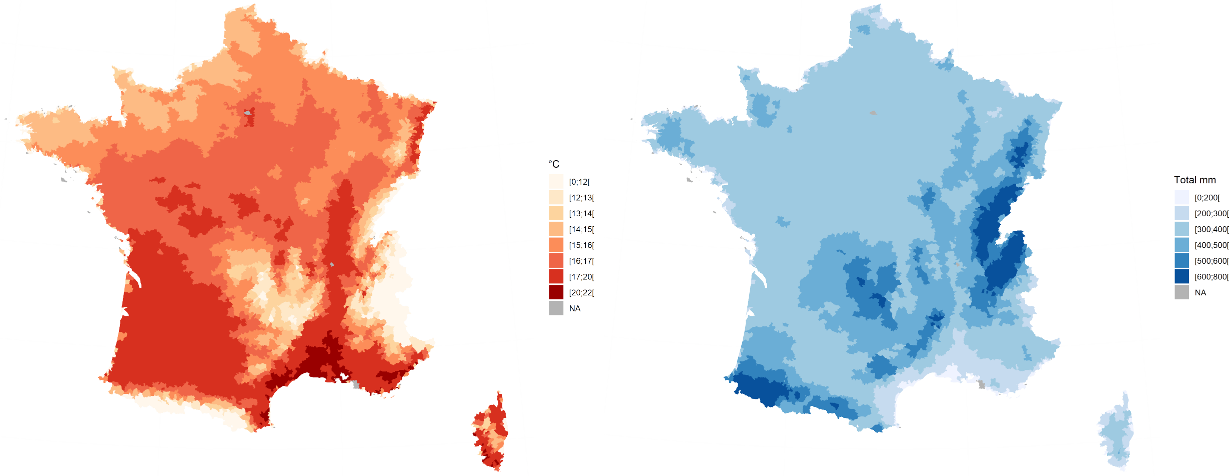
Figure 2 presents the average temperature and the cumulative precipitation during the growing season. It shows that temperature is highest in the south of France, in particular around the Mediterranean basin, and that precipitation is highest in mountain areas.

Agricultural land-use data. To complete our analysis, we need annual agricultural land-use data that can be aggregated to compute useful agricultural area (UAA) per zip code. Detailed land-use data are

[6] Another well documented database is the one administered by the Danish Ministry of Environment and Food (Kudsk et al., 2018; Nielsen et al., 2023), 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.

[7] Pesticide use information 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 available at the zip code level only.

[8] As explained below, we notably recompute the cumulative temperature usually benefiting crops within the growing season (known as growing degree days and denoted GDD_0^{33}, for temperatures between 0°C and 33°C), and those usually harmful to crops (known as harmful degree days and denoted HDD_{33}^{∞}, for temperatures higher than 33°C). Note that we also compute seasonal weather condition to investigate possible heterogeneous weather impacts over time in Section 5.4.



a) Temperature b) Precipitation

Figure 2: Average weather conditions during the growing season (March 1st – August 31th) between 2014 and 2019. Note. The missing values correspond to zip codes having missing data for 2014-2019.

also useful for analysing the heterogeneity of our results regarding agricultural specialization per zip code (see Section 5.4). We specifically rely on the *Land Parcel Information System* (LPIS), provided by the French Geography Institute. The LPIS is the most detailed land-use data for agriculture in Europe, available for 28 crops at the plot level. Based on farmers' declarations regarding the Common Agricultural Policy (CAP), it specifies the crop produced on each plot of the farms receiving CAP subsidies. We aggregate these data at the zip code level for each crop category and compute the UAA as the sum of areas for the 28 categories.[9]

Figure A1 in the online Appendices displays the share of UAA devoted to the four main types of agricultural production (cereals, vines, grasslands and fruits). It shows that French agriculture is mainly orientated towards cereals and other industrial crops, notably around the Paris basin. As to be expected from common wisdom (Urruty et al., 2016), wine- and fruit-production areas are those where pesticide purchases are the highest (Figure 1). The remaining parts of France are mainly covered by grasslands, characterized by low pesticide purchases due to the specialization in livestock and milk production (Figure 1).

3.2 Summary statistics

Data on weather and land-use are merged with pesticide data, leading to a balanced panel of 5,848 zip codes observed between 2014 and 2019. After removing all zip codes for which less than 10% of the area is under agriculture, and those from Corsica and overseas territories, we obtain a balanced panel of 4,861

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

zip codes over 6 years, representing about 94% of the total UAA of mainland France.[10] 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 statistical secrecy.[11] 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 A2, A3 and A4 (see the online Appendices).

Table 1 presents our sample's summary statistics. It shows that more than 50% of pesticide use relates to fungicides. Insecticides are much less used than other pesticides, representing only 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 coefficient of variation of insecticide purchases (6.86≈1.92/0.28, which is three to seven times greater than that of fungicides and herbicides respectively). In particular, Figure 1 shows that herbicide purchases – which represent about 33% of all pesticides applied – are more homogeneously distributed over space than those of fungicides and insecticides (the latter being particularly high in wine-producing regions). In other words, herbicide applications seem much more systematic than for the two other pesticide categories.

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

	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%
Risks for the environment (%)	30.99	20.51	0	16.61	26.16	39.15	100	–
Risks for human health (%)	43.80	24.33	0	22.29	47.55	64.05	100	–
Others (%)	25.21	28.1	0	1.79	12.49	44.30	100	–
Herbicides (kg/ha)	0.99	1.05	0	0.31	0.77	1.37	36.90	1.58%
Risks for the environment (%)	84.52	10.36	0	78.76	86.21	92.14	100	–
Risks for human health (%)	13.58	9.94	0	5.82	11.92	19.47	91.60	–
Others (%)	1.90	4.40	0	0.72	1.18	1.85	100	–
Insecticides (kg/ha)	0.28	1.92	0	0.02	0.05	0.13	111.27	4.26%
Risks for the environment (%)	35.54	26.13	0	14.03	30.41	52.85	100	–
Risks for human health (%)	18.27	18.46	0	5.39	12.90	24.38	100	–
Others (%)	46.19	29.78	0	20.23	46.06	70.62	100	–
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	–
Harmful 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	–
Adjusted UAA (ha)	4,099.31	4,527.99	0.11	799.20	2,452.26	6,101.03	40,173.62	–

NOTE. The figures provide the summary statistics for the sample on which we performed our preferred analyses. The rows in italic indicate the classification of the toxicity of the alternative pesticides as reported in the BNVD, which follows those of the European Chemicals Agency. The last column displays the share of observations with at least one null observation (includes true zeros and observations deleted due to statistical secrecy). Adjusted UAA refers to the UAA excluding fallow and permanent grasslands, to which we assume that farmers do not apply any pesticides.

[10] Note the land-use data suffers from reporting errors for some zip codes of two departments – "*Marne*" and "*Aube*" – located in the north-east of France (for the years 2014 and 2019 in particular). We remove these zip codes from our preferred analyses, but show in Appendix A15 that our preferred estimates are robust to their inclusion.

[11] According to French legislation, statistical secrecy applies when there are fewer than three buyers within the zip codes, or if a single farm represents more than 85% of the total zip code purchases.

Looking at the independent variables, Table 1 indicates that weather during the growing season is also heterogeneous, but 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 equal to 0.97), explaining why we weight the observations by their UAA when estimating the different models (see below).

4 Methods

The previous section shows that pesticide purchases and weather are largely spatially heterogeneous. These elements could reflect a strong relationship between pesticide use and weather, but could simply reflect confounding unobserved spatially-varying factors. A simple cross-sectional regression of pesticide purchases on weather would thus suffer from potential omitted variable bias. To deal with this issue, our econometric approach consists of 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 assessing weather impacts on pesticide use. The first aims to capture the impacts of average weather conditions during the growing season (Section 4.1). The second further investigates potential non-linear impacts of the whole temperature distribution during the growing season (Section 4.2).

4.1 Average weather during the growing season

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

$$\log(X^k_{i(r),t}) = \beta^k_1 \bar{T}_{i(r),t} + \beta^k_2 \bar{T}^2_{i(r),t} + \beta^k_3 \bar{P}_{i(r),t} + \beta^k_4 \bar{P}^2_{i(r),t} + \nu^k_{i(r)} + \mu^k_r(t) + \varepsilon^k_{i(r),t}, \tag{4}$$

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 per hectare of UAA adjusted for fallow and permanent grasslands (to which we assume that farmers do not apply any pesticides), $\bar{T}_{i(r),t}$ is the average temperature during the growing season in t and i, $\bar{P}_{i(r),t}$ is the total amount of precipitation that fell during the growing season of t in 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 squares (WLS), weighting observations by their adjusted UAA (i.e. without fallow and permanent grasslands).[12] According to the literature (Hsiang, 2016), the obtained estimates can be interpreted as causal impacts of contemporaneous

[12]We show in Section 5.3 that our estimates are robust to the use of alternative weights.

weather conditions on pesticide purchases. Under some properties of the weather and climate distributions (Mérel et al., 2024), these estimates could even represent the causal impacts of climate change on pesticide use.

A common challenge in this literature is to deal with the spatial dependency between the observations. This potentially high degree of spatial dependency is notably due to the natural spatial autocorrelation of weather variables, but also to those occurring in other 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 errors in weather variables are also likely to be spatially correlated (Ortiz-Bobea, 2021). These spatially-autocorrelated elements would result in smaller estimated standard errors than they truly are. A standard practice to correct estimations for spatial dependency is to cluster the standard errors *à la* Conley (1999). Specifically, 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, 2021). We proceed similarly in this paper, specifying a threshold of 25 kilometers beyond which we assume no spatial autocorrelation between the observations.

Our baseline estimations include individual fixed effects and regional time trends. The individual fixed effects in equation (4) capture all the time-invariant characteristics at the zip code level that are spatially heterogeneous but that may be correlated with pesticide purchases and weather (e.g. soil conditions). This is important as zip codes often specialize in specific types of farming, with some growing crops that are particularly sensitive to pests (e.g. fruits), while others specialize in more resistant activities (e.g. livestock operations). The consequence is that farmers' intrinsic needs for pesticides vary between zip codes, regardless of weather. Consequently, the inclusion of zip code fixed effects allows us to exploit plausibly exogenous location-specific deviations in pesticide purchases and weather from their location-specific averages to estimate our parameters of interest.[13] Similarly, 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 purchases and that could be correlated with tendency changes in weather or changes in agricultural practices, prices or policies (Fisher et al., 2012). Our preferred specification relies on linear regional time trends, but we demonstrate in Section 5.3 that our results are robust to the use of cubic regional time trends.[14]

[13] Graphically, Figure A2 in the online Appendices shows the annual deviations in pesticide purchases at the zip code level compared to their averages over the period (Figure 1). Our identification strategy consists of explaining such abnormal deviations by similar abnormal deviations in weather (see Figures A3 and A4 in the online Appendices).

[14] Another strategy to capture all common time shocks that are likely to affect pesticide purchases 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 (Fisher et al., 2012), 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 a two-way fixed effects (TWFE) specification in Section 5.3. Specifically, we show there that, in most cases, our TWFE estimates present similar signs to those obtained with our preferred specification but turn significantly null. They are also often noticeably reduced towards zero, suggesting attenuation biases for our TWFE estimates.

Dependent variable. The nature of the dependent variable in equation (4) calls for several comments. First, we successively explain 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 shocks will be similar (IPPC, 2021), it is likely that the use of fungicides, herbicides and insecticides may react differently to similar weather shocks. On top of these specific models per pesticide category, we also estimate a model similar to equation (4) but with an aggregated measure of pesticide purchase ($X_{i(r),t}$) as dependent variable. The estimates obtained with this aggregated measure are notably interesting to compare our results with those obtained in studies that do not differentiate between different pesticide categories (e.g. Jagnani et al., 2021; Bareille and Chakir, 2023), and detect potential aggregation biases.

Second, equation (4) is expressed in kilograms per hectare of UAA *corrected for permanent grasslands and fallows*. As explained before, we assume that farmers do not apply pesticides to such land uses. Supported by agronomic studies (Urruty et al., 2016), the rational behind this assumption is that permanent grasslands and fallows are significantly less productive than other agricultural land uses, such that the costs of pesticide purchase and application would exceed their benefits (see Section 2). Rational farmers would thus not apply pesticides on permanent grasslands and fallows, which nevertheless together represent 36.2% of the whole UAA (see Section 3). As a sensitivity analysis, we re-estimate equation (4) in Section 5.3 reporting pesticide purchases for the whole UAA and show that our results are robust.

Third, the denominator of our dependent variable in equation (4) could also change in response to weather shocks, either in total (i.e. adjusted UAA) or in composition (i.e. crop allocation). In other words, farmers may not necessarily adjust at the *intensive margin* only (as interpreted in Section 2), but additionally at the extensive and super-extensive margin (Graveline and Mérel, 2014). We test whether farmers respond along these others margins in Section 5.5 in order to rule out potential confounding effects. Results from this analysis reassuringly show that the estimates obtained from equation (4) reflect the lower bounds of the farmers' intensive margin responses only.

Finally, the dependent variable of equation (4) is expressed in logarithmic form. This logarithmic transformation allows us to linearize the distribution of pesticide purchase (which is right-skewed otherwise, see Section 3). The problem with this transformation is that we have to drop the null observations, which may bias our estimates. As shown in Table 1, this concerns fewer than 5% of the observations for all pesticide categories (about 1% when we aggregate in total), such that it may not be of primary importance. However, to further investigate this issue, we test its sensitivity in Section 5.3 by using the inverse hyperbolic sine transformation of our dependent variable instead. The advantage of the inverse hyperbolic sine transformation is that it nicely approximates the natural logarithm while accounting for null values (Aihounton and Henningsen, 2021). We also test the sensitivity of our results taking simple linear forms for the dependent variables. These analyses show that our results are robust to these alternative choices.

Approximating pesticide use by pesticide purchase. Estimation of equation (4) relies on the major assumption that farmers adjust their pesticide purchases according to weather shocks, and that the purchased amount roughly corresponds to what is actually used. We believe this assumption is reasonable for at least three reasons. First, we show in Appendix A1 that pesticide purchases are indeed positively correlated to actual pesticide use at the regional level. While not perfect, this correlation suggests similar trends in pesticide purchases and use. The second reason is that we assume that observed pesticide purchases reflect rational farmers' choices (characterized by the cost of the last pesticide unit equaling its productivity; see Section 2). Given this assumption, as long as weather affects either pest pressure, pesticide efficacy or attainable yields, rational farmers are expected to adjust pesticide use and, accordingly, pesticide purchases.

The third reason relies on the fact that pesticide purchases reasonably approximate their use as long as farmers do not store pesticides from one year to another (Nielsen et al., 2023), or only in fixed quantities. There are several reasons supporting the idea that changes in pesticide inventories are limited between years. First, storing more pesticides than anticipated for the year is discouraged due to the potential high toxicity and perishable nature of the active substances. It is indeed considered that, with a few exceptions, pesticides normally have a shelf life of less than two years from the date of production (FAO, 1996). For these reasons, French pesticide retailers themselves encourage farmers to purchase pesticides at a time close to its actual use (UIPP, 2011). Second, in cases where French farmers do not use their pesticides in due time, they are authorized to send back unused products to their retailers (French Senate, 2012) – to our knowledge, this practice is not authorised outside France. Although this is not mandatory, there is no reason for a rational French farmer to conserve such unused pesticides – at least as long as storage costs are higher than transaction costs. Third, there are indeed several elements suggesting that farmers face costs to store pesticides, whether relating to storage space or surveillance of pesticides. Emphasized in all pesticides' user documentation, such surveillance practices can be substantial, involving for example the verification of pesticide storage conditions (humidity, temperature, luminosity, etc.). 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.[15] Hence, given the storage costs and the stability of pesticide prices, rational farmers would not store pesticides in large quantities during a particular year, *unless they anticipate the prohibition of a specific product* (Nielsen et al., 2023).

To test the sensitivity of our results to this possibility, we re-estimate equation (4) in Section 5.3, 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.[16] Finally, there is no reason to believe that farmers within zip codes behave similarly in terms of storage or removal. Since we work at the aggregate zip code level, we can assume that variations in storage and removal practices within the zip code would offset each other in overall terms.

Despite all of the above, we acknowledge that we cannot formally test whether farmers' storage behavior might bias our estimates.

[15] The French monthly pesticide price index never changed 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).

[16] An alternative to account for changes in pesticide policies would be to remove the years around the reforms (Nielsen et al., 2023). However, because our estimations rely on a short panel (6 years), we prefer the former solution.

Directly testing for this issue would require us to observe pesticide stocks, which we do not. The best we can do to address this concern is to provide indirect evidence using lagged variable values. Specifically, we perform three sensitivity analyses with this strategy in mind. In the first, we explain two-year moving averages of pesticide purchases by contemporaneous weather during the growing season. That is, we replace the dependent variable in equation (4) – $\log(X^k_{i(r),t})$ – by the average of contemporaneous and one-time lagged pesticide purchases – $\log(0.5 \times X^k_{i(r),t} + 0.5 \times X^k_{i(r),t-1})$.[17] The intuition for this model is that purchases from last year can be directly used in the next year in response to contemporaneous weather changes. The second sensitivity analysis consists of including past weather events to explain contemporaneous pesticide purchases. In particular, one may expect that lagged weather extremes may explain contemporaneous pesticide purchases because farmers expectations have changed or because they have to stock up their storage again. The third sensitivity analysis relies on dynamic panel model that includes lagged pesticide purchase as an additional predictor of current pesticide purchase – see online Appendix A4 for details of the estimated dynamic model. Such a specification allows us to test whether abnormally high past purchases reduce contemporaneous purchases and whether it changes the weather estimates accordingly. If storage behavior is not an issue for our preferred estimations, then the estimates obtained with the three sensitivity analyses should be of similar magnitude to those estimated with our preferred model – actually for our first sensitivity analysis they should be half those for the preferred model. We show in Section 5.2 that this is indeed the case.

The problem with pesticide storage is that it can create a temporal mismatch between pesticide purchases and formal use. Such potential mismatch also exists spatially. Indeed, the estimation of equation (4) relies on the assumption that pesticides are applied in the same zip code in which the purchases are recorded. Farms are however fragmented over space, such that some pesticides purchased in a particular zip code could be applied in another. To assess how our results might be affected by this assumption, we re-estimate equation (4) in Section 5.2 by aggregating the observations at higher spatial scales. Specifically, we aggregate the observations either at the *Petite Region Agricole* (PRA) level, an administrative area of about 30 km × 30 km (i.e. about 10 times larger than the zip code), or at the *department* (DEP) level, an area of about 75 km × 75 km (i.e. about 70 times larger than the zip code). Our results are robust to these spatial aggregation processes, indicating limited pesticide applications beyond the zip codes of the buyers' headquarters.

Weather elasticities. For the sake of clarity, we report all of our results in Section 5 as weather elasticities of pesticide purchases. Reporting weather elasticities allows us to compare the estimated impacts at the average point, without putting too much emphasis on the non-linearities in the relationships between pesticide use and weather – such non-linearities are typically further explored using another method (see Section 4.2). Taking the case of temperature as an illustrative example, the temperature elasticities of

[17] We do not include purchases from previous years because pesticides' shelf life is less than two years (FAO, 1996).

pesticide purchase of type k – denoted ξ_T^k – are recomputed from equation (4) as:

$$\xi_T^k = (\hat{\beta}_1^k + 2\hat{\beta}_2^k \bar{T})\bar{T}, \tag{5}$$

where $\hat{\beta}_1^k$ and $\hat{\beta}_2^k$ are the estimates recovered from equation (4), 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 point from the average temperature and precipitation 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 non-marginal changes in temperature and precipitation (changes that typically occur with climate change), we additionally simulate in Section 6 the consequences of predicted climate outcomes in 2050 on pesticide use.

Finally, it should be noted that, while the inclusion of average temperature and precipitation as single weather variables is a fairly standard practice in the literature (Blanc and Schlenker, 2017), the estimates $\hat{\beta}_i^k$ obtained from equation (4) may additionally capture confounding impacts coming from other weather shocks, such as changes in wind or soil moisture. To check the impact of these factors on our estimates, we include them as additional controls in Section 5.3, and show that our results are robust.

4.2 Non-linear impacts of temperature

A potential issue with our preferred specification in equation (4) 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 temperature distributions: 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 non-linearities 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:

$$\log(X_{i(r),t}^k) = \int_{\underline{h}}^{\bar{h}} f^k(h)\phi_{i(r),t}(h)dh + \eta_1^k \bar{P}_{i(r),t} + \eta_2^k \bar{P}_{i(r),t}^2 + \nu_{i(r)}^k + \mu_r^k(t) + \varepsilon_{i(r),t}^k, \tag{6}$$

where $\phi_{i(r),t}(\cdot)$ is the reconstructed distribution of temperature in zip code i and year t, $\underline{h}$ 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. As explained in Section 3, 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. Following Schlenker and Roberts (2009), we consider three types of functional form $f^k(\cdot)$ in equation (6). We present these non-linear specifications in online Appendix A5. The other elements in equation (6) are similar to those in equation (4). In particular, we estimate equation (6) by WLS, weighting the observations by their adjusted UAA.

5 Results

This section first describes how the average weather conditions during the growing season affect pesticide purchases (Section 5.1). Section 5.2 provides indirect evidence suggesting that changes in pesticide inventories between years are limited, and thus that our pesticide purchase measurements likely represent pesticide use. Section 5.3 provides evidence on the robustness of our results. Section 5.4 presents the results of heterogeneity analyses with respect to (i) differential weather impacts on pesticide purchases depending on their toxicity, (ii) differential weather effects across seasons and (iii) differential weather effects in function of agricultural specialization. Section 5.5 demonstrates that no alternative farmers' adaptation mechanisms than real pesticide use adjustments could explain our preferred results. Finally, Section 5.6 investigates the possibility for large non-linear temperature impacts on pesticide use, beyond the average temperature effects.

5.1 Average weather during the growing season

Preferred estimates. Table 2 displays the weather elasticities of purchases of fungicides, herbicides and insecticides as well as aggregated pesticide purchases, recomputed using the equation (5)'s formula at the average point and equation (4)'s preferred estimates – the raw estimates are depicted in Table A2 of the online Appendices.[18] Table 2 shows that a one percent increase in average temperature during the growing season raises aggregated pesticide purchase by 1.66%. This effect is mainly driven by fungicide and herbicide purchases, which respectively increase by 1.70% and 1.72% for a one percent increase in average temperature. Insecticide purchases are much less affected by temperature, with an estimated elasticity of 0.37, and globally less precisely identified. Regarding precipitation, Table 2 indicates that a one percent precipitation increase raises the aggregated purchases of pesticide by 0.37%. Here, fungicide purchases alone seem to drive the overall effect. Indeed, they increase by 0.53% for a one percent precipitation increase, that is about twice as much as herbicide and insecticide purchases.

Interestingly, Table 2 suggests no aggregation bias when taking aggregated pesticide purchases as the dependent variable. Indeed, weighting the weather elasticities of specific pesticide categories by their percentage of total purchases indicates aggregated elasticities of 1.57 for temperature and 0.40 for precipitation,[19] that is with less than 10% difference compared to those directly measured in Table 2. This is an important result given that most research on the relationship between weather and pesticides relies on aggregate pesticide measurements (e.g. Jagnani et al., 2021; Bareille and Chakir, 2023). These previous studies thus likely provide consistent estimates of the responsiveness of farmers' aggregated pesticide use to weather shocks.

[18] Temperature elasticities correspond here 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 the temperature measurement unit is not sensitive (Hsiang, 2016). To be clear, a one percent temperature increase 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. Bareille and Chakir, 2023). The precipitation elasticities correspond here to the impacts of an increase of 3.83mm in precipitation on pesticide purchases. Such precipitation elasticities do not suffer from drawbacks similar to those for temperature.

[19] Such aggregated numbers are recomputed ex post using information from Tables 1 and 2. In the case of temperature for example, we obtain the figure from $(1.704\times1.51+1.718\times0.99+0.368\times0.28)/(1.51+0.99+0.28)$.

Table 2: Weather elasticities of pesticide purchases

	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 purchases. The elasticities are computed at sample mean values using the WLS estimates and equation (5). The standard errors are clustered at the zip code level and corrected for spatial dependency 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.

More detailed analyses on the form of the relationships between pesticide purchases and weather in Table A2 in the online Appendices indicate a non-significant non-linear curvature for temperature, but a statistically significant positive concave relationship for precipitation. This suggests that farmers apply more pesticide in a constant manner for marginal temperature increases around the average point, but that they make increasing use of pesticides as precipitation increases, up to a threshold beyond which their use decreases. For example, farmers purchase more (aggregated) pesticides up to 865 mm of total precipitation during the growing season. The threshold is lower for fungicides (809 mm) and insecticides (698 mm), but higher for herbicides (899 mm).

Consistency with the literature. All of our results above are consistent with the agronomic literature. This literature indeed indicates that higher temperature and humidity increase pest pressure at the margin (Delcour et al., 2015), which would lead rational farmers to use more pesticides (see Section 2). Also, because moderate increases in temperature and precipitation typically increase crop yields (Schlenker and Roberts, 2009), rational farmers have greater incentives to protect their crops under such conditions. These two insights align with our results in Table 2. However, the agronomic literature also indicates that runoff associated with high precipitation reduces pesticide efficacy (Bloomfield et al., 2006), which would lead rational farmers to reduce pesticide use. This is what we identify in Table A2 in the online Appendices. On top of these effects, the agronomic literature also documents the fact that high temperatures decrease pesticide efficacy (Delcour et al., 2015), which would lead rational farmers to decrease pesticide use. However, these thresholds appear at much higher temperatures than those surrounding the average point (Möhring et al., 2022), which is consistent with our results in Table A2. Section 5.6 investigates such non-linearities at higher temperatures.

Our results are also in line with the economic literature. For example, they are consistent with those of Chen and McCarl (2001) on US agriculture, even if they conducted their analysis at a coarser spatial resolution – US states specifically – and consequently obtained higher estimates than ours. For example, they found that a one percent precipitation increase raises pesticide expenditure by 2.8%, an effect about eight times greater than ours. This suggests aggregation biases in their analysis, related to the choice of large spatial resolutions (Fezzi and Bateman, 2015; Damania et al., 2020). Our results are consistent with this reasoning, as we find larger weather impacts that those estimated on microeconomic individual data (e.g. Jagnani et al., 2021; Bareille and Chakir, 2023). Indeed, both Jagnani et al. (2021) and Bareille and Chakir (2023) find significantly positive temperature impacts on pesticide use, but to a much smaller extent than those estimated here. Although Jagnani et al. (2021) do not report their results for precipitation, Bareille and Chakir (2023) also indicate smaller impacts of precipitation on pesticide use than those we find in this study – by a factor of about five. 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 individual data which are not exhaustive but based on samples of the whole population.

5.2 Are pesticide purchases a good proxy for their use?

One threat to identification in our previous section is that, while interpreted as if they were pesticide use, our dependent variables fundamentally represent purchases. To investigate whether our previous results reflect purchase rather than use behaviors, this section reports estimates from regressions with various modifications in the spatial and temporal dimensions of the analysis.

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 (see Section 4.1). That is, 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 other zip codes. To test for this possibility, we aggregate our zip code-level observations to higher spatial scales. Table 3 displays the recomputed weather elasticities of these additional analyses, based on the estimates obtained at the PRA and DEP levels (see Table A3 in the online Appendices). Our results remain the same overall, suggesting limited pesticide use beyond the zip codes where the buyers are located. In particular, the elasticities at the PRA level are statistically equal to those at the zip code level. The single difference with Table 2 is that the precipitation elasticities go towards zero when observations are aggregated at the departmental level. This indicates a potential bias induced by aggregating precipitation at too broad a spatial scale (Damania et al., 2020).

Temporal mismatch. Employing pesticide purchase to approximate its use may be incorrect if farmers store pesticides from one year to the next (see Section 4.1). We examine this issue below by (i) excluding banned pesticides and glyphosate (online Appendix A8 displays the obtained estimates), (ii) averaging the purchases over two consecutive years (see online Appendix A9), (iii) using lagged harmful degree day as an additional predictor of pesticide purchases (see online Appendix A10) and (iv) estimating a dynamic panel model (see online Appendix A11). The recomputed elasticities from these analyses are displayed in Table 4. Results from panels A. and B. suggest that the exclusion of banned active substances or glyphosate has minor impact on our estimates, which remain statistically equal with those in Table 2. This suggests that farmers did not massively store pesticides in response to announced or planned bans. Panel C. provides

Table 3: Weather elasticities of pesticide purchases 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 (5). The standard errors are clustered at the adapted geographical scale and corrected for spatial dependency 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.

estimates that are equal to half our preferred estimates. As explained in Section 4.1, this suggests that farmers do not store pesticides from one year to another. Similarly, panel D. shows that the inclusion of lagged extreme temperatures has minor effects for our estimates, suggesting that previous weather extremes do not temper the effect of contemporaneous weather through additional storage. Finally, panel E. indicates that the dynamic model estimates are sometimes statistically smaller than those in our preferred analyses. However, they all consistently remain positive, confirming that farmers tend to purchase more pesticides in response to higher temperature and precipitation, even when they have made substantial pesticide purchases in the previous year. 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 is a reliable approximation of pesticide use and interpret our previous estimates as weather impacts on pesticide use.

5.3 Robustness checks

Our results show that pesticide purchases are positively affected by temperature and precipitation during the growing season. 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 instead of linear regional time trends (see online Appendix A12), (ii) the use of cubic instead of linear regional time trends (see online Appendix A13), (iii) the use of pesticide purchases divided by the whole UAA – including permanent grasslands and fallows – as dependent variables (see online Appendix A14), (iv) the use of the entire sample, including urban and mountain zip codes (see online Appendix A15), (v) the change of functional form, either using the inverse hyperbolic sine or linear transformations (see online Appendices A16 and A17 respectively), (vi) the use of population as alternative weights (see online Appendix A18) or without any weight (see online Appendix A19) and (vii) the addition of other weather controls such as soil

Table 4: Weather elasticities of pesticide purchases with alternative storage assumptions

	All Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	Panel A. Excluding Banned Active Substances			
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. Excluding 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. Lagged harmful degree days			
Average Temperature	1.952***	1.848***	2.010***	0.396*
	(0.142)	(0.213)	(0.148)	(0.208)
Total Precipitation	0.493***	0.639***	0.394***	0.340***
	(0.027)	(0.046)	(0.026)	(0.046)
	Panel E. 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 (5). Underlying estimates in panels A. to D. are obtained using weighted least squares. Underlying estimates in panel E. are obtained using GMM (see online Appendix A4 for additional details on the GMM estimation). The standard errors are clustered at the zip code level and corrected for spatial dependency 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.

moisture and wind (see online Appendices A20 and A21). Figure 3 provides a summary of the estimated weather elasticities of pesticide use in our sensitivity analyses.

Figure 3 demonstrates the robustness of our main findings. Indeed, our sensitivity analyses replicate the results obtained in Section 5.1 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 4, this may be related to the fact that TWFE leaves too little signal for identification (Fisher et al., 2012).[20] Our TWFE results support this phenomenon, as most TWFE estimates seem affected by exacerbated attenuation biases.

[20] 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 that this is the case since our data represents roughly twice the size of an average US state only. The level of remaining variation after adjusting for year effects is likely to be roughly the same.

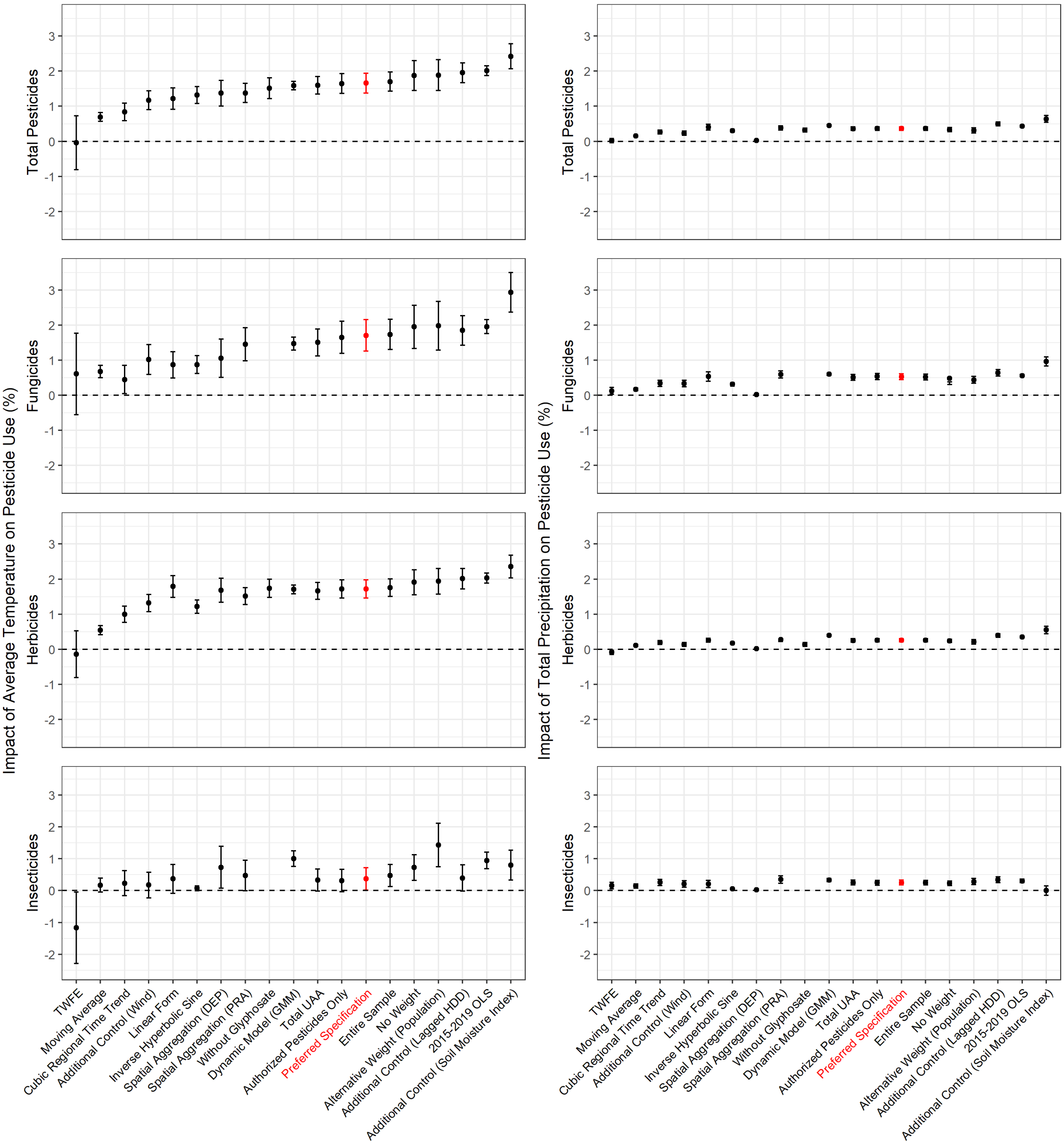


Figure 3: Comparison of impacts of average temperatures and precipitation on pesticide use with alternative empirical choices. NOTE. The graph displays recomputed elasticities of average temperature and total precipitation on pesticide purchases at sample mean value using the alternative empirical choices. The estimates are weighted by the zip code adjusted UAA (corrected for permanent grasslands and fallows). The bars display 95% confidence intervals. The red figures represent the estimates obtained in our preferred analysis, as displayed in Section 5.1.

5.4 Heterogeneous weather effects

Below, we present several analyses exploring potential heterogeneities in weather impacts on pesticide use within our data. Specifically, we perform heterogeneity analyses on the differential weather impacts regarding (i) pesticide toxicity levels, (ii) seasons and (iii) agricultural specialization.

Differential weather impacts across pesticide toxicity levels. An overlooked aspect of our analyses concerns pesticide toxicity. Indeed, while we find that farmers are already likely to increase the quantity of pesticide applied when temperature or precipitation increase, there is a possibility that they might turn to even more toxic products. To explore this possibility, we decompose the purchased pesticide categories based on their toxicity levels specified in the BNVD (that follows the European Chemicals Agency's classification, see Section 3.1). We categorize the various purchased pesticides into three groups: (i) those presenting a risk to the environment, (ii) those presenting a risk to human health and, (iii) the others, not classified as harmful by the European Chemicals Agency.[21] Table 29 in the online Appendices displays the obtained estimates for such an additional analysis. Table 5 shows the recomputed elasticities.

Specifically, Table 5 shows that pesticide purchases in the alternative toxicity categories do not respond homogeneously to similar weather shocks. Looking at aggregated pesticide purchases, we find that those presenting a higher risk to the environment or human health are the most sensitive to weather shocks. These two categories are respectively two to three times more sensitive to temperature shocks than pesticides with no stated risk. When examining specific pesticide categories, those most responsive to weather shocks are (i) insecticides that are potentially harmful to the environment, (ii) herbicides that are potentially harmful to human health, and (iii) fungicides with no stated risk (or those potentially harmful to human health, the difference between the two not being significant at the statistical level of 95%). Overall, our preferred estimates in Table 2 seem primarily driven by pesticides presenting risks to the environment (Panel A. of Table 5). The main difference regards the temperature impacts on purchases of insecticides with no stated risks, which are negative. This latter result is likely to explain why the aggregated temperature impacts on insecticide purchases are smaller than those for fungicides and herbicides in Table 2.

Differential weather impacts over time. If farmers adjust their pesticide use following weather shocks within the growing season, their responses may vary across different periods of the year. There are at least three reasons that could explain these heterogeneous weather impacts over time. First, crops may

[21] Various risk and toxicity indicators can be found in the literature (e.g. Kudsk et al., 2018; Perry and Moschini, 2020; Lee et al., 2023), most of which rely on detailed substance-specific toxicity weights for environmental and health. This information is typically available via the pesticide properties database (http://sitem.herts.ac.uk/aeru/ppdb/). However, the access to this database is not free. Although some of the substance-specific weights can be found in previous papers (e.g. Perry and Moschini, 2020; Lee et al., 2023), we prefer to classify French pesticide purchases based on the three publicly available – but relatively vast – toxicity categories. This approach does not mean that we assume that all substances within one of these three categories present similar toxicity levels. Rather, it means that, because we do not have the substance-specific weights for all active substances, we prefer not to engage in such an analysis. It is important to note that a thorough evaluation of the effectiveness of public policies aimed at reducing pesticide-related risks would require the use of such detailed indicators based on substance-specific toxicity weights.

Table 5: Weather elasticities of pesticide purchases by toxicity-related taxation level

	Total Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	PANEL A. HIGH RISKS FOR THE ENVIRONMENT			
Average Temperature	1.757***	1.499***	1.601***	2.673***
	(0.180)	(0.337)	(0.156)	(0.219)
Total Precipitation	0.474***	0.913***	0.352***	0.233***
	(0.034)	(0.080)	(0.028)	(0.057)
	PANEL B. HIGH RISKS FOR HUMAN HEALTH			
Average Temperature	2.648***	2.426***	3.108***	-0.002
	(0.176)	(0.233)	(0.240)	(0.281)
Total Precipitation	0.067	0.231***	-0.332***	0.215***
	(0.063)	(0.070)	(0.070)	(0.063)
	PANEL C. OTHERS			
Average Temperature	0.899***	3.001***	1.368***	-1.473***
	(0.210)	(0.432)	(0.260)	(0.232)
Total Precipitation	0.313***	0.639***	0.243**	0.264***
	(0.038)	(0.075)	(0.088)	(0.059)

NOTE. Elasticities are computed at sample mean values using WLS estimates and equation (5). The classification of the toxicity of the alternative pesticides is based on those reported in the BNVD, that itself rely on those of the European Chemicals Agency. Those aggregagted in Panels A. and B. are respectively those classified as "potentially hazardous for the environment" and "potentially hazardous for human health", while those in Panel C. are not classified as harmful for the environment and human health by the European Chemicals Agency (thus presenting the lowest toxicity risks with current knowledge). The standard errors are clustered at the zip code level and corrected for spatial dependency 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.

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. Third, some specific crops may be grown outside the traditional growing season. 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.[22] Table A30 in the online Appendices displays the obtained estimates for this additional analysis. Table 6 presents the recomputed elasticities.

Table 6 indicates that our preferred estimates in Table 2 seem heavily influenced by weather 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 shocks during the first half of the growing season. This pattern holds true not only for aggregated pesticide purchases, but also for those of fungicides and herbicides. This result either suggests that crops are predominantly sensitive to pest damage during spring, or that the growth of fungi and weeds is primarily influenced by weather 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 temperature and humidity levels are optimal for their development (Patterson et al., 1999; Delcour et al., 2015). By comparison, Table 6

[22] 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 6: Weather elasticities of pesticide purchases across seasons

	Total Pesticides	**Fungicides**	**Herbicides**	**Insecticides**
	Panel A. Winter (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. Spring (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. Summer (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. Autumn (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 (5). The standard errors are clustered at the zip code level and corrected for spatial dependency 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 respectively. They are 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.

indicates that insecticide purchase is primarily influenced by weather during summer (the temperature effects are statistically significant at the 85% level). This result suggests that insect growth is either particularly sensitive to weather during summer, or that crops are primarily vulnerable to insect damage at that time.

Table 6 not only displays heterogeneous weather impacts within the growing season but additionally reveals that weather outside the growing season also affects pesticide purchases. Specifically, we find that warmer and wetter winters lead to higher pesticide purchases. 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 (by a factor of ten).

Finally, Table 6 reveals clear negative impacts of warmer and wetter autumns on pesticide purchases. This result starkly contrasts with the weather impacts observed in the other seasons. For instance, we observe that a one percent increase in autumn temperature leads to a 0.40% decrease in purchases for all pesticide categories, whereas temperature increase tends to increase pesticide use in all the other seasons. These contrasting results are likely to 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 vines to protect. It is plausible that our results reflect the fact that these particular crops are not subject to the same types of pest damage. To test this hypothesis, the next analysis further explores the role of agricultural specialization.

Differential weather impacts across type of agriculture. Not all French regions specialize in the same types of production (Figure A1), such that they may not exhibit the same cropping practices. In particular, regions specializing in different types of agriculture 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. Table A31 in the online Appendices displays the obtained estimates for this additional analysis. Table 7 shows the recomputed elasticities.

Table 7: Weather elasticities of pesticide purchases by agricultural specialization in each 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)
Average use (kg/ha)	2.525	1.311	0.832	0.313
	PANEL C. FRUIT, VEGETABLES 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)
Average use (kg/ha)	16.216	7.791	1.468	6.643
	PANEL D. VINES			
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)
Average use (kg/ha)	17.274	14.715	1.574	0.474

NOTE. Elasticities are computed at sample mean values using WLS estimates and equation (5). The standard errors are clustered at the zip code level and corrected for spatial dependency 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. Fruits encompasses orchards, nuts, olive trees, rice and vegetables. The average temperature and precipitation in zip codes specializing in Cereals and oilseeds crops are 16.2 °C and 356 mm respectively; 15.8 °C and 427 mm in zip codes specializing in feedcrops and pasture; 17.9 °C and 298 mm in zip codes specializing in fruits and 19.9 °C and 291mm in zip codes specializing in vines.

Table 7 provides several insights. First, zip codes specializing in cereals and oilseed crops – who represent about 52% of our sample, and thus likely to drive our previous findings – do use more pesticides when temperature and precipitation increase, as in the remainder of the paper. The difference stands with the amplitudes of the estimates. In this sample, a one percent temperature increase raises aggregated pesticide use by 2.21%, which is about 150% greater than in Table 2. We find similar larger precipitation impact on aggregated use. For fungicide and herbicide use too, the effect of temperature and precipitation is consistently at least 150 to 200% greater than for the whole sample. Table 7 shows that these zip codes specializing in cereals and oilseed crops are actually the most sensitive to weather shocks.

Second, our preferred estimates also closely align with those obtained for zip codes specializing in forages and pastures (Table 7, Panel B.). This is probably explained by the fact that these latter zip codes represent 42% of our sample. Consequently, our preferred estimates fall in between the estimates obtained in panels A. and B. Here, a one percent temperature increase leads zip codes specializing in forages and pastures to an approximately one percent increase in the use of all pesticide categories, while a one percent precipitation increase results in an approximate one-third of a percentage point increase. In other words, zip codes specializing in forages and pastures exhibit about half the level of sensitivity to similar weather shocks compared to those specializing in cereals and oilseed crops.

Finally, the results obtained for zip codes specializing in fruit production or vines are fairly consistent with those obtained for the other regions, at least for precipitation (Table 7, Panels C. and D.). Estimates for temperature are different yet. Specifically, we observe negative or null effects of temperature on the use of fungicides and herbicides in zip codes specializing in fruit production and vines. This outcome aligns well with the results identified in Table 6 regarding the weather impacts in autumn, when these crops are the main ones remaining to be harvested. Additionally, we find that they exhibit much greater insecticide use adjustments to temperature (compared to the remainder of the sample). This suggests that fruits and vines are more sensitive to insect damage, or that farmers have greater incentives to protect them – these crops are indeed much more profitable than the others. Because fruit production areas use ten to twenty times more insecticides than other zip codes (see Table 7), these results actually suggest that the use of insecticides in France is primarily influenced by temperature shocks in zip codes specializing in fruit production.

One possible explanation for these distinct outcomes in the zip codes specializing in fruits and vines is that they are located in warmer regions than others. Zip codes specializing in vines are for instance located in areas that are three to four degrees Celsius warmer than the average zip code in our sample (Table 7). Our 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 5.6.

5.5 Ruling out alternative mechanisms

We interpreted our previous results as if farmers respond to weather shocks by adjusting pesticide use at the *intensive margin* only. This explanation could however be threatened by two possible alternative mechanisms. First, farmers could adjust to weather shocks at the extensive margin by changing crop allocations (Graveline and Mérel, 2014; Cui, 2020). As such, because crops do not necessarily rely on the same pesticide intensity (see Table 7), crop allocation changes could mechanically modify overall pesticide use, ultimately introducing composition issues in the measurement of our dependent variable in equation (4). Second, farmers could also respond to weather shocks by adjusting at the super-extensive margin (Graveline and Mérel, 2014; Cui, 2020), by either restricting or expanding total farmland. That is, variations in our dependent variable may partly come 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 shocks at the intensive margin only, our approach in this section aims to quantify the extent of the extensive and super-extensive margin responses in order to rule out potential confounding effects of these alternative mechanisms on our estimates of interest.

Formally, we re-estimate equation (4) by changing our dependent variable, conserving all the other estimation elements. The first step is to consider the adjusted UAA as our new dependent variable. Results indicating that farmland area *reduces* in response to higher temperature or precipitation would challenge the validity of our preferred estimates suggesting that hotter or wetter growing seasons increase pesticide use, as they can reflect super-extensive margin response 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 higher temperature or precipitation by shifting their crop allocations towards more pesticide-intensive crops (such as fruits or vines; see Table 7). Table 8 displays the results obtained from such complementary estimations.

Table 8: Weather elasticities of agricultural areas

	Super-extensive	**Extensive**			
	Adjusted UAA	**Cereals**	**Feedcrops**	**Fruits**	**Vines**
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 (5) with alternative dependent variables (see column names). The standard errors are clustered at the zip code level and corrected for spatial dependency 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 include fodder and temporary grasslands. Fruits includes orchards, nuts, olive trees, rice and vegetables.

Table 8 shows that the adjusted UAA is not sensitive to changes in temperature during the growing season. That is, French farmers do not adapt at the super-extensive margin in response to temperature shocks. Because it indicates a constant denominator in the estimation of equation (4), 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. Indeed, results from Table 8 suggest minor changes of crop allocations in response to higher temperature. For example, the share of cereals – which constitute the half of total UAA on average – is not sensitive to temperature shocks. Actually, farmers primarily respond to higher temperature by slightly decreasing the share of fruit and replacing it by smaller expansions of vines and feedcrops. Given that these two crops consume fewer pesticides per unit area than fruit (see Table 7), this means that the changes in crop allocations induced by higher temperatures would actually conduct farmers to use *fewer pesticides* on average. This goes *against* our previous estimates, which are all significantly positive (Table 2). Given the mixed results on the adaptation at the extensive and super-extensive margins induced by temperature changes, 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 temperature in terms of pesticide use.

Looking now at precipitation, Table 8 indicates that farmers do adapt at the super-extensive margin in response to higher precipitation. This means 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 they are positive (Table 2), this implies that the numerator has increased more than the denominator in response to higher precipitation. In other words, our previous estimates actually reflect the *lower bound* of the farmers' intensive margin responses to greater precipitation. The results at the extensive margin 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 them are not significantly different from zero at the 95% statistical level), we believe that these effects are of minor importance for the present debates. At least, they do not reflect any shift from pesticide-extensive crops towards pesticide-intensive crops, indicating that our preferred precipitation estimates should not suffer from strong composition effects.

In summary, Table 8 indicates that adaptation mechanisms at the extensive and super-extensive margins are – at most – limited, and go – in any case – in the opposite directions to the signs of our preferred estimates. In other words, these extra findings imply that our preferred estimates are likely to represent conservative estimates of farmers' intensive margin responses to weather shocks.

5.6 Non-linear temperature impacts

Now that we have presented robust and consistent results using average temperatures during the growing season, we turn to the presentation of the non-linear impact estimates. Previous analyses already reported non-linear concave effects of precipitation on pesticide use (see Table A2 in the online Appendices). We further investigate the non-linear effects of temperature within the growing season by estimating equation (6) using three functional forms (piecewise functions, bins and 9^{th}-order polynomial functions; see online Appendix A5). Figure 4 presents the resulting estimates on pesticide purchase.

Figure 4 reveals that the farmers' pesticide use responses to temperature vary across its entire distribution. It consistently demonstrates, for all pesticide categories, that moderate temperatures have a slightly linear positive effect on pesticide use, but that extreme temperatures strongly reduce it. Such linear responses for moderate temperatures are consistent with that identified in Section 5.1. However, we have not previously identified such a negative relationship for extreme temperatures, indicating that the concave effect of temperature is identified far away from the average. We examine these relationships in more detail here.

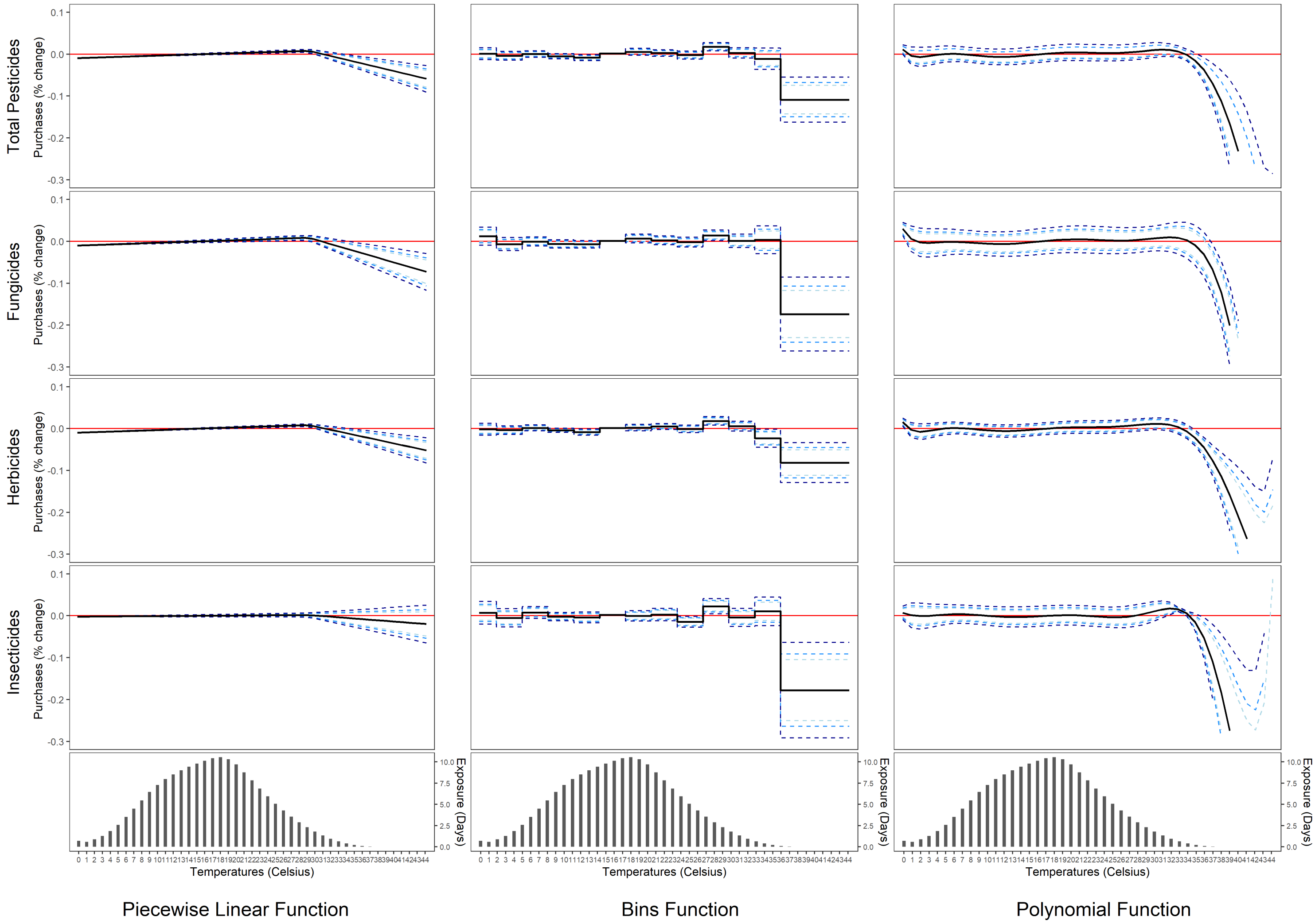


Figure 4: Impacts of temperature distribution on pesticide purchases during the growing season. Note. Graphs display changes in pesticide purchase in kg/ha if crops are exposed for one day to a particular 1°C temperature interval where we sum the fraction of a day during which temperatures fall within 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 4 indicates that exposure to temperatures up to about 25°C has minor impacts on use of all pesticide categories. Pesticide purchase does indeed weakly increase from 8°C up to this threshold for all categories, with most effects not distinguishable from zero. Purchases only significantly increase for temperatures higher than 25°C. For example, an additional day of exposure to 27 to 30°C would increase aggregated pesticide purchases by about 2% relative to average exposure to 16 to 18°C (reference bin). All functions show a negative influence of extreme temperatures on the purchase of all pesticide categories. For example, an additional day of exposure to temperatures above 33°C would decrease fungicide purchase by 10 to 25%. Our findings are similar regarding herbicide purchase, which starts to be negatively affected by temperatures above 30°C. An additional day of exposure to temperatures above 30°C would decrease herbicide purchase by 5 to 15%. Though less precisely estimated, insecticide purchase is also negatively affected by temperatures above 33°C.

These results are consistent with the literature. First, the lower pesticide use induced by extreme temperatures is consistent with the documented negative impacts of heat on (i) weed, fungi and insect growth conditions, (ii) pesticide efficacy and (iii) attainable yields (Patterson et al., 1999; Delcour et al., 2015; Deutsch et al., 2018; Kawasaki, 2023). Our results on insecticide use are particularly consistent with Möhring et al. (2022) and Larsen and McComb (2021) who both identified negative impacts of extreme temperatures on insecticide use. They are also close to Rhodes and McCarl (2020), who found that a high number of hot days (33°C and above) negatively impact insecticide purchases 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 use, but also apply to that of fungicides and herbicides. While the negative impacts of heat on pesticide use are strong and significant, it is essential to weight these results by their very low frequency in our sample. This raises the question of whether the more frequent occurrence of extreme temperature events associated with climate change will decrease pesticide use in the future. We explore these potential future effects in the following section.

6 Simulations of climate change impacts

In this section, we use our previous estimates to project future pesticide use under forthcoming climate conditions. Specifically, we multiply our preferred estimates by the difference in average temperature and precipitation during the growing season between 2014 and 2019 and those projected between 2050 and 2055, assuming all other factors to be constant.[23] We derive information about future temperature and precipitation from the spatially-explicit projections from the ALADIN climate model of Météo-France under the medium emission pathways scenario (RCP 4.5 scenario).[24] Note that the selection of this climate scenario is not intended to provide an accurate forecast of actual pesticide outcomes in 2050. Rather, it serves the purpose of demonstrating the projected implications of our model based on a plausible climate scenario. ALADIN projects a general increase in temperature and a rarefaction of precipitation during the growing season in 2050-2055 under the RCP 4.5 scenario, with an expected rise of average temperature by 1.41°C and an expected decrease of average precipitation by 30 mm (see online Appendix A26). The results of projections of future pesticide use are displayed in Figure 5 and Table 9.

[23] We notably assume constant crop allocation and UAA. If results from Section 5.5 indicate that farmers adjust their total agricultural area and crop allocations to weather shocks in the growing seasons, these adaptation patterns are rather limited and our estimates mostly reflect intensive margin responses.

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

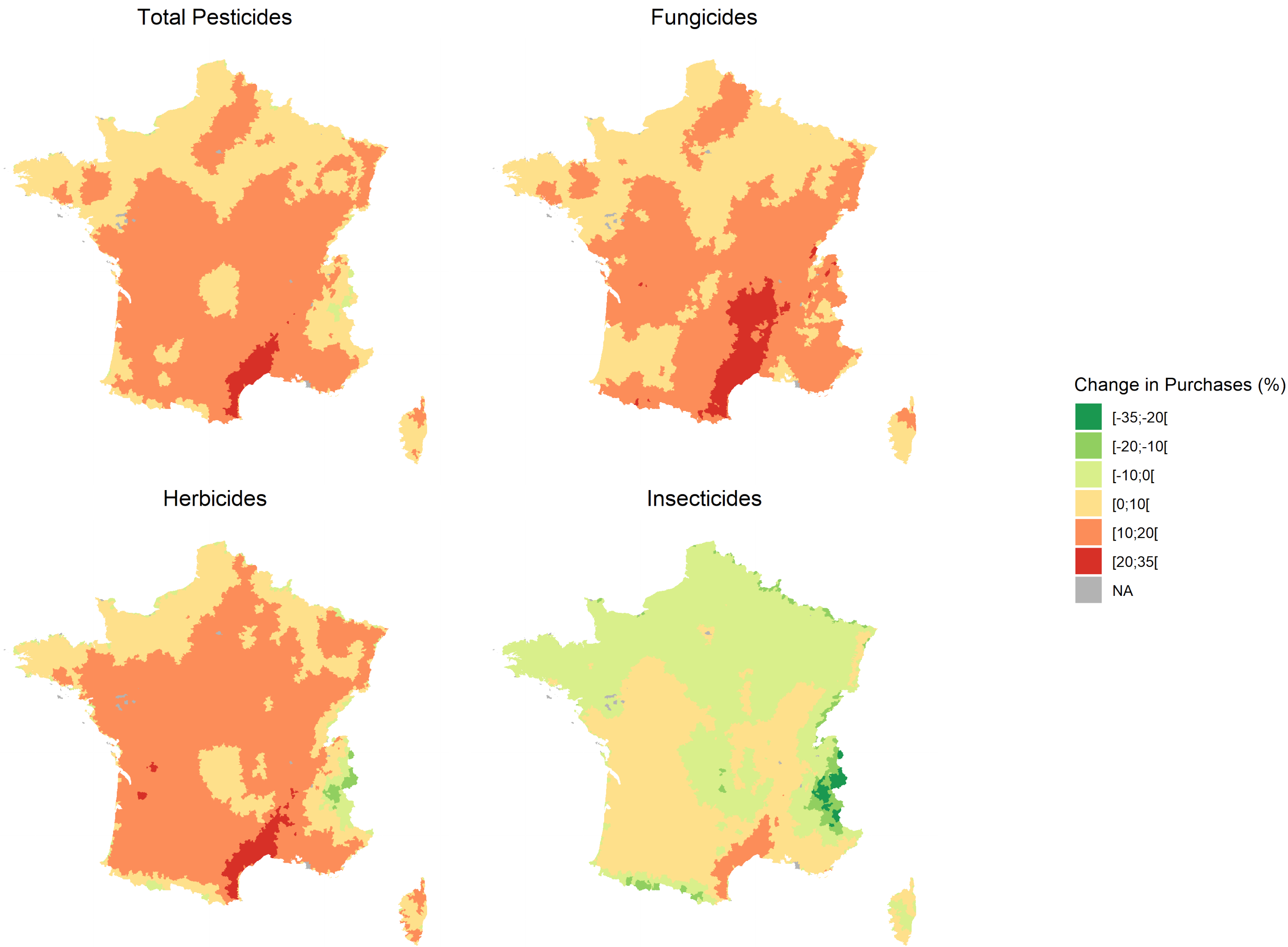


Figure 5: Pesticide use projections in 2050 under RCP4.5 climate change scenario. NOTE. Graphs display estimated changes in pesticide use in percentage if crops are exposed to hypothetical changes in temperature and precipitation during the growing season (from March 1^{st} to August 31^{th}) according to our preferred estimates and to the information provided by the ALADIN climate model for the RCP 4.5 emission pathways scenario between 2050 and 2055.

Figure 5 shows the tailored projections of pesticide use in 2050-2055 compared to 2014-2019 averages when using our preferred estimates obtained with average weather conditions during the growing season (see Section 5.1). It shows that farmers in different regions will react differently to the heterogeneous temperature and precipitation 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 farmers' responses in terms of fungicide and herbicide use. Indeed, although fungicide and herbicide use increases in most locations, it particularly surges in this area. By comparison, Figure 5 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 its use by up to 35%.

Panel A. of Table 9 sums up the overall climate effects when using our preferred estimates obtained with average temperature during the growing season (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. Moreover, Table 9 also displays the results with the piecewise linear function parameters reported in Section 5.6 on the non-linear temperature impacts (see columns "Cum. Temp." in Table 9).

Table 9 provides a clear picture. According to our preferred approach, French farmers would respond to future temperature and precipitation by increasing their aggregated pesticide use by between 7% and 15% on average (Panel A.). This aggregate increase is actually driven by the farmers' responses in terms of herbicide and fungicide use, which would also increase by between 8 and 14%, while maintaining their insecticide use at average 2014-2019 levels. These effects are predominantly driven by the impacts of warmer temperatures. Indeed, Table 9 indicates that higher temperatures projected in the RCP4.5 scenario would increase total pesticide, fungicide and herbicide use by 13 to 15% (Panel B.), while precipitation changes would reduce them by 2 to 4% (Panel C.). In contrast, the climate impact on insecticides is null because the (small) temperature and precipitation impacts offset each other. While slightly smaller in magnitude, these results are consistent when using the piecewise estimates. As such, the more frequent extreme heat events under the RCP4.5 scenario only offset a marginal proportion of the impacts of higher moderate temperatures.

Table 9: Projections of changes in pesticide use in 2050 under a RCP4.5 climate change scenario

	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)
	[6.947,15.201]	[5.002, 10.675]	[3.658,18.399]	[1.804,10.668]	[8.256,14.843]	[6.502,11.799]	[-6.152,5.384]	[-5.962,2.522]
	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)
	[9.666,18.029]	[6.954, 12.486]	[7.642,22.382]	[4.503, 13.652]	[10.189,16.775]	[7.766,12.756]	[-4.289,7.247]	[-4.555,3.728]
	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)
	[-3.652,-1.895]	[-2.798,-0.964]	[-5.228,-2.739]	[-4.049, -1.635]	[-2.792,-1.073]	[-2.015,-0.206]	[-3.037,-0.690]	[-2.478,-0.135]

NOTE. The figures indicate the percentage changes in pesticide use under hypothetical increases in temperature and precipitation during the growing season (from March 1^{st} to August 31^{th}) using our preferred estimates (Avg. Temp.), the piecewise linear function (Cum. Temp.) and average RCP4.5 ALADIN projections between 2050 and 2055. The figures are average effects in France expressed as percentages of initial use. Standard errors are corrected for spatial correlation using Conley (1999) and shown in brackets. 95% confidence intervals are displayed in square brackets. *, **, *** indicate p-values lower than 0.1, 0.05 and 0.01.

7 Concluding remarks

A recent and abundant literature has measured the effects of weather shocks on crop yields 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 (Hsiang, 2016). This paper proposes to elucidate such adaptation behaviors by focusing on pesticide use as an illustrative case. Using an original, exhaustive dataset of purchases of all active substances in France, we show that farmers do adjust their pesticide use to weather shocks. In particular, we find that farmers react to similar weather shocks by purchasing far more fungicides and herbicides than insecticides. Our preferred estimates obtained using average weather conditions during the growing season indicate that a one percent temperature increase leads farmers to purchase additional +1.70% of fungicides, +1.72% of herbicides, but only +0.37% of insecticides. These results are robust to many sensitivity analyses. The lack of evidence of any storage behaviors from one year to another suggests that our dependent variables – that are fundamentally data on pesticide purchases – are actually likely to represent pesticide use. We also show that our preferred estimates are likely to represent the lower bound estimates of the farmers' intensive margin responses to weather shocks. This means that our preferred estimates actually represent the combined effects of weather on (i) pest pressure, (ii) pesticide efficacy and (iii) attainable yields, but do not include change in crop allocation nor in total agricultural area. Additional analyses indicate that our preferred estimates are largely driven by weather shocks during spring, at the time when farmers apply pesticides, and that zip codes specializing in cereals and oilseed crops are much more sensitive to weather shocks than other regions. We also document the fact that the sensitivity of pesticide applications to weather shocks is greater for those with higher risks to human health in the case of herbicides and fungicides, and for those with higher risks to the environment in the case of insecticides. Finally, we identify non-linear, concave weather effects on pesticide use, which appears close to the sample average for precipitation, but far from this point for temperature.

Projections based on our preferred estimates indicate that, *ceteris paribus*, French farmers are likely to increase pesticide use by 7% to 15% on average by 2050 in response to a RCP4.5 climate change scenario. This has significant implications for French and European policymakers. Despite their efforts over the past decades to halve pesticide use (Schebesta and Candel, 2020), our results indeed suggest that achieving such reductions becomes even more challenging in the context of climate change. While some stakeholders might have hoped that climate change would have decreased the incentives to use pesticides (due to anticipated reductions in crop yields; see IPPC, 2021, for example), our findings suggest instead that the climate-induced increase in pest pressure or pesticide efficacy – i.e. the two other channels captured by our estimates – would actually lead rational farmers to *apply more pesticides*. To anticipate these trends, our results call for a strengthening of existing pesticide policies, in particular those in France. Indeed, despite relying on pesticide taxes modulated by toxic risks, our results suggest that the current French tax rates would be insufficient to reduce pesticide use in the country. Given that we predict that the largest climate-induced surges in pesticide applications would concern the most toxic products (those primarily affected by French and European regulations), we believe that this calls in particular for a proactive increase on these substances' tax rates. However, because such taxes would result in hundreds of millions of euros of losses for the French food and farming sector (Bareille and Gohin, 2020),[25] it is likely that they would not be socially accepted.

[25]The reduction of pesticide use is however likely to lead to numerous positive non-market effects. Compiling previous assessments, Bâ et al. (2015) consider that pesticide pollution costs annually from €7.0 billion to €28.4 billion in France (mostly due to the negative health outcomes of insecticide use). Using total sales, this value implicitly

In this context, alternative public policies targeting these most toxic substances may be explored. One possibility would be to redistribute the resulting tax revenues to farmers via lump-sum payments (Chèze et al., 2020), but alternative policy instruments beyond mere financial incentives should also be considered (Finger and Möhring, 2022).

All our results are identified thanks to fine-grained pesticide purchase measured at about 9 km × 9 km on similarly spatially detailed weather shocks. To our knowledge, we are the first to perform this kind of econometric assessment at such a detailed resolution. While this spatial resolution presents clear advantages, it also introduces some limitations. First, the lack of exhaustive data on crop yields and pest pressure at such a detailed spatial definition prevents us from separately identifying the weather impacts on (i) pest pressure, (ii) pesticide efficacy and (iii) attainable yields. Second, while we have provided several elements indicating that our measurements of pesticide purchases are likely to reflect pesticide use, we acknowledge that our analyses would benefit from data on actual pesticide use (particularly on a crop-specific basis), rather than relying solely on purchase data. Unfortunately, the few existing databases on pesticide use are however only available at coarser spatial resolutions, which would have threatened our identification strategy. Third, the impacts that we have identified are short-term in nature, and further research is essential to unveil long-term adaptations to climate change. This includes investigating changes in cropping areas (Cui, 2020), or expansion of the total agricultural area (Graveline and Mérel, 2014). While we argue that our estimates are not immediately affected by these adaptations in the short term, they may influence farmers' pesticide use decisions in the longer run (Burke and Emerick, 2016). Incorporating these elements is necessary to enhance predictions of pesticide use under future climate conditions and, *in fine*, improve our assessment of the costs of climate change (Carleton et al., 2022).

corresponds to a social cost of pesticides between 100 and 400 €/kg. Bareille and Gohin (2020) however show that the reduction in pesticide use in France can be accompanied by negative side-effects on other non-market dimensions (e.g. increase in carbon emissions or increase in fertilizer pollution).

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