water

Article

Decision-Making Process Factors Explain Some of the Heterogeneity of Irrigation Practices among Maize Farmers in Southwestern France

Marine Albert [1,*], Jacques-Eric Bergez [1], Stéphane Couture [2], Robert Faivre [2] and Magali Willaume [3]

[1] AGIR, INRAE, Université de Toulouse, F-31320 Castanet-Tolosan, France; jacques-eric.bergez@inrae.fr
[2] MIAT, INRAE, Université de Toulouse, F-31320 Castanet-Tolosan, France; stephane.couture@inrae.fr (S.C.); robert.faivre@inrae.fr (R.F.)
[3] AGIR, INPT ENSAT, Université de Toulouse, F-31320 Castanet-Tolosan, France; magali.willaume@inrae.fr
* Correspondence: marine.albert@inrae.fr

Abstract: Agricultural practices are heterogeneous among farmers in the face of climate hazards. Structural and material resources as well as risk preferences explain some of this heterogeneity, but little is known about how psychological factors associated with the decision-making process may explain differences in practices among farmers. The aim of this study was to understand whether decision-making process factors help explain the heterogeneity of a specific practice—the date of first irrigation—among maize farmers, along with material and structural factors. We conducted semi-directed interviews with 35 farmers who irrigated maize in southwestern France. We analyzed discriminating factors of the decision-making process, such as reactivity (i.e., capacity to change plans), deliberation (i.e., level of internal information used to make decisions) and assistance (i.e., level of external information used to make decisions). We used two complementary statistical methods (linear regression and regression trees) to analyze the database. Our study confirms the influence of material and structural factors, and also reveals the strong influence of decision-making process factors. A high level of reactivity is associated with adaptive behavior. Moreover, using decision-support tools and technologies helps farmers to manage the use of water resources. These elements could be used by advisors and public policy-makers in the agriculture sector to improve adaptation.

Keywords: adaptation; water scarcity; adaptive capacity; decision-making; irrigation practices; maize-cropping system

Citation: Albert, M.; Bergez, J.-E.; Couture, S.; Faivre, R.; Willaume, M. Decision-Making Process Factors Explain Some of the Heterogeneity of Irrigation Practices among Maize Farmers in Southwestern France. *Water* **2021**, *13*, 3504. https://doi.org/10.3390/w13243504

Academic Editors: Alban Kuriqi and Luis Garrote

Received: 8 October 2021
Accepted: 5 December 2021
Published: 8 December 2021

1. Introduction

Farmers today are facing climate hazards such as floods, droughts and/or frost. In central and southern Europe, farmers are experiencing an increase in the frequency of droughts, with negative impacts on crop productivity [1]. In France, 2011 has been one of the ten driest years in 50 years so far, with a hydric deficit mean of more than 10% and a mean temperature exceeding the reference by 2.6 °C (1971–2000) [2]. The context of agricultural production has become increasingly volatile and unpredictable [3]. Farmers need to adapt to a changing environment with new constraints, such as water scarcity [4]. Their decisions regarding irrigation strategies directly influence the quantity and quality of natural resources [5]. The impact of droughts is particularly severe for summer-irrigated plants, such as maize (*Zea mays* L.).

In France, grain maize is the second most frequently produced cereal after wheat (*Triticum aestvum*), with a national production of 13.5 million t in 2020 [6] over an area of just over 1 million ha, 35% of which was irrigated [7]. The decrease in rainfall directly affects maize yield since it is sensitive to hydric deficit, especially at reproductive development stages. Adaptation strategies, such as changing the amount, timing and frequency of irrigation, can avoid yield losses and make it possible to save water [8,9]. The start of the irrigation season is a key element for crop development and is a milestone that should not be missed; it will make it possible to target high yields and ensure the continuation of irrigation practices. Focusing on the date of first irrigation is therefore a major challenge for farmers in terms of water management. The date of first irrigation for maize usually varies with the region. However, it may also vary from farm to farm in a similar context of water availability. Understanding explicative factors of this heterogeneity is key to enhancing adaptation in agriculture.

Many studies have sought to explain the heterogeneity of farmers' practices. Most of them considered structural and material factors such as farm characteristics and agricultural practices. Several studies attempted to understand farming system management based on the level of resources [10], intensity of agricultural practices [11,12], equipment and socio-economic aspects [13]. However, practices remain heterogeneous even when farmers have similar production situations [14]. For example, differences in chemical input practices have been explained in part by farmers' personal characteristics and their production situation [15,16]. Moreover, farmers' decisions are not completely based on structural and material factors [17]. Recent studies have hypothesized that, in addition to structural and material factors, psychological factors could also explain the heterogeneity of practices among farmers [18]. It appears that two types of psychological factors can explain such heterogeneity: risk preference (i.e., a farmer's degree of reluctance to perform potentially risky practices [19,20]), and decision-making process factors (i.e., psychological factors specific to the decision-making process). The decision-making process is the process by which an individual commits to following a choice when alternatives exist, even when these alternatives are not known or analyzed [21]. Few studies have focused on the influence of decision-making process factors on the heterogeneity of practices [22–25]. Some studies modeled the decision-making process in order to better understand farmers' behavior [18,25,26]. Daydé (2017) developed a conceptual model of the decision-making process and hypothesized that the heterogeneity of the process among farmers explained the heterogeneity of practices. His case study focused on fungicide doses applied to wheat. In Daydé's (2017) model, the farmer's decision-making process was based on three decision-making process factors: reactivity (i.e., the farmer's capacity to change his plans), assistance (i.e., amount of external information used by the farmer), and deliberation (amount of internal information used by the farmer).

Our study aimed to explain the heterogeneity of the date of first irrigation of maize farmers in southwestern France. Our objectives were to study the role of structural and material factors as well as psychological factors through risk preferences and the three decision-making process factors (reactivity, assistance and deliberation). Our study was based on semi-directed interviews with maize farmers. We begin by describing the conceptual framework, survey design and the methods for analyzing the survey data. We then present and discuss the main results, with particular focus on psychological factors specific to the decision-making process and their influence on farmers' decisions to start irrigating.

2. Materials and Methods

2.1. Conceptual Framework

Irrigation practices can be explained by the context within which the farm is exposed. The changing context (price and climate variability) often leads to changes in practices. Price and climate variability are external factors that constitute the main driving forces. However, within the same context, farmers can have different practices. The adoption of practices can also be explained by internal factors, i.e., factors directly linked to the farming system and the farmer (e.g., structure of soil, age of the farmer). The conceptual framework (Figure 1) is based on the association of material, structural and psychological factors previously identified as potential factors that explained the heterogeneity of practices. It assumes that both observable and non-observable factors contribute to the heterogeneity of practices.

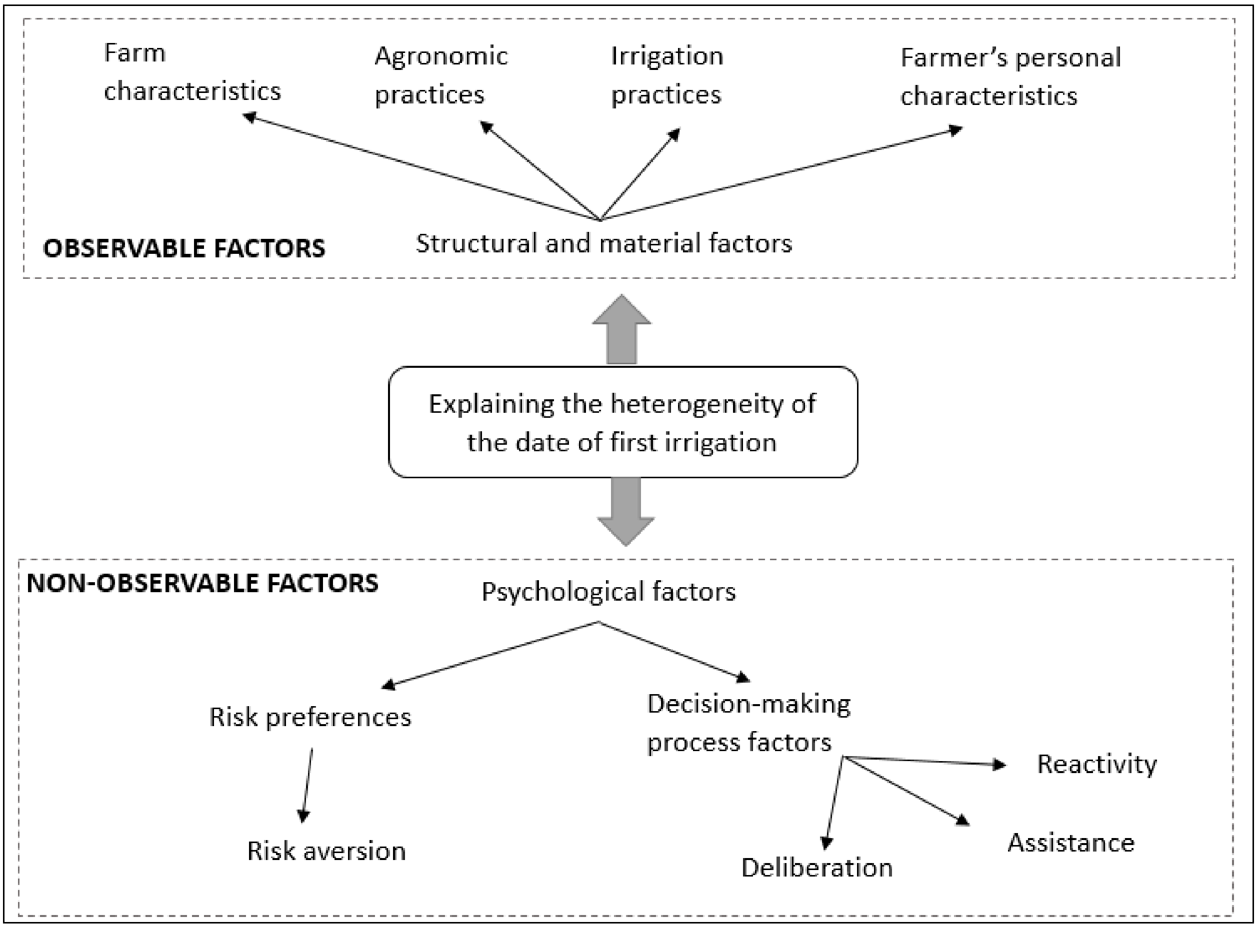

Figure 1. The conceptual framework used to analyze the observable and non-observable factors that a farmer uses to choose the date of first irrigation of an irrigated grain maize crop.

Observable factors (i.e., structural and material; [27]) are categorized into four groups: farm characteristics, agronomic practices, irrigation practices and farmers' personal characteristics (i.e., age, education level, experience as a maize grower). For the non-observable factors, we used the conceptual framework developed by Martin-Clouaire (2017), which considers risk preferences and decision-making process factors. Daydé's (2017) three decision-making process factors are defined as follows:

1. Deliberation: the amount of internal information used by the farmer for decision-making;
2. Assistance: the amount of external information used by the farmer for decision-making;
3. Reactivity: to the farmer's capacity to change his plans in response to new information.

2.2. *Implementation of the Conceptual Framework*

2.2.1. Survey Design

One challenge of the survey design (Figure 2) was to identify ways to obtain subjective data related to non-observable factors. To do this, we used a variety of elicitation methods in the survey questionnaire [28]: a lottery game to assess the level of risk aversion, scenarios to assess the level of reactivity, and a mind map and role-playing to assess the level of deliberation. The level of assistance was assessed using direct elicitation of information by asking a variety of questions. Observable factors were also assessed using direct elicitation of information. We asked about financial data at the end of the interview, when the farmer was more comfortable and more inclined to provide important and confidential data.

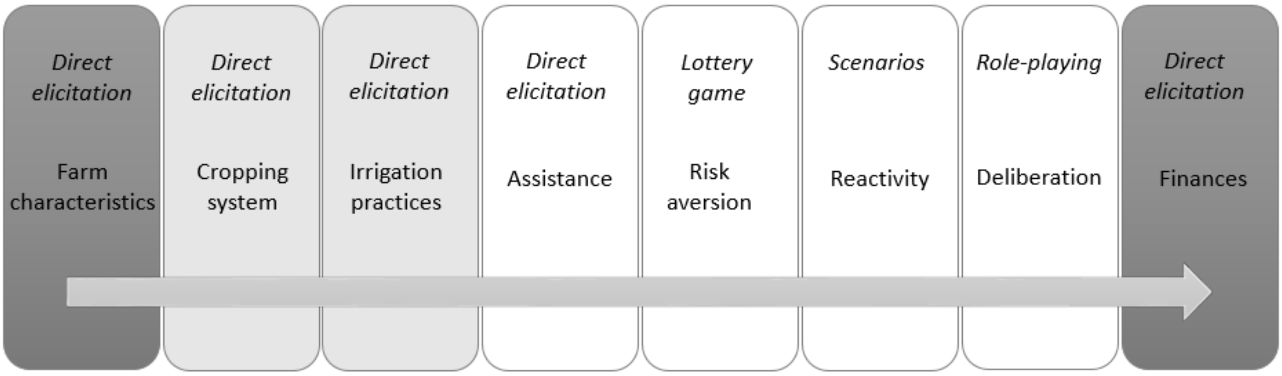

Figure 2. Survey structure and elicitation methods to obtain structural data (dark gray), farming practices data (light gray), and psychological data (white).

2.2.2. Structural and Farming Practice Data

Structural and material factors can be directly measured using closed Likert scales and multiple-choice questions. We captured farm characteristics using indicators such as area, soil type and slope. We also asked about general agronomic practices such as crop sequences, the type of maize grown, percentage of maize in the crop sequence and the use of tillage. We recorded farmers' personal characteristics using indicators such as age, level of education and experience with maize production. Finally, we focused on irrigation practices, including the equipment used, duration of irrigation and the volume of water per irrigation period. Indeed, we assumed that these elements could influence the date of first irrigation. For example, if there is little equipment, irrigation time would be extended, and the farmer would therefore need to start the irrigation campaign earlier. To identify the date of first irrigation, we developed a maize-cropping scenario for a typical year in the temperate climate of the Occitanie region of France and without water restrictions. The interviewer showed temperature, rainfall and evapotranspiration graphs to the farmers and asked them which day they would start irrigating.

2.2.3. Psychological Data

As mentioned, we used the lottery game, role-playing and scenarios as elicitation methods to assess psychological factors. We used a variety of inquiry methods to obtain redundant and complementary data, which minimizes each method's bias and offsets its limits by using other methods, based on the principle of data triangulation [28].

To assess risk preferences, we used a lottery game developed in experimental economics [19]. We asked the farmers to choose one of nine lottery games to play (Appendix A). Each lottery game involved two possible outcomes. The game they chose revealed their level of risk aversion. We then used different approaches to assess the three decision-making process factors (Table 1).

Table 1. Elicitation techniques and indicators for assessment of the three decision-making process factors: deliberation, reactivity and assistance. Assistance is divided into professional assistance, networking assistance and digital assistance.

Decision-Making Process Factors	Indicator for Assessment	Elicitation Technique
Deliberation	Number of pieces of information used to make a decision	Two elicitation techniques: (i) a mind map to obtain a list of information that the farmer used to choose the date of first irrigation; (i) a role-playing activity [29] consisting of placing the farmer in a situation that required making a decision with no information at the outset.

Table 1. *Cont.*

Decision-Making Process Factors	Indicator for Assessment	Elicitation Technique
Reactivity	Number of intention changes (i.e., the number of times an individual changes his choice)	Farmers were asked to express their intentions in scenarios in which water availability could have major impacts on their objectives. We designed four scenarios based on annual weather conditions (temperate year vs. dry year) and on the potential restriction of the water quota (none vs. 25% restriction).
Professional assistance	Number of advisors	Direct questions
Networking assistance	Number of other maize farmers with whom the farmer interacted	Direct questions
Digital assistance	Number of technologies; the use of sensors, decision tools or weather stations; and the number of weather sources.	Direct questions

2.3. Case Study

The case study was based in southwestern France (Figure 3). Maize has high economic and cultural value in southwestern France but requires more water in summer than many other field crops. Maize farms in this region use an average of 54,000 m^3 of water per year. Most of the maize-growing area is irrigated (i.e., 90%, for farms specialized in field crops). The increase in droughts in summer leads to a greater need for irrigation of maize, making these farms economically dependent on irrigation in six out of ten years on average [30].

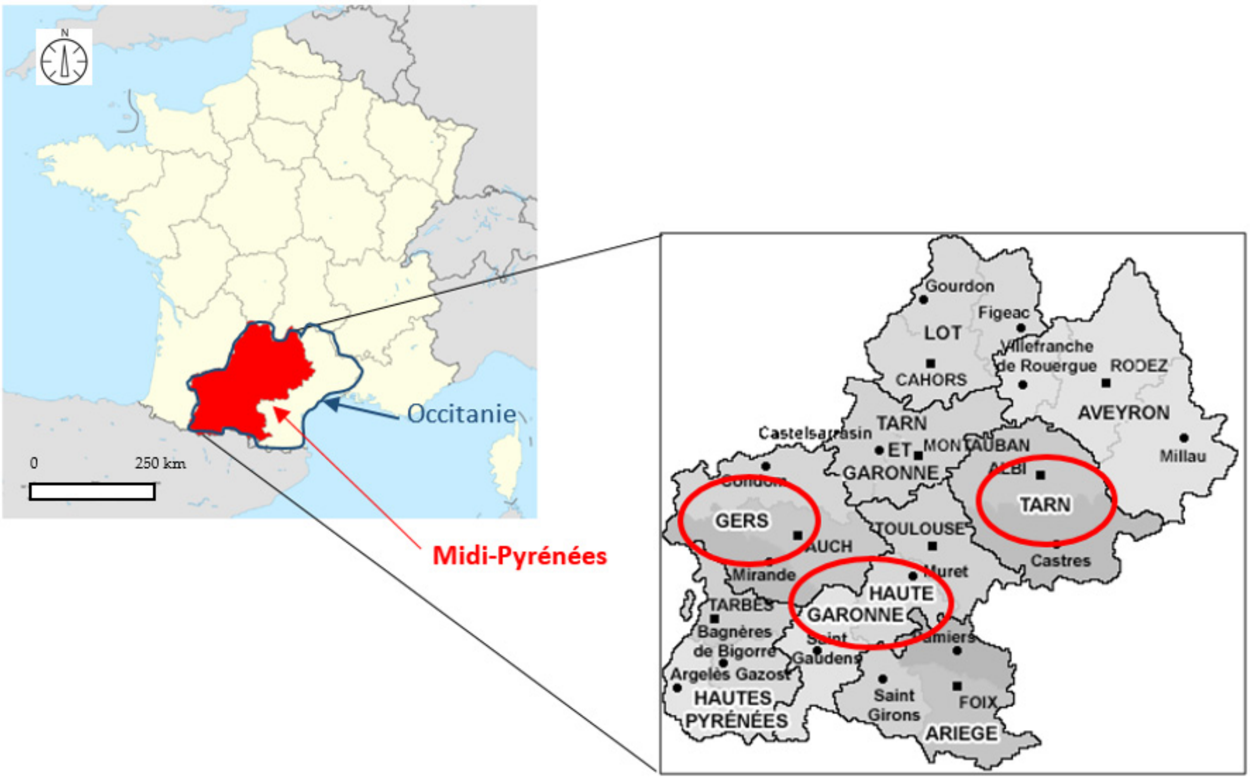

Figure 3. Location of the Tarn, Gers and Haute-Garonne departments in the Midi-Pyrénées sub-region of the Occitanie region of France.

To recruit participants for the survey, the regional Chamber of Agriculture gave us contact information for 69 farmers who grew irrigated maize (waxy, popcorn, grain or seed). We contacted them and 35 farmers responded positively. Their farms were located in the administrative departments of the Tarn (nine farms), the Gers (14 farms) and the

Haute-Garonne (11 farms) (Figure 3). Interviews were conducted in April, May, September and October 2019. Each interview lasted 1–4 h.

2.4. Data Processing and Analysis

The data (quantitative and qualitative) collected in the surveys were entered in a Microsoft Excel® file (35 rows (farmers) × 184 columns (variables)) for further analysis. Before analyzing the data, we cleaned the data in several steps (Figure 4). Step 5 consisted of sorting the 44 variables into the eight groups of observable and non-observable factors: farmers' characteristics, farm characteristics, agronomic practices, irrigation practices, risk preferences, reactivity, assistance and deliberation. When variables in a group remained correlated ($R^2 > 0.4$ for quantitative variables and p-value < 0.05 for qualitative variables), we selected no more than three variables with the greatest influence on the date of first irrigation. Keeping a few variables in each group allowed us to represent each group fairly, and this final step left one response variable (the date of first irrigation) and 24 explanatory variables.

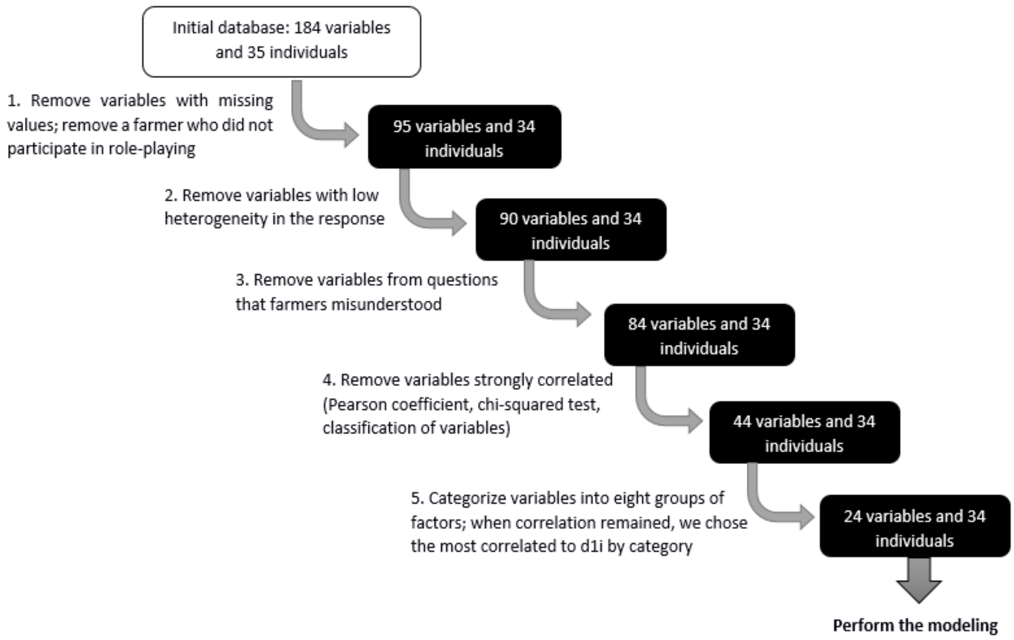

Figure 4. The data cleaning and selection procedure. d1i: date of first irrigation.

Two statistical models were then used to model the influence of these explanatory variables on the date of first irrigation: linear regression and a regression tree (Table 2). The linear regression was performed using stepwise selection (forward and backward). We selected and tested several combinations of the 24 variables to find the best set of explanatory variables. Since linear regression models consider variables additively, without considering non-additive effects, combined effects or interactions, we built a regression tree [31].). Regression trees thus consider local interactions among variables.

Statistical analyses were performed using R software ([32]. We used a classification approach (*ClustOfVar* package ([33]) and the *FAMD* function (of the *FactoMineR* package) to compare all variables and identify redundant information.

Table 2. Characteristics of the two statistical models: linear regression and regression tree.

	Regression Tree	Linear Regression
Definition	The regression tree sequentially divides responses according to the most relevant explanatory variable (i.e., minimizes the locally explained variance)	Linear regression creates many combinations of variables by adding or removing them until it finds the best combination.
Parameters	Stopping rules (minimum number of observations to separate a node (minsplit) = 10, minimum number of observations, into a leaf (minbucket) = 3)	Use of the Akaike Information Criterion to minimize over-fitting. Tests on residuals were performed to check independence (Durbin-Watson test), normality (Shapiro-Will test) and homogeneity (Breusch-Pagan test).
R functions	Rpart function in the rpart package of R (based on the CART model)	Lm and step functions of R

3. Results and Discussion

3.1. Farm Characteristics

Our sample was representative of French farms (Table 3) in terms of the mean age of farmers, legal status and water sources. However, farms in our sample had more utilized agricultural area (UAA) and mean irrigable area than the mean of the Midi-Pyrénées (Midi-Pyrénées is part of the new Occitanie region) region. Having larger farms explained the bigger equipment needed for irrigation (center pivot) and the use of a larger volume of water. Nineteen farmers have received post-secondary education (at least 2 years). Most of the farmers grew grain maize (24/34), did not till the soil (24/34) and did not irrigate at sowing (20/34). Although our sample is not entirely representative of the Occitanie region, potential results of the study can provide knowledge about maize farming systems in Occitanie, in particular, for large farms in terms of surface area and irrigation water consumption.

Table 3. Characteristics of surveyed and reference farms. Reference data are at the regional scale, when available (former Midi-Pyrénées region, corresponding to the western Occitanie region), or the country scale (France). UAA: utilized agricultural area.

Characteristic	Sample	Reference	Scale	Source
Mean (±SD) age (years)	49.8 (±12.0)	49.3	France, all types of farms	[34]
Legal status	Limited-liability farm (13/34)	Limited-liability farm	France, field crops	[35]
Mean (±SD) UAA (ha)	171 (±77)	83	Midi-Pyrénées, field crops	[36]
Mean (±SD) irrigable UAA (ha)	87 (±58)	28	Midi-Pyrénées, field crops	[36]
Water sources	Watercourses (rivers, canals) (21/34) and water storage (hillside lakes) (14/34)	Watercourses and water storage	Midi-Pyrénées	[36]
Irrigation materials	Sprinkler trolleys (19/34) and center pivots (15/34)	More sprinkler trolleys than center pivots	Midi-Pyrénées	[36]
Mean water volume (m^3/ha/year)	2302	1725	Midi-Pyrénées	[37]

3.2. Description of the Variables

The date of the first irrigation ranged from 29 May to 20 July, with a median of 21 June (Figure 5). With a range of 52 days, the date of first irrigation had high heterogeneity. Most dates of first irrigation ranged from 17–28 June (25/34).

Of the 24 explanatory variables selected, those for structural and material factors were mainly farm characteristics (5) and agronomic practices (5), followed by irrigation practices (4) and farmer's characteristics (3). In comparison, the variables for psychological factors were mainly assistance (4), followed by reactivity (2), deliberation (2) and risk preferences (1) (Table 4).

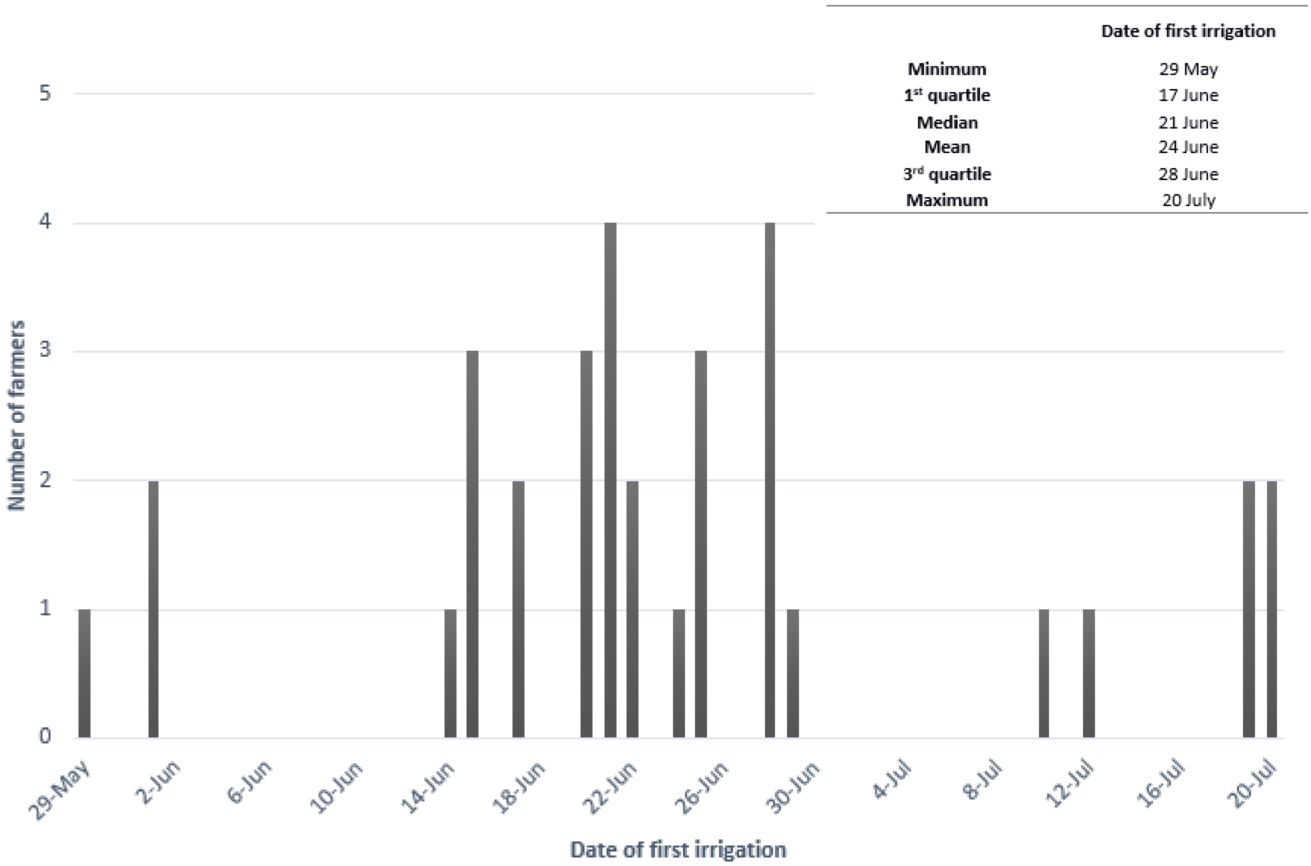

Figure 5. Distribution of the dates of first irrigation for interviewed farmers.

Table 4. Classification, responses and descriptions of the 24 explanatory variables.

Group of Variables	Variable Name	Response (Mean or by Class)	Description
Farmer's characteristics	years-maize	Mean = 32	Number of years of experience with maize production
	education-level	PS: 19, P: 14, O: 1	Level of education (PS: post-secondary, S: secondary, O: other)
Farm characteristics	department	G: 14, HG: 11, T: 9	Administrative department where the farm is located (G: Gers, HG: Haute-Garonne, T: Tarn)
	UAA	Mean = 171	Utilized agricultural area (ha)
	soil-boulb	Yes: 14, No: 20	"boulbène" soil (vernacular name for sandy-clay Luvisol) or not (yes, no)
	soil-water-storage	Low: 11, Moderate: 20, High: 3	Level of soil water-holding capacity (low to high)
	slope-level	Low: 22, Moderate: 1, High: 11	Slope (low to high) (The five initial modalities (score from 1 to 5) were converted to three levels (low, moderate, high))
Agronomic practices	maize-type	p: 6, g: 23, s: 3, f: 1, w: 1	Type of maize (g: grain, s: seed, p: popcorn, w: waxy, f: fodder)
	maize-main	Yes: 14, No: 20	Whether or not maize is the main crop (yes, no)
	tillage	Yes: 11, No: 23	Whether or not the farmer practices tillage (yes, no)
	sow-date	Early: 23, Middle: 4, Late: 7	Date of sowing (early to late) 29 May $\leq$ Early < 16 June $\leq$ Middle < 4 July $\leq$ Late < 20 July
Irrigation practices	sow-irrigat	Yes: 14, No: 20	Whether the farmer practices irrigation at sowing or not (yes, no)
	n-days-cycle	Mean = 6 days	Number of days in the irrigation cycle
	volume	Mean = 230 mm	Volume of water used for irrigation (mm)
	equip-irrig	Pivot: 15, Trolley: 19	Type of equipment used for irrigation (pivot, trolley)

Table 4. *Cont.*

Group of Variables	Variable Name	Response (Mean or by Class)	Description
Risk preferences	risk-level	Low: 6, Moderate: 16, High: 12	Level of risk aversion (low to high) (The nine Initial modalities (score from 1 to 9) were converted to three levels (low, moderate, high))
Reactivity	n-intentions	Mean = 4	Number of intention changes when deciding the date of first irrigation in different scenarios
	irrigation-gap	Mean = 34 days	Interval between the earliest and latest date the farmer would start irrigating
Assistance	n-maize-farmers	Mean = 8	Number of other maize farmers with whom the farmer shares irrigation information
	weather-station	Yes: 16, No: 18	Whether or not the farmer has a weather station (yes, no)
	n-weather-sources	Mean = 2.5	Number of weather information sources the farmer consults
	n-technologies	Mean = 1.1	Number of technologies the farmer uses to obtain weather information
Deliberation	n-info-question	Mean = 2.4	Number of pieces of information the farmer uses to make irrigation decisions (direct question)
	n-info-role play	Mean = 4.2	Number of pieces of information the farmer uses to make irrigation decisions (role-playing)

3.3. Influence of Structural, Material and Psychological Factors

3.3.1. Regression Models Converged for Six Major Variables

The linear regression model selected 12 of the 24 variables to explain the date of first irrigation (Table 5), while the regression tree contained six variables for agronomic practices, irrigation practices, reactivity and assistance. Three of the six variables selected by the tree were decision-making process factors. All variables in the regression tree were also in the linear regression model.

Table 5. Statistical results of the two types of regression models that explain the date of first irrigation. Only variables selected for at least one of the two methods are shown (see Table 3 for a description of the variables). Significance codes: 0 < p < 0.001: ***; 0.001 < p < 0.01: **; 0.01 < p < 0.05: *.

	Group of Variables	Variable and Response	Linear Regression Model		Position in the Regression Tree	Convergence of the Two Models
			Significance	Influence on the Date of First Irrigation		
Structural and material factors	Farmer's characteristics	years-maize	0.00612 **	+	N/A	
	Farm characteristics	Department_HG	0.00336 **	+	N/A	
		Department_T	0.01607 *	+	N/A	
	Agronomic practices	maize-type_g	0.04933 *	+	3a	confirmed
		maize-type_p	0.00114 **	+	3a	confirmed
		maize-type_s	ns	+	3a	
		maize-type_w	ns	+	3a	
		Tillage _yes	ns	+	2	
	Irrigation practices	Sow-irrigat_yes	0.04764 *	+	N/A	
		Volume	0.01508 *	–	4	inversed
		Equip-irrig_pivot	ns	–	N/A	
Psychological factors	Risk preferences	risk-level_high	0.00863 **	–	N/A	
		risk-level_moderate	Ns	–	N/A	
	Reactivity	n-intentions	6.72×10^{-6} ***	+	1	confirmed
		n-maize-farmers	0.01128 *	–	3b	confirmed
	Assistance	weather-station_yes	0.01065 *	+	N/A	
		n-technologies	ns	–	5	inversed

In the linear regression model, the date of first irrigation was significantly influenced by the number of years of experience with maize production, level of risk aversion, department, type of maize grown, irrigation at sowing, total volume of water used during irrigation, number of intention changes, number of other maize farmers with whom the farmer interacted, and number of weather stations (Table 3). In comparison, the variables in the regression tree, presented by decreasing influence, were the number of intention changes, tillage, maize type, number of other maize farmers with whom the farmer interacted, total volume of water used during irrigation, and number of technologies used to obtain weather information. The first branch of the regression tree, the mean date of first irrigation for farmers with high reactivity, is earlier than the sample mean (9 July vs. 24 June). On the other hand, among farmers with low reactivity, tillage application tends to advance the date of first irrigation. Moreover, farmers with big networks tend to irrigate earlier than others (Figure 6).

To offset the limits of each model (e.g., linearity and distribution hypotheses, multicollinearity, complex interactions, local effects), we compared the results of the models before determining how influential each variable was. The variables selected by both models were the type of maize grown, total volume of water used during irrigation, number of intention changes and number of other maize farmers with whom the farmer interacted. As expected, structural and material factors influenced the date of first irrigation, but decision-making process factors (levels of reactivity and assistance) also had an influence in both models. Notably, reactivity was the variable with the most significant influence in the regression tree and the linear regression model (p < 0.001).

The linear regression model explained 77% of the variance (adjusted R^2 = 0.77). The tests of residuals of independence (Durbin–Watson test), normality (Shapiro–Will test) and homogeneity (Breusch–Pagan test) were satisfactory, as was the reliability of the regression tree model, probably due to the choice of a conservative stopping rule (minsplit = 10) to minimize the error.

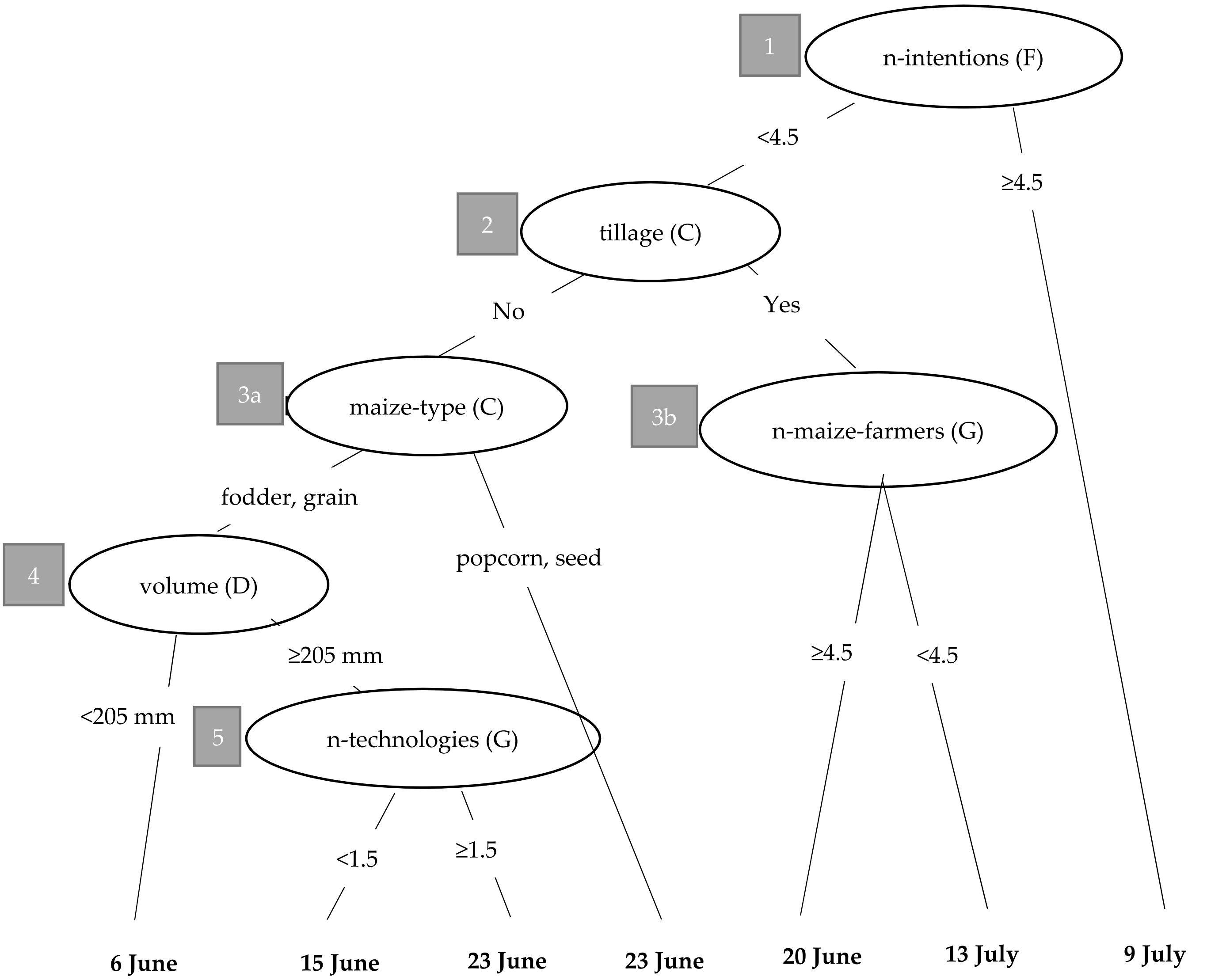

Figure 6. The regression tree model that explained the date of first irrigation. Information on lines includes thresholds or decision variables. Letters in parentheses are variable classes (C: agronomic practices; D: irrigation practices; F: reactivity; G: assistance).

3.3.2. Influence of Structural and Material Factors

All groups of structural and material factors influenced the date of first irrigation in at least one model. The farmer's experiences (Farmer's characteristics) influenced the date of first irrigation in the linear regression model. Experience increases the ability to observe changes in the environment and to rapidly and efficiently make decisions [26,38,39]. The more experienced the farmer was, the later the farmer started irrigating.

The department (Farm characteristics) also influenced the date of first irrigation in the linear regression model. Farmers in the Tarn and Haute-Garonne departments tended to start irrigating later than those in the Gers (mean of +6 and +10 days, respectively). Differences in soil and climate conditions, such as a drier spring season in the Gers (40 mm less rainfall on average), could explain the heterogeneity of the date of first irrigation.

Agronomic practices are of primary interest. In both models, the type of maize had a strong influence on the date of first irrigation. For example, popcorn maize, which has a less dense canopy [40], was associated with a later date of first irrigation in both models. According to the regression tree, seed maize was irrigated later than grain or fodder maize. Later sowing dates for seed maize can explain these later dates of first irrigation. Conversely, fodder maize was associated with an earlier start of irrigation since it is harvested immature and irrigated to optimize early vegetative growth. The influence of grain maize differed between the models due to differences in their mathematical functioning. Maize grain was significantly (p = 0.0493) associated with a later date of first irrigation in the linear regression model but with an earlier date of first irrigation in the regression tree. We considered the regression tree to be more relevant since the influence of maize type was based on interactions with previously chosen variables (e.g., tillage, psychological factors). Since the type of maize was significantly correlated with the department (p = 0.005), soil and climate conditions in the department could also explain indirect effects.

Tillage, another agronomic practice, was associated with a later date of first irrigation in the regression tree (a mean of +8 days) but not in the linear regression model. Direct effects of tillage on water availability for a crop are complex and depend on local conditions and practices since tillage can decrease water infiltration into the soil as well as increase evaporation [41,42]. Tillage can also have an indirect effect since it strongly influences other influential variables in the models, such as cover crop and irrigation at sowing. Tillage was negatively correlated with the variable cover crop (p = 0.010) since tillage is performed mainly in autumn in this area and, conversely, was positively correlated with irrigation at sowing (p = 0.007).

Irrigation at sowing (irrigation practices) was positively correlated with the date of first irrigation and was significant in the linear regression model. Farmers who irrigated at sowing started irrigation later. Irrigation at sowing provides additional water for the maize, which decreases the need for irrigation later.

In both models, the volume of water used for irrigation significantly influenced the date of first irrigation, but the direction of the effect differed. In the linear regression model, increasing volume was associated with an earlier date of first irrigation; the more water the farmer has, the earlier he will irrigate because he does not need to save water since there is no risk of being water-limited later. Conversely, in the regression tree, decreasing volume was associated with an earlier date of first irrigation. Since the volume variable appeared at the end of the tree, only a few of the farmers were concerned by this result, including those who grew fodder maize, who irrigate earlier.

We thus confirmed the influence of farmers' experience, farm location and agronomic practices. The influence of structural and material factors was consistent with the literature [10,11,13,18].

3.3.3. Influence of Psychological Factors

As expected, farmers' risk aversion was negatively correlated with the date of first irrigation: a farmer with greater risk aversion tended to start irrigating earlier. A farmer who is risk-averse will deliberate over a decision as much as possible and will start irrigating earlier to avoid the risk of hydric stress on maize plants before it occurs. Several studies have demonstrated the influence of risk aversion on decision-making [19,26,43,44].

A major result for decision-making process factors was the key influence of the level of reactivity (i.e., number of intention changes). Thus, the more reactive the farmer was, the later the farmer started irrigating. In a previous study of factors that influence fungicide applications on soft wheat [25], a high level of reactivity was associated with adaptive behavior. Similarly, Rodriguez et al. (2011) showed that reactivity (or plasticity) provided greater resilience to change than anticipation (or rigidity) when facing uncertainty since it improved adaptive behaviors and strategies [45].

The level of assistance also had a significant influence. The number of other maize farmers with whom the farmer interacted was negatively correlated with the date of first irrigation in both models. This suggests a mimetic effect: interacting with a larger network of farmers increases the likelihood that one of the farmers in the network will have started irrigating. Several studies indicate that the size of the social network increases the adoption of adaptive behaviors [22,46].

Unlike human factors, technological assistance variables were positively correlated with the date of first irrigation. Farmers who had a weather station or used multiple information technologies were more likely to start irrigating later. The weather-station variable was also significantly correlated with the use of decision-making tools ($p = 0.03$) or weather sensors ($p = 0.03$). We concluded that all types of tools that provide accurate and specific information about the weather could postpone the date of first irrigation. In the same way, Berthold et al. [47] also showed that the use of irrigation tools make it possible to optimize water by making informed decisions. These opposite effects of different types of assistance variables are noteworthy; they suggest that human assistance advances the date of first irrigation, while technological assistance postpones it. In either case, assistance leads to adaptive behaviors.

No variable related to deliberation appeared in either model; thus, unlike reactivity and assistance, deliberation did not influence the date of first irrigation. This result differs from that of Daydé (2017) for whom deliberation increased the adoption of more sustainable practices.

3.3.4. Synthesis of Results

Figure 7 summarizes results regarding factors that influence the decision of the date of first irrigation.

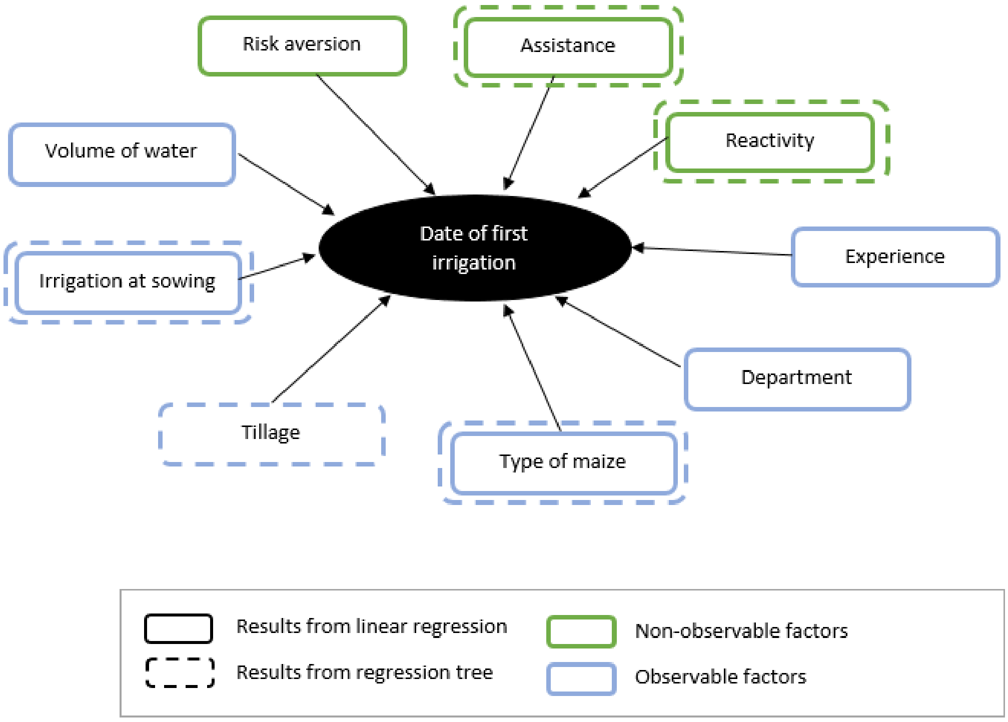

Figure 7. Variables identified as influential factors for the decision of the date of first irrigation.

3.4. *Advantages and Disadvantages of the Method*

The use of different inquiry methods allowed us to identify robust indicators to describe the decision-making process. We removed the subjectivity of personal statements by using methods such as role-playing and different scenarios with farmers.

Preselecting variables based on correlation and agronomic expertise was important to minimize the types of bias that collinear variables can create in linear regression models: high variance in predictors, large or unstable regression coefficients, and coefficient signs that run counter to intuition [48] Because predictors change when explanatory variables are strongly correlated, we preselected only independent variables. However, we could not eliminate all complex interactions and correlations that can disturb linear regression models. To obtain a relatively equal distribution of variables among the groups, variables were excluded only if they were simultaneously in the same group and had high correlations between each other (i.e., $p < 0.05$ for qualitative variables, and Pearson correlation >0.4 for quantitative variables). We used a regression tree to offset these limits of the linear regression model, but it was subject to more local effects since it divided observations into groups and sub-groups until the stopping rule was activated. In particular, variables at the end of the tree must be carefully interpreted because, in this study, they were based on 3–4 individuals. Deep learning from our database was challenging due to its small sample size.

We obtained more robust results by using two types of regression models that have complementary advantages and disadvantages. Although linear regression and regression trees are based on different statistical approaches, each yielded similar results, particularly the strong influence of decision-making process factors (assistance and reactivity) on the date of first irrigation. However, the models sometimes yielded different results due to their functioning or initial descriptions of the data. For example, regression trees can highlight local effects of variables, such as the volume of irrigation water, which obscure the overall influence of these variables for the entire sample. The linear regression model always considered all observations of the sample. However, when two variables were strongly correlated, it selected only the one that best explained the date of first irrigation, and this approach can ignore the influence of the second variable.

The main disadvantage of this study is its relatively small sample size (34 farmers). Since the sample is not entirely representative of the region, the results cannot be considered generic. However, they provide knowledge about the adaptive capacity of large maize farming systems. Moreover, our goal was not to describe or predict behaviors of farmers in the region, but to test the hypothesis that decision-making process factors can influence irrigation practices. We met this goal since we revealed the strong influence of reactivity and assistance on the heterogeneity of the date of first irrigation. For example, the linear model selected the number of intention changes because it had the largest influence on the date of first irrigation, but it ignored the number of technologies because it was redundant.

We studied the influence of multiple factors on the date of first irrigation, which is only one aspect of farmers' irrigation practices. Thus, it could be interesting to study other aspects such as irrigation equipment or duration, which would make it possible to test the influence of decision-making process factors on the entire irrigation strategy. However, the current study did not include multiple factors due to time, means and budget limitations.

3.5. Improving Adaptive Capacity

Although adaptation strategies are studied in the agricultural extension literature, farmers do not always adopt them. According to Öhlmér et al. [49], adaptive capacity can explain the difficulty that farmers experience when implementing new practices recommended by experts. Adaptive capacity is defined as the capacity of actors to implement new adaptation strategies, which leads to resilience [50]. Farmers' behaviors can explain much about their adaptive capacity [51]. In particular, the decision-making process needs to be studied to improve adaptations [52]. Thus, a better understanding of the influence of farmers' decision-making mechanisms on the adoption of practices could improve their adaptive capacity through the design of specific supports and policies.

Understanding farmers' adaptive processes is crucial for improving adaptation strategies. Behavior models that model the decision process using decision-making process factors, such as that of Daydé [23], help explain the heterogeneity of practices and, thus, the reasons for adopting practices. Our study reveals that farmers adopt practices in part due to their decision-making process. For agricultural water management, levels of assistance and reactivity strongly influence the date of first irrigation.

Reactivity could improve the adaptive capacity of farmers since a reactive decision-making process is associated with changes in irrigation practices (i.e., later date of first irrigation). The more reactive farmers are, the more they are able to postpone the date of first irrigation if necessary. Therefore, if farmers are facing a heatwave forecast, they would be able to change their date of first irrigation in order to find a balance between saving water and avoiding water stress.

Better support of maize farmers in southwestern France could encourage them to become more reactive. One way to increase reactive behavior is to encourage greater consideration of new information, increase the ability to observe changes in the environment and make better use of past experiences. One starting point is for farmers to share experiences and re-frame self-criticism of past decisions in discussion groups.

Encouraging access to specific information tools such as weather stations and new technologies is a way to obtain more adaptive behaviors, which may help to optimize water use for irrigation. Communicating with and educating farmers about the use of decision-support tools and technologies could increase adaptation practices. In addition, financial support from agricultural policies for farmers to invest in these tools would be relevant.

Future research should focus on a better understanding of decision-making strategies and the identification of relevant methods to measure them. Research should also focus on understanding how to improve adaptive behaviors. A key element of the decision-making strategy is the information received by the farmer and the farmer's ability to process information. Helping farmers find, access and understand information, compare sources, and rapidly select the relevant information according to the context are initial elements required to improve adaptive behaviors.

Our study contributes to research on adaptations by highlighting the important role of farmers' decision-making strategies. We revealed the need to improve reactive and assistance behaviors to increase adoption of adaptation practices, and to provide ways to improve these adaptive behaviors. These elements should be considered by advisors and included in public policies.

4. Conclusions

To explain the heterogeneity of the date of first irrigation among farmers, we surveyed 35 maize farmers. Our results confirm the role of structural, material and risk-aversion factors. They also highlight the strong influence of decision-making process factors on the date of first irrigation. Reactivity influenced the date of first irrigation more than any other variable. A high level of reactivity is associated with adaptive behaviors. Assistance from decision support tools and technologies also helps farmers adopt more adaptive behaviors. Conversely, other types of assistance such as social networks decrease adaptive capacity. However, assistance always influenced the date of first irrigation, whether it advanced it or postponed it. Advisors and public policies in the agriculture sector could consider these elements as ways to improve adaptation. In the context of water scarcity, our findings could help agricultural advisors to assist maize farmers with their water management practices. Future studies of farmers' irrigation practices could focus on exploring the influence of decision-making process factors on other key explanatory variables such as equipment, irrigation sources or water volumes. Their results would help us to understand the extent to which decision-making process factors influence the irrigation strategies of maize farmers.

Author Contributions: Conceptualization and methodology, M.A., S.C., J.-E.B., M.W.; Writing—Original draft preparation, M.A., S.C., J.-E.B., M.W.; Investigation, M.A.; Formal Analysis, M.A., R.F.; Writing—Review and editing, M.A., S.C., J.-E.B., M.W., R.F.; Funding Acquisition, M.W. All authors have read and agreed to the published version of the manuscript.

Funding: The research was supported by INRAE as part of the VACCARM project of the ACCAF Metaprogram.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Survey instruments and code used in this study are available from the authors upon request.

Acknowledgments: This study was funded by INRAE as part of the VACCARM project of the ACCAF Metaprogram. The authors thank the trainees who helped collect the data and the English proofreaders.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analysis or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A

"In this part, we will assess your preferences toward risk using a lottery game. Nine lottery games are proposed. For each game, two profits are possible (a low one and a high one) with identical chances to occur. We will ask you to choose your favorite lottery game from among the nine proposed".

1	400 €	50%	
	400 €	50%	
2	320 €	50%	
	510 €	50%	
3	240 €	50%	
	640 €	50%	
4	160 €	50%	
	780 €	50%	
5	120 €	50%	
	860 €	50%	
6	80 €	50%	
	915 €	50%	
7	60 €	50%	
	929 €	50%	
8	40 €	50%	
	934 €	50%	
9	10 €	50%	
	935 €	50%	

References

1. IPCC. *Climate Change 2014 Synthesis Report (Unedited Version)*; The Core Writing Team, Pachauri, R.K., Meyer, L., Eds.; IPCC: Geneva, Switzerland, 2014; ISBN 9789291691432.
2. Météo France Bilan du Printemps. 2011. Available online: http://www.meteofrance.fr/contenus-archives/bilan-2011/bilan-du-printemps-2011 (accessed on 26 July 2021).
3. Martin, G.; Magne, M.-A.; Cristobal, M.S. An Integrated Method to Analyze Farm Vulnerability to Climatic and Economic Variability according to Farm Configurations and Farmers' Adaptations. *Front. Plant Sci.* **2017**, *8*, 1483. [CrossRef]
4. Booker, J.F.; Trees, W.S. Implications of water scarcity for water productivity and farm labor. *Water* **2020**, *12*, 308. [CrossRef]
5. Robert, M.; Thomas, A.; Sekhar, M.; Badiger, S.; Ruiz, L.; Willaume, M.; Leenhardt, D.; Bergez, J.E. Farm typology in the Berambadi Watershed (India): Farming systems are determined by farm size and access to groundwater. *Water* **2017**, *9*, 51. [CrossRef]
6. France AgriMer La Filière Céréales. Available online: https://www.franceagrimer.fr/filiere-grandes-cultures/Cereales/La-filiere-Cereales (accessed on 16 July 2020).
7. AGPM. Les Chiffres Clés du Maïs Grain en France. Available online: https://www.maizeurop.com/structure/agpm/chiffres/ (accessed on 10 May 2021).
8. El Afandi, G.; Khalil, F.A.; Ouda, S.A. Using Irrigation Scheduling to Increase Water Productivity of Wheat-Maize Rotation under Climate Change Conditions. *Chil. J. Agric. Res.* **2010**, *70*, 474–484. [CrossRef]
9. Moradi, R.; Koocheki, A.; Nassiri Mahallati, M.; Mansoori, H. Adaptation strategies for maize cultivation under climate change in Iran: Irrigation and planting date management. *Mitig. Adapt. Strateg. Glob. Chang.* **2013**, *18*, 265–284. [CrossRef]

10. Kuivanen, K.S.; Alvarez, S.; Michalscheck, M.; Adjei-Nsiah, S.; Descheemaeker, K.; Mellon-Bedi, S.; Groot, J.C.J. Characterising the diversity of smallholder farming systems and their constraints and opportunities for innovation: A case study from the Northern Region, Ghana. *NJAS-Wagening. J. Life Sci.* **2016**, *78*, 153–166. [CrossRef]
11. Meylan, L.; Merot, A.; Gary, C.; Rapidel, B. Combining a typology and a conceptual model of cropping system to explore the diversity of relationships between ecosystem services: The case of erosion control in coffee-based agroforestry systems in Costa Rica. *Agric. Syst.* **2013**, *118*, 52–64. [CrossRef]
12. Wichelns, D. Do estimates of water productivity enhance understanding of farm-level water management? *Water* **2014**, *6*, 778–795. [CrossRef]
13. Righi, E.; Dogliotti, S.; Stefanini, F.M.; Pacini, G.C. Capturing farm diversity at regional level to up-scale farm level impact assessment of sustainable development options. *Agric. Ecosyst. Environ.* **2011**, *142*, 63–74. [CrossRef]
14. Solano, C.; León, H.; Pérez, E.; Herrero, M. The role of personal information sources on the decision-making process of Costa Rican dairy farmers. *Agric. Syst.* **2003**, *76*, 3–18. [CrossRef]
15. Lechenet, M.; Bretagnolle, V.; Bockstaller, C.; Boissinot, F.; Petit, M.S.; Petit, S.; Munier-Jolain, N.M. Reconciling pesticide reduction with economic and environmental sustainability in arable farming. *PLoS ONE* **2014**, *9*, e97922. [CrossRef] [PubMed]
16. Nave, S.; Jacquet, F.; Jeuffroy, M.H. Why wheat farmers could reduce chemical inputs: Evidence from social, economic, and agronomic analysis. *Agron. Sustain. Dev.* **2013**, *33*, 795–807. [CrossRef]
17. Aubry, C.; Papy, F.; Capillon, A. Modelling decision-making processes for annual crop management. *Agric. Syst.* **1998**, *56*, 45–65. [CrossRef]
18. Martin-Clouaire, R. Modelling Operational Decision-Making in Agriculture. *Agric. Sci.* **2017**, *8*, 527–544. [CrossRef]
19. Reynaud, A.; Couture, S. Stability of risk preference measures: Results from a field experiment on French farmers. *Theory Decis.* **2012**, *73*, 203–221. [CrossRef]
20. Yanuarti, R.; Aji, J.M.M.; Rondhi, M. Risk aversion level influence on farmer's decision to participate in crop insurance: A review. *Agric. Econ.* **2019**, *65*, 481–489. [CrossRef]
21. Klein, G. Naturalistic decision making. *Hum. Factors* **2008**, *50*, 456–460. [CrossRef]
22. Bergez, J.E.; Garcia, F. Is it worth using short-term weather forecasts for irrigation management? *Eur. J. Agron.* **2010**, *33*, 175–181. [CrossRef]
23. Daydé, C. Comprendre le Processus de Prise de Décision Opérationnelle en Agriculture: Une Approche en Rationalité Limitée. Ph.D. Thesis, Université de Toulouse, Toulouse, France, 2017.
24. Malawska, A.; Topping, C.J. Evaluating the role of behavioral factors and practical constraints in the performance of an agent-based model of farmer decision making. *Agric. Syst.* **2016**, *143*, 136–146. [CrossRef]
25. Van Duinen, R.; Filatova, T.; Jager, W.; van der Veen, A. Going beyond perfect rationality: Drought risk, economic choices and the influence of social networks. *Ann. Reg. Sci.* **2016**, *57*, 335–369. [CrossRef]
26. Dury, J.; Garcia, F.; Reynaud, A.; Therond, O.; Bergez, J.E. Modelling the complexity of the cropping plan decision-making. In Proceedings of the 5th International Congress on Environmental Modelling and Software, Ottawa, ON, Canada, 5–8 July 2010; Volume 1, pp. 569–576.
27. Halberg, N. Indicators of resource use and environmental impact for use in a decision aid for Danish livestock farmers. *Agric. Ecosyst. Environ.* **1999**, *76*, 17–30. [CrossRef]
28. Denzin, N.K. *The Research Act: A Theoretical Introduction to Sociological Methods (Google eBook)*; Transaction Publishers: Piscataway, NJ, USA, 1970; ISBN 0202368599.
29. Lewis-Beck, M.; Bryman, A.; Futing Liao, T. *The SAGE Encyclopedia of Social Science Research Methods*; Sage Publications, Inc.: Thousand Oaks, CA, USA, 2012.
30. Agreste. Analyse économique des exploitations agricoles irriguant du maïs grain. *Anal. Occ.* **2017**, *3*, 4. Available online: https://draaf.occitanie.agriculture.gouv.fr/IMG/pdf/dependance_economique_des_irrigants_de_mais_cle8bf8ab.pdf (accessed on 17 July 2020).
31. Lopez, O.; Milhaud, X.; Thérond, P. Arbres de régression et de classification (CART). *L'actuariel Soc. Actuaires* **2015**, *15*, 42–44.
32. R Core Team. R: The R Project for Statistical Computing. Available online: https://www.r-project.org/ (accessed on 10 August 2020).
33. Chavent, M.; Kuentz, V.; Liquet, B.; Saracco, J.; Chavent, M.; Kuentz, V.; Liquet, B.; Saracco, J. Classification de variables: Le package ClustOfVar. In Proceedings of the 43èmes Journées de Statistique (SFdS), Tunis, Tunisie, 23–27 May 2011.
34. Tonini, C.; Vieuille, G. Population des Non-Salariés Agricoles en 2017. Available online: https://statistiques.msa.fr/wp-content/uploads/2018/02/Infostat-CE-2017.pdf (accessed on 17 July 2020).
35. Agreste. Des Grandes Cultures dans Deux Tiers des Exploitations. *Agreste Primeur* **2012**, *283*, 8. Available online: http://www.drome.gouv.fr/IMG/pdf/RA2010_Exploitations_de_grandes_cultures_-_Agreste_Primeur_No283_-_Juin_2012_.pdf (accessed on 12 July 2020).
36. DRAAF Occitanie. Direction Régionale de L'alimentation, de L'agriculture et de la Forêt. L'irrigation Contribue à 18% de la Valeur de la Production Agricole. Available online: https://draaf.occitanie.agriculture.gouv.fr/L-irrigation-contribue-a-18-de-la,505 (accessed on 17 July 2020).
37. ARPE Midi-Pyrénées. Chiffres Clés sur L'eau en Midi-Pyrénées. 2015, 242–249. Available online: https://www.laregion.fr/IMG/pdf/chiffres_cles_eau_mp2015-vdef.pdf (accessed on 17 July 2020).

38. Nuthall, P.L. The intuitive world of farmers—The case of grazing management systems and experts. *Agric. Syst.* **2012**, *107*, 65–73. [CrossRef]
39. McCown, R.L. A cognitive systems framework to inform delivery of analytic support for farmers' intuitive management under seasonal climatic variability. *Agric. Syst.* **2012**, *105*, 7–20. [CrossRef]
40. Severini, A.D.; Borrás, L.; Westgate, M.E.; Cirilo, A.G. Kernel number and kernel weight determination in dent and popcorn maize. *Field Crop. Res.* **2011**, *120*, 360–369. [CrossRef]
41. Alletto, L.; Coquet, Y.; Justes, E. Effects of tillage and fallow period management on soil physical behaviour and maize development. *Agric. Water Manag.* **2011**, *102*, 74–85. [CrossRef]
42. Schwartz, R.C.; Baumhardt, R.L.; Evett, S.R. Soil & Tillage Research Tillage effects on soil water redistribution and bare soil evaporation throughout a season. *Soil Tillage Res.* **2010**, *110*, 221–229. [CrossRef]
43. Roussy, C.; Ridier, A.; Chaib, K. Adoption d'innovations par les agriculteurs: Rôle des perceptions et des préférences. *Work. Pap. Smart-Lereco* **2015**, *15*, 1–22.
44. Brunette, M.; Foncel, J.; Kéré, E.N. Attitude Towards Risk and Production Decision: An Empirical Analysis on French Private Forest Owners. *Environ. Model. Assess.* **2017**, *22*, 563–576. [CrossRef]
45. Rodriguez, D.; deVoil, P.; Power, B.; Cox, H.; Crimp, S.; Meinke, H. The intrinsic plasticity of farm businesses and their resilience to change. An Australian example. *F. Crop. Res.* **2011**, *124*, 157–170. [CrossRef]
46. Acosta-Michlik, L.; Espaldon, V. Assessing vulnerability of selected farming communities in the Philippines based on a behavioural model of agent's adaptation to global environmental change. *Glob. Environ. Chang.* **2008**, *18*, 554–563. [CrossRef]
47. Berthold, T.A.; Ajaz, A.; Olsovsky, T.; Kathuria, D. Identifying Barriers to Adoption of Irrigation Scheduling Tools in Rio Grande Basin. *Smart Agric. Technol.* **2021**, *1*, 100016. [CrossRef]
48. Foucart, T. Colinéarité et régression linéaire. *Math. Soc. Sci. Hum.* **2006**, *173*, 5–25. [CrossRef]
49. Öhlmér, B.; Olson, K.; Brehmer, B. Understanding farmers' decision making processes and improving managerial assistance. *Agric. Econ.* **1998**, *18*, 273–290. [CrossRef]
50. Walker, B.; Holling, C.S.; Carpenter, S.R.; Kinzig, A. Resilience, adaptability and transformability in social-ecological systems. *Ecol. Soc.* **2004**, *9*, 5. [CrossRef]
51. Del Pozo, A.; Brunel-Saldias, N.; Engler, A.; Ortega-Farias, S.; Acevedo-Opazo, C.; Lobos, G.A.; Jara-Rojas, R.; Molina-Montenegro, M.A. Climate change impacts and adaptation strategies of agriculture in Mediterranean-climate regions (MCRs). *Sustainability* **2019**, *11*, 2679. [CrossRef]
52. Urruty, N.; Tailliez-Lefebvre, D.; Huyghe, C. Stability, robustness, vulnerability and resilience of agricultural systems. A review. *Agron. Sustain. Dev.* **2016**, *36*, 15. [CrossRef]