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Identifying the boundaries of the sensory space of red Bordeaux wines using an innovative machine learning approach. Application to the identification of new varieties adapted to climate change.

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ABSTRACT

Climate change is likely to impact wine typicity across the globe, raising concerns in wine regions historically renowned for the quality of their terroir. Among potential changes, modifying plant material (i.e., clones, rootstocks and varieties) is considered to be one of the most promising potential levers for adaption to climate change. However, changing varieties raises the issue of how to protect the region's wine typicity. In Bordeaux (France), extensive studies focus on the identification of varieties that would be more suitable for a warmer and drier climate, but less research has been done concerning their impacts on Bordeaux wine typicity. The present study, conducted on 26 red varieties - including traditional-Bordeaux varieties and non-Bordeaux varieties - over five vintages, aimed to characterise Bordeaux wine typicity and to identify non-Bordeaux varieties that could fit into this sensorial space. Through a random forest analysis of the results of a Check-All-That-Apply (CATA) sensorial analysis and a typicity profiling with an exceptionally large panel of experts (approximately 40 judges), the typical red Bordeaux sensory space was clearly defined with consensus among the judges. Interestingly, one non-Bordeaux variety was found to produce wines with high Bordeaux typicity. Finally, via hierarchical clustering analyses based on multiple correspondence analysis, five non-Bordeaux varieties that produce wines with similar sensorial spaces to the traditional Bordeaux varieties were identified. These results indicate that these cultivars could be introduced to the Bordeaux grape-mix without profoundly altering Bordeaux wine typicity in a context of climate change, if found to be suitable for a warmer climate than the current climate of the Bordeaux region.

KEYWORDS: Climate change, wine typicity, sensory analyses, terroir, random forest, CATA, Vitis vinifera

INTRODUCTION

Typicity is a very broad concept with a strong link to the wine world. It is derived from the French word typicité which was first defined in 1993 as the characteristics of a wine (Casabianca *et al.,* 2011). This concept has been subsequently studied in many different fields within food science, including cheese (Cardin *et al.,* 2022), coffee (Scholz *et al.,* 2018), olive oil (Lukić *et al.,* 2018) or dairy products (Ferrocino *et al.,* 2022). However, wine-related topics still comprise the largest field of research on typicity (Souza Gonzaga *et al.,* 2021).

Wine typicity can be defined as the ability of a product from a distinct region (Cadot *et al.,* 2012), a distinct variety (Schüttler *et al.,* 2015) or a distinct brand (Souza Gonzaga *et al.,* 2021) to be identified and recognised by experts and/or consumers (Salette, 1997). Ultimately, wine typicity is a concept located between the mental representation of the product by the tasters and the actual taste of the wine, leading to many studies addressing the gap between conceptual and perceptual conception of typicity (Ballester *et al.,* 2008; Cadot *et al.,* 2012; Barbe *et al.,* 2021). The notion that embodies both conceptual and perceptual typicity is often referred to as a sensorial space, which was first defined for wines in 2004 (Barbe *et al.,* 2021).

Wine typicity can be assessed and described by different means. An extensive review was published on the topic in 2010 (Maitre *et al.,* 2010), showing its complexity.

One common way to assess typicity was first described by Ballester *et al.,* 2005 in a study revealing the existence of a common sensory space of wines produced from the Chardonnay grape variety. The authors postulate that typicity is such a broad concept that it does not only refer to measurable dimensions, an idea also mentioned by several other authors (Sauvageot, 1994; Casabianca *et al.,* 2011). Instead, they implemented a general approach and asked an expert panel to assess whether the wine was a good example of Chardonnay using an unstructured scale from a very bad example to a very good example. This typicity rating has since been used many times in research and has proven to be efficient in assessing the typicity of wines produced in a specific wine region (Parr *et al.,* 2007; Canuti *et al.,* 2017), from a specific grape variety (Ballester *et al.,* 2005; Schüttler *et al.,* 2015) or to define specific sensory spaces, such as the ageing bouquet of red Bordeaux wines (Picard *et al.,* 2015).

This typicity rating is sometimes coupled with a sorting task to assess the typicity of samples from the same group and compare it with the typicity of samples from outside the group (Ballester *et al.,* 2008; Parr *et al.,* 2010). The so-called napping method provides very interesting results (Perrin, 2008). It is helpful for grouping samples with similar typicity and discriminating groups with different typicity, as well as for evaluating the overlap between the two groups, as wine typicity is a continuous concept.

However, typicity rating and sorting tasks only reveal the existence of a sensory space and do not characterise it; therefore, the previously mentioned methods have been coupled with descriptive sensorial techniques to reveal common attributes within a given sensory space. A methodology based on the perceptual concept of wine professionals of a specific sensory space has recently been established (Leriche *et al.,* 2020). In this research, experts of a specific Protected Denomination of Origin (PDO) wine were asked to list some wine descriptors that would characterise the PDO's typicity. Through a Just About Right (JAR) scaling and a typicity rating, the authors were able to discriminate descriptors positively correlated with the typicity of this PDO. JAR scales have also been found to be efficient in characterising a terroir typicity in the Loire valley (France) when coupled with a Quantitative Descriptive Analysis (QDA) (Cadot *et al.,* 2010).

In all these studies, the choice of panel is important. Except if consumer preferences are targeted, the analysis and characterisation of wine typicity is mainly carried out through the use of expert tasters, as shown in most of the cited studies (Ballester *et al.,* 2005; Cadot *et al.,* 2010; Parr *et al.,* 2010). Indeed, an expert panel tends to share a common conceptual space of the typicity being studied that will depend on their previous experience rather than the reputation of the wine, with a strong agreement among them (Ballester *et al.,* 2008). Such expert panels are also sometimes referred to as a Human Reference Group (Leriche *et al.,* 2020).

Research on wine typicity has considerably increased over the past 15 years, in particular regarding its link with the terroir. Indeed, the "willingness to pay" of the consumers strongly increases for products having specific sensory attributes associated with their terroir, which are thus referred to as typical (Luomala, 2007).

Terroir is a very old French concept officially dating back to 1229 (Casabianca *et al.,* 2011). Terroir has not always been considered as a positive attribute in French winemaking, as it was mainly related to farming and every-day life consumption of poor quality wine (Dion, 1959). However, with the creation of the French PDOs and the desire to protect wine quality, the term "terroir" became increasingly qualitative as it turned out to be the guarantee of a certain wine culture leading to the production of higher quality wines (Capus, 1947). Terroir only exists within a conceptual and perceptual sensory space that is shared by professionals and/or consumers, and is thus intrinsically linked with typicity (Casabianca *et al.,* 2011). Hence, terroir does not stand without typicity.

Terroir is a concept that embodies different interacting production factors, such as cultivar, soil and its water content, climate and human practices (van Leeuwen & Seguin, 2006). For the first time in the history of winemaking, one of these parameters related to the natural environment is changing: the climate (IPCC, 2021). This reality is already having measurable impacts on grape growing and wine composition, including, among others a decrease in grape and wine acidity, an increase in grape sugar content and wine alcohol content, a shift in phenology, with harvests occurring during a warmer period of the season, and modifications to wine aromas. These changes are very well-documented (Mira de Orduña, 2010; Pons *et al.,* 2016; van Leeuwen & Darriet, 2016; Ollat *et al.,* 2017; van Leeuwen *et al.,* 2022).

Winegrowers have always successfully adapted to major events (e.g., phylloxera, powdery and downy mildew, mechanisation, new consumption habits), with minor to severe impacts on wine typicity (Dion, 1959). This adaptative skill needs to be implemented in the context of climate change and many levers have already been identified and discussed in the review by Santos *et al. (*2020).

One of those levers is the changing of varieties, which is thought to be one of the most extreme (in that it is very effective, but also potentially highly impacting) adaptation tools for winegrowers (Wolkovich *et al.,* 2018).While extensive research has been conducted on potential new cultivars for adaptation to climate change in different wine regions through the analysis of different ecophysiological traits (phenology, heat tolerance, drought tolerance and disease sensibility) (Duchêne *et al.,* 2010; Delrot *et al.,* 2020; Parker *et al.,* 2020; Plantevin *et al.,* 2022), very little research has been conducted on their impact on wine typicity.

In light of this, the present study proposes a reversed approach, where new varieties are screened for their potential impact on Bordeaux wine typicity before being analysed for their potential suitability to warmer and drier conditions. Indeed, wine typicity related to origin needs to be preserved as it is the guardian of terroir-expression and consumer willingness to pay.

MATERIALS AND METHODS

1. Vineyard Setting

Wines for the study were produced in Château La Tour Carnet in Saint-Laurent Médoc, 33112, France on one plot within the Haut-Médoc PDO. This plot was planted in 2013 with 26 different red *Vitis Vinifera* varieties. Each row comprises 150 vines of one cultivar. The soil is composed of gravel with some sand. The vineyard is dry-farmed with all varieties being double Guyot-pruned and trained with a vertical shoot positioning trellis at a density of 8,888 vines/hectare. The soil under the vine was tilled to reduce competition from weeds and the inter-row was frequently mowed to limit excessive competition with the cover crop. Due to different climatic hazards, wines from some varieties were not obtained in all five vintages. Twenty-four varieties were harvested in 2018, 25 in 2019, 14 in 2020, 5 in 2021 and 26 in 2022. With the exception of Castets, which was vinified only once (in 2022), and Morrastel, which was vinified only twice (2019 and 2022), all varieties used in the study were vinified in at least three vintages (2018, 2019 and 2022) with some of them also being vinified in 2020 and 2021. The list of the 26 varieties and the vintages in which the wines were produced can be found in Supplementary Materials.

2. Harvest and Vinification

Optimum maturity is difficult to target for varieties with different ripening windows. The harvests took place in every vintage from the end of August to mid-October, allowing each cultivar to reach optimum maturity, which was assessed via standard oenological parameters and by berry tasting. Choice of harvest dates were also dependent on climatic hazards and the sanitary status of the considered variety, as in a classical production context. All varieties were de-stemmed and vinified in 2 or 4 hL stainless steel tanks. Yeast assimilable nitrogen in the must was adjusted to 250 mg/L in two steps. The first adjustment was made at the very beginning of the alcoholic fermentation, using Thiazote® PH, made of diammonium phosphate and hydrochlorate thiamine. The second one was made when the alcoholic fermentation was achieved by 30-35 %, using Nutristart® Org, made of dead yeast. Both products are produced by Laffort (33270, Floirac, France). Four g/hL of sulfur dioxide (SO_2) was added prior to fermentation. All wines were fermented using Zymaflore® XPURE dry active yeast from Laffort (33270, Floirac, France). Malo-lactic fermentation was induced using Lactoenos® B7, also from Laffort. At the end of both fermentations, free SO_2 was adjusted to 40 mg/L and wines were bottled before the end of the year in glass bottles sealed with Diam 5® corks produced by Diam (66400, Céret, France).

3. Sensory Analyses

3.1.Organisation

Several sensory analysis sessions were held within a 10-days period in April 2023, with one vintage being tasted per session. The panel was composed of 33 judges for the 2018 vintage (25 wines), 35 for the 2019 vintage (26 wines), 28 for the 2020 and 2021 vintages (which were tasted during the same sessions with 20 wines) and 39 for the 2022 vintage (27 wines). Twenty-seven of these judges tasted all five vintages, while three tasted one vintage, five tasted two vintages and ten tasted three vintages. The average age of the panel was 37 years old, ranging from 22 to 68 years old. All the judges were considered to be experts, as they were all selected according to the criteria established by Ballester *et al. (*2008):

- Winemakers
- Wine professionals
- Wine scientists with experience in winemaking and/or wine tasting
- Graduate students in Viticulture and Oenology with at least one year of experience of winemaking or who followed wine tasting trainings.

In each session, a maximum of 8 judges was allowed in the dedicated tasting room (complying with the O.I.V requirements (O.I.V, 2015) for sensory laboratories, ISO 8589: 2010) and were separated in individual booths. Twenty mL of wines was poured into covered INAO glasses (ISO 3591:1977) at 18°C, under sodium light to hide the wine colour to avoid any bias from the appearance of the wines. All the wines were presented in random order for comparison by each judge and were identified with random 3-digits numbers. Each judge started the session by tasting two wines: one considered as one of the most typical and one considered as one of the most atypical of the session. The two wines had been selected in a previous tasting session of all the samples by a sub-panel of seven experts as described previously. Each session lasted 45 min.

3.2.Experimental Procedure

Using an electronic tablet and Fizz acquisition software (Biosystem SAS, 21560, Couternon, France), the judges first answered the question “On the nose, do you think this wine is a good example of a Bordeaux wine?”, followed by the question “On the palate, do you think the taste of this wine is a good example of a Bordeaux wine?”. The answers were rated using two 10 centimeter unstructured scales, with “good example” written on the right and “bad example” on the left.

Once those questions had been answered, a check-all-that-apply (CATA) method was used comprising 38 descriptors to be ticked by the judges. The selected descriptors are very common to wine descriptions with some of them known as being characteristics of unripe, just ripe, and over-ripe aromas in wine (van Leeuwen *et al.,* 2022). Among those 38 descriptors, 22 were related to aromas, 9 to mouth sensations and 7 to faults. Finally, when all the judges had finished the session, the normal light was switched on and the judges were asked the following question “Do you think the colour of this wine is a good example of a Bordeaux wine of the vintage X?“, with X being the vintage tasted. The judges had to answer using the previously mentioned unstructured scale.

4.Statistics

4.1.Software

The analyses were run on R Studio version 2022.12.0 using “Dplyr” package version 1.1.0 for descriptive analysis, “Stats” package version 4.2.1 for hierarchical clustering analysis (HCA), “FactoMineR” package version 2.7 for principal component analysis (PCA), Multiple Correspondance Analysis (MCA), Multiple Factorial Analyses (MFA), “RandomForest” package version 4.7.1.1 for random forest algorithm and “Pdp” package version 0.8.1 for random forest 3 dimensions partial dependance plots.

4.2.Data pre-treatment

A considerable amount of data was acquired during the tasting sessions (38 descriptors *45 judges * 94 wines, with two profile tests per wine per judge) requiring several pre-treatments. Three datasets were used during the analysis:

- Profiling (PROF): the dataset of typicity ratings for each judge for each wine (from 0 to 10). This dataset was divided into three parts:
    * Olfactive typicity
    * Palate typicity
    * Visual typicity
- Contingency table of the CATA results (CATA_CT): a contingency table with results of the CATA analysis. Rows are the individuals (the wines), and columns are the variables (descriptors). Each descriptor for each wine per judge was attributed either 1 mark (when it was found in the wine by the judge) or 0 mark (when it wasn’t found in the wine by the judge).
- Percentage of the attributes of the CATA (CATA_PERC): a table, with rows being the individuals (wines) and columns the variables (descriptors). Each descriptor for each wine is associated with a percentage which represents the proportion of the judges that attributed this descriptor to the given wine.

For each session one replicate (sample B) of one of the wines (sample A) was randomly inserted into the selection to study the coherence of the results per judge. Using the PROF dataset, marks of olfactive and palate typicity were then compared between sample A and sample B. Fifteen judges who found the most extreme differences between sample A and B (i.e., above the .95 quartile) were removed from the dataset: 3 judges in 2018 and 4 judges in each of 2019, 2020 and 2022.

Each of the three typicity ratings were then scaled separately per vintage and per judge to buffer their effects. Following, each wine was classified in four classes as a function of their olfactive typicity and palate typicity, with wines in class 1 being the most typical. The classes were simply defined as a function of the quartiles of the typicity.

RESULTS AND DISCUSSION

1.The Bordeaux typicity continuum

Typicity ratings showing that samples are organised on a continuum, from less typical to more typical of the red Bordeaux wine category (Figure 3), have already been shown in the literature (Picard *et al.,* 2015). However, the results of the Cochran Q Test and Fleiss’ Kappa Test did not show any clear agreement among the judges when wines from all classes of typicity were considered (data not shown). This lack of agreement illustrates the complexity of typicity assessments on wine categories.

To study the correlations between the products (i.e., the wines) and their typicity classes a Multiple Factorial Analyses (MFA) of the CATA_PERC dataset was performed and is shown in Figure 1. Wines considered as the most typical (either in terms of olfactive or palate typicity) that belong to class 1 are always located in the bottom left-hand corner of the MFAs with negative correlations with the two first dimensions (Figures 1A and and 1B). The least typical wines (belonging to class 4) are negatively correlated with the individuals of class 1, as they are always found in the upper right-hand corner of the MFAs and have positive correlations with the two first dimensions (Figures 1 A and 1B).

This distinction among the classes of typicity (either olfactive or palate) is less clear with the wines of classes 2 and 3, which tend to be spread along the negative and positives axes of the dimensions. But typicity is a continuous concept, explaining why wines of classes 2 and 3 tend to overlap with the other classes. As such, it can be clearly seen that the wines considered very typical (i.e., belonging to class 1) are all correlated and are negatively correlated with the wines belonging to class 4 (i.e., the most atypical).

Interestingly, in terms of aromatic typicity, of the 18 wines made from traditional Bordeaux varieties (Cabernet-Sauvignon, Cabernet franc, Merlot and Petit Verdot), 13 were classified in class 1 (the most typical), 3 in class 2 and 2 in class 4 (the most atypical). Similar results were found for gustative typicity: 14 wines in class 1 (the most typical), 3 in class 2 and 1 in class 3. It can thus be clearly seen that this typicity continuum was largely skewed by the pool of traditional Bordeaux varieties, and therefore we can assume that the Bordeaux sensorial space is mainly explained by traditional varieties.

However, these first two dimensions only partly explain the variance of the MFA (27.3 %). Hence, to confirm that traditional Bordeaux varieties skew the typicity continuum (these varieties being considered very typical), a one-way ANOVA test was performed to evaluate the differences in typicity (olfactive and palate) for all 25 varieties of the study. Significant differences (with p-values <0.01) were found between the wines, allowing us to reject the null hypothesis, confirming the existence of a common sensory space identified by the judges for the most typical and less typical wines, as the notes were not randomly attributed by the judges. A Tukey HSD test was then performed and confirmed that the differences in typicity between varieties are rather on a continuum of less typical varieties to more typical varieties (as shown in Figure 1), which is largely driven by traditional Bordeaux varieties. Those results are further discussed in Section 3 of this article and are represented in Figure 3.

Our results show that wines described as typical in terms of aroma are also qualified as typical in terms of taste. However, it should be kept in mind that both typicities were rated one after the other, and it is likely that the judges were influenced while rating the wines in the mouth by their orthonasal evaluation of typicity.

2. A machine learning approach to characterising the sensory space of red Bordeaux wines

The correlation found between the very typical wines allowed us to characterise the sensory space of the red Bordeaux wines using the descriptors proposed in the CATA,

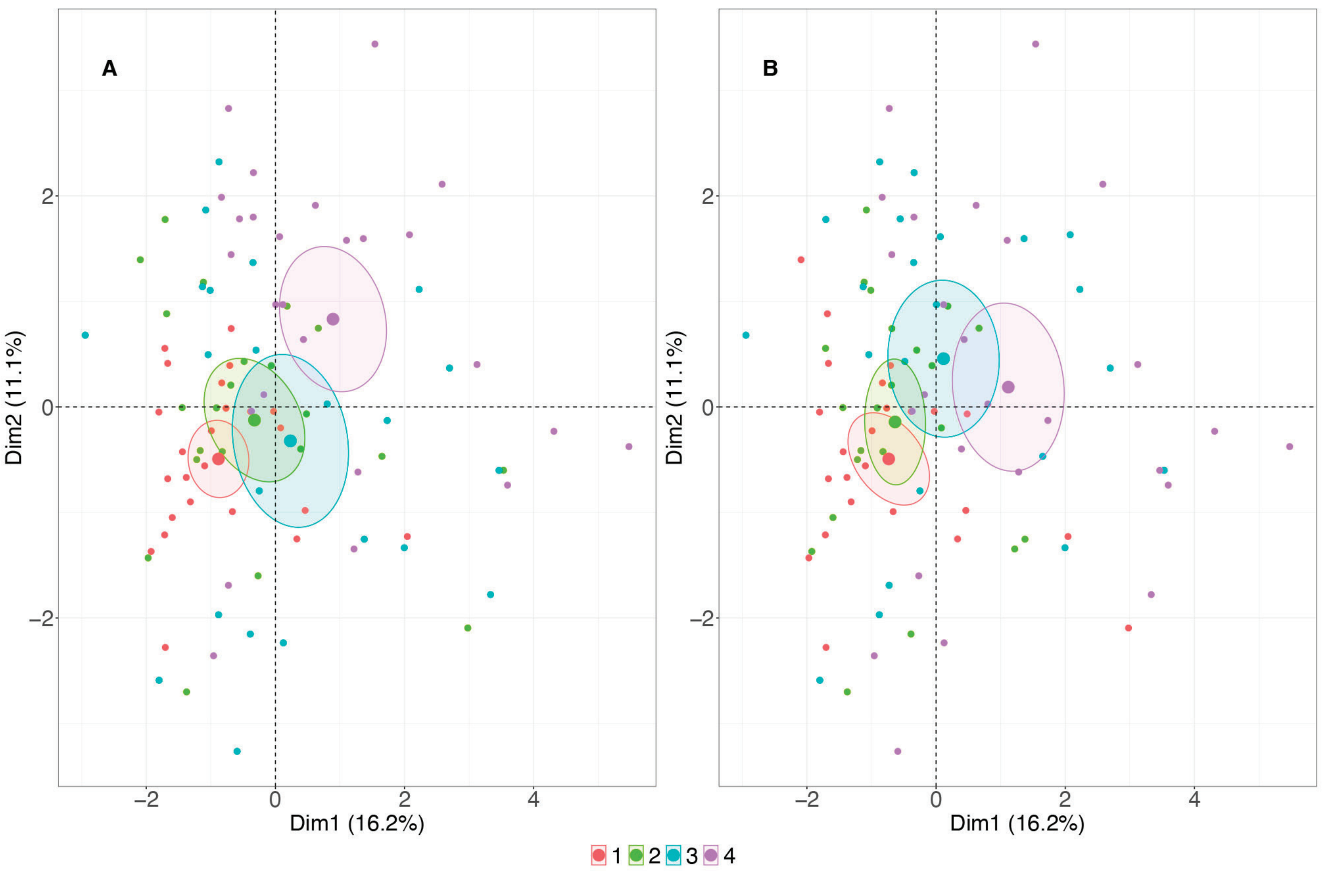

FIGURE 1. Multi Factorial Analysis (MFA) of the Check-All-That-Apply (CATA_PERC) individuals (all 94 wines). Ellipses of confidence at the 0.95 level have been drawn around the four classes of typicity (as supplementary qualitative data), with Class 1 containing the wines that were found to be the most typical. Panel A represents olfactive typicity, panel B palate typicity.

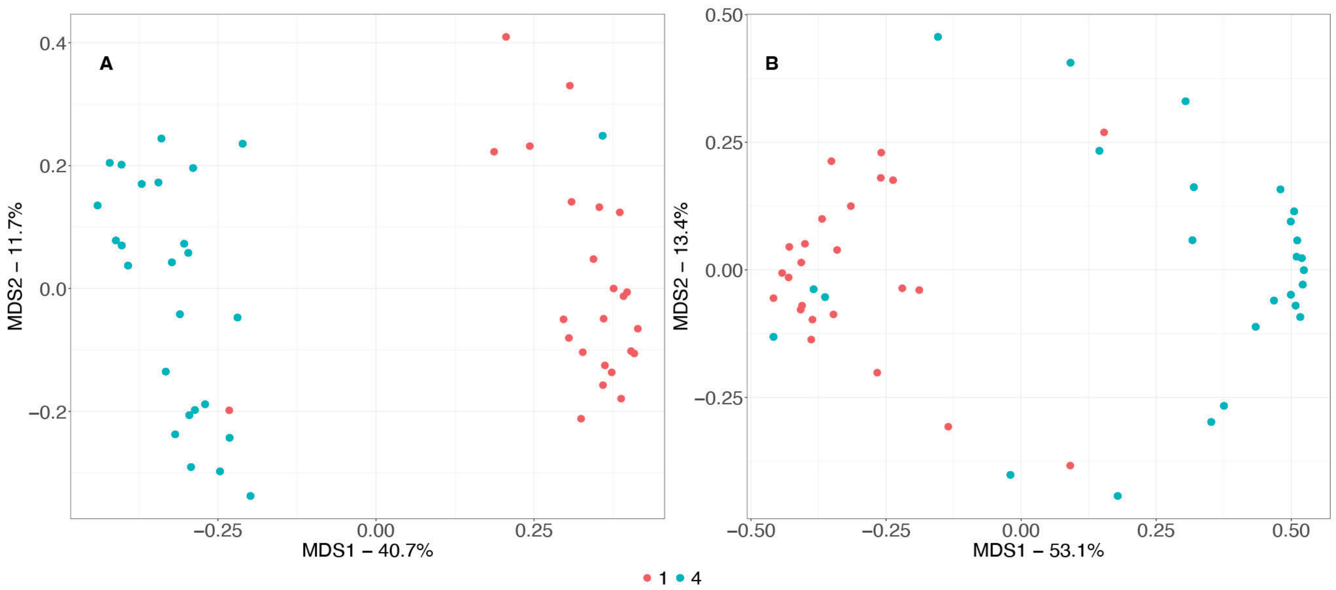

FIGURE 2.1. Multi-Dimensional Scale plot (MDS) using Random Forest proximities of the 23 wines that were either the most typical (class 1) or the least typical (class 4). Panel A represents the olfactive typicity and panel B the palate typicity.

and to understand which descriptors were important when classifying a wine as very typical or very atypical. For this purpose, it is very common to use multivariate analyses, such as MFA or MCA (Basalekou *et al.,* 2023). However, due to the large number of wines, judges and descriptors in this study, multivariate analyses had strong limitations for this study. The two first dimensions explain only a limited percentage of total variance (27.3 % for the MFA, 11.1 % for the MCA) and multicollinearities among the variables may hide some potentially important information.

Two possible ways to overcome these issues are to either select some key variables from the dataset as a function of their known importance (Hastie *et al.,* 2001) or create new variables to replace the original data with, for instance, latent variables in partial least square discrimination (Schüttler *et al.,* 2015). Here, we propose a further approach to understanding the typicity classification of the wines without removing original variables: partial dependence analysis from random forest decision tree algorithms, which gives good insights into the importance of each variable (i.e., descriptors proposed in the CATA) in the classes of wine typicity.

The first step was to create a new dataset from CATA_PERC containing only the wines that belong to classes 1 and 4

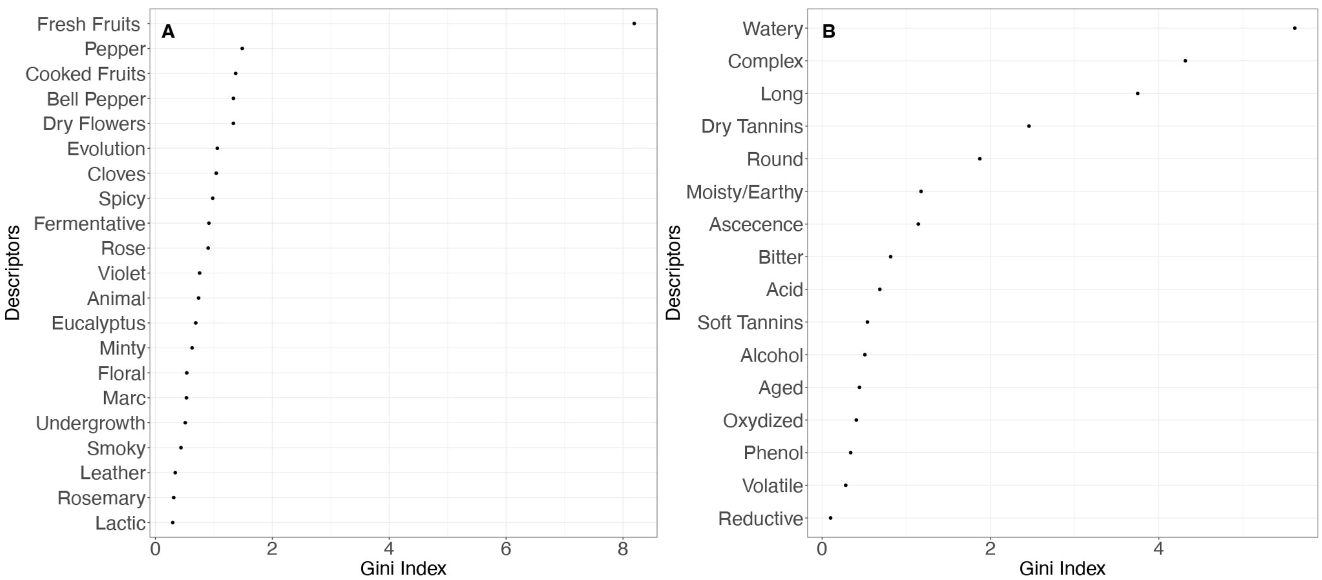

FIGURE 2.2. Gini indexes of the descriptors used in the Check-All-That-Apply (CATA). Panel A expresses the Gini indexes of the olfactive typicity model and panel B the Gini indexes of the palate typicity model.

(i.e., the most typical and the most atypical wines). Then two random forest models were created with 300 trees each and five variables at each node: the first one to predict the class of olfactive typicity and the second one to predict the class of palate typicity of the wines. The models were trained on 75 % of the dataset before being tested on the remaining 25 %, with in both cases highly convincing results being obtained for the classification (for the olfactive typicity: out-of-bag error of 10 %, for the palate typicity: out-of-bag error of 12 %). A common issue in machine learning came to light here: an overfitting of the created models. These results were expected, as the models were only trained on the tested datasets. However, our approach does not aim to predict the typicity of wines in other datasets using the models that were created, but only to better understand the underlying effects of each descriptor on Bordeaux typicity.

The classification of the typical and atypical wines was very good, as can be seen in the Multi-Dimensional Scale plots (MDS) in Figure 2.1., which were drawn using the proximity matrices from the two random forest models. This confirms the results found in Figure 1: very typical wines almost never overlap with very atypical wines.

An interesting outcome of this random forest approach is the Gini index for discriminating the variables (i.e., descriptors) that have the greatest impact on the models and thus on the classification of the wines. The Gini index is a commonly used measure in random forest analysis which represents the decrease in node impurities (averaged over all the trees) for each variable (Hong Han *et al.,* 2016). The higher the Gini index for a given variable, the more it contributes to the accuracy of the model. All Gini indexes for the variables are presented in Figure 2.2.

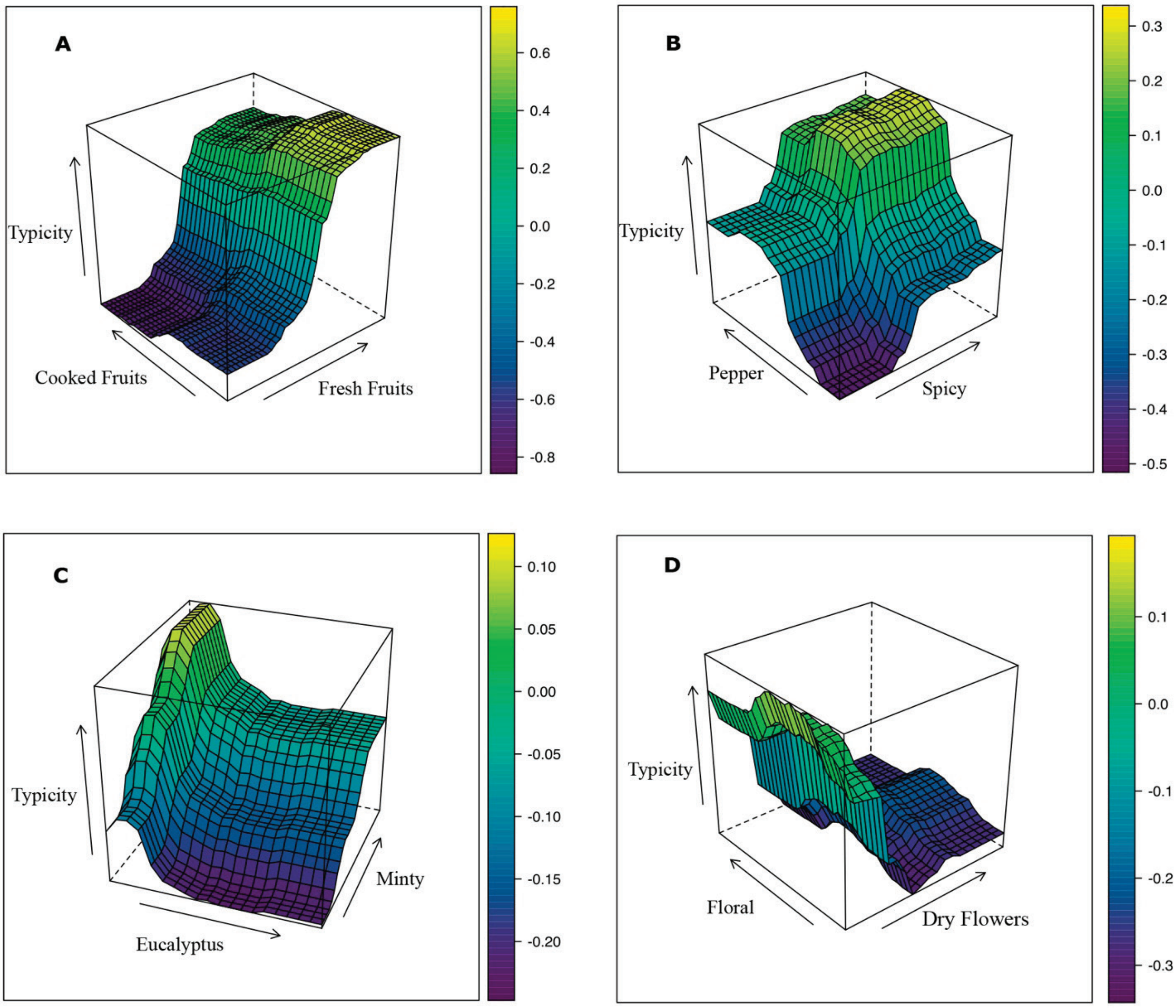

FIGURE 2.3. 3-D Partial Dependence Plots of the random forest model of olfactive typicity. All panels are expressed in logit of probabilities (where negative values indicate probabilities lower than 0.5 and positive values higher than 0.5) and show the probabilities of finding a wine to be typical as a function of the shown descriptors. Panel A shows the descriptors "Cooked Fruits" and "Fresh Fruits", panel B the descriptors "Pepper" and "Spicy", panel C the descriptors "Eucalyptus" and "Minty" and panel D the descriptors "Floral" and "Dry Flowers".

Regarding olfactive typicity, "fresh fruits" (represented by the average of the values for fresh red fruits and fresh black fruits) play a major role in the accuracy of the model when predicting olfactive typicity, followed by the descriptors "pepper", "cooked fruits" or "dry flowers". For palate typicity, more descriptors have high importance in the model, including "watery", "complex" and "long", followed by "dry tannins", "round texture", and "earthy".

The Gini index, however, only expresses the relative importance of each variable in the model when classifying a wine as typical or atypical. It does not reflect the relationship between one variable and typicity and thus in our case it could not answer the question of whether each descriptor positively or negatively impacts the olfactive typicity of Bordeaux wines.

Therefore, a Partial Dependence Plot approach was implemented. The objective was to express the probability that an individual (a wine) would be classified as typical or atypical as a function of each descriptor.

Partial Dependence Plots of some key olfactive descriptors (identified with the Gini indexes) are shown in Figure 2.3 and reveal the very strong positive impact of fresh fruit aromas and the negative impact of cooked fruit aromas for olfactive Bordeaux wine typicity. Interestingly, spiciness also plays a role in red Bordeaux typicity, which, to our knowledge, has not been shown previously. Figure 2.3 B shows that up to a certain point peppery notes increase Bordeaux wine typicity, after which typicity starts decreasing. It is possible that a wine that is too peppery reflects another typicity (potentially from wine regions renown for their peppery aromas such as the Côtes d'Auvergne, France (Geffroy *et al.,* 2016) or Syrah-based

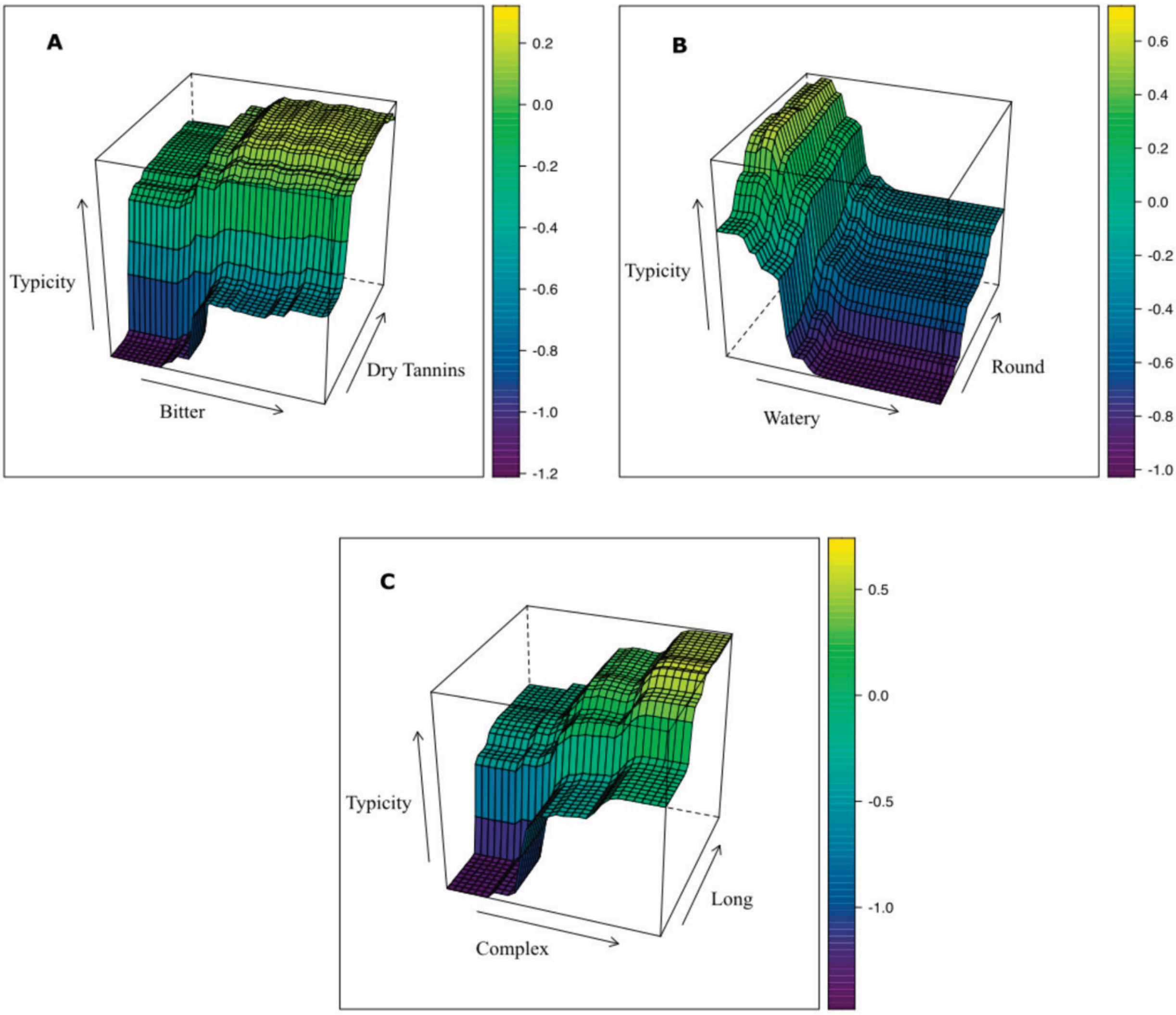

FIGURE 2.4. 3-D Partial Dependence Plots of the random forest model of palate typicity. All panels are expressed in logit of probabilities (where negative values indicate probabilities lower than 0.5 and positive values higher than 0.5) and show the probabilities of finding a wine to be typical as a function of the presented descriptors. Panel A shows the descriptors "Bitter" and "Dry Tannins", panel B the descriptors "Watery" and "Round", panel C the descriptors "Complex" and "Long".

wines in Margaret River, Australia (Mayr *et al.,* 2014)) that do not overlap with Bordeaux typicity. Of less importance (as the scale is smaller with lower probabilities), floral aroma notes seem to contribute to the Bordeaux typicity. However, this floral group is not associated with "dry flowers" (as is the typicity sensorial space of wines from Barolo and Barbaresco, Italy (Smith, 2005)) and thus further research is needed to determine which specific floral aroma notes partly explain Bordeaux typicity (Figure 2.3 D). Similarly, while fresh aromas, especially strong mintiness, increase the probability of finding a wine to be typical of Bordeaux (Figure 2.3 C), "eucalyptus" does not seem to be an important descriptor in Bordeaux typicity. Interestingly, in other published results, "eucalyptus" has been found to be an important descriptor in the typicity of Cabernet-Sauvignon from specific GIs of Australia (Antalick *et al.,* 2015; Robinson *et al.,* 2012) or from California (Heymann & C. Noble, 1987).

Key variables of palate typicity (identified via their Gini indexes) were also investigated for their impact on Bordeaux palate typicity. The partial dependence plots of these variables are shown in Figure 2.4. It is clear that "bitterness" and "dry tannins" (which can both refer to a certain wine roughness) play a major role in the palate typicity of red Bordeaux wines (Figure 2.4 A). Although these descriptors may be perceived as negative, they also tend to be related to the ageing potential of young red wine, which is a positive characteristic (González-Muñoz *et al.,* 2022). Another potential reason for the high probability of these two descriptors explaining Bordeaux typicity is the dumping effect, a well-documented issue in sensorial analyses caused by the omission of a descriptor (Lawless & Heymann, 2010). No descriptors for tannin intensity were proposed in the study, which could explain why the judges chose the descriptors "bitterness" and/or "dry tannins" for tannic wines. Figure 2.4 B shows that a "round texture" rather than a "watery texture" increases the probability of a wine being found typical for Bordeaux. Finally, the descriptors "Complex" and "Long" seem to play a role in Bordeaux wine typicity. These descriptors are clearly positively related to wine quality (Figure 2.4 C). It must be kept in mind, however, that the judges were Bordeaux wine professionals. Hence, an hedonic and/or cognitive bias may be at play, as they may have tended towards positively rating wines with a Bordeaux typicity (using descriptors like "complex" and/or "long").

This innovative decision tree method enabled us to precisely define the Bordeaux wine typicity sensory space (with fresh fruits, some spiciness, some floral notes, bitterness and dry tannins being very important in this sensory space) which

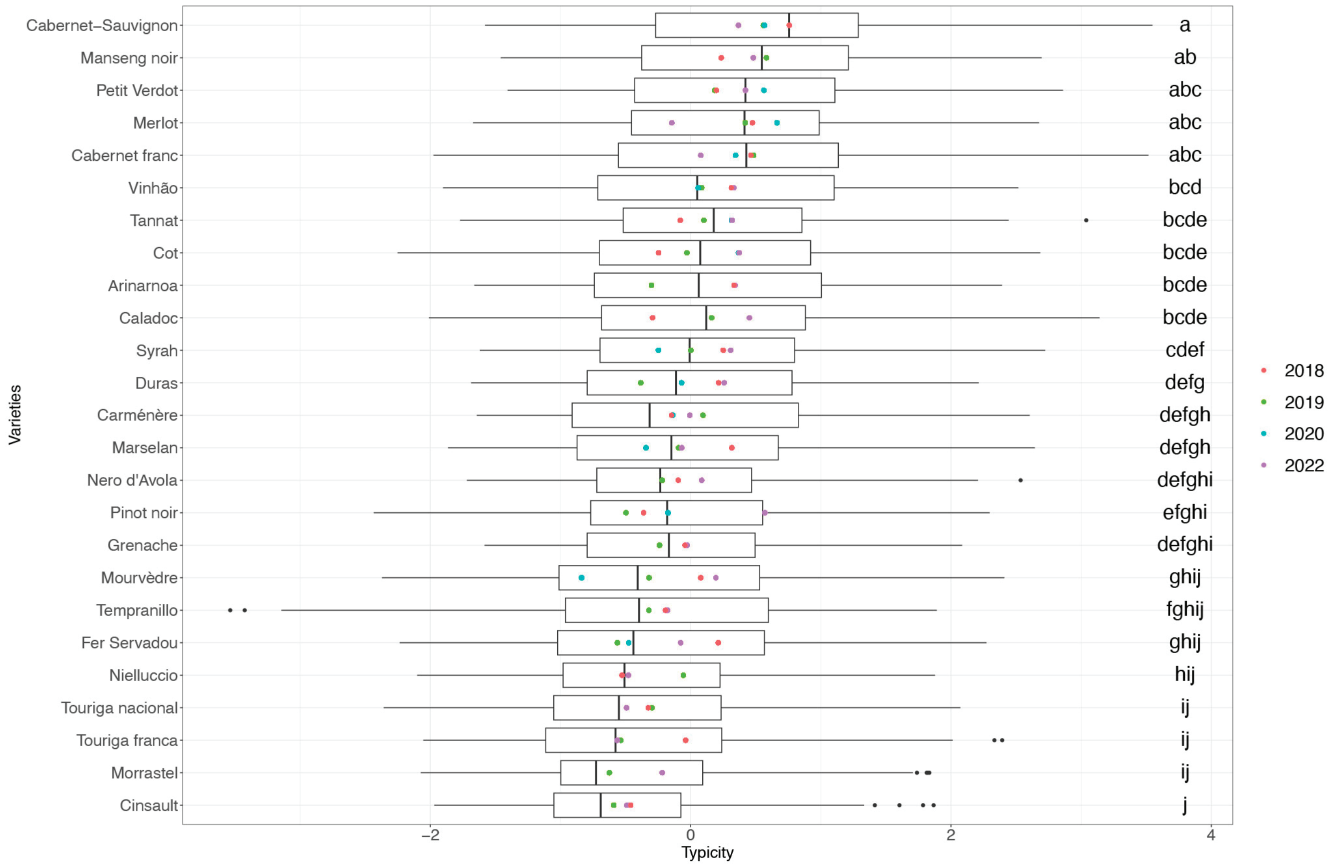

FIGURE 3. Boxplot of olfactive and palate typicity ratings together (scaled by judge and by vintage) for each variety with Tukey significance classifications. Dots represent the mean value for each variety of each vintage. Vintage 2021 was removed from this chart due to the small amount of data available for this vintage. Castets had only one year's worth of data and therefore the results should be carefully interpreted for this variety.

differ from perceptual and or conceptual sensory spaces of other wine regions (Smith, 2005; Cadot *et al.,* 2012; Mayr *et al.,* 2014; Geffroy *et al.,* 2016). Another important outcome of this study was the identification of some boundaries of the sensory space, with descriptors such as rose, eucalyptus or watery texture, that were attributed only to very atypical wines.

3.The Bordeaux typicity of 26 red varieties

This study shows that the sensory space of red Bordeaux wine is well-defined by a limited number of descriptors. The next question to address was whether varieties not traditionally grown in Bordeaux could fit within the sensory space described by our panel.

Figure 3 shows a boxplot of the scaled values of typicity (olfactive and palate) of the wines, averaged by variety (Figure 3). A first group of very typical individuals contains all the major traditional red Bordeaux varieties (Cabernet-Sauvignon, Petit Verdot, Merlot and Cabernet franc), showing the ability of the panel to discriminate Bordeaux typicity. Interestingly, a non-autochthonous variety from Bordeaux also belongs to this group (the Manseng noir, traditionally grown in south-west France) and thus was found to be highly typical of classical Bordeaux red wines.

Despite the broad dispersion of the results, a second group was found to be less typical, which contains two less commonly planted Bordeaux varieties (Carménère and Cot, also named "Malbec"). In this second group some other interesting varieties were found: Tannat (a variety from south-west France, which was probably planted in Bordeaux in the past), Arinarnoa and Marselan (both crosses created by the French National Research Institute for Agriculture, Food and the Environment (INRAE)), with one of the genitors being Cabernet-Sauvignon), Caladoc (a cross obtained in 1958 of Grenache and Malbec), Castets and Duras, which are both ancient Bordeaux varieties. The results for Castets should be taken with caution, as only one vintage was available for this variety (in contrast to at least three vintages for the other varieties). Other varieties include Vinhão (a Portuguese variety), Syrah (which was planted in Bordeaux until the end of the 19th century) and Nero d'Avola (a Sicilian variety).

Finally, all the other varieties were found to be more atypical of Bordeaux wines. This group includes varieties which are not at all related to Bordeaux or south-west France (for instance Grenache, Mourvèdre and Tempranillo), except Fer Servadou which was a relatively important variety in Bordeaux in the past (Bord, 1932).

These results show that Manseng noir is a variety able to produce wines with similar typicity compared to classical Bordeaux varieties. Moreover, even though only mono-varietals wines were tasted (which are not representative of classical production methods in Bordeaux), all the traditional Bordeaux varieties (except Carménère and Malbec, accounting for less than 1 % of the red Bordeaux cultivars) were found to be very typical. It can be concluded that varietal impact is of major importance in Bordeaux wine typicity.

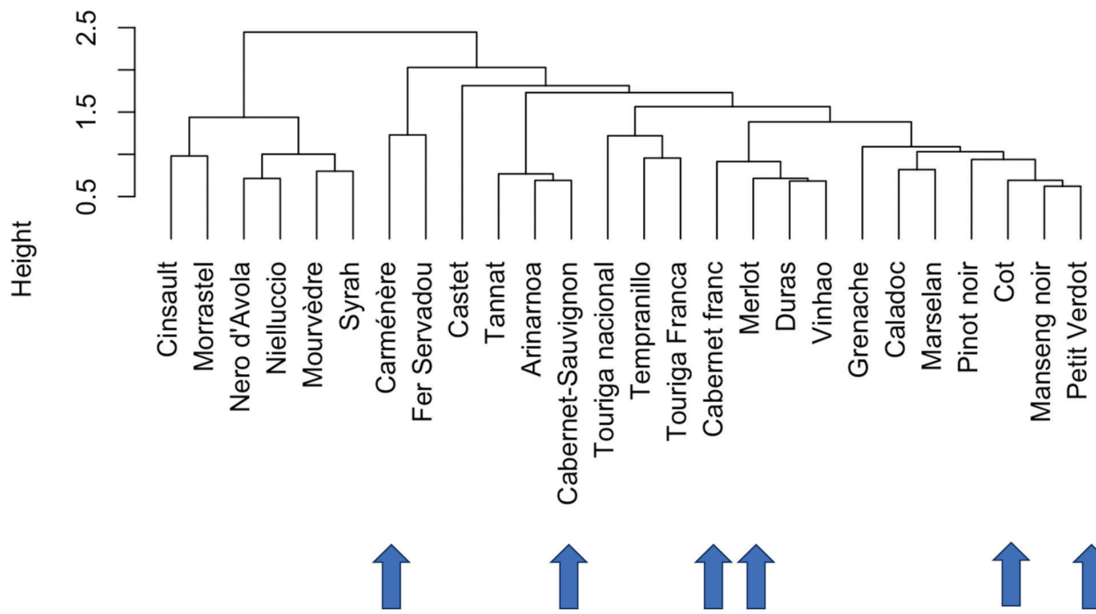

FIGURE 4. Hierarchical Clustering Analysis (HCA) based on of the coordinates of the varieties on all the dimensions of the Multiple Correspondence Analysis (MCA), using the Check-All-That-Apply (CATA_CT) dataset. It shows varieties with similar sensory profiles, without considering specific typicity. Blue arrows show the traditional Bordeaux varieties. HCA was implemented using the Ward method with an Euclidean calculation.

4.Varieties sharing sensorial space with traditional Bordeaux varieties

Knowing that traditional Bordeaux varieties tend to be very typical of Bordeaux wines, the varieties that the panel found to be similar to each of the traditional Bordeaux varieties during the tasting were identified, without considering their specific typicity. A Hierarchical Clustering Analysis (HCA) was performed using the coordinates of the varieties on all the dimensions of the MCA to overcome the previously described multicollinearities issues that have been addressed here, and is presented in Figure 4. This clustering shows the varieties with similar sensorial profiles according to the panel, without considering the specific typicity of Bordeaux wines. Interestingly, all traditional Bordeaux varieties are spread out along the dendrogram,. The sensorial dissimilarity of the red Bordeaux varieties that is presented in Figure 4 has already been shown in a previous study (Garbay *et al.,* 2022). It confirms the idea that typicity is a very broad and complex concept. Indeed, while all these varieties were found to be similar in terms of overall typicity (Figure 3), they still differ in their specific olfactive profiles. Thus, the typicity of wines from a given region or appellation cannot be limited to a particular sensory identity. As demonstrated in this study, the concept of typicity corresponds to different wine profiles sharing essential organoleptic characteristics.

This approach makes it possible to identify the non-autochtonous varieties that share a similar sensorial space with traditional Bordeaux varieties. These non-autochtonous varieties could be introduced as secondary varieties in a Bordeaux blend without substantially changing the wine's typicity. For instance, Merlot was found to be similar to two varieties: Duras (an ancient Bordeaux variety) and Vinhão (a Portuguese variety), which the panel of the study also found to be quite typical of Bordeaux (Figure 3). Hence, they could be of major interest, as the early ripening Merlot was identified as being potentially endangered by the increasingly warm growing conditions in Bordeaux (van Leeuwen *et al.,* 2019). Cabernet-Sauvignon was sensorially close to Arinarnoa. Created in 1956, this latter variety is a cross of Cabernet-Sauvignon and Tannat, and was adopted in 2019 as a cultivar allowed in the Bordeaux wine blend (under strict regulations). This result shows that cultivars with genetic parentage could possibly have overlapping sensorial spaces, an issue that has been addressed in previous studies (Ballester *et al.,* 2005). A similar statement can be made for Carménère, which was found to be genetically closely related to Fer Servadou (Robinson *et al.,* 2013) which were both found to have similar sensorial profiles (Figure 4). This finding is also very interesting, as Fer Servadou (which used to be wrongly named "Béquignol" and was very often confused with this variety) was still planted until the late 1950s in Bordeaux (Duquesne, 2021). Finally, Petit Verdot is very similar to the Manseng noir, which was already identified in this study as a variety that produces very typical wines from Bordeaux. Among these five varieties, only Fer Servadou was found to have a colour not very typical of Bordeaux wines by the panel (data not shown). When considering planting this variety in Bordeaux, winemakers should take notice of this particularity.

CONCLUSION

Our research shows that by working with an expert panel it is possible to differentiate very typical wines from very atypical wines of Bordeaux. An innovative method was applied, implementing random forest modelling, which has not been used previously in sensorial analyses. It was thereby possible to define the sensorial space of red Bordeaux wine typicity using few descriptors. This method was also helpful for determining the boundaries of this sensorial space, as it was possible to identify the descriptors that did not belong to it. Then, our research focused on identifying non-traditional Bordeaux varieties that would fit into this sensorial space. The variety plays a major role in the definition of typicity, as all the major Bordeaux varieties were found to be very typical. However, when investigating their sensorial profiles, it appeared that Bordeaux varieties differed highly, showing again the complexity of the typicity definition: different sensorial profiles can have a relatively high typicity rating.

The typicity ratings showed only one non-autochthonous variety (Manseng noir) to be close to the sensorial space of Bordeaux wines. Using an HCA approach, five varieties not traditionally grown in Bordeaux were identified by the panel as being sensorially similar to one of the classical red Bordeaux varieties. Interestingly, three of these varieties were still being planted less than a century ago in Bordeaux, indicating that some solutions for facing climate change could be found in the history of Bordeaux. This study aimed to identify new varieties potentially of interest in the Bordeaux region for adaptation to climate change. Those varieties were found to correspond to Bordeaux wine typicity. However, their behaviour in warmer and drier climatic conditions still needs to be investigated before they can be adopted within the regulations regarding the Bordeaux varietal mix.

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