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A Decision Support System for Vine Growers Based on a Bayesian Network

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We propose here a decision support system for vine growers to assess the quality of a vineyard to be planted. The quality of a vineyard is defined by the probability of possible profitability of the wine sales he is able to produce. The model, based on a Bayesian network (BN), takes into account environment and the parameters defining vineyard status with their associated interactions. BN are widely used for knowledge representation and reasoning under uncertainty in natural resource management. There is a rising interest in BN as tools for ecological and agronomic modelling. Data were collected from knowledge of vine-growing experts. We developed a C# computer program predicting the likely quality of a vineyard. The model has been validated on existing vineyards with prediction ability around 75 %. This system should ease assessments of the likely impact of the choices and decisions of vine growers on the quality of new vineyards to be planted in any part of the world. No such model has been developed before for vine growers.

Supplementary materials accompanying this paper appear on-line.

Key Words: Bayesian network; Complex systems; Climate change; Expert data; Vineyard quality.

1. INTRODUCTION

A convenient feature of Bayesian networks (BNs) is the ability to learn about the structure and parameters of a system based on observed data (Kragt 2009). Knowledge of the structure of a system can reveal the dependence and independence of variables and suggest a direction of causation. It evaluates the 'optimal' BN structure, based on the highest probability score

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for possible candidate structures, given the data provided and perhaps penalised for the level of complexity (Norsys 2005). Different score metrics can be used to evaluate the BN structure, varying from entropy methods to genetic algorithms.

But, BN are a useful way to model expert knowledge, like we did in our study. We used expert knowledge to create the network and the conditional probability tables. Experts were members of the International Organisation of Vine and Wine. Performing this step, we noticed that sometimes it may be difficult to get experts to agree on the structure of the model and on the nodes that are important to be included. Experts must be challenged to express their knowledge in the form of probability distributions (Uusitalo 2007). Elicitation of expert knowledge requires an iterative process, to ensure that experts are comfortable with the nodes, their states and interrelationship in the BN, before making statements about distributions and confidence intervals of variables (Pollino 2008). Bayesian networks have been used in various fields, including molecular biology (Friedman et al. 2000), computer vision and pattern recognition (Rehg et al. 1997), and have recently been applied to space and aeronautics by NASA (Homayoon et al. 2009). Other methodology could have been used instead of BN, such as fuzzy set theory (Ragin 2000). Fuzzy set method is more appropriate for problems with only a small number of parameters. Neural networks need a big quantity of measurements or observed data we do not have in this study. Neural networks cannot be interpreted directly and generally speaking, the intermediate nodes of most neural networks are discovered features rather than being associated with predicate variables in their own right.

The quality of a vineyard can be defined as its capacity to produce satisfactory numbers of grapes with particular qualitative chemical and physical properties to insure high profitability of wine sales. Wine quality depends directly on the quality of the grapes used to make it (Peynaud 1971). Soil properties, particularly as concerns soil pH and mineral composition (Galet 2000), have been shown to affect grape quality and grapevines clearly grow better in some areas than in others. It has also been known for many decades that climate and meteorological factors are important in viticulture and that regional climate variability affects annual grape yield (Agosta et al. 2012).

All these effects have been studied separately. Our aim in this study was to identify the most relevant vineyard variables, to quantify the interactions between them and to include them in a global network with an engine for the calculation of a probabilistic value predicting the quality of a future vineyard. Climatic indices (CI, HI, DI) defined by Tonietto and Carbonneau are included in the model. Significant progress has already been made towards the representation of climates and terrestrial processes through systematic evaluations against observations and against more comprehensive models (Randall et al. 2007).

2. MATERIALS AND METHODS

2.1. The Vineyard Model

A vineyard is a complex system comprising the geographic area, the chemical and physical properties of the soil and the cultivation system (Abbal 2014). Experts chose to consider

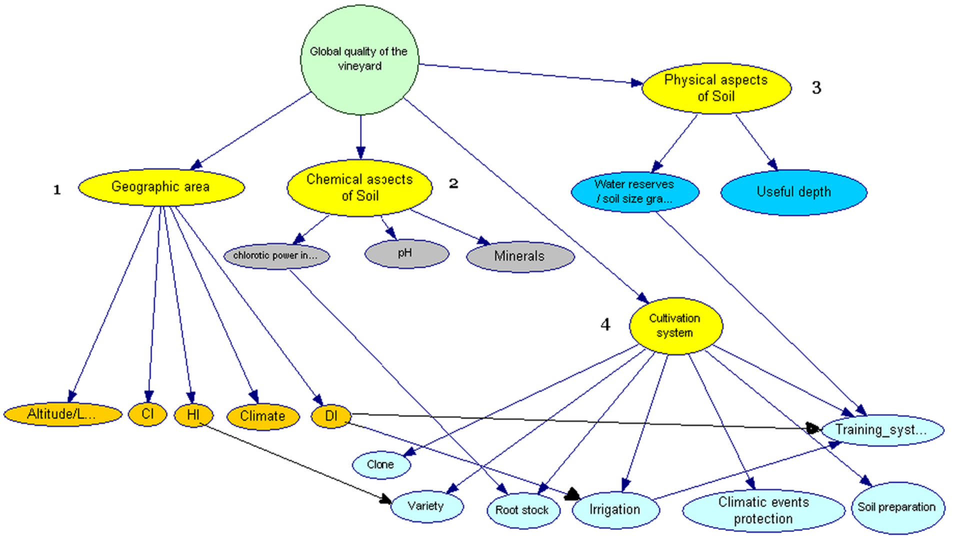

Figure 1. The "vineyard network" created by experts.

variables belonging to these four groups (Fig. 1) because each of these groups includes factors that limit vine cultivation (Carbonneau et al. 2007).

The four yellow nodes are intermediary nodes, useful to better understand the network. Each group of variables has a specific colour. An arrow means a dependency between a node and a variable or between two variables. The sense of the arrow is designed according to retro causality. The geographic area node comprises altitude, latitude, cool night index (CI), dryness index (DI), heliothermal index (HI) and climate type. The node relating to chemical aspects of the soil includes the cholorosis power index, soil pH and mineral content. The third node relates to the physical properties of the soil, including water reserves, soil particle size grading, and useful soil depth. Node four, relating to the cultivation system, concerns irrigation, protection against major climatic events, soil preparation, grape variety, clone, root stock and training systems. Experts added to the network a few interactions between variables (Fig. 1): the choice of the variety depends on HI, the choice of the training system depends both on water reserves, on drought index (DI) and on the irrigation system. Of course, the choice of the root stock depends on the chlorotic power index of the soil.

2.2. GEOGRAPHIC AREA

Altitude and latitude must be considered, together with the type of climate (Galet 1976, Reynier 1991). Nobody with any sense would try to plant vines at the North Pole or in the hotter parts of the Sahara Desert, for example. The following outcomes were used to investigate the role of climate: polar, subarctic, desert, subdesert, equatorial, continental, Mediterranean, oceanic and tropical, as inspired by the classification of Peguy (1970). Climate generally has a major effect, but it would be wrong to claim that it is the most important factor in vine and grape growing, and this view has already been supported by several publications (Carbonneau et al. 2007).

Latitude (L) and altitude (A), when considered together, provide precise information about potential vineyard quality simply because air temperature depends on these two factors (Galet 2000). We included in the model five outcomes for altitude, from 0 to more than 3000 m, and four outcomes for latitude, from 0 to more than 55°.

For climate, Tonietto and Carbonneau (2004) proposed a multicriterion classification method involving multivariate measurements of climate on the basis of three indices: HI, CI and DI. These indices were selected from a long list because they together account for the largest proportion of total climatic variation (90 %) during the growing cycle of the vine.

CI is a night coolness variable that takes into account the mean minimum night temperature during the month in which ripening usually occurs and beyond the ripening period. This index improves the assessment of the quality potentials for wine of vine-growing regions, based on secondary metabolites (polyphenols, aromas) in grapes. CI is the minimum air temperature in the month of September or March (depending on the hemisphere) in °C. We included four temperature levels in our model (Table 1—supplementary data).

We also used HI, the classical HI of Huglin (Huglin and Schneider 1998), in this study. This index provides information about heliothermal potential and approximates the possible sugar content of different varieties as a function of classical cumulative temperatures, thereby providing information about quality. In combination with CI, the HI characterises the climate of a region well, in terms of global heliothermal conditions during the vegetative cycle of the grapes and cool night conditions during the ripening period (Table 2—supplementary data).

DI, the DI, is based on the potential soil water balance index of Riou (Riou et al. 1994), which was developed specifically for vineyard use and makes it possible to characterise the water component of the climate in vine-growing regions. It takes into account the climatic demands of a standard vineyard, evaporation from bare soil and rainfall, with no deductions for surface runoff and drainage. It indicates the potential availability of water in the soil, reflecting the dryness of the region (Table 3—supplementary data).

This climatic factor is particularly important in terms of its effects on grape ripening and wine quality (Jackson and Cherry 1988; Seguin 1983; Mérouge et al. 1998; Carbonneau 1998). DI is a very important factor to be taken into account when choosing the most appropriate vine and rootstock. For this reason, we linked it to the cultivation system node (Fig. 1).

2.3. THE SOIL AND CULTIVATION SYSTEMS

2.3.1. Chemical Aspects of the Soil

The chemical properties of vineyard soils were described by Champagnol (1980). In 2000, Galet studied the effects of the chemical properties of the soil on the quantity and quality of the grapes produced. These properties can be modelled by three variables: chlorosis potential index (CPI), pH and mineral availability. The presence of limestone in the underlying substratum may have a major effect on the iron metabolism of the plant, potentially leading to chlorosis. This index can be defined as follows:

$$\text{CPI} = \text{active limestone (g/100 g)} \times 10,000)/\text{available iron (mg/kg)} \qquad \text{(Juste and Pouget 1972).}$$

Higher CPI values are associated with a higher risk of chlorosis in the vineyard. CPI values determine the choice of rootstock (Table 4—supplementary data).

Mineral levels in the soil must all be taken into account. Nitrogen, potash, phosphoric acid and calcium are very important minerals, deficiencies of which in the soil can decrease vineyard quality (Galet 2000). The availability of these nutrients to the plants depends on soil pH. Extreme pH values decrease the quality of vineyard soils, which should ideally have a pH between 5 and 8 (Tonietto and Carbonneau 2004).

2.3.2. Physical Aspects of Soil and Water Availability

According to Galet (2000), the physical properties of a vineyard soil can be characterised by two parameters: soil gradient and available soil depth. Soil gradient plays a major role in determining water availability and water reserves. Indeed, knowledge of the percentages of silt and clay in the soil makes it possible to calculate the water reserves of the soil (Jamagne et al. 1977). Water is a key component of photosynthesis and is an essential solvent for the transport of minerals from the soil into the plant (Riou 2000). For this reason, the physical aspects of the soil must be linked to DI. Vine roots are more likely to grow well if the soil is appropriate and of adequate depth. Shallow soils are incompatible with high quality in vineyards (Reynier 1991).

2.3.3. Cultivation Systems

A cultivation system integrates a large number of variables: chemical and physical aspects of the soil (described above), clone, variety, rootstock, irrigation, protection against climatic events (frost, hail, etc.), soil preparation and training systems.

For each grapevine variety, there are several types of clones available and the choice depends on the amount and quality of wine desired.

Nurseries can provide grapevine growers with details of the characteristics of the clones they supply and can help growers to select the most appropriate rootstock on the basis of CPI value (Table 4—supplementary data). Soil preparation is an important variable of this node. Trenching or ploughing the soil allows the root system of the vine to develop. A lack of soil preparation greatly compromises the future development of the plants and invariably results in heterogeneous, low-quality vineyards (Carbonneau et al. 2007). Irrigation and protection against climatic events, such as frost or hail, may have an impact on grape yields (Bonnet 1910). Finally, the training system should be selected according to the available water reserves. We included a representative set of training systems in our network, including vase, vertical shoot positioning and lyre systems.

2.4. Bayes' Theorem

Humans can define problems, list possible decision options, identify relevant factors and quantify uncertainty and preferences. However, they are inefficient at combining all the available information and interactions to come to a rational decision. The probability of a particular event occurring in relation to the occurrence of another event was studied by Thomas Bayes in 1765 and this work was extended by the mathematician Laplace in 1774.

Bayesian inference (Bayes 1763/1958) provides a means of determining the probability of an event based on the probabilities of other events that have already been evaluated. In decision analysis theory, Bayesian inference is closely related to discussions of subjective probability. Bayesian inference is defined as the process of deriving logical conclusions on the basis of premises known or assumed to be true. Bayesian networks deal with inferences and the probabilities of variables within the system. It represents a set of random variables and their conditional dependences on a directed acyclic graph (Stanley 1973; Howard and Matheson 1984; Thulasiraman and Swamy 1992). This approach, including inference, is useful in many contexts, including reverse engineering and weather forecasting. We used GeNIe software to create our vineyard network. GeNIe is a development tool for the construction of graphical decision theory models. It was developed by the Decision Systems Laboratory at the University of Pittsburgh and has been made available to the community to promote in the use of decision theory methods in decision support systems (http://genie.sis.pitt.edu). GeNIe has been tested extensively and is widely used for both teaching and research. It is also used in commercial applications. GeNIe stands for Graphical Network Interface. It can be associated with the SMILE interface, a library of functions for graphical probabilistic and decision theory models (http://genie.sis.pitt.edu). SMILE is implemented in Visual C# (Petzold 2002) and draws heavily on MFCs (Microsoft Foundation Classes). As a consequence, it is not always easily transferable, despite running on the Windows operating system, one of the most widely used computer platforms worldwide. GeNIe can be used to build models of any size or complexity, and is limited only by the capacity of the operating memory of the computer used. Models developed with GeNIe can be embedded into any application and run on any computing platform through SMILE, which is fully transferable.

2.5. MODEL CALCULATIONS

Let us consider two non-independent events, A and B, with their associated probabilities, $P(A)$ and $P(B)$, respectively. The model is based on Bayes' theorem, as follows in generic Eq. (1):

$$P(A|B) = \frac{P(B|A)\, P(A)}{P(B)} \tag{1}$$

This theorem (1) has already been demonstrated (Bayes 1763) and the reader must remain a developed version of the theorem (2) for an easier understanding of the process of inference and probability tables.

$$P(A|B) = \frac{P(B|A)\, P(A)}{P(B|A)\, P(A) + P(B|A^C) P(A^C)} \tag{2}$$

Applying Eq. (2), a Bayesian network B can be mathematically defined as a graph G and a set of probabilities θ for each node of the graph conditional on the status of their parents in this graph.

Associating each element of the graph to a random variable, $B = (G, \theta)$ is defined by:

- $G = (X, E)$ directed acyclic graph whose nodes are associated with a set of random variables $X = \{X1, \ldots, Xn\}$.

– $\theta = \{P(Xi|Pa(Xi))\}$, all the probabilities of each node Xi conditioned by the state of its parent $Pa\,(Xi)$ in G.

These two characteristics have been the source of the first names of Bayesian networks, "probabilistic expert systems" where the graph was compared to the set of rules of a classic expert system and the conditional probabilities presented as a quantification of uncertainty about these rules.

Pearl et al. (1991) showed that Bayesian networks allow to represent compactly the joint probability distribution on the set of variables n:

$$P(X1, X2, \ldots, Xn) = \Pi\, P(Xi|Pa(Xi))$$
$$i = 1 \text{ to } n$$

Modeling with Bayesian networks requires the assumption of the Markov property i.e. there are no direct dependencies in the system being modelled which are not already explicitly shown via arcs in the graph.

This decomposition of a global function into a product of local terms dependent only on the node concerned and on his parents in the graph, is a fundamental property of Bayesian networks. It is the basis of the early work on the development of inference algorithms, which calculate the probability of any variable of the model from the same partial observation of other variables. Belief updating in Bayesian networks is computationally complex. In the worst case, belief updating algorithms are NP-hard (Cooper 1990).The graph belief propagation algorithm solves the following marginalisation problem (Weiss and Freeman 2001):

$$P(x_i) = \frac{1}{Z}\int_{j \neq i} \exp(-1/2x^T Ax + b^T x)\mathrm{d}x_j,$$

where Z is a normalisation constant, A is a symmetric positive definite matrix (inverse covariance precision matrix) and b is the shift vector. For example, it can be shown that using a Gaussian model, the solution of the marginalisation problem is equivalent to the maximum a posteriori probability assignment problem:

$$\underset{x}{\operatorname{argmax}}\, P(x) = \frac{1}{Z}\exp(-1/2x^T Ax + b^T x)$$

This problem is also equivalent to the following minimization problem of the quadratic form:

$$\min_x 1/2x^T\ Ax - b^T x.$$

Which is also equivalent to the linear system of equations $Ax = b$ (Shental et al. 2008)

Pearl (1986) developed a message-passing scheme that updates the probability distributions for each node in a Bayesian networks in response to observations of one or more variables. Lauritzen and Spiegelhalter (1988), Jensen et al. (1990), and Dawid (1992) proposed an efficient algorithm that first transforms a Bayesian network into a tree where each node in the tree corresponds to a subset of variables in the original graph. The algorithm then exploits several mathematical properties of this tree to perform probabilistic inference. Few algorithms are detailed further in the text. Of these, best known are probabilistic logic sampling (Henrion 1988), likelihood sampling (Shachter and Peot 1990; Fung and Kuo-Chu

1990), backward sampling (Fung and del Favero 1994), Adaptive Importance Sampling AIS BN (Cheng and Druzdzel 2000), and Approximate Posterior Importance Sampling APIS BN (Yuan and Druzdzel 2003). Approximate belief updating in Bayesian networks has been also shown to be worst-case NP-hard (Dagum and Luby 1993).

Clustering algorithm is the fastest known exact algorithm for belief updating in Bayesian networks. It was originally proposed by Lauritzen and Spiegelhalter (1988) and improved by several researchers, e.g. Jensen et al. (1990) or Dawid (1992).

The clustering algorithm works in two phases: (1) compilation of a directed graph into a junction tree, and (2) probability updating in the junction tree. It has been a common practice to compile a network, and then perform all operations in the compiled version. Research in relevance reasoning (Lin and Druzdzel 1997) has challenged this practice and has shown that it may be advantageous to preprocess the network before transferring it into a junction tree. The clustering algorithm should be sufficient for most applications. Only when networks become very large and complex, the clustering algorithm may not be fast enough. In that case, it is suggested to choose an approximate algorithm, such as one of the stochastic sampling algorithms

The belief updating algorithm for singly connected networks (polytrees) was proposed by Pearl (1986). It is the only belief updating algorithm that is of polynomial complexity, but unfortunately this result and the algorithm works only in singly connected networks (i.e. networks in which any two nodes are connected by at most one undirected path).

The Adaptive Importance Sampling for Bayesian Networks (AIS-BN) algorithm is described in Cheng and Druzdzel (2000). This is one of the best sampling algorithm available, surpassed only by the APIS-BN algorithm (Yuan and Druzdzel 2003). In really difficult cases, such as reasoning under very unlikely evidence in very large networks, it will produce two orders of magnitude smaller error in posterior probability distributions than other sampling algorithms. Improvement in speed given a desired precision is even more dramatic. The AIS-BN algorithm is based on importance sampling. According to the theory of importance sampling, the closer the sampling distribution is to the (unknown) posterior distribution, the better the results will be. The AIS-BN algorithm successfully approximate its sampling distribution to the posterior distribution by using two cleverly designed heuristic methods in its first stage, which leads to the big improvement in performance stated above. This algorithm is described in Fung and Kuo-Chu (1990) and in Shachter and Peot (1990).

Relevance-based algorithms are described in Lin and Druzdzel (1997). Relevance algorithms are very fast and usually lead to substantial savings in computation time.

The Estimated Posterior Importance Sampling algorithm for Bayesian Networks (EPIS-BN) algorithm is described in Yuan and Druzdzel (2003). This is quite likely the best sampling algorithm available. It produces results that are even more precise than those produced by the AIS-BN algorithm and in case of some networks produces results that are an order of magnitude more precise. The EPIS-BN algorithm uses loopy belief propagation to compute an estimate of the posterior probability over all nodes of the network, and then uses importance sampling to refine this estimate.

The likelihood sampling algorithm makes an attempt at improving the efficiency of the probabilistic logic sampling algorithm by instantiating only non-evidence nodes. Each sample is weighted by the likelihood of evidence given the partial sample generated. It is a simple algorithm with little overhead that generally performs well and certainly better than probabilistic logic sampling in cases with observed evidence.

The probabilistic logic sampling algorithm is described in Henrion (1988). This algorithm should be credited as the first algorithm applying stochastic sampling to belief updating in Bayesian networks. Essentially, the algorithm is based on forward (i.e. according to the weak ordering implied by the directed graph) generation of instantiations of nodes guided by their probability. If a generated instantiation of an evidence node is different from its observed value, then the entire sample is discarded. This makes the algorithm very inefficient if the prior probability of evidence is low. The algorithm is very efficient in cases when no evidence has been observed or the evidence is very likely.

In our Bayesian network, each node is described by a probability distribution dependent on its direct predecessors. Nodes with no predecessors are described by prior probability distributions. The vineyard quality node is described by the prior probability distribution for its three outcomes: very high quality (P2), moderately high quality (P1) or unsuitable (P0). This limited number of outcomes is justified to ensure a reliable analysis of all the different effects on vineyard and wine quality. Both the structure and numerical parameters of our network were obtained from experts, but they could have been learned from data, as the structure of a Bayesian network is simply a representation of data dependence relationships. Finally, for implementation of the model, the special SMILE library of C# classes with graphical decision theory methods was used. This library works well with intelligent systems, such as Bayesian networks and influence diagrams. We used it to develop C# software for the input of all decision node values and for processing of the entire network to obtain a final probabilistic value for vineyard quality (Fig. 2). The model was adjusted on the basis of the probability table values. Model adjustment can be a time-consuming process. The adjustment was based on the variability of data within the probability tables. In some cases, the weighting of a variable was increased by using more extreme values from the probability table for the variable concerned (closer to 0 or closer to 1, depending on the desired effect). The system generates an output file containing values and results that can easily be imported into Excel.

2.6. SENSIBILITY ANALYSIS

Good modelling practice requires modellers to provide an evaluation of confidence in their models and thus to evaluate the contribution of each input to output uncertainty. Quantitative model evaluation should include sensitivity analyses and assessments of predictive accuracy. Predictive accuracy refers to a quantitative evaluation of the model, by comparing model predictions with observed data (Pollino et al. 2007). Sensitivity analysis tests the sensitivity of model outcomes to variations in model parameters. Sensitivity analysis in BNs can measure the sensitivity of outcome probabilities to changes in input nodes or other model parameters, such as changes in node's type of states and their coarseness. It can be performed using two types of measures; entropy and Shannon's measure of mutual information (Pearl 1988). The entropy measure is based on the assumption that the uncertainty or randomness of a variable X, characterised by probability distribution $P(x)$, can be represented by the entropy function $H(X) : H(x) = \Sigma Pi(x).\log(Pi(x))$. Reducing $H(X)$ by collecting information in addition to the current knowledge about variable X is interpreted as reducing the uncertainty about the true state of X (Barton and de Vladar 2009). The entropy measure therefore enables an assessment of the additional information required to specify a particular alternative. Shannon's measure of mutual information is used to assess the effect of collecting information about one variable (Y) in reducing the total uncertainty about variable X using: $I(Y, X) = H(Y) - H(Y|X)$

where $I(Y, X) =$ the mutual information between variables. This measure reports the expected degree to which the joint probability of X and Y diverges from what it would be if X were independent of Y. If $I(Y, X) = 0$, X and Y are independent (Pearl 1988). Another way to use the mutual information measure is to compare the impact of gathering information on variables Y and Z on reducing the uncertainty in X. For example, if $I(Y, X) > I(Z, X)$, then the uncertainty in variable X would be reduced more by increased observations about Y then by increased information about Z (Barton and de Vladar 2009). Coupé and Van Der Gaag (2002) and Pollino et al. (2007) propose an additional empirical approach to sensitivity analysis, based on changing each of the parameters and observing the related changes in the posterior probabilities. This approach can be used to identify the most 'sensitive set' of variables in the BN; those that are most influential in affecting change and those that are most affected by variations in parameters. Note that assessing the influence of every single parameter can be a time-consuming process, especially in large networks. Sensitivity analysis is used to address this issue, ordering inputs in terms of their strength and relevance for determining output variation (Saltelli et al. 2008). Local methods involve determining the partial derivative of the output Y with respect to an input factor X_i:

$$\left| \frac{\partial Y}{\partial X_i} \right|_{\mathbf{X}^0},$$

where the subscript $\mathbf{X}^0$ indicates that the derivative is taken at some fixed point in the space of the input (hence the 'local' in the name of the class). In our model, calculations are made through Tornado diagrams, useful to perform sensitivity analysis. For each variable/uncertainty considered, Tornado diagram estimates for what the low, base and high outcomes would be. The sensitive variable is modelled as uncertain value while all other variables are held at baseline values (stable).

2.7. The Experts

Our network was created by completing probability tables with expert data. The chosen international experts were Professor Alain Carbonneau and Professor Jean-Michel Boursiquot, both members of the International Organisation of Vine and Wine. We defined different possible outcomes for each decision node, as explained below. The experts were asked to fill in the probability tables. The questions put to the experts were as follows: for each path leading to a random node, taking into account all the possible outcomes of every decision node, what are the probabilities of attaining a good quality vineyard ($P2$), a medium quality vineyard ($P1$) a poor quality vineyard or a vineyard in which vines cannot grow ($P0$). The hypothesis $\sum_{j=0}^{j=2} Pj = 1$ had to be confirmed.

Table 1. Probability table for the variable pH.

pH	Good_soil_chemical_aspects	Medium_soil_chemical_aspects	Bad_soil_chemical_aspects
Less_than_5	0.0001	0.495	0.4995
From 5 to 8	0.9998	0.01	0.001
More_than_8	0.0001	0.495	0.4995

3. RESULTS AND DISCUSSION

3.1. Inference and Expert Data

After experts concluded data input phase, the data were analysed statistically in order to assess the consistency between experts (Yamada et al. 2003). For example, considering the "variety" variable, the ranking predicted quality (low, medium and high) for each expert was examined to measure the agreement amongst experts. The inter-expert pair-wise comparison using Spearman's rho revealed that approximately more than 90 % of the values of rho in the analyses of the study domain very correlated using the interpretation of Fowler et al. (1999). So, using the method described in Sect. 2.7 with regard to the methodology of eliciting expert knowledge (Uusitalo 2007; Pollino 2008), we filled the probability tables. For example, the table below shows the scores given by the experts for the pH variable of the chemical aspects node (Table 1).

Below, we discuss and substantiate only the major results we got by eliciting expert knowledge.

For node 1, a latitude >55° corresponds to a situation in which it is impossible to establish a productive vineyard. Furthermore, the latitude limits for vineyards decrease with increasing altitude. Thus, grapes can grow at 3000 m, but high **P2** values are obtained only at low latitudes. Thus, regardless of the other decision nodes, desert climates give high P0 values, close to 1. The only exception to this concerns altitudes of between 1200 and 3000 m, with a CI <12 and a HI between 2400 and 3000°C. In such conditions, **P2 may reach 0.5**. Furthermore, an equatorial climate, which is not appropriate for vineyards, gives a high P0 value of 0.95. A subdesert climate is suitable for vines and may yield high **P2** values, depending on the other decision nodes of the model. Equatorial climates are too warm and wet for grapevines. Tropical climates are also not optimal for vines, yielding **P2** values of 0.75 if DI is low (below 100 mm), with a HI between 2400 and 3000°C and a positive CI. Oceanic climates are ideal for vines if conditions are not too wet (DI $\leq$ 150 mm) and altitude is below 600 m. Continental climates are appropriate for vines only if the DI is below 150 mm and the HI is greater than 1500°C. Mediterranean climates are generally optimal for vine growing, particularly if the CI is no greater than 14°C. Regardless of the other decision nodes, a CI greater than 18 is not appropriate for grapevine growth, resulting in a high **P0** value. For lower values of CI, the Bayesian network takes all the other variables into account. Similarly, extreme HI values, below 1500 or above 3000°C, are not suitable for grapevine growth and result in high **P0** values. HI is a determinant variable for the choice of vine variety. A DI value of −100 mm or below, with no possibility of irrigation, results in high **P0** values (desert areas). By contrast, DI values greater than 150 mm indicate an environment that is too wet for a high-quality vineyard.

For node 2, CPI depends on pH and water availability. A high CPI, of more than 90, is associated with high P0 values unless adapted root stocks, such as Fercal (Carbonneau et al. 2007), are used. A pH value below 4.5 or above 8 is also associated with high **P0** values, regardless of the other decision node outcomes. Nitrogen, phosphoric acid and potassium hydroxide are important minerals for vines and, according to the experts, unbalanced soils never yield high **P2** values.

For node 3, soil gradient and useful soil depth play a major role in determining water availability and water reserves (Carbonneau et al. 2007). The percentages of clay, silt and sand in the soil must be known for the determination of water reserves, as a ration in mm of water per cm of thin soil. This value can be obtained with the software we developed, by inputting the percentages of silt and clay. Water availability can be determined by multiplying the value for water reserves by that for useful soil depth. For good **P2** values, water availability must be sufficiently high to avoid severe water stress. However, the presence of excess water may lead to rot, resulting in high **P0** values.

For node 4, a probabilistic evaluation of the quality of each variety was necessary. We therefore asked international experts about the quality of more than 660 varieties of wine grapes (Lacombe et al. 2011). Some very old varieties, such as Storgoziya, from Central Europe and the Caucasus area, have high **P0** values. Other rarely used varieties, such as Pozsonyi and Portan, had high **P1** values. The remaining, better known varieties, such as Pinot Noir, Cabernet Sauvignon, Merlot and Chardonnay, had high **P2** values (Table 5—supplementary data). However, some clones are not of high quality and experts have always considered the clone-variety match to be important. The choice of a specific rootstock should take the CPI value into account. For high CPI values, in limestone soil, special rootstocks such as Fercal, 140 R or 41B, must be used. The use of other rootstocks in such soils invariably leads to high **P0** values. Vines require water, so an absence of irrigation in desert or subdesert climates invariably leads to high **P0** values. By contrast, protection against frost or hail may be required in some areas, and this also affected the probability values given by the experts. Similarly, a lack of soil preparation may have a negative effect on wine quality throughout the life of the vineyard and invariably results in high **P0** values. Finally, the use of a vertical shoot positioning system may lead to high **P0** values if water reserves are not sufficiently high.

3.2. MONITORING SOFTWARE

Using the method described in 2.5, specific software was developed to integrate user choices, probability tables and monitoring of the Bayesian engine GeNIe (Fig. 3). The program supplies the engine with the occurrence of each variable of the situation studied by the user. The engine requires water reserve values, so the software calculates them from the percentages of silt and clay, as described by Jamagne et al. (1977). Once the user has made all the choices required, the software triggers the Bayesian engine to generate the results. The decision system is based on the control variables of the network: clone, variety, rootstock, irrigation system, protection against climatic events, soil preparation and training

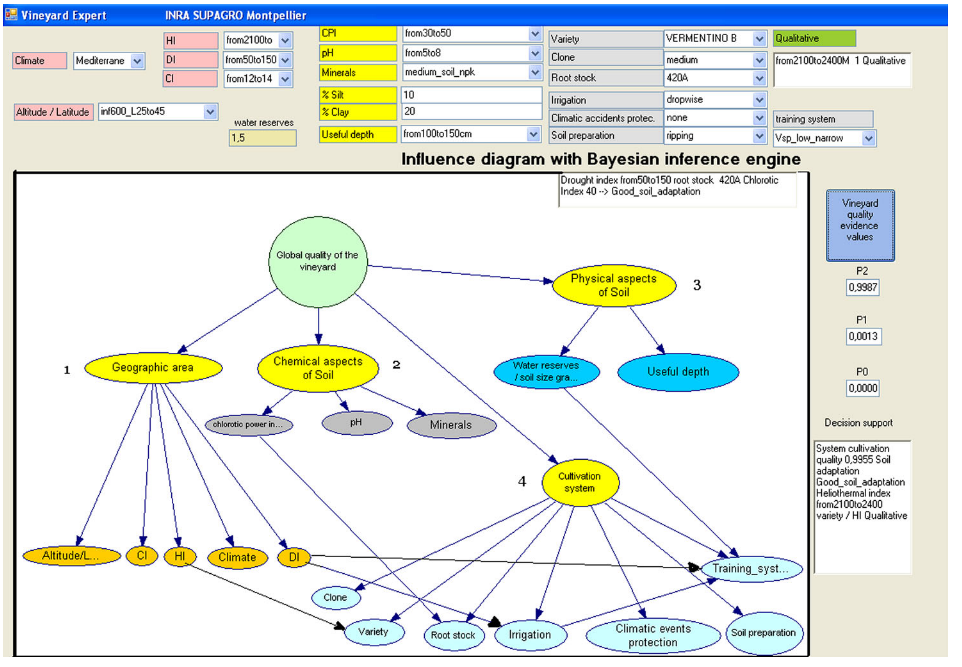

Figure 2. Software with a Bayesian calculation engine.

system. The CPI value is used to select the rootstock, as explained above, and the HI value is used to select the variety, on the basis of earliness. The C# rules were defined to guide the user in the choice of control variable values for the future vineyard as a function of final quality (Fig. 2).

The average sensitivity values of the different variables of our model, provided by GeNIe software, have been ranked in increasing order of impact on vineyard quality (Table 2).

These indices indicate that *climate* has a huge effect on quality in our model. It is due to the fact that extreme climatic situations such as Polar climate are addressed by the BN . *Altitude / latitude, DI, variety, rootstock* and*training system* also have a high sensitivity. The least sensitive variable is *protection against climatic events*.

3.3. VALIDATION

After developing the model's structure and estimating the conditional probabilities, we evaluated our BN. Usual expert model evaluation tools include qualitative feedback from experts and stakeholders, or by comparing model predictions with literature data or with results from similar models (Kragt 2009). Inter-experts comparisons has been made in order to assess the consistency between experts (see Sect. 3.1). To measure the similarity among the experts, correlation coefficients called Spearman's rho (Fowler et al. 1999) were derived from the ranking data. Appendix A shows results with the P0, P1 and P2 probability values. High P0 values were obtained for situations previously identified as difficult or impossible for grapevine growth, as described in the materials and methods. These situations correspond to extreme choices for the most sensitive variables: climate, altitude, latitude and DI. High P1 values were also obtained if poor choices were deliberately made for several con-

Table 2. Sensitivity analysis indices.

Variable	Average sensitivity
Protection against climatic events	6,00915E-24
Irrigation	2,52293E-23
Clone	6,72016E-23
Minerals	6,88071E-22
Water reserves	1,42201E-21
Useful depth	1,78898E-21
HI	2,66054E-21
Soil preparation	9,7018E-19
Chlorotic power index	1,12844E-18
pH	1,83256E-17
CI	1,58944E-14
Rootstock	5,48163E-11
Training system	1,65825E-10
Variety	2,40825E-10
DI	4,1743E-10
Altitude / latitude	3,94494E-06
Climate	0,999996054

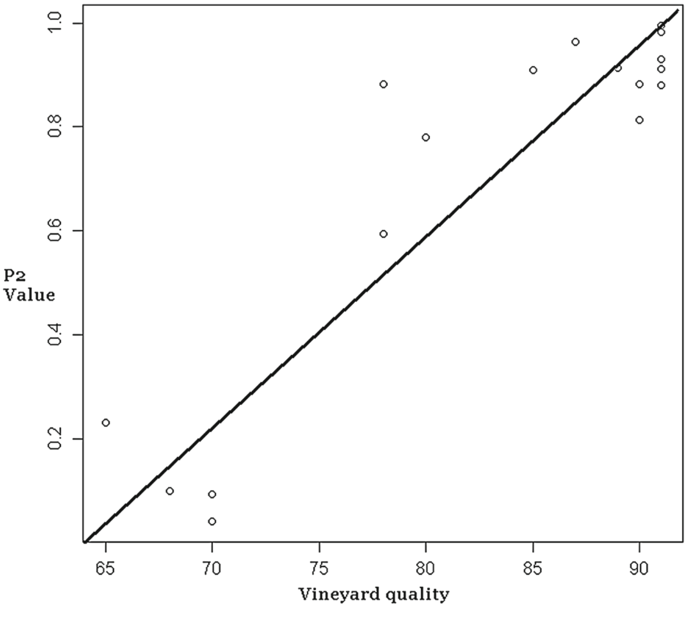

Figure 3. Model validation.

trol variables: variety, rootstock, soil preparation, contrary to the guidance of the decision system. In other cases, high P2 values were obtained. A real validation of such a model is impossible to achieve. We validated our model by testing it with existing vineyards *considering the wine quality obtained using the same oenological processes* for each of them. So, we obtained data relating to the climate, to the soil, to the cultivation system and the corresponding quality of the wines produced for each vineyard by different juries. These results were approved by the experts.

Appendices B shows the results obtained for the existing situations studied, with P_i probability values considered *as a function of the corresponding vineyard quality*, determined either by the press (Wine Spectator, Wine Advocate) or through tasting sessions.

We determined the correlation between P2 value and vineyard quality, scored from 0 to 100 (Fig. 3). A correlation *coefficient of 0.75 indicated that higher P2 values were associated with higher scores for wine quality.* The predictive value of the model may therefore be considered good. This model is now used in experimental conditions by scientists of INRA (Pech Rouge, France) and few winegrowers in south of France in order to test it in more various conditions.

We promote it in international congresses such as GIESCO (International group of experts in wine systems for cooperation) to develop its use. By this way, we will get more results coming from various areas and conditions and will get more feedback to improve the model if necessary.

4. CONCLUSIONS

Bayes' theorem is widely applied in many fields, including science, engineering, medicine and law. Its use in conjunction with prior knowledge and a system able to compute inference data can be very effective. In the system suggested here environment and all the components of a vineyard were linked together in a new model, making it possible to quantify the likely quality of a future vineyard to optimise possible choices through the control values of the network. This study is of potential interest to all winemakers wishing to grow their own grapes and to maximise their chances of establishing a high-quality vineyard. The predictive performance of the proposed BN is around 75 %. Thanks to the software developed in this study, the model will be soon available on line either through INRA web site or through GIESCO international experts web site. It will allow us to get feedback to improve it or to adapt it to more specific situations.

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APPENDICES

APPENDIX A

See the Appendix Table 3,

Table 3. Calculations and results.

Climate	Latitude/altitude	CI (°C)	HI	DI (mm)	CPI	pH	Minerals	% silt	% clay	Useful soil depth (cm)
Subartic	L > 45 A > 1200	<12	<1500	−100 < DI < 50	20	$5 \leq pH \leq 8$	Poor or unbalanced soil	20	40	100–150
Subdesert	0 > L > 25 A < 1200	14–18	2400–3000	−100 < DI < 50	40	$5 \leq pH \leq 8$	Medium-quality_soil	20	40	100–150
Desert	0 > L > 25 A < 1200	<12	2400–3000	−100 < DI < 50	10	$5 \leq pH \leq 8$	Medium-quality_soil	20	40	f100–150
Mediterranean	L25 > L > 45 A < 600	14–18	1800–2100	−100 < DI < 50	10	$5 \leq pH \leq 8$	Rich_soil_NPK_nutrients	60	10	>150
Tropical	0 > L > 25 A < 600	12–14	2400–3000	< 100	20	$5 \leq pH \leq 8$	Rich_soil_NPK_nutrients	50	10	>150
Oceanic	0 > L > 25 A < 1200	14–18	>1500	<150	10	$5 \leq pH \leq 8$	Rich_soil_NPK_nutrients	60	10	>150
Oceanic	0 > L > 25 A < 1200	< 12	>1500	>150	70	$5 \leq pH \leq 8$	Medium-quality_soil	10	60	100–150
Equatorial	0 > L > 25 A < 1200	> 18	>3000	>150	10	$5 \leq pH \leq 8$	Rich_soil_NPK_nutrients	60	10	>150

Climate	Protection against climatic events	Variety	Clone	Rootstock	Irrigation	Soil preparation	Training system	P2	P1	P0
Subartic	winter frost	SHYRAZ	qual.	140R	none	ripping	vase	0	0.001	0.9989
Subdesert	winter frost	MERLOT	qual.	110R	none	subsoiling	vase	0.0011	0.0021	0.9967
Desert	winter frost	PINOT	qual.	Gravesac	dropwise	subsoiling	vase	0.5	0.25	0.25
Mediterranean	winter frost	GRENACHE	qual.	SO4	dropwise	ripping	lyre	0.995	0.005	0
Tropical	none	SHYRAZ	qual.	SO4	furrow	ripping	vase	0.651	0.249	0.101
Oceanic	winter frost	VIOGNIER	qual.	101-14	dropwise	subsoiling	lyre	0.949	0.051	0.01
Oceanic	winter frost	CABERN. SAUV.	qual.	FERCAL	none	subsoiling	vase	0.291	0.349	0.36
Equatorial	none	PINOT NOIR	qual.	SO4	none	subsoiling	vase	0.097	0.101	0.802

APPENDIX B

See the Appendix Tables 4 and 5.

Table 4. Validation with existing vineyards.

Vineyard	Variety	Area	Altitude / Latitude	Climate	CI (°C)	HI	DI (mm)	pH	CPI	Minerals	% silt	% clay
Bois de la ville	CLAIRETTE B	Châteauneuf du Pape	inf600_L25–45	Mediterranean	12–14	2100–2400	_minus100 to 50	5–8	10–30	rich_soil_	20	20
Cabriere	GRENACHE B	Châteauneuf du Pape	inf600_L25–45	Mediterranean	12–14	2100–2400	_minus100 to 50	5–8	10–30	rich_soil_	20	20
La Nerthe	CLAIRETTE B	Châteauneuf du Pape	inf600_L25–45	Mediterranean	12–14	2100–2400	_minus100 to 50	5–8	30–50	rich_soil_	20	10
Terres Blanches	BOURBOULENC	Châteauneuf du Pape	inf600_L25–45	Mediterranean	12–14	2100–2400	_minus100 to 50	5–8	10–30	rich_soil_	20	10
Cabriere	ROUSSANNE	Châteauneuf du Pape	inf600_L25–45	Mediterranean	12–14	2100–2400	_minus100 to 50	5–8	30–50	rich_soil_	20	10
Bois de la ville N	GRENACHE N	Châteauneuf du Pape	inf600_L25–45	Mediterranean	12–14	2100–2400	_minus100 to 50	5–8	10–30	rich_soil	20	10

Table 5. Validation with existing vineyards.

Vineyard	Useful soil depth (cm)	Variety	Clone quality	Rootstock	Irrigation	Protection against climatic events	Soil prep.	Training system	P0	P1	P2	Wine score / 100	Jury
Bois de la ville B	100–150	CLAIRETTE B	Medium	LOT	None	None	Ripping	Vsp*_low_narrow	0.000	0.118	0.882	90	R. Parker
Cabriere	100–150	GRENACHE B	Medium	LOT	None	None	Ripping	Vase	0.000	0.086	0.914	89	Wine Advoc.
La Nerthe	100–150	CLAIRETTE B	Medium	LOT	None	None	Ripping	Vase	0.000	0.120	0.880	91	Wine Advoc.
Terres Blanches	100–150	BOURBOULENC	Medium	R140	None	None	Ripping	Vsp*	0.000	0.089	0.911	91	Wine Advoc.
Cabriere	100–150	ROUSSANNE	Medium	SO4	None	None	Ripping	Vase	0.000	0.083	0.814	90	Wine Advoc.
Bois de la ville N	50 to100	GRENACHE N	High	LOT	None	None	Ploughing	Vase	0.000	0.070	0.930	91	Wine Spect.

Vsp : Vertical shoot positioning system

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