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Accounting for multiple impacts of the Common agricultural policies in rural areas: an analysis using a Bayesian networks approach

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Abstract

In evaluating the potential effects of the reforms of the Common Agricultural Policy, a particularly challenging issue is the representation of the complexity of rural systems either in a static or dynamic framework. In this paper we use Bayesian networks, to the best knowledge of the authors, basically ignored by the literature on rural development.

The objective of this paper is to discuss the potential use of Bayesian Networks tools to represent the multiple determinants and impacts of the Common Agricultural Policies in rural areas across Europe. The analysis shows the potential use of BNs in terms of representation of the multiple linkages between different components of rural areas and farming systems, though its use as a simulation tool still requires further improvements.

KEYWORDS: Bayesian Networks (BNs), farm-household, multiple outcomes.

JEL: Q1 – Agriculture, Q18 - Agricultural Policy; Food Policy

1. INTRODUCTION

The Common Agricultural Policy (CAP) plays major role in EU's rural areas, both providing income for agriculture and rural households (first pillar), and supporting directly Rural Development Programs (RDP) in the second pillar. Since its implementation started at the beginning of the 1960s, the CAP has been subject to continuous reforms. In view of the end of the present programming period (2007-2013) a further reform process has been activated to design the new instruments that will cover the post-2013 period. The issues at stake in this reform have been outlined by the recent communication by the EU Commission (COM 672/2010 "The CAP towards 2020: meeting the food, natural resources and territorial challenges of the future").

Due also to this continuous reform process, as well as for the relevance for EU agriculture and rural economy, the CAP has been widely studied. In particular, a recent wave of research has been stimulated by the perspective of this upcoming reform.

This has generated a wide literature and the tools to evaluate the effects of the CAP are now a very wide and heterogeneous family. One of the main difficulties is that the effects of the Common Agricultural Policies in rural areas are determined by a number of drivers and affect a number of potential dimensions, ranging through a variety of economic, social and environmental issues. Attempts to take into account such complexity are available using SAM approaches or, more consistently with the need of representing multiple links in a flexible way, dynamic networks.

As an example of SAM, Thomson and Psaltopoulos (2007) (see also Balamou et al., 2008) present a combined CGE and SAM model applied to understand the interaction between different rural and urban areas. An example of system dynamic model of agriculture and rural development was developed in the project TOPMARD (Johnson et al., 2008), that has also been used to simulate policy scenarios, e.g. in Bergman et al. (2008). A growing stream of regional (intermediate scale) models is that of Agent-based models (AMB), such as Agripolis and RegMAS (Regional Multi Agent Simulator) (Lobianco and Esposti, 2008). A survey of different model exercises and attempt to yield an evaluation of scientific knowledge about contribution of the CAP to regional growth, taking into account the effects of different measures and the objectives of the Lisbon agenda is provided by Esposti (2008).

In this paper we address the same problems by using Bayesian networks, a tool that, to the best knowledge of the authors, has never been used before in the literature about the impact of the CAP and rural development (with the exception of previous explorative works of the same authors (Sardonini et al., 2010a, Sardonini et al 2010b) .

The objective of this paper is to discuss the potential use of Bayesian Networks tools to represent the multiple determinants and impacts of the Common Agricultural Policies in rural areas across Europe. Within this wider objective we focus in particular on the interaction between the decision to continue farming and other structural change decisions. In our specific application, we focus on the interpretation of data obtained through a survey of farm-household, addressing, in particular, the perspective post-2013 behavior facing different policy scenarios.

The structure of the paper is the following: first we present the background and the methodology introducing the characteristics of Bayesian Networks, the description of the sample, then an application to cases study across Europe. A brief discussion concludes the paper

2. BACKGROUND AND METHODOLOGY

The focus of this work is the analysis of multiple determinants and impacts of the Common Agricultural Policies in rural areas across Europe considering a set of characteristics and determinants at the level of farm-household, taking into account their interconnections and asset management choices. In the agricultural economics literature, the studies regarding the intention of strategy behaviours of farmers are not very numerous and developed. One of the important causes of this moderate interest is that the process of farmers' strategy is very long and complex in terms of farmers' reaction, structural change, social conditions and its dependency from other exogenous variables.

The intention about the future farming activity is driven by a complex behaviour. The main problems concerning the representation of such behaviour can be grouped as follows: i) non-linear relation between variables, ii) too many variables should be consider in the analysis compared to the dimension of available data, iii) high correlation among variables and multiple outcomes are to be taken into account to understand the process.

We try to manage these problems using the Bayesian Networks (BNs) tool. Bayesian networks were developed mostly in the last few decades. In particular, the last decade of the 20th century saw an improvement in instruments for learning Bayesian networks from data. From the first development in artificial intelligence field (NASA, NOKIA software applications), Bayesian networks are increasingly being used for issues in very different areas of research. Fields of applications regard sociology (Rhodes, 2006), medical diagnosis (Beinlich, 1989; Long, 1989) and environmental aspects (Marcot et al., 2006).

BNs are a graphical tool and they are defined as "Direct Acyclic Graphs (DAGs) where the nodes are random variables and certain independence assumption hold" (Charniak 1991) or in other and more simple words BNs consist in a method which "...capture the believed relation between a set of variables which are relevant to some problem" (Netica™). The BNs method offers some interesting advantages: a) the possibility to use incomplete and small data set avoiding dependence problems between variables because the dependencies are encoded; b) the possibility to learn from data: in fact when the causal relationships are expressed then the model can be used for an explanatory analysis; c) the possibility to combine Bayesian statistical techniques with the domain knowledge and data, so that it is possible to add some prior information that the researcher knows especially when data are insufficient or expensive; and d) the simplicity of the graphical interface about the results interpretation (Heckerman, 1996).

BNs, as the name calls to mind, are based on the Bayesian theorem and on the idea of a conditional dependence. The Bayes theorem permits to obtain the probability for an event B given event A. When the events are dependent, then the probability that event B depends on the event A can be expressed as:

$$P(B \mid A) = \frac{P(A \cap B)}{P(A)} = \frac{P(A \mid B)P(B)}{P(A)} \tag{1}$$

The above relation can be applied in a generalized formulation when we have more than two events. A large number of variables and their links increases the degree of complexity in the analysis, therefore the relationships between variables have to be defined using the principle of the conditional dependence.

The conditional dependence (arcs) consists in a defintion of a subset of variables (parents) that influence other variables investigated (children).

In general, given a set of variable X_i, where i=1,…,N, it is possible to assume that X_i can be dependent on a subset of variables (parents) of pa(X) that $P(X_i| pa(X))$. So pa(X) includes only a specified subset of (X). The reduction to a subset of variables, caused by the conditional dependence relation, implies that the dimension of the model decreases (from the full model considering all the variables) so the inference results easier and simplified. When the complexity of relationships in a net (N) of data (D) increases (i.e. when the number of links imposed are large) it is not possible to directly apply the Bayes theorem but it is necessary to use the probabilistic inference, which consists in the process of calculating new beliefs for a set of variables, given some data.

The relation that identifies the probability to obtain that net given data is:

$$P(N \mid D) = \frac{P(D \mid N)P(N)}{P(D)} \tag{2}$$

where P(N) is the prior probability to have that net, P(D) is the probability of data and P(D|N) is the likelihood which represents the probability to observe that data given a net.

The probabilistic inference is the process of finding a posterior distribution, given a prior distribution and some observations. Bayesian nets do probabilistic inference by belief updating by the data learning (parameters learning). The parameter learning is computed by an iterative process then an algorithm has to use. Several algorithms can be used but in this work the EM algorithm[1] and it returns robust parameter estimations.

1 The EM algorithm takes a Bayes net and uses it to find a better one by performing an expectation (E) step followed by a maximization (M) step. In the E step, the algorithm uses regular Bayes net inference with the existing Bayes net to compute the expected value of all the missing data, and then the M step finds the maximum

The result consists in the estimation of the posterior distribution for each variable defined as child. The posterior distribution is estimated considering the data evidence (likelihood). Moreover, another result is the Conditional Probability Table (CPT) that reports the estimated conditional probability for each child category given all the possible combinations of parents categories.

3. CASE STUDY

The empirical application is based on survey data from the project CAP-IRE "Assessing the multiple Impacts of the Common Agricultural Policies (CAP) on Rural Economies", 7th Framework Programme. The network is structured in nodes based on data collected from 2000 farm households.

In the Table 1, the description of the sample is shown. In fact the sample contains data related to the farm-households from 11 case study areas (CSA). The surveys were made in the first part of the 2009 following different ways (telephone, face-to-face or direct) and the questions were concerned both the farming activity and the household in terms of: structure, innovation, chain supply, environment, social aspects and governance.

Table 1. Description of the sample

CSA	**Number of interviews (farm-households)**	**Way**	**Respponse rate**
1 Emilia Romagna (IT)	300	Telephone	62%
2 Noord-Holland (NL)	300	Postal	21%
3 Macedonia and Thrace (GR)	300	Telephone and face-to-face	55%
4 Podlaskie (PL)	249	Face-to-face	95%
5 North East of Scotland (UK)	168	Telephone	68%
6 Andalusia (ES)	201	Face-to-face	75%
7 South-East Planning Region (BG)	273	Face-to-face	92%
8 Centre (FR1)	140	Face-to-face	35%
9 Midi-Pyrénées (FR2)	155	Face-to-face	31%
10 Lahan-Dill District (DE1)	117	Postal	20%
11 Ostprignitz-Ruppin and North-East Brandenburg (DE2)	160	Postal	14.60%
Total	2363		

likelihood Bayes net given the now extended data (i.e. original data plus expected value of missing data) (NeticaTM)

In the following part of the paper some of the main characteristics, which will be used as nodes in the network are shown to describe the sample. In the Table 2 the location of the farms is reported with respect to the altitude and the case study areas (CSA). It is clear that the farm-households of the sample show a different location distribution conditionally to the country.

Table 2. Distribution of farm-households with respect to the altitude

	Altitude				
	Hill	**Mountain**	**Plain**	**Missing**	**Tot**
BG	38.46%	13.55%	47.99%	0.00%	100.00%
DE1	94.02%	0.00%	1.71%	4.27%	100.00%
DE2	0.00%	0.00%	100.00%	0.00%	100.00%
ES	21.39%	1.00%	77.61%	0.00%	100.00%
FR1	18.57%	0.00%	81.43%	0.00%	100.00%
FR2	54.84%	29.68%	15.48%	0.00%	100.00%
GR	67.33%	21.00%	11.67%	0.00%	100.00%
IT	29.33%	19.67%	51.00%	0.00%	100.00%
NL	0.00%	0.00%	100.00%	0.00%	100.00%
PL	39.36%	0.40%	60.24%	0.00%	100.00%
UK	29.17%	0.00%	70.83%	0.00%	100.00%
Tot	34.11%	8.80%	56.88%	0.21%	100.00%

The location is related to farm specialisation (Table 3). For example in Spain the farms with permanent crops prevail, while livestock farming is the main specialisation in The Netherlands and arable farms are more frequent in Italy.

Table 3. Distribution of farm-household respect to the main specialisation

	Main specialisation					
	Arable	**Livestock**	**Mixed**	**Permanent**	**Missing**	**Tot**
BG	41.76%	32.23%	22.34%	2.93%	0.73%	100.00%
DE1	10.26%	35.04%	44.44%	3.42%	6.84%	100.00%
DE2	22.50%	21.25%	48.75%	2.50%	5.00%	100.00%
ES	45.77%	2.49%	10.95%	40.80%	0.00%	100.00%
FR1	45.71%	20.00%	32.86%	1.43%	0.00%	100.00%
FR2	14.19%	36.77%	43.87%	5.16%	0.00%	100.00%
GR	28.67%	3.00%	63.67%	4.67%	0.00%	100.00%
IT	67.33%	8.67%	6.00%	16.67%	1.33%	100.00%
NL	8.67%	68.00%	15.67%	0.00%	7.67%	100.00%
PL	0.80%	57.83%	40.96%	0.00%	0.40%	100.00%
UK	9.52%	13.69%	74.40%	1.19%	1.19%	100.00%
Tot	28.44%	27.89%	34.28%	7.36%	2.03%	100.00%

Another important characteristic is the farm size (Table 4) in terms of total land (land owned + rent-in - rent out). The larger farms are concentrated in France, in United Kingdom and in the second case study of Germany. All the other countries present farms with dimension lower and more concentrated in the medium class.

The size of the farm might depend on the amount of land rent-in or rent-out. In the sample, the tendency is to rent-in land in all CSA, but in some countries the renting-out can also be rather important e.g. The Netherlands and United Kingdom. In Spain and Italy renting is not frequent.

Table 4. Distribution of farm-household respect to the farm size (ha)

	Farm size							
	no_land	**Small** less than 5	**small-medium** 5-|10	**Medium** 10-|50	**medium-large** 50-|100	**Large** 100-|200	**Very large** more than 200	**Missing**
BG	13.92%	10.62%	9.89%	30.40%	15.75%	5.86%	12.45%	1.10%
DE1	1.71%	10.26%	12.82%	38.46%	12.82%	6.84%	1.71%	15.38%
DE2	0.00%	9.38%	6.25%	25.00%	8.13%	11.25%	30.63%	9.38%
ES	0.50%	20.90%	9.95%	40.80%	10.45%	7.46%	8.96%	1.00%
FR1	0.00%	0.71%	0.00%	2.14%	18.57%	47.86%	30.71%	0.00%
FR2	0.00%	0.00%	0.00%	16.13%	30.97%	36.13%	16.77%	0.00%
GR	0.00%	17.33%	38.33%	40.67%	2.33%	1.33%	0.00%	0.00%
IT	2.00%	19.00%	20.00%	45.67%	7.67%	2.33%	1.00%	2.33%
NL	0.67%	5.00%	5.33%	53.33%	25.33%	6.33%	1.00%	3.00%
PL	0.00%	8.03%	14.06%	67.47%	8.84%	1.61%	0.00%	0.00%
UK	0.00%	0.00%	0.60%	14.88%	18.45%	26.19%	31.55%	8.33%
Tot	2.07%	10.28%	12.65%	37.66%	13.75%	10.92%	9.78%	2.88%

In the process of future farming decisions, the CAP could have an important role: analysing the amount of SFP per ha, the majority of the farm-households are distributed on the two intermediate classes (from 50 to 150 €/ha and from 150 to 500€/ha). Only Spain and Greece show a higher percentage of farm-households concentrated in the intervals "more or equal to 500€/ha" and it depends on the specialisation (i.e. olive in Spain).

Half of the sample states that the farming activity gives at least the 50% or more of the household income showing a specialisation in the farming activity, which could also reveal a dependence of household income on agriculture profitability. Some differences are present between the countries; in fact the DE1 and IT farm-households show the higher frequency in a lower weight of farming activity (less than 10%). The case study areas mainly depending on the farming activity are: France (FR1), Greece, The Netherlands, Poland and United Kingdom.

We further report some households characteristics (age, educational level and number of household full-time workers in the farm). The age distribution shows that in general the owners are adult except owners in France (FR1) and Poland that are more frequently young. The higher percentage of old owners is in

Italy (40%). About the educational level, there are some differences between countries even if the high school level is the most frequent in the sample. In fact, Greece, Italy and Spain present the higher percentage of absence of educational level or a lower level, on the other side in Germany, France and The Netherlands present the higher percentage of professionalizing master and it can be interpreted as an institutional commitment for farming activity. The engagement of household in the farming activity in terms of the number of household full-time members working in the farm presents different distributions between countries even if in the sample only one member of the household permanently works on farm.

4. BAYESIAN NETWORKS APPLICATION

The questionnaire was intended to collect information both about the present situation of the farm and household, and about their future under two hypothetical policy scenarios. In the first scenario called ‘Cap scenario’ (baseline) it is assumed that the CAP remains the same after 2013 and in the second one, called ‘No-Cap’, it is assumed that the CAP will be removed after 2013.

One of the crucial step in the BNs application is the identification of a coherent net. In general, BNs structure can be identified in two alternative ways: using a prior information of some experts or/and considering results obtained in other studies. In this study a combination of the prior knowledge of researchers and the results in the project have detected the importance of some variables. In fact, within the project CAP-IRE, several topics were investigated and this allowed to develop a list of candidate variables for the BNs structure.

The list of the variables is divided in two groups: current characteristics (Table 5) and stated intentions (Table 6). In the former table some selected variables, as parent nodes, and in the last the children nodes are considered. The current characteristics (Table 5) represent the structural characteristics connected to the farm and to the household. In this variables set also the policy scenario (CAP) and the Country (CSA) are considered.

Table 5: Current characteristics

Variable	Label
CSA	Case study areas that identifies the country
HH_FULLTIME_NUMB	Number of household fulltime workers in the farm
AGE_CLASS	Age in class. Young less than 40 years old, adult from 41 to 65 years old and old more than 65 years old
IdAltitude	Location of the farm (plain, hill and mountain)
LIVE_ON_FARM	The household lives on the farm
spec_eurostat	Main specialisation of the farm
LAND_TOT_CLASS	Total land of the farm (owned + rent-in – rent-out)
INCOME_FROM_FARM	Percentage of the farm income over the household income
CAP	Hypothetical policy scenario
RENT	It represent the behaviour of the farmers in the rent land behaviour. It is divided in 4 categories: Both= the farmers both rent-in and rent-out, no_rent= the farmers no rent-in and rent-out, rent-in= only rent-in and rent_out=only rent out.
SFP_HA_CLASS	Amount of the SFP per ha divided in 4 classes
EDU	Educational level of the owner
ADVISORY_ASSISTANT	Use of advisory assistant

The stated intentions (Table 6) represent the selected characteristics over which the responds state the intention of changing or not in several aspect.

Table 6: Stated intention

Variable	Label
INTENTION	Reaction to the hypothetical policy scenario
CHANGE_LEGAL_STATUS	Changing in the legal status
PESTICIDES	Changing in the use of pesticides
CHANGE_SELLOUTPUTS	Changing who sells output
LAND_OWNED	Changing farm size (land owned)
MACHINERY	Changing machinery
INNOVATION_01	Adoption of at least one innovation
CREDIT	Changing the use of credit
HH_LAB_IN	Changing the household labour on farm

The network obtained is supported on the cause-effect relations derived from the results of Work Packages in the CAP-IRE project and prior knowledge based on the economic theory. The relationships between nodes are represented in Figure 1. As the derived network is rather complex, a description in 3 separated boxes will be given. In particular, the box 1 shows the relationships between farm characteristics in terms of land, specialisation and location. In detail, the altitude and the farm size influence the main specialisation; the behaviour with respect to the rent depends on the main specialisation; the farm size depends on the place where the household lives and on the income from farm. The box 2 shows the relationships between farm and household characteristics in terms of amount of SFP per ha, presence of advisory assistant, educational level, number of fulltime household members and owners' age. In particular the distribution of the age and of the number of fulltime household members depend on the CSA. The educational level depends on the age and on the CSA. The SFP per ha influences a large set of variables (almost all child nodes) presents in the box 3. This box represents the focus of the analysis and it reports the multiple outcomes to take in account for the analysis. In particular, the node INTENTION has a key role in the net and it depends on the farm size in terms of land owned and land rent. Moreover, INTENTION depends on the percentage of income, age, members number of the family working in the farm, country and the policy scenario. All the outcomes depends on the INTENTION node and on the other nodes. In detail, the node INNOVATION_01 is linked to SFP per ha, educational level, advisory assistant and age; the node LAND_OWNED depends on structural characteristics as: farm size, land rent, location of the farm (altitude), SFP per ha, fulltime household members; the node MACHINERY depends on structural characteristics as land size, behaviour respect to the land rent and SFP per ha and the number of household members working in the farm. At the same time, the intention in MACHINERY is linked to other intentions as the possibility to adopt at least one innovation and the changing in land. The node PESTICIDES depends on structural characteristics as land size, farm specialisation, SFP per ha and the advisory assistant. At the same time, the intention in PESTICIDES depends on the intention in changing the land. The node CHANGE_LEGAL_STATUS depends on the SFP per ha and advisory assistant, the node CHANGE_SELLOUTPUTS depends only on the intention in the innovation adoption and in changing the land. The node CREDIT depends on farm size, SFP per ha and the number of household members, behaviour in renting land and it depends on the intention to adopt at least one innovation. The changing in HH_LAB_IN depends on educational level, current member of household working in the farm, SFP per ha, specialisation, income from farm activity, rent and on the intention to adopt at least one innovation.

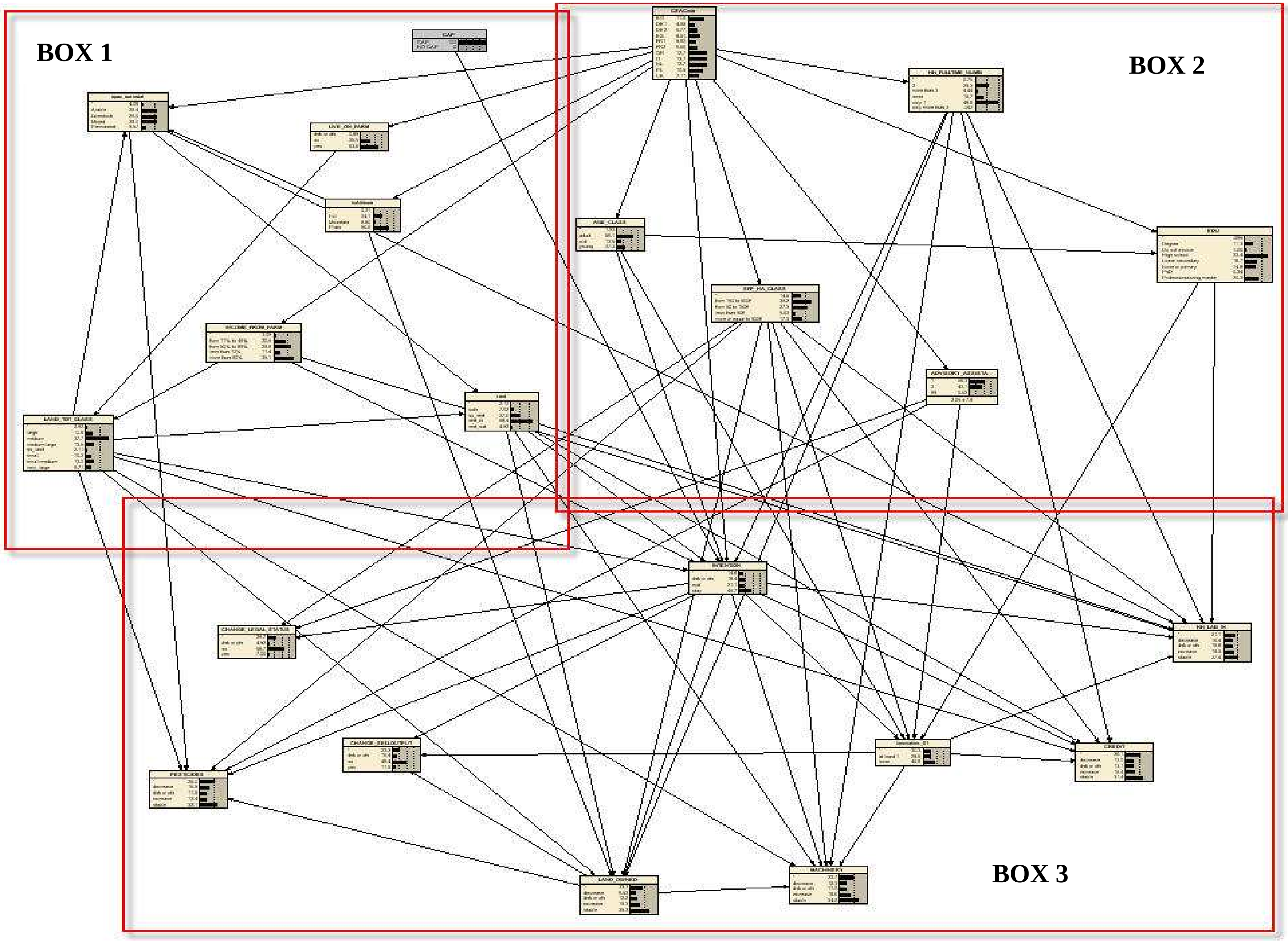
After the description of the constructing process of the net, the net learns from data and it is possible to obtain the children nodes distributions in presence of the dependence conditions. At this stage, the structure of net is imposed by researcher and the goodness of the net have to be investigated. The accuracy investigation is shown by the error rate **Errore. L'origine riferimento non è stata trovata.**for each child nodes. The errors are generally acceptable showing that, for each single multiple outcomes, the net works well. However, the number of misclassification is rather different between nodes and it is generally higher for those nodes that present a lower number of connections to parent nodes.

Table 7: Error rates

Variable	**Error rate**
Intention	1.037
Land owned	8.019
Innovation	5.226
Pesticides	18.05
Machinery	14.85
Change_sell_output	22.37
Change_legal status	11.07
Credit	24.19
Hh_lab_in	10.33

It is possible to analyse and describe the results of the net looking into the CPTs for a combination of nodes and categories selected. The information included in the CPT could not be reported in this paper as the related tables revealed too large. We however account for the main results detectable from the CPT. Specifically, those having intention to adopt at least one INNOVATION_01 are more likely a) young with a degree and b) old but with high level of SFP and high educational level. Those having intention to increase the LAND_OWNED are mostly those that have a medium and medium-large farm size, rented-in already land and there are at least two fulltime household members in farm. Those having intention to increase in MACHINERY are likely those that increase in land and adopt at least one innovation. Those having intention to increase in PESTICIDES are those with livestock and mixed specialisation, SFP in the class 150-|500€ and increase the land. Those having intention to CHANGE_SELLOUTPUT are those increasing in land and adopting at least one innovation.

Figure 1. Bayesian Networks in Cap-Scenario (Baseline)



5. DISCUSSION AND FINAL REMARKS

The analysis shows the potential use of BNs in terms of representation of the multiple linkages between different components of rural areas and farming systems. The method used in this paper, based on survey data and the support of thematic analyses to derive determinants and connections allow the building of a consistent net. The use of learning algorithms also allows a good fit of the net in terms of low error rates.

This work also confirm some of the expected advantages of the BN, namely the simplicity of representation by a graph that describes intuitively the basis of the relationships, the flexibility of use and in the ability to use information from different sources, with a variety of functional relationships.

On the other hand, the paper highlights the need to improve the use of this tool through more robust criteria for network design (identification of nodes and links). In fact, while the structure identification is obtained by the prior knowledge of researchers and by preliminary analysis of individual issues carried out in the project CAP-IRE and supported by economic theory, there is no straightforward rule in using such information for the building of the network. For this reason one of the issues to develop is the structure learning procedures for the net (before parameter learning). Structure learning allows the identification of the causal relationships structure between variables (Cheng, 2002).

The main direction for further research concerns the use of the model to provide simulation of multiple outcomes from farming, assuming different probability distributions of one or more variables in the external parent nodes. This use of BNs results particularly useful in order to extrapolate the estimated system structure and behaviour to regions different from the ones from which the data was used, which could be very relevant in addressing multilevel and multiregional issues. In addition, this could potentially provide for simulation of the impact of changing structural parameters (e.g. farm size) on downstream indicators (e.g. adoption innovation), which could be very useful as a basis for stakeholder involvement and during the policy design phase.

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