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A Bayesian network approach to modeling farmer and scientific knowledge of multifunctional trees in pastures

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A Bayesian network approach to modeling farmer and scientific knowledge of multifunctional trees in pastures

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Abstract

An expert system for the design of ideal livestock pastures using combinations of trees in live fences and on pastures was developed using Bayesian belief networks. The tool was created with information on types of farmers and their preferences, local farmer knowledge about tree species and their benefits, and scientific knowledge about functional traits in the design of silvopastoral systems. The costs and benefits predicted by the model were validated in a follow-up survey in the study area. The model identifies combinations of multifunctional trees which improve ecosystem services provision. Also, it permits the comparison of results obtained with different silvopastoral systems that provide similar services.

Keywords: Adoption, silvopastoral systems, profitability, livestock, ecosystem services, Rivas, Nicaragua.

1 INTRODUCTION

Silvopastoral systems (SPS) are an option for efficient management of cattle farm resources as they potentially provide social, economic and environmental benefits. The benefits provided by trees in paddocks and live fences include provision of shade for cattle, forrage, fruit for human and animal consumption, as well as carbon sequestration, habitat for biodiversity and regulation of the water cycle (Sánchez et al. 2004). Transformation towards silvopastoral systems is needed in areas dominated by monocultures where biodiversity and community resilience have suffered. Despite clear needs and multifunctionality of SPS adaptation towards these systems in Central America has continued to be limited (Mercer 2004, Alonso et al. 2001).

A number of studies provide explanation of the limited adaptation towards silvopastoral systems. Livestock farmers believe that shading from large trees reduces pasture productivity (Marie 2010). In Costa Rica and Nicaragua tree cover lies between 2 and 11,8 % on average (Villacís 2003, Villanueva et al. 2004, Ruiz et al. 2005). Esquivel (2007) found that productivity is not reduced on pastures with less than 20%. Broadly speaking there seems to be substantial potential for increasing tree cover with low risk to farm productivity in the region. For this kind of technology to be adopted (and adapted) by farmers, they should have clear qualitative and quantitative benefits, aceptable levels of risk and be compatible with resources available to the farm, and employ familiar tree species (Somarriba 2009, Rogers 2003).

Adaptation of silvopastoral practices on farm is a multi-dimensional problem in which the farmers knowledge and preferences combines with scientific and technical knowledge through agricultural extension. In this Technical Brief we use bayesian belief networks to construct a model that combines these different knowledge domains for the purpose of evaluating combinations of tree species that meet the multiple needs and aspirations of farmers. Our aim is to demonstrate inductive and deductive approaches to assessing the likelihood of farmers adapting trees to pastures, based on desired ecosystem services, the characteristics of the farmer and the farm.

2 MATERIALS AND METHODS

2.1 Bayesian belief networks

Bayesian networks are cyclical-directed graphs of conditional probability distributions. As such, they are a generic modelling tool both for exploring data structure and for decision analysis under uncertainty. Bayesian belief networks (BBNs) are increasingly being used in ecological, environmental and resource management modeling (Kuikka, Hildén et al. 1999, McCann, Marcot et al. 2006, Barton, Kuikka et al. 2012).

Some advantages to using BBNs for modelling scientific and local knowledge of tree multifunctionality in agrosilvopastoral systems (ASP) include (Barton, Kuikka et al. 2012):

- promoting social learning processes, in the case of this paper between scientists, agricultural extensionists and local farmers;
- better organization of domains of specific knowledge, specifically farmer and scientific knowledge of constraints and possibilities for adoption of multi-functional tree species;
- the explicit acknowledgment of model sensitivity to different levels of resolution of probability distributions, specifically the opportunity to evaluate where scientific knowledge can contribute to local knowledge about tree multifunctionality;
- the facilitation of context dependent decision analysis regarding adoption of ASP practices.

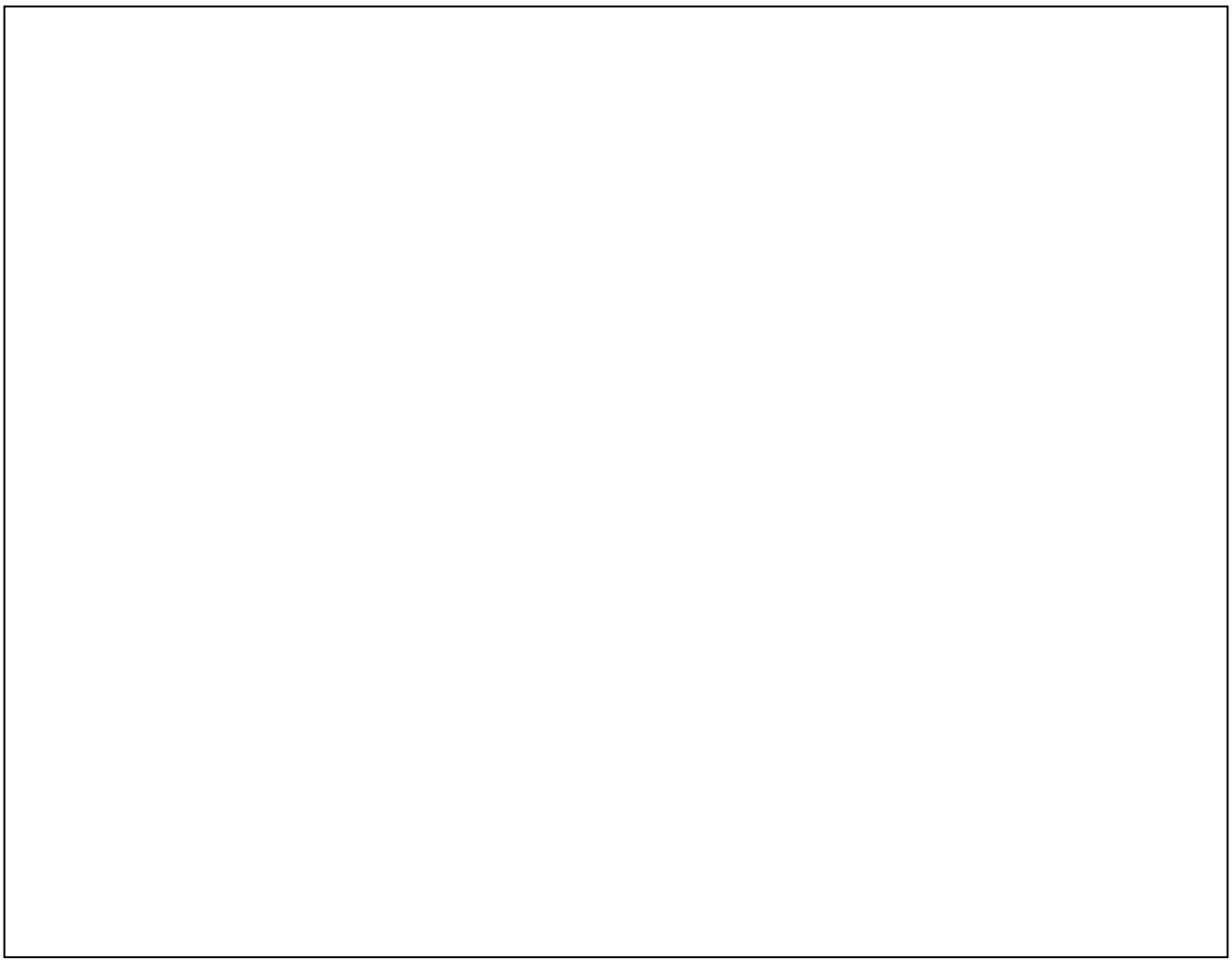
Throughout the paper we will use the terminology Bayesian *belief* network (BBN), whereas Bayesian networks is often also used. In our case the term 'belief' emphasises the importance of subjective or expert judgement in the knowledge contained in the network, both as local knowledge of the farmer and in how it is linked in the network model.

Joshi, Wibawa et al. (2001) used a Bayesian belief network to describe socio-economic variables that influence farmers' decisions regarding plot level management of jungle agroforestry systems in Indonesia. They used participatory rural appraisal techniques and conventional socio-economic to generate data that were collapsed into conditional probability tables of a BN (using Netica software). López, Villanueva and colleagues use BNs to model factors affecting adoption of trees in pasture lands in Nicaragua and Costa Rica (Villanueva, Ibrahim et al. 2003, López, Gómez et al. 2007). They found that the most important decisions that influence on-farm tree cover in Costa Rica are weed control, tree harvesting, live fence pollarding and planting of new live fences (Villanueva, Ibrahim et al. 2003). In Nicaragua, manual vs. chemical weed control in pastures, pruning trees in live fences, harvesting branches and trees for firewood, posts and timber, and land use change were the main factors determining tree cover. Both studies use Netica BN software to model a number of underlying farm practices, ecological and socio-economic factors that in turn determined these main effects.

Sadoddin, Letcher et al. (2005) used BNs to evaluate biophysical, social, ecological and economic factors determining the dryland salinity effects of different management scenarios on terrestrial and riparian ecology in the Darling Basin, Australia. They argue that BNs are particularly useful for communicating risk and uncertainty and providing a framework for analysing cause and effect relationships in natural systems. Their advantage over neural networks is their functionality for also analysing decision processes. Baynes, Herbohn et al. (2008) used BN to model how farmers respond to offers of extension assistance in Leyte, Philippines. They used BNs to evaluate outcomes of a hypothetical expanded agricultural extension programme (Baynes, Herbohn et al. 2008). They argue that BNs are particularly useful in identifying critical success factors and stumbling blocks in scaling up of extension programmes.

Form this brief literature review we find it striking that authors do not apply what is perhaps the greatest advantage of BNs over statistical regression techniques in the technology adoption literature, namely the possibility to carry out diagnostic, inductive reasoning of new cases using knowledge about existing cases (Barton, Kuikka et al. 2012). Furthermore, the non-parametric, qualitative data and the limited size of BBN causal chains capture quite nicely the design principles for computationally efficient and transparent models that should be ideal for validation with farmers (Marcot, Steventon et al. 2006).

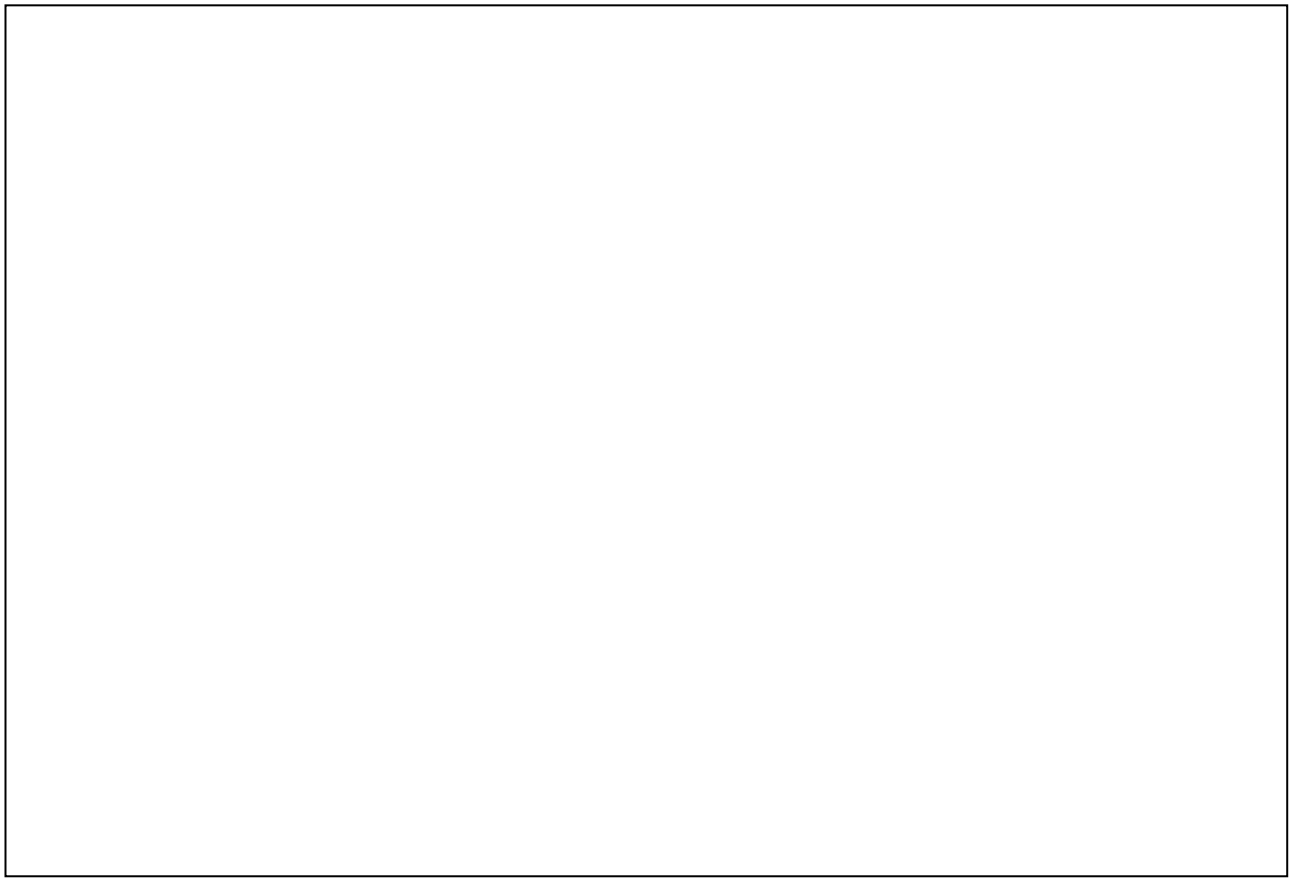
Figure 1 illustrates some desirable properties of BBNs in the integration of different knowledge domains in an expert system on agrosilvopastoral systems. Social scientists collect information on different uses farmers make of trees on their field and relate this to farm location, production system types and farmer characteristics and stated preferences. Biologists and ecologists conduct fieldwork and ethno-botanical interviews to determine the morphological and functional traits of tree species that are attractive to farmers through experience. Field experiements may be carried out to determine the relationship between morphological traits and ecological functions. Scientists have observed across case study sites that ecological functions have ecosystem services. The scientific knowledge and expert belief (based on prior experience) about which ecosystem services are supplied by portfolios of tree species may not be compatible with the actual and desired uses of trees expressed by farmers (Figure 1).



The BBN is used as a 'meta-modelling tool' to connect sub-models from different knowledge domains (Barton, Saloranta et al. 2008). The BBN can be used deductively to reason from causes-to-effects. In figure 1 this might be the observation of what kind of farmer and farm conditions which tree species are adopted, which conditions and combination of functional traits are present on the farm which, in turn, conditions the ecosystem services that are expected to be provided by trees on-farm.

The word 'conditioned' is used instead of 'caused' to emphasise that each dataset or knowledge domain in Figure 1 is set up as a conditional probability table (CPT) in a Bayesian belief network. The Word 'expected' is used to emphasise that the BBN can then provide a probability distribution for ecosystem services conditional on the farm and farmer characteristics. To determine the direction of causality we assume here is that it is the farmer who adapts species to the farm system, rather than the farmer who adapts to farm conditions. With an assumption of causality established by the direction of the causal links in the network BBNs can then also be used for 'inductive' reasoning. Given a list of ecosystem services suggested by the extensionist or uses preferred by the farmer, what is the portfolio of species most likely to provide them (given the likelihoods defined by the conditional probability tables in the network)? From figure 1 we can see that the direction of reasoning is reversed.

BBNs use Bayes Theorem to compute conditional likelihoods. Bayesian networks are unique in providing this inductive analysis capability, compared to spreadsheets (e.g. Excel) or simulation-based causal chain models (e.g. Analytica) (Barton, Kuikka et al. 2012).



In models with multiple knowledge domains, where each submodel may have a number of nodes/variables, it can quickly become challenging to use the network to communicate the causal structure of the model to a non-technical audience. This is potentially a drawback because one of the strengths of a BBN is clearly weakened with complexity – a clear visualisation of the problem structure. For this reason, we used a hierarchical model which nests some intermediate nodes in sub-networks (Figure 2). These networks are called object-oriented Bayesian networks (OOBNs) (Barton, Bechmann et al. 2008).

2.2 Study area and questionnaire

The study was conducted in the Department of Rivas, Nicaragua. This is a semi-arid zone 100-200 m.a.sl. with average annual temperature of de 26,1°C (1971-2000) m average annual precipitation of 1519 mm (Ineter 2012). Soils are vertisols and molisols (Sánchez et al. 2004).

Local knowledge was collected through semi-structured interviews with 55 farmers. The interviews collected information on farm and farmer characteristics and in particular, on the present and ideal composition of trees in the pasture according to the farmer. Obtaining detailed information on the current and desired state of the pasture was facilitated by the use of a board representing a typical pasture on the farm (Figure 3). Using markers specific for the common tree species in the área, the farmer illustrated the current composition of the typical pasture. The farmer was then asked to modify the composition and abundance of trees until he obtained what he considered to be an "ideal "pasture.

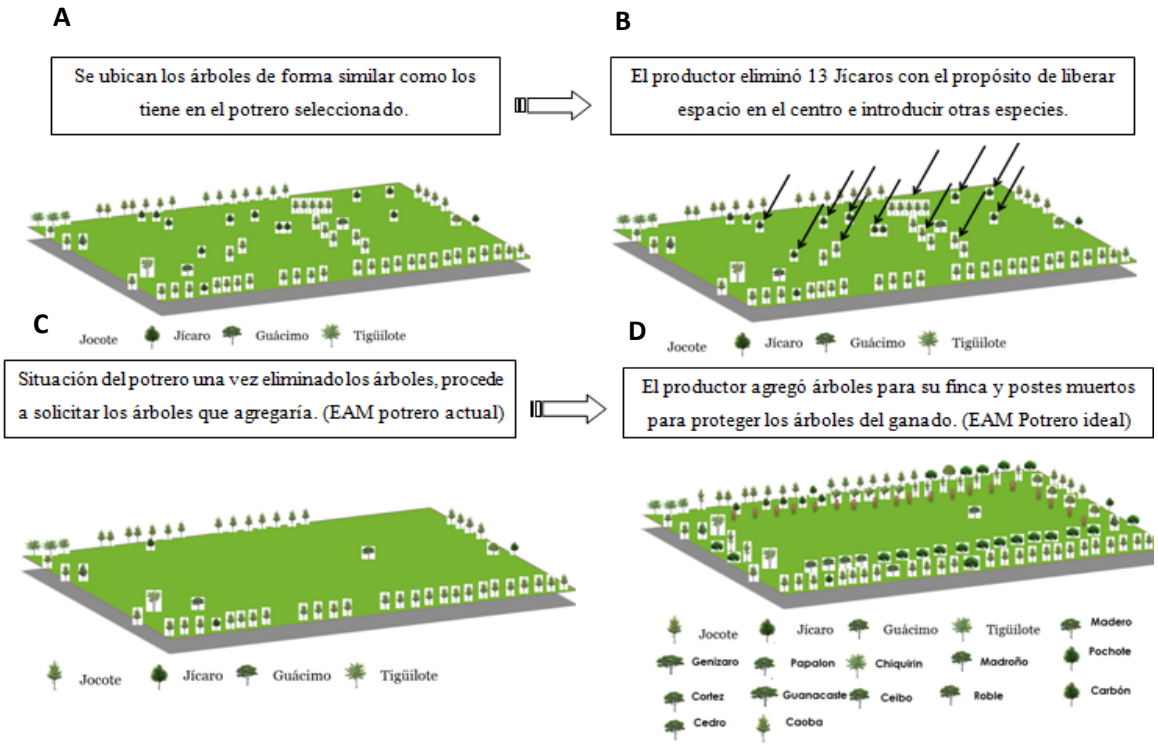
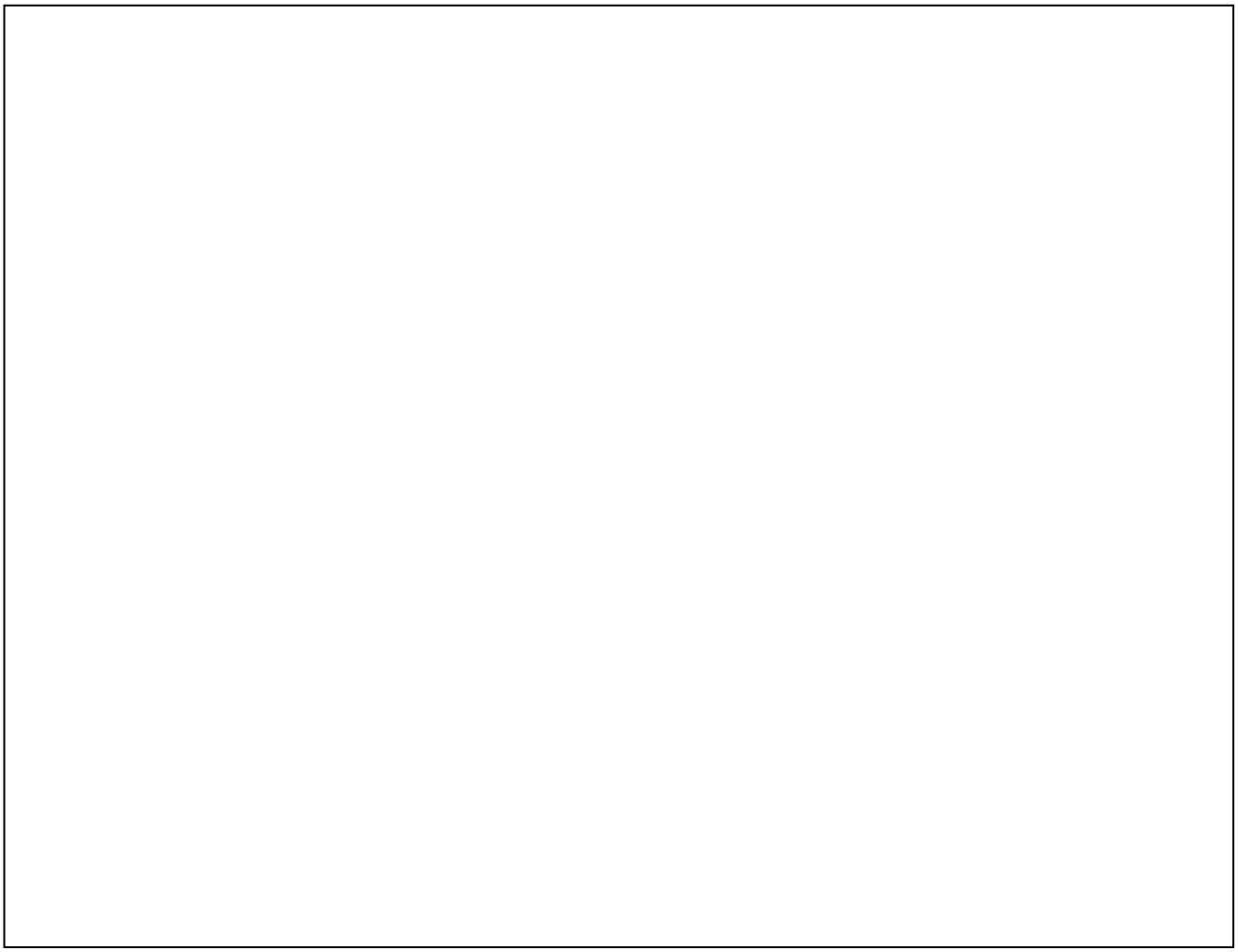


Figure 3. Example of the process of defining the current pasture and adaptation to the ideal pasture. **A**: Trees are arranged on the board similarly to the position in the pasture . **B:** The farmer eliminated 13 'jícaro' (*Crescentia alata*) trees in order to introduce new species. **C**: Pasture without 'jícaro' trees. **D**: The farmer added trees and poles along the fence to protecte the trees from livestock (Salazar 2012).

2.3 Design of an expert model

Who is the expert in our expert model? In order to judge the usefulness we might think of a model farmer or agricultural extensionist who is in a position to integrated farmer perception and practice with findings in the scientific literature. We used Hugin Expert ® software to integrate the different knowledge domains in a Bayesian belief network.

The model aims to identify the composition of the ideal pasture conditional on the following information provided by the farmer and scientific experts: (1) the types of ecosystem services desired by the farmer (2) functional traits of trees desired by the farmer or recommended by experts; (3) financial income expected from different species densities; (4) average size of tree crown; (5) tree density desired by the farmer; (6) type of tree species desired by the farmer (Figure 3).



The BBN model could be described as the collective knowledge of farmers selected in the study area complemented by scientific knowledge of specialists regarding selected technical aspects such as functional traits. Furthermore, the network contains nodes that 'translate' terminology regarding 'beneficial uses' of the farmer to the 'ecosystem service' terminology used by the researcher.

Figure 4 illustrates the broad structure of the BBN. In addition to information on species composition and abundance collected through the pasture simulation exercise, the network includes farmer beliefs (motivations, limitations, solutions).

The direction of the links in the network illustrates the underlying assumption about causality in the network. This determines what is meant by 'deductive' and 'inductive' types of analysis.

The network can be used to determine species composition in an ideal pasture conditional on potential ecosystem services that are desired by the farmer, requirements for financial return and farm typology. Farm typologies are members of different farm characteristics, explaining why the direction of the causal link is typology->characteristics.

Given the large number of nodes and complexity of the integrated or meta-model, we visualised only key nodes that we considered would be of relevance to an agricultural extensionist (Figure 5). We used the object-oriented bayesian network (OOBN) feature of Hugin Expert to 'hide' details of the nodes used for calculating financial returns to species. These are illustrated by nodes in white (Figure 5).

The sources of information for constructing the BBN are illustrated in colour legend (Figure 4). Nodes in yellow represent information that was collected through a primary survey (Salazar 2011). Farm typology was based prior studies in the area (Marie 2010). Part of the primary survey collected farm data on income and outcome (nodes in blue). This had to be completed for some species with values from the literature. Prior studies at the same site had collected farmer local knowledge of functional traits of tree species (nodes in bright green) (Mosquera, 2010). Interviews of experts were carried out for potential ecosystem services of trees and some assumptions required for the financial submodel (nodes in red).

The model distinguishes between ecosystem services, functional traits, financial returns for the current pasture (left hand side) and the 'ideal' pasture (right hand side of the network). The detailed model is illustrated in Figure 5 and discussed in the following.

2.4 Network nodes

We used information on farmer knowledge of six ecosystem services identified in prior studies (Mosquera 2010) – firewood, animal fodder, erosion control, soil improvement, drought resistance and protection of water sources). Of the 27 species listed in the study the most frequently mentioned were selected for use in the simulation exercise of the 'ideal' pasture carried out with farmers as part of the survey.
The nodes in the network contain the following conditional probability tables:

Functional traits – local knowledge: is conditional on the composition and abundance of species mentioned by the farmer in the simulation exercise for the current and ideal pasture. It shows the conditional probabilities of a function or trait being mentioned for each species across different farmers. When a species was not mentioned by farmers all traits were coded as having no information, i.e. equally probable[5] .

Functional traits – expert knowledge: This is a 'translation' node used in the original Spanish version of the network to translate farmers' terminology to that used by experts. Experts interpreted response categories of farmers into scientific terminology (in Spanish) by making a farmer-expressed functional trait 100% probable to correspond to a scientific term. Some local terms could not/were not interpreted in terms of functional traits by the experts (no ash, durable, locally adapted) and were assigned equal no information probabilities.

Ecosystem services (local knowledge): This node captures the relationship between trees species and ecosystem services expressed by farmers in the study by Mosquera (2010). Probabilities are derived based on the sample frequency of association of an ecosystem service with a particular tree species. We also included the information on disservices mentioned by farmers in Mosquera(2010).

[5] The following species have no traits information: *Simarouba amara*, *Swietenia humilis*, *Cedrela odorata*, *Bursera simarouba*, *Cordia alliodora*, *Byrsonima crassifolia*, *Pachira quinata*.

Ecosystem services (expert knowledge): Eight experts were interviewed regarding positive correlation or not between functional traits mentioned by farmers in the survey and ecosystem services as defined by experts. Thix node expresses the relative frequency with which a functional trait was defined as positively associated with an ecosystem service by the group of experts (Figure 6).

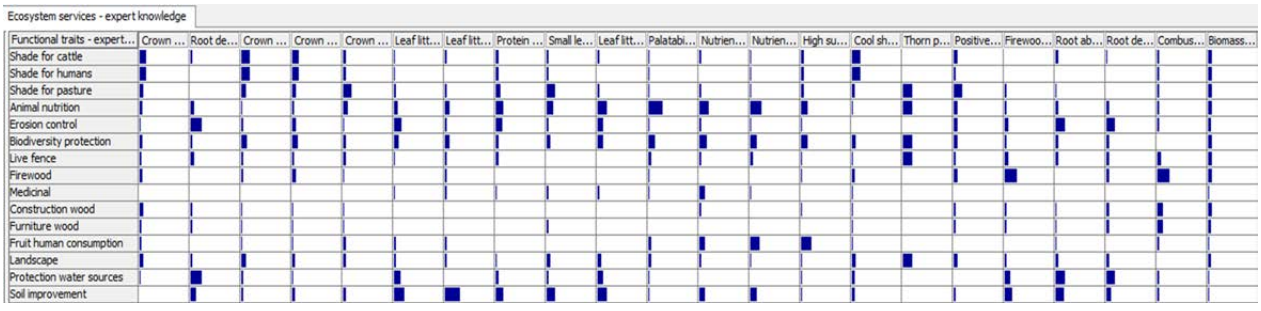
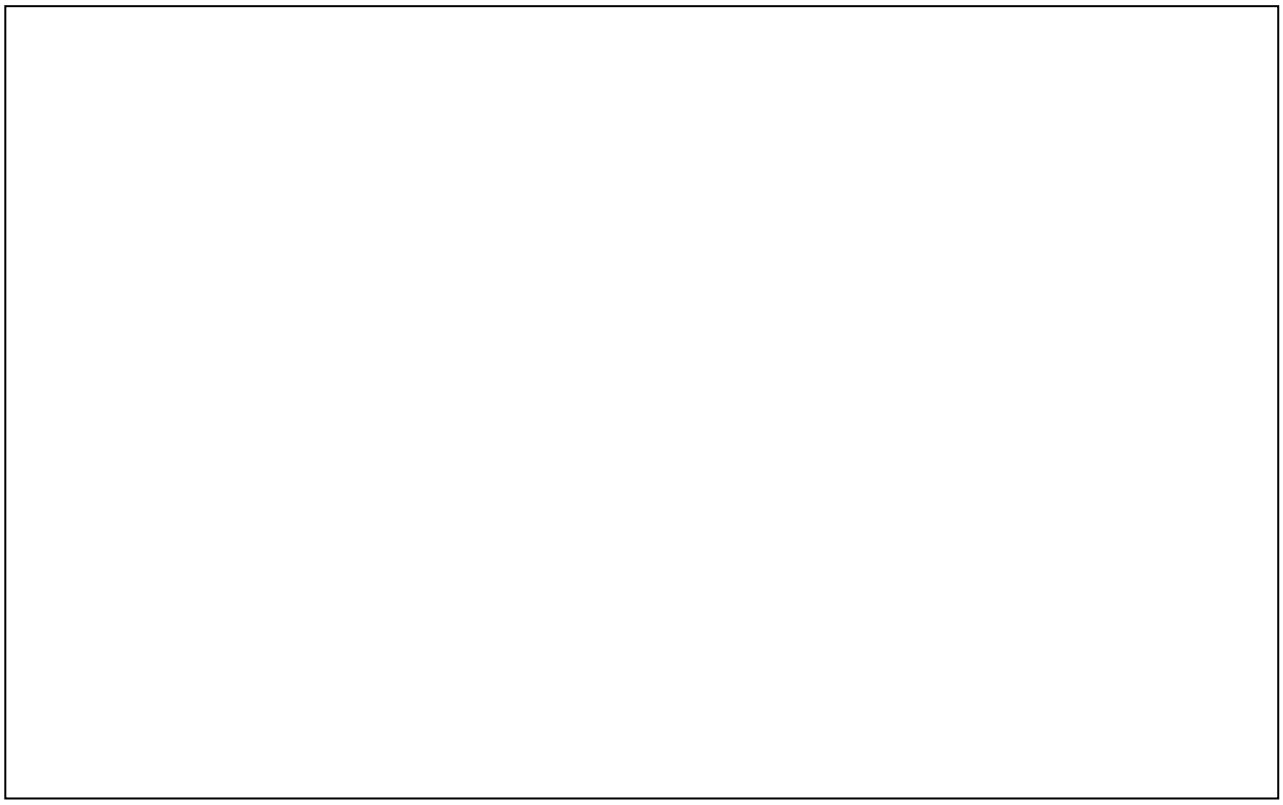


Figure 6. Pooled expert definition of relationship between functional traits and ecosystem services. Rows are ecosystem services; columns are functional traits. Bars represent relative number of times an expert mentioned a trait as having a positive relationship with an ecosystem function.

The ecosystem service node for experts illustrates that there is linguistic uncertainty in operationalizing scientific and local terminology in an expert system.

2.5 Farmer beliefs regarding limitations, motivations and solutions.

Data for these nodes came from Limitations, motivations and solutions for adoption of tree species at the level of the farm as a whole was discussed with farmers during the farmer survey. Probabilities are derived from the frequency a particular item was mentioned across the sample.



2.6 Financial benefits and costs subnetwork.

Figure 7 provides an overview of a subnetwork structure implemented in four different places in the main network. The financial subnetwork calculates one-time costs of planting and net annual benefits of ecosystem services minus management costs for live fences and trees in pasture for the current and new trees in the 'ideal' plot. *Gross income node* and *management costs node* are derived from the financial questions in the survey, determining net annual income per tree. The *tree crown diameter node* was based on CATIE-NINA's SILPAS database of 1821 observations of 21 different species in the study area. *The additional trees* node is calculated based on information from the 'ideal' pasture simulation exercise in which farmers removed and added additional trees until obtaining their ideal crown coverage. The number of trees per species and information on average crown size was used to calculate the tree crown cover percentage that would result from farmers' choices. Net annual income from managing the whole plot was calculated using the above information as shown in Figure 7.

3 RESULTS AND DISCUSSION

3.1 The ideal pasture

Table 1 summarises tree density, tree cover, implementation/planting costs and net income calculated using survey data, conditional on farm type and the ecosystem service profile selected. Selection of an 'ecosystem service profile' means that the network is used to populate the ideal pasture with tree species likely to provide that service according to local knowledge.

Survey data and interviews showed that farmers prefer increasing tree density in live fences before doing so in the pasture. They prefer trees that grow easily with economic benefits and want to eliminate species with few uses and those which reduce pasture productivity due to excessive shading. In these general terms the results confirm that farmers prefer planting trees that provide direct ecological benefits, for example to soil fertility (Cerdán et al. 2012). The ecosystem services most often referred to are ensuring dry season fodder for animals, diversifying farm products such as fence posts, construction materials and firewood and providing scenic beauty to the surroundings.

According to Esquivel (2007), pasture productivity may start to decline as crown cover exceeds 30% or more. Tree cover in current pasture is around 15% on average, while farmers indicate in the simulation exercise that they would like tree cover of around 42% on average. An average farmer in the sample has 12 trees/ha in live fences, but would add 36 trees in an ideal plot. An average farmer currently has 7 trees dispersed in the pasture and would add 18 in an ideal pasture.

En live fences, the most common species are *Cordia dentata, Gliricida sepium* y *Spondias purpurea.* In improved live fences farmers would add mostly *Pachira quinata*. Currently, the most common trees dispersed in pasture are *Guazuma ulmifolia* y *Cordia alliodora*, while the farmer would add *G. sepium, P. quinata, C. dentata*.

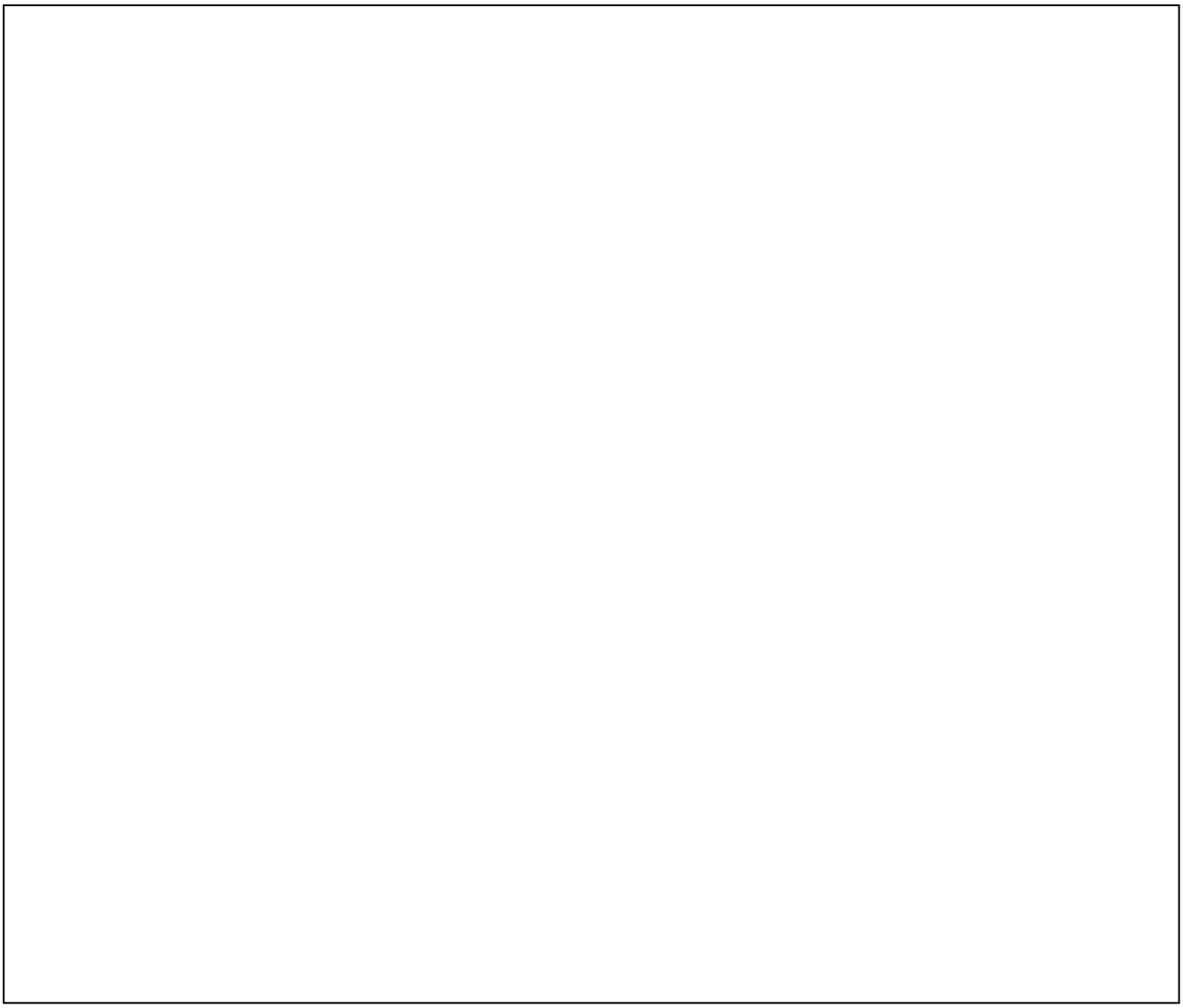
3.2 Crown size and importance for adoption

Crown size is an important factor when considering to change tree density in pasture. For example, species such as *Enterolobium cyclocarpum* and *Albizia saman,* provide ample fruit for animal fodder, but are not preferred by farmers due to their wide crown. Species with a wide crown reduce pasture productivity. On the other hand, hardly any farmers chose to eliminate *E. cyclocarpum* and *A. saman* from their current pastures. Species with a crown size above average represent 20% of the trees chosen by farmers for the ideal pasture, including *Cassia grandis* (255 m^2), *A. saman* (175 m^2), *E. cyclocarpum* (130 m^2), *P. quinata* (122 m^2), *Leucaena* sp (102 m^2), *G. ulmifolia* (75 m^2). For example, despite its crown size *P. quinata* is the third most common species in pastures in the area. Farmers mention other characteristics that outweigh the disadvantages of shading such as good survival rates, rapid growth, commercial demand for wood and use as fenceposts. It is also believed to have great landscape value.

3.3 Financial analysis

Farmers are continually working towards their 'ideal' pasture. In practice a number of constraints such as limited access to labour, capital and own time make the current pasture different from the ideal. Farmers have a limited budget and will not experiment with new technologies at high risk (Alonso et al. 2001).

A couple of comments are noteworthy regarding net income estimates from trees in the study. The estimates for the ideal pasture show relatively little variation across different kinds of ecosystem service profiles. This may reflect that there is relatively little variation in the tree species selected for the ideal pasture. Also, net income estimates in Table 1 are is the total calculated for a 25 year cycle. However, average annual income per year does not accurately reflect financial barriers to implementation. Compared to agricultural returns, returns from increasing tree density take longer to materialise. For example, the farmer must wait at least 2 years for any benefits of *Gliricidia sepium* (Thangata y Alavalapati 2003, Alonso et al. 2001). In this sense the 25 year estimates of expected returns have limited relevance for the decision to introduce new species or not.



3.4 Ecosystem service profiles – farm system diagnostics using BBN

So far we have reviewed the survey data in tabular form (Table 1). Now let's turn to the advantages of making the same data available in a BBN.

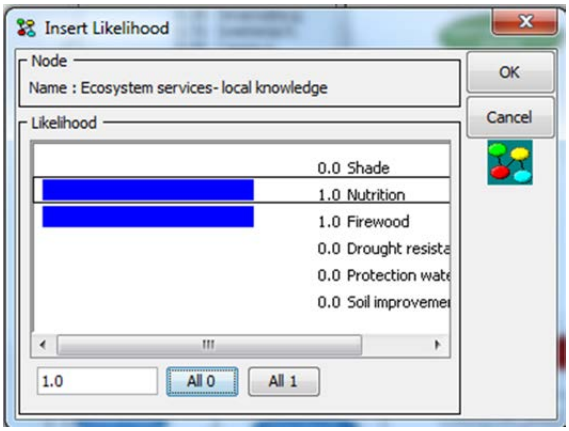


Figure 9. Ecosystem service profiles can be entered in the BBN to diagnose portofolios of species that are likely to provide them according to farmer or expert knowledge.

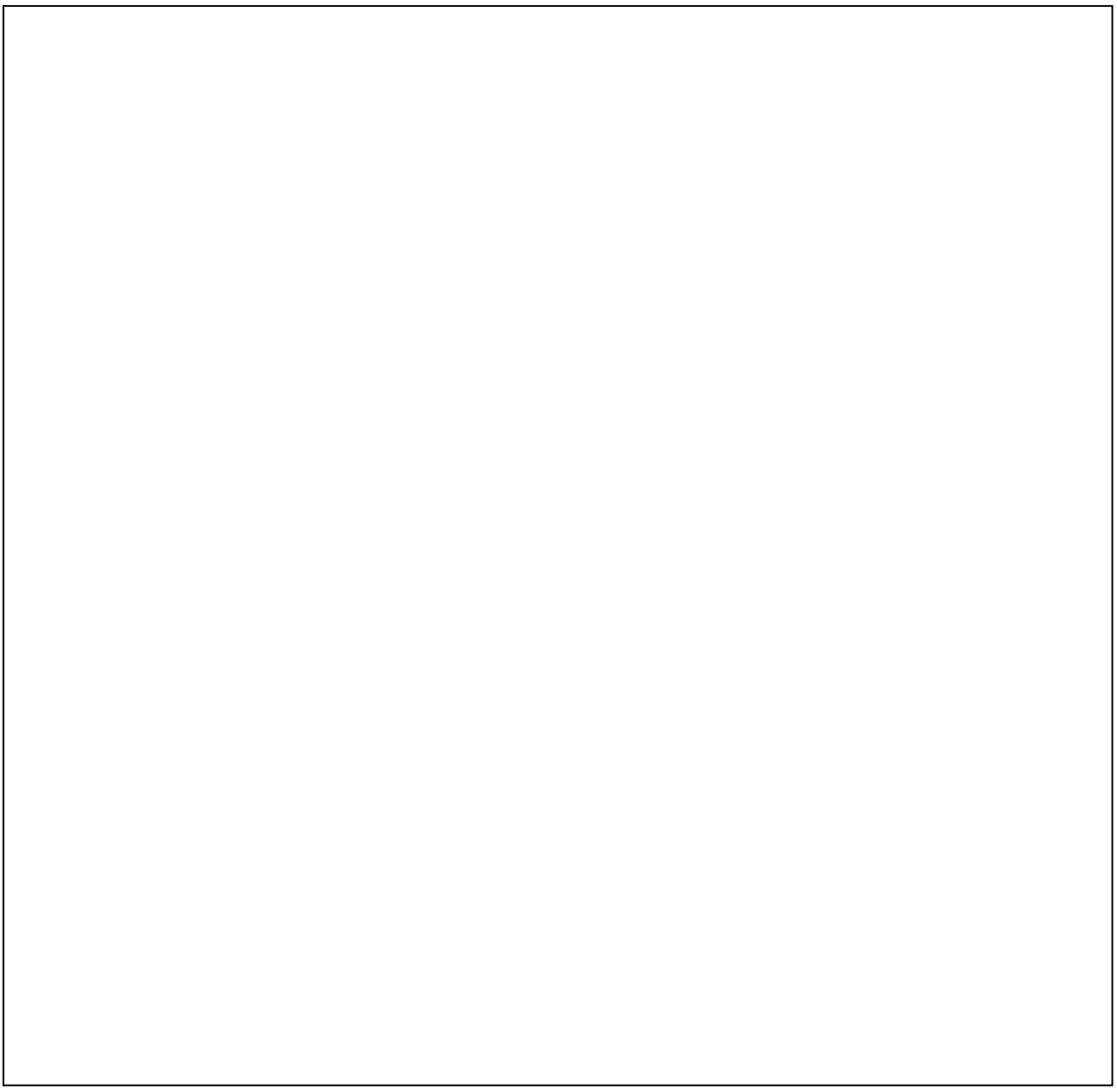
Farmers were asked to associate tree species functional traits with specific ecosystem services. Figure 8 shows the causal direction of the network as functional trait -> ecosystem service. In other words, we can ask the deductive question, 'which traits cause which ecosystem services?' In a BBN the information can also be analysed inductively - diagnostically - to ask which combination of functional traits and species corresponds to a particular set of desirable ecosystem services.

In Figure 8 we select "Shade" as a desirable ecosystem service. Farmers have stated that shade is *likely* to be a service when the functional trait of trees allows the 'grass to grow' characteristics of high, sparse shade, a high, wide, spare crown in high trees. Other functional traits are mentioned less frequently.

Profiles of multiple services may also be specified in the BBN software Hugin Expert. In Figure 9 we see an example of a graphical user interface where the 'ecosystem service' node has been selected. Furthermore, we specify that we want to diagnose the likelihood species given ' nutrition' and 'firewood' as favoured ecosystem services on the ideal pasture.

In addition, we may specify that likelihood of trees should also be conditional on the type of farm (extensive, intensive or subsistence). In Figure 10 the likelihood of tree species conditional on ecosystem services ' nutrition' and 'firewood ' and conditional on subsistence farms is illustrated using the BBN. The most likely species to fit these conditions are *Gliricidia sepium, Cordia dentata* and *Calycophyllum candidissimum.* The careful reader will notice that the selected probabilities for 'nutrition' and ' firewood' are not equal (Figure 10), while they were set as equally preferable in the definition of the diagnostics analysis (Figure 9). This is because the 'nutrition' and 'firewood' probabilities' are calibrated to be proportional to their relative frequency in the actually observed sample.

Figure 10 simple diagnostic analysis is an example of why a BBN may be considered 'expert' system.



4 CONCLUSIONS

An expert model using Bayesian belief networks was used to describe the farm and farmer characteristics, functional characteristics, ecosystem services and disservices of silvopastoral systems in Rivas, Nicaragua. We illustrated how a Bayesian belief network can integrate different domains of scientific and farmer knowledge, both primary data and previously published results. The BBN was used for predictive, deductive ('if-then') of for example the probability of observing a portfolio of tree species conditional on specific farm characteristics.

We also demonstrate some desirable properties of BBN as an 'expert system' - the use of diagnostic, inductive analysis. Furthermore, greater emphasis is being placed on systematic use of local knowledge combined with scientific knowledge.

Diagnostics and systematic updating of knowledge are particularly interesting features of BBN not shared with other types of models. In particular the possibility to specify a 'profile' of desired ecosystem services or functional traits of trees and to identify the likelihood of a 'portfolio' of trees corresponding to these characteristics. This is the essence of a so-called multi-functional approach to silvopastoral systems.

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FUNCiTREE

Functional Diversity:
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Based on the principles of functional ecology, FUNCiTREE addresses the provision of multiple services of silvopastoral systems (SPS) in semi-arid regions in Africa and Central America. FUNCiTREE aims to provide farmers in the regions with a portfolio of regionally suitable tree species that are capable of providing multiple services. The project integrates theories and concepts from agroforestry and ecological science and will provide a scientifically based model for the design of modernized SPS.

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CIRAD (France): Research on agro-ecosystems for international sustainable development, environmental, and climate research

CSIC (Spain): Research at the Arid Zones Research Station,

ISRA (Senegal): Priority areas relate to agronomic, animal and forest production, and rural economy

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