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Diagnosing agrosilvopastoral practices using Bayesian networks

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Abstract This article discusses the potential of BNs to complement the analytical toolkit of agricultural extension. Statistical modelling of the adoption of agricultural practices has tended to use categorical (logit/probit) regression models focusing on a single technology or practice, explained by a number of household and farm characteristics. Here, a Bayesian network (BN) is used to model household-level data on adoption of agrosilvopastoral practices in Tiby, Mali. We discuss the advantages of BNs in modelling more complex data structures, including (i) multiple practices implemented jointly on farms, (ii) correlation between probabilities of implementation of those practices and (iii) correlation between household and farm characteristics. This paper demonstrates the use of BNs for 'deductive' reasoning regarding adoption of practices, answering questions regarding the probability of implementation of combinations of practices, conditional on household characteristics. As such, BNs is a complementary modelling approach to logistic regression analysis, which facilitates exploring causal structures in the data before deciding on a reduced form regression model. More uniquely, BNs can be used 'inductively' to answer questions regarding the likelihood of certain household characteristics conditional on certain practices being adopted.

Keywords Bayesian network (BN) · Bayesian belief network (BBN) · Agrosilvopastoral system (ASP) · Probability of adoption · Agroecological knowledge system

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Introduction

Statistical modelling of adoption of agricultural practices has tended to use categorical (logit/probit) regression models focusing on a single technology or practice, explained by a number of household and farm characteristics. The adoption of ASP technologies and practices is determined by multiple social, cultural and economic factors, and the factors that influence the decision to adopt or reject practice vary across technologies, practices and communities. Farmer characteristics determining adoption of new

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ASP technologies are often reported as significant (sign of the effect, in brackets), including the following: family income (+), farm size (+), education (+), age (−), contact with extension agencies (+), accessibility of the households to credit (+), membership in farmers' associations (+) and ownership right to land (+) (Akinwumi et al. 2000; Chianu and Tsujii 2004; Cramb 2005; Garcia 2001; Lapar and Pandey 1999; Levasseur et al. 2009a; Scherr 1995).

Some studies have also assessed farmer motivations associated with adoption. In the South Nyanza districts of Kenya, Scherr (1995) found that historical increases in tree domestication and management intensity may be responses to declining supply of uncultivated tree resources, increased subsistence and commercial demand for tree products, and perceived risks of ecological degradation. In this setting, adoption of ASP is most likely consistent with economic incentives for land use change. In Argao in the Philippines, Garcia (2001) carried out an analysis of farmer decisions to adopt soil conservation technology in different adoption stages. In the initial stage, non-economic variables such as the perception of the soil erosion problem play dominant roles in the adoption of soil conservation technologies. However, in later stages conservation investment determines the degree of conservation effort and farmers evaluate their decision based largely on economic factors. Adesina et al. (2000) showed that econometric modelling using farmer and village characteristics, and socio-economic and institutional variables can support more effective targeting to farmers and locations where higher adoption rates may occur. Ayuk (1997) studied how the adoption of live hedges depended on traditional practices utilized to protect home gardens from animals, and how these practices had evolved over time using a logit model. Berthe et al. (1999) studied the benefits of soil and water conservation on rural productivity in the cotton belt in Mali. Soil and water management activities in general and particularly "contour line management" were evaluated with survey data. A logit model was used to understand factors determining the adoption of technologies. Significant variables explaining adoption were the level of information on the head of rural households, land tenure and some household socio-economic factors. Levasseur et al. (2009b) studied factors affecting adoption and non-adoption of live fences in the Segou region, Mali, using both statistical analyses for quantitative data and logit regression analyses for the qualitative data. They found that the key factors determining non-adoption of live fences in the Segou region were (i) insecure land ownership, (ii) lack of sufficient labour and (iii) resource-poor nature of the households.

This brief review of ASP adoption studies in Africa reveals that the dominant modelling approach has been regression-based logit model with a single practice as a dependent variable. Where studies have evaluated several different practices, separate regression functions have been implemented for each technology or combination of technologies. The objective of this study is to demonstrate an alternative approach to modelling adoption of multiple ASP technologies, using Bayesian networks to analyse farm survey data.

Bayesian networks (BNs) are a generic modelling tool both for exploring data structure and for decision analysis under uncertainty that are increasingly being used in ecological, environmental and resource management modelling (Aguilera et al. 2011; Barton et al. 2012; Haines-Young 2011; Kuikka et al. 1999; Landuyt et al. 2013; Marcot 2012; McCann et al. 2006; Uusitalo 2007; Varis 1997) Bayesian networks—also known as Bayesian belief networks—have been used in different decision-making settings including directive, strategic, tactical and operational contexts (Barton et al. 2012). In *directive* decision support, modelling the focus of BNs is on exploring long-term causal structures, with less emphasis placed on the detailed estimation of conditional probabilities in the data. In *strategic* decision support modelling, BNs are used to explore the cumulative and jointly uncertain impacts of the many different possible outcomes to several important decisions, with the aim of finding, evaluating and selecting acceptable outcomes in the medium-to-long term. In a *tactical* context, decision support models account for repeated observations and help managers react to short-term predictions. In *operational* contexts, artificial intelligence and operations research approaches are used to conduct fast calculus in identification, classification and diagnosis problems. In this paper, we discuss the use of BNs on ASP adoption for tactical employment in both a deductive (scenario) and inductive (diagnostic) sense. In the case of deductive reasoning regarding adoption of practices, practitioners working in agricultural extension may want to answer questions regarding the probability of implementation of combinations of practices, conditional on household characteristics. In the case of inductive analysis, BNs can be used to identify potential participants in ASP extension. The extensionist knows the ASP practices that are proposed for adoption, but wants to find the combination of household characteristics that maximize the likelihood of adoption.

To our knowledge, there have been few published applications of BNs to agroforestry and silvopastoral systems analysis (Baynes et al. 2011; Frayer et al. 2014; Joshi et al. 2001; López et al. 2007; Sadoddin et al. 2005; Villanueva et al. 2003). Joshi et al. (2001) used a BN to describe socio-economic variables that influence farmers' decisions regarding plot-level management of tropical agroforestry systems in Indonesia. López, Villanueva and colleagues used BNs to model factors affecting adoption of trees in pasture lands in Nicaragua and Costa Rica (López et al. 2007; Villanueva et al. 2003). More recent studies have discussed the directive and strategic advantages of BNs. Sadoddin 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. Baynes et al. (2011) used BN to model how farmers respond to offers of extension assistance in Leyte, Philippines. Frayer et al. (2014) applied BNs to identify proximate causes and underlying drivers that influence the decisions of farm households in Yunnan province, China, to plant trees on former cropland. Although not focusing on agricultural technology adoption, BNs have also been employed to model ecosystem service delivery of farm and forest management options (Barton et al. 2008; Gret-Regamey et al. 2013; McVittie et al. 2015).

In this paper, we apply BN to the analysis of survey data from the Millennium Villages[1] of Tiby, Mali, and discuss the potential and limitations of BNs to complement the toolkit of ASP extension and research.

The paper is structured as follows. "Materials and methods" section describes the study area, the data and BN method used to model the adoption data. "Results" section presents the modelling results visually as conditional probability tables in a Bayesian network, demonstrating both deductive and inductive reasoning regarding adoption probabilities and likelihoods. "Discussion" section discusses possible further developments of research in adoption modelling using BN. "Conclusion" section offers conclusions on the potential of BN in technology adoption research.

[1] http://millenniumvillages.org/the-villages/tiby-mali/.

Materials and methods

Study area

The study was undertaken in the Millennium Villages Project intervention area located in the Dioro and Farakou Massa rural communes made of 39 villages hosting more than 70,000 people (Fig. 1). These rural communities are in the Ségou region located between latitudes 12°30 and 15°30 and longitudes 4° and 7°. The Ségou region is the fourth administrative entity of Mali covering 60,947 km^2 (5 % of the national territory) with approximately 1.8 million inhabitants. The Ségou area consists of parkland ecosystems representative of the Sudan savannah of the Sudano-Sahelian belt of West Africa. Rainfall is scarce, with an average annual between 1994 and 1998 of 586 mm, virtually all of it falling between June and September. Land management practices in the rain-fed farming systems have evolved in this parkland system, where annual crops are grown in association with *Faidherbia albida* and other large trees scattered on farmlands. As a risk management strategy, farmers in the region have developed a 'ring cultivation system' with 'village' and 'bush' farms.

Data

The research activities were carried out in villages of the rural communes of Dioro and Farakou Massa. Of the 39 villages in the area, 15 villages covered by the Millennium Villages Project were selected for the study sample. The sample included the 8 'research villages' designated for data collection to document progress in achieving the Millennium Development Goals and 7 others drawn by random from the remaining 31 villages, making a sampling rate at village level of 38 %. A census was carried out by 4

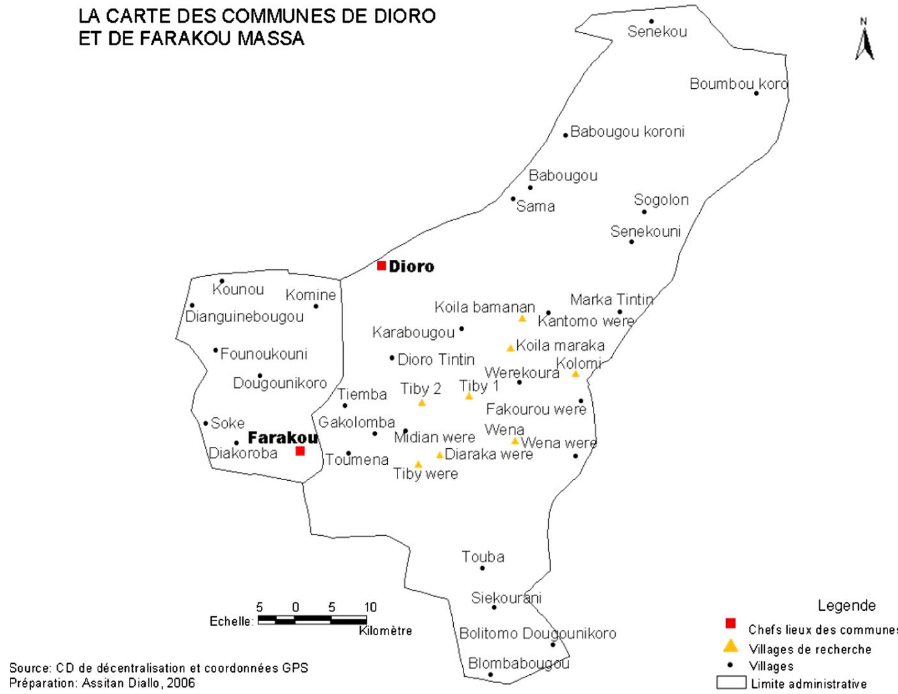

Fig. 1 Study area including municipalities of Dioro and Farakou Massa

enumerators of the FUNCiTREE project[2] in order to establish the list of all the households in the selected villages.

Prior to the survey, a village plenary session was organized. The village plenary session identified three distinct user groups—crop growers, pastoralists and women. The plenary sessions also enabled the development of a common understanding of the functioning of the ASP systems of the area. The three focus groups were then asked to discuss the constraints and priorities of increasing the use of trees in ASP systems, and the multi-functionality of different species. Focus groups then filled out a questionnaire in plenary sessions involving all members of the villages without any exclusion of activity, gender and age.

After village plenary and focus group discussions and questionnaires had been completed, individual interviews were conducted. The households interviewed were selected by the different user groups based on their knowledge of representative households. The sample was therefore not random, but purposive based on whom villagers thought would be good representatives of crops growers, livestock breeders and women' ASP practices, and designed to obtain a balance between the three groups. A sample of 302 households was selected from a total 1735 households in the 15 villages. All 302 responses—including incomplete responses—were used in the Bayesian network analysis.

To demonstrate BN, we modelled the five most common ASP practices at farm household level in the 15 villages that were surveyed. *Food banks* are plots planted with species for human consumption only (e.g. leaves from baobab, fruit from mango and jujube orchards.). *Protective live fences* are planted to keep animals away from other crops. *Boundary live fences* are planted to delimit property boundaries between neighbours. *Village woodlots* are collectively planted and managed by a village to meet their needs for fire wood, building materials for own use and for sale. *Family woodlots* are managed exclusively to meet family needs for fire wood, building materials and income. These practices have 25 % participation or more and illustrate the potential diagnostic capability of BNs when there are sufficient observations. BNs as a diagnostic tool can in principle be used with any

[2] FunciTree: Functional Diversity. An ecological framework for sustainable and adaptable agroforestry systems in landscapes of semi-arid and arid ecoregions. Co-funded by the EU 7th Frame Programme.

available information. However, for demonstration purposes and model compactness we left out *Fodder banks* as there were few observations in the sample (1.8 % of households).

Bayesian network specification

BNs are acyclic directed graphs of conditional probability distributions. In BN terminology, variables are called 'nodes' and causal links between nodes are called 'edges'. The causal structure of a Bayesian network may be theory driven, data (or other knowledge source) driven or a combination of both. The steps followed in this study for specifying a Bayesian network using survey data were as follows: (1) node selection (2), structuring constraints, (3) structure learning, (4) establishing structure uncertainties, (5) assessing data dependencies, (6) establishing prior distribution knowledge and (7) network structure learning from data (expectation maximization (EM) learning) (Hugin 2014). These steps are explained in detail in Supplementary Material.

Farmer characteristics included in the model were selected based on a technology adoption study by Cisse et al. (2013) based on the same survey material. BNs are non-parametric models and allow for a mix of variable formats, including numerical, ordered and categorical. This allows researchers to use categories familiar to respondents directly in the model: respondent age (years), household wealth level (poor, medium, rich), able farm hands (persons), membership of village association (y/n), farmer participation in training (y/n), accessibility to village land (y/n), distance to nearest urban centre (km), soil erosion level in village (none, low, high), village accessibility in rainy season (good, poor) and cattle herd of farmer (important, very important). Continuous variables were discretized into intervals. A pedagogical advantage of BNs is that the distributions and basic statistics of variables are described directly in the model interface, reducing the need for separate tables of descriptive statistics. We follow this presentational style in this paper by presenting variable histograms in the model itself (Fig. 1).

Results

In Fig. 2, the BN 'baseline model' shows the distribution of the data for each variable generated from the farmer survey. For example, the 'village' node shows that most observations were obtained in the village of Konou (22.85 %). Regarding adoption of ASP practices/technologies, the survey data show proportions as follows: food banks (37.73 %), live fences (43.66 %), family woodlots (38.15 %), village woodlots (43.53 %) and property fencing (61.99 %). The EM learning algorithm in Hugin identified correlations between the adoption of 'live fences', 'food banks' and 'family woodlots'. The model is spatially explicit through the variable 'villages'. Villages at different distances to the nearest urban centre have different 'erosion levels', 'accessibility', 'cattle herd size' and presence of 'village woodlot'.

Figure 3 illustrates a deductive type of reasoning with the BN where we asked the model the likely adoption rate of the different practices under conditions of 'very degraded soils'. The sample data show the following changes in adoption probability distributions compared to the baseline model (with no new evidence) : food banks (−29.0 %), protective live fences (−15.3 %), family woodlots (−31.5 %), village woodlots (−15.3 %) and boundary live fencing (+4.9 %).

Figure 4 illustrates the use of the BN for inductive or diagnostic reasoning. In this form of analysis, we asked the question, 'what is the likelihood of combinations of village and household characteristics where we observed adoption of combinations of ASP measures?' The village of Koila Markala, for instance, has a disproportionate likelihood of households adopting all the five practices evaluated here. Relative to the sample mean, in villages with adoption of all practices, soils are more likely to be somewhat degraded (+2.6 %), but less likely to be very degraded (−15.2 %); it is more likely to have poor accessibility in the rainy season (+8.6 %); more likely to consider cattle herd size as very important for their livelihoods(+5.2 %); households are more likely to have access to land (+9 %); more likely to have had training (+2.7 %); more likely to be members of an association (+4.2 %); more likely to have a small number of working hands (0-8; +5.9 %); and more likely to have a household head in the age of 50–68 (+18.1 %). These overall tendencies of the sample hide practice-specific combinations. For example, protective live fences by themselves are more likely if the number of able farm hands is larger. The likelihood of a practice being adopted is also

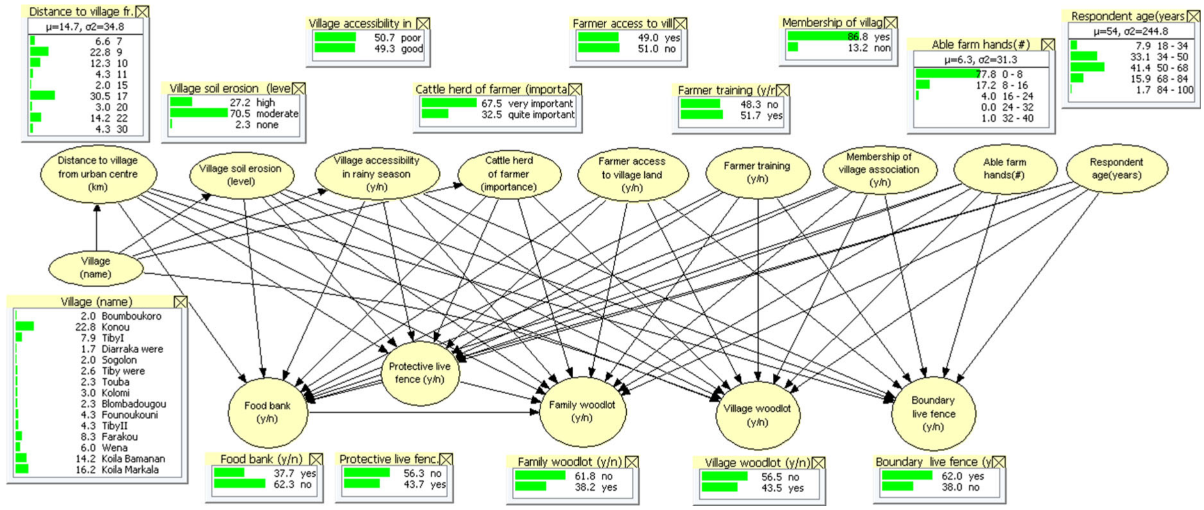

Fig. 2 Bayesian network of adoption of factors affecting agrosilvopastoral practices in villages, Tiby region, Mali. *Note* probability *tables in the figure* show the distribution of data for the sample, before evaluating any evidence on particular household and village characteristics. Performance statistics of EM learning algorithm. Log-likelihood: −2222.22; AIC: −488433; BIC: −1.39046e+006

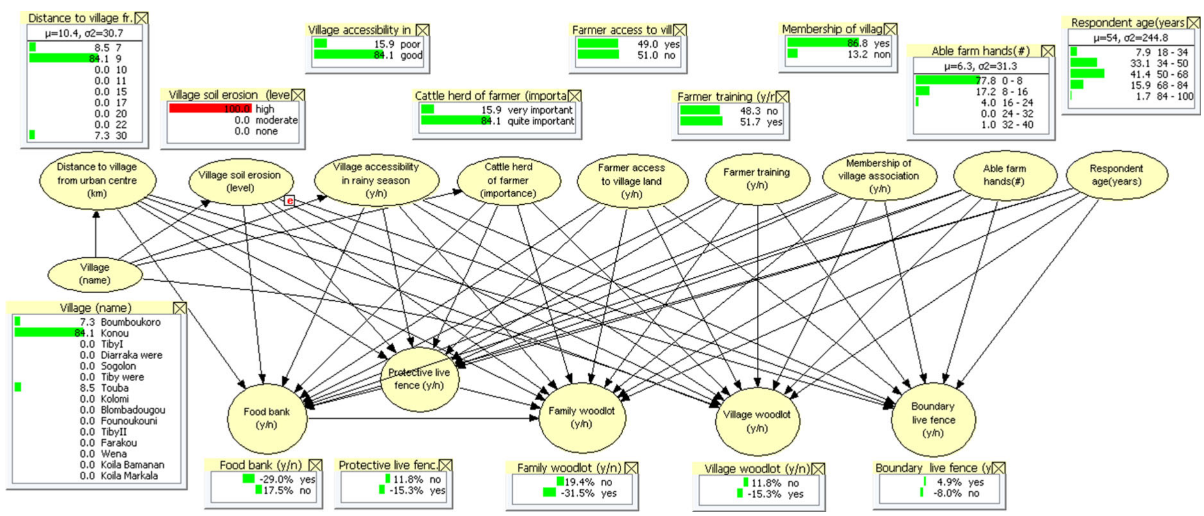

Fig. 3 Using the BN for deductive or scenario analysis—changes in adoption rates in areas with 'very degraded soil' relative to the overall survey sample

conditional on which practices have already been adopted. The reader can observe these features in the online version of the BN model.[3]

Figure 5 shows the correlation between 'live fences', 'food banks' and 'family woodlots', providing an estimation of the inter-dependency between the adoption of different practices. Where households have adopted live fences, they are 31 % more likely to have food banks, and 33 % more likely to have family woodlots. The model structure learned on the data shows that live fences and village woodlots are not conditional on other practices being adopted. Field technicians report that if the owners do not apply any protection measures such as fencing, the planted trees would not survive the intensive impact of free grazing

[3] http://demo.hugin.com/example/DiagnosingAgrosilvopastoralPractices.

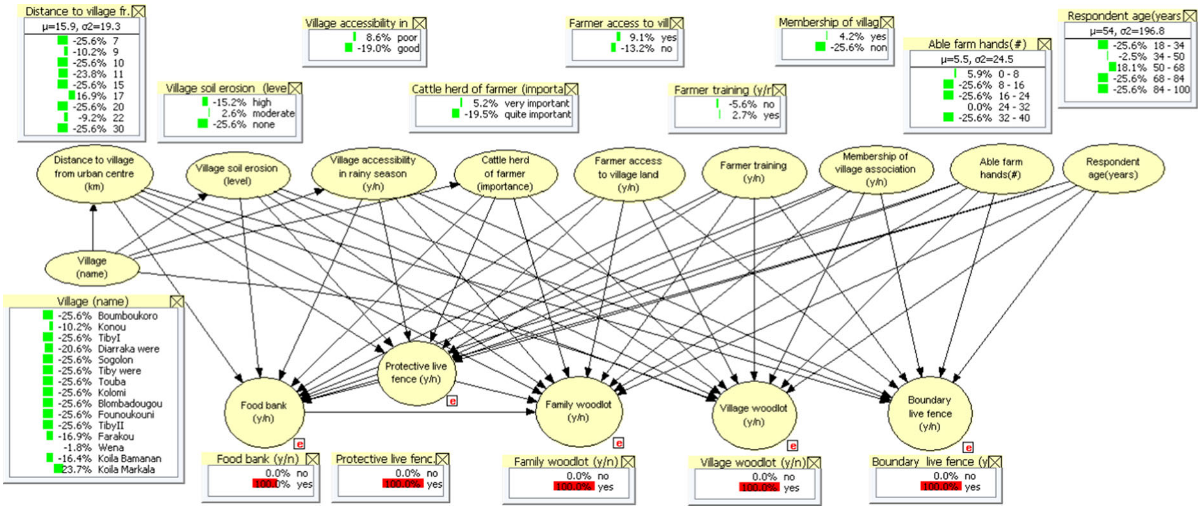

Fig. 4 Using the BN for inductive analysis—identify likely village and household characteristics associated with combined adoption of agrosilvopastoral measures

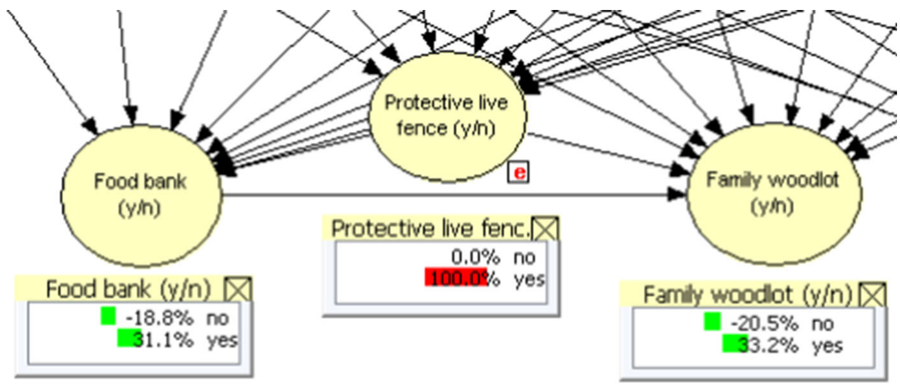

Fig. 5 Correlation between agrosilvopastoral technologies

by cattle and other ruminants in the dry season. Thus, it makes sense for the individuals interested in these technologies to take appropriate measures and, hence, their adoption of live fences. The combination of the diagnostic using the BN and field technical experience provides arguments for additional protection of food banks and family woodlots with live fences, especially at early age. Conversely, the lack of live fences may be restraining the adoption of food banks and woodlots.

Analysis of individual practices mostly conforms to expectations regarding the need of farm labour. Households with 0–8 working hands are generally less likely to implement practices individually; food banks are −6.06 % less likely compared to the sample mean; live fences are −5.07 % less likely; family woodlots are −5.8 % likely; and village woodlots are −2.0 % less likely. Only boundary fences are more likely with less available labour at +4.68 %.

The data suggest synergy effects between live fences, food banks and family woodlots. We can diagnose the combination of practices relative to specific farm characteristics, for example small family farms with 0–8 working hands. For these small family farms, we find the following relationships: live fences–food banks (+0.85 % likely with $P(e) = 0.220$), live fences–family woodlots (+2.99 % likely with $P(e) = 0.222$) and food banks–family forests (+2.46 % likely with $P(e) = 0.202$). It would seem that for small farms in particular, practices are (weakly) pairwise positively correlated, although we see from $P(e)$ that there is only around 20 % of the sample implementing any two combinations.

Discussion

Adesina et al. (2000) found that soil erosion problems play dominant roles in the adoption of soil conservation technologies, especially at early stages of the soil erosion process. However, in later stages, conservation investment determines the degree of conservation effort and farmers evaluate their decision based largely on economic factors. We also find that households adopting practices are more likely to live in villages with somewhat degraded soils. Berthe et al. (1999) evaluated soil and water management activities in general and particularly "contour line management". Significant variables explaining adoption were the level of information on the head of rural households, land tenure and some household socio-economic factors. We did not analyse formal tenure, but our results show that household access to land is the factor most likely to increase adoption rates. We also find that socio-economic factors are important, in particular whether households with relatively few working hands in the household are more likely to adopt all conservation practices. Like Levasseur et al. (2009a), we who found that households not adopting live fences were likely to have fewer working hands than adopters.

An important overall finding of joint modelling of adoption of silvopastoral practices is that practices condition one another. We therefore focus the rest of the discussion on a comparison of BN relative to discrete choice logit regression modelling in ASP technology adoption studies. Technology adoption studies at farm household level may require large samples for detecting significant explanatory variables as there is high variability in individual farmers' tree-growing strategies reflecting differences in resources and livelihood strategies, and household-level returns to ASP relative to site-specific alternative options (Scherr 1995). In addition, the BN modelling approach is subject to omitted variables in the same way as logit regression. Nevertheless, BNs' graphical user interface (GUI) provides assistance to the modeller in evaluating network structure learned from the data before estimating the conditional probabilities. Conducting diagnostics in a BN may be an approach to identifying promising "cases" where, for example, pilot projects on multiple practices may have a higher likelihood of leading to multiple adoptions.

BNs' other advantages over the logistic regression approach includes the possibility to define hierarchical structural models with explicit hypotheses about the direction of causality, for example, that village location determines farm characteristics which in turn determine adoption probabilities. BN expected maximization (EM) learning algorithm (Hugin 2014) is a non-parametric approach. This allows for very large flexibility in what kind of data can be analysed in the same model (Frayer et al. 2014), including binary, categorical, numerical and continuous (discretized) data.

Multiple adoption practices can be evaluated simultaneously and more interactions between multiple practices can be specified. BNs allow for explicit correlation between explanatory variables, whereas a logit regression assumes independence of explanatory variables when interpreting the sign and significance of model parameters. Although we did not use the 'a priori knowledge' feature of the software in this study, it will be an advantage in the future to update existing survey data where this is available and compatible with a new study. In practice, such opportunities seldom arise because of a possible publishing bias towards innovative studies that survey new variables. The advantage is clearest outside research, in ASP extension and monitoring, where the same data are often collected repeatedly. Once a BN has been implemented, it can be used 'live' with no run-time and, as such, is ideal for training and extension purposes or for implementation online on the web.[4]

The disadvantages of BNs (Kuikka et al. 1999; Marcot 2012; Uusitalo 2007) are shared with other types of quantitative analysis, although their negative consequences seem to be more readily observable. The non-parametric analysis requires continuous data to be discretized, in place of making assumptions about the parametric distribution that continuous variables should follow in regression approaches (logistic, normal, etc.). How finely the data are partitioned into discrete intervals defines the resolution of the model (Uusitalo 2007), and this can have a large impact on whether links between variables contain information

[4] See http://funcitree.hugin.com/for examples of other online BN models.

or not (Marcot 2012). Hugin BN software provides optimal discretization algorithms, but conscious choices about which resolution is necessary to build more parsimonious models (Marcot et al. 2006) still need to be made by the researcher (e.g. whether we need to distinguish between household with 0–4 working hands and 5–8 working hands, or whether they can be analysed as one category).

Hugin software does not provide classical statistical tests of significance, which may be perceived as a drawback by a number of researchers. Instead, value-of-information analysis (Kjærulff and Madsen 2013) may be used to evaluate the relative importance of different variables in explaining any hypothesis variable in the network (see Supplementary material for examples). Marcot (2012) discusses a number of other metrics for evaluating performance and uncertainty of Bayesian networks.

The ease with which causal links can be specified means that very complex likelihood functions may result, which may be overspecified relative to the amount of data collected. This can be seen in our model structure in Fig. 1 where we purposefully commanded the Hugin learning tool to find all correlations between all farm characteristics and ASP practices. Each practice is conditioned by 10 farm characteristics, as well as being correlated with other practices. This leads to very large conditional probability tables that have the advantage of capturing any signal that might be in the data, but also capture 'noise'. The GUI interface and visualization of the overspecified model may lead to interpretation bias, as it initially seems that all links that are visualized in Figs. 1, 2 and 3 are significant. However, when using an estimated BN 'live' by carrying out scenario analyses or diagnoses, it quickly becomes apparent which nodes have information content. Value-of-information analysis tools also quickly make it apparent which variables have explanatory power (See Supplementary material).

Conclusion

A Bayesian network (BN) was used to model household-level data on adoption of ASP practices in Tiby, Mali. Statistical modelling of adoption of agricultural practices has tended to use categorical (logit/probit) regression models focusing on a single technology or practice, explained by a number of household and farm characteristics. BNs allow non-parametric modelling of more complex data structures, including (i) multiple practices implemented jointly on farms, (ii) correlation between probabilities of implementation of those practices and (iii) correlation between household and farm characteristics. BNs can be used for deductive 'what-if' reasoning regarding adoption of practices, answering strategic questions regarding the probability of implementation of combinations of practices, conditional on household characteristics. While 'what-if' analysis is a common feature of many modelling tools, BNs can also be used inductively to answer tactical questions regarding the types of households that are most likely to adopt specific practices or combinations of practices. In this way, BNs provide a useful complement to the toolkit of agricultural extension. BNs can be used alone or as a complement to logistic regression analysis, for exploring causal structures in the data before deciding on a reduced form regression model.

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