

Modeling Grazing Livelihood Systems in the Australian Outback Using Participatory Bayesian Networks

Alexandridis, K.¹ and T. G. Measham¹

¹CSIRO Sustainable Ecosystems, Townsville, QLD, Australia
Email: Kostas.Alexandridis@csiro.au

Keywords: *Livelihoods, participatory Bayesian Belief Networks, pBBN, sustainability; social Networks*

EXTENDED ABSTRACT

This paper describes the use of participatory Bayesian Belief Networks (pBBN) as tools for modelling a representative livelihood system for the graziers of the Outback areas in Northern Queensland (Upper Burdekin region). We use qualitative participatory techniques (community interviews, stakeholder and expert feedback) to manage for uncertainty in decision making related to key determinants of grazing livelihoods in the region. The process yielded the “BOLNet”, a livelihood representation, graph-theoretic network of relationships between key aspects of living within the grazing community. BOLNet is a combination of graphical and qualitative representations of livelihood linkages and relationships. It is a form of “graphical narrative” that bridges the traditional divisions between an extrapolative or descriptive measurement and prescriptive or normative observation. Using a combination of Bayesian Belief network analysis for the strength of the relationships and graph-theoretic network metrics for the structure of the network, we highlight a set of important findings that can aid communities, stakeholders, decision makers and policy makers to improve the quality and efficiency of sustainability approaches and actions.

1. INTRODUCTION AND RATIONALE

The scope for this research undertaking is an attempt to understand the rural livelihoods of the grazing systems in the Australian outback regions. These grazing systems of the outback Australia are characterized by multiple competing trajectories to regional social and economic viability. Holmes (2006) argues that this is evidence of multifunctional transition, that affects all scales, complexity and heterogeneity of rural occupancy. Nevertheless, the viability of the outback Australian regions is not uniform across the landscapes and communities, but greatly depends on the function and form of livelihood systems present (i.e., Chambers and Conway, 1992; Maru, in Stafford Smith et al., 2003). The livelihoods

concept is receiving increased attention in Australia, especially in the context of understanding and analysing the complex linkages between social and ecological systems in rural environments. Sustainable livelihoods are not just subject to stationary definitions, but vary and variate across different biophysical, social and economic contexts. In order to systematically study and explore these issues, a detailed case study is presented in this paper, focusing on the factors affecting livelihoods and livelihood elements in the upper Burdekin catchment of Northern Queensland, Australia. The upper Burdekin region is predominantly pastoral, and is comprised mainly by owner-operated, family-based, medium-to-small enterprises. This paper explores and showcases a methodological pathway for understanding and analysing the factors that influence outback Australian livelihoods, through a participatory, graph-theoretic Bayesian Belief Network approach.

2. THE LIVELIHOODS APPROACH

The use of the livelihoods concept can be traced back to 1987, to the World Commission on Environment and Development (1987) that raised the significance of social and environmental pressures on resource-poor households in areas under considerate ecological stress. In addition to most of the research on development issues of livelihoods that primarily focussed at the household level of activities, additional approaches have been linked to both the community-based natural resource management (Marschke and Berkes, 2005), and occasionally at the collective domain of rural settings and towns (Black, 2005).

This research, operating under the assumption and to the degree in which such a sustainable livelihoods framework can function under relatively different social, cultural and socioeconomic domains, redefines livelihood as an organic, dynamic and multi-dependent concept. This notion of a “subjective livelihoods” is thus determined and iterated in relation to and in interaction with an individual’s or a group’s

socioeconomic environment. Consequently, within any given socio-economic context (e.g., the socioeconomic context of outback Australia), one might soon discover that the degree to which an ensemble of individual subjective livelihoods differ (or, equivalently, a variational collective livelihood) is strongly associated with the degree of difference across changing environments (e.g., outback and urban Australia). As these differences in terms of landscape and geographical composition, physical and psychological influence, and socioeconomic conditions determine individual and group perspectives, they also influence the composition and variation of subjective livelihoods within a given community.

3. PARTICIPATORY BAYESIAN NETWORKS AND LIVELIHOODS

The livelihoods framework described above enables us to entertain and assert the proposition that it bears base similarities and contextual definitions to the notion of “subjective probability”, known from Bayesian statistics. In contrast to the traditional, “frequentist” approach to probability, subjective probability represents the degree of belief in a certain direct or indirect state or outcome. In the context of individuals’ subjective livelihoods, such a belief is related to individuals’ or collective perceived environment. This convergence also provides a central point for establishing a valid link between qualitative social science and the emergence of Bayesian probabilistic inference as tools for quantifying and measuring uncertainty in coupled social and natural systems. It is the missing “micro-to-macro” link described earlier in this section (see also Dittrich et al., 2003; Goldstein, 1999). As such, it provides valuable insights on the role and the explanatory primacy (Sawyer, 2005) of individuals over collective social phenomena, and vice versa. Adopting a Bayesian network approach to the sustainable livelihoods framework affirms an indirect commitment to the phenomenon of social emergence as a manifestation of a wider systemic property of complex systems (Batten, 2001; Durlauf and Young, 2001).

The use of *participatory Bayesian Belief Networks* – *pBBN* (Alexandridis and Pijanowski, 2006; Cain et al., 1999) allowed us to construct a methodological mapping in which the network elements and characteristics are directly mapped against four mental attributes related to the livelihoods framework, shown in Figure 1.

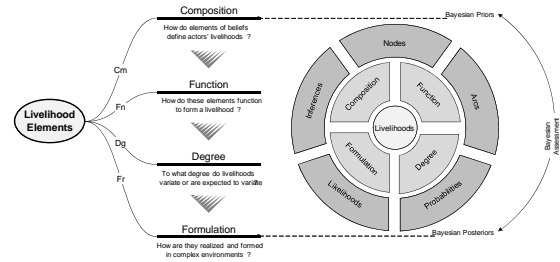


Figure 1. The theoretical approach and the conceptual framework for the construction of the Bayesian livelihoods network used for the BOLNet model.

Such mapping, although highly mechanistic and probably inadequate to capture the importance of dynamic interactions and stochasticity in real complex environments, nevertheless conveys a basic representational framework that interactively grounds the process of Bayesian probabilistic assessment (from a prior Bayesian probabilistic set of relationships to a posterior one) to the sustainable livelihoods paradigm.

4. CASE STUDY DESCRIPTION

A small study area was used for analysing the livelihood elements of a small regional grazing system. The area is the upper Burdekin region of Northern Queensland (Figure 2). It is located west of Townsville and represents a sub-catchment of the Burdekin River.

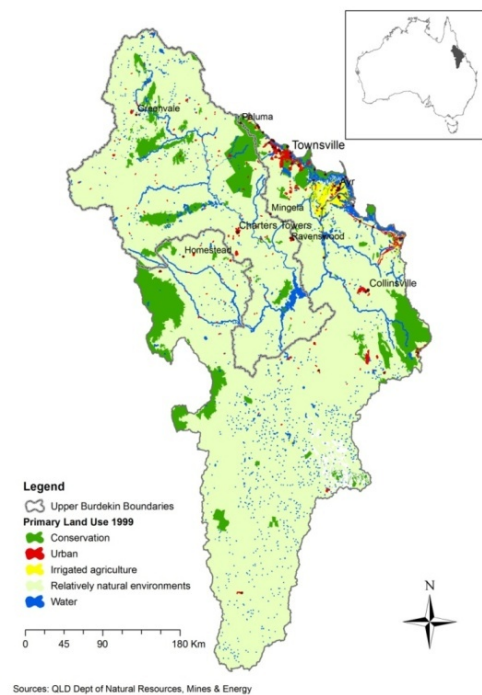


Figure 2. Regional extent and land use of the BOLNet study area.

The region consists of a number of relatively large cattle grazing properties, relatively robust and resilient grazing enterprises (a.k.a., cattle stations or cattle ranches) and relatively limited resource availabilities, service access and remoteness. There are a number of detached, small communities included in the region. These communities, often by-products of highly productive, yet no longer extant mining operations, are experiencing gradual decline in growth, infrastructure and opportunities over time. Often, the communities are struggling to retain their elusive regional identities, especially in the face of an emerging and growing world of inter-connectedness, cross-scale linkages, and global processes. Similarly, more often than not, the contrast between social and community dynamics and the growing competitive economic pressures of the grazing enterprises are apparent in many dimensions.

4.1. Interviews and Data

A series of in depth interviews with a total of 18 participants was conducted in the region between September 2003 and December 2003. The interviews focused on actors' attitudes and self-reported viability characteristics of landholders and town residents in the upper Burdekin rangelands region. The interviews formed the basis of the assessment for constructing the Burdekin Outback Livelihoods Network (BOLNet) model, using qualitative analysis¹. Forty-nine livelihood element nodes, and 815 relationship ties were identified using the qualitative analysis steps (shown in the following Figure 3).

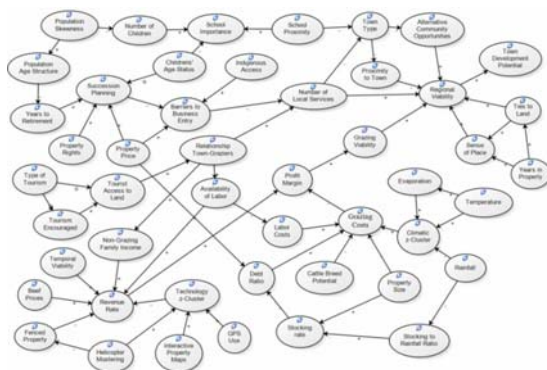


Figure 3. The BOLNet Bayesian Outback Livelihoods Network structure as a result of qualitative analysis. The signs adjacent to directed arcs denote the type of qualitative structural relationship in the model.

¹ For a more detailed description of the qualitative analysis for the BOLNet model see Alexandridis and Measham (2007).

After performing the prior probabilistic assessment of the node states from available additional quantitative and qualitative data, the prior Bayesian distributions yielded the BOLNet model shown in the following Figure 4.

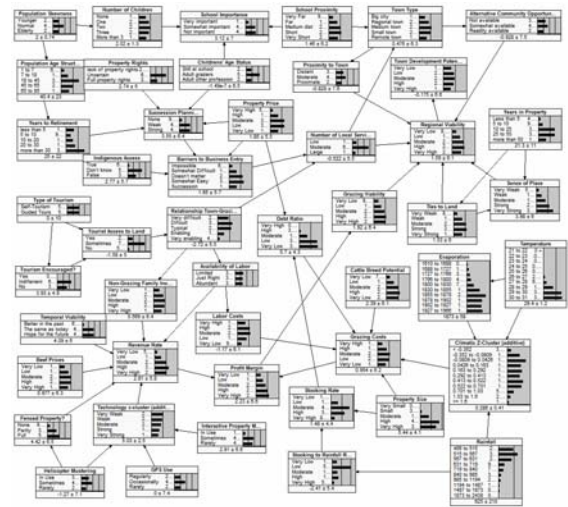


Figure 4. The prior Bayesian distributions of the BOLNet Bayesian Outback Livelihoods Network model for the upper Burdekin basin.

5. CONSTRUCTION OF BOLNET QUANTITATIVE COMPONENTS

Beyond the qualitative analysis of the interview responses used to inform the livelihoods network structure, a number of quantitative livelihood elements were parameterized using empirical distributions from historical data existing for the upper Burdekin region. These distributions are incorporated as prior information into the BOLNet model. Two main livelihood element distribution parameterizations are presented here as an example, namely the climatic conditions (parameterized from spatio-temporal data distributions) and the beef cattle prices (parameterized from historical time series for the Burdekin region).

5.1. Climatic conditions

The climatic conditions in the upper Burdekin area are of specific importance, as the relationship with nature and the everyday climate significantly affects the livelihoods of the graziers. The spatial distributions of the mean, minimum and maximum values of the three climatic conditions were used to parameterize a probabilistic climatic index cluster. For each of the 50x50 m² raster cell of the region shown in Figure 5, the mean, minimum and maximum values for each of the annual average temperature, evaporation and rainfall were used as data inputs

for the model construction. Two forms of a climatic index or cluster were considered in two sequential stages of estimation: A simple additive form, and a multiplicative one, estimated in the first stage as row class probability density. The raw index values were normalized across the spatial empirical distributions using their scaled z-scores. Given the fact that the original values for each of the climatic components (temperature, evaporation and rainfall) represent an average over several sequential years, the final z-score computation following the relevant model training (learning) and estimation, represents a combined (weighted) distribution of climatic conditions over both space and time. The strength of the climatic relationships in the Burdekin outback livelihoods network is measured in two ways, by altering the mathematical formulation of the z-cluster computation in the database. The additive and a multiplicative form of z-cluster was computed for each measurement point in the area (50m x 50m cell). The produced data were used to train an empty network in two main learning methods: the Expectation-Maximization algorithm (EM), and the gradient descent learning algorithm. The results are shown in Figure 5. The trained network does not contain the original input values since they were used to train the aggregate climate condition nodes.

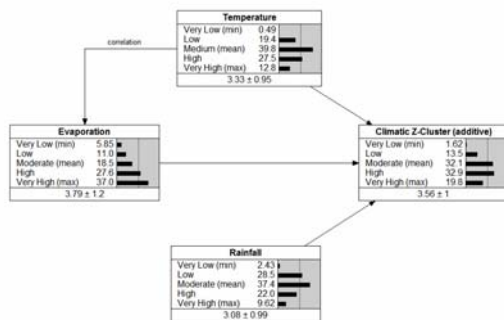


Figure 5. Schematic and probabilistic representation of the Burdekin outback livelihood networks' climatic cluster, prior to the data training and learning.

5.2. Beef cattle quantity and prices

The beef cattle prices were estimated using two main data sources: the quantities of beef cattle produced and sold in the Burdekin area, and the prices achieved for both domestic and export markets. The data sources for the former came from ABARE data (1978-2005) and the latter from MLA data (2000-2006). They were used to perform a Gaussian kernel density estimation of the probability for each of the beef cattle quantity classes (bandwidths). The final density estimation of the proportion of live exports to the total number of beef cattle sold is used to calibrate the

probability distribution of beef cattle prices in the probabilistic assessment of the relevant livelihood element node and to calibrate the relative price ranges for the density estimation. Seasonal (weekly) variation of beef cattle prices for the region (cents per carcass net weight sold in four main global markets: the US cow market, the Japan Ox market, the Korean Steer market, and the Trade Steer market). All four of the price parameters were used to estimate the livelihood element node of beef prices in the region (Figure 6). The same procedure was followed for the domestic price variations from 2000 to 2007.

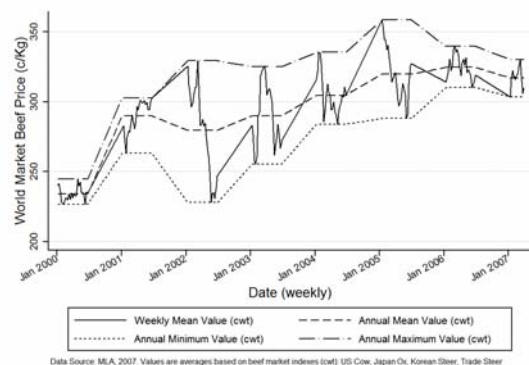


Figure 6. Seasonal (weekly) variation of beef cattle export values in the Northern Queensland region (in cents/Kg). Lines display the weekly and annual means, and the minimum and maximum annual prices.

The estimated data obtained from both the prices and quantities and their relative proportions of domestic and global markets were used to perform parameter learning of the probabilities in the Burdekin Outback Livelihoods Network, analysed in the next session.

6. PROBABILISTIC ASSESSMENT OF THE LIVELIHOODS NETWORK (LEARNING)

6.1. Climate learning components

For the climate component, the learning results yielded in four trained sub-network components (clusters):

- an additive climatic z-cluster component, trained with the EM algorithm (example shown in Figure 7);
- an additive climatic z-cluster component, trained with the gradient learning algorithm;
- a multiplicative climatic z-cluster component, trained with the EM algorithm;
- a multiplicative climatic z-cluster component, trained with the gradient learning algorithm.

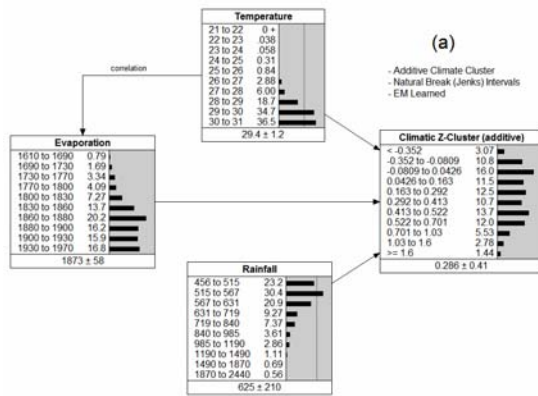


Figure 7. EM-learned probabilistic configuration of the additive climatic z-cluster component.

The learning results of the four types of climatic z-cluster index indicate a general robustness of the data structure. The major distributional pattern choice is the type of cluster (additive vs. multiplicative). The additive model performs better in capturing the variability of weather patterns in the upper Burdekin region (local), but the multiplicative model performs better in informing the mean expected values of the index, thus providing a more robust distribution (global). In terms of their algorithmic learning behaviour the two methods (E-M vs. Gradient learning) are producing very similar results.

6.2. Beef prices learning components

The beef cattle quantities sold and their estimated proportions were used to parameterize the decision node of the type of farm-gate price in the subgraph shown in the example of the following Figure 8. This is a two-step process: first the network was trained on the domestic prices (with 80% confidence), and on the live export prices (with 20% confidence) and their joint distribution was obtained. The Expectation-Maximization (E-M) training and learning algorithm was used (Moon, 1996) in the Netica software platform (Norsys, 2005), and iterative maximum likelihood estimates were obtained for all the training exercises. All learning steps succeeded to minimize the ML error estimates. The joint price distributions obtained from the training and learning exercise are shown in Figure 8. The final result of this learning exercise is the estimation of the seasonal beef cattle price probability distributions shown in the furthest right node in Figure 8. The learned distribution was used in the BOLNet model to inform the livelihood components on the beef prices distribution in the region.

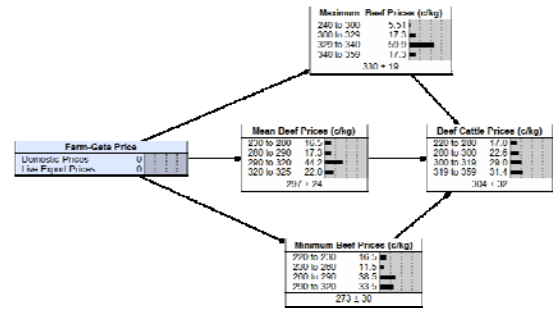


Figure 8. Joint EM learning of Gaussian probability estimation threshold of both domestic (80%) and export (20%) beef cattle process in the Burdekin region, based on time-weighted data series (1978-2005).

7. NETWORKS SENSITIVITY AND CONCLUSIONS

The research approach has showcased the methodological and technical elements of a participatory Bayesian livelihoods network for grazing systems in outback Australia. We have demonstrated how Bayesian modelling can be employed to combine qualitative and quantitative approaches in an innovative way to construct a livelihoods network that demonstrates issues of viability and sustainability in grazing livelihoods. A background to the livelihoods concept and discussed the relevance of this concept for outback regions of Australia showed that developing an understanding of outback livelihoods can assist in promoting resilience amongst grazing regions. This is particularly the case for family operated businesses due to the emphasis on the household within the livelihoods framework. The literature reviewed clearly showed that diversification is a crucial way to maintain a viable income in rural Australia given the proportion of Australian farm households which is dependent on off-farm income. The next steps following the networks' posterior estimation was the sensitivity analysis using social network approach and graph-theoretic aspects of network elements. The network analysis demonstrated that revenue rates and regional viability are the two livelihood elements with the highest degree of centrality, followed by grazing costs and succession planning. The revenue rate is the most important factor of grazing operations, whilst, understandably, the issue of regional viability also affects the entire upper Burdekin community. Nodes like the barriers to business entry, and the town-graziers relationship are not central livelihood elements for the network, despite the fact that they are important elements of connectivity. The critical path structure also demonstrates which different order effects are propagated through the network. Significantly, a change in the system that affects tourism-related

livelihood components is more likely to affect and impact the relationship between town residents and graziers, rather than the number of local services.

8. ACKNOWLEDGMENTS

This research was funded by Tropical Savannas CRC and CSIRO Sustainable Ecosystems. The authors would like to thank Duan Biggs, Nadine Marshall, Art Langston, Karin Hosking, Jo Savill, Alexander Herr and Samantha Stone-Jovicich for their useful comments and suggestions throughout the development of the research project.

9. REFERENCES

- Alexandridis, K. T. and Measham, T. G. (2007). *Modelling Regional Grazing Viability in Outback Australia Using Bayesian Livelihood Networks*. CSIRO Technical Report. Canberra, ACT: CSIRO Sustainable Ecosystems, pp. 65.
- Alexandridis, K. T. and Pijanowski, B. C. (2006). Modular Bayesian Inference and Learning of Decision Networks as Stand-Alone Mechanisms of the MABEL Model: Implications for Visualization, Comprehension, and Policy-Making. In C. M. Macal, M. J. North, and D. L. Sallach (Eds.), *Agent 2005 Conference on: Generative Social Processes, Models, and Mechanisms*. Gleacher Center, Chicago IL, October 13-15, 2005: Argonne National Laboratory and the University of Chicago, pp. 419-438.
- Batten, D. F. (2001). Complex landscapes of spatial interaction. *The Annals of Regional Science*, 35, 81-111.
- Black, A. (2005). Rural Communities and Sustainability. In C. Cocklin and J. Dibden (Eds.), *Sustainability and Change in Rural Australia*. Sydney: University of New South Wales, pp. 20-37.
- Cain, J., Batchelor, C., and Waughray, D. (1999). Belief Networks: A Framework for the Participatory Development of Natural Resource Management Strategies. *Environment, Development and Sustainability*, 1(2), 123-133.
- Chambers, R. and Conway, G. R. (1992). *Sustainable Rural Livelihoods: practical concepts for the 21st Century*. IDS Discussion Paper No. 296. Brighton, UK: Institute of Development Studies, pp. 33.
- Dittrich, P., Kron, T., and Banzhaf, W. (2003). On the Scalability of Social Order: Modeling the Problem of Double and Multi Contingency Following Luhmann. *Journal of Artificial Societies and Social Simulation*, 6(1), <http://jasss.soc.surrey.ac.uk/6/1/3.html>.
- Durlauf, S. N. and Young, H. P. (2001). *Social dynamics*. Washington, D.C. Cambridge, Mass: Brookings Institution Press MIT Press, Economic learning and social evolution, pp. x, 238.
- Goldstein, J. (1999). Emergence as a Construct: History and Issues. *Emergence*, 1(1), 49-72.
- Holmes, J. H. (2006). Impulses Towards a Multifunctional Transition in Rural Australia: Gaps in the Research Agenda. *Journal of Rural Studies*, 22(2), 142-160.
- Marschke, M. and Berkes, F. (2005). Local level sustainability planning for livelihoods: a Cambodian experience. *International Journal of Sustainable Development & World Ecology*, 12(1), 21-33.
- Moon, T. K. (1996). The Expectation-Maximization Algorithm. *IEEE Signal Processing Magazine*, 13(6), 47-60.
- Norsys. (2005). Netica: Advanced Bayesian Belief Network and Influence Diagram Software (Version 3.19). Vancouver, Canada: Norsys Software Corp. (www.norsys.com).
- Sawyer, R. K. (2005). *Social emergence : societies as complex systems*. Cambridge ; New York: Cambridge University Press, pp. ix, 276 p.
- Stafford Smith, M., Walker, D., Maru, Y., Stoeckl, N., Herr, A., Breen, J., and Greiner, R. (2003). *Options for Understanding Regional Dynamics in Northern Australia*. Tropical Savannas CRC Project Report. Alice Springs: CSIRO, pp. 10.
- World Commission on Environment and Development. (1987). *Our Common Future (The Brundtland Report to the UN)*. Oxford, UK: Oxford University Press, pp. 416.