



# Identifying interactions among reforestation success drivers: A case study from the Philippines



Hai Dinh Le<sup>a,b,\*</sup>, Carl Smith<sup>b</sup>, John Herbohn<sup>b,c</sup>

<sup>a</sup> Vietnam Forestry University, Xuan Mai, Chuong My, Hanoi, Viet Nam

<sup>b</sup> School of Agriculture and Food Sciences, The University of Queensland, St. Lucia, Brisbane, Qld 4072, Australia

<sup>c</sup> Tropical Forests and People Centre, University of the Sunshine Coast, Maroochydore, Qld 4556, Australia

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## ABSTRACT

Reforestation is an expensive undertaking. It is a long-term, complex, and trans-disciplinary process and it involves uncertainties and changing conditions. There is also a complex array of drivers (including biophysical, technical, socio-economic, institutional, and management drivers) that affect reforestation success. Previous research has documented the independent effects of biophysical and technical, environmental and socio-economic drivers on reforestation success. However, research over the last decade has revealed that the outcome of multiple factor interactions is commonly non-additive (i.e. synergies and antagonisms). Therefore, in order to provide better decision support for reforestation planning and policy setting it is necessary to understand the interactive effects that drivers have on reforestation success. To understand these interactive effects, we developed a Bayesian network model based on data collected from 43 reforestation projects on Leyte Island, the Philippines. Non-additive interactions among reforestation success drivers (i.e. synergies and antagonisms) were found to account for up to 90% of interactions tested. This result suggests an urgent need to account for these non-additive interactions in reforestation policy and planning in order to avoid unanticipated outcomes, wasted effort and missed opportunities.

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## 1. Introduction

Reforestation is the process by which trees are returned to areas from which they have been previously cleared. Reforestation can take many forms, ranging from establishing timber plantations of fast-growing exotic species through to attempting to recreate the original forest type and structure using native species (Le et al., 2012). Hence the focus of our study was on reforestation projects that aimed to establish trees on formerly forested land.

It is clear from the conceptual model developed by Le et al. (2012) that there is a complex array of drivers and indicators involved in determining reforestation success and that these interact. The conceptual model for reforestation success consists of four main groups of indicators, including establishment success indicators, forest growth success indicators, environmental success indicators, and socio-economic success indicators (Le et al., 2012). Therefore, reforestation success is the result of complex interactions between ecosystems and social systems (Poteete and

Ostrom, 2002; Sajise, 2003; Southworth and Nagendra, 2010). Previous research on reforestation success, however, has tended to focus on the individual effects of biophysical and technical, environmental and socio-economic drivers (Chokkalingam et al., 2006a, 2006b; de Jong et al., 2006; Günter et al., 2009; Mexal et al., 2008; Nawir et al., 2007; Zhang et al., 2002) and as a result there is little known about how reforestation outcomes respond to interactions among their influential drivers (Breitburg et al., 1998; Breitburg and Riedel, 2005; Folt et al., 1999; Schindler, 2001). Without an understanding of these interactions, opportunities for mutually beneficial interventions may not be identified and reforestation strategies may have unintended consequences or unexpected outcomes (Ramakrishnan et al., 1994).

Systems models have been widely applied to understand interactions within complex social, economic and environmental systems (Bellamy et al., 2001; Clayton and Radcliffe, 1996) by relating both ecological and socio-economic components (Mansourian et al., 2005). There are several approaches to systems modelling, including genetic algorithms, neural networks, rule-induction algorithms, hierarchical Bayesian, coupled component models, agent-based models, and expert systems. Any modelling approach applied to understanding interactions within reforestation systems must be flexible, able to integrate a broad range of biophysical

\* Corresponding author at: Vietnam Forestry University, Xuan Mai, Chuong My, Hanoi, Viet Nam. Tel.: +84 34840705; fax: +84 34840233.

E-mail addresses: [haifuv@yahoo.com](mailto:haifuv@yahoo.com), [haifuv@gmail.com](mailto:haifuv@gmail.com) (H.D. Le).

and socio-economic variables, able to handle variability and uncertainty in knowledge, and be useful to local decision makers (Cain et al., 2003).

In this study we used Bayesian networks (BNs) to understand interactions within reforestation systems on Leyte Island, the Philippines. BNs provide an efficient means of integrating social, economic and ecological variables (Castelletti and Soncini-Sessa, 2007; Smith et al., 2005), and have the potential to be used and understood by non-modelling specialists because they are graphical models (e.g. Cain et al., 2003; Castelletti and Soncini-Sessa, 2007; Smith et al., 2005). BNs also accommodate uncertainty in knowledge by relating variables using conditional probabilities (e.g. Cain et al., 2003; Castelletti and Soncini-Sessa, 2007; Marcot, 2005; McCann et al., 2006; Smith et al., 2005; Uusitalo, 2007) and have previously been used to test for synergistic and antagonistic interactions within systems (e.g. Menzie et al., 2007; Moe, 2010; Sánchez-Marré et al., 2008; Stewart-Koster et al., 2009). We developed a Bayesian network model using data collected from 43 reforestation projects on Leyte Island, with the objective of determining the extent to which synergistic and antagonistic interactions exist within reforestation systems and what the implications of these are for reforestation policy.

## 2. Materials and methods

### 2.1. Study location description

The study was conducted on Leyte Island with a total land area of 750,000 ha (Groetschel, 2001) (Fig. 1), which is the eighth largest island in the Philippines (Wernstedt and Spencer, 1967). Leyte Island is located in the Eastern Visayas region (Region 8), at about 9°55' N–11°48' N latitude and 124°17'–125°18' E longitude, covering a latitudinal range of 214 km from north to south (Langenberger et al., 2006). The average annual precipitation is relatively high, at about 2900 mm (Kucharski, 2010). The island regularly experiences typhoons with winds that sometimes reach more than 100 km/h (Dargantes, 1996).

As in most parts of the Philippines, forests were the major natural resource on Leyte in the early 1900s. Large-scale logging operations and conversion of forest into agriculture, however, have resulted in a massive decline of forest cover (Groetschel, 2001). Records show that the island had a forest cover of about 42% in 1939, and by 1987 the cover had been reduced to 12%, a loss of around 240,000 ha of forest (Dargantes, 1996). In 1994 only 2% of the island's area remained under primary forest (Dargantes and Koch, 1994). More recent data shows that about 40% of the land area of Leyte is now covered by grassland and barren land, resulting from abandoned cultivation and grazing land that lost productivity through erosion and nutrient leaching (DENR, 1998). About 40% of the island's area is under coconut plantations. The remaining area is composed of settlements, agricultural land and forest.

Reforestation efforts in the Philippines in general and Leyte Island in particular started almost a century ago and were meant to restore forest cover, provide environmental services, supply timber, and more recently contribute to local livelihoods. The common perception is that the efforts were largely a failure, with little to show on the ground and logging and livelihood pressures continuing to degrade remaining forests (Chokkalingam et al., 2006a). Therefore, understanding reforestation success drivers will be central to the success of the programme and others like it around the world.

### 2.2. Data collection and statistical analysis

A conceptual model for assessing reforestation success in tropical developing countries developed by Le et al. (2012) (Fig. 2) was

the basis for data collection. The survey covered a subset of the both success indicators and drivers from Le et al. (2012) (identified in italics in Fig. 2).

Data were collected from 43 out of a possible 62 reforestation projects on Leyte (see Le et al., 2014) for project selection criteria (Online Appendix 1). We collected both biophysical and socio-economic data from the selected reforestation projects (survey methods are described in Le et al. (2014)). We broke the data collection, which covered both reforestation success indicators and drivers, into two sections, namely an 'interview' section and a 'field survey' section. The 'interview' section comprised of a questionnaire designed to collect data on general project characteristics, project reforestation process, technical aspects of site management, project socio-economic aspects, and project institutional aspects. The 'field survey' section was designed to collect data on project site biophysical characteristics, tree establishment success, forest growth performance and forest environmental performance.

Data collected from the interviews and field surveys were subjected to stepwise multiple regressions in order to identify drivers significantly related to reforestation project success indicators. A set of significant drivers for each indicator was the result of the stepwise regressions. Relationships among these significant drivers and indicators were then tested for using Pearson's correlation. Details of the statistical tests used are described in Le et al. (2014). The end result was a set of significant driver-indicator, indicator-indicator and driver-driver relationships (Fig. 3) that was used to identify a system of relationships that affect reforestation success and used to guide construction of a BN model of reforestation success in the study area.

### 2.3. Development of the BN model

Netica software version 3.25 was used to construct the BN model. The graphical structure of a BN is a map of causal dependence and independence among variables. The causal dependencies among reforestation success indicators and drivers were determined from statistical analysis conducted on data collected from reforestation projects in the study area (Le et al., 2014). In order to keep the BN model as simple as possible, only those drivers that were identified in the statistical analysis as being significantly related to reforestation success indicators were included.

The states (categories) of variables included in the BN were determined in two ways (Online Appendix 2). First, for discrete variables, states were based on those categories used in the data collection interviews or field surveys (e.g. was grazing management applied at the reforestation site? Yes or No). Second, for continuous variables, states were based on previously established cut-offs (e.g. the requirement in the Philippines is that after 1 year of planting, reforestation projects must obtain a minimum threshold of 80% tree survival in order to be eligible for CBFMA tree planting payments), or statistical cut-offs (e.g. the median elevation of surveyed reforestation sites was 204 m), or cut-offs estimated by local forestry experts (e.g. MAI of tree volume for trees with DBH  $\geq 5$  cm is considered low if less than  $20 \text{ m}^3 \text{ ha}^{-1} \text{ yr}^{-1}$ , and high if greater than or equal to  $20 \text{ m}^3 \text{ ha}^{-1} \text{ yr}^{-1}$ ).

To parameterise the BN model (populate the conditional probability tables for variables), we used Netica's default counting-learning algorithm (Spiegelhalter et al., 1993). The data used for parameter learning was the raw interview and field survey data collected from the 43 reforestation projects in the study area.

### 2.4. Validation of the BN model

To validate the BN model we used model behavioural, calibration and model accuracy tests. Sensitivity to findings analysis (as described by Pearl, 1988) was used as a model behavioural

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