BAYESIAN NETWORKS AND GIS TECHNIQUES FOR MODELLING THE CAUSALITY, INTENSITY AND EXTENT OF LAND DEGRADATION IN DRYLANDS

A Thesis Submitted to the Committee on Graduate Studies
in Partial Fulfillment of the Requirements for the
Degree of Master of Science
in the Faculty of Arts and Science

Trent University
Peterborough, Ontario, Canada

Applications of Modelling in the Natural and Social Sciences

M.Sc. Program

January 2008

Your file Votre référence
ISBN: 978-0-494-31709-9
Our file Notre référence
ISBN: 978-0-494-31709-9

Abstract

Bayesian Networks and GIS Techniques for Modelling the Causality, Intensity and Extent of Land Degradation in Drylands

Oumer Ahmed

In this thesis, a new probabilistic approach to assess land degradation and its causes in dry lands is introduced. The suitability of Bayesian Networks for modelling the causality of land degradation intensity and extent through the integration of driving forces, pressures, states impacts and responses (DPSIR) is evaluated. In an attempt to describe the relationships between bio-physical states of degradation to their social, economic and demographic causes, the proposed DPSIR framework offers a new probabilistic approach to the establishment of the major root causes of the states of degradation in a study area, resulting in a practical Bayesian network modelling application and implementation to land degradation data.

A Bayesian network model has been constructed and tested using DPSIR indicators of land degradation in El Alegre watershed, San Luis Potosi, Mexico, using data obtained from measurements recorded in field forms and questionnaires applied during interviews with farmers and herders and local experts and officials. These data were used as input to the model developed using Netica^{TM} software.

The Bayesian network model was developed by linking indicators of Drivers and Pressures to State indicators based on their presumed cause-effect relationships. These relationships were derived from expert knowledge and available combination of data sources in the study area. Values (intensity or

extent) of status were assigned to each degradation indicator based on all combinations of the status (intensities or extents) of each of its identified causes. The final built model enables the visualization of the causality, intensity, and extent (of coverage over the area) of each indicator (drivers, pressures and states) within the model and to identify the most probable causes (drivers and pressures) of each of the state Indicators of land degradation from the sensitivity analysis of the model. This determines the most influencing causes for each indicator of the state of degradation. The causal relationships predicted by the model were validated independently through a confusion matrix and the Cohen's Kappa technique using local farmers' perceptions of the causes for a given type of degradation collected from interviews in the field through questionnaires. The results showed that the agreement between farmer perceptions of causes for each degradation state and the predicted causes by the model was good, but modest. This modest agreement was attributed, to a large extent, to the degree of subjectivity involved in interpreting vague farmer responses in the questionnaires. However the causality model proved empirically accurate according to the knowledge of local experts. Finally, using GIS the results of the present states of degradation of such dry lands, and their causes (drivers and pressures) were mapped coding each degradation indicator in an ad-hoc map legend, including their intensity, spatial extent and most influencing causes.

Acknowledgements

First and for most I would like to thank my supervisor Dr. Raul Ponce Hernandez whose esteemed, constructive and consistent follow-up and guidance helped me throughout this work.

I also wish to extend my gratitude to the members of my thesis supervisory committee Dr. Kenzu Abdella and Dr. Ben Sonneveld for their helpful input and encouragement.

I would like to express my spatial thanks to the people who provided me with a valuable data on the processes of the research.

I am also very grateful to the AMINS secretary and members of the graduate office for their kindness to facilitate the necessary administrative procedures to carry out my study.

I would also like to thank all my friends and those who gave me support and encouragement throughout this journey.

Finally, I would like to thank my family for their continuous support, care and encouraging advice. None of my accomplishments would have been possible with out you.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Land Degradation Definitions and Concepts

The rise and fall of ancient civilized societies can be related to land use or miss use. Fertile soils on the flood plains of major rivers in different parts of the world gave rise to early agrarian societies and land degradation was one of the major causes of their decline. Deforestation and soil erosion up stream resulted in floods that overwhelmed many early agrarian societies. Our modern industrial society is exerting even greater stresses upon the worlds land resources.

There are several definitions of land degradation, but all focus on the negative effect that human interventions have on the quality of land/soil and its productivity, due to natural processes, but mainly because of miss-management and human interventions.

Land degradation generally means the temporary or permanent decline in the productive capacity of the land (FAO, 1993). It can be considered in terms of the loss of actual or potential productivity or utility as a result of natural or anthropogenic factors showing a decline in the land quality or reduction in its productivity. The emphasis on land rather than soil broadens the focus to include natural resources such as micro-climate, water, landforms and vegetation. Land resources can suffer degradation from human activities, which in turn affect water and biological resources. Often land degradation undermines the ability of communities to depend on their environment for their livelihoods. This is seen clearly when land resources potential is diminished through desertification.

Desertification is land degradation occurring in arid, semiarid and dry sub humid areas caused by a combination of climatic factors and human activities (UNCCD, 1993). This process occurs in dry lands which span a third of the earth's land surface in over 110 countries influencing the lives of people including many of the world's poorest and most marginalized populations. Desertification induces mass migration of people and also has the potential of adversely affecting local, regional, and even global political and economic stability (UNCCD, 1993). The societal and political impacts of desertification also extend to non-dry land areas. Droughts and loss of land productivity are predominant factors in movement of people from dry lands to other areas. An influx of large numbers of migrants may reduce the ability of the population to use ecosystem services in a sustainable way. Such migration may exacerbate urban sprawl and by creating competition for scarce natural resources, bringing about internal and cross-boundary social, ethnic, and political strife. According to GEF-IFAD (2002) Land degradation affects an estimated 20% of world's dry lands and each year 12 million hectares are lost to deserts which is enough land to grow 20 million tons of grain.

Land degradation is one of the most serious environmental problems in the world today because it highly affects the sustainability of agricultural production, food security and ecosystem services in the natural environment. As indicated by

Pimentel (1993), more than 97% of the total food for the world's population is derived from land, the remaining being from aquatic systems. Since the world's population is growing at an ever faster rate, there is a need for increasing agricultural production to meet increased food demand. So, to produce the required amount of food to feed the growing population Woldeamlak (2003) suggests that this could be achieved by increasing agricultural production and this could be possible by bringing more land to cultivation, increasing the productivity of the land already under cultivation or a combination of the two. Because nearly all of the cultivable land is already under use, the option of "pushing into marginal lands" seems less feasible. Hence increasing productivity of the land already in use remains the best available option to increase food production and feed the world's population. On the other hand, physical, chemical and/or biological degradation is claming 6 million hectares of the global land per annum.

Land degradation through water erosion, is induced by human and physical factors, amongst which the removal of vegetation by humans and livestock, and the infrequent and irregular distribution of precipitation with increasing erosive force are becoming the major factors of the problem worldwide (Woldeamlak, 2003). Severe land degradation affects a significant portion of the earth's arable lands decreasing the productivity, wealth and undermining economic development of nations. Kaen (1999) reported that the economic impact of land degradation is extremely severe in densely populated areas of developing countries of South Asia and sub–Saharan Africa. Earth's landmasses have been and will continue to be divided into many nations. Unfortunately, the quality and quantity of land resources amongst the nations vary widely. In land rich nations there is an abundance of arable land, and a low density of rural population. Their high standard of living is supported by a high energy input agriculture, manufacturing, and international trade. At the opposite extreme are land-poor nations where rural population has long exceeded the land's carrying capacity at present levels of input and management, and poverty is widespread. For the land-rich nations, major issues for sustainable land management in the future would be to prevent and reduce soil, water and air pollution from agriculture and industry, and to convert to and preserve more land for forest, grassland and wildlife habitats. In the land-poor nations land degradation is set to continue unless economic and technical assistance is provided by the international community, which can be through the provision of funds for environmental conservation projects and for sharing technical know-how with the local authorities and agricultural experts on ways and means for stopping and reversing the degradation. The situation in the majority of nations lies between these two extremes.

The link between a degraded environment and poverty is direct and intimate (Woldeamlak, 2003). As land resources become less productive, food security becomes endangered and competition for diminishing resources increases, species diversity will be lessened and often lost as lands are cleared and converted to nutrient-exporting agriculture. Thus a downward eco-social spiral is created when marginal lands are nutrient depleted, polluted or eroded by unsustainable land management practices resulting in loss of soil productivity and stability leading to permanent damage.

Assessing the seriousness, causes and consequences of land degradation is a major challenge. Few assessments carried out to date worldwide have clear policy relevance and relating the impacts of land degradation to conservation interventions has proved extremely elusive. Yet, the need to promote practices that provide for food security and to design sustainable rural livelihoods becomes ever more urgent.

Finally, soil, water, vegetation and mineral resources are basic components of land. The health of the worlds land resources is vital to the very survival of humans, as well as all plant and animal species. For better or worse humans have altered the face of the earth significantly during the past 300 years so that the land and other natural resources have been exploited in almost every corner of the planet (Kaen, 1999). Technological success has enriched our lives but has impoverished the earth's natural resources. In recent years the issue of causes of land degradation and its related effects on the society and general environment are attracting more public concern, in turn demanding the attention of governments and researchers world wide.

Various attempts have been made to assess land degradation at multiple spatial scales from local to global. Prior methodologies, in general, show a strong bias towards assessing only biological and physical factors of land degradation, ignoring the equally significant social and economic factors.

In this study, a new probabilistic approach to assess land degradation and its causes in dry lands is introduced. The suitability of Bayesian Networks for modelling the causality, intensity and extent of land degradation through the integration of driving forces, pressures, states impacts and responses (DPSIR) is evaluated. These efforts attempt to integrate the biological and physical to the social and economic factors of land degradation in a given area of concern. Linking various land degradation types with their multiple biological, physical, social and economic causes to arrive at the most probable causes for a given type of land degradation.

1.2 Thesis Outline

The presented thesis comprises seven chapters:-

Chapter 2: Provides a background on the review of related research literature including an overview of the available methods and models for assessing land degradation.

Chapter 3: In this chapter the research problem and overall objectives of this research are stated.

Chapter 4: Presents the approaches and methods used to build the Bayesian network model and the model building process in detail, for a case study in El Alegre sub watershed, San Luis Potosi, Mexico, starting with the general description of the study area.

Chapter 5: Summarizes the model results obtained for the study area followed by their discussion, statement of general applications and validation of the model.

Chapter 6: States procedures for mapping model analyses results using GIS.

Chapter 7: Presents concluding remarks and recommended future related areas of research.

Chapter 2

Literature Review

2.1 The States of Land Degradation and Their Indicators

There are several states of land degradation, associated with different degradative processes. Mechanisms that initiate land degradation include physical, chemical, and biological processes (Lal, 1994). Each of the processes creates typical symptoms, which can be helpful in assessing the degree and extent of degradation that has occurred.

Depending on the process involved land degradation can be distinguished as Physical, Chemical and Biological see figure 2.1.

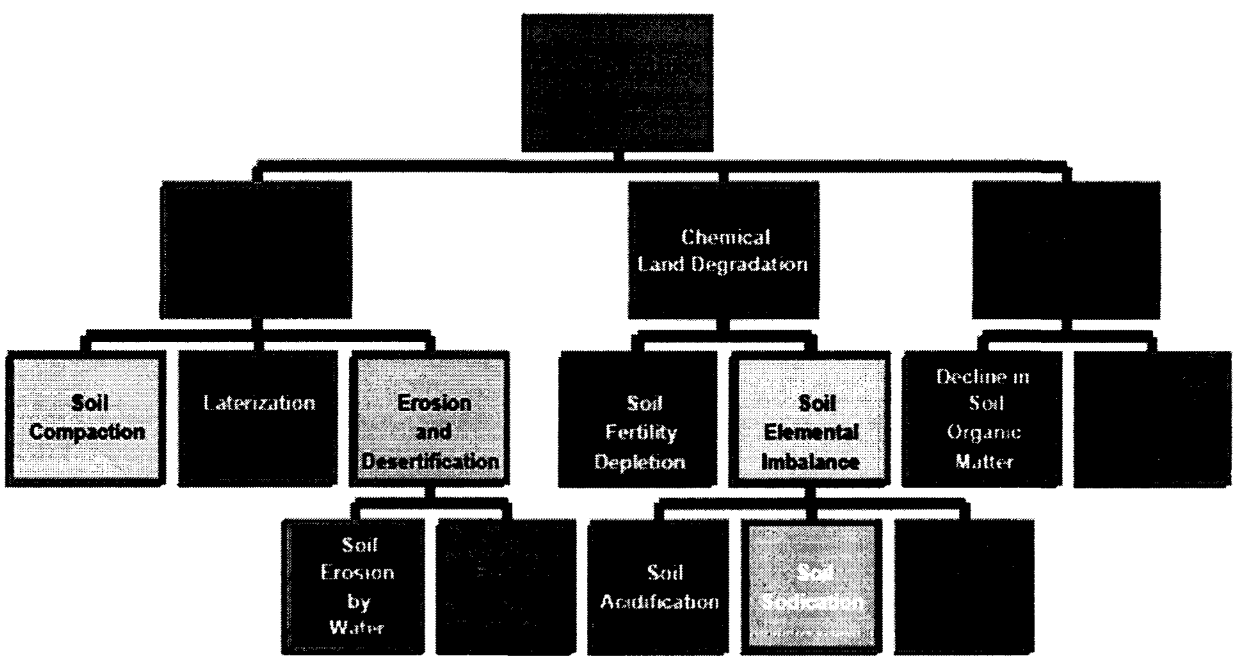


Figure 2.1 Land degradation types and processes (Ponce-Hernandez and Koohafkan, 2004)

Physical degradation processes are those which create the disturbance of the soil profile often responsible for the loss of the humus rich organogenic layer or the A horizon (Snakin et al., 1995). This loss is caused in part by wind and water erosion. The other disturbance caused by this process is the accumulation of sediments in which its degree of degradation depends on the depth of sedimentation and the properties of its material. The disruption of water movement through the soil which is a result of saturation and water logging in or above the compacted layer is also considered as one of the physical processes.

On the other hand, the primary consequence of Chemical processes is the reduction of the nutrients like nitrogen, phosphorus, potassium, etc from the soil (Snakin et al., 1995). Among others, decline in soil fertility is one of the indicators of the occurrence of a chemical degradation process. The content of soluble salts reflects salinization processes, which is shown by the change in soil electrical conductivity (Soil EC). Here the criterion of chemical soil degradation is the increase in ESP. Another indicator of chemical degradation is the toxic pollution of soil, which lowers the quality of the soil productivity. This can be assessed by the index of excess of permissible pollutant concentration or the degree of soil pollution. The other process worth mention here would be the soil acidification. This process is indicated by the significant decrease in pH value of the soil. If soil acidity is not managed, acidification of the soil will eventually lead to lower yields and reduced pasture.

Biological degradation processes are expressed by the reduction or loss of living organisms in the soil, which play the key role in cycling nutrients in decomposition of organic debris in soils, in detoxification of pollutants and in suppressing pathogenic micro-organisms (Snakin et al., 1995). For this processes microbiological tests often provide early diagnosis of the content of the active microbial biomass as an informative indicator of soil biological function.

Land degradation is caused by various processes including the above mentioned, and most if not all of these processes are closely interrelated and the occurrence of one usually leads to the occurrence of one or more of the others.

The effect of a land degrading process differs depending on the inherent characteristics of the land, specifically soil type, slope, vegetation and climate (Stocking and Murnaghan, 2002). Thus, an activity that, in one place, is not degrading may, in another place, cause land degradation because of different combination of soil characteristics, topography, climatic conditions or other circumstances. So, equally erosive rainstorms occurring above different soil types will result in different rates of soil loss. It follows that the identification of the causes of land degradation must recognise the interactions between different elements in the landscape, which affect degradation and also the site-specificity of degradation.

Land degradation manifests itself in many ways. Vegetation, which may provide fuel and fodder, becomes increasingly scarce. Water courses dry up. Thorny weeds predominate in once-rich pastures. Footpaths and rills disappear into gullies. Soils become thin and stony. All of these manifestations have potentially severe impacts for land users and for people who rely for their living on the products from a healthy landscape.

It is difficult to grasp land degradation in its totality. The "productive capacity of land" cannot be assessed simply by any single measure. Therefore, we have to use indicators. These are integrating variables, which may show that land degradation has taken place but they might not necessarily be the actual degradation itself. The piling up of sediment against a down slope barrier may be an 'indicator' that land degradation is occurring upslope. Similarly, decline in yields of a crop may be an indicator that soil quality has changed, which in turn may indicate that soil and land degradation are also occurring. The condition of the soil is one of the best indicators of land degradation (Stocking and Murnaghan 2002). The soil integrates a variety of important processes involving vegetation growth, overland flow of water, infiltration, and land use and land management. Soil degradation is, in itself, an indicator of land degradation. But, in the field, further variables are used as indicators of the occurrence of land degradation. Types of soil degradation include among others soil erosion by water, soil erosion by wind, soil fertility decline, water logging, increase in salts, sedimentation or soil burial, lowering of the water table, loss of vegetation cover and increased stoniness and rock cover of the land.

Single indicators give singular items of evidence for land degradation or its impact. They are susceptible to error, misinterpretation and change (Stocking and Murnaghan 2002). This is true, particularly in the case of field assessment where many of the measurements can only be described as 'rough-and-ready'. The use of only one indicator say, a tree mound to conclude definitively that land degradation has occurred, is problematic. Therefore it is important to combine indicators for more robust conclusions to be entertained, even to the extent that quite different types of measure may be placed alongside each other to obtain a fuller understanding as to whether land degradation is happening.

2.2. The Causes (Drivers and Pressures) of Land Degradation and Their Indicators.

Depending on their inherent characteristics and the climate and the intrinsic physical chemical and biological characteristics derived from pedogenetic processes, lands vary from highly resistant, or stable, to those that are vulnerable and extremely sensitive to degradation. Fragility, understood as extreme sensitivity to degradation processes, may refer to the whole land, a particular degradation process or a soil property. Stable or resistant lands do not necessarily resist change. They are in a stable steady state condition with the new environment and have retained or change minimally their productivity. Under stress, fragile lands degrade to a new steady state and the altered state is unfavourable to plant growth and less capable of performing environmental regulatory functions. Unless conservation measures are taken this state will prevail and even worsen due to the existing causes of degradation in the area.

Causes of land degradation are the agents that determine the rate of degradation. About 200 million ha of soil, equivalent to 15 per cent of the earth's land area have been degraded through human activities. (GACGC, 1994). Although degradation processes do occur without interference by humans, these are broadly at a rate which is in balance with the rate of natural rehabilitation. So, for example, water erosion under natural forest corresponds with the subsoil formation rate. Here, if there is erosion in deep Amazon forests this can be taken as a typical example of situations where the impact of human activities is absent or very limited. Accelerated land degradation is most commonly caused as a result of human intervention in the environment. The effects of this intervention are determined by the natural landscape. In the context of land productivity, land degradation results from a mismatch between land quality and land use (Beinroth et al.,1994). Human activities contributing to land degradation include unsuitable agricultural land use, poor soil and water management practices, deforestation, removal of natural vegetation, frequent use of heavy machinery, overgrazing, improper crop rotation and poor irrigation practices. Natural disasters, including droughts, floods and landslides, also contribute to land degradation. These causes can be distinguished as biophysical (e.g. land use and land management, including deforestation and tillage methods), socioeconomic (e.g. land tenure, marketing, institutional support, income and human health), and political (e.g. incentives, political stability) forces that influence the effectiveness of processes and factors of land degradation.

The impacts of land degradation are seen more in developing countries than in the developed world because of the high population growth rate and the associated rapid depletion of natural resources (Feoli et al., 2000). High population density is not necessarily related to land degradation; it is what a population does to the land that determines the extent of degradation. People can be a major asset in reversing a trend towards degradation. However, they need to be healthy and politically and economically motivated to care for the land, as subsistence agriculture, poverty, and illiteracy can be important causes of land and environmental degradation.

2.3 Methods and Models for Assessing Land Degradation

The assessment of a degraded land is the first stage to address degradation causes, impacts and solutions. However there is no commonly accepted method to assess land degradation in all of its forms and extents linking the social and economic drivers or causes of land degradation to its bio-physical states and to the impacts of these on people's livelihoods, and the responses given by people to such state of degradation and its causes.

The study of land degradation can be quite complicated due to its multi-facet nature and it is limited by several factors. The main issues include the definition of land degradation, the complexity of causes and processes of land degradation, the temporal changes of degradation and the variation in spatial scale of the processes.

More to its complexity some forms of degradation are not readily visible, for example, soil compaction, acidification and reduced biological activity. Lack of data and analytical tools for measuring such differences prevents or limits estimation of their impact on productivity, and makes scaling up to the national or regional level problematic. There are no internationally agreed criteria or procedures for estimating the severity of degradation and many surveys do not make reliable assessments (Tiffen et.al., 1994). Consequently, land degradation has been studied for a range of purposes using a variety of approaches. The scope, focus and scale of study are generally purpose-driven, and this purpose also determines the methods and technologies used for data collection and analysis.

The approaches differ widely, depending on the intended purpose in terms of the temporal timeframe to be studied (Ponce-Hernandez, 2005). Medium to long term monitoring of land degradation trends of change over time differ from the generally more detailed, large scale studies that provide a 'picture in time' of the current state of land degradation.

There are many processes that lead to a given state of land degradation. The states are the result and consequence of the pressures acting on the land resource. Such pressures, in turn, emerge or are created by the "drivers" or different driving forces. Both driving forces and pressures can be social, economic, political or policy and even infrastructural, physical and biological in nature. Thus, the study and assessment of land degradation can be a complex proposition that may limit the ability for comprehensive holistic study. There must be a balance between accurately representing reality in a holistic and integrative manner and maintaining a manageable level of complexity adequate for practical purposes.

Natural scientists studied for many years the bio-physical processes of land degradation but the human, social, economic and cultural dimensions of land degradation have been less studied and poorly understood. Even less understood are the linkages between the biophysical processes and the socio economic factors, driving forces and pressures that cause land degradation.

Yet, the current land degradation assessment methods tend to focus on the bio-physical aspects. These provide estimates of the intensity and extent of individual types of land degradation but these estimates are lacking a link to the causes of land degradation processes amongst the social, economic, cultural and demographic factors.

These sentiments are reflected in FAO/UNEP Land Degradation in Dry land Areas (LADA, 2004) global initiative, which focuses on developing a holistic approach to land degradation assessment in dry lands and establishes that combating land degradation and desertification requires the assessment and monitoring of the type and severity of land degradation, and the analysis of its causes.

Van Lynden and Kuhlman in 2002, as part of the LADA project, reviewed the existing methods for land degradation assessment. A variety of methods were examined and evaluated to determine their usefulness for the LADA project. The methods include:

- Expert Opinion (subjective assessment)
- Remote sensing based methods (satellite imagery and aerial photographs, linked with ground observations).
- Field monitoring (stratified sampling and analysis and long term field observations).
- Productivity changes (observation of changes in crop yields and livestock output).
- Land users' opinion / field criteria (farm level studies on a sample bases).
- Modelling (prediction of degradation hazard and for extrapolating the results on observed degradation).

An overview of the features of each of these methods, as described by Van Lynden and Kuhlman (2002), is provided in table 2.1

Table 2.1 Characterization of land degradation assessment methods (Van Lynden and Kuhlman, 2002).

Method / Features	Expert opinion	Remote sensing	Field Monitoring	Productivity changes	Land users opinion/ field criteria	Modelling
Applicability/ adaptability	Flexible	Vegetation, soil, terrain, etc	Flexible: soil, vegetation ... status (direct); risk (derived).	Yields, production; trends	Flexible	Flexible
Scale	Any, but most appropriate for small scale	Any, but most appropriate for small scale	Local	Local	Local	Local (mostly) to global
User-friendliness	High	Low	Medium	Medium	High	Medium
Cost per unit area	Low	Medium	High	High	Medium to High	Variable
Outputs	Spatial/ Point	Spatial	Point	Point	Point	Point/ spatial
Replicability	Low	High	High	High	Low to medium	High
Comparability or compatibility	Low	High	Medium	Medium	Low	Variable
Subjectivity	High	Low	Low	Medium	High	Low
Stakeholders involvement	Variable	Low	High	High	High	Low
Socio-Economic issues	Low	Low	Medium	High	High	Medium
Overall	Good method for quick first overview, reconnaissance	Stand alone assessment or complement other methods.	"Hard" local data, can complement other methods	Information on impact of degradation	Perception of local stake-holders	Scientific understand-ing of process

For the use of these methods Van Lynden and Kuhlman made the following recommendations:

- Degradation hot spots could be identified in a generic small scale assessment with the use of a combination of expert opinion and remote sensing.
- The identified degradation types of the hot spots could be further explored using more detailed and location specific methodologies such as field monitoring, assessing productivity changes and land users opinion.
- Existing models can at times be used for extrapolating the results of the latter to areas with similar conditions not directly covered by these methodologies.

Expert judgements are potentially a valuable source of information in land degradation assessment, especially in areas where data paucity impedes the use of quantitative models. However, expert opinions are also much disputed because they are not tested for consistency, abstain from formal documentation, while their quantitative interpretation is inherently unidentifiable (Sonneveld, 2002).

Recognising that land degradation includes a wide range of issues and is the result of a series of complex processes, there is an inevitable trade-off between comprehensiveness of the methodology and its user-friendliness. (Ponce-Hernandez, 2005). Assessments are at risk of being either, very generic so that they are easy to apply or overwhelmingly complex. However, it was noted that the frequently observed desire to have "simple" assessment methods is not realistic. The results of such an assessment would be limited to applications for informative and educational purposes; however when results are intended for use in planning and decision making regarding remediation, instances where detailed and accurate data are required, a more detailed assessment is necessary, regardless of the complexity.

The importance of methodological integration cannot be overemphasized. The integrative nature of any methodological framework needs to look at integration not only from the discipline-oriented stand point but also integration of the cyclic nature of degradation processes, incorporating issues leading to and consequence of the land degradation process. There is a decided biophysical bias in most current land degradation assessment methods and weakness with regards to assessing the social, economic, demographic, political and even gender issues of land degradation.

In their review, Van Lynden and Kuhlman, (2002) concluded that at that time no ready-developed methodology was available for off-the-shelf application to assess all aspects of land degradation. In response to these findings, FAO commissioned, through a consultancy, the development of a comprehensive framework approach to land degradation assessment in dry land areas. The consultancy report (Ponce-Hernandez, 2002) was later simplified and streamlined incorporating a set of tools for the assessment (Ponce-Hernandez and Koohafkan, 2004). This report describes a holistic and integrative approach to assess the physical, biological, social, economic and infrastructural issues related to land degradation in dry land areas that is based on a modified pressure-state-response model that incorporates too the driving forces and impacts of land degradation, becoming the DPSIR approach. The approach to land degradation described by Ponce-Hernandez and Koohafkan (2004) attempts to provide a multi scalar, comprehensive assessment using a "tool box" of methods and procedures to be selected from and combined as relevant to the conditions of the study area and scale of the assessment

Various qualitative assessments of land degradation have been used for some global or sub continental studies, such as the Global Assessment of Human-Induced Soil Degradation (GLASOD; Oldeman et al. 1991), the Assessment of Soil Degradation in South and Southeast Asia (ASSOD; van Lynden and Oldeman 1997) or in the context of the Soil Vulnerability Assessment in Central and Eastern Europe (SOVEUR; van Lynden 2000).

These assessments are to some extent subjective since they are based on the perception of experts on the intensity of the degradation process and the impact on agricultural suitability, biotic function or decline in productivity.

Semi quantitative sets of criteria were suggested for water and wind erosion in relation to soil depth and for salinization, and qualitative criteria for other kinds of degradation, such as nutrient depletion. See Tables 2.2 - 2.4 from the GLASOD guidelines, (Oldeman 1988).

Currently there is no available quantitative assessment of soil degradation at small scales (for example at continental scales).

Table 2.2 Degree of present degradation due to water erosion (Oldeman, 1988).

Slight:	- In deep soils (rooting depth more than 50 cm): part of the topsoil removed, or with shallow rills 20–50 m apart, or both. - In shallow soils (rooting depth less than 50 cm): some shallow rills at least 50 m apart. - In pastoral country the ground cover of perennials of the original or optimal vegetation is in excess of 70%.
Moderate:-	- In deep soils: all topsoil removed, shallow rills less than 20 m. apart or moderately deep gullies 20–50 m apart or a combination. - In shallow soils: part of topsoil removed, shallow rills 20-50 m apart, or both. - In pastoral country: ground cover of perennials of the original or optimal vegetation ranges from 30 to 70%.
Severe: -	- In deep soils: all topsoil and part of subsoil removed, moderately deep gullies less than 20 m. apart, or both. - In shallow soils: all topsoil removed: lithic or leptic phases or with exposed hardpan. - In pastoral country: ground cover of perennials of the original or optimal vegetation is less than 30%.

Table 2.3 Degree of present degradation due to salinization (Oldeman, 1988).

Salinization should be considered as the relative change over the past 50 years in salinity status of the soil, the latter being defined as follows:

Non-saline:	- Electrical conductivity less than 5 dS/m; E.S.P<15%; pH<8.5
Slightly saline:	- Electrical conductivity 5-8 dS/m; E.S.P. < 15%; pH < 8.5
Moderately saline:	- Electrical conductivity 9-16 dS/m; E.S.P. < 15%; pH < 8.5
Severely saline:	- Electrical conductivity more than 16 dS/m; E.S.P. < 15%; pH < 8.5

The present degree of human-induced salinization can be identified as a change in salinity status as follows:

Slight:	- From non-saline to slightly saline; from slightly to moderately saline, or from moderately saline to severely saline.
Moderate:	- From non-saline to moderately saline, or from slightly saline to severely saline.
Severe: -	- From non-saline to severely saline.

Table 2.4 Degree of present degradation due to nutrient depletion (Oldeman, 1988).

Criteria to assess the degree of present degradation are the organic matter content; the parent material; climatic conditions. The nutrient depletion by leaching or by extraction by plant roots without adequate replacement is identified by a decline in organic matter, P, CEC (Ca, Mg, K).

Slight:	- Cleared and cultivated grassland or savannas on inherently poor soils in tropical regions. - Cleared or cultivated formerly forested land in temperate regions on sandy soils or in tropical (humid) regions on soils with rich parent materials.
Moderate:	- Cleared and cultivated grassland or savannas in temperate regions, on soils high in inherent organic matter, when organic matter has declined markedly by mineralization (oxidation). - Cleared and cultivated formerly forested land on soils with moderately rich parent materials in humid tropical regions, where subsequent annual cropping is not being sustained by adequate fertilization.
Severe:	- Cleared and cultivated formerly forested land in humid tropical regions on soils with inherently poor parent materials (soils with low CEC), where all above-ground biomass is removed during clearing and where subsequent crop growth is poor or non-existent and cannot be improved by N fertilizer alone.
Extreme:	- Cleared formerly forested land with all above-ground biomass removed during clearing, on soils with inherently poor parent materials, where no crop growth occurs and forest regeneration is not possible.

Tables 2.2 to 2.4 show suggested semi quantitative and qualitative sets of criteria by Oldeman (1988).

In the ASSOD assessment the seriousness of degradation was expressed in terms of the impact of degradation on productivity rather than its degree of severity.

In SOVEUR, both degree (as in GLASOD) and impact (as in ASSOD) were assessed, the degree reflecting the intensity of the process, such as tonnes of soil lost by erosion, the impact reflecting the inferred change in productivity.

Table 2.5 shows the comparison of these assessment methodologies.

Table 2.5. Comparison of qualitative soil degradation assessment methodologies (van Lynden, S. Mantel and A. van Oostrum, 2004).

	GLASOD	**ASSOD**	**SOVEUR**
Coverage	global	South and Southeast Asia (17 countries)	Central and Eastern Europe (13 countries)
Scale	1:10M (average)	1:5M	1:2.5M
Base map	Units loosely defined (physiography, land use, etc.)	Physiography, according to standard SOTER methodology	Physiography and soils, according to standard SOTER methodology
Status assessment	Degree of degradation + extent classes (severity)	Impact on productivity + extent percentages	Degree and impact + extent percentages
Rate of degradation	Limited data	More importance	As for ASSOD
Conservation	No conservation data	Some conservation data	No conservation data
Detail	Data not on country basis	Data available per country	Data available per country
Cartographic possibilities	Maximum 2 degradation types per map unit	More degradation types defined, no restrictions for number of types per map unit	As for ASSOD, but special emphasis on pollution
End product	One map showing four main types with severity	Variety of thematic maps with degree and extent shown separately	As for ASSOD
Database/ GIS	Digital information derived from conventional map	Data stored in database and GIS before map production	As for ASSOD
Source	Individual experts	National institutions	National institutions

Following is the summary of advantages and disadvantages of qualitative assessments as described by van Lynden, S. Mantel and A. van Oostrum, 2004.

Their advantages include:

• A wide range of different degradation types can be addressed simultaneously, at multiple scales.

• They can provide a relatively quick overview for national and regional planning.

• They enable identification of hot spots and bright spots (problem areas and examples of effective responses) for further study.

• They constitute a good tool for awareness rising.

• The data requirements are limited: adequate expert knowledge, though preferably supported by hard data, is sufficient.

Some of their disadvantages are:

• A general lack of hard supporting data.

• The potentially subjective character.

• The information being based on expert knowledge and existing data, may not always be up to date.

The current methodology for land degradation assessment at multiple scales from local to global are based on the existing (GLASOD) the global assessment of human induced land degradation approach (Oldman et al., 1991). The GLASOD database contains information on soil degradation within map units as reported by numerous soil experts around the world through questionnaires. It includes the type, degree, extent, and rate of soil degradation on a map. Its major objective is to strengthen the awareness of policy makers and decision makers of the dangers resulting from inappropriate land and soil management, and leading to a basis for the establishment of priorities for action programmes. The major problems of the GLASOD methodology include: it is an expert-driven (opinion) which is not a real assessment derived from measured observations of variables or indicators and its methodology also has a strong biophysical bias ignoring important social and economic factors.

On the other hand there are a number of models used to estimate and/ or predict the level of a specific degradation type in a given area. These include models devised to estimate soil erosion by water, wind and models for estimation of chemical transport in soils.

It is a fact that one of the principal causes of land degradation is soil erosion by water. Land degradation is sometimes taken as synonymous with soil degradation. However, soil degradation is the prominent form of land degradation (Lal and Stewart 1990). Land degradation due to water erosion is a serious threat to the quality of the soil, land, and water resources. Soil erosion is defined as the detachment and transportation of soil from land surface. One important feature of soil erosion by water is the selective removal of the finer and more fertile fraction of the soil. Agents of soil erosion are water and wind, each contributing a significant amount of soil loss. A study by Bobe (2003) indicated that water erosion had accounted for about 55% of the 2 billion ha of the degraded soils in the world.

Modeling soil erosion is the process of mathematically describing soil particle detachment, transport, and deposition on land surfaces. Erosion models can be used as predictive tools for assessing soil loss, conservation planning, soil erosion inventories and project planning. Moreover; they can be used as tools for understanding degradation processes and their impacts (Nearing et al., 1994).

In this area one of the most commonly used model is the Universal Soil Loss Equation model (USLE) widely used to estimate rates of soil loss caused by rainfall and associated overland flow. This model is used to compute potential long term average annual soil loss in tons per acre per year taking into consideration the following factors: - The rainfall intensity in the area, the soil type and its erodability, the slope length, the slope steepness, land cover and its management with in the area, and lastly the support practice, if any, in the area constructed to protect against soil erosion.

With regards the available models, a good model should satisfy the requirements of reliability, universal applicability, ease of use with a minimum data, comprehensiveness in terms of the factors and erosion processes included and the ability to take account of changes in land use and conservation practice (Morgan, 1995).

2.4 The Driving force, Pressure, State, Impact, Response (DPSIR) Approach to Land Degradation Assessment

Land degradation is a set of processes, which are considered to be responsible for possible decreases in productivity. In order to evaluate the input of conservation measures or cultural practices necessary to avoid such productivity loss, the state of degradation must be evaluated in its type, intensity and extent, together with its most likely causes.

The DPSIR framework is the result of an approach to ecosystem assessment used for soil and land degradation assessments developed by the European Environment Agency, for describing, monitoring and controlling environmental problems (Bridges, et al, 2001). The framework was originally developed for environmental reporting purposes and allow for the structuring of the description of the environmental problems by formalising the relationships between various sectors of human activity and the environment as causal chains or links. The DPSIR approach is an analytical tool often selected to handle complex interactions between the socio-economic (humankind processes) and the natural system (ecosystem processes). It adopts a circular reasoning, which allows to link human activities as drivers and pressures, to environmental degradation, as states and impacts (See figure 2.2).

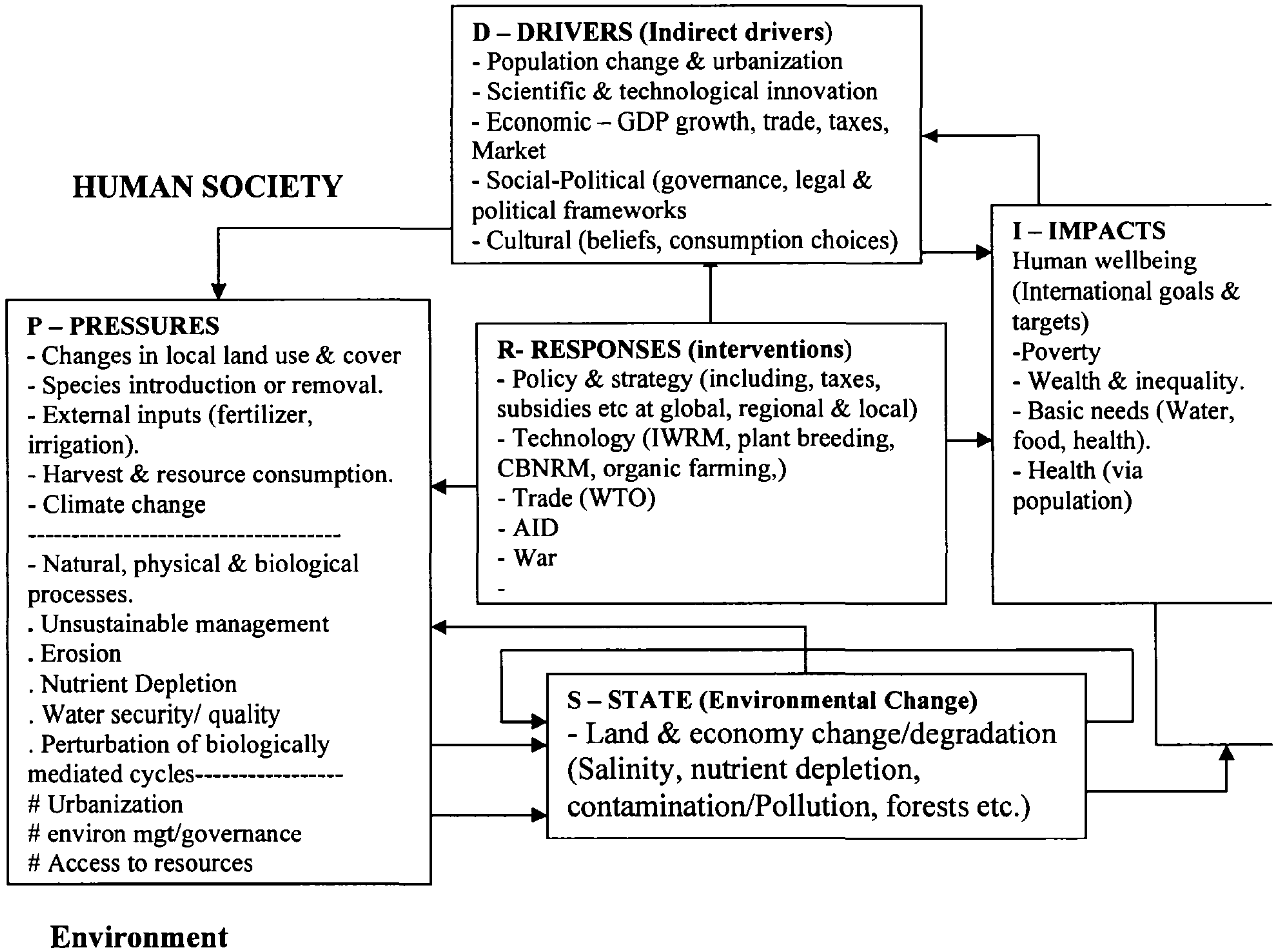


Figure 2.2 The UNEP Human – Environment Interaction analytical approach: - built on the Drive, Pressure, State, Impact and response (DPSIR) framework

The interaction is multi-scalable and indicates generic cause and effect relations within and among:

- DRIVERS: The drivers are sometimes referred to as indirect or underlying drivers or driving forces and refer to fundamental process in society, which are drivers or activities having a direct impact on the environment;
- PRESSURES: The pressure is sometimes referred to as direct drivers as in the methodological framework. It includes in this case the social and economic sectors of society (also sometimes considered as Drivers). Human interventions may be directed towards causing a desired

environmental change and may be subject to feedbacks in terms of environmental change, or could be intentional or un-intentional by-products of other human activities (i.e. pollution);

- STATE: Environmental state refers to the current condition of a resource, also including trends, often referred to as environmental change, which could be both naturally and human induced. One form of change, such as climate change (referred to as a direct driver in the MA framework) may lead to other forms of changes such as biodiversity loss.
- IMPACTS: These consist of observable and even measurable effects (positive or negative) on people's livelihoods. Environmental change may positively or negatively influence human well-being through changes in ecological services and environmental stress. Vulnerability to change varies between groups of people depending on their geographic, economic and social location, exposure to change and capacity to migrate or adapt to change. Human well-being, vulnerability and coping capacity is dependent on access to social and economic goods and services and exposure to social and economic stress; and
- RESPONSES: Responses consist of the actions taken by the recipients of the impacts to mitigate or reverse the effects of the impacts. The elements among the drivers, pressures and impacts which may be used for managing society in order to improve the human – environment interactions.

The DPSIR framework is a system for organising information that emphasises cause-effect relationships designed for environmental problem solving. A methodological framework (or guideline) for decision-makers that summarises key information in the form of indicators of each component of the DPSIR from different sectors (Anita, et al 2004). The DPSIR approach is based on the use of indicators, which may be direct or indirect, ecological, technical, socioeconomic or cultural. The approach involves two main questions; the first is - what is the driving force behind the problem? The problem itself is then sub divided in three stages: the pressure, deriving from the driving force, the state that the pressure creates, and the impact that results from the state. The second question is how to respond so as to change the driving forces in order to alleviate the pressure and to reverse the problem. In other words DPSIR is a sequence, which shows how the existing driving forces produce pressures that result in the current state of land resources with a negative impact on society and the environment, and this in turn, may stimulate a response. Here there is an important notion that human activity may directly or indirectly influence the degradation or rehabilitation process at every stage.

Various organisations, within the United Nations system (UNCSD) in 1996, as well as research groups (ESI, 1998), on behalf of the European Commission, have developed a framework based on such DPSIR approach (Berger-Schmitt and Noll, 2000). The DPSIR approach is being increasingly applied to environmental issues and is for example being applied amongst other things to land degradation and soil erosion by the European Environment Agency.

Because the DPSIR approach is playing such an important role in current environmental policy, it is useful to explain it in relation to desertification (Brandt and Geeson, 2001). Land degradation is mainly driven by human activities, such as intensive agriculture, overgrazing, deforestation and changes in the local population, in combination with adverse physical environmental conditions. In order to understand and manage desertification, policy makers required a framework that should take into account the various human activities (driving forces) that exert pressure on the physical environment together with changes in its quality (state). The changing physical environment, in turn, has impacts on other environmental and socio-economic issues such as loss in plant productivity, a decrease of farm income and flooding. Society usually responds to the changes and impacts by implementing environmental, general economic and social policies. A good example of a global response to desertification is the LADA project of UNEP/FAO, (2004).

The DPSIR approach has been adopted by the LADA framework for the integration of the bio-physical to the social, economic, cultural and policy factors of land degradation, and it is applied in the context of the interplay between the five capitals: natural, social, financial, physical and human (Ponce-Hernandez and Koohafkan, 2004). It is believed that land degradation indicators can be developed to define the degradation risk for a certain piece of land and for continued environmental monitoring. Such indicators can be divided into a number of different types according to different criteria: e.g. driving forces indicators related to intensification of agriculture, overgrazing, increase of local population, and increase of tourism. Pressure indicators result from the driving forces, their manifestation is in terms of unsustainable land use practices and overexploitation of natural resources (e.g. deforestation, forest fires, ground water overexploitation, etc.). State indicators result to the actual condition of the physical environment (e.g. soil water availability, soil erosion vulnerability) and describe the extent to which an area is affected by land degradation. Impact indicators reflect the degree by which livelihoods are affected by land degradation. Impacts may be related to on-site loss in plant productivity, loss in farm income or off-site impacts, such as flooding of lowland, dam sedimentation. Response indicators relate to implementation of programs to tackle the drivers and pressures and improve the state or condition of the land such as protecting areas from desertification, the application of sustainable farming systems, terracing, ground water recharge, storage of runoff water, controlled grazing, protection forest from fires, amongst many others.

Within the DPSIR framework the task of decision makers is therefore that of assessing the land degradation by identifying the acting driving forces, their pressures, the consequences on state indicators and their ultimate Impact, i.e. their negative externalities. From the assessment of Impacts decision-makers should determine appropriate responses, in order to direct the final effect of interventions in the desired direction.

2.4 Bayesian Networks: Theory and Their Applications

Over the last few years, a method of reasoning using probabilities has emerged as a response to the need for modelling uncertain behaviour in natural and human-made phenomena. Bayesian networks, belief networks, knowledge maps, and probabilistic causal networks are some of the terms used to describe these models within the artificial intelligence, probability and uncertainty modeling community.

Probabilistic models based on directed cyclic graphs have been a long and rich tradition, which began with the geneticist Sewall Wright (1921). Variants have appeared in many fields; within cognitive science and artificial intelligence, such models are known as Bayesian networks. Their initial development in the late 1970s was motivated by the need to model the top down (semantic) and bottom up (perceptual) combination of evidence in reading. The capability for bidirectional inferences, combined with a rigorous probabilistic foundation, led to the rapid emergence of Bayesian networks as the method of choice for uncertain reasoning in artificial intelligence and expert systems (Shafer and Pearl, 1990).

Bayesian networks are networks of relationships. Named "Bayes" after Reverend Thomas Bayes, (1702-1761), a British theologian and mathematician who published (1763) a basic law of probability, which is now called Bayes rule. Bayes Rule, for any two events: A and B can be written:

$$P(B/A)=\frac{P(A/B)*P(B)}{P(A)} \qquad 2.1$$

Where 'P(A)' is "the probability of A", and 'P(A|B)' is "the probability of A given that B has occurred" (Gelman and Meng, 2004). Classical inferential models do not permit the introduction of prior knowledge into the calculations. For the rigours of the scientific method, this is an appropriate response to prevent the introduction of extraneous data that might skew the experimental results. However, there are times when the use of prior knowledge would be a useful contribution to the evaluation process.

The essence of the Bayesian approach is that it provides a mathematical rule explaining how to change existing beliefs in light of new evidence. In other words, it allows for combining new data with existing knowledge or expertise (Friedman, 2001). The complex way of expressing Bayes' rule includes a hypothesis, past experience and evidence:

$$P(H/E,c) = \frac{P(H/c) * P(E/H,c)}{P(E/c)} \qquad 2.2$$

where we can update our belief in hypothesis H given the additional evidence E, and the background context or past experience c.

The left-hand term, P(H|E,c) is called the posterior probability, or the probability of hypothesis H after considering the effect of the evidence E on past experience c. The term P(H|c) is called the a-priori probability of H given c alone. The term P(E|H,c) is called the likelihood and gives the probability of the evidence assuming the hypothesis H and the background information c is true.

Finally, the last term P(E|c) is independent of H and can be regarded as a normalizing or scaling factor (Niedermayer, 1998). It turns out that Bayes' rule is very powerful and is the basic computation rule that allows updating all the probabilities in a network, which can be extended to multiple variables with multiple states, of which the equations are far more complex to compute by hand so this requires a computer program with imbedded algorithms to solve them effectively.

Bayesian Networks are computational and mathematical objects that represent compactly, joint probability distributions by means of a directed acyclic graph denoting dependencies and independencies among variables and conditional probability distributions of each variable, given its parents in the graph (Aliferis, et al., 2003). The directed acyclic graph structure of the network contains nodes representing stochastic variables, and arcs between nodes representing probabilistic dependencies. While constructing Bayesian networks from databases, nodes are used to represent database attributes or variables which might be discrete, continuous, or propositional (true/false). Arcs specify the independence assumptions that must hold between the attributes. The values taken on by each attribute represented by a node is referred to as a “state”. When two nodes are joined by an arc, the causal node is called the “parent” of the other node. It is also possible to see the words “node” and “variable” used interchangeably but “variable” usually refers to the real world or the original problem, while “node” usually refers to its representation within the Bayesian network (Alferis, et al., 2003).

There are two components in a Bayesian network: the qualitative, which is the graphical structure, and the quantitative, which is the assessment of probabilities for each node.

The independence assumptions between the nodes determine what probability information is required to specify the probability distribution among the attributes in the network (Charniak, 1991). Here the concept of conditional probability is very useful; there are countless real world examples where the probability of one event is conditional on the probability of a previous one. Conditional probabilities represent likelihoods based on prior information or past experience. The probability of any node in the Bayesian network being in one state or another without current evidence is described using a conditional probability table. Probabilities on some nodes are affected by the state of other nodes, depending on causality. Prior information about the relationships among nodes may indicate the likelihood that a node in one state is dependent on another node's state. Every node has a conditional probability table, or *CPT*, associated with it. A conditional probability is stated mathematically as $P(x \mid p_1, p_{2\ldots}, p_n)$, i.e. the probability of variable X in state *x* given parent P_1 in state p1, parent *P2* in state *p2*, and parent Pn in state *pn*. That is, for each Parent and each possible state of that parent, there is a row in the CPT that describes the likelihood that the child node will be in some state (Niedermayer, 1998).

In the past, when scientists, engineers, and economists wanted to build probabilistic models of worlds, so that they could attempt to predict what was likely to happen when something else happened, they would typically try to represent what is called the "joint distribution". This is a table of all the probabilities of all the possible combinations of states in that world model. Such a table can become huge, since it ends up storing one probability value for every combination of states, this is the multiplication of all the numbers of states for each node, while the sum and product rules of probability theory can anticipate this factor of conditionality. For example, the prospect of managing a scenario with 6 discrete random variables (2^6-1= 63 discrete parameters) might be manageable but an expert system for monitoring patients with 37 variables resulting in a joint distribution of over 2^{37} parameters with 137,438,953,472 variables would not be manageable. This shows that for models of any reasonable complexity, the joint distribution can end up with millions, trillions, or an unbelievably large number of entries. Clearly a better way is needed.

Using a Bayesian Network offers many advantages over traditional methods of determining causal relationships, which use the product rules of probability theory for joint distributions. Bayesian networks decompose the joint probability distribution with the graph of conditional independence, the graphical structure factorizing the joint probability distribution (Ramoni, 2003). Using Bayesian networks, independence among variables is easy to recognize and isolate while conditional relationships are clearly delimited by a directed graph edge: two variables X and T are conditionally independent given the set of variable Z if and only if P(T/X,Z)=P(T/Z) (Tsamardinos, et al, 2003). Simply, if all the paths between the two nodes are blocked given that the edges are directional, hence we can utilize the graph both visually and algorithmically to determine which parameters are independent of each other. Instead of calculating all joint probabilities, we can use the independence of the parameters to limit our calculations since a Bayesian network only relates nodes that are probabilistically related by some sort of causal dependency, an enormous saving of computation can result. There is no need to store all possible configurations of states. All that is needed to store and work with is all possible combinations of states, between sets of related parent and child nodes or families of nodes. This makes for a great saving of table space and computation, that is, not all the joint probabilities need to be calculated to make a decision. Extraneous branches and relationships can be ignored by optimizing the graph, every node can be shown to have at most k number parents. Therefore, the algorithm can run in linear time based on the number of edges instead of exponential time based on the number of total parameters (Niedermayer, 1998).

Although Bayesian probability has been around for a long time it is only in the last few years that efficient algorithms and tools to implement them have been developed to enable propagation in networks with a reasonable number of variables. For larger nets with many dependencies and nodes that can take on more than two values, doing the propagation in such cases is in fact generally very difficult. There were no universally efficient algorithms for doing these computations. This observation, until relatively recently, meant that Bayesian networks could not be used to solve realistic problems. However, in the 1980s researchers discovered propagation algorithms that were effective for large classes of Bayesian networks. With the introduction of software tools that implement these algorithms as well as providing a graphical interface to draw the graphs and fill in the probability tables it is now possible to use Bayesian networks to solve complex problems without doing any of the Bayesian calculations by hand. Since the Bayesian propagation computations are very complex and cannot be calculated manually, with these algorithms it is possible to perform fast propagation in large Bayesian networks with numbers of nodes and millions of state combinations. The recent explosion of interest in Bayesian networks is due to these developments, which mean that for the first time realistic size problems can be solved. These recent developments make Bayesian networks the best method for reasoning about uncertainty.

Generally, the algorithms can be grouped into two categories: one category of algorithms uses heuristic search methods to construct a model and evaluates it using scoring methods. This process continues until the score of the new model is not significantly better than the old one. The other category of algorithms constructs Bayesian networks by analyzing dependency relationships among nodes. The dependency relationships are measured by using some kind of conditional independence test (Cheng, et al, 1997).

In Bayesian networks the conditional independence implied by the absence of any connecting arrows, greatly simplifies the modeling process by allowing separate sub-models to be developed for each conditional relationship indicated by presence of an arrow. These sub models may be derived from any combination of process knowledge, statistical correlations, or expert judgment depending on the extent of information available about that particular relationship (Borsuk, et al, 2002). Knowledge of the Bayesian network representing the joint distribution is useful for causal discovery, prediction, classification and diagnosis for every variable of interest T. A reasonable compromise to learning the full Bayesian network is to discover only the local structure or neighbourhood around the target variable of interest T. The set of variables in this structure is called the "Markov blanket" (Tsamardinos, et al, 2003). The set of parents, children and spouses or parents of common children of T in a Bayesian network has special properties given the values of these variables, the probability distribution of T is completely determined and knowledge of any other variable in the network becomes superfluous.

Bayesian networks are powerful modeling tools for condensing what is known about causes and effects into a compact network of probabilities. When there is an evidence of an effect, the inferred most likely cause is called diagnostic, or bottom up reasoning, since it goes from effects to causes. Bayesian networks can also be used for causal or top down reasoning, hence are often called generative models (Murphy, 1998). The built network is a model which reflects the states of some part of a world that is being modeled and it describes how those states are related by probabilities. The most important aspect of a Bayesian network is that they are direct representations of the world not of the reasoning process. The arrows in the diagram represent real causal connections and not the flow of information during reasoning. The reasoning process can propagate information in any direction (Perl and Russell, 2000).

Bayesian networks also allow for vague, incomplete, and uncertain information, both about the past and about the current situation (Russell, Norvig.P, 2003). Uncertainty arises in many situations. For example, experts may be uncertain about their own knowledge, there may be uncertainty inherent in the situation being modeled, or uncertainty about the accuracy and availability of information. Because Bayesian networks offer consistent semantics for representing uncertainty and an intuitive graphical representation of the interactions between various causes and effects, they are a very effective method of modeling uncertain situations that depend on cause and effect.

Another reason Bayesian networks are proving so useful is that they are so adaptable. Bayesian networks are useful for both inferential exploration of previously undetermined relationships among variables as well as descriptions of these relationships upon discovery (Friedman and Goldszmidt, 1997). The benefit of such a process is evident in the ability to describe the discovered network in the future. The network can be started off small, with limited knowledge about a domain, and grow as new knowledge is acquired. Furthermore, when applied, it is not necessary to have a complete knowledge about the instance of the world that it is applied to. It allows using as much knowledge as it is available, and the network will do as good a job as it is possible with the available knowledge.

Bayesian networks can be used in any walk of life where modeling an uncertain reality is involved and hence probabilities are present wherever it is helpful to make intelligent, justifiable, quantifiable decisions that will maximize the chances of a desirable outcome (Norsys, 2004)

Although Bayesian networks were introduced a mere fifteen years ago, they have already led to a long series of pioneering applications. It is proven useful in practical applications including medical diagnosis, diagnosis of mechanical failures, and adaptive human interfaces for computer software.
Its most celebrated use has been by Microsoft ™ where Bayesian networks underlie the help wizards in Microsoft Office ™ and also underlie the interactive printer fault diagnostic system on the Microsoft web site. It is also most commonly used for diagnosis particularly medical diagnosis. An example of the use of Bayesian networks in this area is "Pathfinder" (Heckerman, 1990), a program to diagnose diseases of the lymph node.

Bayesian networks can also be used for prediction since the links signify cause-effect relationships between parent and child nodes it is possible to supply evidence of past events and then run the network to see what the most likely future outcomes will be. Bayesian networks are used for weather forecasting, stock market prediction and ecological modeling. For making such predictions their strength is that they are very robust to missing information and make the best possible prediction with whatever information is present.

Among others, Bayesian networks are also being heavily used in modeling ecosystems. Often fish and wildlife experts are faced with the difficult task of suggesting land use policy. They must balance the interests of industry, community, and nature and they need scientifically sound and justifiable arguments to back-up their analyses and decisions. With Bayesian networks they can model an ecosystem and derive sound probabilities on whether certain species are at risk by certain industrial developments (Marcot, 2002).

Bayesian networks proved its application in Sensor fusion, which refers to the class of problems where data from various sources must be integrated to arrive at an interpretation of a situation. For instance, industrial sensors might each report on the state of a machine and only by joining all their readings together that one gets the complete picture. Often, in sensor fusion problems one must deal with different temporal or spatial resolutions and one must solve the correspondence problem, that is, deciding which events from one sensor correspond to the same events as reported in the other sensors. Because Bayesian networks are robust to missing data and they combine information well, whereas each sensor has only a limited chance of giving a correct interpretation, the combination of all the sensors typically increases the likelihood of a valid interpretation (Norsys, 2004).

To conclude, Bayesian networks have the great power to offer assistance in a wide range of endeavours. They support the use of probabilistic inference to update and revise belief values. Bayesian networks readily permit qualitative inferences without the computational inefficiencies of traditional joint probability determinations. In doing so they support complex inference modelling including rational decision making systems. As such they are useful for causality analysis and through statistical induction they support a form of automated learning, which can involve network discovery and causal relationship discovery. Bayesian networks on their own enable us to model uncertain events and arguments. The intuitive visual representation can be very useful in clarifying previously opaque assumptions or reasoning hidden in the head of an expert. With Bayesian networks it is possible to articulate expert opinion about the dependencies between different variables. This allows the application of scientific rigour when the probability distributions associated with individual nodes are simply expert opinions. The breadth and eclectic foci of the many individuals, groups and corporations researching this topic makes it one of the truly dynamic areas within the discipline of artificial intelligence and environmental modeling.

CHAPTER 3

Statement of Research Problem and Research Objectives.

3.1 Statement of the research problem.

The current methodology for land degradation assessment at multiple scales from local to global is based on the existing global assessment of human induced land degradation (GLASOD) approach (Oldman et al, 1991). In essence the GLASOD database contains information on soil degradation within map units as reported by numerous soil experts around the world through questionnaires. It includes the type, degree, extent, and rate of soil degradation on a map.

The major drawbacks of the GLASOD methodology include: (1). It is an expert-driven (opinion) assessment, not a real assessment derived from measured observations of variables or indicators, (2) Its methodology also has a strong biophysical bias ignoring important social and economic factors. In addition, (3) Prior land degradation assessment methodologies including GLASOD do not allow linking the final state of land degradation and its most probable causes, which is important for policy formulation and remediation of the process.

Since the links between the states of land degradation and its multiple causes are very complex they cannot be known and modelled deterministically, therefore a new probabilistic approach must be followed. For practical purposes, it would be useful to policy-makers to count on a modelling tool, which could determine the most likely causes of the final states of land degradation process in a given area of concern. The probabilistic approach to causal relationships lends itself readily to causal exploration and could prove very useful as a tool to examine and to establish the causes of the states of land degradation and their intensity and extent in a given area of concern.

3.2 Research Objectives

Given the problem of the need for a methodology which links the bio-physical states of land degradation to its social, economic, and policy causes, and the need for a probabilistic approach to determine such causes, the research reported in this thesis has as its objectives the following:

(1). Introduce a model based on the DPSIR approach to link land degradation states (i.e. intensity, type and extent) to its causes (i.e. drivers and pressures). The complexity of such relationships makes the model to take the form of a network. A network of causal chains.

(2). Examine the advantages of introducing a new Bayesian probabilistic approach to the establishment of root causes of land degradation through Bayesian networks of causal chains applicable to assessments.

(3) Develop a practical application and implementation of a Bayesian network of causal chains model to land degradation data.

(4). Evaluate the suitability of Bayesian Networks for land degradation causal exploration through the application of a Bayesian Network Model to existing data sets of land degradation indicators gathered from a dry land area.

(5). To translate the findings from the objectives above to a model for automated causal exploration. Which will be a useful tool in land degradation assessment work.

(6). Finally, explore the technical issues related to using GIS to map out the causes, intensity and extent of land degradation in the dry land area under study.

In summary, the above objectives of the research are intend to explore Bayesian networks of causal chains (BNCC) as a suitable approach to the establishment of the most probable causes of land degradation in dry lands and to develop a computer based model to implement BNCC within the Driving force – Pressure – State – Impact – Response (DPSIR) methodology.

CHAPTER 4

Approach and Methods

Given the research objectives established in the preceding chapter, a model of Bayesian Networks of causal chains for land degradation assessments requires field data for its development and for examining its applicability. Data from a dry land study area in Mexico were available and are used in this research.

4.1 General Description of the Study Area

4.1.1 Location and Physiography

The study area is located in central part of Mexico. A sub watershed which includes most of the Ejido lands of El Alegre village in the municipality of Salinas, in the state of San Luis Potosi. El Alegre covers an area of 4445 hectares (44.45 square kilometres), with a perimeter of 28.96 km; and both, the circular ratio and shape index indicate that the micro-watershed is elongated. Geographically the micro-watershed is located within the coordinates: longitude 101° 44′ to 101° 39′ W and latitude 22° 35‘ 37.95” to 22° 30’44.28” N. The area has a mean slope of 5.35 percent and mean altitude of 2200 m.a.s.l.(Amante Orozco, et al.,2002).

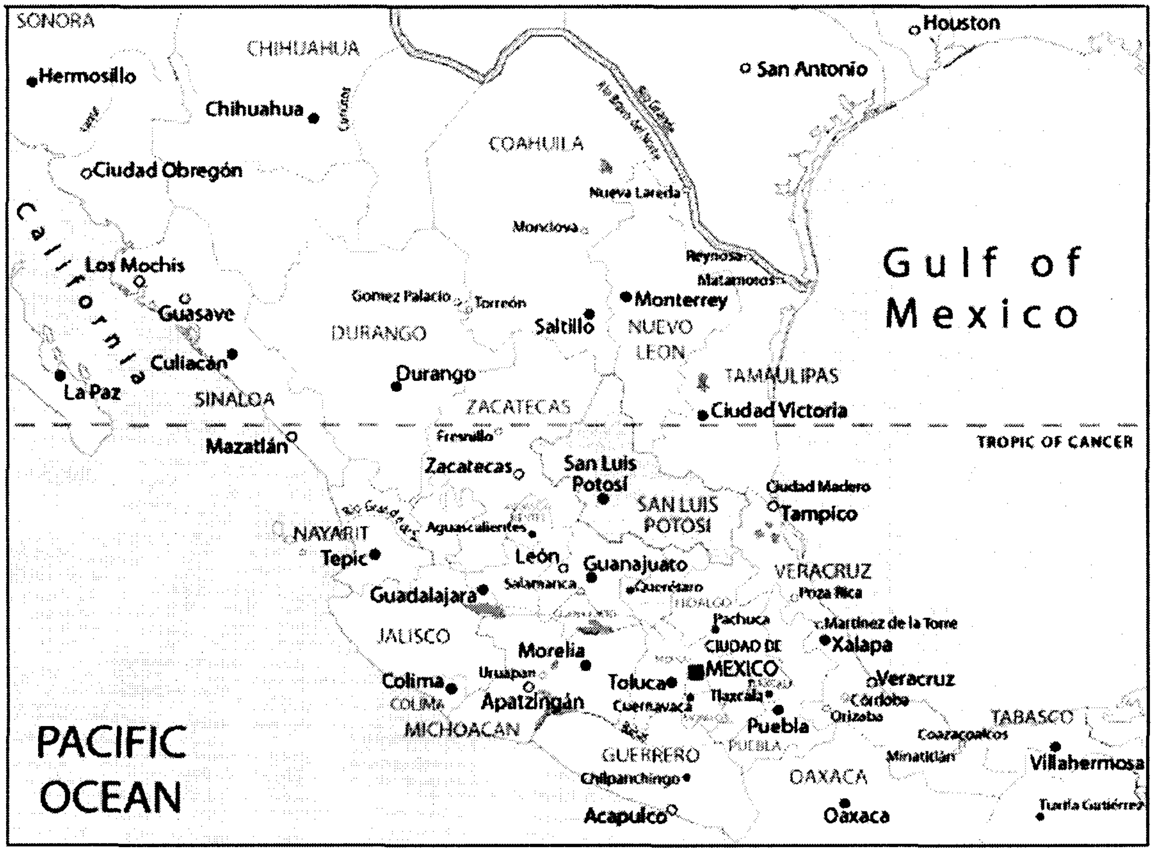


Figure 4.1. Location of the state of San Luis Potosi in Mexico.

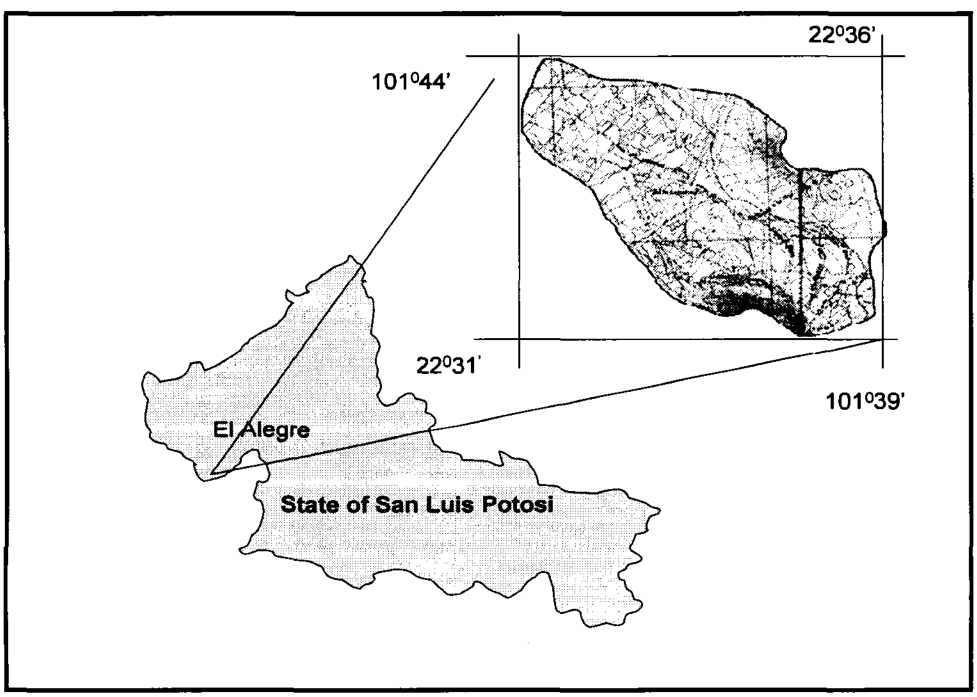


Figure 4.2. Location of El Alegre study area in San Luis Potosi, Mexico.

Figure 4.3 Three dimensional view of the study area (Google Earth, 2006).

The study area is within the highlands of the central continental plateau, a vast intermountain arid basin, geographically sheltered by two of the highest and longest mountain ranges in Mexico: the Sierra Madre Oriental to the east and the Sierra Madre Occidental to the west. The topography is generally flat, with gently sloping and elongated alluvial fans and pediments, and a flat sedimentary basing surrounded by two small hills and a small sedimentary, post-orogenic mountain - (El Penon Blanco).

The geology of El Alegre is comprised of Lower Cretaceous-aged volcano-sedimentary rocks consisting of flysch (siltstone, gravel ywacke, limestone, and marls) and andesites. Post-orogenic continental debris, including coalesced alluvial fans, clastic sediments with minor quantities of carbonates and evaporites are also mixed with scattered mafic to silicic volcanic rocks.

4.1.2. Natural Resources

Climate

Dry and temperate climate is the dominant type of climate in the area with rainy season in the summer, and having winter rainfall between 5 and 10 mm. The mean annual precipitation ranges between 300 and 500 mm. The mean annual temperature is 16.4 °C and the maximum evaporation in the micro-watershed is 1,560.9 mm.

According to 13 years of data from the meteorological station at Colegio de Postgraduados, Campus San Luis Potosí, the precipitation in the study area is concentrated in the months from June to September (figure 4.4), with the presence of a dryer period in the months of July and August. The mean annual precipitation is 376.68 mm, with a minimum precipitation of 193.3 and a maximum of 562.45 mm.

According to 13 years of data from the meteorological station at Colegio de Postgraduados, Campus San Luis Potosí, the precipitation in the study area is concentrated in the months from June to September (figure 4.4), with the presence of a dryer period in the months of July and August. The mean annual precipitation is 376.68 mm, with a minimum precipitation of 193.3 and a maximum of 562.45 mm.

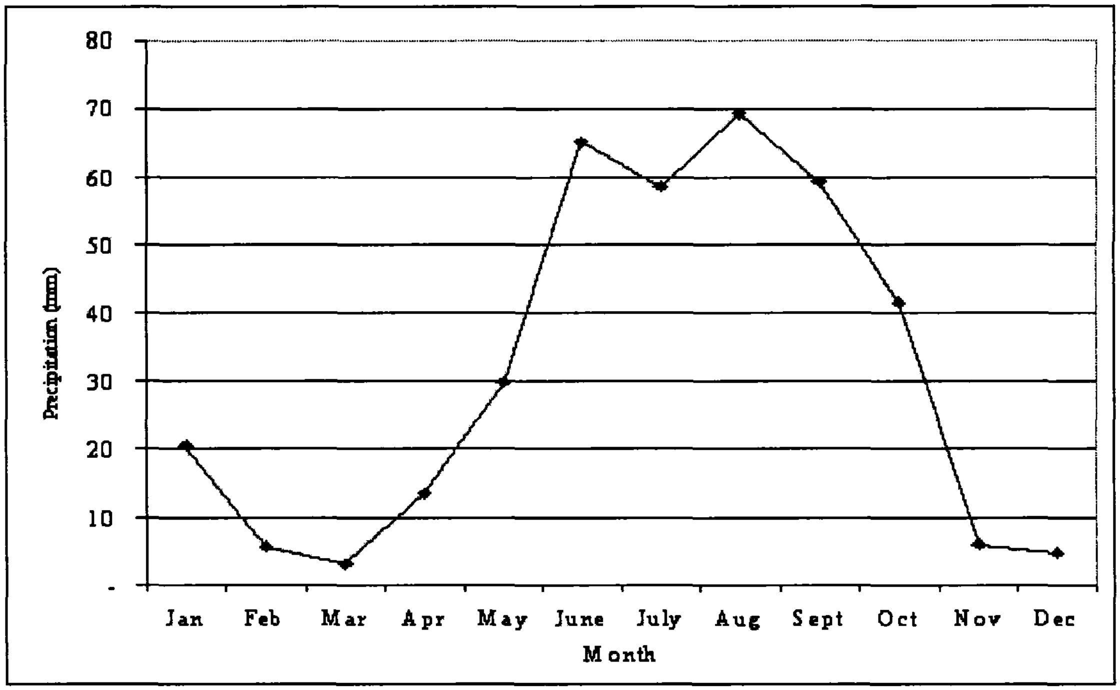


Figure 4.4 Monthly distribution of precipitation in El Alegre (R.L. Dixon, et al. 2002)

Soil

Approximately 53 percent of the drainage area is covered by medium-textured soils classified as Eutric Litosols (Le), primarily on slopes ranging from 8 to 10 percent, causing reduced potential for moisture retention and shallow depths. The remaining 47 percent of the study area has soils classified as Phaeozem (Hi). These are mature soils with medium textures on flat or slightly undulated lands with slopes less than 8 percent (figure 4.5).

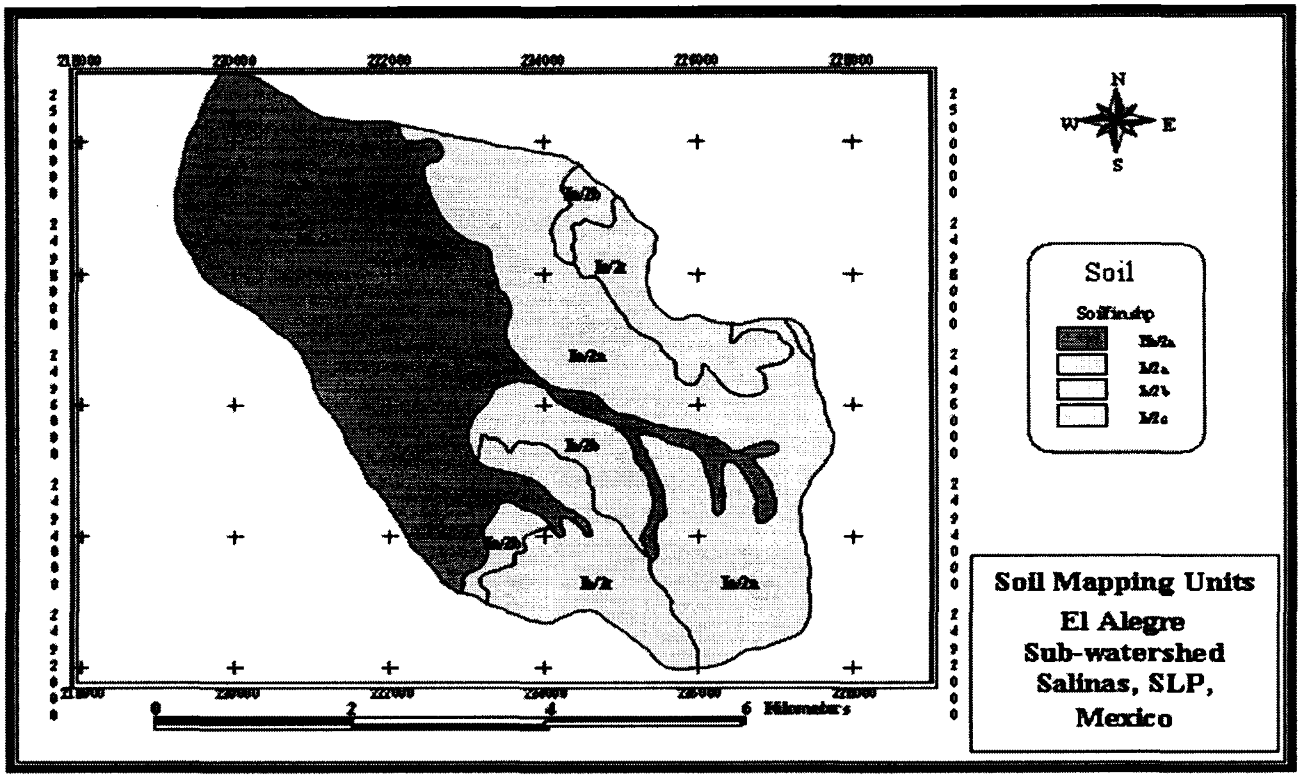


Figure 4.5 Soil map of El Alegre (R. L.Dixon, et al., 2002)

Vegetation

The dominant vegetation type in the sub-watershed is an association of thorny shrubs, low level prickly brush and natural grasslands, punctuated by some varieties of cacti. Characteristic of shallow soils, "cenizo" (Leucophylum frutescens) is found in the area, along with "gobernadora" (Larrea tridentata), "espino negro" (Acacia amentacia), "lechugilla" (Agave lechuguilla), and grass species such as Bouteloa curtipendula, B. gráciles, and B. Escorpionidae, which cover approximately 20 percent of the area of study. Associations of thorny shrubs (mesquites, huizaches, amargoso, grangeno), with cacti known locally as "nopales" (Opuntía leucotricha, O. robusta, O estreptacantha, among others) are also common (table 4.1 figure 4.6).

Table 4.1 Land use and land cover in the sub-watershed El Alegre (R.L.Dixon, et al., 2002).

Land Use/ Land Cover	Code	Area (Ha)	% Area
Permanent annual rainfed Agriculture	AtpA	307.96	6.93
Permanent annual rainfed Agriculture – Prickly Shrubs	AtpA-S(Ms)	1,577.27	35.48
Brush	Ch	53.23	1.20
Shrubs	Mi	35.61	0.80
Shrubs-Crasirosulipholious-Natural Pastureland	Mi-CR-Pn	217.17	4.89
Shrubs-Natural Pastureland	Mi-Pn	621.95	13.99
Prickly shrubs-Izotal-Crasirosulipholious	Ms-Iz-CR	179.45	4.04
Prickly shrubs-Cacti (Nopal)	Ms-No	292.24	6.57
Prickly shrubs-Cacti (Nopal)- Crasirosulipholious	Ms-No+CR	679.64	15.29
Prickly shrubs-Cacti (Nopal)-Izotal	Ms-No-Iz	289.6	6.51
Cacti (Nopal)_ Crasirosulipholious	No-CR	123.26	2.77
Cacti (Nopal)-Izotal- Thorny Prickly shrubs	No-Iz-Ms	37.67	0.85
Urban Zone	Z. Urbana	30.16	0.68
Total		4,445.22	100.00

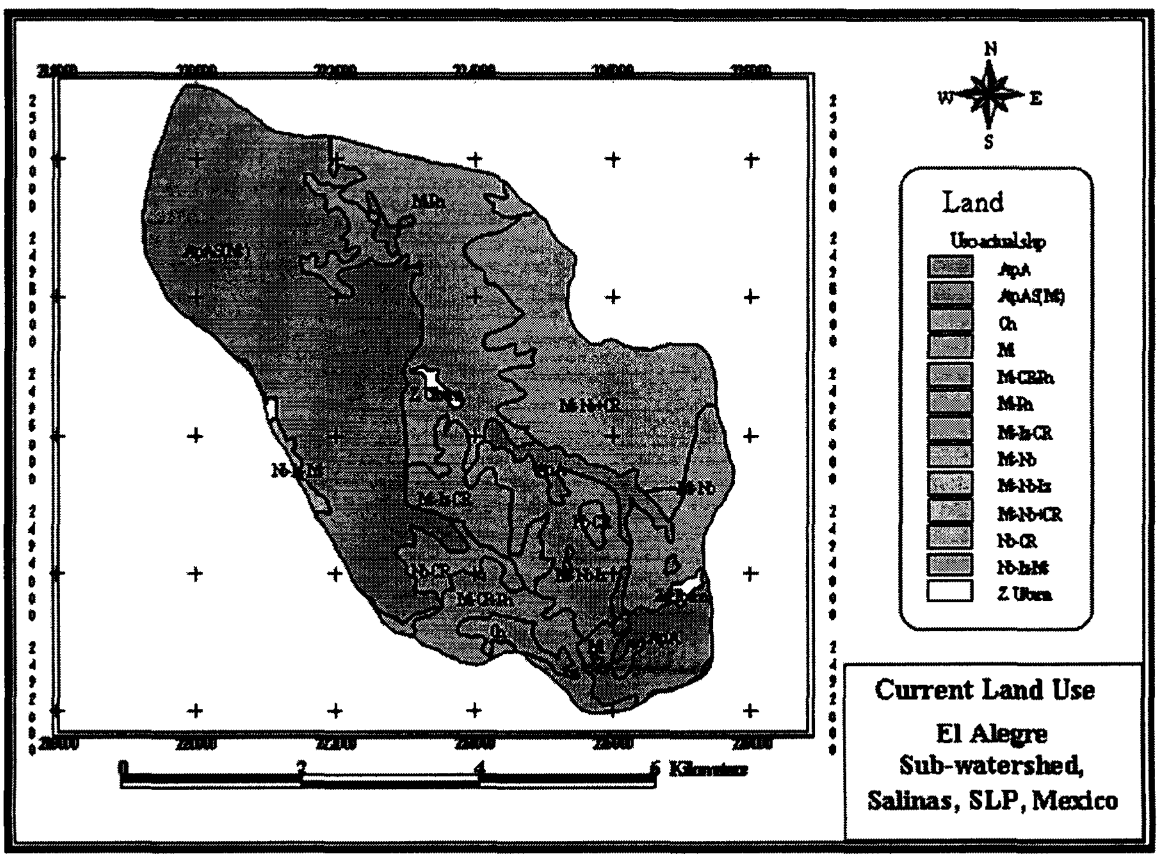


Figure 4.6 Land Use in the sub-watershed “El Alegre” (R.L.Dixon, et al., 2002)

Potential Land Use

About 55.28% of the area of the micro-watershed is covered by lands with capability class IV according to the USDA land capability classification system. These lands show very severe limitations for agricultural crop production. To put these soils under cultivation, conservation measures would be required. Even when these soils are cultivated, they can only be so for a reduced group of crops, particularly pastures, forests or wildlife. Their main constraints are shallow depth and being highly vulnerable to erosion by water and wind.

About 24.4% of the land belongs to capability class VIII. These lands have limitations for their use in commercial crop farming, the development of pasturelands or forestry enterprises. Lands in this class should be used for wildlife and water supply only. The main limiting factors are soil depth and the slope, causing low water retention capacity in the soil profile which favours surface runoff and consequently increase erosion risk; this reaches very high levels, as a consequence of deficient range management and the surfacing of the rock and boulder outcrop.

The remaining 26% of the area in the micro-watershed are lands of fifth, sixth and seventh capability class (table 2 and figure 6).

Table 4.2 Land Capability Classification in El Alegre (R.L.Dixon, et al., 2002)

Capability Class	Total	% Area
IV/Sc	1,925.37	43.31
V/S	532.18	11.97
VI/S	575.60	12.95
VI/Sc	320.90	7.22
VII/S	6.74	0.15
VIII	552.06	12.42
VIII/T	532.36	11.98
Total	4,445.215	100.00

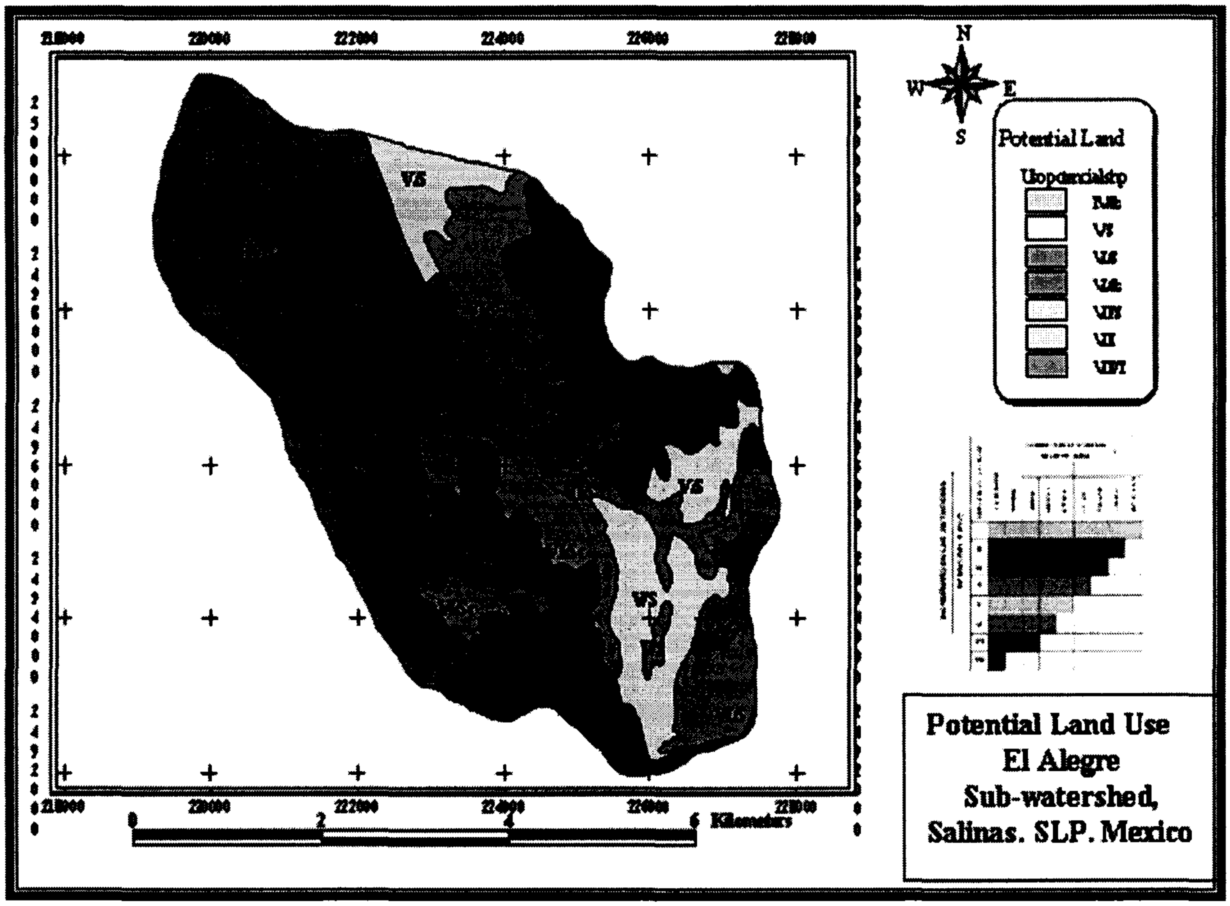


Figure 4.7 Land Capability Classifications for El Alegre (R.L.Dixon, et al., 2002).

The above mentioned types of potential land capability classes in the study area and their characteristics, combined with improper biomass range management and heavy livestock pressures, have encouraged severe erosion in the area (table 4.3 and figure 4.8).

Table 4.3 Land affected by different degree of erosion in El Alegre. (R.L. Dixon, et al., 2002)

Erosion (t/ha)	Area Affected (ha)	% Area
<10	365.98	8.23
10-20	2,627.19	59.10
20-50	782.83	17.61
50-100	12.84	0.29
100-250	165.06	3.71
250-500	194.63	4.38
500-1000	283.69	6.38
>1000	13.00	0.29
Total	4,445.22	100.00

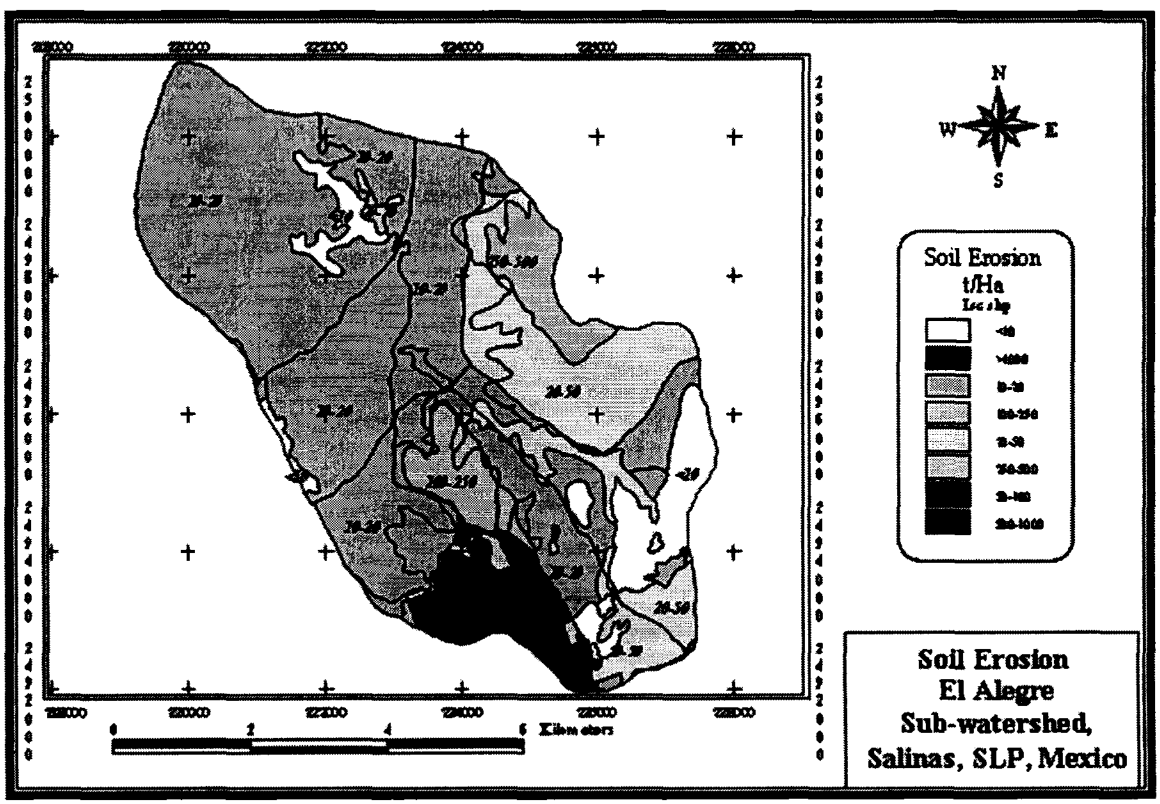


Figure 4.8 Soil Erosion (tones/hectare) in El Alegre (R.L.Dixon, et al., 2002).

4.1.3 Demographics

Social Setting

El Alegre has a total population of 271 inhabitants with 139 men and 132 women (General Census of Population and Housing, 2000). Around 37 inhabitants are identified to be the economically active category having a constant income, from these, a highest percentage involved in primary production.

The census also indicated that El Alegre has 48 privately inhabited houses, 23 of them have roofs constructed of sheets of cardboard, or other waste materials and all but 13 have dirt floors.

El Alegre has electrical and rural telephone services and water is collected manually from several communal wells throughout the ejido with none of the houses in the village having private potable water or pluming. Regarding health facilities there is no health clinic in EL Alegre, the nearest is 10 km away in Salinas de Hidalgo. In the sector of education El Alegre has a kindergarten, a primary school and a television-based, distance-learning secondary school.

In terms of waste disposal there is no organized garbage collection and treatment in the village solid wastes are burned, dumped on streambeds or left dispersed around the village, due to the lack of common dumping area with in the village.

It is possible to access the EL Alegre all year round through a dirt road that intersects with the San Luis Potosi–Zacatecas highway but there is no public transport to or from the village.

Economic Setting

Rain-fed agriculture is the predominant economic activity practiced in El Alegre, with a very small proportion of fields under irrigation producing mostly corn and beans. The other major economic activity practiced in the village is extensive livestock production dominated by cows and goats and to a lesser extent they raise sheep and pigs.

The agricultural practice in the village is a traditional no input farming incurring high levels of risk and low productivity. In addition the agriculture suffers erratic rainfall and drought in various seasons.

For years there is lack of assistance and resource availability to the farmers and even if there is adequate production, there are problems of commercialisation and sale of products.

Even though the area has favourable growing conditions, very few families cultivate vegetables or fruit trees. This shows the lack of tradition in the management, selection and care of fruit trees in the area and lack of extension services to train the farming population to this end.

The inhabitants earn a very low income and the majority live in absolute poverty. Other than agricultural production and the collection and sale of rangeland products there are very few sources of employment in El Alegre. The villagers have a very limited access to credit facilities and the support from aid agencies, government assistance and subsidies are inadequate as compared to the burden of problems faced by the inhabitants of the village.

4.2. The Model Development Approach

This approach to model development involves the combined use of Driving Force, Pressure, State, Impact, and Response (DPSIR) methodology and Bayesian networks in an attempt to model the state (i.e. intensity and extent) of land degradation and its causes in the study area.

DPSIR is an analytical approach often used to handle complex interactions between the social, economic or demographic processes and the natural system or ecosystem processes. The approach adopts a circular reasoning, which allows to link human activities as drivers that create pressures, to the states of environmental degradation and their impacts. DPSIR has become a methodological framework or guideline for decision-makers that summarises key information in the form of indicators for each DPSIR component from different sectors. As Land degradation cannot be assessed by any single measure, therefore, it is important to use indicators or proxy variables, which integrate the aspects of the degradation processes. These indicators are selected for each DPSIR component to show the evidence that land degradation has occurred in a given area, together with its nature, intensity and its spatial extent.

Therefore, the Driving Force- Pressure- State-Impact- Response (DPSIR) approach lends itself as the most suitable framework for investigating the formalization of the networks of causality and states of land degradation.

Since one of the main objectives of this thesis is to investigate a procedure for linking the multiple causes of land degradation to its states, from the entire set of

DPSIR components, the model developed in this thesis is only directly concerned with the first three components, namely, Driving Force, Pressure and State. This decision was made due to the unavailability of data about impacts on livelihoods and on responses by farmers to such adverse conditions. This reduction in DPSIR components considered in the model does not affect causal exploration, which is directly related to the first three, i.e. Drivers, Pressures and States. In turn, this helps to reduce output complexity as a result of exclusion of the last two DPSIR components.

A much simpler approach to integrate the indicators and establish causality, than the use of Bayesian Networks can be through the use of analogue or "manual" process, where by on a paper the user (typically a local expert) selects indicators relevant to the existing condition from the list, or adds other indicators not listed, which are considered locally relevant. Then he or she establishes casual links or networks according to the expert's own experience and knowledge of the circumstances in the geographic area where the assessment is being performed, supported by data from interviews, documented evidence in reports and other available information. This method will enable showing only the causality between the indicators of Driving Forces, Pressures and the State of land degradation not allowing room for the inclusion of the intensity and extent of the degradation. An example from (Ponce-Hernandez and Koohafkan, 2004) is shown bellow in (figure 4.9).

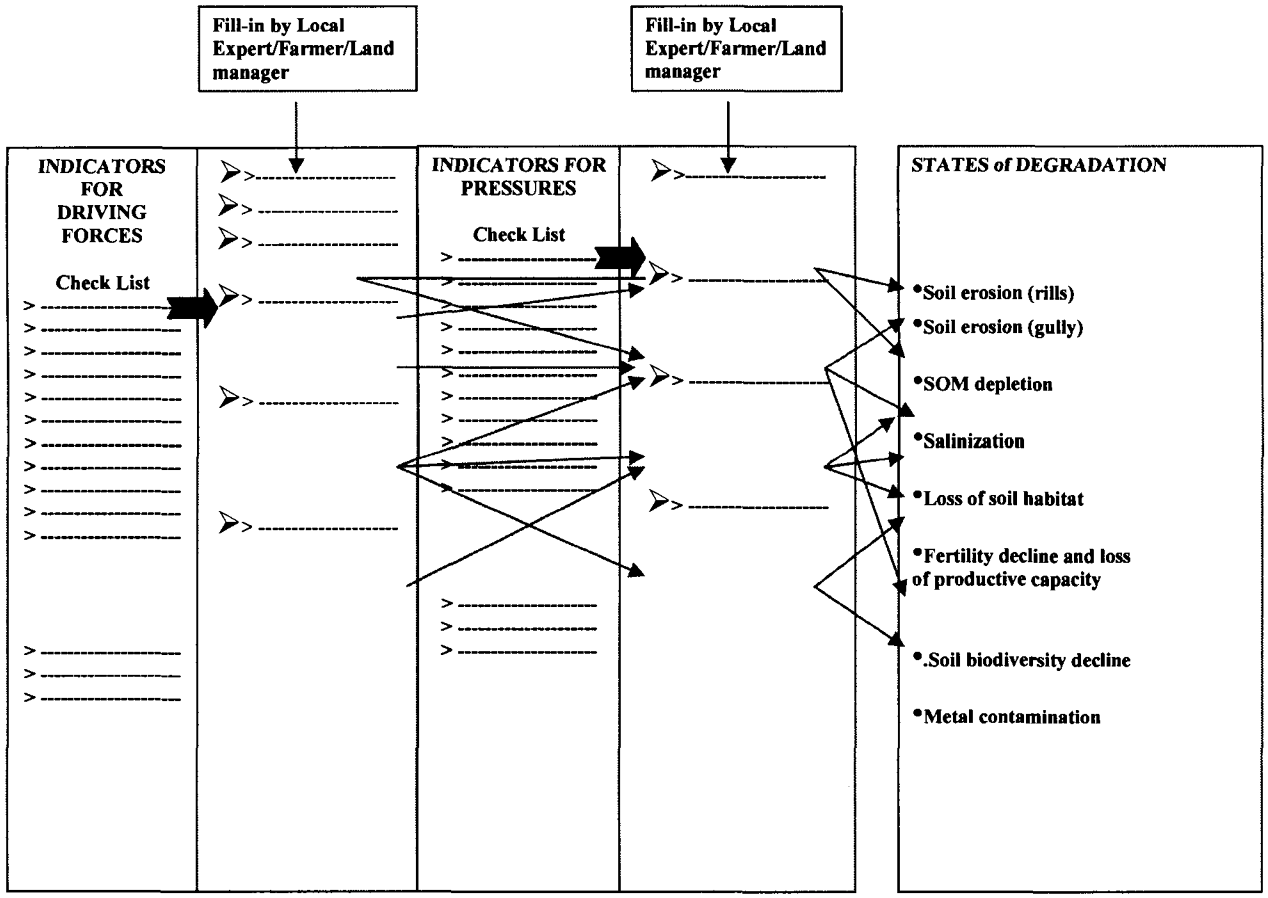


Figure 4.9 Fill-in forms for casual analysis through manual procedure (Ponce-Hernandez and Koohafkan, 2004)

An alternative and enhanced approach to the previous method will be to use a Bayesian Network to model the interactions between the Driving Forces, Pressures and State indicators of land degradation.

A Bayesian Network is a directed acyclic graph (DAG) consisting of a set of nodes and a set of directed arcs, which allows the representation of a complex causal chain linking events or actions to outcomes (Pearl, 2000). There are two components in the Bayesian Networks: the qualitative, which is the graphical structure (DAG) and the quantitative, which is the assessment of probabilities for each node. Random variables can be discrete and are represented by nodes. Causal relations between variables within the domain are denoted by arc connections between nodes and signify conditional dependence not absolute causal relations. Conversely, the absence of arcs between two nodes signifies conditional independence between the two variables. Nodes without incoming arcs are known as parent nodes while nodes with incoming arcs are known as child nodes.

The graphical structure of Bayesian networks provides a compact way of depicting and communicating substantive assumptions and relationships between variables and facilitates economical representation of joint probability functions and efficient inferences from observations (Pearl, 2000). The simplicity and intuitiveness allows alternative models representing different plausible explanations and competing hypotheses to be constructed easily, thus providing a means of enhancing the quality of causality assessments. In addition, it also provides an effective technique for making use of existing knowledge and provides a coherent framework, which is easily updatable to incorporate new evidence or knowledge into the network.

An example using a Bayesian Network Directed Acyclic Graphical structure (DAG) to represent the causality interactions between Driving Force – Pressure–state indicators of land degradation is shown bellow in (figure 4.10)

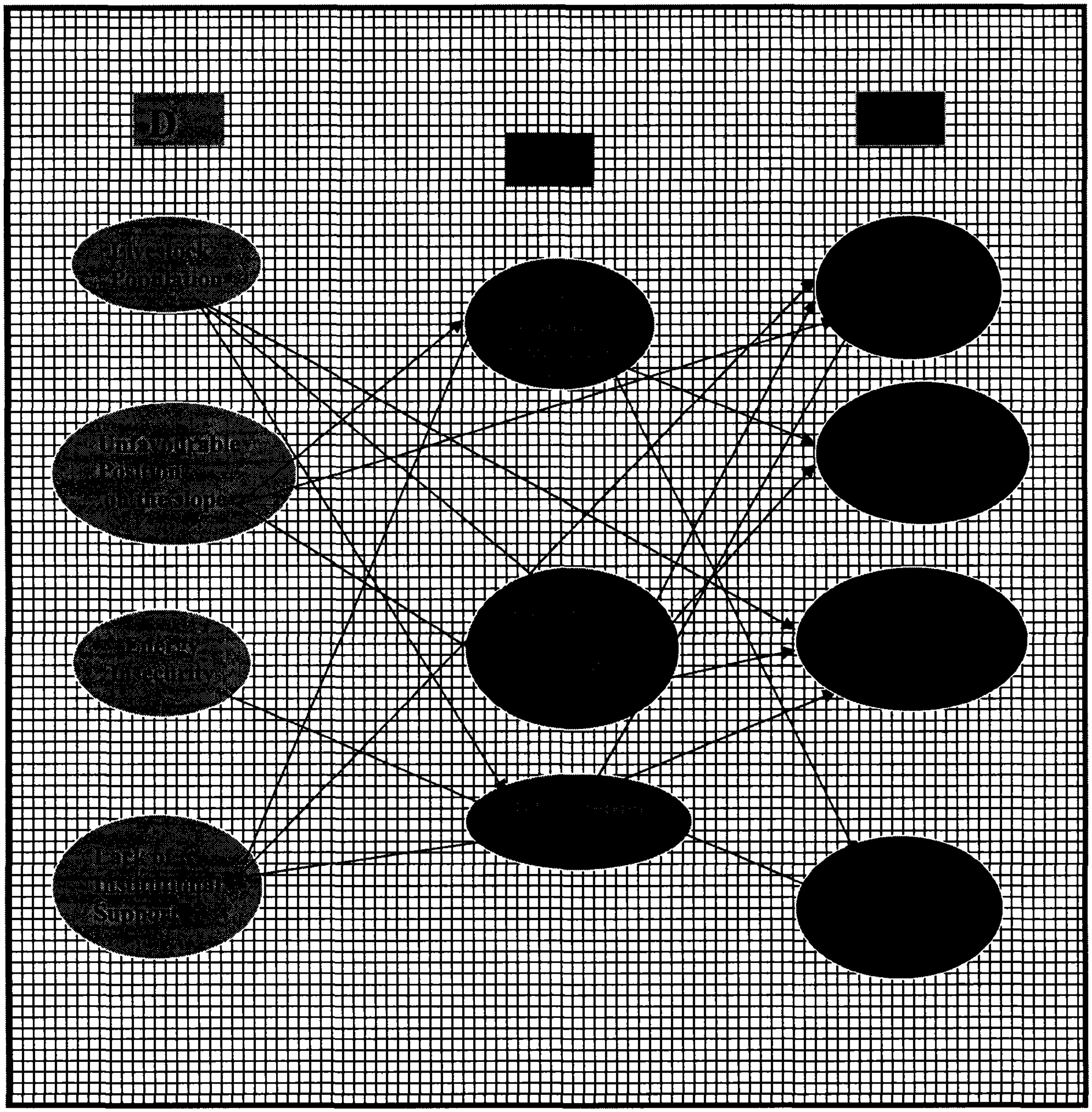


Figure 4.10 Bayesian network graphic representation for DPS indicators.

In addition to the previously listed advantages the directed acyclic graph structure can also be used to easily obtain the so called "Markov Blanket" of strongly relevant casuistic variables or indicators, which are the causes with the highest likelihood or probability for the specified state of degradation. The Markov blanket for a node in a Bayesian Network is the set of nodes composed of its parents, its children, and its children's parents.

A reasonable compromise to learning the full Bayesian Network is to discover only the local structure or neighbourhood around a target indicator (variable) of interest or a set of targets. Ideally, for causal discovery and manipulation of target indicator, the local structure of interest is a set of direct causes of the indicator, which is for every indicator of interest the set of parents, children and spouses (i.e. parents of common children), called the "Markov Blanket".

The set of indicators that make up the Markov Blanket have very special properties. Given the values of these indicators, the probability distribution of the target indicator is completely determined and knowledge of any other indicators in the network becomes unnecessary.

In this thesis the Markov Blanket of a target variable or any state indicator will be the minimum conditioning set of driving force and pressure indicators which make the target independent of all other indicators. Here, the absence of arcs between two indicators means independence.

Based on this, using our previous example (figure 4.10) if we examine the Markov blanket for one of the state indicators; for example Soil Erosion by water (by Rills), its Markov blanket of strongly causistic indicators are the following

Unfavourable position on the slope, Lack of institutional support, Decrease in biomass and livestock feed, and Deforestation. (See figure 4.11).

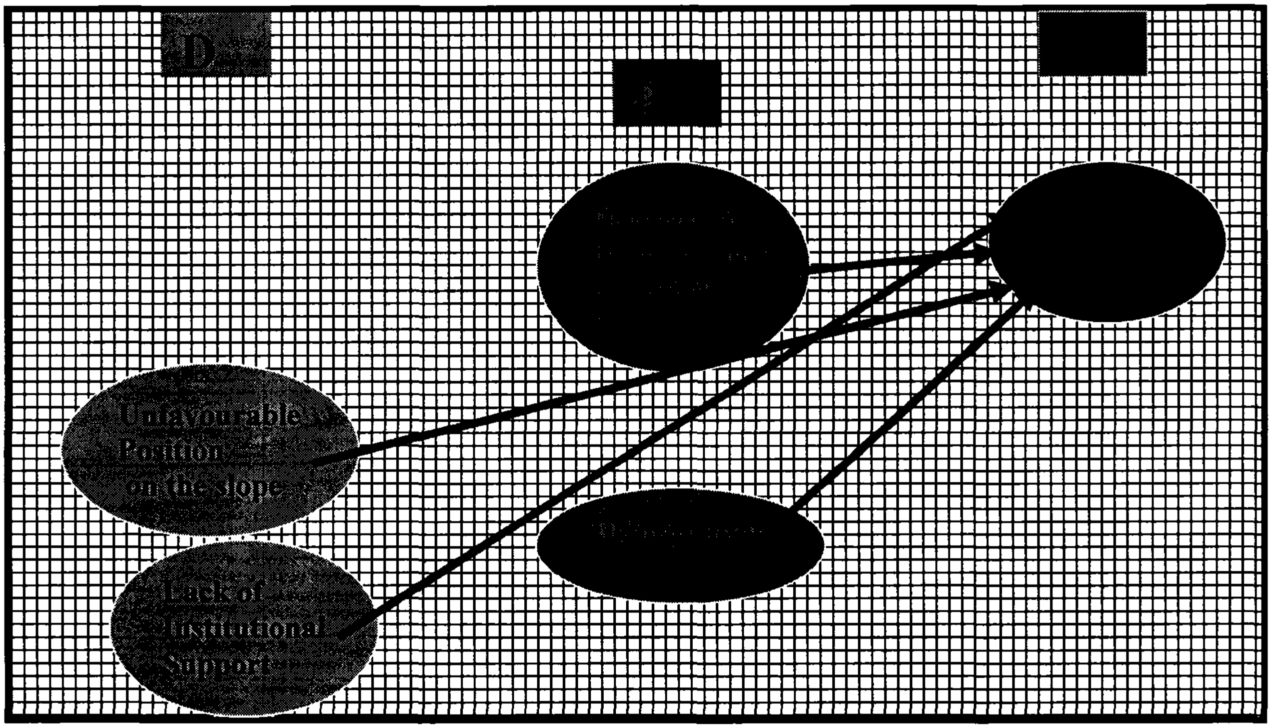


Figure 4.11 Markov blanket for Erosion by water (Rills)

This indicates that the use of the Markov blanket in the network will enable us to identify the most probable causes for any specified state indicator of land degradation, assisting in tracing back the causes for the specified states of degradation.

Besides the graphical structure, the other very important component of Bayesian Networks is the quantitative component, which involves the assessment of probabilities for each node. The relationships between nodes are defined by conditional probability functions. Nodes without incoming arcs or parent nodes are described by marginal probability and for the nodes with incoming arcs when the variables are discrete; the conditional probability function takes the form of conditional probability tables (CPTs), also called link matrices. A CPT describes the likelihood of the states or sub classes of a node given the states or sub classes of the node's immediate predecessors or parents. It contains entries of a priori probabilities for every possible combination of states of a node's parents. The CPTs must be specified for the joint condition and incorporate any interactions that might exist. Similarly, CPTs can be constructed using empirical data, output from process models, theoretical insight, probabilistic or deterministic functions, ancillary data from empirical studies independent of the constructed system, and expert judgements (Cain, 2001). The initial values in any CPT are refined through successive iterations and refinement of the model, as knowledge of the behaviour of the system reflected in the model is gained. The accuracy of causality determination also increases with iterations.

The impact of changing any variable is transmitted throughout the network in accordance with the relationships encoded in the conditional probability tables and the joint probability distribution of the entire network conditioned on these observations is inferred or calculated for other variables using Bayes' Theorem.

Bayesian Networks are well suited to the task of modelling a situation in which causality plays a role, but where our understanding is incomplete, so we need to describe events probabilistically (Charniak, 1991).

Given the multiple complex interrelationships between causes and states of land degradation and their uncertainties, a probabilistic Bayesian approach was deemed as the most suitable for modeling the networks of causality.

This thesis explores Bayesian Networks of causal chains as suitable theoretical and practical approach to the establishment of the most probable causes of land degradation in a given dry land area and develops a computer-based model to implement Bayesian Networks of causal chains within the Driving Force-Pressure- State methodology for their automated causal exploration.

This model will enable a user to graphically and interactively calculate the linkages and establishing the networks of chains of causality linking or integrating driving forces to pressures and onto states of land degradation, based on empirical evidence, data or on expert knowledge of the circumstances and complex relationships at play in the area of study.

The result of establishing these causal chains can be used to obtain a Markov blanket of strongly relevant causistic variables, which are the most likely causes for the specified state of degradation. The model can also help to show the extent and or intensity of each degradation indicator in the network through the available graphical applications.

In the approach adopted in this thesis, the major interacting variables of the model, amongst Driving force, Pressure and State indicators will be identified and selected, from a set of indicators. These selected indicators will be those relevant to the study area and a synthetic representation of the model will be built. The interactions between the indicators which are characterized based on causality will be established by means of available data, empirical knowledge and expert judgments.

The model proposed and developed in this thesis is based on three key elements, namely:

1) Nodes representing Driving Forces, Pressures and State indicators (e.g. Livestock population, unfavourable position on the slope, deforestation, etc...) Each variable will be discrete and will have a finite set of mutually exclusive states (e.g. high, medium, low or slight, moderate, intense etc. for which continuous, discrete or categorical values are used to parameterize them).
2) Links representing causal relationships between these nodes (from parent node to child node, i.e. from cause to effect);

3) A set of conditional probabilities describing the relationship between the nodes. Probabilities are attached to each node and quantifying the believed relationships between connected links based on available data, empirical knowledge and expert judgments. These probabilities are contained within the conditional probability tables (CPT), which lay behind each node and define the probability that the node will be in any given state, according to the combined probability of its parent nodes. For each state of a given child node the model calculates a probability, based on the configuration and states of all parent nodes. In the absence of quantitative data, expert and traditional ecological knowledge is used to define probabilistic links between nodes.

Taking these features together allows for the creation of a model capable of drawing not only the mathematically expressed physical relationships, but also subjective elements corresponding to the experience of the local people and experts, who are in many cases, an integral part of the system being modeled.

4.3 The Development of Bayesian Network Model Based on the DPSIR Approach for Causal Exploration of Land Degradation Indicators in El Alegre Sub- Watershed

4.3.1 Data Acquisition for Modelling

To construct a biophysical and social base for the development of the Bayesian Network model of DPS indicators of land degradation in El Alegre sub watershed, existing data sets and information were collated and reviewed.

The field and interview data were obtained directly from the project 'Application of the LADA Framework Approach for Land Degradation Assessment in Dry Lands' (Rebecca L. Dixon, 2003). The study in this thesis, therefore, can be considered as the continuation and extension of Dixon's work into the modelling aspects of causality of land degradation. Most of the dataset used for this modeling effort originated from the dataset collected for this research by Dixon (2003). From the two case studies in Dixon's study, El Alegre sub-watershed was selected for our case study in modeling causality. The selection is made on the basis of availability of more complete and relevant data to be used in our approach. The study area El Alegre is located in the dry land part of central Mexico which is one of the areas experiencing the advance of desertification, which is understood as degradation in arid, semiarid and dry sub-humid areas of the world.

Land units (i.e. Land Systems and Land Facets) were used for stratification of natural variability. Land Systems are assemblages of relatively homogeneous landscape units or land facets following an integrated terrain classification approach, proposed by Webster and Beckett (1970). The definition of land facets is based on landform, rock, soils, moisture regime, and land cover. Five distinct land facets were defined in the sub-watershed. These are shown in figures 4.12, 4.13 and table 4.4.

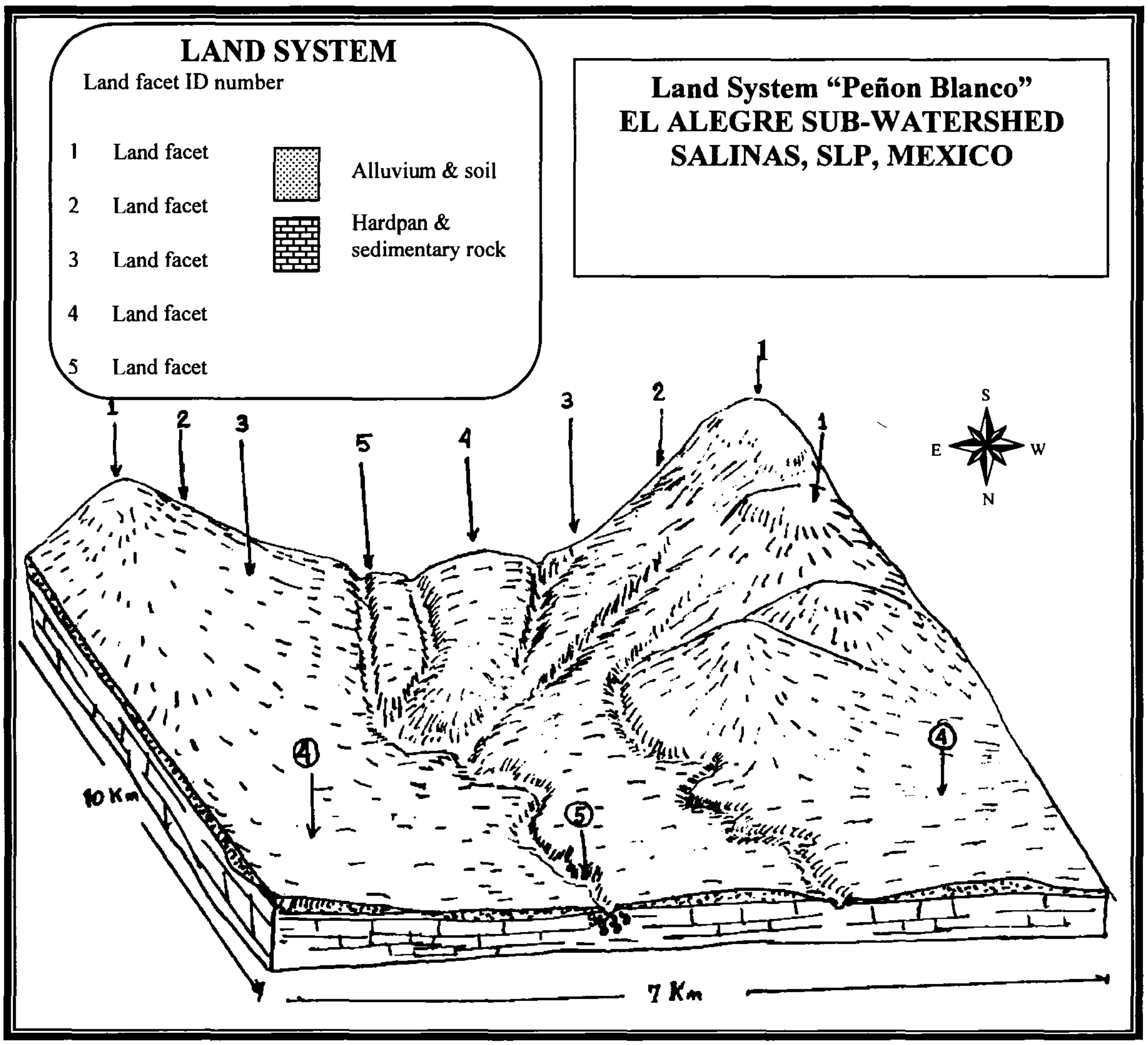


Figure 4.12 Land System Peñon Blanco. (Dixon, 2003)

Facet ID	Land form	Rock	Soils	Land Use Type/ Land cover	Hydrology and Moisture Regime
1	Crests and medium-size and small mountain-hilltops	Lower Cretaceous volcano-sedimentary rocks: flysch (siltstone, greywacke, limestone, marls) and andesites	Euthric Lithosol, skeletal and extremely shallow	Sub-thorny and thorny brush and shrubs, crassicaule cacti	Contributing site, limit of watershed, head waters of seasonal streams, low water retention capacity
2	Steep mountain and hillside slopes	Lower Cretaceous volcano-sedimentary rocks: flysch (siltstone, greywacke, limestone, marls) and andesites	Skeletal Euthric Lithosol and bare rock. Soils are gravely or stony and shallow.	Sub-thorny and thorny brush and shrubs, crasicaule cacti	Contributing site, excessive surface drainage, extremely low water retention capacity
3	Extended slopes of coalesced alluvial fans and pediments, and dip-slopes of cuestas.	Post-orogenic continental debris including clastic volcanic debris, sediments and Quaternary alluvium with minor quantities of carbonates and evaporites and scattered mafic or silicic bodies and igneous rocks, andesites mixed with siltstones, limestones and marls.	Predominantly Eutthric Lithosol, shallow and gravely with a petrocalcic phase consisting of a calcareous hardpan within the top 20 cm of depth. Inclusions of Haplic Phaeozem in petro-calcic phase and presence of the near-surface calcareous hardpan and an impervious, surface-sealing clay crust	Natural pastures underlying a sub-thorny and thorny brush, and shrubs mixed with scattered rosulifolious and crasicaule cacti. Small areas of annual permanent agriculture interspersed with natural pastures.	Intermediate site, receiving considerable runoff contributions from steeper hillside slopes, thinly veneered with fluvial gravels of steep, seasonally draining streambeds, arroyos and gullies dissecting areas with considerable laminar surface runoff
4	Gentle extended slopes of alluvial fans and pediments coalescing with extended alluvial valleys with clastic and alluvial deposits strongly dissected by seasonal streambeds	Quaternary alluvium and sediments overlain and mixed with clastic volcanic debris with a few carbonated and scattered mafic or silicic bodies and igneous rocks, andesites mixed with siltstones, limestones and marls.	Predominantly Haplic Phaeozem with a petro-calcic phase consisting of a near-surface (<50 cm) calcareous hardpan, inbedded in deeper and fine alluvial material (silts and clays) and an impervious surface sealing clay crust.	Mainly annual permanent agriculture, corn and bean crops with small areas of oats. Agricultural areas surrounded by natural pastures, cacti of various kinds and sub-thorny bush	Receiving sites, mostly through seasonal runoff of laminar kind, and through seasonal streambeds and gullies. Extensive presence of rills of various sizes and gullies. Medium water holding capacity.
5	Flat or gently sloping alluvial and fluvial valleys and banks near streambeds	Quaternary alluvium and sediments overlain and mixed with classic volcanic and fluvial debris and gravels	Haplic Phaeozem with a deep petro-calcic phase of a calcareous hardpan, imbedded in deeper and fine alluvial material (silts and clays) and mixed with fluvial debris, sands and gravel.	Annual permanent agriculture with corn, beans and rarely other miscellaneous crops, where not impeded by fluvial debris, with thorny shrubs and cacti at the edges.	Receiving sites, medium to high moisture retention capacity and occasional seasonal flooding with important accumulation of fine and coarse sediments near stream banks.

Table 4.4 Characterization of Land Facets of the Land System "Peñon Blanco". (Dixon, 2003)

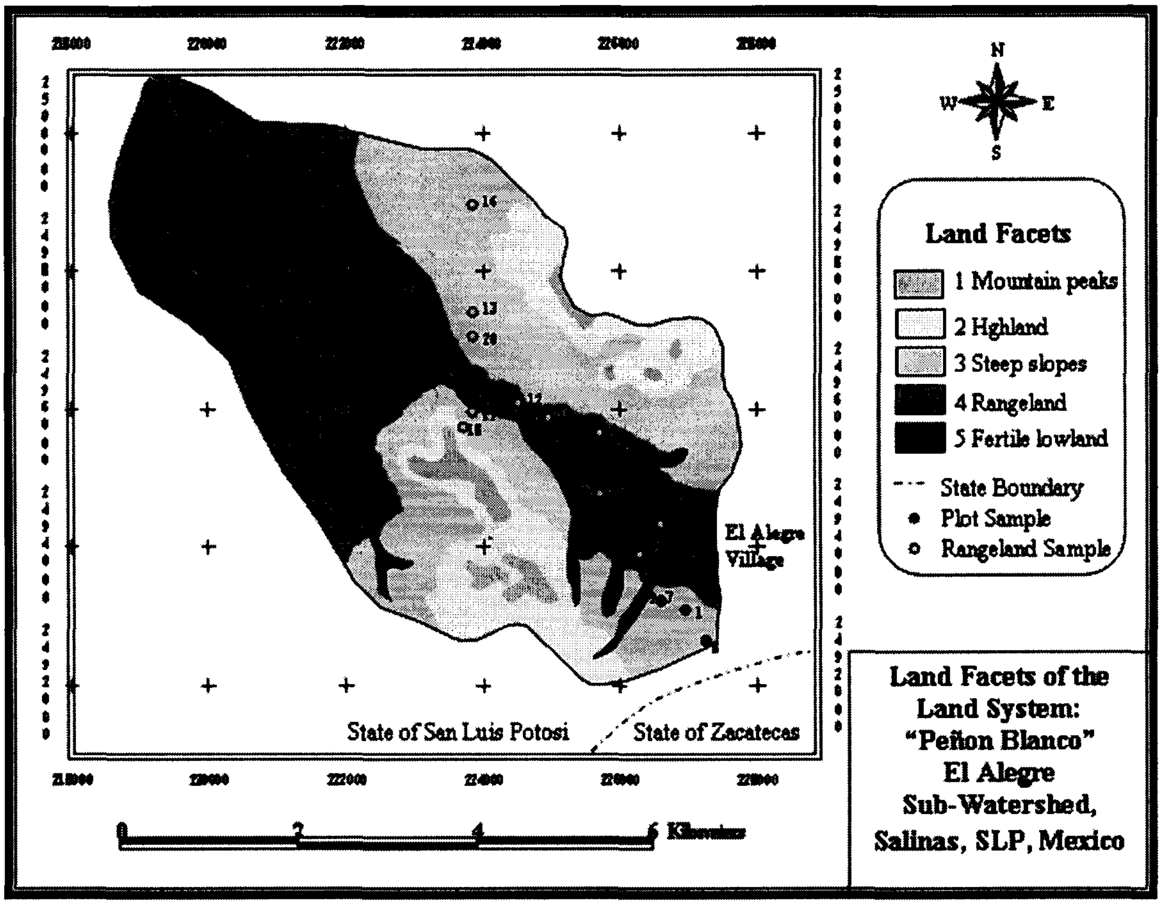


Figure 4.13 Land facets of the land system Peñon Blanco. (Dixon, 2003)

The sampling methods used in the field study, for observation and measurement of indicators, included interviews with officials, farmers and other members of households, field surveys of agricultural plots and rangelands. In the course of the study, informal interviews were conducted with Marcial Rodriguez, the elected official of El Alegre; Oscar Martin Posadas Leal, the chief of the Rural Development District Office (Office Number 127) in Salinas; Guillermo Lopez Forment Villa, Senior Officer at the Sub-Secretariat of Environment and Natural Resources (SEMARNAT Federal office) and Alfonso de la Rosa Vasquez, Director of the Forest Management at the federal office of SEGARPA. Formal Interviews were conducted with nine farming households; physical surveys were collected on their agricultural plots. Eleven sites on the ejido rangeland were sampled, each with an area of approximately 1 hectare. Sample locations are displayed in (figure 4.13) and the number of samples per land facet is indicated in (table 4.5).

Table 4.5 Samples per land facet and land use

Facet	No of samples	Rangeland	Plot
1	0	0	0
2	1	1	0
3	7	4	3
4	8	6	2
5	4	0	4
Total	20	11	9

The nine household production systems sampled and surveyed represent 18.75% of households in the community (Ejido). However, many alternative data sources (i.e. interviews with elected officials, personal communications with local experts and local government reports and records) to supplement the sample information were used, in order to minimise the risk of inaccuracy, which might arise from a small sample size.

4.3.2 Model Variables (Driving Forces, Pressures and States), Data Sources Used to Discretize Model Variables for the Probability Model

The two main tasks in Bayesian Network modelling are construction of a graphical structure, and the construction of CPTs for each node. To formalize the graphical model as a BN model, variables had to be clearly defined.

Each indicator or variable to be included in the model is identified and assigned to either Driving Force, Pressure or State categories, based on a preliminary indicator list suggested in a FAO Consultation Report (Snell and Bot, 2002).

The definition of model variables (DPS indicators), their included states (sub classes) and the placement of break points in each indicator were established using the field survey forms and questionnaires from Dixon (2003), aided by relevant literature and consultation with an expert which have a considerable experience in the study area.

Since we have categorical states (sub-classes) for each indicator in the model we need to use discrete variables for all indicators having a well-defined finite set of possible values for each state (sub-class) i.e. each state should be represented by a single number, and there should be no representing number between the states of an indicator. Table 4.6 summarizes model variable definitions, data source used to discretize variables (indicators) and the units used to construct the probability model.

Table 4.6 Summary of model variable definitions, data sources used to discretize variables (indicators) and their limits to construct the probability model.

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned	Variable Sub States and their Limits
Climatic variability	D	Calculation of temperature changes and intensity of rain using meteorological station data, spatial interpolation and making monthly and annual comparisons.	% of study area covered with variable climatic conditions over the last few years.	The entire study area show **Slight Annual Variation.** With erratic rains and drought frequency in various seasons.
Food Insecurity	D	Interviewing house holds based on calories/ capita.	% of house holds affected in the area.	**25 %** of the households are **Secure** and **75 % Not secure.**
Main Fuel Sources	D	Extracted from databases of government agency and records and from farming household surveys.	Categorical (Type and proportion of use)	**22 %** use **Fuel Wood, 67 %** Use **Fuel Wood and Gas** and the other **11%** use **Gas.**
Land Policies	D	National and local regulatory frameworks and Policies.	Effective in the total area	In appropriate land policies are affecting the **Total Area**
Animal Populations	D	Calculation from field survey and agricultural statistics reports and household surveys.	Heads of livestock per household.	**33 %** of the house holds have **No Cattle, 32 %** have **11 – 20 Heads, 11%** have **21 – 60 Heads** and **22 %** have greater than **60 Heads.**
Poor water Management	D	Estimation from field surveys, government agency records and interviews with local experts.	% of area covered	Water management is identified to be **Poor** in the entire study area.

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned	Variable Sub States and their Limits
Inadequate sewer systems and solid waste disposals	D	Field survey and government agency reports and household interviews.	% area based on Adequacy of facilities for sewer and solid waste disposal	**70.8 %** have **inadequate** and **29.2%** have **adequate** disposal systems.
Unfavourable position on the slope	D	Measurement of slope gradient and its variability across the landscape.	Taking slope percentage	Areas with >6% slope percentage and **Steep with runoff** account for **56%** of the area and the rest **42 %** have a slope <6% i.e. **Gentle to Flat**.
Lack of Institutional Support	D	Assessment by review of documents of government structures and institutions and interviews with the farming households.	Percentage household with Access for support in the study area	Only **15 %** of the households in the area are **Supported** through various institutions and **85% Not Supported**.
Low Literacy Rate and Education	D	Review and extraction of data from census databases	Proportion of literate and illiterate population	**22.5 %** are **literate** and **77.5%** of the inhabitants are **Illiterate**
Micro Economic Policies	D	Review of regional development plan documents. Enterprise regulatory frame works, export and market orientation of farms and enterprises. Cost and price regulations.	Percentage study area suffering from the unfavourable nature of the micro economic policies	The entire study area is suffering from **Unfavourable** economic policies.

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned	Variable Sub States and their Limits
Inaccessibility of Extension services Agricultural or Education	D	Examination of records and reports about extension services and agricultural education from ministry of agriculture and census databases	Proportion of households with access to extension services and agricultural education	**25%** of the households **Have Access** to extension services and the rest **75%** are **With Out Access**.
Affordability Of Alternative Energy Source	D	From questioners and interviews with house holds.	Proportion of households who afford and do not afford an alternative energy source to fuel wood in the area.	Only **25 % afford** and the rest **75% can not afford** an alternative energy source
Increased Distance to Water supply	D	Through household replies to questioners, digital map calculations and field measurements.	Proportion of households traveling for longer distance than they used to in the last few years.	Here the classes are - **60.6%** of house holds are traveling **Increased Distance** than previous years. - **39.4%** travel the **Usual Distance** getting water from same area in the past few years.
Decrease in rural employment	D	From questioners and interviews with house holds.	Proportion of rural workers who lost their job in the past year.	Slight or No Decrease 15% Sharp Decrease 85%

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Increased Drought Frequency	P	Household interviews Meteorological station data and spatial interpolation of data points	Consecutive occurrence of drought in number of years	**Highly** frequent for every 2 yrs **Moderately** frequent for 2 – 4 yrs **Less frequent** for > 4 yrs
Increased Frequency of Erosive Rainfall events and surface runoff	P	Estimated from meteorological station data and rainfall intensity pluviographs. ΔR from nomographs and spatial interpolation.	Percentage area with various degrees of effect "Subjective"	**Slightly Affected** **Moderately Affected** and **Highly Affected**, Areas with frequent erosive rainfall events.
Increased Frequency of High velocity Winds causing dust storms in fields	P	Derived from meteorological station records. Time series of wind velocity measurements.	Percentage area affected with increased frequency of high velocity winds. "Subjective"	**Slightly Affected** **Moderately Affected** and **Highly Affected,** areas with increased frequency of high velocity winds and dust storms.
Crop Yield Losses in the Last 3 years	P	Assessed through time series records of crop yield records and questioner interviews from farmers.	Proportion of farm households with a given percentage amount of crop loss in the last 3 years	households with **- Less than 25%** Yield loss, **- 25% - 50%** and **- Grater than 50%** loss.

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Rangeland Biomass in Scarcity (years)	P	Review of agricultural statistics and rangeland surveys.	Number of years the rangelands experienced biomass insecurity.	Proportion of the range lands in the area experiencing - **Less than 5 years** - **From 5 to 10 Years** and - **More Than 10 yrs** of biomass insecurity.
Decrease in Livestock Feed in Rangelands in last 3 years	P	Review of agricultural statistics and rangeland surveys.	Proportion of rangelands in the area based on Percentage feed decline in the last 3 years	Percentage observed feed decline in the range lands - **Less than 30** percent - **From 30% to 50%** and - **More than 50 Percent** decline.
Land Abandonment (migration) due to insecurity	P	Extracted from census statistics and from field surveys and interviews of farm households.	Percentage migrants per type of migration	The two migration types considered are: - **Permanent** and - **Temporary** migration.

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Surpassed Animal Carrying Capacity of Rangelands	P	Review of agricultural statistics, rangeland surveys and computation of carrying capacity and comparison to current livestock density.	Carrying capacity of range lands Hectare per head	Used carrying capacity classes **- 2 hectare per head,** **- 10 hectare per head** and **- 10 to 14 hectare per head**.
Deterioration of water quality (increased turbidity and /or contamination)	P	Inspection in the field of sampling, water observation points and records from water agency.	Proportion of available water in the study area with degree of quality deterioration in terms of turbidity and contamination.	Sub states used are **- Clear and Clean** **- Slightly Turbid** but still potable after filtration but not contaminated. **- Highly Turbid and Contaminated.**
Change In Access To Water Per Capita	P	Estimation of water accessibility from field inspection, agency records and interviews.	percentage of households in the area with and without access to water	The two classes used are people - **With Access** and - **With Out Access** to water in their villages.
Increased demand for Forest Products	P	Household interviews	Proportion of households which show an increase in the demand for forest product.	Sub states used are **- Increased demand** per household and those having their demand **- Same as previous years** with no change or a decline in demand.

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Uncertainty of Land Tenure	P	From local agency records, questionnaires and interviews of farm households.	Proportion of farm households based on certainty of their farmland ownership	Households - **Certain** and - **Un Certain** regarding their land tenure.
Unregulated, Unrestricted Use of Common Lands	P	Review of communal lands rights records and field information from interviews with local authorities and farm households.	Proportion of common lands affected with such practices	In the entire study area use of Common lands is - **Unrestricted** by low or any regulations.
Lack of Banking and Credit Institutions	P	Review of census data and records from Ministry of Agriculture and Finance	Proportion households having access to banking and credit institutions	Classes are assigned on bases of households getting:- - **Full** support and having local access to use these institutions. - **Partial** for those who get same service but limited and not sufficient support to improve productivity. And households who get - **No support** from any of these institutions.

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Soil Erosion By Water Rills	S	Direct observation through field surveys and expert opinions.	Fields and farm plots with no rill formation are classified as not affected, areas with few and very shallow rills as slightly affected, areas with the formation of many small and shallow rills classified as moderately affected and finally fields with many, wide and shallow rill formations are classified under intensely affected areas.	Its states include - **Not Affected** - **Slightly** affected - **Moderately** Affected and - **Intensely** affected with rill activities.
Soil Erosion By Water Gullies	S	Field estimation through measured values of volume of soil loss from gullies.	Measured using Volume soil loss estimated through W= Average width of cross section of gully; L = Total Length of the gully. H = Average height or depths measured along many cross sections along the length of the gully. Then classified based on the calculated Volume loss	- Plots showing no gully formation are classified **Not Affected** - gullies with the volume loss of soil < 1,000,000 M^3 are identified as **Slightly** affected - From 1,000,000 – 2,500,000 M^3 of soil loss classified as **Moderately** affected - and those with > 2,500,000 M^3 loss are classified as **Intensely Affected**

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Soil Erosion by Wind	S	Direct observation from field survey, meteorological records and from local experts.	Proportion of the study area with different degrees of impact through frequent wind erosion. “Subjective”	Degrees of observed effects of wind erosion in the area, classified as - **Not Affected** - **Slightly Affected** - **Moderately Affected** and - **Intensely Affected**
Decline In Effective Soil Depth to Armour layer	S	Field measurement and soil survey reports.	Using the average measured effective soil depth of the sample plots	Classified as areas showing:- - **Intense Decline** have effective soil depth < 25 cm, - **Slight Decline** from 25 – 50 cm. - **No Decline** having depth more than 50 cm.
Organic Matter and Carbon Depletion	S	Estimation through time series of analytical values of organic mater depletion and expert opinion.	Percentage area with observed slight or high depletion of organic matter.	Classified as - **Slightly Depleted** and - **Highly Depleted**

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Recess of Land Cover of the Area	S	Computation through land cover area changes from satellite image interpretation over past three years.	Area with increased exposure to erosive forces (extent of cleared area)	The states include - **No Recess** for areas with intact land cover - **Moderate Recess** for areas which have vegetation but going through the process of deforestation with moderate pace. - **Intense Recess** for areas deprived of most of their cover and with alarming deforestation rate.
Crusting and Sealing	S	Through field observation and Calculated results using crusting index $CI = (Zf + Zc)/C$ in the sample plots	Zf = % fine silt (2-20µm) Zc = % Coarse Silt (20 – 50µm) C = % Clay CI is unit less $CI \geq 1.5 \rightarrow$ shows crusting $CI \geq 2.5 \rightarrow$ Intense Crusting	Having class limits with - **Not Observed** for areas with no sign of crusting and sealing - **Slight Crusting** for areas where CI is between 1.5 – 2.5 and - **Intense Crusting** where $CI \geq 2.5$
Crop Yield Losses and decline in primary productivity of the land in the Last 3 years	S	Assessed through time series records of crop yield records and questioner interviews from farmers.	Proportion of farm households with a given percentage amount of crop loss in the last 3 years due to the decline in the productivity of the land.	Designated limits of losses per household are - **Less than 25%** Yield loss, - **25% - 50%** and - **Grater than 50%** loss.

Table 4.6 (continuation)

Model Variable (Indicator)	DPS	Source for Discretizing Variables	Units Assigned as Specified by Causes (parents)	Variable Sub States and their Limits
Change in Soil Reaction (pH)	S	Using pH meter and analytical methods	Percentage study area showing considerable change in soil reaction or pH	- Areas having pH value < 5.6 are assigned as showing **Increased Acidity,** - With 5.6 – 8.4 as areas showing **No Change About Neutral** in pH - And areas which have pH value > 8.4 as **Increased Alkalinity**
Decrease In crop Yields in the past 3 years	S	Comparison of estimates of crop yields in the time interval from existent records Kg/ha.	Percentage of farm households affected with the decline in yields in the past 3 years	**No Decline** for farm house holds with no decline **Moderate Decline** for farm house holds with < 25 % decline **Intense Decline** for > 25% decline.

4.3.3 A Driver- Pressure - State Bayesian Network (DPS – BN) Model Development for El Alegre Sub-Watershed, Mexico

The spatial boundary of the model encompasses approximately 4445 hectares located in central part of Mexico, a sub-watershed which includes most of the Ejido lands of El Alegre village in the municipality of Salinas, in the state of San Luis Potosi. In addition to data availability, El Alegre is selected because of its location in the dry land part of Mexico which makes it one of the areas experiencing desertification i.e. extreme land degradation.

The data obtained from El Alegre sub-watershed using field forms and questionnaires based on measurements and observations at farmers and herders fields and interviews from local experts and officials, summarized in (table 4.6) is used as input in the construction of the model. The variable sub states (classes) and limits indicated in table 4.6 are also used to define break points for each sub state of an indicator or node.

In this study the BN modelling was carried out using the software Netica™ application version 3.19 (Norsys Software Corp. Canada January, 2007).

From the available software platforms Netica was selected based on number of functionality criteria including; built-in model size limits of the software, its flexible operating system, the interactivity of the graphic user interface (GUI), its customization to other computer programs and last but most determinant was the cost of software. Netica™ is the most widely used Bayesian network development software designed to be simple, reliable, and high performing for managing uncertainty.

Using the data from (table 4.6) the variables, their sub-states and limits were set in each individual node, i.e. each variable or land degradation indicator in the study area with its sub-states was made to be contained in a single node, allowing for one node for one variable.

The land degradation indicators (model variables) from El Alegre sub-watershed were put in a row according to their fitting into each of the Driving Force, Pressure or State category. Each node in the graphical BN model was systematically reviewed to determine the variable (indicator) it represented and to determine to which one of the components In the DPS category it belonged based on the Preliminary Indicator List Suggested in FAO Consultation Report (Snell and Bot, 2002).

The definition of the probabilistic links or the cause-effect relationships between indicators was achieved based on empirical data from Dixon (2003), local expert consultation, and intensive review of related literature. With respect to overall graphical structure, checks were performed to ensure that most parentless nodes represented indicators of Driving Forces and those most childless nodes describe the final resulting State indicators of land degradation in the study area. Node connections, relationships and probability structure were reviewed thoroughly in reference with the questionnaires and comprehensive consultation with an expert who has a considerable familiarity with the study area.

In this modeling probabilities for conditional probability tables (CPTs) of the various model variables or indicators were specified using a combination of functional relationships from questionnaires, measured data and expert judgments. Although the approach has been described in a linear manner, the development of the graphical model and construction of CPTs for each node in the model proceeded in parallel and in an iterative manner. The process of developing sub-models using available data and information to ensure conditional dependencies between variables often led to re-thinking and refinement of the graphical structure.

Since the major objective of this research is to model the causality, intensity and extent of the degradation in the study area, from the a range of BNs applications, this research uses the ability of BNs to reason backwards, along the network of cause and effect to identify the most likely causes for the given state indicator of land degradation. In addition, the model enables to show each indicator's extent or intensity in the study area through the available BNs graphical structure.

The complete model consists of 38 nodes representing Driving force, Pressure and State indicators of land degradation, 92 links between the indicators and 3465 conditional probabilities. The constructed BN model graphical structure is shown in (figure 4.14). The most readable graphical structure of the model is shown in Appendix 1.

DPS - BN Model

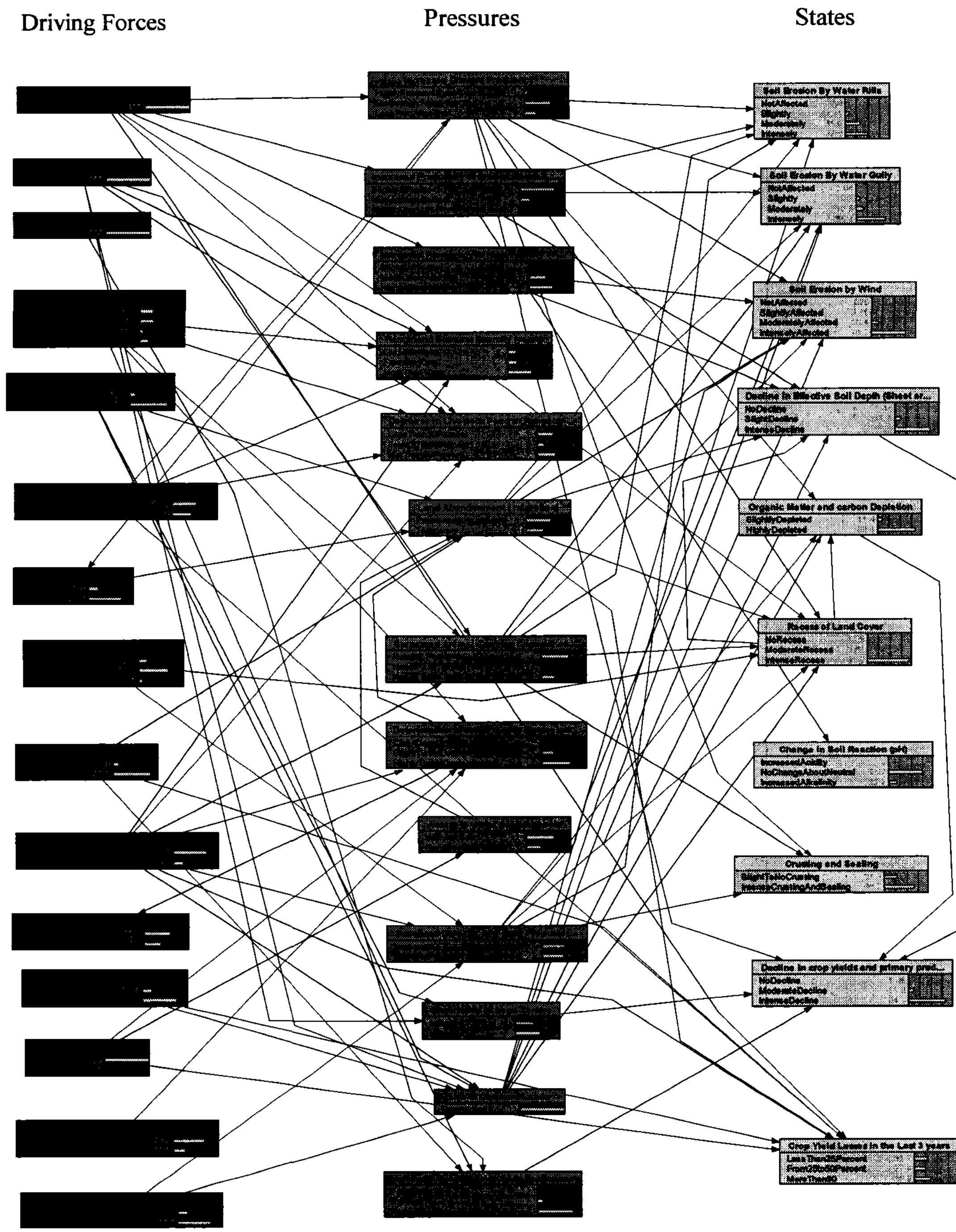


Figure 4.14 Bayesian Network Model for DPS indicators in El Alegre Sub-Watershed

For each indicator in the Pressure and State set of the model CPTs are constructed based on all probable combinations of the sub states of its parents. While for those indicators without parents, like in most cases of Driving Forces, the indicators take their own probability, which is called the marginal probability.

For a network model to be fully specified there must be a relation stored at each node or indicator set in the conditional probability table. It expresses the value of that indicator in terms of its parents or as a constant, if the indicator has no parents.

If the node is deterministic like in the case of some of the driving forces and pressures having only one known sub- state (for example, the use of common lands is unrestricted through out the entire study area that covers all 100% or all common lands), such node will have a probability of one, which means that the probability of the existence of a common land in the study area where the inhabitants will do any kinds of activities with no restrictions or regulations in place to protect such common lands, is absolute and certain. In such cases, then the relation will provide the single value for the child indicator for the single configuration of parent value.

If the indicator is probabilistic, as most in our model, then the relation must provide a probability for each sub-state of the child, for each possible configuration of parent values.

From the model it is possible to obtain the relation stored in conditional probability tables of each indicator through the available relation dialog box in Netica see (figure 4.15).

Examples of these types of relationships, in the model developed are the following:, the nodes for

→ "**Main fuel sources in the area**" which takes the sub-states

"Fuel wood", "Fuel wood and Gas", "Gas"

→ "**Accessibility of extension services**" which takes the sub-states

"*People with Access*" and "*No Access*" to these services, and

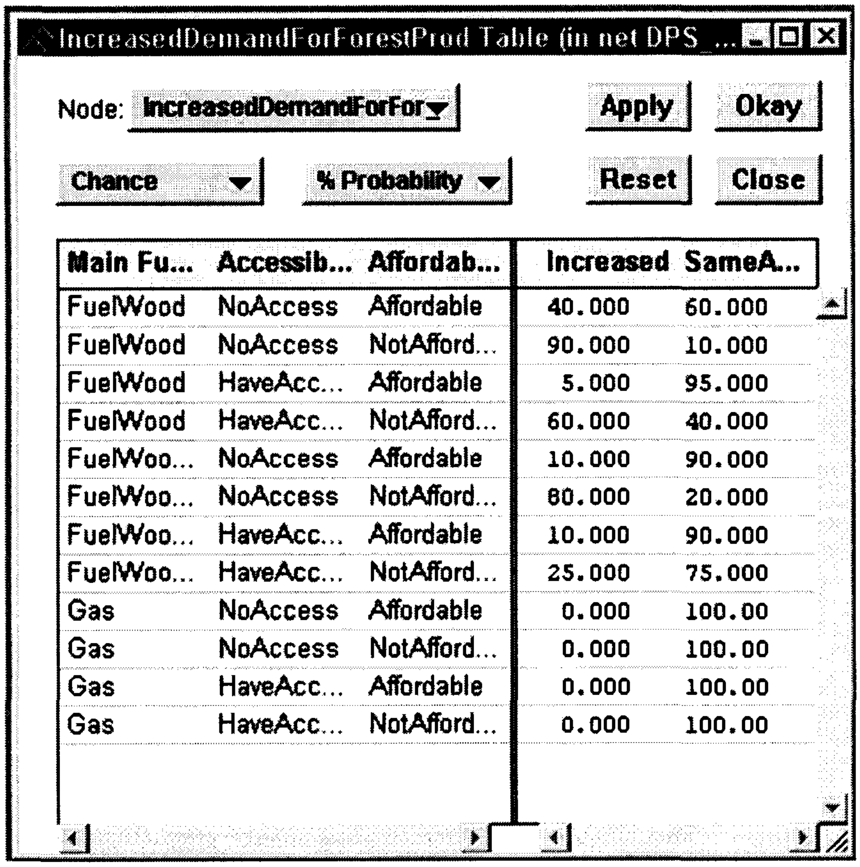
→ "**Affordability of alternative energy source**" which takes the Sub states "*Affordable*" and "*Not affordable*".

These three nodes contain the parents or the causes for the node:-

→ "**Increased demand for forest products (Deforestation)**" which takes the sub states

"*Increased*" in demand and "*Same as previous years*" to show no demand change in forest products for the last 3 years.

It is best to think of the relation between them as being located at the node **"Increased Demand for Forest Products"** (the child node), and its stored relation dialog box is shown in (figure 4.15).



Main Fu...	Accessib...	Affordab...	Increased	SameA...
FuelWood	NoAccess	Affordable	40.000	60.000
FuelWood	NoAccess	NotAfford...	90.000	10.000
FuelWood	HaveAcc...	Affordable	5.000	95.000
FuelWood	HaveAcc...	NotAfford...	60.000	40.000
FuelWoo...	NoAccess	Affordable	10.000	90.000
FuelWoo...	NoAccess	NotAfford...	80.000	20.000
FuelWoo...	HaveAcc...	Affordable	10.000	90.000
FuelWoo...	HaveAcc...	NotAfford...	25.000	75.000
Gas	NoAccess	Affordable	0.000	100.00
Gas	NoAccess	NotAfford...	0.000	100.00
Gas	HaveAcc...	Affordable	0.000	100.00
Gas	HaveAcc...	NotAfford...	0.000	100.00

Figure 4.15 Relation dialog box for the increased demand for forest products

On the left-hand side there is a vertical list of all the configurations of parent values. On the right-hand side there is one column for each sub-state of "**increased demand for forest products**". The numbers in the table provide conditional probabilities for the values of increased demand for forest products, given that the parents take on the configuration of their row. For example, the 40.000 i.e. 40 (percent) in the upper left corner means that

P (increased demand for forest products= increased, given that the Main fuel sources = Fuel wood, Accessibility of Extension Services = Not Accessible and Alternative energy source = Affordable) = 40%

In other words, households in the area using Fuel Wood as their main energy source, who have no access to extension services and who can afford alternative energy sources; - in the households which fulfill this conditions an increase in demand for forest products, has been seen in 40% of the households. Using the same method all the stored relations for each indicator in the model can be interpreted.

4.3.4 Sensitivity to Findings Analysis for Identification of the Most Probable Causes for the State Indicators of Degradation

After establishing and compiling the network model, it is possible to perform sensitivity analysis of findings. This analysis is used to determine which parts of the model most affect the variables of interest, i.e. which nodes most influence the outcome in any given node of interest.

Since the major objective of this research is to use the capabilities of BNs to "reason" backwards along the chain of cause and effect to identify the most likely causes for a given state indicator of land degradation, sensitivity analysis of findings was performed in order to identify network variables (indicators of drivers and pressures of land degradation) which have the greatest influence on indicators of the state of degradation in the study area. Denoted as 'query nodes' these state indicators include; soil erosion by water (rills), soil erosion by water (gullies), soil erosion by wind, decline in effective soil depth, organic matter and carbon depletion, recess of land cover, change in soil reaction (pH), crusting and sealing, decline in crop yields and primary productivity of the land (in past 3 years), crop yield losses (last 3 years).

Netica provides a built- in function for this type of analysis. It allows for the possibility of identifying how sensitive is our belief in a given node's value to the findings of other nodes. For each given query node, the "Sensitivity to Findings" function in Netica was used to identify the network variables that were of greatest influence. These influencing variables are referred as 'findings nodes'.

Essentially, the Sensitivity to Findings function calculates and reports on a number of different sensitivity measures. In our case, for nodes with categorical states, the sensitivity measures used in Netica are calculations of entropy reduction or mutual information (Norsys Software Corp. 1997-2007).

Shannon's entropy denoted as H (Q), is the average amount of information contained in the random (query) variable, Q. The equation for Shannon's entropy (Pearl, 1991) is given as:

$$HQ = -\sum_{qeQ} pr(q) * \log pr(q) \qquad 4.1$$

Measuring the effect of one variable on another is referred to as mutual information. Mutual information is the expected reduction in entropy of one node (measured in bits) due to a finding at another node denoted as I(Q/F) (Pearl, 1991), and given by the equation:

$$I(Q/F) = H(Q) - H(Q/F) \qquad 4.2$$

Where F is the findings variable. When H(Q/F) is subtracted from the original uncertainty in Q prior to consulting F (i.e. H(Q)), the total uncertainty-reducing potential of F is obtained (Pearl, 1991). This potential is known as Shannon's mutual information (or "entropy reduction" in Netica) and basically describes the expected reduction, I, in mutual information of a query variable, Q, due to a finding, F.

The greater the entropy reduction value associated with a finding node, the greater the influence on the query node. Entropy reduction is calculated as (Pearl, 1991).

$$I = \sum_{q}\sum_{f} pr(q,f)\log[pr(q,f)/((pr(q)*pr(f))] \qquad 4.3$$

Where q is a state of the query variable, Q; f is a state of the findings variable, F, and the summations refer to the sum of all states q of f of variables Q or F (Pearl, 1991). The maximum possible decrease in entropy of the query node is when entropy goes to zero, i.e. all uncertainty is removed. This happens when a finding is obtained for the query node itself.

Netica lists in decreasing order the affecter (finding) nodes in decreasing influence on the query node. The output from entropy reduction or mutual measures can be used to rank indicators according to the capacity of the entered values for these variables to change the posterior probability of the query node. Since entropy reduction describes the reduction in uncertainty in a query node when information is available for a findings node, it can be used to help identify the most probable affecting causes of a given state of degradation by indicating which variables (causes) to target in order to achieve a significant change.

CHAPTER 5

Results, Validation of the Model and Discussion

The constructed Bayesian network model graphical structure provides a compact way of depicting and communicating substantive assumptions and relationships between the land degradation indicators in El Alegre sub watershed. It also demonstrates the overall intensity and extent of the influence of each indicator considered in the study area, based on its causes in the DPS chain (shown in figure 4.15). From the model, it is possible to learn that most of the state indicators of degradation in the area are in their worst case scenario (i.e. high degradation intensity) providing a complete picture of how highly the area is under the effects of diverse degradation types and states which resulted from the various driving forces and pressures of land degradation included in this study.

The joint probability or coverage results obtained for each state indicator and its intensity or extent in El Alegre sub watershed in relation to its causes is summarized (see table 5.1).

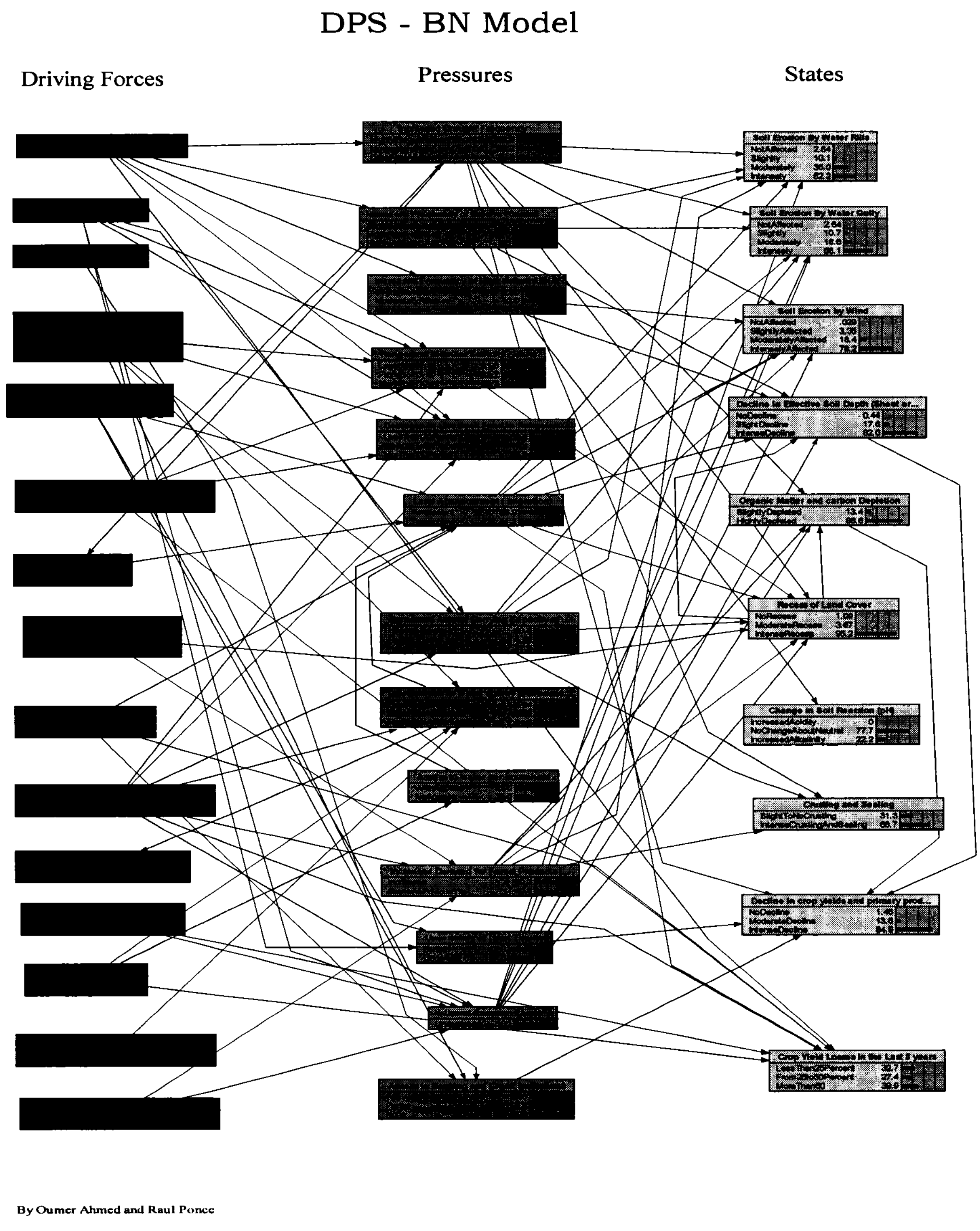


Figure 5.1 Bayesian Network Model for DPS Indicators in El Alegre Sub-Watershed

Table 5.1 Joint probability results obtained for state indicators in relation to their causes

State Indicator	The Most Likely Causes (Markov Blanket)	Sub-states and Joint probability (coverage) values
- Soil Erosion By Water Rills	- Increased Frequency of Erosive Rainfall Events - Surpassed Animal Carrying Capacity of range lands - Increased Demand For Forest Products - Use of Common Lands - Drought Frequency - Land Abandonment	- Not Affected 2.64 % - Slightly Affected 10.1 % - Moderately Affected 35.0 % - Intensely Affected 52.2 %
- Soil Erosion By Water Gully	- Increased Frequency of Erosive Rainfall Events - Surpassed Animal Carrying Capacity of range lands - Increased Demand For Forest Products - Use of Common Lands - Drought Frequency - Land Abandonment	- Not Affected 2.64 % - Slightly Affected 10.7 % - Moderately Affected 18.6 % - Intensely Affected 68.1 %
- Soil Erosion by Wind	- Increased Drought Frequency - Increased Frequency of strong Winds and Dust Storms - Surpassed Animal Carrying Capacity of range lands - Increased Demand For Forest Products - Use of Common Lands - Land Abandonment	- Not Affected .029 % - Slightly Affected 3.35 % - Moderately Affected 18.4 % - Intensely Affected 78.2 %

Table 5.1 (continuation)

State Indicator	The Most Likely Causes (Markov Blanket)	Sub states and Joint probability (coverage) values
- Decline In Effective Soil Depth	- Frequency of Erosive Rainfall Events - Increased Frequency of strong Winds and Dust Storms - Land Abandonment - Use of Common Lands - Recess of Land Cover	- No Decline 0.44 % - Slight Decline 17.6% - Intense Decline 82 %
- Organic Matter and carbon Depletion	- Increased Drought Frequency - Use of Common Lands - Increased Demand For Forest Products - Recess of Land Cover	- Slightly Depleted 13.4% - Highly Depleted 86.6%
- Recess of Land Cover	- Increased Drought Frequency - Rangeland Biomass Scarcity - Surpassed Animal Carrying Capacity of range lands - Increased Demand For Forest Products - Use of Common Lands - Main Fuel Sources - Land Abandonment	- No Recess 1.09 % - Moderate Recess 3.67 % - Intense Recess 95.2 %
- Change in Soil Reaction (pH)	- Frequency of Erosive Rainfall Events	- Increased Acidity 0 % - No Change About Neutral 77.7 % - Increased Alkalinity 22.2 %

Table 5.1 (continuation)

State Indicator	**The Most Likely Causes (Markov Blanket)**	**Sub states and Joint probability (coverage) values**
Crusting and Sealing	- Increased Drought Frequency - Increased Demand For Forest Products - Surpassed Animal Carrying Capacity of range lands	- Slight to No Crusting 31.3 % - Intense Crusting and Sealing 68.7 %
Decline in crop yields and primary productivity of the land (decreases in past 3 years)	- Increased Drought Frequency - Uncertainty of Land Tenure - Access to Banking and Credit Institutions - Organic matter and Carbon Depletion - Decline in Effective Soil Depth	- No Decline 1.46 % - Moderate Decline 13.6 % - Intense Decline 84.9 %
Crop Yield Losses in the Last 3 years	- Climatic Variability - Unfavourable Position on the Landscape (slope) - Accessibility of Extension Services - Low Literacy Rate and Education - Lack of Institutional Support - Water Management - Land Abandonment	- Less than 25 Percent loss 32.7 % - From 25 to 50 Percent loss 27.4 % - More Than 50 Percent 39.9 %

Sensitivity analysis to findings was performed for each individual query node (State Indicator) resulting from a list of network variables or finding nodes, in order to identify network variables which have the greatest influence on a given state indicator of degradation in El Alegre sub watershed. The influencing indicators are then ranked according to their sensitivity values for entropy reduction or mutual information.

In the model, the resulted pattern of relative influence of the various network variables included for each state indicator reflects the combined effect of the graphical structure (the created network structure) and the probability structure between the indicators stored in the CPTs.

The results have been organized into a matrix with the variables of State indicators of degradation in columns and the findings nodes or the causes in rows (table 5.2).

The values in each cell of the table refer to the rank of the network variable with respect to its influence on the query variable (State indicator), with a rank of 1 representing the indicator of greatest influence to cause the given state. The calculated entropy reduction value associated with each related findings node, (I), or causing indicator, has also been provided in the table to give an indication of the relative sensitivity of each variable.

The driving forces and pressures that have the greatest influence on a state indicator of degradation tend to be immediate parent indicators or those that are separated by at most one intermediate indicator. This pattern of relative influence is reflected in the top ranked causes for each state indicator in the model.

In general if distance is measured in terms of the number of nodes lying between the finding node and the query node, then those finding nodes closer to the query node will have a greater impact. The influence of findings nodes, which are further away from the query node tend to be 'diluted' because each intermediate node has a CPT which introduces more conditional uncertainty into the effect (Lee, 2000; Cain, 2001). In addition, some of the intermediate nodes have additional parents representing factors which must also be considered when investigating how the findings node affects the query variable. Both these features of BN structure tend to attenuate the impact of a findings node on query variable (Cain, 2001).

Using the results from the sensitivity analysis it is possible to get a ranking of the most probable causes of a given state of land degradation. This would enable decision-makers to determine where more effort is needed for conservation and protection, to establish priorities for policy-design and conservation interventions. This will direct our focus to those variables of Driving forces, Pressures and even States of degradation with the greatest influence on creating a specific state of degradation on a quantitative basis. In turn, it would be possible to identify which degradation indicators should be prioritized for remediation or prevention of further degradation of a certain state and even to overcome the overall degradation process in the study area. This also can be used to prioritize investment of research effort and drafting of policies towards the prevention of these causes according to their influence.

Table 5.2 Sensitivity to findings result for variables of state indicators of degradation in El Alegre sub watershed. The rank of each indicator (findings node) with respect to the state indicator (query variable) is given by the value at the top in each cell a rank of 1 representing the indicator with the greatest influence on the state indicator. In the next row the entropy reduction value associated with each findings node, I, is also given in each cell.

Model Variables	Soil Erosion By Water (Rills)	Soil Erosion By Water (Gully)	Soil Erosion by Wind	Decline In Effective Soil Depth	Organic Matter and carbon Depletion	Recess of Land Cover	Change in Soil Reaction (pH)	Crusting and Sealing	Decline in crop yields and primary productivity of the land (decreases in past 3 years)	Crop Yield Losses in the Last 3 years
Livestock Population	**2** 0.07636	**3** 0.03020	**4** 0.00802			**2** 0.02287		**2** 0.01988		
Unfavorable Position on the Landscape (slope)		**9** 0.00226	**6** 0.00307		**7** 0.00228				**2** 0.01209	**1** 0.11150
Main Fuel Sources		**11** 0.00129			**6** 0.00252					
Lack of Institutional Support										**3** 0.00713
Accessibility of Extension Services or Agricultural Education		**13** 0.0007			**8** 0.00158					**4** 0.00480

Table 5.1 (continuation)

Model Variables	Soil Erosion By Water (Rills)	Soil Erosion By Water (Gully)	Soil Erosion by Wind	Decline In Effective Soil Depth	Organic Matter and carbon Depletion	Recess of Land Cover	Change in Soil Reaction (pH)	Crusting and Sealing	Decline in crop yields and primary productivity of the land (decreases in past 3 years)	Crop Yield Losses in the Last 3 years
Affordability Of Alternative Energy Source		**10** 0.0015			**3** 0.00800					
Increased Drought Frequency		**7** 0.0073	**2** 0.01962		**2** 0.01268	**5** 0.0032		**7** 0.0004	**1** 0.03567	**2** 0.03855
Increased Frequency of Erosive Rainfall events and surface runoff	**3** 0.0387	**2** 0.0333		**1** 0.0142			**1** 0.0069		**11** 0.00004	
Increased Frequency of High velocity Winds causing dust storms in fields			**1** 0.02881	**2** 0.0056						

Table 5.1 (continuation)

Model Variables	Soil Erosion By Water (Rills)	Soil Erosion By Water (Gully)	Soil Erosion by Wind	Decline In Effective Soil Depth	Organic Matter and carbon Depletion	Recess of Land Cover	Change in Soil Reaction (pH)	Crusting and Sealing	Decline in crop yields and primary productivity of the land (decreases in past 3 years)	Crop Yield Losses in the Last 3 years
Rangeland Biomass Scarcity (years)	**5** 0.0127	**8** 0.0051	**8** 0.00150		**12** 0.00020	**1** 0.0392		**4** 0.0040		
Decrease in Livestock Feed in Rangeland in last few years	**4** 0.0294	**4** 0.0115	**5** 0.0038		**13** 0.00016	**3** 0.0183		**3** 0.0088		
Land Abandon-ment (migration)				**3** 0.00325						
Surpassed Animal Carrying Capacity of Rangeland	**1** 0.0825	**1** 0.0335	**3** 0.0084			**4** 0.0140		**1** 0.0215		

Table 5.1 (continuation)

Model Variables	Soil Erosion By Water (Rills)	Soil Erosion By Water (Gully)	Soil Erosion by Wind	Decline In Effective Soil Depth	Organic Matter and carbon Depletion	Recess of Land Cover	Change in Soil Reaction (pH)	Crusting and Sealing	Decline in crop yields and primary productivity of the land (decreases in past 3 years)	Crop Yield Losses in the Last 3 years
Increased Demand for Forest Products		**6** 0.00862	**7** 0.00216		**1** 0.01895					
Uncertainty of Land Tenure									**8** 0.00028	
Access to Banking and Credit Institutions									**9** 0.00022	**5** 0.00071
Soil Erosion By Water (Rills)		**5** 0.00910	**9** 0.00136	**4** 0.00054	**11** 0.00023	**7** 0.00091	**2** 0.00033	**5** 0.00187	**10** 0.00020	**9** 0.00021

Table 5.1 (continuation)

Model Variables	Soil Erosion By Water (Rills)	Soil Erosion By Water (Gully)	Soil Erosion by Wind	Decline In Effective Soil Depth	Organic Matter and carbon Depletion	Recess of Land Cover	Change in Soil Reaction (pH)	Crusting and Sealing	Decline in crop yields and primary productivity of the land (decreases in past 3 years)	Crop Yield Losses in the Last 3 years
Soil Erosion By Water (Gully)			**10** 0.0005		**14** 0.00009	**9** 0.0003	**3** 0.0002	**6** 0.0011	**7** 0.00029	**7** 0.00040
Soil Erosion by Wind		**14** 0.0005		**5** 0.0001	**9** 0.00058			**9** 0.0002	**6** 0.00046	**6** 0.00045
Decline In Effective Soil Depth		**15** 0.0004					**4** 0.0001		**4** 0.00219	
Organic Matter and carbon Depletion						**6** 0.0027			**3** 0.00800	**8** 0.00027
Recess of Land Cover		**16** 0.0003			**5** 0.00278			**8** 0.0003		
Crusting and Sealing		**12** 0.0011				**8** 0.0003				

Table 5.1 (continuation)

Model Variables	Soil Erosion By Water (Rills)	Soil Erosion By Water (Gully)	Soil Erosion by Wind	Decline In Effective Soil Depth	Organic Matter and carbon Depletion	Recess of Land Cover	Change in Soil Reaction (pH)	Crusting and Sealing	Decline in crop yields and primary productivity of the land (decreases in past 3 years)	Crop Yield Losses in the Last 3 years
Decline in crop yields and primary productivity of the land (decreases in past 3 years)					**4** 0.00317					
Crop Yield Losses in the Last 3 years					**10** 0.00027				**5** 0.00160	

In the model the largest intensive coverage in a state of degradation is exhibited by **Recess of Land Cover** accounting for 95% of the study area, affected with its most probable causes. As the results from the Sensitivity to Findings Analysis show (table 5.2) the top three ranked causes of **Recess of Land Cover** are **Rangeland Biomass Scarcity**, **Livestock Population** and **Decrease in Livestock Feed in Rangelands** respectively, while **Crusting and Sealing** and **Soil Erosion by Water** having the least impacts.

The summarized results from the above table also suggest that some of the causes of degradation have a noticeable dominant influence in most of the variables of state indicators. The most dominance is displayed by **Surpassed Animal Carrying Capacity of the Rangelands** which is ranked 1st – 4th for having the greatest influence on 5 state indicators out of the 11. This indicator is identified as the 1st responsible cause, contributing the highest influence for causing **Soil Erosion by Water (rills)**, **Soil Erosion by Water (Gullies)** and **Crusting and Sealing**, and it is ranked 3rd, and 4th in its influence for causing **Soil Erosion by Wind**, and **Recess of Land Cover**.

The second most dominant cause is also related to the existence of animal population in the area, i.e. the **Livestock Population**, which is ranked from 2nd – 4th for its highest influence in causing 6 states of degradation out of 11. It has been ranked the 2nd most influencing cause for creating **Soil Erosion by Water (Rills)**, **Recess of Land Cover** and **Crusting and Sealing** and the 3rd major cause for **Soil Erosion by Water (Gully)** and the 4th major cause for **Soil**

Erosion by Wind and **Decline in Crop Yields and Primary Productivity of the Land** in El Alegre.

We can learn from the fact that extensive livestock production is one of the primary sources of income and security in El Alegre, undertaken by approximately two thirds of the population (Dixon, 2003) (figure 5.1). The results from the questionnaires and field forms indicated that about 32% of the range lands serve more than 10 heads/ha and 43% of the range lands show more than 50% decrease in livestock fed.

Livestock is thought by most of the inhabitants as a means to financial security or insurance, rather than as an investment that requires timely management. The livestock population is greatly exceeding that which can be sustained on the rangeland resources, causing a depletion of vegetative cover, increasing exposure to erosive forces, sealing and crusting of the soil surface, decrease in grass species diversity, and ultimately poor health of the livestock. Such practices also put an enormous pressure on the fragile rangeland resources, leading to overgrazing and insufficient feed for livestock.

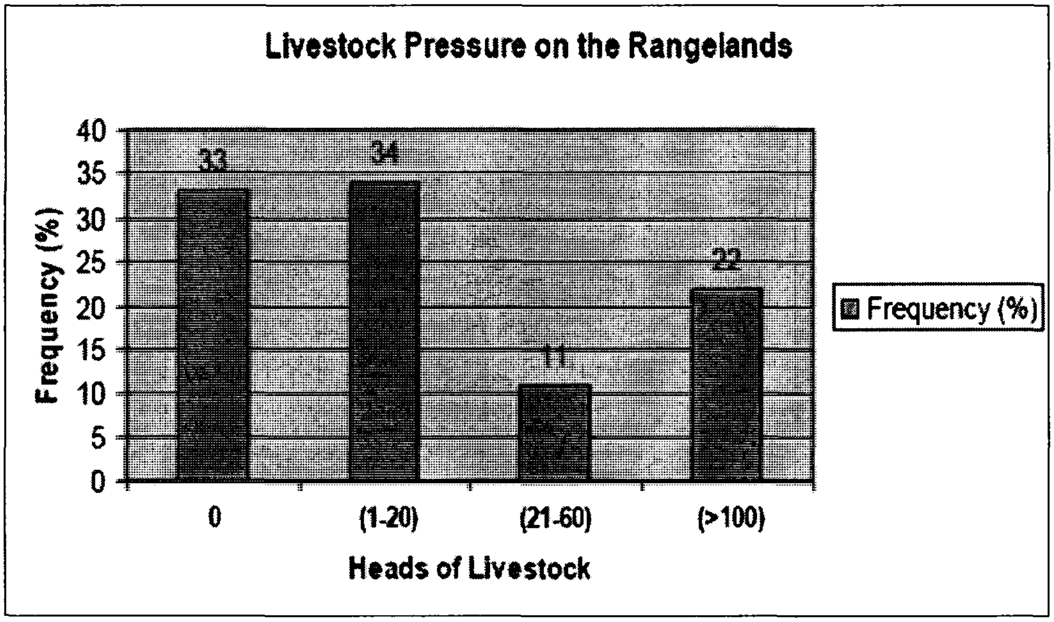


Figure 5.1 Live stock pressures in the range lands (Dixon, 2003)

Generally the ranks obtained from the analysis results provide an indication of which variables it would be most useful to study and deal with first, in order to stabilize or even reduce the intensity and extent of a given state indicator of degradation. Thus it can be used for identification of which indicators to prioritize in the remediation and research efforts to determine the sequence of decisions that can be taken in the future.

In recent years, environmental decision support systems have been developed to integrate the best available knowledge for informed decision making. Among the various kinds of decision support systems Bayesian networks demonstrated its use as a modeling approach which can integrate quantitative information and data as well as qualitative expert knowledge with in the scope of environmental management including The Implementation of a Bayesian Network for Watershed Management Decisions (Ahmed Said 2004), Stakeholder

Consultation for Bayesian Decision Support Systems in Environmental Management (Baran and Jantunen 2004), Bayesian networks for decision analyses - an application to irrigation system selection (Robertson and Wang 2004). An example in the field of water resource management is given by Batchelor and Cain, (1999) with application of belief networks to water management studies.

Bayesian Network models also demonstrated their use in ecological management which includes a restoration strategy for a temperate lake in Finland, Modelling Salmon Fisheries Management in the Baltic Sea (Varis and Kuikka, 1999), Evaluating Fish and Wildlife Population Viability Under Land Management Alternatives (Marcot et al., 2001), and Ecological and Modelling Approach to Flood-Fish Relationships in the Mekong River Basin (Baran and Chain 2001),

The DPS-BN model constructed in this study offers advantages in communicating substantive assumptions about the relationships between the degradation indicators, which are clearly and transparently documented in the graphical and probability structure and are immediately accessible to model users. A further advantage of this model is that the Bayesian framework enables the model to be explicitly updated and improved with the acquisition of new information on the existing or new indicators to be included.

The completed DPS-BN model can be validated using independent information, when available, through independent assessment by a third-party. However, this can be a challenging endeavour when no new data become available for assessing the BN model developed. Unless long standing experimental or monitoring plots had been set for this purpose with reasonable area coverage, the rigorous assessment of accuracy in identification of the most probable causes of different states of degradation becomes a challenging problem. Else, the model accuracy has to be assessed indirectly through empirical evidence and through knowledge and information gathering from local experts (i.e. farmers and local technical staff) opinion on the nature and meaning of the obtained results, in light of their own personal experience and interpretations.

Since we could not find any previously made independent assessment to validate our model results, which would have been the preferable and recommended method to get a reliable measure for the validation. We used alternative available data source collected from the study area to validate the model results.

In this research an attempt has been made to validate the model results using local farmers' perception on the causes for each type of degradation included in the model. As indicated in chapter four, the data set used for construction of the model is obtained through combination of sources including empirical data, field forms and questioners based on measurements and observations at farmers and herders fields and interviews from local households, experts, and officials. Unlike the former data sources the data set used for the validation of the model was obtained from independent interviews made with 11 farmers and land owners in El Alegre sub watershed from Dixon's 2004 study. The extraction of the questionnaires and the construction of the matrix was a very challenging task since the questionnaires were not initially designed for the purpose of validating this model and unlike the other data sources from the area these needed to be translated from Spanish language. Therefore it becomes necessary to interpret the farmer responses to construct the matrix for each state indicator. Helped by a translator to interpret their response it was possible to construct the matrix as to which causes (indicators) contributed for the formation of the specific type of degradation within the area, according to farmers' and herders' perception.

Farmer interviews extracted from the questionnaires were used for the construction of a matrix for each state of degradation tabulating model rankings against farmer perceptions of the most probable causes for each state of degradation and comparing them directly against those predicted by the model as the main causes. The constructed interview and model results matrix for each state of degradation are summarized in Tables 5.3 – 5.12.

Tables 5.3 – 5.12 Show the tabulated summery for model rankings of probable causes against questioner results from interviews made with local farmers and land managers in El Alegre sub watershed.

Table 5.3 Results for soil erosion by water (rills)

Soil Erosion by Water (Rills)						
Model Ranking of Probable Causes		**Farmer Perception of Causes (questionnaires)**				
		Surpassed Animal Carrying Cap	Livestock Population	Increased Frequency of Erosive Rain	Decrease In Livestock Feed	Rangeland Biomass Scarcity
1	Surpassed Animal Carrying Cap	**9**	1	0	0	1
2	Livestock Population	1	**8**	0	0	1
3	Increased Frequency of Erosive Rain	2	3	**4**	1	1
4	Decrease In Livestock Feed	0	1	0	**10**	0
5	Rangeland Biomass Scarcity	1	0	0	0	**10**

Table 5.4 Results for soil erosion by water (gully)

Soil Erosion by Water (Gully)							
Model Ranking of Probable Causes		**Farmer Perception of Causes (questionnaires)**					
		Surpassed Animal Carrying Capacity	Increased Frequency of Erosive Rain	Livestock Population	Decrease In Livestock Feed	Soil Erosion by Water Rills	Increased Demand for Forest Prod
1	Surpassed Animal Carrying Capacity	**9**	1	0	0	1	0
2	Increased Frequency of Erosive Rain	1	**4**	1	0	2	3
3	Livestock Population	1	0	**8**	0	0	1
4	Decrease In Livestock Feed	1	0	0	**10**	0	0
5	Soil Erosion by Water Rills	3	5	2	0	**0**	1
6	Increased Demand for Forest Prod	1	0	1	1	0	**8**

Table 5.5 Results for soil erosion by wind

Soil Erosion by Wind					
Model Ranking of Probable Causes		Farmer Perception of Causes (questionnaires)			
		Increased Frequency of Strong Winds	Inc Drought Frequency	Surpassed Animal Carrying Cap	Livestock Population
1	Increased Frequency of Strong Winds	**9**	1	1	0
2	Increased Drought Frequency	1	**9**	0	1
3	Surpassed Animal Carrying Cap	0	1	**9**	1
4	Livestock Population	0	0	3	**8**

Table 5.6 Results for decline in effective soil depth

Decline In Effective Soil Depth			
Model Ranking of Probable Causes		Farmer Perception of Causes (questionnaires)	
		Increased Frequency of Strong Winds	Increased Drought Frequency
1	Increased Frequency of Erosive Rain	**4**	7
2	Increased Frequency of Strong Winds	2	**9**

Table 5.7 Results for organic matter depletion

Organic Matter Depletion				
Model Ranking of Probable Causes		Farmer Perception of Causes (questionnaires)		
		Increased Demand for Forest Prod	Drought Frequency	Affordability Of Alternative Energy Source
1	Increased Demand for Forest Prod	**9**	1	1
2	Increased Drought Frequency	1	**10**	0
3	Affordability Of Alternative Energy Source	2	1	**8**

Table 5.8 Results for recess of land cover

Recess Of Land Cover							
Model Ranking of Probable Causes		Farmer Perception of Causes (questionnaires)					
		Rangeland Biomass Scarcity	Livestock Population	Decrease In Livestock feed	Surpassed Animal Carrying Capacity	Increased Drought Frequency	Organic Matter Depletion
1	Rangeland Biomass Scarcity	**10**	0	0	1	0	0
2	Livestock Population	1	**8**	0	1	0	1
3	Decrease In Livestock feed	1	0	**10**	0	0	0
4	Surpassed Animal Carrying Capacity	0	1	0	**9**	1	0
5	Increased Drought Frequency	0	1	0	1	**9**	0
6	Organic Matter Depletion	1	1	1	3	5	**0**

Table 5.9 Results for change in soil reaction pH

Change In Soil Reaction pH		
Model Ranking of Probable Causes		**Farmer Perception of Causes (questionnaires)**
		Increased Frequency of Strong Winds
1	Increased Frequency of Erosive Rain	0

Table 5.10 Results for crusting and sealing

Crusting and Sealing				
Model Ranking of Probable Causes		**Farmer Perception of Causes (questionnaires)**		
		Surpassed Animal Carrying Capacity	Livestock Population	Decrease In Livestock feed
1	Surpassed Animal Carrying Capacity	**9**	1	1
2	Livestock Population	2	**8**	1
3	Decrease In Livestock feed	1	0	**10**

Table 5.11 Results for decline in crop yields

Decline in Crop Yields				
Model Ranking of Probable Causes		**Farmer Perception of Causes (questionnaires)**		
		Increased Drought Frequency	Unfavourable Position on the Slope	Organic Matter Depletion
1	Increased Drought Frequency	**9**	1	1
2	Unfavourable Position on the Slope	4	**7**	0
3	Organic Matter Depletion	1	4	**6**

Table 5.12 Results for crop yield losses in the last three years

Crop Yield Losses in the Last 3 years				
Model Ranking of Probable Causes		**Farmer Perception of Causes (questionnaires)**		
		Unfavourable Position on the Slope	Increased Drought Frequency	Lack Of Institutional Support
1	Unfavourable Position on the Slope	**8**	2	1
2	Increased Drought Frequency	1	**9**	1
3	Lack Of Institutional Support	0	4	**7**

The eleven farmers and land managers sampled and surveyed represent about 24% of the farmer population in El Alegre village.

Even though the farmers perception is limited to the extent where the causes are determined only on the bases of observation their perception is developed through considerable years of experience and observation while residing and earning a living in the area. The local farmers are the first to witness the acting forces or causes of degradation in the area and the principal victims of the consequences to follow. As they are the integral part of the environment to be modeled, when necessary, the dataset collected from the farmers can be used as an alternative means for testing the model results for most of the state indicators. In other words, it is important to note that in areas where there is a need for technical or laboratory analysis to determine the existence of some of the indicators as in the case of Soil Reaction (pH) the local farmers understanding regarding the existence of such indicators in the area is quite limited or none. Therefore in such exceptional cases it is not a rational decision to use their perception to validate the results. This can be considered as one of the limitations of the implemented validation technique.

The constructed matrix has been used to validate the model performance by calculating Cohen's Kappa for each matrix (degradation state indicator table).

The Cohen's kappa coefficient (k) is a statistical measure of Inter-rater agreement, or Concordance, which is the degree of agreement among raters. It gives a score of how much homogeneity, or consensus there is in the ratings given by judges. It is generally a more robust measure than simple percent agreement calculation since κ takes into account the agreement occurring by chance. Cohen's kappa measures the agreement between only two raters who each classify *N* items into *C* mutually exclusive categories. Kappa has a range from 0 -1, with larger values indicating better reliability. Generally, a Kappa > .70 is considered as having a satisfactory (agreement). If the raters are in complete agreement then κ= 1. If there is no agreement among the raters (other than what would be expected by chance) then κ ≤ 0.

Cohen's kappa is often used in accuracy assessment of spatially explicit remote sensing data to get the attribute accuracy of maps.

The equation for k is:

$$K = \frac{(d-q)}{N-q} \qquad 5.1$$

Where

d = number of cases in the diagonal cells

q = number of cases expected in the diagonal cells by chance, and

N = Total number of cases

The calculated Cohen's kappa value for each state indicator matrix (tables 5.3 – 5.12) is shown in table 5.13.

Table 5.13 Calculated Cohen's kappa value for each state indicator table.

	Indicator Table	Calculated Kappa value
1	Soil Erosion by Water (Rills)	0.68
2	Soil Erosion by Water (Gully)	0.52
3	Soil Erosion by Wind	0.72
4	Decline In Effective Soil Depth	0.5
5	Organic Matter Depletion	0.73
6	Recess Of Land Cover	0.63
7	Crusting and Sealing	0.72
8	Decline in Crop Yields	0.5
9	Crop Yield Losses in the Last 3 years	0.59

While analysing individual Kappa results higher rates of agreement are seen in identifying and ranking the causes for Organic Matter Depletion with 73% of agreement between the model prediction and farmer perceptions, along with Soil Erosion by Wind, and Crusting and Sealing showing 72% agreement.

Lower agreement results are obtained for state indicators; Decline in Crop Yields and Decline in Effective Soil Depth with 50% agreement.

Subsequently merging Kappa values of each state indicator the final aggregate model agreement have been assessed. While taking the aggregate average, exclusion has been made concerning the state indicator Soil Reaction (pH) from the calculation for the reason that the results obtained for this model variable will cause a bias in the assessment results due to the local farmers limited knowledge about the existence of this indicator in the area, since its identification can only be confirmed using laboratory analysis and/or field experiments.

Using this alternative validation method, the total model prediction agreement with the farmers' perception indicates that the model agrees with the perceptions in 62% of the cases through identifying and ranking the causes for a given type (state) of degradation. The result shows a modest above average agreement between the model results and farmer perceptions.

It is important to note that this rate of agreement does not show the low performance of the model. This modest agreement was attributed, to a large extent, to the degree of subjectivity involved in interpreting vague farmer responses in the questionnaires, which were not purposely designed for this validation.

Many factors can be mentioned which affected the obtained result, one of the main factors is that the data used for validation of the model where extracted from previously collected data sources (Dixon, 2004). Where the questionnaires were not initially designed for the purpose of validation of this model, therefore their interpretation and translation to the matrix (table) might contain some subjectivity introduced by the interpretation of the translator. The other major reason worth mention here is that, each farmer's response to the interview questions also involves subjectivity affecting, in turn, the outcome.

Even though the best method for the validation of this model could have been through the use of independent assessment made in the area. Using available data this alternative validation method proved useful and it can also be used to assess the relative performance of the model in relation to local farmer's perceptions.

CHAPTER 6

Mapping the Results

Using GIS, the various types and states of degradation including their intensity, extent and their most probable causes in El- Alegre sub watershed were mapped using the results obtained from the analysis. First, the indicators were coded on the basis of the indicator list from (Ponce-Hernandez and Koohafkan, 2004) and their intensity classes were defined to fit in the map legend see (table 5.3 and table 5.4).

The legend is constructed in order to contain the type of degradation, its state, intensity and extent including the top three ranked most influencing causes of each state of degradation as identified by the model analysis. This legend design can be considered as an enhancement over the design in (Ponce-Hernandez and Koohafkan, 2004) and (Ponce-Hernandez, 2005) where the idea of the legend design for indicators of land degradation first appeared.

Table 5.14 Coded Driving Force and Pressure indicators used in the legend from (Ponce-Hernandez and Koohafkan, 2004) with some adjustments

Driving Force Indicators	**Code**
Climatic Variability	CV
Land Policies	LP
Micro Economic Policies	ME
Animal Population	AP
Decrease in rural employment	LO
Unfavourable Position on the Landscape (slope)	AL
Food Insecurity	FI
Main Fuel Sources	FS
Lack of Institutional Support	IS
Accessibility of Extension Services or Agricultural Education	AE
Low Literacy Rate and Education	ED
Water Management	WM
Inadequate sewer systems and solid waste disposals	SW
Affordability of Alternative Energy Source	EI

Pressure Indicators	**Code**
Increased Drought Frequency	CV1
Increased Frequency of Erosive Rainfall events and surface runoff	CV3
Increased Frequency of High velocity Winds causing dust storms in fields	CV4
Rangeland Biomass Scarcity (years)	PP6
Decrease in Livestock Feed in Rangelands in last few years	PP7
Land Abandonment (migration)	DC5
Surpassed Animal Carrying Capacity of Rangelands	AP2
Access to water per household	WI1
Deterioration of water quality (increased turbidity and /or contamination)	WI4
Increased Demand for Forest Products (Deforestation)	EI4
Uncertainty of Land Tenure	LT1
Use of Common Lands	LP1
Access to Banking and Credit Institutions	AC1

Table 5.15 codes for the states of land degradation indicators and their intensities used in the mapping legend

Code	State Indicator	Intensity
Ser	Soil Erosion By Water Rills	(1) Not affected
		(2) Slightly affected
		(3) Moderately affected
		(4) Intensely affected
Seg	Soil Erosion By Water Gully	(1) Not affected
		(2) Slightly affected
		(3) Moderately affected
		(4) Intensely affected
Sw	Soil Erosion by Wind	(1) Not affected
		(2) Slightly affected
		(3) Moderately affected
		(4) Intensely affected
Se	Decline In Effective Soil Depth	(1) No decline
		(2) Slight decline
		(3) Intense decline
Om	Organic Matter and carbon Depletion	(1) Slightly depleted
		(2) Highly depleted
Ic	Recess of Land Cover	(1) No recess
		(2) Moderate recess
		(3) Intense recess
Csr	Change in Soil Reaction (pH)	(1) Increased acidity
		(2)No Change about neutral
		(3) Increased alkalinity
Cr	Crusting and Sealing	(1) Slight to no crusting
		(2) Intense crusting and sealing

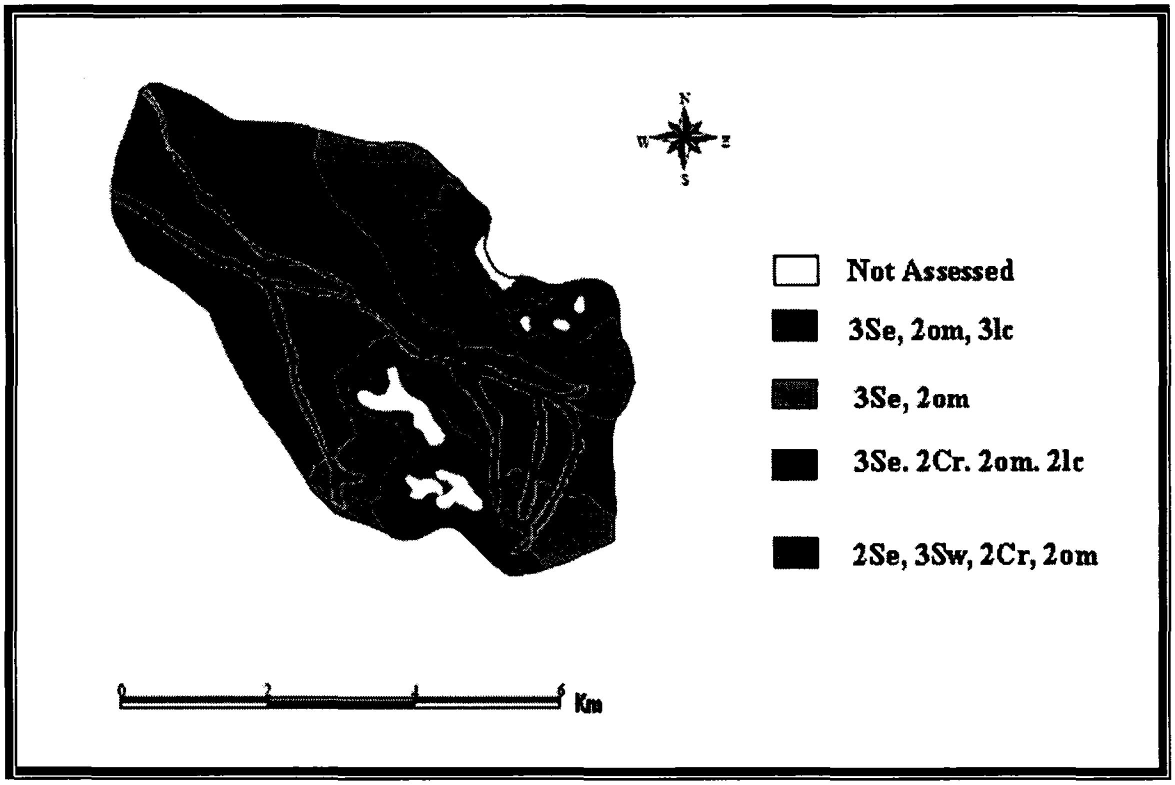


Figure 5.2 The state and intensity of land degradation in El Alegre

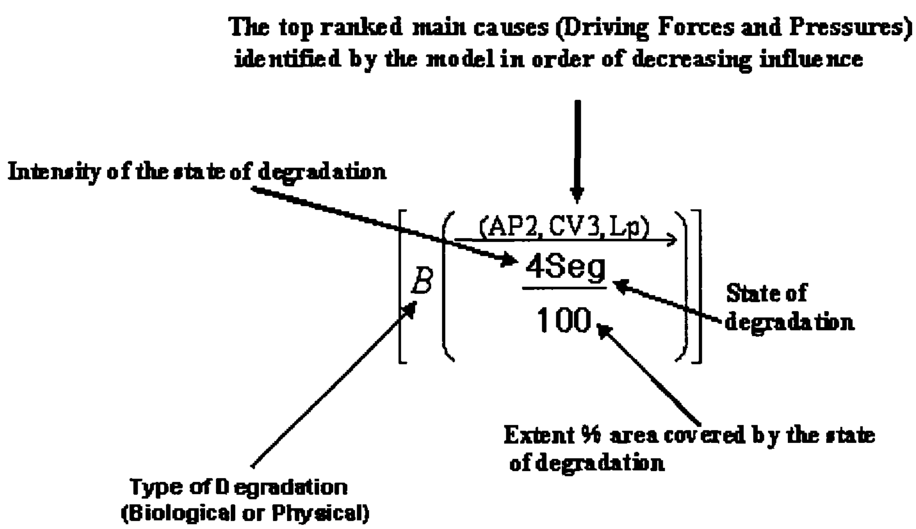


Figure 5.3 Composition of the coding for degradation indicators (type, state, intensity and extent) in El Alegre

Facet 2

$$\left[P \left(\frac{\overset{(AP2,\ CV3,\ Lp)}{4Seg}}{100} \right) ; \left(\frac{\overset{(AP2,\ Lp,\ CV3)}{4Ser}}{100} \right) ; \left(\frac{\overset{(CV4,\ CV1,\ AP2)}{4Sw}}{100} \right) B \left(\frac{\overset{(CV1,\ EI4,\ EI)}{2OM}}{100} \right) ; \left(\frac{\overset{(PP6,AP,PP7)}{3lc}}{100} \right) \right]$$

Facet 3

For croplands:

$$\left[P \left(\frac{\overset{(AP2,\ CV3,\ Lp)}{4Seg}}{30} \right) ; \left(\frac{\overset{(AP2,\ Lp,\ CV3)}{4Ser}}{60} \right) B \left(\frac{\overset{(CV1,\ EI4,\ EI)}{2OM}}{100} \right) ; \left(\frac{\overset{(PP6,AP,PP7)}{3lc}}{80} \right) \right]$$

For rangelands:

$$\left[P \left(\frac{\overset{(AP2,\ CV3,\ Lp)}{3Seg}}{90} \right) ; \left(\frac{\overset{(AP2,\ Lp,\ CV3)}{2Ser}}{80} \right) ; \left(\frac{\overset{(CV4,\ CV1,\ AP2)}{4Sw}}{50} \right) B \left(\frac{\overset{(PP6,AP,PP7)}{2lc}}{80} \right) \right]$$

Facet 4

For croplands:

$$\left[P\left(\frac{\overset{(AP2,\,CV3,\,Lp)}{4Seg}}{50}\right);\left(\frac{\overset{(AP2,\,Lp,\,CV3)}{3Ser}}{80}\right);\left(\frac{\overset{(CV3,\,CV4,\,DC5)}{2Se}}{90}\right);\left(\frac{\overset{(CV4,\,CV1,\,AP2)}{3Sw}}{90}\right);\left(\frac{\overset{(AP2,\,Lp,\,PP7)}{1\,Cr}}{90}\right) B\left(\frac{\overset{(CV1,\,EI4,\,EI)}{1\,OM}}{90}\right);\left(\frac{\overset{(PP6,AP,PP7)}{2lc}}{80}\right)\right]$$

For rangelands:

$$\left[P\left(\frac{\overset{(CV3,\,CV4,\,DC5)}{2Se}}{100}\right);\left(\frac{\overset{(CV4,\,CV1,\,AP2)}{3Sw}}{90}\right);\left(\frac{\overset{(AP2,\,Lp,\,PP7)}{1\,Cr}}{100}\right);\left(\frac{\overset{(AP2,\,Lp,\,CV3)}{2Ser}}{20}\right) B\left(\frac{\overset{(CV1,\,EI4,\,EI)}{1\,OM}}{100}\right);\left(\frac{\overset{(PP6,AP,PP7)}{2lc}}{100}\right)\right]$$

Facet 5
For croplands

$$\left[P\left(\frac{\overset{(CV3,\ CV4,\ DC5)}{2Se}}{100}\right);\left(\frac{\overset{(CV4,\ CV1,\ AP2)}{3Sw}}{90}\right);\left(\frac{\overset{(AP2,\ Lp,\ PP7)}{1\ Cr}}{100}\right);\left(\frac{\overset{(AP2,\ Lp,\ CV3)}{2Ser}}{20}\right)\ B\left(\frac{\overset{(CV1,\ EI4,\ EI)}{1\ OM}}{100}\right);\left(\frac{\overset{(PP6,AP,PP7)}{2lc}}{100}\right)\right]$$

For rangelands

$$\left[P\left(\frac{\overset{(CV3,\ CV4,\ DC5)}{2Se}}{80}\right);\left(\frac{\overset{(AP2,\ Lp,\ PP7)}{1\ Cr}}{100}\right);\left(\frac{\overset{(CV4,\ CV1,\ AP2)}{3Sw}}{90}\right)\ B\left(\frac{\overset{(CV1,\ EI4,\ EI)}{1\ OM}}{100}\right);\left(\frac{\overset{(PP6,AP,PP7)}{2lc}}{80}\right)\right]$$

Figure 5.4 Legend coding for land degradation types and their states, causes, intensities and extents in El Alegre sub watershed

CHAPTER 7

Conclusion

The integration of Bayesian networks to a DPSIR approach to describe the relationships between bio-physical states to social, economic and demographic causes of land degradation is proven to be a promising tool for modeling the causality intensity and extent of degradation. Bayesian networks bring a new probabilistic approach to the establishment of the major root causes of states of land degradation in El Alegre sub watershed. This integration allows for a combination of data obtained from various sources, namely, empirical data, questionnaires, interviews with farmers, field surveys of agricultural and rangeland plots and interviews with government officials. Moreover the modeling approach enables expert knowledge to be incorporated into the model on the same basis as more objectively-derived data, which other modeling tools usually do not encompass. Such features allow for the creation of a model which may contain mathematical relationships as well as subjective elements corresponding to the experience of the people who are, in many cases, an integral part of the system being modelled.

The model also provides a compact way of depicting and communicating substantive assumptions and relationships between the land degradation indicators, including physical and social components, in the study area and facilitates economical representation enhancing the quality of causality assessments. Moreover, it also provides an effective technique for making use of existing knowledge and offers a coherent framework which is easily updatable to incorporate new evidence or knowledge into the network, when available.

The model gives enough flexibility as to be able to accommodate for different situations of data, scale and required detail. In its current form the approach can be transferred to any dry land area of the world with the only condition of data availability. Model complexity and its computation time depends on the extent of the area to be considered and the amount of collected data from this area. In regional or nation wide level applications the complexity of the model will increase in number of degradation indicators which leads to a much complex causality relationship among them resulting, in turn, longer computation time to run the model.

While the legend and coding of driving forces, pressures and states including type, extent and intensity produced in this modeling approach display all the required information, in their current composition they require background knowledge to become intuitive. However, they still provide a clear map representation.

The ultimate validation of the model can be achieved using independent information, if available, through other independent assessments. This can be challenging when no data become available for assessing the developed model, as in our case. In such circumstances, it is imperative to use alternative available source for validating the model results and test its performance. Hence we used a data source, which is collected through questionnaires from local farmer interviews, and then calculated the agreement between the model and the interview results using Cohen's Kappa. The results showed that the agreement between farmer perceptions of causes for each degradation state and the predicted causes by the model was modest, showing above average agreement. The obtained agreement (Kappa) value does not indicate low performance of the model rather the Kappa value can be attributed, to a large extent, to the degree of subjectivity involved in interpreting vague farmer responses from the questionnaires. This occurred due to the use of a data source (questionnaires) which are not designed for the purpose of validation of this model, consequently while extracting the questionnaires there might be substantial subjective interpretations in transcribing the questionnaires to the matrix by the translator. In best situations, validation of the model can be made through the integrated use of independent studies and farmer interview analysis results. In this case the questionnaires have to be designed in order to yield less subjective outcomes. They should contain straightforward, non ambiguous and less subjective questions regarding the perception of the farmers on the main causes of degradation in their area.

Even though the data used for validation are not expected to give a best reliable measurement of performance they provide an alternative means to see the general relative performance of the model in identifying and ranking the root causes for a state of degradation in the study area. On the other hand, the model proved empirically accurate according to the knowledge of local experts.

Experience has shown that it is not enough to develop and implement technical solutions to the dry land management problems but it is equally important to address the root causes of land degradation in order to secure positive results of investments in projects and programs (FAO, 2002).

This model can be used to communicate to policy-makers and decision-makers at all levels, the nature and status of degradation within which they are operating. By simplifying complex relationships and allowing them to attribute responsibility for outcomes to activities of the population and to agencies. The overall picture emerging from this type of assessments will enable those with economic and political power locally and nationally to understand the benefits of addressing the main causes of degradation in the sub watershed.

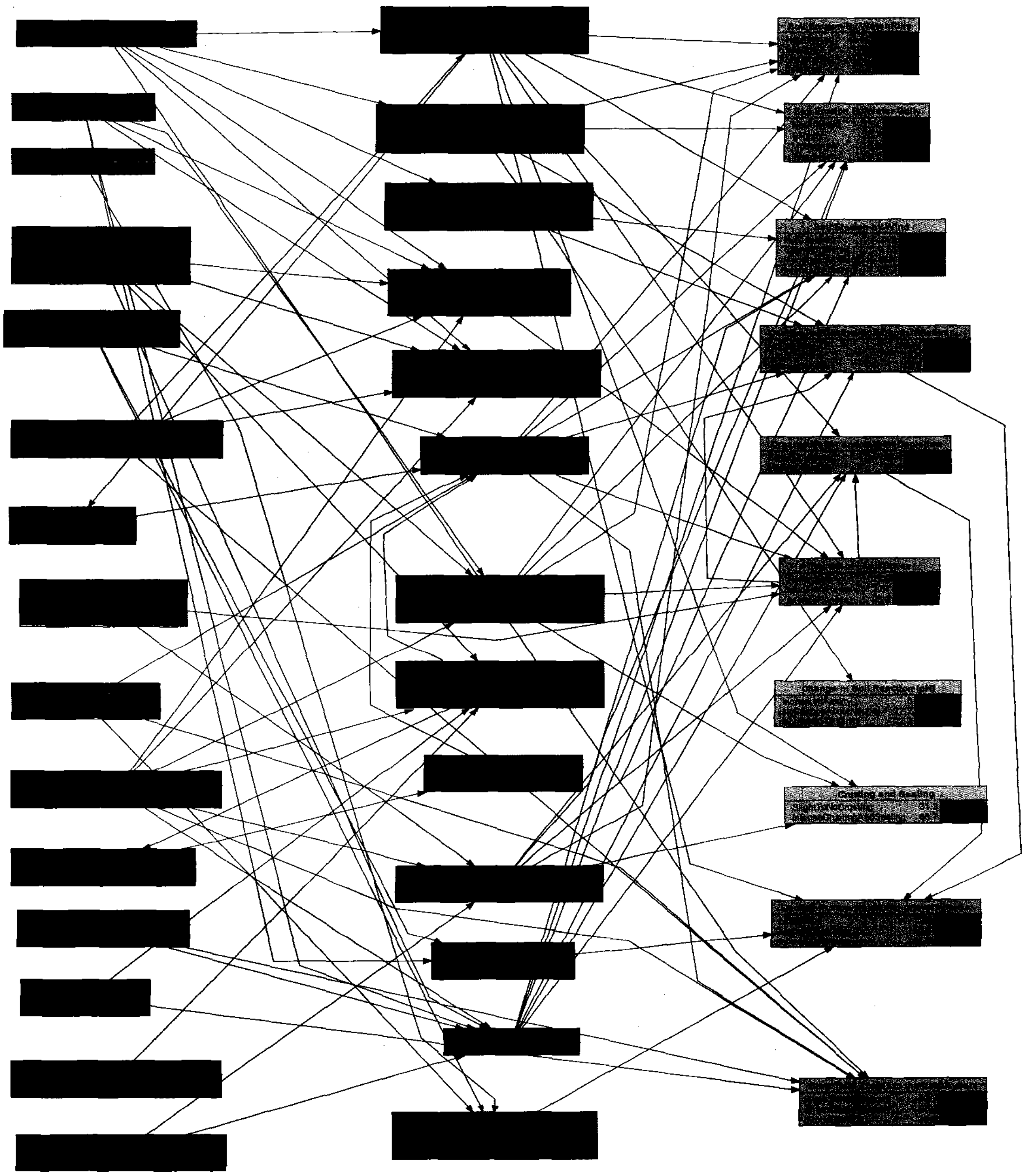
The results obtained from the model can also be used as a tool for advising decision makers in their formulation of environmental protection, conservation and remediation plans, for combating the intensity and spread of land degradation types and processes in a local or regional scale. The implementation of such plans would enable decision makers to employ solutions that simultaneously stop and reverse the degradation process through giving priority to the identified most determinant probable causes for a given state of degradation in the area. Tools such as Bayesian Network would provide a more logical answer to the question "Where is more effort needed to stop and reverse the current status of land degradation?".

Due to the scope of the research objectives in this thesis our modelling efforts consider only Driving Forces, Pressures and the States. The approach did not look beyond the states of degradation to the impacts and responses. Despite the complexity of collecting and integrating social, economic and demographic data and policy information to biophysical data in terms of causal chains, the DPSIR methodology represents a promising paradigm.

In future research efforts despite the complexity and the challenge we recommend the inclusion of the impacts of various states of degradation and the human response to all the degradation processes (the last two in the DPSIR chain) into the modelling effort in order to have a more complete assessment of the degradation within the framework.

DPS - BN Model

Driving Forces Pressures States



By Oumer Ahmed

List of Acronyms

ASSOD	The Assessment of Soil Degradation in South and Southeast Asia
DPSIR	Driving Forces-Pressures-State-Impact-Response approach
ESP	Exchangeable sodium percentage in the soil
FAO	Food and Agricultural Organization of the United Nations
GACGC	German Advisory Council on Global Change
GFE	Global Environment Facility (GEF), established in 1991, helps developing countries fund projects and programs that protect the global environment.
GLASOD	Global Assessment of Human-induced Soil Degradation
IFAD	International Fund for Agricultural Development
LADA	Land Degradation Assessment in Dry Lands
SOVEUR	Soil Vulnerability Assessment in Central and Eastern Europe
UNCCD	United Nations Convention to Combat Desertification
UNCSD	United Nations Commission on Sustainable Development
UNEP	United Nations Environment Programme
USDA	United States Department of Agriculture

Glossary

Acyclic graph: A graphical model of cause and effect in which return pathways, or loops, do not exist.

Assessment: suggests judgement, evaluation or comparison. It makes necessary the definition of a baseline or reference level for the evaluation or comparison.

Causes: are the direct agents that promote change resulting in a given state of land degradation and they are the direct pressures exerted on land resources under which the onset of degradation or deterioration processes occur.

Cause and effect: In the context of Bayesian Networks, the direction of influence between two or more nodes using a uni-directional arrow. Cause and effect may be direct or indirect.

Conditional probability: When two or more factors or causal variables affect another (i.e., a child node) within a Bayesian Network, the condition of the child node is contingent on the values of the causal nodes.

Conditional probability table: Within a Bayesian Network node, the supportive table or matrix that includes all possible combinations of categorical values from two or more parent nodes.

Decision support: Are tools and techniques for making improved decisions.

Desertification: has been defined in the United Nations Convention to Combat Desertification (UN-CCD) as land degradation occurring in arid, semiarid and dry subhumid areas caused by a combination of climatic factors and human activities. Hence only land degradation occurring in drylands as defined above is considered as part of a desertification process.

Drylands: comprise areas having a ratio of P/PET < 0.65, where P is precipitation and PET is potential evapo-transpiration. A further breakdown of this range yields definitions of **"hyper-arid"** (P/PET< 0.05) **"arid"** (0.05 < P/PET< 0.20) **"semi-arid"** (0.20<P/PET< 0.50), and **"dry sub-humid"** (0.50<P/PET< 0.65).

Expert judgment/opinion: The estimation or prediction of a measure through the informed opinion of one or more specialists.

Extent: indicates distribution in both, spatial and temporal dimensions. Typically the mapping of the spatial dimension is the foundation for the monitoring of temporal variations.

Gully: A miniature valley or gorge caused by the erosive effect of running water. The water wears away a deep channel in the land surface. Typically water only runs through gullies after rains.

Indicators: are variables, parameters (even in the statistical sense), or measures which provides evidence of a condition, change of quality, or change in state of something valued (Dumanski and Pieri, 1996). Land quality indicators, for instance, include statistics that report on the condition and quality of the land resource itself.

Intensity: refers to the severity of the process or state of degradation and suggests the definition of a scale of severity, whether categorical or numerical.

Methodological Framework: is a framework whose constituents are methods and procedures. A methodological framework provides the structure, configuration, organization and composition of methods and procedures to be used for a finite set of objectives.

Rill: A small channel formed on the soil surface during erosion. Rills often appear during heavy rains. They are seasonal, in that they can be eliminated by normal agricultural practices.

Soil Fertility: The soil's ability to produce and reproduce. It is the aggregate status of a soil consequent upon its physical, chemical and biological well-being.

Bibliography

1. Amente Orozco, A., Cedillo Martinez, I., Rubio Granados, E., Quero Carrillo, A.R., Tarango Arambula, L.A. and Talavera Magana, D. : 2002 Governing Plan of Production Conservation of the El Alegre Micro Watershed in the state of San Luis Potosi Salinas de Hidalgo, S.L.P., Mexico: Colegio de postgraduados, Campus San Luis Potosi. Directly translated version by Raul Ponce and Rebecca Dixon.

2. Andrew Gelman and Xiao – Li Meng: 2004, Applied Bayesian Modeling and Causal Inference from Incomplete Data Prospectives.

3. B.G.J.S. Sonneveld: 2002, Land Under Pressure the impact of water erosion on food production in Ethiopia.

4. Causality: Models, Reasoning, and Inference. Judea Pearl. Cambridge University press: 2000.

5. Daryle Niedermayer, I.S.P.: 1998, An Introduction to Bayesian Networks and their Contemporary Applications.

6. Economic and Social Commission for Western Asia (ESCWA): Assessing Land Degradation in the ESCWA Region: a Methodological Framework. Beirut, July, 2005.

7. Economic and Social Commission for Western Asia (ESCWA): December, 2005, Manual on the Application of a Land Degradation Assessment Framework in the ESCWA Region. Beirut, December 2005.

8. FAO: 1996, Land husbandry – components and strategy: FAO SOILS BULLETIN. Food and Agriculture Organization of the United Nations, Rome, Italy.

9. Foster, G.R: 1988, Modelling soil erosion and sediment yield, soil erosion research methods, Soil and Water Conservation society.

10. FAO/UNEP: 1978, Report on the FAO/UNEP Consultation on Methodology For Assessing Soil Degradation. Rome, Italy.

11. Global Assessment of Soil Degradation (GLASOD): October, 1990, World Map of the Status of Human-Induced Soil Degradation. An Explanatory Note.

Keith Wiebe: 2003, Linking Land Quality, Agricultural Productivity and Food security.

12. Haan, C. T., Johnson, H. P., and Brakensiek, D.L.: 1982 Hydrologic modeling of small watersheds: St. Joseph: American Society of Agricultural Engineers (ASAE).

13. Helmut J. Geist and Eric F. Lambin: 2004, Dynamic Causal Patterns of Desertification.

14. James R. Norris: 1997, Markov Chains.

15. Kevin Murphy: 1998, A Brief Introduction to Graphical Models and Bayesian Networks.

16. Khon Kaen: 1999, Report of the Second International Conference on Land Degradation and Desertification, Thailand.

17. Lal, R. and Pierce, F.J.: 1991, Soil Management for sustainability. Soil and water Conservation, IWOA: Soil and Water Conservation society.

18. Lal, R. and Stewart, B.A.: 1990 Soil Degradation. New York.

19. Michael Stocking and Niamh Murnaghan: 2000, Land Degradation – Guidelines for Field Assessment. Overseas Development Group, University of East Anglia, Norwich, UK.

20. Millennium Ecosystem Assessment: 2005, Ecosystem and Human Well-Being: Synthesis.

21. Morgan, R.P.C.: 1995, Soil erosion and conservation (Second edition). Harlow: Longman.

22. Pearl and Shafer: 1990, Bayesian Networks.

23. Raul Ponce-Hernandez and Parviz Koohafkan Report on a Consultancy as Visiting Scientist for Food and Agriculture Organization of the United Nations (FAO), Land and Water Development Division. Methodological Framework for Land Degradation Assessment in Dry lands (LADA): Rome, August, 2004.

24. Rebecca L. Dixon: 2003, Application of the LADA Framework Approach for Land Degradation Assessment in Dry Lands.

25. Robert L. Winkler: 1972, Introduction to Bayesian Inference and Decision.

26. Subramani Mani, Marco Valtorta and Suzanne Mcdermott: 2005, Building Bayesian Network Models in Medicine: The Mentor Experience.

27. Vaskin V.Snakin, P.P. Krechetov, T.A. KKuzovnikova, I.o. Alyabina, A.f.Gurov, A.v. Stepichev: August, 1995, The System of assessment of soil degradation.

28. Wischmeier, W. H., and Smith, D.D.: 1978, Predicting rainfall erosion losses: A guide to conservation planning. U.S. Department of Agriculture. Agriculture Handbook No.537, Washington, D.C., U.S. Government printing office.

29. Woldeamlak Bewket: 2003, Land degradation and farmers' acceptance and adoption of conservation technologies in the Digil Watershed, north-western highlands of Ethiopia. Social Science Report Series no.29, OSSREA, Addis Ababa, Ethiopia.