Chapter 6

Climate Model Output and the Insurance Industry

6.1 From Complex Models to Complex Decisions

In the analysis of nonlinear and chaotic low-dimensional models, the focus has so far been on understanding the role of IC uncertainty in the predictability of climate under climate change. The results in chapters three, four and five convey the need for large IC ensemble experiments to detail the changing variable distributions associated with evolving model attractors and pseudo-attractors in response to altered parameter conditions. Throughout these chapters, the experiments have been contextualised by the interests of the climate change adaptation community and specifically the needs of the insurance industry. Here the messages relating to climate predictability amidst uncertainty explored in previous chapters are considered in the context of insurance decisions which are sensitive to climate change. The objective is to present an analysis outlining the needs of insurers, concerning the uptake and use of climate model information in the decision making process, and to expose the challenges in using existing climate model output to inform decisions.

In this chapter, the use and interpretation of climate model information is explored with respect to strategic decisions faced by the insurance industry. The initial part of the chapter focuses on the specific interests of insurers and highlights the relevance of the previous chapters in the interpretation of model-based projections. In section 6.2, the time horizons over which climate information might be deemed relevant for informing decisions linked to specific strategic insurance issues are identified. The rest of the chapter presents the results of a case study analysing the use of Bayesian Networks (BNs) to inform the viability of index-based crop microinsurance (a sector of strategic interest to insurers) for a region in India sensitive to changing climate patterns. Section 6.3 provides an overview of BNs and explains how they have previously been used to tackle climate change decision problems. The scope of the case study is introduced in section 6.4, detailing the geography of the focus area and highlighting the recent development of index-based microinsurance for climate-related perils. Section 6.5 documents the methodology adopted and provides a preliminary analysis of the data which is used in the BN analysis. The BN results are presented in section 6.6, illustrating different ways to combine model information with past observations of climate to inform decisions using the BN framework. Section 6.7 concludes the chapter with a discussion of the case study results, an appraisal of the methodology and ideas for future work to extend the research.

6.2 The Use of Climate Model Information for Strategic Decision-Making in the Insurance Industry

6.2.1 Interpretation of model output for assessing insurance risks

This thesis aims to combine the insights from simple model experiments with research regarding the relevance of model output for insurance industry decisions to guide the future design of climate model experiments. The previous three chapters present the results for a wide ranging set of experiments conducted with low-dimensional nonlinear models considered analogous to the climate system. The analysis serves a dual purpose in providing a conceptual basis for understanding climate under climate change and in underpinning the design of future experiments on more complex climate models. Although the models used in chapters three, four and five are much less complex than GCMs, the results highlight a number of issues which are relevant to insurers tasked with interpreting the output from climate model projections to guide insurance decisions.

Insurers are ultimately interested in return periods of loss events. Utilising climate science to estimate the frequency and magnitude of damaging meteorological events is therefore an important element in the process of designing insurance products. The analysis presented in chapter three shows that estimating frequency distributions of variables in nonlinear systems using a single trajectory can be problematic; even if it displays transitive behaviour. The results in section 3.7 reveal that a transitive system does not always display ergodicity. The combined effects of resonance and hysteresis in the L63 model climate distributions limit the use of single model realisations to understand the climate of the model. Even in the absence of climate change the results suggest that utilising past observations to estimate frequency distributions of climate variables can be misleading.

Under transient climate change, the predictability of climate variable frequency distributions becomes further complicated by the potential for the underlying dynamic behaviour of the climate system to be forcing dependent. Analysis of the L84 and LS84 models in chapters four and five respectively reveals the impact of altering key parameters on the predictability of the model climate distributions. The shift from transitive regions of parameter space to intransitive or almost-intransitive regions of parameter space, in response to fluctuations in the model parameters, leads to nonlinear responses in the model pseudo-attractor evident in the properties of the IC ensemble distributions. By analogy, the irregularity of the variable frequency distributions imply that estimating recurrence probabilities for climate variables under climate change requires an acknowledgement of the potential for nonlinear shifts in variable distributions and the possibility of abrupt changes in the system's dynamic behaviour.

The use of return periods to estimate insurance risks becomes somewhat confusing in the context of climate change. The notion of a 1 in 200 year loss event implies stationarity, or at least an element of periodicity in the system. Dailey et al. (2009) state that "the 200-year loss has a

0.5% probability of occurring in any given year; that is, it is the loss that can be expected to occur or be exceeded on average once every 200 years". However, as explained in previous chapters, the climate attractor (or pseudo-attractor) is continuously changing in response to altered forcings and boundary conditions so the probability of a 1 in 200 year event, for a system which is undergoing systematic change, is ill-defined. Even in the absence of climate change the magnitude of a hazard with 0.5% probability of occurring is continuously being altered from year to year. Under climate change, the problem of identifying hazard probabilities is exacerbated.

6.2.2 The ergodic assumption in insurance

Part of the motivation for studying the dynamics of the L63, L84 and LS84 models is to establish the limitations of the ergodic assumption in understanding climate under climate change. Insurers also invoke the ergodic assumption when pricing risk based on observational data. For weather and climate-related perils, historical meteorological datasets are utilised to assess the hazard component of the insured risk. Implicit in the use of such data is the notion that the past is a good guide to the future. In estimating the hazard component of the risk, insurers usually assume that the PDF estimated from observed records of meteorological data at a given location is equivalent to the PDF of a meteorological event occurring in the next insurance period.

It is well acknowledged that nonstationarity poses a significant challenge to the insurance industry (Herweijer et al. (2009), Lloyd's (2011a)). For nonlinear dynamical systems, the ergodic assumption has been shown to be misleading in the presence of internal modes of climate variability and forced climate change. To better understand the impact of the ergodic assumption on insurance decisions, it is important to establish how sensitive decisions are to the use of climatology and time series data as opposed to forecast model information in the form of ensemble distributions conditioned on IC uncertainty. Yet until large IC ensembles are run routinely, climate scientists and insurers will not be able to distinguish model uncertainty from errors related to the ergodic assumption. This inevitably hampers the efforts of climate modellers to appropriately communicate model uncertainty to decision makers within the insurance industry. The case study presented in this chapter provides a possible method for evaluating the impact of the ergodic assumption on insurance decisions. As a precursor to the development of the case study, the next section outlines the main strategic issues which would benefit from the appropriate interpretation of climate model output.

6.2.3 Identifying the relevant strategic issues

Climate change is one of a number of strategic issues facing policymakers within the (re)insurance industry. Mills (2009) presents climate change as an issue "bound up in the very fabric of the [insurance] industry and its business environment". The insurance industry is generally better placed than other societal sectors to cope with the changing nature of risks associated with climate change and can have an important role to play in communicating climate risks to society (Dlugolecki et al. (2009)). However, the insurance industry is vulnerable to an increase in losses associated with the changing frequency and magnitude of climate-related perils. In examining the hazard component of climate-related insurance risks for specific business lines, insurers inevitably turn to the climate modelling community to provide quantitative and qualitative guidance to inform the decision-making process.

Within the elaborate and complex trading structures of the insurance industry, the decision-making process can become convoluted with actions taken at a variety of organisational levels. Decisions are often multifaceted and are seldom made by one individual. In relation to the use of climate model projections, decisions are likely to be mainly strategic rather than operational. In section 6.3, the results of a case study exploring the use of climate model output in the emerging microinsurance sector is presented. The decision to focus on microinsurance was informed by the identification of strategic issues in this field that may benefit from climate model information.

Establishing the planning time horizons for strategic insurance issues is important in determining how model information can best be incorporated into the decision making process. Preliminary research involved analysis of the existing literature relating to long-term insurance interests and the extent to which climate affects the planning process (documented in section 2.3). In addition, informal discussions were held with insurance practitioners from a number of insurance institutions. Structured interviews were not deemed appropriate due to the exploratory nature of the research. The practitioners involved were selected based on their expertise in the application of climate information to insurance decision making. The preparatory questions used to facilitate discussion are given in Appendix D.

The relevant literature and discussion outcomes were used to construct the planning time scale diagram in figure 6.1. Ten strategic issues were identified (see table 6.1) and subjective estimates for their respective planning time horizons assessed. The information contained in figure 6.1 illustrates the time scales over which climate model predictions may be used to inform policy decisions.

Because of the lack of formal guidance in the use of model information for insurers on the longer time scales associated with anthropogenic climate change, this chapter is focused on strategic issues which have "long" planning horizons. The issues considered to have a long planning horizon in figure 6.1 are those which extend to 10 years or more. Nevertheless, the definition of climate as the distribution of states conditioned on IC uncertainty is as relevant for short term risk analysis as it is for long-term climate change impacts assessments. In determining the forecast distribution of a particular climate variable, a large IC ensemble is required because of the absence of stationarity and potential lack of ergodicity in the climate system. In the PMS, the climate-related risks could be exactly calculated but given imperfect models, IC ensemble distributions are best used to highlight areas of agreement (or disagreement) between different model forecasts.

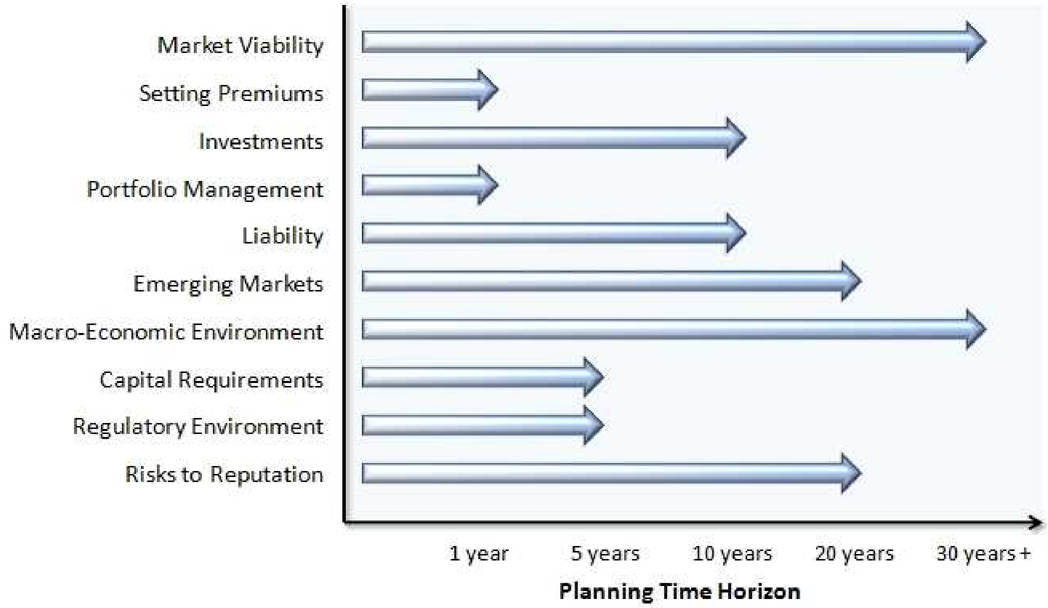


Figure 6.1: Subjective assessment of planning time horizons for strategic non-life insurance issues which could be directly or indirectly impacted by climate change.

For strategic planning climate risk becomes entangled with many other pressures facing the industry. The relative importance of climate variability and climate change compared to other strategic considerations will depend on an insurer's specific exposures and lines of business. Nevertheless, as mentioned in section 2.3.1, the global auditing company Ernst & Young have stated that for insurers, climate change is a more pressing concern than demographic change, emerging markets and regulatory intervention (Ernst & Young (2008)). However, such concerns are not necessarily mirrored in the views of insurance company board executives. Lloyd's of London and the Economist Intelligence Unit (EIU) have published a joint report assessing corporate risk priorities and attitudes around the world (Lloyd's (2011b)). Of the 50 identified strategic risks, climate change was ranked 32nd behind "Strikes and industrial action" and just ahead of "pandemics". However, as shown in figure 6.1, knowledge of the impacts of climate change can influence other strategic concerns. Notably in the Lloyd's (2011b) report, "reputational risk" was identified as the third most important strategic risk, behind "loss of customers" and "talent and skills shortages" yet climate change has the potential to affect the reputation of an insurance company. For example, if an insurer fails to acknowledge changes in the risk of a loss event of a climate-related peril and suffers increased losses as a result, this can affect the confidence of policyholders and shareholders. These issues are highlighted in the Lloyd's (2011b) report which states, "as the impacts of climate change accumulate, [insurers] may be failing to grasp the very real threats that natural catastrophes pose to business continuity".

As described in this section, when considering future loss events it is essential for insurers to understand climate risk in the context of other socio-economic factors. In sections 6.3 to 6.6, a

Strategic Issue	Description
Market Viability	The capacity for a given business line or insurance activity to remain profitable.
Setting Premiums	Determining the price or percentage of the maximum indemnity to be charged to the policyholder.
Investments	Allocation of capital in externally managed assets, funds or other financial products.
Portfolio Management	Assessing the collective performance of a number of insurance products.
Liability	The legal responsibility of the insurer to account and communicate the risks covered for a particular line of business.
Emerging Markets	New lines of business in established markets and/or existing lines of business in burgeoning economies.
Macro-Economic Environment	The large scale external drivers of societal and economic change which affect business performance and influence decisions.
Capital Requirements	The level of capital required to underwrite insurance policies and cover payouts in the event of a loss.
Regulatory Environment	Political, financial, environmental and social obligations by which insurers must operate.
Risk to Reputation	Negative implications for a particular insurance company as result of unpopular business activities and/or behaviour before, during or following loss events.

Table 6.1: Description of the strategic issues identified in figure 6.1.

case study is presented to address two strategic insurance issues identified in figure 6.1; market viability and emerging markets. Climate model output is used directly to explore the viability of microinsurance[1] in relation to the use of climate information and other important decision factors in an emerging economy, India.

[1]Microinsurance refers to insurance characterised by low premiums and low coverage limits.

6.3 Case Study: Using Climate Model Output to Inform the Pricing of Weather Index Microinsurance

In order to exemplify the issues related to the use of climate model output for decision making within the insurance industry, a case study is developed. A Bayesian Network (BN) is constructed to explore the viability of index-based microinsurance (defined in section 6.4.1) in providing crop coverage against drought and excess rainfall in Kolhapur, western India. The following analysis outlines the methodology adopted and presents the results in relation to the key themes of the thesis; model uncertainty, the use of the ergodic assumption and decision making under uncertainty and ambiguity. A key objective is to establish whether or not climate model output in it's current format is useful and usable by insurance practitioners.

6.3.1 The Bayesian Network approach

A number of techniques can be applied by insurers and practitioners in using climate model output to inform the pricing of weather index insurance. Fitting statistical distributions to model output data is one such method to estimate tail probabilities. The *Poisson* distribution is often used in risk analysis within the insurance sector to generate estimates of the expected frequency of claims (Embrechts et al. (2003)). With specific regard to rainfall data, other statistical distributions with positive "fat tails", such as the Weibull distribution, can be fitted to climate data to determine the probability of exceeding defined thresholds. Yet fitting statistical distributions requires assumptions to be made about the nature of the data which may be unrepresentative. Furthermore, when combining different types of quantitative information to inform pricing decisions, it is useful to consider techniques that can handle and propagate multiple sources of data. A number of decision tools are available to combine multiple sources of data. Decision trees have been used to propagate probabilistic information to inform climate sensitive decisions (e.g. Hobbs et al. (1997)). However, there is only a one-way flow of information in a decision tree and it can be useful to consider a two-way flow of information to make inferences. Hall et al. (2005) shows how different types of inference diagrams can be used in climate impacts analysis stating that "influence diagrams can communicate knowledge in a formal but accessible manner". BNs are simply one form of inference diagram that can be used to propagate probability distributions combining continuous and discrete data. Given the uncertainties associated with climate change, it is not always appropriate to characterise climate uncertainties in probabilistic terms (see section 2.2.5). However, a BN analysis can be used to highlight sensitivities and in this section, the BN approach is adopted to explore the sensitivity of pricing assumptions to different sources of climate information to assess the viability of weather index insurance under climate change.

A BN is a graphical model with an underlying probabilistic framework, which characterises and quantifies an outcome of interest, the relevant variables and the causative interactions (Donald et al. (2009)). BNs update probabilities throughout the network according to Bayes Theorem given in equation 6.1:

$$P(A\,|B) = \frac{P(B\,|A)\,P(A)}{P(B)} \tag{6.1}$$

The BN constructed here is a decision tool which provides a means for quantifying and communicating the output from complex computer models in relation to other factors and pressures facing decision makers. The approach benefits from the input of experts across disciplines and, more importantly, direct communication with the end user. Unlike traditional sector-based climate impact assessments, the tool is designed to be tailored to a specific decision for a particular user. BNs allow for the explicit quantification of risk and uncertainty combining evidence from diverse sources incorporating subjective beliefs and objective data (Fenton and Neil (2004)). Cain (2001) distinguishes between two potential uses of a BN:

1. BNs can be developed to provide a mathematically optimal decision on the basis of the information provided to the BN.
2. BNs can be used in a way that promotes the improved understanding of the system, leaving the decision makers to reach their own conclusions on the basis of that knowledge.

Given the large number of inherent uncertainties associated with climate prediction, it is more appropriate to use BNs to promote improved understanding rather than attempting to provide optimal decisions based on incomplete information. Indeed, although the network developed here aims to be exhaustive with regards to the factors included, the network doesn't have to be complete in order for the BN to act as an instrument for consultation (Ouerdane and Tsoukias (2009)).

The BN approach has been used extensively in a wide range of research fields and industrial sectors as a tool for structuring and informing the decision-making process (Heckerman et al. (1995), Fenton (2007)). Advances in research over the past few decades, led by Pearl (1986) and Lauritzen and Spiegelhalter (1988), have enabled a transition from a computationally inefficient and time-consuming process towards the development of a powerful tool which can be employed in many real-world applications (Fenton and Neil (2007)). The tool has been applied to a small number of climate-related studies which each address specific decision problems (Kuikka and Varis (1997), Wooldridge et al. (2005), Musango and Peter (2007)). However, in these studies BNs are not used to test the sensitivity of decisions to multiple climate information sources. Here the approach is developed to investigate whether or not the BN tool is useful in providing a framework to inform insurance decisions using data from multiple climate models in combination with observed data.

6.3.2 Example Bayesian Network: winter forecasts for salt stocks

In this section, an example BN is described to demonstrate how a BN can be used to inform a decision. A hypothetical example, depicted in figure 6.2, shows how the decision of whether

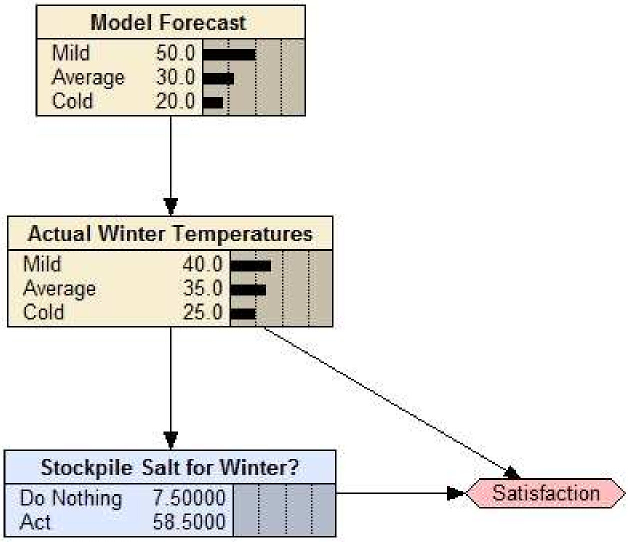


Figure 6.2: BN for an example decision problem; whether or not to stockpile extra salt for the coming winter.

or not to stockpile extra salt for the forthcoming winter might be aided by a seasonal forecast of mean temperature. The software used to create the eBN is Netica (Software Corp. (1998)); this software is also used to develop the microinsurance case study. The two yellow nodes denote the variables (*Model Forecast* and *Actual Winter Temperatures*) and the linking arrow represents a relationship between the two variables; *Model Forecast* is called the *parent* node and *Actual Winter Temperature* is the *child* node. The horizontal bars show the probabilities associated with each state and in each variable node the probabilities must sum to 100. Arrows typically denote a causative relationship but in this example the actual winter temperatures are clearly not conditional on the model forecast. Rather, the arrow represents a relationship between the actual winter temperatures and the model forecast based on verification statistics of past forecasts. The conditional probability table (CPT) associated with the *Actual Winter Temperatures* node is given in table 6.2. The values in the table are illustrative but they could be derived from observations and verification statistics of the seasonal forecast. Based on the information in the CPT and the probabilistic model forecast, the probabilities given in the *Actual Winter Temperatures* node show that mild conditions is the most likely outcome (40%), average conditions is the second most likely outcome (35%) and cold conditions is the least likely outcome (20%).

Model Forecast	**Actual Winter Temperatures**		
	Mild	Average	Cold
Mild	67	20	13
Average	15	70	15
Cold	10	20	70

Table 6.2: Conditional probability table for the *Model Forecast* node in figure 6.2.

The blue decision node (*Stockpile Salt for Winter?*) shows two possible decisions that can be made: do nothing or act (where acting means to stockpile salt). The pink *Satisfaction* node calculates the utility for each decision in the decision node based on the input data from the *Actual Winter Temperatures* node. The numbers given in table 6.3 are also illustrative but show the plausible utility values associated with the six potential outcomes. The values would be defined by the user to represent objective economic measures or subjective preferences. The values are relative to each other so they do not need to add up to a specific total. The scale is linear and values can be negative to convey dissatisfaction; here a value of *-200* is used to highlight a deeply unsatisfactory outcome.

Actual Winter Temperatures	**Stockpile Salt for Winter?**	**Satisfaction**
Mild	do nothing	100
Mild	act	0
Average	do nothing	50
Average	act	60
Cold	do nothing	-200
Cold	act	150

Table 6.3: Utility node outlining the satisfaction of the user based on the information in figure 6.2.

The numbers displayed in the decision node, next to the two options (*act* and *do nothing*), show the expected utility of each decision based on the information in the network; the higher the value the more favourable the option. Unlike in the variable nodes, the values are not probabilistic and need not add up to 100. In the example BN in figure 6.2, the optimal decision would be to “act”. Based on the model forecast, the relationship with actual temperatures and the values in the utility node, the risk of a cold winter is sufficient to warrant stockpiling salt.

In this simple example, the probabilities are well known and the utility of options are assumed to be representative so taking the optimal decision is sensible. However, when using the BN tool with imperfect and incomplete information the network is more appropriate for challenging the user’s preconceptions regarding the relative utility of the available options. The chapter now proceeds to introduce the focus and scope of the BN case study.

6.4 Case Study Description: Weather Index Insurance for Drought and Excess Rainfall cover in Kolhapur, India

6.4.1 Index-based microinsurance

Traditional forms of crop insurance cover multiple perils, including weather-related perils such as hail and drought as well as non-weather-related perils such as pest and disease outbreaks. However, as explained by Skees et al. (1999), many of the risks covered by private and public insurance schemes in the developed world are considered infeasible in developing countries. The costs of administering traditional claims-based insurance products to low-income farmers in developing countries becomes prohibitively expensive for private insurers. Skees et al. (1999) state that index-based insurance provides an attractive alternative for developing countries. For a weather index insurance scheme, "loss estimates are based on an index, or proxy for loss rather than upon the individual loss of each policyholder" (Skees et al. (2007)). This means that once a proxy is triggered (e.g. rainfall accumulation falls below a certain threshold) all policyholders in the affected area receive a payout. The administration costs of index insurance schemes are significantly lower as the claims-handling process is bypassed. Consequently, over the past decade there has been a huge increase in the research and deployment of crop index-based microinsurance for weather-related perils such as drought, excess rainfall and wildfire.

For weather-related perils, traditional claims-based insurance and reinsurance premiums are typically derived from available loss data-sets as well as established relationships between meteorological events and accumulated losses. However, it is challenging to disentangle the climatic and socio-economic components of claims-based insurance losses because damages are non-trivially related to the magnitude of the hazard (i.e. weather event), exposure to the hazard and vulnerability of insured assets. For index insurance schemes, the uncertainties associated with the response of the physical climate system are disaggregated from socio-economic considerations so a direct sensitivity analysis of a given insurance pricing structure to climate input data can be achieved. Yet from an insurance perspective, setting the thresholds at which payouts for a given peril are triggered is often problematic, given the need for robust relationships between meteorological conditions and insured losses. Index insurance is therefore associated with significant "basis risk" which represents the chance that the payment a policyholder receives when the proxy measure is triggered does not match the actual loss experienced. A study prepared by GlobalAgRisk states that basis risk can deter consumers because individuals may not have sufficient confidence that payouts will reflect the losses that occur in reality (USAID (2006)). Skees (2008) therefore states that index-based schemes are not replacements for traditional insurance but rather they serve as a foundation for developing financial mechanisms in new markets.

The United Nations has advocated the use of index insurance as a "soft" climate change adaptation measure[2] within developing countries but it is important that the index insurance

[2]See UNDP best practice project, available at http://unfccc.int/adaptation/nairobi_work_programme/

policies are themselves resilient to climate change. There is a need to ensure that pricing mechanisms are fair and utilise the available climate information. Alderman and Haque (2007) note that in order for index insurance to be effective, indices ought to be easily measured, objective, transparent, independently verifiable, and available in a timely manner. They also comment that the probability distributions ought to be reliably estimated implying the need for a stable time series' of information. Yet in the context of climate change, meteorological variable time series' are unlikely to be stationary so index-based insurance policies, derived from past data alone, may be at risk of over or underestimating the probabilities of triggering payments. Nonetheless, current weather index insurance products are priced according to past times series of ground-based observations. A report by the World Bank (2011) states that in order to derive an appropriate premium for a weather index insurance product, 30 years of continuous daily data are ideally required meaning that weather index insurance products are typically contingent on the availability of long time series' of observations. The BN analysis presented here, which incorporates climate model forecast information, therefore represents a step beyond the reality of how index insurance pricing decisions are currently made.

Hochrainer et al. (2008) state that the viability of microinsurance schemes can be viewed from two perspectives: from the view of insurers (or supply-side perspective) or from the view of the clients (the demand-side perspective). This study investigates whether climate model information can inform the supply-side in guiding the appropriate pricing of index insurance and determining the viability of weather index insurance under altered climatic conditions.

6.4.2 Focus region: Kolhapur, India

The focus region for the case study is Kolhapur district, in western India. The region was chosen for a number of reasons. Initially, India was chosen because a large volume of high resolution RCM data has recently been made available by the HighNoon project; a project exploring the future water resource of the Ganges river basin (Wiltshire et al. (2010)). It is therefore advantageous to choose India as the focus developing country, given data is available to demonstrate the use of climate model output within a BN framework in guiding index-based microinsurance policy design. Kolhapur was specifically chosen as it is located at the edge of the core monsoon region (see figure 6.3) so the region's climate is highly influenced by the variability associated with the summer monsoon rains. Changes in the timing and/or magnitude of the monsoon would therefore have a significant impact on the region's crop yields. In addition, the microinsurance company MicroEnsure have recently begun a pilot project for farmers in the area (Hazell et al. (2010)). There is evidently a market and a need for appropriately designed microinsurance in this region of India[3].

Kolhapur district has a population of approximately 3.5 million people, with almost 30% living

knowledge_resources_and_publications/items/4748.php.

[3]The results are not being directly used by MicroEnsure or any other microinsurance companies.

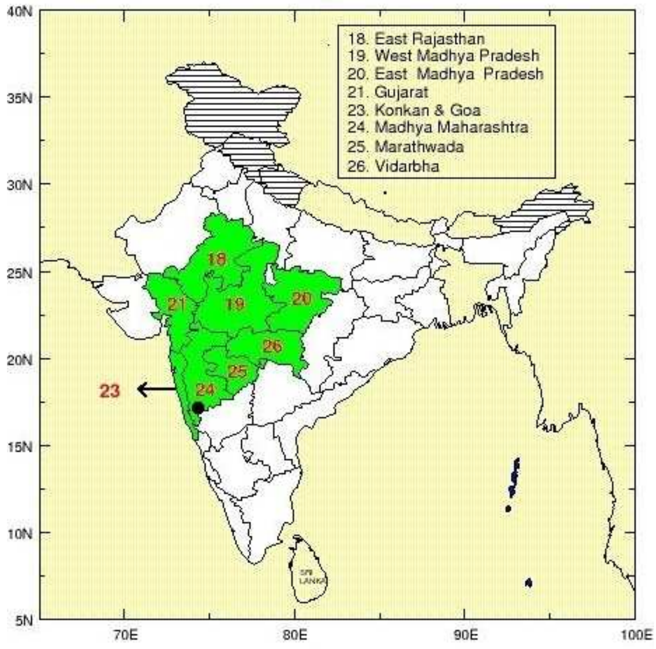


Figure 6.3: Indian Core Monsoon Region (highlighted in green). The black circle denotes the location of Kolhapur City in Madhya Maharashtra, India (IITM (2011)).

in urban areas, most of whom live in the district's main city also named Kolhapur[4]. The district has a total land area of 768,500 hectares, of which 104,000 hectares (13.5%) are devoted to rice production, making it the main crop for local farmers and the regions main commercial crop. The rice crop is a Kharif crop which means the main growing period occurs in summer during the monsoon period. The BN developed for this study focuses on the meteorological triggers at which payouts might occur for losses associated with rice yields in Kolhapur.

[4]Data correct for 2001 - available from Collector Office, Kolhapur (2009).

6.5 Methodology

6.5.1 Constructing the Bayesian Network

An approach developed by Ames et al. (2005) in relation to watershed management, and adapted by Daron and McNeall (*in preparation*) for climate change impacts assessments, is used in this study. The approach consists of seven key steps (given below) to guide the construction of the BN. Implementation of the seven steps is described in this section with each step taken in turn.

1. Identify management endpoints
2. Identify alternative decision pathways
3. Identify critical intermediate and exogenous variables
4. Establish discretization states for network variables
5. Decide on the causalities in the network
6. Identify data sources
7. Interpret the meaning of the probabilistic results

As the initial step aims to identify user objectives, the approach is decision-oriented and therefore consistent with an "assess-risk-of-policy" framing rather than a "predict-then-act" approach (Dessai and Wilby (2011)). Consequently, the BN is tailored to the needs and interests of the user and inherently excludes irrelevant and superfluous information.

Implementing the methodology

To address the first step in the BN construction methodology, informal discussions were held with insurance experts from Lloyd's of London and Willis Reinsurance to determine possible management endpoints for the case study being developed. The discussions were centred on the current use of climate information in designing crop microinsurance products in emerging markets. It became apparent that strategic decisions and pricing decisions, related to index-based microinsurance policies, are challenging for a number of reasons. From an actuarial perspective, the primary concern results from the lack of reliable and detailed historical loss data and meteorological data within many developing countries meaning that the estimation of return periods for crop loss events is difficult. Additionally, minimising basis risk and building trust between the policyholders and the insurers was expressed to be of paramount importance. Discussants also highlighted the issue of price volatility in yields which can hinder the development of successful insurance products[5]. Discussants agreed that the objective of

[5]Battisti and Naylor (2009) argue that whilst food price volatility presents a daunting short-term challenge for the markets, the long-term impact of climate change on food production is far more serious.

the BN approach should be to demonstrate the sensitivity and viability of various pricing assumptions to different sources of climate information, including model projections and observational data. The management endpoint was therefore established as a determination of the viability of insurance premium/payout structures under the current climate and plausible future climates.

In addressing the second step in the methodology, the possibility of alternative decision pathways was considered but only one decision pathway was identified. The management endpoint of establishing the viability of the product is a function of the threshold exceedance probabilities, utilising different climate information sources, and the pricing structure. The decision options are therefore constrained to adjusting the pricing structure or withdrawing the product. If the study were to be broadened in future research, to analyse the development of index insurance across different perils and regions, the number of possible decision pathways may increase.

A number of possible variables were considered in step three of the methodology. The agricultural sector in India is dependent on the timing and magnitude of the summer monsoon rains. The risk of drought is most acute for rain-fed agriculture where crops can suffer from water stress leading to low crop yields (Gadgil and Kumar (2006)). Using data from 306 rain gauges across India from 1871 to 1978, Mooley and Parthasarathy (1984) show that historically about 75 to 90% of annual rainfall occurred during the summer monsoon months, June to September. The primary variable nodes were therefore identified as the cumulative precipitation totals for key periods in the monsoon season. This information would feed into threshold exceedance estimates for the perils under consideration; excess rainfall and rainfall deficit. In addition, the sources of climate information (model/observations) are key to the objectives of the BN study and accordingly a variable which can weight/select the climate information sources is necessary. Given the focus on past and future climate the time scale of interest becomes a variable node. Finally assumptions about premium prices and policy expenses are included in the network.

Step four involved establishing the states to which the data is discretised. For the rainfall data, the states of interest correspond to the thresholds at which payouts occur. Whilst the thresholds change according to the crop-type, location, soil-type and actuarial judgements, typical values are selected for drought and excess rainfall conditions for the rice-crop. Rajagopalan (2009) states that the rice crop requires about 1200 mm of rain over the monsoon season and Veeramani et al. (2005) uses similar figures whilst citing a monthly requirement of between 250 and 350 mm. Another study by Bhuiyan (1992) gives a suitable range for rice crop production between 700 and 1500 mm over the monsoon season. Veeramani et al. (2005) states that the rice crop is more sensitive to drought than flooding. Threshold values for rainfall deficit and rainfall excess are therefore chosen with reference to the available literature as well as exercising an inevitable element of subjective preference. Maximum indemnity payouts for drought are assumed to be issued for precipitation totals below 150mm per month and maximum payout for excess rainfall is assumed to be issued for precipitation totals above 600mm per month. As illustrated in section 6.6.1, intermediary thresholds are also selected for partial payouts related to decreased but not failed yields.

The causalities are determined in step five of the methodology. The input data is determined by the climate time scale of interest and by the choice of observational data, model data or a weighted combination. The combined or individually selected data determines the expected distribution of precipitation for the period of interest. This data then translates into threshold exceedance values for rainfall deficit and rainfall excess. The losses are determined from the threshold exceedance probabilities and the expected utility is a function of the losses, the premiums and the expenses.

The sixth step involves identifying the data on which the BN is conditioned. A recent project funded by the European Commission, "HighNoon", aims to assess the impact of Himalayan glacier retreat and possible changes in the Indian summer monsoon on the water availability in northern India (HighNoon (2009)). With help from the UK Meteorological Office, data was made available for use in this study. The model output covers the Kolhapur region and a detailed explanation of the model runs and model output is included in sections 6.5.2 and 6.5.3. Observational data was also available for the period 1961 to 2004 from the APHRODITE project which has developed high resolution (0.25° x 0.25°) gridded daily precipitation datasets for Asia (Yatagai et al. (2008), Yatagai et al. (2009)). The project predominantly used data from rain-gauge observations across Asia, including India, and refined algorithms in collaboration with climate modellers and data users.

The final step of the methodology refers to the use of probabilistic information for informing decisions. The objective of the insurer is to ensure that the index insurance provided to farmers is fair, representative and profitable. To maintain profitability, the insurer has various options. The most simple option is to adjust the premium to reflect the underlying risk. However, the insurer can also change the thresholds at which payouts occur, the value of the payouts at each threshold and target decreases in the expenses (per policy) to make the premiums more affordable. The probabilities in the BN can therefore be used to stress-test pricing assumptions to enable insurers to find suitable policy structures which are profitable but ultimately appealing and affordable to the policyholders. In the results section of this chapter (section 6.6), a number of different BNs are presented to show how the methodology can be used to contrast different network assumptions and climate model choices.

6.5.2 Description of the climate model and observational data

The HighNoon project utilises data from the UK Hadley Centre regional model, HadRM3 (Jones et al. (2004)). The configuration of HadRM3 used in the model simulations has a horizontal resolution of 25km, with 19 vertical levels in the atmosphere and includes MOSES II (Met Office Surface Exchange Scheme), a tiled land surface scheme (Essery et al. (2001)). Whilst the study is focussed on the Ganges river basin, RCM runs have been performed for a domain which covers India and a broad area of southern Asia, as shown in figure 6.4.

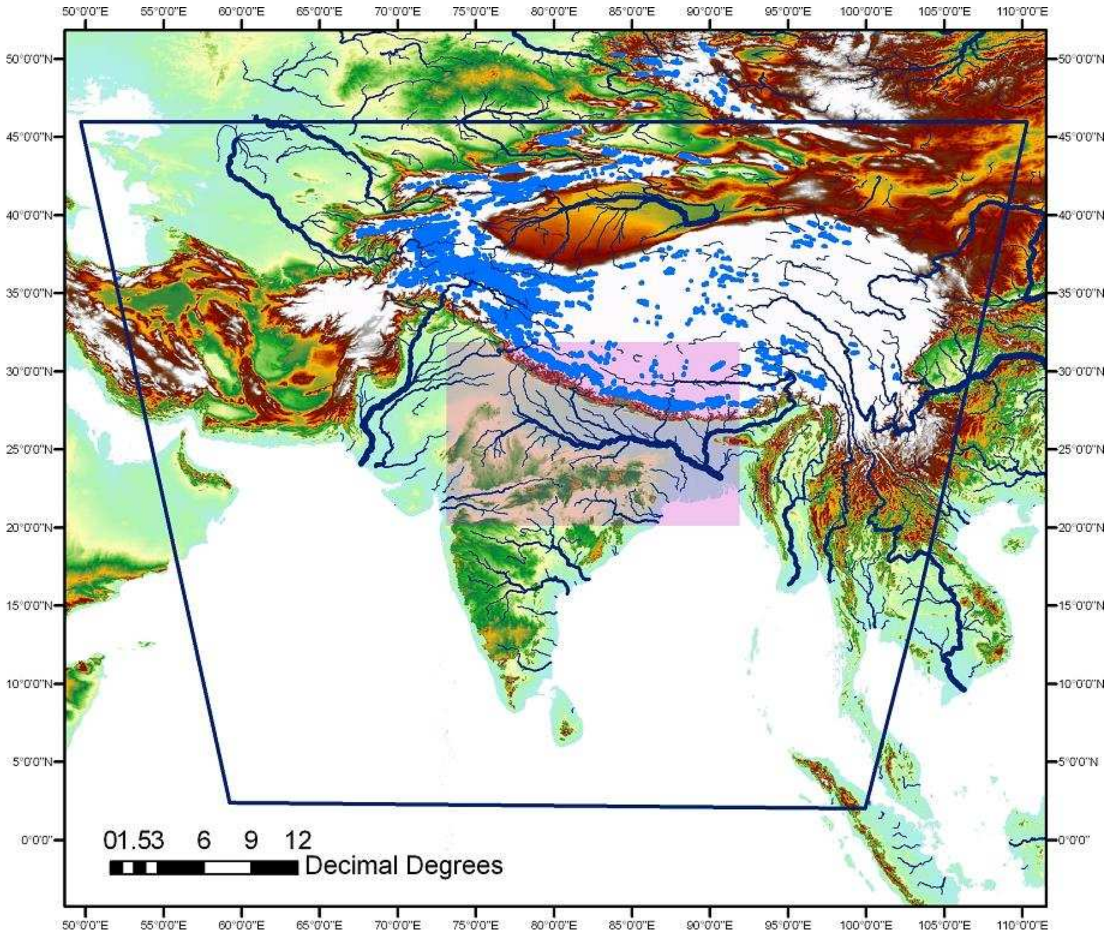


Figure 6.4: HighNoon model domain used for the HadRM3 RCM runs (blue box) where the pink shaded area is the Ganges sub-region considered in the HighNoon project (reproduced from Wiltshire et al. (2010)).

The HadRM3 model was run using boundary conditions from two GCMs, ECHAM5 (Roeckner et al. (2003), Hagemann et al. (2006)) and HadCM3 (Gordon et al. (2000), Pope et al. (2000), Collins et al. (2001)). The GCM climate change simulations are based on a single emissions scenario; the SRES A1B scenario which assumes rapid economic growth, a convergent world and a balanced emphasis on all energy sources (Nakićenović et al. (2000)). Consequently, the projections do not account for forcing uncertainty from alternative future anthropogenic emissions trajectories. However, the simulations do provide an opportunity to test the sensitivity of RCM results to the driving GCM. In addition, the HadRM3 model was run using boundary conditions from ERA-Interim data (Simmons et al. (2010)) and the reanalysis climate time series data is included in this study.

With a focus on drought and excess rainfall risk in Kolhapur, precipitation data for the 25km grid cell which encapsulates the latitude and longitude values of Kolhapur city (16°70'N, 74°23'E) was extracted from the HighNoon data archive with help from the UK Met Office Hadley Centre. The data consists of monthly precipitation totals. The ERA-Interim model reanalysis data used in this study is given for the period 1990 to 2008 whilst the time series' from the two driving GCMs consists of monthly data for the period 1960 to 2099.

6.5.3 Preliminary data analysis

The model data extracted from the HadRM3 runs driven by HadCM3, ECHAM5 and ERA-Interim is compared to the observational data from the APHRODITE project. The precipitation data from the RCM runs was available as raw model output so does not include any bias corrections. Figure 6.5 shows cumulative precipitation data for the monsoon months (June to September) for the period 1960 to 2099. The figure includes observational data (black) for the period 1961 to 2004 and the output of the RCM driven by ERA-Interim reanalysis data (purple) for the period 1990 to 2004. The blue short dashed line shows the output from the RCM driven by the HadCM3 GCM and the long dashed red line shows the output from the RCM driven by the ECHAM5 GCM.

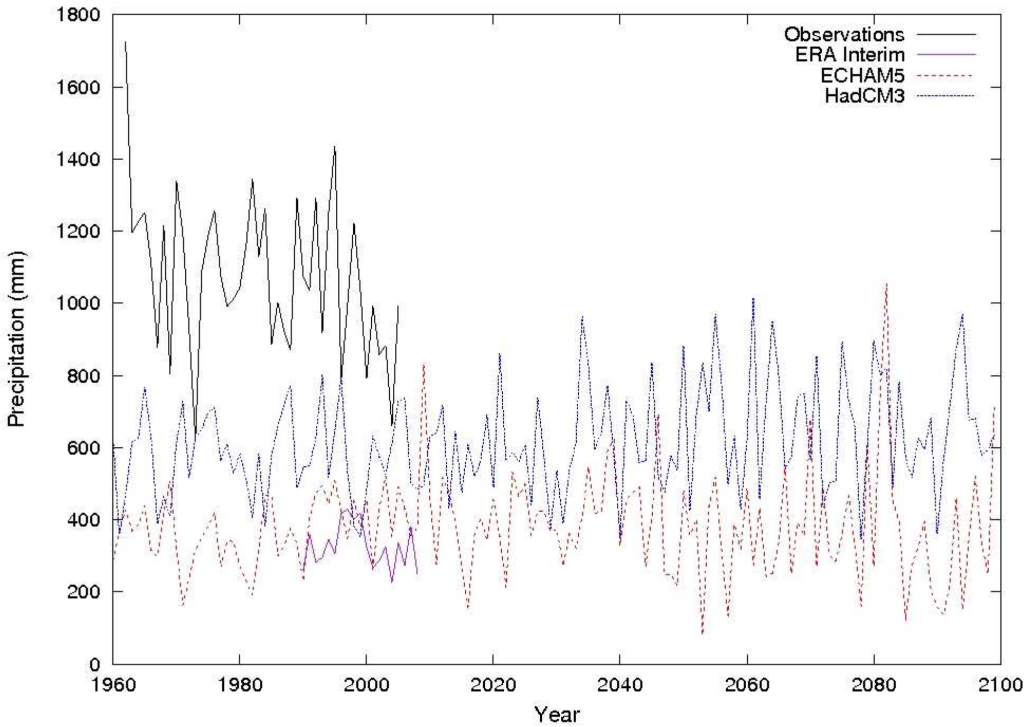


Figure 6.5: Model and observational cumulative precipitation data for Kolhapur, India for the monsoon months June to September. Observational data from APHRODITE is shown for the period 1961 to 2004, ERA-Interim data is shown for the period 1990 to 2008 and the HadRM3 data driven by HadCM3 and ECHAM5 is shown for the entire period, 1960 to 2099.

The data shown in figure 6.5 reveals large systematic biases between the model output and the observational data. Summary statistics of the data are provided in the table in figure 6.6. The summary statistics for the model projections are given for 1961 to 2004 (to provide a comparison to the observed results); for 2020 to 2049 (the extent of the planning time scale for developing insurance products in emerging markets); and for 2070 to 2099 (to highlight the long-term changes in rainfall projections). There is a large difference in the mean of the observations and the RCM output for both GCMs and the ERA-Interim reanalysis data. The HadCM3 driven output for the period 1961 to 2004 produces a mean rainfall value almost half the observed value of 1073.64mm whilst the ECHAM5 and ERA-Interim driven output produce roughly three times less mean rainfall than the observations. The annual variability in the observations also appears greater than the RCM output. The ERA-Interim data produces a relatively low standard deviation (61.87mm) in the precipitation values. The relatively high annual variability in the observed data suggests that the ERA-Interim reanalysis does not capture the annual rainfall patterns accurately. Both sets of GCM driven data suggests that the variability increases under future climate conditions, indicated by the increased standard deviations and ranges in precipitation values in columns four and eight of figure 6.6 respectively.

Data Source	Time Interval	Mean	Standard Deviation	Trend	Min	Max	Range
Observations	1961 to 2004	1073.64	213.93	-5.78	621.60	1725.68	1104.08
ERA-Interim	1990 to 2008	325.82	61.87	-1.93	225.62	429.13	203.51
HadCM3	1961 to 2004	573.89	119.13	0.28	353.46	800.66	447.20
HadCM3	2020 to 2049	603.10	145.91	0.30	351.26	962.78	611.53
HadCM3	2070 to 2099	651.45	159.59	1.43	347.37	969.45	622.08
HadCM3	1961 to 2099	617.13	147.36	0.92	347.37	1016.73	669.36
ECHAM5	1961 to 2004	367.23	88.47	1.69	163.62	522.17	358.54
ECHAM5	2020 to 2049	409.07	119.23	-0.54	212.35	693.63	481.28
ECHAM5	2070 to 2099	383.31	212.33	-3.40	121.70	1054.98	933.28
ECHAM5	1961 to 2099	381.84	140.38	0.04	80.57	1054.98	974.41

Figure 6.6: Summary statistics for cumulative precipitation in Kolhapur for the monsoon season (June to September) from observations and the HadRM3 output driven by ERA-Interim, HadCM3 and ECHAM5 for given time intervals. The units of the precipitation values in columns 3, 4, 6, 7, and 8 are mm while the units for the trend values in column 5 is $mm year^{-1}$.

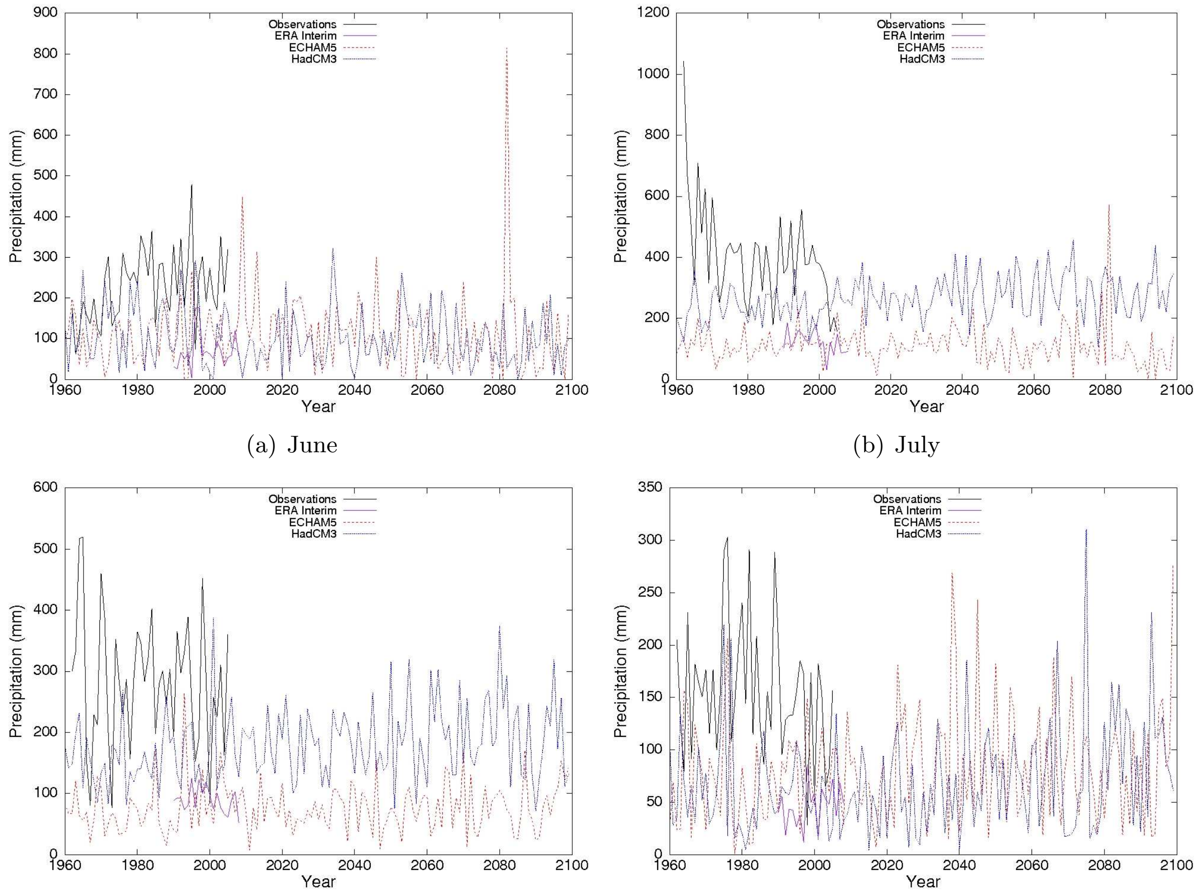
Given discrepancies in the data, either the observations are overestimating the rainfall in the Kolhapur region or the model results are providing an underestimate. There are a number of reasons why the RCM runs might underestimate the rainfall totals. Firstly, systematic errors in the GCM precipitation fields are not uncommon (Schmidli et al. (2006)). Figure 6.5 reveals large differences between the precipitation totals from HadCM3 compared to ECHAM5, despite using the same regional model. In the latest IPCC report, the individual model projections of precipitation over India show large differences in the accumulations over the region. The mechanisms that lead to precipitation are often challenging to model in GCMs and therefore RCM output associated with imperfect GCM driving data produces precipitation values that are subject to large errors. The regional model results from the IPCC AR4 report show a multi-model mean change in summer precipitation over western India of between 5 and 10% for the 2080 to 2099 period, using 1980 to 1999 as a base period (Christensen et al. (2007b)).

However, approximately half of the AR4 GCMs show a mean increase in rainfall in central western India while the other half GCMs show a mean decrease in rainfall. The disagreement between the ECHAM5 model and HadCM3 model is therefore indicative of wider disagreement amongst GCMs.

Furthermore, whilst the HadRM3 model provides a much better representation of the land surface and the local orography when compared to GCMs, many of the small scale orographic features are still not adequately represented by a 25km $\times$ 25km gridbox. Enhancing horizontal model resolution further ought to reduce biases resulting from errors in the specification of orography and the land surface. The resolution of the observational grid is $0.25° \times 0.25°$, approximately equal to a 28km $\times$ 28km gridbox, which is slightly larger than RCM horizontal resolution (25km $\times$ 25km). Perhaps more importantly, the model grids may not be representing exactly the same area and may therefore account for areas with different orography and rainfall characteristics. Situated to the west of Kolhapur is the southern extent of the Sahyadri hills. The enhanced orography is typically associated with increased rainfall and as the dominant wind direction during the monsoon is south-westerly, eastern parts of Kolhapur district often receive significantly less rainfall than the western parts. A detailed analysis of the gridbox formulation would elucidate the discrepancies in coverage and help to attribute the systematic biases evident in the model precipitation data.

In addition to the possible discrepancies from systematic GCM errors and poor RCM gridbox representation, the differences between the time series data may be partly caused by uncertainties associated with the observations and the use of rain-gauge stations. Wiltshire et al. (2010) states, "the uncertainties associated with observed precipitation are potentially large primarily due to known gauge undercatch errors (which are often corrected in post-processing) as well as the high spatial variability of precipitation which is often statistically undersampled".

To further understand the trends and discrepancies associated with the data, it is useful to analyse the separate monthly rainfall totals for June, July, August and September. Figure 6.7 displays a breakdown of the observational data and the RCM data for each of the individual months in the summer monsoon period (note different scales on y-axis). The observations show higher precipitation values than the model projections and the reanalysis data for all months but there are periods when the observed data falls within the range of variability associated with the model projections. During the first ten years of the time series for June, shown in figure 6.7(a), interannual variability in the observations is broadly consistent with the RCM projections driven by HadCM3 and ECHAM5 but from the 1970s onwards the observations shift to higher values than those associated with model projection data. The monthly plots highlight the differences between the HadCM3 and ECHAM5 model responses. In July and August, the HadCM3 results show precipitation totals that are approximately a factor of two greater than the totals given by the ECHAM5 model. Over this period, the ECHAM5 model results are in close agreement with the ERA-Interim results. In the absence of observational data, one might therefore be inclined to conclude that results should be weighted more strongly in favour of the ECHAM5 model.



(a) June (b) July

(c) August (d) September

Figure 6.7: Model and observational cumulative precipitation data for Kolhapur, India for individual months in the summer monsoon. Observational data from APHRODITE is shown for the period 1961 to 2004, ERA-Interim data is shown for the period 1990 to 2008 and the model data driven by HadCM3 and ECHAM5 is shown for the entire period 1960 to 2099.

However, the HadCM3 model results, although still significantly lower, appear to be much closer to the observational data than the ECHAM5 results. On this evidence, one might conclude that the HadCM3 data should be weighted more favourably. Certainly the model trajectory appears to capture the increase in rainfall observed during July, which impacts the peak monsoon rains. Yet the lack of IC runs needed to elucidate the complete model distributions, and the large discrepancy between all RCM output and the observations suggests that weighting of model results isn't appropriate.

July has the highest observed monthly precipitation values. Rainfall during this month is particularly important for the success of the rice crop in the Kolhapur region (Bhuiyan (1992)). If the rainfall is significantly delayed, the season's crop risks failure. Therefore the BN analysis presented in the following sections is centred on the use of observations and model estimates of July precipitation under past and future climates. Focusing on the month of July is both sufficient to illustrate the issues in using model data and also clarifies those issues by excluding

Data Source	Time Interval	Mean	Standard Deviation	Trend	Min	Max	Range
Observations	1961 to 2004	405.06	162.36	-6.42	155.99	1043.76	887.77
ERA-Interim	1990 to 2008	120.90	37.93	-3.00	31.31	185.80	154.50
HadCM3	1961 to 2004	234.01	54.72	0.27	121.82	361.96	240.14
HadCM3	2020 to 2049	269.00	66.89	0.45	146.59	409.41	262.83
HadCM3	2070 to 2099	284.66	76.61	-0.22	106.22	456.50	350.28
HadCM3	1961 to 2099	266.68	69.15	0.52	106.22	456.50	350.28
ECHAM5	1961 to 2004	111.57	40.57	0.12	27.07	229.69	202.63
ECHAM5	2020 to 2049	119.27	46.44	-0.36	31.64	229.68	198.05
ECHAM5	2070 to 2099	103.85	108.86	-2.97	1.00	572.70	571.70
ECHAM5	1961 to 2099	110.38	64.94	-0.11	1.00	572.70	571.70

Figure 6.8: Summary statistics for cumulative precipitation in Kolhapur for July from observations and the HadRM3 output driven by ERA-Interim, HadCM3 and ECHAM5 for given time intervals. The units of the precipitation values in columns 3, 4, 6, 7, and 8 are mm while the units for the trend values in column 5 is $mm\ year^{-1}$.

unnecessary complexity.

The summary statistics for the July precipitation data are provided in the table in figure 6.8. There are large differences in the mean of the observations and the model output data which is likely to be attributable to systematic errors in the representation of precipitation in the driving GCMs. The systematic biases and model anomaly information is utilised in sections 6.6.3 and 6.6.4 to assess the impact of corrective adjustments in the model output on the losses associated with the index insurance pricing structure. The linear trends shown in column 5 show that there has been a decrease in total July rainfall ($-6.42\ mm\ year^{-1}$) over the observed period. The magnitude of the trend is influenced by the anomalously high value in the first year but there is still a decrease of $-4.75\ mm\ year^{-1}$ even if this value is omitted. The ERA-Interim reanalysis data also shows a decreasing trend over the period, 1990 to 2008, but the HadCM3 and ECHAM5 driven output do not show decreasing trends over the observed period. The HadCM3 output for July rainfall over the entire period (1961 to 2099) reveals an upward trend with an increase in annual variability shown in the increasing standard deviation values and the ranges for future periods. Conversely, the ECHAM5 output shows a weak decreasing trend over this period but the annual variability increases and notably a very significant event occurs in 2081 where the rainfall reaches a value of 572.7 mm. The occurrence of this event shows the ability of the model to produce an extreme event.

The systematic biases in the model output suggest that caution must be applied when interpreting the impact of climate change on the future precipitation patterns in the Kolhapur region. Given the multiple sources of uncertainty, and without further investigation, it is not clear which data should be considered more or less reliable. However, the aim of this chapter is not to provide definitive results regarding the optimum pricing strategy for index insurance in

Kolhapur but rather to demonstrate a methodology one could use to investigate the sensitivity of pricing assumptions to input climate information. The preliminary analysis of the raw model output suggests that decision makers, and particularly insurers interested in designing weather index products, should be cautious in relying on one source of climate information to form policy. Using multiple sources of climate information in the design phase of insurance products may increase the uncertainty but, used appropriately, could lead to a more robust analysis of the appropriate meteorological triggers for payouts. The BN approach, introduced in the following section, is designed to understand how this data could be used to determine weather index insurance viability under climate change.

6.6 Bayesian Network Results

The software Netica (Software Corp. (1998)) is used here to develop the BN. Netica provides an interactive graphical interface to allow users to switch between nodes and select options to develop an understanding of the variable dependencies. The images included in this section are extracted from the Netica user interface. The methodology outlined in section 6.5.1 is implemented here to derive a range of BNs with different levels of complexity. Section 6.6.1 focusses on BNs which utilise the July precipitation observational data only. The BNs presented in section 6.6.2 combine observations with climate model forecast data. Results presented in section 6.6.3 show BNs with bias corrected model output. Finally, section 6.6.4 presents BNs which are driven by observational data adjusted using anomaly information identified in the analysis presented in the previous section.

6.6.1 BNs using observational data

The BNs listed in this section assess pricing structure using observational data only to illustrate how premiums might be determined if reliant solely on a single observed time series. A payment structure, shown in figure 6.9, is adopted using a payout profile with three tiers, each corresponding to a fixed proportion of the maximum indemnity (total insured sum) per policy. Rainfall thresholds are chosen to correspond to each tier and although the threshold triggers are only illustrative they are considered plausible given the evidence presented in section 6.5.1. In this payment structure, the maximum payout equates to a *Tier 3* payment and this sum would be paid to policyholders if the observed July precipitation was below 150mm or above 600mm. If the precipitation was between 150 and 180mm or between 570 and 600mm, then a specified fraction of the maximum indemnity (*Tier 2*) would be paid to each policyholder. Similarly, if the precipitation was between 180 and 210mm or between 540 and 570mm, then a smaller specified fraction of the maximum indemnity (*Tier 1*) would be paid to each policyholder. No payout would be given for precipitation totals between 210 and 540mm.

For many index insurance products, the payout increases linearly to the maximum payout but a step-wise function (similar to a collar graph) is chosen in this study for two reasons. Firstly, existing weather index products for rainfall deficit are often structured using a step-wise function in the payouts (MicroEnsure (2010)) and secondly if payouts increased linearly then there would have to be many more states within the *rainfall deficit* and *excess rainfall* nodes to incorporate probabilities effectively. Later in this section, a BN using a seven tiered structure is illustrated (see figure 6.12) to demonstrate an alternative payout structure and highlight the problems associated with using more tiers.

The BN shown in figure 6.10 utilises the three tiered payout structure and consists of four nodes linking observed July precipitation to losses. As discussed in section 6.5.3, July is chosen as the time period of interest as the month is typically associated with the highest rainfall totals during the monsoon season (see figure 6.7(b)). In practice, the period for which individual

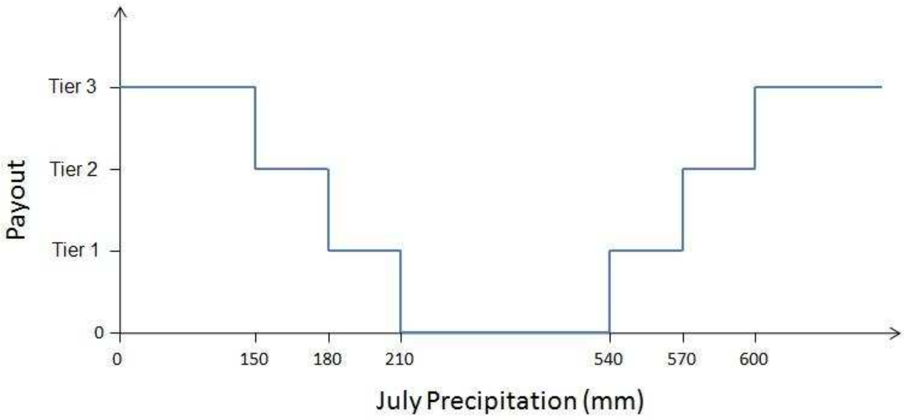


Figure 6.9: Example payout profile for for an idealised index insurance policy covering rainfall deficit and excess rainfall.

index insurance providers offer coverage will vary according to specific crop requirements and user demands.

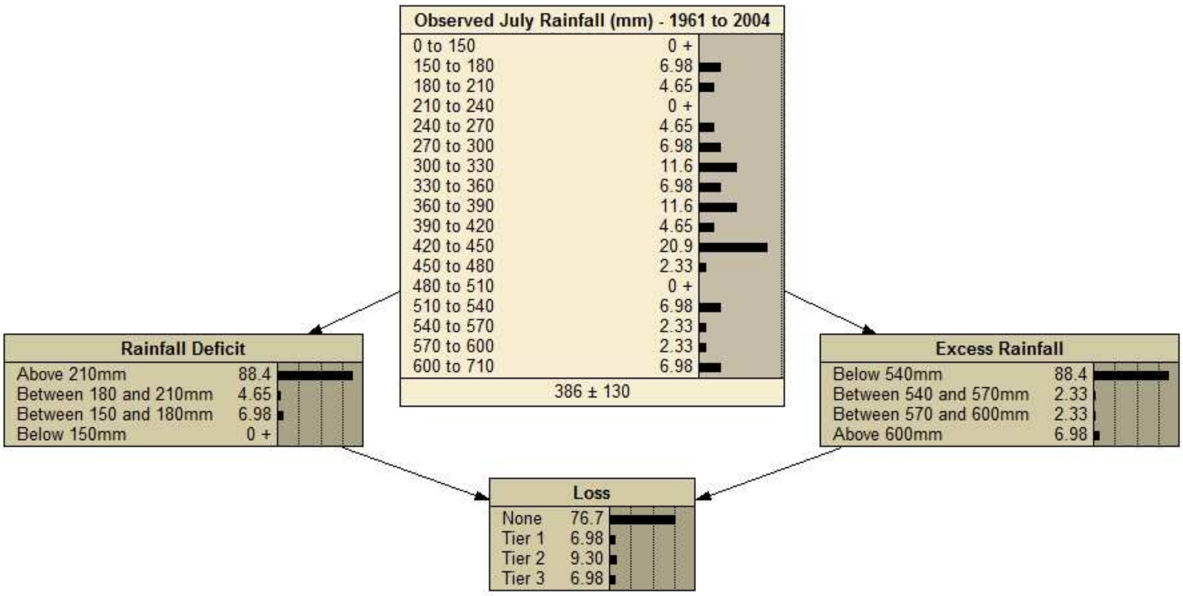


Figure 6.10: BN for rice crop index insurance in the Kolhapur region with a three tiered payout structure, using observational data from the APHRODITE project (Yatagai et al. (2009)).

The parent node in figure 6.10 incorporates observational data from the APHRODITE project for the period 1961 to 2004[6]. The two child nodes simply propagate the probabilities in the parent node to present the probability of rainfall exceeding specific thresholds. The *rainfall deficit* and *excess rainfall* nodes in figure 6.10 are the parent nodes for a final variable node.

[6]The node therefore includes 44 data points so a probability of 2.33% for a particular bin indicates that one year in the 44 year time series has a July precipitation value that falls within the bin range.

The *Loss* node combines the probabilities in the parent nodes to generate a combined probability of paying out on an individual policy. The BN shows that 76.7% of the observed years would have been associated with no losses meaning the insurer would not have been required to payout on any of the policies. The remaining years would have resulted in losses with 6.98% of years resulting in a maximum payout to each policyholder.

Figure 6.10 demonstrates the capability of a BN to handle and propagate continuous data, albeit with relatively few nodes. Figure 6.11 includes four additional nodes; a decision node, a utility node and two constant nodes. The *Premium* and *Expenses* nodes are given constant values which can be adjusted to influence the viability of the pricing structure based on information in the *Loss* node. Their values are represented as percentages of the total insured value.

The *Loss* node combines the values in the parent nodes to produce probabilities for the different tiers of loss. It then multiplies these by the payout values for each tier, shown in table 6.4, to produce an expected loss value (E). The example values in table 6.4 represent possible proportions of the total insured value (maximum indemnity) that could be paid out if the relevant threshold is surpassed. The first value at the bottom of the *Loss* node denotes E and the second value is the standard deviation (σ) in E (assuming a normal distribution about the expected loss). In figure 6.11, $E = 11.7$ and $\sigma = 27$ based on the three tiered payout structure contained in the BN.

Loss	Payout (% of total insured value)
None	0
Tier 1	15
Tier 2	40
Tier 3	100

Table 6.4: Payout values assigned to individual states in a three tiered payout structure embedded in the *Loss* node.

The utility node (U) incorporates equation 6.2 to calculate the expected utility for each decision state in the decision node; in this context there is only one state (*Yes*). The value of the state in the decision node conveys the viability of the policy pricing structure. If the value is positive, then the premium is sufficient to cover the expected loss and expenses thus declaring the insurance viable. If the value is negative, then the premium is not sufficient to cover the expected loss and expenses, thus declaring the insurance not viable (i.e. negative *yes* means *no*).

$$Utility = Premium - Loss - Expenses \tag{6.2}$$

Expenses are assumed to be 3% of the total insured value which means that a premium value of 15% is necessary in order for the policy to be profitable for the insurer (i.e. to yield an expected utility of greater than zero).

One of the ways to increase the expected utility without adjusting the premium or expenses values is to create a different payout structure. Figure 6.12 shows the same BN illustrated in

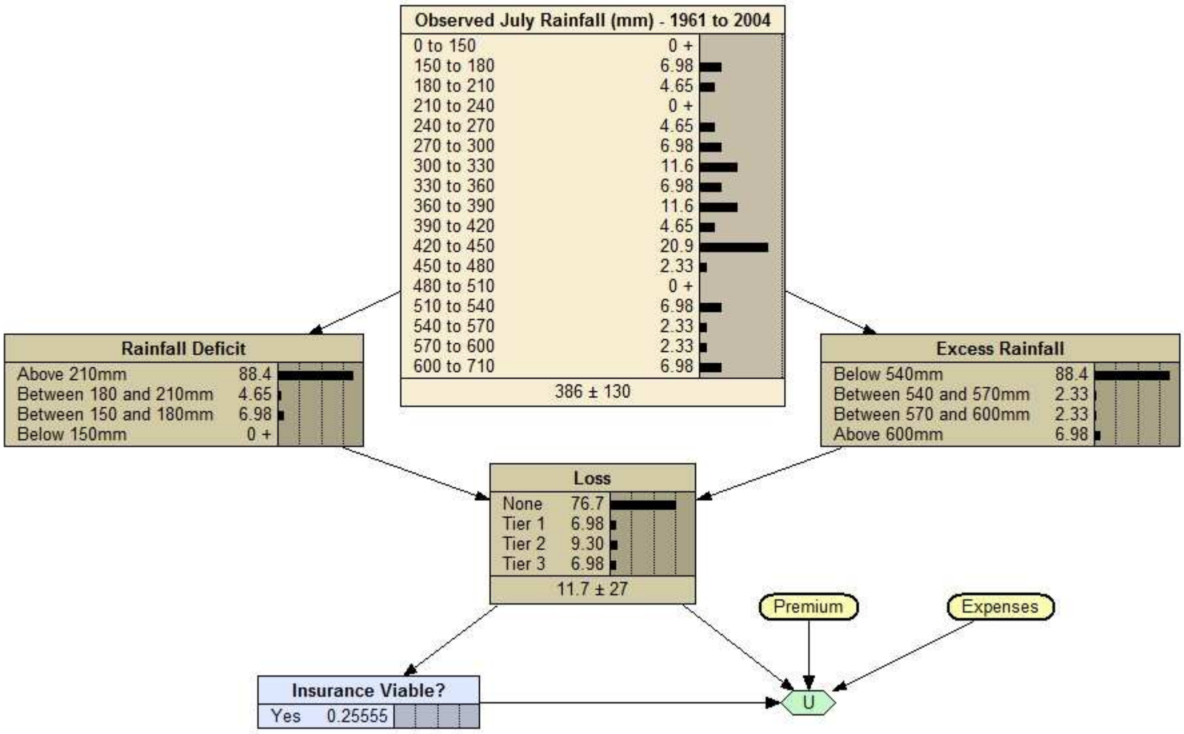


Figure 6.11: BN for rice crop index insurance in the Kolhapur region with a three tiered payout structure, including a decision node to assess the viability of insurance given APHRODITE observational data and assumptions about premium and expenses values; premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

figure 6.11 but with a seven tiered payout structure; the payout percentage values assigned to each tier are given in table 6.5. The payout values were selected so that E is approximately the same in the three-tiered and seven-tiered policy structure.

Loss	Payout (% of total insured value)
None	0
Tier 1	5
Tier 2	10
Tier 3	15
Tier 4	25
Tier 5	35
Tier 6	50
Tier 7	100

Table 6.5: Payout values assigned to individual states in a seven tiered payout structure embedded in the *Loss* node.

Increasing the number of tiers should mean that the level of payment can be more closely correlated to the actual losses thus reducing the basis risk and making the policy more attractive to both the insurer and the policyholder. However, as evident in figure 6.12 even when assuming a stationary climate, a limited observational data set means that the probabilities within each

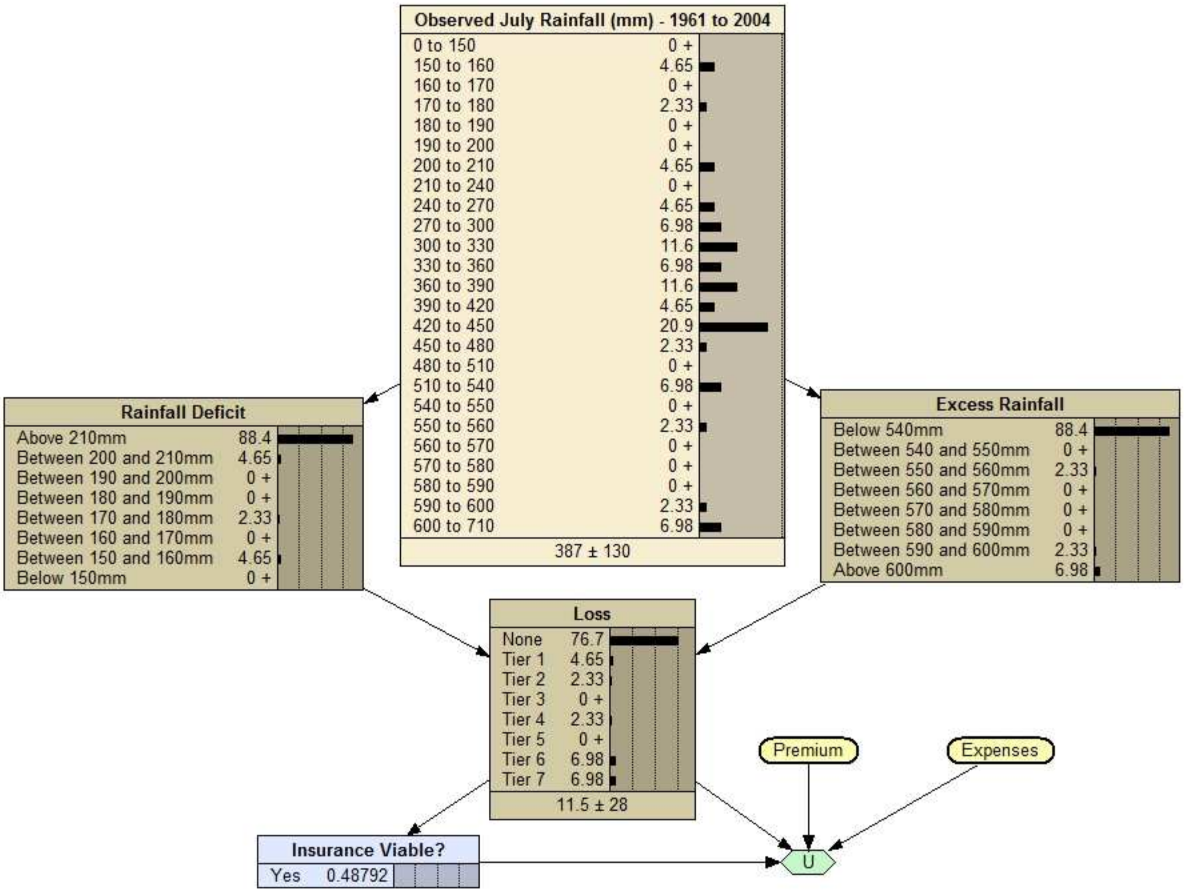


Figure 6.12: BN for rice crop index insurance in the Kolhapur region with a seven tiered payout structure, including a decision node to assess the viability of insurance given APHRODITE observational data and assumptions about premium and expenses values; premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

payment tier are not well defined. In tier 3 and tier 5, the probability is zero according to the data in the BN. Of course the real probability is very likely to be non-zero. Insurers may typically choose to fit a distribution to the data to make the estimated losses smoother but this approach is problematic. Firstly, the choice of distribution can significantly impact the probability of tail events and the losses are highly sensitive to assumptions about tail probabilities, though this is a well known problem amongst insurers and risk modellers (Haimes (2009)). Secondly, the climate is nonlinear and non-stationary. In previous chapters experiments with simpler models reveal that assuming stationarity and invoking the ergodic assumption is problematic in nonlinear systems subject to altered forcings. In the observational data set used here, it is likely that the temporal distribution of events does not fully represent the probability distribution of expected losses for the present climate. Indeed, figure 6.7(b) shows that there has been a downward trend in precipitation values for July suggesting that the probability of a year with rainfall deficit may have increased in recent years whilst the probability of a year with excess rainfall may have decreased. Alternative sources of climate information may help to improve the probability estimates and in the next section, BNs which combine observational data with climate model data are presented.

6.6.2 BNs combining observational and model data

The BN illustrated in figure 6.13 provides a simple view (node names only) of a BN which incorporates multiple sources of data. The parent node, *Climate Timescale*, listed in the first row determines the period for which model data is used. The second row displays the four sources of data used in this case study; the APHRODITE observations and the three HadRM3 runs driven by HadCM3 and ECHAM5 for hindcasts and future projections and ERA-Interim reanalysis data. The information contained in each data node (listed in the second row) can be individually selected or combined, using the *Model Choice* node. With the exception of the *Model Choice* node, rows three, four, five and six are identical to figure 6.11.

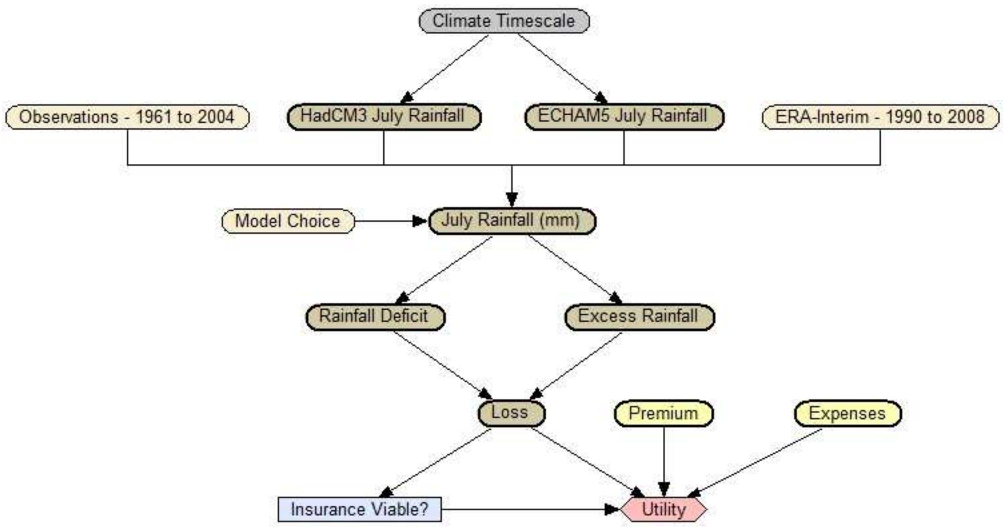


Figure 6.13: BN developed for weather index insurance in the Kolhapur region, including multiple sources of climate information using node names only.

Following exactly the same approach as that utilised in the UKCP09 projections (UKCP09 (2011)), 30 year time intervals are selected from the available data and centred on the decade of interest; for example, the 2030s are represented using the data from 2020 to 2049. To derive probability distributions from the model projections to inform the threshold exceedance probabilities in the future, it is therefore necessary to apply the ergodic assumption. As expressed in section 6.2.2 and discussed extensively throughout the previous chapters, the ergodic assumption can be misleading and potentially undermine robust climate change adaptation decisions. By employing the ergodic assumption, the BN analysis here simply serves to illustrate how current climate model data might be used to explore possible future climates. This BN framework could be improved if large IC ensemble distributions were available.

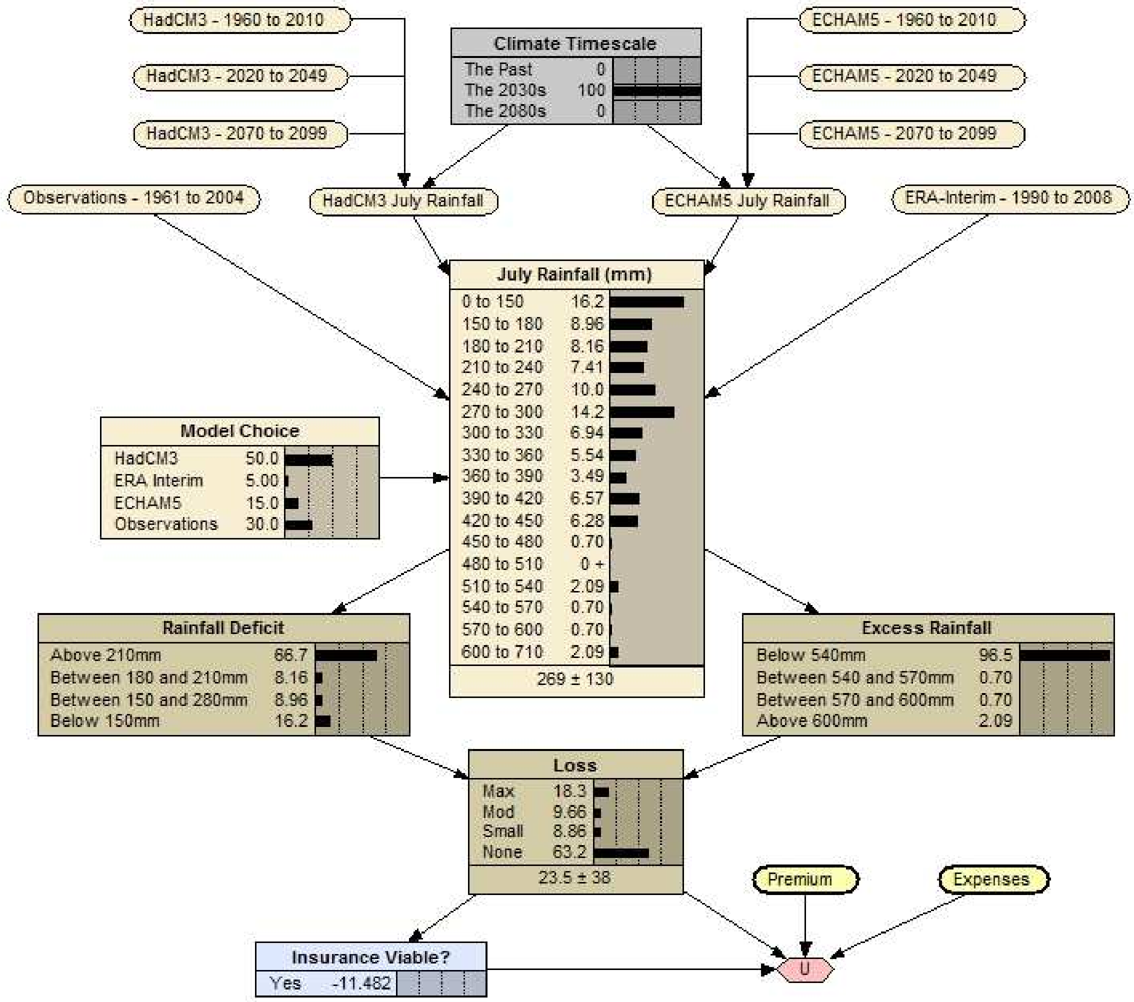


Figure 6.14: BN to inform viability of weather index insurance for rice production in Kolhapur, India. The relative weights of the states in the *Model Choice* node have been arbitrarily selected and the *Climate Timescale* set to the 2030s. Constants are given the values: premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

Figure 6.14 shows an expanded version of the BN depicted in figure 6.13. The BN utilises the three tiered payout structure (see fig. 6.9) and consists of 20 nodes: 16 variable nodes, 2 constant nodes, 1 decision node and 1 utility node. Of the 16 variables nodes, only two (*Climate Timescale* and *Model Choice*) consist of discrete states, the remaining 14 incorporate continuous data. The three parent nodes for the *HadCM3 July Rainfall* node and the three parent nodes for the *ECHAM5 July Rainfall* include frequency distributions for the model precipitation data over Kolhapur for the given time intervals. The propagation of the probabilities is controlled by selecting one of three different states in the *Climate Timescale* node. In this BN the combination of model data, reanalysis data and observational data is determined by the probabilities (weights) dictated by the *Model Choice* node. The configuration shown in figure 6.14 gives a 50% weighting to the HadCM3 model, 35% to the APHRODITE observations, 15% to the ECHAM5 model and 5% to the ERA-Interim data; these values are arbitrarily chosen.

Weighting the data is problematic (see discussion in section 6.7) but is illustrated in figure 6.14 for demonstration purposes; further examples are given where individual models are selected. The time scale in the BN shown in figure 6.14 is set to the 2030s (for the same versions of the *weighted* BN in the past and 2080s, see Appendix D, figures D-1 and D-2). The climate risks in the 2030s are of particular interest to insurers developing products in emerging markets (see figure 6.1). The resulting probabilities show that a premium of 15% of the maximum insured value (assuming expenses of 3%) is not viable given the probabilities and assumptions in the BN for any time period. According to the BN, there is a 16.2% chance that rainfall during July in the 2030s will be below 150mm. The chance of a maximum payout is therefore too large to deem the premium and policy structure viable; indicated by a negative utility of -11.482 in the decision node. Increasing the premium to 27% would make the expected utility positive but this premium is likely to be less acceptable to policyholders. Further work on the demand-side could establish thresholds at which the premiums become unaffordable for a particular community. Combining supply-side and demand-side studies should enable progress to be made in understanding the viability of index-based insurance mechanisms in a changing climate.

In the BN developed, the user can select each state in the *Model Choice* node exclusively to see how each source of information alters the probabilities in the network. Figure 6.15 shows the BN when the HadCM3 model is selected in the *Model Choice* node. The time scale is set to 2080s (for the past and 2030s see Appendix D, figures D-3 and D-4). Recall from figure 6.7 that the precipitation totals from the HadCM3 model are significantly lower than the observational data during the monsoon season. During July the HadCM3 data increases markedly from the June values but still does not approach the observed totals. The *July Rainfall* node in figure 6.15 shows the spread of precipitation values and despite an average increase in precipitation values compared to the past and 2030s (figs. D-3 and D-4), all of the probability density remains below the 540mm threshold for excess rainfall payout. There is density below the rainfall deficit threshold values with 3.45% (one year out of the 30 year sample) below 150mm. With a premium of 15% of the total insured sum, the expected utility is 5.619. A premium value of 10% would therefore be sufficient to ensure the profitability of the product based on the network assumptions and the use of the expected utility value as a measure of profitability.

If one believed the precipitation values associated with the raw HadCM3 model output, climate change would therefore appear to pose no real threat to the long-term sustainability of index-based insurance in the Kolhapur region (at least on the supply side). However the raw model output from the RCM driven by the ECHAM5 model suggests that the pricing structure is wholly inadequate under past and future climate conditions. Figure 6.16 shows the impact of selecting the ECHAM5 model as the driving GCM on the threshold exceedance probabilities for rainfall deficit and excess rainfall in the 2080s. 86.2% of the data falls below the 150mm threshold associated with the maximum rainfall deficit payout. Clearly, if this data were credible, then the index insurance would not be viable based on the thresholds selected. By considering the ECHAM5 raw output data in the policy design, insurers would therefore need to be prepared to

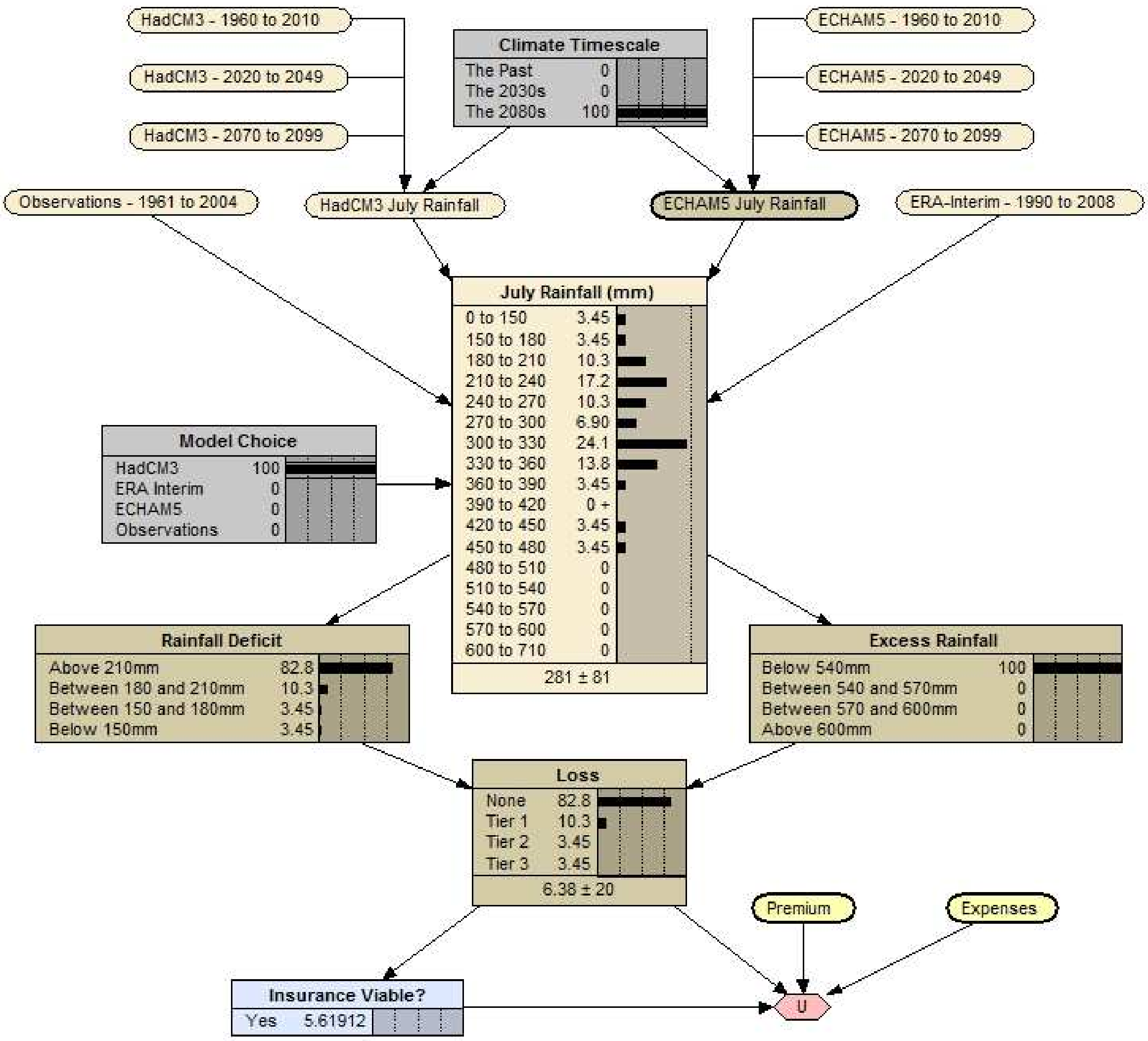


Figure 6.15: BN to inform viability of weather index insurance for rice production in Kolhapur, India. The HadCM3 model has been selected in the *Model Choice* node and the *Climate Timescale* set to the 2080s. Constants are given the values: premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

eventually decrease the thresholds at which payouts for rainfall deficit occur and/or dramatically increase premiums. Of course the reliance of the rice crop on rainfall totals greater than 150mm per month would mean that a significant decrease in the thresholds would render the product unfit for purpose. Moreover, analysis of the hindcast ECHAM5 data (shown in Appendix D, figure D-5) shows that the probability of rainfall being below the 150mm value in July does not change considerably throughout the time series. Clearly, if the actual precipitation accumulations are this low, farmers would not be able to harvest the rice crop using rain-fed irrigation methods. The use of the ECHAM5 model data is therefore brought into question; the HadRM3 model driven by output from ECHAM5 does not appear to adequately reproduce the correct precipitation patterns over the Indian subcontinent.

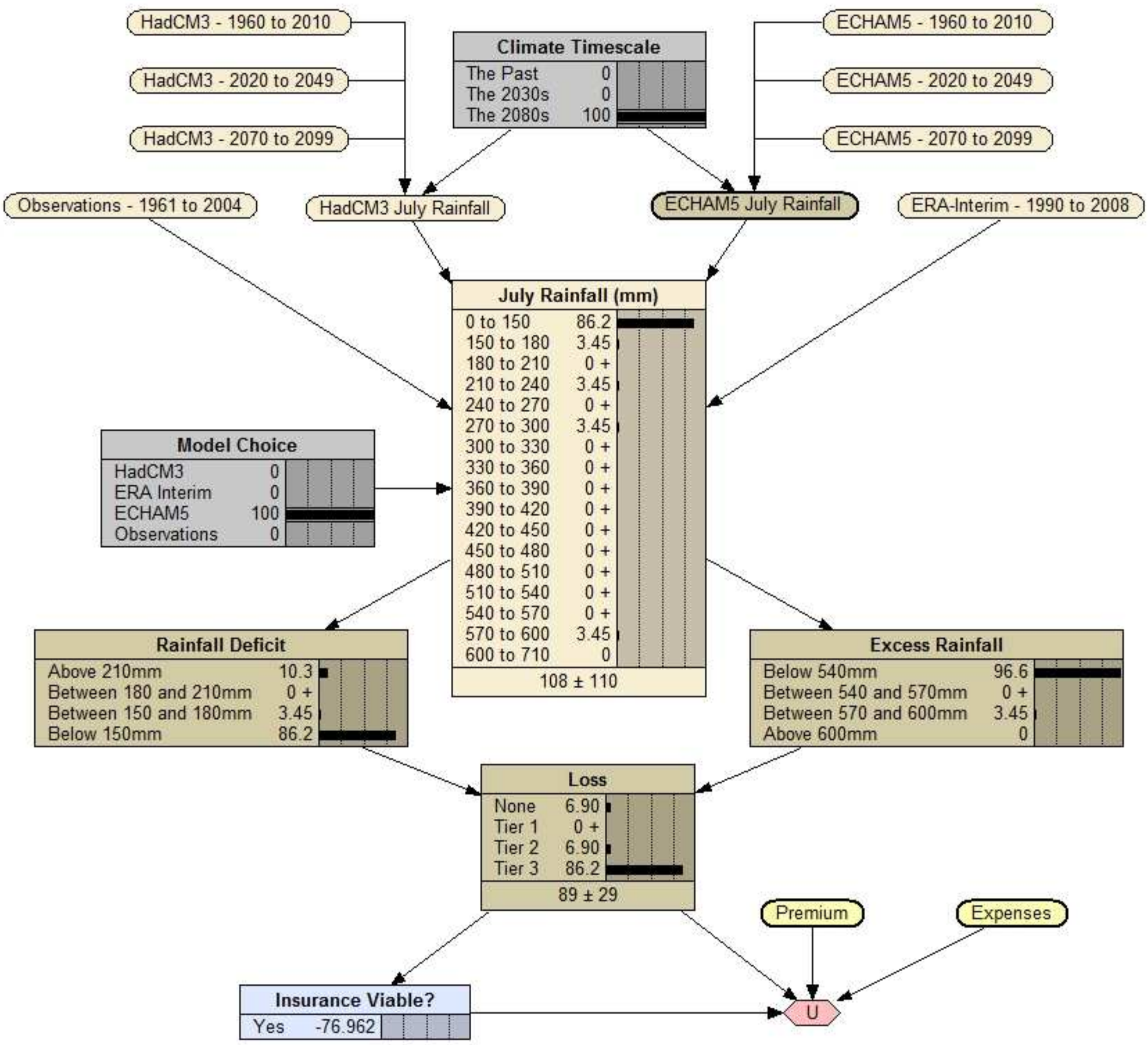


Figure 6.16: BN to inform viability of weather index insurance for rice production in Kolhapur, India. The ECHAM5 model has been selected in the *Model Choice* node and the *Climate Timescale* set to the 2080s. Constants are given the values: premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

The choice of driving GCM is clearly a crucial factor in determining the viability of an index-based product under climate change, at least in the case study explored here. However, given the evidence of systematic model errors described in the analysis of the raw model output in section 6.5.3, an obvious next step is to examine the effects of introducing bias corrections to the model output. In the next section, simple bias corrections are made to the model data and the impact on the BN probabilities is analysed.

6.6.3 BNs incorporating bias corrected model data

The preliminary data analysis in section 6.5.3 and the BN results presented in section 6.6.2 reveal large systematic errors in the raw model output. Accounting for these biases is possible in the BN framework. Yet whilst the process of bias correction is common in climate science, the introduction of statistical bias corrections requires careful consideration so as not to create misleading information which can lead to maladaptation. Statistical bias corrections to precipitation data from a GCM with a closed hydrological cycle has questionable physical implications. Artificially decreasing or increasing the precipitation data with reference to observed data means that the total moisture content in the model is altered. The reasoning behind statistical bias corrections therefore needs to be clear and justifiable. Additionally, in the context of climate change, bias corrections assume that the past is an appropriate guide for the future. Haerter et al. (2011) note that all bias correction methods make assumptions about the applicability of statistical transfer functions from observed climate to future climate and caution that the extent of the impact on the climate signals of model projections is uncertain. Furthermore, Haerter et al. (2011) claim that existing bias correction methods do not take into account that oscillations occur on different time scales caused by disparate physical mechanisms. The authors suggest a "cascade of bias corrections" to address this problem. However, in projecting climate change, it is not obvious whether the oscillatory patterns observed in the past will continue or change their behaviour under future forcing conditions. Certainly the evidence from simple nonlinear systems explored in previous chapters, particularly in the experiments on the LS84 model, suggests that the internal climate variability can be forcing scenario dependent.

In section 5.6, it is shown that the dynamic behaviour of the LS84 model is qualitatively different as the parameter F is decreased from a transitive region of parameter space to an almost-intransitive region of parameter space. In the climate system it is possible (and perhaps even likely) that the dynamics of the climate system will be altered under future forcing conditions, at least on regional scales. The use of a bias correction for future climate model projections explored here is therefore purely demonstrative of the approach one could adopt if there was sufficient reason to believe that biases and systematic errors identified using past observed data might apply under altered climate conditions. A bias correction could include high order moments, adjusting for variance, skewness and other statistical properties of the observed precipitation distribution. However, given the errors in the model results described in section 6.5.3, it is inappropriate to introduce a complicated bias correction method. Therefore, the simplest form of bias correction is used where distributions are simply shifted according to a mean change[7]. This is sufficient to show how one may incorporate bias corrected data in a BN framework.

In this section, the BNs presented show the sensitivity of the insurance viability to bias corrected model output. The summary statistics presented in section 6.5.3 are used to bias correct the model projections. The difference between the mean of the observed precipitation data and the means of both the ECHAM5 and the HadCM3 driven RCM data, over the same period (1961 to 2004), is added to the time series data in each forecast period. Table 6.6 shows the biases of the model output fom different sources.

[7] A bias correction using the first moment.

Data Source	Mean Bias (mm)
HadCM3	-171.05
ECHAM5	-293.49
ERA-Interim	-284.16

Table 6.6: Mean biases of model output data using the observed July Rainfall over Kolhapur from 1961 to 2004.

Figure 6.17 shows how a mean bias correction to the HadCM3 output data for the 1961 to 2004 period affects the threshold exceedance probabilities and the viability of the index insurance product. The consequence of the bias correction is that there is no density in the lower range of precipitation values so there are no rainfall deficit losses. As the variability in the HadCM3 precipitation values (standard deviation of 54.72) is less than the observed variability (standard deviation of 162.36), a shift in the mean does not lead to large probabilities of exceeding excess rainfall thresholds. The expected loss is $E = 0.213$ (% of the maximum insured value) so a very low premium would render the product financially viable for an insurer. However the policyholder may be reluctant to purchase insurance if the bias corrected model probabilities were accurate given the very low probability of any thresholds being exceeded.

Figure 6.18 shows the effect of the bias correction on the HadCM3 driven output in the 2080s. The bias corrected distribution shows increased density in the higher range of the precipitation values when compared to the output shown in figure 6.17. There remains a 90.7% probability of no loss with a 5.77% probability of the maximum payout being triggered for excess rainfall. Given no probability of a loss from rainfall deficit, the policy structure is viable, conditioned on a 10% (or higher) premium.

The effect of the bias correction when applied to the ECHAM5 driven output for the past and 2080s is shown in the results provided in appendix D, figures D-7 and D-8. Because of the narrow range of the precipitation values from the RCM driven by ECHAM5 model for the period 1961 to 2004 (see figure 6.8), the effect of a mean bias correction shifts all precipitation values to the range between 270 and 540 mm so no losses are triggered. In the 2080s, there is a small amount of density in region associated with rainfall excess but 93% of the distribution does not trigger a payout so the insurance pricing structure appears viable on the supply-side.

Another approach is to measure the anomalies between model forecast periods and add these anomalies to the observed data. Section 6.6.4 presents BNs which incorporate observational data which is adjusted according to the anomalies in the model output.

6.6.4 BNs with observational data altered using model output anomalies

In assessing the impacts of climate change, it is common to use anomaly data from climate model simulations instead of the raw model output because of large systematic biases (e.g. Hudson and Jones (2002)). The reasoning is that whilst the absolute values extracted from

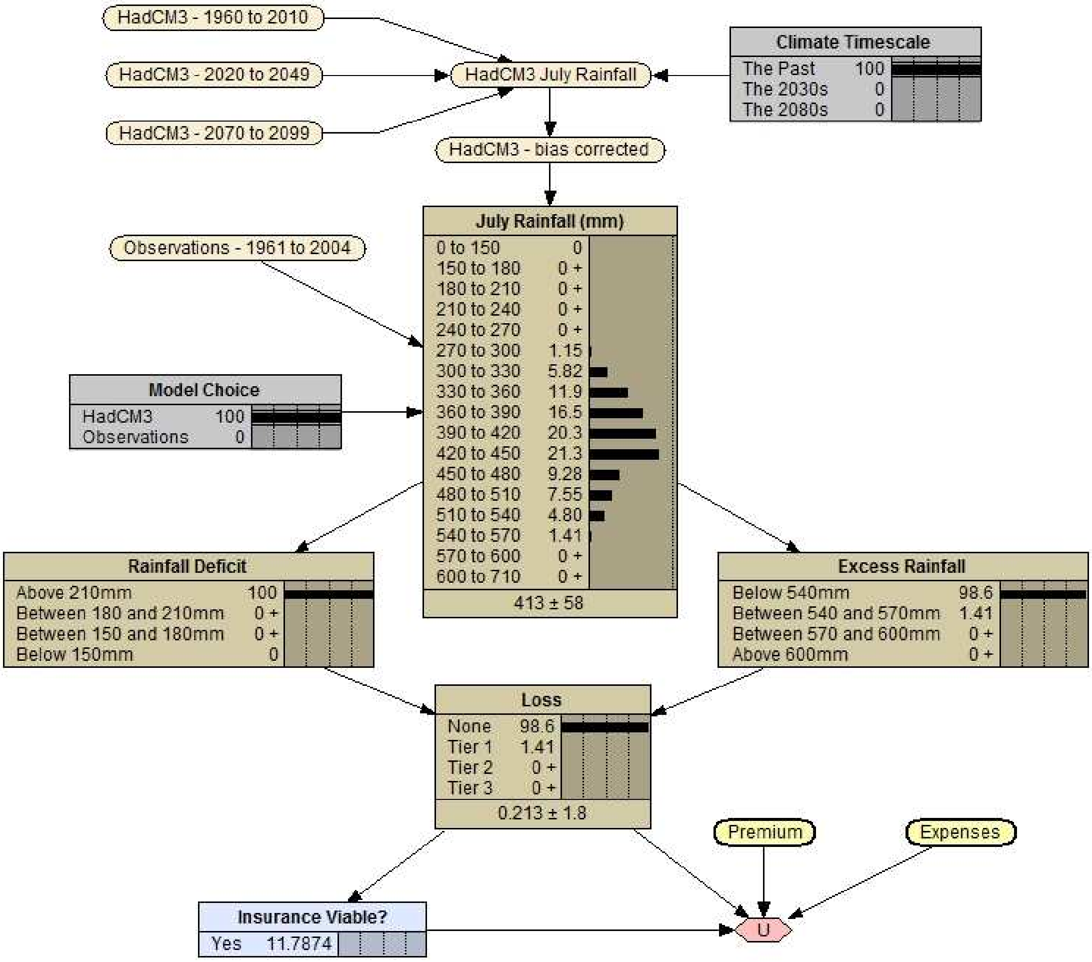


Figure 6.17: BN to inform viability of weather index insurance for rice production in Kolhapur, India. The HadCM3 model has been selected in the *Model Choice* node and a bias correction has been applied according to table 6.6. The *Climate Timescale* is set to the past. Constants are given the values: premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

the raw model output may be subject to systematic errors, the relative change in the statistics of climate from one period to another provide useful information regarding the direction and magnitude of possible changes. In this section, the RCM anomalies (changes in the mean) are used to adjust the observational data for future climate periods to assess the impact on the losses associated with the weather index-based insurance product. Table 6.7 shows the change in the means of the future precipitation time series' relative to the observational period, 1961 to 2004, for the RCM output driven by the HadCM3 and ECHAM5 GCMs. These values are added to the mean of the observational data for July precipitation from 1961 to 2004.

Here the ECHAM5 BN results are presented to demonstrate the effect of incorporating anomalies with different signs in the 2030s and 2080s. Figure 6.19 illustrates the effect of adding the mean change in the ECHAM5 output in the 2030s to the observational time series data. The change in the mean is only 7.7 *mm* so the effect on the losses is small. Compared to the losses associated with observational data shown in figure 6.11, there is a slight decrease in the chance of a deficit

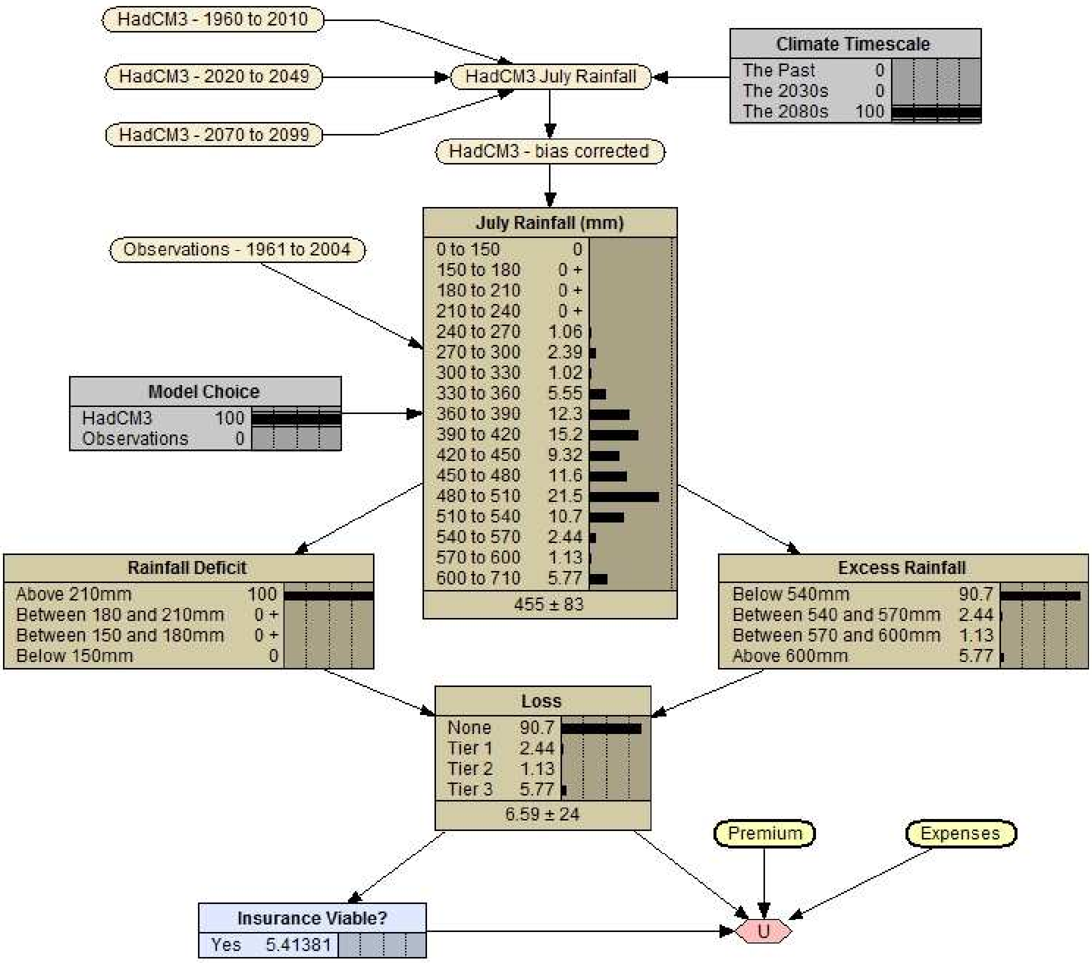


Figure 6.18: BN to inform viability of weather index insurance for rice production in Kolhapur, India. The HadCM3 model has been selected in the *Model Choice* node and a bias correction has been applied according to table 6.6. The *Climate Timescale* is set to the 2080s. Constants are given the values: premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

rainfall and a small increase in the chance of rainfall excess but the changes are not significant enough to affect the viability of the pricing structure. In the 2080s, the ECHAM5 model shows a decrease in the mean precipitation; the high precipitation event in 2081 prevents the decrease in the mean being more significant. Figure 6.20 shows that the perturbed observational data is shifted to lower precipitation values and an increase in the risk of rainfall deficit below 150 mm means the existing pricing structure is no longer viable (as shown by the negative expected utility value in the decision node). The change in the mean precipitation is only $-7.72mm$ but because the pricing structure is sensitive to changes in the tails of the distribution, a small shift in the mean can result in significant changes in the estimates of product viability.

The anomalies associated with the HadCM3 output are larger in magnitude than the ECHAM5 output and this causes the observed time series data to be shifted to higher precipitation values. Figures D-9 and D-10 in appendix D show the results when the HadCM3 anomalies are used.

Data Source	Time Period	Mean Change from Past (mm)
HadCM3	2030s	34.99
HadCM3	2080s	50.65
ECHAM5	2030s	7.70
ECHAM5	2080s	-7.72

Table 6.7: Anomaly data showing the change in the means of the RCM precipitation output driven by HadCM3 and ECHAM5 for given future time period relative to the observational time period 1961 to 2004.

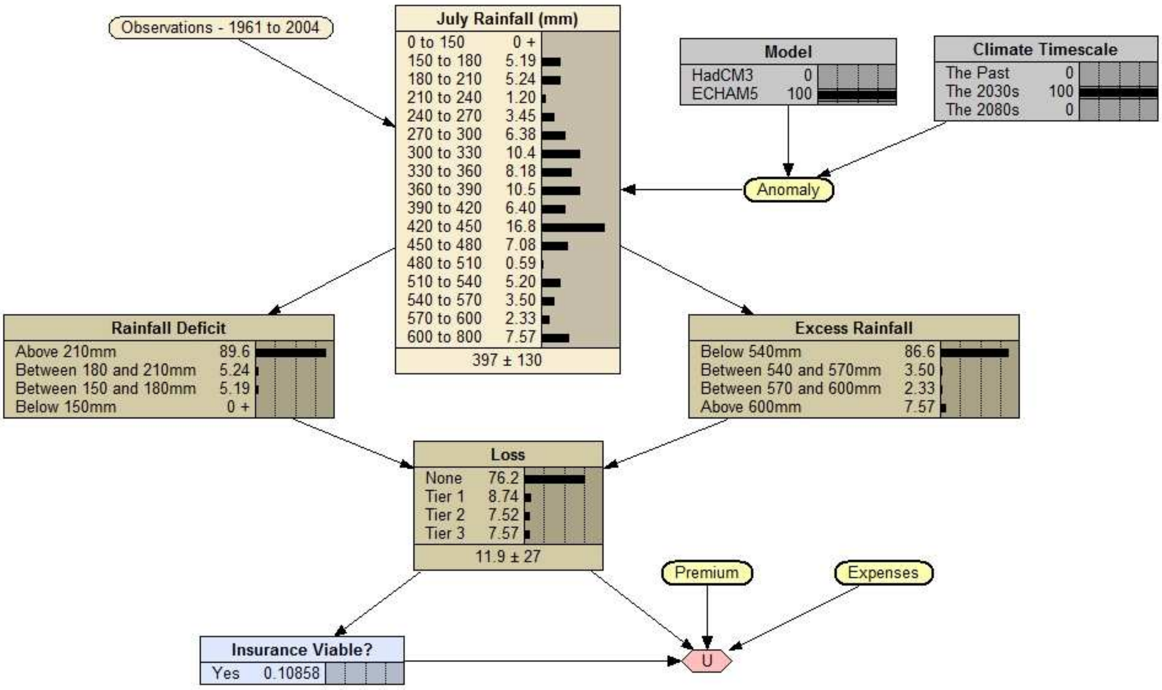


Figure 6.19: BN to inform viability of weather index insurance for rice production in Kolhapur, India. Observational data is altered using anomaly information from the ECHAM5 model projections according to table 6.7. The *Climate Timescale* is set to the 2030s. Constants are given the values: premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

The BN pricing structure isn't viable in either the 2030s or 2080s and a higher premium would be required to offset the increased expected losses and render the product viable for the insurer.

6.6.5 Acknowledging model error

Perhaps the main barrier to the formal uptake and use of the BN approach to assess future climate risk in index based insurance products is the existence of large errors in climate model projections. The HadRM3 model output data, driven by the HadCM3 and ECHAM5 GCMs and the ERA-Interim reanalysis data, significantly underestimates the observed precipitation occurring in Kolhapur in the monsoon season. Capturing the complex interactions which control the monsoon rains and the corresponding flood/drought risk is challenging given a lack of

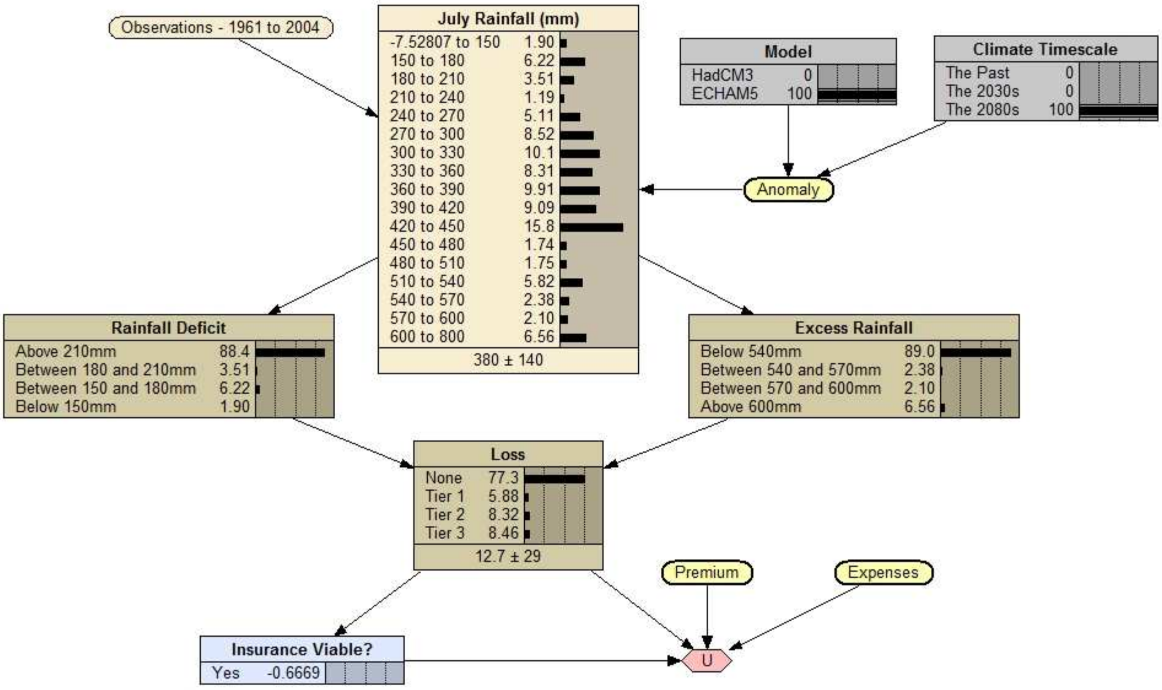


Figure 6.20: BN to inform viability of weather index insurance for rice production in Kolhapur, India. Observational data is altered using anomaly information from the ECHAM5 model projections according to table 6.7. The *Climate Timescale* is set to the 2080s. Constants are given the values: premium = 15% of maximum indemnity and expenses = 3% of maximum indemnity.

computing capacity and limited process understanding. A number of studies have attempted to model the monsoon rainfall under altered climate forcings. Recently, Lucas-Picher et al. (2011) examined the ability of a four RCMs to simulate the Indian monsoon concluding that the timing of the monsoon onset was broadly consistent across the models and reanalysis data but that the monsoon withdrawal was less well simulated. Meehl et al. (2000c) refer to the modelling results of Meehl and Washington (1993) and Kitoh et al. (1997) to suggest that under a range of future climate scenarios, increasing year-to-year monsoon precipitation variability will increase the likelihood of drought and flood during the monsoon season. However, Lal et al. (2001) use a coupled AOGCM to study the climate of India under GHG warming and the model results suggest no significant change in the year-to-year variability in rainfall in central India during the monsoon season. The inconsistencies in the conclusions from different modelling approaches suggest that a consensus regarding the future trends and magnitudes of the monsoon rainfall in RCMs and GCMs for specific emissions scenarios is unlikely to be achieved in the near future. In the absence of reliable model projections, subjective expert judgements concerning the trend and magnitude of change for precipitation in the Monsoon region could be elicited and incorporated into the BN.

The BN presented in this chapter could be updated with improved model information if and when it becomes available. However, in guiding decisions made now the BN approach can be used to assess system sensitivities and provide an analysis tool to develop pricing structures which are robust to uncertainty. Incorporating results from additional models, both GCMs and RCMs, would allow for a greater exploration of the model uncertainty. Yet given the large biases in the model data, it may be some time before model forecasts can replace observational data in guiding the pricing of insurance. However, the knowledge gained from climate model experiments in combination with other sources of climate knowledge, such as climate analogues and remote sensing data, can add value to the decision making process and strengthen the channels by which science is utilised in the insurance industry.

6.7 Discussion of Results

6.7.1 Using climate model output to inform insurance strategies

In this chapter, the use of climate model output as a source of information to guide insurance decisions has been investigated. Section 6.2.3 presents the planning time horizons associated with ten strategic insurance issues. As articulated in this chapter, there is a desire to provide relevant climate model information to guide the management of strategic decisions but the specific information requirements of (re)insurers varies depending on the business activities and perils of interest. The underlying commonalities are the need for transparency in the assumptions made by climate modellers and the need for information which spans the range of plausible uncertainty in future climate states.

In using climate model forecasts to inform insurance decisions, it is important to understand how the climate system and climate models behave in order to gain confidence in quantitative projections. Chapter five showed the existence of regimes and almost intransitive behaviour for a model with subsystems operating on different time scales. Abrupt shifts in climate are therefore not to be unexpected and identifying the risks of such occurrences for regions of interest can have profound effects for insurance decisions. Whilst the analysis presented in this chapter utilised single model realisations to estimate changes in return periods, a more useful approach would utilise IC ensemble projections which can highlight the transient nature of climate under climate change. Embedding large IC ensembles within model forecasts to rigorously explore uncertainty and establish the differences between model climate distributions is therefore important in providing useful climate model information to the insurance industry.

6.7.2 Lessons from the BN case study

As emphasized by Cain (2001), "a BN should be used as a 'tool for thinking' not as an automatic answer provider". In the case study the BN approach provides a framework for combining climate model information with observational data to inform a specific decision problem subject to many competing decision factors. The existence of model errors, possible uncertainties in the observations and the reliance on the ergodic assumption mean that the assessment of utility of a particular index insurance pricing structure for Kolhapur is unlikely to be accurate. However the BN tool does allow an insurer to test system assumptions and sensitivities in a transparent manner. The primary aim of building the BN is not to provide an optimal pricing structure but to demonstrate how one might assess the sensitivity of various pricing structures to the input climate data. For example, in section 6.6.2 it is shown that a premium of 27% is required to yield the policy structure profitable for the supply-side under the assumptions embedded in the BN design. Determining such values and sensitivities could be of a real use in guiding the provision of index-based microinsurance under current and future climate scenarios.

The case study presented in this chapter focuses on the viability of index insurance for the rice crop in Kolhapur, India. The methodology outlined could be easily extended to other weather index-insurance products covering a number of climate-related perils. The BN tool demonstrates how insurers might utilise climate model output in combination with observed data to inform themselves about potential return periods and threshold exceedance probabilities for variables of interest. Four sources of quantitative information are used in the case study. Preliminary data analysis presented in section 6.5.3 shows that the model precipitation output is associated with large model biases. The results in sections 6.6.3 and 6.6.4 show how these biases can be accounted for but the methodology is purely demonstrative and there are a number of reasons for urging caution in bias correcting precipitation data. Given the possibility of nonlinear changes in the climate variable distributions of chaotic systems, explored rigorously in this thesis, care should be taken when utilising imperfect model projections to inform return periods. Manipulating data to remove biases can compromise the value of model forecast distributions which can contain information about the dynamics of the climate within the model.

The BN is designed so that each data source can be individually selected or assigned a weight (relative probability). The result in figure 6.14 (and in figures D-1 and D-2 in the appendix) show the effect of weighting the sources in the network. However the decision to weight different model projections is contentious and depends on appropriate estimates of a model's ability to represent the climate system; a topic discussed in more detail by Tebaldi and Knutti (2007). Numerous methods have been developed to establish different metrics and measures of skill to weight models. Tebaldi et al. (2005) uses climatological mean temperatures to evaluate model skill whilst Greene et al. (2006) focuses on the ability of models to capture trend behaviour. However, the decision to weight models based on their ability to capture observations or key climatic processes has been questioned in a study by Weigel et al. (2010) which states:

> "When internal variability is large, more information may be lost by inappropriate weighting than could potentially be gained by optimum weighting...results indicate that for many applications equal weighting may be the safer and more transparent way to combine models".

The BN approach has the potential to add transparency to the decision-making process. The tool can distil complex information into a usable format and perform what-if scenarios to ensure that decisions are robust. There is clearly more work to be done in order to better align the approach with existing insurance decision structures but the research presented in this chapter represents an important step in improving the handling of climate model information in the insurance decision making process.

6.7.3 Limitations

The focus of the case study is on the burgeoning index insurance sector. The BN developed cannot be easily adjusted to address traditional insurance practices. The primary reason for the lack of a generalisation is the different nature of the payout process for index insurance and traditional claims based insurance. Traditional insurance payouts are impacted by many risk factors as opposed to a single proxy measure. This impacts the determination of estimates for return periods and threshold exceedances for individual policy premiums. For weather index insurance, the maximum payouts for policies occur once a threshold has been surpassed while the maximum payouts for claims-based insurance are a function of the precise magnitude of the hazard. Using climate model output to inform traditional insurance therefore carries additional uncertainties and requires a more complex analysis.

The success of the BN approach in quantifying and communicating the risks of climate variability and climate change to the index insurance sector is dependant on a number of factors. Perhaps most importantly, there needs to be a decision (or set of decisions) which are sensitive to uncertain climate information. Whilst this seems to be an obvious consideration for policies designed to address weather- and climate-related perils, the regulatory and societal constraints (especially for microinsurance in developing economies) may deem the use of alternative sources of climate information irrelevant for policy design and loss estimates. For example, an insurer needs to be able to communicate what the insurance is based on and users may not be willing to accept premiums based on forecasts. Additionally, the user of the BN (in this case the insurer) must be willing and able to interpret probabilistic information conditional on a number of assumptions. In the case study explored in this chapter, the absence of reliable quantitative model projection data means that choices considered optimal based on the BN expected utility values will potentially lead to maladaptation and risk significant losses to insurers. In a climate change context, the tool ought therefore be used to examine preconceptions and guide decision makers rather than to optimise decisions.

The factors considered in the case study are not exhaustive and other potential factors which affect the viability of insurance could be included. For example, additional nodes could represent a detailed breakdown of expenses and administration cost options, the volatility in the price of the crop yields, the willingness of consumers to pay and/or alternative coverage periods. Inevitably, the number of nodes and data requirements could become very large. Without a specific user involved in the construction process, the content of the BN and the application of the approach is therefore limited.

An important additional uncertainty not considered in this study is the impact of emissions scenario uncertainty. For estimates of the change in climate risk in the 2030s the emissions scenario is unlikely to be a major factor but by the 2080s the emissions scenario used to drive model projections is likely to be a critical consideration. The BN approach would also allow for a comparison of model results under alternative emissions scenarios.

6.7.4 Further work

Research could be extended to further examine the use of climate model information to guide the pricing and policy structures of index insurance. An area which has been acknowledged but not explored in detail is the potential to utilise BNs with climate model forecasts to inform premiums on an annual or seasonal basis. There is an element of seasonal to inter-annual predictability of the Indian monsoon, largely due to the El Niño Southern Oscillation (ENSO) phenomena. Droughts (floods) during the Indian monsoon are often accompanied by developing El Niño (La Niña) events in the Pacific Ocean (Krishnamurthy and Goswami (2000)). Selvaraju (2003) shows that the phase of ENSO has a significant correlation with food production in India. Comparing different model projections on seasonal forecast time scales using the BN approach could be beneficial to insurers who are interested in pricing insurance premiums to reflect seasonal forecast information.

If the pricing structure of an index based product is risk-based (employing actuarial assessments), the pricing signal can also be used to communicate risk to the policyholder. Carriquiry and Osgood (2008) state:

> "Insurance prices may communicate forecast information when farmers do not have direct access to the forecast. Studies exploring the potential of insurance prices as aggregators of forecast information would be valuable."

The work presented in this chapter could therefore be extended to consider the demand-side perspective. How climate model projections can be utilised to communicate the changing nature of weather risks under climate change through an index insurance product would be a valuable extension of the work presented here. Moreover, the BN approach could be developed to include different assumptions about socio-economic variables, such as *willingness to pay* which is a critical factor in the successful provision of index insurance.