PAPERS

MODELLING ECOLOGICAL RISKS FROM MINING ACTIVITIES IN A TROPICAL SYSTEM

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ABSTRACT

The mining industry has a long legacy of causing major environmental impacts. Due to mounting pressure, regulations to moderate the negative effects of mining operations have been adopted by most developed countries. Consequently, the mining industry is faced with the difficult task of ensuring its activities do not cause unacceptable changes to the environment. Nonetheless, predicting changes in ecosystems due to environmental contaminants is often limited by the poor understanding of pollution pathways encompassing the mechanisms and interactions between physical, chemical and biological factors in dynamic ecosystems. Risk assessment and management is an approach that has been adopted by regulatory agencies and the mining industry to reduce environmental impacts. The approach is intended to provide practical and implementable solutions to managers, particularly by focussing on high priority risks.

Bayesian network (BN) models are particularly useful tools in risk assessments for quantifying ecological effects and evaluating the effectiveness of management scenarios in situations where the cause-effect relationships are complex and poorly known. In this paper we discuss the potential for BNs to be used for modelling the ecological risks from mining activities to aquatic ecosystems. A BN model was developed to predict the effects of changes in water chemistry and loss of physical habitat on fish communities in the Ok Tedi and Fly River system (Papua New Guinea). The model was used to assess the impacts of future mine operation scenarios on fish biomass.

Key words: ecological risk assessment; Bayesian network; mining impacts; modelling; ecotoxicology.

INTRODUCTION

The Ok Tedi copper and gold mine, operated by Ok Tedi Mining Limited (OTML), is located in the Star Mountains of the Western Province of Papua New Guinea. The mine has been operating since 1984. The mine currently discharges approximately 164 000 tonnes of waste rock and 82 000 tonnes of tailings per day to the Ok Tedi (a large tributary of the Fly River), with mine-derived sediments being transported downstream to the Fly River. Median daily flow in the Fly River at Nukumba is 2100 m^3s^{-1} and 2650 m^3s^{-1} at Obo (see Figure 1 for locations). Based on the OTML mine plan at the time of this study, riverine disposal of materials will continue from now until closure in 2012.

Studies investigating the impacts of mine-derived materials in the Ok Tedi-Fly River system have raised concerns that acid rock drainage (ARD) and the associated liberation of increased concentrations of heavy metals, in particular copper, may cause additional environmental damage by increased toxicity (Rogers et al. 2005) and changes to aquatic food webs (Storey 2005). Geochemical studies (EGi 2005a) showed that mine waste, particularly the tailings, discharged to the Ok Tedi-Fly River system were increasingly prone to ARD production, due to higher sulphur and lower limestone contents in mine waste and tailings. The locations considered most at risk from ARD are the sand bars in the upper Ok Tedi, the Bige dredge stockpiles (Figure 1) and the lower Ok Tedi, and the mid Fly River where this material is being deposited on levees and the floodplain.

Geochemical test work suggested that without mitigation of ARD, significant changes in water chemistry (particularly increased bioavailable metal concentrations) are predicted to occur in the future, with subsequent impacts on aquatic and terrestrial resources (EGi 2005b). Field surveys in 2005 found examples of ARD production on bars in the upper Ok Tedi (Reach A, Figure 1), and on the levees of the Fly River (Reaches C and D, Figure 1).

In order to assist decision-making regarding future mine operations, OTML decided to undertake an ecological risk assessment, with the aims:

- to assess the risks to environmental values in the Ok Tedi and Fly River system from ARD; and
- to test the effectiveness in mitigating these risks by removing 85% of sulphur from the tailings before they are discharged to the river system.

A description of environmental values defined by OTML can be found in OTML (2005). The removal of 85% sulphur was only used as a test mitigation scenario. For a full description of mitigation options, see OTML (2006).

The OTML study was undertaken in two phases. Phase 1 focussed on formulating the problem and Phase 2 focussed on quantitatively assessing the risks to the environmental values using five Bayesian decision network (BN) models. This paper describes the risk assessment approach used in the study, introduces the risk analysis modelling tool Bayesian Networks, and briefly describes and demonstrates the use of a model for predicting the effect of the OTML operations on fish.

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ECOLOGICAL RISK ASSESSMENT

Risk is defined as the likelihood of an adverse event with specific consequences occurring within a defined timeframe (Suter 1993). Risk assessment is a tool that has been developed to facilitate informed decision-making by assessing risk, and the risk assessment process is based on quantifying the uncertainty of an undesirable event occurring either now or in the future (Suter 1993). The risk assessment process is iterative (Figure 2), where each iteration seeks to improve the understanding of system complexity and to reduce associated uncertainty.

Past approaches to risk assessments have predominantly focussed on single stressor (mostly chemical) problems and have not explicitly incorporated risk management actions. Current risk assessment approaches enable better quantification of the effects of multiple stressors on multiple endpoints and enable testing of the effectiveness of risk management strategies. By integrating information on exposures over time, pathways, sources, and/or routes for a number of stressors, decisions in risk management can be better informed. Such approaches allow for a more complete view of a system, enabling a more holistic view to decision-making (Pollino and Hart 2008).

Uncertainties and Risk Management

Ecological Risk Assessments (ERAs) facilitate a more formalised approach to risk management. A robust ERA should consider the complexity and associated uncertainties within inherently variable ecosystems, and our lack of knowledge of ecosystems. Acknowledging and incorporating complexity and uncertainty in an ERA can reduce ambiguity and encourage a more transparent process in decision-making, identify realistic strategies for management and promote adaptive management, decision-making and modelling processes (Pollino et al. 2007a). Accordingly, when analysing risk, communication of uncertainties is essential.

In a risk assessment, the major sources of uncertainties that need consideration are: lack of knowledge of complex systems; the inherent variability or stochasticity associated with ecological systems; and the error in representing complex systems, particularly in risk analysis models. While uncertainties associated with lack of knowledge and model error can be addressed iteratively by targeted research and monitoring and data analysis, inherent variability or stochasticity is irreducible and something we should seek to capture in risk analysis models.

Ideally, risk analysis models should promote a framework for iterative updating, with models being updated in an adaptive framework as new knowledge and data become available (Pollino et al. 2007a). Such models also need to communicate natural variability, particularly when models and their predictions are applied over broad ecological scales. Such predictions are intrinsically linked with changeability, particularly as the longer the timescale and the more dynamic an ecosystem, the greater the uncertainty will be in predictions. Both the reducible and unreducible uncertainties need to be communicated to environmental managers and decision-makers to provide an understanding of the risks associated with management options.

Risk analysis models also need to have direct applicability in risk management, providing recommendations on managing or mitigating high or unacceptable risks, a robust program to monitor progress to ensure the strategies are working, and a review and feedback process for making changes if needed. To be effective, this risk management plan needs to be supported by peer-reviewed science that underpins an evidence base for a specific course of risk management action (Pollard et al. 2008).

We have found that Bayesian Networks (BNs) are of value for the risk analysis, and can be used more broadly to facilitate the risk assessment and management processes (Pollino and Hart 2008). BNs are particularly useful in assisting risk management decisions, where considerable uncertainties exist, and for fulfilling the adaptive or iterative aspects of a risk assessment (Hart and Pollino 2008; Pollino et al. 2007a; Pollino et al. 2007b).

BAYESIAN NETWORKS

BNs are a form of Bayesian statistical inference in which evidence or observations are used to update or to newly infer the probability that a hypothesis may be true. The name "Bayesian" comes from the use of Bayes' theorem (see Equation 1) in the inference process. Bayes' theorem was first derived by the Reverend Thomas Bayes (1702 – 1761) (www.wikipedia.com).

BNs are widely being used as model-based decision support tools, modelling situations where there is considerable uncertainty. Recently, there has been much activity in using the BN modelling framework to develop decision support tools to aid in the management of ecological systems. Unlike many other models for decision support, BNs offer a pragmatic and scientifically credible approach to modelling complex ecological systems. BNs can integrate quantitative and qualitative forms of knowledge, with uncertainties being represented as probability distributions.

BN models explicitly link environmental processes and ecological outcomes with environmental management actions. They provide a framework to assemble masses of information, to better understand systems and processes, test hypotheses, and evaluate the effectiveness of alternative management policies. They are particularly useful for tying together different bodies of data, aiding in the identification of salient, necessary and sufficient features of a system (Hilborn and Mangel 1997).

Modelling of ecological processes using BNs is particularly useful since these models use Bayesian inference to update the scientific knowledge as new information is made available (Reckhow 2002). This type of iterative improvement of models improves the representation of the system in the model and fits into the ecological risk assessment paradigm and adaptive management frameworks (Pollino et al. 2007a). BNs can also be extended for risk management planning and decision-making, where other non-scientific factors (e.g. cultural, economic) can be included in models (Pollino and Hart 2008).

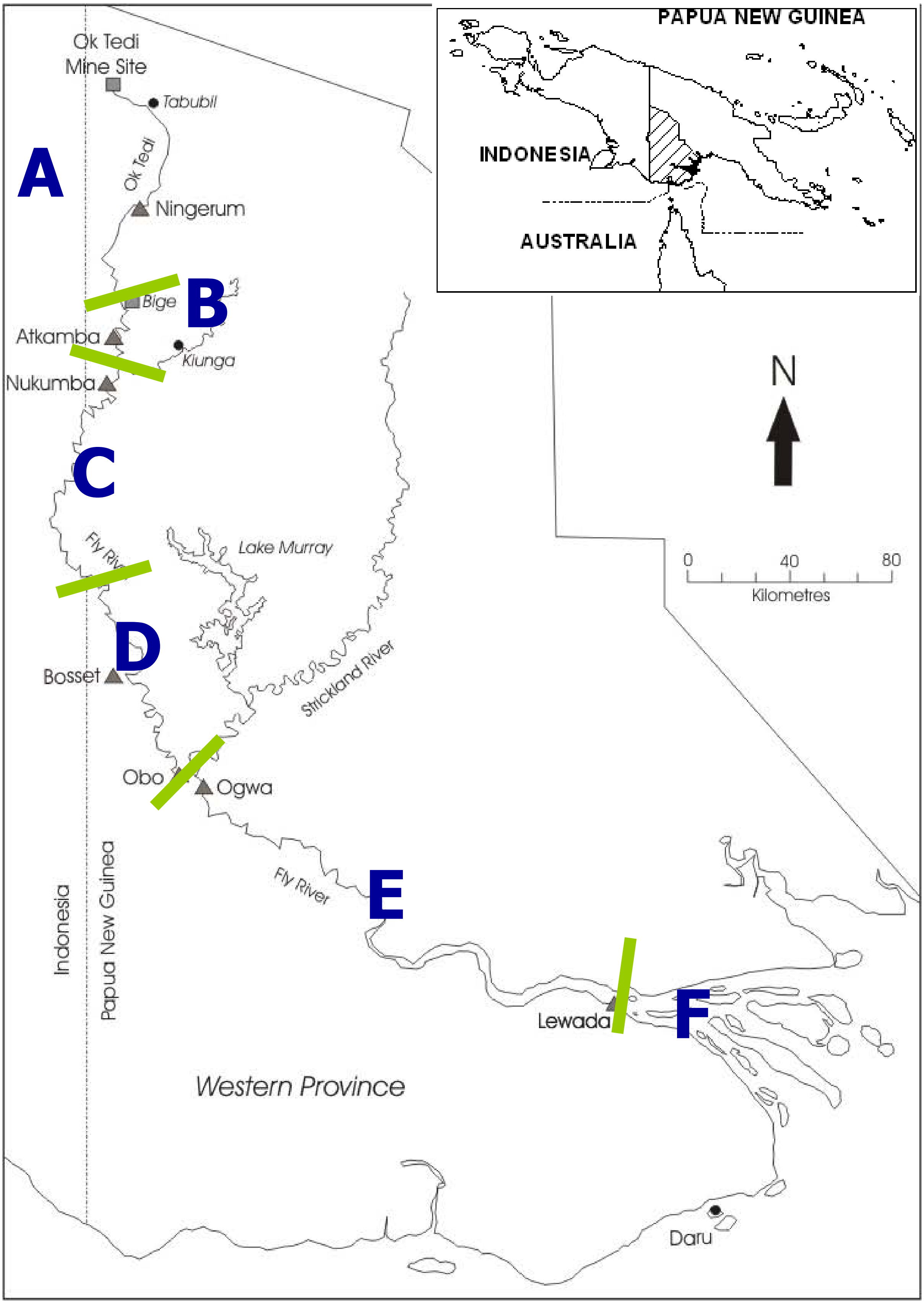

Figure 1. The Ok Tedi and Fly River showing reaches A to F.

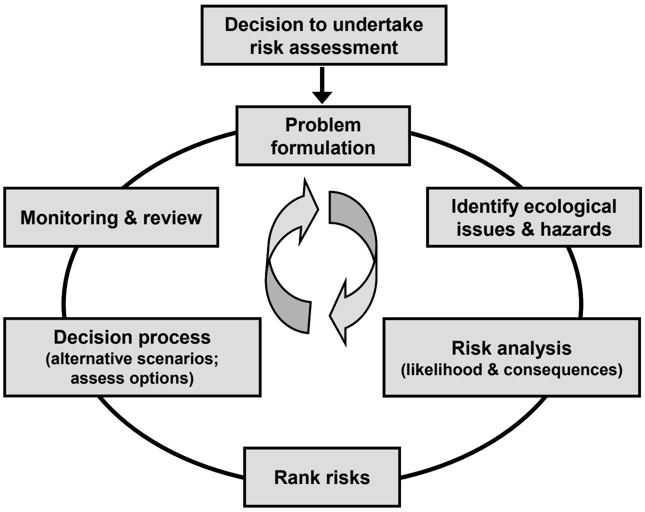

Figure 2. Risk assessment and management framework (Hart et al. 2005a).

How do they work?

BNs are graphical models made up of a collection of nodes, each with mutually exclusive states, which represent important environmental variables. Arrows (arcs) represent causal dependencies between nodes. A probability distribution is used to describe the relative likelihood of the state of each variable, conditional on every possible combination of parent (up arrow) variables. If a node has no parents, it can be described probabilistically by a marginal (unconditional) probability distribution (Pearl 1988).

A prior (unconditional) probability represents the likelihood that an input parameter will be in a particular state; the conditional probability calculates the likelihood of the state of a parameter given the states of input parameters affecting it, and the posterior probability is the likelihood that a parameter will be in a particular state, given the input parameters, the conditional probabilities, and the rules governing how the probabilities combine. The network is solved when nodes have been updated using Bayes' Theorem:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \qquad \text{(Equation 1)}$$

where P(A) is the prior distribution of parameter A. After collection of data B, P(A|B) represents the posterior (new) distribution of A given the new knowledge (B). P(B|A) is the likelihood function that links A and B.

The modelling shell Netica (www.norsys.com) was used to construct OTML Bayesian networks. For a full description of BNs, see Korb and Nicholson (2004) and Pearl (1988).

DESCRIPTION OF OTML FISH BN

Information about the OTML models is available in the reports by Pollino and Hart (2005, 2006). Further information about constructing BN models is available elsewhere (Pollino et al. 2007b).

In this paper, a subset of one BN (the fish model) is introduced, where the endpoint used is the availability of fish (measured as biomass in kg).

Model scales

Spatial scale: The Ok Tedi and Fly River system was divided into six reaches (Reaches A to F) representing different vegetative, geomorphic and ecological types (Figure 1). Two reaches where no mining activity occurs were also included in this study as a means of testing model behaviour (Pollino and Hart 2005). Only results for Reach C (Figure 1) are shown in this paper.

Temporal scale: The temporal periods considered in the BN are:

Mine operating period	
Pre-dredge	1983 – 1998
Dredge	1998 – 2005
Now to end of mine life	2005 – 2012
Post-mine	2012 – 2025
	2025 – 2045
	2045 – 2060

Changes in mining operations, and how this altered water chemistry and channel aggradation behaviour, were considered as part of this assessment.

Climate: Different climatic conditions (El Niño and 'Normal') for model simulations can be selected. These conditions are assumed to span the entire time period selected. The results in this report are based on the 'Normal' climate scenarios, with a distribution of low (25th percentile), median (50th percentile) and high (75th percentile) flows. It is important to note that flow conditions are different at each of the river reaches.

Structure of the Bayesian network

The model causal structure was based on a conceptual model developed in Phase 1 of the ERA (conceptual model not shown here, reported in Hart et al. (2005b). As shown in the schematic (Figure 3), variables were organised into a series of interacting sub-models that integrate into a single framework. Two major riverine processes are examined in the system: water chemistry and sediment processes. These are both relevant to OTML operations. Water chemistry is influenced by ARD processes (ARD and no ARD scenarios can be tested). Channel aggradation is influenced by sediment transport. The outcomes of sub-models are integrated into endpoint variables, described below. Activities at the mine and their subsequent influence on system processes and model endpoints are the focus of management activities in models. The full model is shown in Figure 4.

In many commercial BN packages, such as Netica (Norsys 2005), continuous distributions must be approximated by discrete equivalents (referred to as states). The number of

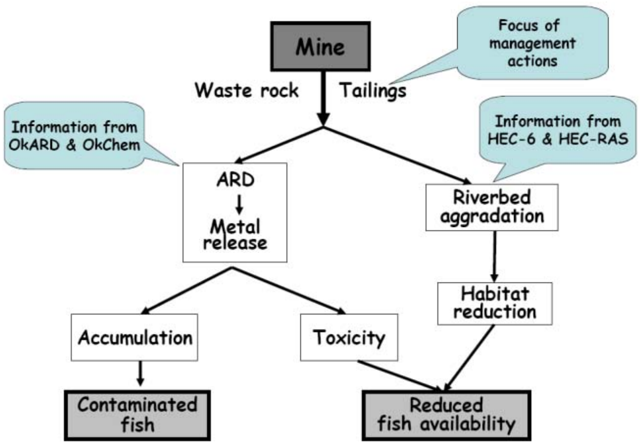

Figure 3. Schematic of the OTML fish model.

states for each variable were assigned on an individual basis, and where possible, recognised classifications or thresholds were used. The remaining nodes were discretised based on expert opinion or using the literature as guidance. For a full description of the models see Pollino and Hart (2006).

Model Endpoints

Four endpoints can be investigated in the fish model (Figure 4). These are (1) Suitable fish habitat, (2) Exceedance of toxicity thresholds, (3) Contamination/Edibility, and (4) Change in biomass/Resource availability. Endpoints 1 and 2 are also parent nodes of endpoints 3 and 4. For endpoints 2, 3 and 4 outcomes can be assessed for important species, important species groupings or total fish biomass. The results for endpoint 4 only are shown in this paper. Results will only be shown for total fish biomass. The total fish biomass endpoint is discretised according to percentiles (0 to 50, 50 to 75, 75 to 90, 90 to 95, 95 to 99 and 99 to 100) in the Fly River.

Source data

Surface Water Chemistry Processes

ARD processes were modelled using the OkARD model (Miller et al. 2003). OkARD predicts percentage sulphur, acid neutralising capacity (ANC), net acid production potential (NAPP) and acid loads from now to 2060. The OkARD model takes into account the current mine plan and expected changes in mine waste geochemistry through time.

Water chemistry changes were modelled using the OkChem model (EGi 2005b). OkChem is a derivative of PHREEQc (USGS 2005), and is regarded as a companion to the OkARD model. OkChem uses acidity outputs calculated by OkARD to predict possible changes in river water quality associated with mining, processing and waste management operations by OTML.

In addition to the modelled water chemistry data, data from the OTML water quality monitoring program was also used in the BN model.

Erosion / Deposition Processes

HEC-6, a sediment transport model, has been used to model erosion and depositional rates in the Middle Fly River (Pickup 2003; Pickup and Cui 2003). These data were used to calculate predictions of channel aggradation. In addition to modelled data, field channel aggradation data from routine monitoring in parts of the Fly River was also used in the BN model (Marshall 2002).

Fish Data

Routine monitoring of fish biomass has taken place along the length of the Ok Tedi and Fly River since 1983. OTML fish datasets assembled by Storey (2004) were used in this study.

Model Parameterisation

To define continuous probability tables for a node, the model needs to be parameterised (see Pollino et al. 2007b for details). The majority of model relationships were parameterised (trained) using data. This was done by fitting a network to a set of observed cases (Henrion et al. 1996). A library of cases (called a case file) was generated using described data sources. A single case is composed of a set of findings/observations, which are entered into the BN for case-based learning (i.e. calibrating/training the BN).

The learning algorithm used for model parameterisation was the expectation maximisation (EM) algorithm. An expectation-maximisation (EM) algorithm is used to find the maximum likelihood estimates of parameters in probabilistic models, where the model depends on unobserved latent variables (http://en.wikipedia.org/); accessed 20 January 2009). EM alternates between performing an expectation (E) step, which computes an expectation of the likelihood by including the latent variables as if they were observed, and a maximisation (M) step, which computes the maximum likelihood estimates of the parameters by maximising the expected likelihood found on the E step. The parameters found on the M step are then used to begin another E step, and the process is repeated. As implemented in Netica (Norsys 2005), the EM algorithm solves a network by finding the posterior probability for each node based on information in the cases, where initial parameters are iteratively refitted to the data updated model until convergence is achieved (Kalacska et al. 2005). Where no information was available, probabilities were equally distributed, representing an unbiased parameter estimate (Pollino et al. 2007b).

Model parameterisation and evaluation were done using a random 80% / 20% split of the dataset. For fish biomass measures, 20 664 cases (observations) were assembled from the OTML monitoring data. Of these, 16 532 cases (80%) were selected at random and used for model parameterisation. The remaining 4133 cases (20%) were used to test the predictive accuracy of the model (see Model evaluation).

Model Evaluation

Sensitivity analysis (sensitivity to findings only) and predictive accuracy tests were conducted on the fish model. Using the 4133 cases isolated for model testing, the predictive accuracy of the model (biomass only) was found to be 70%

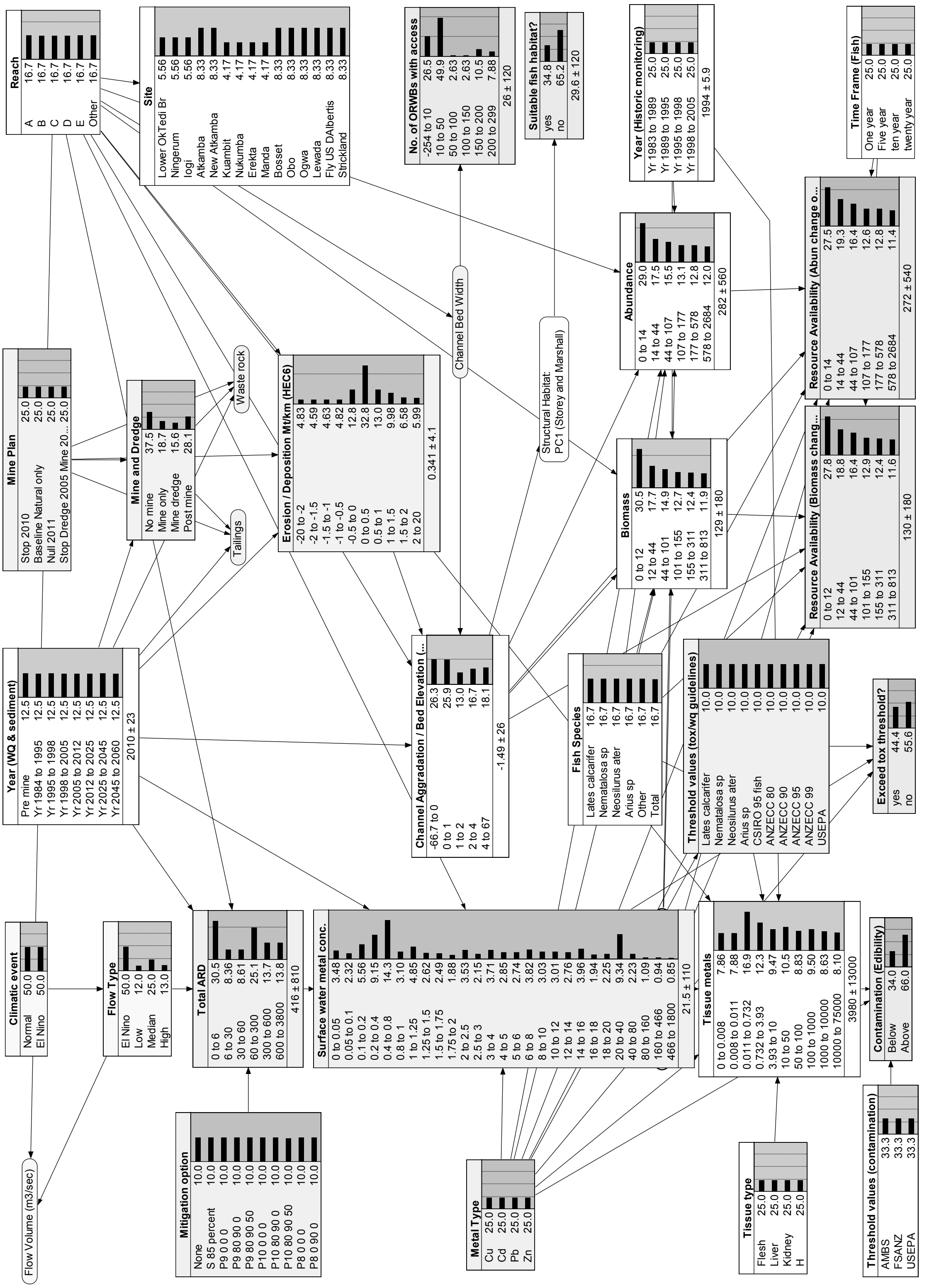

Figure 4. OTML BN fish model.

(Pollino and Hart 2005). This outcome demonstrates that the model is a fair representation of the system. The greatest error in model predictions occurred in the higher biomass categories.

Predictive accuracy of the model could be further improved by targeting expert elicitation at defining optimal conditions for fish communities in the Ok Tedi and Fly River. Further information on outcomes of model evaluation is available in (Pollino and Hart 2006) and will be presented in a forthcoming paper. Sensitivity results are discussed below.

Model Limitations

Full details on model limitations can be found elsewhere (Pollino and Hart 2005).

The key model limitations were:

- Continuous distributions must be represented as intervals (i.e. discretised), which can lead to information loss,

limiting the accuracy and representation of parameters (e.g. water quality measures) (Barton et al. 2008).
- Potential impacts due to climate change are not considered in the model. Given that the model has projections through to 2060, change in weather patterns could influence ARD potential in the system, by changing river flow patterns.
- Data collected at fine scales were used to draw inferences about processes occurring over much broader spatial scales. Consequently, it is assumed that processes occurring at a fine scale are transferable to processes occurring at a broad scale.
- The Bayesian networks are specific to riverine processes and habitat processes (as defined in original project scope). Off-river water bodies (ORWBs) are important habitats for aquatic species. With less dilution potential of ARD and associated bioavailable metals in ORWBs and the potential loss of connectivity with ORWBs due to in-filling of tie channels, aquatic communities could be at risk.

ASSESSMENT OF ALTERNATIVE MINE OPERATION SCENARIOS

The BN was used to investigate a series of mine operation scenarios. For the purposes of this paper, only the outcomes of two mine operation scenarios are shown. These are:

- Null scenario: No removal of sulphur from mill tailings,
- Mitigation scenario: Removal of 85% sulphur from mill tailings (at the mine site).

The mitigation scenario is theoretical only. For a full outline of mitigation scenarios tested for OTML, refer to Pollino and Hart (2006). The full range of scenarios considered by OTML is not considered in this paper.

Probability distributions of total fish biomass (in kilograms) under these two scenarios are graphed in Figure 5. Eight time periods (between 1983 and 2060) are shown (see temporal periods above). The cut-offs for the ranges of total fish biomass graphs were determined using percentiles (see Model endpoints description above).

All fish biomass predictions account for loss of fish due to toxicity of copper (Cu) and loss of fish habitat due to channel aggradation. When interpreting the results in Figure 5, it is important to note that they are probability distributions, accommodating uncertainty due to model error, lack of knowledge and natural variability.

Predictions using OTML fish data show that a loss of fish biomass has occurred at a number of river reaches between 1983 and 2005. A decline in total biomass was observed between early mine life (1983 to 1989), and the latter monitoring periods (1989 to 1995, 1995 to 1998 and 1998 to 2005). In early mine life, the dominant biomass was the 44 to 101 kg category, but this declined to the 12 to 44 kg category in the latter years. This is supported by other research (Storey 2004).

With the mitigation scenario, predictions with the OTML fish model suggest that the 12 to 44 kg category will continue to dominate fish biomass in Reach C (Figure 5). Where no mitigation of tailings takes place, the 0 to 12 kg category of biomass is more prevalent in the distribution for 2012 to 2025 and 2025 to 2045 time periods. These declines in biomass could be manifested as a fish kill, as indicated by the toxicity exceedance endpoint (results shown in Pollino and Hart 2005).

Using sensitivity analysis, the ranking of parent variables in importance to the endpoint (which is an indicator of the importance of variables in predicting the endpoint), changed according to mine operation scenario, climate type, river reach and temporal period. Trends in sensitivity show that since mine operation, the dominant influence on fish abundances was driven by physical habitat, via channel aggradation. Predictions beyond 2012 show the increased importance of surface water metal concentrations influencing fish communities, particularly in El Niño dominated climate patterns. This changing importance of processes reflects the ARD-related processes occurring in the Fly River.

ROLE OF BNS IN MINING-RELATED ERAS

Mining has a dramatic impact on a landscape, invariably causing environmental damage. Pressure from the public and government have resulted in greater controls being placed on minimising mining impacts on environmental values. The decision-makers who are charged with these responsibilities often need to draw on quite disparate information, where the relationships between decisions on managing mine activities and the resultant impact on environmental values are poorly linked. This is despite both extensive research and monitoring on various aspects of a mine's operations and investigations of mine impacts.

A key strength of the BN approach introduced in this paper is the ability to link mining operation scenarios with environmental processes that describe chemical and physical changes in the Ok Tedi and Fly River, and in turn integrate these outcomes with readily measurable and observable environmental values. Management scenarios or system changes were investigated, model predictions being described as likelihoods, and therefore were directly applicable to risk management. Overall, the project drew together disparate datasets and models, and opened a dialogue between experts in each field to holistically examine how decisions regarding mine operations can impact on environmental values. The outcome of the ERA is a series of models that can be used to inform decision-making where considerable uncertainties exist, advise on impacts of alternative mine operating scenarios, advise on key gaps in knowledge and data, and be updated to improve the robustness of models and subsequent decision-making.

Using the results of the final model scenarios report (Pollino & Hart 2006) and other studies, OTML commissioned and built a sulfide recovery plant at the mine site aimed at removing most (approximately 99%) of the sulfide from the tailings stream. This material is piped down to secure storage dams at the Bige dredge site. The cost of the project was estimated to be $US 212 million.

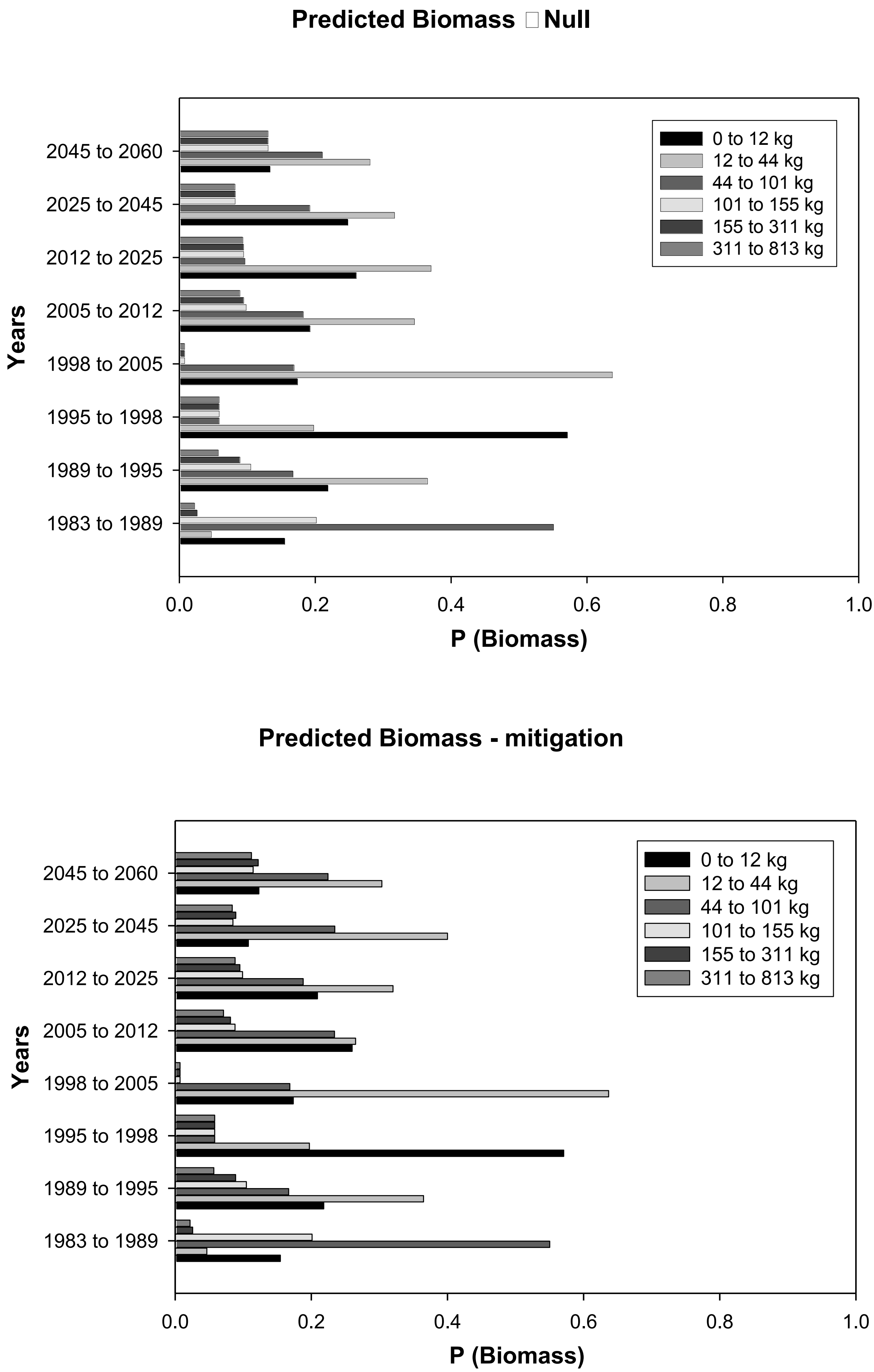

Figure 5. Predictions of fish biomass (Null and mitigation scenarios) using the OTML fish BN.

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