internal report **435**

Uncertainty analysis of data, linking conceptual models to on-site management and communicating risk

Discussion series on ARRTC Key Knowledge Needs: Powerpoint presentation and accompanying notes

Presentation for *eriss* Planning Workshop

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June 2003

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Contents

Key Knowledge Needs

Managing ecosystems in the face of uncertainty

- Uncertainty analysis of data
- Linking conceptual models with on-site management & communications

The uncertainty principle in ecosystem management

- Society invests heavily in research & management of natural systems
- Yet world is filled with spectacular failures in fisheries, forests, food & biodiversity - WHY?
- Main reason – task is DIFFICULT because of uncertainty
  - environmental variability
  - observation error
  - lack of essential knowledge
  - human factor
- Worse than uncertainty itself - we tend to underestimate it
- Place too much confidence in our predictive models or none at all

Discussion paper: ARRTC key knowledge needs

1. Uncertainty analysis of data
2. Linking conceptual models with on-site management &communications

These two questions are linked under the one heading ‘Managing in the face of uncertainty’, introduced through the following discussion points.

1. The Classical approach to science - testing single null-hypotheses with experiments.
2. The New approach – testing multiple hypotheses with observations & using models to evaluate hypotheses.
3. What is uncertainty and how to model it?
4. Models for understanding, prediction and decision.
5. How to confront models with data – the new tools.
6. Examples – from conceptual to operational.
   - Ecological risk assessment of Ranger – downstream water quality
   - Ecological risk assessment of mimosa on Oenpelli Floodplain
   - Comparison of mining & non-mining ecological risks
7. Communicating with models and the modelling process, including decision-making.

1. The Classical approach to science

Science is a process for learning about nature in which competing ideas about how the world works are measured against observation (Feynman 1965).

Our descriptions of nature are almost incomplete and our measurements involve uncertainty and inaccuracy. Hence, we need to use methods to assess the concordance of competing ideas and observations, and this is the domain of statistics. Platt (1964) describes the classical Scientific Method as a ‘learning tree of critical experiments involving strong inference’. He identifies four steps:

1. devise alternative hypotheses;
2. devise experiment(s) to exclude or more of then;
3. get unambiguous results (ie significant, reject null hypothesis); &
4. recycle procedure with sub-hypotheses or sequential hypotheses.

According to Platt (1964) this was the ‘first great intellectual revolution’, the second being the ‘multiple working hypotheses’ (see below). His views are an extension of Karl Popper’s views that revolutionized science in the 20th Century by arguing that hypotheses cannot be proved, only disproved. The essence of Popper’s view is to challenge a hypothesis repeatedly with critical experiments. If it stands up to the assault it is still not validated but acquires a degree of respect (& in practice is treated as if were true). Coinciding with Poppers views were the statistical works of Fischer and others who developed the field of hypothesis testing. In hypothesis testing we focus on a single hypothesis, the null hypothesis, and calculate the probability that the data would have been observed if the null hypothesis were true. If p is small enough then we reject it ($p<0.05$ by convention). However, to complete the calculation, we must also compute the statistical power associated with the test. The power is the probability that if the null hypothesis was actually false, and we were given the same data, we would actually reject it (~ Type I & II errors). Key elements of the Classical approach are:

1. confrontation between a single hypothesis & data
2. central idea of a critical experiment
3. falsification as the only 'truth'

Popper basically provided the philosophy and Fisher et al the statistical tools. The most rapid progress in science is those fields in which such experiments are routine (eg glass house agricultural experiemnts, medicine trials, molecular genetics).

2. A new approach for ecology – testing multiple hypotheses with observations and using models to evaluate hypotheses

Ecology is dominated by studies where clear experiments and 'hard data' are rare. At best the classical view is narrow and does not fit many ecological situations; at worst it's dangerous (eg you can accept an experiment as true even though it has low power). For example, how do we manage natural systems such as Magela with a high degree of certainty, over a 30 year time span, given that there is no possibility for experimental manipulation, none for replication, the system is subject to envirommental variability and has cross-scalar components (hydro geomorphic scales varying in hours-days-weeks & ecological scales in seasons-years-decades). The following attributes of ecological systems in general make experimentation difficult or impossible:

1. long time scales (seasons, years, decades);
2. poor replication (to none); and
3. lack of 'true' controls.

The lack of precise knowledge about natural system processes for the Magela and associated uncertainties is probably the main reason for embedding the Precautionary Principle as a 'bottom line' in all levels of water quality management at Ranger.

Nevertheless, with modelling, we could design an 'experimental tree' for many hypotheses and use observations rather than experiments to differentiate between them. The geologist T.C. Chamberlain apparently first introduced the concept of testing multiple hypotheses that was published at the end of last century. Ecology is considered more an earth science than a biological science because the fields are very similar. With both, experiments are difficult to perform, so by necessity we rely on observation, inference, good thinking and models to guide our understanding.

It's important to note that models can never be 'validated'; alternative models are simply options with 'varying degrees of belief'. If one model clearly fits the existing data and has proven ability to explain new data, then we have a 'high degree of belief'. There can never be a 'correct' model, only a 'best' model that is more consistent with data among several competitors. To choose the 'best' model we need new analytical tools where we confront models (or concepts/ideas) with data. That is, we determine which model is more consistent with the data. The validation of a model is not that it's 'true' but that it has form of utility.

If we allow that either Model M_1 & M_2 is true, we can associate probabilities with the two models given the data. We refer to this as the 'probability of the model' or the 'degree of belief in the model'. How do we do this? There are three basic steps:

1. characterise the available data (maps, graphs, spatial & temporal patterns, processes);
2. convert pictorial or verbal models into a mathematical description (ie some kind of mathematical model so that data can be compared to model predictions); and
3. confront the model with the data by comparing predicted and observed results.

When we get to Step 3 there are three broad approaches for this confrontation (& see below for details).

1. Classical hypothesis testing: we confront each model separately with the data

Ho: Model M_1 is true

Ha: Some other model is true (M_2 ..... M_k).

Using a mathematical description of the models we construct a 'p value' for the hypothesis that M_1 is true. We repeat the process with M_2 and so on for k alternative models. However, other than collecting more data and more alternative models, there is no guidance about how we should view the accumulated models.

2. Likelihood approach: we use the data to arbitrate between the models

That is, we ask 'how likely are the data given the model'. What is the chance, or likelihood, that the model is the appropriate description of the world given the data (ie turning this question on its head we compare the likelihoods of the two models given the data)?

3. Bayesian approach: we may have other information that allows us to judge, *a priori*, which model is more likely to be true

Such information can be summarised in a 'prior probability that M_1 is true'. The Reverend Thomas Bayes invented the theory, which was introduced by Sir Harold Jeffereys (1948) as 'inverse probability' 200 years later. It's particularly useful where studies cannot be replicated (eg assessment of the risk & safety of particular environmental settings in which 'expert opinion' is sought).

3. What is uncertainty and how to model it?

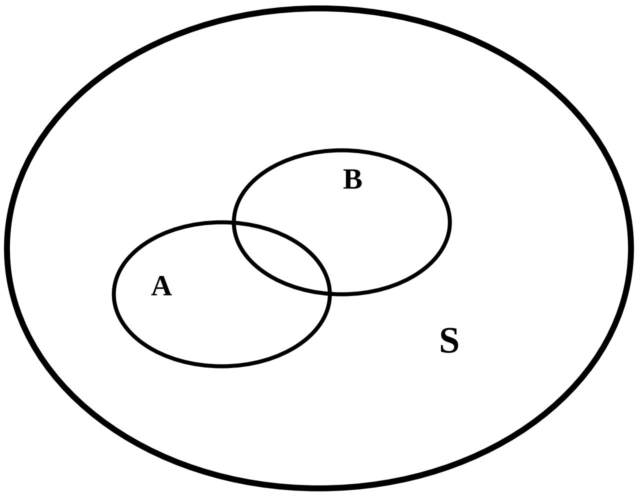
Soulé (1997) identified three key issues for conservation: (1) the effects of various chance events (on species, populations, communities & ecosystems); (2) the time frame used in planning; and (3) the degree of security sought. The first involves a scientific solution and, in contrast, the last two involve society value judgements (ie economic, social, cultural & political dimensions). Not all variation in the natural world is due to chance events, much is due to deterministic (cause-effect) relationships. There is little difference between purely random events and results of processes that are little understood; both remain unpredictable. A process in which a variable outcome is random or uncertain is a stochastic process. Stochasticity is variability in part due to chance or random events and this is what we mean by uncertainty. Gillman (1997) states that, in a deterministic world, everything is predictable. However, no ecosystem is purely deterministic because of unexpected or unpredictable events that may be entirely random (which he calls stochastic events). But randomness depends also on the time-scale used. For example, it is difficult to predict the probability of storms from day to day, but we are more certain from month to month. So an unpredictable (& effectively random) event at one time-scale may be predictable (& effectively deterministic) at another time scale. And similarly for different spatial scales. Additionally, add to this the inaccuracies of our observations or samples of nature.

3.1 Probability and probability models

Hence, data we encounter in ecology may encompass different kinds of randomness. Many ecological models simply describe the average value of a parameter, but when we compare models to data we need methods for determining the probability of individual observations given a specific model and mean value for the parameter. This means that we need to describe the randomness in the data. When we build a model we need some way to quantify the *probability distribution* of the data. For example, we regularly use the familiar normal or Gaussian distribution ('bell' shaped curve) in statistical Sums of Squares (SS) analysis of data. However, most distributions in nature are not normal. There is a range of useful probability distributions suitable for descriptions of ecological data depending whether or not such data are discrete or continuous (eg binomial, negative binomial, geometric, Poisson). Monte Carlo simulation can be used to generate data and test models. In probability theory we are interested in the occurrence of 'events' that can be thought of as 'outcomes' of experiments. Hence, the probability of an event A is denoted by:

Pr {A} = probability that event A occurs

We can visualise probability using Venn Diagrams.



where S denotes all possible outcomes. A smaller collection of outcomes, A, has probability defined in some way as the 'area' of A divided by the area of S. Hence,

Pr {A} = probability that event A occurs = (area of A)/(area of S)

Continuing with this visualisation, we see that the probability that one of two events A or B occurring is:

Pr {A or B} = Pr{A} + Pr{B} – Pr{A and B}

That is, the AB interaction term must be accounted for (deducted).

3.1.1 Conditional Probability

If event A occurred what is probability that event B occurred given knowledge about A? This is a common question in ecology as we use models to make predictions about data, and data to make inferences about different models. If A occurred then the collection of all possible outcomes is no longer S but must be A. Hence,

Pr {B occurred given A occurred} = (area common to A & B) / (area A)

= Pr {B|A} = Pr {A,B} / Pr {A}

If A & B are independent then they are interchangeable.

3.1.2 Bayes Theorem

The challenge in analysis (& probably all statistical science) is to determine how to use the information contained in data and Bayes Theorem is a very powerful method (the extreme LHS & RHS of formula below).

Pr {B|A} = Pr {A,B} / Pr {A} = Pr {A|B} Pr {B} / Pr {A}

It's a very useful theorem when there are a number of possible but mutually exclusive outcomes B_1, B_2 ..... B_k, one of which must occur when A occurs.

3.1.3 Embedding Stochasticity in Ecological Models: Process & observation uncertainties

How can we model uncertainty? Ecological models often begin with a description of a process (eg spread rate of a weed, energy or mass transfer, water flow etc). These types of models are called 'process' models. Uncertainty enters into these processes because parameters vary in unpredictable ways in the real world. For example, the spread rate of a weed may vary seasonally and annually due to environmental variation such as rainfall that drives seed dispersal rates. This is called 'process uncertainty', 'process error' or 'process noise' (depending on the field of science). Additionally, to collect data about an ecological system we observe it and, hence, there will usually be uncertainty associated with the observations.

So we have two models, one is the observation model and the other is the process model. We combine both models into a 'full model' of the simple system. For example, the colonisation of a weed can be modelled as:

Process model: $Aweed_{t+1} = Aweed_t + sr_t + PE_t$

Observation model: $Aweed_{obs,t} = Aweed_t + OE_t$

Where $Aweed_{t+1}$ is the area extent of the weed at time t+1 which is dependent on the area extent of the weed at previous time t, sr_t is the spread rate of the weed at time t, $Aweed_{obs,t}$ the observed extent of the weed at time t, OE_t is the observation error and PE_t is the process error.

But before we confront models with data we need some knowledge of the probability distributions (pdfs – probability density functions) that might describe the various kinds of uncertainty. Comparison of models with bootstrap data sets lets us mimic the Bayesian approach (ie use Monte Carlo simulation to resample data) and is gaining popularity.

4. Models for understanding, prediction and decision

4.1 Types and uses of models

There are different kinds of models because there are different kinds of investigations. Models can be classified according to many dichotomies and, as a general rule, scientists and institutions gravitate towards extreme paradigms.

4.1.1 Deterministic vs stochastic

Deterministic models have no components that are inherently uncertain; there are no parameters in the model that can be characterised by a probability distribution. For fixed starting values we always get the same result. In a 'stochastic model' some parameters are uncertain and can be characterised by probability distributions (ie instead of being a constant mean value it's a variable). With stochastic models we get many different results depending on the actual values that the random variables take.

4.1.2 Statistical (predictive) vs Scientific (consonant)

Scientific models begin with a description of how the system might work (=consonant with nature), and proceeds from this to a set of predictions relating dependent and independent variables. In contrast, a statistical (empirical) model forgoes any attempt to explain why variables interact the way they do, and describes the relationship with the assumption that it extends past the measured values (eg polynomial regression models).

4.1.3 Static vs dynamic

Dynamic models link the response variables between one time period and the next.

4.1.4 Quantitative (precision) vs qualitative (fuzzy)

A quantitative model leads to a detailed numerical prediction about responses. In contrast, a qualitative model leads to a general description about responses. Qualitative models are used more broadly to describe regions in which one response is expected and regions in which different reponses are expected. In contrast, a quantitative model attempts to describe the precise location of the boundary between regions.

4.1.5 Models for understanding, prediction & decision

In addition to different kinds of models there are different uses of models. We may model a system to broadly test our understanding of it. However, models usually lead to numerical predictions in which case we can extract qualitative, intuitive understanding from the broad patterns of the numerical predictions. However, a model may be used solely for the purposes of prediction. Such prediction may be qualitative (system will/won't respond to this effect), or quantitative (the level of response will be X). A model is most effective if it provides both understanding (insight) of known patterns and predictions about situations not yet encountered. Hence, model prediction and understanding are not mutually exclusive.

Finally, we can use a model as part of a decision-making process. Hence, the model may provide a means of evaluating the potential effects of different decisions (eg management scenarios or treatments). This is where models have the most to offer in terms of practical application, but it is also where the greatest danger lies.

4.2 Model complexity

Ecological systems are complex; we can only observe a small proportion of all possible variables. Levins (1966) sums it up very well – 'The multiplicity of models is imposed by the contradictory demands of a complex, heterogenous nature and a mind that can only cope with a few variables at a time. Models, while essential for understanding reality, should not be confused with that reality itself'. Needless to say complexity is both a fascination and a frustration in ecology. We often ask 'how complex should a model be'. A model can be intractable if too complex and, at the other extreme, it can be unrealistic and useless if too simple. There are other caveats: with simple models we risk leaving out important bits, and if models are too complex there may be insufficient information in the data to distinguish parameter values.

For any model and amount of data, prediction error will decrease and then increase as complexity increases. That is, there is an optimal level of model complexity. There are quantitative methods to determine the optimum size of a model. Lishardt and Zucchini (1986) provide a formal framework for considering different levels of model complexity with respect to reliability of model predictions. Their approach distinguishes between prediction error due to approximation (which decreases as model complexity increases) and prediction error due to estimation (which increases as model complexity increases). Optimal model size has been found to be much less that intuition suggests. Hence, 'wrong' models can often perform better than 'right' models. But this generality will depend also on whether or not the models are used to make decisions. Simple models tend to underestimate uncertainty, which is integral to robust risk assessment associated with decisions. At the end of the day we may need to iterate between alternative models to understand their strengths and weaknesses, with the realisation that the most appropriate model will change from application to application.

5. How to confront models with data – the new tools

There are basically three methods to confront models with data briefly outlined above.

1. Sums of Squares
2. Likelihood and Maximum likelihood
3. Bayesian Goodness of Fit.

5.1 Sums of Squares (sum of squared deviations)

The simplest technique to confront data and has three selling points: (i) it really is simple, we don't need to make assumptions about how uncertainty enters process or observation systems; (ii) it has a long and successful history in science, a proven winner (eg the agricultural revolution, advances in medicine); and (iii) modern computers allows us to make sophisticated and elegant SS computations. Additionally, we can conduct sensitivity analyses by systematically varying one parameter and searching over the others to find the values that minimise the SSs. But note that all SS models (GLMs) implicitly assume normally distributed uncertainty.

But how do we choose from the accumulated alternative models? Use minimum SSs? Interrogate the model with other data sets? The problem is that we don't often have other data sets. We can use the Bootstrap method to resample, which is getting closer to the Bayesian/Lakatosian approach (ie confrontation of multiple hypotheses with data as the arbitrator). However, the choice of 'best' model implies that in some way we reject others and select the 'best' one. In contrast, the Bayesian approach allows us to assign relative degrees of 'belief' to competing models.

5.2 Likelihood and Maximum Likelihood

The SS methods can be used to find the best fit of a model under minimal assumptions of uncertainty. However, there are many cases in which the ‘form’ of the probability distributions of the uncertain terms can be justified. For example, if the deviations of the data from average closely follow a log normal distribution then it makes sense to assume that the sources of uncertainty are also log normally distributed. In such cases we can go beyond the SS and use Likelihood methods. Such methods allow us to calculate confidence bounds on parameters (something the SS doesn’t allow), and to test hypotheses in the traditional manner. In addition, Likelihood forms the foundation of Bayesian analysis. We use the probability distributions to characterise uncertainty in the model to: (i) find parameters of a given model that provide the best fit to the data (called Maximum Likelihood Estimation); (ii) compare alternative hypotheses (using the Likelihood Ratio test); and (iii) calculate confidence bounds.

Additionally, the results of statistical tests depend not only on what variation is in the data, but also on how we believe uncertainty enters it. For example, in standard linear regression analysis we assume no observational uncertainty (Y), just process uncertainty (X). But when X is measured imprecisely it’s impossible to estimate variances for both observation and process simultaneously. You can try but often the result is ambiguous. Hence, the simultaneous estimation of process and observational uncertainty is complex. However, assuming only one kind of uncertainty can often provide a reasonably good fit to the data, although neither model is correct. Hilborn and Mangel (1997) suggest that, as a general rule, if the data are ‘informative’ then the assumption about how uncertainty enters a model does not matter greatly as each has strengths and weaknesses.

5.3 Robustness – do we let outliers ruin our day?

The problem with Likelihood is that some observations are just too unlikely and will therefore dominate any estimation. Robust estimation has two meanings (Huber 1981): (i) what happens when the assumption of normally distributed uncertainty is inappropriate, which is often the case for ecological data; and (ii) how do we deal with data points that are highly irregular? (eg via weighted data points?). However, in some risk analyses where rare events (outliers) lead to irretrievable system failure (the event we try to avoid), we need to be concerned about so called ‘outliers’. In this sense Likelihood and Bayesian analyses, whilst attractive for many reasons, may be inappropriate.

5.4 Bayesian Goodness of Fit

Bayesian methods provide a framework for using prior information that may be valuable and should not be lost in analysis. We analyse ecological data to determine the relative probability of competing hypotheses and, at the end of the day, we want to say how well the data support each alternative hypotheses given all the available data, not just the results of the current study (or experiment). This is really the goal of science and we do it informally anyway because we need to report the results of our work in relation to all other work. Bayes’ Theorem provides a simple way to use all possible information, but has a long and bitter debate amongst scientists (eg why bother?). It goes like this - if event A is the data and event B is the hypothesis Hi, we replace Pr {A|B} with the likelihood L {data|Hi} of the data given the hypothesis, and Pr {B} with the prior probability Prior {Hi} assigned to the hypothesis.

$$\Pr\{Hi|data\} = L\{data|Hi\}\ Prior\{Hi\} / \Pr\{data\}$$

Here Pr {Hi|data} is the probability of the hypothesis given the data (posteriori probability). The prior probability of Hi summarises what we know before the study (or experiment) and is the posteriori probability emerging from the previous study. The numerator is the joint probability of the data and Hi. The denominator is the sum of such joint probabilities, summed overall possible hypotheses. Hence, Bayes' Theorem can also be written as:

$$\Pr\{Hi|data\} = L\{data|Hi\}\ \mathrm{Prior}\{Hi\} / \Sigma_j\ L\{data|Hj\}\ \mathrm{Prior}\{Hj\}$$

References

Most of this discussion paper summarises the central themes from the following two books:

Gillman M & Hails R 1997. *An introduction to ecological modelling: Putting theory into practice*. Methods in Ecology series, Blackwell Science, Oxford.

Hilborn R & Mangel M 1997. *The ecological detective. Confronting models with data*. Monographs in Population Biology 28, Princeton University Press, Princeton, NJ.

Powerpoint presentation

ARRTC key knowledge needs

Discussion Outline

- Classical science – testing single null hypotheses with experiments
- New Science – testing multiple hypotheses with observations
- Using models to evaluate hypotheses
- What is uncertainty & how to model it
- Models for understanding, prediction & decision
- How to confront models with data – the new tools
- Examples – conceptual to operational
  - Ecological Risk Assessment of RUM & downstream WQ
  - Managing invasive species, mimosa at Oenpelli
- Communicating & making decisions – use modelling process

Some definitions

Theory: Considerable evidence in support of a general principle explaining certain phenomena

Hypothesis: Unproved theory, basis for further investigation

Model: Generalised, metaphorical (symbolic) description used to analyse or explain something

Models can be tools to evaluate hypotheses, but they are not hypotheses themselves

Data: Observations or measurements

Uncertainty: Chance or random events, upredictable or unexpected events, lack of knowledge, variability, stochastic process, process & observation uncertainty (or error)

Coping with uncertainty – Soulé (1990) & viable populations for conservation

- Identified 3 key issues for conservation of species, populations, communities & ecosystems

    1. Effects of various chance events
    2. Time frame used in planning
    3. Degree of security sought

- The first requires scientific solution, 2 & 3 are society value judgments (socio-economic, cultural & political dimensions)

Classical approach to science

- The Scientific Method: "a learning tree of critical experiments involving strong inference (Platt 1964)" – 4 steps

    1. devise alternative hypotheses
    2. devise experiments to exclude 1 or more of them
    3. get unambiguous results (i.e. significant p-value, reject null hypothesis)
    4. recycle process with sub-hypotheses or sequential hypotheses

- Extension of Karl Poppers (1939) revolutionary view - hypotheses cannot be proved, only disproved – "falsification"
- Challenge hypothesis repeatedly with critical experiments, if it survives the assault it is still not validated
- However – it acquires a degree of respect & treated as if true
- Popper provide the philosophy, Fisher *et al*. the statistical tools
- This was the "first great intellectual revolution" (Platt 1964)

Classical approach to science

- Has 3 key elements
  - confrontation between a single hypothesis & data
  - central idea of a critical experiment
  - falsification as the only “truth”
- Most rapid progress in science are fields where such experiments are routine (e.g. chemistry, genetics)
- For ecological studies - this view is too narrow at best & dangerous at worst (e.g. can accept an experiment as true even though it has low power)

Classical approach - limited use in ecology

- Ecology dominated by studies where clear experiments & “hard data” often not possible
- e.g. How do we manage mine contaminants downstream of RUM, within a World Heritage National Park, with a high degree certainty over a 30 year time span, given:
  - no possibility for experimental manipulation
  - none for replication (only one Magela Creek)
  - none for use of “true” controls
  - system dominated by environmental variability
  - & cross-scalar effects between biological & physical processes
- Main reasons for use of “Precautionary Principle” as a bottom line

The new approach to Science

- If experiments not possible need to go beyond the single null-hypothesis approach
- Use models to design an "experimental tree" for many hypotheses
- Use observations, rather than experiments, to differentiate between them
- This is the second great intellectual revolution - the "multiple hypotheses" (Platt 1964)

The new approach to ecology is the old approach to geology

- TC Chamberlain introduced concept of "multiple hypotheses" end last Century
- Ecology is more an earth science than a biological science
- In both - descriptions of the world are incomplete & measurements involve inaccuracy & uncertainty
- In both - experiments are difficult or impossible to perform
- Hence - rely on observation, inference, good thinking & models to guide our understanding of the natural world

Ecologists are modellers at heart

- Profile of an ecologist – a creative problem solver, works in the field & lab, uses statistics & computers, often works with ecological concepts that are model based if not model driven, asks the following questions:
  - how do we make the field & laboratory coherent?
  - how do we link models with data?
  - how do we conduct experiments & relate them to the world?
  - how do we integrate modelling & statistics?
  - how do we confront multiple hypotheses with data & assign different degrees of belief ?
  - how do we deal with time series (where data are linked from one measurement to the next)?
  - or put multiple sources of data into one inferential framework
- All these questions are relevant to ERISS

Model validation & degrees of belief – the new religion

- If one model clearly fits existing data & has proven ability to explain new data, we have a "high degree of belief"
- Models cannot be validated – alternative models are just options with "varying degrees of belief"
- Levins (1966) sums it up well:
  - all models are both "true" & "false"
  - validation of model is not that it's "true" but that it has some form of utility
  - multiplicity of models simply reflects a complex, heterogeneous nature & minds that can only handle a few variables at a time
  - whilst models are essential for understanding reality, they should not be confused with reality itself

Confronting models with data

- Because models are symbolic descriptions of nature, we can use them to test hypotheses
- And help evaluate the confrontation between ideas (concepts) & data
- But no "correct" model, only a "best" model
- So ..... how do we choose the "best" model?
- We confront models with data & ask which is more consistent

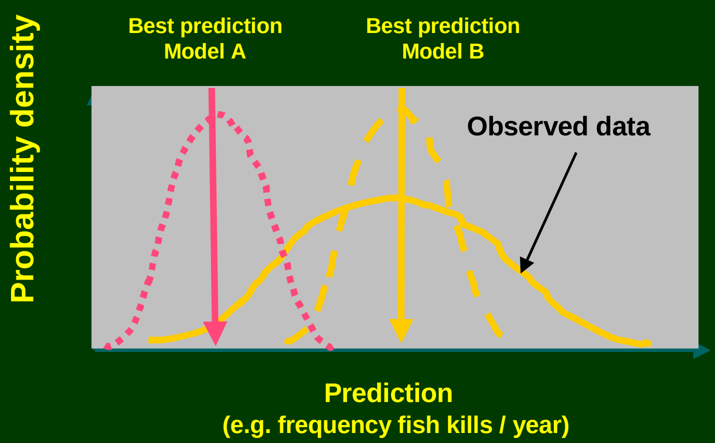
The confrontation

- We associate probabilities to competing models given the data
- The probability of the model is the "degree of belief" in the model
- So - what is the process?

1. Characterise available data – maps, graphs, spatial & temporal patterns
2. Convert pictorial or verbal models into a mathematical description or model so that data can be compared to model predictions
3. Confront the model with the data by comparing predicted & observed results

Step 3 - comparing predicted & observed results

Models & data have central tendencies & variances (uncertainties)



The confrontation tool box

Three broad approaches

1. Sums of Squares (backbone of Classical approach)
   - simple, no assumptions how uncertainty enters process or observation systems
   - proven winner – long history of success
   - but no guidance about how we should view accumulated alternative models
2. Likelihood & Maximum Likelihood
   - use data to arbitrate between models – “how likely are the data given the model?” (or what’s the likelihood's of the 2 models given the data)
   - can calculate confidence bounds on parameters & use probability distributions to characterise uncertainty
3. Bayesian Goodness of Fit
   - *a priori* information allows us to judge which model is more likely to be true (summarised in the “prior” probability that a model is true)
   - useful where studies cannot be replicated, or where “expert opinion” is sought
   - but exists a long & bitter debate

What is uncertainty?

Gillman – Introduction to Ecological Modelling (1989)

- In a deterministic world everything is predictable (cause = effect)
- But no system is deterministic because of unexpected or unpredictable events, which may be entirely random (stochastic)
- But randomness depends on temporal & spatial scales used – an unpredictable event at one scale may be predictable at another
- Add to this the inaccuracies of observations or samples of nature

Uncertainty

Stochasticity in ecological models

- Two types of uncertainty
  - Process uncertainty
  - Observation uncertainty
- Ecological models may begin with a description of a process (e.g. mass transfer, water flow, spread rate of a weed etc) – "process models"
- Uncertainty results from model parameters varying in unpredictable ways
- e.g. predicted U-conc increase at 009 is a function of instantaneous loads at mine site exit points & flow rate at 009, which are all variable within & between years – called process uncertainty
- To collect data about a system we observe it & there is uncertainty associated with the observations – called observation uncertainty

Uncertainty

Stochasticity in ecological models

Full model = (process model + process error)
+ (observation model + observation error)

- Before confronting models with data we need to know the probability distributions that describe various kinds of uncertainty or stochasticity associated with model parameters
- Replace mean parameter values with a probability distribution function (pdf) – i.e. they are now random & unpredictable variables, not constants
- Many pdfs available "off the shelf" for discrete or continuous data (e.g. normal, binomial, negative binomial, geometric, lognormal, gamma)

Types of models – the many dichotomies

1. Deterministic vs stochastic
- Deterministic models - no components inherently uncertain
- Stochastic models – some parameters uncertain & can be characterised by a pdf

2. Statistical (predictive) vs scientific (consonant)
- Scientific models begin with a description of how nature may work, & proceeds to a set of predictions relating dependent & independent variables
- Predictive models forgo any attempt to explain why variables interact & assumes the relationship extends past measured values (e.g. regression, frequency)

3. Static vs dynamic
- Response variables linked between one time period & next

4. Quantitative (precision) vs qualitative (fuzzy)
- Qualitative model – general description about responses; region where one response expected & regions in which different responses expected
- Quantitative model – detailed description about responses; a description of the precise location of boundary between regions

Types & uses of models – the one we want !

5. Models for understanding, prediction & decision

- Models used to broadly test our understanding of how nature works or to predict
- Predictions can be qualitative (system will / won't respond) or quantitative (the level of response will be X ....)
- Effective models provide both understanding & future predictions
- But strong case for hybrid models – stochastic process models
- Models can be part of a decision making process - evaluate potential effects of different decisions
- Where models have the most to offer in terms of practical application
- But - also where the greatest danger lies

Model types reduce to two

Process-based Models

- Built on scientific knowledge of processes
- Need comprehensive data sets
- Often over-parameterised
- Outputs sensitive to parameter values
- Scale issues
- Uncertainties handled poorly
- Transferable

Empirical Models

- Built on empirical (statistical) relationships
- Range of univariate & multivariate approaches
- No process understanding
- Need good data sets
- Not easily transferable

Potential for hybrid models

How complex should models be ?

- Ecosystems are complex - we only observe a small proportion of all possible variables
- A model can be intractable if too complex; at the other extreme it can be unrealistic if too simple
- For any model & amount of data, prediction error will decrease & then increase as complexity increases
- Methods exist to determine “optimum” model size which distinguishes between prediction errors due to approximation & estimation
- Optimum model size generally much less than intuition suggests

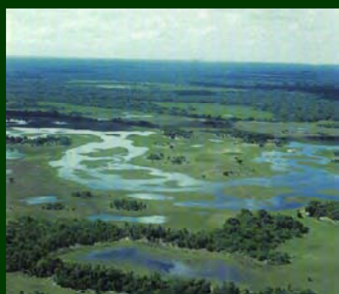
Examples of uncertainty analysis of data
Context - ecosystem “health” in ARR

- Multiple problems caused by multiple threats
- Key threats include
  - toxic contaminants from mining
  - invasive species
  - climate change effects
  - infrastructure
- Natural systems characterised by
  - variability
  - complexity
  - uncertainty
- Only certainty is that managers need predictive tools (e.g. ecological risk assessment)

Example 1: Ecological risk assessment of RUM (managing WQ in Magela Creek DS Ranger)

- Introduction to quantitative Ecological Risk Assessments (ERA)
- Frequentist statistics (effects & exposure)
- Bayesian statistics
- EWLS "whole of mine model" (deterministic)
- Need for a hybrid model = statistical model + process model
  = stochastic process model

Ecological Risk Assessment Framework for the ARR



Qualitative risk assessment

Likelihood exposure	Consequences exposure		
	Little	Serious	Catastrophe
Low			
Medium			
High			

But need to know what are behind the ratings

Why do we need quantitative ERA's?

- Qualitative ERA's often fail because
  - subjective assessments generally biased – so unreliable
  - humans not good at subjectively assessing risk
  - uncertainties not treated explicitly
- Need quantitative tools that are
  - rigorous
  - transparent
  - internally consistent
  - free from ambiguity
  - allows comparisons (of hypotheses or management options)

Risk Assessment Tools

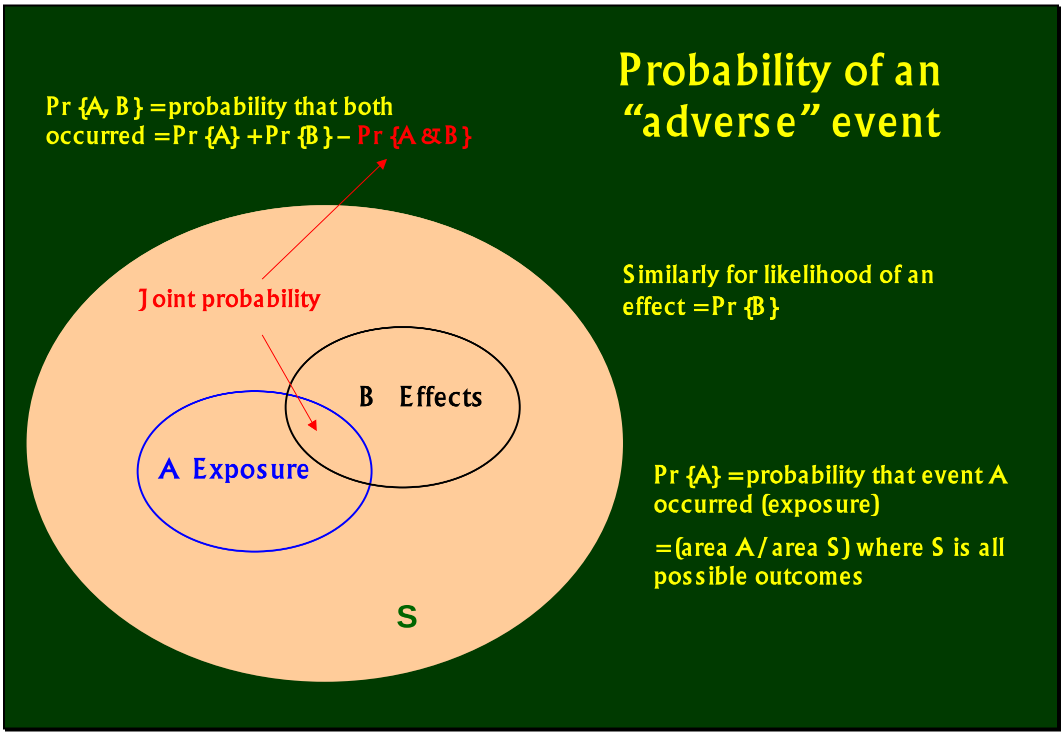
- Diversity of methods available
  - worst case scenario
  - what if analysis
  - decision analysis
  - probability theory (frequency, Monte Carlo simulation, bootstrap)
  - Bayesian analysis (prior knowledge)
- All address uncertainty associated with variability
- Software now available to assist (e.g. RAMAS, RiskOpt)
- Knowledge uncertainty - more difficult

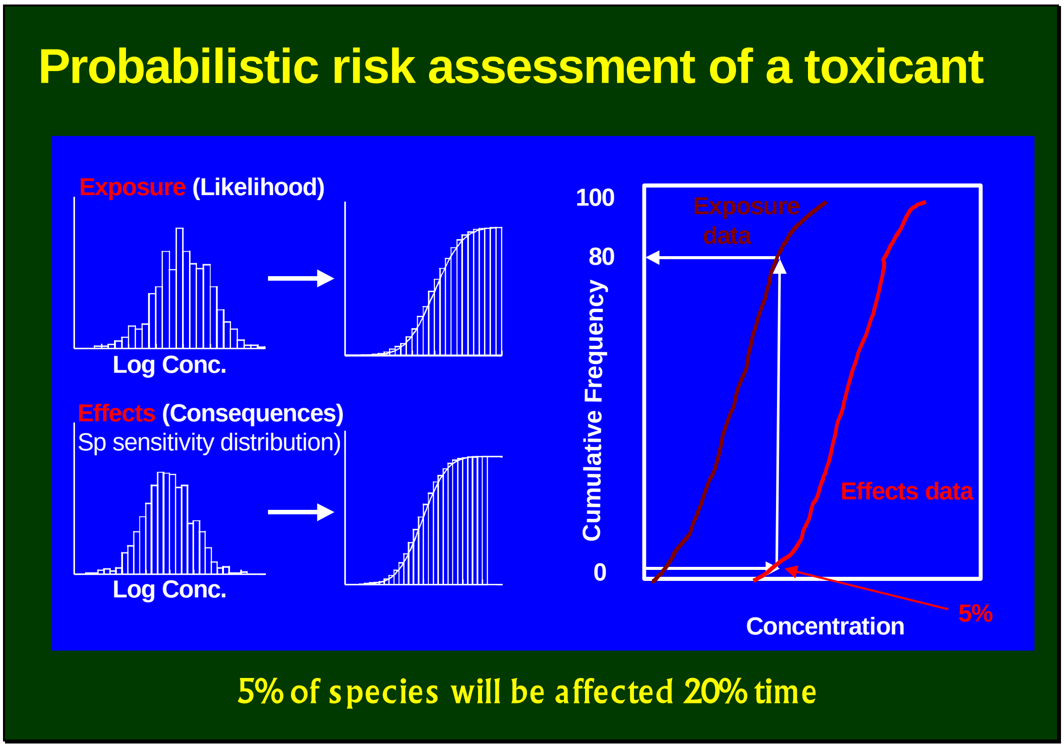
Ecological Risk Assessment

- Risk assessment is about estimating the probability of an adverse event
- Two main components of risk
  - Effects consequences of adverse event
  - Exposure likelihood of exposure to adverse event

$$\boxed{Pr\ (Risk) = Pr\ (effects) \times Pr\ (exposure)}$$

- Also need to consider scale
  - spatial (creek, river, catchment, region)
  - temporal (now, 20y, 50y)


Probability of an "adverse" event
Pr {A, B} = probability that both occurred = Pr {A} + Pr {B} – Pr {A & B}
Joint probability
B Effects
A Exposure
S
Similarly for likelihood of an effect = Pr {B}
Pr {A} = probability that event A occurred (exposure)
= (area A / area S) where S is all possible outcomes

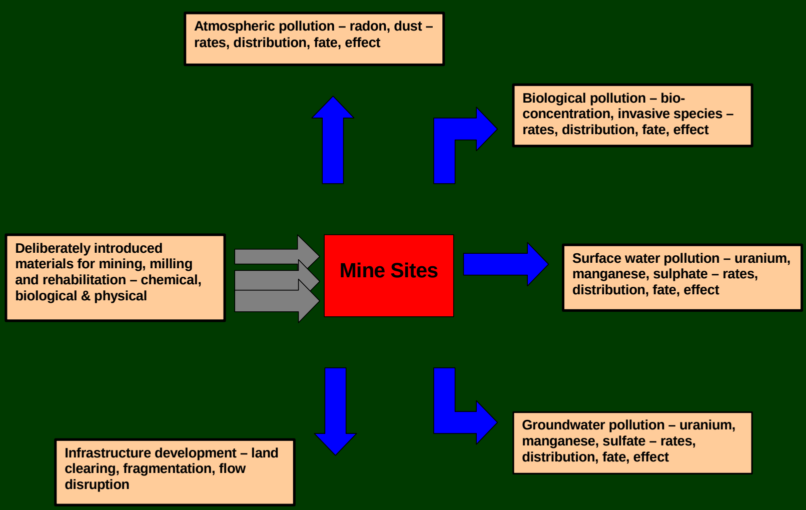

Probabilistic risk assessment of a toxicant
Exposure (Likelihood)
Log Conc.
Effects (Consequences)
Sp sensitivity distribution)
Log Conc.
100
80
0
Cumulative Frequency
Exposure data
Effects data
5%
Concentration
5% of species will be affected 20% time

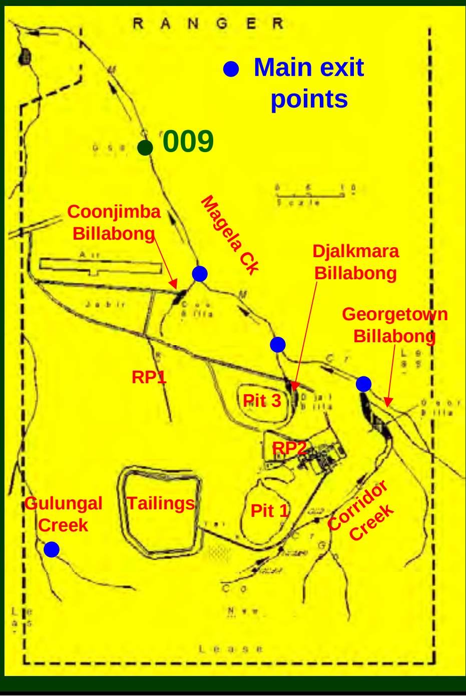
Where do we begin ?

- First build conceptual models
  - big picture models (e.g. catchment-scale)
  - system - specific models (e.g. local-scale)
- Then build mathematical models which describe the system of interest
  - but generally lack knowledge about how ecosystem processes work & the effects of stressors

System specific - Transport Pathways Conceptual Model

Conceptual model of ecosystem processes & pathways for pollutant/propagule transport in the environment of ARR



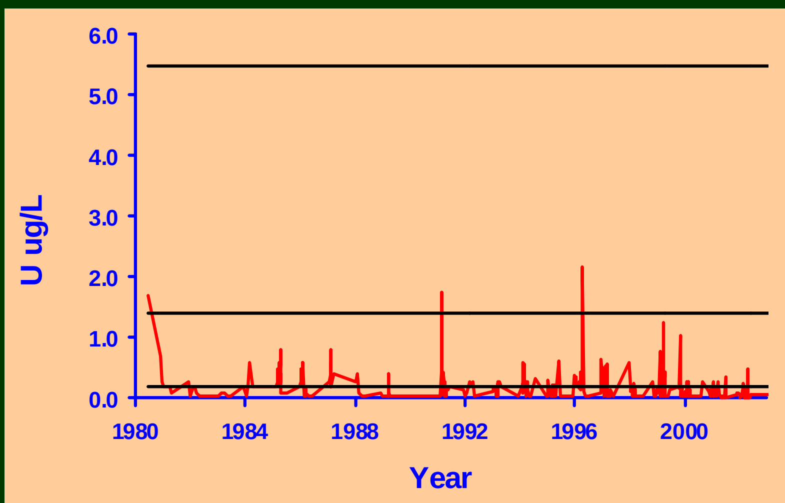


Can be spatially explicit model

System-specific model at mine site scale: surface water pollution exit pathways at RUM

U - concentration data at Magela 009 weekly readings over wet season

Background +anthropogenic spikes

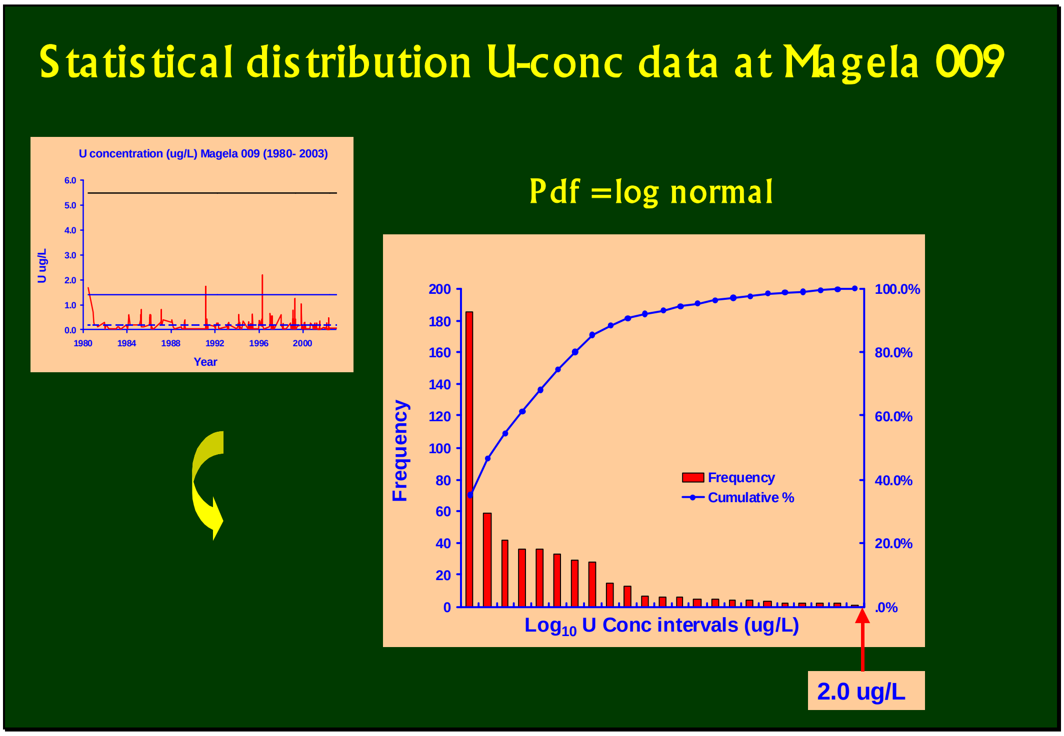


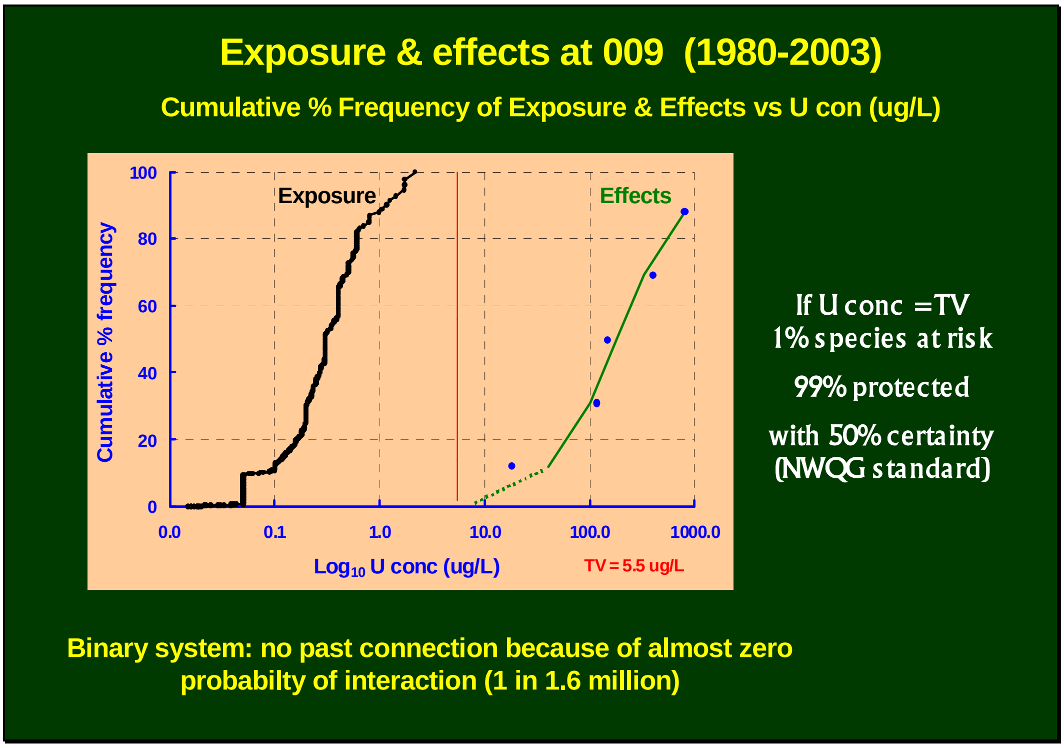
Ecotox TV = 5.5

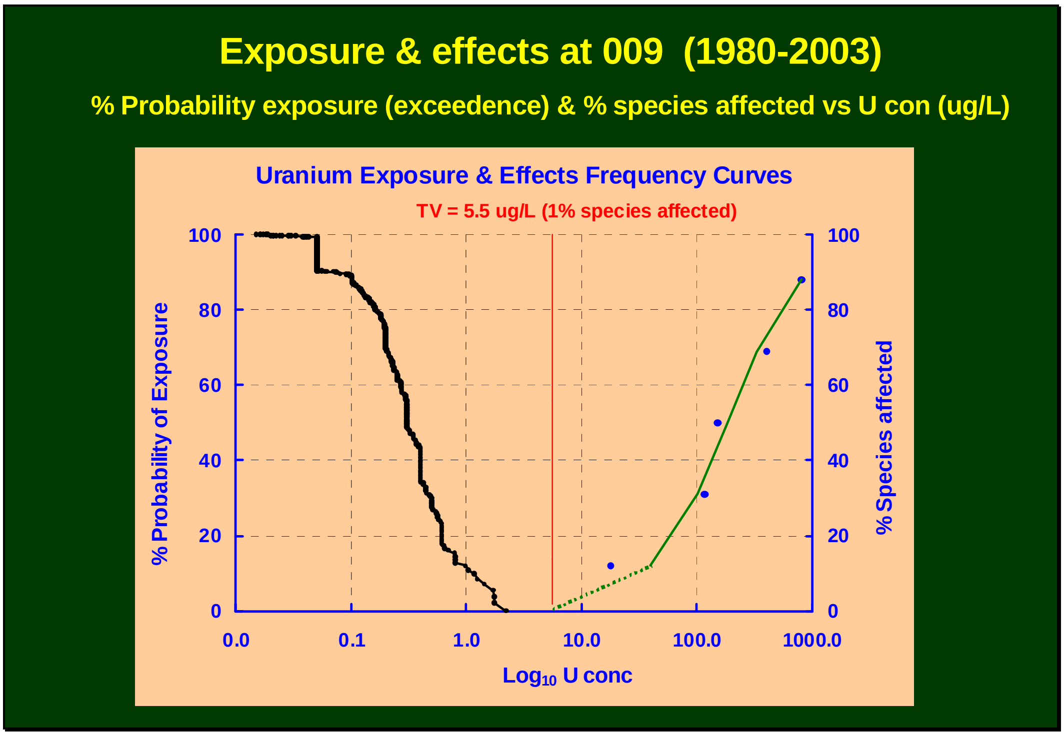
ERA Action Level = 1.4

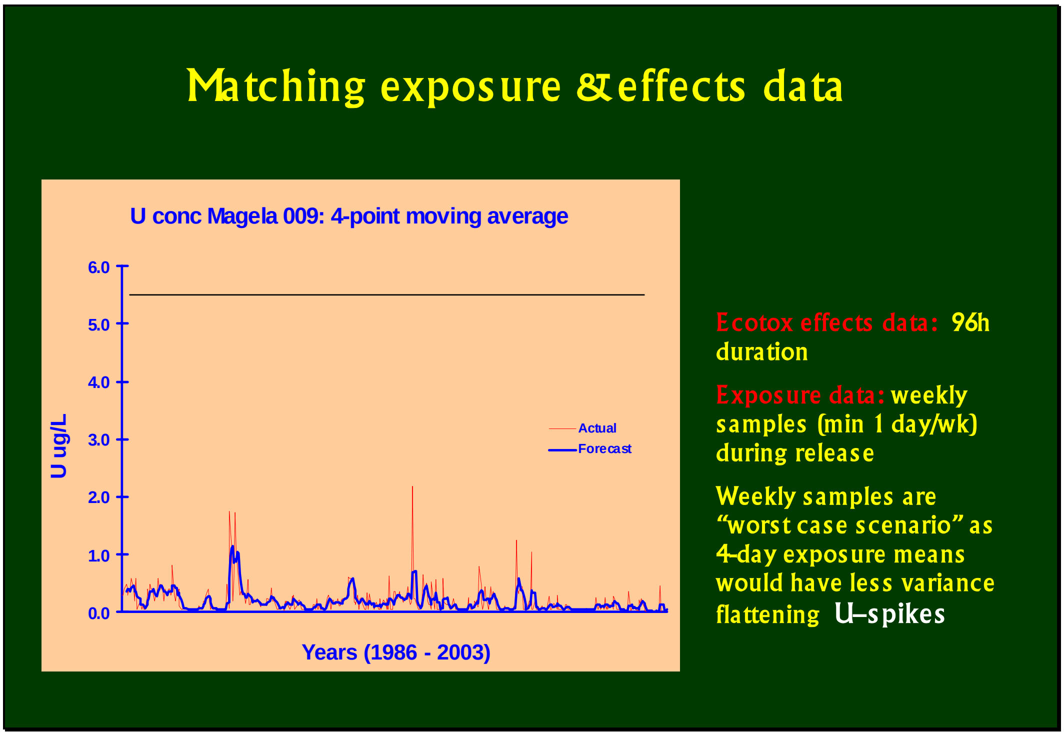
ERA Focus Level = 0.2

Background = 0.1


Statistical distribution U-conc data at Magela 009
U concentration (ug/L) Magela 009 (1980- 2003)
U ug/L
Year
Pdf =log normal
Frequency
Cumulative %
Log10 U Conc intervals (ug/L)
2.0 ug/L

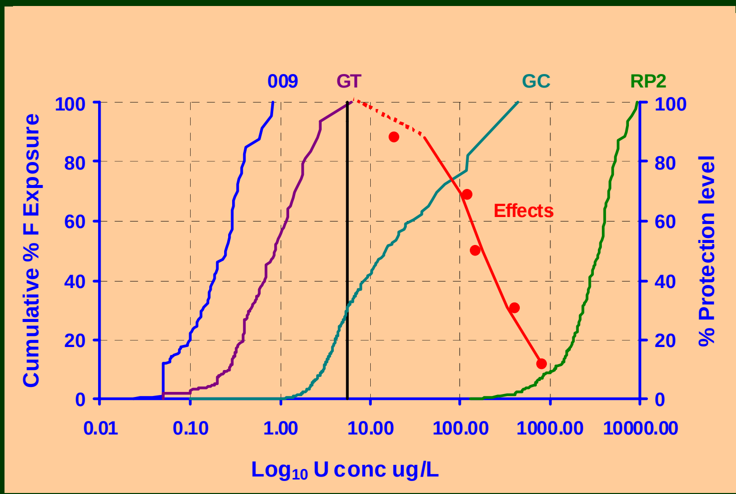

Exposure & effects at 009 (1980-2003)
Cumulative % Frequency of Exposure & Effects vs U con (ug/L)
Cumulative % frequency
Exposure
Effects
Log10 U conc (ug/L)
TV = 5.5 ug/L
If U conc = TV
1% species at risk
99% protected
with 50% certainty
(NWQG standard)
Binary system: no past connection because of almost zero
probabilty of interaction (1 in 1.6 million)


Exposure & effects at 009 (1980-2003)
% Probability exposure (exceedence) & % species affected vs U con (ug/L)
Uranium Exposure & Effects Frequency Curves
TV = 5.5 ug/L (1% species affected)
% Probability of Exposure
% Species affected
100
80
60
40
20
0
0.0
0.1
1.0
10.0
100.0
1000.0
Log10 U conc


Matching exposure & effects data
U conc Magela 009: 4-point moving average
U ug/L
6.0
5.0
4.0
3.0
2.0
1.0
0.0
Actual
Forecast
Years (1986 - 2003)
Ecotox effects data: 96h duration
Exposure data: weekly samples (min 1 day/wk) during release
Weekly samples are "worst case scenario" as 4-day exposure means would have less variance flattening U-spikes

Family of "on-site" exposure curves for RUM (1986 – 2003)

Cumulative % frequency vs $\log_{10}$ U conc (ug/L)



Dilution

TV = 5.5 ug/L

How do they relate to ecological risk off-site at 009?

Chance of an adverse event at 009

=the probability of a "rare" event or system failure

Problem – estimate the ecological risk at the U-TV boundary (5.5 ug/L at 009), given log normal distribution of uranium exposure & effects data

Pr (ecological risk) =Pr (exposure) x Pr (effects or consequences)

- Pr (exposure) = 0.0000304521 (1 in 32,828)
- Pr (effects, 1% species affected) = 0.01 (1 in 100)
- Pr (ecological risk) = 0.0000003045 (1 in 3.3 million)

- Note Pr (1% effects) is only 50% certain (NWQG), however
- Pr (ecological risk) =Pr (exposure) x Pr (effects)
- =(0.0000304521) x [(0.01 x 0.50)/(1.00 x 0.50)]
- = 0.0000003045 (1 in 3.3 million)

Bayesian theory – hypothesis confronted with data

$$\Pr\{Hi|data\} = \frac{L\{data|Hi\}\ Prior\{Hi\}}{\Pr\{data\}}$$

- Hi is >1% species not protected (U = > TV 5.5 ug/L)
- Pr {Hi|data} is the probability of the hypothesis given the exposure data (posteriori probability)
- L {data|Hi} is the likelihood of the data given the hypothesis
- Prior {Hi} - probability of Hi summarises what is previously known, the posteriori probability emerging from previous ecotox effects study

Ecological Risk at RUM & Bayesian Statistics

Posteriori hypothesis – backcasting with observational data (exposure)

H_{11}: TV reached (P = 0.0000304521)

H_{12}: false, TV not reached (P = 0.9999695479)

Prior or additional knowledge – Ecotox lab work (SSDs - effects)

H_{21}: 1% species affected at TV (P = 0.50 x 0.01 = 0.005)

H_{22}: false, 1% not affected at TV (P = 0.50 x 0.99 = 0.495)

Pr {H1|both data} $= P\{H_{11}\}\,P\{H_{21}\} / [P\{H_{11}\}\,P\{H_{21}\} + P\{H_{12}\}\,P\{H_{22}\}]$

= 0.0000003045 (1 in 3.3 million)

= 1 in 3.3 million

EWLS "Deterministic" Model - RUM

- Attempts to develop a "whole of mine" predictive process model to better manage WQ on site (Klessa)
- Predicts change in WQ (EC us/cm & U ug/L) at compliance point 009
- Uses point source data – contributions to solute load at 009 from 3 main surface water exit pathways
  - Corridor Ck /Georgetown Billabong
  - RP1 / Coonjimba Billabong
  - Direct release of ponded water from Djalkmara Billabong
- Does not account for diffuse sources (shallow ground water fluxes, seepage to Gulungal from Tailings dam & land application), or differential lag times in flow rates

EWLS Model - RUM

- MODEL predicts incremental increase in solutes over background (as measured upstream of mine at GS821067)

  PCI = (L1 + L2 + L3) / F
- Where PCI is predicted concentration increase; L1, L2 & L3 instantaneous loads at 3 exit points; F is instantaneous flow rate (m^3s^{-1}) at 009
- Assumes Corridor Ck & RP1 catchments similar in size, no Djalkmara release & 100 x dilution of waters into Magela. Model simplifies to

  PCI = 0.01 (C1 +C2)
- Where C1 & C2 are measured concs at those 2 exits
- Hence, site operational model =

  Predicted concentration at 009 = PCI + Baseline mean
- Used in conjunction with risk assessment decision making process ("traffic lights" approach w.r.t. focus & action levels)

EWLS Model - RUM

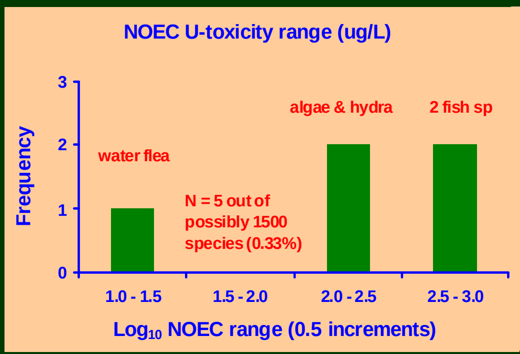
- A start but long way to go
- Model “validation” - compared D - U differences for 3 wet seasons but was a poor fit (2 of 3 cfs were conservatively consistent with model)
- The overall confrontation between model & data is weak – does not use advanced analytical tools
- Biggest problem - process & observation uncertainties not explicitly defined – basically a simple deterministic model with boundary conditions approximated; uses mean values & smoothing to hide variability
- Need a hybrid model to combine key processes with probability
- And a comprehensive quantitative risk assessment & decision analysis (if model to be used for on site WQ management)

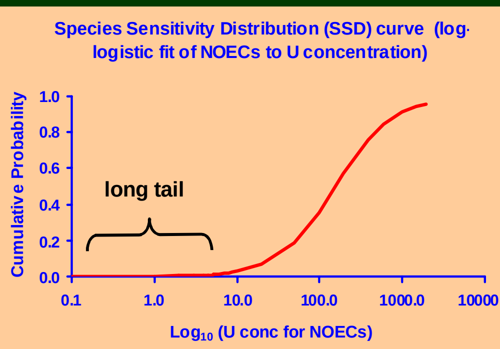
Where next for Ecological Risk Assessment of RUM ?

- Make the U- Effects model more robust - the ERA shows that it’s the weaker partner although a huge work in itself
- Model other major chemicals & explore interactions between them
- Develop a hybrid “process & statistical” model:
  - consistent with historical data
  - has ability to predict future events at 009 in relation to on-site WQ management
  - has an acceptable level of uncertainty
- Incorporate decision analysis into the risk assessment framework

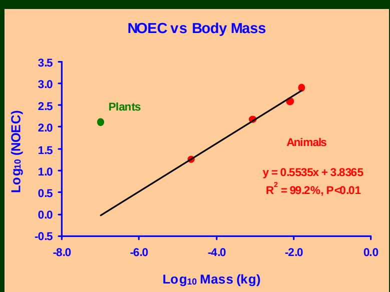
Making the effects model more robust

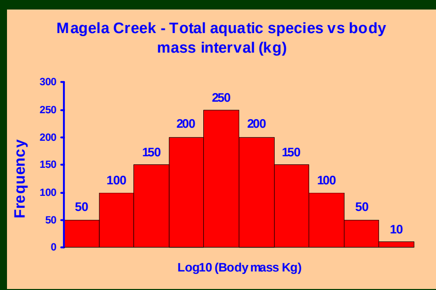
- Strength: deliberate range of species across trophic levels used
- Weakness: small sample (5/1500 = 0.33%) & Log - Logistic assumption leads to "long-tail syndrome"
- Long extrapolation to critical part of risk model – closes the binary gap; in ecotox generally LL model weak assumption; when tested only half true

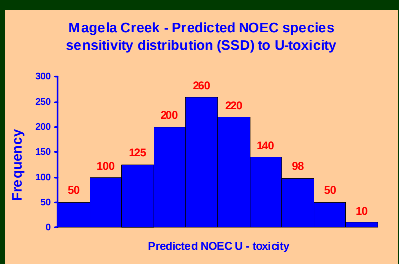




Strengthening existing ecotox SSD risk model using "desk-top" life history analysis



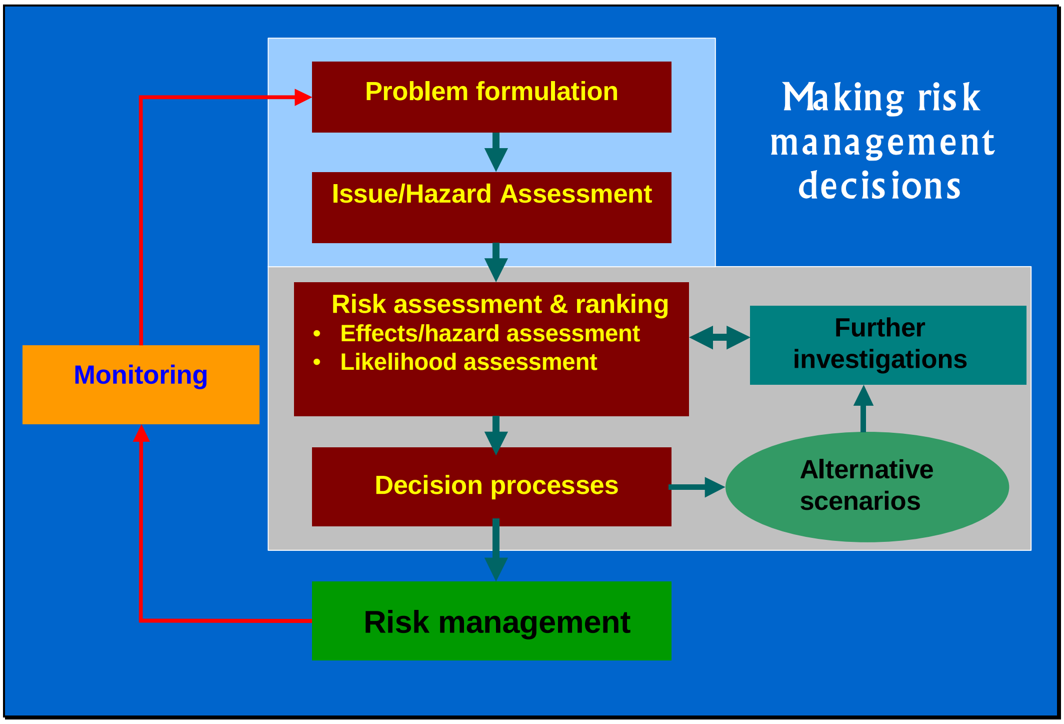




Aim:

Determine best probability distribution function to describe variation in NOECS for Magela aquatic ecosystem to enhance quantitative ERA

Using models to help make risk management decisions



Decision needs: Type I & II errors

Environmental managers seek to balance chance of making 2 kinds of mistakes

1. False security (Type II)
predict no impact (safe) when there is one

2. False alarm (Type I)
predict an impact when there is none

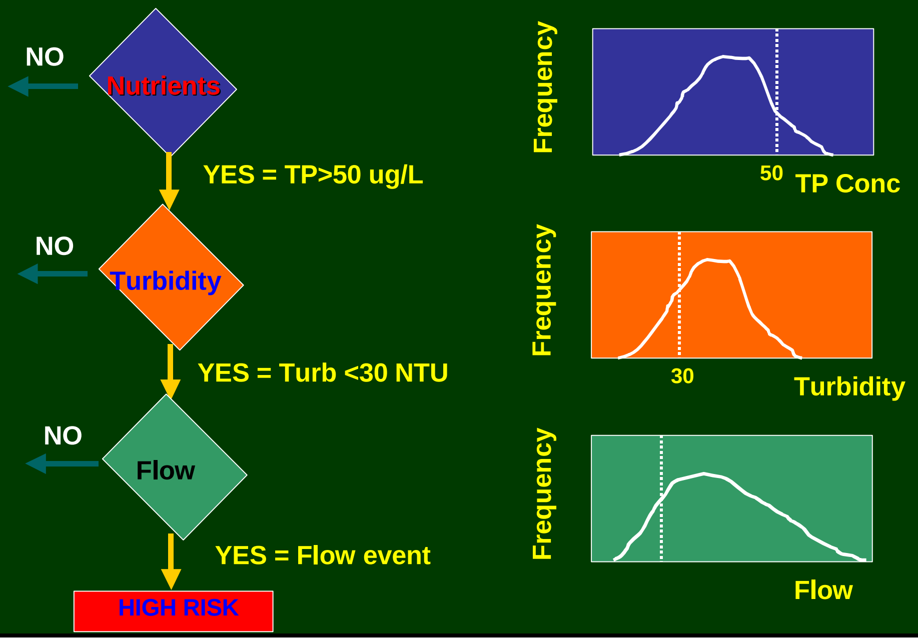
		Predicted response	
		Impact	No impact
True response	Impact	Y Y	N Y Type II error
True response	No impact	Y N Type I error	N N

Decision needs – safety in numbers

- Trade off between Type I & II errors
- Need Power = 1 – β (Type II error rate)
- Hence need lots data or replication

		Predicted response	
		Impact	No impact
True response	Impact	? Y Y	X N Y Type II error
True response	No impact	X Y N Type I error	? N N

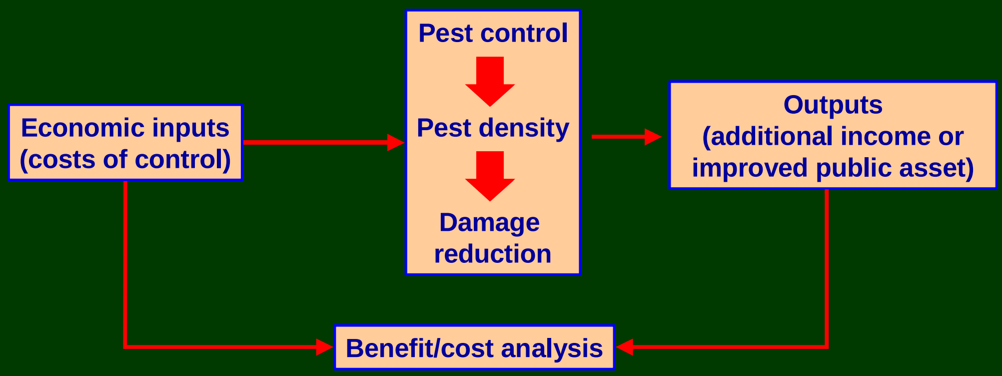
Incorporate Decision tree" models (e.g. algal blooms)



Example 2: Conceptual & operational models for managing invasive species impacts at landscape scales (mimosa on Oenpelli Floodplain)

- Conceptual bioeconomic framework
- Key predictive sub-models for on-site operations
- Ecological risk assessment
- Further improvements in ERA process
- Comparing mining & non-mining ecological risks

Conceptual bioeconomic model for invasive species management

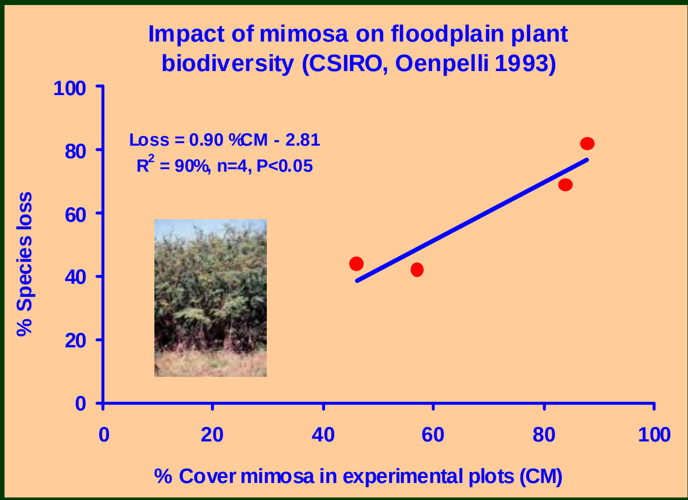


Monetary benefit/cost analysis
Benefit maximisation
Cost minimisation

Three key predictive sub - models

1. Damage – pest density relationship
2. Cost- of- control curve
3. Population growth response

1. Mimosa: Damage – density relationship

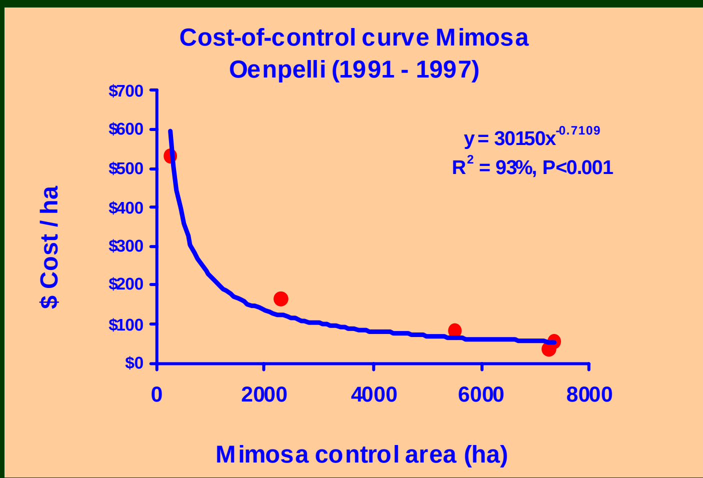


Model predicts 87% loss plant species on floodplain with 100% cover mimosa

Pr (effects) = 0.87

Experimental data (Cooke *et al.* 1990)

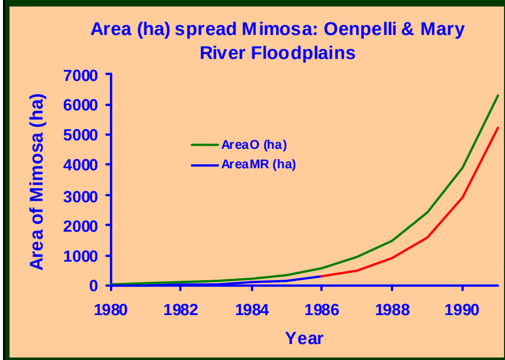
2. Mimosa: cost - of - control



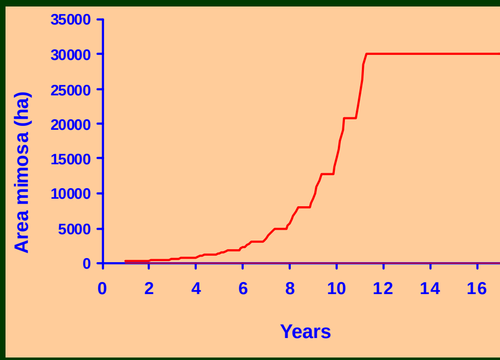
Operational costs only

3. Mimosa: rate of spread or colonisation (exposure)

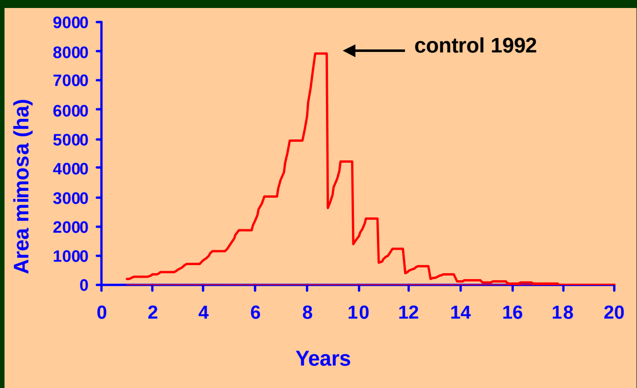
Observed data



Model: exponential growth with "ceiling"



Mimosa control Oenpelli Floodplain Combined sub-models



COST-OF-CONTROL		
	Costs/ha	Total Costs
Initial cost ($/ha)	$51	$404,162
Mean annual maint cost ($/ha/yr)	$236	$242,106
Total cost ($/ha) for	$1,231	$1,614,692

$1.6 mill matches operating costs in annual reports. But actual costs including capital & OHs 1992 – 1997 = $6 - 7 million

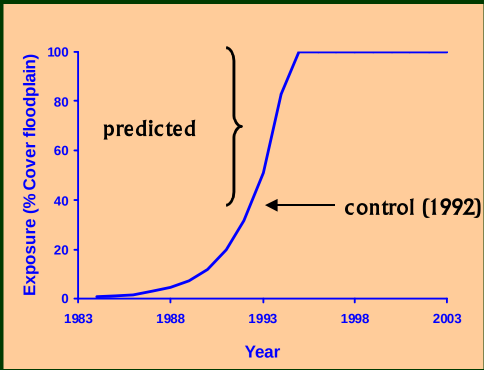
ERA of mimosa plant biodiversity impacts Oenpelli Floodplain

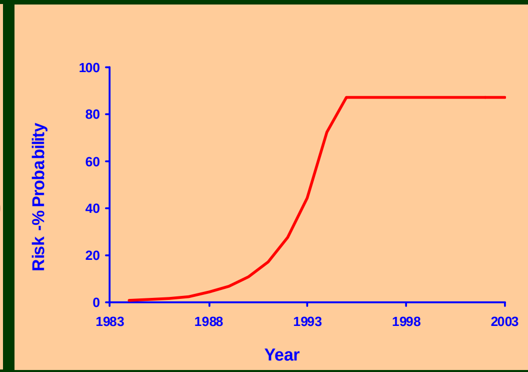
Frequentist approach – predicted exposure & effects over time (1984 – 2003)

Risk prob =Pr (effects) x Pr (exposure)

Risk prob =Pr (0.87) x (α of floodplain with 100% mimosa cover)

1992 Risk prob =0.87 x 0.27 =0.23





Mimosa risk management

- Further model improvements in pipeline to reduce uncertainty in decision making
  - include environmental stochasticity (rainfall effects on spread rates)
  - make model spatially explicit (use life-history & habitat knowledge in GIS)
  - enhance risk assessment model – include benefits & costs of monitoring (e.g aerial & ground search, remote sensing)

Comparing mining & non-mining ecological risks

Risk Probability = Pr {effects} x Pr {exposure}

Mimosa Oenpelli

When control commenced 1992 P risk (1992) = 0.23 ~ 1 in 4

If no control commenced in 1992 P risk (2003) = 0.86 ~ 1 in 1

RUM (1980 – 2003) - 22yrs

Bayesian & conditional prob models P risk = 0.0000006090 ~ 1 in 3.3 million

Comparing 22 yrs RUM risk with 1 yr mimosa risk (1992)

Factor of ~756,00 difference

which does not reflect differential research

& management investment

Communicating Risk

Amongst scientists

- Use modelling process to bring scientists together into an integrated & coherent expert system
- Cuts across disciplines, imparts common ownership, helps resolve differences & conflicts

With environmental & NR managers

- Involve in modelling process from outset
- With ownership more likely to use models

With stakeholders & general public

- Communicate risk through excitement of new approach to science
- Highlight need to accept & live with degrees of uncertainty

Workshop Outcomes

- Need to ask – has ARRTC covered all bases? What's not on their list?
- A summary matrix would be useful, one that identifies for each KKN
  - what the issue is – is it really an issue?
  - what are the key knowledge gaps?
  - who is best able to fill the gap (Eriss, EWLS, other)?
  - if within Eriss – who, how & when?
  - how & when to collaborate with EWLS? Start now?
- How do existing projects fit the new needs? If not when do they phase out? Or can they be made to fit?

ARRTC Key Knowledge Needs

1. Contaminant movement within biophysical pathways (CH)
2. Contaminant movements through groundwater (KE & PM)
3. Linking ecotox knowledge & biophysical pathways (CH)
4. Human health risks associated with biophysical pathways (PM)
5. Radiological effects on people (PM)
6. Linking conceptual models with on-site management (PB)
7. Completion criteria & shared reclamation objectives (KE)
8. Ecosystem establishment techniques (KE)
9. Sustainability of rehabilitation (PB & CH)
10. Final landform - radon emanation & bioaccumulation of radionuclides (PM)
11. Adequate baseline data to underpin indicators of success (CH)
12. Demonstrated ability to reconstruct an ecosystem (KE)
13. Uncertainty analysis of data (PB & KE)

14 & 16 Communications – later; 15?

ARRTC Key Knowldge Needs reduce to 2 clusters - pathway analysis & the rehabilitation process - both are linked & essential for managing risks to humans & ecosystems

KKN	Pathway	Risk Ecosystem	 Human
1	Biophysical	x	x
2	Groundwater	x	x
3	Biophysical	x	x
4	Biophysical - human		x
5	Radiological		x
6	Pathways model & ERA	x	x
10	Radiological		x
13	Pathways model & ERA	x	x
	Rehabilitation process		
7	Rehabilitation	x	x
8	Rehabilitation	x	x
9	Rehabilitation	x	x
11	Rehabilitation	x	x
12	Rehabilitation	x	x

Comparison of research foci before after future mine closure

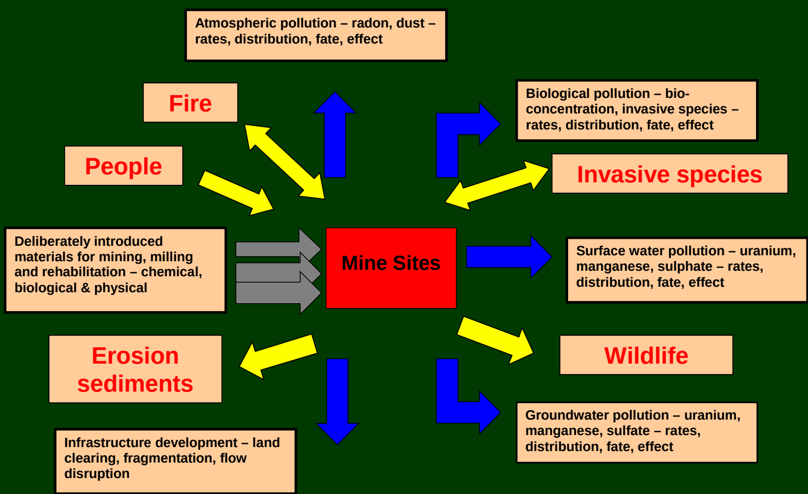
Outcome areas	Before closure Operational mine	After closure Rehabilitation
Management focus	Off-site	On & off-site
Primary focus transport pathway	Surface water & release into Magela (009)	Groundwater & surface water Erosion & surface water transport (sediments) Direct gamma Dust
Secondary focus transport pathway	Direct gamma dust	
Primary focus response uptake	Aquatic organisms	Bush tucker (fruits/yams/vert wildlife) Drinking water Bioaccumulation
Secondary focus response uptake	Bush tucker Drinking water Bioaccumulation	
Primary contaminants	U Mg SO4 Radon	Sediments U SO4 NH4 Mn
Landscape-wide impacts considered Time frame Degree of security	Yes 23-30 yrs Very High	Yes 100 + yrs? High
Modelling requirements		
Transport pathways (GW, SW, air)	Yes	Yes
Ecological risk assessment	Yes	Yes
Landform evolution	No	Yes
Vegetation succession/dynamics	No	Yes
Catchment model	Yes	Yes

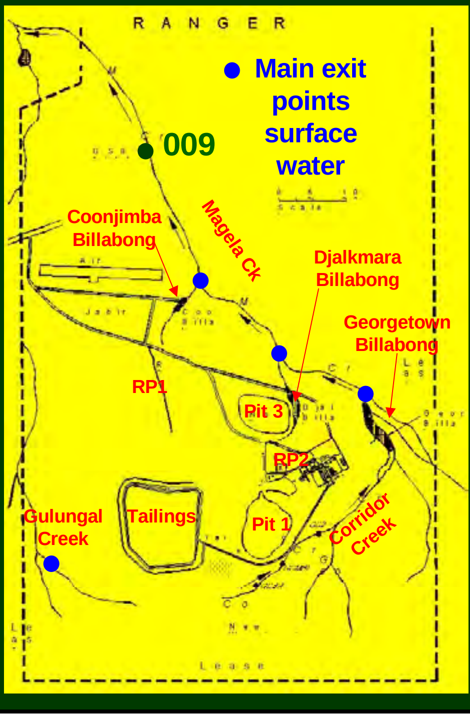
One approach to ARRTC KKNs – use transport pathways model within an ecological risk assessment framework for the ARR

Allows coherent transition between research centred on an operational mine & the rehabilitation phase

Original Transport Pathways Model + rehab additions

Conceptual model of ecosystem processes & pathways for pollutant/propagule transport in the environment of ARR





Use a spatially explicit model for all pathways

For model simulation during pre- & post mine closure, risk analysis, decision analyis, monitoring & communications

Uncertainty & ecosystem rehabilitation in ARR

- Multiple problems caused by multiple threats
- Key threats include
  - toxic contaminants from past mining
  - erosion/sediments
  - invasive species (e.g. pigs & weeds)
  - unmanaged fire
  - climate change effects
  - infrastructure & people
- Natural & rehabilitated systems characterised by
  - variability
  - complexity
  - uncertainty
- Only certainty - managers need predictive tools (e.g. ecological risk assessment, ecological models)

Ecological Risk Assessment

- Risk assessment is about estimating the probability of an adverse event
- Two main components of risk
  - Effects — consequences of adverse event
  - Exposure — likelihood of exposure to adverse event

$$\boxed{Pr\ (Risk) = Pr\ (effects) \times Pr\ (exposure)}$$

- Also need to consider scale
  - spatial (creek, river, catchment, region)
  - temporal (now, 20y, 50y)

Risk Assessment Tools

- Range of methods available
  - worst case scenario
  - what if analysis
  - decision analysis
  - probability theory (frequency, Monte Carlo simulation, bootstrap)
  - Bayesian analysis (prior knowledge)
  - GLMs (least squares, likelihood)
- All address uncertainty associated with variability
- Knowledge uncertainty – more difficult – need new research to fill key gaps

Use ecological models for understanding, prediction & decision

- Models generally used to test our understanding of how a system works or to predict
- Most useful models provide both (e.g. stochastic process models)
- Models can be part of the decision making process – used to evaluate potential effects of different decisions within a risk assessment framework
- Where models have the most to offer in terms of practical application, but also where the greatest danger lies

Ecological Risk Assessment of Ranger

- Make U- Effects model more robust using Life History analysis
- Model exposure of other major chemicals & explore interactions between them (Mg, SO_4, Mn, Ca etc)
- Develop stochastic process model for Ecological Risk Assessment
  - consistent with historical data
  - ability to predict future events at 009 in relation to on-site WQ management
  - has an acceptable level of uncertainty
- Incorporate decision analysis into the risk assessment framework
- Model other pathways (ground water, air)
- Extend risk assessment framework to encompass rehabilitation phase

Invasive species management - 3 key predictive sub-models

1. Damage – pest density relationship
2. Cost- of- control curve
3. Population growth response

For:

- Mimosa, salvinia, paragrass, major terrestrial weeds
- Pigs

Risk management of invasive species in the ARR

- Further model improvements to reduce uncertainty in decision making
  - incorporate effects of environmental variability on population dynamics of pest species
  - make model spatially explicit (via life-history & habitat knowledge in GIS environment)
  - enhance risk assessment model – include benefits & costs of monitoring (e.g aerial & ground search, remote sensing)

Do our existing ERA projects fit the new Key Knowledge Needs?

	2002-03 Projects	Fits ARRTC KKNs?	How?	Theme	End Pt
	LANDSCAPE				
1	Weed risk assessment KNP	Yes	Rehab	Invasive sp	03-04
2	Feral animal management KNP	Yes	Rahab	Invasive sp	03-04
3	Boggy Plain - multiple impacts	Yes	Rehab	Invas sp, fire, climate change Control site mining impacts	06-07
4	World Heritage values - Waterbirds ARR	Yes	Rehab	WH values, climate change	06-07
5	Mangrove response to coastal environmental change	Yes	Rehab	Climate change	05-06
6	Ecological risk assessment Ranger	Yes	Rehab/TP model	Mine-site management	04-05
7	Ecological risk assessment Jabiluka?	Yes	Rehab/TP model	Mine-site management	04-05
8	Ecological modelling (= ERA & TP model)	Yes	Rehab/TP model	Mine-site management	06-07
9	Catchment management Arnhem Land	No			
	ECOTOX				
10	Current ecotox projects (Mg, SO4, NH4, Mn)	Yes	Rehab/TP model	Mine-site management, WQ	03-04
11	Strengthen SSD ecotox effects model using life history analysis	Yes	Rehab/TP model	Mine-site management, WQ	03-04
	REHABILITATION				
	Integrate all YESs into REHAB projects See following			Mine-site management, WQ	?

REHABILITATION

= Landscape gardening on a grand scale ?

Rehabilitated mine site area will be an open system

- Rehab sites are open systems subject to disturbance or change (e.g. fire, invasive species)
- Ecosystem will hence exhibit non-equilibrium dynamics (including multiple equilibria, dynamic equilibrium, unstable equilibrium)
- NE Ecosystem dynamics characterised by diversity, complexity & uncertainty
- May exist many local "domains" of attraction with boundaries separated by breakpoints or thresholds (hysteresis effect)
- Transition to a local phase may be irreversible (wrt to rehab, would entail costly intervention to reverse change)
- System outcomes generally unpredictable because of sensitivity to initial conditions

Role for adaptive experimental management in rehabilitation?

- YES – rehabilitation sites are open systems with uncertain outcomes
- Adaptive Management is:
  - about managing in the face of uncertainty (process, observational & chance events)
  - a structured process of "learning by doing" via experimental management; one step beyond better ecological monitoring & response to unexpected impacts
- Rehabilitation programs have great scope for AM of landscapes (vegetation, landforms) & populations
- An opportunity to improve management by resolving key uncertainties

Adaptive Management

- Begins by integrating existing knowledge into models that attempt to make predictions about impacts of alternative actions
- The crucial modelling step has 3 functions
  - problem clarification & enhanced communication amongst scientists, managers & other stakeholders
  - screening of options to eliminate those unlikely to do much good
  - identification of key knowledge gaps that make model predictions suspect
- Models are constantly improved with structured manipulation of management treatments, in combination with monitoring & feedback loops
- But not without problems – modelling plagued by cross-scalar effects (rapid hydrologic change vs long-term ecological response), lack of data on key processes & so on

Monitoring approaches

- Traditional quantitative ecological assessment (e.g. structure & composition vegetation)
- Vital Ecological Attributes (VEA)
- Ecosystem Function Analysis (EFA)
- Remote sensing (structure, pattern & composition)
- Faunal recolonisation (abundance & composition)
- Other indices of ecosystem recovery
- These monitoring approaches need not be mutually exclusive & can be incorporated into a range of working frameworks (e.g. risk assessment, adaptive management)

Vital Ecological Attributes (VEA)

- Characteristics, or attributes, that are correlated with, and can serve as, indicators of ecosystem structure and function
- Basic approach to plant succession that defines minimum set of plant attributes needed to predict plant community dynamics subject to recurrent disturbance such as fire & floods. e.g.
  - perenial & annual plant species richness
  - abundance invasive species
  - spectrum of plant life forms
  - total cover of the vegetation
  - viable seed bank in the soil
  - recruitment, growth & survival of key indicator plants
  - soil surface conditions
  - organic matter content in the soil
- Liked by Max, Chris, 1 ARRTC member & myself, but not by mining companies (e.g ERA-EWLS) & CSIRO SE

Ecosystem Function Analysis (EFA)

- Developed by CSIRO SE for rangelands & other disturbed landscapes such as mine sites. Provides assessment on effects of stress/disturbance on landscapes. Has 3 modules:
  - landscape function
  - vegetation composition and dynamics
  - habitat complexity
- Apparently assumes an equilibrium end-point
- Liked by mining companies (e.g ERA-EWLS) & CSIRO SE, but not by Max, Chris, 1 ARRTC member & myself

Rehabilitation

7. Completion criteria & shared reclamation objectives (KE)

Key issues

Knowledge gaps

Possible project

Who, where & when?

Rehabilitation

8. Ecosystem establishment techniques (KE)

Key issues

Knowledge gaps

Possible project

Who, where & when?

Rehabilitation

9. Sustainability of rehabilitation (DW/JB & CH)

Key issues

- Depends on mine site closure criteria & rehab goals (wrt analogue or reference site?)
- What success criteria & indicators? & how to monitor?
- What approach or model? – EFA, VEA or other (e.g. use remote sensing); need not be mutually exclusive – tells us when to intervene (& what benefits for what costs)

Knowledge gaps

- Disturbance ecology - invasive species (weeds & pigs), fire, people & their interactions
- Soil-vegetation-fire dynamics of surrounding landscape & rehabilitated area
- How to manage contaminated sites & erosion – identify all potential transport pathways
- Lessons from Nabarlek?

Rehabilitation

9. Sustainability of rehabilitation (DW/JB & CH) - continue

Possible projects

- Initial modelling exercise using available knowledge comparing VEA, EFA & other approaches, & a range of success indicators (including multivariate indicators)
- Revamp existing weed & pig control projects to deal with specific rehab issues (eg ground disturbance & weed invasion risk, interactions with fire; pig impacts etc)

Who, where & when?

- Across Eriss, EWLS, NLC, PAN (?), TOs; Nabarlek & Ranger; 2003 – 2004 Work Plan

Rehabilitation

10. Final landform - radon emanation & bioaccumulation of radionuclides (PM)

Key issues

Knowledge gaps

Possible project

Who, where & when?

Rehabilitation

11. Adequate baseline data to underpin indicators of success (CH)

Key issues

Knowledge gaps

Possible project

Who, where & when?

Rehabilitation

12. Demonstrated ability to reconstruct an ecosystem (KE)

Key issues

Knowledge gaps

Possible project

Who, where & when?

Rehabilitation

13. Conceptual Transport Model & Ecological Risk Assessment Framework

Key issues

- Now – mine operational. Risks of "off-site" impacts associated with all transport pathways (surface & ground water, air) & contaminants/propagules
- Future – mine closure/rehab. Risks of "on & off-site" impacts associated with all transport pathways (surface & ground water, air, biophysical) & contaminants/propagules

Knowledge gaps

- As discussed in seminars & this workshop

Possible project

- Develop stochastic process sub-models of Conceptual Transport Model
- Undertake ecological risk assessment

Who, where & when?

- Now – across Eriss, EWLS; Ranger; 2002-03 & 2003-04
- Future – across Eriss, EWLS, PAN (?), TOs, other stakeholders; Ranger; 2003-04