Integrated Assessment and Information Systems for Catchment Management

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Abstract: To meet the challenges of sustainability and the so-called triple bottom line, catchment management, and natural resources management in general, requires an approach that assesses resource use options and environmental impacts integratively. Assessment must be able to integrate several dimensions. These dimensions include the consideration of multiple issues and stakeholders, the key disciplines within and between the human and natural sciences, multiple scales of system behaviour, cascading effects both spatially and temporally, models of the different system components, and multiple databases. Integrated Assessment (IA) is an emerging discipline and process that attempts to address the demands of decision makers for management that has ecological, social and economic values and considerations. This paper summarises the features of IA and argues the role for models and information systems as a prime activity. Given the complex nature of IA problems, the broad objectives of IA modelling should be to understand the directions and magnitudes of change in relation to management interventions so as to be able to differentiate between associated outcome sets. Central to this broad objective is the need for improved techniques of uncertainty and sensitivity analysis which can provide a measure of confidence in the ability to differentiate between different decisions. Three examples of problems treated with an IA approach are presented. The variations in the way that the different dimensions are integrated in the modelling are discussed to highlight the sorts of choices that can be made in model construction. The conclusions stress the importance of IA as a process, not just as a set of outcomes, and define some of the deficiencies to be overcome.

Keywords: Integrated assessment; Modelling; Catchment management sustainability; Uncertainty

1. INTRODUCTION

Integrated natural resource and environmental management is increasingly becoming an objective of government policy internationally, with a strong trend towards taking account of many values – particularly the triplet of ecological, social and economic values - in decision making processes. Ewing et al. [1997] state that this has been a consequence of the increasing dissatisfaction that decision makers feel with the outcomes resulting from 'narrowly-focussed, incremental and disjointed' environmental management. They argue that earlier approaches have usually failed to deal with the many interconnections and complexities within and between the physical and human environment.

In water resources management, this view of past approaches is echoed by Born and Sonzogni [1995] who state that it has been of limited purpose, focussing on only a portion of the watershed and implemented incrementally. It is quite clear that in many cases the management of water resources has concentrated on the physical control of water. In other cases management has attended to the economic as well as the engineering, but that economic aspect has been largely concerned with basic financial analyses. On the whole, environmental and social effects have at best been given token consideration as has the involvement of local communities in decision making processes. This is now changing, especially in Australia with the introduction of integrated catchment management policies [eg Murray-Darling Basin Ministerial Council, 2001] that seek to implement management which leads to resource use that is ecologically sustainable.

The aim of this paper is to put a case that it is now possible to assess the effects of resource use and management in an integrated way that provides good guidance for decision making. The increasing availability of spatial databases and improving information technology are facilitators for such assessment. More importantly the science of Integrated Assessment (IA) is maturing to the point where knowledge and practice of this discipline should now accelerate to provide positive benefits for assessing the ecological, social and economic effects of decisions as well as guidance on the ways that management may be effective. This is not to deny that there are still advances required in the toolbox of methods that is required for improving the effectiveness of IA. However it is mainly by continuing to perform IA and its related modelling that natural resource management will be better informed, lessons will be learnt and priorities effectively set for advancement of the IA process.

In Section 2 the features of IA are outlined. In Section 3 the role of models and environmental information systems in IA is argued. The broad objectives of IA modelling (IAM) are covered in Section 4. This includes a discussion of simulation versus optimization, the nature of scenario simulation and some of the key considerations in IAM. Particular emphasis is given to the need for adaptive methods of sensitivity analysis. In Section 5 an example of IA undertaken in the Mae Chaem catchment, Northern Thailand is discussed and the results illustrate the tradeoffs that IA can produce. Two examples of IA problems in catchment management in Australia are presented in Section 6: for the Namoi Basin and the Yass catchment. These three examples are very different in scale and issues, and in Section 7 the according variations in the way the modelling was constructed are delineated. Section 8 contains the conclusions.

2. FEATURES OF INTEGRATED ASESSMENT

The trend to more integrative or holistic assessment and management of our resources requires the corresponding development of our science. The evolving discipline of integrated assessment, having much of its infancy in global change impact assessment, attempts to address these scientific needs; see for example CIESIN [1995], Rotmans and van Asselt [1996], Morgan and Dowlatabadi [1996], Park and Seaton [1996], Risbey et al. [1996], Janssen and Goldsworthy [1996], Rothman and Robinson [1997], Villa and Costanza [2000], Guerts and Joldersma [2001], and Parker et al. [2001]. A summary of the common features of IA, taken from the above and our experiences, is provided in Table 1.

Therefore, in natural resource assessment, integration has several dimensions. These dimensions include the consideration of multiple issues and stakeholders, the key disciplines within and between the natural and human sciences, multiple scales of system representation and behaviour and cascading effects both spatially and temporally. In IA modelling this integration extends to models of the different system components and the incorporation of multiple databases.

Table 1. Common features of Integrated Assessment.

- A problem-focussed activity, needs driven; and likely project-based
- An interactive, transparent framework; enhancing communication
- A process enriched by stakeholder involvement and dedicated to adoption
- Linking of research to policy
- Connection of complexities between natural and human environment; recognition of spatial dependencies, feedbacks, and impediments
- An iterative, adaptive approach
- A focus on key elements
- Recognition of essential missing knowledge for inclusion
- Team-shared objectives, norms and values; disciplinary equilibration
- Science not always new but intellectually challenging
- Characterisation and reduction of uncertainty in predictions

3. ROLE FOR MODELS AND ENVIRONMENTAL INFORMATION SYSTEMS

The development and use of models is a major activity of integrated assessment, as is their incorporation in environmental information systems and computer-based decision support systems. This is because people think and communicate in terms of models as simplifications of reality. As pointed out by Parker et al. [2001], the types of models include:

- Data models that are representations of measurements and experiments
- Qualitative conceptual models as verbal or visual descriptions of systems and processes
- Quantitative numerical models that are formalisations of qualitative models
- Mathematical methods and models used to analyse the numerical models and to interpret the results

- Decision making models that transform the values and knowledge into action

Documenting models and/or putting them into computer code makes their nature and assumptions more explicit and allows integration to be made with other models. Such explicit models allow us to represent the complexities and interactions within and between human and environmental systems effectively. When incorporated in computer software, models allow us to run scenarios more efficiently and in particular to calculate and assess the ensuing tradeoffs among indicators of environmental, economic and social outcomes (see Section 4.1).

Environmental information and computer-based decision support systems can increase the value of models and information in integrated assessment. These values are summarized in Table 2.

Table 2. Value of Environmental Information Systems and Computer-based Decision Support Systems.

Value of EIS and DSS
• A way of exploring and explaining tradeoffs
• A tool for adoption and adaptation by stakeholders
• A longer term memory of the project methods
• A library of integrated data sets
• A library of models, methods, visualisation and other tools
• A focus for integration across researchers and stakeholders
• A training and education tool
• A potentially transparent tool

While the software available for environmental modelling and simulation is very advanced, some of the desirable features of decision support systems cannot be easily delivered using such software [Rizzoli and Young, 1997]. These features include representation of spatial data, provision of expert help and model reuse and integration. Platforms which fully support the development of such DSS are considered to be a long way off.

4. BROAD OBJECTIVES OF IAM AND KEY CONSIDERATIONS

4.1 Simulation or Optimisation

Once models are constructed and parameterised to link the various parts of a resource system that requires integrated assessment, the question arises as to how to then produce the information needed to assist the making of decisions. At one extreme is the option of implementing optimisation of the system with respect to a specified or preferred set of outcomes, usually multiple objectives. In this situation the controllable variables in the system are allowed to vary within a practical range to best meet those outcomes. The main problem with this approach is that it tends to obscure the complexities and dependencies in the system being modelled, simplifying the process.

An alternative is to utilise simulation as a way of more fully exploring the effects of controllable and uncontrollable scenario variables in terms of indicators of system response. This approach allows one to develop a better understanding of interdependencies and may lead to the identification of outcomes which are considered better tradeoffs than prespecified optima. Initially it is a more cumbersome approach, but the range of input variations explored can be reduced as understanding of the modelled system behaviour accrues.

4.2 Types of Scenarios and Indicators

In IA modelling, whether mechanised as pure simulation, pure optimisation or a mixture of both, scenarios and indicators are selected. In optimisation the scenarios may be automatically adjusted to meet prespecified values, or optimised multi-objective functions, of the indicators. Or, as with simulation, the scenarios may be constrained to simulate effects on certain indicators that lie within a specified range.

Scenarios may be characterised in various ways but a first, useful dichotomy is between controllable and uncontrollable influencing variables. For the latter a credible IAM exercise will establish the sensitivity or variability of the model outputs/indicators to the range, and preferably frequency, of uncontrollable variables. Climatic influences will invariably be one of these. Boundary conditions to the problem will constitute another set of uncontrollable influences. These may be items we cannot or do not wish to model eg world price changes for agricultural inputs or products, labour market status, and transborder water supply and quality upstream. Controllable variables are ones that can be influenced by instruments such as regulation, education, incentives, subsidies and other investments by the public or private sector.

4.3 Broad Objectives of Integrated Assessment and Modelling

Given the complexities and uncertainties of integrated modelling, its broad objective should be to increase understanding of the directions and magnitudes of change under different options. Typically, it should not be about accepting or treating system outputs as accurate predictions. It should be aimed at allowing differentiation between outcomes, at least with a qualitative confidence; for example, a particular set of outcomes or indicator values are overall better than another set (for instance a do-nothing, current situation) with good confidence, reasonable confidence, or little confidence. This accordingly facilitates a decision as to the worth of adopting a policy or other controllable change that produces a predicted set of outcomes.

Ideally, predictions would be produced with a quantitative confidence level but in most situations this is impractical at present. As expressed in Section 4.5, methods for quantifying uncertainties have limitations and new research is required to address this glaring deficiency.

4.4 Key Modelling Considerations

What to include and what not to incorporate in an IA modelling activity should be addressed at the outset as explicit considerations. The system being modelled should be defined clearly as well as its physical, socioeconomic and institutional boundaries. Boundary conditions can then be modelled as constraints or as input scenarios whose values can be perturbed in line with stipulated assumptions. Some of the following modelling considerations should commonly arise with respect to the management of natural resources:

- Climate variability and episodes – these often have a profound effect on outcomes. Variability can affect the returns of an investment in production as well as the response of an ecosystem while episodes such as a floods can have an inordinate effect on outputs. Both raise issues of appropriate time periods and time steps over which to model (see Section 4.4.1).
- Model process complexity – once the basic processes and causal relations are decided upon, often there is still much scope for selecting the level of underlying detail including the spatial and temporal discretisation. Data paucity, especially of system behaviour, should limit the model complexity. For example, in modeling of flow and transport, spatial data on catchment attributes may be very useful to structure and discretise a model in fine detail but this complexity is unwarranted if flux measurements used for model calibration cannot support the level of parameterisation [eg Jakeman and Hornberger, 1993].
- Beyond business-as-usual scenarios – the nature of environmental or social decline may mean substantial changes to the current situation are required. Other public and private investments, policy incentives and institutional arrangements will be needed to change resource activities.
- Model long leads and lags – the timeframes for returns on investments and for ecosystems to respond to changes affects both the period and the temporal resolution over which models are run and indicators computed.
- Narrowing modelling objectives – in addition to simplifying types of models, scales, system boundaries etc., it is critical to keep the level of integration of issues and disciplines manageable.
- Model uncertainty – it is desirable to reduce and, where possible, characterise uncertainty; the latter needs methodological attention by IA researchers (see Section 4.4.2).
- Error accumulation – this is mostly ignored and also needs methodological attention (see Section 4.4.2).
- System representation – the extent of the capacity to characterise feedbacks and interactions while keeping model components and linkages effective but efficient.
- Nodal network structure for river networks– this is addressed below in Section 4.4.1.

4.4.1 Scales and nodes of analyses and outputs

Scale includes the temporal periods and spatial extents over which a model must be run (the domain), as well as the time and space step (the discretisation) of the model. Selection of spatiotemporal scales for the different subsystem components of an IA problem is one of the key considerations for credible IA modelling. Scale should be selected fine enough to capture the required level of variability of system response but not finer than is warranted by the availability and quality of corresponding input data and other model calibration data – a tradeoff between model

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The specific breakdown of a system into its subsystem components depends upon the management questions being asked of the modelling exercise and the nature of the data and other prior knowledge available. Even then, the real objectives are not often broadly based, or can be simplified and remain useful for management, so that one may be able to ask questions of a modelling exercise that are less demanding than perceived on initial reflection [Jakeman, 1989].

In resource management there are certain immutable factors which guide the selection of scale. One is the levels at which decisions require support; another is the desirable location and nature of model output indicator functions. In catchment management problems, these locations translate minimally into nodal positions in the stream network (and their associated, residual subcatchments) where management and land and water use can be evaluated for their effects, comparatively with respect to changes or scenarios and with respect to other nodes.

4.4.2 Uncertainty and sensitivity needs

Natural systems, even without human interactions, present considerable difficulties for modellers [see eg Jakeman et al., 1994]. Compared with engineered systems, for instance, these difficulties arise from several factors. One is the sheer complexity of internal system behaviour arising from dynamic and multidimensional interactions that are physical, and possibly chemical and biological; another factor is that interactions may occur in more than one medium, each of which is spatially heterogeneous; and the range of time and space scales characterising the various media or subsystems is likely to be quite wide [Chapman, 1990]. Compounding this complexity is a lack of capacity both to measure internal system states and outputs comprehensively, and to perturb system inputs and parameters, so that individual aspects or modes of system behaviour can be observed and understood [Young, 1978]. All of this means that IA modelling has a large degree of uncertainty which, if IAM is to be credible, must be characterised and preferably reduced as far as possible. Credibility requires that model components are identifiable, plausible and explain system output behaviour satisfactorily [Jakeman et al., 1994]. Here identifiability is taken loosely to mean not just that parameter values estimated are unique but also that they possess a tolerable measure of covariation [eg Norton, 1986].

Integrated models therefore possess many uncertainties. These include: measurement and sampling errors in data inputs and other data used to calibrate models, model structure assumptions, model parameter values and assumed constants. Some of these errors can accumulate as simulations progress sequentially - as outputs of one model are used as inputs to another. This can occur through spatial cascading along catchment nodes and through interaction of two models within a nodal area.

There is very little technology that has been directed towards assessing uncertainty of integrated models and their outputs. If reliable conclusions are to be drawn from complex models, a key task is to assess the sensitivity of outputs to uncertainty in the following items: inputs, parameters and model structure features. An additional value of sensitivity analyses is that they can point to how models can be simplified. Some of the limitations of conventional sensitivity assessment based on perturbation and Monte Carlo trials are the effort and trials required to discover which combinations of uncertain items are most important and how far they can vary before the model output changes significantly. A new approach [Norton et al., 2001] being investigated by the authors and colleagues at the University of Birmingham and The Australian National University is the posing of sensitivity analysis as exploration of the feasible set of parameters, inputs or model structure indices giving a specified range of output behaviour. The output behaviour is defined as a set characterised by a collection of constraints on realistic, acceptable behaviour or the boundaries of behaviour leading to a given qualitative solution. The focus on sets removes the need to assume linearity between cause and effect, continuity of the output or a quantification of the output. The new approach will be adaptive, combining searches, Monte Carlo trials and feature extraction by descriptive multivariate analysis.

Another aspect requiring attention is the control of error accumulation. The first task here is to identify model points where accumulation is problematic, through a combination of analysis and comprehensive simulation. Techniques are then required to control the problem through model structure modification or through constraints. Consider for example a situation where a hydrograph of stream flow at a downstream node accumulates a trend through computational biases at upstream nodes. One of the remedies here is to undertake computations at multiple time steps where the longer time steps may have less resolution but lower bias. Scaling procedures may then be applied to constrain the ordinates of the hydrograph computed at shorter time steps by knowledge of the total volume of the hydrograph computed at the longer time step, a mass balance constraint. Suffice it to say here that much research is required on this general issue.

5. IWRAM PROJECT IN NORTHERN THAILAND

5.1 Issues, Disciplines and Stakeholders

Throughout the world, deforestation, agricultural expansion and the associated competition for water resources produce environmental, economic and social impacts. In parts of the developing world these problems are often more striking because of faster growing populations and the associated rapidity of the manifested problems. Ghassemi et al. [1995] provide information on the extent and distribution of the world's water and arable land resources and land degradation types.

In Northern Thailand, agricultural expansion has produced competition for water at various scales and has resulted in erosion problems, downstream water quality deterioration, groundwater depletion, biodiversity loss, and shifts in the distribution of economic and social well-being and equity. The monsoonal nature of rainfall also intensifies demand for water in the dry season and, with the seasonal shift in flow regimes especially at larger scales where dam regulation is more considerable, exacerbates instream biodiversity and habitat.

The Integrated Water Resource Assessment and Management (IWRAM) project has been developing a methodology to assess these issues. The focus has been on working at the subcatchment scale (~100 km^2) in the Mae Chaem catchment (4,000 km^2), principally with the Royal Project Foundation and Land Development Department in Thailand, to provide them with a landuse planning toolkit. With respect to issues, initial attention has been given to the spatiotemporal distribution of water supply, erosion, rice deficit and farm income throughout case study catchments in relation to input drivers such as climate, commodity prices, technological improvements, government regulations and investments. Lessons from this prototyping project are fully expected to facilitate the incorporation of other impacted sectors such as groundwater and water quality in the near future through a project focus in other northern catchments with these issues.

Necessarily the toolkit requires integration of various disciplinary contributions including agronomy, climatology, economics, hydrology and soil science. In order to enhance the utility, interactivity and transparency of the approach, the toolkit has been imbedded within a decision support system that allows scenarios to be generated as inputs to the toolkit and a range of biophysical and socioeconomic indicators as outputs. The main stakeholder focus for the DSS is the Land Development Department which aims to utilise the DSS to assist its landuse planning activities. However other agencies and groups have now become involved. Adoption is being facilitated by training workshops on the individual model components and the DSS itself.

5.2 Models and Scales

The model components currently in the DSS are a crop model [CATCHCROP, Perez et al., 2001], a rainfall-runoff model [IHACRES, Jakeman and Hornberger, 1993], a sheet erosion model [USLE, Wischmeier and Smith, 1978] and an economic model [Scoccimarro et al., 1999]. The links between these models are indicated in Figure 1.

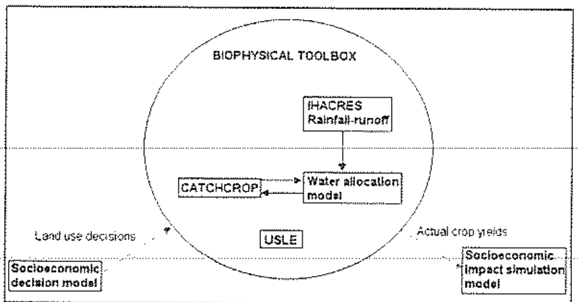

Figure 1. Conceptual framework for IWRAM DSS.

The spatial scales utilised by the biophysical models are given in Table 3 in Section 7 but range from point (infiltration processes) to grid (30 m Digital Elevation Model) to land unit (0-1km^2 but variable based on the homogeneity of land capability) to subcatchment node. Time steps of the models range from daily to 10 days whilst outputs may be aggregated up to seasonal, annual and higher depending on the length of simulation. The spatial scale of the economic modelling in the initial project is at the level of the household [Scoccimarro et al., 1999] where activities are optimised with respect to income and constraints subject to the land and water resources available and external drivers mentioned above. The temporal scale of the economic modelling is seasonal.

A unifying spatial scale for the modelling is the node. Nodes are identified through the stream network as distinct zones of activity in catchments between which tradeoff of indicators is required. Thus the time clocks of the various models are synchronised at these nodes.

Despite the apparent availability of model component candidates from the literature, much innovation was required in the modelling. All of the models integrated into the toolkit and DSS required some development to take into account data inadequacies, either in the form of inputs and parameters to drive the models or as outputs to assist in the calibration of models. Least modification was required for the erosion model where the inputs, rainfall erosivity factor and topographic factor, were adjusted for the higher rainfall and steeper slopes of Thailand [Liengsakul et al., 1993; NRC, 1997] compared to the original areas in the USA where the USLE was developed. The crop model required simplification of the detail in infiltration, runoff and percolation processes to circumvent the lack of detailed field measurements in the catchments. The simulation of discharge provided perhaps the greatest challenge because of the need to predict flows at nodal sites that were ungauged, and to predict nodal flows under changes in landcover conditions. This required a regionalisation approach to relate the ratio of parameters of the IHACRES model (from gauged calibrated nodes to ungauged and/or landcover-modified nodes) to the ratios of either runoff, deep drainage or runoff plus deep drainage inferred by the crop model [see Merritt et al., 2001].

5.3 Results

Figure 2 demonstrates some simple results for the IWRAM models to illustrate the nature of the scenarios and the indicators that can be computed to allow tradeoffs to be made on a given set of issues. For the Mae Uam subcatchment two scenarios are constructed: the first is the current situation, which involves households having the same access to land and water as in 1990; the second is an increase in land available for agriculture, decreasing forest cover by 3.2% from 1990. The set of indicators computed for both scenarios includes erosion, stream volume available for other users downstream including the environment, household cash, and rice deficit per household. A crude indicator of biodiversity has also been appended in terms of the forest cover used as input.

Figure 2 captures the differences in indicators between these two scenarios and shows their sensitivity to different climate history: a wet year (using 1988 daily climate), an average year (1990) and a dry year (1993). Among other things, it illustrates the hypothetical environmental cost of removing the rice deficit, in terms of increased erosion, a slight reduction in forest cover but no significant change in stream volume. In this case, the results for rice deficit are strongly sensitive to historical climate.

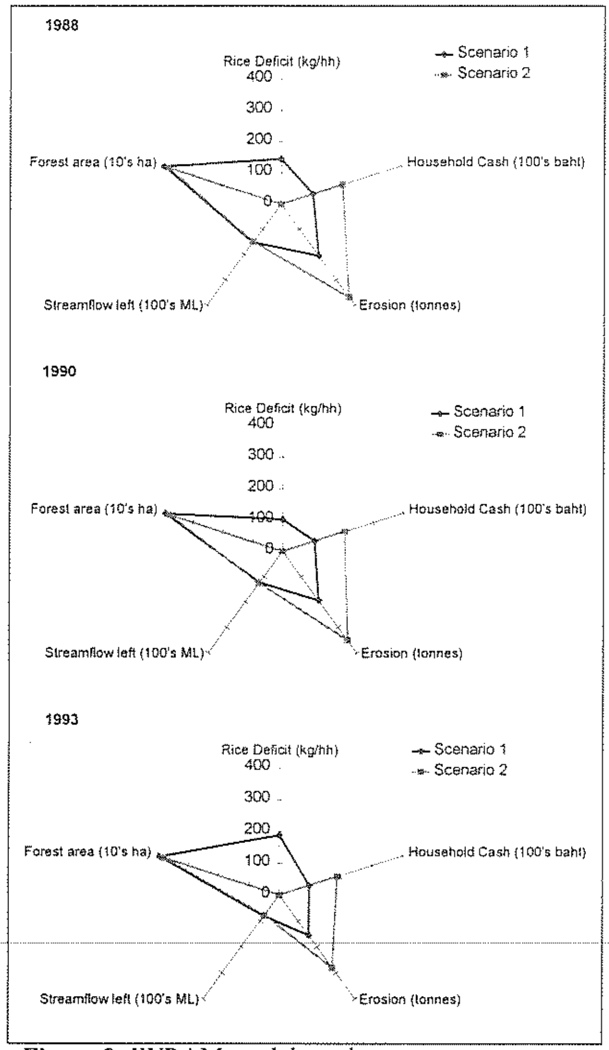

Figure 2. IWRAM model results.

6. TWO AUSTRALIAN CASE STUDIES

6.1 Yass Catchment Study

The aim of this project [Gilmour et al., 2000 and 2001] is to examine the effects of water resource policy and substantial changes in land use, using the Yass catchment in New South Wales as a case study. Policies applied are those for volumetric conversions of licences on unregulated rivers, farm dam capture limits and expansion of farm forestry for salinity abatement. The expansion of viticulture on land previously used for grazing and rural residential subdivision are also considered.

As with the Thai case study, insufficient gauges were available within the catchment to capture important economic and social nodes. Regionalisation and disaggregation techniques were used to construct models capable of predicting streamflows at ungauged sites in the catchment, under changed forest cover and farm dam capture conditions. The model uses a nodal-network approach to integration between hydrological and economic models. Links between the hydrological and economic components occur in three ways: the impact of changed forest cover on runoff; the change in runoff due to farm dam capture of different supplementary irrigation scenarios; and, through direct extraction from the stream. Integration between the economic and hydrological models has reflected these complexities. Economic units are smaller than the nodal scale, and have been referred to as land management units (LMU). These LMUs are defined on the basis of alternative production activities and soil properties. One to several LMU models may be integrated with the hydrological model at the node. Economic decisions are simulated using both linear programming to maximise farm profit as well as using an option for prescribed areas of farm forestry. These decisions are simulated over a twenty year time period, using a fixed level of capital for each land use option.

6.2 Namoi Catchment Study

This project aims to develop a tool for investigating the catchment scale trade-offs involved with various options for water allocation in the Namoi River catchment in Northern NSW, Australia [Letcher, 2001]. The trade-offs which are considered are between economic and environmental outcomes. The development of this tool has been undertaken in response to needs expressed by stakeholder groups in the catchment, and has been focussed by stakeholder input at various stages of model development [Letcher et al., 2000]. A long-run, regional scale economic modelling approach was used to simulate decision making of regional farmers under a variety of water allocation scenarios. These long-run models simulate both long and short run decisions for the region given limits of land and water available. Short-run decisions are simulated for possible levels of land, water and capital using a linear programming algorithm to maximise annual profit. Long-run decisions on the level of investment in on-farm storage, area laid out to irrigation, and irrigation efficiency are simulated using a dynamic programming algorithm.

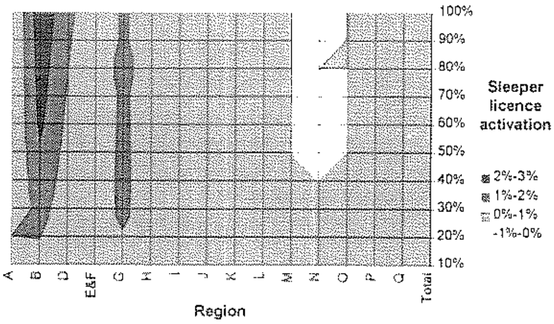

Figure 3. Percentage impact on total farm profit of sleeper licence activation.

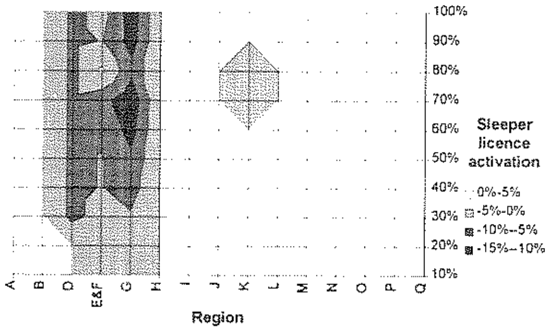

Figure 4. Percentage impact on median non-zero flows of sleeper licence activation.

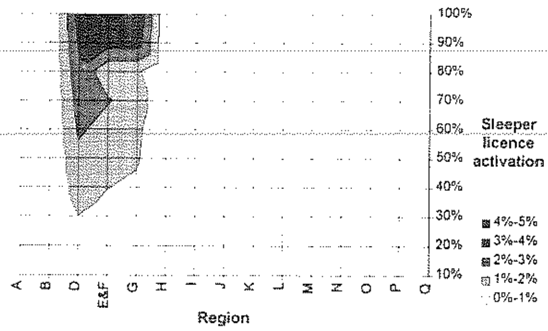

Figure 5. Percentage impact on the number of zero flow days of sleeper licence activation.

The regional scale economic models are then integrated with a hydrological flow network using a policy model and a daily extraction model. Daily flows are simulated using a modified version of the IHACRES rainfall-runoff model [Jakeman and Hornberger, 1993]. These flows from the hydrological network are used to provide surface water extraction limits for each year in a twenty year period to the regional farmers, depending on surface water extraction policies. The impact of economic decisions on flow left at each node is also simulated.

Table 3. Comparison of case studies

	MAE CHAEM	YASS	NAMOI
Spatial scales Catchment (km^2) Number of nodes	 100 (x5 subcatchments) 2	 1000 4	 40,000 16
Activities	Seasonal irrigated and dryland crops (extractive)	Farm forestry Viticulture (supplementary irrigation) Irrigated cropping (extractive) Grazing	Rotation based irrigated and dryland options
Policies	Erosion control Forest encroachment Upland development Infrastructure investment	Farm Dams Volumetric conversions Daily flow extraction rules Forestry/Salinity Environmental Flow	Off-allocation Groundwater allocation reductions Sleeper licence activation Volumetric conversion Daily flow extraction rules Environmental flows
Time Scales ***H = hydrology*** ***E = economics*** ***C = crop***	H – daily E – seasonal (multi-period) C – 10 day	H – daily E –20 years C – subannual	H – daily E – 20 years C – non-varying
Economic modelling	Short run LP Expectations-based decisions	Short run LP Perfect knowledge assumed	Long run DP Short run LPs Perfect knowledge
Production/Yield	Crop-water balance model Climate influenced	Empirical Climate influenced	Empirical Not climate influenced

Extracted flows are then routed to downstream nodes using a variable parameter Muskingum-Cunge method [Ponce and Yevjevich, 1978]. In this way the impact of decisions made by regional farmers at upstream nodes is simulated on downstream users. Figures 3, 4 and 5 illustrate the types of results which are able to be generated using the model. Figure 3 shows the percentage change in total farm profit from the base case (or current situation) over the simulation period for each of the model regions for a range of percentage activation of sleeper licences in all regions. This shows the economic impact of sleeper licence activation across regions. Figure 4 shows the impact on median non-zero flows as a percentage change from the base case (current situation) and Figure 5 shows the impact on the number of zero flow days at each node in the system. These two charts describe the impact of policy changes on streamflow.

These Figures illustrate the way in which trade-offs between regions as well as between environmental and economic indicators may be portrayed very simply and assessed quickly using the decision support tool.

7. DIFFERENT TREATMENT OF IAM AMONG THE THREE CASE STUDIES

In the previous case studies, many factors affected the way the integrated assessment and modelling was undertaken. These factors included the nature and scale of the issues, the data and information available, modelling requirements, time constraints for producing an assessment, and the stakeholders involved. Table 3 captures some of the differences to illustrate that IA is a subjective process where the context shapes the approach. Necessarily then, the process should be a transparent one where the assumptions and other limitations are spelt out as far as possible. This assists in validating the process

with stakeholders. The process needs also to be an adaptive one where new or improved information can be incorporated.
Appropriate processes for validating IA models have yet to be fully developed, however practitioners of IA modelling agree that this validation should not just be the traditional 'history matching' approach to validation that is undertaken in other areas of modelling [Parker et al., 2001]. An important component of the process of validating IA models is an adaptive feedback between stakeholders and researchers. Allowing stakeholders to alter key system assumptions where they feel results do not reflect realities on the ground is an important part of this process, both for validation and for increased adoption of results and recommendations arising from the IA modelling exercise.

A key difference among the case studies is the scale of the IA problem. Clearly in a 100 square kilometre catchment (Mae Chaem subcatchments), relationships can, and often need to, be modelled in more detail than in one of 40,000 km^2 (Namoi). Thus a crop and water balance model is used in the former case but only empirical relationships are applied to predict yields in the latter. Correspondingly, the capability to represent the effects of climate variability have been included in the two smaller scale case studies and could have been applied in the larger one for a little more effort. However, more complex, long run dynamic programming is used in the Namoi because of the special interest in incorporating the effects of capital investment on the water allocation decisions. On the other hand the hydrology is modelled daily in all case studies because of the need to consider extractions from the rivers on that time step, and because even in the Namoi it is technically feasible to model accurately enough on a daily step.

The way in which the economic component is treated in the three case studies differs depending on both the scale of the modelling and the issues being considered by the model. In the Namoi case study, regional farmers are given a relatively small number of possible crop rotations to choose from, but a broader range of capital investment decisions. This is due to the long run, capital intensive nature of the off-allocation water issue for which the model was developed. In the Yass case study a very broad range of farm types and land use activities are considered, but in a simpler short run decision framework. In this catchment at this scale, water issues were seen as being impacted by a broader range of land uses, both through direct extractions from the stream and indirectly by forest cover and farm dam development change. Capital investment was not considered to be a crucial part of this system and so was not modelled. In the Thai case study, the focus on the household scale meant that factors influencing household decision making capabilities, such as a lack of certainty about outcomes, were taken into account, but decisions to invest in capital were not considered to be crucial in this system.

8. CONCLUSIONS

Effective and equitable management of our natural resources has many dimensions. Integrated assessment is a process which attempts to address these dimensions and the need for more informed management. IA modelling and information systems recognise the complexity of natural systems and human interactions with them. The three examples presented illustrate the potential value of IA modelling in quantifying the biophysical and socioeconomic impacts that may result from management interventions and uncontrollable factors.

In particular, our conclusions are that:

- Analysis frameworks for characterising integration problems have come of age, but there is still much that is problem-specific: scales, models and their linkages vary. However it is mainly by continuing to perform IA on specific problems that this emergent discipline will fully mature.
- Enhanced credibility and utility of IA for decision makers necessitates more comprehensive model testing and in particular the development and application of methods of uncertainty characterisation. For complex, data-deficient systems of the type that occur in IA problems, this is a challenge which is essential to meet.
- Data availability is a severe constraint for obtaining more informed and confident decision support. Increased confidence in outputs of IAM exercises begs for high leverage measurements, on the nature of which modelling itself can provide guidance. Typically, more measurement information is required about system behaviour such as fluxes of water and pollutants, as well as key information on social and economic systems within catchments.