Incorporating uncertainty into adaptive, transboundary water challenges: a conceptual design for the Okavango River basin

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Abstract: In this paper, we present a review and conceptual design to integrate hydrological/ecological models, global uncertainty and sensitivity analysis, integrative modelling and decision analysis for complex and adaptive transboundary challenges. The research uses the transboundary issues within the Okavango River basin, a shared water resource among the nations of Angola, Namibia and Botswana, as an example for constructing these integrated tools. The objective of this paper is to present a design that integrates a set of tools that builds systematically on past basin modelling research to incorporate the inherent uncertainty within the system and its application for answering practical management questions.

Keywords: Okavango River basin; uncertainty analysis; AM; adaptive management; global sensitivity analysis; QnD model; decision analysis.

Reference to this paper should be made as follows: Kiker, G.A., Muñoz-Carpena, R., Wolski, P., Cathey, A., Gaughan, A. and Kim, J. (2008) 'Incorporating uncertainty into adaptive, transboundary water challenges: a conceptual design for the Okavango River basin', *Int. J. Risk Assessment and Management,* Vol. 10, No. 4, pp.312–338.

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1 Introduction

Water-limited ecosystems in southern Africa have challenged humans, flora and fauna to thrive within a highly variable climate (Kniveton and Todd, 2006; Mendelson and Obeid, 2004). Recent research and development in the Okavango River basin have highlighted both opportunities and obstacles in maintaining one of Africa's last pristine river basins flowing into a internationally recognised wetland system (Kgathi et al., 2006; Mendelson and Obeid, 2004; Turton et al., 2003). Several internationally funded scientific/management efforts have provided basin authorities with systematic data, models and tools for international cooperation and development (EU, 2007; TWINBAS, 2007; USAID, 2007). Given these previous efforts in modelling, monitoring and data analysis, an appropriate next step is to systematically incorporate uncertainty analysis into modelling tools within the Adaptive Management (AM) structures.

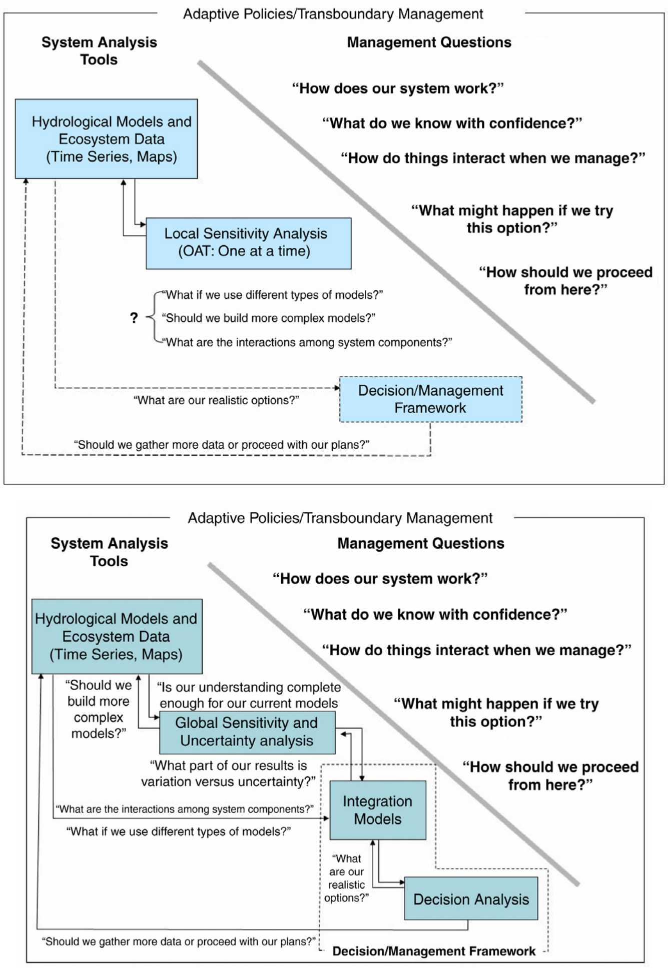
Hydrological and water quality models are often complex and require a large number of inputs. Such mathematical models are built in the presence of uncertainties of various types (input variability, model calibration data and scale). In addition, there is a growing interest in evaluating the contribution of model structural uncertainty (i.e. from model algorithms and design) to the overall uncertainty of the model outputs (Beven, 1993; Beven and Binley, 1992; Draper, 1995).

The role of uncertainty analysis is to propagate all these uncertainties onto a model output, while sensitivity analysis is used to determine the strength of the relation between a given uncertain input and a model output. Thus sensitivity analysis identifies the key contributors to uncertainties, while uncertainty analysis quantifies the overall uncertainty, so that together they contribute to a reliability assessment of the model (Scott, 1996). Although these analyses are critical to efficiently guide the inverse calibration of models as well as to document the validity of the model outputs for management or decision tasks, they are rarely applied in most practical modelling research (Beven, 2006; Shirmohammadi et al., 2006). Currently, this is the case with the previous modelling efforts in the Okavango River basin.

One of the principle objectives of AM is to incorporate uncertainty within practical management (Gunderson et al., 1995). Much of the academic literature on AM emphasises the necessity of embracing the inherent uncertainty that pervades most complex ecological challenges without providing functional tools for its analysis and understanding. Because practical tools are few, most functional management of transboundary resource issues effectively ignore systematic treatment of uncertainty issues. Figure 1(a) shows the interactions of current analysis tools within a management/policy context. More often than not, fundamental management questions are left unanswered by the systems analysis tools focusing on matching data and model complexity.

Incorporation of these uncertainty issues within adaptive water management challenges demands an organised and methodical tool set that can help to parse through the often disparate and complex data that are integrated within an AM framework. Figure 1(b) shows the advantages in utilising additional tools focused on uncertainty and integration. Recently developed tools include global sensitivity/uncertainty analysis methods (Muñoz-Carpena et al., 2007; Saltelli et al., 2004) and integration/decision analysis tools (Kiker et al., 2005, 2006). The authors suggest that these additional tools can help to answer both technical model/data questions as well as the functional management questions listed in the upper right corner of Figure 1(b).

Figure 1 (a) While systems analysis tools address technical questions concerning model development and data accuracy, often there are gaps between these tools and the actual management questions that need to be answered and (b) additional tools and methods can help to address the technical questions concerning model development and data accuracy while linking the information from models and data to systematic decision analysis tools to specifically address practical management questions (see online version for colours)



The primary objective of this paper is to provide a conceptual framework for incorporating systematic uncertainty and decision analysis tools into adaptive transboundary management. These tools can build upon previous modelling and monitoring efforts to allow researchers, decision makers and stakeholders to work together in addressing functional decision-relevant issues within highly variable environments. The objectives of the paper include the following:

- Provide a brief review of relevant concepts including:
  - Okavango River basin management issues and past modelling efforts
  - recent tools available for addressing sensitivity, uncertainty and parameter estimation

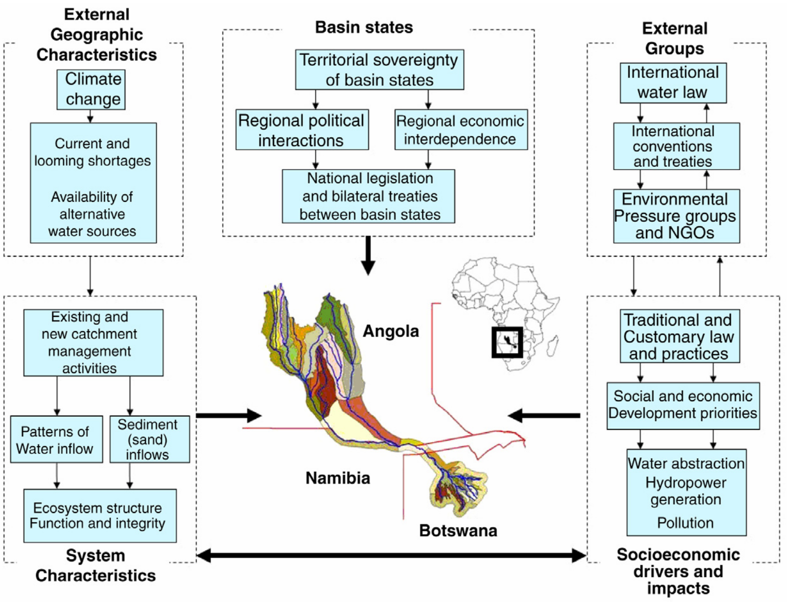
– AM and decision analysis methodologies along with their use in governmental agencies.

- Provide a conceptual design for a set of tools that incorporate past modelling information and monitoring data into a management-focused system that can functionally incorporate uncertainty issues into AM frameworks.

2 Conceptual review: transboundary issues and hydrologic modelling in the Okavango River basin

Authors have described the Okavango River basin as the contributing areas of the perennially-flowing Cuito and Cubango/Okavango Rivers entering into the Okavango delta (Mendelson and Obeid, 2004). Some basin descriptions also describe the areal contribution from the Omatako River and other dry fossil basins which have rarely had any direct contact with the Okavango basin or its flow into the greater Makgadikgadi basin system (Ashton and Neal, 2003). Because of its perennial flows, pristine water, low levels of human development and its internal drainage into the internationally recognised delta (Ellery and McCarthy, 1994), the Okavango River basin has attracted a significant amount of scientific and social attention concerning its ecosystems, its management and its future state (Ellery and McCarthy, 1994; Kniveton and Todd, 2006; Mendelson and Obeid, 2004; Ramberg, 1997; Turton et al., 2003). Figure 2 shows a conceptual map (adapted from Ashton and Neal (2003)) of the issues facing basin management focusing on the three basin states (Angola, Namibia and Botswana) as trustees of the national-scale interests of citizens. Climatic, hydrological and socio-economic issues are often intertwined among various national and international interests within the basin.

Figure 2 Conceptual diagram of key strategic issues that influence decision making in the Okavango River Basin (see online version for colours)



Source: Adapted from Ashton and Neal (2003).

As a mechanism for addressing these complex transboundary issues, the three nations that share the primary basin formed the Permanent Okavango River Basin Water Commission (OKACOM). Under a primary guiding principle of 'three countries, one river', OKACOM has the following mission objectives (OKACOM, 2007):

- determine the long term safe yield of the river basin
- estimate reasonable demand from the consumers
- prepare criteria for conservation, equitable allocation and sustainable utilisation of water
- conduct investigations related to water infrastructure
- recommend pollution prevention measures
- develop measures for the alleviation of short term difficulties, such as temporary droughts.

The 'hydropolitical' dynamics of this region are fundamental to implementing and maintaining a collaborative/AM framework in the Okavango Basin as OKAKOM has no formal mechanisms for enforcement (Turton et al., 2003). Within these management dynamics inherent to complex transboundary issues, Turton et al. (2003) describes the important role of 'uncontested data'. One vital aspect is the systematic testing of this data with modelling tools to provide a systematic understanding of how the uncertainty inherent in such varying data can be used to provide viable management strategies. Once these basic data and modelling elements are established via consensus, various management schemes can be brought forward for consideration by transboundary managers. These data and modelling tools should help to address not only current issues such as flow quantity but also help to set analysis strategies for emerging/uncertain issues such as sediment load and water quality.

Table 1 summarises past and recent hydrologic modelling efforts in the Okavango basin. These models represent flow in the basin using various techniques including rainfall-runoff simulations in the river, flooding extents within the delta and/or outflow from the delta. This list includes both numerical models and flood map models based on satellite imagery. It is important to note that each of these modelling efforts attempted to address different questions of concern to river basin managers. These basic questions are presented along with a technical summary of the model structure and execution.

Modelling efforts in the Okavango River, upstream from the delta, have largely involved the Pitman model. The Pitman model (Pitman, 1973) was developed for southern Africa and is a rainfall-runoff model that consists of storages linked by functions. Since its conception, the Pitman model has gone through a number of revisions none of which have introduced uncertainty analysis. The model simulates soil moisture and runoff taking into account impervious area, interception, catchment absorption, surface runoff, groundwater recharge, evaporation, dam storage and abstractions (Hughes et al., 2006). To run the model, the minimum data requirements consist only of monthly rainfall and potential evaporation. Andersson et al. (2003) incorporated the Pitman model into SPATSIM to model the hydrology of both the Okavango River and delta. Most of the basin-level modelling efforts listed in Table 1 sought to provide a fundamental rainfall dataset (Wilk et al., 2006) and a basic hydrological model platform (Hughes et al., 2006) for simulating future development and climate change scenarios in the upstream areas (Andersson et al., 2006).

Table 1 A summary of hydrological models applied to sections of the Okavango River basin

Author/Date	*Title*	*Portion of basin modelled*	*Model conceptualisation*
Pitman (1973)	A mathematical model for generating river flows from meteorological data in South Africa	Okavango River upstream from the panhandle	Rainfall/runoff model
Andersson et al. (2003)	Water flow dynamics in the Okavango River basin and delta – a prerequisite for the ecosystems of the delta	Okavango River, panhandle and delta	Rainfall, runoff model combined with a linked reservoir model
Andersson et al. (2006)	Impact of climate change and development scenarios on flow patterns in the Okavango River	Okavango River upstream from the panhandle	Rainfall, runoff model for different climate changes and development scenarios
Hughes et al. (2006)	Regional calibration of the Pittman model for the Okavango River	Okavango River upstream from the Panhandle	Rainfall/runoff model
Wilk et al. (2006)	Presentation of a historical database for rainfall-runoff modelling (Pitman model) for the Okavango River basin	Okavango River upstream from the panhandle	Database and rainfall/runoff model
Dinçer et al. (1987)	A simple mathematical model of a complex hydrologic system – Okavango swamp, Botswana	Delta and panhandle	Linked reservoir model
SMEC (1990)	Southern Okavango Integrated Water Development	Delta and panhandle	Linked reservoir model
Scudder et al. (1993)	The IUCN review of the Southern Okavango Integrated Water Development Project	Delta and panhandle	Linked reservoir model
WTC (1997)	Feasibility study on the Okavango River to Grootfontein link of the Eastern National Water Carrier	Delta and panhandle	Linked reservoir model
Geiske (1997)	Modelling outflow from the Jao/Boro system in the Okavango Delta, Botswana	Boro River	Linked reservoir model
Bauer et al. (2003)	A spatially distributed hydrological model for the Okavango Delta	Delta and panhandle	Finite difference surface and groundwater model based on MODFLOW
Gumbricht et al. (2004)	Forecasting the spatial extent of the annual flood in the Okavango Delta, Botswana	Delta and panhandle	GIS based regression model of maximum annual flood inundation
Wolski et al. (2002)	Assessing future change in the Okavango Delta: the use of a regression model of the maximum annual flood in a Monte Carlo simulation	Delta and panhandle	Annual lumped regression model of flooding and satellite flood images

Table 1 A summary of hydrological models applied to sections of the Okavango River basin (continued)

Author/Date	*Title*	*Portion of basin modelled*	*Model conceptualisation*
Wolski et al. (2006)	Modelling of the hydrology of the Okavango Delta	Delta and panhandle	Integrated reservoir and GIS model
Murray-Hudson et al. (2006)	Modelling the effects upstream hydrology and landuse changes on hydro-ecological components of the Okavango Delta	Delta and panhandle	Integrated reservoir and GIS model
TWINBAS (2007)	Comparison of five international River basins for Integrated Water Resources Management using MIKE/MIKE-SHE modelling suite	Delta and panhandle	MIKE SHE, MIKE 11

Note: The models are listed by date and by area of application within the basin.

Several hydrologic modelling efforts in the delta (Dinçer et al., 1987; Gieske, 1997; Scudder et al., 1993; SMEC, 1990; WTC, 1997) used linked reservoir models to represent the physical hydrology of the system. Specifically, studies conducted by Dinçer et al. (1987), SMEC (1990) and Scudder et al. (1993) were initiated to explore the question of how much delta water could safely be extracted for human use and development (Wolski et al., 2006). In addition, the WTC (1997) and Gumbricht et al. (2004) efforts explored the level of upstream abstractions that would negatively affect the delta. Wolski et al. (2006) and Murray-Hudson et al. (2006) also explored different climate drivers and upstream influences. As a linkage to upstream modelling efforts, Murray-Hudson et al. (2006) provides both climate change and land use change scenarios for possible long and short term effects on delta hydrology and selected ecological (vegetative/trophic) processes. These authors also suggest that sediment load and water quality factors, two lesser studied systems drivers, could play a significant role in determining the ecological health of the delta.

As a result of some modelling efforts, inconsistencies were found in the outputs when modelling a number of years: the first years were representative of the system but accuracy dropped off after several years. Various explanations were offered for this discrepancy. Dincer et al. (1987) and SMEC (1990) proposed that temporal changes in channel morphology altered the flows. Conversely, Scudder et al. (1993) and WTC (1997) proposed that errors in rainfall data caused the inconsistency and applied rainfall correction factors to the models. Gieske (1997) modelled groundwater fluctuations as a result of antecedent rainfall conditions to increase model accuracy and explain the discrepancy.

Subsequent modelling efforts in the delta have involved the use of a variety of techniques. Bauer et al. (2003a,b) and Bauer (2004) used a model based on MODFLOW to simulate surface and groundwater interactions in the delta. Gumbricht et al. (2004) used a GIS regression model based on satellite imagery to forecast the maximum annual flooding extent in the delta. Wolski et al. (2002) considered future flooding patterns within the delta based on a Monte-Carlo simulation using both a regression model and modelled flood maps. The question of inconsistencies and declining accuracy between modelled and observed data mentioned earlier was resolved by Wolski et al. (2006) to be attributable to longer term effects of surface water-groundwater interactions-based results of earlier simulations (Wolski and Savenije, 2006). One fundamental uncertainty highlighted by Murray-Hudson et al. (2006) is the role of consistency and accuracy of the various General Circulation Model/Global Climate Model (GCM) predictions of future basin climates. The authors noted that the variation in these predictions often had more influence over delta processes than land use changes in the upper basin. While Table 1 shows that a variety of modelling efforts have been conducted in the Okavango basin, the net result is an impressive body of modelling analysis which nevertheless lacks in integration and has yet to provide the 'uncontested data' sought by basin managers. Furthermore, there is a conspicuous lack of uncertainty and sensitivity analysis within the models.

3 Tools for incorporating uncertainty into model development and parameterisation

3.1 Global sensitivity analysis and uncertainty

Often when model sensitivity analysis is performed simple derivation techniques (variation of the model output over the variation of the model input) are employed. As an alternative, sometimes a crude variational approach is selected in which, instead of a derivative, incremental ratios are taken by moving factors one at a time from the base line by a fixed amount (e.g. 5%) without prior knowledge of the factor uncertainty range. Traditional sensitivity analysis methods are limited since they only explore a prescribed (and usually small) parametric range, and only can only consider efficiently a few inputs since they based on One-parameter-At-a-Time (OAT) approaches (Saltelli et al., 2005).

When the model output response is non-linear and non-additive, as with most complex model outputs, the derivative techniques are not appropriate and global techniques that evaluate the input factors of the model concurrently over the whole parametric space (described by probability distribution functions) must be used. Different types of global sensitivity methods can be selected based of the objective of the analysis (Cacuci, 2003; Saltelli et al., 2000, 2004). This study proposes a model evaluation framework (Muñoz-Carpena et al., 2007) around two such modern global techniques, a screening method (Morris, 1991) and a quantitative variance-based method (Extended Fourier Analysis Sensitivity Test (FAST) Cukier et al., 1978; Saltelli et al., 1999). The screening method allows an initial reduction in the number of parameters to use in the quantitative FAST sensitivity and uncertainty analyses. The proper use of global sensitivity methods can yield four main products for the Okavango application: assurance on the model's behaviour (absence of errors), ranking of importance of the parameters for different outputs, effect of changing modelling structure and type of influence of the important parameters (first order or interactions) (Saltelli, 2004). In addition, based on the outputs derived from this analysis a complete uncertainty assessment of the model application can be obtained and used as the basis for the risk assessment of proposed management scenarios for the region.

3.2 Spatial sensitivity analysis

Spatial models are complex and involve various types of data (static versus dynamic, raster versus vector, quantitative versus qualitative or categorical, 1D versus 2D or 3D) that can have different lineage (different data acquisition sources) and hence can have different types of associated uncertainty (Crosetto and Tarantola, 2001; Heuvelink, 1998). Virtually, all data stored in GIS are in some extent contaminated by error (Heuvelink and Burrough, 1993).

Despite the need for the evaluation of confidence in a model for reliable decision making, the deterministic approach has been most widely adopted in the field of the GIS modelling (Crosetto and Tarantola, 2001). In fact, most GIS do not even carry information about the uncertainty of source maps in the spatial database (Heuvelink 1998).

Global SA and UA can help to explore model behaviour, identify factors with smallest and largest influence on outputs, identify factors that need to be estimated more accurately, characterise interactions between factors and determine possible simplifications of the model (Wallach et al., 2006). The global UA and SA techniques allow the user to adopt a stochastic approach to GIS-based modelling, that is, to consider the propagation of errors (Crosetto and Tarantola, 2001) which is especially important for risk assessment.

SA and UA can support the development and implementation of spatial (GIS-based) hydrologic models. Both techniques can be used synergistically for evaluating complex spatial models, as described by Crosetto and Tarantola (2001). This approach involves preliminary analysis by the Modified Morris Method and variance-based Extended FAST methods and is very suitable for the optimisation of implementation of complex systems and for spatial models development.

Since the implementation of stochastic approach is expensive, SA and UA can be used for optimisation of resources. One of the most important (and resources demanding) aspect of spatial modelling is data acquisition. SA can optimise the allocation of resources for data acquisition by indicating which factors are the most important for the output of interest. If the uncertainty of the model output is larger than decision maker wishes to accept, it is necessary to improve the quality of the input factors, starting from the inputs with the highest impact.

Another approach to SA of spatial models was presented by Hall et al. (2005), where the method of Sobol (1990) and the Replicated Latin Hypercube Sampling have been applied for uncorrelated and correlated factors, respectively.

As discussed by Hall et al. (2005) input factors may not be universally important across the model domain. The location of the input factor within the domain may affect model output variably. In that case the SA can be performed for spatially desegregated factors for indicating not only factors of importance but also their location in the domain.

3.3 Inverse parameterisation

When modelling a complex system like the Okavango basin the modeller faces the challenge of identifying the appropriate model parameters for the specific application conditions. Parameters needed to run the model could be obtained from field measurements as well as by inverse calibration of the model based on varying the parameter set to match observed data. When possible, local hydrological data (rainfall, evapotranspiration, runoff, river flow rate, soil moisture through the watershed, etc.) should be collected to support the modelling predictions. Although manual model calibration is often used based on the collected data, this procedure generally lacks objectivity and the outcome is linked to the expertise of the user. An automated inverse optimisation procedure can be used as an objective and robust model calibration alternative. This procedure provides effective parameters in the range of the particular model applications and overcomes the drawbacks of manual calibration (Ritter et al., 2003). Different techniques have been developed in the past to numerically solve inverse problems. Among others, we may consider methods such as the Steepest Descendent, Newton's, Gauss, Levenberg-Marquardt, Simplex and Global Optimisation Techniques (Hopmans and Simunek, 1999). Each of these has its own advantages and drawbacks, and the success of finding the global minimum depends generally on the presence of multiple local minima in the objective function. In addition to these algorithms, the Global Multilevel Coordinate Search combined with a Nelder Mead Simplex (GMCS-NMS) is a powerful available alternative because it is adapted for solving complex non-linear problems accurately and efficiently, does not require powerful computing resources and initial values of the parameters to be optimised are not needed (Lambot et al., 2002; Ritter et al., 2003). This consists in the sequential combination, as described by Lambot et al. (2002), of the global optimisation algorithm developed by Huyer and Neumaier (1999) and the classical Nelder-Mead Simplex (Nelder and Mead, 1965). This procedure offers confidence intervals of the optimised factors which can be used on the uncertainty analysis on the model as described above. As discussed later in this research, this robust and efficient optimisation technique was selected to calibrate management models to existing data in the Okavango basin.

4 AM and decision analysis tools within governmental agencies

4.1 AM and its implementation within governmental agencies

Water resource management in the Okavango basin is a complicated task due to hydropolitical dynamics, the complexity of the system and its transnational scale. AM has been advocated for the management of such natural resources because it explicitly addresses the uncertainty that exists in complex and variable systems by basing decisions on learning-by-doing experiments (Parma and NCEAS Working Group on Population Management, 1998; Shea and NCEAS Working Group on Population Management, 1998). AM recognises that the nature of conservation plans is often experimental rather than proven.

AM is an understood, if not standardised, framework for approaching natural resource management. The definition of AM takes on different forms depending on the context, approach and involved stakeholders (Agrawal, 2000; Johnson, 1999; Parma and NCEAS Working Group on Population Management, 1998; Walters and Holling, 1990). The recent publication *AM for Water Resources Project Planning* (NRC, 2004) provides a comprehensive six-step description of AM processes.

1 management objectives which are regularly revisited and accordingly revised

2 a model of the system(s) being managed

3 a range of management choices

4 monitoring and evaluation of outcomes

5 a mechanism(s) for incorporating learning into future decisions

6 a collaborative structure for stakeholder participation and learning.

Satterstrom et al. (2006) provides a review of US federal agency implementation of the six AM principles. Modelling and monitoring (steps 2 and 4) figure prominently in agency AM plans. However, few AM efforts explicitly discuss updating and revising objectives as new information is acquired (step 5). In addressing the range of management choices (step 3), most examples include ‘passive’ AM efforts centred around a single policy instead of a range of management choices. Additionally, the models generally only address ecological processes, leaving out decision alternatives as well as costs and social considerations.

Anderson et al. (2003) present a useful description of adaptive decision making and its relationship with uncertainty. In addition, the authors highlight the linkage of decision heuristics with internal and external social contexts to help select the most appropriate form of AM. A significant challenge to advocates of AM is the accounting of various social and institutional drivers that create unstable and uncertain foundations upon which adaptive framework can unwittingly be constructed.

For large spatial regions that include natural resources such as wildlife and water, an Adaptive Co-Management (AC-M) framework which incorporates AM with cooperative management may be appropriate (Olsson and Folke, 2004). Within AC-M this learning by doing framework is paired with the acknowledgment of the importance of the shared responsibilities and rights of stakeholders (Ruitenbeek and Cartier, 2001). With AC-M this learning by doing framework is paired with the acknowledgement of the importance of the shared responsibilities and rights of stakeholders. AC-M also incorporates through participation the traditional knowledge, values and beliefs inherent within a complex system (Olsson and Folke, 2004). An important characteristic of AC-M is the acknowledgement that different scales of governance working in a cooperative fashion are a necessity to successful natural resource management. The power sharing and decision-making process must be shared across community-based resource managers, government agencies and any other invested stakeholder, such as non-governmental organisations. The complexity of the institutional design and collaboration amongst stakeholders whose dependence on the system’s resources varies presents a difficult challenge that increases uncertainty with increasing geographic and human relation scales (Sneddon, 2002).

Natural resource management within an complex system is described by Murphree (2000) as a mosaic of interacting community land units, each having their own rights and resources, With collective action, caution must be taken that the imposition of a national or regional level adaptive strategy does not weaken the local, traditional structures and subsequently decrease the amount of resilience in a system (Gelcich et al., 2006). To be successful, AC-M requires flexible processes that incorporate the multiple levels of participation and knowledge. If laws and policies remain in a fixed procedural process the ability of an AC-M to properly manage resources over a large geographical scale becomes restrained (Tarlock, 1994).

4.2 Decision analysis and Bayesian tools for uncertainty analysis

Decision analysis is a tool for contributing to better decisions by helping managers to structure the problem, balance risks and compare options based on outcomes and expressed preferences (Figueira et al., 2005; Keeney and Raiffa, 1976). Various alternatives are assessed in terms of multiple, user-selected criteria for a systematic analysis of tradeoffs. Often an optimised solution does not exist when incorporating various stakeholder values into the weighting of criteria. The primary focus of these decision analysis techniques is the identification of trade-offs among alternatives. Kiker et al. (2005) provides a review of various multicriteria decision analysis techniques as well as their implementation within environmental risk analysis applications.

Bayesian analysis, a fundamental concept in decision analysis, is an approach to quantify the uncertainties and can be used to quantify how additional information might affect the likelihood of alternative 'states of nature' (e.g. hypotheses) and trace how research could alter decisions. The advantage of Bayesian analysis is that the approach is a practical and theoretically attractive way for updating beliefs about uncertainties in light of information from empirical observation, modelling or expert judgment. For example, the actual state of a system is unknown, along with the structure or parameters of its dynamics. Beliefs about these can be represented by so-called 'prior' probability distributions, while Bayes' law can use new information (from experiments, monitoring or expert judgment) to 'update' those distributions, resulting in 'posterior' distributions. Additional information on this relationship is found in the Appendix (2). Management can take actions to observe the system (e.g. modelling, lab experiments, mesocosm manipulation, large scale experiments) and to control the system (alter its structure or state). The rigorous assessment of the value of decreasing uncertainty through these potential management actions requires explicit consideration of the likelihood of alternative possible outcomes of the research and monitoring and the effects of that information on decisions.

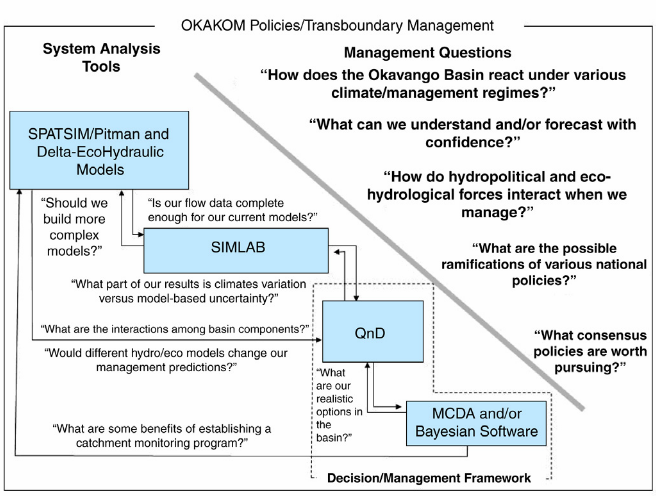
The Bayesian decision analyses can yield various indices that interest decision-makers that aid in ranking decision alternatives. These indices include: quantification of value, analysis of the performance penalty that results from disregarding uncertainty (i.e. the expected cost of ignoring uncertainty) and the quantification of expected improvement in performance associated with decreased uncertainty through information acquisition or new study (i.e. expected value of perfect or imperfect information).

This approach has been applied to environmental decision problems such as contaminated site remediation to estimate the value of information with a simple analytical loss function (Dakins et al., 1996), monitoring for water quality management (Varis and Kuikka, 1999), greenhouse gas mitigation (Manne and Richels, 1991), Lake Erie ecosystem management (Kim et al., 2003) and wetlands management under climate change uncertainty (Bloczynski et al., 2000).

5 Integrated water resource modelling and uncertainty analysis: a conceptual design

The following sections highlight a conceptual model of how modelling research, uncertainty analysis, AM and decision analysis can be linked to help answer management questions. This conceptual design is offered as a starting point for discussions concerning the integration of recent modelling and monitoring efforts within a systematic treatment of uncertainty in service to an adaptive, transboundary, basin management plan. Figure 3 provides a conceptual blueprint with specific tools and Okavango-related questions.

Figure 3 A conceptual design for integrating systems analysis tools to address practical management questions within the Okavango River Basin (see online version for colours)



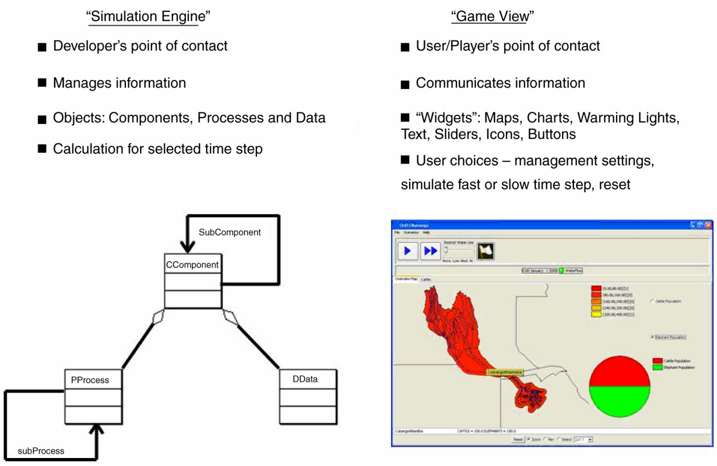
5.1 *Management-focused, integration models: introduction to the QnD system*

The Questions and Decisions™ (QnD™) model system was created to provide an effective and efficient, open-source, decision education tool. QnD incorporates ecosystem, management, economics and socio-political issues into a user-friendly model/scenario framework (Kiker and Linkov, 2006; Kiker et al., 2006). The QnD model utilises a basic finite difference approach with simple Euler numerical integration of various rate transformation and mass-balance transfer equations (Keen and Spain, 1992) as defined by the input files.

The model is written in object-oriented Java and can be deployed as a stand-alone program or as a web-accessed tool. The QnD model links the spatial components within GIS (ArcInfo Shape) files to the abiotic (climatic), biotic and chemical/contaminant interactions that exist in a watershed. The model can be constructed using any combination of detailed technical data or estimated interactions of the ecosystem elements. The model development is iterative and can be initiated quickly through conversations with users or stakeholders. Model alterations and/or more detailed processes can be added throughout the model development process. QnD can both provide rigorous modelling to mimic system elements obtained from scientific data or to create a 'cartoon' style depiction of the system to promote learning and discussion among decision participants.

The QnD system has two primary parts: the game view and the simulation engine as shown in Figure 4. The game view has several types of outputs that can be configured by the user via e**X**tensible **M**arkup **L**anguage (XML) file inputs. By presenting selectable outputs, QnD allows users to choose how they want to see their output, including the following output options: GIS Maps that are updated on each time step; Warning lights that change at user-selected critical levels; Mouse-activated charts and text for individual spatial areas (pie charts and text line descriptions); Time-series charts (listed on several tabbed pages); Text output files (in comma separated format).

Figure 4 QnD model structure (see online version for colours)



Source: After Kiker et al. (2006).

The QnD simulation engine is made of objects linked together into simple or complex designs, determined by the needs of decision participants. The most elemental objects of QnD are Components, Processes and Data as shown in Figure 4. A Component is an object that is of interest to the user, such as a specific pollutant or biological entity (i.e. elephants, trees, fish or benthic invertebrates). Processes are the actions that involve Components and their Data. Data are the descriptive objects assigned to various Components. Components objects are situated into the virtual QnD landscape and can interact with each other over space and time. Within the QnD object framework, both simple and complex designs are possible. In more complex designs, building block components and processes designed as clusters of subcomponents or subprocesses.

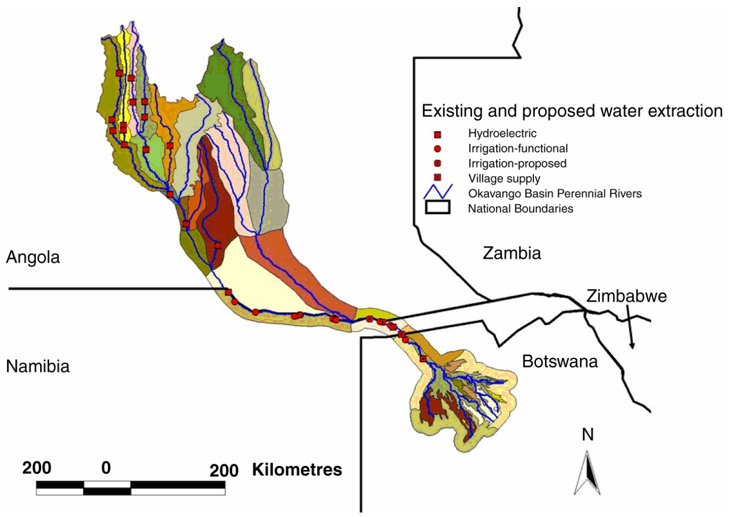
Upon startup, specialisd internal QnD objects read the relevant XML input files and create all the engine parts (Components, Processes and Data) as well as the game view (maps, charts and management options) required for the simulation. Users can manipulate the game view in the following ways: Set some management options (using the slider bars); View the map page and switch between maps; View the various Chart pages; Simulate time steps at user-defined levels; Reset the game to the startup conditions.

5.2 *QnD:Okavango: a design for integrating previous modelling research into an AM framework*

Initial design and implementation of QnD within the Okavango Basin follows an iterative structure described in Kiker and Linkov (2006). The structure of the model can be established and altered iteratively to allow discussions concerning the most appropriate level of detail to achieve management objectives. Figure 5 shows an initial conceptual design of QnD:Okavango. The scope and initial design builds upon the recent modelling research for the river basin and delta (Andersson et al., 2006; Hughes et al., 2006; Murray-Hudson et al., 2006; Wolski et al., 2006). We propose that the individual 24 river subcatchments of the Okavango Basin (Hughes et al., 2006) be used for the river basin section with some additional features added. Subcatchments that cross national borders are divided to reflect the catchment areas and river reaches controlled by each nation. As the delta region was represented by one large area in the original coverage (USAID, 2005), the subcatchment coverage was merged with a coarse vegetation map of the delta to allow a simplified simulation of the delta biomes of interest. Any ecological and/or vegetation modelling within QnD:Okavango would be based upon the elementary relationships described qualitatively in Murray-Hudson et al. (2006) or through ongoing modifications to this work. The resulting map in Figure 5(a) gives 47 different areas for individual simulation within QnD:Okavango. The initial engine design can be configured with SPATSIM/PITMAN simulation results for each basin/subbasin combination upstream of the delta. As with Andersson et al. (2006), flow scenarios can be simulated with simplified ecological algorithms or with estimated in-stream flow requirements. In addition, abstractions from various planned or proposed water schemes from each nation could be instituted on a month by month basis.

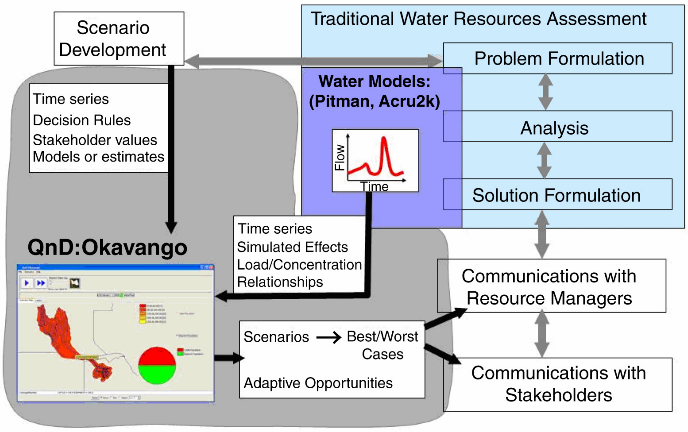
Once constructed, the QnD:Okavango can be used to simulate various 'what-if' scenarios for exploring the AM strategies with respect to water releases or abstractions from various catchments (Figure 5(b)). Tactical options on a month by month basis can be simulated in a game-style fashion to facilitate potential decision heuristics for analysis in longer term simulations. In addition, strategic options of when to implement specific abstraction projects can be explored through Monte-Carlo style simulations linked with Multi-Criteria Decision Analysis (MCDA) software.

Figure 5 (a) An initial spatial design for QnD:Okavango focusing on river subcatchments, national borders and delta vegetation zones and (b) implementation of QnD model versions within adaptive water resources planning (see online version for colours)



(a)

Figure 5 (a) An initial spatial design for QnD:Okavango focusing on river subcatchments, national borders and delta vegetation zones and (b) implementation of QnD model versions within adaptive water resources planning (see online version for colours) (continued)



(b)

Source: GIS Data Sources: USAID (2005).

5.3 Model integration with SIMLAB

The proposed global analyses methods are based on randomised sampling of sets of points from joint probability distributions of the model input factors that are used in turn to perform model simulations. Selected outputs are then obtained from each for the analyses. In general, as depicted in Figure 6, the proposed analysis procedures follow six main steps:

1 selection of input factors and construction of probability distribution functions

2 generation of input sets by pseudo-random sampling of input PDFs according to the selected analysis method

3 model simulations for each input set are done and selected outputs collected from each simulation

4 global sensitivity analysis is performed according to the method selected

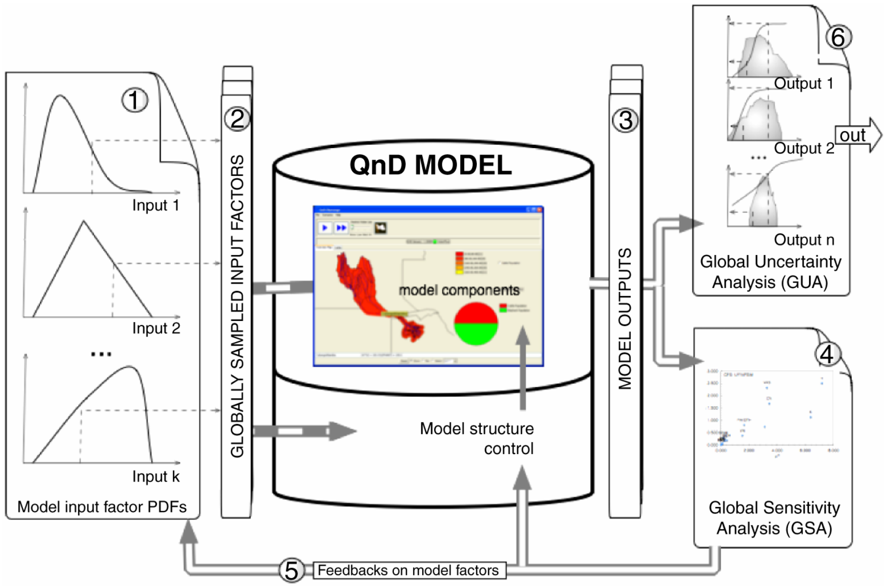
5 if a screening method is selected a subset of important parameters is selected and steps 2–4 are repeated using the variance-based methods, in addition, feedback is obtained about potential model errors, effect of multiple model structures on output and possible modifications to the model

6 uncertainty is assessed based on the outputs from the randomised variance-based model results by constructing PDF/CDFs and the results are communicated to the end-users.

The software package, SIMLAB v2.2 (Saltelli et al., 2004) is used in the global sensitivity and uncertainty analysis of the Okavango QnD application. SIMLAB is designed for pseudorandom number generation-based uncertainty and sensitivity analysis. SIMLAB's Statistical Pre-Processor module executes step 1 in the procedure

(Figure 6) based on PDFs provided by the user and the method selected and produces a matrix of sample inputs to run the model (step 2, Figure 6). The QnD code has been altered to allow the incorporation of SIMLAB-derived matrices for automatic simulation. The program automatically substitutes the new parameter set into the input files, runs the model and performs the necessary post-processing tasks to obtain the selected model outputs for the analysis (step 3, Figure 6). The outputs from each simulation are stored in a matrix containing the same number of lines as the number of samples generated by SIMLAB. With the input and output matrices the Statistical Post-Processor module of SIMLAB is used to calculate the sensitivity indexes of the Morris and extended FAST method (step 4, Figure 6). Finally the output probability distributions are constructed in SIMLAB based on the set of variance-based sensitivity run results to quantify the uncertainty (step 6, Figure 6).

Figure 6 General schematic for the global sensitivity and uncertainty analysis of the proposed QnD-Okavango model (see online version for colours)



Note: Numbers in circles represent the steps in the global evaluation procedure explained in the text.

5.4 *Model integration with decision analysis*

Another interface with QnD has been designed for connecting model results with MCDA. Once a viable modelling engine has been established by creating the various process objects, or by simply importing time series inputs from another model, simulations can begin. Results for selected alternatives or policies can be simulated over time under user-defined stochastic drivers. The simulation results can be used to populate the prerequisite matrix of alternatives and criteria that constitute MCDA approaches.

Within our conceptual design, simulation results by models such as the Pitman model or QnD simulated can be used within MCDA structures for specific decisions. If national managers are considering several options for the implementation of water abstraction projects on a certain reach, then simulation results could be mapped with ecological, economic, socio-political factors into a structure for weighing specific trade-offs under both certain and uncertain conditions. Thus, transboundary partners have a transparent forum for exploring the various trade-offs that will occur under varying environmental conditions and management regimes. Both MCDA and Bayesian analysis tools allow managers or scientists to explore the value of implementing decisions immediately or waiting for more information. For example, Bayesian analysis can allow the managers to quantify the value of a monitoring option which can reduce the variance of inputs in step 1 (Figure 6). If the decision based on the reduced variance through monitoring is different with the decision based on without the information, the monitoring option at cost may be valuable. Alternatively, if there are several monitoring options and the decision makers want to prioritise the options due to a constrained budget, the value of information analysis can be used to analyse the prioritisation.

6 Conclusions

This paper highlights the role of additional systems analysis tools to build upon the significant modelling research that has been conducted within the Okavango River Basin. The primary advantage of these tools is to allow researchers and basin managers to systematically assess four basic questions:

1. What levels of uncertainty currently exist in the system due to natural variation or due to the representation of the hydrologic system into mathematical models?
2. What role do model inputs as well as the model structure play in the passing along of uncertainty into various model and scenario predictions?
3. How do these various uncertainties interact among hydrological, ecosystem and social factors in the basin?
4. How do these factors influence the practical management policies or decisions within this transboundary basin?

In this paper, we have proposed a conceptual design to link the various components required to provide a beginning-to-end integration of environmental data, models, analysis tools and decision methods. To complement this design, we have reviewed recent modelling research in the basin, uncertainty methods and tools, AM concepts and model integration tools, all focused on addressing practical management issues with respect to the Okavango River basin. This design builds upon the existing modelling efforts to provide one potential way forward in creating integrated model/decision systems.

The tools highlighted in this design are all currently available at little or no cost to users and can be implemented immediately and iteratively. The primary advantage of this approach is not to seek more ecosystem data or to build ever-expanding models, a common pitfall of AM implementation. Alternately, these tools provide a set of systematic methods to assess and plan for what level of information and model representation are necessary to match current system understanding with management objectives.

Transboundary water issues are inherently challenging and require greater amounts of coordination, consensus and complimentarity among people, their management processes and their systems analysis tools. Within our review and conceptual design, the complexity and uncertainty are not ignored, nor are they are they trivialised. Uncertainty and its translation through data analysis and model calculations can be systematically incorporated into management-level understanding of the inherent risks within the basin.

Acknowledgements

We are grateful for the computing and funding resources provided by NSF:IGERT AM: Wise Use of Water, Wetlands and Watersheds. Funding for this project was obtained from the South Florida Water Management PO no.: 4500005607. The authors wish to acknowledge Zuzanna Zajac for the details provided on the model spatial analysis approaches and Mindy Kiker for editorial guidance.

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Appendix

1 Global sensitivity and uncertainty analyses techniques: Morris and Extended FAST

1.1 Screening method: the method of Morris

Morris (1991) proposed conducting individually randomised experiments that evaluate the elementary effects of changing one parameter at a time. Each input may assume a discrete, equispaced values, called *levels*, which are selected from an allocated range of variation for the factor. The elementary effect ($d_i(x)$) for factor X_i is defined as:

$$d_i(x) = \frac{\left[y\left(x_1, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, x_k\right) - y(x)\right]}{\Delta} \tag{A1}$$

where $x_i + \Delta$ is the perturbed value of x_i; k is the number of factors, $i = 1, \ldots, k$.

The principle of Morris method is to calculate the elementary effects (local derivative of output in respect to input) for values sampled at each level of factor X_i (in the k-dimensional inputs space). The resulting probability distribution of the elementary effects of factor X_i is characterised with its mean and standard deviation.

For each parameter, two sensitivity measures are proposed by Morris (1991):

1 the mean of the elementary effects, μ, which estimates the overall effect of the parameter on a given output

2 the standard deviation of the effects, σ, which estimates the higher-order characteristics of the parameter (such as curvatures and interactions).

Since sometimes the model output is non-monotonic, Campolongo et al. (2005) suggested considering the distribution of absolute values of the elementary effects, μ, to avoid the cancelling of effects of opposing signs, and thus, μ^* and σ were adopted as global sensitivity indexes in this method. Previous studies (Campolongo et al., 1999; Saltelli et al., 2000) have demonstrated that the required number of simulations (N) to perform in the analysis results as:

$$N = r(k+1) \tag{A2}$$

where r is the sampling size r for search trajectory ($r = 10$ produces satisfactory results), k is the number of factors.

Although elementary effects are local measures, the method, is considered global, as the final measure μ^* is obtained by averaging the elementary effects which eliminates the need to consider the specific points at which they are computed (Saltelli et al., 2005).

To interpret the results in a manner that simultaneously accounts for the mean and standard deviation sensitivity measures, Morris (1991) suggested plotting the points on a $\mu - \sigma$ Cartesian plane. Morris (1991) recommended applying μ (or μ^* thereof) to rank parameters in order of importance. Saltelli et al. (2004) suggested applying the original Morris (1991) measure, σ when examining the effects due to interactions. The meaning of σ can be interpreted as follows: if its value is high for a parameter, X_i, the elementary effects relative to this parameter are implied to be substantially different from each other, which means it is sensitive to the chosen values of other parameters that constitute the remainder of the input space. Because the Morris method is qualitative in nature, it should only be used to assess the relative parameter ranking.

1.2 Variance-based method: extended FAST and uncertainty analysis

When a quantitative measure of sensitivity is to be obtained a variance-based method like the FAST can be used (Cukier et al., 1973, 1978; Koda et al., 1979). Cukier et al. (1978) proposed that for independent factors, the total output variance can be expressed as:

$$V(Y) = \sum_i V_i + \sum_{i<j} V_{ij} + \sum_{i<j<l} V_{ijl} + \cdots + V_{123\ldots k} \tag{A3}$$

where multiple combinations of subindices (*ij*, *ijl*,…, 123…*k*) represent interactions of the factors.

Although FAST was originally developed to estimate the first-order effects of orthogonal inputs on a given model output, it has been extended to incorporate calculation of the total-order effects by Saltelli (1999).

FAST decomposes the total variance $(V = \sigma_Y^2)$ of the model output, $Y = f(X_1, X_2, \ldots, X_k)$, using spectral analysis so that:

$$V = V_1 + V_2 + V_3 + \cdots + V_k + R \tag{A4}$$

where V_i is the part of the variance that can be attributed to the input factor X_i alone, k is the number of uncertain factors and R is a residual. The fraction of the total output variance attributed to a single factor can then be taken as a measure of global sensitivity of Y with respect to X_i, that is, the first order sensitivity index S_i, as

$$S_i = \frac{V_i}{V} \tag{A5}$$

It is standard practice to assume that all parameters are uniformly distributed in [0, 1] (Saltelli et al., 2004, 2005), thereby permitting all parameters to be mapped from the unit hypercube to their actual distribution. The space in which the model output function f is defined is thus itself a k-dimensional unit hypercube. To calculate S_i, the FAST technique randomly samples the k-dimensional space of the input parameters using the replicated Latin hypercube sampling (r-LHS) design (McKay, 1995; McKay et al., 1979). The number of evaluations required in the analysis can be expressed as,

$$N = M(k + 2) \tag{A6}$$

where M is a number between 500 and 1000.

Higher-order interaction terms in Equation (A3) correspond to the residual R contained in Equation (A4). Therefore, the sum of all S_i is that fraction of the total variance attributed to the sum of all the first-order effects. For a perfectly additive model, $\Sigma S_i = 1$; that is, no interactions are present and total output variance is explained as a summation of the individual variances introduced by varying each parameter alone. In general, models are not perfectly additive and $\Sigma S_i < 1$.

Extended FAST (Saltelli et al., 1999) allows for the determination of the higher order terms, which indicate the degree of parameter interaction. Another index, S_{Ti}, (total sensitivity index for X_i) is calculated as the sum of the first order index and all higher order interaction-indices of a given parameter. For example, for parameter number 1:

$$\begin{aligned} S_{T1} &= S_1 + S_{1i} + S_{1jk} + \cdots + S_{1\ldots n} \text{ and then} \\ S_{T1} - S_1 &= S_{1i} + S_{1jk} + \cdots + S_{1\ldots n} \end{aligned} \tag{A7}$$

For a given parameter, X_i, interactions can be isolated by calculating $S_{Ti} - S_i$, which makes the extended FAST a powerful method for quantifying the individual effect of each parameter alone (S_i) or through interaction with others ($S_{Ti} - S_i$). If individual quantification of the higher order interaction groups is desired Saltelli (2004) proposes the use of the method of Sobol (1990), although, since it is based on Monte-Carlo sampling, it typically requires a larger number of simulations than the Extended FAST.

An additional benefit of the Extended FAST analysis is that the results, since they are derived from a randomised sampling procedure, can be used as the basis for the uncertainty evaluation by constructing cumulative probability functions (CDFs) for each of the selected outputs.

It should be noted that the results of any model evaluation are specific to the particular application of the model. A 'worst case scenario' where all the potentially sensitive model parameters are allowed to vary across their total (potential) parametric space could be implemented, in particular applications. It is important, however, that the user restricts the potential variation range or fixes some parameters, based on local field data or other information available. This practice can substantially change the uncertainty predictions, especially if the model is sensitive to the parameters that are fixed or have reduced range.

2 Bayesian estimation

A useful and systematic overview for incorporating uncertainty within probability distributions is found in Small (1990) which includes a comparison of classical statistical and Bayesian estimation methods. The Bayesian approach begins with an initial prior distribution for a parameter of interest (r), based on whatever information (e) that is known to the user before observing additional data. This initial (or prior) distribution is described as $f(r|e)$. Given that the additional observations or information will provide $\underline{x} = (x_1, x_2, \ldots, x_m)$, the resulting change (or updating) of the distribution would be described as a posterior distribution $f(r \mid \underline{x}, e)$. Bayes rule allows the user to calculate the posterior value through the equation:

$$f(r \mid \underline{x}, e) \equiv \frac{f(r, \underline{x} \mid e)}{f(\underline{x} \mid e)} = \frac{f(\underline{x} \mid r, e) \times f(r \mid e)}{\int f(\underline{x} \mid r, e) \times f(r \mid e) \mathrm{d}r} \tag{A8}$$

Thus, the role of increased information can be used to update and change the various characteristics of the parameter. Significant literature exists on these techniques in various risk assessment (Morgan and Henrion, 1990) and social science applications (Gill, 2002).