Journal of Hydroinformatics | 11.3–4 | 2009

A new method for spatial and temporal analysis of risk in water resources management

Slobodan P. Simonovic

ABSTRACT

Uncertainty in water resources management is in part about *variability* and in part about *ambiguity*. Both are associated with lack of clarity because of the behavior of all system components, lack of data, lack of detail, lack of structure to consider the water resources management problems, working and framing assumptions being used to consider the problems, known and unknown sources of bias, and ignorance about how much effort it is worth expending to clarify the management situation. The two major sources of variability are temporal and spatial heterogeneity. Temporal variability occurs when values fluctuate with time. Other values which are affected by spatial variability are dependent upon location of an area. A major part of the water resources management risk confusion relates to an inadequate distinction between the objective risk (real, physical) and subjective (perceived) risk. Because of the confusion between the two concepts, many characteristics of subjective risk are believed to be valid also for objective risk. The main objective of this paper is to initiate a discussion of the possible methodology for the reliability analysis of water resources systems that will be capable of: (a) addressing water resources uncertainty caused by variability and ambiguity, (b) integrating objective and subjective risk and (c) assisting the water resources management based on better understanding of temporal and spatial variability of risk.

Key words | fuzzy sets, risk, space, time, water resources

Slobodan P. Simonovic
Department of Civil and Environmental Engineering,
University of Western Ontario,
London Ontario,
Canada N6A 5B9
E-mail: *simonovic@uwo.ca*

A DEFINITION OF RESEARCH CONTEXT

Water resources management under uncertainty

Uncertainty is, in plain language, defined as *lack of certainty*. It has important implications for what can be achieved by water resources systems management. All water management decisions should take uncertainty into account. Sometimes the implications of uncertainty are *risk* in the sense of *significant potential unwelcome effects of water resources system performance*. Then managers need to understand the nature of the underlying threats in order to identify, assess and manage the risk. Failure to do so is likely to result in adverse impacts on performance and, in extreme cases, major performance failures. Sometimes the implications of uncertainty are an opposite form of risk, significant potential *welcome* effects. Then managers need to understand the nature of the underlying opportunities in order to identify and manage the associated decrease in risk. Failure to do so can result in a failure to capture good luck, which can increase the risk. For example, a development of a regional water supply system which generates unexpectedly rapid urbanization of the area may prove a disaster if the increasing demand cannot be met in the future; a pipeline construction project activity which finishes early may not result in a following activity starting early, and later delays will not be avoided by this good luck if it is wasted; a structural flood protection measure which generates new opportunities for the development of

doi: 10.2166/hydro.2009.018

floodplain may increase the future damage in the case of a more severe flood event.

Uncertainty is in part about *variability* in relation to physical characteristics of the water resources systems. But uncertainty is also about *ambiguity* (Ling 1993; Simonovic 1997). Both variability and ambiguity are associated with lack of clarity because of the behavior of all system components, lack of data, lack of detail, lack of structure to consider the water resources management problems, working and framing assumptions being used to consider the problems, known and unknown sources of bias, and ignorance about how much effort it is worth expending to clarify the management situation.

Time and space

Uncertainty caused by variability is a result of inherent fluctuations in the quantity of interest (hydrologic variables). The three major sources of variability are temporal, spatial and individual heterogeneity. *Temporal variability* occurs when values fluctuate with time. Other values which are affected by *spatial variability* are dependent upon location of an area. The third category of *individual heterogeneity* effectively covers all other sources of variability. In water resources management variability is mainly associated with the spatial and temporal variation of hydrological variables (precipitation, river flow, water quality parameters, etc.).

The more elusive type of uncertainty is ambiguity, which is due to a fundamental lack of knowledge. It occurs when the particular values that are of interest cannot be presented with complete confidence because of a lack of understanding or limitation of knowledge.

Risk definition

An attempt to come up with a standardized definition of risk concluded that a common definition is perhaps unachievable and that authors should continue to define risk in their own way. As a result, numerous definitions can be found in the current literature. At a conceptual level, risk is defined as *a significant potential unwelcome effect of water resources system performance* or *the predicted or expected likelihood that a set of circumstances over some timeframe will produce some harm that matters*. More pragmatic treatments view risk as one side of an equation, where risk is equated with the probability of failure or the probability of load exceeding resistance. Other symbolic expressions equate risk with the sum of uncertainty and damage or the quotient of hazards divided by safeguards (Lowrance 1976).

Three cautions surrounding risk must be taken into consideration: risk cannot be represented objectively by a single number alone, risks cannot be ranked on strictly objective grounds, and risk should not be labelled as *real*. Regarding the caution of viewing risk as a single number, the multidimensional character of risk can only be aggregated into a single number by assigning implicit or explicit weighting factors to various numerical measures of risk. Since these weighting factors must rely on value judgement, the resulting single metric for risk cannot be objective. Since risk can't objectively be expressed by a single number, it is not possible to rank risks on strictly objective grounds. Finally, since risk estimates are evidence-based, risks can't be strictly labelled as *real*. Rather, they should be labelled *inferred* at best.

Objective and subjective risk

A major part of the risk management confusion relates to an inadequate distinction between three fundamental types of risk: (i) *objective risk* (real, physical), R_o, and objective probability, p_o, which is the property of real physical systems.; (ii) *subjective risk*, R_s, and subjective probability, p_s: probability is here defined as the degree of belief in a statement. R_s and p_s are not properties of the physical systems under consideration (but may be some function of R_o and p_o); and (iii) *perceived risk*, R_p, which is related to an individual's feeling of fear in the face of an undesirable possible event, is not a property of the physical systems but is related to fear of unknown. It may be a function of R_o, p_o, R_s and p_s. Because of the confusion between the concepts of objective and subjective risk, many characteristics of subjective risk are believed to be valid also for objective risk (Slovic 2000). Therefore, it is almost universally assumed that the imprecision of human judgment is equally prominent and destructive for all water resources risk evaluations and all risk assessments. *This is perhaps the* *most important misconception that blocks the way toward more effective societal risk management*. The ways society manages risks appear to be dominated by considerations of perceived and subjective risks, while it is objective risks that kill people, damage the environment and create property loss.

The main objective of this paper is to initiate a discussion of the possible methodology for the reliability analysis of water resources systems that will be capable of: (a) addressing water resources uncertainty caused by variability and ambiguity; (b) integrating objective and subjective risk and (c) assisting the water resources management based on better understanding of the temporal and spatial variability of risk.

The following section provides an overview of previous work. The introduction of state-of-the-art methodology based on the spatial fuzzy reliability analysis follows. A discussion of possible ideas for completion of research–extension of the spatial fuzzy reliability analysis to include temporal variability–is in the last section of this paper.

PREVIOUS WORK

Probabilistic approach

Probability is a concept widely accepted and practiced in water resources systems management. To perform operations associated with probability, it is necessary to use sets–collections of elements, each with some specific characteristics.

In the classical interpretation of probability (Equally Likely Concept), the probability of an event E can be obtained from $\Pr(E) = m(E)/m(S)$, provided that the sample space contains N equally likely and different outcomes, i.e. $m(S) = N$, n of which have an outcome (event) E, i.e. $m(E) = n$. Thus $\Pr(E) = n/N$. This definition is often inadequate for water resources applications. For example, if failures of a pump to start in a water supply plant are observed, it is unknown whether all failures are equally likely to occur. Nor is it clear if the whole spectrum of possible events is observed.

In the frequency interpretation of probability, the limitation on the lack of knowledge about the overall sample space is remedied by defining the probability as the limit of n/N as N becomes large. Therefore, $\Pr(E) = \lim_{N\to\infty} (n/N)$. Thus, if we have observed 2,000 starts of a pump in which 20 failed, and if we assume that 2,000 is a large number, then the probability of the pump failure to start is $20/2{,}000 = 0.01$. The frequency interpretation is the most widely used classical definition in water resources management today.

Problems with probabilistic approach

The probabilistic (stochastic) reliability analysis has been extensively used to deal with the problem of uncertainty in water resources systems management. Prior knowledge of the probability density functions of both resistance and load and/or their joint probability distribution function is a prerequisite for the probabilistic approach. In practice, data on previous failure experience is usually insufficient to provide such information. Even if data is available to estimate these distributions, approximations are almost always necessary to calculate system reliability (Ang & Tang 1984). The subjective judgment of the water resources decision-maker to estimate the probability distribution of a random event–subjective probability approach of Vick (2002)–is another approach to deal with data insufficiency. The third approach is Bayes's theory where engineering judgment is integrated with observed information.

Until recently the probabilistic approach was the only approach for water resource systems reliability analyses. However, it fails to address the problem of uncertainty that goes along with human input, subjectivity, lack of history and records. There is a real need to convert to new approaches that can compensate for the ambiguity or uncertainty of human perception.

Fuzzy set approach

Fuzzy set theory was intentionally developed to try to capture people's judgmental beliefs, or the uncertainty that is caused by the lack of knowledge. Relative to the probability theory, it has some degree of freedom with respect to aggregation operators, types of fuzzy sets (membership functions), etc., which enables the adaptability to different contexts. Probability and fuzziness are related, but different concepts. Fuzziness is a type of deterministic uncertainty. It describes the *event class ambiguity*. Fuzziness measures the degree to which an event occurs, not whether it occurs. At issue is whether the event class can be unambiguously distinguished from its opposite. Probability arises from the question whether or not an event occurs. Moreover, it assumes that the event class is crisply defined and that the law of non-contradiction–*for any property and for any definite subject, it is not the case both that the subject possesses that property and that the subject does not possess that property*– holds. Fuzziness occurs when the law of non-contradiction (and equivalently the law of excluded middle–*for any property and for any individual, either that individual possesses that property or that individual does not possess that property*) is violated. However, it seems more appropriate to investigate the *fuzzy probability* for the latter case than to completely dismiss probability as a special case of fuzziness.

In essence, whenever there is an experiment for which we are not capable of "computing" the outcome, a probabilistic approach may be used to estimate the likelihood of a possible outcome belonging to an event class. A fuzzy theory extends the traditional notion of a probability when there are the outcomes that belong to several event classes at the same time but to different degrees. The fuzziness and probability are orthogonal concepts that characterize different aspects of human experience. Hence, it is important to note that neither fuzziness nor probability govern the physical processes in Nature. They are *introduced* by humans to compensate for our own limitations.

TOWARDS A NEW METHODOLOGY FOR SPATIAL AND TEMPORAL ANALYSIS OF RISK IN WATER RESOURCES MANAGEMENT

Fuzzy risk definition and analysis

A new methodology starts with a definition of partial failure that provides for the water resource systems reliability analysis using three fuzzy performance measures: (i) a combined reliability–vulnerability index, (ii) a robustness index and (iii) a resiliency index (El-Baroudi & Simonovic 2004). The calculation of performance indices depends on the exact definition of unsatisfactory system performance. Water resources systems reliability analysis uses load and resistance to define the state of a system. The failure state occurs when resistance falls below the load. It is difficult to arrive at a precise definition of failure because of the uncertainty in determining system resistance, load and the accepted unsatisfactory performance threshold. Figure 1 depicts a typical system performance (resistance time series), with a constant load during the operation horizon. According to the classical definition, the failure state is the state when resistance falls below the load, margin of safety (difference between the resistance and load) $M < 0.0$ or safety factor $\Theta < 1.0$, which is represented by the ratio between the system's resistance and load, shown in Figure 1 by the dashed horizontal line.

Due to the fluctuation of load and resistance in the management of water resources systems, *partial failure* may be acceptable. The precise identification of failure is neither realistic nor practical. A degree of acceptable system failure is introduced using the solid horizontal line, as shown in Figure 1. The region between the dashed and the full line in the figure is the region of partial failure that will be called acceptable failure.

The boundary of the acceptable or partial failure region is ambiguous and varies from one decision-maker to another, depending on the personal perception of risk. Fuzzy sets are capable of representing the notion of imprecision better than ordinary sets and therefore the acceptable level of performance can be represented as a fuzzy membership function shown in Figure 2.

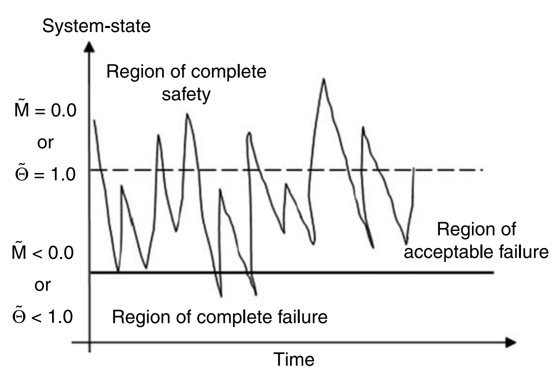

Figure 1 | Variable system performance.

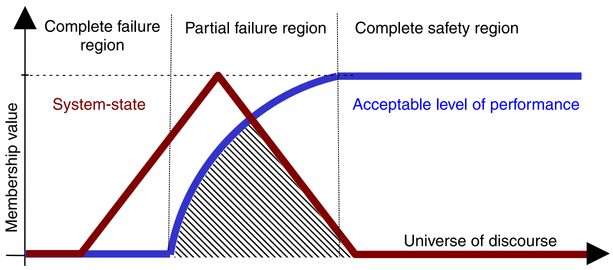

Figure 2 | Fuzzy representation of the acceptable level of performance and system state.

The reliability assessment, discussed here, involves a comparative analysis of the *system-state membership function* (see Figure 2) and the predefined *acceptable level of the performance membership function*. Therefore, the compliance of two fuzzy membership functions can be quantified using the fuzzy compatibility measure. Possibility and necessity lead to the quantification of the compatibility of two fuzzy sets. The possibility measure quantifies the overlap between two fuzzy sets, while the necessity measure describes the degree of inclusion of one fuzzy set into another fuzzy set.

Analysis of the overlap between two fuzzy membership functions provides for definition of reliability and vulnerability as a complete descriptor of system performance. Once an acceptable level of performance is determined in a fuzzy form, the anticipated performance in the event of failure as well as the expected severity of failure can be determined. A comparison between the fuzzy system-state membership function and the predefined fuzzy acceptable level of performance membership function provides information about both system reliability and system vulnerability at the same time.

Robustness measures the system's ability to adapt to a wide range of possible future load conditions. The fuzzy form of change in future conditions can be obtained through a redefinition of the acceptable level of performance and a change in the system-state membership function. As a result, the system's robustness is defined as the change in the compatibility measure–overlap of two fuzzy membership functions.

Resilience measures how fast the system recovers from failure state. The time required to recover from the failure state can be represented as a fuzzy set. A series of fuzzy membership functions can be developed to allow for various types of failure. The maximum recovery time is used to represent the system recovery time. The center of gravity of the maximum fuzzy recovery time can be used as a real number representation of the system recovery time. Therefore, system resilience is determined to be the inverse value of the center of gravity.

Fuzzy reliability analysis has been successfully tested on the City of London (Ontario, Canada) Regional Water Supply System (El-Baroudi & Simonovic 2006).

Spatial fuzzy reliability analysis

Integration of fuzzy performance indices computation with GIS allows for spatial fuzzy reliability analysis. Each cell in a GIS map is considered a decision-making location for which the computation of fuzzy indices is done as described in the previous section (Ahmad & Simonovic 2007). The utility of the methodology has been tested in reliability analysis of floods. The fuzzy flood damage membership functions for agricultural land, residential land, one- and two-story buildings are developed based on the flood damage data. The compliance of the flood damage membership function with different acceptable levels of flood damage is assessed for every grid cell. The maximum value of the compatibility measures for every grid cell in space is combined into a single raster image. The designated maps are used to determine the fuzzy combined reliability–vulnerability, fuzzy robustness and fuzzy resiliency indices. An example of the spatial fuzzy reliability analysis of Medway Creek (Ontario, Canada) flooding is shown in Figure 3. The final map of fuzzy reliability–vulnerability index is in Figure 3(a). Figure 3(b) shows the values of fuzzy robustness index for Medway Creek. A single flood damage recovery time is used to determine the fuzzy resiliency index for each grid cell and the final map is shown in Figure 3(c).

THE REMAINING WORK

Risks in water resources management have three main characteristics: (i) spatial structure and relationships among risk characteristics; (ii) interactions among the spatial risk characteristics and (iii) changes or alterations in risk characteristics over time. Any effort to understand and

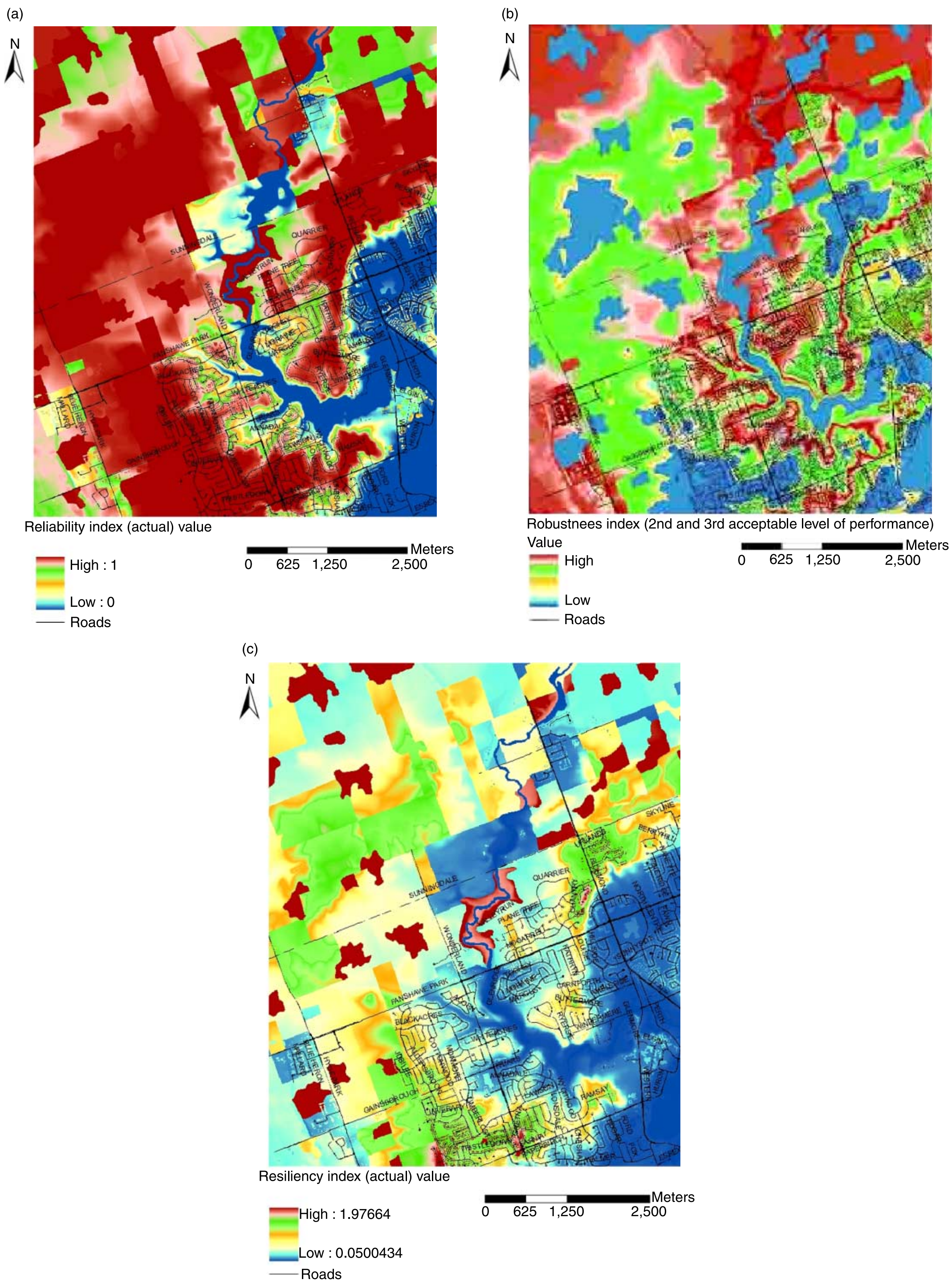

Figure 3 | Spatial fuzzy indices for Medway Creek flooding.

describe a dynamics of water resources risks requires the ability to deal with these interrelated aspects. Traditional modeling approaches focus on either temporal or spatial variation, but not both. There is an important feedback between time and space, i.e. variability of risk in time is affected by the change of risk characteristics in space. To understand risk dynamics, patterns in time and space need to be examined together. Thus, work progresses on the development of a new modeling framework that not only captures feedback-based dynamic processes in time and space but also integrates different modeling tools required for solving complex water resources management problems. Modeling environments that can link social, economic and environmental consequences of water resources risks are fundamental to an understanding of the impacts of proposed management decisions. Integrated modeling framework enhances our ability to understand complex water resources systems and helps to generate adequate information/scenarios to help decision-making.

There are three modeling paradigms that hold potential for describing dynamic processes in time and space. These include: cellular automata (CA), geographic information system (GIS) and system dynamics (SD).

Cellular automata have attracted the attention of researchers in geography, ecology and other environmental sciences because of their ability to model and visualize complex spatially distributed processes. Examples of CA applications include urban growth simulation models, diffusion models, spatially explicit ecological models and forest fire simulations. Cellular automata have also been used to model landscape changes, regional modeling, water absorption in soils, water infiltration in unsaturated porous media and estimation of discharge using satellite imagery. Cellular automata modeling has some shortcomings. First, it is difficult to include processes where global variables are important in describing the behavior of a system. For example, both local and regional interactions between two or more locations in space cannot be handled easily. Second, at least in deterministic cellular automata, transition rules do not change during the course of a simulation. This is an important limitation because change in risk is rarely constant over time. Attempts have been made to deal with some of the limitation of CA by integrating them with GIS (Xia & Gar-On 2000). However, certain limitations still exist. The assumptions of regularity (equal sized cells), homogeneity (each cell is updated according to the same rules), universality (CA fall into a few basic behavior classes and within each class they exhibit qualitatively similar behavior) and closure (basing its new state on the state of immediate neighbors) of standard CA are indeed difficult to reconcile with real-life situations. Interfacing CA with databases also has its limitations. Cellular automata are better suited for discrete event simulations rather than continuous time simulations.

The *Geographic Information System* (GIS) approach has been extensively used for spatial modeling in a variety of application areas. Use of map algebra and geo-algebra in GIS extends the potential for dynamic modeling of spatio-temporal processes: however, certain limitations still exist. Most significant is the current limitation of GIS for temporal modeling (Langran 1992). The main body of literature offers four approaches for modeling spatio-temporal processes using GIS, which are: (a) space–time cube; (b) sequent snapshots; (c) base state with amendments and (d) space–time composite. Temporal visualization currently draws upon the animation technology of multiple snapshots recorded in sequence and replayed to create an impression of motion. There have been some recent advances in GIS's capability to develop and implement dynamic models. The advent of geo-object modeling offers an opportunity for formulating a GIS representation of rivers and watersheds in a manner that was not feasible using the geo-relational data model. Olivera *et al.* (2000) have reported the development of a global-scale flow routing model using a source-to-sink algorithm that has been completely developed within GIS using Visual C++. One limitation of this approach is its rigidity, for example for water resources reliability applications operating rules cannot be modified during a simulation. Despite the efforts to build modeling functions into GIS directly and the suitability of specific GIS packages, it is likely that most numerical models, especially those requiring exhaustive calibration, will need to parallel, rather than to work within, the GIS.

System Dynamics (SD) is a rigorous method of system description, which facilitates feedback analysis via a simulation model of the effects of alternative system structures and control policies on system behavior

(Simonovic 2008). Advantages of system dynamics simulation include: (a) the simplicity of use of system dynamics simulation applications; (b) applicability of system dynamics general principles to social, natural and physical systems; (c) ability to address how structural changes in one part of a system might affect the behavior of the system as a whole; (d) combined predictive (determining the behavior of a system under a particular input conditions) and learning (discovery of unexpected system behavior under a particular input conditions) functionality and (e) active involvement of stakeholders in the modeling process.

The strength of the system dynamics approach is in representing temporal processes. SD models, however, do not adequately represent spatial processes. For example, SD models can be used for analysis of different flood management policies and estimation of flood damages (as a function of time). However, SD modeling provides no easy way to map these damages in space. In order to have a flood damage model take into account the spatial aspects, such as the effect of land use and gradient on water movement, a simple SD model is inadequate.

Given the strength of SD in representing temporal processes with restricted spatial modeling capabilities, and the competency of GIS for spatial modeling with limited representation of temporal aspects, a logical alternative is the integration of SD with GIS to model spatial dynamic systems. An attempt has been made to add spatial dimensions to SD models by Ahmad & Simonovic (2004). A new approach, referred to as *spatial system dynamics* (SSD), capable of modeling dynamic processes in time and space is developed by coupling a system dynamics simulation and a geographic information system. This is achieved through a dynamic data exchange between SD and GIS. The main strength of the SSD approach is a two-way exchange of data and information between SD and GIS, providing feedback in time and space. Initially, GIS provides spatial information to the SD model. The SD model, through dynamic modeling, identifies changes in spatial features with time and communicates them back to GIS. These changes in space in turn impact decisions/policies in time. Thus, processes can be modeled in time and space in an integrated way while capturing the feedback.

When modeling distributed parameter processes, parameter values at any point in space are the average of parameter values at immediate neighboring points. Thus, using the SSD approach requires the area of interest to be divided into cells. Then, a system dynamics model is developed for each cell that communicates with its neighboring cells as shown in Figure 4. Preparation, analysis and presentation of an enormous amount of spatial data are required for modeling spatially distributed dynamic processes. Therefore, GIS is very helpful in dealing with these tasks. GIS serves the following three purposes: (1) as a spatial data storage and management system, (2) as a driver to feed models with different types of data and (3) to analyze and display results. Using GIS as the SD model's pre- and post-processor has the benefits of reducing the data preparation work, enhancing the spatial data display and revealing hidden spatial relations.

For the SSD approach of Ahmad & Simonovic (2004) different architectures for coupling SD with GIS (embedded coupling, tight coupling and loose coupling) were considered. Finally, the integration under a common interface, also known as tight coupling, was used. This type of integration requires that a model is developed outside of the GIS environment and has its own data structure.

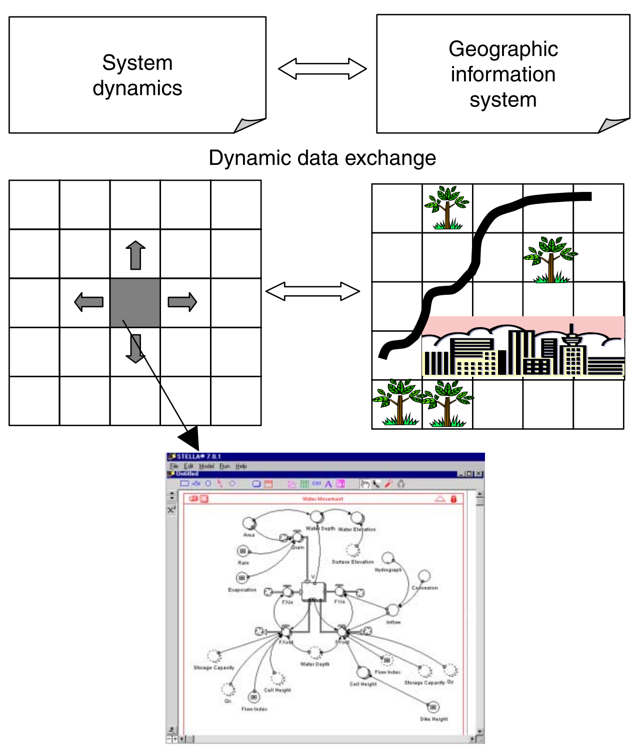

Figure 4 | Architecture of the spatial system dynamics approach.

The data transfer between GIS and the model is required. The link is provided through a common interface that supports the integration of a GIS with several different models. The approach has been tested in overland flooding simulation for the Red River Basin (Manitoba, Canada). One example of the final result of spatial system dynamics simulation is shown in Figure 5.

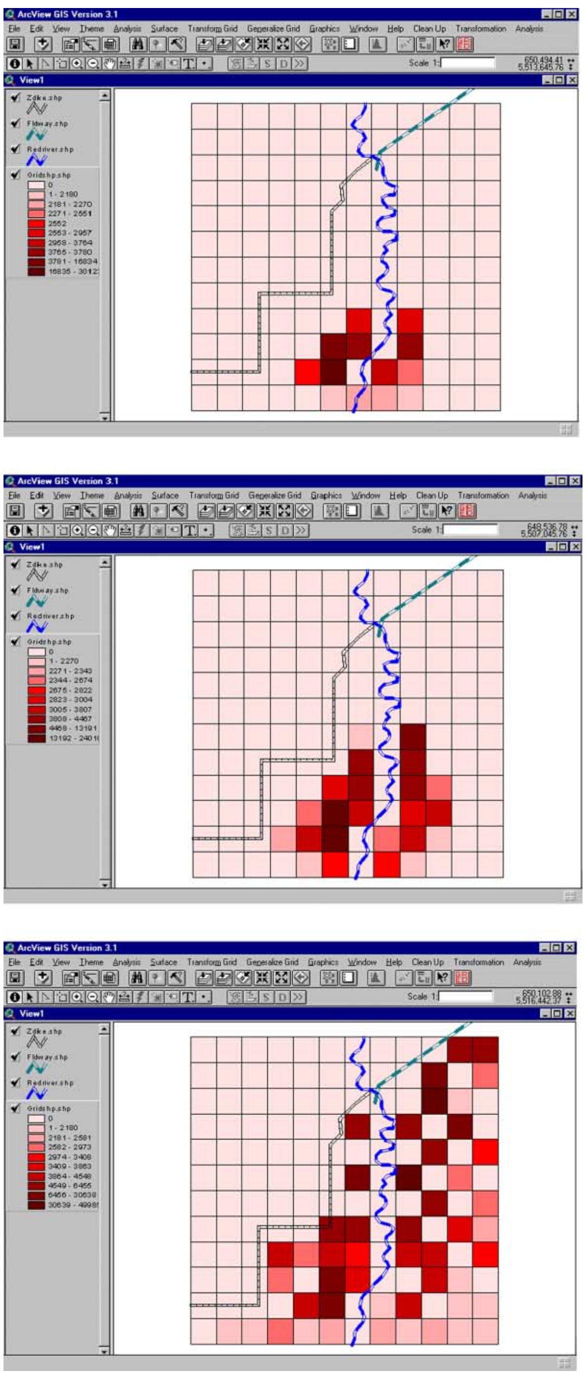

Figure 5 | Damages in the floodplain at selected timesteps (26 April–15 May 1997).

The SSD approach provides the decision-makers and planners with a much needed capability to capture the spatially referenced feedback processes in dynamic systems and display their temporally varying characteristics. The application of SSD to the overland flooding case study reveals that the approach enables the decision-maker to anticipate the flood damages (both the location and timing) that may result from the operation of flood control structures.

In the SSD approach the integration of SD and GIS adds value beyond the inherent value in the SD model or GIS used separately. SD is able to deal with spatially explicit information while allowing fundamental laws to be expressed at the cellular level. The power of GIS for temporal modeling is enhanced as well. By integrating the modeling techniques a broader perspective and a richer set of methods is provided to explore the interdependencies, nonlinear responses, spatial structure and interaction between local and regional scales that are characteristic of complex dynamic systems. This can build confidence in the model, especially if the fundamental laws are well understood and the spatial simulation can be checked against a GIS. The main difference from previous attempts to integrate SD and GIS is that all physical processes are described within SD, thus eliminating the need to link with another simulation model. The interactive power of SD approach has been preserved. The model is easy to modify and dynamic transition rules can be changed during simulation that is not possible in both CA and GIS modeling environments. The main limitation of the approach is that the relationship between time and space is not explicit.

INSTEAD OF CONCLUSIONS

Research in progress discussed in this paper is focusing on the possible methodology for the reliability analysis of water resources systems that will be capable of: (a) addressing water resources uncertainty caused by variability and ambiguity; (b) integrating objective and subjective risk and (c) assisting the water resources management based on a better understanding of temporal and spatial variability of risk.

Use of fuzzy reliability analysis provides for addressing water resources management uncertainty caused by variability and ambiguity. Risk is described using a combined fuzzy reliability and vulnerability, fuzzy robustness and fuzzy resiliency. Innovative risk definition required for the application of fuzzy reliability analysis integrates objective and subjective aspects of water resources management risk. Fuzzy reliability analysis has been successfully extended into a spatial fuzzy reliability analysis for taking explicitly into consideration spatial variability of water resources management risk.

The remaining work will further the development of the methodology to include temporal variation in water resources management risk. Very limited work is available on understanding dynamic characteristics of water resources risk and their relations with its spatial variability. System dynamics simulation of military risk without spatial variability considerations has been investigated by Johnson (2005, private communication). A spatial system dynamics method of Ahmad & Simonovic (2004) is being considered for implementation with spatial fuzzy reliability analysis.

The methodology for spatial and temporal analysis of risk in water resources management being developed has the potential to enhance the modeling capabilities in numerous application areas, where the main interest is the interaction between time and space in understanding uncertainty and its consequences. It can be helpful in management of floods; studies involving flow of pollutants through the environment; management of forests; drought analyses; spread of fires; spread of infectious diseases; expansion of deserts; loss of wetlands; issues related to biodiversity; and other application areas related to atmospheric processes.

ACKNOWLEDGEMENTS

Funding from the Public Safety and Emergency Preparedness (PSEP) and the National Sciences and Engineering Research Council (NSERC) of Canada to carry out this work is greatly appreciated. Concepts discussed in this work are the product of my collaboration with Dr. Sajjad Ahmad (University of Nevada, Las Vegas, USA), Dr. Ibrahim El-Baroudy (PINTER and Associates Ltd, Saskatoon, Canada) and Mr. Shohan Ahmad (University of Western Ontario, London, Canada).

REFERENCES

Ahmad, S. & Simonovic, S. P. 2004 Spatial system dynamics: a new approach for simulation of water resources systems. *J. Comput. Civil Eng. ASCE* **18** (4), 331–340.

Ahmad, S. & Simonovic, S. P. 2007 A methodology for spatial fuzzy reliability analysis. *Appl. GIS J.* **3** (1), 1–42. (Available at: http://arrowprod.lib.monash.edu.au:8000/access/detail.php?pid = monash:5115).

Ang, H.-S. & Tang, H. 1984 *Probability Concepts in Engineering Planning and Design*. Wiley, New York.

El-Baroudy, I. & Simonovic, S. P. 2004 Fuzzy criteria for the evaluation of water resources systems performance. *Water Resour. Res.* **40** (10), W10503.

El-Baroudy, I. & Simonovic, S. P. 2006 Application of the fuzzy performance measures to the City of London water supply system. *Can. J. Civil Eng.* **33** (3), 255–266.

Langran, G. 1992 *Time in Geographic Information Systems*. Taylor and Francis, London.

Ling, C. W. 1993 *Characterising Uncertainty: A Taxonomy and an Analysis of Extreme Events*. MSc Thesis, School of Engineering and Applied Science, University of Virginia, WV.

Lowrance, W. W. 1976 *Of Acceptable Risk*. William Kaufman, Los Altos, CA.

Olivera, F., Famiglietti, J. & Asante, K. 2000 Global-scale flow routing using a source-to-sink algorithm. *Water Resour. Res.* **36** (8), 2197–2208.

Simonovic, S. P. 1997 Risk in sustainable water resources. In *Sustainability of Water Resources Under Increasing Uncertainty*, (ed. D. Rosbjerg, *et al.*), pp. 3–17. Wallingford, UK, IAHS Publ. 240.

Simonovic, S. P. 2008 *Managing Water Resources: Methods and tools for a systems approach*. UNESCO, Paris and Earthscan James & James, London.

Slovic, P. 2000 *The Perception of Risk*. Earthscan, London.

Vick, S. G. 2002 *Degrees of Belief: Subjective Probability and Engineering Judgment*. ASCE Press, New York.

Xia, L. & Gar-On, Y. A. 2000 Modeling sustainable urban development by the integration of constrained cellular automata and GIS. *Int. J. Geogr. Inf. Sci.* **14** (2), 131–152.

First received 13 March 2008; accepted in revised form 29 May 2008