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Uncertainty Assessment Of The Integrated Hydrological Ensemble Prediction System Designed For The Nattai River Catchment

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UNCERTAINTY ASSESSMENT OF INTRGRATED HYDROLOGICAL ENSEMBLE PREDICTION SYSTEM DESIGNED FOR THE NATTAI RIVER CATCHEMNT

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Integrated hydrological ensemble prediction systems provide a probabilistic assessment of future stream flow predictions replacing the traditional forecast method of a single deterministic flow forecast. The ensemble forecasting system includes multi model approaches where the hydrological forecasts model was driven by weather prediction model outputs to generate an ensemble stream flow forecast predictions. The performance of the IHEP systems intent to increases the credibility of the stream flow predictions at the point of interest. However, the quality of the stream flow predictions is influenced by uncertainties originating from various sources in the forecasting chain. This paper describes the assessment of the uncertainty sources in IHEPS forecast system and provides the best available techniques or tools to acknowledge and reduce their impact on the stream flow predictions. In order to undertake the uncertainty assessment, the uncertainty sources were classified based on the generic engineering classification into two groups. The classification considered in what manner the uncertainties arose. The first group was categorised due to a lack of knowledge about the behaviour of the hydrological system known as an epistemic uncertainty in the forecasting chain. The second group was categorised due to randomness in the natural system known as an aleatory uncertainty. Both types of uncertainties were addressed with different approaches in order to acknowledge them and reduce them.

This discussion paper is focuses on the IHEPS set up for the Nattai River Catchment. Where the hydrological component of the forecasting system is based on the fully distributed MIKE SHE hydrological model integrated with the grid based short term ensemble prediction system STEPS as a rainfall forecast input. Outcomes of the uncertainty assessment of the Nattai IHEPS are presented with the recommendation for further studies to improve the IHEPS forecasting capability.

INTRODUCTION

Traditionally forecast systems provided a single deterministic stream flow prediction using the lumped hydrological forecast models (Skotner et al. 2005) and (Butts et al. 2007). Sydney's largest drinking water reservoir inflow prediction system was based on the same concept (Sakal et al. 2006, 2009). The reservoir inflow predictions were configured with empirical rainfall scenarios. Those rainfall scenarios were derived from significant inflow events and represented as a uniform catchment average rainfall volume, not considering an actual rainfall forecast (Sakal et al. 2008).

The newly available Short Term Ensemble Prediction System (STEPS) (Bowler et al. 2006, 2013) ensemble rainfall forecast in real-time mode made it possible to replace the empirical forecast scenarios with actual rainfall forecast. To integrate the STEPS ensemble rainfall forecast with the current forecast system that was based on lumped hydrological models. It required a fully distributed hydrological model that permits the use of grid based rainfall input. The MIKE SHE (Graham & Butts 2005) physically based fully distributed hydrological model was selected and developed for the Nattai River catchment. The Nattai River is one of the inflow sites for Sydney's largest drinking water reservoir.

This paper describes the development of the uncertainty framework through assessment of the uncertainty sources in the forecast processes. The uncertainty sources were classified based on their characteristics and nature into epistemic and aleatory uncertainty sources. This classification helped to choose the technique or tool to acknowledge and account for the uncertainty sources in the forecast processes.

This paper also describes the integration of the newly available STEPS ensemble rainfall forecast coupled with MIKE SHE hydrological forecast model with the current forecast system that forms the Integrated Hydrological Ensemble Prediction System (IHEPS).

UNCERTAINTY INVESTIGATIONS

Hydrologist used to handle uncertainties associated with natural variability (Santhi et al. 2008). Spatial variations in nature's force are well known; in fact it is not possible to reduce the uncertainties related to the spatial natural randomness of the environment (Beven 2004). The impact of rainfall errors on predicted flow has been highlighted by many authors, including (Sun et al. 2000), (Kavetski et al. 2006a, 2006b), (Bardossy and Das 2008), and (Moulin et al. 2009).The data on environmental variables such as rainfall, evaporation and river flow form the basis of driving force in hydrological forecast. Moreover, hydrological models not including all the natural processes in an accurate mathematical description of all the relevant physical processes. Therefore to compensate for the lack of knowledge concerning the representation of those physical processes the model structure uncertainty (Refsgaard et al. 2006) and the model parameter uncertainty (Madsen 2006) subject to a form of knowledge uncertainty.

Understanding the characteristics and the nature of uncertainty sources in the forecast processes was the key factor to categorise them. From the literature the aleatory and the epistemic uncertainty category was adapted (Kundzewicz 2006). The aleatory uncertainty represents the natural variability of the random and unpredictable natural processes in the hydrological cycle. This uncertainty source cannot be reduced or accounted for. On the other hand the epistemic uncertainty source represents the lack of knowledge and of the physical system and through sufficient study this type of uncertainty can be reduced or eliminated.

UNCERTAINTY FRAMEWORK

To manage or account for the uncertainty sources in the forecast processes the uncertainty framework was developed, see Figure 1. In the uncertainty framework the natural hydrological processes were related to the modelled hydrological processes in the forecast system and the uncertainty sources were distinguished based on their characteristics and nature into aleatory and epistemic uncertainty sources. This type of classification provides a better understanding of the unknown therefore indicating how to manage the unknowns in the forecast processes.

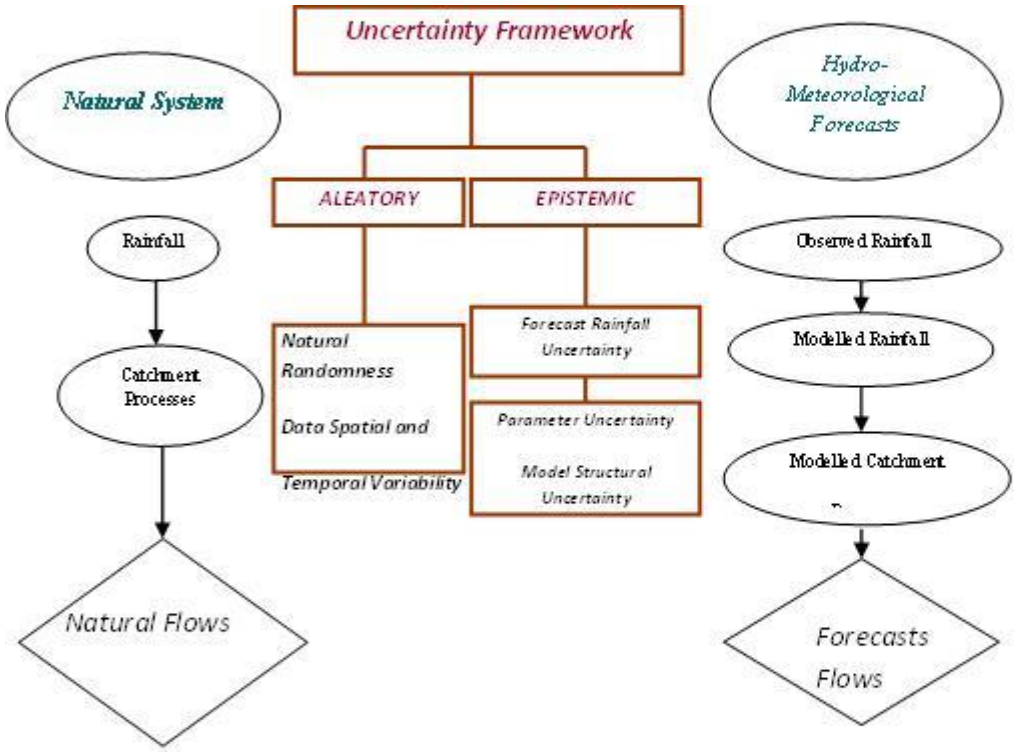

Figure 1. Uncertainty Framework

Aleatory Uncertainty

The aleatory uncertainty represents the processes taking place in the natural system, where the natural randomness of the spatial and temporal variability needs to be accounted for. In the forecast system, rainfall was characterised as an aleatory uncertainty source where the uncertainty arose from the rainfall natural variability. This uncertainty in the forecast system became epistemic because the forecast rainfall was generated by meteorological forecast model therefore it was treated as an epistemic and aleatory uncertainty. Therefore the meteorological component of the forecast system represents a complex uncertainty source. Moreover it was stated in the literature review that the aleatory uncertainty source cannot be reduced or eliminated.

To account for this uncertainty source the newly available STEPS ensemble rainfall forecast was introduced. The STEPS ensemble rainfall forecast was based on radar observations that account for the rainfall spatial variability and are also based on actual rainfall figures.

The introduction and integration of the STEPS ensemble rainfall forecast largely reduced the uncertainty source of meteorological components of the forecast system.

Epistemic Uncertainty

The epistemic uncertainty represents the uncertainty sources in the hydrological forecast model, due to the lack of knowledge. The behaviour of the hydrological cycle was mimicked in the hydrological model. The hydrological model simulates the physical processes in the catchment, where the uncertainty arose due to the lack of knowledge of the physical system. In the literature the model uncertainty is subdivided into a model structure (Refsgaard et al. 2006) and parameter uncertainty (Madsen 2006) sources. Through sufficient study this type of uncertainty can be reduced or eliminated.

To account for this type of forecast uncertainty in the hydrological forecast model the model parameter estimation was undertaken (Madsen 2006).

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CASE STUDY

The Nattai River catchment's current forecast system (Sakal et al. 2006, 2009) was used as a base for this study. The Nattai River is located 150km south west of Sydney and drains an area of 446km2. The Nattai River is one of the tributaries of Sydney's largest drinking water reservoir. Figure 2 shows the locations of the Nattai catchment, of the reservoir and the location of Sydney.

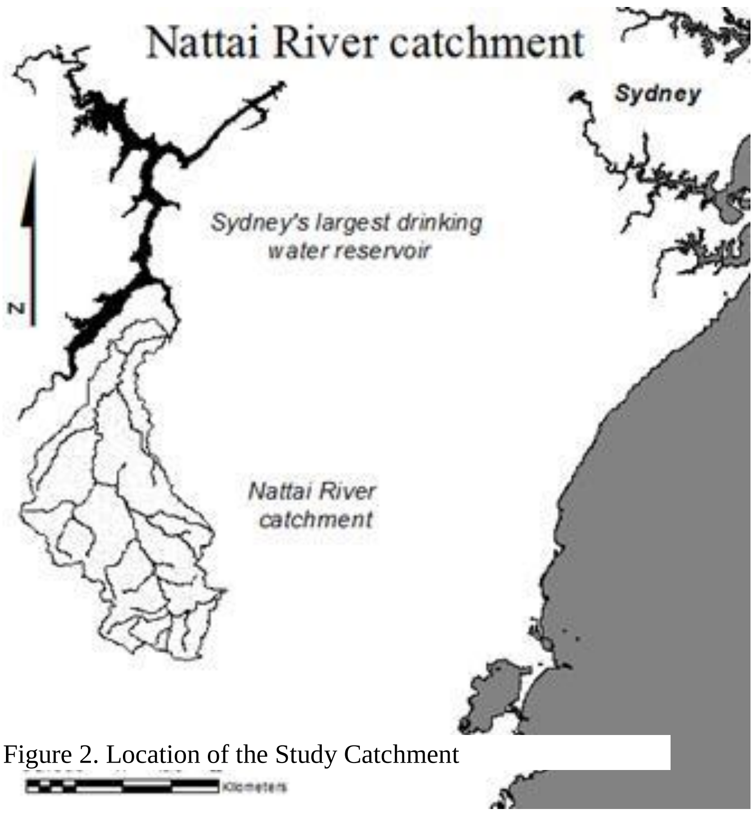

Figure 2. Location of the Study Catchment

To ensure that Sydney's largest drinking water reservoir operations were effective inflow predictions were critical. The current forecast system was implemented in 2005 utilising the DHI's MIKE FloodWatch forecast shell (Sakal 2006). The forecast system manages the data handling and forecast processes. The forecast system runs the hydrological forecast models, creates the model inputs on the fly and extends it with rainfall forecast scenarios to provide future reservoir inflow predictions.

IMPLEMENTATION OF THE UNCERTAINTY FRAMEWORK

The forecast system consists of two major components, the first being the hydrological and the second the meteorological component. Both contain a different degree of uncertainty. The uncertainty sources were classified based on their characteristics and nature. This type of assessment helped to account for the uncertainty sources in the forecast system with the most advanced techniques and tools.

The hydrological component of the forecast system was identified with the epistemic uncertainties. To account for this uncertainty source the parameter optimisation process was undertaken on the Nattai MIKE SHE hydrological forecast model. The Nattai MIKE SHE model was manually calibrated to obtain an initial set of model parameters that were adequately calibrated to allow the subsequent rigorous sensitivity analysis and parameter optimisation. During this process it was recognised that one set of optimal parameters would not represent the whole range of flows in the Nattai River. Therefore the dual-model realisation was introduced to account for long lasting dry conditions and high flow events. The ten most sensitive model parameters were selected with the sensitivity analysis and for both weather conditions were used for the optimisation process with the Population Simplex Evolution (PES) algorithm. Two sets of optimal parameters were estimated to manage or account for the epistemic uncertainties in the forecast processes. The optimised parameter set are presented in Table 1 for both weather conditions.

Table 1 Parameter set for the dual model realisations

MIKE SHE modules	MIKE SHE model componenet	analysed model parameters	Optimal set of parameters for drought year 2009	Optimal set of parameters for wet summer Feb 2010
Land Use	Cleared Land	LAI - leaf area index	1	0.1
	Tableland Forest	LAI - leaf area index	4.18	6
	Drained Perennial	LAI - leaf area index	2.86	4.63
	Slope Forest	LAI - leaf area index	4.1	2.9
Rivers and Lakes	River Network	Leakage coefficient	$5e^{-6}$	$5e^{-6}$
Overland Flow	Over Land Flow	Manning number	7.09	8.54
		Detention Storage	2.35	1.08
Unsaturated Flow	Soil Profile Definitions	ByPassFlow - Tableland Sand	0.696	0.56
		ByPassFlow - Slope Gorge Sand	0.452	0.319
Saturated Zone	Geological Layers	Horizontal Hyd Cond	$5e^{-6}$	$5e^{-6}$
		Vertical Hyd Cond	$3.79e^{-7}$	$1e^{-6}$
		Specific Storage	$1e^{-4}$	$1e^{-4}$
	Geological Lenses	Horizontal Hyd Cond	$1e^{-6}$	$2.99e^{-7}$
		Vertical Hyd Cond	$1e^{-6}$	$1.55e^{-6}$
		Specific Storage	$1e^{-4}$	$1e^{-4}$
	Drainage	Drainage level	-3.14	-3.41

Both model realisations were coupled with the STEPS ensemble rainfall forecast to provide reliable reservoir inflow predictions in real-time operations.

The meteorological component of the forecast system was characterised with both aleatory and epistemic uncertainty sources. To account for this complex uncertainty source in the forecast processes the STEPS ensemble rainfall forecast was utilised in real-time.

Integration of the forecast components and the uncertainty framework resulted in the IHEPS forecast system that provides a comprehensive ensemble reservoir inflow prediction. Replacing the deterministic single forecast, based empirical forecast scenarios with an advanced forecast techniques and tools to manage the uncertainty sources in the forecast processes. Figure 4 shows the ensemble reservoir inflow predictions where the hydrological model is driven with the radar derived rainfall in the hindcast mode and with STEPS ensemble rainfall forecast in the forecast mode. To produce more reliable and comprehensive forecast information.

CONCLUSION

Implementation of the coupled MIKE SHE fully distributed hydrological forecast model with the STEPS ensemble rainfall forecast was introduced. The integrated IHEPS forecast system's uncertainty sources were investigated and classified into epistemic and aleatory uncertainty sources. Both uncertainty sources addresses to manage or account for the forecast uncertainty sources.

The model parameter uncertainty assessment resulted in dual-model realisation for the IHEPS forecast system that cover wider range of flows and provide a forecast spread of possible reservoir inflow predictions.

The STEPS ensemble rainfall forecast replaced the empirical rainfall scenario with a realistic radar derived rainfall forecast. The coupled hydrological and meteorological forecast components greatly improved the forecast system with advanced forecast techniques and tools. The IHPES forecast system accounts for the uncertainty sources in the forecast processes and provides comprehensive reservoir inflow predictions.

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