

**AN AUTOMATED FRAMEWORK FOR
PRECIPITATION-RELATED DECISION MAKING**

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**AN AUTOMATED FRAMEWORK FOR
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Department of Computer Science & Engineering

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DECLARATION

I declare that this is my own work and this dissertation does not incorporate without acknowledgment any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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ABSTRACT

With the effects of rapid urbanization and climate change, weather forecasting plays a vital role in disaster risk controlling and mitigation activities. Generating weather forecasts using numerical weather prediction methods is a tedious process as it requires multiple combinations of weather model workflows. Due to the weather's chaotic nature, field experts frequently modify these static workflows to cater to their decision-making requirements. Moreover, infrequent weather events make these workflows more complicated and challenging to handle manually. There is a need for a decision support system (DSS) to build and update workflows dynamically with these circumstances. After studying the architectures of existing DSSs from different fields, we understand that they cannot handle all weather-related decision-making requirements. Therefore, we present a generic decision support system framework to create and control complex and dynamic weather model workflows. The proposed framework supports three types of decision-making conditions: accuracy-based, infrequent-event, and pump/gate control. The framework can terminate or dynamically update weather model workflow paths in accuracy-based decisions. In infrequent-event decisions, the framework identifies the weather events. In pump-control decisions, the framework attempts to find an optimized control strategy that minimizes the flood risk in the given catchment area. In addition to the above decisions, the system provides relevant workflow strategies for handling unexpected weather conditions. To demonstrate the utility of accuracy-based decision-making, we executed four workflow runs over six months (on randomly selected days for each month). We were able to achieve a 100% accuracy level with manual verification. Pump/gate control strategies were tested using the data from the 2010 Flood event in the Kelani basin area in Sri Lanka. Pump strategy decisions also had 100% accuracy on logic evaluation and model selection. The proposed framework is deployed in a Google cloud platform of the Center for Urban Water, Sri Lanka, for flood-related forecasts.

Keywords — decision support system, dynamic workflow management, weather forecasting

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LIST OF ABBREVIATIONS

CPU	Central Processing Unit
CUrW	Center for Urban Water
DAG	Directed Acyclic Graph
DSS	Decision Support System
FTP	File Transfer Protocol
GCP	Google Cloud Platform
GIS	Geographic Information System
KLB	Kelani Lower Basin
KUB	Kelani Upper Basin
NWP	Numerical weather prediction
RAM	Random Access Memory
RMSE	Root Mean Squared Error
SF	Statistical Forecasting
VM	Virtual Machine
WRF	Weather Research Forecasting