UNIVERSITY OF SOUTHERN QUEENSLAND

DEVELOPMENT OF FLOOD RISK MONITORING AND FORECASTING SYSTEM WITH ARTIFICIAL INTELLIGENCE PREDICTIVE MODELS FOR COMMUNITY RISK MANAGEMENT IN FIJI

A Thesis Submitted by

MOHAMMED MOISHIN

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ABSTRACT

Floods are frequently occurring natural disasters that can cause significant damage to human lives, natural resources, and the civil infrastructures. The devastating impacts of flood events warrant the need to develop innovative means of both monitoring and forecasting of flood events to assist in reducing the damage caused by such events. In this research project, new mathematical methods designed to provide an objective explanation of the progression and forecasting of future flood events in Fiji are explored. Firstly, a flood monitoring tool known as the Flood Index (I_F), is used to study flood events that occurred in Fiji over the period 1991-2019. I_F is generally recognized as an objective means to determine the flood state solely based on rainfall datasets. In addition, the I_F makes it possible to mathematically derive the duration, severity, and the intensity of flood situations. In this research study, the flood events identified for nine study sites in Fiji are quantified using I_F, and their duration, severity, and intensity (based on I_F derived from rainfall dataset) were successfully determined. Next, the convolutional version of Long Short-Term Memory Network (ConvLSTM), which is a hybrid deep learning algorithm integrating LSTM and CNN (Convolutional Neural Network) algorithms, is used to develop a flood forecasting system. The newly designed deep learning model (*i.e.*, ConvLSTM) uses significant lagged I_F values and the antecedent rainfall dataset as a predictor (or input) variable, in order to forecast the I_F value at the 1, 3, 7 and the 14 day ahead timescales, to depict the progression of a likely flood event after torrential rainfall events. When compared with the benchmark predictive models, the objective model (*i.e.*, ConvLSTM) reveals a superior performance, and thus demonstrates good forecasting accuracy of a likely flood event. The final objective of this research project is to develop a Decision Support System (DSS) as a convenient digital platform to compute both the daily and the hourly flood monitoring and forecasting indices using *Streamlit* software as the systematic platform. The study adopts *Streamlit*, as it is a platform that can be used to easily build data-driven, web-based applications using the Python programming language. The proposed DSS platform is able to provide a portable online interface required to build and evaluate ConvLSTM predictive model for daily and hourly flood forecasting systems. The proposed methodologies in this project were shown to be significantly

innovative in terms of flood monitoring and forecasting with a focus on their applications to the Fiji Islands where natural disasters such as tropical cyclones are likely to bring flood inundations almost every year and pose serious community risk. The results presented in this research study is expected to be an important step-forward in the development of both mathematical and artificial intelligence (AI) based flood monitoring and forecasting systems to address flood impacts and community risk management. An AI-based decision support system is also expected to become valuable for meteorologists, government, disaster management committees and other climate risk decision makers to be better prepared for future flood risk, particularly, by developing better strategies to mitigate the harmful impacts of flood events, and consequently, use such systems to lives and infrastructure.

CERTIFICATION OF THESIS

This Thesis is the work of MOHAMMED MOISHIN except where otherwise acknowledged. The majority of the authorship in the research papers presented as a Thesis by Publication has been undertaken by the Student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Principal Supervisor	:	Professor Ravinesh C Deo
External Supervisor	:	Dr Ramendra Prasad
Associate Supervisor	:	Dr Nawin Raj
Associate Supervisor	:	Dr Shahab Abdulla

Student and supervisors signatures of endorsement are held at the University.

JOURNAL PUBLICATIONS AND STATEMENT OF AUTHOR CONTRIBUTIONS

The following presents the contributions of the student and the co-authors of the publications presented in this thesis.

Article 1: Chapter 4

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The percentage contributions for this paper are MM 65%, RCD 15%, RP 10%, NR 5%, and SA 5%.

Author	**Tasks Performed**
Mohammed Moishin (*Candidate*)	Programming, data analysis, preparation of tables and figures, compiling and writing the manuscript.
Ravinesh C. Deo (*Principal Supervisor)*	Supervised all aspects of the research work done, editing, and proof reading of the manuscript. Submitted paper to journal and located reviewers.
Ramendra Prasad (*External Supervisor*)	Editing, proofreading of the manuscript, and provided feedback.
Nawin Raj (*Associate Supervisor*)	Proofreading of the manuscript and provided feedback.
Shahab Abdulla (*Associate Supervisor*)	Proofreading of the manuscript and provided feedback.

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Mohammed Moishin (*Candidate*)	Model development, training, testing, analysis, preparation of tables and figures, compiling and writing the manuscript.
Ravinesh C. Deo (*Principal Supervisor*)	Supervised all aspects of the research work done, editing, and proof reading of the manuscript. Submitted paper to journal and located reviewers.
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Author	**Tasks Performed**
Mohammed Moishin (*Candidate*)	Development of the Decision Support System (DSS), testing, analysis, preparation of tables and figures, compiling and writing the manuscript.
Ravinesh C. Deo (*Principal Supervisor*)	Supervised all aspects of the research work done, editing, and proof reading of the manuscript. Submitted paper to journal and located reviewers.
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LIST OF ACRONYMS

AI	Artificial Intelligence
ANN	Artificial Neural Network
AWRI	Available Water Resource Index
CNN	Convolutional Neural Network
d	Willmott’s Index (Index of Agreement)
D_F	Duration of Flood
DKT	D'Agostino's K^2 Test
DFT	Dickey-Fuller Test
DNN	Deep Neural Network
DSS	Decision Support System
FJD	Fijian Dollar
FC-LSTM	Fully Connected LSTM
GDP	Gross Domestic Product
GUI	Graphical User Interface
I_F	Flood Index
I_F^{acc}	Flood Severity
I_F^{max}	Peak Danger
LME	Legate-McCabe Efficiency Index
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MSE	Mean Squared Error
NSE	Nash-Sutcliffe Efficiency Index
P	Precipitation
PACF	Partial Autocorrelation Function
P_E	Effective Precipitation
r	Pearson’s Correlation Coefficient
r^2	Coefficient of Determination
ReLU	Rectified Linear Unit
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network

SPCZ	South Pacific Convergence Zone
SPI	Standardized Precipitation Index
SVM	Support Vector Machine
SVR	Support Vector Regression
SWAP	Standardized Weighted Average of Precipitation
WAP	Weighted Average of Precipitation
WRI	Water Resources Index
$WRI_{24-hr-S}$	24 Hour Water Resources Index
$WRI_{48-hr-S}$	48 Hour Water Resources Index
$WRI_{72-hr-S}$	72 Hour Water Resources Index
$WRI_{96-hr-S}$	96 Hour Water Resources Index

CHAPTER 1: INTRODUCTION

1.1 Background

Floods are one of the most commonly occurring natural disasters (Doocy et al. 2013). Severe flood situations usually result in the loss of lives and damages to infrastructure which causes a significant economic impact. The unpredictable behavior of floods results in a challenging problem for meteorological organizations, hydrological system modelers and national disaster management experts. However, advanced statistical approaches and Artificial Intelligence (AI) techniques can be used to develop practical tools for flood risk monitoring and forecasting, respectively. These tools would assist communities to be better prepared for potential flood situations and apply effective risk mitigation strategies in a timely manner. As such, it has become increasingly important to apply emerging technologies to develop new cost-effective and efficient flood monitoring and forecasting systems that can be used to save lives and resources.

The Flood Index (I_F) (Deo et al. 2015) and Water Resources Index (WRI) (Deo, Byun, et al. 2018) are two flood monitoring tools that largely rely on accumulated rainfall data to quantify flood situations. Out of these two indices, the WRI is normally used for hourly flood monitoring and I_F is applied for daily monitoring of floods. However, both of these tools are in line with the rationale by (Lu 2009), which states that apart from precipitation, other hydrological conditions such as evaporation, transpiration, seepage and surface run-off needs to be considered for a flood monitoring index. I_F and WRI have been applied at various places around the globe and have shown to deliver highly accurate results (Deo et al. 2014, 2015; Deo, Adamowski, et al. 2018; Deo, Byun, et al. 2018). Therefore, using I_F and WRI in this study is expected to provide a more effective assessment of the duration, severity, and intensity of past floods in the country.

Moreover, apart from analyzing previous flood events, it is extremely important to be able to forecast future flood situations. However, developing early flood warning systems have been a challenge as the development of such systems require several technologies and expertise in a wide array of areas (Krzhizhanovskaya et al. 2011). Such challenges are more evident in developing countries where scientific research is limited. Therefore, a cost-effective solution with readily available technology is required for an early flood forecasting system in these countries. Over the years, several AI-based approaches have been used for flood forecasting (Campolo et al. 1999; Nayak et al. 2005; Tran & Song 2017). These AI-based methods are cost-effective and have been able to deliver good forecasting performance. Consequently, efficient, and cost-effective early flood warning systems can be developed by using the latest AI techniques and mathematical flood monitoring tools.

Furthermore, since the mid 1970’s, Decision Support Systems (DSS) have been developed in several studies, which addressed various areas of flood risk management (Loucks & Da Costa 1991; Simonovic 1999; Ahmad & Simonovic 2006; Mahmoud & Gan 2018). Despite this, a DSS that is based on mathematical flood monitoring tools such as I_F and hourly WRI have not been built till date. As stated, WRI is based on a similar rationale as the I_F, but can be used to monitor flood situations at hourly timescales (Deo, Byun, et al. 2018). Therefore, as these mathematical tools have shown good performance in quantifying flood situations, development of a data driven DSS that uses these tools is expected to enable a cost-effective approach for monitoring and forecasting flood situations. Consequently, the proposed DSS would also make it easy for organizations to use mathematical flood monitoring and forecasting tools.

1.2 Statement of the Problem

Flood events can cause significant damages to infrastructure, ecology, human lives, economic strength and several other tangible and intangible resources (Messner & Meyer 2006). It is one of the most common forms of natural disasters in many areas around the globe such as the study area for this research, Fiji. This South Pacific island nation has faced some of the severest floods in the past (Yeo & Blong 2010; Brown et al. 2016). It is estimated that the damage caused by the January 2012 floods totaled around 48.6 million FJD for the Ba and Penang river catchments combined (Brown et al. 2016). These are huge costs for low-income countries such as Fiji. Brown et al. (2016) stated that due to changes in climate, such disasters are expected to be more severe in the future and this will cause more damages. Therefore, there is an urgent need to develop innovative and cost-effective tools using emerging technologies that can assist stakeholders to be better prepared for flood events and therefore possibly mitigating the harmful impacts resulting from such natural disasters.

1.3 Research Questions

The following research questions are designed in accordance with the objectives of this MSCR study:

(1) Can we develop a flood monitoring system to investigate the duration, severity and intensity of flood events that have occurred in the Fiji Islands over a thirty-year period (1990-2019) and how this information can be used for better disaster risk management?

(2) How can the occurrence of future flood events be forecasted using an AI-based, deep learning-based approach and how accurate will these flood predictions be in ensuring an accurate flood warning system be implemented for community risk management in Fiji?

(3) Will a Decision Support System (DSS) to assist in computing mathematical flood monitoring indices and providing means of forecasting these indices be useful for flood risk mitigation and will it increase the usage of mathematical and AI-based models for flood monitoring and forecasting?

This project will answer the above questions using flood monitoring indices, to study previous flood events in Fiji. Following this, the flood indices will be used with an AI-based approach including deep learning algorithms to forecast the future occurrence of flood events. Finally, a new DSS will be developed for flood monitoring and forecasting to answer the third research question

1.4 Aims and Objectives

The aim of this research project is to develop data driven flood monitoring and AI-based flood forecasting tools and test its application on various flood prone sites in Fiji. These tools are expected to be helpful for relevant organizations in mathematically quantifying previous floods and forecasting the possible occurrences of future flood situations. Hence, to achieve the key aim, the objectives of this research is to:

1. Develop the relevant programming codes required to calculate the flood monitoring index, I_F, based on effective precipitation, P_E and water resources index, $AWRI$. Furthermore, the flood index will be used to derive the duration, severity and intensity of all flood events that occurred during the study period using the computed I_F for various sites in the Fiji Islands.
   [The outcomes of Objective 1 have been published in *Stochastic Environmental Research and Risk Assessment* journal]

2. Use ConvLSTM hybrid deep learning algorithm and develop a cost-effective early flood warning system. Furthermore, to compare the performance of the ConvLSTM model with CNN-LSTM, LSTM and SVR and determine the suitability of the objective model in forecasting floods at 1, 3, 7 and 14 day ahead timescales.
   [The outcomes of this Objective 2 have been published in *IEEE Access* journal]

3. Build a robust online DSS that can be used to compute daily and hourly flood monitoring indices. In addition, the DSS was expected to have interfaces for easily building and testing daily and hourly flood forecasting AI-based models.
   [The outcomes of this Objective 3 will be submitted to *Stochastic Environmental Research and Risk Assessment* journal]

The journal paper resulting from the completion of objective one has been published in *Stochastic Environmental Research and Risk Assessment* (https://doi.org/10.1007/s00477-020-01899-6) and the paper produced for completing objective two has been published in *IEEE Access* (https://doi.org/10.1109/ACCESS.2021.3065939). The journal paper produced for completing objective three will be submitted to Stochastic Environmental Research and Risk Assessment.

1.5 Thesis Layout

This thesis has been organized into seven chapters as follows:

Chapter 1 This chapter provides background about the research, discusses the statement of problem, presents the research questions, and outlines the main objectives of the study.

Chapter 2 This chapter provides the literature review for the study and presents details of the concepts and tools used during this research.

Chapter 3 This chapter discusses the study sites, data and provides an overall overview of the experimental methods used in this research. The content presented in this chapter lays the foundations for the following chapters.

Chapter 4 This chapter presents a published journal article. The paper presented is titled "Development of Flood Monitoring Index for daily flood risk evaluation: case studies in Fiji" (https://doi.org/10.1007/s00477-020-01899-6) and was published in the journal, *Stochastic Environmental Research and Risk Assessment*. It addressed objective one of this study.

Chapter 5 This chapter also presents a published journal article. The paper presented is titled "Designing Deep-based Learning Flood Forecast Model with ConvLSTM Hybrid Algorithm" (https://doi.org/10.1109/ACCESS.2021.3065939) and was published in the journal, *IEEE Access*. It addressed objective two of this study.

Chapter 6 This chapter presents a journal article which will be submitted to *Stochastic Environmental Research and Risk Assessment*. The paper presented is titled "A Web-based Flood Monitoring and Forecasting Decision Support System with Streamlit *Online* Platform". This paper addressed objective three of this study.

Chapter 7 This chapter concludes the thesis by presenting a summary of the study, listing the limitations, and by providing recommendations for future works.

CHAPTER 2: LITERATURE REVIEW

This section discusses the literature review for this thesis. It has been divided into several sections, with each section elaborating on a specific important concept used for this research.

2.1 Flood Monitoring

Over the years, several mathematical tools have been developed for monitoring floods using mathematical means and rainfall data. These include the I_F, WRI, Standardized Precipitation Index (SPI) (Seiler et al. 2002), Available Water Resources Index ($AWRI$) (Byun & Lee 2002), Weighted Average of Precipitation (WAP) (Lu 2009) and the Standardized WAP ($SWAP$) (Lu et al. 2013). Among these tools, the tool which is one of the most common is the SPI. However, the major drawback of using this approach for this study was its incapability to quantify floods for short time periods (e.g., daily timescales) (Lu 2009). In addition, other hydrological conditions which are important for a flood monitoring tool such as evapotranspiration and seepage is not considered by SPI. Hence due to these factors, SPI was not suitable for flood monitoring in this study as the monitoring of floods at daily and hourly timescales was required for the purposes of this research.

Furthermore, two of the standardized tools that are useful for monitoring floods at daily timescales include the I_F and $SWAP$. These indices are the normalized version of Effective Precipitation (P_E) (Byun & Chung 1998) and WAP, respectively and both of these follow the rationale presented by (Lu 2009). This rationale states that the occurrence of a flood on any day is dependent on the antecedent and current days precipitation. This was also stated by (Ma et al. 2014) in terms of considering the remaining volume of water after a flood for the assessment of floods. In addition, the effect of earlier days rain on current days flood gradually decreases due to different hydrological conditions. These include conditions such as percolation and groundwater flow (Lu 2009). As shown in Figure 2.1, this rationale is used by P_E. Moving on, one of the major drawbacks of $SWAP$ is that is has not been widely applied for flood monitoring. On the other hand, I_F has been tested for its applicably at many places with different environmental conditions (Nosrati et al. 2010; Deo, Adamowski, et al. 2018). Therefore, using I_F for daily flood monitoring in this research is expected to produce better and more accurate results.

Moreover, the tool which is based on a similar principle as the I_F, but can be used for flood monitoring at hourly timescales using earlier hours rainfall data is the WRI. The only drawback of this index is that is has not been widely applied in various studies. However, during its usage for monitoring floods in South Korea and Australia, it was seen to be a good statistic of flood situations at hourly timescales (Deo, Byun, et al. 2018). Consequently, due to this and the underlying principle of the WRI, it is selected to be applied and evaluated for the hourly flood monitoring tasks during this research.

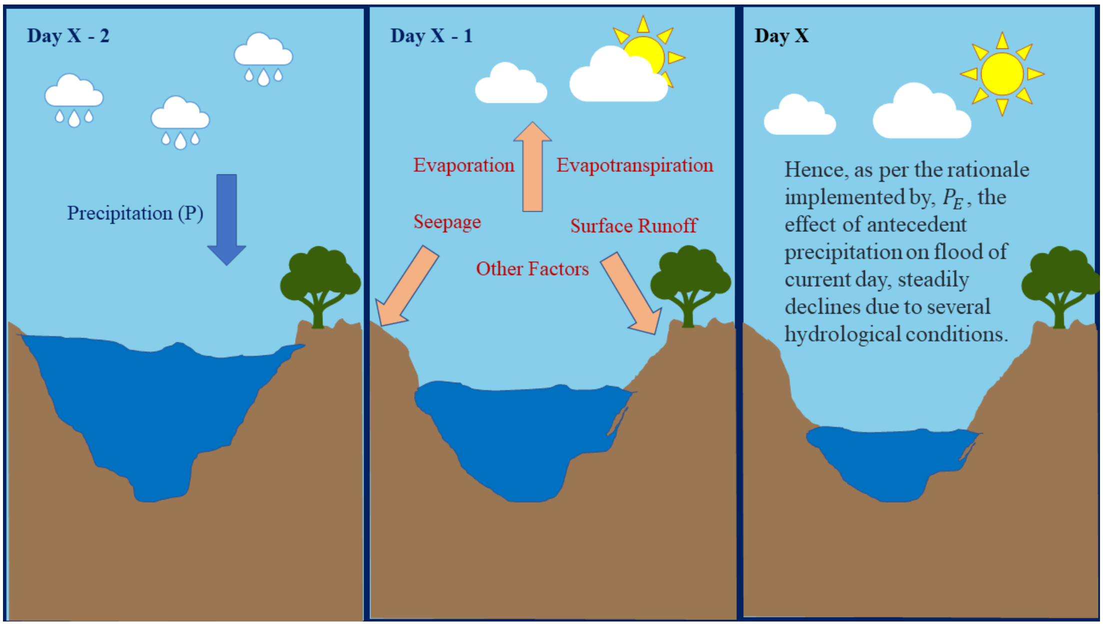

Figure 2.1: Demonstration of Rationale used by P_E (Depleting Water Resources after Over time due to Several Hydrological Conditions)

2.2 Flood Forecasting

There are several AI-based tools that have been developed in the recent years for forecasting floods. These tools have made used of various techniques with machine learning and deep learning approaches to forecast floods. Some examples of these methods include a river flood forecasting neural network model by Campolo et al. (1999), Support Vector Machine (SVM) based method by (Han et al. 2007), deep learning approach using RNN (Recurrent Neural Network) and LSTM (Long Short-

Term Memory) network by (Tran & Song 2017) and Artificial Neural Network (ANN) deep approach for decentralized flood forecasting by (Sit & Demir 2019). Hence, these examples clearly demonstrate the ability of AI-based methods for flood forecasting. Consequently, using flood monitoring tools such as I_F and WRI with AI approaches to forecast floods is expected to open a new means of forecasting floods using timeseries data.

Furthermore, it is expected that using hybrid deep learning approaches that combines multiple deep learning algorithms for specific forecasting tasks should deliver better performance when compared with standalone machine and deep learning algorithms. Some of the examples of hybrid deep learning algorithms include CNN-ELM (Duan et al. 2018) which combines Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM) algorithms, DNN-BTF (Wu et al. 2018) which used Deep Neural Networks (DNN), RNN and CNN for improving prediction performance, and ConvLSTM (Kim et al. 2017) which combined CNN and LSTM. In terms of individual algorithms from this list, LSTM has been previously used to forecast floods and has also shown good performance for time-series forecasting (Yunpeng et al. 2017; Siami-Namini et al. 2018). Consequently, using ConvLSTM, which is a hybrid deep learning model, and a variant of LSTM is expected to provide better accuracy and performance when forecasting floods using timeseries data.

2.3 Online Flood Decision Support System

According to Eom and Kim (2006), research involving DSS's can be classified into three general categories. These include studying the reference disciplines, theory building and application development. In addition, an interdisciplinary research approach is required for developing DSS's, involving fields such as computer science, statistics and knowledge engineering (Eom 1999). Over the years, several DSS's with the purpose of flood management and related decision making has been developed. These include the DSS developed by (Ahmad & Simonovic 2006) for assisting during the various phases of flood management and the operational DSS developed by (Todini 1999). However, a DSS that uses flood monitoring indices such as I_F and WRI for monitoring and forecasting floods at daily and hourly timescales is not available. Consequently, the development of such DSS is expected to provide a convenient and cost-effective means of analyzing and forecasting floods.

Web-based DSS's, despite its challenges, have a number of advantages including being platform independent, distributed and accessibility from remote locations that has internet connectivity (Bhargava et al. 2007). Furthermore, in recent years, several technologies have been developed to build powerful web applications. These include PHP (Welling & Thomson 2003), JavaScript (Crockford 2008) and ASP.Net (Galloway et al. 2012). However, these tools are not fully suitable for data driven applications. A platform that can be used to build data driven web-based applications easily and quickly is Streamlit (Streamlit 2021). This platform allows the user to use Python programming language (Sanner 1999) which is a popular language for data analysis, machine learning and data visualization. Hence, a Streamlit based DSS for providing means of monitoring and forecasting floods would enable an innovative means for flood risk mitigation.

2.4 Summary

In summary, for monitoring of floods, I_F and WRI appears to be better indices for daily and hourly monitoring of floods, respectively. These indices take antecedent rainfall and other hydrological conditions such as percolation, surface run-off and evapotranspiration into consideration to deliver accurate flood analysis results. When it comes to forecasting floods and developing early warning systems for floods, deep learning approaches such as CNN and LSTM have shown to produce better results when compared with the conventional machine learning models. Therefore, using the ConvLSTM hybrid deep learning model to forecast floods will provide better forecasting ability. In addition, developing an online DSS that uses rainfall-based flood monitoring tools to analyze and forecast floods will be a cost-effective means for flood management and risk mitigation. Furthermore, the online capability of this system will allow users to easily access and use the platform. These works are expected to be a novel and innovative means for analyzing and forecasting flood situations which will assist decision makers prepare efficient plans for flood mitigation, evacuation, and disaster risk management.

CHAPTER 3: DATA, STUDY AREA AND METHODS

This chapter presents the study area, data and methods used during this research.

The emphasis of this research is on Fiji, which is an island nation in the southwest Pacific (Lal 1992). The Fiji group consists of 332 islands (110 inhabited) and has an area of 18,000 km^2. The country has a population of less than a million and majority of the people live on Viti Levu and Vanua Levu, which are the two largest islands among the group of islands (Government of Fiji 2017). Furthermore, Yeo et al. (2007) stated that floods are a serious threat to Fiji and that over the recent decades, the number of floods occurring in the country has increased. Two of the priorities for improving management of flood risk in the Pacific is to invest in early warning systems and improve capabilities for emergency management (Yeo et al. 2017). Therefore, it became increasingly important to develop and apply cost-effective and innovative methods to reduce the impact of floods on lives and infrastructure in Fiji and other Pacific island countries.

Adding on, due to the study area being small, majority of the flood prone areas of the country are covered during this research. The daily and hourly rainfall data for various sites around Fiji are successfully obtained from the Fiji Meteorological Services. Prior to discussing the new methods of flood monitoring that has been explored in this research, it is worth to mention that currently the tool that is used in Fiji for flood and rainfall analysis is the SPI (Nawai et al. 2015; Fiji Meteorological Service 2018). The following contents have been divided into three subsections. Each subsection will briefly discuss the study area, data, and methods specific to completing each of the three objectives of the research. A detailed overview of the study area and methodology for these objectives has been discussed in the published and submitted journal papers presented in chapters 4, 5, and 6 of this thesis for objectives 1, 2 and 3, respectively.

3.1 Objective 1: Daily Flood Monitoring using I_F

Study Area and Data: Daily rainfall data from 1st January 1990 to 31st December 2019 (30 Years) for eleven areas around Fiji was successfully obtained. These areas included Ba, Labasa, Lautoka, Nadi, Nausori, Navua, Rakiraki, Savusavu, Sigatoka, Suva, and Tavua. However, since Navua and Tavua had lots of missing data, they are not used during the experiments. The other sites had fewer missing data, and these are filled using the calendar mean before using it in the computations. While addressing this objective, the major town and city centers of the Fiji group are covered.

Methodology: The platform used to develop the code for obtaining the I_F is MATLAB (MathWorks 2019). Once the missing data was filled using calendar means, the first variable to compute is the P_E. P_E provides the sum of the accumulated rainfall over an annual period (365 days), with the effect of antecedent day's rainfall on current day's P_E gradually decreasing based on a time-dependent reduction function (Byun & Chung 1998). The first metric derived from the P_E is the $AWRI$, which is obtained simply by dividing the P_E over the combined weight (W) of an annual cycle. Finally, the most useful metric, I_F, which is the normalized form of P_E is derived. Once the I_F has been computed, the onset, end, duration, severity, and intensity of floods that had occurred during the study period is determined.

3.2 Objective 2: Daily Flood Forecasting using ConvLSTM

Study Area and Data: The nine sites used for objective one is also used for objective two. However, in terms of data, apart from raw daily rainfall data, the computed I_F from the results of objective one is also used. These are the two features to be used as inputs for the forecasting model. The other computed data from objective one (P_E and $AWRI$) was also tested for its applicability in the forecasting model but is removed after the feature selection process.

Methodology: The daily flood monitoring results which was obtained when addressing objective one is used to develop a deep ConvLSTM (Xingjian et al. 2015) based flood forecasting system. The purpose of the model is to forecast future I_F values based on lagged I_F and rainfall data. Partial Autocorrelation Function (PACF) is used to choose the number of lagged days to be used by the model and prior to training the model, the input data is scaled to be between 0 and 1. Furthermore, the programming language used for developing the models is Python (Sanner 1999). Three other benchmark models are developed using CNN-LSTM (Livieris et al. 2020), LSTM (Le et al. 2019) and SVR (Drucker et al. 1997) and their performance in terms of forecasting accuracy is evaluated and compared against the objective model. The models are trained using various combinations of hyperparameters until the model performance is optimum. Once the models are developed, their performance with both the training and testing data is thoroughly evaluated using several statistical score metrics.

3.3 Objective 3: Decision Support System for Flood Monitoring and Forecasting

Study Area and Data: The proposed DSS is to be used for both daily and hourly flood monitoring and training and testing flood forecast models. The daily rainfall data was available for the nine sites from previous objectives. However, for hourly flood monitoring and forecasting, rainfall data from various sites in Fiji was obtained at 10-minute intervals for the period starting from 1st January 2014 to 31st December 2019. These datasets are added at hourly intervals to get rainfall amounts at hourly timescales. Once the proposed DSS is developed, the daily and hourly data from three sites, Ba, Nadi and Rakiraki, are used to test its practical application, performance, and accuracy.

Methodology: Streamlit online platform, which uses Python programming language, is used to build a DSS to compute the daily I_F and hourly WRI. The proposed DSS also provides an interface for building and testing ConvLSTM based models to forecast future I_F and WRI values as a means of developing AI-based flood forecasting models. The theoretical monitoring and forecasting approaches used by the proposed DSS is like the approaches used when addressing objectives one and two. This has been demonstrated in Figure 3.1, which shows the link between the methods and results of the first two objectives of this research being used for completing this objective (Objective 3). Consequently, the proposed DSS is built to be a generic system that can be easily used to apply mathematical flood monitoring tools at any location, using only daily or hourly rainfall data.

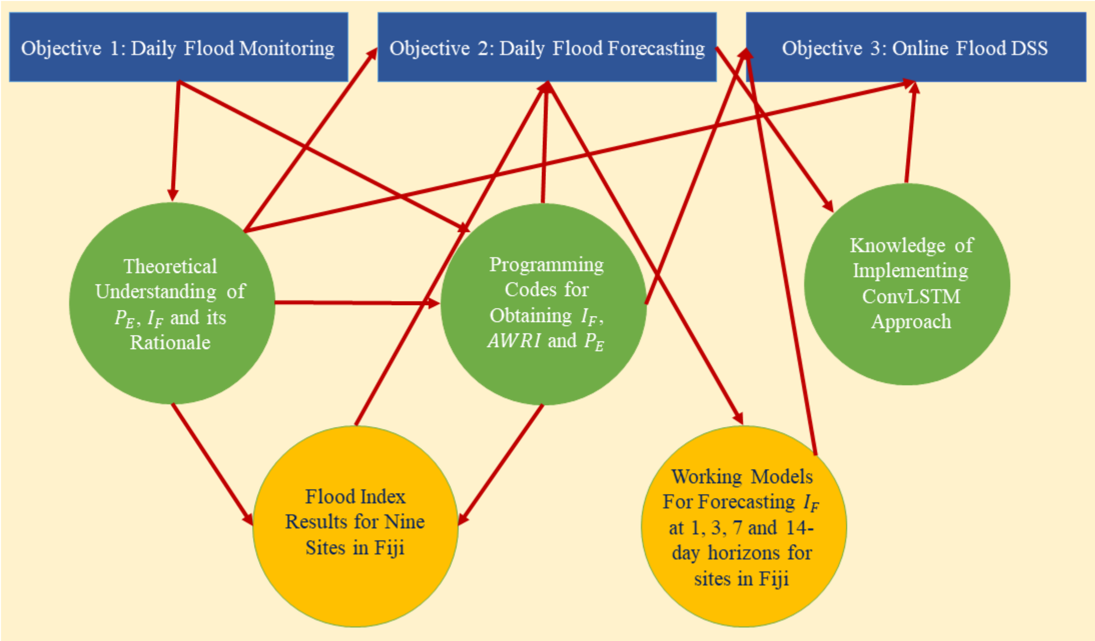

Figure 3.1: Link between Methods and Results of Objectives One and Two being Used to Complete Objective Three

CHAPTER 4: FLOOD MONITORING SYSTEM DESIGN AND IMPLEMENTATION

Foreword

In this chapter, a copy of the paper with the title "Development of Flood Monitoring Index for daily flood risk evaluation: case studies in Fiji", which is published in the journal, *Stochastic Environmental Research and Risk Assessment* has been presented. In the paper, the code for obtaining the I_F was developed and applied to nine sites around Fiji Islands to mathematically quantify the floods that occurred in those regions over a 29-year period (1991-2019). Using the computed daily I_F, the duration, severity, and intensity of the floods during the analysis period was successfully determined. The results illustrated that floods are common throughout the country and they usually occurred during the November to April wet season in the country. Furthermore, this study also established I_F as a cost-effective and accurate mathematical tool for daily flood monitoring in island nations. The results obtained in this study are useful for governments, organizations, and individuals in Fiji. These outcomes can assist them in building efficient flood risk mitigation strategies and mitigate the impacts of future floods that the country faces.

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ORIGINAL PAPER

Development of Flood Monitoring Index for daily flood risk evaluation: case studies in Fiji

Mohammed Moishin[1] · Ravinesh C. Deo[1] · Ramendra Prasad[2] · Nawin Raj[1] · Shahab Abdulla[3]

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Abstract

Both fluvial and pluvial floods are a common occurrence in Fiji with fluvial floods causing significant economic consequences for island nations. To investigate flood risk and provide a mitigation tool on daily basis, the Flood Index (I_F) is developed based on the rationale that the onset and severity of an event is based on current and antecedent day's precipitation. This mathematical methodology considers the notion that the impact of daily cumulative precipitation on a particular flood event arising from a previous day's precipitation, decreasing gradually over time due to the interaction of hydrological factors (*e.g.*, evaporation, percolation, seepage, surface run-off, drainage, etc.,). These are accounted for, mathematically, by a time-reduction weighted precipitation influencing the magnitude of I_F. Considering the duration, severity and intensity of all identified events, the applicability of I_F is tested at 9 study sites in Fiji using 30-year precipitation datasets (1990–2019) obtained from Fiji Meteorological Services. Newly developed I_F is adopted at flood prone sites, with results demonstrating that flood events were common throughout the country, mostly notable between November to April (or the wet season). Upon examining the variations in daily I_F, the flood properties were determined, showing that the most severe events generally started in January. Flood events with the highest severity were recorded in Lautoka [I_F^{acc} (flood severity) ≈ 149.14, I_F^{max} (peak danger) ≈ 3.39, D_F (duration of flood) ≈ 151 days, t_{onset} (onset date) $=$ 23rd January 2012], followed by Savusavu ($I_F^{acc} \approx 141.65, I_F^{max} \approx 1.75, D_F \approx 195$ days, $t_{onset} =$ 27th November 1999) and Ba ($I_F^{acc} \approx 131.57, I_F^{max} \approx 3.13, D_F \approx 113$ days, $t_{onset} =$ 9th January 2009). The results clearly illustrate the practicality of daily I_F in determining the duration, severity, and intensity of flood situation, as well as its potential application to small island nations. The use of daily I_F to quantify flood events can therefore enable a cost-effective and innovative solution to study historical floods in both developing and first world countries. Our methodology is particularly useful to governments, private organizations, non-governmental organizations and communities to help develop community-amicable policy and strategic plans to prepare for flood impacts and undertake the necessary risk mitigation measures.

Keywords Flood monitoring · Flood Index · Risk mitigation

List of symbols

D_F	Duration of flood
I_F	Flood Index
I_F^{acc}	Flood severity
I_F^{max}	Peak danger
P	Precipitation
P_E	Effective Precipitation

Abbreviations

AWRI	Available Water Resource Index
FJD	Fijian Dollar
GDP	Gross Domestic Product
SPCZ	South Pacific Convergence Zone
SPI	Standardized Precipitation Index
SWAP	Standardized Weighted Average of Precipitation
WAP	Weighted Average of Precipitation

✉ Ravinesh C. Deo
ravinesh.deo@usq.edu.au

Mohammed Moishin
u1127003@umail.usq.edu.au; mmoishin@gmail.com

[1] School of Sciences, University of Southern Queensland, Spring Mountain, QLD 4300, Australia

[2] Department of Science, School of Science and Technology, The University of Fiji, Lautoka, Fiji

[3] USQ College, University of Southern Queensland, Toowoomba, QLD 4350, Australia

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1 Introduction

Floods are a common occurrence in most parts of the globe. More than two billion people were affected by floods between 1998 and 2017 (Wallemacq and House 2018). Adding on, floods resulted in 142,088 deaths and amounted to a total of 656 billion USD in economic losses for the 20-year period. In contrast to first world countries, the effects of such disasters are more devastating in developing countries (Keoduangsine et al. 2014). Fiji, which is a developing country has faced some of the severest floods in the past. One of the worst disasters that the country faced was the 1931 hurricane and flood in which at least 225 people lost their lives (Yeo and Blong 2010). It is estimated that the damage caused by the January 2012 floods totalled around 48.6 million FJD for the Ba and Penang river catchments combined (Brown et al. 2016). These are significant losses for a country with a GDP of less than 6 billion USD (The World Bank Group 2019) and a population of less than a million. According to Brown et al. (2016), floods will be more frequent and severe in the future, resulting in increasing annual losses due to climate change. Therefore, this brings up the need to develop and apply innovative and cost-effective solutions that can assist to mitigate the impacts caused by floods in developing countries such as Fiji.

Subsequently, scientific tools with practical applications in the 21st century are necessary considering the current trends of water resources (Yevjevich 1991). Over the years, there have been many flood monitoring methods that have been used to quantify flood events including the Standardized Precipitation Index (SPI) (Seiler et al. 2002), Weighted Average of Precipitation (WAP) (Lu 2009) and the Flood Index (I_F) (Deo et al. 2015). These methods have been used to monitor floods at different places around the globe and have been accepted as suitable tools for flood monitoring. Such quantification of floods assists in understanding more about these floods and helps in better decision making in the future. Consequently, using historical precipitation data for the flood prone areas in Fiji, flood monitoring indices could be used to examine the duration, severity and intensity of flood events that have occurred in these areas, in the past. Yet, a key drawback of these widely used methods for flood analysis and monitoring is that they largely rely on total rainfall data therefore its practicality needs to be investigated before implementation.

The SPI (McKee et al. 1993) was initially developed for drought assessments but many studies have used it for monitoring floods (Guerreiro et al. 2008; Seiler et al. 2002; Wang and Cao 2011). SPI makes use of historical precipitation data to determine if a year is a flood or drought year for that area. However, monitoring floods and droughts for a short timescale is not possible using SPI because it does not consider the previous day's precipitation. For instance, if there was no rainfall for a short period (for example, less than a week), the index will classify the period as a drought even if there was heavy precipitation on the days which led to a flood prior to that short period. Therefore, due to the inability of SPI to monitor flood situations for short timescales, the daily monitoring of the start, duration and strength of floods, which is required for this study, is not possible using SPI (Lu 2009). In addition, SPI does not consider other factors such as percolation, evaporation and surface run-off which are critical hydrological conditions to be considered when monitoring floods.

The fluctuations of remaining volumes of water due to heavy precipitation over time should be considered for assessing the possibility of floods (Ma et al. 2014). The extent of a flood is based on the current day and antecedent days' precipitation whereby the impact from the previous day's precipitation gradually decreases due to factors such as evapotranspiration, percolation, groundwater flow and surface runoff (Lu 2009). Two of the monitoring indices which account for the previous days precipitation are the WAP (Lu 2009) and I_F (Deo et al. 2015). Both WAP and I_F can be used for monitoring floods on shorter time scales (example daily) and considers other hydrological conditions such as evaporation and surface run-off, which is not accounted for by SPI (Lu 2009). Consequently, in terms of evaluating flood properties at short timescales based on rainfall, WAP and I_F appears to be a better option when compared with the commonly used SPI.

I_F is a standardized metric which makes use of Effective Precipitation (P_E). P_E is deduced from daily rainfall by placing emphasis on recent precipitation, based on a time-dependent reduction function (Byun and Chung 1998; Deo et al. 2014). When compared with WAP and its standardized version, SWAP (Lu et al. 2013), I_F has been more widely applied at various places around the globe to determine the duration, severity and intensity of flood events at short timescales (Deo et al. 2014, 2015, 2018a; Nosrati et al. 2010). Also, unlike WAP, the computation of I_F also does not require parameters that needs to be chosen empirically (Lu 2009). As I_F has been more widely applied and tested when compared to WAP and its due to its ability to monitor flood events on a daily basis while accounting for various hydrological factors, I_F was selected as the suitable flood monitoring tool to be used in this research.

SPI is the tool that has been generally used for analysis of rainfall and floods in Fiji (Fiji Meteorological Service 2018; Nawai et al. 2015). Therefore, an index which considers previous days' precipitation and other hydrological factors has not been used to monitor floods in the country till date. Therefore, using I_F to quantify floods will be an innovative and highly accurate method to determine the duration, severity, and intensity of previous flood events in Fiji Islands. This study is expected to provide results that can be used to analyse past floods in the country and potentially allow for better flood related decision making in the future.

The main objectives of this paper are threefold:

i. To compute Effective Precipitation (P_E), and successively determine Available Water Resource Index (AWRI) and Flood Index (I_F).
ii. To apply I_F at various study sites in the Fiji Islands.
iii. To investigate the duration, severity and intensity of flood events that have occurred at the study sites from 1991 to 2019.

Moving forward, this paper is structured as follows. Firstly, the study area and the characteristics of the rainfall data obtained for the computations will be discussed. Then, the methods used in computing the I_F will be specified. After this, the results will be presented and discussed. Finally, the conclusion will report the key insights from the results and state the usefulness of I_F as a tool for monitoring flood events.

2 Materials and methods

2.1 Study area

This paper has been focused on the Fiji Islands. The group of islands are in the south-west Pacific Ocean and has an oceanic tropical climate. The location of the South Pacific Convergence Zone (SPCZ) has a great influence on Fiji's rainfall and climate (Feresi et al. 2000). The country experiences higher than expected rainfall during the La Niña years, which leads to regular flooding, particularly through the wet season (Fiji Meteorological Service 2018). The Fiji group consists of more than 300 islands spread over 1.3 million square kilometres of the South Pacific Ocean (Feresi et al. 2000). Multiple areas from the two largest islands (Viti Levu and Vanua Levu) have been covered in this paper. 87% of the total land area is covered by these two islands (Feresi et al. 2000). As the study region is small and floods are common in most parts, it was possible to cover most major towns and cities of the country during this research. Figure 1 shows the map of the study area and labels the respective sites.

2.2 Dataset

The daily rainfall data for Labasa, Savusavu, Rakiraki, Tavua, Lautoka, Nadi, Ba, Navua, Suva, Nausori and Sigatoka from January 1990 to December 2019 (30 years) were successfully obtained from the Fiji Meteorological Service. Table 1 summarizes the relevant metadata of rainfall dataset and the respective study sites. The calendar means imputation method was used to fill-in the missing data. The standard data period used in the computations was from 1st January 1990 to 31st December 2019. However, I_F was calculated from 1991 as antecedent precipitation of 365 days was required in the calculations. Furthermore, to accommodate for leap years (366 days), the rainfall amount for February 29th was added to March 1st. Two sites, Tavua and Navua, were excluded from further analysis because data was not available for the entire period and that could have affected the comparison results.

2.3 Flood Index computation

MATLAB (MathWorks 2019) was chosen as the software package to develop the flood index and perform the relevant computations in this study.

The following steps were taken to obtain the I_F. The first step was to calculate the Effective Precipitation (P_E). P_E is determined using a time-dependent reduction function and is the sum of the precipitation for current and antecedent days (Byun and Chung 1998). In the calculation of the P_E for a particular day, the precipitation of the antecedent days is also considered, but with reduced weights. Therefore, if 365 days prior precipitation is to be considered, the influence of precipitation from 1 day prior would be 100%, for 2 days prior would be 85%, 77% for 3 days prior and eventually approximately 0.0423% for the precipitation that occurred 365 days prior (Deo et al. 2018a). This concurs with the rationale of Lu (2009) which states that due to conditions such as evaporation, seepage, and runoff, the influence of previous days precipitation on current days water balance gradually decays. The essence of this method is that the recent most precipitation is assigned more weight which essentially has more effect on the current weather than the ones occurring in the past. Therefore, as this mathematical model accounts for the daily depletion of water due to various hydrological conditions, it assists in the accurate monitoring of flood situations. The current day's P_E is determined using the following equation:

$$P_{E_i} = \sum_{N=1}^{D} \left[\frac{\sum_{m=1}^{N} P_m}{N} \right] \quad (1 \le m \le 365) \tag{1}$$

where P_m is the recorded rainfall for any day, m and N is the duration of the antecedent period (365 days).

After the P_E was calculated, the AWRI value was obtained. AWRI is the combined precipitation (P) over an annual cycle and used weight (W) (Byun and Lee 2002). As presented in Eq. (2), the mathematical equation for

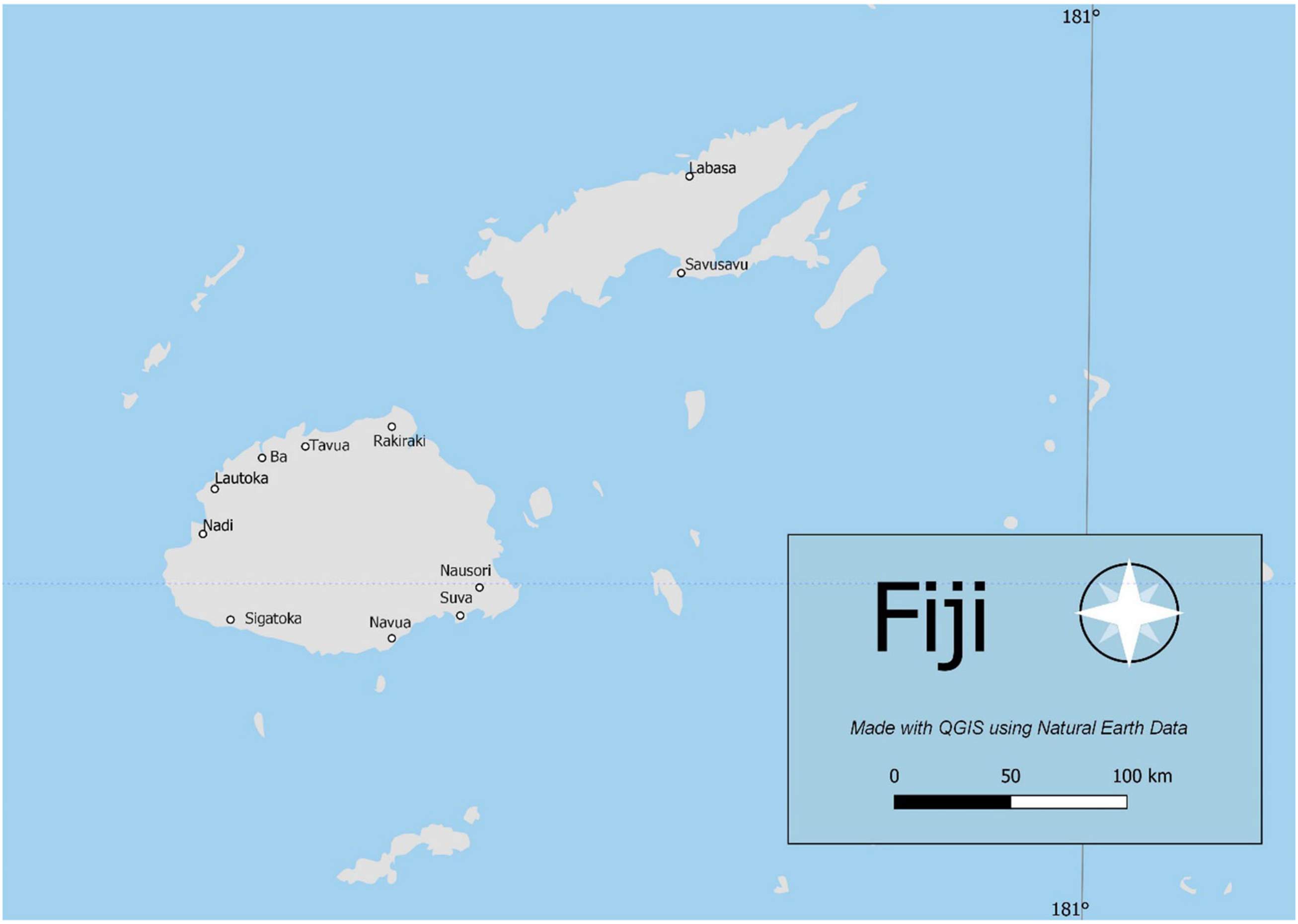


Fig. 1 A map of Fiji showing the different study sites

obtaining the AWRI is simpler than rainfall-runoff models and this makes it more advantageous in the assessment of water reserve balances (Deo et al. 2018a). Generally, a larger magnitude of AWRI that is higher than the normal implies a surplus of water resources and the likelihood of a flood situation (Han and Byun 2006).

$$AWRI = \frac{P_E}{W} \tag{2}$$

$$W = \sum_{n=1}^{n=D} \frac{1}{n} \tag{3}$$

where D is the duration of the antecedent period (365 days) and n will range from 1 to D (365).

Flood Index (I_F) is the normalized version of P_E. If I_F for a day is greater than zero ($I_F > 0$), it is generally regarded as a flood situation. However, the criteria to classify a flood situation can be delineated to capture better precision. For all $I_F > 0$, the are many flood events that have insignificant impacts, hence a low severity flood occurs when I_F is between 0 and 1. To account for higher significant floods, the classification measure is to be adjusted. For instance, to only account for extreme floods, $I_F > 2$ benchmark is used to classify such flood situations. Table 2 shows the different categories for classification of floods that can be used on the basis of earlier studies by Deo et al. (2015). This flexible criterion makes I_F advantageous overusing raw values of P_E or AWRI in determining a flood situation. In Eq. (4), which shows the mathematical formula of obtaining the I_F, ${}^{2019}_{1991}\overline{P_E^{max}}$ and $\sigma\left({}^{2019}_{1991}\overline{P_E^{max}}\right)$ are the means and standard deviations of yearly maximum daily Effective Precipitation for the 1991–2019 period.

$$I_F = \frac{P_E - {}^{2019}_{1991}\overline{P_E^{max}}}{\sigma\left({}^{2019}_{1991}\overline{P_E^{max}}\right)} \tag{4}$$

In accordance with the running-sum methodology by Yevjevich (1967), the following mathematical approaches to derive the severity, duration and intensity of flood situations from computed values of I_F was presented by Deo et al. (2015). The severity of the flood $\left(I_F^{acc}\right)$ is the sum of positive I_F from the first day of the flood situation (t_{onset}), until the last day (t_{end}). The duration of flood (D_F) are the

Table 1 Characteristics of the raw dataset for the different study sites (*Source*: Fiji Meteorological Services)

Site name (A–Z)	Location	Data range	Missing data (%)	Average recorded P (mm)	Maximum recorded P (mm)
Ba	17.53 °S, 177.66 °E	(01/01/1990, 31/12/2019)	1.15	6.23	500.00
Labasa	16.43 °S, 179.36 °E	(01/01/1990, 31/12/2019)	2.36	5.94	272.40
Lautoka	17.62 °S, 177.45 °E	(01/01/1990, 31/12/2019)	1.46	5.44	390.60
Nadi	17.78 °S, 177.44 °E	(01/01/1990, 29/02/2020)	0.02	5.43	356.20
Navua	18.22 °S, 178.17 °E	(01/01/1992, 01/12/2019)	6.35	9.75	255.00
Nausori	18.03 °S, 178.56 °E	(01/01/1990, 29/02/2020)	0.24	8.02	260.00
Rakiraki	17.39 °S, 178.07 °E	(01/01/1990, 31/12/2019)	0.23	6.29	450.40
Savusavu	16.78 °S, 179.34 °E	(01/01/1990, 31/01/2020)	1.08	5.64	243.00
Sigatoka	18.14 °S, 177.51 °E	(01/01/1990, 30/11/2019)	5.34	4.79	183.00
Suva	18.13 °S, 178.45 °E	(01/01/1990, 29/02/2020)	0.12	8.17	272.00
Tavua	17.44 °S, 177.86 °E	(01/01/1990, 31/03/2009)	19.25	4.99	404.60

Table 2 Classification of severity of flood based on the value of I_F

Flood Index Measure	Severity category
$I_F \leq 0$	Very low (drought)
$I_F > 0$	Low
$I_F \geq 1$	Moderate
$I_F \geq 1.5$	Severe
$I_F \geq 2$	Extreme

number of days between the start and end dates of the flood situation. The flood intensity (I_F^{max}), which is the peak danger during the flood situation is the maximum I_F during the flood period. Equations (5–7) presents the mathematical equations to calculate these metrics. When computing these metrics, the first and the last day of the flood situation can be adjusted based on the severity levels in Table 2.

$$I_F^{acc} = \sum_{t=t_{onset}}^{t=t_{end}} I_{F_i} \quad where\ I_{F_i} > 0 \tag{5}$$

$$D_F = t_{end} - t_{onset}\ \text{(days)} \tag{6}$$

$$I_F^{max} = \max(I_F)_{t_{onset}-t_{end}} \tag{7}$$

The process of obtaining the I_F is illustrated in Fig. 2. Furthermore, the results shown in Fig. 3 for one of the sites demonstrates the practicality of using the I_F in computing the different flood properties.

3 Results and discussion

The practicality of the daily I_F is graphically evaluated as in Fig. 3. Accordingly, the flood events that occurred from the 8th to the 16th of January 2009 were quantified (Office of the Prime Minister 2009). This was initially done for the location, Ba as it was one of the highly impacted sites. The results obtained with the benchmark for a flood situation being $I_F > 0$, shows that the onset of the flood was the 9th of January and the end was the 1st of May, totalling a duration of 113 days and severity of 131.57, with the peak danger being 3.13. However, even though the area was in flood situation for 113 days, the impact of the flood situation was severe for 27 days, from the 11th of January to the 6th of February. Adding on, the severity of the flood was extreme only for 16 days from 11th to the 26th of January. These results showed the practicality of the I_F in determining the duration, severity and intensity of flood situations and its ability to categorize the severity of flood situations.

The flood situation for the other eight sites for the same period (first 180 days of 2009) were then determined. As shown in Fig. 4, the duration, severity, and intensity of the floods in all these sites were different. This showed that even though the study area is small with most study sites being close by, there is a need to study the flood situation in all these areas separately. An analysis of the results illustrates that floods which started in January 2009 were only severe in the western side of the main island (Viti Levu) of Fiji [Ba ($I_F^{acc} \approx 131.57$), Rakiraki ($I_F^{acc} \approx 33.22$), Lautoka ($I_F^{acc} \approx 35.87$), Nadi ($I_F^{acc} \approx 35.85$) and Sigatoka ($I_F^{acc} \approx 128.59$)]. The northern areas of the second main island (Vanua Levu) [Labasa ($I_F^{acc} \approx 6.91$) and Savusavu ($I_F^{acc} \approx 6.76$)] had low severity while the severity in the central division [Nausori (*No Floods*) and Suva ($I_F^{acc} \approx 0.03$)] was very low. Adding on, only the floods in Ba and Sigatoka reached extreme peak severity. The floods in other areas of the western division reached severe peak danger.

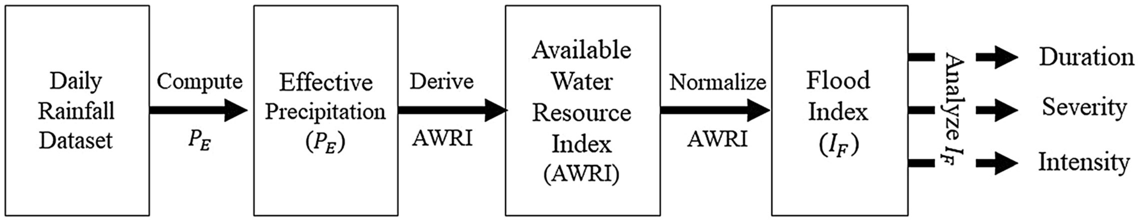


Fig. 2 Process of obtaining the Daily Flood Index

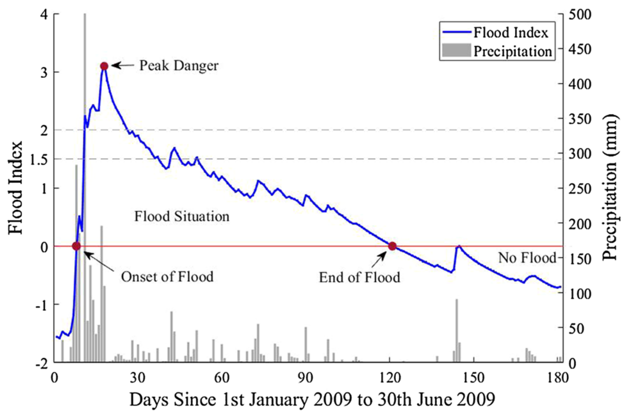


Fig. 3 Flood Index applied to 2009 floods in Ba. It shows how the index is used to determine the duration, severity, and intensity of floods

The frequency of flood events during the 29-year period differed slightly for the nine sites. Figure 5 shows this distribution. The frequency of flood situations with different severity levels is also compared in this graph. It shows that even though there are many flood situations, only a handful of them are severe. For instance, Suva recorded 38 flood events during the study period but only 2 of them were severe. Labasa and Lautoka recorded 45 and 42 flood situations, respectively. Out of these, there was only one severe flood situation in Labasa and only two in Lautoka. Furthermore, when considering total number of flood situations for all study sites, out of the 352 flood situations, there were only 8 events during the 29-year period that reached extreme severity and 32 reached severe severity.

Most tropical cyclones and hurricanes in Fiji occur between November to April. These events sometimes also take place in October and May (Campbell 1984). Floods are more likely to occur during this period as well. This is shown in Fig. 6, which illustrates that most of the severe flood situations started between January and May. As the highest number of floods had started in the first few months of the year, this shows the need for effective flood risk mitigation strategies to be implemented for these months. On the other hand, no severe flood events were recorded to have started between June and December and no floods started in August and September during the study period. The flood preparation strategies for the next wet season can potentially be developed during these months as there is a low probability that resources will need to be diverted for flood damage rehabilitation during this period.

Based on Fig. 7, the severity of floods which started from November to April is also quite high when compared to the other months of the year. It is interesting to note that the severity of flood events which commenced in January $\left(I_F^{acc} \approx 1277\right)$ is higher than the combined severity of flood events starting in the other months $(I_F^{acc} \approx 1130.79)$. Furthermore, the combined severity of floods starting in months apart from November to April period is very low $\left(I_F^{acc} \approx 66.12\right)$. Figure 8 presents the combined flood severity for each year during the 29-year period. Significant severity in floods are were seen in 1997, 2000, 2002, 2014, 2017, 2018 and 2019. However, floods were most severe in 1999, 2008, 2009 and 2012.

The peak severities as demonstrated in Fig. 9 shows that the floods starting from January till April reach higher peaks when compared to other months. It is observed from the graph that the highest peak was reached in the month of January $(I_F^{max} \approx 3.39)$. This is followed by March $(I_F^{max} \approx 3.21)$ and April $(I_F^{max} \approx 2.55)$. The amount of rainfall during flood situations is also highest during these months. This trend is depicted in Fig. 10. It shows the total amount of rainfall during flood events per month and the maximum amount of rainfall during a flood situation that started during that month. The floods which started in January had a total of 36,725 mm of rainfall. This is followed by flood situations starting in March and April, which experienced a total of 18,542 mm and 11,536 mm of rainfall, respectively. The maximum amount of rainfall for a flood situation was recorded for a flood event which started in January (2504 mm). This measure was also followed by March (994.2 mm) and April (692 mm).

Figure 11 compares the severity of floods based on the geographical divisions in Fiji. This has been done by getting the sum of severity for all flood events at each division and then evaluating the mean of the combined severity based on the number of sites at each division. Ba, Lautoka, Nadi, Sigatoka and Rakiraki which lie in the western division had the highest average combined severity. This was followed by the northern division which consist of Labasa and Savusavu. Average severity of floods was the

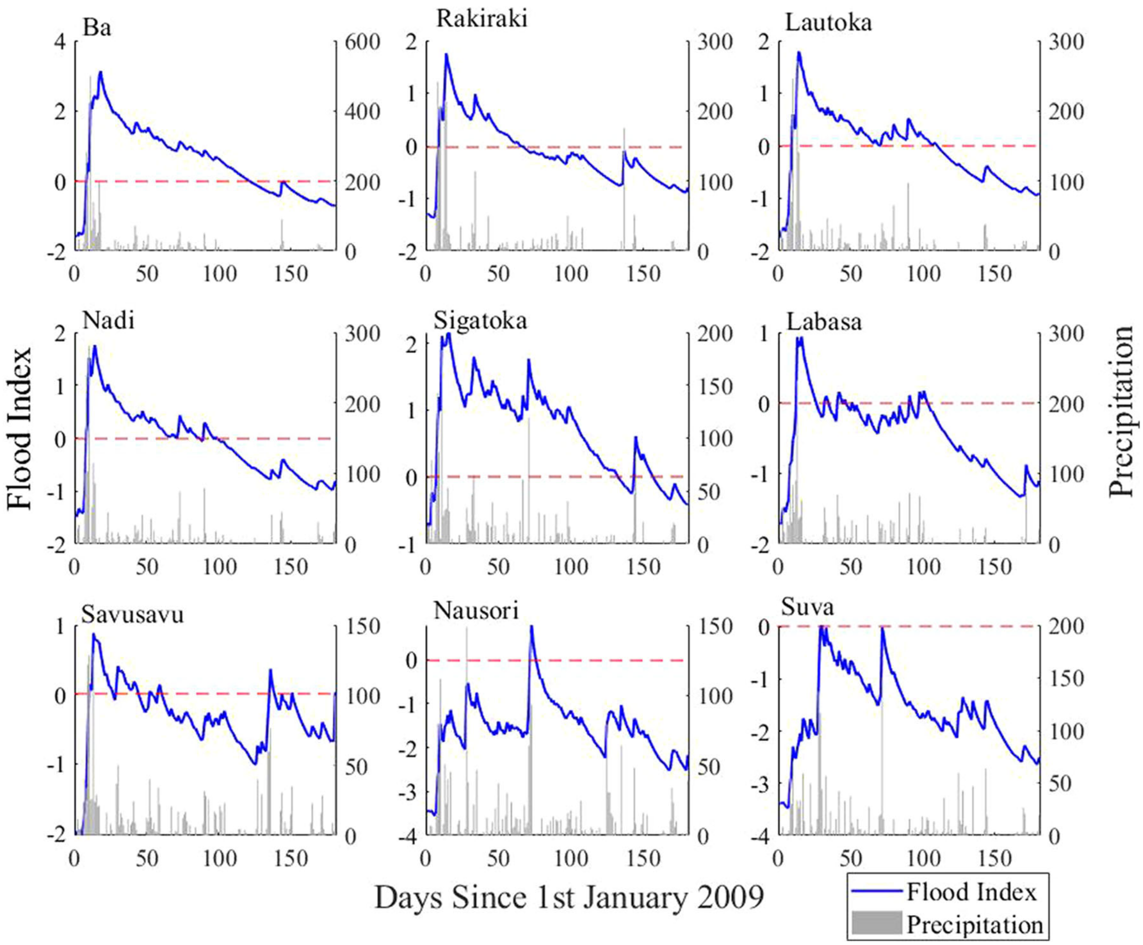


Fig. 4 Flood Index monitored for different parts of Fiji from 1st January 2009 to 30th June 2009 (180 days)

Fig. 5 Frequency of flood occurrences based on severity levels at the 9 sites between 1991 and 2019

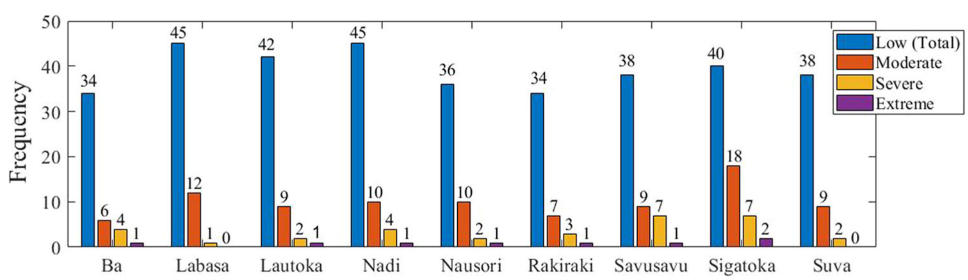
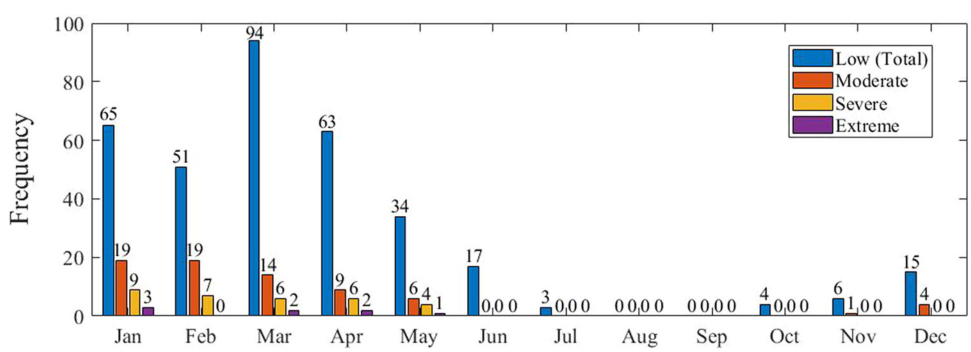


Fig. 6 Frequency of flood situations per month based on severity for the 9 sites combined between 1991 and 2019



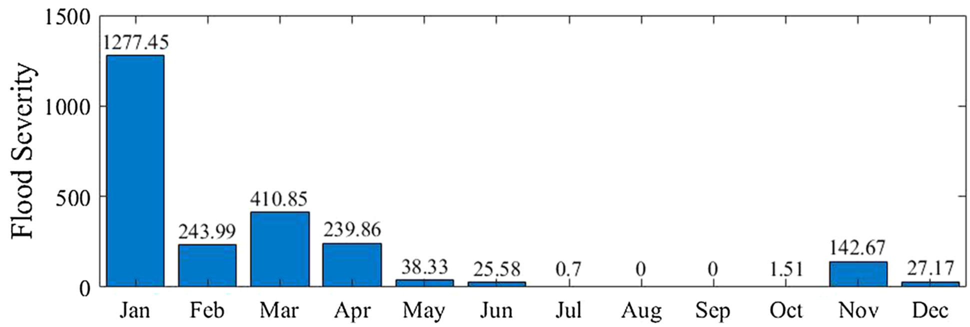


Fig. 7 Monthly combined severity of flood situations for the 9 sites between 1991 and 2019

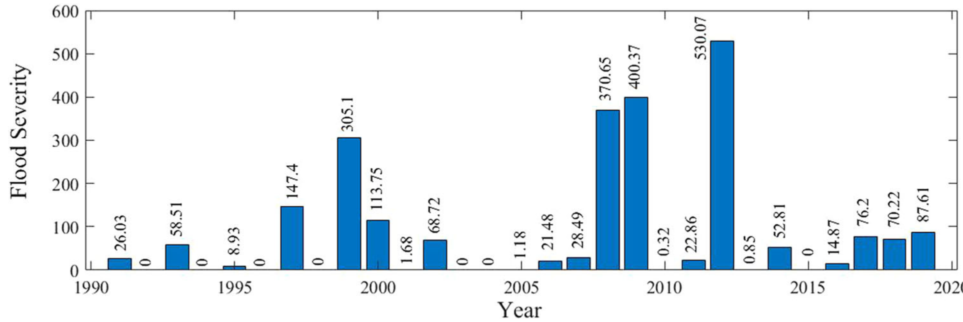


Fig. 8 Yearly combined severity of flood situations for the 9 sites between 1991 and 2019

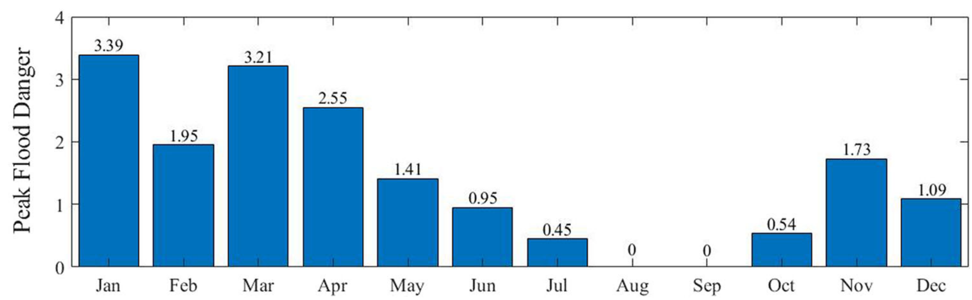


Fig. 9 Monthly peak flood severity of floods between 1991 and 2019

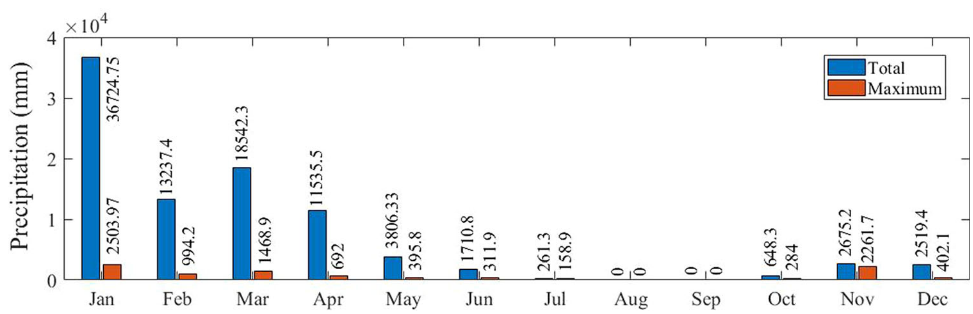


Fig. 10 Monthly total and maximum precipitation during flood situations

lowest in the central division. Suva and Nausori are part of the central division. It is interesting to note that the central division generally experiences more rainfall when compared to the western and northern division, but the severity of flood is the lowest in this area. Furthermore, the average maximum peak severity during a flood situation in the western division was 2.89. This measure was 2.12 in the northern division and 2.25 in the central division. This illustrates that when compared with flood events in the northern and central division, the floods of the western division reach higher peak danger.

The statistics of the severest floods that occurred at each of the 9 study sites during the study period has been presented in Table 3. It presents the five-number summary for the P, $AWRI$ and I_F for the severest flood at each site. The flood with the highest I_F^{acc} has been classified as the most severe. It can be evaluated from these results that in all areas, the severest flood started between November and

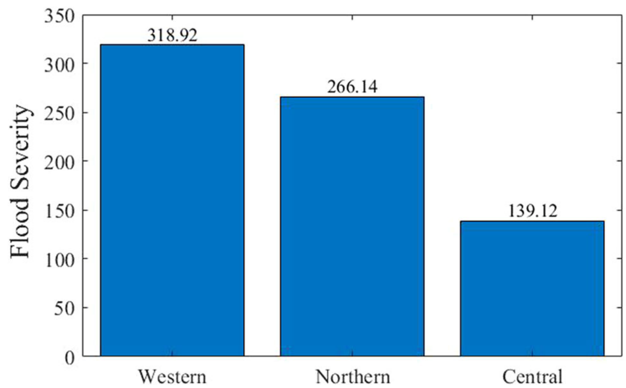


Fig. 11 Average flood severity for the different geographical divisions in Fiji

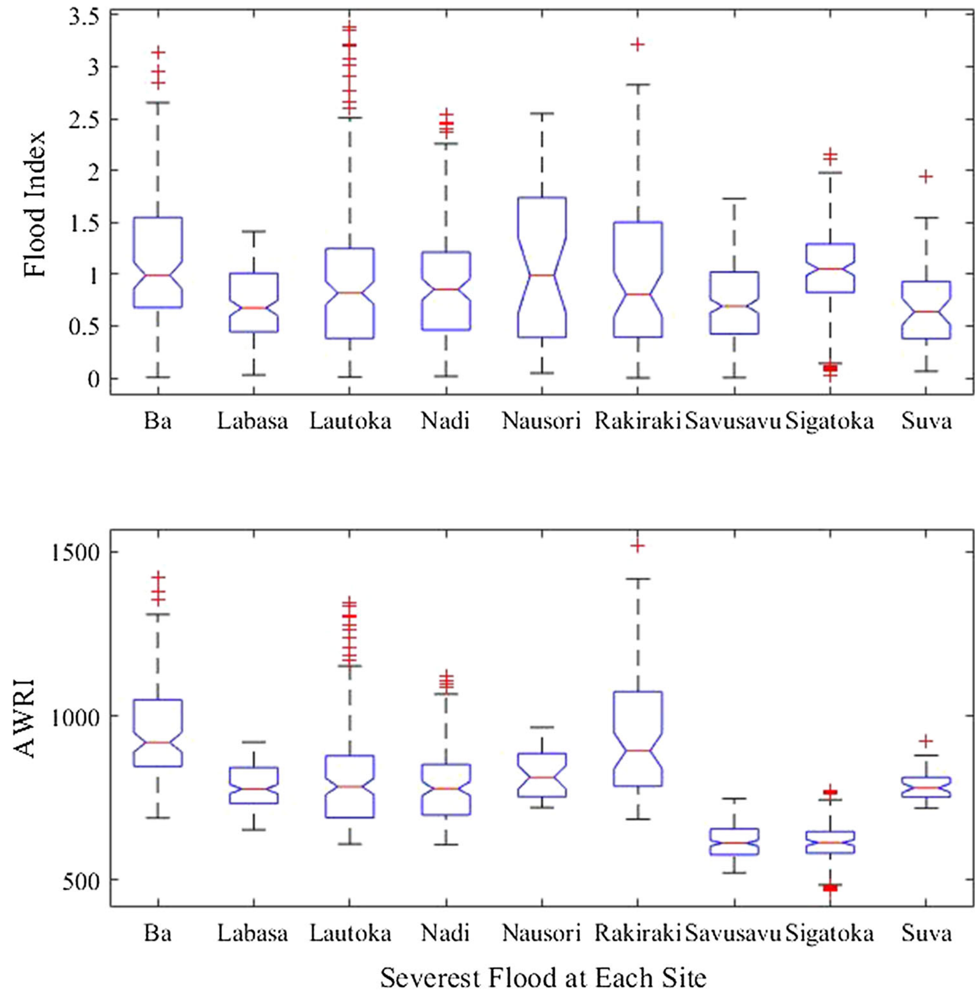
April. The severest flood at five out of the nine sites started in January. The highest amount of rainfall during a flood situation was recorded for Ba followed by Rakiraki and Lautoka. Apart from Savusavu, the severest flood for each site occurred after the year 2008. Lautoka recorded the maximum peak danger among these events with a value of 3.39 for the January 2012 flood. Nadi's severest flood also started in January 2012 and reached a peak danger of 2.53. The highest mean I_F was during the Ba flood ($Mean\ I_F \approx 1.16$) and the lowest average was during the Suva flood ($Mean\ I_F \approx 0.69$). The flood events prior to 2010 mostly coincide with the list of flood situations in Fiji between 1840 and 2009 presented by McGree et al.

Figure 12 shows the distribution of the I_F and $AWRI$ for the major floods in each area in the form of box plots. It shows that only the severest floods in Ba, Lautoka and Rakiraki reached extreme severity ($I_F \geq 2$). The distribution shows that the median I_F was around 1 (Low–Moderate) for most of the flood situations. The peak danger values from Table 2 are mostly identified as outliers in the box plot, with the exclusion of flood events in Labasa, Nausori and Savusavu, which have no outliers. The AWRI for all the flood situations approximately ranged between

Table 3 Statistics of the severest flood event for each of the 9 study sites

Statistic		Minimum	Lower quartile, Q1	Median, Q2	Upper quartile, Q3	Maximum	Mean, μ	Standard deviation, σ
Ba (January 2009)	P	0.00	0.00	3.20	16.40	500.00	20.28	56.07
	$AWRI$	689.44	848.76	919.27	1046.13	1419.60	960.16	163.68
	I_F	0.00	0.69	0.99	1.53	3.13	1.16	0.70
Labasa (January 2008)	P	0.00	0.00	2.25	15.90	225.80	15.19	30.43
	$AWRI$	654.26	733.97	777.95	842.47	920.00	787.38	67.91
	I_F	0.03	0.45	0.67	1.01	1.41	0.72	0.35
Lautoka (January 2012)	P	0.00	0.00	0.61	8.50	362.60	16.58	48.13
	$AWRI$	610.39	690.84	785.50	878.15	1343.04	822.12	173.43
	I_F	0.01	0.38	0.82	1.25	3.39	0.99	0.80
Nadi (January 2012)	P	0.00	0.00	0.20	9.38	291.90	16.00	42.25
	$AWRI$	607.99	699.08	779.10	852.60	1122.86	790.92	120.59
	I_F	0.02	0.46	0.85	1.21	2.53	0.91	0.59
Nausori (April 2019)	P	0.00	0.40	1.10	11.00	132.40	17.50	34.05
	$AWRI$	721.89	755.10	813.28	885.76	964.83	824.28	75.02
	I_F	0.05	0.39	0.99	1.74	2.55	1.10	0.77
Rakiraki (March 2012)	P	0.00	0.00	0.00	3.50	450.40	17.34	64.32
	$AWRI$	685.83	788.55	893.57	1070.38	1516.77	947.32	203.02
	I_F	0.00	0.40	0.81	1.49	3.21	1.01	0.78
Savusavu (November 1999)	P	0.00	0.00	1.00	12.75	170.30	11.60	24.00
	$AWRI$	522.97	577.97	613.20	656.35	749.08	617.75	53.40
	I_F	0.00	0.42	0.69	1.02	1.73	0.73	0.41
Sigatoka (January 2009)	P	0.00	0.00	0.80	11.00	183.00	11.98	26.55
	$AWRI$	469.86	582.69	614.40	648.03	771.33	611.17	69.48
	I_F	0.03	0.83	1.05	1.29	2.16	1.03	0.49
Suva (February 2014)	P	0.00	0.20	6.00	11.45	206.60	19.22	39.17
	$AWRI$	719.48	753.55	781.52	812.42	923.31	787.68	42.48
	I_F	0.06	0.38	0.64	0.92	1.95	0.69	0.39

Fig. 12 Box plot of the Flood Index and AWRI for the severest flood event recorded at each site based on Table 2



500 and 1500 mm. The maximum AWRI was recorded at Rakiraki and the minimum at Sigatoka. However, these have been classified as outliers in the box plot. Savusavu, Suva and Sigatoka generally have a smaller AWRI range when compared to the other sites. Rakiraki has the biggest range, followed by Ba and Lautoka.

Table 4 consists of a set of sub tables that lists the 10 severest flood events for each of the nine sites that occurred during the study period. The classification of floods in this table has been done with the criteria $I_F > 0$. It clearly shows the onset date, severity, peak danger, duration, total AWRI, total precipitation and maximum AWRI for the nine sites. The flood situations for each site are ranked according to their severity with 1 being the most severe and 10 being the least severe. The flood and water intensive properties can be extracted from these tables for further analysis. A brief analysis of the three most severe flood events at each study site has been discussed as well.

The analysis of floods in Ba (Table 4(a)) indicate that the town faced its severest floods in 1999, 2009 and 2012. All these floods started in January and the one in 2009 was the severest and the one which started in 1999 was the least severe. The 2009 flood has been described previously in Fig. 3. The 2012 flood lasted for 118 days. Interestingly, this duration was longer than that of the severest flood whereby the flood lasted for 113 days. The severity of the 2012 flood was 74.03 and it reached a peak danger of 1.95. Approximately, 2259.93 mm of rainfall was recorded during this flood period. The duration of the 1999 event was 112 days with severity 51.09 and it reached peak danger of 1.19. Approximately, 2104.4 mm of precipitation was recorded during this flood. All the 10 severest floods in Ba started between January and May and on average, the ones which started in January were the most severe.

As seen in Table 4(b), the most significant flood event recorded in the town of Labasa reached total severity of 101.19 and lasted for 140 days. This flood started in January 2008 and reached a peak danger of 1.41. Approximately, 2127.2 mm of rainfall was recorded during this event. The second severest flood at this site occurred in February 2002 and reached a peak severity of 1.8. The total severity of this event was 34.1 and this event lasted for

Table 4 Analysis of 10 severest flood situations for (a) Ba, (b) Labasa, (c) Lautoka, (d) Nadi, (e) Nausori, (f) Rakiraki, (g) Savusavu, (h) Sigatoka, (i) Suva from 1991 to 2019

Site	Onset date t_{onset}	Severity I_F^{acc}	Peak danger I_F^{max}	Duration (days)	Total AWRI (mm)	Total precipitation (mm)	Maximum AWRI
(a) *Ba*							
1	9-1-2009	131.57	3.13	113	108,498.30	2292.00	1419.60
2	25-1-2012	74.03	1.95	118	98,504.41	2259.93	1143.55
3	18-1-1999	51.09	1.19	112	89,016.81	2104.40	967.28
4	22-2-2008	21.58	0.82	66	50,464.86	980.20	878.65
5	24-3-2007	7.19	0.89	18	14,068.33	359.50	895.58
6	8-3-1997	5.70	0.95	17	13,030.82	399.90	909.57
7	29-1-2008	4.94	0.49	19	14,230.87	502.10	803.51
8	28-1-1997	3.68	0.71	13	9805.91	347.90	854.61
9	5-3-2011	3.30	0.40	17	12,470.94	260.00	781.24
10	18-2-2011	1.76	0.42	8	5916.71	234.30	786.18
(b) *Labasa*							
1	14-1-2008	101.19	1.41	140	110,233.00	2127.2	920.00
2	20-2-2002	34.10	1.80	52	40,273.33	877.40	994.02
3	15-2-2017	27.98	1.04	54	40,395.16	994.20	848.96
4	6-4-2000	23.24	1.29	46	34,296.49	682.70	896.02
5	4-2-2006	20.21	1.06	39	29,175.15	728.40	852.53
6	17-4-1997	15.54	1.14	37	26,980.84	547.30	866.71
7	4-4-2018	13.21	1.17	24	18,102.58	498.30	872.86
8	5-3-1997	7.16	0.82	20	14,344.65	413.30	806.31
9	13-1-2009	6.91	0.94	14	10,407.04	388.10	828.90
10	31-3-1995	4.54	0.51	15	10,600.17	252.60	747.25
(c) *Lautoka*							
1	23-1-2012	149.14	3.39	151	124,140.4	2504.00	1343.04
2	18-1-1999	41.95	1.34	72	52,868.45	1449.90	898.66
3	10-1-2009	35.87	1.79	60	44,255.15	1197.10	997.00
4	25-1-1997	9.88	0.93	23	16,125.25	491.20	809.24
5	12-3-2009	7.92	0.52	40	26,034.53	441.10	720.70
6	7-3-1997	6.94	0.86	18	12,448.88	298.00	793.48
7	22-2-2008	6.05	0.59	21	14,078.19	319.40	735.71
8	16-4-1999	5.84	0.59	24	15,857.69	273.70	735.01
9	31-1-2008	3.52	0.41	16	10,491.25	314.00	696.77
10	6-3-2011	3.09	0.34	19	12,221.40	315.30	681.09
(d) *Nadi*							
1	23-1-2012	116.60	2.53	128	101,237.80	2048.30	1122.86
2	27-1-1999	40.45	1.18	103	70,536.55	1399.80	845.92
3	8-1-2009	35.85	1.76	63	45,417.79	1318.30	964.49
4	3-3-2017	16.77	1.04	38	26,400.97	534.70	818.15
5	11-3-2000	11.09	0.86	34	22,820.32	481.70	779.66
6	7-2-2017	7.97	0.65	22	14,928.24	626.80	738.18
7	7-6-2012	7.61	0.86	25	16,667.72	311.90	781.26
8	26-2-1993	7.00	0.85	22	14,730.79	731.30	778.09
9	7-3-1997	5.79	0.89	15	10,251.57	377.80	787.18
10	4-4-2016	5.33	0.89	14	9552.28	362.20	786.65
(e) *Nausori*							
1	16-4-2019	36.35	2.55	33	27,201.38	577.60	964.83
2	19-1-2019	20.52	1.35	32	24,946.59	656.50	848.60

Table 4 (continued)

Site	Onset date t_{onset}	Severity I_F^{acc}	Peak danger I_F^{max}	Duration (days)	Total AWRI (mm)	Total precipitation (mm)	Maximum AWRI
3	21-4-2002	16.28	1.25	26	20,231.53	391.50	838.77
4	17-12-2016	7.48	1.09	11	8616.91	372.80	823.48
5	9-12-1999	6.90	0.93	11	8560.06	257.40	807.26
6	5-4-1993	6.86	0.91	14	10,708.43	216.70	805.39
7	2-1-1993	5.49	1.67	10	7706.65	325.20	879.94
8	12-3-1993	3.68	0.88	8	6096.06	273.90	802.45
9	3-4-2002	3.54	0.43	16	11,820.88	237.80	758.87
10	26-3-2019	3.13	1.03	7	5325.35	136.70	817.24
(f) *Rakiraki*							
1	28-3-2012	69.85	3.21	69	65,364.81	1196.40	1516.77
2	16-1-2008	66.82	1.48	109	91,992.43	1762.10	1068.36
3	4-3-1997	45.33	1.54	95	76,834.75	1468.90	1083.74
4	9-1-2009	33.22	1.76	57	47,661.10	1277.50	1141.15
5	24-1-2012	25.43	1.01	57	45,644.09	1102.40	947.62
6	28-4-2000	15.41	0.72	44	34,140.72	692.00	872.53
7	30-1-1997	4.02	0.76	13	9948.46	337.00	882.66
8	9-3-2000	3.43	0.48	17	12,537.72	333.80	810.74
9	16-2-2011	3.22	0.50	14	10,427.80	338.70	815.59
10	17-6-2000	2.92	0.40	16	11,719.36	233.80	789.89
(g) *Savusavu*							
1	27-11-1999	141.65	1.73	195	120,460.60	2261.70	749.08
2	14-4-1997	35.89	2.44	52	31,876.56	691.00	842.04
3	15-1-2008	28.78	1.75	47	28,331.59	729.30	751.33
4	23-6-2008	10.40	0.95	27	15,472.41	294.80	646.92
5	10-1-2009	6.76	0.88	17	9770.38	437.30	638.39
6	9-4-2008	4.98	0.77	18	10,060.12	217.00	623.49
7	13-5-2008	4.68	0.59	17	9497.20	221.70	599.88
8	21-2-2002	4.15	0.54	21	11,518.62	354.40	593.70
9	7-3-1991	3.98	0.50	15	8361.13	247.70	588.50
10	29-1-2009	3.05	0.41	16	8761.42	202.00	576.56
(h) *Sigatoka*							
1	8-1-2009	128.59	2.16	125	76,395.63	1497.39	771.33
2	14-1-2008	102.54	1.43	138	78,766.74	1418.20	667.53
3	29-3-2012	43.69	1.61	57	32,723.18	615.40	693.16
4	18-3-2000	35.32	1.46	65	35,264.69	634.20	671.84
5	26-3-2018	34.55	1.55	56	30,965.17	588.10	684.26
6	30-1-2012	18.96	0.81	49	25,501.07	496.50	580.92
7	10-2-2017	17.23	0.95	45	23,393.47	549.53	600.34
8	26-2-2014	9.19	0.49	37	18,530.93	401.17	535.05
9	13-2-2018	9.07	0.47	34	17,115.92	429.00	531.96
10	9-2-2000	8.11	0.66	26	13,255.84	275.20	559.54
(i) *Suva*							
1	26-2-2014	32.62	1.95	47	37,021.16	903.30	923.31
2	24-3-1993	22.72	1.44	36	28,111.03	565.90	868.86
3	18-4-2019	21.49	1.76	29	22,990.68	511.40	902.80
4	2-2-1991	12.52	1.09	28	21,305.83	454.40	831.07
5	31-3-2012	11.40	0.82	28	21,185.44	456.80	800.92
6	16-5-2014	9.83	1.40	17	13,177.47	372.00	864.67

Table 4 (continued)

Site	Onset date t_{onset}	Severity I_F^{acc}	Peak danger I_F^{max}	Duration (days)	Total AWRI (mm)	Total precipitation (mm)	Maximum AWRI
7	2-12-1999	6.29	0.70	16	12,081.88	402.10	788.44
8	21-4-2002	5.82	0.78	20	14,880.44	335.40	797.02
9	19-4-2007	4.69	0.84	14	10,483.14	288.40	804.03
10	4-5-2007	3.54	0.91	8	6083.63	141.60	811.52

52 days. Other notable floods occurred at this site in 2000, 2006 and 2017 and reached peak dangers of 1.29, 1.06 and 1.04, respectively. Apart from the severest flood, all other flood situations recorded accumulated rainfall of less than 1000 mm. The 10 severest flood events at this site started during the first 5 months of the year.

As per Table 4(c), the severest flood in the city of Lautoka started in January 2012 and amounted to a total severity of 149.14 and reached extreme peak severity of 3.39 during the 151 days of flood situation. This was also the severest flood event for the 29-year period among all the study sites. During this event, approximately, 2504 mm of rainfall was recorded. The next severest flood at this site occurred in January 1999 and reached peak danger of 1.34 while experiencing total rainfall of about 1449.9 mm. This event lasted for 72 days and had a combined severity of 41.95. The January 2009 floods at this site had a duration of 60 days and reached peak danger of 1.79. This event had a total severity of 35.87 and recorded approximately 1197.1 mm of rainfall. All the 10 severest floods at this site started between December and April.

The most severe floods in Nadi are listed in Table 4(d). The site's severest flood occurred in January 2012 and lasted for 128 days. The accumulated severity during this period was 116.6 and an extreme peak danger of 2.53 was reached. Approximately, 2048.3 mm of precipitation was recorded during this event. The second most severe flood for Nadi started in January 1999 and had a duration of 103 days during which it reached a peak severity of 1.34 and combined severity of 41.95. In January 2009, the site recorded a flood situation that lasted for 63 days and reached peak danger of 1.76. It had a severity of 35.85.

Based on Table 4(e), the severest flood in Nausori lasted for only 33 days but reached extreme peak danger of 2.55 and had a total severity of 36.35. This event started in April 2019. The second most severe flood in the area had a duration of 32 days. This flood reached peak severity of 1.35 and had a combined severity of 20.52. This flood occurred in January 2019. Another notable flood in Nausori occurred in April 2002 which had a duration of 26 days and reached peak danger of 1.25. The total severity of this flood event was 16.28. Approximately, 577.6 mm, 656.5 mm and 391.5 mm of rainfall was recorded for these three flood situations, respectively.

Table 4(f) lists the severest floods in Rakiraki. The March 2012 flood was the severest for the area. The flood lasted for 69 days and reached peak danger of 3.21. It had a combined severity of 69.85 and recorded approximately 1196.4 mm of precipitation during the flood situation. The second and third severest floods in the area had a duration of 109 days and 95 days, respectively. The former had a combined severity of 66.82 and reached peak danger of 1.48 while the latter had a total severity of 45.33 and reached peak severity of 1.54. These two flood events started in January 2008 and March 1997 and recorded rainfall amounts of about 1762.1 mm and 1468.9 mm, respectively.

The severest flood event in Savusavu had the longest duration amongst all sites during the 29-year period. As shown in Table 4(g), the flood started in November 1999 and lasted for 195 days, during which it had reached a peak danger of 1.73 and recorded total severity of 141.95. Approximately, 2261.7 mm of rainfall was recorded during this flood situation. The second most severe flood in the area reached extreme peak danger of 2.44 during the 52 days period. This event, which started on April 1997, recorded approximately 691 mm of rainfall, and had a severity of 35.89. The January 2008 flood event lasted for 47 days and reached peak danger of 1.75. This event had a severity of 28.78 and total rainfall of about 729.3 mm.

The most severe flood events in Sigatoka started in January 2009, January 2008, and March 2012. The January 2009 flood lasted for 125 days, reached peak danger of 2.16 and had a combined severity of 128.59. Approximately, 1497.39 mm of rainfall was recorded during this period. The 2012 flood event had a duration of 138 days and reached a peak severity of 1.43 while amounting to a total severity of 102.54. This event recorded about 1418.2 mm of rainfall. The flood which started in March 2012 experienced approximately 615.4 mm of precipitation during the 57 days and reached peak danger of 1.61. This flood situation had a severity of 43.69. The list of the 20 severest flood events in Sigatoka is presented in Table 4(h).

Based on Table 4(i), the severest flood in Suva started in February 2014 and lasted for 47 days. This flood had a total severity of 32.62 and reached peak severity of 1.95. Approximately, 903.3 mm of rainfall was recorded during this event. The second most severe flood started in March 1993 and had a severity of 22.72 and reached a peak danger of 1.44. This event lasted for 36 days and experienced approximately 565.9 mm of rainfall. The April 2009 flood in Suva had a duration of 29 days during which it recorded about 511.4 mm of rainfall. This event had a severity of 21.49 and peak danger of 1.76.

Table 5 lists the flood situations with extreme severity during the 29-year period. These are flood situations which have $I_F > 2$. Flooding's of 2009 and 2012 were the most extreme. Significant damages were caused by floods during these years (Lal 2009; Yeo 2013). Labasa and Suva did not record any extreme flood events. The duration of extreme floods in Savusavu, and Sigatoka was low as well. The most extreme flood events occurred in Ba, Lautoka, Nadi and Rakiraki and all these sites are in the western side of Fiji. The Ba and Lautoka floods were extreme for 16 and 18 days singly while the Nadi and Rakiraki floods were extreme for 8 and 9 days, respectively.

As shown in Fig. 13, the seasonality of rainfall and AWRI was investigated for each of the nine study sites. This was done by obtaining the daily average precipitation and daily average AWRI for the 29 years for each study site. All sites exhibited a generally similar pattern whereby there is a higher occurrence of rainfall and greater AWRI values in the first few months and the last 2 months of the year. The sites in the western side of Fiji generally experience less rain the middle of the year when compared to the other sites. It can also be seen that Suva and Nausori experiences consistent rain almost throughout the entire year and generally have higher AWRI. It is interesting to note that the rainfall pattern in Savusavu is quite similar to the central division and the rainfall pattern in Labasa resembles more closely to the western division even though both Labasa and Savusavu are on the same island in the northern division.

The results obtained in this study for the nine study sites used I_F, which is the normalized form of $AWRI$. As presented in these results, I_F made it easier to determine a flood situation when compared to $AWRI$ or raw precipitation data. This is because a simple condition $I_F > 0$, can be used to classify a flood situation. Such a condition cannot be used with $AWRI$ and raw precipitation values. The comparison of determining flood based on the two can be done using Figs. 4 and 13. In Fig. 4, I_F and P for the first 180 days of 2009 are plotted for each site and in Fig. 13, average $AWRI$ and average P for the 29-year period for each site are plotted.

4 Conclusion

The Flood Index (I_F) was successfully computed and the duration, severity and intensity of flood events that occurred between 1991 and 2019 for the nine sites in Fiji was determined and analysed. I_F was determined to be a good measure to monitor flood events based on its ability to accurately determine flood situations in different parts of Fiji. The capability to categorize a flood event based on the value of I_F allowed the classification of flood severity as either low, moderate, severe, or extreme.

Results showed that severe floods in the country were more likely to occur between November to April, which is also the wet/cyclone season in Fiji. Most of the severe floods in the western side of Fiji occurred in the month of January. Overall, the severity of floods in January were high as well. This shows that effective flood preparation and risk mitigation strategies need to be implemented for these months. Likewise, almost all the study sites experienced high rainfall during these months. To add on, on average, floods in the western side of Fiji were more severe and reached greater peak dangers showing the vulnerability of the sites in this region to floods.

A major outcome of this research was presenting the water and flood intensive properties of the 10 severest flood events for each site. Statistics such as these and the evaluation of the severest flood at each site during the study period can be further explored by relevant organizations to get more insights on previous flood situations. These insights on past events can be explored to make informed decisions regarding future flood threats. Furthermore, as mentioned previously, the method presented in this study uses a time-dependent reduction function to account for physical and geographical factors that contribute to a flood situation, and even though this method has been accepted to be fairly accurate, further studies are required to test the various time reduction functions against how they reduce P_E by experimental methods. In addition, studies on how a physical rainfall-run off model can be connected to further improve the time factor could assist in enhancing the presented method further.

A key benefit is that the methods applied in this study can easily be replicated in studying flood events in other small Pacific Island countries which are resource constrained and face huge flood risks. Furthermore, it will also be interesting to monitor flood events in these countries on hourly timescales such as a recent study performed in Brisbane, Australia (Deo et al. 2018b). However, this study in Fiji and other Pacific Island nations is subjected to the availability of hourly rainfall data for different sites, which ae rather difficult to collect in developing nations. Overall, the results presented in this paper can be used by the

Table 5 Analysis of flood situations with extreme severity at the 9 study sites from 1991 to 2019

Site	Onset date t_{onset}	Severity I_F^{acc}	Peak danger I_F^{max}	Duration (days)	Total AWRI (mm)	Total precipitation (mm)	Maximum AWRI
Ba	11-1-2009	38.86	3.13	16	20,086.07	1236.30	1419.60
Labasa	No extreme floods						
Lautoka	30-3-2012	49.27	3.39	18	21,626.62	692.70	1343.04
Nadi	31-3-2012	18.63	2.53	8	8649.45	326.50	1122.86
Nausori	23-4-2019	13.71	2.55	6	5635.16	213.60	964.83
Rakiraki	1-4-2012	22.52	3.21	9	11,997.25	564.10	1516.77
Savusavu	4-5-1997	4.60	2.44	2	1647.83	148.00	842.04
Sigatoka	11-1-2009	2.11	2.11	1	763.85	183.00	763.85
	15-1-2009	4.32	2.16	2	1541.56	84.30	771.33
Suva	No extreme floods						

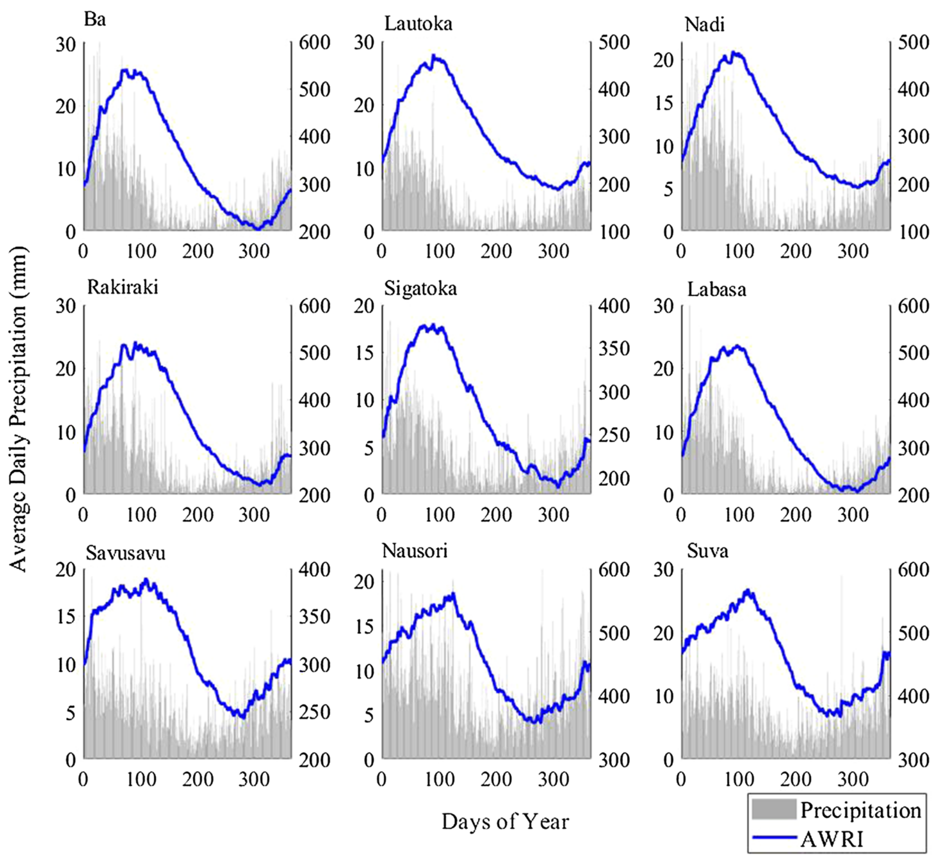


Fig. 13 Daily average rainfall (precipitation) and daily average AWRI for the nine study sites from 1991 till 2019

government, organizations, and individuals to better prepare for floods and to develop efficient flood mitigation strategies that will help to save lives, money, and other resources. To conclude, based on the performance of I_F in determining the duration, severity and intensity of flood situations, the index can be accepted as a viable and cost-effective tool for monitoring floods.

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CHAPTER 5: FLOOD FORECASTING SYSTEM DESIGN AND IMPLEMENTATION

Foreword

In this chapter, a copy of the paper with the title "Designing Deep-Based Learning Flood Forecast Model with ConvLSTM Hybrid Algorithm", which is published in the journal, *IEEE Access* has been presented. In the paper, a hybrid deep learning algorithm known as ConvLSTM which combines LSTM and CNN algorithms was used to develop a flood forecasting model. The predictive model uses lagged I_F and rainfall data to forecast I_F at future timescales. The developed model was evaluated using several statistical score metrics and generally showed fine performance for forecasting I_F at 1, 3, 7 and 14 day ahead forecast horizons. In addition, when the performance of the objective model was compared with the benchmark models that were build using LSTM, CNN-LSTM and SVR algorithms, the performance of the former was more superior for all forecast horizons and all study sites. Based on the results, it can be established that the proposed ConvLSTM flood forecasting system which is presented in this paper is a cost-effective and efficient means of flood forecasting that can be used for community flood risk mitigation in Fiji and around the globe.

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Designing Deep-Based Learning Flood Forecast Model With ConvLSTM Hybrid Algorithm

MOHAMMED MOISHIN[1], RAVINESH C. DEO[1], (Senior Member, IEEE), RAMENDRA PRASAD[2], NAWIN RAJ[1], AND SHAHAB ABDULLA[3]

[1]School of Sciences, University of Southern Queensland–Springfield, Springfield, QLD 4300, Australia
[2]Department of Science, School of Science and Technology, The University of Fiji, Lautoka, Fiji
[3]USQ College, University of Southern Queensland, Toowoomba, QLD 4350, Australia

Corresponding authors: Ravinesh C. Deo (ravinesh.deo@usq.edu.au) and Mohammed Moishin (mmoishin@gmail.com)

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ABSTRACT Efficient, robust, and accurate early flood warning is a pivotal decision support tool that can help save lives and protect the infrastructure in natural disasters. This research builds a hybrid deep learning (ConvLSTM) algorithm integrating the predictive merits of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Network to design and evaluate a flood forecasting model to forecast the future occurrence of flood events. Derived from precipitation dataset, the work adopts a Flood Index (I_F), in form of a mathematical representation, to capture the gradual depletion of water resources over time, employed in a flood monitoring system to determine the duration, severity, and intensity of any flood situation. The newly designed predictive model utilizes statistically significant lagged I_F, improved by antecedent and real-time rainfall data to forecast the next daily I_F value. The performance of the proposed ConvLSTM model is validated against 9 different rainfall datasets in flood prone regions in Fiji which faces flood-driven devastations almost annually. The results illustrate the superiority of ConvLSTM-based flood model over the benchmark methods, all of which were tested at the 1-day, 3-day, 7-day, and the 14-day forecast horizon. For instance, the Root Mean Squared Error (RMSE) for the study sites were 0.101, 0.150, 0.211 and 0.279 for the four forecasted periods, respectively, using ConvLSTM model. For the next best model, the RMSE values were 0.105, 0.154, 0.213 and 0.282 in that same order for the four forecast horizons. In terms of the difference in model performance for individual stations, the Legate-McCabe Efficiency Index (LME) were 0.939, 0.898, 0.832 and 0.726 for the four forecast horizons, respectively. The results demonstrated practical utility of ConvLSTM in accurately forecasting I_F and its potential use in disaster management and risk mitigation in the current phase of extreme weather events.

INDEX TERMS ConvLSTM, deep learning, flood forecasting, flood index, flood risk management.

I. INTRODUCTION

Early detection of natural disasters such as floods can greatly assist humans in reducing the extent of the damage caused by such events. In the Fiji Islands, where this study is focused, recent flood events resulted in major damages amounting to millions of dollars [1]. The loss of at least 225 lives during the 1931 flood event in Fiji was primarily due to the unavailability of efficient flood warning systems [2]. Although there have been improvements in early warning systems since then, many other emerging technologies, which are somewhat constrained in developing nations, have strong potential to deliver robust and cost-effective solutions for disaster risk and flood event management.

One simple, yet a robust mathematical tool used to determine the flood state at a particular time for a given area is the Flood Index (I_F) [3]. This approach represents the standardized form of 'Effective Precipitation' (P_E) based on the rationale that a flood event on any particular day is dependent on the current and the previous day's precipitation with the effect of previous day's precipitation on current day's flood state gradually reducing due to the effect of hydrological factors [4]. I_F has been applied at various locations globally and is generally accepted as an accurate data-driven mechanism to monitor flood state and, to determine the duration, severity, and intensity of flood situations [5]–[8]. However, as a flood monitoring index, I_F cannot be currently used to determine

The associate editor coordinating the review of this manuscript and approving it for publication was Bo Pu.

the flood state ahead of time unless a predictive model for this index is built and tested. If a model is successful in predicting the flood event, the exploration of its predictive skill for multiple forecast horizons is paramount so that early warning of the flood state can be dissimilated, setting up flood risk mitigation and adaptation measures. This is the subject of the present research paper.

To make practical use of I_F in forecasting future flood situations, an Artificial Intelligence (AI) based predictive model can be developed to accurately forecast the future values of I_F based on antecedent (lagged) values over a given period. Notably, AI models have shown good potential in forecasting floods based on metrics other than I_F, with continuous improvement in AI-based methods over the past decade. A study on classifying flood severity based on weather radar and rainfall data showed that Artificial Neural Network (ANN) which is an AI-based machine learning algorithm, had good potential to deliver major improvement in the speed compared with conventional hydraulic simulators [9]. A more recent AI approach that uses representation learning with several levels of feature representation is deep learning [10]. One popular deep learning approach used for time-series forecasts is Long Short-Term Memory Network (LSTM) [11]. LSTM is a type of Recurrent Neural Network (RNN) that can address the vanishing gradient problems in RNNs [12]. This approach has been applied in applications e.g., short-term fog forecasting and language processing [13], [14]. When LSTM was compared with ANN, the former performed better and was relatively stable to simulate rainfall-runoff process [15]. Therefore, when compared with conventional machine learning algorithms such as ANN, deep learning LSTM seems to be a better option to forecast flood events especially using time-series flood monitoring data, such as the current research using I_{F}.

In AI-based methods, multiple deep learning models are normally integrated to deliver a better performance accuracy. One common model known to provide effective performance when combined with LSTM is Convolutional Neural Network (CNN) [16]. In Liu, *et al.* [17], a ConvLSTM module was used to predict short-term traffic flow, combining convolution and LSTM models, outperforming the benchmark models. ConvLSTM was applied for precipitation nowcasting to show excellent performance [18]. These studies generally illustrate the good performance of ConvLSTM compared with others in similar machine learning problems. It is thus expected that ConvLSTM may deliver a better performance in forecasting future flood events using daily I_F and rainfall data but no previous study has built this approach into real-time, multiple-step flood prediction problems.

As an AI-based deep learning model has not been used to forecast floods using I_F, this novel technique adopted to forecast the occurrence of future events is expected to provide an alternative to traditional mathematical means such as using the Standardized Precipitation Index (SPI) for early flood warnings [19]. The cost-effectiveness and accuracy of deep learning approaches explored in this paper, is also expected to provide a suitable tool for efficient flood forecasting in developing and developed nations.

By making significant contribution to disaster risk mitigation, the purpose of this article is to design an AI-based predictive model trained as a practical and highly accurate tool in forecasting the onset of flood state using daily I_F and precipitation data. The research objectives, which advance the application of data-driven methods, make significant contributions to flood forecasting and mitigation, as follows:

(1) Build flood monitoring and validation system by deriving daily I_F from rainfall data obtained from Fiji Meteorological Service at nine flood-prone sites in Fiji over a 30-year period.

(2) Develop multi-step predictive model using ConvLSTM, as an objective model, with alternative methods of LSTM, CNN-LSTM and SVR that can also determine the flood state at 1-day, 3-day, 7-day, and 14-day forecast horizons.

(3) Evaluate the performance of predictive models using a diverse range of statistical score metrics, infographics, and visual analysis of forecasted and ground-truth dataset.

(4) Compare the evaluation results of objective model with benchmark models and elaborate on the suitability of the ConvLSTM model in accurately forecasting future flood situations.

The structure of the paper is as follows. In next section, the related works are presented. Then in section 3 this research presents the problem and motivation for this study and a theoretical overview of ConvLSTM and I_F. In section 4, this study presents experimental methods where the study area and data used for this study are presented briefly. Next, the method employed to develop flood forecast models are explained. After this, the results are presented, and this is followed by the discussion of the limitations, practicality, and contributions of the proposed method. Finally, the paper concludes by presenting insights from this study.

II. RELATED WORKS

Over the years, several data-driven early flood forecasting systems have been developed. These have made use of machine learning algorithms to develop models that show promising results. Some of these studies are presented in this section.

In one of the earliest examples, Campolo, *et al.* [20] developed a neural network river flood forecasting model illustrating promising results at short timescales. However, a rapid decrease in forecasting performance was evident with a longer time horizon. Another short-term flood forecasting approach was presented by Nayak, *et al.* [21] using neuro-fuzzy technique. The results illustrated the viability of their models for short-term river flow forecasting. Moving on, Han, *et al.* [22] applied Support Vector Machine (SVM) for flood forecasting. However, they mentioned that although their objective model performed better than the benchmark models, it required considerable amount of efforts to ensure the better performance of the objective model

Sit and Demir [23] explored the use of artificial deep neural networks for flood prediction and mentioned the usefulness of neural networks for flood forecasting using time-series data.

The approaches presented so far have made use of conventional machine learning to forecast flood situations. A study by Tran and Song [24], however, used deep learning algorithms i.e., RNN and LSTM to forecast water levels as a practical means to develop a solution for flood forecasting in urban areas. Their results indicated that all deep learning models had high accuracy. Therefore, in this paper, hybrid deep learning approaches are used to forecast floods at both short and long timescales, expecting that these newly developed models are a step forward in data-driven-based early flood warning systems.

III. METHODOLOGY

A. PROBLEMS AND MOTIVATIONS

Owing to the insidious and 'creeping' nature of flood events, designing robust systems for early flood warnings is a challenge. This is because the design of early warning systems requires expertise in different technologies [25]. It is understandable that this could be a bigger challenge for developing nations e.g., Fiji. Therefore, a cost-effective solution that requires a minimum investment in such technologies is desirable for flood forecasting purposes. The new flood modeling method presented in this research will address these problems. A data-driven model that requires only the daily rainfall data to deliver an accurate result is expected to be a cost-effective solution for nations with limited resources where technological advancements has not penetrated yet. Furthermore, another motivation behind this study is the recurrent destructions that flood events have caused in the present study area over many years. Through this study, the authors hope to develop and validate a new flood forecasting model that can be used to mitigate the impact of floods not only in island nations but also elsewhere by enabling the people and organizations to be better prepared for future flood events.

B. THEORETICAL OVERVIEW

To date, there are only a handful of flood monitoring indices that can determine the flood state for any day based on antecedent day's rainfall [3], [26]. These are categorised into data-driven mathematical models and have generally been accepted to produce accurate results. As mentioned previously, I_F is adopted for this study as it conforms to the rationale of Lu [26]. Basically, I_F uses current and antecedent day's rainfall data to determine the flood state of current day. The contributory influence of previous day's precipitation on current day's possibility of a flood decreases gradually in agreement with a time-dependent reduction function. Through this, the flood index can account for the loss of water due to hydrological factors e.g., evaporation, percolation, evapotranspiration and surface run-off [3]. This makes the flood index a practical tool to determine the flood state solely using daily rainfall data that is advantageous in regions without sophisticated flood monitoring technologies. In a previous paper, I_F applied in Fiji was shown to be an effective tool for flood monitoring at short timescales [7]. In many other related works [4]–[6], [27], [28], I_F has already been adopted for flood monitoring studies but none of these studies have built a deep learning forecast model using the I_F. Hence I_F-based data-driven models trained over multiple forecast horizons, as undertaken in this study, is a proactive step in estimating the flood extent of any day-ahead period, based on which flood risk mitigation and disaster response can be implemented.

The objective model in this study adopts hybrid ConvLSTM algorithm, a dual combination of deep learning method. ConvLSTM is a hybrid variant of LSTM architecture that uses convolutional operators instead of matrix multiplication for its input to the state and the state-to-state transition. This enables the algorithm to handle spatiotemporal data and determine the upcoming state(s) of a particular cell in grids using local neighbours' inputs and previous states [18]. Equations 1 to 5, retrieved from earlier studies of Medel [29] and Xingjian, *et al.* [18], expresses the operational mechanisms of ConvLSTM. In these equations, '$*$' and '$\circ$' denotes convolution operator and Hadamard product, respectively. The i, f and o represents each timestamp's input, forget and output gates, separately. H denotes each timestamp's hidden state, C represents each timestamp's cell outputs, and X denotes all the inputs. The activation is denoted by σ while W is used to denote the weighted connections between the states.

$$i_t = \sigma\left(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \circ C_{t-1} + b_i\right) \quad (1)$$

$$f_t = \sigma\left(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \circ C_{t-1} + b_f\right) \quad (2)$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh\left(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c\right) \quad (3)$$

$$o_t = \sigma\left(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_o\right) \quad (4)$$

$$H_t = o_t \circ \tanh\left(C_t\right) \quad (5)$$

Theoretical explanations of benchmark models, LSTM [30], CNN-LSTM [31] and SVR [32] (Support Vector Regression), are available in studies elsewhere.

C. OVERVIEW OF THE PROPOSED PREDICTIVE MODEL

In previous sub-sections, an overview of I_F and ConvLSTM is provided. In this section the overall architecture of the proposed model is presented. As evident in Figure 1, the main information needed to build the predictive model is daily rainfall. The antecedent raw rainfall data and rainfall derived, daily I_F data are used as two inputs to the selected algorithm. The algorithm is used to forecast I_F for 1-, 3-, 7- and 14-day forecast horizons.

IV. EXPERIMENTS

A. STUDY AREA

The focus of this study is on towns and cities in Fiji. The Fiji group covers an area of 18,270 km^2 in the South Pacific Ocean [33]. Fiji has an oceanic tropical climate with the South Pacific Convergence Zone (SPCZ) having a strong influence

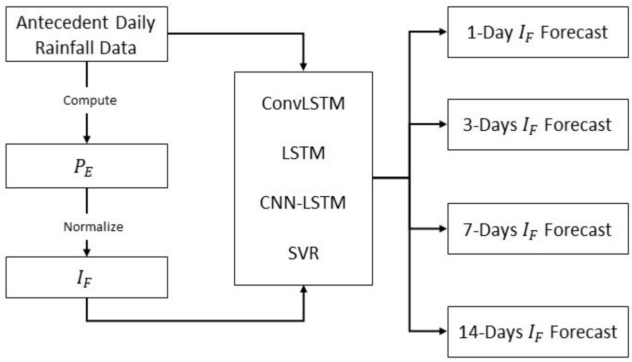

FIGURE 1. Overview of proposed experimental architecture.

on the climate of this small island nation [34]. The wet season in Fiji is usually between November and April and during this time, the SPCZ is positioned over Fiji. As heavy rain is experienced during this time, this results in regular flood situations around the flood prone areas in the country [35]. This study covers nine towns and cities from the two largest islands in Fiji. These are Viti Levu and Vanua Levu and they have an area of 10,400 and 5,540 km^2, respectively [34]. As seen in Figure 2, due to the small area of the Fiji group, this study has covered most of the major towns and cities of the archipelagic nation.

B. DATASET

The daily rainfall data for eleven sites from 1st January 1990 to 31st December 2019 (30 Years) was successfully acquired from Fiji Meteorological Services. These sites are illustrated in the map from Figure 2. During data pre-processing, the following actions were taken for simpler computations and more accurate results. Firstly, calendar mean was used to fill in the values for missing data points. Two sites, Navua and Tavua, which had high proportion of missing values, were excluded.

These two sites did not record precipitation for extended duration of the study period. For leap year the rainfall for 29th of February was added to 1st March following other works [6], [27], [28]. This resulted in all years having 365 data points to facilitate the computation of I_F. To visualize, in Figure 3, the trend of precipitation using data from Ba site over a 30-year period is presented.

C. FLOOD INDEX COMPUTATION

The computation of I_F and relevant metrics associated with I_F was performed using MATLAB [36] software. In computing the I_F, the first step was to obtain Effective Precipitation (P_E) [4]. The mathematical formula used to obtain the P_E is presented in equation 6. In this equation, N is the duration of antecedent period and P_m is the recorded precipitation for day m. P_E accounts for the depleting earlier days precipitation using a time-dependent reduction function. Moving on, once the P_E is computed, it can be used to get the Available Water Resource Index ($AWRI$) [37]. The $AWRI$ is obtained simply by dividing the P_E over the accumulative weight (W) of the antecedent period and this is shown in equation 7. Next, the I_F is calculated [3]. As shown in equation 9, I_F is the standardized version of P_E. In this equation, $\sigma({}^{2019}_{1991}P_E^{\bar{m}ax})$ and ${}^{2019}_{1991}P_E^{\bar{m}ax}$ denote the standard deviation and mean of the yearly maximum daily P_E during the study period. The duration, severity and intensity of floods can be successively determined using equations presented in earlier studies [7].

$$P_{E_i} = \sum_{N=1}^{D} \left[\frac{\sum_{m=1}^{N} P_m}{N} \right] (1 \leq m \leq 365) \quad (6)$$

$$AWRI = \frac{P_E}{W} \quad (7)$$

$$W = \sum_{n=1}^{n=D} \frac{1}{n} \quad (8)$$

$$I_F = \frac{P_E - {}^{2019}_{1991}P_E^{\bar{m}ax}}{\sigma({}^{2019}_{1991}P_E^{\bar{m}ax})} \quad (9)$$

D. PREDICTIVE MODEL DESIGN

To develop an AI-based flood forecast model, Python [38] programming language was used. As Python offers an efficient environment for machine learning data analysis, it was selected to design the forecast model [39]. Some machine learning packages for Python included Scikit-Learn [40], Tensorflow [41] and Keras [42], as these are popular packages solving machine learning problems that have also been used in previous studies to build efficient forecast models [43]. The scope of this study was to develop flood-forecasting models using deep ConvLSTM models and to compare the suitability of the algorithm in forecasting of flood situations using daily I_F.

Prior to data pre-processing, analysis of available data was done. The I_F for all the nine study sites were analysed. Firstly, the D'Agostino's K^2 Test (DKT) [44] was done to perform the statistical normality (or otherwise) test. The results showed that none of the data were Gaussian. Next, the Dickey-Fuller Test (DFT) [45] was performed to test for stationarity in data. The I_F data were stationary for all study sites. The next step for data analysis was to figure out the number of lag inputs that would be significant for the time-series forecasting. Partial Autocorrelation Function (PACF) was used for this purpose. After the impact of other variables are eliminated, the supplementary information given by lagged data is explained by PACF [46]. As seen in Table 1, two and three days of lagged inputs were significant for five and four study sites, respectively. This table also presents the results of other data analysis.

In the data pre-processing stage, the data was divided into training, validation, and testing subsets. 29 years (10,585 data points at daily time-steps) of I_F were calculated for each study site. The features used as model inputs included antecedent I_F and precipitation. 80% of these data were assigned for model training with 20% of the training data used for model validation purposes. The remaining data were used for testing the model's implementation. As there is no specific rule for

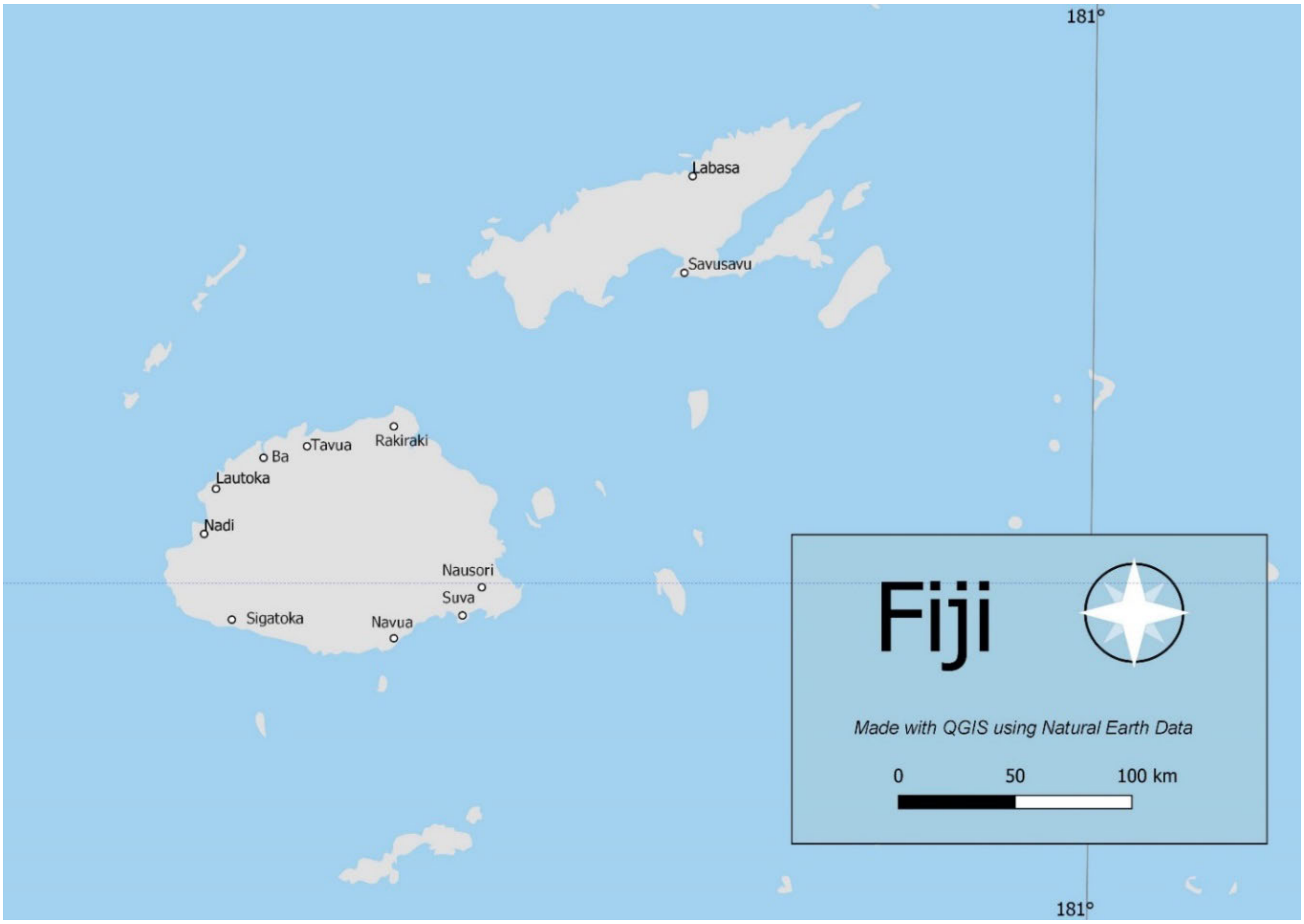

FIGURE 2. Map of the Fiji Islands showing study sites where the ConvLSTM model was developed.

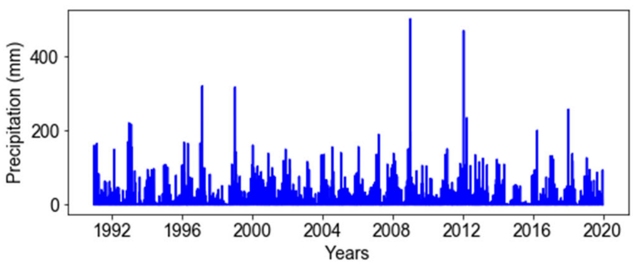

FIGURE 3. Daily Rainfall for the study site (Ba) over 1991 to 2019.

TABLE 1. Results from statistical tests.

Flood Site	Gaussian?	Stationary?	95% significant lagged IF
Ba	No	Yes	3
Labasa	No	Yes	3
Lautoka	No	Yes	2
Nadi	No	Yes	2
Nausori	No	Yes	2
Rakiraki	No	Yes	3
Savusavu	No	Yes	2
Sigatoka	No	Yes	2
Suva	No	Yes	3

the splitting ratio, the study adopted 80% for training data based on a study that used a similar ratio [47]. To verify this ratio, the effect of having 10%, 20% and 30% of data in the testing set was later compared. Upon comparison, all three ratios had relatively similar performance, and this verified the adoption of 20% of data as testing data during the experiments.

The ConvLSTM model type used for the experiment was Multiple Input Multi-Step Output model [48]. As more than one feature was to be used as input and the model had to forecast I_F at multiple forecast horizons, the Multiple Input Multi-Step Output model was determined to be the most suitable for this use case. The data were first structured to make them appropriate for Multiple Input Multi-Step Output supervised learning. Input feature set consisted of I_F and P at $t-1$ and the target consisted of I_F at t. After this, all variables in these data were scaled between [0, 1]. Scaling these data before running the model led to an improvement in speed and accuracy during training and testing phases. Next, the data were reshaped to the format to be accepted by the predictive model. This shape was adjusted based on forecast horizon for which the model was being built for and

TABLE 2. Optimal parameters of the developed model.

Predictive Model	Parameter Names	Optimal Parameters
ConvLSTM	Filter 1	128
	Activation	ReLU
	Optimizer	Adam
	Batch Size	100
	Epochs	50
CNN-LSTM	Filters	128
	Max Pooling 1D	Pool Size = 2
	LSTM Cell	50
	Activation	ReLU
	Optimizer	Adam
	Batch Size	100
	Epochs	50
LSTM	LSTM Cell 1	100
	LSTM Cell 2	50
	Activation	ReLU
	Optimizer	Adam
	Batch Size	100
	Epochs	50
SVR	Kernel	rbf
	degree	3 (Default)
	Gamma	Scale

TABLE 3. Architecture of the deep learning models.

Model	ConvLSTM	CNN-LSTM	LSTM
Layer 1 (L1)	128 Filters	128 Filters	100
L1 Type	ConvLSTM2D	Conv1D	LSTM
L1 Activation	ReLU	ReLU	ReLU
Layer 2 (L2)	-	Pool Size – 2	50
L2 Type	Flatten	MaxPooling1D	LSTM
L2 Activation	-	-	ReLU
Layer 3 (L3)	-	-	-
L3 Type	Dense	Flatten	Dense
Layer 4 (L4)	-	50	-
L4 Type	-	LSTM	-
L4 Activation	-	ReLU	-
Layer 5 (L5)	-	-	-
L5 Type	-	Dense	-

the number of lagged days considered. Once the data was prepared, the models were trained using different combinations of hyperparameters. These combinations of parameters were adjusted manually until the most optimal set of hyperparameters were attained. As the same set of parameters were the most optimal for all sites and horizons, this assisted in a more effective comparison of the performance of the models at different forecast horizons.

Table 2 presents optimal parameters of all models. Table 3 shows the architecture of deep learning models. The objective model, ConvLSTM consisted of three feature layers. The first was a ConvLSTM2D layer with 128 filters and rectified linear unit (ReLU) as the activation function. The second layer was a flattening layer, and the final layer was a dense layer. As the inputs consisted of only two features, this simple configuration was enough to achieve the optimal model. Furthermore, a batch size of 100 was chosen, with Adam as the optimizing algorithm.

Several statistical metrics were used for thorough evaluation of models developed in this study. These performance metrics included Root Mean Squared Error (RMSE), Pearson's Correlation Coefficient (r), Mean Absolute Error (MAE), Coefficient of Determination (r^2), Willmott's Index (Index of Agreement; d), Nash-Sutcliffe Efficiency Index (NSE), and Legate-McCabe Efficiency Index (LME). Apart from Sci-Kit Learn, two other Python packages, HydroEval [49] and HydroErr [50] were used to apply these performance metrics. The mathematical representation of these metrics is presented from Equations 10 to 15, respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{10}$$

$$r = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}} \tag{11}$$

$$MAE = \frac{1}{n}\sum_{i=0}^{n}|S_i - O_i| \tag{12}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - \bar{O}| + |O_i - \bar{O}|)^2} \tag{13}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{14}$$

$$LME = 1 - \frac{\sum_{i=1}^{n}|S_i - O_i|}{\sum_{i=1}^{n}|O_i - \bar{O}|} \tag{15}$$

where S is the forecasted value of I_F, $\bar{S}$ is the mean of the forecasted values of I_F, O is the observed value of I_F and $\bar{O}$ is the mean of the observed values of I_F.

E. RESULTS

This section presents the results of performance evaluation of AI-based models (ConvLSTM, CNN-LSTM, LSTM and SVR) adopted to forecast future flood situations in Fiji, and these are shown for different flood forecasting periods (i.e., 1-day, 3-day, 7-day, and 14-day). The evaluation results from four forecast horizons and nine study sites expectedly verifies the robustness of the objective ConvLSTM model in forecasting future flood situations. The results are aggregated to enable the paper to deliver an extensive comparative outcome for all locations and forecast horizons.

To begin with, the results from the nine sites were averaged so that the performance of the models can be easily compared. The performance evaluation of the models using RMSE and MAE is presented in Table 4. It can be clearly seen from this table that ConvLSTM demonstrated the minimum errors when compared with the benchmark models for all the four forecast horizons. In addition, as expected, the error measure increases as the forecasting period increases. For instance, the average RMSE for 1-day forecasting using ConvLSTM

TABLE 4. The performance of ConvLSTM with benchmark models in terms of average RMSE and MAE for nine sites for 1-day, 3-day, 7-DAY, and 14-day flood forecasting.

Models	RMSE			
	1 Day	3 Day	7 Day	14 Day
ConvLSTM	0.101	0.150	0.211	0.279
LSTM	0.105	0.154	0.213	0.282
CNN-LSTM	0.126	0.169	0.225	0.290
SVR	0.350	0.348	0.351	0.369
	MAE			
ConvLSTM	0.048	0.077	0.118	0.172
LSTM	0.058	0.090	0.131	0.185
CNN-LSTM	0.064	0.094	0.135	0.187
SVR	0.340	0.332	0.323	0.324

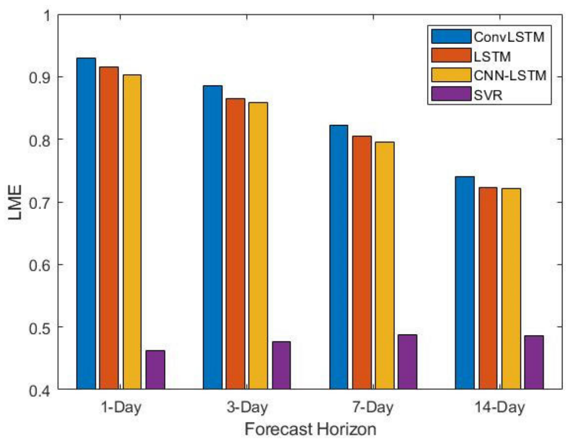

FIGURE 4. The performance of ConvLSTM with benchmark model in terms of average LME for nine sites for 1-day, 3-day, 7day and 14-day Flood Forecasts.

was 0.101, whereas for 14-days, it was 0.279. Similar trend is seen with MAE. Therefore, based on RMSE and MAE measures, the performance of ConvLSTM for flood forecasting is the optimal. This is followed by LSTM, CNN-LSTM and SVR.

In accordance with Equation (15) LME was used to evaluate the accuracy of models. Figure 4 illustrates average LME for all sites at all forecast horizons. Again, these results clearly demonstrated the better performance of ConvLSTM. The performance of the objective model is significantly better than the other models for all the forecast horizons. However, like error measures, the accuracy of all the models decrease as the forecast horizons is extended to 14-days. Also, after ConvLSTM, the best performing models in terms of LME were LSTM, CNN-LSTM and SVR, respectively. As seen in Figure 4, for the benchmark models, LSTM and CNN-LSTM's performance were reasonable but the performance of SVR was below 0.5 for all the forecast horizons.

In addition to the results from the aggregated data being used to show the show the performance of the four algorithms at the four forecast horizons, the LME analysis for Rakiraki site is presented in Table 5 to compare if the

TABLE 5. Comparing the performance of ConvLSTM with the benchmark models in terms of LME for Rakiraki site for 1-day, 3-day, 7-DAY, and 14-day flood forecasting.

Models	LME			
	1 Day	3 Day	7 Day	14 Day
ConvLSTM	0.939	0.898	0.832	0.726
LSTM	0.927	0.891	0.827	0.707
CNN-LSTM	0.881	0.830	0.768	0.711
SVR	0.407	0.409	0.414	0.407

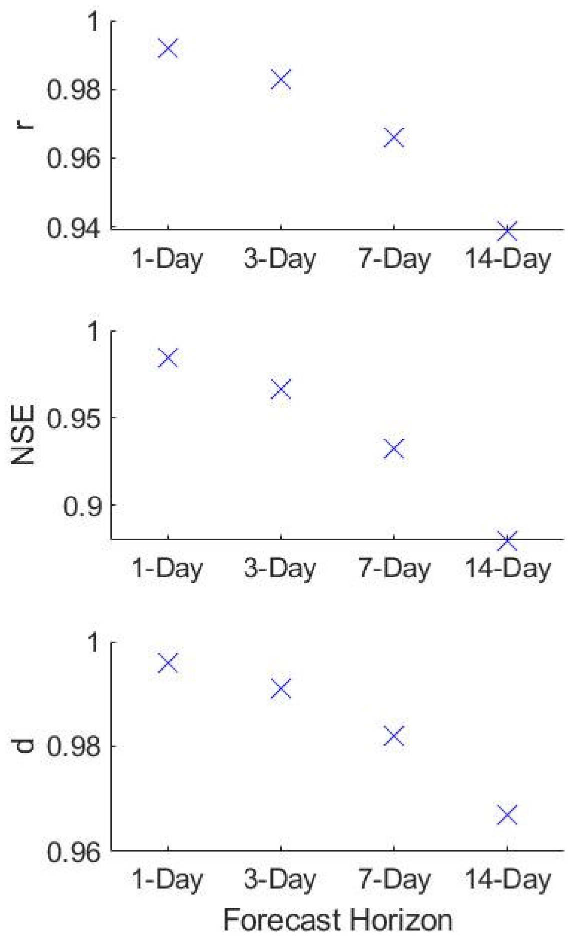

FIGURE 5. Evaluating the performance of ConvLSTM using average r, NSE and d values for 1-day, 3-day, 7-day and 14-day Flood Forecasting.

model performances are similar with non-aggregated data. This table shows similar trends in performance as with the aggregated data whereby ConvLSTM performs the best for all forecast horizons, followed by LSTM, CNN-LSTM and SVR. Also, as the forecast horizons increases, the performance accuracy drops. As the trends and measures with the non-aggregated data is close to the aggregated data, it verifies the use of aggregated data when presenting the performance evaluation results.

Based on the previous results, it can be clearly established that ConvLSTM performs the best out of the four models.

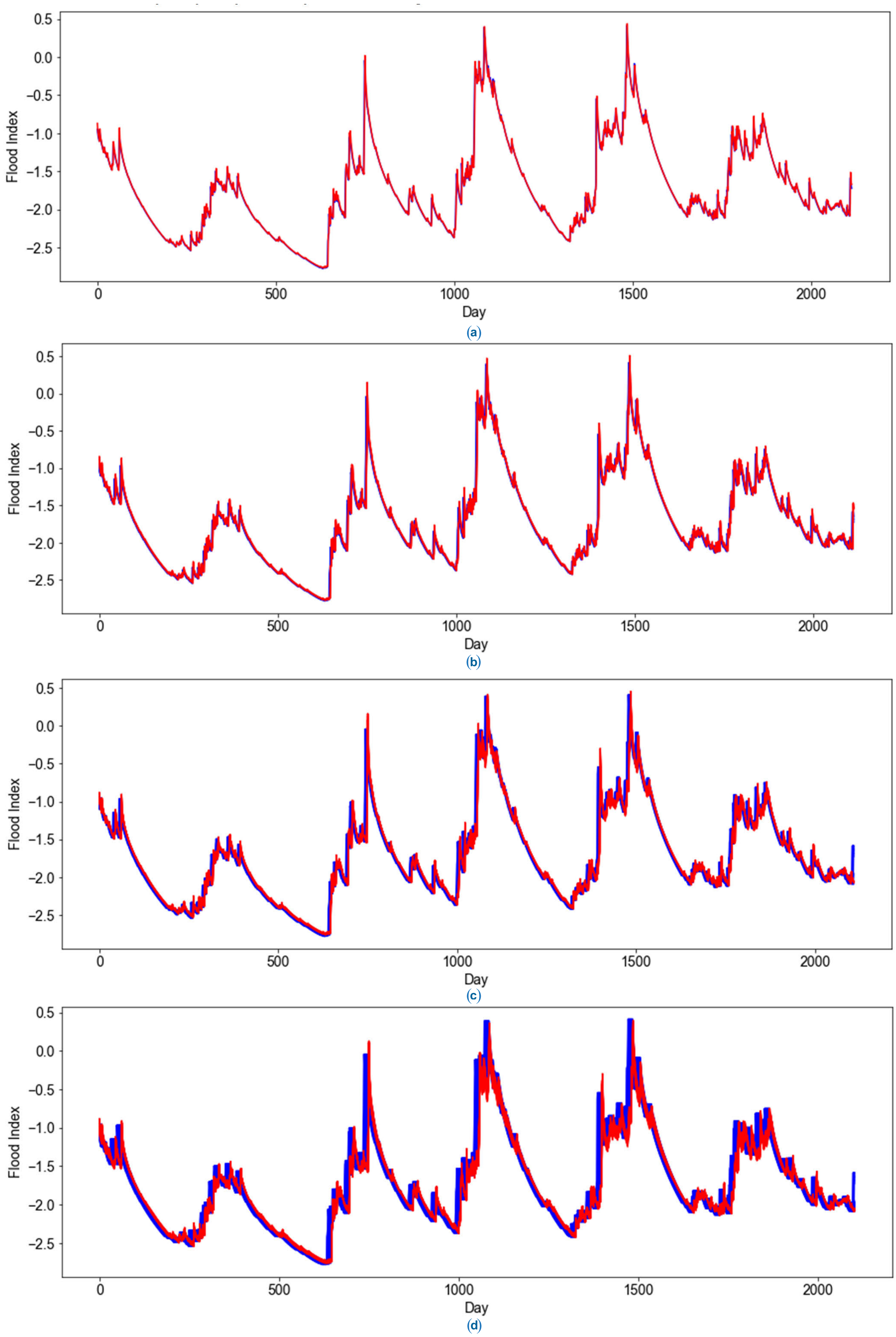

FIGURE 6. **(a) Actual versus 1 -day forecasted I_F for Ba Site using ConvLSTM. (b) Actual versus 3-day forecasted I_F for Ba Site using ConvLSTM. (c) Actual versus 7 -day forecasted I_F for Ba Site using ConvLSTM. (d) Actual versus 14 -day forecasted I_F for Ba Site using ConvLSTM.**

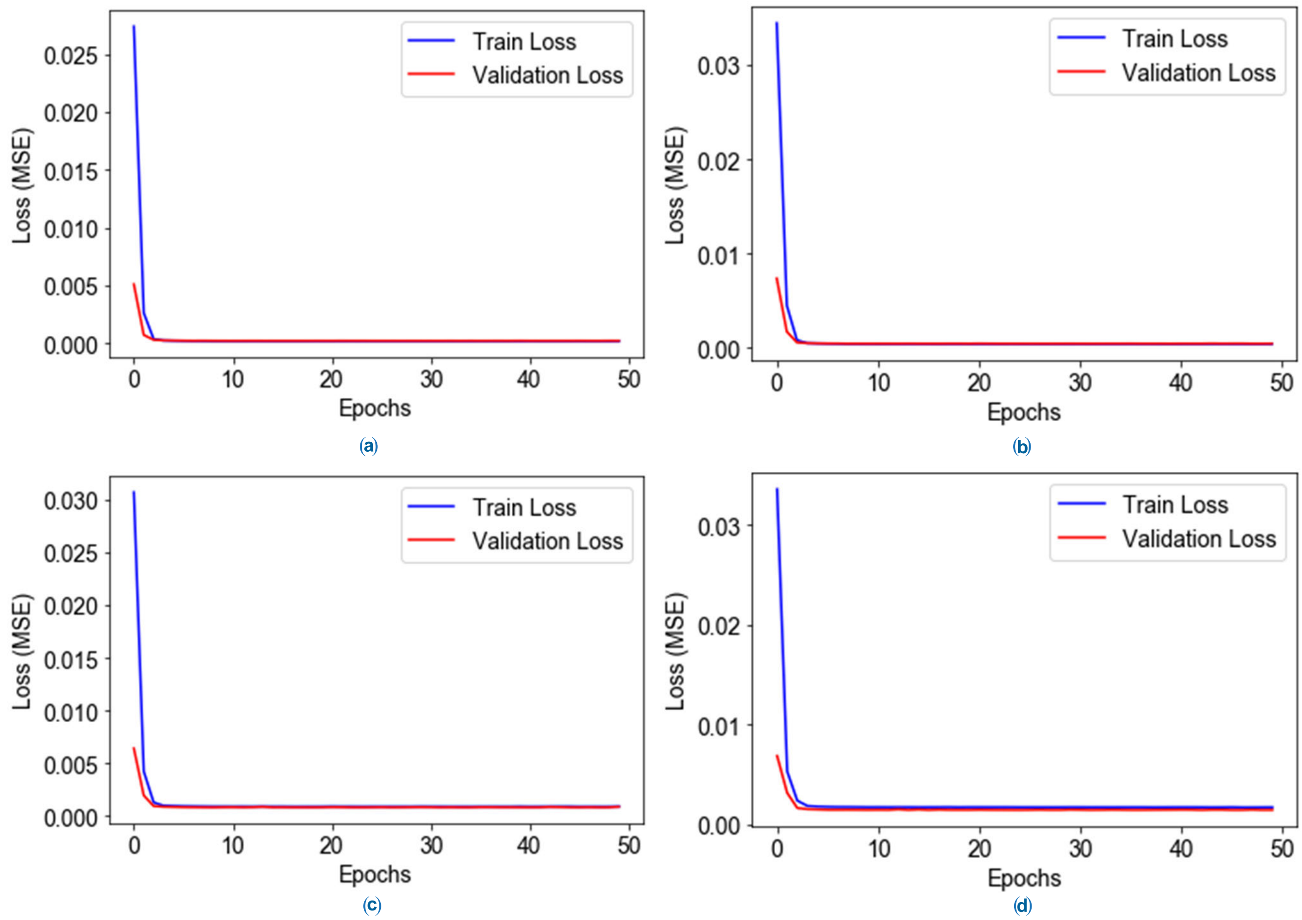

FIGURE 7. (a) Model Loss for 1 -Day I_F Forecasting using ConvLSTM for Ba Site. (b) Model Loss for 3-Day I_F Forecasting using ConvLSTM for Ba Site. (c) Model Loss for 7 -Day I_F Forecasting using ConvLSTM for Ba Site. (d) Model Loss for 14 -Day I_F Forecasting using ConvLSTM for Ba Site.

Next, r, NSE and d were used to further evaluate the performance of ConvLSTM for flood forecasting. As seen in Figure 5, for all the forecast horizons, the measures of r, NSE and d were greater than 0.93, 0.85 and 0.95, respectively. This clearly shows that ConvLSTM can be used to forecast I_F at longer timescales without a significant impact on its performance. Considering that only two features are used for building the forecasting model, these results illustrated the good performance of the model despite the usage of few variables.

Moving on, Figures 6 a-d shows the graphical view of 1-day, 3-day, 7-day, and 14-day I_F forecasting using testing results from Ba site and ConvLSTM algorithm. This view assists in understanding how close the forecasted values of I_F are with the actual values. As the forecast horizons increase, the difference in the forecasted and actual values of I_F also increased. However, even with this increase, the graphs clearly illustrate that the forecasted results are very close to the actual I_F for all the forecast horizons.

Finally, the model loss in terms of Mean Squared Error (MSE) during training and validation of the ConvLSTM for 1-day, 3-day, 7-day and 14-day flood forecasting using data from Ba site is presented in Figures 7 a-d, respectively. As seen in these figures, the models achieve minimum training and validation losses in less than 5 epochs. This is potentially due to only two features being used for the forecasting task. This further affirms the results, which showed good performance of the ConvLSTM model. Despite having only two input features, the proposed hybrid deep learning I_F forecasting model, i.e., ConvLSTM, provided very good forecasting performances at four forecasting horizons that can serve as the core of an early flood warning system.

F. DISCUSSION

The results presented in the previous section illustrate the feasibility of the ConvLSTM based $\boldsymbol{I_F}$ forecasting model to determine the possibility of flood situations at 1, 3, 7 and 14 day ahead forecast horizons. In this section, the limitations, restrictions, and recommendations for future research regarding the proposed flood forecast system is presented.

To begin with, one of the major limitations of this study is that the predictive model that was developed during this research only used two input features. Even though, only two features were used, good forecasting performance was achieved, it is expected that adding more useful features as input will assist in developing a more robust model with better forecasting accuracy at extended forecast horizons. It is recommended in future studies, that the model is enhanced by identifying and applying additional relevant features.

Another limitation of the study is in terms of the $\boldsymbol{I_F}$. $\boldsymbol{I_F}$ has been previously applied in Fiji and has shown suitability as a means of quantifying floods [7]. Therefore, it was acceptable to develop $\boldsymbol{I_F}$ based forecasting system for Fiji. However, for areas where the suitability of $\boldsymbol{I_F}$ has not been established yet, the forecasting method presented in this paper may not be appropriate for those areas. It is recommended that during the application of the proposed method in new study areas the suitability of $\boldsymbol{I_F}$ for that location should be evaluated before the development of the forecasting model.

Furthermore, another limitation is in terms of applying the proposed model at the study site for regular flood forecasting. Even though it is expected that the model can be easily incorporated into the workflow replacing classical forecasting techniques, the major challenge surrounding this would be regularly obtaining accurate data and finding expertise to implement these advanced techniques in the relevant organizations. Therefore, it is recommended that in future research more user-friendly tools for flood forecasting be developed and other deep learning and machine learning algorithms be tested for $\boldsymbol{I_F}$ forecasting. The results from this research can be set as a comparison benchmark for the newly build models.

V. CONCLUSION

In this paper, a hybrid deep learning based flood forecasting approach was presented. This novel approach made use of daily lagged I_F and precipitation time series data to determine flood situations at multiple forecast horizons. The practicality of the model was tested using datasets from nine locations in Fiji. Among the deep learning models evaluated, ConvLSTM, which was the objective model showed the best performance. The following are the main contributions of this paper:

1. This research was the first to use I_F with a hybrid deep learning algorithm to develop an AI-based model for flood forecasting.
2. The robustness of the objective model, ConvLSTM, was presented during this research whereby it illustrated better performance when compared with deep learning (LSTM and CNN-LSTM) and machine learning models (SVR) for 1-day, 3-day, 7-day and 14-day flood situation forecasting using datasets from nine sites.
3. Using various statistical score metrics, the accuracy of the model for multi-step flood situation forecasting was clearly established.
4. The application of the model at various sites in Fiji illustrated the practicality of the approach in accurately forecasting floods at multiple timescales in a cost-effective manner.

To conclude, the approach presented in this paper could be further enhanced to forecast flood situations at hourly time scales. Accurate forecasting at shorter timescales is expected to result in more time for informed decision making by governments, organizations, and individuals to be better prepared for flood situations and therefore saving lives and protecting infrastructure resources.

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MOHAMMED MOISHIN received the bachelor's degree in software engineering from The University of the South Pacific, Fiji, in 2019. He is currently pursuing the Master of Science Research degree with the Advanced Data Analytics Group, School of Sciences, University of Southern Queensland–Springfield, Australia. His research interests include flood risk mitigation, artificial intelligence and machine learning, and software development.

RAVINESH C. DEO (Senior Member, IEEE) is currently a Professor with research interests in artificial intelligence and deep learning. He was awarded internationally competitive Queensland Smithsonian, JSPS, Chinese Academy, Australia-India Strategic Fellowship, and Endeavour Fellowships and supervised 20 Ph.D./M.Sc. degrees, received employee excellence awards, Faculty Research Excellence, Elsevier Highly Cited Paper, Publication Excellence, and Teaching Commendation. He is also an academic and industry mentor through grants worth \$2.6M and services editorial boards of *Stochastic Environmental Research and Risk Assessment*, IEEE ACCESS, *Remote Sensing*, *Energies*, and *Journal of Hydrologic Engineering*. He has published 220 articles, including 150 journals (85% Quartile 1), and six books in Elsevier, Springer, IGI, with 23 Book Chapters. His work has cumulative citations exceeding 6200 with an H-index 43.

RAMENDRA PRASAD received the B.Sc. degree in mathematics and physics and the M.Sc. degree in physics from The University of the South Pacific, Fiji, and the Ph.D. degree in modeling and simulations from the University of Southern Queensland, Australia, in 2019. Since 2018, he has been a Lecturer with The University of Fiji. He has authored 15 articles in peer-reviewed journals and reputed conferences. His research interests include advanced machine learning approaches, data analytics, hydrological modeling, energy modeling, energy management, environmental, atmospheric modeling, and ocean wave modeling.

NAWIN RAJ received the B.Sc., B.Ed., PGDMA, and M.Sc. degrees in computational fluid dynamics from The University of the South Pacific, and the Ph.D. degree from the University of Southern Queensland, Australia, in 2015. From 2007 to 2010, he was a Lecturer with Fiji National University. He is currently a Lecturer with USQ. His research interests include artificial intelligence, deep learning, non-linear oscillation, computational fluid dynamics, and oceanography. He is also a member of the Australian Mathematical Society and the Queensland College of Teachers.

SHAHAB ABDULLA is currently a Senior Lecturer of (Mathematics/Communication). His interdisciplinary interests include artificial intelligence models and bioinformatics (health, energy, biomedical, control systems, control science, and sustainable agriculture) under these Codes (0103) Numerical and Computational Mathematics, (0502) Environmental Science and Management, (0701) Agriculture, (01) Mathematical Sciences, and (08) Information and Computing Sciences. Designing expert systems to his research interests, including deep learning, convolutional neural, and long- short-term memory networks. His leadership was recognized by many awards. He has served on several committees. He was the Chair of IEEE conference. He collaborates with researchers in Middle East, USA, Japan, Europe, China, and Canada, delivered over 30 seminars. In last three years, his articles were cited more than 200 times. With more than 25 publications (largely in Q1 journals), he leads the Advanced Data Analytics Modeling Research Simulation Group, as a Principal Supervisor and an Associate Supervisor of more than ten Ph.D./master's/HDR students. He has supervised more than five Ph.D./master's thesis/dissertations and examined a number of theses locally and overseas.

CHAPTER 6: DECISION SUPPORT SYSTEM DESIGN AND IMPLEMENTATION

Foreword

In this chapter, a copy of the paper with the title “A Web-based Flood Monitoring and Forecasting Decision Support System with Streamlit *Online* Platform”, which will be submitted to the journal, *Stochastic Environmental Research and Risk Assessment*, is presented. In the paper, a platform that is used for developing data-driven web applications and is known as Streamlit is used to develop a DSS. The proposed DSS consisted of four modules. These modules were built for easily computing daily and hourly flood monitoring indices and building the respective flood forecasting models using ConvLSTM hybrid deep learning algorithm. The practicality of the proposed DSS was tested using data from three sites in Fiji. The results indicated that the DSS is able to accurately determine the characteristics of floods using the monitoring indices. Moreover, the proposed DSS is also able to build robust flood forecasting models using the default parameters set for the ConvLSTM models in the system. The proposed DSS is expected to allow more organizations to easily apply flood monitoring indices for monitoring past flood events and assist in building AI-based models for forecasting future flood situations.

A Web-based Deep Learning Flood Monitoring and Forecasting Decision Support System with Streamlit *Online* Platform

Mohammed Moishin[1] [1]School of Sciences, University of Southern Queensland, Springfield, QLD 4300, Australia. Email: u1127003@umail.usq.edu.au

Ravinesh C. Deo[1*] [1]School of Sciences, University of Southern Queensland, Springfield, QLD 4300, Australia. * Corresponding author: ravinesh.deo@usq.edu.au

Ramendra Prasad[2] [2]The University of Fiji, School of Science and Technology, Department of Science, Saweni, Lautoka, Fiji. Email: ramendrap23@gmail.com

Nawin Raj[1] [1]School of Sciences, University of Southern Queensland, Springfield, QLD 4300, Australia. Email: Nawin.raj@usq.edu.au

Shahab Abdulla[3] [3]USQ College, University of Southern Queensland, QLD 4350, Australia. Email: Shahab.abdulla@usq.edu.au

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Abstract

Availability of user-friendly and robust system for monitoring and forecasting flood situations are effective scientific contrivances of flood risk mitigation. In this research, *Streamlit* an enigmatic-free tool is adopted to purposely develop a web-based data-driven application with Python programming to build a new Decision Support System (*DSS*) for flood risk mitigation. The *DSS* is a user-friendly system tailored to compute the metrics, and further analyse the proposed Flood Index (I_F) and Water Resources Index (WRI) from rainfall data including the training and testing of Artificial Intelligence (AI) based models to forecast the daily and hourly I_F and WRI values, enabling the decision-makers to continuously monitor the progression of a flood event. In the proposed *DSS*, both the I_F and WRI are mathematically based metrics previously used to determine the characteristics of a flood event. The newly proposed *DSS* consists of four distinct modules: the first and second module computes and visualizes the I_F and WRI, respectively, utilising only the rainfall as an input variable. The third and fourth module is used to build and optimize a convolutional neural network version of Long Short-Term Memory Network (*i.e*., ConvLSTM) deep learning model that is suited for daily and hourly flood risk forecasting. The proposed platform is tested using datasets from three flood prone sites in Fiji Islands. The system reveals its successful capability to compute flood metrics in a fast, efficient, and user-friendly manner, including its predictive modelling skill to be capitalised as a robust forecast system for both I_F and WRI. The results indicate good performance of the proposed *DSS*, particularly for flood risk monitoring and forecasting in regions where the flood management is an important task for community risk reduction, flood risk policy devising and other decision-making in a natural disaster or extreme weather events.

Keywords Decision Support System, Flood Risk Forecasting, Flood Index; Flood Monitoring; Water Resource Index

1 Introduction

User-friendly Decision Support Systems (*DSS*) for flood risk mitigation are useful decision-making tenets in analysing flood events and developing efficient damage reduction and risk mitigation strategies to address future disaster threats. A risk evaluation system is termed as a *DSS* if designed to support key decision-making tasks, such as, but not limited to platforms like the geographical information system, software agents, and analytical processing systems (Power, 1997). Over the past years, *DSS* has gained prominence in several areas of flood risk management (Ahmad & Simonovic, 2006; Mahmoud & Gan, 2018; Simonovic, 1999) but many of these physical systems based on satellites, remote sensing and radar meteorology capabilities are data expensive and overly complex in their technical and physical requirements.

These issues may limit the applicability of existing *DSS* in smaller economies or island nations (*e.g*., the Fiji Islands) where such infrastructure and scientific resources may not be available. In addition, the adoption of a *DSS* to investigate problems associated with water resources are being developed since the mid-1970's (Loucks & Da Costa, 1991). However, a *DSS* that utilizes rainfall-derived daily and hourly flood monitoring indices, and has the ability to delineate the onset, progression and rapidly evolving characteristics of a future flood event hasnot yet been developed although these types of indices have demonstrated a good performancein quantifying a flood situation. Therefore, developing a new *DSS* that is able to continuously monitor, visualize, and implement a built-in artificial intelligence AI-based method to forecasta flood event by using an objective flood monitoring index can be a cost-effective approach forflood risk mitigation.

There currently exist several mathematically based flood indices (*e.g*., the one in the proposed *DSS* platform) that need to utilise only the rainfall data to quantify an incoming flood situation. Some of these indices include the Available Water Resource Index (*AWRI*) (Hi-Ryong Byun & Lee, 2002), the Flood Index (I_F) (Ravinesh C. Deo, Byun, Adamowski, & Kim, 2015), the Weighted Average of Precipitation (*WAP*) (Lu, 2009), the Standardized *WAP* (SWAP) (Lu et al., 2013) and the Water Resources Index (WRI) (R. C. Deo, Byun, Kim, & Adamowski, 2018). Many of these tools are mathematically based approaches that have generally been accepted as suitable methods for monitoring the flood risk (Ravinesh C Deo et al., 2018; Moishin, Deo, Prasad, Raj, & Abdulla, 2020; Nosrati, Saravi, & Shahbazi, 2010). However, these approaches are currently not widely adopted in real-time by disaster risk management organizations. The possible reasons for this, off course, stems from a potential lack of interest driven by the complexities in developing a program or code to compute such metrics and an apparent lack of a forecast model utilising the metrics for risk prediction. To address such deficits, new research that can implement a consolidated *DSS* platform while also computing and visualizing the flood risk situation both in current time (*i.e*., for the purpose of *now-casting*) and at a future period (*i.e*., for *forecasting*) can lead to a better practical system for its use in real-time. This research aims to build such a *DSS* platform to encourage disaster management organizations in its greater adoption and the use of such user-friendly mathematical tools to quantify, analyse and model flood situations in different nations, and extreme weather contexts.

According to Jansen (1998), the success of any software-based decision tool is dependent on a good graphical user interface (*GUI*) design. Hence, providing a user-friendly *GUI* for the proposed *DSS* is necessary task to encourage greater usage and ongoing improvements in the system and the continuity of usage by relevant end-user organizations. In this research, we have identified one software-based decision tool with a quick and easy platform for conversion of data-driven applications into the *GUI*-based web applications, is *Streamlit* (Streamlit, 2021). *Streamlit* has been employed to share various data-driven applications. It is scripted in Python programming language (Sanner, 1999) and is freely available as a web system. Having a *DSS* for flood risk monitoring and forecasting as a web-based application can eliminate the need to install various programs on every computer while also having a similar speed and interactivity as an installed program (Zepeda & Chapa, 2007). This study therefore adopts *Streamlit* as a portable platform to build an easily accessible *DSS* for flood risk mitigation. The outcomes are expected to make it easy for government organizations, or individuals working in disaster management to access a user-friendly flood monitoring, analysing and forecasting system.

Among the various other flood monitoring tools, the I_F used in this study is considered to be a robust flood metric risk tool that has been applied at various places globally (Australia (Ravinesh C. Deo et al., 2015), Bangladesh (Ravinesh C Deo et al., 2018), Fiji (Moishin et al., 2020), and Iran (Nosrati et al., 2010)). It had shown good performance for daily monitoring of a flood event. In its own right, the I_F is considered as a normalized form of the Effective Precipitation (P_E) (Hui-Ryong Byun & Chung, 1998). P_E is designed to use the current and the previous day's precipitation to quantify an emerging flood situation, with the impact of an antecedent day's precipitation taken to be gradually decreasing based on a time-dependent reduction function by implementing the rationale of other researchers *e.g.*, Lu (2009) that postulate that the rainfall of a previous day contributes to the flood in a current day, but the effect of the previous day's rainfall should gradually decline due to hydrological conditions such as drainage, seepage, surface run-off, evaporation and percolation within the soil layer, in accordance with rainfall run-off models. Furthermore, another index that is based on a similar principle but can be used for flood risk monitoring over hourly timescales, is the WRI (R. C. Deo et al., 2018). In its initial research work, the WRI has been applied at two study locations in Australia and South Korea; concluding its capability as a versatile indicator of an emerging flood situation (R. C. Deo et al., 2018). Therefore, due to the wide applicability of the I_F for daily flood risk monitoring, and the capability of WRI for hourly flood risk monitoring, this paper, for the first time, aims to select these metrics to be implemented within a *Streamlit* platform to enable its computation, visualization, modelling, and practical representation in the proposed *DSS* platform.

Moving on, apart from monitoring a flood event, it is equally important for any proposed *DSS* platform to be able to provide added advantage to build and test a future flood forecast model. Such models would enable efficient flood warning in a flood-prone region and therefore enable an early evacuation of communities in danger of a possible flood threat (Chau, Wu, & Li, 2005). Over the years, several deep learning and machine learning algorithms have been used for flood forecasting. For instance, in a study by Elsafi (2014), an Artificial Neural Network (ANN) method was used for flood forecasting in Sudan, and in another study, a neuro-fuzzy model was developed by Nayak, Sudheer, Rangan, and Ramasastri (2005) for river flow forecasting. In a study by Le, Ho, Lee, and Jung (2019), the Long Short-Term Memory (LSTM) Network method was applied for 1-, 2- and 3-day flood flow forecasting in Vietnam. These methods have illustrated the possibility of using an AI approach for the forecasting of a flood event. Furthermore, in a previous study, the ConvLSTM hybrid deep learning model was proposed whereby the lagged I_F and precipitation was used to forecast the future I_F values asa method for daily forecasting of a flood situation (Moishin, Deo, Prasad, Raj, & Abdulla, 2021). However, such forecasting models are yet to be developed for hourly timescales, whichare crucial for short-term and near real-time decision-making tasks in natural disaster management situations. In addition, a versatile flood monitoring and forecasting *DSS* platformusing any of these tools (i.e., I_F, & *WRI*) is currently not available. Since these tools can help decision-makers in determining the state of a flood event more accurately than just using rainfall dataset, there exist research gaps to combine the I_F and *WRI* with AI-based techniquesto develop quick and efficient flood forecasting models that can predict both the hourly and daily onset, progression and features of an emerging flood situation.

A set of popular AI algorithms previously used to model time series data include the LSTM, ANN, and Convolutional LSTM methods (Babu & Reddy, 2014; Liu, Zheng, Feng, & Chen, 2017). Out of these, the ConvLSTM is considered to be a hybrid deep learning method that combines two deep learning algorithms *i.e.*, Convolutional Neural Network (CNN) (Albawi, Mohammed, & Al-Zawi, 2017) and LSTM (Hochreiter & Schmidhuber, 1997). When this hybrid algorithm was used for the nowcasting of precipitation, researchers found themethod outperformed the benchmark models including the fully connected LSTM (FC-LSTM)and ROVER algorithm (Xingjian et al., 2015). In addition, when comparing the ConvLSTM with the Bi-directional LSTM for short-term traffic flow prediction against the existingtraditional approaches, the former methods resulted in a much better performance (Liu et al., 2017). Also as mentioned previously, when the ConvLSTM was used for I_F forecasting at a daily scale, this method showed a superior performance (Moishin et al., 2021). Therefore, due to the robustness of algorithm, this study has utilized ConvLSTM in the proposed *DSS* platform to build and optimize daily and hourly flood forecasts.

The overarching aim of the study is to build and evaluate a user-friendly web based *DSS* application capable of calculating four of the robust daily and hourly flood monitoring indices. In addition, AI approaches are to be built into the same *DSS* to allow the users to develop flood forecasting models using the results from the flood monitoring computations. The proposed *DSS* is expected to be useful for meteorological organizations and disaster management bodies to be able to quantify flood situations mathematically. Based on these proposed outcomes, the objectives of this research are as follows:

1. To develop a user-friendly web based *DSS* that can be used to compute robust flood monitoring indices such as P_E, $AWRI$, I_F and WRI.
2. To build into the proposed *DSS*, an interface that can be used to build and test the AI-based daily and hourly flood forecasting models.
3. To test the practicality of the proposed *DSS* for real-world application by using data from Ba, Nadi and Rakiraki, which are three flood-prone areas in Fiji.

Hence, the paper presents the study area, data and methodology used for developing and testing the flood monitoring and forecasting *DSS* platform. It then evaluates the practical application of the *DSS* and analyses the accuracy of the results obtained using test data. Then further analysis of limitations, recommendations, benefits, and constraints of the proposed *DSS* is discussed. Finally, the paper concludes by presenting the key insights from the study.

2 Materials and Methodology

2.1 Study Area and Data for Testing the Proposed *DSS*

Three flood prone sites from Fiji Islands, Ba, Nadi, and Rakiraki were selected to test the proposed flood monitoring and forecasting *DSS*. These three sites are highlighted in the map shown in figure 1. Daily and 10-minute rainfall data were obtained from the Fiji Meteorological Services. The data period was from 1st January 1990 to 31st December 2019 and from 1st January 2014 to 31st December 2019 for the daily and 10-minute rainfall data, respectively. Necessary routine data pre-processing steps were taken to ensure that correct inputs were used to calculate the flood monitoring indices. Firstly, for the daily rainfall data, calendar mean was used to fill in the missing values. Once these missing values were computed, the rainfall for 29th of February was added to the 1st of March to accommodate for leap years as the daily flood monitoring tool used for this study considered 365 days of antecedent precipitation. These two operations were automated and built into the proposed *DSS*.

Figure 1 - Study Sites Highlighted (With Red Dots) from the Map of Fiji

Secondly, for the 10-minute datasets, the missing values were filled by averaging the respective hourly rainfall. This was done manually due to the small number of missing values. Once the missing data were filled, the 10-minuted data set was converted to hourly by summing up the 10-minute precipitation at hourly intervals. To illustrate the characteristics of the rainfall data obtained, Figures 2 and 3 show the daily and hourly rainfall data trends for Nadi site, respectively.

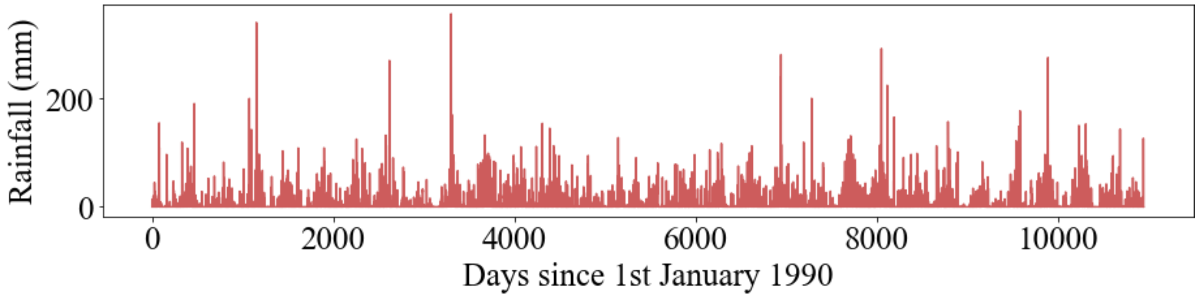


Figure 2 - Daily Rainfall Trend for Nadi Site from 1st January 1990 to 31st December 2019

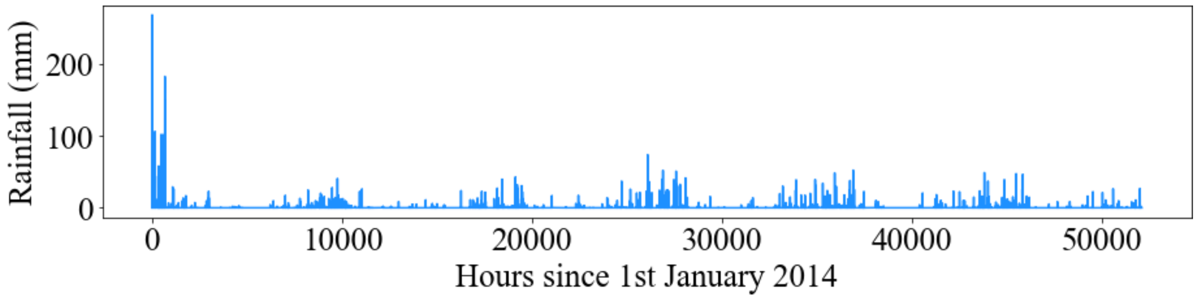


Figure 3 - Hourly Rainfall Trend for Nadi Site from 1st January 2014 to 31st December 2019

2.1 Overview and Development of the Proposed *DSS*

Streamlit, which uses Python (Sanner, 1999) programming language, was used for developing the proposed web-based flood monitoring and forecasting *DSS*. The proposed *DSS* is to be used for daily and hourly monitoring of floods and for building and optimizing AI-based models for daily and hourly flood situation forecasting. The flood monitoring indices to be computed in the proposed platform were I_F and WRI for daily and hourly flood monitoring, respectively. As mentioned earlier, these robust indices are based on the rationale that flood on any day is dependent on the current and earlier days rainfall, with the impact of earlier days rainfall on current days flood situation steadily declining based on a time-dependent reduction function due to the interaction of hydrological factors such as seepage and evapotranspiration (Ravinesh C. Deo et al., 2015; Lu, 2009). Figure 4 shows an overview of the proposed *DSS*. It can be seen from this figure that the proposed *DSS* consists of four modules (Labelled M1-M4). The details of these modules have been presented in the following sections.

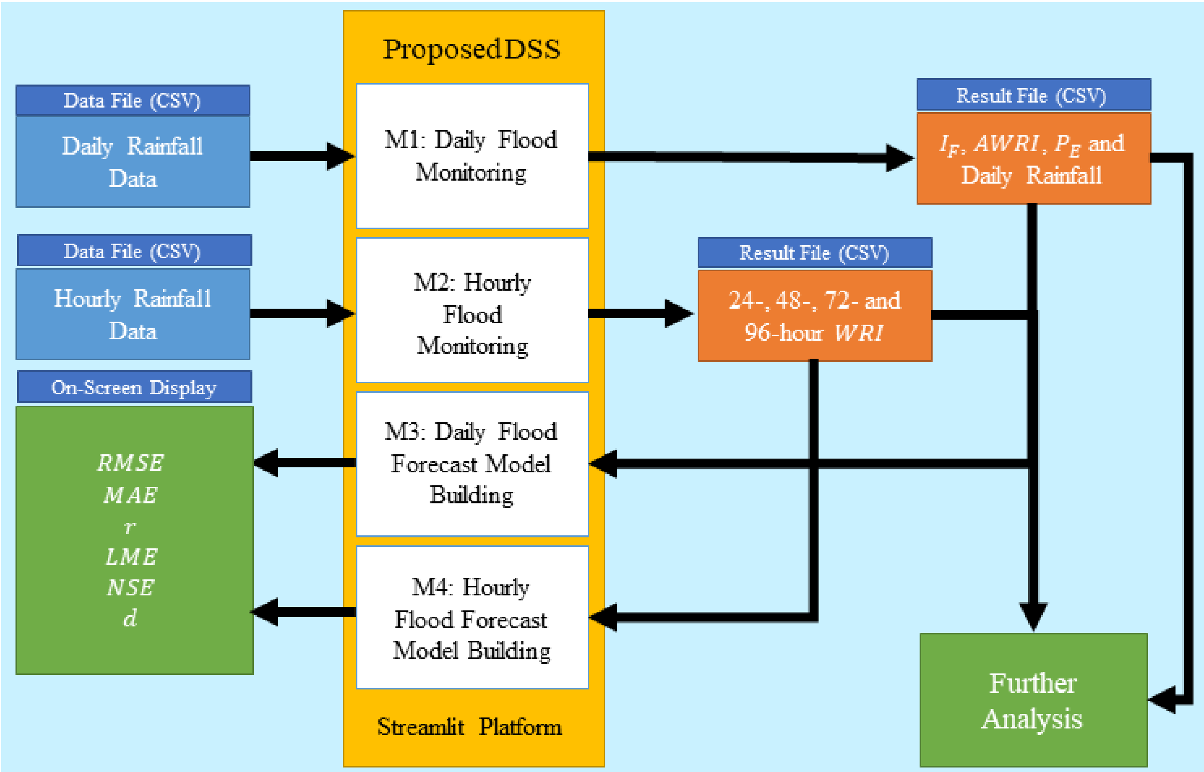


Figure 4 - Overview of the Proposed *DSS*

2.1.1 Module 1 - Daily Flood Monitoring

To calculate the daily I_F, first the P_E needs to be calculated (Hui-Ryong Byun & Chung, 1998). Then the P_E is normalized to get the final I_F measure. The mathematical methods to compute these daily flood monitoring indices have already been presented comprehensively in previous studies and therefore, it is not presented here (Ravinesh C Deo et al., 2018; Moishin et al., 2020). When computing the I_F, antecedent rainfall of 365 days is usually considered, and the index can determine the duration, severity, and intensity of flood situations mathematically. As seen in figure 4, the proposed *DSS* only requires the user to upload a CSV file containing the date and the respective daily rainfall amount in mm. Once the file is uploaded, the user can select the date range to be used during the computations. In addition, at least ten years of data is needed to be used in the computations and the *DSS* will not perform the computations if the data period is less than ten years. The *DSS* converts all date strings to date format and then splits each date into day, month, and year, to accommodate for different date formats. If a date format is unrecognized, the system is expected to throw an error. Therefore, the user is expected to ensure that correct data file is uploaded to get the most accurate results. Next, the *DSS* then computes the P_E, $AWRI$ and I_F. Once these are computed, the platform derives the history of floods and performs some basic analyses. The results produced by the *DSS* are available for download, which the user can then use to perform advanced analytics and make flood risk mitigation related decisions.

2.1.2 Module 2 - Hourly Water Resources Index

In terms of the short-term hourly WRI, equation 1 presents the mathematical overview of its computation, based on a previous study (R. C. Deo et al., 2018). In this equation, *D* represents the number of antecedent hours to consider during the computation. For instance, if $WRI_{24-hr-S}$ was being computed, the rainfall for the past 24 hours would be considered. The proposed *DSS*, which is developed in this study, computes $WRI_{24-hr-S}$, $WRI_{48-hr-S}$, $WRI_{72-hr-S}$, and $WRI_{96-hr-S}$. Through the accumulation of previous days rainfall, WRI can convert hourly rainfall into non-zero values, especially for the longer time horizons. This makes the index more advantageous over raw rainfall data being used for evaluating flood risk (Deo, R. C. et al. 2018). In the proposed *DSS*, the user is only required to upload a CSV file consisting of the hourly rainfall with its corresponding date and hour, and like the daily flood monitoring module, the date range to be used for the computations can be selected. The *DSS* then computes the $WRI_{24-hr-S}$, $WRI_{48-hr-S}$, $WRI_{72-hr-S}$, and $WRI_{96-hr-S}$ and produces a downloadable file that the user can use to perform more analytics and make relevant disaster mitigation decisions.

$$WRI_{D-hr-s} = P_1 + \frac{[P_2(W-1)]}{W} + \frac{[P_3(W-1-\frac{1}{2})]}{W} + \frac{[P_4(W-1-\frac{1}{2}-\frac{1}{3})]}{W} + \cdots + \frac{[P_D(W-1-\frac{1}{2}-\cdots-\frac{1}{D})]}{W} \quad (1)$$

2.1.3 Module 3 and 4 – Building Flood Forecast Models

Once the daily or hourly flood monitoring computation is completed and the results file is obtained, it can be used to build and test the respective forecasting models using the proposed *DSS*. When the user uploads the results file and adjusts the hyperparameters, the *DSS* platform uses ConvLSTM algorithm to build the forecasting models. For forecasting future values of I_F, the system uses antecedent rainfall and I_F and for forecasting WRI, antecedent $WRI_{96-hr-S}$ is used as the feature to forecast future $WRI_{96-hr-S}$ values. The general architecture of the daily and hourly forecast models used by the proposed *DSS* is presented in Table 1. The default parameters and features for daily forecasting are based on an earlier study by Moishin et al. (2021). To select the default parameters and features for hourly forecasting, a series of operations were performed using data from three various sites for three forecast horizons. Apart from adjusting the parameters, the user is also required to enter the forecast horizon and number of lagged days or hours to be used by the predictive model. An advanced user can use tools such as the Partial Autocorrelation Function (PACF) to identify the lagged timesteps. Once the parameters are set and the data file is uploaded, the platform starts training and testing the model. Once the model training has completed, the platform displays the performance of the model using the testing data in terms of six statistical score metrics. These include the Mean Absolute Error (MAE), Root Mean Squared Error ($RMSE$), Legate McCabe Efficiency Index (LME), Pearson's Correlation Coefficient (r), Nash-Sutcliffe Efficiency Index (NSE) and Willmott's Index (d). Using these measures, the user can decide on whether ConvLSTM algorithm is suitable for their use case in building a flood forecasting model.

Table 1 - General Architecture of the ConvLSTM Model Implemented in the Proposed Platform

Model	Model Training Parameters	Default Value	Adjustable Range
Daily	Testing Data Split Ratio	0.2	[0.01, 0.99]
	Validation Data Split Ratio	0.2	[0.01, 0.99]
	ConvLSTM Filters (Layer 1)	128	[8, 512]
	Activation	ReLU	-
	Optimizer	Adam	-
	Batch Size	100	[1, 1000]
	Epochs	50	[1, 1000]
Hourly	Testing Data Split Ratio	0.1	[0.01, 0.99]
	Validation Data Split Ratio	0.2	[0.01, 0.99]
	ConvLSTM Filters (Layer 1)	256	[8, 512]
	ConvLSTM Filters (Layer 2)	128	[8, 512]
	ConvLSTM Filters (Layer 3)	64	[8, 512]
	Activation	ReLU	-
	Optimizer	Adam	-
	Batch Size	100	[1, 1000]
	Epochs	75	[1, 1000]

3 Analysis of Practical Application

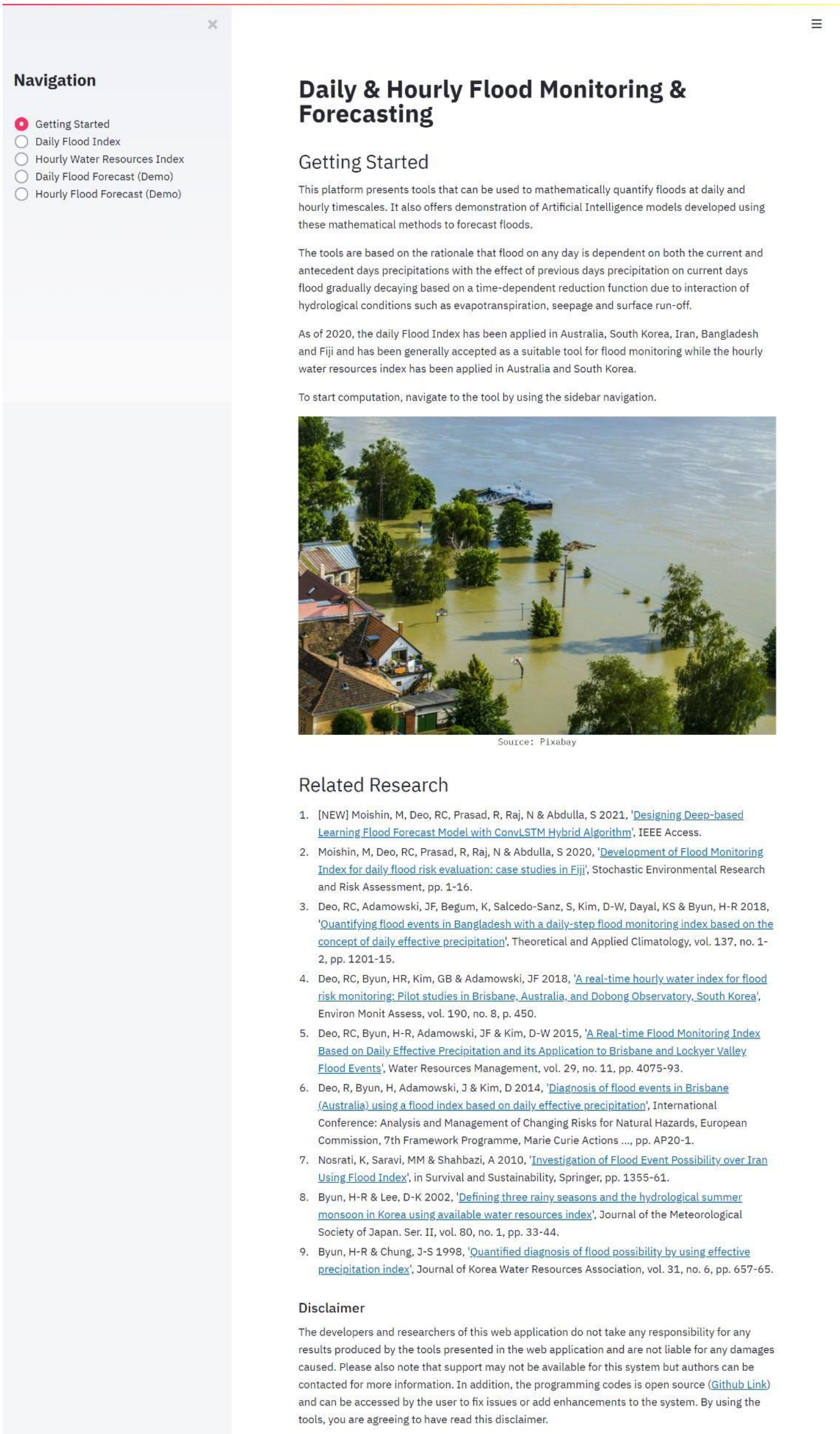
The proposed *DSS* was tested for its practical application using data from three flood prone sites in Fiji. The newly developed *DSS* platform, operating under *Streamlit*, can be accessed using the following link: https://bit.ly/32R7NqA. The results from these tests performed on the *DSS* has been used to evaluate the system's performance and accuracy in the next section.

3.1 Overview of the *DSS* Interface

Firstly, the user interface of the proposed *DSS* is analysed. When the user accesses the platform's home page, a description of the platform is presented, as seen in Figure 5. This page also presents related research papers that led to the development of the system and has a disclaimer at the bottom. These descriptions and listings demonstrate the authenticity of the platform to the users and gives them a fair understanding of the purpose of the proposed *DSS*. In addition, the simple navigation menu on the left of the page allows the user to access different modules of the proposed *DSS*. The location of this navigation menu is consistent across all the pages of the platform.

Furthermore, figures 6 and 7 show the daily and hourly flood monitoring pages of the proposed *DSS*, respectively. The user interface for these modules is simple and the user only needs to upload the required data file and select the date range to perform the computations. During the computation, the progress is shown on the left side bar, and once the computation is completed, the result file is available for download and simple analyses are presented on the page. This simple interface is expected to increase the usage of I_F and WRI for monitoring floods mathematically at daily and hourly timescales, respectively.

In terms of the daily and hourly flood forecast model development modules, figures 8 and 9 show the respective web pages. As seen in these figures, the *DSS* platform provides the user a range of options to configure the hyperparameters of the ConvLSTM algorithm. The purpose of these options is to allow the user to easily determine if ConvLSTM is the suitable algorithm for their use cases. Apart from setting the parameters, the user also has the flexibility to set the number of lagged timesteps and forecast horizon. The data file required for these modules are the results file obtained from the flood monitoring sections of this *DSS* platform. Once the model is trained, the results in terms of statistical score metrics with the testing data are presented.



Navigation

- Getting Started
- Daily Flood Index
- Hourly Water Resources Index
- Daily Flood Forecast (Demo)
- Hourly Flood Forecast (Demo)

Daily & Hourly Flood Monitoring & Forecasting

Getting Started

This platform presents tools that can be used to mathematically quantify floods at daily and hourly timescales. It also offers demonstration of Artificial Intelligence models developed using these mathematical methods to forecast floods.

The tools are based on the rationale that flood on any day is dependent on both the current and antecedent days precipitations with the effect of previous days precipitation on current days flood gradually decaying based on a time-dependent reduction function due to interaction of hydrological conditions such as evapotranspiration, seepage and surface run-off.

As of 2020, the daily Flood Index has been applied in Australia, South Korea, Iran, Bangladesh and Fiji and has been generally accepted as a suitable tool for flood monitoring while the hourly water resources index has been applied in Australia and South Korea.

To start computation, navigate to the tool by using the sidebar navigation.

Source: Pixabay

Related Research

1. [NEW] Moishin, M, Deo, RC, Prasad, R, Raj, N & Abdulla, S 2021, 'Designing Deep-based Learning Flood Forecast Model with ConvLSTM Hybrid Algorithm', IEEE Access.
2. Moishin, M, Deo, RC, Prasad, R, Raj, N & Abdulla, S 2020, 'Development of Flood Monitoring Index for daily flood risk evaluation: case studies in Fiji', Stochastic Environmental Research and Risk Assessment, pp. 1-16.
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4. Deo, RC, Byun, HR, Kim, GB & Adamowski, JF 2018, 'A real-time hourly water index for flood risk monitoring: Pilot studies in Brisbane, Australia, and Dobong Observatory, South Korea', Environ Monit Assess, vol. 190, no. 8, p. 450.
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6. Deo, R, Byun, H, Adamowski, J & Kim, D 2014, 'Diagnosis of flood events in Brisbane (Australia) using a flood index based on daily effective precipitation', International Conference: Analysis and Management of Changing Risks for Natural Hazards, European Commission, 7th Framework Programme, Marie Curie Actions ..., pp. AP20-1.
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Disclaimer

The developers and researchers of this web application do not take any responsibility for any results produced by the tools presented in the web application and are not liable for any damages caused. Please also note that support may not be available for this system but authors can be contacted for more information. In addition, the programming codes is open source (Github Link) and can be accessed by the user to fix issues or add enhancements to the system. By using the tools, you are agreeing to have read this disclaimer.

Figure 5 - Home Page of the Proposed *DSS* Platform

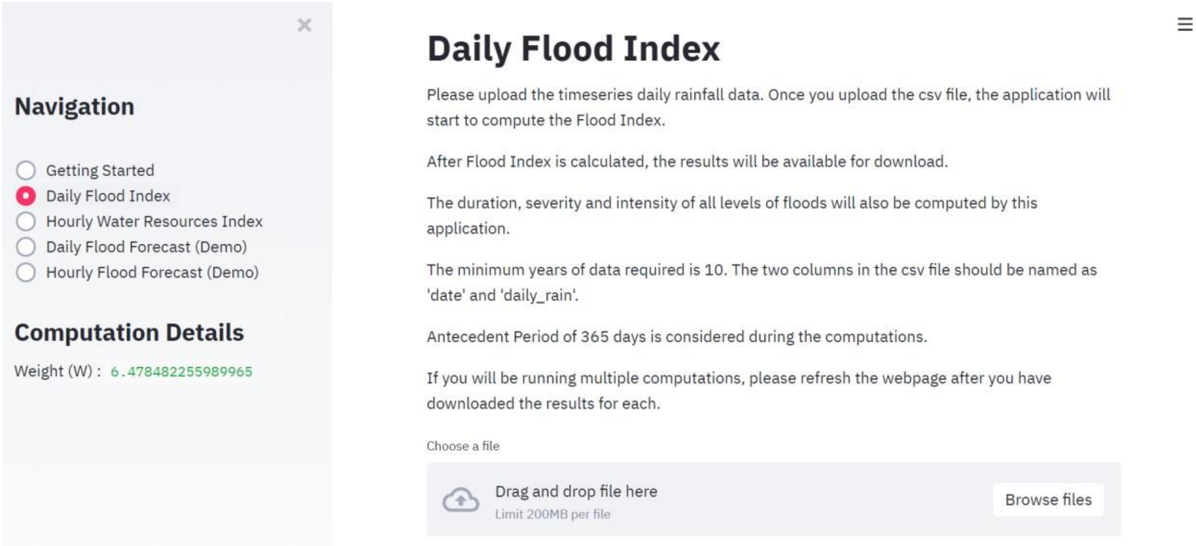

Figure 6 – Daily I_F Computation Page in the Proposed *DSS*

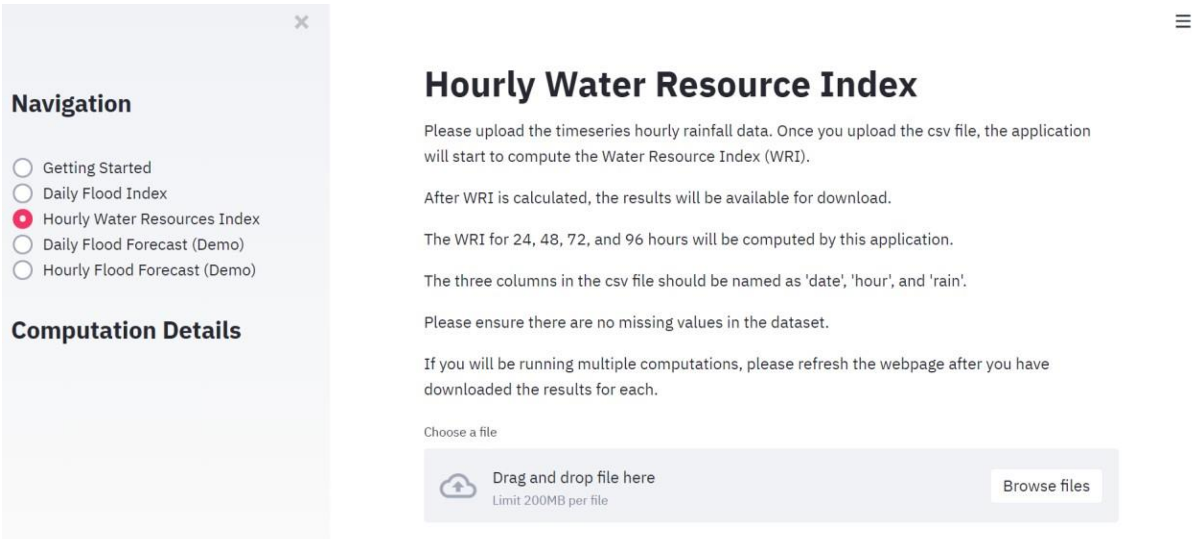

Figure 7 – Hourly WRI Computation Page in the Proposed *DSS*

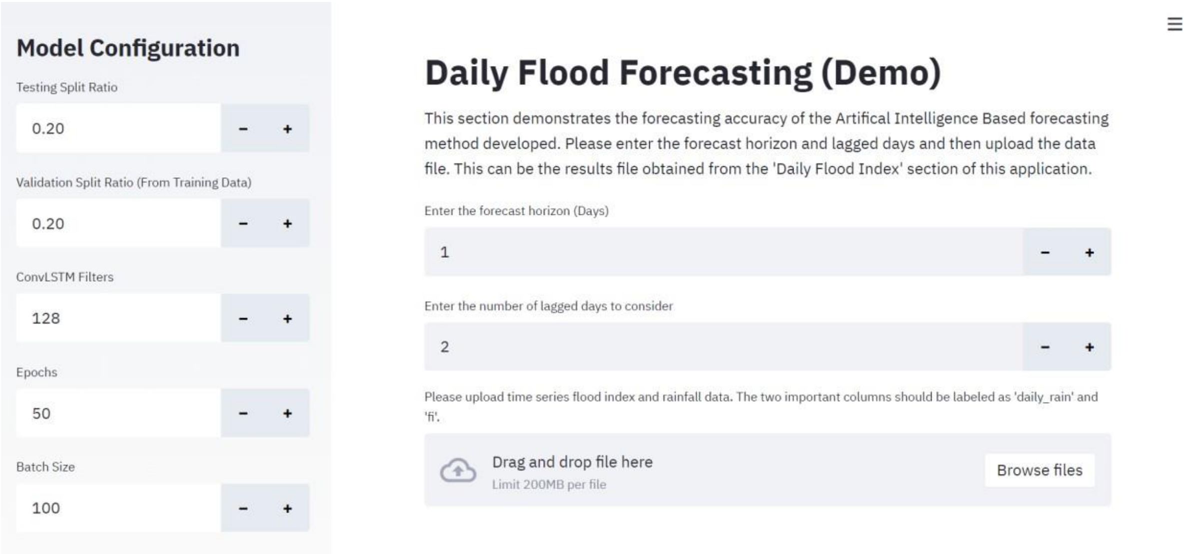

Figure 8 – Daily I_F Forecast Model Development Page in the Proposed *DSS*

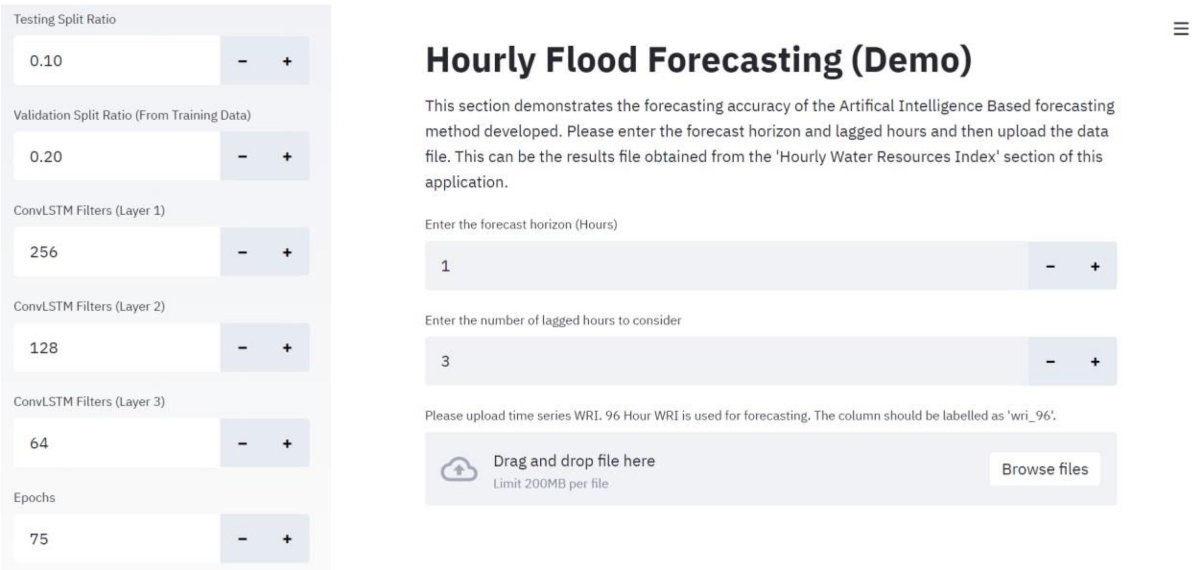

Figure 9 – Hourly WRI Forecast Model Development Page in the Proposed *DSS*

3.2 *DSS* Performance Analysis

In this section, the results obtained from the proposed *DSS* platform are used to evaluate the performance and accuracy of the system. To comprehensively present the results using data from all sites, the performance of each module in the proposed *DSS* is presented using one of the three study sites. Firstly, the daily rainfall data from Rakiraki site is used to evaluate the results obtained from the daily flood monitoring module of the proposed *DSS*. Based on the results obtained from the module, the details of the five severest floods between 1991 and 2019 at Rakiraki site, derived using daily I_F is presented in Table 2. It can be seen in this table that the severest flood recorded had reached a peak severity of 3.21. Furthermore, the area was in a flood state for 69 days and experienced 1196.40mm of rainfall during the flood period. The graphical representation of this flood event is shown in Figure 10. Such representation, which can be easily made using the results produced by the proposed *DSS*, makes it easier to interpret the computed I_F.

Table 2 - Flood Properties of the Five Severest Floods at Rakiraki site, Fiji Islands.

No.	Onset	End	Duration (Days)	Severity	AWRI	Precipitation (mm)	Maximum AWRI	Peak Severity
1	28-03-2012	04-06-2012	69	69.85	65364.81	1196.40	1516.77	3.21
2	16-01-2008	04-05-2018	109	66.82	91992.43	1762.10	1068.36	1.48
3	04-03-1997	06-06-1997	95	45.33	76834.75	1468.90	1083.74	1.54
4	09-01-2009	06-03-2009	57	33.22	47661.10	1277.50	1141.15	1.76
5	24-01-2012	21-03-2012	57	25.43	45644.09	1102.40	947.62	1.01

Next, the hourly rainfall data from Nadi site is used to evaluate the WRI results obtained from the hourly flood monitoring module of the proposed *DSS*. Fiji faced a severe storm in 2016, Tropical Cyclone Winston (Robie & Chand, 2017). It caused damages and flooding across many areas in the country. The cyclone made landfall in Fiji on the 20th of February in 2016 and therefore this period is used to demonstrate the flood situation at Nadi site using $WRI_{24-hr-S}$. As seen in figure 11, WRI results derived from the proposed *DSS* is accurately able to determine the state of flood in Nadi from the first day of the disaster. It also illustrates that the area was in a severe flood risk for about 50 hours. This conforms with the reports of high amounts of rainfall being recorded at the site and flood warnings being issued during these periods (Davies, 2016). Hence, these reports confirmed the accuracy of the proposed DSS and the suitability of WRI for hourly flood monitoring.

Furthermore, as stated, the daily forecasting approach used in the respective module of the proposed DSS, was based on the findings presented by Moishin et al. (2021). To show the performance of this module in the proposed system, the computed daily I_F results from Nadi site is used. The performance of the model is evaluated using default parameters in the DSS at 1-, 3-, 7- and 14 day forecast horizons. The results, in terms of $RMSE$ and MAE, is presented in Figure 12. It can be seen that the forecasting errors are minimum for 1-day forecasting and as the forecast horizons increase, the error measures also increase. However, the RMSE and MAE errors do not exceed 0.25 and 0.14, respectively. This indicates that despite the decrease in performance, there is not a significant drop in performance at longer forecast horizons. Consequently, it illustrates the robustness of the model for forecasting floods at daily timescales. It also illustrates the suitability of the default parameters set in the proposed DSS.

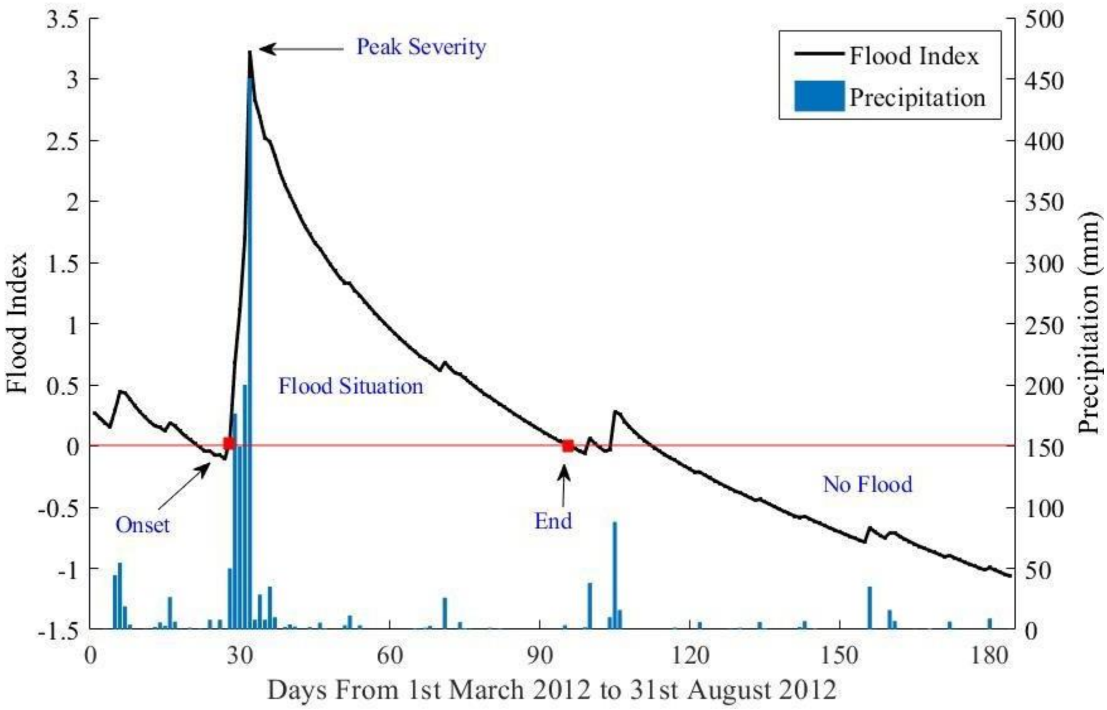

Figure 10 - Graphical Representation of the Severest Flood at Rakiraki Site using I_F

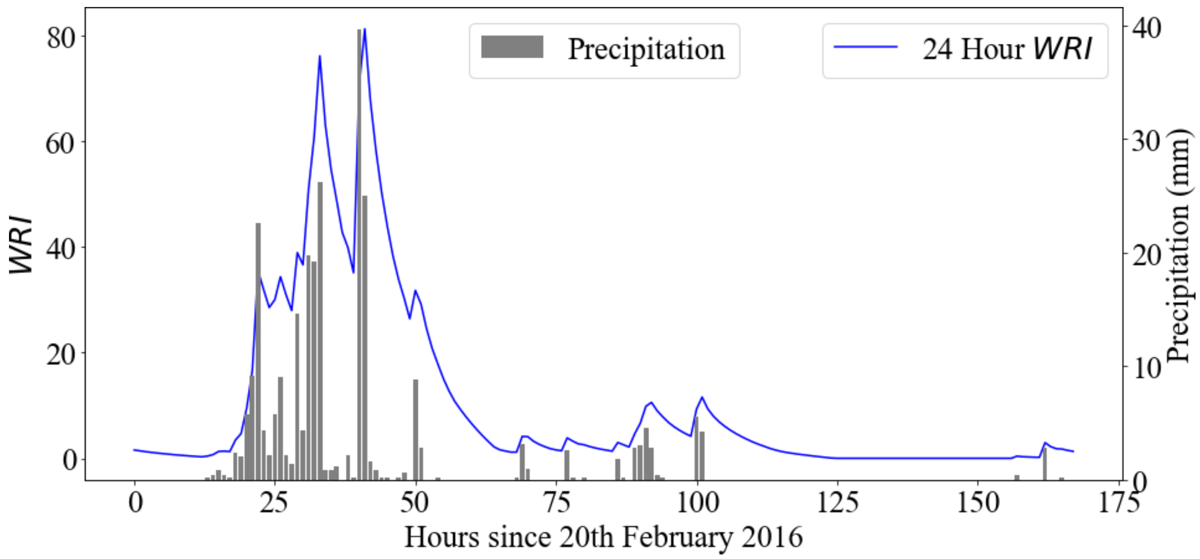

Figure 11 - Evaluating WRI at Nadi Site from 20th February 2016 to 26th February 2016

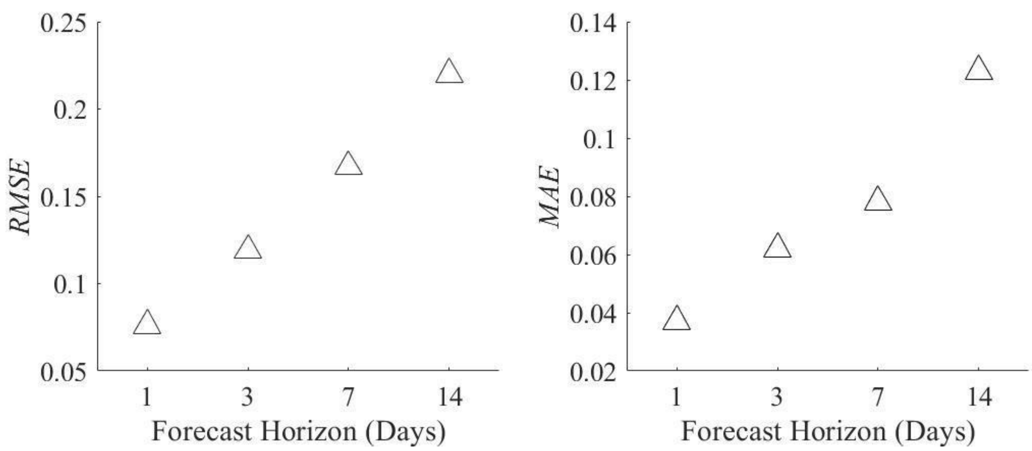

Figure 12 - Evaluating Daily I_F Forecasting Performance using Data from Nadi Site in terms of $RMSE$ and MAE at 1-,3-,7-, and 14-day Forecast Horizons

Next, to present the hourly forecasting module of the proposed DSS, WRI results obtained using hourly rainfall data from Ba site is used. When the model was trained and tested with the default parameters, it showed good performance. This is presented in Figure 13, whereby the performance of the model with the testing data is evaluated using d, NSE and LME. All three metrics show good performance of the model for 1, 3 and 6 hour forecast horizons. In addition, like daily flood forecasting, when the forecast horizon is increased, there is a decrease in performance. However, this decrease in performance is not massive as the measures for d, NSE and LME remains very high with values greater than 80 %. Therefore, these results illustrated the robustness of the WRI for hourly flood forecasting. It also showed the suitability of the default hyperparameters used by the DSS to achieve this task.

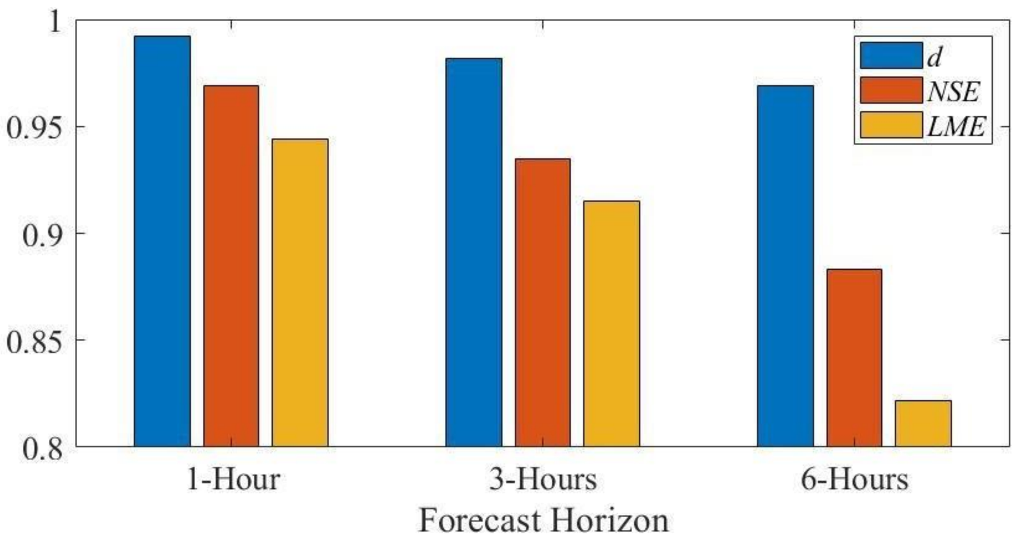

Figure 13 – Evaluating Hourly WRI using data from Ba Site in terms of d, NSE and LME for 1-, 3-, and 6-hour Forecast Horizons

4 Discussion

The accuracy and robustness of the proposed DSS has been presented in the previous section. In this section, the limitations, benefits, and constraints of the proposed DSS are presented. Some relevant recommendations for future works are also discussed. Firstly, one of the major limitations of the system is in terms of the time taken for the algorithm in the DSS to compute the I_F. Currently, significant amount of time is required for this computation to complete and therefore this may not be feasible for real-time operations. This time is dependent on the processing speed of the computer the user uses to access the platform. Hence, it is recommended that in future research, the algorithm is further optimized to allow for faster and efficient computations whereby less compute resources are used. This optimization of the algorithm should further encourage the application of I_F for daily flood monitoring and assist in quicker flood related decision making.

Moving on, a limitation associated with WRI is discussed. The WRI used in the proposed *DSS* is not standardized and therefore, it is difficult to compare the different severity levels of floods, as it is possible with I_F. Therefore, it is recommended that in future studies, a standardized version of WRI is developed. This will allow for better classification of flood risks and make it easier for users of the tool to make relevant flood risk mitigation decisions. In addition, a standardized index will also enable effective comparison of different flood eventsat different sites. This should also allow for the adoption of WRI for hourly flood monitoring at more locations around the globe. Furthermore, the flood forecasting models developed withthe standardized index is expected to be more useful for better prediction of the extent of floodrisk expected.

The next limitation is associated with the ConvLSTM models used for daily and hourly flood forecasting in the proposed *DSS*. When selecting the default parameters, the model had to be run multiple times and continuous adjustment of the hyperparameters was needed to ensure the most effective performance. Some of the benchmark models did not require this amount of optimization. However, eventually, the best performance was achieved with ConvLSTM and therefore it was selected to be the default model in the proposed *DSS*. It is recommended that in future studies other machine and deep learning models are tested for daily and hourly flood forecasting.

In addition, currently the *DSS* only trains the ConvLSTM model and presents the performance metrics. Therefore, the platform itself cannot be used to show flood forecast results but can only be used to train the models and show the performance in terms of statistical score metrics. Therefore, it is recommended that in future research, capabilities are built into the *DSS* so that the user can enter lagged data manually and the *DSS* can present the forecast results without having to train the model every time. This was not possible with the version of *Streamlit* used for this research as the developed models could not be saved for future use (The Keras command “model.save()” did not work in the live version but if researchers modify the code and run on their machines, they will be able to save the developed models using that command). If this capability can be developed for the live version in future research, it will further increase the usefulness of the proposed *DSS*.

Furthermore, a constraint of the proposed *DSS* is that it is web based and therefore internet connection is required to access the modules. Nevertheless, this constraint is also a benefit as the proposed *DSS* is not platform dependent and can be accessed on any device with a web browser and stable internet connection, irrespective of the operating system. To add on, another benefit of the *DSS* is that it will be open source and therefore users and developers can access the programming codes and make changes to the system to improve its features, enhance its interface or assist in fixing bugs found in the system after deployment. Consequently, having the programming codes open to the public will enable organizations to audit the code prior to usage in their organizations.

5 Conclusion

In this study, a web based *DSS* platform was developed using *Streamlit* and Python as a means of easily computing the daily and hourly flood monitoring indices. The indices used in the platform for daily and hourly flood monitoring were I_F and WRI, respectively. Two other modules that were built into the proposed *DSS* were interfaces for building and optimizing ConvLSTM models for daily and hourly flood forecasting. The developed *DSS* canbe accessed using the following link: https://bit.ly/32R7NqA. During this research, this proposed *DSS* was developed, comprehensively evaluated, and the results have been presented in this paper.

The main contributions of this paper are as follows:

1. This study was the first to develop a web based *DSS* for computing daily I_F and hourly WRI.
2. This study builds on previous study where ConvLSTM was used for daily flood forecasting by proposing a similar approach for hourly flood forecasting using WRI in the proposed *DSS*.
3. The *DSS* was tested using data from three flood prone sites in Fiji and these showed the accuracy and robustness of the proposed *DSS* in terms of mathematical flood monitoring and for building flood forecast models.
4. The proposed *DSS* is open source. Therefore, other researchers and access the source codes and make further improvements to the *DSS* or customize it for their research needs.

To conclude, the *DSS* developed during this study is expected to provide an easy means of computing flood monitoring indices at daily and hourly timescales. In addition, the proposed system also allows users to easily build and test ConvLSTM-based models for flood forecasting and decide whether the ConvLSTM-based model will be suitable for their use case. Finally, it is expected that the proposed *DSS* shall make it convenient for more organizations to apply data-driven mathematical indices for daily and hourly flood monitoring and forecasting.

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CHAPTER 7: SYNTHESIS AND CONCLUSION

7.1 Summary of Research

To summarize, this research has achieved three objectives. Firstly, I_F was first used as a tool for evaluating the past floods at nine sites around Fiji over a 29-year period. The duration, severity and intensity of these floods were successfully determined and I_F was accepted as an accurate means of mathematically assessing flood situations at short timescales in Fiji. Next, I_F was used to develop a robust time-series based flood forecasting model using a hybrid deep learning algorithm, ConvLSTM. The developed flood forecasting model was evaluated to be a robust means of forecasting occurrences of future flood events for up to 14-day forecast horizons. When compared with the benchmark models, the ConvLSTM objective model showed better performance at all study sites and forecast horizons. Finally, using the principles and theory from the first two objectives, an online DSS was developed using the Streamlit platform for easily computing flood monitoring indices and building flood forecast models using the ConvLSTM algorithm. Once developed, the proposed DSS was tested for its practical application using data from three areas in Fiji.

7.2 Contributions and Novelty

This research has made significant contributions to knowledge and has presented a novel method of forecasting occurrences of future flood situations. In this section some of these are highlighted. Firstly, this study was the first to apply I_F, which is a daily flood monitoring index that uses rainfall data and considers depleting water resources due to several hydrological factors to quantify floods in Fiji. Such a mathematical method was not previously used for analyzing floods in the country. Secondly, using daily I_F as a means of forecasting floods was also not done prior to this research. In this study, I_F was used to develop deep learning models that can forecast floods at multiple forecast horizons and study areas.

In addition, to build the forecasting models, the objective model chosen was ConvLSTM. ConvLSTM is a new hybrid deep learning algorithm that combines LSTM and CNN, which are two of the most popular deep learning algorithms, with

LSTM being a well-tested model for timeseries forecasting. When the predictive capabilities of multiple deep learning methods are combined, it is likely to perform better than standalone deep learning or conventional machine learning models. Moving on, ConvLSTM can be implemented as a black box model whereby the inner workings of the model is not required to be known. To add on, the steps to develop ConvLSTM model, as discussed in Chapter 5, is similar to how any machine learning model is developed, with slight variations in some steps such as parameter setting.

Furthermore, the performance of the model was tested using data from various sites in Fiji. This was significant because this was the first-time flood forecasting models were developed for Fiji using hybrid deep learning methodology. Finally, one of the major contributions of this research was the development of the web based DSS for computing flood monitoring indices and building flood forecast models. This DSS would allow users to perform the methodologies applied in this research conveniently and get results quicker, without the need to develop any programming codes.

7.3 Limitations and Recommendations

The objectives of this research have been successfully completed. However, there are some limitations that could be addressed in future studies. The general limitations of the study are mentioned in this section as the limitations associated with addressing specific objectives have already been discussed in the papers, presented from chapters 4-6 of this thesis. To begin with, one of the main limitations is that the forecasting model developed in this study only uses two features to perform the forecasting task for daily flood forecasting and only one feature for hourly flood forecasting model. In future studies, more useful features could be identified and that would further enhance the performance and robustness of the proposed model. Furthermore, adding more useful features could also improve the forecasting abilities of the model for longer forecast horizons. To add on, studies are recommended that can forecast floods more than 14 days prior to a flood situation.

Moreover, other deep learning and machine learning algorithms can be tested for its applicability for forecasting future values of I_F and WRI. In this research, comparison of the performance of the objective model was only done with three other algorithms.

Therefore, in future research more algorithms can be tested for its ability to accurately forecast I_F and WRI. Furthermore, the focus of most of the tasks was on Fiji. Therefore, it is highly recommended that the methods applied in this study are replicated and enhanced to develop flood monitoring and forecasting tools in other developed and developing countries. The proposed DSS can be used for easily achieving this. As the source code for the DSS is openly available, future researchers can easily modify the code and enhance the performance and address the limitations of the proposed DSS.

To conclude, as the methods presented in this research are cost-effective and largely rely on only rainfall data, it is particularly useful for flood prone areas that do not have the financial and scientific means of investing in advanced flood monitoring and forecasting systems. Adding on, further research is recommended on the approaches presented in this study so that the methods can be further enhanced and improved. Finally, it is expected that more developing countries would use the means of flood analysis and forecasting that has been presented in this research for flood risk mitigation.

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