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Research Article

Improving Sub Daily Scale Storm Forecasting for Kelani River Basin based on Temporal Distribution of Rain Events

Dantanarayana M[1*], Herath S[1], Weerakoon SB[3*]

[1]Centre for Urban Water, Metro Colombo Urban Development Project, Sri Lanka; [2]Faculty Department of Civil Engineering, University of Peradeniya, Peradeniya, Sri Lanka

ABSTRACT

Improving accuracy of extreme rain event forecast is very important for the sustainable development of emerging economies, especially for reducing losses and damages in urban areas, which are often the engines of the economy. This study addresses the evaluation and improvement of near future sub-daily scale precipitation forecast for heavy rainfall events in the Kelani river basin in Sri Lanka. Precipitation forecasts of 16 models in 15 minutes temporal resolution were evaluated using Normalized Root Mean Square Error (NRMSE), Temporal Match Percentage (TMP) and their Normalized Standard Deviations (NSD). Station wise model selection base on TMP delivered better performing forecast compared to models selection based on NRMSE.

Keywords: WRF; Rainfall forecast; Sub daily; Temporal performance; Kelani River; Model selection

INTRODUCTION

Sri Lanka has a tropical climate with two distinct monsoons as Northeast (December-March) and Southwest (May-September). During monsoon seasons the Kelani, Kalu, Nilwala, and Gin river basins are subjected to severe flood inundation. Frequently this flooding causes a serious damage to properties and lives in the flood plains of aforementioned river basins.

The Kelani River is the second largest river in Sri Lanka which spreads across 2300 km^2 and receives an annual average rainfall around 2400 mm. Topographically, the Kelani river basin can be distinctly characterized as upper and lower basins. The mountainous upper basin is mainly covered with vegetation types such as tea, rubber, grass and forest while the lower basin is heavily urbanized. The river discharges a peak flow of about 800-1500 m^3/s during monsoons to the Indian Ocean [1].

Floods cause large scale social and economic losses that can be minimized if a proper disaster management system is implemented. The major reason for the poor disaster management system is the inability to achieve accurate flood forecasts in terms of timing and extent. Numerical Weather Predictions (NWP) deliver an extensive set of weather parameters including precipitation which flood forecasting simulations ingest as one of the major weather parameters effecting floods. Such NWPs range from short term (few hours to few days) to medium term (up to 10 days and more) which allows implementing effective action plans to minimize near future flood risk [2].

At present, the Department of Meteorology of Sri Lanka publishes precipitation forecasts which are prepared using outputs of numerical weather prediction models of India Meteorological Department and European Centre for Medium Range Weather Forecasting (ECMWF) as guidance [3]. Published forecasts include 36-hour general weather forecast for main cities, 9-day daily precipitation forecast contour maps for Sri Lanka and weekly rainfall anomaly forecast maps for a part of Asia region [4]. In recent times, the Centre for Urban Water (CUrW) of the Metro-Colombo Urban Development Project provides refined forecast at finer scale [5] and the contents given in this paper is part of the work carried out under that program.

Sub-daily scale time of concentrations at sub-basins and rapid water level rises in Metro Colombo canal system, lead to sudden changes in canal water levels in short time periods. Such water level variations would not be able to simulate with daily or coarser precipitation forecasts. Recent rainfall observations have shown trends that follow a pattern of high intense rainfalls within a short duration of time period (Figure 1). These produce flash floods and affect the businesses and productivity in cities. Also a high spatial

Correspondence to: Muditha Dantanarayana, Centre for Urban Water, Metro Colombo Urban Development Project, Sri Lanka, Tel: +94715532191; E-mail: muditha.danta@eng.pdn.ac.lk

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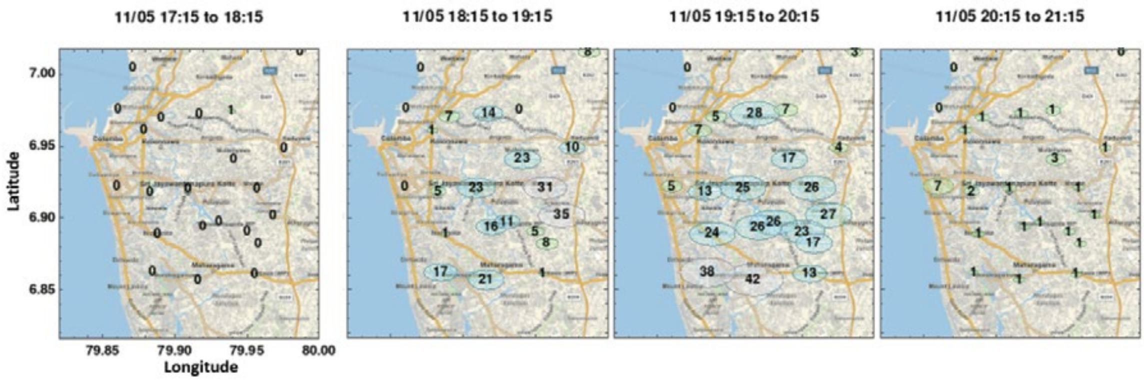


Figure 1: Spatial and temporal variability of observed rain events in Metro Colombo Region

Table 1: Parameters considered in past studies.

Parameter	[13]		[14]		[15]		[16]	
	Test	Result	Test	Result	Test	Result	Test	Result
mp_physics	Goddard, WSM6, WDM6, Thopmson, Thompson A, Morrison G, Morrison H, NSSL	Goddard for rain, WDM6 vertical profile	WSM3 Ferrier	Ferrier	WDM5 D1, WDM6 D2	WDM5 WDM6 (No clear selection of one scheme)	Kessler WSM5 WSM6	Kessler, WSM5, WSM6 (No clear selection of one scheme)
cu_physics	New SAS		Kain-Fritsch		Kain-Fritsch		Kain-Fritsch, BMJ	
ra_lw_physics	RRTMG		RRTM		RRTM		RRTM	
ra_sw_physics	RRTMG		Dudhia		Dudhia		Dudhia	
sf_sfclay_physics	revised MM5		Monin-Obukhov					
sf_surface_physics	NOAH LSM		RUC		NOAH LSM		NOAH LSM	
bl_pbl_physics	YSU		YSU		YSU		YSU	

variation in rainfall magnitudes can be seen in figure 1 even within a spatial extent of a tenth of a degree. Therefore, a high temporal and spatial resolution precipitation forecast is required for flood and inundation modelling in the lower reaches of the Kelani river basin including Metro Colombo area to provide effective early warning as well as to estimate potential loss so that optimized investments on flood control interventions could be made supporting the sustainable development of the basin.

Research into WRF corrections in sub-daily scale is very limited for the region and studies show that the performance of proposed corrections has high variations compared to observations at different stations even within the same catchment [6]. The conventional bias correction methods are only capable of correcting the magnitude of rain events but not the timing of rain which is an important measure of a reliable sub-daily scale rainfall prediction. Therefore, this study is focused on improving the temporal performance of rainfall prediction in sub-daily scale for the Kelani basin in the means of regional model selection.

The study assesses the performance of NWP models for now casting sub-daily scale precipitation in terms of both magnitude and temporal distribution for the Kelani river basin and develop criterion for the selection of best performing model for a given location.

LITERATURE REVIEW

Global NWP models are used to produce short and medium range weather forecasts (out to 10-15 days) of the state of the atmosphere, with a horizontal resolution of typically 10-25 km and a vertical resolution of 10-30 m near the surface increasing to 500 m-1 km in the stratosphere. Forecasters use these products as guidance to issue forecasts and ensembles provides estimate of uncertainty and global NWP models are used to provide boundary conditions for regional NWP models [7]. Downscaling global NWP model outputs to regions or local scales is a common practice for operational weather forecast in order to correct the model outputs at sub grid scale [2].

Global NWP

National Centre for Environmental Prediction (NCEP) (NCEP, 2019) and European Centre for Medium-Range Weather Forecasts (ECMWF) (ECMWF, 2019) are pioneers in global NWPs. The global data set Global Forecasting System (GFS) produced by NCEP has been the most popular dataset for downscaling with WRF which is freely available through the NOAA National Operational Model Archive and Distribution System (NOMADS) [8]. Recent data of up to 15 days back can be accessed through NCEP Product Inventory [9] and archived data is available from NOAA National Operational Model Archive and Distribution System (NOMADS).

Downscaling

There are several ways to downscale global NWPs: Regional Climate Models (RCM) or Dynamical Downscaling, Empirical Statistical Downscaling (ESD), Hybrid Dynamical-Statistical approach, Spatial Disaggregation technique, Stretched Grid and High-resolution global time slice approaches are some of them. The RCM calculates the rainfall and temperature from differential equations describing how pressure affects winds (geostrophic dynamics) and the movement of energy and mass through the atmosphere. The ESD approach, on the other hand, captures dependencies between processes that are not explicitly coded into models, and makes use of the information embedded in the observational data [10].

According to Hamill (2004), much of the important weather for hydrology occurs at scales smaller than those resolved by the global weather forecast models and their ensembles. Therefore, when downscaling to sub-grid scale with RCM, the model must be parameterized according to the interested region. Such parameterizations include land surface, cloud microphysics, radiative transfer, orographic drag, turbulent diffusion and interactions with surface [11]. The ARW-WRF model solves the atmospheric equations and physical schemes selected, to transform and forecast the meteorological forcing in the domain resolution scale [12].

Parameterization

Physical schemes utilized in parameterization implicitly include the effect of physical processes in WRF [12]. Past studies done in the region and for tropical regions including Korea and Hawaii were referred to find out commonly used schemes matching the region's behaviour and their performance as in Table 1 [13-16].

Evaluation

Traditional evaluation statistical measures are commonly focused on comparing the magnitude of rain with the Root Mean Square Error [17,18]. Past studies concluded that a single combination of schemes could not be found which perform significantly over others even in a single region, but better performing schemes in different regions have been identified [13,14].

METHODOLOGY

GFS forecast with 0.5 arc degree resolution, 18hr model cycle runtime, and 72-hour duration was used in the simulations. WRF-ARW model was used to downscale GFS data into 3 km spatial and 15 minute temporal resolution. Downscaling was carried out in 3 steps with a one-way nest to define smaller domains, d03 being the smallest domain representing the land surface of Sri Lanka. Domain extent details are shown in figure 2 and table 2.

Table 2: Domain configuration.

Domain	Resolution (km)	WE length (km)	SN length (km)
d01	27*27	3159	3159
d02	9*9	1089	1089
d03	3*3	327	525

NWP simulations were run to cover heavy rainfall events. Heavy rainfall events that occurred flooding conditions in the Metro Colombo area and high water levels in the Kelani river were selected as the basis for identifying events of interest. Data from real-time water level stations shown in at Janakala Kendraya which represent the water level in the Metro Colombo are and the water level gauging station at Kaduwela bridge over the Kelani river were used to identify the heavy flood events. Rainfall data for the flood events was gathered from real-time weather stations at Madiwela, Waga, Mahapallegama, Kithulgala and Maskeliya which represent different hydrologic regions of the Kelani river basin (Figure 3). These stations are under Centre for Urban Water, Sri Lanka (CUrW) [5]. Accordingly, heavy rainfall events from 15th to 17th, from 24th to 26th September, 2019 and from 29th to 30th November, 2019 shown in figure 4 are selected for forecast simulations.

From 15th to 17th of September, 2019

α. 72-hour session starts at 2019-09-13 18:00 UTC (2019091318)

β. 72-hour session starts at 2019-09-14 18:00 UTC (2019091418)

From 24th to 26th of September, 2019

α. 72-hour session starts at 2019-09-22 18:00 UTC (2019092218)

β. 72-hour session starts at 2019-09-23 18:00 UTC (2019092318)

From 29th to 30th November, 2019

α. 72-hour session starts at 2019-11-28 18:00 UTC (2019091318)

First four sessions were used for calibrating the models selection process and the last session was used for verification of forecast.

Following the studies by Zhang et al. (2012) [17], Song & Sohn (2018) [13], Nandalal et al. (2012) [14], Rodrigo et al. (2018) [15] and Darshika & Premalal (2015) [16] and the User's Guide for the Advanced Research WRF (ARW) Modelling [12], schemes for

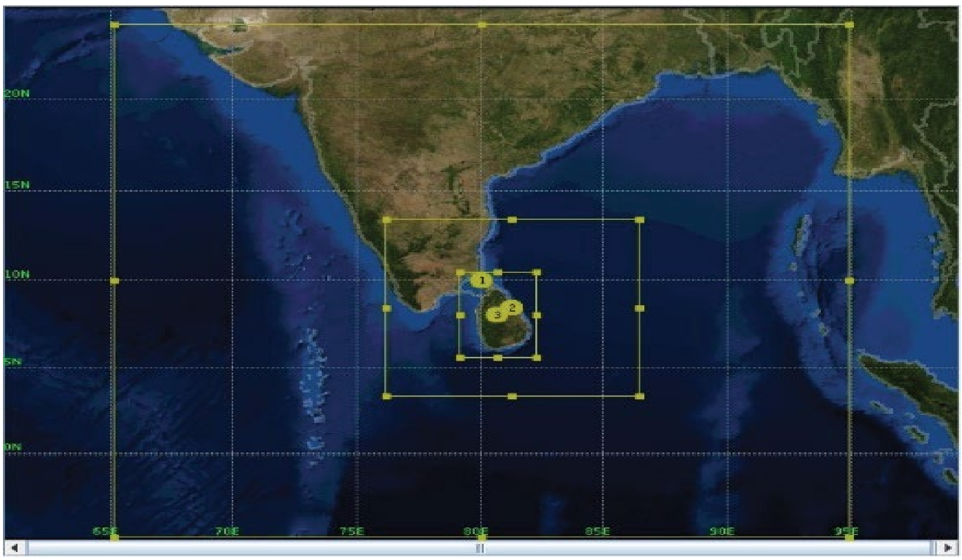


Figure 2: Domain layout (Illustration from WRF Domain Wizard).

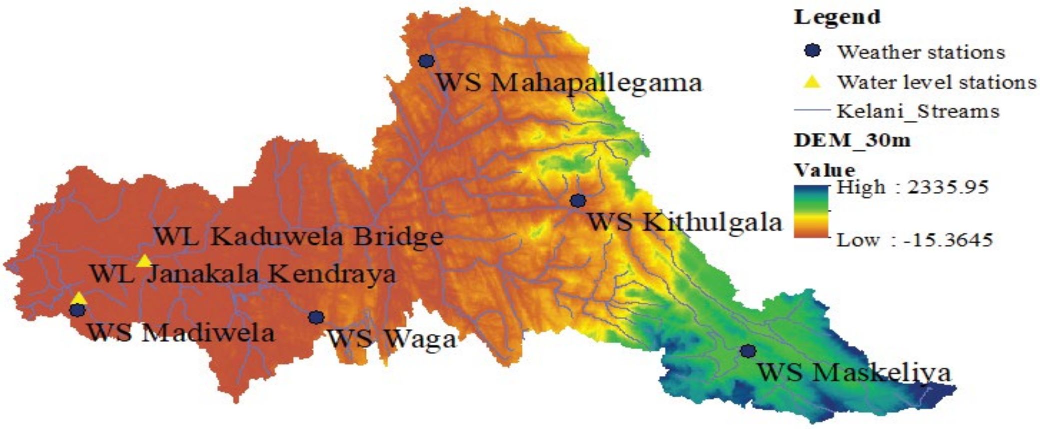


Figure 3: Distribution of rain gauges and water level gauges.

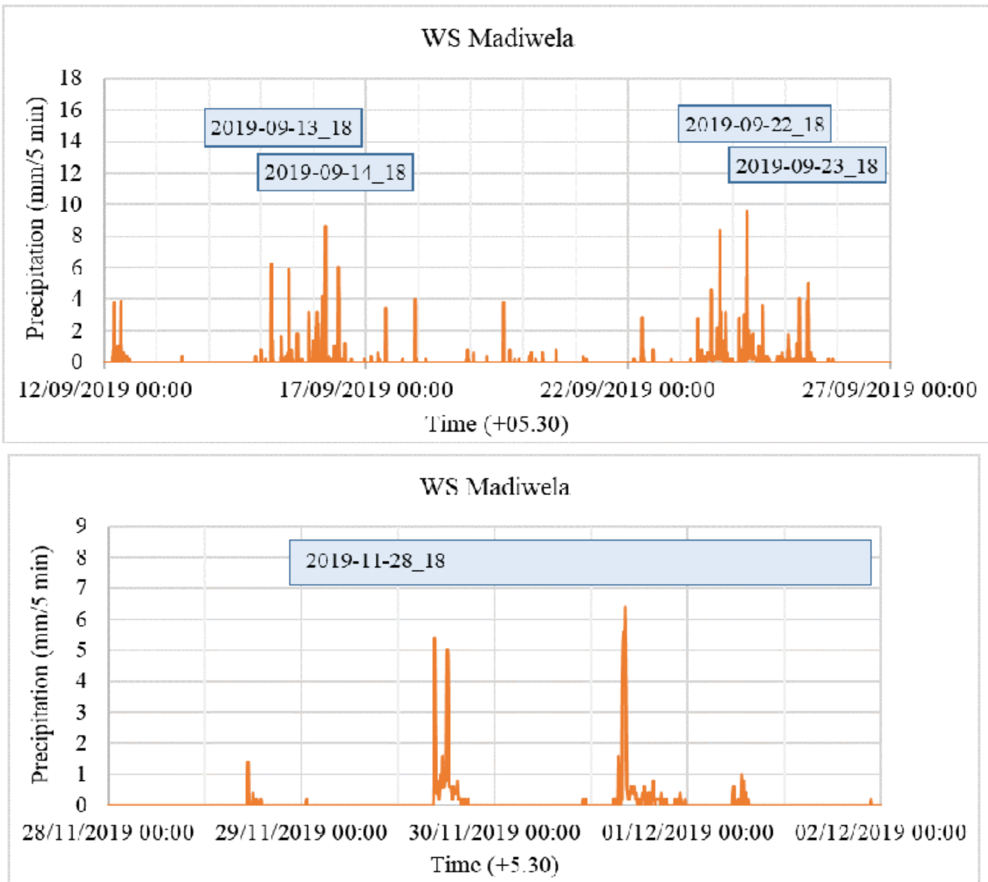


Figure 4: (a): Simulation schedule for model selection, (b): Simulation schedule for verification.

Table 3: Utilization of mp_physics and cu_physics schemes.

	mp_physics						cu_physics		
	WSM3	WSM5	WDM5	WDM6	Eta	Kessler	BMJ	KF	GF
M1	X						X		
M2	X							X[a]	
M3		X							X
M4	X							X[b]	
T4					X		X		
T5				`		X	X		
T6			X				X		
T7				X			X		

[a]Kfeta_trigger on; [b] Kfeta_trigger off

mp_physics and cu_physics parameters as in table 3 were evaluated. Eta operational parameterization was utilized for other parameters.

Convection can easily occur between mesoscale model grid boxes but not significantly in sub-grid scale. Therefore, these models were also evaluated without cu_physics parameterization for the highest resolution domain (domain 3). Accordingly, a total of 16 models were tested, viz: M1_On, M1_Off, M2_On, M2_Off, M3_On, M3_Off, M4_On, M4_Off, T4_On, T4_Off, T5_On, T5_Off, T6_On, T6_Off, T7_On and T7_Off, where "On" and "Off" represent the cu_physics scheme turning on and off for domain 3.

Station based evaluations were carried out for 5 weather station locations (figure 3) representing different regions of the Kelani river basin for four WRF 18 hour runtime cycle simulation sessions. WRF model performance was statistically evaluated by comparing monitoring stations' observed data with the nearest WRF grid point's forecast data. Precipitation forecasts of 16 models in 15-minute temporal resolution were evaluated for both the magnitude and temporal distribution aspects using, Normalized Root Mean Square Error (NRMSE) (equation 1), Temporal Match Percentage (TMP) (equation 2) and Normalized Standard Deviations (NSD) (equation 4,5) of NRMSE (NRMSE NSD) and TMP (TMP NSD). NSD allows measuring the consistency of NRMSE and TMP over different sessions. A Performance Score (PS) incorporating magnitude, temporal distribution and their variation factors was introduced to evaluate the model performances (equation 3,6-8).

TMP is based on the rain no-rain classification of each time step. Rain and no-rain condition is defined on two threshold values for observation and forecast. Precipitation observation stations are equipped with tipping bucket rain gauges of 0.2 mm resolution. These could record a 0.2 mm rain even in no-rain situation due to partial accumulated of water in the tipping bucket from previous rain event or due to condensation inside the gauge. To omit such data, a 0.4 mm threshold value was introduced in classifying an observed rain time step. For WRF data, a threshold of 0.04 mm was introduced keeping a margin for a 10 times bias.

For evaluating a single simulation

Normalized Root Mean Square Error:

$$NRMSE_{\mathrm{mod}} = \left[\overline{\left|cp_{\mathrm{mod}} - cp_{obs}\right|^{2}}\right]^{0.5} / \, Average(cp_{obs}) \quad \text{(Equation 1)}$$

Temporal Matching Percentage:

$$TMP_{\mathrm{mod}} = \frac{Count\_if[(ip_{\mathrm{mod}} \geq 0.04) \,\&\, (ip_{obs} \geq 0.4)]}{Count\_if(ip_{obs} \geq 0.4)}\% \quad \text{(Equation 2)}$$

Table 5: Statistics for selection of models.

Stations	Models from NRMSE_PS				Models from TMP_PS			
	Model	NRMSE_PS	TMP_PS	OPS	Model	NRMSE_PS	TMP_PS	OPS
Madiwela	M3_On	64	34	49	T5_On	37	71	54
Waga	M3_Off	58	52	55	M2_On	36	59	48
M'pallegama	T5_Off	46	4	25	M1_On	38	53	45
Kithulgala	M4_On	62	61	61	M2_On	47	76	61
Maskeliya	T5_On	36	32	34	T5_Off	25	52	39
Average		53	37	45		37	62	49

Table 6: Statistics for verification without bias correction.

Station	Without bias correction							
	Models from NRMSE				Models from TMP			
	Model	NRMSE	TMP	PS	Model	NRMSE	TMP	PS
Madiwela	M3_On	76	58	41	T5_On	63	53	45
Waga	M3_Off	56	65	55	M2_On	79	54	37
M'pallegama	T5_Off	50	37	44	M1_On	100	42	21
Kithulgala	M4_On	52	63	55	M2_On	70	91	61
Maskeliya	T5_On	42	48	53	T5_Off	34	52	59
Average		55	54	50		69	58	45

Table 7: Statistics for verification with bias correction.

Station	With bias corrected							
	Models from NRMSE				Models from TMP			
	Model	NRMSE	TMP	PS	Model	NRMSE	TMP	PS
Madiwela	M3_On	56	58	51	T5_On	42	53	56
Waga	M3_Off	50	65	58	M2_On	60	54	47
M'pallegama	T5_Off	19	37	59	M1_On	62	42	40
Kithulgala	M4_On	69	63	47	M2_On	75	91	58
Maskeliya	T5_On	100	48	24	T5_Off	48	52	52
Average		59	54	48		57	58	51

Table 8: Thiessen polygon factors.

	Madiwela	Waga	M'pallegama	Kithulgala	Maskeliya
Areas (km^2)	358.61	597.6	363.99	623.4	396.65
Factors	0.15	0.26	0.16	0.27	0.17

Table 9: Basin averaged bias corrected improvements.

Session	Bias corrected NRMSE			TMP			PS		
	Reference T4_On	Selected Models	Improvement	Reference T4_On	Selected Models	Improvement	Reference T4_On	Selected Models	Improvement
2019091318	95.2	70.8	24.4	46.3	85.4	39.1	25.6	57.3	31.8
2019091418	49.9	31.8	18.1	53.3	87.8	34.5	51.7	78	26.3
2019092218	22.8	16.8	6	59.3	75.6	16.3	68.3	79.4	11.2
2019092318	20.8	9.9	10.9	93.3	86.8	-6.5	86.3	88.5	2.2
2019112818	61.1	49.1	12	42.4	94.4	52	40.7	72.7	32

Table 10: Improvements gained for verification session without bias correction.

Station	Regional selection				Basin scale selection T4_On			Improvement		
	Model	NRMSE	TMP	PS	NRMSE	TMP	PS	NRMSE %	TMP %	PS %
Madiwela	T5_On	63	53	45	84	37	27	21	16	18.5
Waga	M2_On	79	54	38	77	16	20	-2	38	18
M'pallegama	M1_On	100	42	21	115	10	-3	15	32	23.5
Kithulgala	M2_On	70	91	61	104	0	-2	34	91	62.5
Maskeliya	T5_Off	34	52	59	68	28	30	34	24	29
Average								20.4	40.2	30.3

Table 11: Improvements gained for verification session with bias correction.

Station	Regional selection				Basin scale selection T4_On			Improvement		
	Model	NRMSE	TMP	PS	NRMSE	TMP	PS	NRMSE %	TMP %	PS %
Madiwela	T5_On	42	53	56	33	37	52	-9	16	3.5
Waga	M2_On	69	54	43	62	16	27	-7	38	15.5
M'pallegama	M1_On	70	42	36	79	10	16	9	32	20.5
Kithulgala	M2_On	25	91	83	76	0	12	51	91	71
Maskeliya	T5_Off	41	52	56	55	28	37	14	24	19
Average								11.6	40.2	25.9

Performance Score:

$$PS_{\text{mod}} = 100 - Average[NRMSE_{\text{mod}} + (100 - TMP_{\text{mod}})] \quad \text{(Equation 3)}$$

For evaluating multiple simulations

Standard Deviation:

$$I\ SD_{\text{mod},c,l} = \sqrt{\left[I_{\text{mod},c,s,l} - Average(I_l)\right]^2} \quad \text{(Equation 4)}$$

Normalized Standard Deviation:

$$NRMSE\ PS_{\text{mod}} = 100 - Average[NRMSE\ AVG_{\text{mod}} + NRMSE\ NSD_{\text{mod}}] \quad \text{(Equation 6)}$$

Performance score of Normalized Root Mean Square Error:

$$NRMSE\ PS_{\text{mod}} = 100 - Average[NRMSE\ AVG_{\text{mod}} + NRMSE\ NSD_{\text{mod}}] \quad \text{(Equation 6)}$$

Performance score of Temporal Matching Percentage:

$$TMP\ PS_{\text{mod}} = 100 - Average[100 - TMP\ AVG_{\text{mod}}) + TMP\ NSD_{\text{mod}}] \quad \text{(Equation 7)}$$

Overall performance score:

$$OPS_{\text{mod}} = 100 - Average[NRMSE\ AVG_{\text{mod}} + NRMSE\ NSD_{\text{mod}} + (100 - TMP\ AVG_{\text{mod}}) + TMP\ NSD_{\text{mod}}] \quad \text{(Equation 8)}$$

Where,

cp: stands for cumulative precipitation,

ip: instantaneous precipitation,

mod: model output values,

obs: observed values,

SD: standard deviation,

I: NRMSE and TMP,

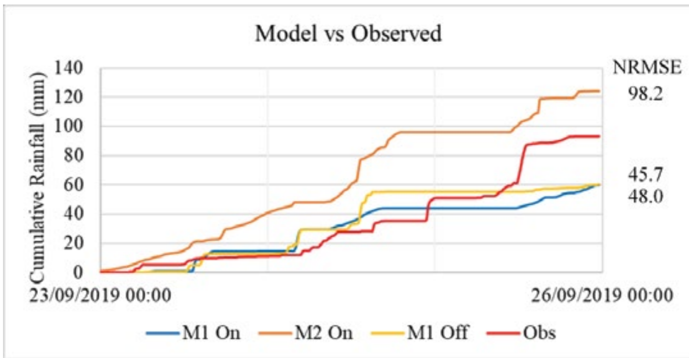
Average: arithmetic mean and,

Count_if: calculating the number of instances which the condition is met.

Two methods were tested for model selection process, one based on NRMSE and the other based on TMP.

RESULTS AND DISCUSSION

Considering a single simulation session (2019092218), table 4 shows the statistical indices for each model at Kithulgala, where the best performing models for each index are highlighted. Accordingly, there is a difference in best performing models when compared based on NRMSE, TMP or PS. A bias correction was performed on the forecasted cumulative time series, where the difference with the overserved value at the end of spin-up period was subtracted from rest of the time series to match observed and forecasted cumulative rainfall value at the end of spin-up time (Figure 5b). The precipitation time series before and after bias-correction are shown in figure 5a & 5b respectively. Bias corrected time series



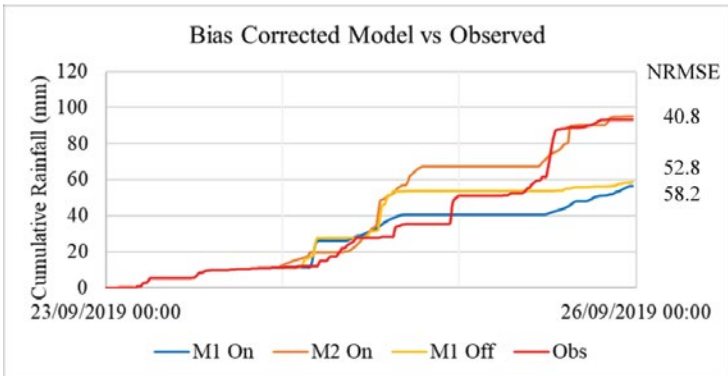


Figure 5: (a): Cumulative precipitation time series before bias correction, (b): Cumulative precipitation time series after bias correction.

result in NRMSE of 58.2, 40.8 and 52.8 respectively for M1_On, M2_On and M1_Off. This shows that, bias correcting the model selected based on TMP, lead to the best forecast both in magnitude (NRMSE) and temporal performance (TMP) aspects combined.

Table 4: Statistics for 22nd September, 2019 simulation session at Kithulgala.

	NRMSE	TMP	PS	Bias Corrected NRMSE	Bias Corrected PS
M1_On	48	42.6	47.3	58.2	42.2
M1_Off	45.7	16.4	35.4	52.8	31.8
M2_On	98.2	52.5	27.2	40.8	55.9
M2_Off	106.6	13.1	3.3	116.8	-1.8
M3_On	51.8	37.7	43	70.5	33.6
M3_Off	77.8	29.5	25.9	111.2	9.2
M4_On	46.9	34.4	43.8	44.1	45.2
M4_Off	117.9	3.3	-7.3	123.5	-10.1
T4_On	54.8	16.4	30.8	59.6	28.4
T4_Off	95	26.2	15.6	115.6	5.3
T5_On	58.3	23	32.4	84.1	19.5
T5_Off	61.4	21.3	30	74.8	23.3
T6_On	54.2	32.8	39.3	61.3	35.8
T6_Off	80.5	18	18.8	59	29.5
T7_On	96	14.8	9.4	101	6.9
T7_Off	146.1	11.5	-17.3	62.9	24.3

Considering all the models for calibration, the best performing models selected based on NRMSE_PS and TMP_PS of the forecast simulations are shown in table 5. In table 5, OPS indicate the Overall Performance Score which accounts for the combination of magnitude, temporal performance and their variance. Accordingly, models selected from TMP_PS deliver the higher OPS at most of the stations in contrast to the models selected from NRMSE_PS. Model selection process is illustrated in figure 6. It included two steps at the final selection where,

Step 1: Filter to remove models with, an Average TMP less than the 3rd quartile and a TMP NSD greater than 1st quartile, in order to assure the consistency of results.

Step 2: Select the model with highest TMP PS from the filtered models.

Above process resulted in selecting T5_On, M2_On, M1_On, M2_On and T5_Off as the best performing models for Madiwela, Waga, Mahapallegama, Kithulgala and Maskeliya. When the results are averaged over the basin, T4_On performs best with 52.9% OPS.

These results were further verified with the session for verification, with statistics shown in table 6 and table 7, highlighting the models with best PS. Them proves that the models selected considering temporal performance result in the best overall perforance with bias correction.

In order to compare the station wise model selection with basin scale selection, the selected models at regional scale were compared with the best performing model at basin scale (T4_On). Basin average rainfall time series for observed and forecasts were calculated with thiessen polygon factors as given in figure 7 and table 8.

Table 9 shows the basin averaged improvements gained in terms of TMP, NRMS and OS for each forecast session. Accordingly, for the majority of the sessions, model selection has resulted in improved forecast. Even though 2019092318 sessions's TMP doesn't show any improvement, it is evident that the forecasts are performing well with the observations figure 8.

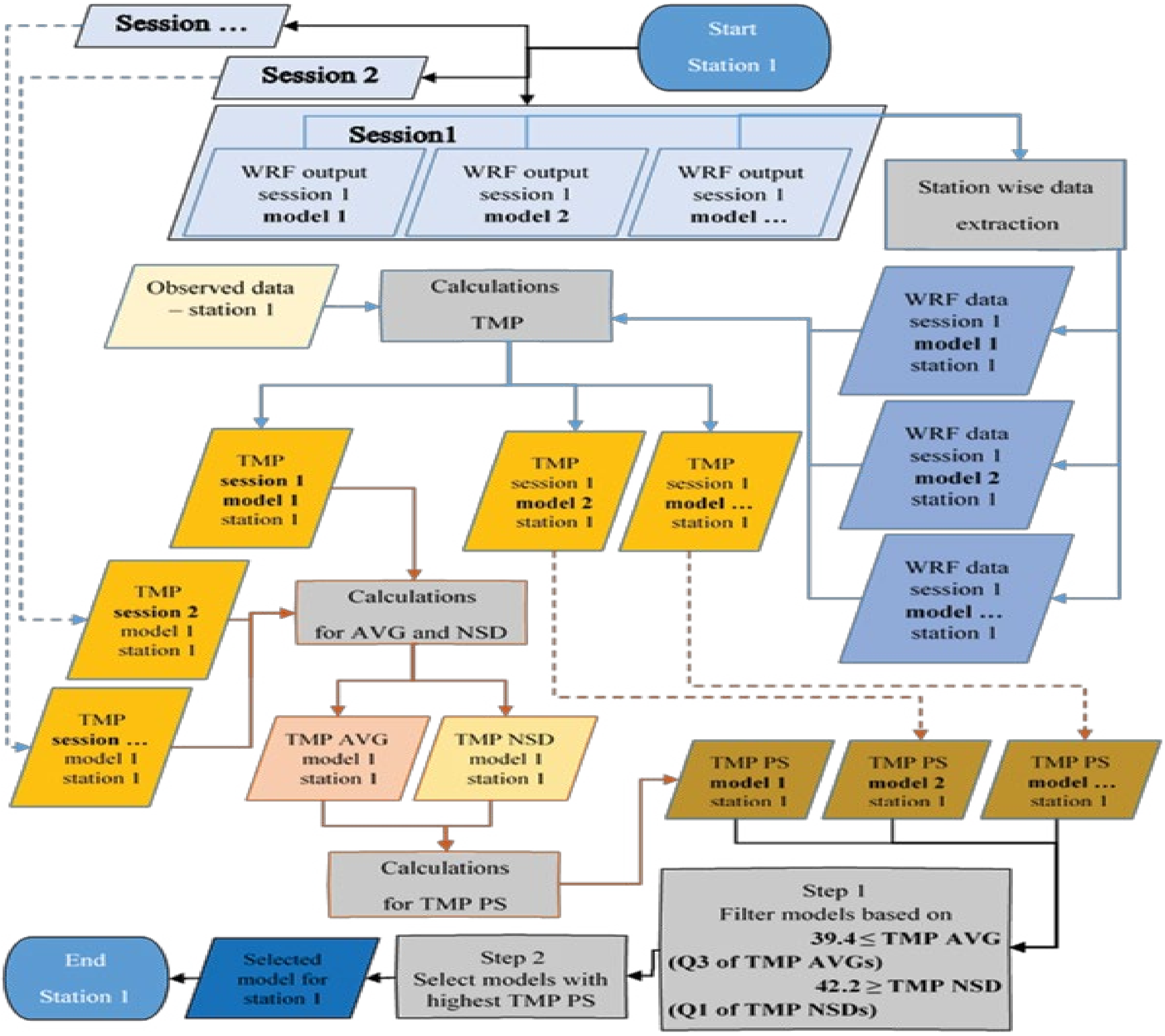


Figure 6: Model selection process flow chart.

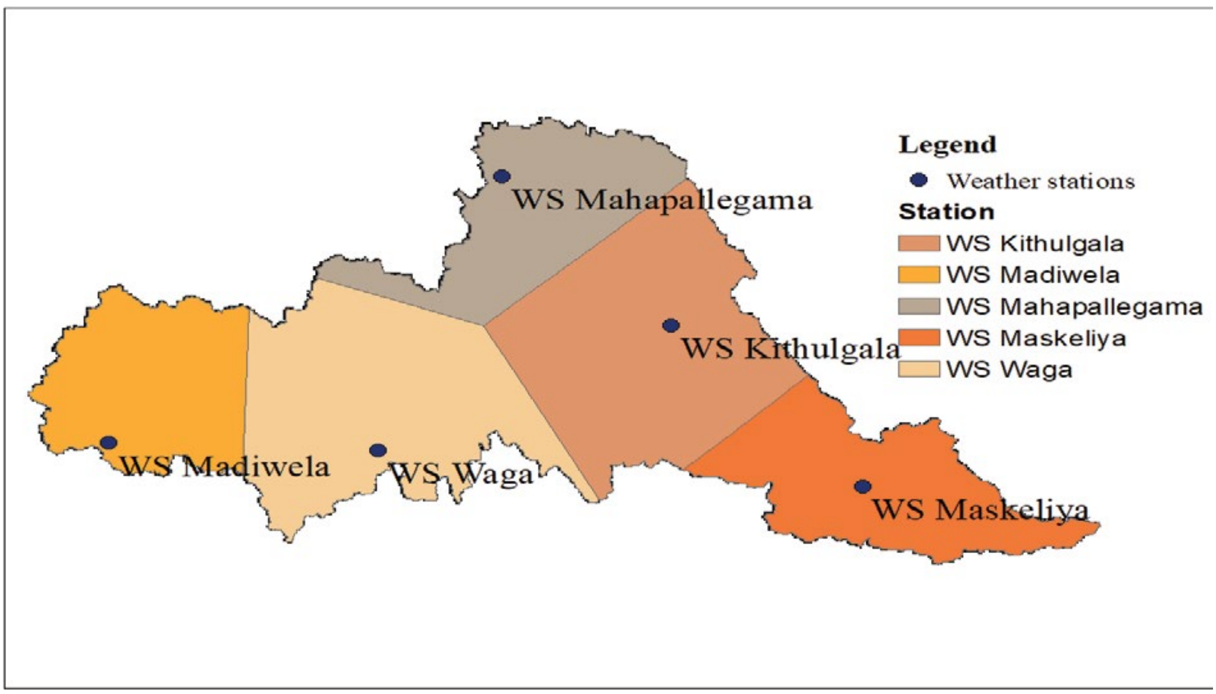


Figure 7: Thiessen polygons.

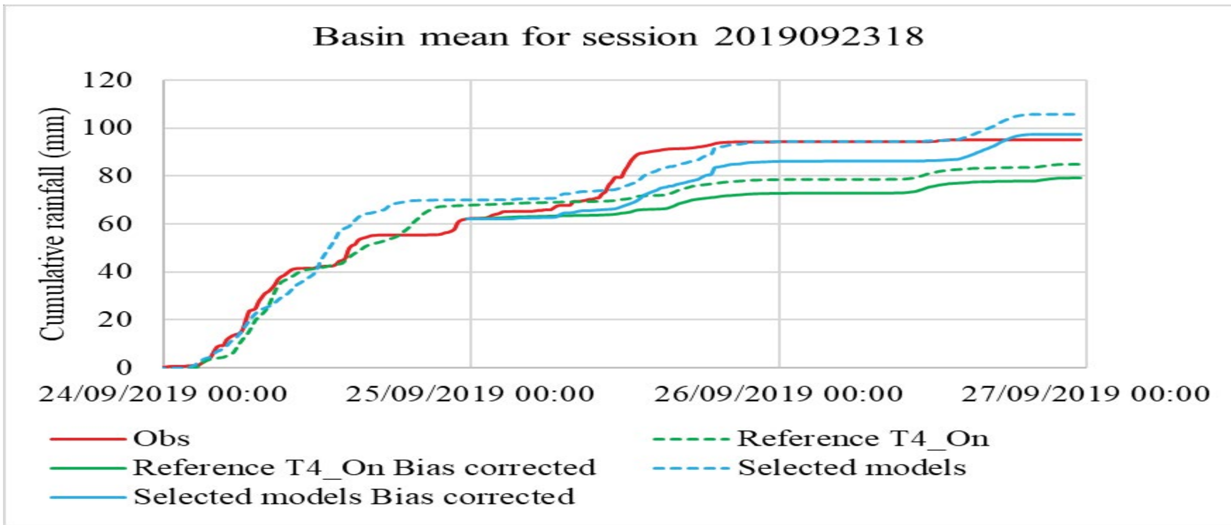


Figure 8: Basin mean cumulative rainfall for session 2019092318.

The station wise improvements gained are shown in table 10 without bias correction and in table 11 with bias correction.

CONCLUSIONS

Study concludes that sub-daily scale near future NWP model performances differ significantly in different regions within the Kelani river basin. Considering such variations, the study has shown that the station wise model selection method leads to a better forecast over the basin rather than selecting a basin wide single model.

Incorporating temporal distribution (TMP) of rain events for model selection and later performing a bias correction is recommended for obtaining a reliable sub-daily scale precipitation forecast rather than bias correcting the models selected based on precipitation magnitudes (NRMSE).

These gains in improved forecasts should be translated to effective early warning to reduce losses and damages so that disasters related to extreme events do not wipe out years of economic progress.

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