Various Rainfall Forecasting Methods for Estimation of Pit Lake Flooding Duration in Indonesia

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Presentation's Outline

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3. Data
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Introduction

- Indonesia is the largest coal exporting country in the world:
  - with most mines using open-pit mining methods due to the geological conditions of the coal deposits.
- Most of these open pit mines leave void at the end of their mining period,
  - due to technical reasons for mining operations and/or operating at a low stripping ratio (< 5)
  - resulting in a lack of backfilling material.
- The voids, hydrologically can be flooded, forming pit lakes
  - which can be utilized for water supply, flood control, recreational opportunities, environmental rehabilitation and protection.
- It is imperative to be able to calculate and predict the variability water balance of the pit lake
  - The water balance of the pit lake alongside the stage volume curve of the pit lake is important to predict the flooding duration of the pit lake.
  - Runoffs are a major part of water balance and are directly governed by rainfall depth
  - characterizing OF rainfall conditions and their variability and the selection of forecasting methods are important.

This paper aims to explore the **applicability of various models and approaches in the forecasting of monthly rainfall depth.**

Methods (1/2)

There are extensive models and approaches in the forecasting of monthly rainfall. In this study, models and approaches used in the forecasting of monthly rainfall are as follows (Latif et al., 2023; Maia & de Carvalho, 2011; Nwokike et al., 2020):

- Monthly average (overall). *The approach is an average using all training data*
- Linear regression. *The approach uses a linear trendline of all training data*
- Statistical Approach (seasonality). The training data is divided into groups based on months (January-December). The mean/average value, quartile-1(Q1) and quartile-2 (Q2) of each month are calculated
- Winter-Holt's and Seasonal Arima Methods. *The approach is based on exponential smoothing and seasonality forecasting using training data*
- Time Series Decomposition. *The approach is based on calculating the trend and seasonality of the training data to make the forecasting*.

Methods (1/2)

The error of the model or approach forecasting of monthly rainfall is evaluated using RSME/root mean squared error, which is calculated as follows:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{p,i}-P_{a,i}\right)^2}$$

where $P_{p,i}$ is the predicted monthly rainfall and $P_{a,i}$ is the actual monthly rainfall. The error value is expected to be minimum for a good forecasting model.

A hypothetical void of a coal mine is used

- with a specific stage-volume curve and the catchment area.
- The void started to be filled, at the same time as the start of the forecasting time.
- The majority of water input is from runoff, thus the runoff volume of water into the void to form the pit lake is roughly estimated using the following equation

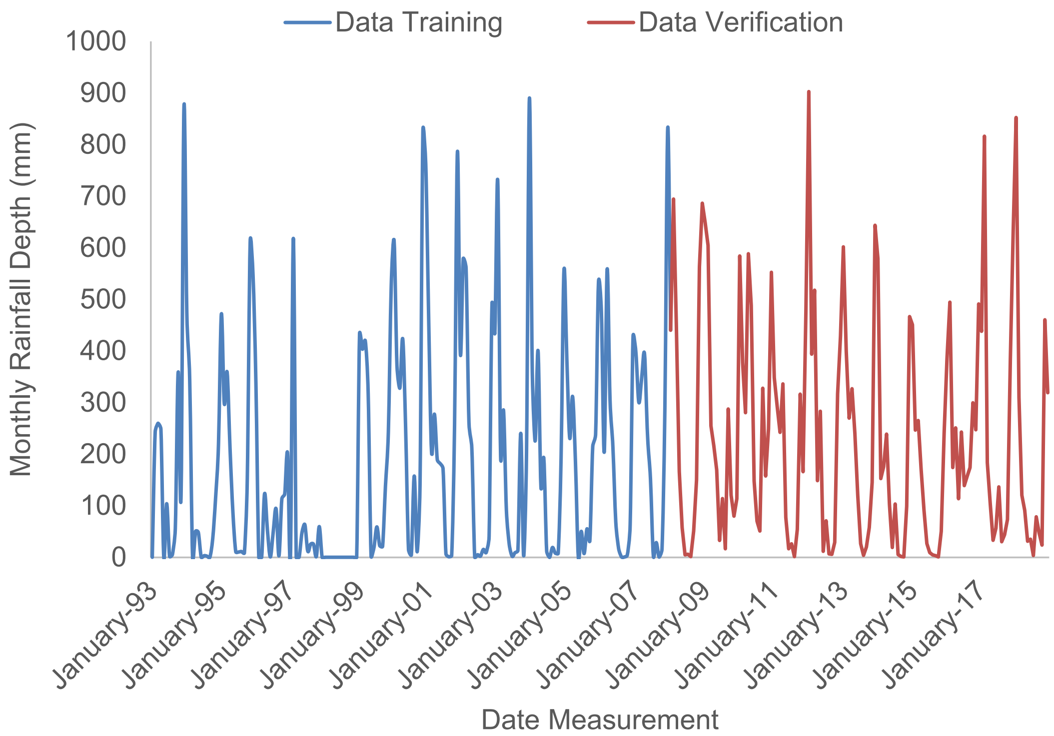
Water Input at n-th month, $Vn = \sum_{i=1}^{n}(\mathbf{C} \times P_{p,i} \times \mathbf{A})$

- Where C is the runoff coefficient (0.7), $P_{p,I}$ is the predicted monthly rainfall and A is the catchment area of the mine void
- The actual monthly rainfall depths are also used to estimate the actual flooding duration. Pit lake flooding duration is the time in the n-th month that Vn ≥ maximum volume of void.

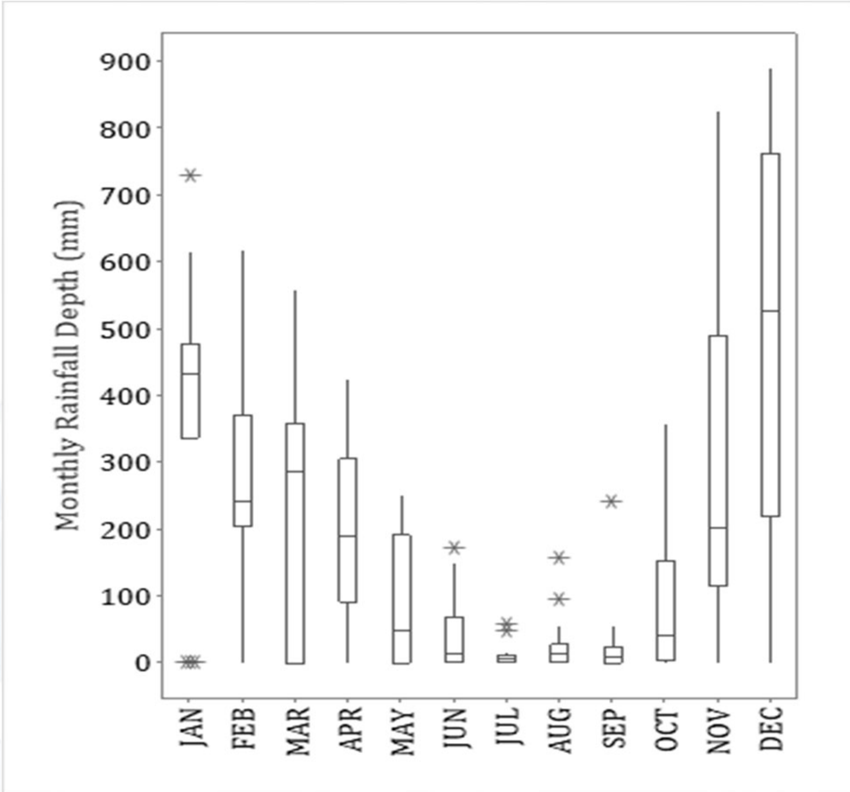
Data (1/3)
Monthly Rainfall Datasets and Mine Void Condition

- Monthly rainfall datasets of 26 years
  - ranging from January 1993 to December 2018, are used in this study.
  - The first 15-year dataset (from January 1993 to December 2007) is used as input for rainfall forecasting methods
  - the last 11-year dataset (from January 2008 to December 2018) is used to verify the methods.
  - The RSME is evaluated for verification dataset from January 2008 to December 2018
- A hypothetical void of a coal mine is used with a specific stage-volume curve and the catchment area as
  - estimated catchment area of 440 hectares. (The longest dimension is 1800 meters, shortest dimension is 730 meters).
  - The void is estimated to be filled with a maximum of 48 Mm^3 of water.

Data (2/3)
Monthly Rainfall Datasets

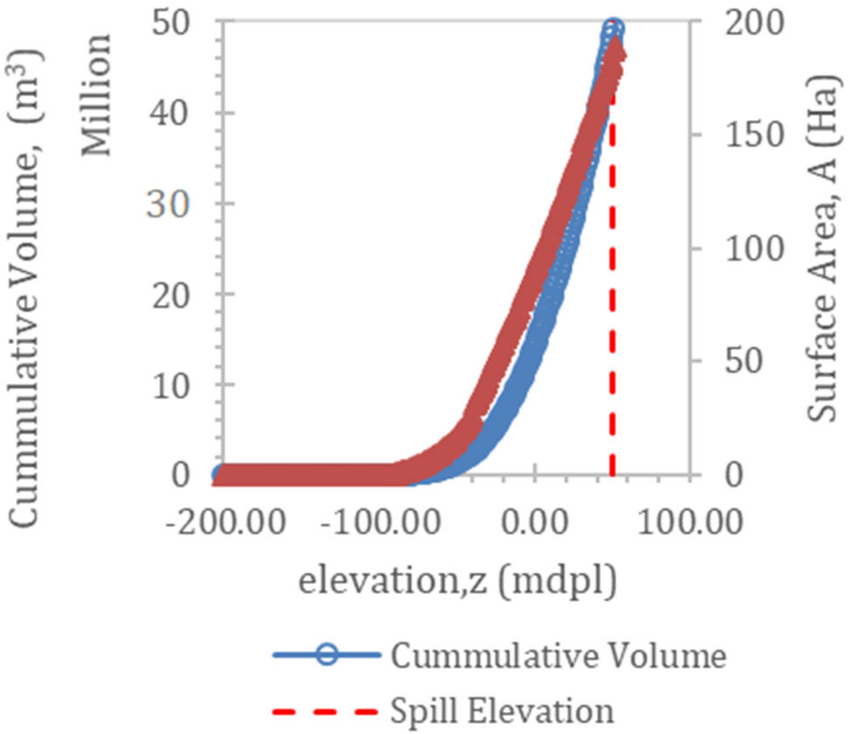


Time series of monthly rainfall datasets (Data Training and Verification)

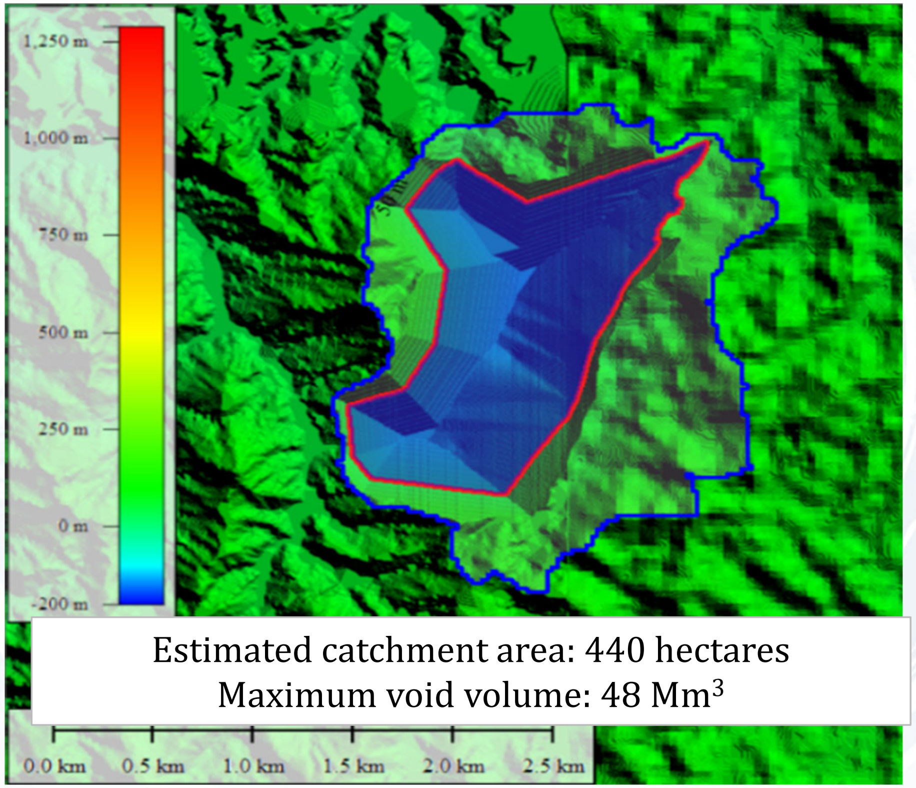


Boxplot of Monthly Rainfall Depth

Data (3/3)
Mine Void Condition



Staging curve
(elevation, surface area and volume) of void

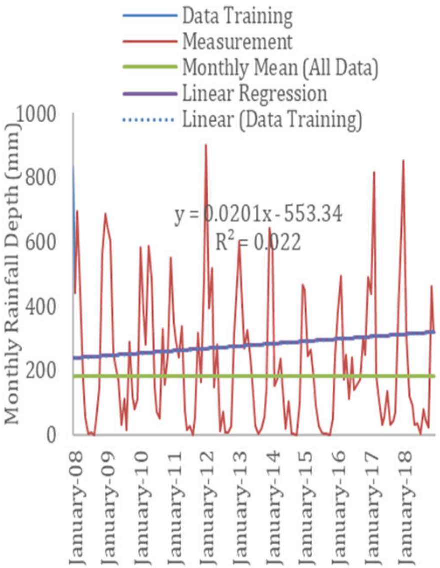


Catchment and Elevation map of void

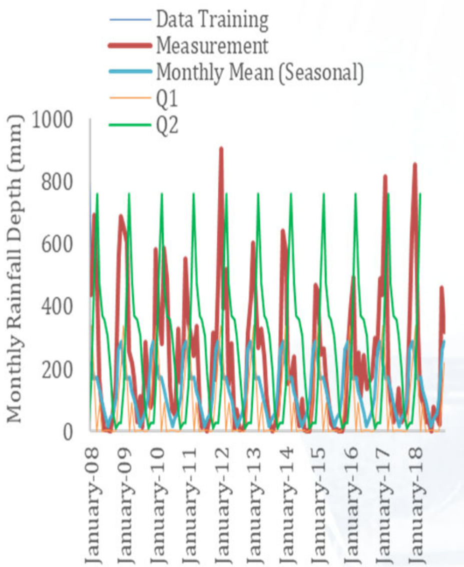
Results (1/4)

Models and approaches for the prediction of monthly rainfall

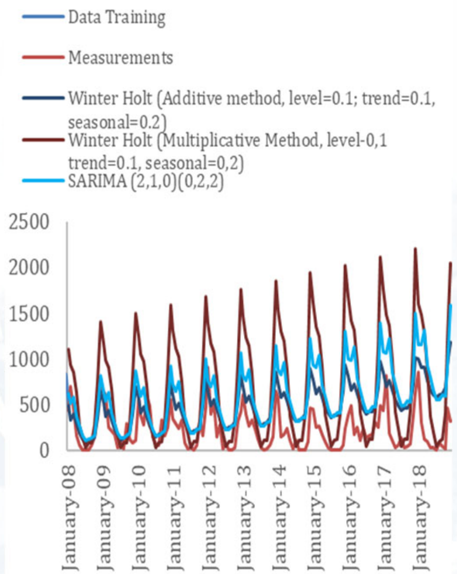
The predicted result of monthly rainfall for each model and approach vs. the actual monthly rainfall depth from January 2008 to December 2018 are shown below:



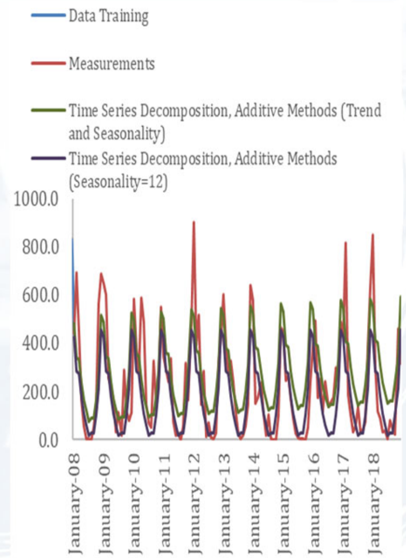
Actual values vs prediction of monthly rainfall using overall monthly average and linear regression



Actual values vs prediction of monthly rainfall using a statistical approach (mean seasonality, Q1-seasonality, Q2-seasonality)

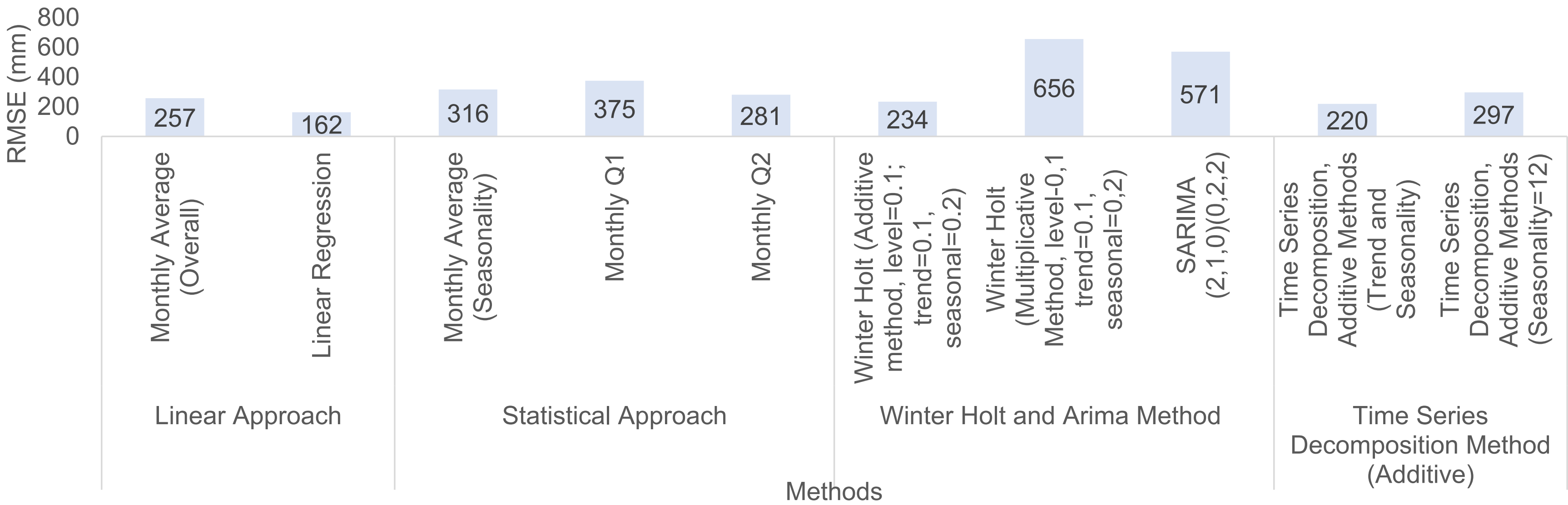


Actual values vs prediction of monthly rainfall using the Winter-Holt and seasonal ARIMA approaches



Actual values vs prediction of monthly rainfall using time series decomposition additive methods

Results (1/3)
Error calculation (RSME)



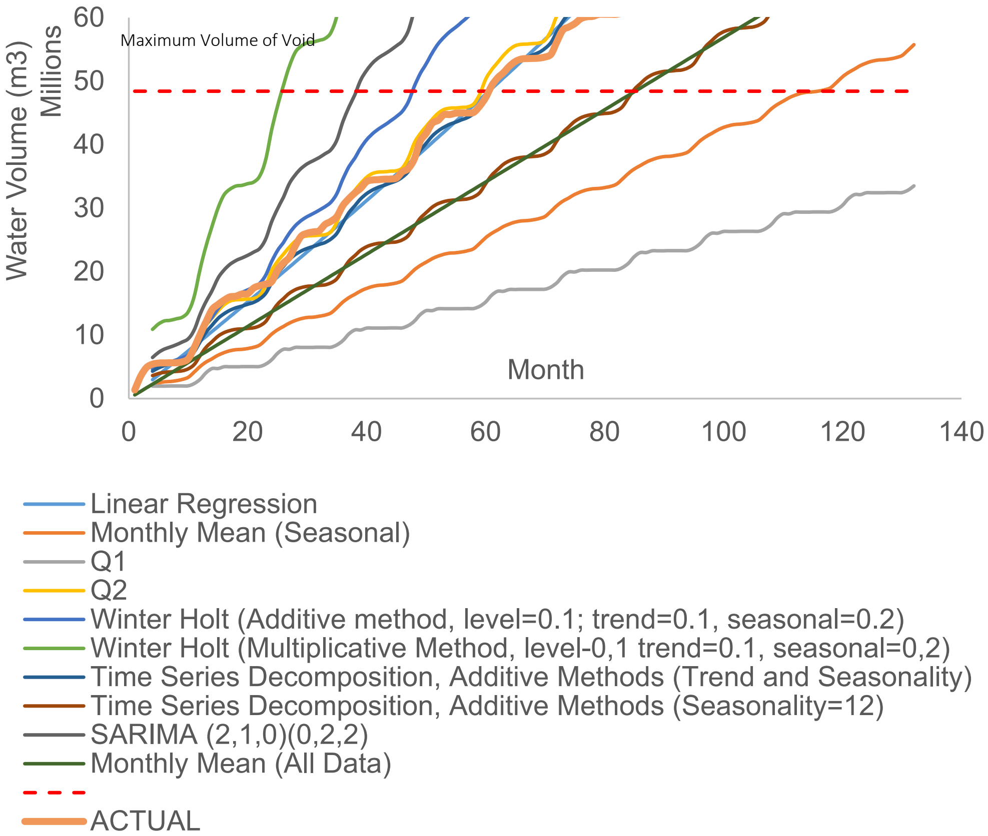
error resulting from the difference between predicted and actual monthly rainfall

- RSME of Linear approaches < The RSME values time series decomposition methods < RMSE by statistical approaches.
- The Winter-Holt and seasonal ARIMA methods produced varying RSME values, which indicates the models are more volatile than the others.

The simple models or approaches produced the lowest RSME but could not xplain the seasonal nature of the monthly rainfall depths.

Results (3/3)

Pit-Flooding Curve and Duration



The pit flooding volume curve

- shows the changing volume of the water inside the void based on above mentioned assumptions.
- The estimated pit lake flooding duration using actual rainfall is 61 months.
  - Methods using linear regression, statistical approach (Q2) and time series decomposition, additive methods (trend and seasonality) show the most accurate prediction of flooding (60 – 61 months).
  - due to several low monthly rainfall depths in the training datasets, some methods overestimating the flooding duration
  - The Winter-Holt and seasonal ARIMA methods predicted shorter estimated time to flood due to overestimating the value of the monthly rainfall in the later prediction months

Results (3/3)
Pit-Flooding Curve and Duration

Estimated pit lake flooding duration

Methods/Approach	Estimated Time to Flood (months)
Actual	61
Monthly Mean (All Data)	86
Linear Regression	61
Monthly Mean (Seasonal)	116
Statistical Approach Seasonal Q1	>132
Statistical Approach Seasonal Q2	60
Winter-Holt (Additive method, level=0.1; trend=0.1, seasonal=0.2)	48
Winter-Holt (Multiplicative Method, level-0,1 trend=0.1, seasonal=0.2)	26
Seasonal ARIMA (2,1,0)(0,2,2)	39
Time Series Decomposition, Additive Methods (Trend and Seasonality)	61
Time Series Decomposition, Additive Methods (Seasonality=12)	85

Conclusions

- The monthly precipitation series recorded in the stations of the study area shows seasonal behaviour, reflecting the typical unimodal rain regime from the basin.
- The simple models or approaches produced the lowest RSME but could not explain the seasonal nature of the monthly rainfall depths.
- The estimated pit lake flooding duration using actual rainfall was 61 months.
    - Methods using linear regression, statistical approach (Q2) and time series decomposition, additive methods (trend and seasonality) predicted flooding most accurately.
    - Based on the ability to explain the seasonality of the monthly rainfall data, yearly trend, and predictive accuracy, time series decomposition using additive methods (trend and seasonality) were the best option to predict monthly rainfall depth and to calculate the flooding duration.
- Different methods show substantial differences in flooding duration. In addition, the methods differ in their abilities to portray uncertainties in mid-term and long-term hydrometeorological conditions, such as climate changes and climate pattern.

Acknowledgements and References

Acknowledgements

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References

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