Tanzania Journal of Science
Volume 51(4), 2025
journal homepage: https://commons.udsm.ac.tz/tjs/

# Performance comparison of Kriging models used for estimation of rainfall variability in the northern coast of Tanzania

Salma Suleiman[1] and Clement Mromba[2*]
*[1]Tanzania Meteorological Authority (TMA), P.O. Box 3056, Dar es Salaam, Tanzania*
*[2]Department of Geography, University of Dar es Salaam, P.O. Box 35049, Dar es Salaam, Tanzania*
*Emails: mromba.clement@udsm.ac.tz & salma.suleiman@meteo.go.tz*

**Keywords**

Kriging Models;
Cross-validation;
Spatial Interpolation;
Rainfall Estimation;
Northern Coast

## Abstract

Accurate rainfall estimation underpins effective disaster preparedness and sustainable socioeconomic planning. The performance of Ordinary Kriging (OK), Universal Kriging (UK), and Simple Kriging (SK) in estimation of rainfall variability were assessed across eight stations in the northern coast of Tanzania for the period from 1960 to 2020. Using ArcGIS 10.3, each method was evaluated and cross-validated using six performance metrics, namely; Mean Error (ME), Mean Square Error (MSE), Root Mean Square Error (RMSE), Root Mean Standardized Square Error (RMSSE), Average Standardized Error (ASE), and the Coefficient of Determination ($R^2$). Performance comparison results indicate OK to have achieved the lowest bias, best overall accuracy, and the highest $R^2$. UK underperformed, while SK performed comparably, but slightly lower than OK. These results demonstrate that OK provides the most reliable and precise spatial rainfall predictions. While performance metrics have indicated OK to be more accurate, the standard deviation also shows that OK delivers more consistent performance across spatial scales. It is the best linear unbiased prediction which minimizes estimation variance, although suffer from non-linear spatial patterns. This study recommends that Kriging models be adopted and integrated into TMA's forecasting and early warning system to enhance spatial precision in rainfall estimation.

## Introduction

Rainfall variability influenced by both natural and anthropogenic changes is becoming a critical concern for ecosystem, agriculture, water resource planning and management, and disaster preparedness, especially in regions dependent on rain-fed systems (Tefera et al. 2024). In Africa, rainfall variability manifest as changes in the onset, duration, intensity, and distribution of rainfall, leading to droughts, floods, and crop failures (Taye and Dyer 2024). Over 85% of the population depends on rain-fed agriculture, making them particularly susceptible to both excessive and insufficient rainfall (Chanda et al. 2024, Coulibaly et al. 2020). Droughts and floods are the most frequent and widespread natural disasters in Africa, causing substantial economic losses and affecting millions annually (Lombe et al. 2024). In recent years, West Africa has experienced severe flooding events, such as the 2022 floods in Nigeria that resulted in approximately 603 deaths and displaced more than 1.4 million people (Olanrewaju et al. 2019).

Northern Africa, dominated by the Sahara Desert, experiences Arid conditions and erratic rainfall patterns (Tanarhte et al. 2024). While Mediterranean coastal regions like Morocco, Tunisia, and Algeria receive seasonal rainfall during winter, they are vulnerable to intense and short-duration storms. For example, Algeria experienced deadly flash floods in 2014 and Morocco suffered severe infrastructure damage and displacements due to heavy rainfall in February 2020 (Chaqdid et al. 2023). The intensity and frequency of such floods are projected to increase by the mid-21st century, exacerbated by sea level rise, thus affecting densely populated, agriculturally important coastal zones (Cisse et al. 2022). In Eastern Africa, rainfall variability continues to trigger both extreme droughts and frequent floods with severe consequences on livelihoods. Around 203 million people, nearly 30% in Kenya and Ethiopia are regularly affected by these events (Taye and Dyer 2024). Climate projections suggest that with a 2 °C global temperature increase, likely between 2030 and 2052, the frequency and severity of heavy rainfall events will rise, further threatening socio-economic stability across East Africa (Chang'a et al. 2020).

---

[*] Corresponding Authors E-mail: mromba.clement@udsm.ac.tz or mrombac@yahoo.com

Received 27 Nov 2024, Revised 18 July 2025, Accepted 14 Dec, Published 24 December 2025
https://doi.org/10.65085/2507-7961.1106

ISSN 0856-1761, e-ISSN 2507-7961

Tanzania, like other East African countries is increasingly experiencing extreme weather events, particularly floods, which have led to loss of life, displacement of people, and outbreaks of disease (Msemo et al. 2021). Flooding occurs nearly every year, with significant events such as the 2014 flash floods in Morogoro and Mbeya highlighting the recurring nature of the hazard (Mauya and Matilya 2023). The northern coast of Tanzania is vulnerable to rainfall variability due to its heavy reliance on rain-fed agriculture, which is sensitive to climate extremes (Joseph et al. 2021). This vulnerability is exacerbated by rapid population growth and the expansion of settlements into flood-prone areas. The region has faced multiple flood events in the past decade, notably in 2020, 2019, 2014, and 2011, each causing fatalities and substantial economic disruption. For example, in 2011, the government allocated billions of shillings to relocate communities at high risk to safer areas (John 2022, Mhache 2022). These trends underline the urgent need for improved flood risk management, early warning systems, and climate-resilient planning in the coastal zones of Tanzania (Ringo et al. 2024).

It is against this background that critical importance of developing accurate estimations and timely forecasting systems raise. As climate extremes intensify, the ability to anticipate and respond to heavy rainfall becomes ever more vital. Advancements in estimation methods that can better capture the spatial and temporal dynamics of rainfall is paramount. However, rainfall forecasting and flood prediction in Tanzania remain challenging due to complex climate variability and limitations in current methods applied by the Tanzania Meteorological Authority (TMA). For many years, TMA has been relying on statistical techniques like the Mann-Kendall trend test and dynamic models such as the Weather Research and Forecasting (WRF) model. Despite improvements in parameterization schemes such as Kain-Fritsch cumulus, Lin microphysics, and Asymmetric Convective Model version 2 (ACM2) for the planetary boundary layer (Lungo et al. 2020a), forecast accuracy remains limited, particularly for rainfall onset, cessation, and intensity. Again, high-resolution modeling such as nested WRF domains over Dar es Salaam (27 km, 9 km, 3 km), has improved event-scale predictions but continues to suffer from uncertainties and sparse observational data. These limitations hinder prediction accuracy and preparedness, thus affecting line sectoral response, leading to economic losses and risks to human life.

To improve estimation of rainfall variability and strengthen long-term climate resilience and planning, geostatistical methods, particularly Kriging, offer a robust alternative that can overcome prediction uncertainty. The use of Kriging models can enhance accuracy in rainfall variability analysis in vulnerable regions like the northern coast of Tanzania. These models provide predictions with quantifiable accuracy and uncertainty, which is critical for improving early warning systems and guiding targeted responses. In addition to its practical applications, the study contributes to the existing body of knowledge on which Kriging methods are more suitable for rainfall analysis in data-scarce environments, which is not addressed much in previous studies. Therefore, the aim of this paper is to evaluate suitable Kriging models for estimation of rainfall variability in the northern coast of Tanzania.

## Materials and Methods

### Description of the study area

The study area is the northern coast of Tanzania extending from 4°S to 8°S and 39°E to 40°E, encompassing the regions of Dar es Salaam, Tanga, Pwani, and the islands of Unguja and Pemba (Figure 1). This area has elevations ranging from 9 to 183 meters above mean sea level. This contributes to spatial variation in rainfall distribution and challenges in rainfall estimation as variation in elevation requires topographic corrections when estimating rainfall variability using interpolation methods like Kriging. The elevation range affect local climate as areas at higher elevation, particularly the East Usambara located in Tanga receive slightly more rainfall due to orographic lifting. The lower-lying coastal areas of Dar es Salaam and Pwani regions experience less rainfall as they are influenced by maritime humidity and Indian ocean breeze circulations. The main rainy seasons are March to May (MAM) as the long and heavy rains, and October to December (OND) as the short rains (Joseph et al. 2021). Occasionally, the onset of MAM rains is delayed due to ocean-atmosphere interactions (Msemo et al. 2021). Bimodal rainfall patterns are primarily influenced by the Intertropical Convergence Zone (ITCZ), the El Niño–Southern Oscillation (ENSO), and other large-scale atmospheric systems (John 2022, Mhache 2022). This makes the area to have tropical climate, characterized by hot and humid conditions throughout the year.

The area exhibits varied and complex terrain, with a narrow coastal strip bordering the western Indian Ocean thus suitable for comparative evaluation. The area is the home to coastal thickets, patches of lowland forest, East African mangroves, mangrove swamps that are vital habitats for wildlife on land and water, and has numerous coral reef systems offshore. The coastline is indented by shallow bays providing natural harbors, coastal estuaries, and is drained by major rivers including the Pangani, Wami, Ruvu, and Rufiji rivers with deltaic environment such as Pangani and Rufiji Delta. The northern coast of Tanzania was selected due to its high exposure to flood hazards, particularly flash floods, which are intensified by increased extreme and unpredictable rainfall events (John 2022, Mhache 2022). The area has experienced frequent and severe flood events in recent years, becoming more intense due to rapid urbanization, high population density, and expansion of informal settlements in flood-prone areas which further vulnerability.

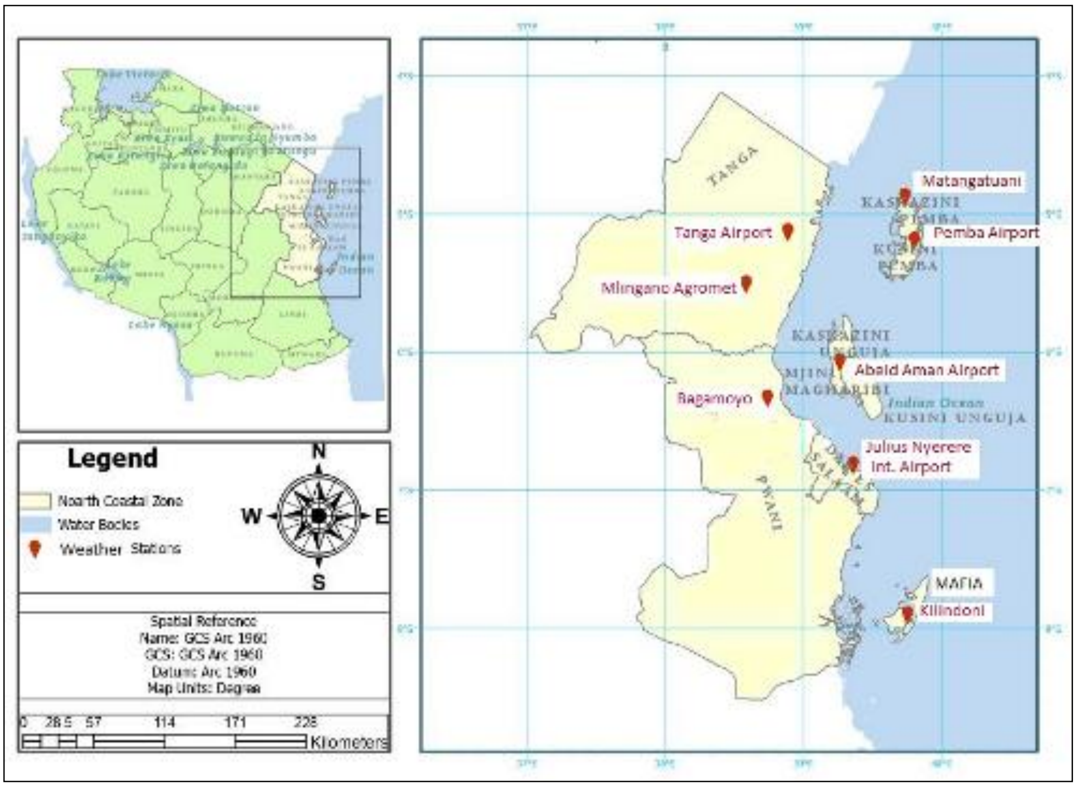


Figure 1: Location of the northern coast of Tanzania

### Data acquisition

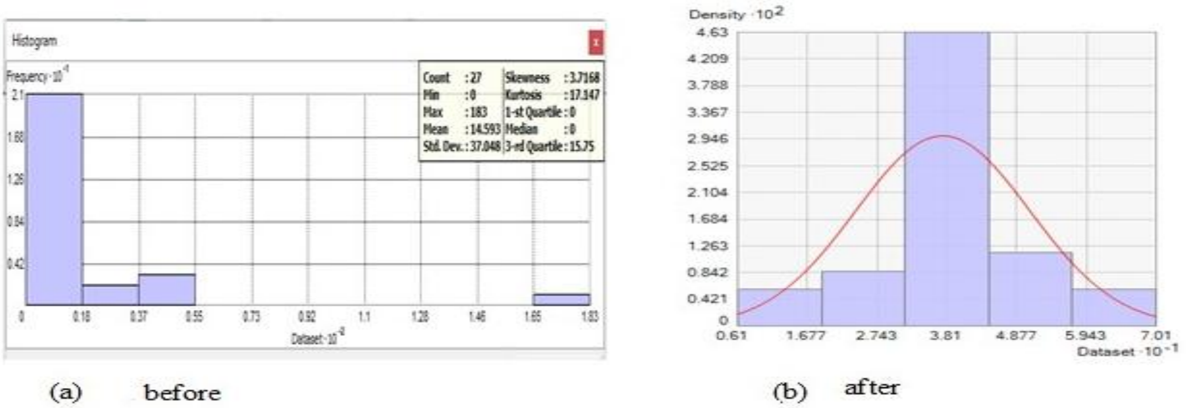
This study used both spatial and non-spatial secondary data. Spatial data included regional administrative boundary layers of Tanzania. Non-spatial data were daily rainfall data over a 60 years' period (1960-2020) obtained from eight TMAs meteorological stations distributed across the northern coast of Tanzania (Table 1). Choice of this time frame for the analysis allowed the incorporation of data from all of the existing meteorological stations.

**Table 1:** Meteorological stations used in this study

| Station ID | Station name | Latitude (S) | Longitude (E) | Elev. (m) | Period (Years) |
|---|---|---|---|---|---|
| 09439018 | Matangatwani | 4° 56' 24" | 39° 44' 24" | 40 | 1960-2020 |
| 09538011 | Mlingano Agromet | 5° 4' 0" | 38° 55' 0" | 183 | 1960-2020 |
| 09539015 | Tanga Airport | 5° 5' 32" | 39° 4' 16" | 46 | 1960-2020 |
| 09539026 | Pemba Airport | 5° 15' 16" | 39° 48' 41" | 24 | 1960-2020 |
| 09639028 | Zanzibar Airport | 6°13' 19" | 39° 13' 29" | 18 | 1960-2020 |
| 09638000 | Bagamoyo | 6° 26' 0" | 38° 54' 0" | 09 | 1960-2020 |
| 09639029 | JNIA | 6° 48' 0" | 39° 17' 0" | 53 | 1960-2020 |
| 09739003 | Kilindoni - Mafia | 7° 56' 0" | 39° 67' 0" | 21 | 1960-2020 |

### Data normalization and quality control

Rainfall data were analyzed using ArcGIS 10.3, with an initial assessment of data normality using the histogram tool. The results showed a positively skewed (right-skewed) distribution, indicating non-normality of data containing many low values and a few high ones. Since Kriging methods assume normally distributed data for optimal unbiased prediction, a normal score transformation (NST) method was applied to ensure normal distribution. Geostatistical analyst tool embedded in ArcGIS 10.3 was used to transform and adjust rainfall data to closely resemble a standard normal distribution. In performing transformation adjustment, data were first sorted and ranked, an equivalent rank from a standard normal distribution value was assigned within the dataset, then frequency distribution was selected in the ranking processes, and average monthly dataset for each month was examined, and finally a transformation tool was used to obtain normality of data as indicated in figure 2.



(a) before (b) after

**Figure 2:** Histogram of data normality before and after transformation

Outlier is a data point or value that exhibits an exceptionally high or low value compared to the rest of the values in the dataset (Javari 2017). Global and local outliers were examined using histogram and Voronoi tool in ArcGIS 10.3. Mean Voronoi tool was used to identify existence of local variations between neighboring points. Using the mean Voronoi tool, values were assigned to polygons and averaged from polygons to its neighboring polygons. The mean rainfall value was calculated within each polygon as well as the average polygon area. Outliers were then determined by relating specific station values to the average rainfall of neighboring Voronoi cells. Stations with values that diverged from the local average were marked as possible outliers as shown in figure 3. The dark brown color polygon shows a high value and light yellow low values.

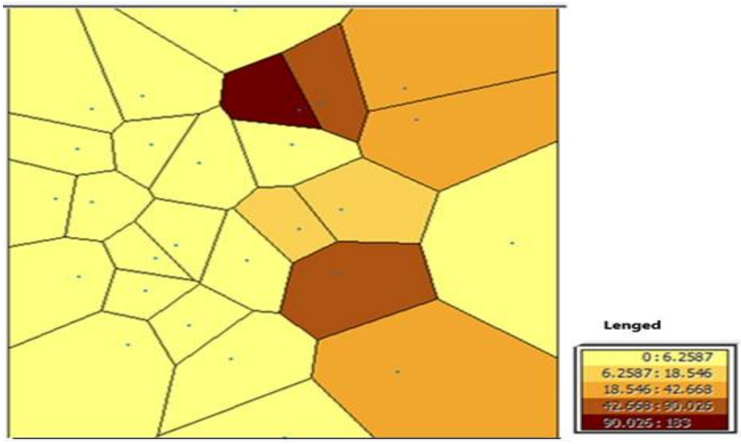


**Figure 3:** Voronoi map depicting outliers

Bias adjustment was then employed to correct abnormal values while maintaining data consistency. This involved adjusting the outlier station's rainfall values toward the mean of its adjacent Voronoi neighbors, using a weighted interpolation method based on the inverse distance to neighboring stations. After adjustment, updated rainfall values were validated by comparing with recorded rainfall data, then RMSE was used to evaluate the improvement. All steps were implemented using ArcGIS 10.3 spatial analyst and visualization tools.

Data quality control procedures were implemented to handle missing data using Inverse Distance Weighting (IDW) method. Homogeneity testing which is essential for spatial and non-spatial analysis was conducted to depict consistency of time series data. Single mass curve analysis was employed for all meteorological stations. Results for all stations shown nearly straight line without detected change points in the cumulative rainfall trends (Figure 4), implying consistency and homogeneity in dataset. Percentage of missing rainfall data for Zanzibar airport (1%) and Matangatuani station (1.3%) indicated high consistency as their values were below trend line threshold of ±5% (Peterson et al. 2022). Hence, the datasets were scientifically robust and suitable for Kriging modeling.

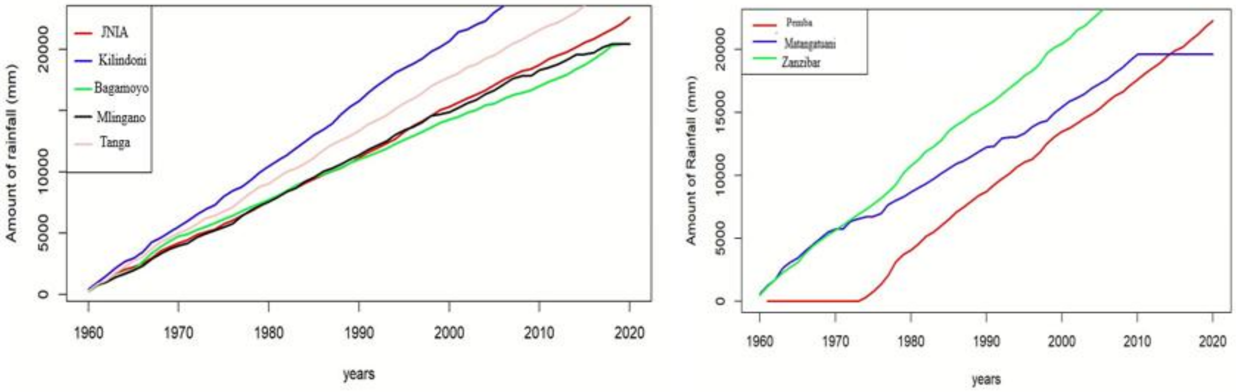


**Figure 4:** Single mass curves of rainfall data for studied meteorological stations

## Data analysis

The methodological framework adopted for spatial interpolation of rainfall data involved the use of Ordinary Kriging (OK), Universal Kriging (UK) and Simple Kriging (SK) described in Hu et al. (2019). OK uses a single variable and relies on spatially dependent variance to provide an unbiased estimate of the variable value at a target location based on known sample values from surrounding locations. The weights in OK were determined to minimize estimation variance and ensure the estimator remains unbiased. This unbiasedness was achieved by constraining the sum of the Kriging weights to equal one. Hence, the OK weight was obtained using experimental semivariogram model of monthly average rainfall. The semivariogram for each monthly average rainfall was calculated and fitted with a spherical model to capture trends using the interpolation wizard in embedded in ArcGIS 10.3.

UK is a method designed to handle non-stationary spatial data by incorporating a deterministic trend into the model, thereby allowing the mean to vary smoothly across space. It is used when the mean is assumed to vary according to a polynomial function of spatial coordinates. Usually, UK includes a trend surface equation in the Kriging process, which can either be a first-order polynomial or a quadratic surface defined by a second-order polynomial. With UK method, average rainfall was used to make a prediction, the prediction was computed when the weights were such that the prediction is unbiased and the variance is minimized. UK weight was estimated using semivariogram model and fitted using linear with quadratic drift in spatial analyst tool of ArcGIS.

SK estimates the value of a spatially distributed variable such as rainfall at unsampled locations based on known values at sampled points. It is used with assumption that the mean is constant and known. In SK, weights were determined by summing the Kriging weights of the measured values at the data points along with the known stationary mean. The known mean was calculated from the rainfall data and assumed to remain constant throughout the entire study area. The weight was derived using a semivariogram function. Semivariograms of SK were produced using an experimental semivariogram fit with a spherical model in geostatistical wizard of ArcGIS 10.3

Cross-validation was used to evaluate the predictive performance of geostatistical interpolation models. Cross-validation help identifying the model that produced the smallest prediction errors by comparing the differences between observed and estimated values. The geostatistical analyst tool in ArcGIS 10.3 was used to calculate and generate statistical summaries using six metrics, which were then used to compare model accuracy and determine the most suitable interpolation method. The Mean Error (ME) quantifies the average difference between predicted and observed values, serving as an indicator of systematic bias; values close to zero suggest minimal over-estimation or under-estimation. The Mean Standardized Error (MSE) assesses the average standardized bias, calculated by dividing each prediction error by its associated standard error. This measure helps determine whether the model's predictions are unbiased in terms of uncertainty. The Root Mean Square Error (RMSE) measures the overall magnitude of prediction errors, with lower values indicating higher accuracy and better model performance.

The Root Mean Square Standardized Error (RMSSE) evaluates the consistency of predicted standard errors by comparing them to actual residuals; an RMSSE value close to one indicates that the model reliably estimates prediction uncertainty. The Average Standardized Error (ASE) calculates the average of the standardized prediction errors, providing insight into how well the model's predicted standard errors reflect the actual variability in errors. Additionally, the Coefficient of Determination ($R^2$) is used to evaluate how well the interpolation model explained the variance in the observed rainfall data. $R^2$ values range from 0 to 1, where values closer to 1 signify a stronger correlation between observed and predicted values, indicating a better-fitting model. Collectively, these statistical metrics were used to compare OK, SK, and UK, and identify the method that provided the most accurate and reliable representation of spatial rainfall variability.

## Results and Discussion

### Evaluation of models performance using mean error

Values of ME performance test for OK range from 1.2 to -5.8. However, majority of ME values across months are close to zero (0), which indicates low bias. Months like March and April show slight underestimation, while

June and August show mid-overestimation, Overall OK provides consistent and balanced predictions with minimal bias across months. Hence OK demonstrates good accuracy and low mean error, making it reliable for rainfall prediction. Values of ME performance test for SK range from 17.8 to -5.5. ME for SK is relatively low in most months. It has shown best performance with low mean error in June and July, but with slight overestimation in October and November and relatively high overestimation in January and February. Hence SK shows low bias comparable to OK, but with slightly overestimation in some months. ME performance test for UK range from 126.8 to -90.8, with extreme fluctuations and variations. UK exhibit higher overestimation from November to February, peaking in April, while high underestimation being depicted in May. UK indicates high bias and unstable performance in many months. Hence, the UK is less reliable in this context due to high variability and potential overfitting models (Figure 5).

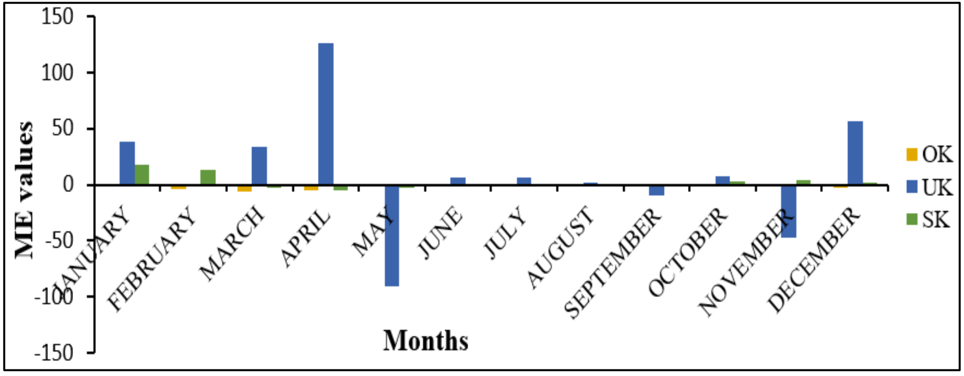


**Figure 5:** Evaluation of models performance using mean error

### Evaluation of models performance using mean standardized error

Values of MSE performance test for OK range from 0.04 to -0.05. MSE values for OK are mostly close to zero (0) from November to February indicating trivial underestimation. This indicates stable and consistent predictions with minimal error and higher prediction accuracy. However, the month of June, August and October have moderate overestimation error though still close to zero (0). Values of MSE performance test for SK range from 0.17 to -0.25. MSE values for SK shows both high overestimation in January and August, and high underestimation in February and December, indicating less stable predictions, possibly due to strict assumptions about the known mean. High estimation errors in February and December are signs of poor model performance. Values of MSE performance test for UK range from 0.23 to -0.13. MSE values for the UK shows high overestimation in May and June and high underestimation in August and September (Figure 6). This suggested higher inconsistent, variability and instability in model performance across months. The observed MSE values advocate OK method as the most reliable method for rainfall estimation in the northern coast of Tanzania. UK might be helpful if strong external trends such as elevation and distances from the sea are driving rainfall, but it needs careful validation. SK shows occasional spikes in error, making it less favorable for overall estimation.

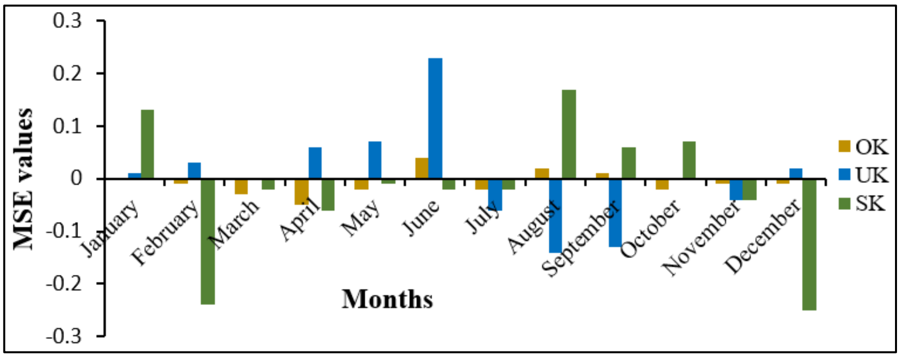


**Figure 6:** Evaluation of models performance using mean standardized error

### Evaluation of models performance using root mean square error

Values of RMSE performance test for OK range from 12.1 to 164.8. OK performs better than others two models from May to October, and November as has low RMSE values, except in July where is outstripped by SK. Values of RMSE performance test for SK range from 11.7 to 162.3. SK has lower RMSE values from July to October, indicating better performance and predictive accuracy in most months than other two models, although OK performs quite well and often close to SK. Values of RMSE performance test for UK range from 31.5 to 1404. This indicates that UK has the highest RMSE values in nearly all months, suggesting predicted values to have deviated far from observed values, thus a poor fit model. All three models result indicate similar and relatively lower RMSE values from July to October, although SK had best performance than other two models (Figure 7).

Hence, SK could be used as the primary model for rainfall variability in northern coast of Tanzania based on RMSE. OK can serve as a backup in certain months while UK should be used with caution.

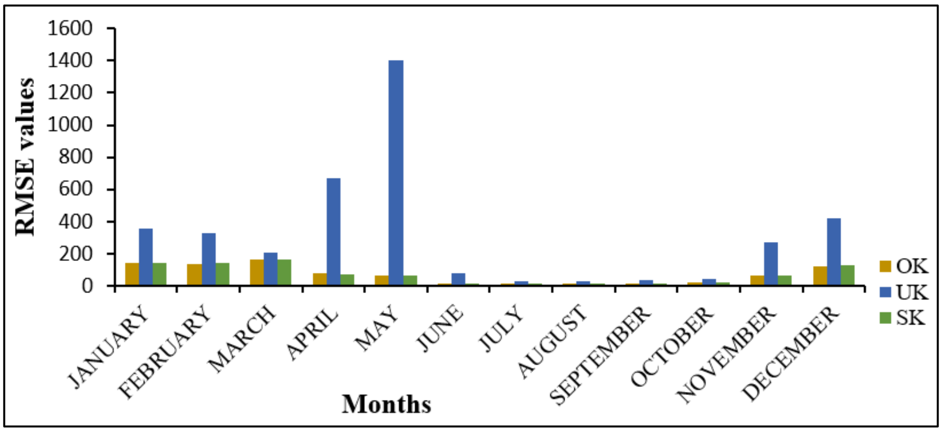


**Figure 7:** Evaluation of models performance using root mean square error

**Evaluation of models performance using root mean square standardized error**

Values of RMSSE performance test for OK range from 0.9 to 1.2 which is an indicator of moderate consistent and balanced model with overall better performance across all months. This model produces more reliable predictions with less overestimation of uncertainty. Worthwhile, SK had the lowest RMSSE values for most months, ranging from 0.6 to 2.1. Exception is observed in December and February which have overestimated variance, indicating poor prediction reliability. Generally, SK has RMSSE values closer to 1, but has two picking values in December and February making it relatively unstable. The UK has the highest RMSSE values across all months ranging from 0.9 to 1.6 indicating overestimates of variability and uncertainty, and less reliable predictor. For modeling rainfall variability along the northern coast of Tanzania, the SK model is likely the most suitable, particularly for months exhibiting stable RMSSE values (Figure 8).

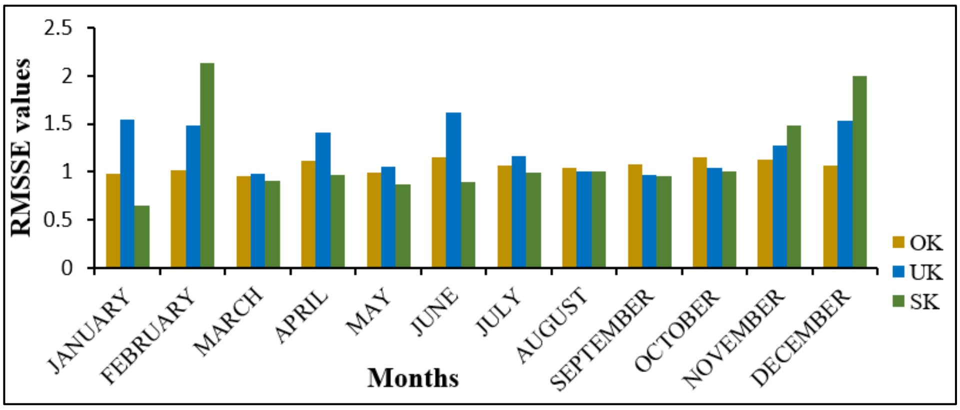


**Figure 8:** Evaluation of models performance using root mean square standardized error

**Evaluation of models performance using average standard error**

Values of ASE performance test for OK range from 11.0 to 164.2. OK show the lowest ASE values in most of months, indicating that it is most consistent and accurate model than SK and UK. Values of ASE performance test for UK range from 40.6 to 1443.6. UK has consistently high ASE values, especially from November to May. This indicates poor performance and high uncertainty in predictions. Values of ASE performance test for SK range from 11.8 to 211.5, indicating better performance better the UK, though still generally lower than OK. However, SK slightly outperforms OK in some months, particular, from August to December. Although SK has good performance, it less consistent than OK (Figure 9). Thus, making OK to be the most suitable model for analyzing rainfall variability in northern coast of Tanzania based on the ASE metric. UK has poor performance and is not recommended due to high ASE values, probably due to over fitting or improper trend modeling. Therefore, OK and SK are more reliable, especially during short-rain seasons from June to October as they offer stable and consistent prediction, while the UK is less suitable because of overestimating uncertainties.

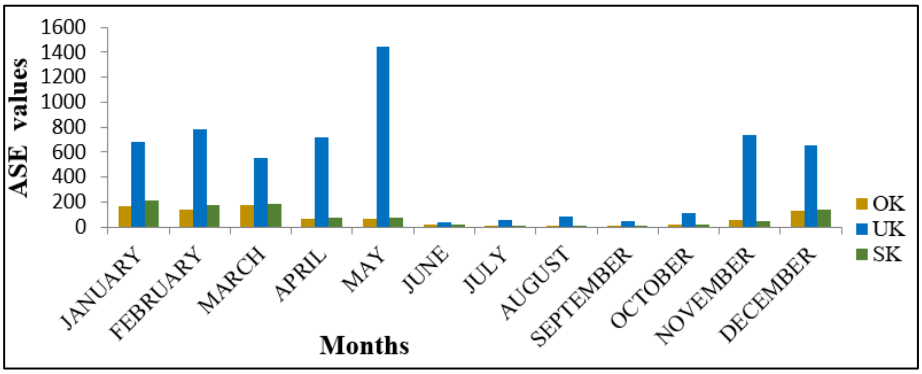


**Figure 9:** Evaluation of models performance using average standard error

**Evaluation of models performance using coefficient of determination**

Based on R², the OK model performs consistently well in both dry and wet seasons, indicating that it is the best-performing model across all weather conditions. SK performs surprisingly well during dry season (February, July and November), indicating that when rainfall is spatially consistent, the SK performance is relatively poor. In January and July, OK and SK perform equally better than the UK model (Figure 10), suggesting that sample mean assumption of SK or local variogram of OK work better than trend modeling of UK. In April, May, and August, all models perform relatively poorly, whereas their performance improves in November. The UK model performs notably better in February and March.

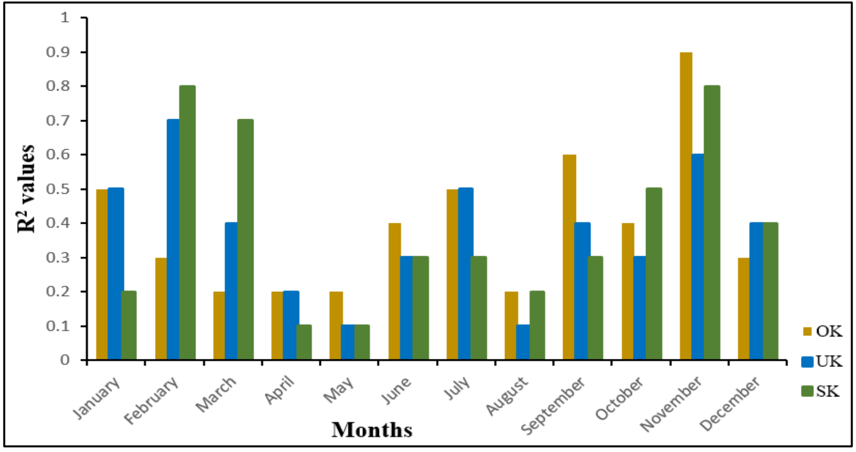


**Figure 10:** Evaluation of models performance using coefficient of determination

The performance of OK, UK, and SK in modeling rainfall variability was assessed through 10-fold cross-validation (Table 2). With ME, OK has smallest standard deviation of 2.27 mm while UK has the largest standard deviation of 50.7 mm. With MSE, OK has smallest standard deviation of 0.02 mm while SK has the largest standard deviation of 0.13 mm. When comparing RMSE, SK has smallest standard deviation of 57.85 mm while UK has the largest standard deviation of 394.07 mm. For RMSSE, OK has smallest standard deviation of 0.1 mm while SK has the largest standard deviation of 0.47 mm. On ASE, OK has smallest standard deviation of 65.38 mm while UK has the largest standard deviation of 434.92 mm. In case of R², SK has smallest standard deviation of 0.19 mm while UK has the largest standard deviation of 0.25 mm. Based on standard deviation measure, OK demonstrated not only higher predictive accuracy but also more stable performance across spatial domains, making it the most reliable method for analyzing rainfall variability.

**Table 2:** Standard deviation across all cross-validation metrics

| Model | ME | MSE | RMSE | RMSSE | ASE | $R^2$ |
|---|---|---|---|---|---|---|
| OK | 2.27 | 0.020 | 58.12 | 0.1 | 65.38 | 0.21 |
| UK | 50.87 | 0.100 | 394.07 | 0.26 | 434.92 | 0.25 |
| SK | 6.67 | 0.130 | 57.85 | 0.47 | 75.15 | 0.19 |

The observed standard deviation of cross-validation metrics offers vital understandings into the reliability and stability of the three Kriging methods evaluated. While the six performance metrics have indicated OK to be more accurate, standard deviation has also shown OK to be more consistency in performance across spatial scale. In modeling rainfall variability, this is particularly vital due to the fundamentally heterogeneous and dynamic nature of rainfall patterns in the northern coast of Tanzania. The results demonstrate that UK not only attained high mean error values in most cross-validation metrics, but also exhibited the largest standard deviation across metrics, demonstrating that its estimates were less stable and insensitive to rainfall variability. In contrast, UK has shown reasonable errors and variability, suggesting medium robustness under varying rainfall conditions. Thus, observed standard deviation scores serves as a significant indicator of OK model reliability, supporting the assumption that OK is better suited for applications in the northern coast of Tanzania.

### Performance comparison of the three models

Comprehensive standards were used in the comparing average values of OK, UK, and SK instead of computing individual months. As indicated in table 3, OK has the smallest absolute values in most of cross-validation metrics used in this study, which means its predictions are closest to unbiased but slightly underestimate rainfall. This suggests OK to be fairly accurate in terms of bias, as the average error is very small. UK has positive absolute values in all metrics used in this study with the smallest MSE value, indicating overestimation bias. This means the UK is consistently predicting higher rainfall values than actual observed values. SK has a positive ME, which also overestimates rainfall but to a lesser extent when compared with UK. OK and UK have smallest negative and positive MSE values, respectively, which are very close to zero. This suggests that the two models have lowest prediction errors and that the two models perform well than SK. Although OK is a comparative best model with an overall $R^2$ of 43%, its percentage is still low, perhaps due to absence of explanatory variables such as topography, wind, humidity, pressure, and temperature which are not integrated in this study.

**Table 3:** Comparative performance of the OK, UK and SK

| Model | ME | MSE | RMSE | RMSSE | ASE | $R^2$ |
|---|---|---|---|---|---|---|
| OK | -1.37 | -0.008 | 70.23 | 1.04 | 67.59 | 0.43 |
| UK | 18.75 | 0.004 | 323.63 | 1.23 | 491.93 | 0.39 |
| SK | 2.32 | -0.019 | 62.43 | 1.14 | 82.23 | 0.38 |

Results in table 3 clearly show that OK is the most suitable model for estimating monthly rainfall in the northern coast of Tanzania. Its superior performance in terms of accuracy and minimal bias reinforces the importance of accounting for local spatial structures rather than relying heavily on deterministic trends, especially in coastal tropical regions with complex climatic influences. Given this spatial and temporal variability, models like OK, which depend on local spatial autocorrelation without requiring a deterministic trend or known mean, perform best in capturing localized rainfall variation. The observed differences in the six cross-validation metrics used in this study play a critical role in determining the practical utility of Kriging methods. OK which has outperformed UK and SK across the six metrics, imply that it is more operational in capturing spatial trends in rainfall, especially when external variables such as distance from coast and elevation are incorporated (Luhunga 2022). With both accuracy and reliability consideration, OK which has less error is essential for a well-informed, risk-sensitive decision-making in rainfall-dependent sectors such as agriculture, tourism, water resources and supply, hydro-electric and energy, forestry, livestock and pastoralism, and floods and disaster management.

The current finding concurs with Ndomeni et al. (2018) who found OK to have outperformed UK in East African coastal zones, where rainfall is patchy and influenced by sea-land interactions rather than large-scale gradients. As well, Ananias et al. (2021) found minimum OK error when predicting the unknown values of daily rainfall because it estimates the data linearly based on weightage from observed data. Also, Vizi et al. (2011) found unfair performance of UK than other Kriging methods in analyzing rainfall (climate variable) in Slovakia. However, in the current study, UK produced fewer good results in the analysis of monthly rainfall for the northern coast of Tanzania. However, results obtained in the northern coast of Tanzania contradict with a study by Zhang (2011) who demonstrated Cok-TRMM model to be more effective at producing a spatial precipitation distribution on the China Tibetan Plateau and performed better than OK.

## Conclusion and Recommendations

All three Kriging methods have revealed spatial and seasonal rainfall variability in northern coast of Tanzania. While OK provides the most consistent results, UK and SK offers useful comparative insights into how external drift and constant means affect rainfall estimation. These results underline the complex nature of rainfall dynamics in tropical coastal environments. It has been established by this study that OK is the most robust and reliable for modeling rainfall variability in the northern coast of Tanzania due to its accuracy, consistency, and minimal bias. Simple Kriging (SK) is a useful secondary method, particularly where spatial consistency is strong. Universal Kriging (UK) is less suitable in this context due to overfitting and poor calibration. Due to sparse weather stations coverage in Tanzania, for operational implementation, TMA should integrate OK in rainfall forecast systems for estimation of rainfall and producing suitable rainfall maps. To improve the accurateness and spatial coverage of rainfall estimations, the TMA must integrate OK with multi-model ensemble approaches and satellite-derived precipitation data in regions with sparse observations. This can minimize uncertainty and increase estimation robustness. Finally, Geostatistical models should be adopted and integrated into TMA's forecasting and early warning system to enhance spatial precision in rainfall prediction.

## References

Ananias DRS, Liska GR, Beijo LA, Liska GJR and Menezes FS 2021 The assessment of annual rainfall field by applying different interpolation methods in the State of Rio Grande do Sul, Brazil. *J. Appl. Sci.* 3(7): DOI:10.1007/s42452-021-04679-1.

Chanda T, Chisebe S, Gilbert M and Mulenga D 2024 Climate change and increasing drought frequency in African countries: A Systematic Analysis. *GSJ* 12: 232-250.

Chang'a L, Mhita M and Ng'ongolo H 2020 Climate change and variability over East Africa. *Clim. Risk Manage.* 28: 100215.

Cisse COT, Brempong EK, Taveneau A, Almar R, Sy BA and Angnuureng DB 2022 Extreme coastal water levels with potential flooding risk at the low-lying Saint Louis historic city, Senegal (West Africa). *J. Front. Mar. Sci.* 9: 993644. https://doi.org/10.3389/fmars.2022.993644.

Coulibaly M, Wade CT and Sylla MB 2020 Rainfall variability and trends in Africa. *Theor. Appl. Clim.* 141: 1-13.

Hu Q, Li Z, Wang L, Huang Y, Wang Y and Li L 2019 Rainfall spatial estimations: A review from spatial interpolation to multi-source data merging. *Water.* 11(3): 579.

Javari M 2017 Spatial monitoring and variability of daily rainfall in Iran. *Int. J. Appl. Environ. Sci.* 12(5): 801.

John, R. (2022). Disaster-induced resettlements: The resilience of flood-affected households in Dar es Salaam, Tanzania. *J. Geog. Environ. Sustain.* 15: 88-98. 10.24057/2071-9388-2021-027.

Joseph JE, Rao KPC, Swai E, Ngwira AR, Rötter RP and Whitbread AM 2021 Analysis of rainfall variability and trends for better climate risk management in the major agro-ecological zones in Tanzania. Working Paper. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Lombe P, Carvalho E and Rosa-Santos P 2024 Drought dynamics in Sub-Saharan Africa: impacts and adaptation strategies. *Sustainability*. 16(22): 9902. https://doi.org/10.3390/su16229902.

Chaqdid A, Tuel A, El Fatimy A and El Moçayd N 2023 Extreme rainfall events in Morocco: Spatial dependence and climate drivers, *J. Weath. and Clim. Extr.* 40, https://doi.org/10.1016/j.wace.2023.100556.

Luhunga PM 2022 Projection of extreme climatic events related to frequency over different regions of Tanzania. *J. Water Clim. Change* 13(3): 1297-1312. https://doi.org/10.2166/wcc.2022.357.

Lungo JH, Msemo E and Kimaro D 2020a Improving rainfall forecasts in Tanzania using advanced WRF parameterization schemes. *Tanzania J. Sci.* 46(1): 45–59.

Mauya EW and Matilya D 2023 Geospatial analysis of flood occurrences in selected sub wards of Morogoro Municipality-Tanzania. *Int. J. Environ. Monit. Anal.* 11(1):15-23, doi: 10.11648/j.ijema.20231101.12.

Mhache EP 2022 Floods recurrence and effects on socio-economic livelihoods of communities in Dar es Salaam region, Tanzania. *J. Meteor. Clim. Sci.* 21(1).

Msemo HE, Taylor AL, Birch CE, Dougill AJ, Hartley A and Woodhams BJ 2021 What do weather disasters cost? An analysis of weather impacts in Tanzania. *J. Front. in Clim.* 3:567162. doi: 10.3389/fclim.2021.567162.

Ndomeni W, Cattani E, Merino A and Levizzani V 2018 An observational study of the variability of East African rainfall with respect to sea surface temperature and soil moisture. *Quart. J. Roy. Meteo. Soc.* 144(710), 2571–2585. https://doi.org/10.1002/qj.3255.

Peterson MJ, Lang TJ, Logan T, Wee Kiong C, Gijben M, Holle R, Kolmasova I, Marisaldi M, Montanya J and Pawar SD 2022 New WMO certified megaflash lightning extremes for flash distance and duration recorded from space. *Bull. Amer. Meteor. Soc.* 103(4): 257–261.

Olanrewaju CC, Chitakira M, Olanrewaju OO and Louw E 2019 Impacts of flood disasters in Nigeria: A critical evaluation of health implications and management. *J. Disaster. Risk. Studies.* 11(1). https://doi.org/10.4102/jamba.v11i1.557

Ringo J, Sabai S and Mahenge A 2024 The status of response to the flood early warnings in Kilosa district, Tanzania. *Int. J. Disaster. Risk Reduct.* 113: https://doi.org/10.1016/j.ijdrr.2024.104838.

Tanarhte M, De Vries AJ, Zittis G and Chfadi T 2024 Severe droughts in North Africa: A review of drivers, impacts and management. *Earth Sci. Rev.* 250(4): https://doi.org/10.1016/j.earscirev.2024.104701.

Taye TM and Dyer E 2024 Hydrological extremes in a changing climate: A review of extremes in East Africa. *Curr. Clim. Change Rep*. 10: 1-11. https: doi.org/10.1007/s40641-024-00193-9.

Tefera ML, Seddaiu G, Carletti A and Awada H 2024 Rainfall variability and drought in West Africa: Challenges and implications for rain-fed agriculture. *J. Theor. Appl. Climatol.* 156(1): 41.

Vizi L, Hlásny T, Farda A, Stepanek P, Skalák P and Sitková Z 2011 Geostatistical modeling of high resolution climate change scenario data. *Idoejaras.* 115(1-2): 71-85.

Zhang Y 2011 Introduction to geostatistics, course notes. Department of Geology & Geophysics, University of Wyoming.