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Evaluating Weather Research and Forecasting Model in Simulating March-May Rainfall in Tanzania: Implications of Selecting Parameterization Schemes

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Keywords

Seasonal rainfall; Numerical weather prediction; WRF model; Cumulus scheme; Microphysics scheme

Abstract

The current study evaluates the performance of the Weather Research and Forecasting (WRF) model in simulating seasonal rains of March-May (MAM) in Tanzania, based on the implication of selecting parameterization scheme combinations. The model was configured into two domains with horizontal resolutions of 36 km and 12 km and the initial and lateral boundary conditions were provided by the Climate Forecast System Version 2 at 00 UTC. However, only the inner domain of 12 km was used for analysis, which has a fine horizontal resolution that accounts for small scale features such as terrains. Twelve simulations have been performed using four Cumulus and three Microphysics schemes to determine the best scheme combination for MAM seasonal rainfall. The model outputs were compared with the Climate Hazards Group InfraRed Precipitation with Station and gauged rainfall data. The performance of the model in simulating MAM seasonal rainfall was analyzed using standard statistical measures and ranking transformation analysis. The results indicated that Grell-Freitas (GFE) and Betts-Miller-Janjic (BMJ) cumulus schemes when combined with the WRF Double Moment 6 (WDM6) class microphysics scheme performed reasonably better in simulating MAM seasonal rainfall in Tanzania. Moreover, the combination of New Tiedtke (TDK) cumulus and Kessler (KSS) microphysics was found to be the less accurate combination among all. Therefore, in improving operational seasonal prediction in Tanzania and increase the confidence of the forecast, the study recommends that GFE-WDM6 and BMJ-WDM6 scheme combinations should be used for operational forecasting of MAM seasonal rainfall.

Introduction

The seasonal rainfall forecast is an essential source of information for planning of end users' socio-economic activities such as agriculture, construction, hydrology, industries, hydropower production and many others. It is also useful for early warning concerning natural disaster caused by less or more rainfall such as drought and flood. Seasonal forecasting is the prediction of future average weather conditions of a particular region at monthly interval (Stockdale et al. 2010). It concentrates on providing the users with a general idea on how the expected season may behave and generally covers a period of three months. (Harrison et al. 2007).

The main approaches for seasonal rainfall forecasting can be categorized as statistical and dynamical models (Schepen et al. 2012).

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However, statistical models often employ linear regression, time series analysis and canonical correlation analysis based on historical data and this approach has been used since late 1800s (Troccoli 2010). Dynamical models, sometimes known as Numerical Weather Prediction (NWP) models, are the models that forecast the future of atmospheric conditions by using a system of dynamical equations to describe the fluid flows. (Stensrud 2007, Hirani and Mishra 2016). Although, there are several NWP models, this study adopts the use of the Weather Research and Forecasting model (WRF) to simulate the March-May seasonal rainfall in Tanzania. The WRF model is based on a set of nonlinear partial differential equations (PDEs) derived from the physical laws that govern the motion of the atmosphere.

The WRF model as other NWP models depend on the physical parameterizations process (Li et al. 2014). Physical parameterization is a process by which physical processes that cannot be resolved explicitly by a numerical model are represented in a simplified process (Stensrud 2007). Commonly parameterized processes include radiations, clouds generation, turbulence mixing and exchange, evaporation, condensation and among others. These processes are typically too complex, too small in scale, or insufficiently understood to be represented explicitly in numerical models (Warner 2011). Nevertheless, accurately representing these processes through parameterization is essential for the overall performance and realism of NWP models (Stensrud 2007).

The WRF model has several physical parameterization schemes options categorized into five main group. These include microphysics schemes, cumulus schemes, planetary boundary layer schemes, land-surface model schemes, long and short-wave radiation schemes (Skamarock et al. 2019). However, the choice of these physical parameterizations depends on the region, seasons, spatial and temporal resolutions or nature of the weather phenomena of the region (Warner 2011). Consequently, the suitable model setting for one region might not work properly for another region (Kondowe and Aniskina 2015).

In Tanzania, there are relative few studies that have been conducted using WRF model. For example, Kondowe and Aniskina (2015) assessed the performance of different WRF model physical parameterization schemes on the quality of the forecast of meteorological variables over Tanzania, and found that Purdue Lin microphysics, Grell 3d cumulus and Asymmetric Convective Model planetary boundary scheme performs better for April rainfall prediction over the coastal areas of the Indian Ocean. Ngailo et al. (2018) evaluated the skills of physical Parameterization schemes in simulating extreme rainfall events in Dar es Salaam, Tanzania using WRF model and concluding that, the combination of Kain-Fritsch cumulus scheme, Lin microphysics scheme and Asymmetric Convection Model 2 planetary boundary layer scheme performed better than any other combinations. Lungo et al. (2020), studied the sensitivity of the WRF model in Simulating extreme events during wet and dry seasons over Tanzania and discovered that, the combination of Lin et al microphysics and multi-scale Kain-Fritch cumulus schemes has high skills during the wet and dry seasons. Most of these studies focused on simulation of the weather patterns that were associated with specific meteorological phenomena or extreme events like heavy rainfall. However, most of them have concentrated on short time scales and small area coverage with two or more parameterization scheme combinations. Notably, none of these studies have attempted to simulate seasonal rainfall forecast using various parameterization scheme combinations across the entire country. Therefore, this study, aims to investigate and identify the performance of various parameterization scheme combinations on a longer period of up to seasonal time scale and spatial areal coverage over entire country.

Materials and Methods

Study Area

The study area covers the entire country of Tanzania which contains an area of 947,303 square km and located within latitudes 1ºS - 12ºS and longitudes 29ºE - 40ºE. It lies between large water bodies like Lake Tanganyika to the west, Lake Victoria to the north, Lake Nyasa to the south and Indian Ocean to the East. The countries experience two types of rainfall regimes; those are bimodal and unimodal rainfall regimes. The bimodal rainfall regime is described by two types of rainfall seasons identified as long rain season spanning from March to May (MAM) and short rain season lasting from October to December (OND). On the other hand, unimodal rainfall regime characterized only one extended rain season and occurs from November to May (NDJFMA) (Nyenzi 1992, Basalirwa et al 1999).

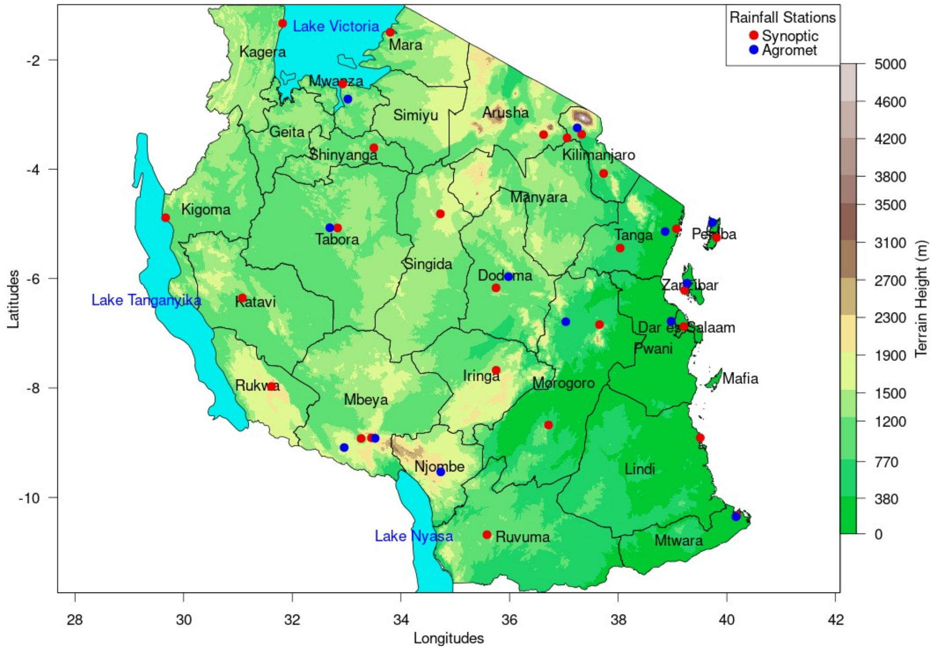

Figure 1: A map of Tanzania showing topography and distribution of rainfall stations.

Data used

The WRF model requires meteorological variables including moisture, temperature, pressure and winds for initial and boundary conditions. In this study, the forecast data from National Centers for Environmental Prediction (NCEP) Climate Forecast System Version 2 (CFSv2) at 00 UTC were used to provide the initial and boundary conditions for the model. The gauge rainfall data for MAM 2018 was retrieved from the Tanzania Meteorological Authority (TMA), while satellite-based rainfall estimates were sourced from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset, which has a spatial resolution of 0.05° × 0.05° (Funk et al., 2015).

Model Configuration

The domain of the study was created by using Domain Wizard tool with a Mercator map projection option at a fixed grid ratio of 1:3. It was projected with 35 vertical sigma levels whereas 50 hPa was set at the top of the model. The model domain configuration is shown in Figure 2 below, where the outer domain was set at 36 Km horizontal resolution and inner domain which is a study area was set at 12 km resolution. The outer domain was set up with 277 x 253 grid points, which was enough to cover most parts of Africa with some main ocean areas, while the inner domain was set up with 274 x 211 grid points.

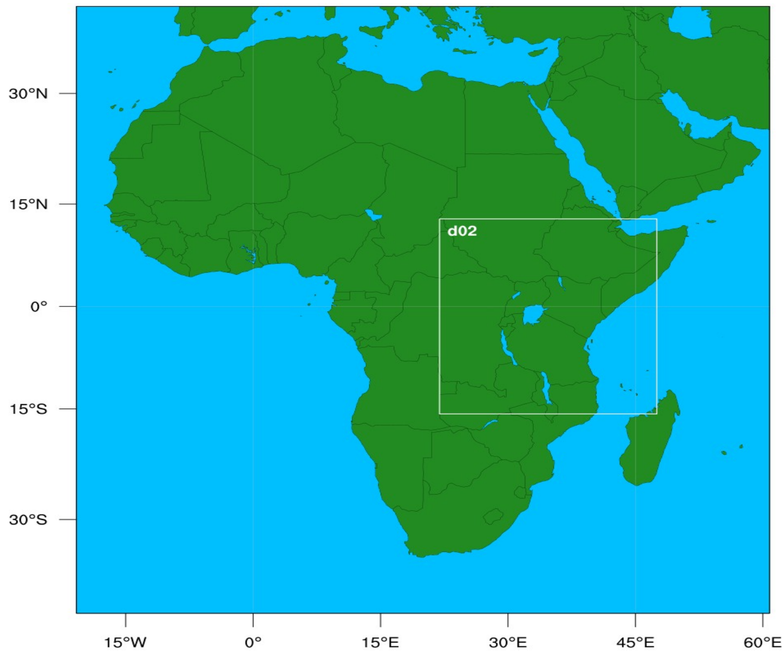

Figure 2: Domain configuration used for model simulations

This study involved the simulations of MAM seasonal rainfall over Tanzania using Advanced Research solver of the non-hydrostatic WRF model version 4.2. The simulations were carried out from 28th February up to 1st June 2018 before and after the period of interest in order to guarantee time for model spin-up and model stability. CFSv2 data at 0000UTC was used as the Initial and boundary conditions which updated after every 6-hours. The top of the model was kept at a constant pressure surface with a terrain following dry hydrostatic pressure vertical coordinate. The horizontal grid format handled by Arakawa C grid staggering with 5th order advection option for spatial discretization was implemented. Runge-Kutta 3rd order time-split integration scheme was employed for time integration throughout the simulations (Skamarock et al., 2008). All these settings were kept constant throughout the simulation.

For parameterization schemes, all model settings were held constant except for the cumulus and microphysics schemes which were parameterized. Twelve possible WRF model simulations were set up with twelve different combinations of four cumulus and three microphysics schemes. The selected cumulus and microphysics schemes used are summarized as follows:

(i). Betts, Miller and Janjic (BMJ) Cumulus scheme:

The BMJ scheme (Janjic 1994, 2000) is a convective adjustment type of scheme, where vertical profiles of temperature and moisture are adjusted until stability is attained. The scheme comprises a deep and shallow convective profile as well as adjustment time. (Skamarock et al. 2008). There is no explicit downdraft or updraft as well as no cloud detrainment exists (Betts and Miller 1986 and Janjic 1994).

(ii). Grell-Freitas (GFE) Cumulus Scheme:

(iii). The Grell-Freitas scheme (Grell and Freitas 2014) is a conventional mass flux adjustment scheme which takes into account a stochastic approach to cumulus convection. It has been improved to operate across grid sizes ranging from mesoscale to convective scales (Skamarock et al. 2019). Low level vertical velocity, moisture convergence or convective available potential energy (CAPE) is used as a closure assumption (Flaounas et al. 2011).

(iv). Multi-Scale Kain-Fritsch (MsKF) Cumulus Scheme:

(v). The Multi-Scale Kain-Frisch (Zheng et al. 2016) scheme is a conventional mass flux scheme that was modified in order to be used when the grid-size decreases from the mesoscale to convective scales. The key modification includes an adjustment time scale for CAPE removal and scale-dependent lifting condensation level-based entrainment. Also, the scheme includes improved grid-scale vertical motion using sub grid scale updraft mass fluxes.

(vi). New Tiedtke (TDK) Cumulus Scheme:

(vii). This is a mass flux adjustment scheme which based on the modification of the Tiedtke scheme. The upgrades from original Tiedtke involves the trigger functions for deep and shallow convection, convective adjustment time scale, closures for deep and shallow convection. Similarly, the entrainment and detrainment rates for all types of convection, conversion from cloud water/ice to rain/snow and options for momentum transport where modified (Skamarock et al. 2019).

(i). Kessler (KSS) Microphysics scheme:

Kessler scheme (Kessler 1969, 1995) is a simple warm cloud single moment scheme that includes only water vapor, cloud water and rain. It involves the processes of the production, fall and evaporation of rain, accretion and auto-conversion of cloud water and production of cloud water from condensation (Wicker and Wilhelmson 1995, Skamarock et al. 2008).

(ii). Purdue Lin et al (Lin) Microphysics scheme:

Purdue Lin et al scheme (Lin et al. 1983) is a mixed-phase single moment scheme, which comprises the mixing ratios of 6 class moisture variables. The moisture variables can be in form of water vapor, cloud water, rain water, cloud ice, snow and graupel as a prognostic variable. It takes into account mixed-phase microphysics where ice and water particles interact.

(iii). WRF Double Moment 6 class (WDM6) Microphysics scheme:

This is a double moment scheme that involves both mixing ratios and number concentrations for different water species. The mixing ratios include water vapor, cloud water, rain, snow, ice and graupel. Also, the scheme consists the number concentrations of rain and cloud water, together with Cloud Condensation Nuclei (CCN) (Hong and Lim 2010).

Lastly, for each simulation that conducted termed as a combination of cumulus and microphysics schemes. Twelve possible different combinations of the cumulus parameterization scheme (CPS) and microphysics parameterization scheme (MPS) and their acronyms that used in the study were summarized in the Table 1.

Table 1: Summary of the selected combinations for CPS and MPS schemes with their acronyms.

No.	CPS name	MPS name	CPS acronym	MPS acronym	Combination Acronym
1.	Multi-Scale Kain-Fritsch	Kessler	MKF	KSS	MKF-KSS
2.	Betts-Miller-Janjic	Kessler	BMJ	KSS	MBJ-KSS
3.	Grell-Freitas	Kessler	GFE	KSS	GFE-KSS
4.	New Tiedtke	Kessler	TDK	KSS	TDK-KSS
5.	Multi-Scale Kain-Fritsch	Purdue Lin	MKF	LIN	MKF-LIN
6.	Betts-Miller-Janjic	Purdue Lin	BMJ	LIN	BMJ-LIN
7.	Grell-Freitas	Purdue Lin	GFE	LIN	GFE-LIN
8.	New Tiedtke	Purdue Lin	TDK	LIN	TDK-LIN
9.	Multi-Scale Kain-Fritsch	WRF Double Moment 6	MKF	WDM6	MKF-WDM6
10.	Betts-Miller-Janjic	WRF Double Moment 6	BMJ	WDM6	BMJ-WDM6
11.	Grell-Freitas	WRF Double Moment 6	GFE	WDM6	GFE-WDM6
12.	New Tiedtke	WRF Double Moment 6	TDK	WDM6	TDK-WDM6

Methods Used:

The model's outputs from WRF simulations were compared with CHIRPS and observed gauge stations data to evaluate the model's performance. From March to May 2018, the spatial pattern of each simulation was compared to CHIRPS data in a spatial map. In other side, the interpolated WRF model data output at various cumulus and microphysics scheme combinations with observing gauge stations data were used for statistical forecast evaluation. These statistical measures include Mean Bias Error (MBE), Root Mean Square Error (RMSE) and the Pearson Correlation Coefficient (CORR). Each measure briefly summaries as follows: -

MBE gives direction and indicates whether the forecast values underforecast or overforecast the magnitude of the observed values but may not consider the magnitude of the forecast error. A negative bias (Bias <1) indicates underforecast of the model while the positive bias (Bias >1) indicates overforecast and zero bias (Bias = 0) indicates an unbiased forecast exists (Stanski et al. 1989, Wilks 2011). MBE calculated mathematically as presented in the equation below;

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(F_i - O_i) \qquad (1)$$

RMSE used to calculate the differences between the values forecasted by a model and the actual observation over the entire period of seasons under consideration. It ranges from 0 to ∞ with optimal value at 0 (Wilks, 2006). RMSE calculated mathematically as shown in equation below;

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2} \qquad (2)$$

For easier interpretation, MBE and RMSE, were normalized by the long-term mean (LTM) of the observed MAM seasonal rainfall.

Pearson Correlation Coefficient indicates the association of the forecast to the observation. A high (low) correlation coefficients value indicates a strong (weak) association between forecasts and observations. The coefficient ranges −1 and +1 (Wilks 2011) and is calculated mathematically as follows;

$$CORR = \frac{N(\sum_{i=1}^{N} F_i O_i) - (\sum_{i=1}^{N} F_i)(\sum_{i=1}^{N} O_i)}{\sqrt{\left[N(\sum_{i=1}^{N} O_i^2) - (\sum_{i=1}^{N} O_i)^2\right]}\sqrt{\left[N(\sum_{i=1}^{N} F_i^2) - (\sum_{i=1}^{N} F_i)^2\right]}} \qquad (3)$$

Where F_i is the forecast value, O_i is the observed values and N is the total number of forecast or observation.

Rank Transformation

In order to find the overall best and worst CPs and MPs schemes combinations, each model simulation was ranked according to the statistical measures that are explained above. In this study, a simple rank transformation technique was used. The rank transformation refers to the substitution of the data by their ranks, or average ranks in the event of ties, prior to performing standard statistical procedures on the ranks. There are various ways of transforming the data into ranks, but the present study used RT-1 simple rank transformation. The method is based on the comparison of the magnitude of the measures such as MBE and RMSE. Finally, the best and worst model performance for CPs and MPs scheme combinations are recommended depending on the combined rank for each statistical measure ranked.

Results

This part presents results obtained from various approaches, in particular, spatial analysis performed using WRF simulated outputs that were compared against CHIRPS data. Other approaches included Pearson's correlation coefficient, mean bias error, root mean square error and ranking transformation. All analyses were performed based on the simulation outputs from the inner domain of the WRF model at 12 km grid resolution.

Figures (3a - 3m) depict the March 2018 rainfall distributions based on the CHIRPS climatology and WRF model simulation runs. The CHIRPS climatology spatial map for March shows that different amounts of rainfall were received in different areas in Tanzania. According to CHIRPS data, areas across Lake Victoria Basin (LVB), the southern and the western parts of the country experienced rainfall ranging from 170 mm to 250 mm during the month of March. In addition, some locations in central, North-Eastern Highland (NEH) and Northern Coast (NC) received rainfall ranging from 70mm to 150mm. Furthermore, the southern and western parts of the country received significantly higher rainfall amounts in March than in the rest of the country.

However, when compared with CHIRPS climatology, the BMJ-KSS and GFE-KSS underestimated the rainfall over the entire country except over the coastal areas towards southern part where they captured well the simulated pattern. The MKF-KSS captured rainfall well over

LVB and southern part, but underestimated rainfall in other areas of the country. The TDK-KSS underestimated rainfall in most areas. This scheme combination showed poor performance among all the scheme combinations. The BMJ-LIN and BMJ-WDM6 captured simulated rainfall well over the LVB, South Western Highland (SWH), southern and western parts of the country. It overestimated rainfall over central, NC and NEH. The TDK-LIN, TDK-WDM6, MKF-LIN, MKFWDM6, GFE-LIN and GFE-WDM6 captured rainfall well over most part of the country but underestimated it over SWH, West (W) and southern part. These combinations overestimated rainfall over NC and NEH.

In general, the BMJ-LIN, BMJ-WDM6 TDK-LIN, TDK-WDM6, MKF-LIN, MKFWDM6, GFE-LIN and GFE-WDM6 overestimated and mis-located the March rainfall simulation. Also, the BMJ-KSS, GFE-KSS, MKF-KSS and TDK-KSS underestimated the simulation rainfall in most parts of the country. BMJ-WDM6 and BMJ-LIN attempted to capture well the rainfall simulations during the month of March. The Poor performances were shown by the BMJ-KSS, TDK-KSS and GFE-KSS which dried up in most parts of the country.

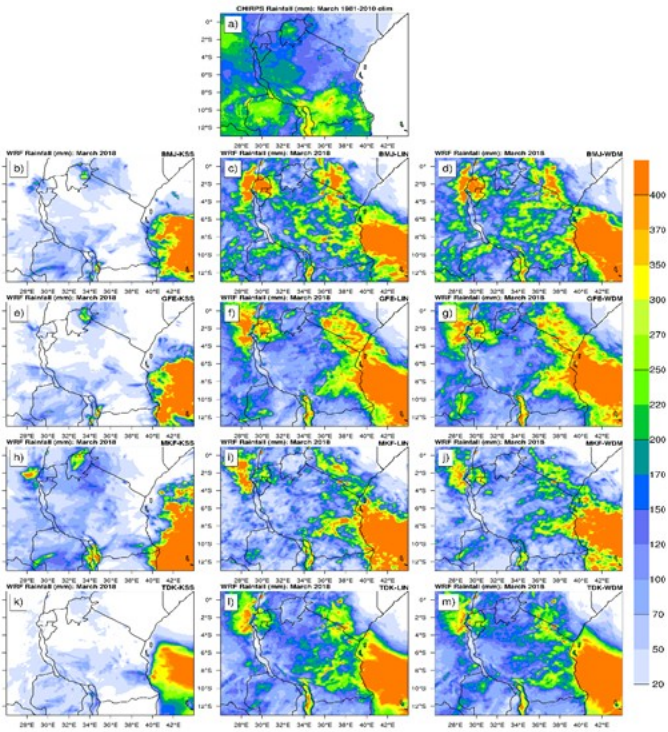

Figure 3: Spatial distribution for simulated March rainfall with various scheme combinations.

Figures (4a - 4m) illustrate the April 2018 rainfall distributions based on the CHIRPS climatology and WRF model simulation runs. The CHIRPS climatology spatial map for the month of April shows that different amounts of rainfall were received in different areas of Tanzania. From CHIRPS observation, the rainfall in April varied from 80 mm to 250 mm and above in all parts of the country except at the central parts, where it varied from 0 to 70 mm.

Conversely, when compared with CHIRPS climatology, the BMJ-KSS and GFE-KSS were able to capture well the rainfall patterns for the month of April in the coastal and southern parts. In other parts of the country, the scheme combinations underestimated the April rainfall. The MKF-KSS underestimated rainfall over LVB, NEH, NC towards central areas while overestimated rainfall in other parts of the country. This combination performs differently when compared with other combinations in April rainfall pattern. The BMJ-LIN and BMJ-WDM6 performs well over most part of the country although it underestimated rainfall over NEH and some parts of NC of the country. The GFE-LIN and GFE-WDM6 perform well over coastal areas toward southern part. It underestimated rainfall over NEH, SWH, LVB, central and western part of the country.

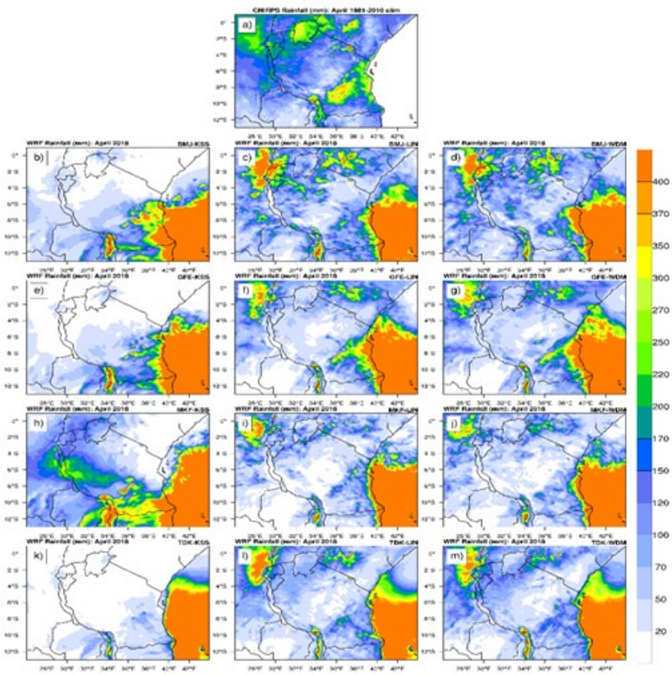

Figure 4: Spatial distribution for simulated April rainfall with various scheme combinations.

The MKF-LIN, MKF-WDM6, TDK-LIN and TDK-WDM6 attempt to capture the rainfall over LVB, towards West of the country and coastal areas towards southern part of the country. These combinations underestimated rainfall over NEH, central and SWH. TDK-KSS underestimated rainfall over most parts of the country. The GFE-WDM6 and GFE-KSS underestimated rainfall over most parts of the country. The BMJ-LIN, BMJ-WDM6 and TDK-WDM6 effectively captured well the rainfall pattern for the month of April from the coast to the southern areas of the country.

On the other hand, the TDK-KSS, BMJ-KSS and GFE-KSS showed poor performances for the entire country as compared to the CHIRPS. The MKF-KSS attempted to overestimate and mis-locate the rainfall simulation for April. The GFE-LIN, MKFLIN, MKF-WDM6, TDK-LIN and GFE-WDM6 underestimated the rainfall simulation. Scheme combinations such as TDK-WDM6, BMJ- WDM6 and BMJ-LIN were able to capture rainfall pattern for the month of April more effectively.

Figures (5a - 5m) represent the May 2018 rainfall distributions based on the CHIRPS climatology and WRF model simulation runs. The CHIRPS climatology spatial map for May shows different amounts of rainfall were received in different areas in Tanzania. The rainfall for the month of May varied from 70 mm to 250 mm in all parts of LVB, NHE, the entire coast and the western part of the country as per CHIRPS data. Other areas of the country, experienced rainfall totals of less than 70 mm.

BMJ-KSS and GFE-KSS overestimated rainfall over entire coastal towards southern part while underestimated rainfall over other areas of the country in month of May. MKF-KSS overestimated rainfall over entire coast, southern part, SWH toward W whereas in the LVB, some parts of central and NEH was clearly underestimated. These combinations underestimated rainfall over LVB and NEH. The MKF-LIN, TDK-LIN, MKF-WDM6, TDK-WDM6 and TDK-KSS combinations clearly underestimated rainfall over most parts of the country, whereas in the coastal areas were overestimated. These combinations captured rainfall well over the central areas. The BMJ-LIN, BMJWDM6, GFE-LIN and GFE-WDM6 attempted to capture the rainfall patterns well along the coast and in the east of the LVB, southern and central areas. Furthermore, rainfall in the west of the LVB, W and SWH was underestimated in these scheme combinations.

The poor performances were shown by BMJ-KSS, TDK-KSS, MKF-KSS and GFE-KSS scheme combinations. The GFE-KSS, MKF-KSS, and BMJ-KSS overestimated rainfall simulation in May. The MKF-LIN, MKF-WDM6, TDK-LIN and TDK- WDM6, underestimated the rainfall. The BMJ-LIN, BMJ-WDM6, GFE-LIN and GFE-WDM6 performed better as compared to other scheme combinations during May.

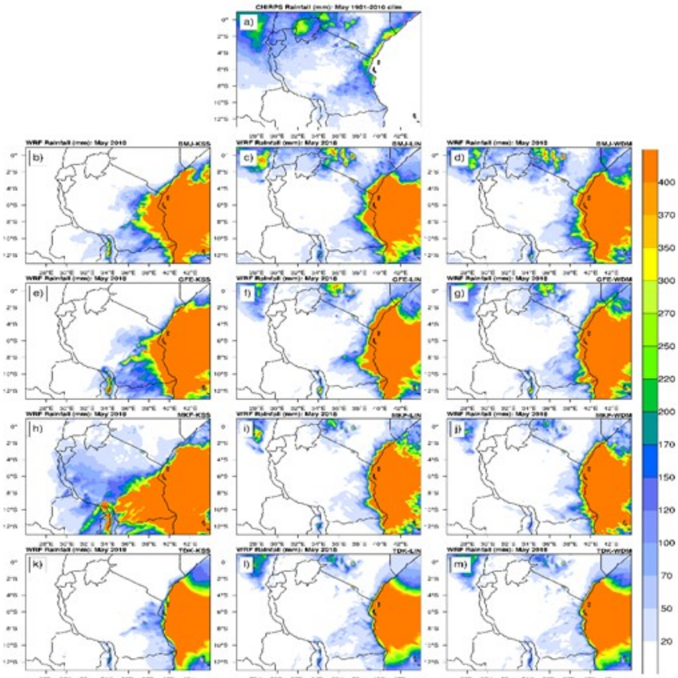

Figure 5: Spatial distribution for simulated May rainfall with various scheme combinations.

Figures (6a - 6m) depict the MAM 2018 seasonal rainfall distribution based on CHIRPS climatology and WRF model simulation. The CHIRPS climatology spatial Map, shows that different amounts of MAM rainfall were received in different areas in Tanzania. Although rainfall amounts of 50 mm to 500 mm dominated the areas, the overall rainfall amount received during this period ranged from 20 mm to 700 mm and above. There were places that received rainfall in the range of 200 mm to 700mm and above, mostly evident in the LVB, coastal areas, NEH, SWH, western and southern parts. In contrast, there were several areas in central, NEH, SWH and Songea that got rainfall ranging from 20 mm to 300 mm. In comparison to the other regions, the western side of LVB, NEH, SWH and coastal areas received significantly higher rainfall amounts.

In comparison to CHIRPS climatology as explained above, simulations conducted by BMJ-KSS and GFE-KSS forecasted well MAM seasonal rainfall over central areas but overestimated over entire coast towards Morogoro and Lake Nyasa. These combinations were underestimated rainfall in other areas of the country. Simulations done by BMJ- LIN and BMJ-WDM6 somehow resemble each other. Both simulations use the same cumulus scheme (BMJ) but different microphysics scheme (LIN and WDM6) which simulate rainfall over most parts of the country but underestimate rainfall over LVB and some areas of the southern part. They overestimate the amount of rainfall over the entire coastal and central areas. Simulations performed by GFE-LIN and GFE-WDM6 also somehow resemble each other. Both simulations use the same GFE cumulus but different microphysics (LIN and WDM6) which underestimate rainfall over most parts of the country. However, it overestimates the rainfall amounts over the entire coastal areas towards Morogoro and the southern part. These combinations somehow perform well over the central areas.

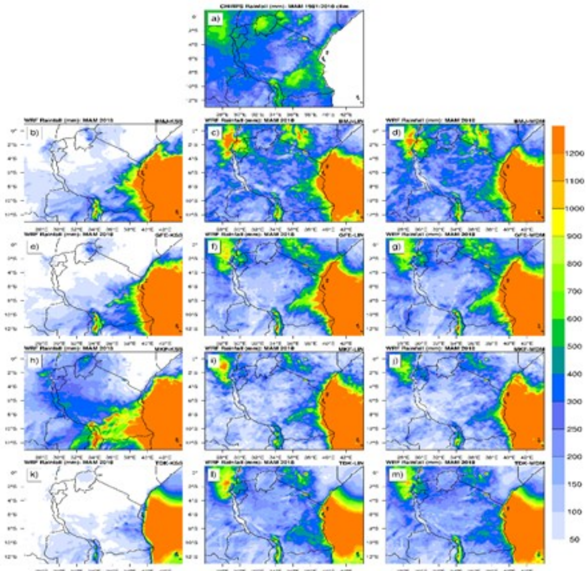

Figure 6: Spatial distribution for simulated MAM rainfall with various scheme combinations.

The simulations of MKF-LIN and MKF-WDM6 are seemed to be similar with the simulations of the TDK-LIN and TDK-WDM6. These scheme combinations attempted to capture the rainfall in the Coastal areas, Morogoro region, Lake Nyasa, parts of the NEH and central areas. These combinations underestimated rainfall over most areas of the country but overestimated it over the entire Coastal belt. The MKF-KSS combination resulted in a unique simulation that differs from others and was mostly seen in the central, coastal areas toward the south and western part of the country. The combination overestimated rainfall over the coast toward the southern part of the country and underestimated it over LVB, W and NEH. The TDK-KSS was apparently found to unable to reasonably capture MAM seasonal rainfall at all. So, this scheme was clearly observed to perform poorer in the simulation of rainfall as compared to the CHIRPS climatology data. It underestimated significantly the rainfall amount throughout the country with the exception of the coastal zone which overestimated rainfall.

In general, the worst simulations were shown by the scheme combinations of TKD-KSS, BMJ-KSS GFE-KSS and MKF- LIN with less rainfall captured. The MKFWDM6, GFE-LIN, TDK-WDM6, TDK-LIN and GFE-WDM6 underestimated the MAM rainfall simulation. The MKF-KSS overestimated the MAM rainfall simulation especially over the coastal areas to the southern part of the country. However, all of the scheme combinations captured effectively the MAM seasonal rainfall over the central area of the country. As a result, when compared to other scheme combinations, the BMJ-LIN and BMJ-WDM6 scheme combinations followed by GFE-LIN and GFE-WDM6 provided the best MAM seasonal rainfall simulation over Tanzania.

The overall results from spatial distribution show that the BMJ-WDM6 and BMJ-LIN scheme combinations tend to capture the MAM rainfall simulation quite well. This can be due to the fact that, the BMJ scheme involves the adjustment of the lapse rates of moisture and temperature due to moist and dry convection. It does better when there is weaker convective available potential energy. This means that the scheme reduces or removes the conditional instability of the atmosphere by adjusting moisture and temperature. If the atmosphere does not have enough moisture, the scheme will probably not work properly. In addition, the scheme describes the change in total moisture at each layer in the column but it does not describe the vertical moisture flux or entrainment within the convective profile. As a result, the BMJ cumulus scheme is primarily based on convection strength which is highly dependent on total moisture. This implies that the greater the amount of moisture in the atmosphere, the stronger the convection is.

Contrarily, the worst simulations were shown by the TDK-KSS, BMJ-KSS, and GFE-KSS combinations. The other scheme combinations either underestimate or overestimate the rainfall simulation. The MKF, TDK and GFE cumulus schemes depend on strong convection influenced by the availability of heat and moisture with stronger convective available potential energy. Due to the MAM rainfall mechanism, which requires little convection of heat and moisture with a weaker convective available potential energy, these schemes did not perform well.

The MKF cumulus scheme considers moist updrafts and downdrafts within a parcel of air and the removal of CAPE in a grid column within a convective time scale. It is triggered when the temperature of an air parcel at its lifting condensation level is higher than the temperature of the surrounding air. In most cases, this scheme works well in severe convective situations. The TDK cumulus scheme performs poorly for the reason that the scheme was developed to provide a practical scheme for global climate forecast models. The GFE cumulus scheme is a scale awareness scheme, despite the fact that it is dependent on vertical heat, low level moisture transport and atmospheric instability. Its modification to be used when the grid-size decreases from the mesoscale to convective scales favor it in attempting to capture a rainfall simulation.

Regardless of the poor performance with the BMJ cumulus scheme which tends to capture well the rainfall simulation in the MAM season, the KSS microphysics scheme still shows poor performance with TDK and GFE cumulus schemes. In this case, the KSS microphysics scheme, which has only three moisture variables compared to the LIN and WDM6 schemes, could be the source of the error. Both LIN and WDM6 microphysics schemes contain 6 moisture variables and attempt to perform well when combined with the BMJ, TDK and GFE cumulus scheme.

Furthermore, spatial distribution shows that switching from a simple microphysics simulation to a more sophisticated microphysics simulation had a visible impact on the distribution of rainfall during the MAM rainfall. Moisture variables such as water vapor, cloud water, rain water, cloud ice, snow and graupel are included in the LIN and WDM6 microphysics schemes. In addition, the WDM6 microphysics scheme calculates the number concentration of rain and cloud water variables with cloud condensation nuclei which contribute to cloud development. Because of the dynamic interaction of various moisture variables within these schemes, they outperform the KSS microphysics scheme. The KSS microphysics scheme includes only water vapor, cloud water and rain with no ice phase. As a result, the BMJ-WDM6 and BMJ-LIN scheme combinations tend to capture the MAM rainfall simulation well in terms of spatial distribution.

Figure (7a - 7l) illustrates the rainfall spatial bias for all scheme combinations used in simulating the MAM 2018 seasonal rainfall from the WRF model. This part examined the differences between the model simulation results and the CHIRPS climatology data. The results demonstrated that the BMJ-LIN and BMJ-WDM6 combinations have homogeneous spatial biases. It shows a moderate to high negative bias towards the Southern Region (SR), SWH, LVB and western parts of the country. A low to high positive bias was observed over coastal areas extending to the central, NEH and the few areas around LVB. It means that the model slight to moderate underestimated MAM seasonal rainfall over SR, SWH, LVB and western parts of the country while overestimating the MAM seasonal rainfall over other areas in the country.

Likewise, the GFE-LIN and GFE-WDM6 combinations produced similar spatial biases. It exhibits a low to high negative bias in some areas of the LVB, SWH, SR, NEH, W and central. coastal regions, as well as a few areas in the NEH and central regions, experienced low to high positive biases. It implies that the model overestimated MAM seasonal rainfall over coastal regions, NEH and central regions but underestimated the rainfall over other areas in the country. However, the BMJ-LIN, BMJ-WDM6, GFE-LIN and GFE-WDM6 combinations show good performance as likened to what was observed.

The BMJ-KSS and GFE-KSS scheme combinations experienced moderate to high negative bias over the SWH, SR, NEH, and LVB while low to moderate over some parts of the central areas. The positive bias is clearly visible along the coast and in a few areas around the central part. These combinations show that it underestimates MAM seasonal rainfall over SWH, SR, NEH, LVB, and central areas while overestimating the rains over the coastal belt and few areas around the central part of the country. The MKF-KSS combination indicated a low to moderate negative bias over the central extending to the northern parts of the country. However, the coastal and southern parts of the country experienced the highest positive bias. Generally, BMJ-KSS, GFE-KSS and MKF-KSS scheme combinations perform poor as compared to the observed MAM 2018 seasonal rainfall.

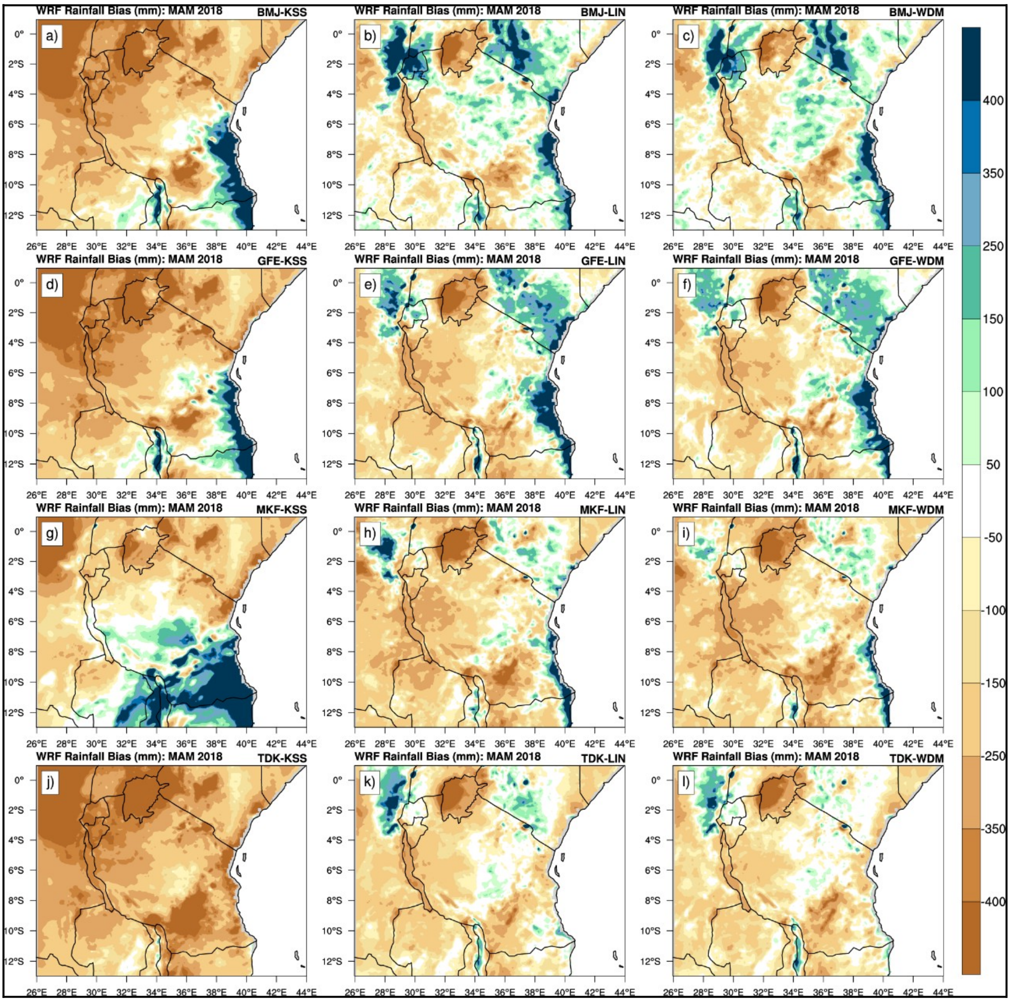

Figure 7: Spatial bias for simulated MAM rainfall with various combinations.

The MKF-LIN and MKF-WDM6 combinations show a low to high positive bias over some parts of the central, NEH and coastal belt but a moderate negative bias dominated over the rest of the country. The TDK-LIN and TDK-WDM6 combinations show a low positive bias over central, NEH, SWH, and coastal areas, but moderate negative bias dominated over the rest of the country. In general, MKF-LIN, MKF-WDM6, TDK-LIN and TDK-WDM6 combinations perform poorly as compared to the observed MAM 2018 seasonal rainfall. The TDK-KSS combination clearly shows the highest negative bias over most parts of the country. This shows that the WRF model strongly underestimated the rainfall over most areas of the country when the TDK-KSS combination was applied. Therefore, the TDK-KSS was observed as the worst performing scheme combination among other combinations.

Figure 8 show the results of correlation coefficients between the observed and simulated MAM seasonal rainfall at different scheme combinations. The correlation coefficients scored for each scheme combination in Figure 8 are given as BMJ-KSS (0.13), GFE-KSS (0.06), MKF-KSS (-0.05), TDK-KSS (0.14), BMJ-LIN (0.20), GFE-LIN (0.29), MKF-LIN (0.25), TDK-LIN (0.19), BMJ-WDM6 (0.22), GFE-WDM6 (0.30), MKF-WDM6 (0.23), and TDK-WDM6 (0.20).

The results show that the observed and simulated MAM seasonal rainfall for the entire period were generally weak to moderate over most of the scheme combinations. All of the scheme combinations had a positive correlation coefficient but only the MKF-KSS scheme combination had scored negative correlation. This means that as observed rainfall increases, the simulation rainfall for various scheme combinations increases as well. The correlation coefficients indicate that, the GFE-WDM6 scheme combination is superior to other scheme combinations, with a correlation value of 0.30. This is because the WDM6 microphysics scheme predicts both moisture variables and their concentration unlike other microphysics schemes which predict only moisture variables.

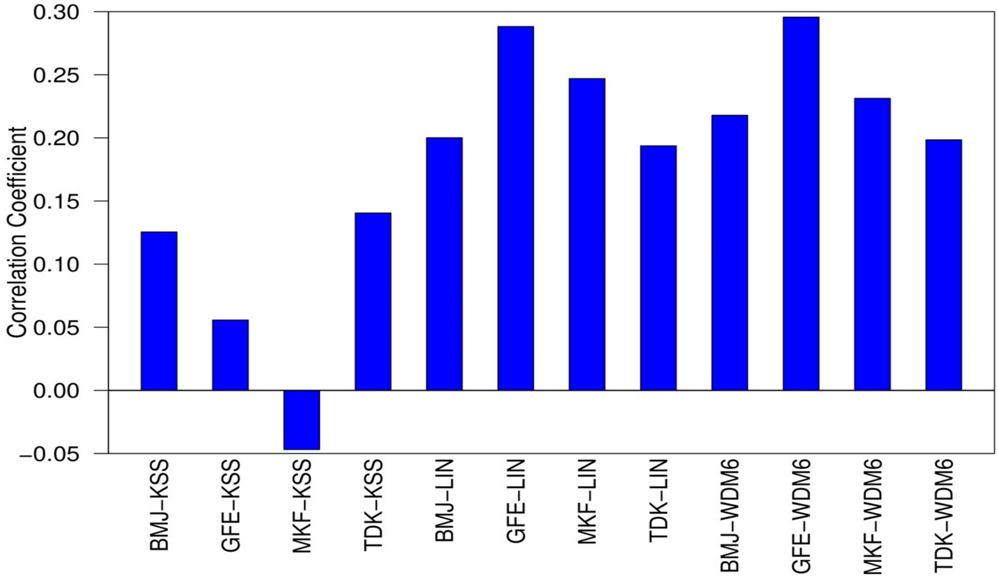

Figure 8: Correlation coefficients of various WRF scheme combinations considered.

Similarly, the correlation coefficient indicates that the MKS-KSS scheme combination is inferior to other scheme combinations with a correlation value of -0.05. This means that, the MKS-KSS scheme combination simulates seasonal rainfall that has an inverse relationship with the observed seasonal rainfall. In this scheme combination, its associated MPS scheme (KSS), predicts only three moisture variables without considering their concentrations. In addition, its CPS counterpart of the forming scheme combination (MKF), works well in a severe convective situation in most cases. This hinders the performance of the scheme in MAM seasonal rainfall.

In general, the results show weak to moderate significant relationship between observed and simulatedMAM2018 seasonal rainfall for each scheme combination across the entire country. The variability in the data and the occurrence of an outlier in a dataset may result in this weak correlation.

Figure 9 display the Normalized Mean Bias Error (NMBE) results for MAM 2018 seasonal rainfall simulations. The NMBE scores for each scheme combination given as; BMJ-KSS (-0.36), GFEKSS (-0.51), MKF-KSS (-0.30), TDK-KSS (-1.29), BMJ-LIN (-0.22), GFE-LIN (0.12), MKF-LIN (-0.22), TDK-LIN (-0.78), BMJ-WDM6 (-0.13), GFE-WDM6 (-0.06), MKF-WDM6 (-0.58), and TDK-WDM6 (-0.78). All of the scheme combinations in Figure 9 produced negative NMBE values, with the exception of the GFE-LIN scheme combination, which produced a positive NMBE. This means that all of the scheme combinations generally underestimated the MAM 2018 rainfall across the country, except for the GFE-LIN scheme combination which overestimated the rainfall amount. The GFE- WDM6 scheme combination had the smallest magnitude of NMBE (0.06) followed by the GFE-LIN scheme combination with NMBE (0.12) compared to other scheme combinations. According to the NMBE assessment, the GFE-WDM6 and GFE-LIN scheme combinations are preferable for simulating seasonal rainfall over Tanzania.

The NMBE of BMJ cumulus scheme which combined with WDM6 and LIN microphysics schemes are -0.13 and 0.22 respectively. The BMJ-WDM6 and BMJLIN combinations show minimal error as compared with MKF and TDK cumulus schemes when combined with others microphysics schemes. BMJ cumulus scheme with WDM6 and LIN microphysics schemes performed well due to its tendency to adjust humidity and temperature lapse rates due to moist and dry convection. It considers the changes in total moisture at each layer in the column and avoid its vertical moisture flux or entrainment within the convective profile.

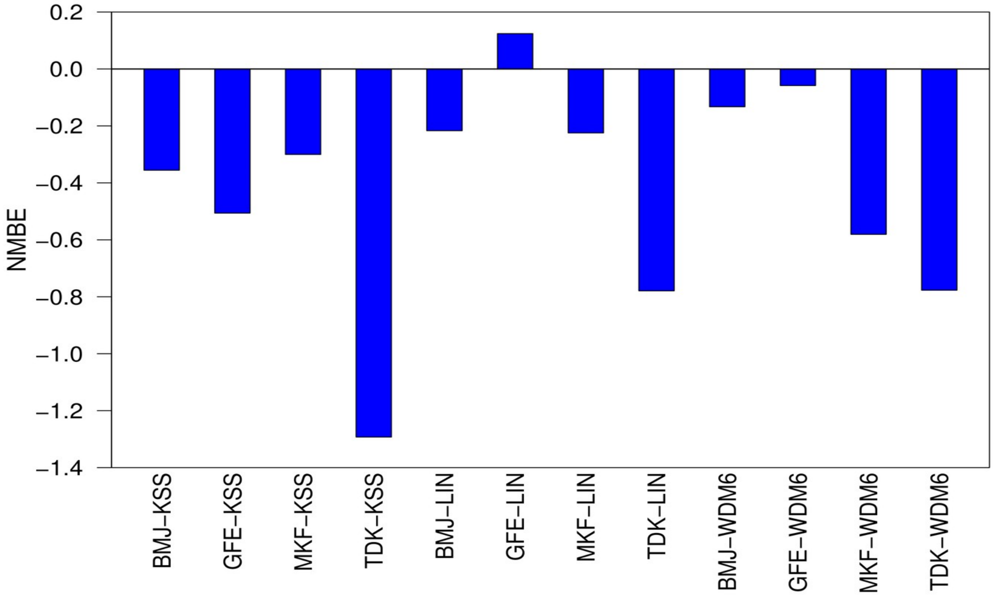

Figure 9: ormalized mean bias Error for various WRF scheme combinations.

The worst performance was shown by the TDK-KSS scheme combination. This scheme combination had the highest magnitude of NMBE (1.22) compared with other scheme combinations. This shows that the TDK-KSS scheme combination is the most underestimating simulation of the seasonal rainfall in the country. This is due to the MAM rainfall mechanisms, which involves little convection of heat and moisture with a weaker convective available potential energy. Unfortunately, TDK scheme depends heavily on strong convection, which is influenced by the amount of heat and moisture availability during the convective process. Also, the TDK cumulus scheme may perform poorly for the reason that the scheme was designed to provide a practical scheme for global climate forecast models.

The results of Normalized Root Mean Square Error (NRMSE) for MAM 2018 seasonal rainfall simulations are shown in Figure 10. From Figure 10, the NRMSE score for each combination is as follows; BMJ-KSS (1.76), GFE-KSS (1.81), MKF-KSS (1.90), TDK-KSS (1.71), BMJ-LIN (1.47), GFE-LIN (2.01), MKF-LIN (1.63), TDK-LIN (1.37), BMJ-WDM6 (1.53), GFE-WDM6 (1.67), MKF-WDM6 (1.41) and TDK-WDM6 (1.36). The NRMSE analysis for MAM seasonal rainfall revealed that, the TDK-WDM6 scheme combination had the lowest NRMSE of 1.36, followed by the TDK-LIN scheme combination with NRMSE of 1.37.

According to the NRMSE analysis, the TDK-WDM6 scheme combination, followed by the TDK-LIN scheme combination, had the best performance in simulating seasonal rainfall across the country. The TDK-WDM6 and TDK-LIN scheme combinations underestimated the MAM rainfall simulation in terms of spatial distribution, although having the lowest NRMSE. The NRMSE of the BMJ-LIN and BMJ-WDM6 schemes are found to be of the order 1.47 and 1.53 respectively.

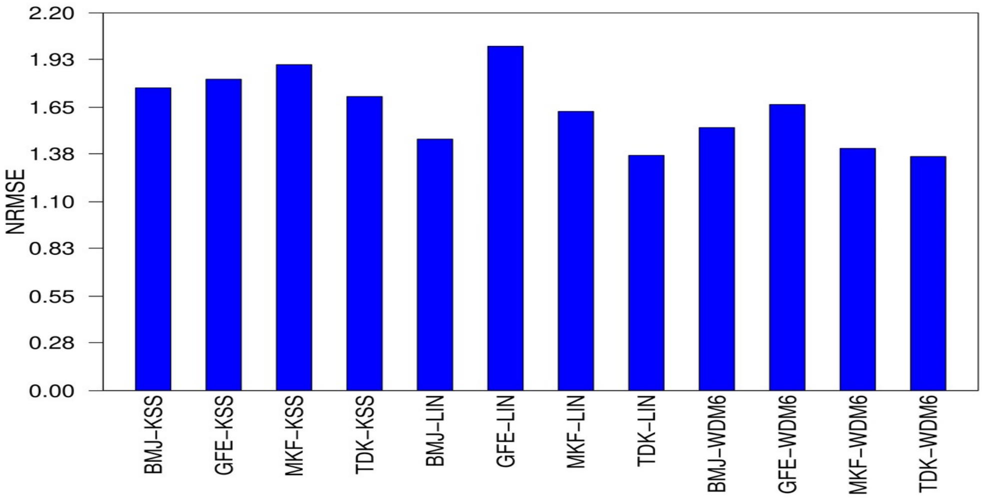

Figure 10: Normalized root mean square Error for various WRF scheme combinations.

As previously mentioned, the BMJ cumulus scheme involves the adjustment of the lapse rates of moisture and temperature due to moist and dry convection. It performs well when there is a small amount of convective available potential energy. This means that the scheme reduces or removes the conditional instability of the atmosphere by adjusting moisture and temperature. The scheme defines the change in total moisture at each layer in the column without defining the vertical moisture flux or entrainment within the convective profile. Furthermore, the LIN and WDM6 microphysics schemes, which incorporate moisture variables such as water vapor, cloud water, rain water, cloud ice, snow and graupel, may contribute to the performance of the BMJ cumulus scheme. Because these variables interact with one another within the scheme, they contribute to the development of the cloud. As a result, the BMJ-WDM6 and BMJ-LIN scheme combinations tend to capture the MAM rainfall simulation well.

When compared to other scheme combinations, the GFE-LIN scheme combination had the highest NRMSE value of 2.01. This indicates that the GFE-LIN scheme combination had the lowest performance in simulating seasonal rainfall across the country. It was unable to resolve all the MAM 2018 seasonal rainfall systems in the area. Other combinations which show poor performances with their NRMSE are MKF-LIN (1.63), TKD-KSS (1.71), BMJ-KSS (1.76), and MKF-KSS ((1.9), as shown in Figure (10).

From above analysis, MKF and TDK schemes appear many times more than GFE schemes in most of these poor simulation schemes, but GFE performs worse than others in terms of RMSE. The MKF and TDK are mass flux schemes similarly to the GFE scheme, where both are influenced by strong convectional with the availability of heat, moisture and strong convective available potential energy. These schemes failed to perform well due to the MAM rainfall mechanism, which requires little convection of heat and moisture with a weaker convective available potential energy.

Despite being combined with the BMJ scheme, which tends to capture well the rainfall simulation in the MAM season, the BMJ-KSS scheme combination performs poorly. Regardless of the poor performance with the BMJ cumulus scheme, the KSS microphysics scheme still shows poor performance with other cumulus schemes. In this case, the KSS scheme combination, which has only three moisture variables compared to the LIN and WDM6 schemes, could be the source of the error. Both LIN and WDM6 contain 6 moisture variables and perform well when combined with the BMJ scheme. Even with 6 moisture variables in the LIN microphysics scheme, it still shows less sensitivity to the MKF and GFE cumulus schemes. This may be due to the cumulus schemes themselves, which work well in deep convective moisture and heating with strong convective available potential energy that denies MAM seasonal rainfall favorable conditions.

To determine the optimal scheme combination for the MAM seasonal rainfall simulation, the NMBE and NRMSE results for each scheme combination were used. The simple ranking method was used to determine the rank for each scheme combination. The NMBE and NRMSE scores generated by each simulation for each scheme combination, as well as their individual ranking, were summarized in Table 2. In the ranking process, the lowest rank indicates the scheme combination with the best simulation results while the highest rank shows the scheme combination with the worst simulation results.

Table 2: Ranking of 12 scheme combinations during MAM seasonal rainfall simulation.

No.	Scheme Com-binations	Nmbe	Nrmse	Nmbe Rank	Nrmse Rank	Total Rank	Rank Score
1.	BMJ-KSS	-0.36	1.76	6th	9th	15th	7th
2.	GFE-KSS	-0.51	1.81	7th	10th	17th	9th
3.	MKF-KSS	-0.30	1.90	5th	11th	16th	8th
4.	TDK-KSS	-1.29	1.71	10th	8th	18th	10th
5.	BMJ-LIN	-0.22	1.47	4.5th	4th	8.5th	2nd
6.	GFE-LIN	0.12	2.01	2nd	12th	14th	6th
7.	MKF-LIN	-0.22	1.63	4.5th	6th	10.5th	3rd
8.	TDK-LIN	-0.78	1.37	9.5th	2nd	11.5th	5th
9.	BMJ-WDM6	-0.13	1.53	3rd	5th	8th	1st
10.	GFE-WDM6	-0.06	1.67	1st	7th	8th	1st
11.	MKF-WDM6	-0.58	1.41	8th	3rd	11th	4th
12.	TDK-WDM6	-0.78	1.36	9.5th	1st	10.5th	3rd

With the exception of the GFE-LIN scheme combination which had a positive NMBE, the rest of the scheme combination had a negative NMBE, as shown in Table (2). In terms of NMBE magnitude, simulations with the scheme combination GFE-WDM6 produced the lowest value and thus ranked in the 1st position, while simulations with the scheme combination TDK-KSS produced the highest value and thus ranked 10th position. The model simulation using the scheme combination TDK-WDM6 produced the lowest NRMSE of 1.36, ranking it in the 1st position, while simulation with the GFE-LIN produced the highest NRMSE of 2.01, ranking it to 12th position.

The overall ranking between cumulus and microphysics schemes produced by BMJ-WDM6 scheme combination with NMBE value of 0.13, NRMSE value 1.53 and thus ranked in 1st position. The BMJ-WDM6 was followed by GFE-WDM6 with NMBE value of 0.06, NRMSE value of 1.67 and thus ranked in 1st position. The second scheme combination that performs well is the one that employs the BMJ cumulus scheme in combination with the LIN microphysics scheme. The BMJ-LIN scheme combination has a NMBE value of 0.22 with a NRMSE value of 1.47, thus ranked in 2nd position. When compared to BMJ-WDM6 and GFE-WDM6 scheme combinations, the TDK-WDM6 scheme combination has the lowest NRMSE of 1.36 but the highest NMBE of 0.78, hence ranking at 10.5th position. As a result, the BMJ-WDM6 and GFE-WDM6 scheme combinations outperformed other scheme combinations, with the BMJ-LIN coming in second.

From the above analysis, the BMJ-WDM6 and BMJ-LIN scheme combinations perform well in simulating MAM rainfall. As mentioned earlier, the BMJ cumulus scheme involves the adjustment of the lapse rates of moisture and temperature due to moist and dry convection. It performs well when there is little convective available potential energy. Moreover, the GFE WDM6 scheme combination was a surprising combination that has emerged to perform crucial work on the simulation of MAM rainfall over Tanzania. This implies that the scheme combination outperformed other mass flux schemes that show a contradiction with the MAM rainfall mechanism. As explained before, the GFE cumulus scheme is a scale awareness scheme that depends on the vertical heat, low level moisture transport and instability of the atmosphere. Furthermore, switching from a simple KSS microphysics simulation to a more sophisticated WDM6 microphysics simulation contributes to its performance.

The TDK-KSS scheme combination performed poorly, with a higher NMBE value of 1.29 and NRMSE value of 1.71, thus ranking in 10th position in score (Table 2). This was followed by the GFE-KSS scheme combination in poor performance with a higher NMBE of 0.51 and NRMSE of 1.81, thus ranking in 9th position. This could imply that the TDK- KSS scheme combination is inadequate for simulating MAM 2018 seasonal rainfall across the country, followed by the GFE-KSS combination. Also, scheme combinations that involve combinations of BMJ, MKF with KSS microphysics scheme show poor performances according to the rank score in Table (2).

Furthermore, the eyeball, NMBE and NRMSE results both revealed that the TDK-KSS scheme combination is the worst performing combination. This shows that the TDK-KSS scheme combination was one of the most scheme combinations that performed poorly in the MAM rainfall simulation. This is due to the MAM rainfall mechanisms, which involve little heat and moisture convection with a weak convective available potential energy. Unfortunately, the TDK cumulus scheme depends heavily on strong convection, which is influenced by the amount of heat and moisture availability during the convective process. Also, the TDK cumulus scheme performs poorly for the reason that the scheme was designed to provide a practical scheme for global climate forecast models.

Therefore, after assessment of all selected parameterization schemes using different methods, it has been found that BMJ-WDM6, GFE-WDM6 and BMJ-LIN scheme combinations were the best available schemes to simulate MAM seasonal rainfall in Tanzania. This suggests that BMJ and GFE cumulus schemes when combined with the WDM6 microphysics scheme can simulate MAM rainfall better than other schemes. This followed with the BMJ cumulus scheme when combined with the LIN microphysics scheme. Moreover, it has been found that the TDK-KSS scheme combination was one among the foremost scheme combination that performed poorly in the MAM rainfall simulation. This suggests that the TDK cumulus scheme when combined with the KSS microphysics scheme simulates the MAM rainfall poorly than the other schemes.

Conclusion

The seasonal rainfall forecast is an essential source of information for planning of end users' socio-economic activities such as agriculture, construction, hydrology, industries, hydropower production and many others. This study has evaluated the performance of simulating the MAM 2018 rainfall season in Tanzania using the WRF model. The CFSv2 data were used to provide the initial and boundary conditions to the

WRF model. The main objective of the study was to improve the seasonal rainfall forecasts from the WRF model. To achieve this, five approaches were used to evaluate the performance of the WRF model in simulating the MAM 2018 seasonal rainfall. These approaches enveloped the eyeball analysis (spatial), Pearson correlation coefficient, MBE, RMSE, and ranking transformation analysis. For spatial analysis, the WRF model outputs were compared with CHIRPS, and the observed rainfall stations data from TMA observation network respectively.

The study evaluated the performances of the CPS and MPS of the WRF model in forecasting the MAM 2018 seasonal rainfall in Tanzania. In particular, four CPS and three MPS respectively were used and summing up to a total of 12 parameterization scheme combinations which were evaluated. The CPS schemes involved BMJ, GFE, MKF and TDK whereas the MPS schemes involved KSS, LIN and WDM6. The idea was to obtain the best parameterization scheme combination(s) of the WRF model that can reasonably represent well the accurate forecast of the MAM rainfall in Tanzania. It should be noted that, the performance of the parameterization schemes was achieved using the WRF simulations driven by 0000 UTC CFSv2 initial condition.

The findings showed that, the BMJ-WDM6, GFE-WDM6 and BMJLIN scheme combinations perform good and surpasses other scheme combinations considered in this study. These scheme combinations can be recognized to evidently characterize well the WRF forecast of the MAM rainfall season in Tanzania. In fact, the BMJ-WDM6 scheme combination can be prioritized in forecasting the MAM rainfall season from the WRF model, followed closely by the GFE-WDM6 and BMJ-LIN scheme combinations. But in generality, all the three scheme combinations (BMJWDM6, GFE-WDM6 and BMJ-LIN) can reasonably represent well the MAM rainfall simulations from the WRF model. On the other hand, the TDK-KSS scheme combination was found to be the worst combination among all. The scheme combination was unable to represent well the simulation of MAM rainfall season from the WRF model.

It's worth noting that this study considered the WRF simulations of the MAM 2018 season only. But the performance of WRF parameterization scheme can depend on areas where the simulations are to be performed and time of which the simulations are performed. The study suggests the performance assessment of the different parameterization scheme combinations from the WRF model be performed on the seasonal rainfall of MAM for more than one year. Similarly, the study had considered only the parameterization scheme categories of CPS and MPS, but can also be carried out considering other categories like the planetary boundary layer and radiation schemes. The study considered only MAM rainfall season, other rainfall seasons such as OND and NDJFMA might be taken into considerations.

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Conflicts of Interest

The authors declare no conflicts of interest concerning publication of this study.

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