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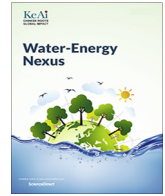
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Research Paper

Validation of CORDEX regional climate models to simulate climate trends and variability across various agro-ecological zones of North Shewa, Ethiopia

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ABSTRACT

Climate variability significantly affects the overall agricultural production and productivity over space and time. To quantify the effect of climate variability on natural systems on Earth in the future, the use of regional climate models (RCMs) as a tool is mandatory. Thus, the use of well-validated RCM provides efficient climate data, and predicts future climate variability over agroecological zones (AEZs). Eleven RCMs from CORDEX-Ethiopia were evaluated to simulate maximum temperature ($T_{\max}$), minimum temperature ($T_{\min}$) and rainfall variability over space and time, to validate their performance and to select the best-fit models. The temporal variability $T_{\max}$ and rainfall was smaller with a CV of 10 %, indicating uniform distribution over stations. However, CV for $T_{\min}$ over stations shows satisfactory distributions. Most of the evaluated RCMs have a better capability to capture the spatial variability of rainfall, $T_{\max}$, and $T_{\min}$ in some stations. However, some of the RCMs can handle the spatial variability of $T_{\max}$ while others are not. None of the RCMs can handle the spatial variability of $T_{\min}$ in Debre Birhan, Majete, and Kewat AEZs. In general, most RCMs can capture the spatial and temporal variability of rainfall and temperature. It might be better to use the ensemble average of the output from these RCMs for precise estimation of data than specific RCMs. Therefore, this work could suggest the use of high-resolution RCMs for the projection of temperature and rainfall over different AEZs.

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1. Introduction

Climate change is a major concern of this world as it affects the overall systems on the earth both with spatial and temporal patterns (Gebrehiwot and Veen, 2013). However, its effect is more significantly observed in developing countries than in developed countries (Asfaw et al., 2021). It has considerably affected African agriculture and it might increase exponentially in the future (Thornton, 2010). Because developed countries have established tools to reduce the existing and emerging impact of climate change. Nonetheless, developing nations hardly formulate such a kind of tool in local conditions. Ethiopia has diverse agroecological zones (AEZs) with a variety of micro-climatic, soil, and topographic conditions (Astawseg, 2014). But, the availability of climatic data at different local scales is insignificant. Therefore, the use of regional climate models (RCMs) to generate climatic information

for simulating crop growth, planning agricultural management, and farm decisions is quite important.

Temperature and rainfall are the major climate parameters that have a great impact on overall ecosystems (Li et al., 2019). There is a consensus among scholars that rainfall variability is increasing and trends decreasing temporarily, and increasing of temperature trends in many parts of the of world, and the same is true in Ethiopia. These would have a strong implication on crop production and be a challenge for adaptation planning and management (Kassahun, 2011). The use of RCMs is important to generate historical and future climate data and to assess the impact of climate change on agriculture (Wilks, 1999). Thus, they are a standard component of decision support systems in agriculture (DSSAT), environmental management, and hydrology (Munangv, 2010). Moreover, the projection of temperature and rainfall with precise and validated RCMs is needed to set up adaptation mechanisms on climate change.

Validation of RCMs about real observed data provides the best-fit model for the given locality. According to the (IPCC, 2007), the Intergovernmental Panel on Climate Change's (IPCC) fourth report

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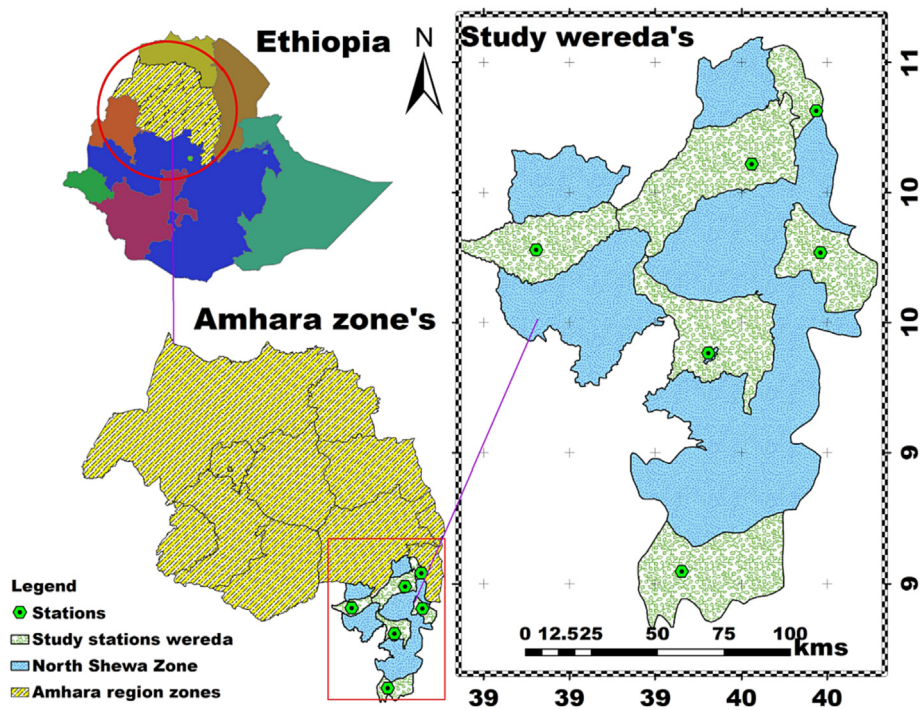


Fig. 1. Geographical location of the study area.

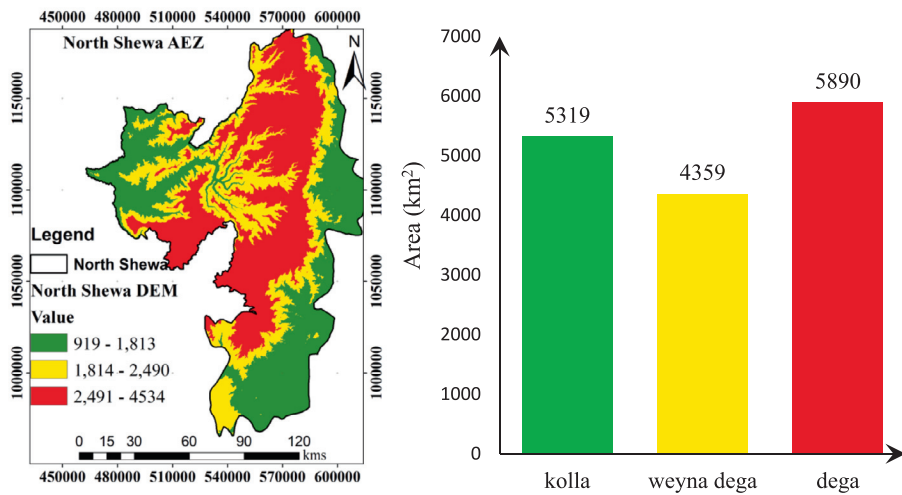


Fig. 2. Agro-ecology based classification of North Shewa zone.

confirmed that some extremes are changing continuously due to human interventions. According to the IPCC 5 report, the variability of climate conditions would be increased exponentially (Birch, 2014). Regional downscaling of GCMs is used to provide climate information at the smaller scales (Flato et al., 2013). There is limited information in the literature regarding AEZ-based validation of RCMs in North Shewa. Since the launch of the Coordinated Regional Downscaling Experiment (CORDEX) Africa programme, a few studies have evaluated the RCMs' performance over parts of Ethiopia (Alemu and Sisay, 2021). Now a time, the output from GCMs is of insufficient spatial and temporal resolution (Giorgi et al., 2009). In this study, about 11 RCMs from CMIP 5, CORDEX for Ethiopia, were employed. The RCMs which have high precision

would be used to project future trends of temperature and rainfall (Gutowski et al., 2016).

The simulation of rainfall and temperature from CORDEX output is assessed by using the taylor diagram (Taylor, 2001), root mean square error (RMSE), correlation coefficient (R), and coefficient of determination (R^2). Based on previous studies, RCMs are well reproduce rainfall and temperature in some regions but not captured in other areas of Ethiopia. For example, the use of an ensemble average of RCMs with bias correction is important to capture the variability (Kim et al., 2014). Hence, to select the best RCMs for a specific location, evaluating their performance is necessary. Therefore, this proposal was initiated to 1) describe the temporal and spatial distribution of temperature and rainfall in the

Table 1
List of regional climate model and their driven global climate model.

No.	Name of institutions	GCM name	RCM name
1	Canadian Centre for Climate Modeling and Analysis, Canada	CCCma-CanESM2	CRCM4
2	Canadian Centre for Climate Modeling and Analysis, Canada	CCCma-CanESM2	RCA4
3	The Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	MIROC-MIROC5	RCA4
4	Bjerknes Centre for Climate Research, Norwegian Meteorological Institute, Norway	NCC-NorESM1-M	RCA4
5	Max Planck Institute for Meteorology, Germany	M-MPI-ESM-LR	RCA4
6	Max Planck Institute for Meteorology, Germany	MPI-M-MPI-ESM-LR	CFCM5
7	Centre National de Recherches Météorologiques, Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique France	CNRM-CERFACS-CNRM-CM5	RCA4
8	Geophysical Fluid Dynamics Laboratory, USA	NOAA-GFDL-GFDL-ESM2M	RCA4
9	Irish Centre for High-End Computing Ireland European Centre Earth global climate model system	ICHEC-EC-EARTH	HIRHAM5
10	Irish Centre for High-End Computing Ireland European Centre Earth global climate model system	ICHEC-EC-EARTH	RACMO22T
11	Irish Centre for High-End Computing Ireland European Centre Earth global climate model system	ICHEC-EC-EARTH	RCA4

Table 2
Temporal variability of temperatures and rainfall over the stations.

Stations	Parameters	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ave	RME	CV
DB	T _{max}	20	21	21	21	22	22	19	18	19	19	19	19	20	1	6
	T _{min}	5	6	8	9	8	8	9	9	7	4	4	4	7	2	32
	RF	9	12	33	36	32	41	239	316	64	16	4	3	804	101	13
MM	T _{max}	19	19	19	19	19	20	18	17	17	17	17	18	18	1	6
	T _{min}	6	7	8	8	9	9	8	8	8	6	5	5	7	1	19
	RF	16	23	55	45	40	41	268	252	74	24	7	5	850	91	11
AK	T _{max}	26	27	28	28	28	27	22	21	23	25	25	25	25	2	10
	T _{min}	13	14	14	15	16	15	12	12	12	12	12	12	13	1	10
	RF	7	19	46	48	55	70	280	308	141	24	10	9	1016	105	10
AR	T _{max}	27	28	29	29	30	29	25	26	26	26	26	25	27	2	7
	T _{min}	9	11	13	14	16	15	14	15	14	13	11	8	13	3	21
	RF	10	29	51	62	32	76	232	233	94	42	15	9	886	79	9
KW	T _{max}	29	30	32	33	34	36	33	31	31	31	30	29	31	2	7
	T _{min}	10	13	15	15	17	18	18	14	12	12	11	11	14	3	21
	RF	28	48	58	86	81	24	144	182	84	39	14	48	836	50	6
MJ	T _{max}	26	27	29	30	31	33	31	29	27	27	25	24	28	3	10
	T _{min}	12	13	15	16	17	18	17	16	16	14	12	12	15	2	15
	RF	31	40	72	99	64	25	221	297	104	45	28	23	1049	86	8

DB-Debre birhan, MM-Mehal meda, AK-Alem Ketema, AR-Arerti, KW-Kewat, MJ-Majete.

three AEZs 2) validate the performance of RCMs and select the best-fit RCM.

2. Materials and methods

2.1. Description of the study areas

The study was conducted in the three AEZs of North Shewa, one of the administrative zones in Amhara Regional State, Ethiopia. The study area includes two metrological stations from each AEZs, Kewat (KW) and Majete (MJ) stations, Alem Ketema (AK) and Arerti (AR), and Debre Birhan (DB) and Mehal Meda (MM) stations from low lands, mid-altitude, and highlands respectively. The geographical locations of the study area is presented in (Fig. 1).

2.2. Source of observed and modeled data

The observed maximum and minimum temperature, and rainfall data (1990–2020) were obtained from National Metrological Service Agency (NMSA). Before using the data, data quality management like data arrangement, outlier detection, and handling of missing data was performed. Outliers were detected by using an interquartile range test on an Excel sheet treated as missing values and filled by normal ratio methods. Modeled monthly observational and reanalysis of temperature and precipitation data were retrieved from CORDEX- Ethiopia, which is a CMIP 5 product with the same period as the actual observed data. A statistical comparison between observed and modeled data is a major part of overall validation but provides valuable information on the behavior of the data.

2.3. Area analysis on agro-ecological zones

Agroecology can be classified based on altitude and rainfall patterns. Fortunately, Ethiopia exhibits all AEZs and the same is true for the Amhara region. AEZ-based classification of the area is the

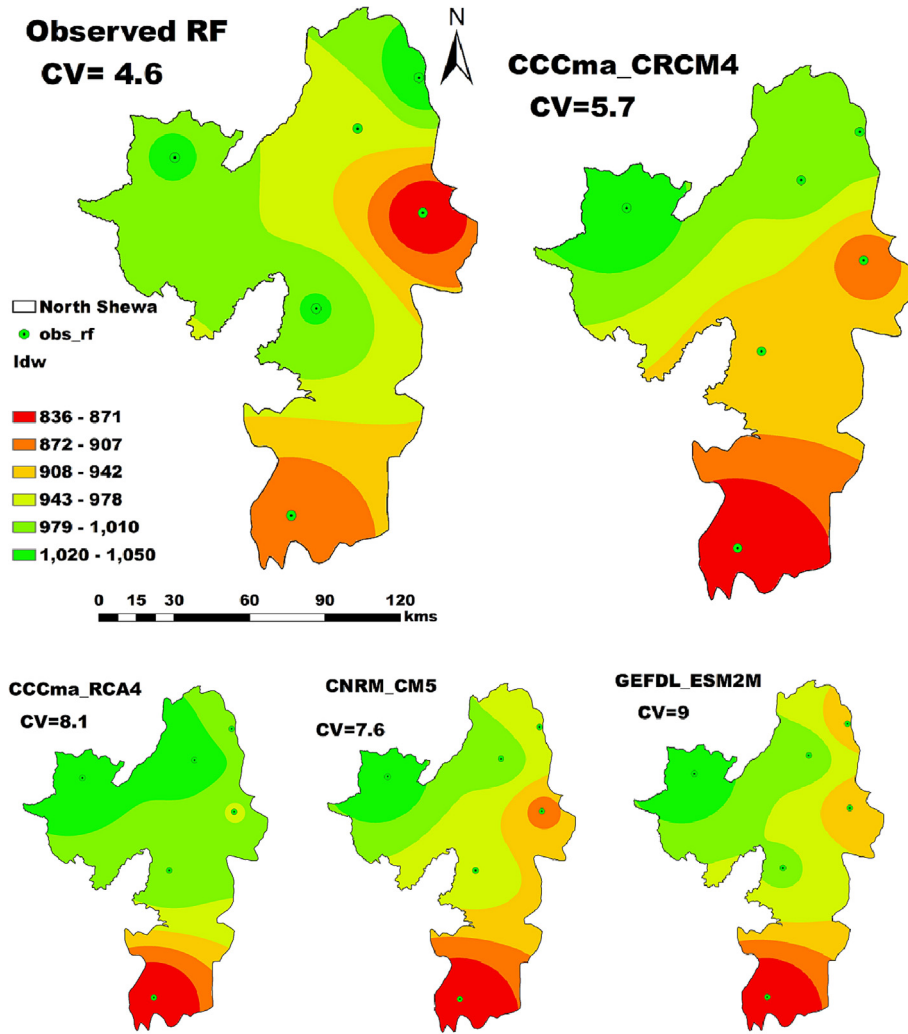


Fig. 3. The spatial map of rainfall extremes distribution across locations.

spatial grouping of the landscape into areas of similar agricultural and ecological characteristics (Hurni, 1998). As coated by Hurni (1998), Dove (1890) reported major agricultural zones in Northern Ethiopia more precisely as being 'low land' at altitude below 1800 m.a.s.l, 'midaltitude' for altitude between 1800 m.a.s.l to 2400 m.a.s.l, and 'high land' for areas above 2400 m.a.s.l. In this study, the areal classification of North Shewa was done by using Arc GIS software based on the above traditional altitudinal classification methods.

2.4. Validation criteria on regional climate models

The generated data from RCMs are compared with the observed data with statistical indicators like: - root mean square error (RME), coefficient variations (CV), correlation coefficient (R), coefficient of determination (R^2), and index of agreement (d). A lower RME indicates that better performance of the model and vice versa. The CV values are considered as excellent if smaller than 10%, good if between 10 and 20%, fair if between 20 and 30%, and poor if larger than 30% (Mekonen and Berlie, 2019). The higher the CV value indicates more variability of the data and vice versa. The index of agreement (d) was proposed to measure the degree to which the observed data come up to the predicted data (Willmott, 1982). It is a measure of the predictive ability of the models. It ranges

between zero and one, with "0" indicating no agreement and "1" indicating a perfect agreement. It powerfully expresses the modeled data with the observed data based on R, RME, and d. The RME, CV, and d value was determined by the Equations (1)–(4)

$$RME = \left[\frac{1}{n} \sum_{i=1}^n (p_i - O_i)^2 \right]^{0.5} \quad (1)$$

$$CV = \frac{1}{O_i \bar{A}} * \sqrt{\frac{\sum (p_i - O_i)^2}{N}} * 100 \quad (2)$$

$$d = 1 - \frac{\sum (P_i - O_i)^2}{\sum (|P_i - O_i \bar{A} - | + |O_i - O_i \bar{A} - |)^2} \quad (3)$$

$$r = \frac{\sum_{i=1}^n (P_i - \bar{p_i}) * (O_i - \bar{O_i})}{\sqrt{\sum_{i=1}^n (P_i - \bar{p_i})^2} * \sqrt{\sum_{i=1}^n (O_i - \bar{O_i})^2}} \quad (4)$$

Whereas: p_i is the model predicted value, O_i is the observed individual value, n is the number of observations, $O_i \bar{A}$ is the mean of the observed value, and $\bar{P_i}$ is the mean of the predicted value.

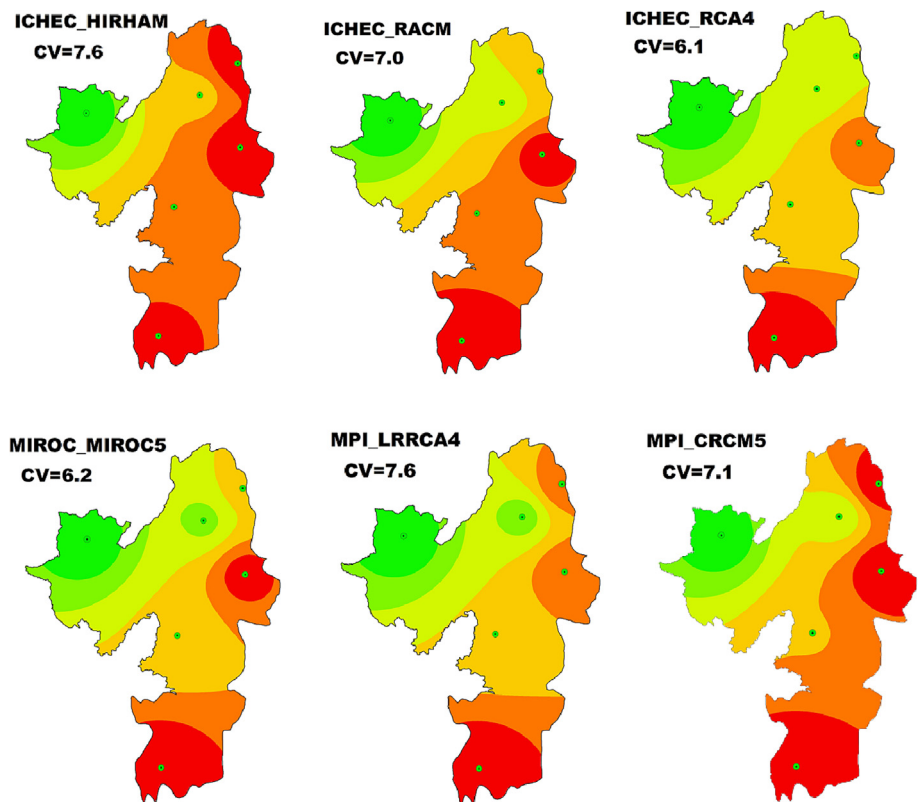
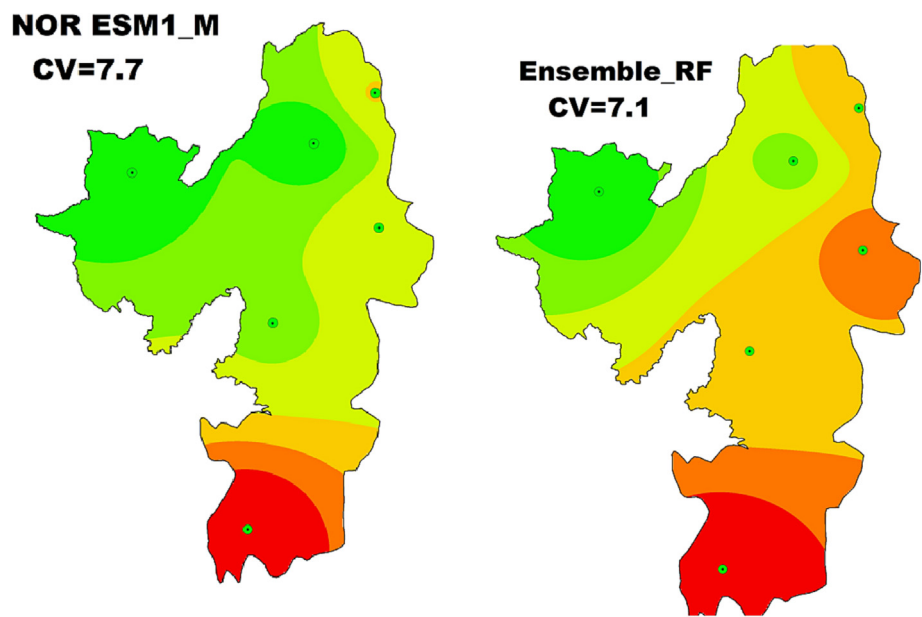


Fig. 3 (continued)



3. Result and discussions

3.1. Area classification of North Shewa based on agro-ecology

North Shewa covered a total area of 15,568 Km², of which is 5319 km² (34.2%) categorized as Kolla (low land) for altitudes below

1800 m, 4359 km² (28%) being as weyna Dega (midaltitude) for altitudes between 1800 and 2400, and 5890 km² (37.8%) considered as Dega (high land) for above altitudes of 2400 m (Fig. 2). This classification is crucially important to understand which RCMs would well reproduce on which agroecology, which crop potentially grown and guide to undertake measures on the existing and emerging situations.

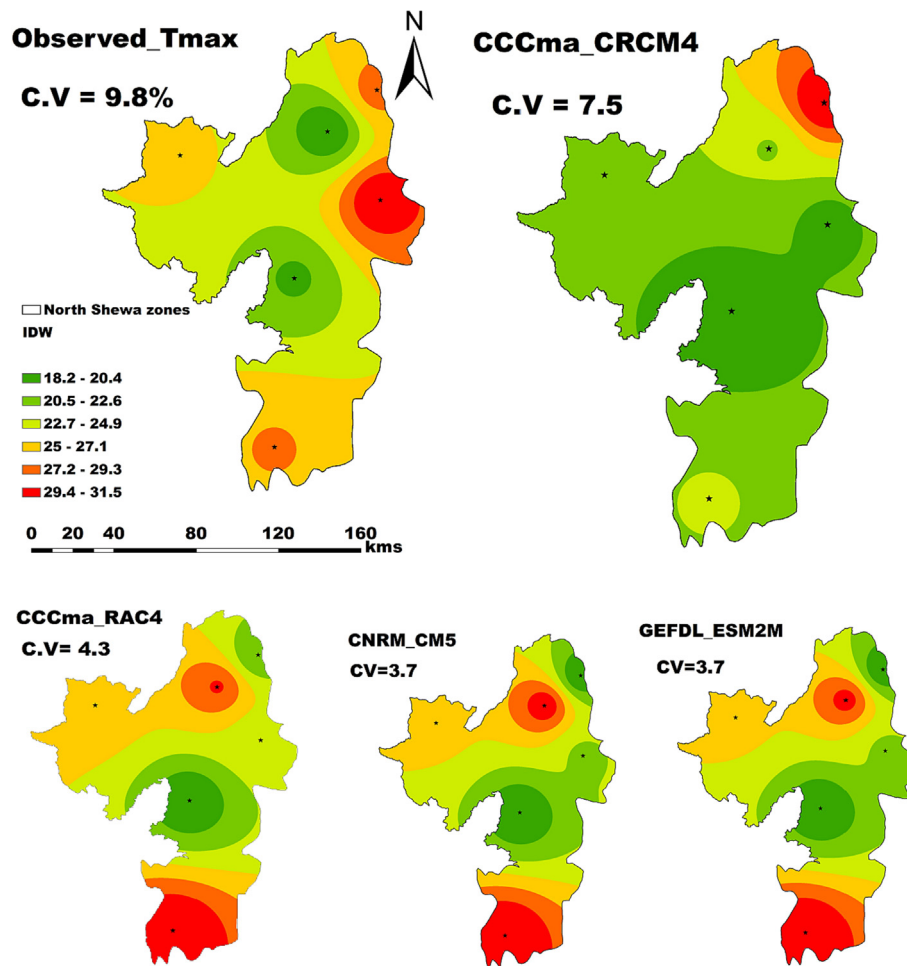


Fig. 4. The spatial map of maximum temperature distribution across locations.

3.2. Temporal variability of temperature and rainfall

As presented in Table 1, the temporal variability and distribution of rainfall under the three AEZs of North Shewa show uniform with a smaller CV. This shows a sound effect on agricultural production and productivity by optimizing the soil moisture and temperature. The monthly $T_{\max}$ and rainfall were in the acceptable threshold value within all stations. However, rainfall is highly variable in the lowland than highland AEZ, $T_{\min}$ shows a slight variability and satisfactory distributions in all stations except AK (Table 2).

3.3. Spatial analysis of monthly rainfall and temperatures

The spatial distribution of the annual rainfall, $T_{\max}$, and $T_{\min}$ was determined by inverse distance weighted (IDW) interpolation methods. Since North Shewa has a diverse climate with temperature and rainfall variability, the ability of RCMs to handle the spatial variability in contrast to the observed value was examined. The developed spatial map from average rainfall from different RCMs indicated below shows that most of the RCMs' performance was moderate to good agreement with the observed spatial distribution. The RCMs' rainfall and air temperature data were downloaded from a public website, with the required data in Arc GIS. The spatial map for rainfall in Fig. 3 indicates that the spatially interpolated value of distributed rainfall from the gauging stations of each RCM across locations was quite different from the observed values.

The RCMs, which have the closest values to the observed, indicate the better capability of the model to interpolate the rainfall distributions over the area. For instance, in mid-AEZ (AR and AK) all RCMs can capture the spatial variability of rainfall (Fig. 3). Of the all RCMs, ICECH-HIRHAM, ICHEC-RACM and MIROC5 were well represent the rainfall pattern of MM and CCCma-CRCM4, ICHEC-RCA4, CRCM5, LRRCA4, MIROC5 were well reproduce the rainfall in DB station. While other RCMs either under estimate or over estimate the rainfall extremes. Similarly, for Majete (CCCma-RCA4 and CCCma-CRCM4) and KW stations (CNRM-CM5, HIRHAM, ICHEC-RACM, MIROC5) well reproduce the rainfall patterns respectively. According to (Alemu and Sisay, 2021), RCA4 was well performed in both simulating rainfall and air temperature over the Wabi Shebele basin. However, in this study, RCMs have variable performance over AEZs of North Shewa. The CV value for observed rainfall data mapping was smaller (5.9%), indicating smaller rainfall variability in North Shewa. For instance, CCCma-CRC4, ICHEC-RCA4, and MIROC5 models showed relatively close agreement with the observed having a CV of 6.6%, 7.2%, and 7.6%, respectively.

The spatial variability of $T_{\max}$ (Fig. 4) for the observed data was in the acceptable range (12%). The CV values for models ICECH-HIRHAM and CCCma-CRCM4 were 11.1% and 8.9%, which was similar to the observed spatial distribution of the $T_{\max}$ value. These models can handle the spatial $T_{\max}$ variability. However, for other RCMs the observed CV values were smaller than the observed, indicating the inability of the models to catch up with the variability in $T_{\max}$. According to Dong et al. (2018), of the evaluated five RCMs

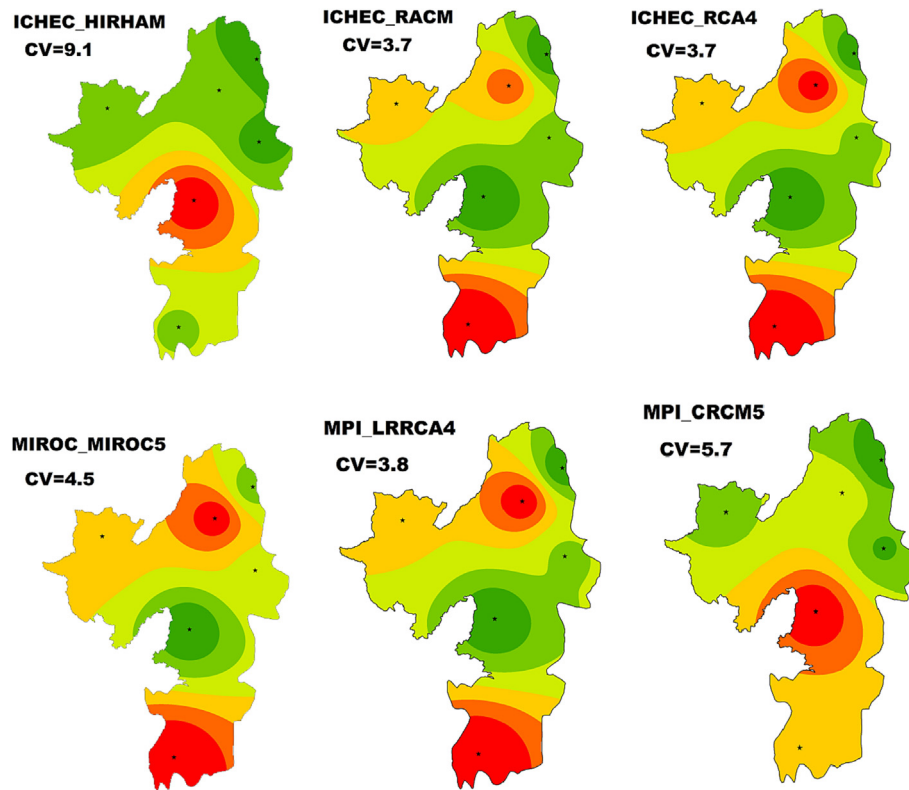


Fig. 4 (continued)

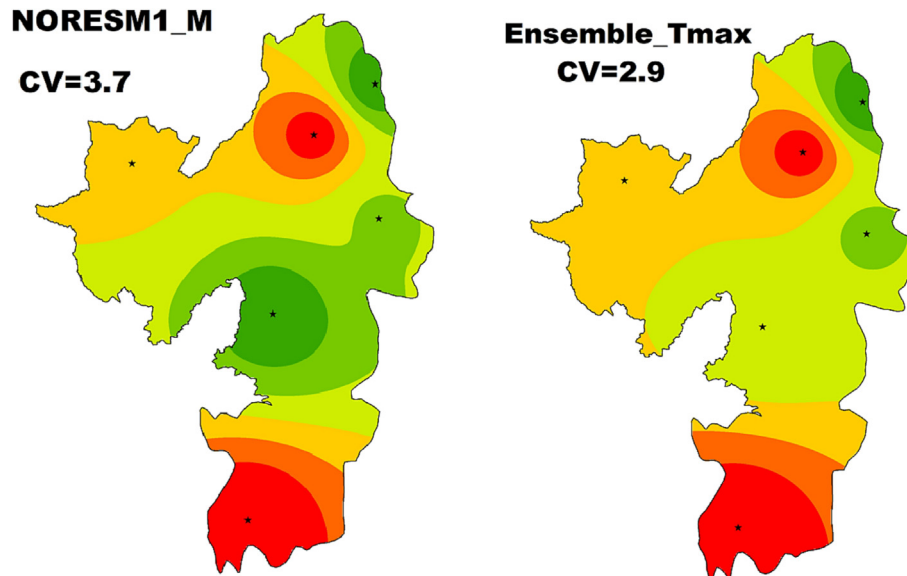


Fig. 4 (continued)

none of them can capture the spatial patterns of the temperature and precipitation, either overestimated or underestimated. In general, the spatial distribution of mean monthly $T_{\max}$ for most of RCMs looks less variable across locations as the CV values are smaller. However, for mid-AEZ all RCMs can capture the spatial pattern of $T_{\max}$ except CCCma-CRCM4, ICHEC-HIRHAM, and MPI-CRCM5 (Fig. 4). For highland AEZ, all RCMs capture the spatial pattern of $T_{\max}$ except ICHEC-HIRHAM and MPI-CRCM5. However, for Kewat stations all RCMs do not capture the spatial patterns, and for

Majete station only CCCma- CRCM4 well reproduce the patterns of $T_{\max}$.

The spatial variability of observed $T_{\min}$ (Fig. 5) across locations was 20.5%, which indicates higher variability and uneven distributions. The CV values for all RCMs were nearly 11%, which is smaller than the observed value by half. This shows no RCMs are capable of reproducing the $T_{\min}$ across locations in the observed spatial distributions. This primarily influences all agricultural activities either positively or negatively. As shown in Fig. 5, all RCMs can handle

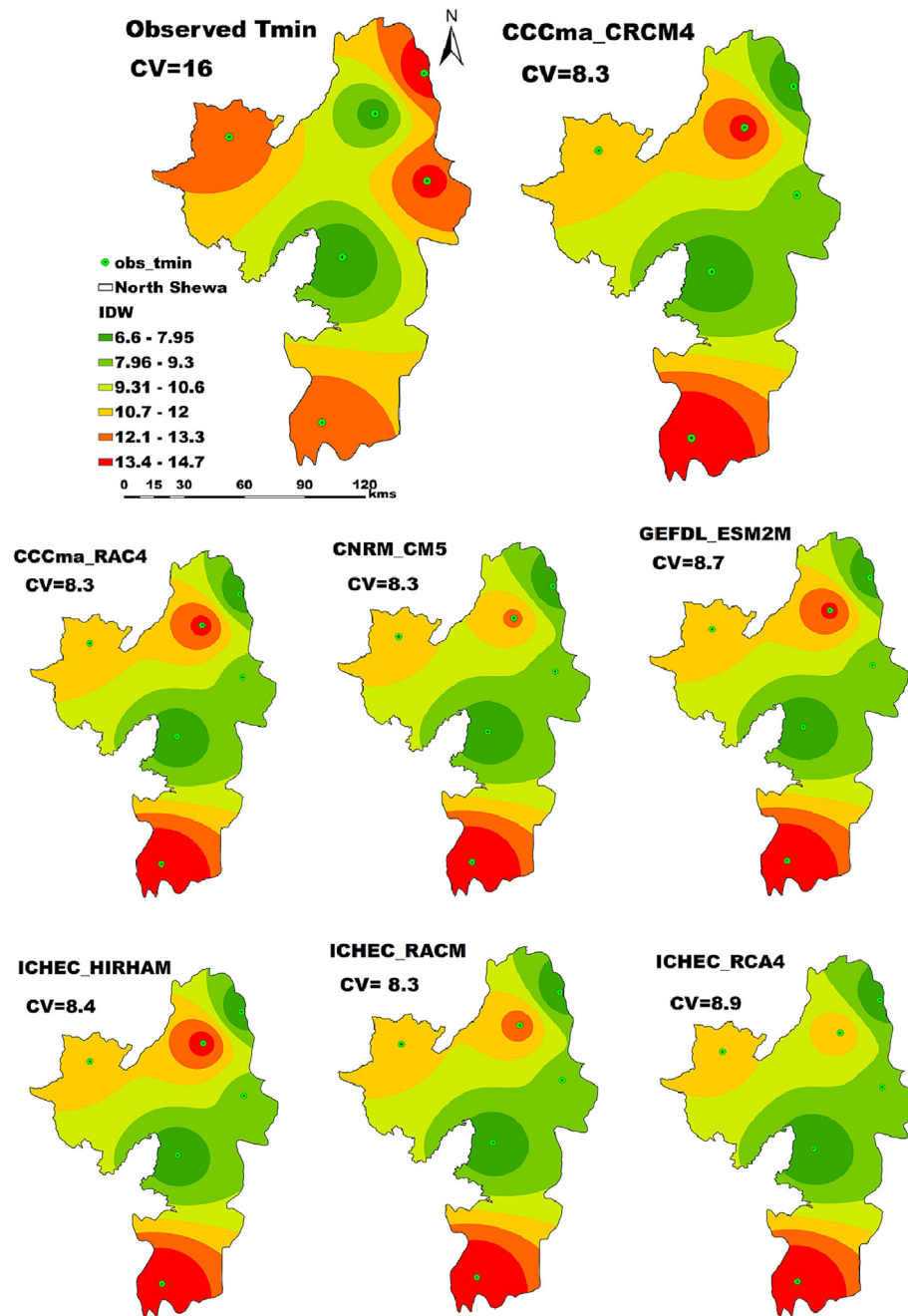


Fig. 5. The spatial map of minimum temperature distribution across locations.

the spatial patterns of $T_{\min}$ for all stations in mid-AEZs. For Debre Birhan station all RCMs can capture the spatial pattern of $T_{\min}$. But, for the stations of Mehal Meda, Majete, and Kewat neither of the RCMs is able to handle the pattern. In general, all RCMs are simulated $T_{\max}$ and $T_{\min}$ variably over locations. However, Kim et al., (2014) found that RCMs well reproduce $T_{\max}$ than $T_{\min}$ in Ethiopian highlands.

3.4. Validation metrics of regional climate models

The fitness of each RCMs is determined based on how the root mean square error (RME) value is smaller and indicates close estimates to the historical observed values. The minimum RME for $T_{\max}$ was observed for CNRM-CM5 and the maximum RME was observed in ICHEC-EARTH1 at DB station. Almost all of the RCMs account for a smaller RME value for $T_{\max}$ in DB and AK. The RME

value for $T_{\max}$ observed for all RCMs under the stations of MM, KW, and MJ was relatively larger. Similarly, the MIROC 5 model for $T_{\min}$ recorded the smaller RME value in AK station. All climate models showed smaller RME values in $T_{\min}$ for AK and larger RME values for MJ stations. The RME value obtained for $T_{\min}$ in mid altitudes is relatively smaller than that of the highlands and lowlands for most of the climatic RCMs. This indicates that most RCMs performed well in mid-altitudes (AK and AR) for the simulation of $T_{\max}$ and $T_{\min}$. Whereas for rainfall, the minimum RME value was observed in AR and KW stations nearly for all models. However, the value of RME in the AK station was relatively larger than others in the case of all models. The RME value for DB and MM in simulating rainfall was relatively larger in most of the RCM. The RME value of rainfall for highlands is larger than mid and low lands in most of the RCMs. That means, there is greater rainfall variability in the highland areas. The mid altitude agro-ecology relatively

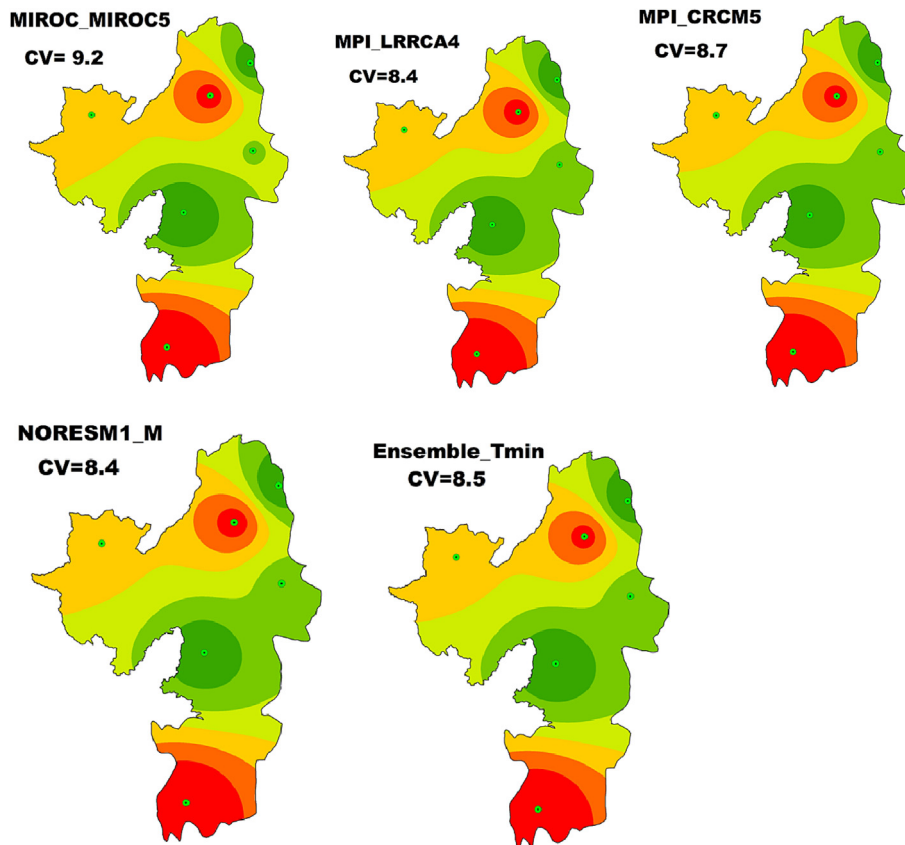


Fig. 5 (continued)

shows a high RME value for rainfall and low RME for temperature in all models (Fig. 6).

The CV for T_{max} in AR station was found smaller (values close to 5%) of all stations and followed by AK stations (values between 5% and 10%). This indicates the variation between the observed T_{max} and the produced output from models is smaller, thereby nearly all models are well performed in generating historical T_{max} for areas that have no meteorological station. Nevertheless, the differences amongst the models in simulating T_{max} were insignificant. Similarly, nearly for all models in KW and MJ stations, the results show relatively moderate CV values for T_{max} , which is between 10% and 15%. This indicates the models can predict the T_{max} for lowland areas. DB station shown smaller CV values (under 10%) for T_{max} in the case of all models except ICHEC-EARTH1 and MPI-LR2 models (above 30%). All models predicted T_{max} poorly in the highland stations (MM stations and DB for some RCMs). From this output, the produced T_{max} values were not significantly different from model to model; but varied from station to station. All RCMs are well reproduced T_{max} in mid-altitude stations (AK and AR) as the CV values are smaller (Fig. 7).

The CV values of T_{min} for all models are smallest in the AK and AR stations, which is in the acceptable range of 15% to 20%. The maximum CV values for T_{min} (above 30%) were observed in MM and followed by DB stations. The CV values for low-altitude stations (KW and MJ) in reproducing T_{min} were higher (23–30%). The variation between the observed values and the produced values are significantly different, hence the models are not well-performing for prediction purposes especially for lowlands and highland stations. The obtained CV values in the case of T_{min} were relatively higher than those of T_{max} in all stations for all models. This indicates the variability of T_{min} is higher than T_{max} in all stations. However, all models are well reproduced T_{min} and T_{max} in mid-altitude stations (AK and AR) as the CV values are smaller

and all models reproduced T_{min} poorly in the highland stations (MM and DB (Fig. 7)).

The CV for rainfall in AR, MJ, and KW stations shown an acceptable range of 8% to 10% nearly for all RCM. This shows smaller variations of the RCMs produced output rainfall and the observed rainfall data, thereby the models can predict the future rainfall events. However, there was no significant variability among models output in simulating rainfall. For stations of AK, MM, and DB the CV values were also in the acceptable ranges (10% to 13%), and provided a smaller variation in rainfall between the observed and model output.

The observed T_{max} and the produced T_{max} from all models for stations of AK and AR were in good agreement, as the index of agreement was in the range of 85% and 90%. However, for stations of MM, KW, and MJ the index of agreement was smaller. For DB station, the index of agreement value was satisfactory (35–40%) for most RCMs except CNRM-CM5 model. This indicates for mid altitude stations nearly most of the models can produce T_{max} efficiently, and for lowlands and highlands, the RCMs poorly reproduce T_{max} , as the index of agreement value is smaller. In line with this (Worku et al., 2018) reflected that the RCMs show bias at higher elevations, but work well for low-elevation regions. The higher index of agreement for reproducing T_{min} was observed in AR station (80–85%), and followed by DB stations (75–80%). The index of agreement for KW station in most of the RCMs was moderate (45% to 50%). Unlikely, for stations of AK, MM, and MJ, the index of agreement was smaller (30% to 40%), indicating the satisfactory agreements of most RCMs to the observed records.

However, there was an insignificant difference among the RCMs. The results are in line with Kumar, et al. (2008), who concluded that better agreements of observed and simulated monthly climate data in the majority of the weather parameters. A majority

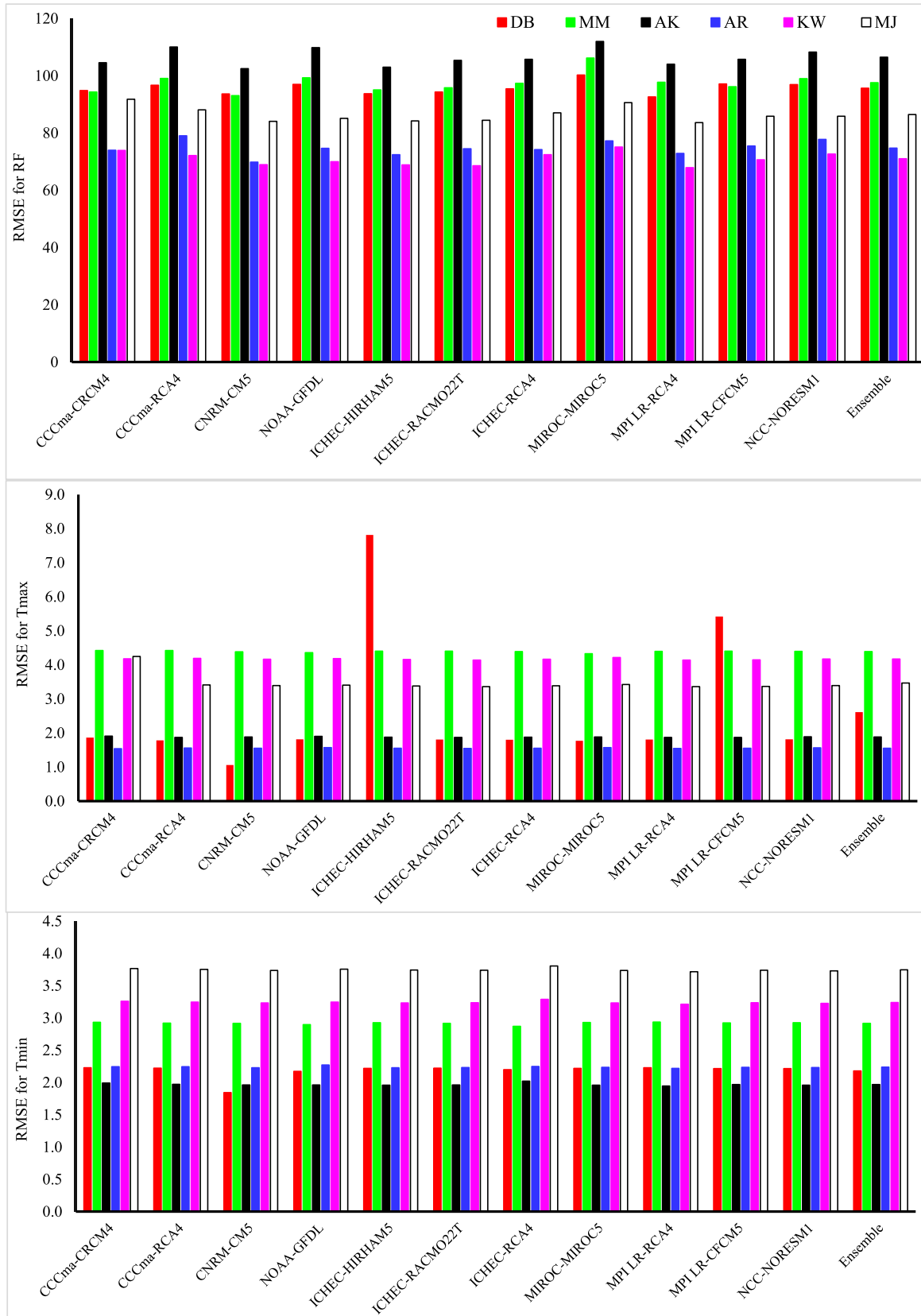


Fig. 6. The Root mean square value of RCMs for T_{max} , T_{min} , and rainfall.

of RCMs can simulate the most reliable annual and seasonal rainfall and air temperature estimations (Worku et al., 2018). In general, nearly most of the RCMs for a station of AR showed the best

agreement with observed T_{min} values (Fig. 8). The index of agreement values of all models to reproduce monthly rainfall was close to 100%, which indicates there was a highest agreement between

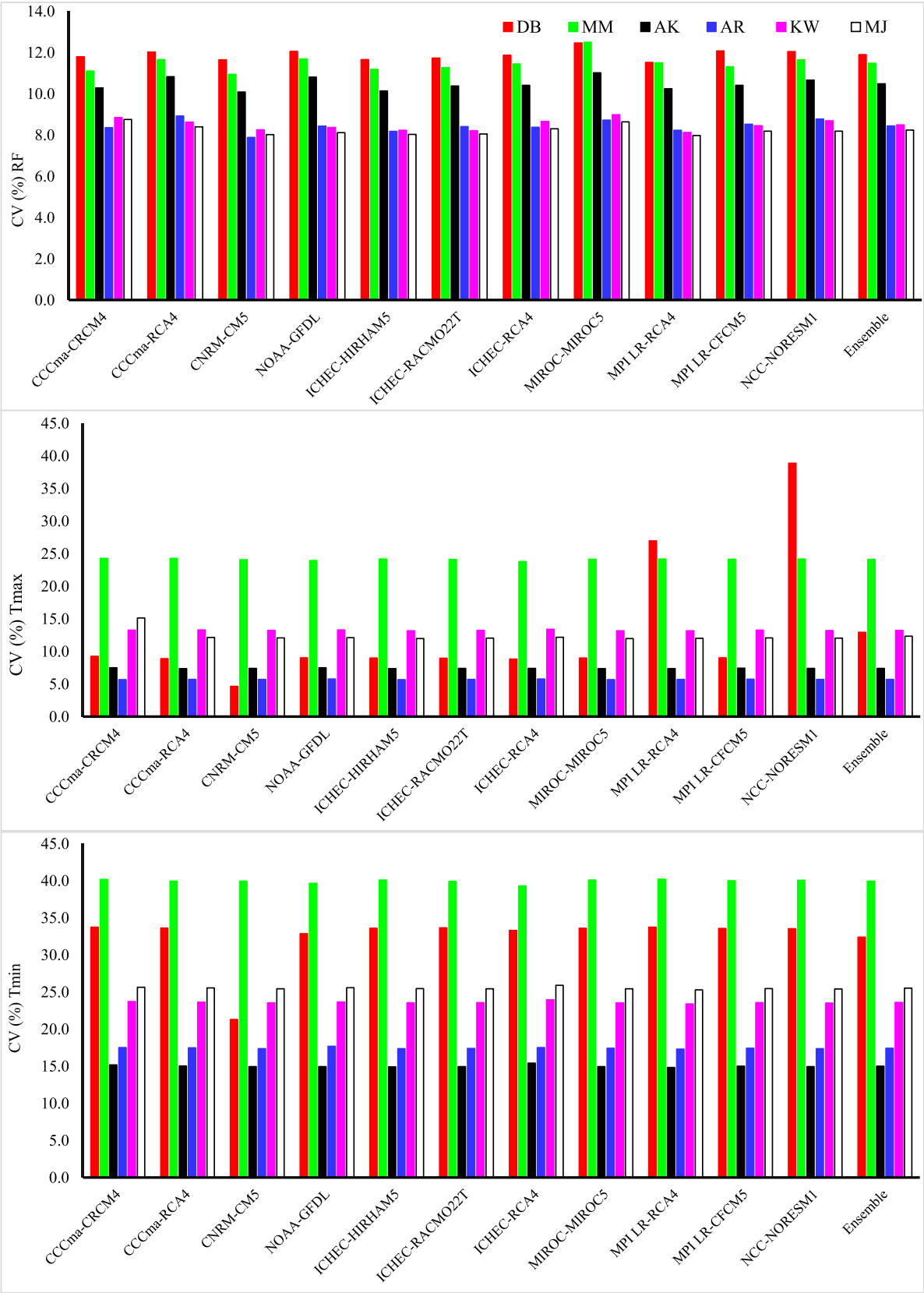


Fig. 7. The coefficient of variations of RCMs for simulating T_{max} , T_{min} , and Rainfall.

RCMs and the observed monthly rainfall. Even though there were insignificance variations among RCMs, they were efficient for reproducing the rainfall in all stations.

The higher correlation coefficient (R) values were observed in stations of AK and AR (90–100%) nearly for most of the RCMs. For the DB station, the observed R-values were also highest in most

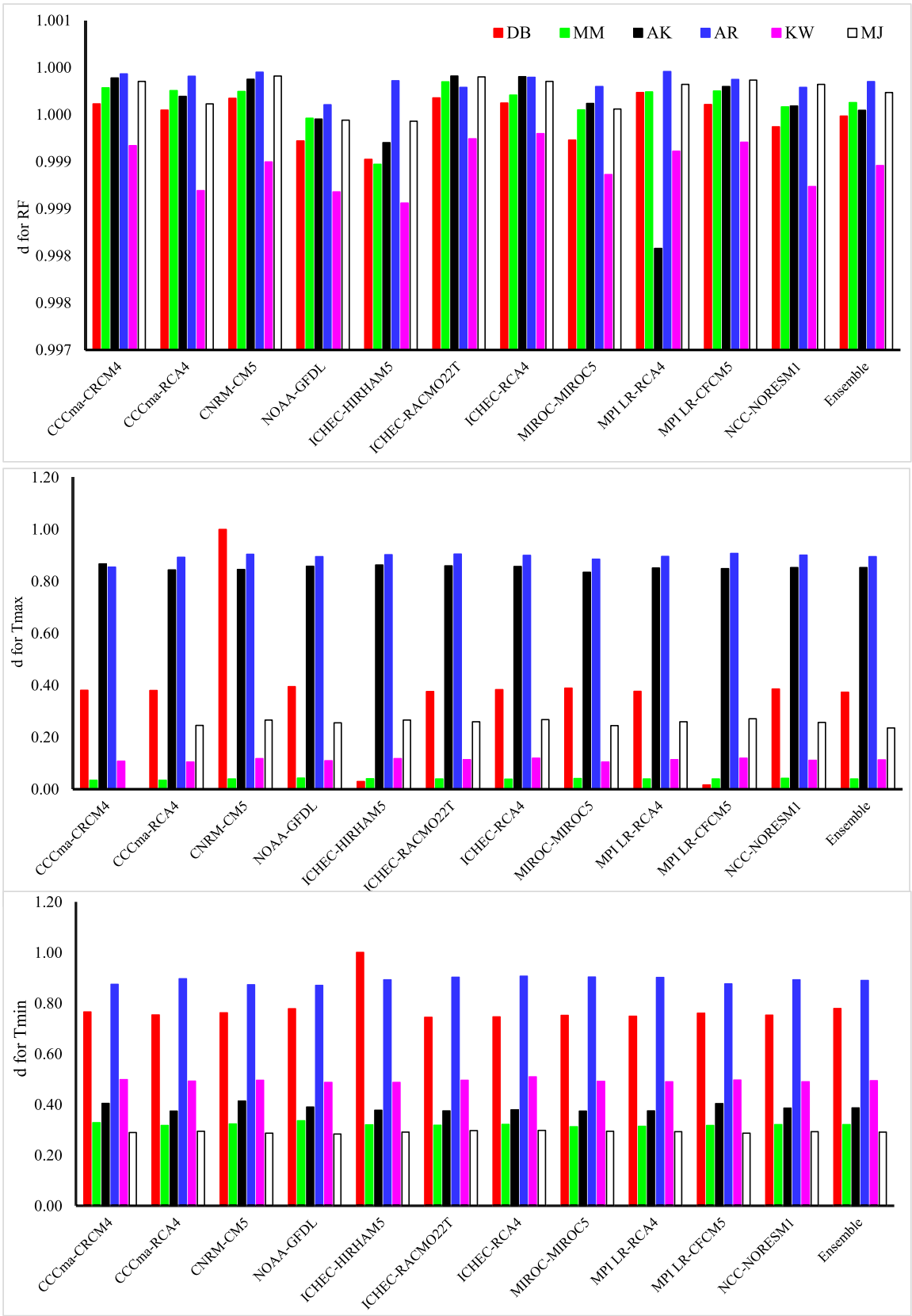


Fig. 8. The index of agreement of RCMs in simulating T_{max} , T_{min} , and rainfall.

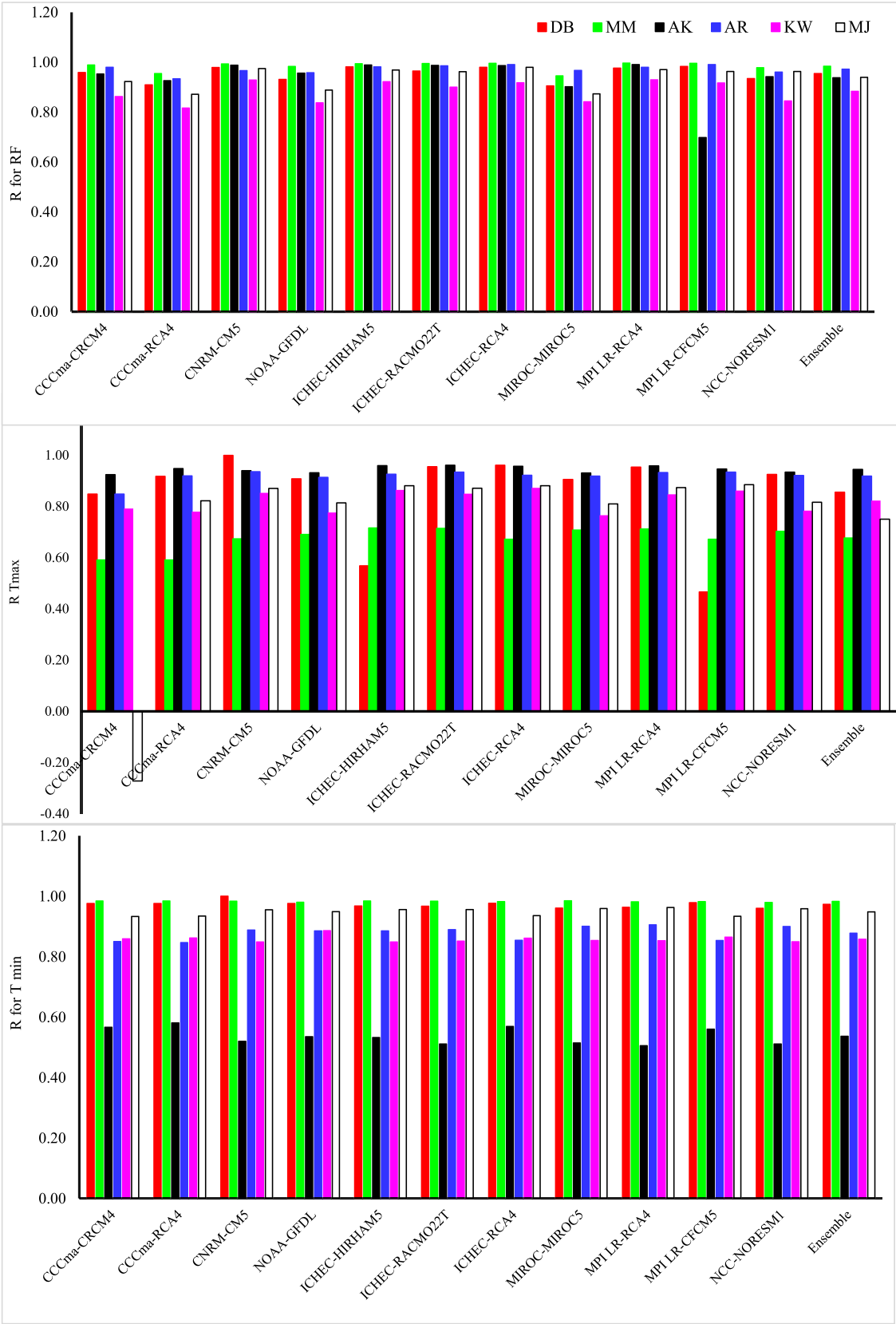


Fig. 9. The correlation coefficient of RCMs in simulating T_{max} , T_{min} , and rainfall.

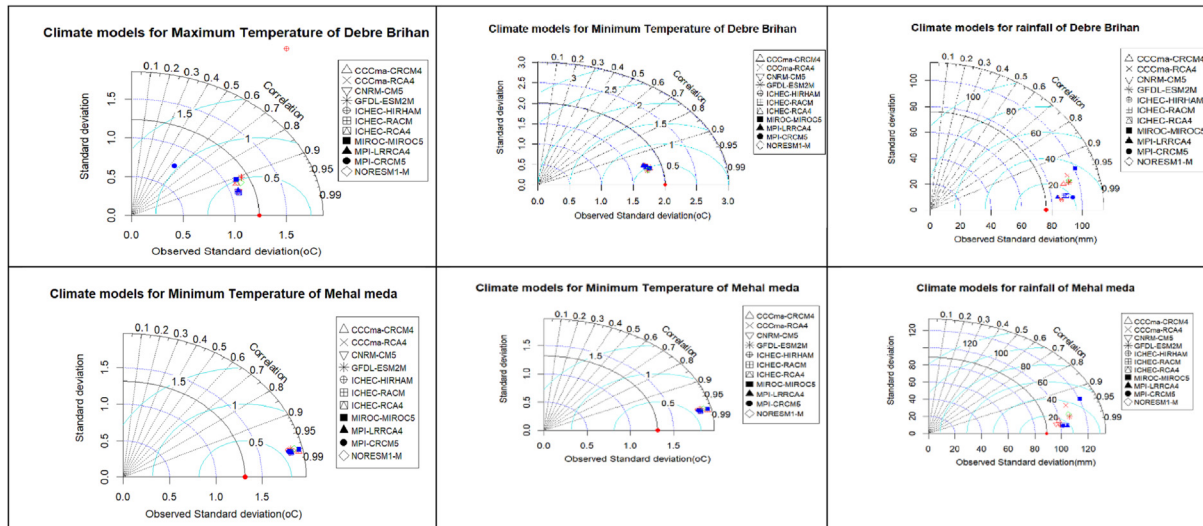


Fig. 10. Taylor diagram of RCMs in simulating T_{max} , T_{min} , and rainfall in highlands area.

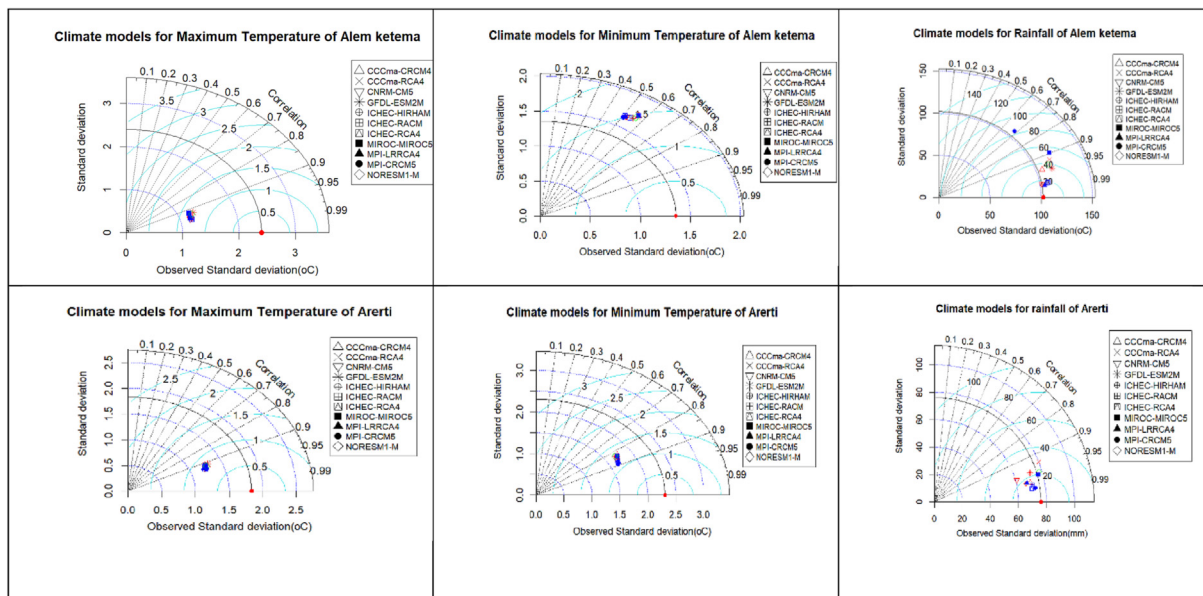


Fig. 11. Taylor diagram of RCMs in simulating T_{max} , T_{min} , and rainfall at mid-altitudes.

of the RCM (above 90%) except for ICHEC-HIRHAM and MPILR-CFCM5 models (R-values of 57% and 47% respectively). This indicates a strong relationship between observed T_{max} and RCMestimated T_{max} values. The R-value for stations of MM, KW, and MJ was in the acceptable value (70% to 90%) for most of the RCM except CCCma-CRCM4 at KW stations (R-value of (−27%). In general, most of the RCMs have a positive correlation with the observed T_{max} in most of the stations, especially in AK.

The value of R for stations DB and MM as most of RCM produced T_{min} was nearly 100% (above 95%). Similarly, for stations MJ, KW, and AR, the R-value was observed as higher (85–95%) for most of the RCM, indicating a strong positive relation with the observed T_{min} . Nevertheless, for a station of AK the observed R-value of all models to produce T_{min} was relatively smaller, moderate values (50% to 60%). However, the degree of the relation of RCM with the observed T_{min} does not reflect a significant difference. The simulated T_{min} , T_{max} , and rainfall by all RCMs compared well with

observed T_{min} , T_{max} , and rainfall over most stations (Philbert et al., 2016).

The R-values observed in stations of DB, MM, AK, and AR were near 100% (above 95%) for most of the RCM in reproducing monthly rainfall except MPILR-CFCM5 at AK station (70%). This shows a positive correlation of most RCM with the observed rainfall data. As per the investigation of Abiy et al., (2021), the ensemble of RCMs fits with the observed data than single RCMs. Similarly, for stations of KW and MJ, the observed R-value was in the range of 75% to 95% for most of RCM, which is in the acceptable range. There was no significant difference in RCMs for most stations in reproducing the monthly rainfall (Fig. 9).

Taylor diagram indicates the RCMs' ability to simulate the pattern and amplitude of the observed inter-annual variation of temperature and rainfall. As the Taylor diagram showed (Figs. 10–12), for each parameter the distance of all points (RCMs) from the red point (observed value) was nearly equal. That means, there is no

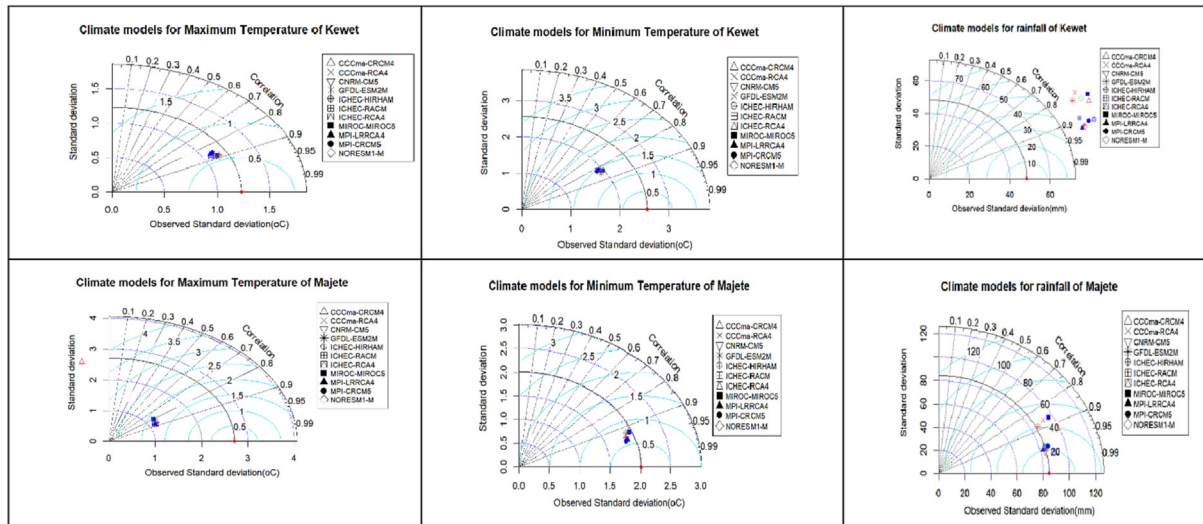


Fig. 12. Taylor diagram of RCMs in simulating T_{max} , T_{min} , and rainfall at lowlands.

clear picture to identify which RCMs exhibit the shortest distance (smallest standard deviation) and the highest R-value compared with the observed value.

For a station of DB, the SD and R values were smaller for some of the RCMs and larger for some of the RCMs. MPI-CRCS5 simulates T_{max} differently from others with a SD value between 0.5 and 1.0 °C and exhibits an R-value of 0.57. In the case of MM, the RCM model shows relatively the shortest distance from the red point and has the highest R-value. For other RCMs, there is no clear visualization to select which models are better. For MM and DB, the SD value was found between 0.5 & 0.6 °C and the R value of nearly one. In general, most of the RCMs are outperformed in simulating T_{min} for highlands areas rather. Unlike T_{max} and T_{min} , for the simulation of rainfall, the Taylor diagram powerfully explained the performances of RCMs. In DB and MM stations, ICHEC-HIRHAM relatively exhibits the shortest distance (smallest SD of 20 mm) and the largest R-value (0.99), followed by the RCMs of MPI-CRCS5, CNRM-CM5, ICHEC-RACM, ICHEC-RCA4. For other models, the SD value of 20 to 40 mm, and R-value between 0.95 to 0.99 was observed.

For AK and AR stations, the SD was found between 0.8 & 1 °C and 1.3 to 1.5 °C respectively; and the R value was in the range of 0.9 to 0.92. As shown in Fig. 11, most of the RCMs exhibit nearly equal SD and R-value for the simulation of T_{max} . For instance, for AK and AR, SD ranges between 1 & 1.5 °C. But, the R-value for AK is in the range of 0.5 and 0.6, for AR between 0.8 & 0.9. On the other hand, at the station of AK, ICHEC-HIRHAM, ICHEC-RACM, ICHEC-RCA4, CNRM-CM5, MPI-LRCA4 shows an SD of 20 mm and R-value of 0.99. Other RCMs account for variable SD and relatively lower R-value (Fig. 11). At AR, most of the RCMs show an SD under 20 mm and an R-value of above 0.95.

Most of the RCMs can capture the temporal variability of T_{max} and T_{min} . For MJ, the SD of T_{max} ranges between 1.8 and 2 °C for most of the RCMs except CCCa-CRCS4. For KW stations, nearly all RCMs are unable to capture rainfall variability (all RCMs points fall out of the Taylor diagram), indicating high SD and R value. In MJ stations, ICHEC-HIRHAM, ICHEC-RACM, ICHEC-RCA4, CNRM-CM5, MPI-LRCA4, MPI-LRCS5, NORESM1-M shows an SD of 20 mm and R-value of above 0.95. However, other RCMs exhibit an SD value of 40 to 60 mm and an R-value from 0.85 to 0.9. With the exception of the KW station, all RCM points fall out of the Taylor diagram, indicating the largest SD and R-value.

The performance of RCMs in simulating T_{max} , T_{min} , and rainfall over different stations is presented in (Figs. 10–12), and it can be

concluded that from the above analysis, most of the RCMs simulate T_{min} more than T_{max} over stations. All parameters simulated by most of the RCMs are positively correlated with the observed values. This result is in close agreement with that of Philbert, et al. (2016), who found a better simulation of T_{min} than T_{max} ; and RCMs simulate T_{min} and T_{max} better than rainfall in most stations they were studied. They suggested the use of CORDEX RCMs in representing the variability of T_{max} and T_{min} over the Tanzania region. Similarly, the majority of RCMs are highly correlated with observed and ERA-Interim data in most areas of South Africa and they adequately capture precipitation (Mxolisi, et al., 2015).

The index of agreement of most of the RCMs is found as sound on stations of AK and AR for simulating T_{max} ; DB and AR for simulating T_{min} and all stations in the simulation of Rainfall. In line with these results Ifeka, et al., (2021), evaluated two RCMs and found both CCCma-CanRCM4 and MPI-LR-CFCS5 agrees with the observed data. Based on the Taylor diagram, most of the RCMs are outperformed to simulate T_{max} and T_{min} . However, there is a slight difference among RCMs in simulating the seasonal changes of rainfall. Hussen et al. (2013), support this as some of the evaluated RCMs have been outperformed concerning the observed GPCP and others have not yet; however, the multimodal ensemble is found generally closer to the GPCP than individual models. According to (Tamene and Chala, 2021), all four RCMs simulated the seasonal rainfall, and to some extent biased around a warm climate zone in simulating T_{max} and T_{min} .

This result is supported by Kiya et al., (2020), who investigated that all models were found best in capturing the observed rainfall, but no individual model is best in all performance measures. The ensemble of models is better at simulating the characteristics of rainfall than the individual models and is best in all performance measures. The RCMs from the CORDEX indicated a better performance in reproducing the rainfall characteristics over the Mbarali River catchment (Mutayoba and Kashaigili, 2017). These RCMs were recommended for use for climate change impact and adaptation studies in water resources management in the selected cities.

4. Conclusion and recommendation

In this research agro-ecological classification, temporal and spatial variability, trends analysis of rainfall, maximum and minimum temperature, and validation of eleven RCMs under various climatic agro-ecological zones of North Shewa were addressed. North

Shewa exhibits the three AEZ categories of 34.2% Kolla, 28% Weyna Dega, and 37.8% Dega. The temporal variability of observed $T_{\max}$ and rainfall is smaller with a CV of 10%, and shows uniform distributions over stations. Whereas, the CV value for $T_{\min}$ over stations shows satisfactory distributions. The spatial variability of rainfall is significantly higher than that of $T_{\max}$ and $T_{\min}$. Since agriculture is directly impacted by climate change (an increase in temperature and rainfall variability), well-validated RCMs are needed.

The performance of the RCMs were found to be variable in the simulation of rainfall and temperature in all AEZs of North Shewa. Most of the RCMs can capture the spatial variability of rainfall and temperature in mid-AEZs. However, some of the RCMs can slightly handle the spatial variability of $T_{\max}$ and $T_{\min}$ while others not. None of the RCMs captured the spatial variability of $T_{\min}$ in the highland and lowland AEZs. This work highlights the use of high-resolution RCMs for the projection of $T_{\max}$, $T_{\min}$, and rainfall across locations and to develop strategic plans to alleviate the impacts of future climate change in all AEZs of North Shewa and other similar regions.

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Authors' contributions

Biruk Getaneh Ayele did Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Formal analysis, Methodology. Ayele Desalegn Woldemariam did Conceptualization, Data curation, Writing – review & editing, Visualization, Investigation, Formal analysis, Methodology, Supervision, Resources and Hailu Kendie Addis did Funding acquisition, Writing – review & editing, Visualization, Supervision and Project administration.

Declaration of competing interest

The authors declare no conflict of interest.

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