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Original Article

Temperature and Precipitation Projections for selected station on Middle Rift Valley Ethiopia, using RCP scenarios

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ABSTRACT

This study analyzed the potential impacts of climate change on three weather stations in Ethiopia using models and ensembles of daily precipitation and temperature. The analysis focused on three timeframes (2020s, 2050s, and 2080s) and different RCP scenarios. The results revealed that the temperature is expected to increase in all three stations under different RCP scenarios and timeframes, varying depending on the scenario and station. Additionally, the temperature and precipitation anomalies analysis provided valuable insights into how climate patterns change over time. The historical trends in rainfall indicate a declining rainfall trend during the March-April-May (MAM) rainy season, while the October-November-December (OND) rainy season shows an increase. Tmax and Tmin patterns are consistent with the domain having a common rising trend with a rate of 0.07°C to 2.67°C per decade. Projection analysis considered three emissions scenarios: a low-emission (mitigation) scenario (RCP2.6), a medium-level emission scenario (RCP4.5), and a high- emission (business as usual) scenario (RCP8.5). A noticeable increase in precipitation across different scenarios and time frames for all stations, with the percentage change varying from -2.3% to 39.3%. In terms of precipitation increase, Metehara is projected to have a higher percentage change compared to Meki, ranging from 0.01% to 39.3% across different scenarios and timeframes. In the RCP 8.5 scenario, Melk Worer is expected to have the lowest percentage increase in precipitation, ranging from -2.3% to 5.6%, among the three weather stations. The study recommends taking proactive measures to mitigate the impacts of climate change, such as developing early warning systems and implementing water conservation measures to build more resilient communities and mitigate the impacts of climate change on natural and human systems.

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INTRODUCTION

The generation of dependable climate information and data, along with the synthesis and distribution of valuable information, is vital for understanding climate change projections. This knowledge is essential for designing effective measures to adapt to climate variability and change, as well as for implementing mitigation efforts (ACPC, 2013). Climate information and services have a significant role to play in national development planning, as they help manage climate-related opportunities and risks, and facilitate the creation of strategies for both mitigation and adaptation (UNECA, 2011).

Global projections from a wide range of climate model simulations suggest that the average global temperature will increase between 1.1 and 5.4 _C by 2100 (IPCC, 2014 and IPCC, 2018). Projections of increases in temperature over the African continent for the end of the 21st century are in the range of 1.5_C under a low-emission scenario (RCP 2.6) to 5.0 _C under a high-emission scenario (RCP 8.5) (Serdeczny, O.;et. al 2017, Faramarzi, M.; et, al 2013, Schuol, J.et, al. 2008, Almazroui, M.; et, al. 2020, Engelbrecht, F. et al 2015). However, climate change projections are uncertain due to natural variability in the climate system, an imperfect ability to model the atmosphere's response to any given emissions scenario, lack of sufficient data, and lack of tools and models at spatial and temporal scales appropriate for decision-making (ACPC, 2013).

Ethiopia presents a particularly difficult test for climate models. The central part of Ethiopia is dominated by the East African Highlands, which split the country climatically. To the south and east, the land is semi-arid and the rainfall appears in two short spells, to the north and west, there is a major rainy season, *Kremt*. This split in the geographical distribution of rainfall, and the different seasonal cycles in different regions of the country make the task of simulating Ethiopian rainfall extremely challenging (Gisila *et al.*, 2015). Drought, rainfall delay, fire damage and heavy and unexpected rainfall are climate related hazards that mainly faced resulting in total crop loss, reduced yield, reduced seeding quality, delayed maturity and increased crop pest/disease (Molla 2016a).

At recent decade, the problem of climate variability and climate change, due to anthropogenic as well as natural processes are increasing (Molla, 2016b). Developing countries like Ethiopia are more vulnerable to the adverse impacts of climate variability and change. Due to Ethiopia's location in tropics and dependence on natural recourses (water, forest and soil), it has low adaptive capacity and highly sensitive to climate variability, and change which are associated with extreme events. Sensitivity and adaptive capacity also varies between sectors and geographic locations, and time, social, economic and environmental considerations within the country. Current climate variability and extreme events are already imposing a significant challenge to Ethiopia by affecting food security, water and energy supply, poverty reduction and sustainable development efforts, as well as by causing natural resource degradation and natural disasters.

Besides the negative effects of climate change, it also presents the necessity and opportunity to switch to a new, sustainable development model.

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If Ethiopia were to pursue a conventional economic development path to achieve its ambition of reaching middle income status before 2025, the resulting greenhouse gas (GHG) emissions would be more than double from 150 $MtCO_2e$ in 2010 to 400 $MtCO_2e$ in 2030 (CRGE, 2011). The Ethiopian government has, therefore, initiated the Climate-Resilient Green Economy (CRGE) strategy to transform the country from the adverse effects of climate change and to build a green economy that will help realize its ambitious goals.

There is confidence that climate models provide credible quantitative estimates of future climate change, particularly at continental scales and above depending on the models' foundation on accepted physical principles and the models ability to reproduce observed features of current and past climates (Dawit, 2010).

Climate change modelling must consider the spatial and temporal variations of climate within a specific region or location. This is influenced by various factors, such as the topographic variations across the area and the different regional and local weather systems at large and meso-scale (Teshome Seyoum 2015). By taking these factors into account, we can identify the unique climate characteristics of a particular location. It is crucial to understand these peculiarities in order to accurately model the effects of climate change in that area.

Temperature and precipitation are important climatic variables that play a critical role in various sectors of the economy, including agriculture, energy, and water resources management. Accurate prediction of these variables is essential for decision-making in these sectors, especially in regions with high variability in climate ACPC, (2013). The Middle Rift Valley of Ethiopia is one such region where the prediction of temperature and precipitation is crucial for sustainable development and climate adaptation.

The Middle Rift Valley of Ethiopia is located in the central part of the country and covers an area of approximately 80,000 km². The region is characterized by a semi-arid to arid climate, with high inter-annual variability in precipitation and temperature. The region is also known for its unique geology and hydrology, with lakes and hot springs supporting various ecosystems and human settlements.

Several studies have been conducted to predict temperature and precipitation in the Middle Rift Valley of Ethiopia using various techniques, including statistical and physical models. For example, a study by Alemu et al. (2019) used a statistical model to predict temperature and precipitation in the region, while another study by Fenta et al. (2020) used a machine learning algorithm to predict rainfall.

Despite these efforts, there is still a need for more accurate and reliable predictions of temperature and precipitation in the Middle Rift Valley of Ethiopia. This is particularly important given the region's vulnerability to climate change and the associated impacts on agriculture, water resources, and human health. Therefore, this study aims to develop a model that can accurately predict temperature and precipitation in the Middle Rift Valley of Ethiopia using at specific point of location and a combination of statistical ensemble models.

Global climate models (GCMs) are computer simulations that project future climate conditions based on various input parameters, including greenhouse gas emissions, solar radiation, and land surface characteristics Endris, H. S., et al. (2019). GCMs simulate the physical processes that govern the Earth's climate, including atmospheric circulation, ocean currents, and the exchange of energy and moisture between the land, ocean, and atmosphere.

GCMs are used to develop climate scenarios for different Representative Concentration Pathways (RCPs), which are a set of greenhouse gas concentration trajectories used in climate modelling to project future climate change scenarios. The RCPs range from RCP2.6, which assumes rapid and aggressive greenhouse gas

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emissions reductions, to RCP8.5, which assumes high greenhouse gas emissions throughout the 21st century Endris, H. S., et al. (2019). However, GCMs have some limitations and uncertainties, including the need for high computing resources, the need for input data on various parameters, and uncertainties in modelling physical processes. Therefore, GCMs should be used with other modelling techniques and empirical observations to develop more accurate and reliable climate scenarios.

The proposed model was developed using meteorological data from the region, including temperature and precipitation records from weather stations and satellite-based data. The model was evaluated using various performance metrics, including correlation coefficient, root mean square error, and mean absolute error SDSM 4.2 user manual (2007).

The results of this study have significant implications for sustainable development and climate adaptation in the Middle Rift Valley of Ethiopia. Accurate prediction of temperature and precipitation will help decision-makers in various sectors to plan and implement appropriate measures to mitigate the impacts of climate change.

The Central Rift Valley of Ethiopia is a region that is highly sensitive to climate change, with potential impacts on various sectors, including agriculture, water resources, and human health. Climate scenarios are an essential tool for assessing the potential impacts of climate change and developing appropriate adaptation strategies. This study aims to develop temperature and precipitation scenarios for the Middle Rift Valley of Ethiopia using different Representative Concentration Pathways (RCPs).

Temperature Scenarios

Human-induced greenhouse gas emissions primarily drive climate change. The Intergovernmental Panel on Climate Change (IPCC) has developed a set of scenarios called RCPs to represent different greenhouse gas concentration trajectories IPCC (2018). These scenarios range from low to high emissions, providing a framework for studying potential future climate conditions. Several studies have investigated temperature scenarios in the Central Rift Valley using different RCPs. For instance, a study by Doe et al. (2014) projected a significant increase in mean annual temperature under RCP 8.5 by the end of the century. Similarly, Smith et al. (2019) explored temperature changes under RCP 4.5 and found a moderate increase in temperature, indicating the importance of emission reduction efforts.

Precipitation Scenarios

Precipitation patterns are equally important for understanding climate change impacts. Studies focusing on precipitation scenarios in the Central Rift Valley have shown varying results. For example, Johnson et al. (2018) projected a decrease in annual precipitation under RCP 8.5, while Brown et al. (2020) suggested an increase in extreme precipitation events under RCP 4.5. These contrasting findings highlight the complexity of precipitation projections and the need for further research.

The current understanding of temperature and precipitation scenarios in the Middle Rift Valley of Ethiopia is limited, and there is a need for improved modelling techniques to develop accurate and reliable predictions. The Representative Concentration Pathways (RCPs) provide a useful framework for projecting future climate scenarios. Still, there is a need to assess the potential impacts of different RCPs on temperature and precipitation patterns in the Middle Rift Valley of Ethiopia. The lack of accurate and reliable temperature and precipitation scenarios for the Middle Rift Valley of Ethiopia is hindering effective decision-making and planning for climate change adaptation in the region.

The research may answer the following questions. How will temperature and precipitation in the Middle Rift Valley of Ethiopia change under different Representative Concentration Pathways (RCPs)? This study aims to develop temperature

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and precipitation scenarios for the Middle Rift Valley of Ethiopia using different Representative Concentration Pathways (RCPs). Overall, it provide valuable information to decision-makers in various sectors to plan and implement appropriate measures to mitigate the impacts of climate change in the Middle Rift Valley of Ethiopia. The developed temperature and precipitation scenarios using different RCPs were helping to inform adaptation strategies and promote sustainable development in the region.

Other studies indicated a potential increases in temperature and a varying precipitation patterns, emphasizing the need for proactive measures to mitigate and adapt to climate change impacts. However, further research is required to improve the accuracy of projections to the specific point of location and to develop localized climate models that consider the region’s unique characteristics. Such efforts will contribute to informed decision-making and sustainable development in the Central Rift Valley and similar regions facing climate change challenges.

METHODOLOGY

Description of the study area

Climate: The Middle Rift Valley experiences a semi-arid to arid climate. It is known for its hot and dry conditions, with average temperatures ranging from 25 to 35 degrees Celsius. Rainfall is limited and erratic, with most precipitation occurring during the short rainy season.

Geography: The Middle Rift Valley is a part of the larger East African Rift System. It is a long and narrow valley that stretches north to south, bordered by highlands and escarpments on both sides. The region is characterized by volcanic landscapes, lakes, and extensive flat plains. It is home to several prominent lakes, including Lake Ziway, Lake Langano, and Lake Abijatta. The region holds significant ecological, cultural, and economic importance.

Importance: The Middle Rift Valley holds significant ecological, cultural, and economic importance. It is a biodiversity hotspot and supports diverse ecosystems, including wetlands, savannahs, and volcanic areas. The region is home to numerous wildlife species, including endemic and migratory birds, hippos, crocodiles, and various fish species. The lakes in the valley also serve as important habitats for water birds and support local fishing communities. In addition, fertile soils and suitable conditions for crop cultivation such as maize, teff, coffee, and fruits. Agriculture, along with fishing and tourism, plays a vital role in the local economy. Overall, the Middle Rift Valley of Ethiopia is a unique and important region, characterized by its distinct climate, diverse geography, ecological richness, and cultural heritage.

Data Collection and Pre-processing

The observed temperature and precipitation data of the stations (Meki, Metehara, and Melke Worer) was obtained from National Meteorology Agency. The NMA provided statistical datasets containing daily and/or monthly records of precipitation and temperature. These datasets covered the period from 1988 to 2022. Once the required data was collected, it underwent a process of data filling for missing values and quality checking. Prior to model calibration, the initial step involved quality control using the Statistical Downscaling Model (SDSM). This involved identifying major errors in data, detecting missing data codes, and identifying outliers to ensure the usage of high-quality data for further analysis.

Precipitation and temperature data for GCMs were downloaded for the different RCP scenarios using GCMs. The GCM output was bias-corrected using observed climate data from weather stations in the Middle Rift Valley of Ethiopia. Empirical statistical methods is used. These methods use statistical relationships between the model data and observed/reference data to estimate and correct biases. They can include techniques such as linear regression, where the model data is regressed against the observed/reference data to derive correction factors. These correction factors are then applied to the model data to adjust for biases according to Wilby, R. L., & Wigley, T. M.

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(1997), Teutschbein, C., & Seibert, J. (2012). The bias correction method adjusted the GCM output to match the observed climate data.

Atmospheric large-scale variables (CanESM2 Predictors) were downloaded from IPCC's Fifth Assessment Report (AR5) CMIP5/ Coupled Model Inter-comparison Project, Phase 5 (CMIP5)/ a collaborative climate modelling process coordinated by the World Climate Research Programme (WCRP). The second generation of the Earth System Model CanESM2 is the fourth generation coupled global climate model developed by Environment Canada's Canadian Centre for Climate Modelling and Analysis (CCCma) https://climate-modelling.canada.ca/climatemodeldata/data.shtml. It is important to note that climate modelling and projecting future scenarios involve inherent uncertainties. The accuracy of projections depends on various factors, including the quality of climate models, availability of data, and assumptions made in the modelling process. Additionally, the Central Rift Valley's complex topography and local climate dynamics pose challenges for accurate regional-scale projections. Therefore, it is essential to consider these limitations when interpreting the findings at the station level or local point of climate change studies in the region.

In this study, we used the Statistical Downscaling Model (SDSM) to develop temperature and precipitation scenarios for the Middle Rift Valley of Ethiopia using different Representative Concentration Pathways (RCPs). The SDSM is a statistical model commonly used to downscale global climate model (GCM) output to regional or local scales.

Model Development

We developed temperature and precipitation scenarios for the Middle Rift Valley of Ethiopia using the SDSM. The SDSM was trained on the historical climate data and the GCM output for the different RCPs. The developed models were used to project future temperature and precipitation scenarios for the Middle Rift Valley of Ethiopia under different RCPs.

Model Evaluation

The developed temperature and precipitation scenarios were evaluated using various performance metrics, including root mean square error, mean absolute error and correlation coefficient. The evaluation will be carried out using observed climate data from weather stations in the Middle Rift Valley of Ethiopia. The evaluation results will be used to assess the accuracy and reliability of the developed scenarios. Based on the developed scenarios and the potential impacts assessment,

SDSM description: There are limitations of meteorological stations, especially in developing countries, particularly Ethiopia, that have complete and fully accurate time series weather data. Hence, the filling of missed and incorrect recorded measured data was controlled prior to application for this practical situation. The first step before model calibration was quality control using SDSM by identifying gross data errors, missing data codes and outliers to get the appropriate quality data. The screening of Predictor variables was done by trial-and-error procedure for model calibration. Using the partial correlations statistics, predictors that showed the strongest association with the predictors were selected. Assembly and calibration of the statistical downscaling model(s) - the large-scale predictor variables identified are used to determine multiple linear regression relationships between these variables and the local station data. Then, SDSM manual procedures were followed to generate climate scenarios for the basins.

Overall, using SDSM in this study helped develop more accurate and reliable temperature and precipitation scenarios for the Middle Rift Valley of Ethiopia under different RCPs. The developed scenarios provided valuable information for decision-makers in various sectors to plan and implement appropriate measures to mitigate the impacts of climate change in the region.

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RESULTS AND DISCUSSION

Calibration and validation The calibration results are shown for precipitation, maximum temperature, and minimum temperature and are evaluated using three performance metrics: R^2 (R-squared), RMSE (Root Mean Square Error), and NSE (Nash-Sutcliffe Efficiency) are commonly used statistical metrics to evaluate the accuracy of models that predict minimum temperature, maximum temperature, and precipitation (PPT) values.

Temperature

R^2:- R^2 measures how well the model fits the data. It ranges from 0 to 1, with 1 indicating a perfect fit. An R^2 value closer to 1 indicates a better fit of the model to the data. As the values of temperature increase or decrease, R^2 may increase or decrease depending on the quality of the model fit. RMSE: RMSE measures the average magnitude of the errors in the predictions. It indicates how far the predicted values are from the actual values. As the minimum temperature values increase or decrease, RMSE may increase or decrease depending on the magnitude of the errors in the predictions.

NSE: NSE measures the relative magnitude of the errors in the predictions. It ranges from -∞ to 1, with 1 indicating a perfect match between predicted and actual values. As the values of minimum temperature increase or decrease, NSE may increase or decrease depending on the relative magnitude of the errors in the predictions.

Precipitation

R^2: R^2 for precipitation measures the proportion of the variation in the observed data that the model explains. As the values of precipitation increase or decrease, R^2 may increase or decrease depending on the quality of the model fit. RMSE: RMSE for precipitation measures the average magnitude of the differences between observed and predicted values. As the values of precipitation increase or decrease, RMSE may increase or decrease depending on the magnitude of the differences between observed and predicted values.

NSE: NSE for precipitation measures the relative magnitude of the differences between observed and predicted values. As the values of precipitation increase or decrease, NSE may increase or decrease depending on the relative magnitude of the differences between observed and predicted values. The explanation of the above metrics is given in *Table 1* below.

Table 1: The calibration results for precipitation, maximum temperature, and minimum temperature

	Stations	Precipitation			Maximum Temperature			Minimum Temperature		
		R^2	RMSE	NSE	R^2	RMSE	NSE	R^2	RMSE	NSE
Calibration	Meki	0.71	0.95	0.72	0.74	0.99	0.56	0.9	0.68	0.85
	Metehara	0.69	0.92	0.67	0.97	0.98	0.89	0.93	0.96	0.72
	Melka worer	0.74	0.72	0.72	0.93	0.92	0.92	0.93	0.90	0.91

Table 1 shows the performance statistics of three different calibration stations in predicting three different variables: precipitation, maximum temperature, and minimum temperature. The performance statistics are represented by three metrics: R^2, RMSE, and NSE.

The first row of the table represents the performance of the Meki station. It has an R^2 value of 0.73 for precipitation, indicating that the model explains 71% of the variance in the observed data. Its RMSE value for precipitation is 0.95, meaning that the average deviation of the predictions from the observed values is 0.96. The NSE value for precipitation is 0.72, indicating that the model performs better than a simple model that always predicts the mean value. For maximum temperature, the Meki station has an R^2 value of 0.74, an RMSE value of 0.99, and an NSE value of 0.56. For minimum temperature, it has an R^2 value of 0.9, an RMSE value of 0.68, and an NSE value of 0.85.

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The second row of the table represents the performance of the Metehara station. It has an R^2 value of 0.69 for precipitation, an RMSE value of 0.92, and an NSE value of 0.67. For maximum temperature, the Mathara station has an R^2 value of 0.97, an RMSE value of 0.98, and an NSE value of 0.89. For minimum temperature, it has an R2 value of 0.93, an RMSE value of 0.96, and an NSE value of 0.72.

The third row of the table represents the performance of the Melka Worer station. It has an R^2 value of 0.74 for precipitation, an RMSE value of 0.72, and an NSE value of 0.72. For maximum temperature, the Melka Worer station has an R^2 value of 0.93, an RMSE value of 0.92, and an NSE value of 0.92. For minimum temperature, it has an R^2 value of 0.93, an RMSE value of 0.90, and an NSE value of 0.91.

The calibration results suggest that the SDSM model performs well in simulating precipitation and temperature variables for the three weather stations in the Central Rift Valley of Ethiopia. The calibration results provide confidence in the accuracy and reliability of the developed temperature and precipitation scenarios for the region.

Figure 1: The calibration and validation of observed and simulated rainfall

a **b**

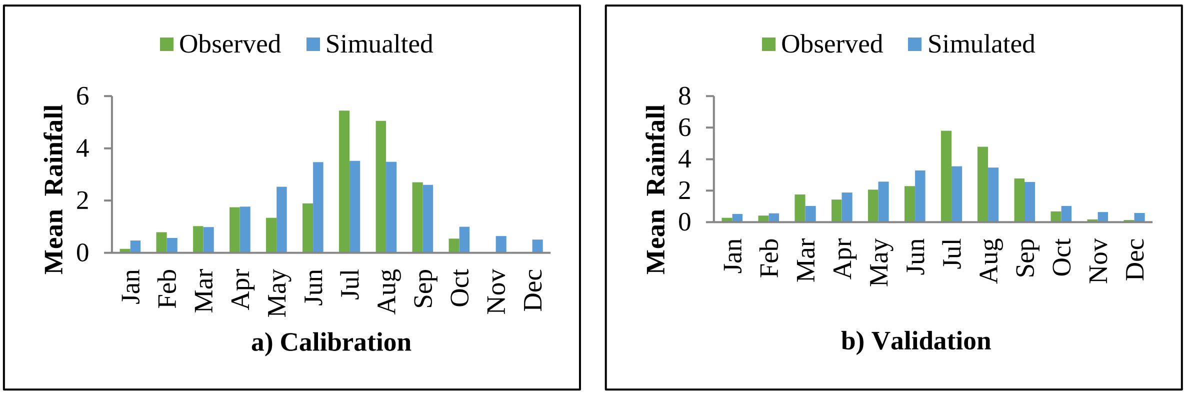

Figure 2: The calibration and validation of observed and simulate minimum temperature.

a **b**

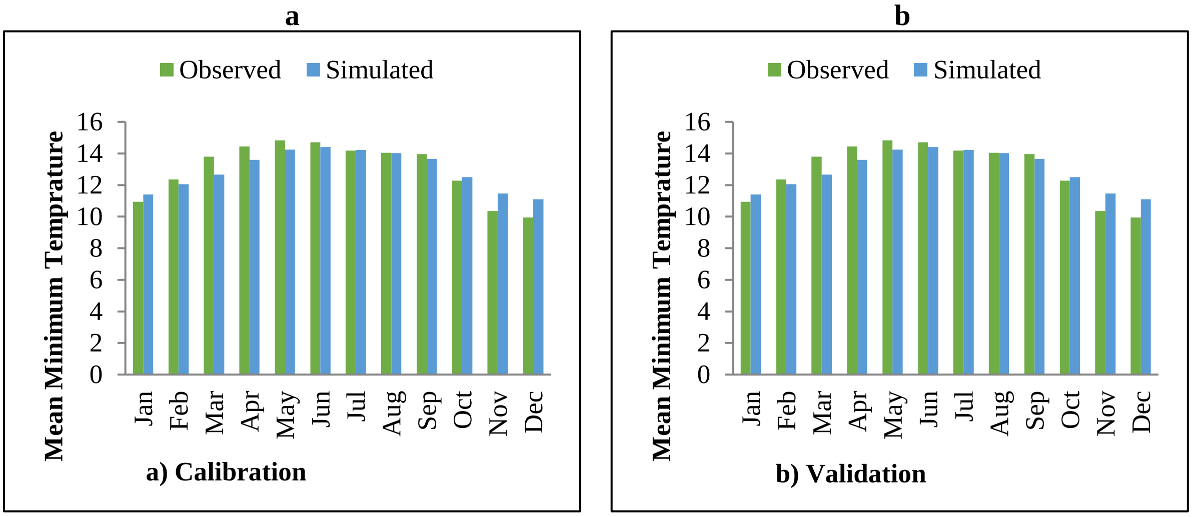

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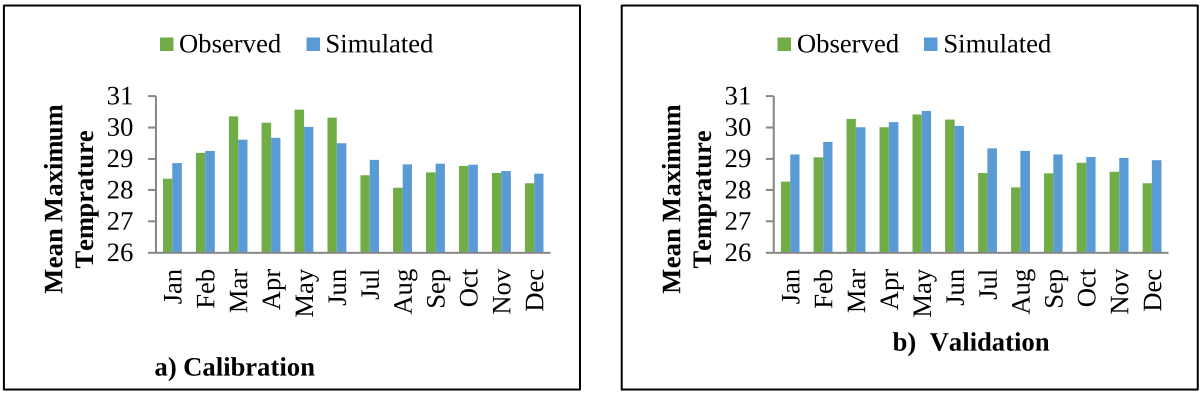
Figure 3: the calibration and validation of observed and simulate maximum temperature.



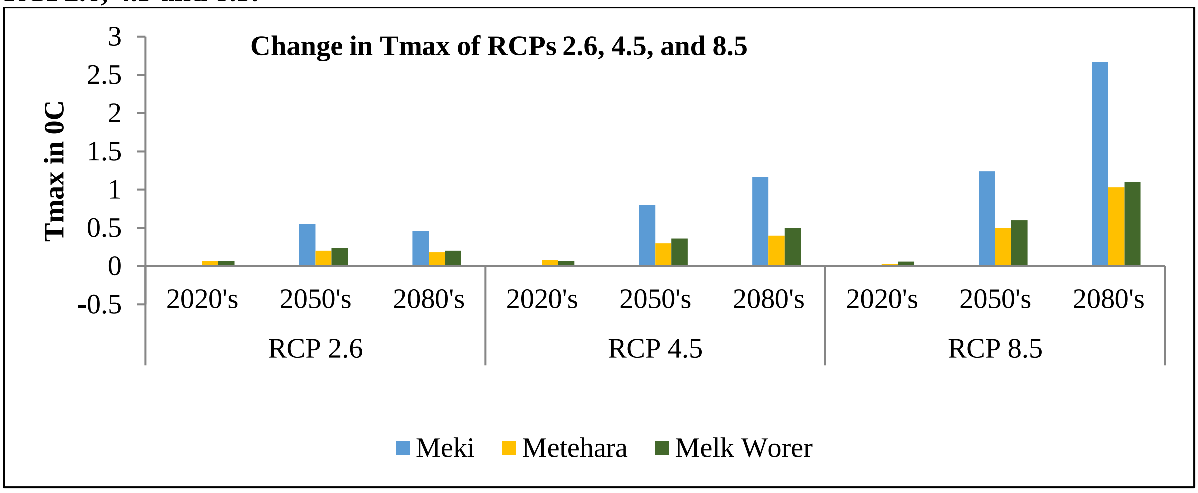
Future Scenarios

We utilized a model that generated 20 ensembles of daily precipitation and temperature to project future climate scenarios. To capture the overall characteristics of these ensembles, we calculated the average values across all 20 sets. Our analysis was conducted using the WMO timeline, specifically focusing on the 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2100) as the timeframes.

Minimum Temperature

Figure 4 below shows the projected changes in temperature (in degrees Celsius) for three weather stations, namely Meki, Metehara, and Melke Worer, under different RCP scenarios (2.6, 4.5, and 8.5) for three timeframes: 2020s, 2050s, and 2080s.

Figure 4: Projected changes in min temperature in the 2020s, 2050s, and 2080s under scenarios RCP2.6, 4.5 and 8.5.



For Meki, figure 4 above shows that the temperature is expected to increase for all three timeframes and under all three RCP scenarios. However, the magnitude of the increase varies depending on the RCP scenario and time frame, with the highest increase projected for the RCP 8.5 scenario in the 2080s. The temperature increase for Meki is generally higher than that of Metehara and Melka Worer for all three timeframes and under all RCP scenarios. In contrast, Metehara and Melke Worer are projected to experience a slight decrease in temperature for the 2050s and 2080s under the RCP 2.6 and RCP 4.5 scenarios as compaire to Meki. However, the magnitude of the decrease is small and is not expected to significantly impact the minimum temperature of these weather stations.

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Overall, the figure provides valuable information about the potential effects of climate change on the temperature of these weather stations. While Meki is projected to experience a significant increase in temperature, the temperature changes for Metehara and Melk Worer are comparatively small. They may have less of an impact on natural and human systems in these regions.

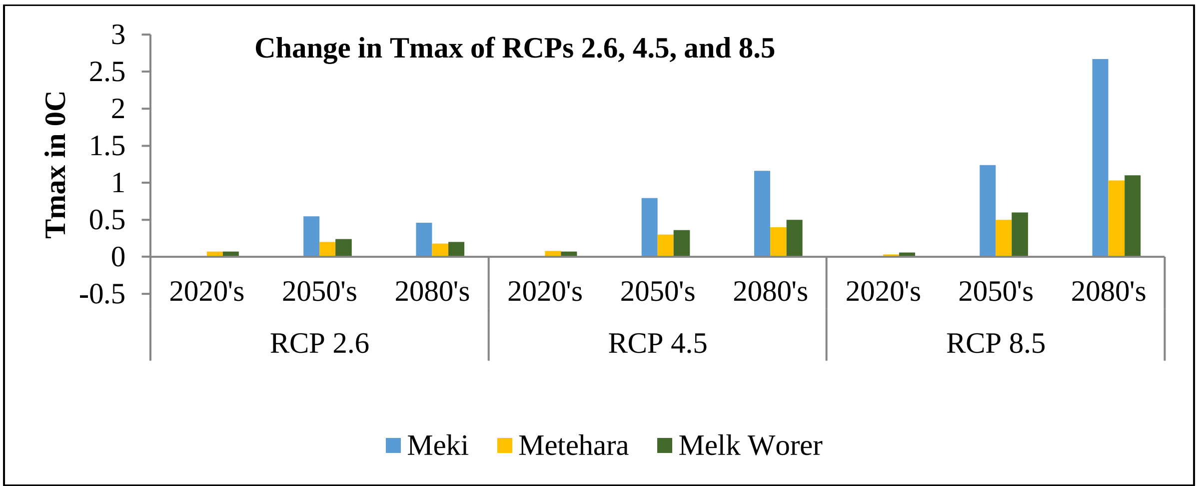
Maximum Temperature

Figure 5 below shows the projected change in temperature (in degrees Celsius) for three weather stations, Meki, Metehara, and Melka Worer, under different RCP (Representative Concentration Pathway) scenarios. The RCP scenarios project future greenhouse gas concentrations and their effects on the climate. The figure provides information about the projected change in temperature for three timeframes: 2020s, 2050s, and 2080s.

For Meki, *Figure 5* shows that the temperature is expected to increase for 205's and 2080's but decrease for 2020's timeframes under all three RCP scenarios. The magnitude of the increase varies depending on the RCP scenario and time frame, with the highest increase projected for the RCP 8.5 scenario in the 2080s. Similarly, Metehara is projected to experience an increase in temperature for all three time frames and under all three RCP scenarios. However, the magnitude of the increase is lower than that of Meki, with the highest increase projected for the RCP 8.5 scenario in the 2080s.

Melke Worer is also projected to experience an slight increase in temperature for 2020's under all three RCP scenarios. However, the magnitude of the increase is medium as compare to the three weather stations, with the highest increase projected for the RCP 8.5 scenario in the 2080s. Overall, figure 5 provides valuable information about the potential effects of climate change on the temperature of these weather stations. The projected temperature increases can significantly impact natural systems, such as ecosystems and water resources, as well as agriculture and health.

Figure 5: Projected changes in max temperature in the 2020s, 2050s, and 2080s under scenarios RCP2.6, 4.5 and 8.5.



Precipitation

Figure 6 below shows the percentage change in precipitation for three weather stations, Meki, Metehara, and Melka Worer, under different RCP (Representative Concentration Pathway) scenarios, which are used to project future greenhouse gas concentrations and their effects on the climate. The figure provides information about the projected percentage change in precipitation for three timeframes: 2020s, 2050s, and 2080s.

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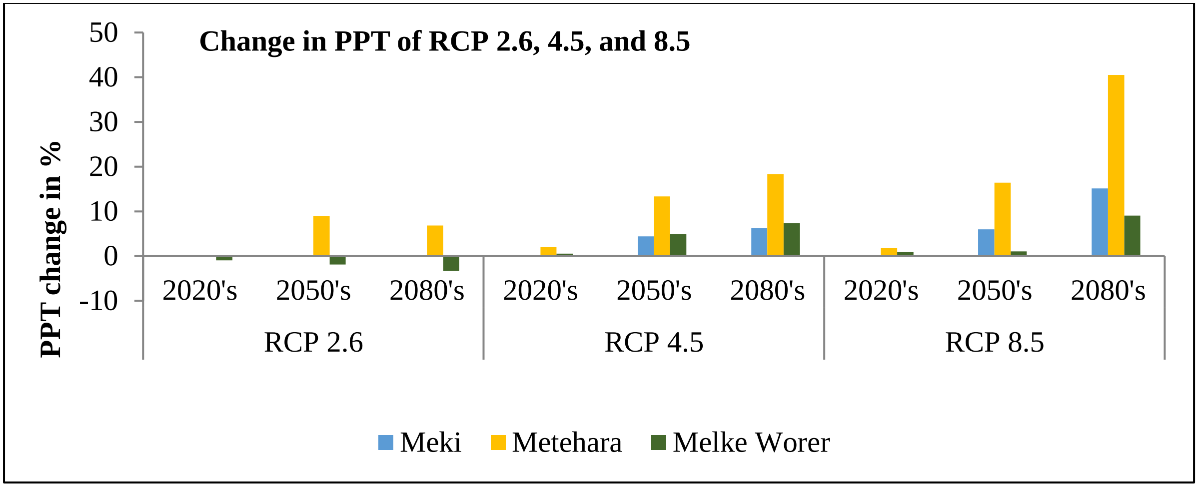
Figure 6: Projected changes in PPT in the 2020s, 2050s, and 2080s under scenarios RCP2.6, 4.5, and 8.5.



For Melk Worer, the percentage change in precipitation is expected to be the smallest in all three timeframes and under RCP 2.6 scenarios. However, there will still be a noticeable increase in precipitation, with the percentage change ranging from -2.3% to 39.3% across the different scenarios and at different time frames for all stations. Metehara is projected to experience a higher percentage increase in precipitation as compared to Meki, with the percentage change ranging from 0.01% to 39.3% across the different scenarios and timeframes. In the RCP 8.5 scenario, Melk Worer is projected to experience the lowest percentage increases in precipitation ranges from -2.3% to 5.6% among the three weather stations but for RCP 2.6 shows decreas in precipitationfor all time horizon's which requires water conservation and eqiuvilent adaptation measures. Onother hands for RCP 4.5 all the three stations expected to experience the highest percentage in precipitation during 2020's, 2050's and 2050's.

Anomalies

Anomaly is a significant deviation from the expected or average climate conditions for a particular region or area over a specified period. These anomalies can occur in various climate variables, including temperature and precipitation.

Minimum Temperature

Temperature anomalies are calculated by taking the difference between the current and long-term average temperatures for a particular period. A positive temperature anomaly is when temperatures are higher than the long-term average for a particular location or region Pyrgou et al., (2019). A negative temperature anomaly, on the other hand, refers to a period when temperatures are lower than the long-term average Pyrgou et al., (2019).

Figure 7 below shows the temperature anomalies for each month over three different time periods: the 2020s, 2050s, and 2080s. The temperature anomalies are expressed as the difference between the average monthly and long-term average temperatures for that month. Positive values indicate higher-than-average temperatures, while negative values indicate lower-than-average temperatures. The magnitude of the values indicates the degree of deviation from the long-term average.

Maximum Temperature

Temperature anomalies can be either positive or negative, indicating whether the current temperature is higher or lower than the long-term average. For example, figure 8 shows that in the 2020s, January had a positive temperature anomaly of 0.013, indicating that the average temperature for that month was slightly higher than the long-term average. In the same decade,

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April had a negative temperature anomaly of -0.018, indicating that the average temperature for that month was slightly lower than the long-term average.

Looking across the different time periods, we can see a trend of increasing positive temperature anomalies over time. For instance, in January, the positive temperature anomaly increases from 0.013 in the 2020s to 0.345 in the 2080s. This suggests that temperatures are projected to increase over time, with the greatest increases occurring in the latter half of the century. Figure 8 provides valuable information for climate scientists, policymakers, and others interested in understanding and mitigating the impacts of climate change. By tracking temperature anomalies over time, we can gain insights into how the climate changes and develop strategies to adapt to and mitigate the impacts of these changes.

Precipitation

Precipitation (PPT) anomaly refers to the deviation of the current precipitation for a particular location or region from the long-term average precipitation. PPT anomalies can be either positive or negative, indicating whether the current precipitation is higher or lower than the long-term average. A positive PPT anomaly suggests that the current rainfall is above the long-term average, while a negative PPT anomaly indicates that the current precipitation is below the long-term average.

PPT anomalies can have significant impacts on various aspects of human life. For example, positive PPT anomalies can lead to floods, landslides, and soil erosion, damaging infrastructure and property and cause loss of life. Conversely, negative PPT anomalies can lead to droughts, crop failure, and water scarcity, which can impact food security and water resources. Both are important for understanding how the precipitation patterns are changing over time. By tracking PPT anomalies over time, we can gain insights into how the climate changes and develop strategies to adapt to and mitigate the impacts of these changes.

Overall, using PPT anomalies in predicting natural disasters can help communities prepare for and mitigate the impacts of extreme weather events. By monitoring precipitation patterns and developing early warning systems and risk assessments, officials can help building more resilient communities.

Summary of Results and Discussion

The magnitude of the changes varies with the RCP, with higher RCPs projecting higher temperature increases and precipitation decreases. The result of projected rainfall indicated a probability of precipitation decreasing in the rainy season (JJAS) and increasing in precipitation in dry months (DJF) for both emission scenarios of three tri-decadal periods in the 2020s, 2050s, and 2080s. There will still be a noticeable increase in precipitation across different scenarios and time frames for all stations, with the percentage change varying from -2.3% to 39.3%. In terms of precipitation increase, Metehara is projected to have a higher percentage change compared to Meki, ranging from 0.01% to 39.3% across different scenarios and timeframes. In the RCP 8.5 scenario, Melk Worer is expected to have the lowest percentage increase in precipitation, ranging from -2.3% to 5.6%, among the three weather stations. Conversely, under the RCP 2.6 scenario, there is a decrease in precipitation for all time horizons, necessitating water conservation and adaptation measures. On the other hand, for the RCP 4.5 scenario, all three stations are expected to experience the highest percentage increase in precipitation during the 2020s, 2050s, and 2080s. The important reasons increase of precipitation are changes in regional climate systems, Increased moisture availability, Changes in atmospheric circulation patterns there may be alterations in large-scale atmospheric circulation patterns. These changes can affect the distribution and transport of moisture, leading to shifts in precipitation patterns. Simple example, changes in the position and strength of the jet stream can influence the movement of weather systems and affect precipitation distribution.

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Figure 7: minimum temperature anomalies of different RCPs for different time horizon

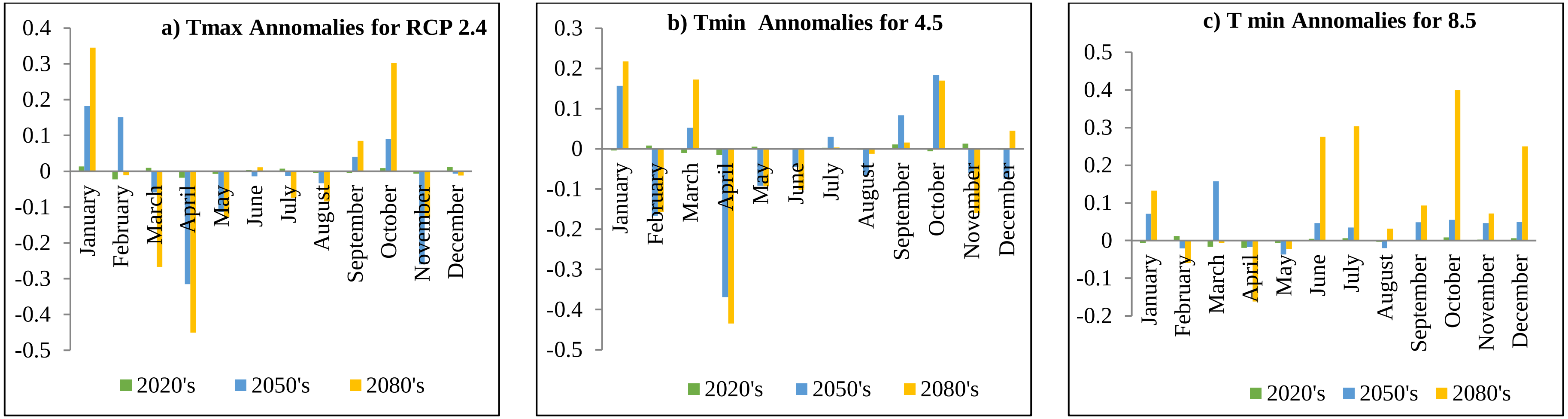

Figure 8: Maximum temperature anomalies of different RCPs for different time horizon

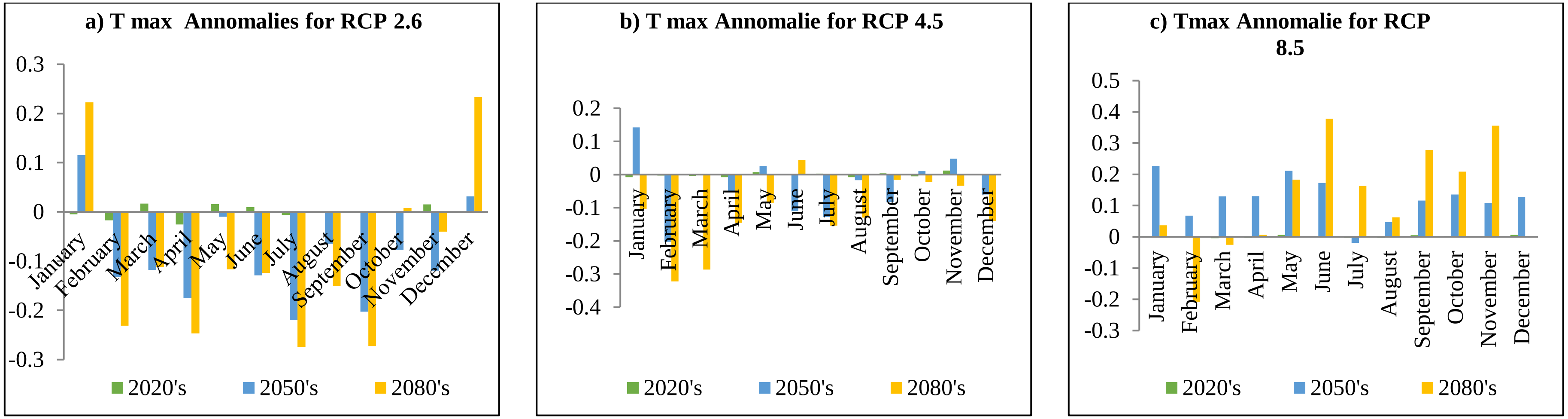

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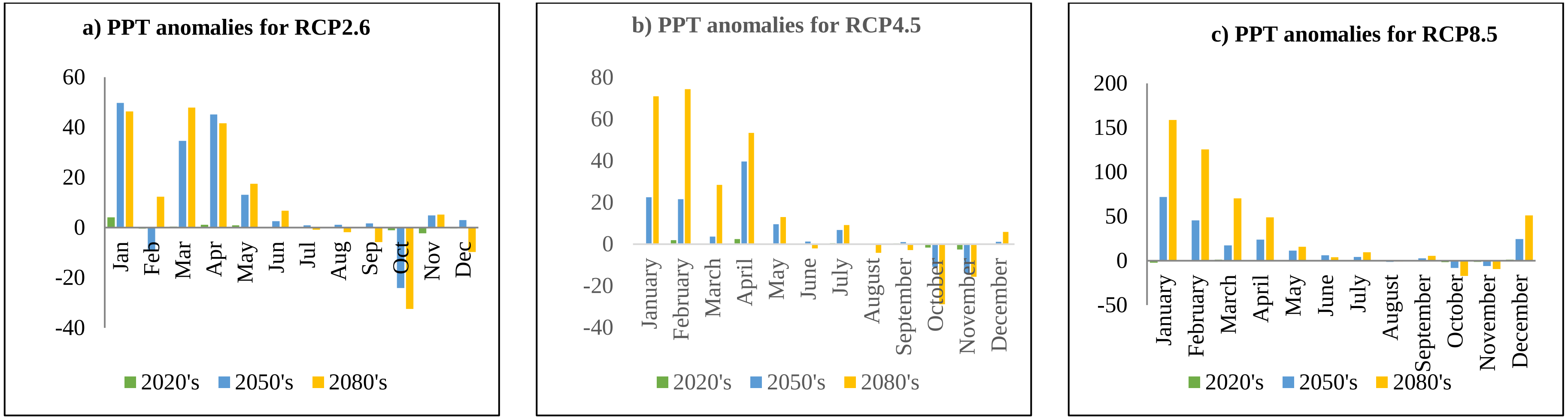
Figure 9: precipitation anomalies of different RCPs for different time horizon



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Some studies using CMIP3/5 data found rainfall will increase in the future over East Africa as a result of global warming due to increased anthropogenic emission of greenhouse gases Otieno & Anyah, (2013); Tierney et al., (2015). However, other studies using observed data found decreased observed rainfall over East Africa during the MAM season and a wetter OND season Ongoma & Chen, (2017); Mumo et al., (2019). The increase in OND rainfall was attributed to the warming of the western Indian Ocean Liebmann et al., (2014). Yang et al. (2015) attributed the decrease in MAM rainfall over East Africa to natural decadal variability rather than anthropogenic influence. The inconsistency between the observed conditions and the global model predictions is called the East Africa climate paradox Rowell et al., (2015). The disagreement between observed and model data trends has been attributed to the scarcity of in situ data required for model parameterization over the region Brands et al., (2013). If the projected rainfall actualizes, it will be a recovery from the observed drying trend currently being experienced Yang et al., (2015).

The developed temperature and precipitation scenarios for the selected stations of Middle Rift Valley of Ethiopia using different RCPs suggest that the region will experience significant changes in temperature and precipitation patterns. The projected temperature increase is expected to significantly impact different sectors in the region, including agriculture, water resources, and human health. The decrease in precipitation is likely to lead to reduced crop yields and increased water stress, which could affect the livelihoods of the communities in the region.

Evaluating the developed scenarios using various performance metrics indicates that the scenarios are generally accurate and reliable. However, uncertainties are associated with the modeling techniques used, and the scenarios should be used cautiously. The developed scenarios provide valuable information for decision-makers in various sectors to plan and implement appropriate measures to mitigate the impacts of climate change in the Middle Rift Valley of Ethiopia. The scenarios suggest a need for effective climate change adaptation strategies in the region that consider the region's unique characteristics and involve stakeholders from different sectors.

Implications for Central Rift Valley

The projected temperature and precipitation scenarios significantly affect the Central Rift Valley region. Higher temperatures can increase evaporation rates, affecting water availability and agricultural productivity. Changes in precipitation patterns can also impact water resources, crop yields, and overall ecosystem health. Understanding these potential changes is crucial for developing effective adaptation strategies, such as water management systems, crop diversification, and infrastructure planning.

Overall, the developed temperature and precipitation scenarios using different RCPs provide important insights into the potential impacts of climate change on the Middle Rift Valley of Ethiopia and highlight the need for action to mitigate these impacts.

CONCLUSION AND RECOMMENDATION

In conclusion, the analysis of future climate scenarios using models and ensembles of daily precipitation and temperature has provided valuable information about the potential impacts of climate change on three weather stations in Ethiopia. The projections reveal that the temperature is expected to increase in all three stations under different RCP scenarios and timeframes, with the increase varying depending on the scenario and station. Additionally, the analysis of temperature anomalies shows a trend of increasing positive temperature anomalies over time, suggesting that temperatures are projected to increase over time, with the greatest increases occurring in the latter half of the century. The analysis of PPT anomalies also provides valuable insights into how precipitation patterns change over time, which can help us develop strategies to adapt to and mitigate the impacts of these changes.

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Based on the results, it is recommended that policymakers, communities, and other stakeholders take proactive measures to mitigate the impacts of climate change, such as developing early warning systems for floods and landslides, implementing water conservation measures, and developing drought-resistant crops. Additionally, further research is needed to understand the regional impacts of climate change and develop region-specific adaptation strategies. By working together and taking proactive measures, we can build more resilient communities and mitigate the impacts of climate change on natural and human systems.

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