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Comparison of the Performance of CMIP5 and CMIP6 in the Prediction of Rainfall Trends, Case Study Quebec City †

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Abstract: Climate change affects many meteorological parameters which could result in spatiotemporal variations of the hydrological cycle. These variations can affect local rainfall intensities or design storms; therefore, it is necessary to assess the local effects of climate change in different areas. Therefore, the current research aims at evaluating the accuracy of the precipitation data of the most recent Coupled Model Intercomparison Project phases 5 and 6 (CanESM2 from CMIP5 and CanESM5 from CMIP6 models), over a historical period from 1953 to 2010, as well as the predicted data for the future between 2010 and 2050 for the Quebec City rain gauge station (Jean Lesage Intl). In this regard, precipitation data were analyzed using a statistical Index to find the most accurate model for the study area. The results of this evaluation showed that CanESM5 is more accurate than CanESM2 for most of the evaluation indexes. However, both of these models did not perform well since the precipitation prediction for CanESM5 (as the accurate model) R index was 0.48 for the monthly and 0.75 in the seasonal scale. In addition, the Bias index revealed that both models underestimated rainfall prediction with negative index values for both scales and models. The trend of future precipitation under Socio-Economic scenarios (4.5 (pessimistic) and 8.5 (optimistic)) show that the changes in future precipitation is not significant. Also, for scenario 4.5, the trend of precipitation decreases for almost half of the year, while for scenario 8.5, the magnitude of the decrease and the number of months with decreasing trend of precipitation are significantly reduced when compared to scenario 4.5.

Keywords: precipitation; CMIP; Quebec; Mann-Kendall test; GCM

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1. Introduction

Global warming has caused significant changes in the climate. In recent years, the severity of droughts, floods and extreme events has increased in different parts of the globe. The Intergovernmental Panel on Climate Change (IPCC) has been established to identify its effects and especially how human activities affect it. In order to conduct climate change studies, climate variables under the influence of greenhouse gas emissions must first be simulated [1].

One of the important consequences of climate change is the change in meteorological parameters' trend, especially precipitation trend [2]. Therefore, a lot of research has been conducted to evaluate climate change's effect on extreme rainfall events. These studies showed that global warming is affecting and causing climate changes based on Coupled Model Intercomparison Project Phase 5 (CMIP5) and Coupled Model Intercomparison Project Phase 6 (CMIP6) climate reports in Canada [3]. Compared to other methods such as the multi-model ensemble (MME), CMIP5 and CMIP6 models showed better performance. Also various methods can be used to reduce their uncertainty [4]. With the release of the sixth report (CMIP6), the desire to examine the performance of this report compared to the fifth report (CMIP5) has increased among researchers. One of the major improvement in CMIP6 is the introduction of socio-economic scenarios [5]. Examining the difference between the data of report 5 and 6 climate models for temperature and precipitation shows that for the fixed time intervals, most of the temperature indices show higher predicted changes in CMIP6 when compared to CMIP5 in Canada. Rainfall changes in CMIP6 mainly occurred in extreme precipitation indices [3]. However, it is clear that the method of General Circulation Models (GCM) ensembles can lead to different estimates of future mean changes and different levels of uncertainty in those estimates [4]. Overall, current research has shown that the CMIP6 ensemble provides a narrower band of the uncertainty of future climate projections specifically for North America and brings more confidence to hydrological impact studies [6]. The importance of such analysis is in assessing risk, and future vulnerability and implementing efficient measures to control the changes made in the flow of rivers and their ability to warn of floods [5,7].

It is necessary to examine the system's response as a general unit for determining the possible effects of climate changes such as the increase in the concentration of greenhouse gases and the impact of socio-economic activities on the climate system [5]. For this purpose, it seems necessary to use climate models. These models include the main stages that occur in the climate system and calculate the corrections of different components when responding to the changes in the forcing factors. Therefore, evaluating the accuracy of the data of these models and choosing the most efficient and adaptable models is an important and necessary step for any forecasting [8]. This assessment is more important for precipitation, which has a more significant behavioral complexity than other meteorological phenomena. Therefore, identifying the mechanism and evaluating the effectiveness of atmospheric general circulation models in estimating precipitation and knowing their temporal and spatial frequency significantly affects the preparedness for such extreme events. Therefore, in this research, the effectiveness of the CMIP5 and CMIP6 for predicting extreme rainfall events are assessed, and the future trend of rainfall reported by the superior model has been evaluated.

2. Methods and Materials

2.1. Data and Models

Monthly precipitation records of the Jean Lesage Intl station (Figure 1) were collected from Canada Gov. historical meteorology data records [9]. The dataset period was from 1953 to 2020 (67 years). In addition, CMIP5 and CMIP6 models were used to investigate the accuracy and evaluate future climate change under different scenarios. For these purposes, 2 different models (one from each CMIP) were selected according to previous research results [3,5]. These models were reported in Table 1. The historical period for evaluating the accuracy of the selected models was chosen. For CMIP5, this period was between 1953 to 2005 and for CMIP6, the period from 1953 to 2010 was selected.

Figure 1. Selected station position.

Table 1. The selected CMIP models.

Model	CMIP	Scenario	Resolution
CanESM2	5	RCP 2.6, 4.5, 8.5	0.5° × 0.5°
CanESM5	6	SSP 2.6, 4.5, 8.5	0.5° × 0.5°

2.2. General Circulation Models

Climatic variables are simulated under the influence of increasing or decreasing greenhouse gases. There are different methods for this task, however the most reliable is the use of atmospheric general circulation models or GCMs. GCMs can be used to understand the dynamics of the physical components of the atmosphere that are related to climate change phenomena. The purpose of using GCMs is to obtain spatial-temporal patterns of climate changes as well as long-term forecasting of climate variables [5]. Climate modeling is an important tool for understanding past, present and future climate changes [2]. In other words, currently the most reliable tool for investigating the effects of climate change on different systems is the use of GCM. These models are able to model the trends of atmospheric and oceanic parameters for a long-term period using approved IPCC scenarios [2]. Their main weakness is the low spatial resolution and the simplification they consider for climate processes. To overcome the weakness of low resolution, it is necessary to scale the output of these models before using them in climate change impact assessment studies [1].

2.3. Mann-Kendall Trend Analysis

The Mann-Kendall method was first presented by Mann (1945) and then expanded and developed by Kendall (1970). Among the non-parametric tests, the Mann-Kendall test is the best choice for checking the uniform trend in series [10]. This test is used to determine the randomness and trend in the series. First, to determine the non-parametric nature of the statistical series, data is arranged and ranked in ascending order and then based on that, the randomness of the data with no trend is specified. If there is a trend in the data, then it is non-random.

The null hypothesis of the Mann-Kendall test indicates randomness and the absence of a trend in the data series, and the acceptance of the one hypothesis (rejection of the null hypothesis) indicates the existence of a trend in the data series [10].

2.4. Evaluation of Performance

Five types of statistical indices are employed to assess the performance of the CMIP datasets. The correlation coefficient (R) (Equation (1)) as a correlation-based index, Normalized Root Mean Square Error (NRMSE) (Equation (4)), BIAS (Equation (2)), Root Mean

Square Relative Error (RMSRE) (Equation (5)), and Slope (Equation (3)). The mathematical definitions of the mentioned indices are as follows:

$$R = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(x_i - \bar{x})^2}} \tag{1}$$

$$Bias = \frac{\sum_{i=1}^{n}(x_i - y_i)}{n} \tag{2}$$

$$SLOPE = \frac{\sum(xi - \bar{x})(yi - \bar{y})}{(n-1)S^2x} \tag{3}$$

$$NRMSE = \frac{1}{\bar{y}}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{4}$$

$$RMSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - y_i}{y_i}\right)^2} \tag{5}$$

where xi and yi are the ith samples of the estimated and actual values (respectively), $\bar{x}$ and $\bar{y}$ are the average of the estimated and actual values (respectively), n is the number of samples, and S^2x is the Variance of x.

3. Results

3.1. Evaluation the Performance of the Models

The performance of CMIPs' models is shown in Table 2, which reported the accuracy of the models to compare to the observation data. Five different indexes are used for evaluation at two different time scales. Based on the correlation coefficient (R), CanESM5 has better performance when compared to CanESM2 model. Nevertheless, the correlation coefficient on a monthly scale is poor since R values are less than 0.5, although if the scale changes to the seasonal, they will improve ideally (between 0.65 and 0.75).

Table 2. Performance of CMIP models.

Model	Scale	R	NRMSE	RMSRE	Bias	Slope
CanESM2	Monthly	0.43	0.40	0.36	−85.6	−0.30
CanESM5		0.48	0.54	0.30	−58.7	0.20
CanESM2	Seasonal	0.65	1.51	0.96	−11.8	0.50
CanESM5		0.75	1.08	0.67	−10.3	0.13

Also, Normalized Root Mean Square Error (NRMSE) results shows that CanESM5 has better performance when compared to CanESM2 on the seasonal scale. These results are promising and show that the model can estimate precipitation within acceptable errors because the NRMSE values are close to one, which means that the deviations in precipitations estimates are small.

The RMSRE is a criterion like RMSE; their main difference is that RMSRE is divided by projected values. The best value for these criteria is 0, meaning there is no difference between projected and observed values. Based on Table 2, CanESM 5 model performs better with RMSRE of 0.3 and 0.67 for the monthly and seasonal scales, respectively.

Mean Bias deviation shows the systematic error in the amount of precipitation. A value of zero indicates that the difference between the observed and predicted precipitation amount is not systematic, while a large bias indicates that the amount of precipitation deviates greatly from the observed amount of precipitation. The fact that the bias parameter is close to zero also indicates the model's accuracy in the simulation. A negative bias indicates underestimation, while a positive bias indicates overestimation. Based on the results in Table 2, both models underestimate precipitation at this station.

Finally, the Slope is used to assess the direction of the projection line or the angle coefficient. If the Slope is negative, the relationship between the 2 variables (X and Y) will be inverse, and the Slope expresses the amount of change in Y relative to each unit of change in X. For this index, a slope of 1, or regression 1:1 between the 2 variables, means perfect correlation. The value of Slope in Table 2 shows that the estimated data are far from the regression line (1:1) and the value of the slope statistic for both models are equal or less than 0.5.

Taylor diagrams provide a visual framework for comparing a suite of variables from one or more test data sets to one or more reference data sets. Commonly, the test data sets are model experiments while the reference data set is a control experiment or some reference observations (e.g., Station datasets). Generally, the plotted values are derived from climatological monthly, seasonal or annual means. Because the different variables (e.g.: precipitation, temperature) may have widely varying numerical values, the results are normalized by the reference variables. The normalized variances ratio indicates the model's relative amplitude and observed variations [11]. Figures 2 and 3 provide information about monthly and seasonal Taylor diagrams of the CanESM2 and CanESM5. It is clear that CanESM5's performance on the monthly scale is better than CanESM2, although both models have poor performance on the seasonal scale. All in all, CanESM5 can provide better results compared to CanESM2.

In summary, the values obtained by the models show that the efficiency of the CanESM5 model in estimating the amount of precipitation is better than CanESM2 model. Also, due to the closeness of the indicators that take into account the number of deviations and compare the estimated and actual time series, the mentioned model can detect fluctuations and precipitation trends in the selected station.

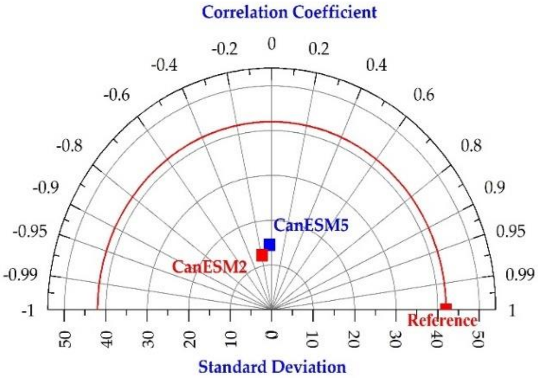

Figure 2. Models' performance in monthly scale.

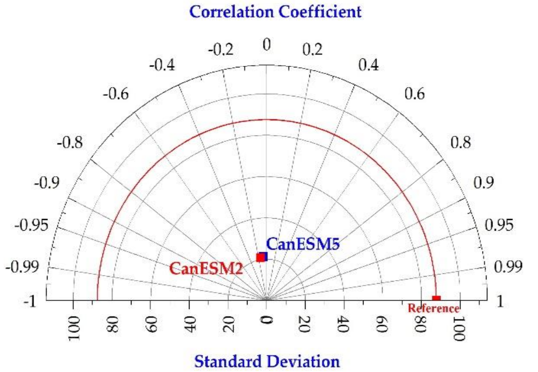

Figure 3. Models' performance in seasonal scale.

3.2. Precipitation Future Trend

It is more suitable to use non-parametric methods for series that cannot be fitted with a special statistical distribution and have high skewness or elongation. Mann-Kendall test is one of the most common and widely used non-parametric trend analysis methods of time series. Data changes are identified using the Man-Kendall method, and their type and time are determined [12]. According to the essential role of precipitation in providing water resources, it is vital to study the process of its changes in the future. This study will help the authorities with planning and managing water resources. Since international reports have given serious warnings about the crisis and even the physical lack of water in the future for different parts of the world, knowing the predicted variability of this important meteorological parameter is essential [13]. Although the evaluation of the models' performance on historical data has shown that the models do not have a high ability to estimate the amount of precipitation, but the comparison of the projected and observed time series shows a slight deviation and an acceptable agreement between the two data sets. Therefore, the future forecast of the precipitation by the selected model (CanESM5) is an effective step in understanding the precipitation pattern in the future.

Table 3 presents the Mann-Kendall parameters (Test Z) for the different time scale rainfall future trends (between 2020 to 2049) using the best-fit model (CanESM5) for the two socio-economic (SSP) scenarios. The selected SSP scenarios for this study were 4.5 (Pessimistic) and 8.5 (Optimistic). The time scales are Monthly (Jan to Dec), Seasonal (Spring to Winter) and Annual for the selected model's scenarios (4.5 & 8.5). For the scenario 4.5, rainfall changes are decreasing for February, June to August, while for other months, these changes are increasing. These outputs can be find based on Test Z values in the Table 3. Moreover, rainfall changes in the seasonal scale are also decreasing in the Summer and Fall. Trend analysis results for May, July in the monthly scale and Summer and Fall in seasonal scale show that the downward trend is more intense, since the value of Test Z (Kendall's score) has reached more than −1 in this period of time.

On the other hand, for scenario 8.5 (Table 3), rainfall changes are increasing in the most of the months. Although, like scenario 4.5, the decreasing trend remains. However, the intensity of the downward trend becomes less prominent when compared to the scenario 4.5. In addition, rainfall changes in the spring tend to decrease unlike 4.5 scenario.

Table 3. Mann-Kendall test Z values for 4.5 and 8.5 scenarios.

Time Series	4.5 Test Z	8.5 Test Z	Time Series	4.5 Test Z	8.5 Test Z
Jan.	1.48	0.04	Jul.	−1.78	1.89
Feb.	−0.30	0.25	Aug.	−0.36	1.53
Mar.	0.16	−0.71	Sep.	1.30	0.14
Apr.	−0.43	−0.79	Oct.	2.02	2.86
May.	−1.07	1.46	Nov.	1.30	0.18
Jun.	−0.46	−0.09	Dec.	1.48	1.71
Spring	0.71	−0.18	Annual	0.00	2.82
Summer	−1.25	0.39			
Fall	−1.32	2.32			
Winter	1.78	2.21			

4. Conclusions

The results showed the studied models do not have a high ability to estimate precipitation in Jean Lesage Intl station. According to the results of the studied statistics such as the correlation coefficient (R) and Slope, the accuracy of the models was poor and the correlation coefficient in all models is less than 0.5 on a monthly scale. But in the seasonal scale, the correlation value can be reached 0.75 in the best model. The slope index is also consistent with the correlation coefficient; Because in the two investigated models, the distribution of precipitation data is rarely very close to the regression line (1:1) and the slope value is usually less than 0.5. Also, the results of the two selected models are close to each other, but the CanESM5 model is more accurate than the other model in the studied station. The deviation of the projected data and the station data is very small, which can be shown based on the NRMSE index in all the investigated models is less than 2. In addition, in the selected station, the Bias index indicated both models would underestimate rainfall trend in both time scales. The comparison of the obtained findings shows that the present research results are largely consistent with some other researchers. For example, Hidalgo and Alfaro (2014) showed that most of the CMIP5 models have a low ability to estimate precipitation in the central regions of the United States [11]. Rupp et al. (2013) showed that although CMIP5 model rainfall data has less accuracy compared to other grided data such as NCEP and ERA40, it estimates the seasonal cycle of precipitation with the same accuracy as networked data in the northwestern regions of America [12]. Mehran et al. (2014) concluded that CMIP5 model rainfall data is consistent with GPCP data in most parts of the world, but does not perform well in dry areas [13]. Ebtehaj and Bonakdari (2023) concluded that the results of the comparison of CanESM5 and CanESM2 models strongly depend on the month and season, and the results of CanESM5 are slightly better compared to the other model [5].

Finally, the precipitation trend analysis results for the CanESM5 model and under two scenarios 4.5 and 8.5 show that the trend of precipitation changes at the Jean Lesage Intl station will not be significant. Also, in scenario 4.5, the precipitation trend decreases in almost half of the year, while in scenario 8.5, the intensity of the decrease and the number of months with decreasing trend of precipitation is significantly reduced.

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