GENERAL CIRCULATION MODEL REGIONAL PREDICTIONS USING MOS TECHNIQUES: SEASONAL FORECASTING

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Abstract

Ocean and atmospheric Coupled Global Climate Models (CGCMs) have been widely used to provide more accurate and coherent seasonal forecasts. However, they still show some limitations. Model Output Statistics (MOS) approaches may improve performance if observed and forecast values are available for a long record. This study investigates the skills of a MOS approach on ECHAM4p5 in simulating rainfall and temperature on a seasonal time scale over the South West (SW) Ontario region. ECHAM4p5 model has 20 ensemble members and those 20 members along with their mean are compared with real time observational data collected locally by Environment and Climate Change Canada (ECCC) weather stations. Presently, the ECHAM4p5 model is run by the Foundation Cearense for Meteorology and Water Management (FUNCEME), Brazil. The model is run at the beginning of every month based on persisted Sea Surface Temperature (SST) from 0000 of 1st day of that month. An ensemble average of 20 realizations is used for the forecasts. The model uses for eight-month weather predictions ahead of the start date. Historical model data were available from International Research Institute for Climate and Society (IRI), Columbia University and used together with Global Precipitation Climatology Centre (GPCC) rainfall data and average daily temperature obtained from the Climatic Research Unit (CRU) at University of East Anglia. Ten years of daily forecasts for SW Ontario from the ECHAM4p5 model are used to develop Regional Correction Factors (RCF) to help in improving the model seasonal forecast confidence level. The basic (bias correction based) MOS technique is applied for seasonal and regional bias corrections. Our focus has been on the first three months of the forecast and comparisons are made against Meteorological Terminal Air Report (METAR) and other data for SW Ontario. The comparison of tuned data and observations has been made over SW Ontario. The motivation of taking this domain is that our industrial partner is mainly working with the farmers in SW Ontario. The approach used had given encouraging results (based on

personal communication) in larger geographic areas and improved seasonal predictions in Pakistan. The results so far in the much smaller SW Ontario domain, with a somewhat different climatology, have not been as successful but have provided ideas for future research. We have worked on both monthly and daily precipitation and temperature, but in particular we have focused to investigate day to day differences between different ensemble members to see what information might be gained from them. Our results show that there is huge variation among 20 ensemble members and those variations are canceled out while taking their mean for ensemble mean forecasting technique. Furthermore, while comparing individual ensemble members with observation data, we also get the idea that few ensemble members are following observation data closely. We also compare the same method for larger domain to improve our forecasting results.

Acknowledgements

The work was initiated under an NSERC Engage grant with Weather Innovations Network as the industrial partner, and in collaboration with Dr. Khalid Malik, now with the Pakistan Meteorological Service.

Initially, I would like to express my wholehearted thanks and courtesy to all the researchers whose journals are cited here and became treasures to enhance my knowledge to complete this thesis.

At first, I would like to thank my supervisor Prof. Dr. Peter Taylor; his commendable guidance, professional supervision and elaborative instructions made my research and thesis work came to completion as this document. Secondly, I would like to thank my family, namely my father (Damber Dhoj Thapa), mother (Angur Thapa), sister (Mamata Thapa), brother (Milan Dhoj Thapa) and wife (Suraksha Khadka), for their constant support, motivation and inspiration through all ups and downs during last two years and further. In addition to this, I would like to thank my co-supervisor Dr. Khalid Malik for his support and guidance and my committee chair Prof. Dr Neil Tandon for his constructive instruction and guidance. I am always thankful to my friends, Amit Shrestha and Mathbar Singh Raut who keep me always motivating to explore new things.

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1 Introduction

Seasonal weather forecasting methods are generally categorized as classical statistics, perfect prog and Model Output Statistics (MOS). Seasonal forecasts generally provide a weather outlook for a season (warmer than average, wetter than average) over relatively broad geographic areas and at specific locations. We are trying to use the detailed model output that these forecasts are based on to provide additional information on day to day variability. This is to help farmers and other groups who are interested in a more detailed seasonal weather outlook. Our first project goal is to improve the temporal resolution of seasonal weather prediction by tuning up any climate model, removing bias and applying correction factors using MOS (Glahn and Lowry, 1972) techniques. Ours is a very basic MOS approach. In general MOS can involve adjustments based on multiple predicted and observed variables. Our second goal, noting that most seasonal forecasts use an ensemble average approach, is to see what information is available if we look at individual ensemble members and at the variability among the multiple ensemble members. We actually inspired from the work and research done by Khalid Malik (co-supervisor of this research) in Pakistan. He has done forecast for National Agromet Centre (NAMC) Pakistan Meteorological Department. For some example from his work, in Figures 1.1 and 1.2, the output of the latest model forecasts for June, 2017 indicate that average to below average rainfall is expected all over Pakistan with rainfall above average during June. An average to below average rainfall is expected during the season all over Pakistan. There is an above average rainfall is expected over the country during the month of June for the whole Pakistan. In addition to this, a slightly average rainfall is expected over the southern parts of Pakistan including Sindh during the month of June. The rainfall is expected below normal in the northern parts of the country during June. Pre-monsoon rainfall may start from third week of June and intermittent rain will be happening in the country. The primary region of pre-monsoon rainfall would be central Punjab and lower Sindh.

He has used categorical method (Contingency table) to verify weather forecast and besides that we have not found any other statistical method to claim for the successful reliable
forecast.

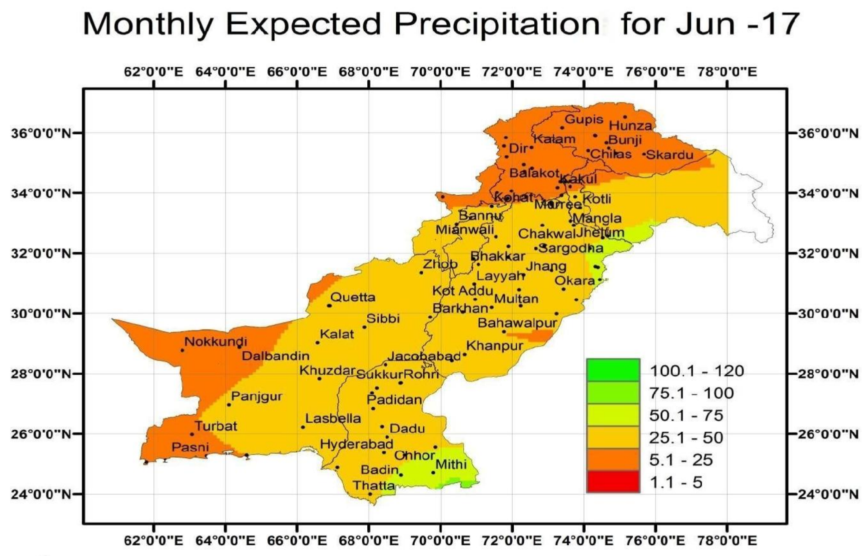


Figure 1.1: Monthly expected rainfall for June, 2017

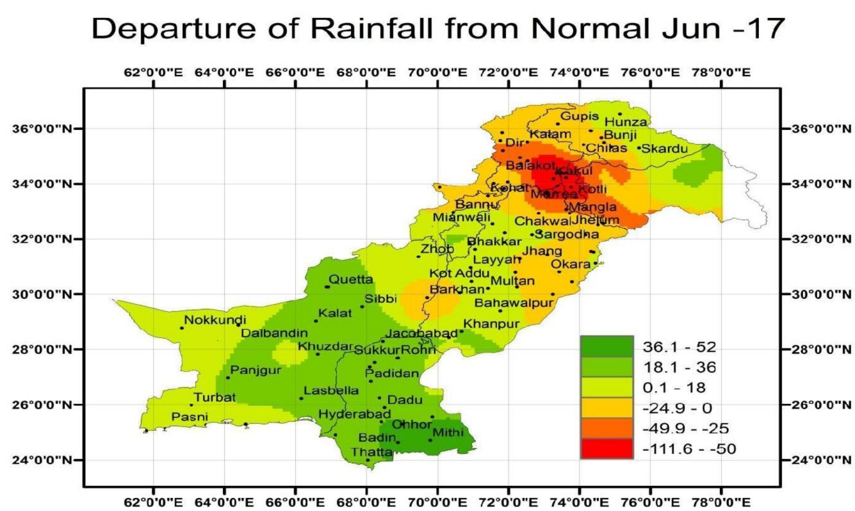


Figure 1.2: Departure of monthly rainfall from normal for June, 2017

In this thesis we have used four different sources of data. Hourly climate model data is from ECHAM4p5 developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) and Max Plank Institute (MPI), Hamburg, Germany (Roeckner et al., 2003) and currently run by FUNCEME, the Brazilian water resources department. In order to tune the climate model precipitation forecasts we have used historical forecasts and GPCC (Adler et al., 2003) data developed by the Global Precipitation Climatology Center (GPCC) which is operated by NCAR (National Center for Atmospheric Research) and Deutscher Wetterdienst (DWD), a German contribution to the World Climate Research Programme (WCRP) and the Global Climate Observing System (GCOS). Furthermore, to tune up temperature forecasts we have used data from CRU (Harris et al., 2014) which is developed by the Climatic Research Unit at University of East Anglia (UK). In order to compare recent forecasts in our project, we have used data from 27 weather stations run by Environment Canada (McKague et al., 2003) in our primary domain which has been South Western Ontario.

The current forecast testing is done on a monthly basis. Every month we get model data from the Brazilian water department (FUNCEME) and mask that out to our domain i.e. South Western Ontario. Daily forecasts are then tuned with Regional Correction Factors (RCF), based on historical data, for refining our project forecast. We then prepare nesting (nested one into another) of the observed GPCC and CRU data (when they are available) or ECCC station data to compute area weighted daily precipitation and temperature for our domain.

We initially focused on the ensemble means and our results were not encouraging in that there was little day to day variation. We then started to look at the variation among ensemble members noting that the FUNCEME output provides 20 ensemble members and averaging them misses all the day to day variability. The latter approach has indeed provided insightful results which will be discussed in findings and results section later.

In future, we are considering applying the same technique with output from the Canadian Seasonal to Interannual Prediction System (CanSIPS) (Merryfield et al., 2013) model run by

Environment Canada or the SEAS5 model run by ECMWF (Johnson et al., 2019) if we can gain access to their hourly or daily forecast data from all ensemble members.

The synopsis of this thesis follows. In Chapter 2, we describe the background of various data types including the model data which we have used, the organizations which have provided us with the weather data to complete this thesis and the information about data resolution and data availability periods. In Chapter 3, we discuss the theory of the forecasting procedure and techniques and in Chapter 4, we discuss the forecasting results for a whole year (2019-2020) and in Chapter 5, we draw some conclusions and give a brief account of our work to date and some ideas on future work.

2 Background of model and data

Classical statistics (Best and Pryor, 1983) basically uses means, data stratification and simple statistical models to assist forecast related problems. Some earlier applications related with this technique were climatology tables, local studies based on the deviation between observed data like surface observations and upper air soundings and observed weather later in the same day, rules of thumb, and simple regression models or discriminant functions.

The perfect prog method (Klein, 1971) establishes diagnostic relationships among real time observed upper air parameters and observed sensible weather elements. In another word, the perfect prog develops a relationship between the predictors like observed pressure and humidity from the analysis of a dynamic model and the predictand like observations of precipitations. Multivariate regression is used to evaluate the degree to which parameters are important in the above relationships and in the assessment. Once a satisfactory diagnostic relationship in the form of a statistical equation is found, the equations were fed with the dynamic model forecast fields (or prognoses) and the solution of these fields and treated as future analyses. This method depends on the condition which considers that the prognoses are perfect (Veigas, 1966). This method is little advanced over the simplistic classical method explained earlier. Since the only condition of perfectness in the progs in this method balances the growing error with time advancement, hence, in the real world with no perfect progs leads to bias factor in future prediction of weather elements.

In 1972 Glahn and Lowry introduced the idea to use the bias factor that appeared in the perfect prog method as a source of predictability in their dynamical weather prediction model. Model Output Statistics is a weather prediction method where forecasts are made by establishing a statistical relationship between model predictions and observations or additional model data.

Different techniques and methods are adopted for the bias corrections of model outputs for a region. The one most assessed is the analog-based MOS down-scaling method (Grouillet et al., 2016) for climate change studies. The MOS technique is widely used to improve the confidence level of medium and long-range weather prediction. The objective of our project is to provide accurate and timely medium and long-range seasonal weather information to the farming community. Many climate models provide medium and long-range seasonal weather prediction, but their confidence level is not very satisfactory. We hope to improve issued medium and long-range seasonal weather information of the models by eliminating bias factors of any particular geographical area. For this project we have used a basic MOS technique to develop correction factors for South Western Ontario. These correction factors will then be used to tune the issued weather prediction for that region. This helps to eliminate bias factors of model output predictions and help to improve the confidence level of the output seasonal weather prediction. For this thesis, we used base model prediction data and observational data.

2.1 Base model prediction data:

The evaluation of seasonal predictability is assessed by using ECHAM forecast dataset archived at the IRI data library. The Max Plank Institute for Meteorology developed the ECHAM atmospheric general circulation model. ECHAM initially branched from an early version of the global numerical weather prediction model developed at the ECMWF. The model was run by the International Research Institute (IRI) from the period 2002-2016. Presently, the ECHAM4p5 model is run under the Brazilian water resources department, Fundao Cearense de Meteorologia e Recursos (FUNCEME), Brazil. The model is run every month based on persisted SST of 0000 of the 1st day of each month. The model is making eight-month weather prediction ahead, with output data resolution of $2.8^{\circ} \times 2.8^{\circ}$. The model has 20 ensembles. We use forecasts out to a lead time of one to three months.

2.2 Observational Data:

The Global Precipitation Climatology Center (GPCC), NCAR data (Becker et al., 2013) are used as observational data for precipitation. The real time daily precipitation data are derived from quality controlled station data and gauge-based gridded monthly precipitation data sets of resolution of $0.25^{\circ} \times 0.25^{\circ}$ for the global land surface. The real time data are available 5 days after the observation month. Daily mean temperature, monthly average daily maximum and minimum temperature data are developed by the Climatic Research Unit (CRU) (Harris and Jones, 2017) at University of East Anglia (UK) are used for temperature climatology data. The data are gridded and derived from quality controlled stations having resolution of $0.5^{\circ} \times 0.5^{\circ}$. The real time data are updated on a monthly basis to include the latest month within about four weeks of its completion. The annual update of data is done around May or June each year. In addition to this, we have also used observational data at 27 ECCC weather stations in South Western Ontario (McKague et al., 2003).

2.3 ECHAM 4p5 Model

The fourth-generation atmospheric general circulation model (ECHAM-4) developed at the Max Planck Institute for Meteorology (MPI) is the earlier version (Simmons et al., 1989) in a series being developed originally from the spectral weather prediction model of the European Centre for Medium Range Weather Forecasts (ECMWF).The latest version is the fifth-generation atmospheric general circulation model (ECHAM-5). We are actually working with the earlier version i.e. ECHAM 4p5. This ECHAM 4p5 model has many similar features with ECMWF model. A notable difference is the employment of a semi-Lagrangian advection scheme for all variables in the ECMWF model but not in the ECHAM-4 model. The ECHAM 4 version was introduced to overcome certain limitations of previous model i.e. ECHAM 3. Some limitations are to address some hidden shortcomings of the ECHAM3, by removing the spectral transform method (Roeckner et al., 1996) for positive definite variables like water vapor and cloud water, by including the transport of atmospheric trace gases and aerosols at both large and grid scales, by taking account of the radiative effect of all greenhouse gases and aerosols present in the atmosphere, and by adding the climate change effect into the model.

In addition to this, a new data-set of land surface parameters are added to ECHAM 4 but some biases observed for the ECHAM 3 version remain the same in ECHAM 4. For instance, the polar upper troposphere and lower stratosphere are still too cold, the errors in zonal wind are still very large above the 200 hPa level, and the simulation of the Indian summer monsoon is not accurate(Gettelman et al., 2004). The notable advancements compared to ECHAM3 are smaller errors found in the land surface temperature and precipitation than earlier
version.

In order to create ensemble members, an appropriate probability density function (PDF) (Molteni et al., 1996) is used in the atmosphere's phase space to approximate the real atmosphere. The PDF at initial time is estimated using a finite sample of possible initial conditions. At any finite time interval, the PDF is assumed to be linear and the axes of maximum instability can be found using the eigenvectors or Singular vectors (SV). These unstable SV's calculated from a three level quasi-geostrophic model are then used to approximate initial perturbations for a multilevel primitive-equation model. To illustrate creation of ensemble members better, we can refer the statement from the paper by F. Molteni et al. ”The ensemble statistics will approximate the correct PDF if

(i) the sample of initial states provides a realistic estimate of the probability distributionof analysis errors; and

(ii) the phase-space trajectories computed by the numerical model are good approximationsof atmospheric trajectories.”

The SW Ontario has two default grids as suggested by ECHAM model. Those grids lies in dark blue and orange color in the SW Ontario map as shown in Figure 2.1 below.

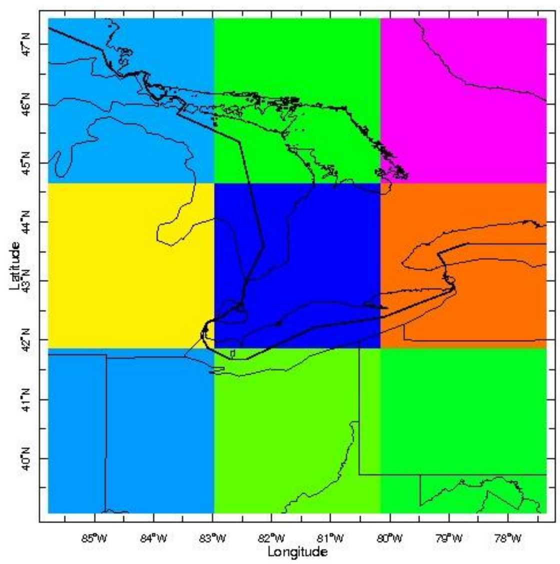


Figure 2.1: Grids, which we have named 78 (centered on 78,25W, 43.254N) and 81 (81.5625W, 43.254N) which cover SW Ontario

2.4 Climatic Research Unit (CRU)

The Climatic Research Unit (CRU) was founded in the School of Environmental Sciences (ENV) at the University of East Anglia (UEA) in Norwich in 1972. The notable area of CRU’s work is the production of the world’s land-based gridded (currently using 5° by 5° data resolution) temperature data set (Jones and Briffa, 1992). This work is continuing by adding more data yearly and updating and advancing the recorded global data and providing them to people awaiting publication of the observed temperature data for the past year around the world. The most recent data sets available up to 2019 are global data in the form of HadCRUT4 data sets. In addition, CRU provides a quality-controlled global precipitation data base. CRU's data base contains monthly average daily maximum and minimum temperature, precipitation, diurnal temperature range and vapour pressure information for all the world's inhabited land areas.

2.5 Global Precipitation Climatology Center (GPCC)

Precipitation plays an important role in the global energy and water cycle (Schneider et al., 2008). The reliable data of precipitation helps calculating surface fresh water, to give a climate picture for agriculture and hydrology while other uses might include improving predictions of flood and drought. In order to help a lot of organizations depending on precipitation data, the Global Precipitation Climatology Centre (GPCC) was established in 1989 at the request of the World Meteorological Organization (WMO). It is operated by Deutscher Wetterdienst (DWD, National Meteorological Service of Germany) as a German contribution to the World Climate Research Programme (WCRP). GPCC provides the global analysis of monthly precipitation on Earth's land surface based on rain gauge data. The objective of the GPCC is to provide a precipitation database with the accuracy of the gridded precipitation analyses and timeliness of the database availability. All GPCC database, gauge-based gridded monthly precipitation data sets for the global land surface, are available with spatial resolutions of 1.0° x 1.0° and 2.5° x 2.5° latitude by longitude, non real-time products based on the complete GPCC monthly rainfall station data-base (data collected from more than 97,000 different stations) are also available in 0.5° x 0.5° resolution. GPCCs new global precipitation climatology version came out in 2015 and are available in data resolution of 2.5° x 2.5°, 1.0° x 1.0°, 0.5° x 0.5°, and 0.25° x 0.25° while data fo 75,000 stations are used as background climatology for other GPCC analyses.

2.6 Environment and Climate Change Canada and its stations in South-Western Ontario

Canada is a geographically huge and environmentally diverse country that poses many hidden problems in the establishment of weather stations in isolated and distant areas, for instance in the Arctic (Mekis et al., 2018). Some sample applications within Environment and Climate Change Canada (ECCC) or simply Environment Canada are the severe weather warning program and climate research and services. In order to get accurate forecasts weather stations should have greater spatial density and more frequent observations rather than better accuracy. In order to achieve accuracy in weather forecasting, one requires long and homogeneous sets of historical database records with high quality and minimal interruptions from weather stations for each particular region. Measurements of precipitation over Canada from many sensors, including weather radar, are integrated into an analysis tool called the regional Canadian Precipitation Analysis (CaPA), which produces operational 6 h and 24 h, 10 km gridded accumulation maps. These CaPA products including the Canadian Land Data Analysis System (also known as CaLDAS) which provides surface initial precipitation conditions to drive numerical weather prediction (NWP) models, for example, the ECCC 2.5 km High-Resolution Deterministic Prediction System. The operational observation system of the Meteorological Service of Canada (MSC), part of ECCC, is comprised of a set of networks that can be further divided into three main types: stations running with automatic instruments, stations running with human managed, and the stations running with radar network.

For this thesis, we have used 27 weather stations in South-Western Ontario region. The list of 27 stations (there are more than 27 stations in figure but some of them are automated stations without temperature and precipitation data are neglected) in South-Western Ontario are given below (figure 2.2).

We selected the domain as South-Western Ontario for two reasons. First our industrial partner, Weather INnovations (WIN), were interested to see weather forecasts for this region rather than for the whole of Ontario and the second reason is that this region has less diverse terrain than northern part of Ontario which is good for accuracy of weather forecasts. We have used 15 years CRU (temperature)and GPCP (Precipitation) data to calculate tuning factors, however, we have used Environment Canada weather stations precipitation and temperature data as observation data while comparing with tuned forecasting data from ECHAM. Our first motive is to use our own Canadian weather data so that later we can use same theory to CANSIPS model. We have also compared the 15 years data of CRU and GPCP to 15 years Environment Canada weather stations data and it is found that they are

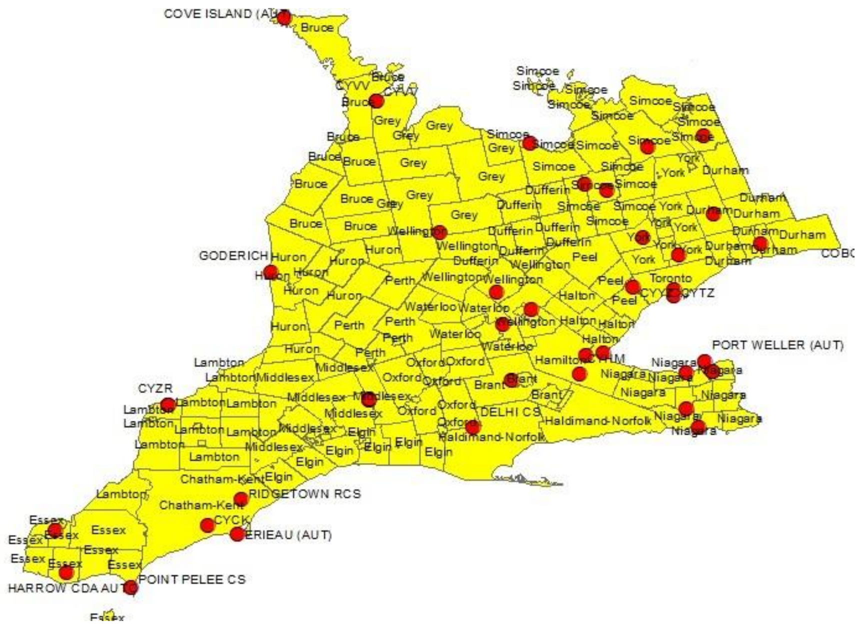
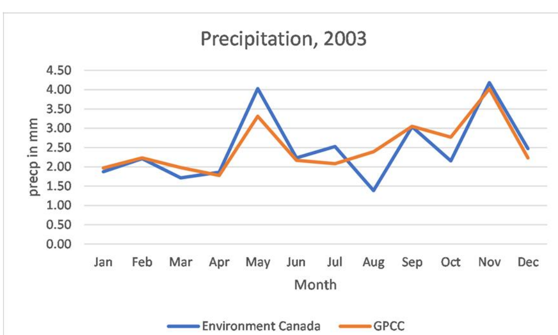


Figure 2.2: All ECCC stations in South-Western Ontario region

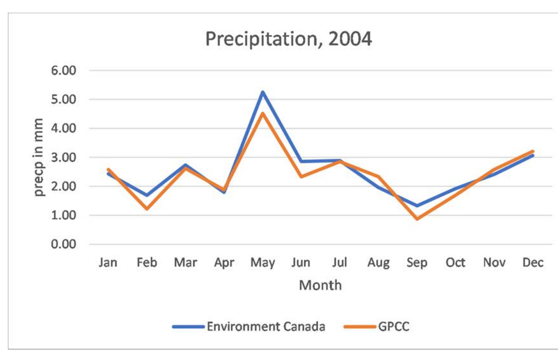
Stations name	Longitude	Latitude	Stations name	Longitude	Latitude
Chatam	-82.08	42.31	Peele	-82.52	41.95
Delhi_cs	-80.55	42.87	Port_colborne	-79.25	42.88
Elora	-80.42	43.65	Ridgetown	-81.88	42.45
Goderich	-81.72	43.77	Roseville	-80.47	43.35
Grimbsy mountain	-79.56	43.18	Sarnia	-82.31	43
Guelph	-80.22	43.55	Sarnia_cl	-82.3	43
Hamilton	-79.94	43.17	Strathory	-81.64	42.98
Harrow	-82.9	42.03	Toronto airport	-79.63	43.68
Kincardine	-81.62	44.17	Toronto city	-79.4	43.63
Kingsville	-82.67	42.04	Trillsonberg	-80.72	42.86
London	-81.15	43.03	Vineland	-79.4	43.18
Newglassgow	-81.64	42.51	Windsor_a	-82.96	42.28
Oakville	-79.69	43.51	Windsor_riverside	-82.93	42.33
Oshwa	-78.88	43.92			

Table 2.1: All ECCC stations in South-Western Ontario region with name and their longitude and latitude

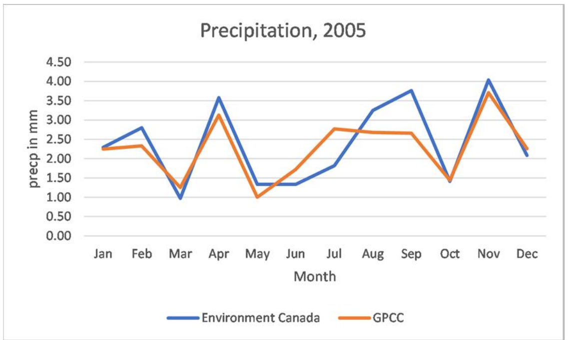
more consistent during most cooler months (Nov - April), than most warmer months (May - October). These differences does not have shown impact on tuning process where we can easily notice that tuning is more or less consistent in cooler months as well as warmer months. In Figure 2.3, the historical precipitation comparisons reveal that observed precipitation data from GPCC and ECCC or Environment Canada are following closely with some exceptions.



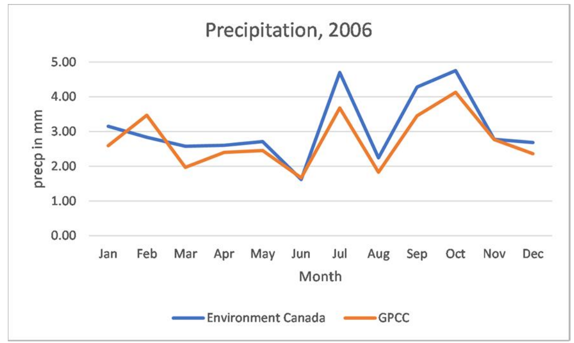
(a) Precipitation comparison, 2003



(b) Precipitation comparison, 2004



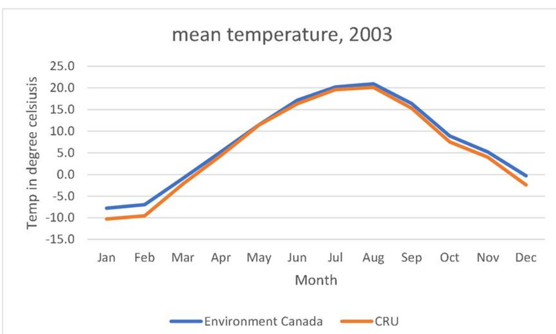
(c) Precipitation comparison, 2005



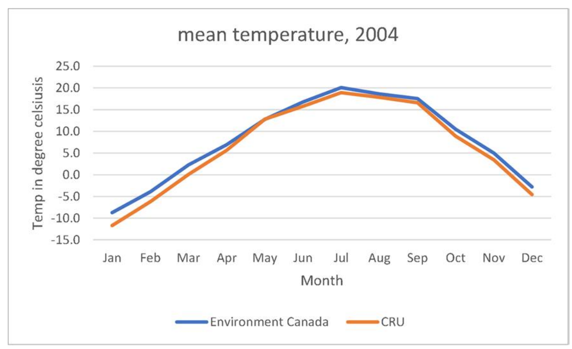
(d) Precipitation comparison, 2006

Figure 2.3: Historical precipitation comparisons

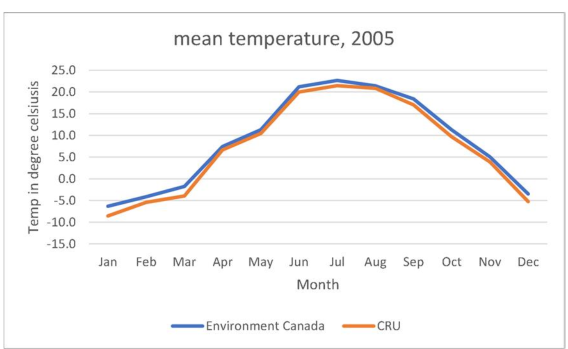
In Figure 2.4, the mean temperature comparison reveals that Environment Canada mean temperature are found to be little higher than the CRU mean temperature.



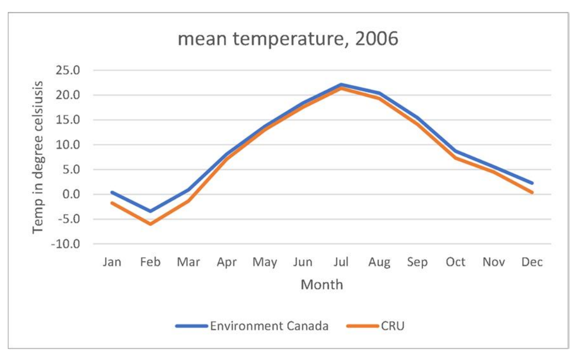
(a) Mean temperature comparison, 2003



(b) Mean temperature comparison, 2004



(c) Mean temperature comparison, 2005



(d) Mean temperature comparison, 2006

Figure 2.4: Historical mean temperature comparisons

2.7 Precipitation and surface temperature characteristics of Ontario

In Canada, a lot of research (Rapai´c et al., 2015; Vincent and Mekis, 2006; Zhang et al., 2000) has been done for the study of temperature and precipitation patterns in recent years. Those studies have suggested that mean annual temperature has increased by 1° C while total annual precipitation increased by 5%-35% during the last half of the twentieth century. For regional comparison, a study (Mohsin and Gough, 2010) was done using the pattern for the 1970-2000 period. They found that the annual mean and minimum temperatures in the highly populated Greater Toronto Area (GTA) has increased by 0.18° C more than rural areas. A study was done (Razavi et al., 2016) to find the historical and upcoming trends in temperature and precipitation across the Hamilton region of Ontario using a range of down scaled climate models. Their result showed that the mean and maximum temperature and annual total precipitation over various time periods in recent decades are increasing. These kind of increasing trends in climatic conditions will have some unwanted consequences for the environment and all living beings in Canada. A study (Vincent and Mekis, 2006) has found that fewer cold nights, cold days, and frost days but rather found more warm nights, warm days, and summer days are occurring across Canada together with more days with precipitation and a decrease in the maximum number of consecutive dry days. While considering regional scale, another study (Bonsal et al., 2001) was done which showed increasing trends in both lower and higher percentiles of daily maximum and minimum temperatures from 1900 to 1998 for the southern part of Canada.

A recent study (Wazneh et al., 2017) was done in Ontario’s South western region using data from 1951 to 2013. The outcomes showed that the numbers of extremely cold days decreased and hot nights increased and that nighttime warming was greater than daytime warming. Annual total precipitation and the total number of extreme precipitation events also increased. They also added that the spatial variability of precipitation indices is much higher than that of temperature indices.

Convective storms (Alexander et al., 2018) happen frequently in between the months of June and August in Southern Canada. SW Ontario having the highest annual average storms which produce severe weather including gusts, large hail and flash flooding. The lake-breeze fronts would often triggers the first storms of the day, which in turn later generated gust fronts that might initiate subsequent storms.

The Mesoscale Convective System (MCS) (Stull, 2017) has a narrow line of thunderstorms with heavy precipitation, followed by additional scattered thunderstorm cells. These thunderstorms often merge into a single, huge stratiform cloud. This type of stratiform provides light to moderate precipitation and can be triggered by the terrain, by synoptic systems (like cold fronts), or by the gust fronts from a smaller number of thunderstorms. In order to exist, they should have large convective instability and large wind shear over a deep layer of the environment.

3 Forecasting methodology

3.1 IRI Software

We have used the online data computing software developed by the IRI (International Research Institute for Climate and Society), Columbia University, USA. The IRI Data Library , https://iridl.ldeo.columbia.edu/, is a very helpful tool to extract weather data from different models and organize it easily according to our region of interest from global data sets. It is a free online data repository and analysis tool that allows everybody to view, analyze, and download huge climate-related data through a web browser. The aim of this IRI software is to help climate researchers create analyses of data ranging from simple averaging to advanced

Empirical Orthogonal Function (EOF) analysis using the Ingrid Data Analysis Language. This allows one to monitor climate conditions with maps and analyses in the map room, to create visual representations of data including animations and to download data in a variety of commonly-used formats such as Netcdf, text etc.

3.2 Forecasting technique

In order to tune up the forecast from Echam4p5 model, we need to take care of bias factors in the model data with the help of observation data. The ECHAM model seasonal weather prediction data are used as the base line and we then tuned this data by eliminating bias factors in it. The model is run every month by using persisted sea surface temperature of 0000 of 1st day of that month. The bias factor is named as a Regional Correction Factor (RCF) calculated on a monthly and domain basis. The RCF is calculated by using model

	January	February	March	April	May	June	July	August	September	October	November	December
L1	1.51	1.27	1.61	1.42	1.08	0.97	0.81	0.73	0.73	0.79	1.18	1.34
L2	1.43	1.27	1.60	1.40	1.08	0.92	0.80	0.72	0.70	0.81	1.20	1.38
L3	1.44	1.21	1.59	1.37	1.03	0.91	0.80	0.71	0.71	0.79	1.18	1.39

Table 3.1: RCF table for precipitation

long range (2002-2016) prediction for the respective area during each respective month for each lead time from month 1 to month 3. The RCF factor based on month and lead time and can be calculated as ratio of the mean of model monthly forecast precipitation ($\overline{F_P}$) model data (2002-2016) to the mean of observed precipitation data (2002-2016) ($\overline{O_P}$) i.e.

$$RCF = \frac{\overline{F_P}}{\overline{O_P}} \tag{3.1}$$

Thus, calculated RCF is then used to divide all the gridded model data of the month involved to get the tuned up forecast for the domain.

Here, if model issued data in September and we have to prepare forecast for next three months, September is first leading month and for September prediction we have to use L1 row and September column value (0.73). October is second leading month and for October prediction we have to use L2 row and select September column value (0.7). November is third leading month and for November prediction we have to use L3 row and select September column value (0.71).

For temperature correction factor, the mean of model monthly observed temperature ($\overline{O_T}$) model data (2002-2016) is subtracted from the mean of forecast temperature data (2002-2016) ($\overline{F_T}$)

$$RCF = \overline{F_T} - \overline{O_T} \tag{3.2}$$

The RCF table of temperature is as shown in the table below.

	January	February	March	April	May	June	July	August	September	October	November	December
L1	-2.2	-2.5	-0.5	0.5	0.5	-0.6	-2.1	-3.6	-3.3	-3.5	-0.4	-0.7
L2	-2.13	-2.56	-0.48	0.49	0.7	-0.7	-2.2	-3.54	-3.32	-2.91	-0.93	-2.14
L3	-2.1	-2.39	-0.84	0.59	0.57	-0.6	-2.1	-3.64	-3.21	-2.86	-0.5	-1.25

Table 3.2: RCF table for temperature

To tune up temperature forecast done on September, 3.3 is added to model forecast of September. In addition to this, to tune up leading month forecast we respectively use data of L1, L2 and so on.

The comparison among all the twelve months RCF factors with three leading months is also done. In both figures below, L1, L2 and L3 represent the first leading month, second leading month and third leading month respectively. In Figure 3.1, RCF values vary less whereas in Figure 3.2, RCF values vary from 0 to 3.5 throughout the year.

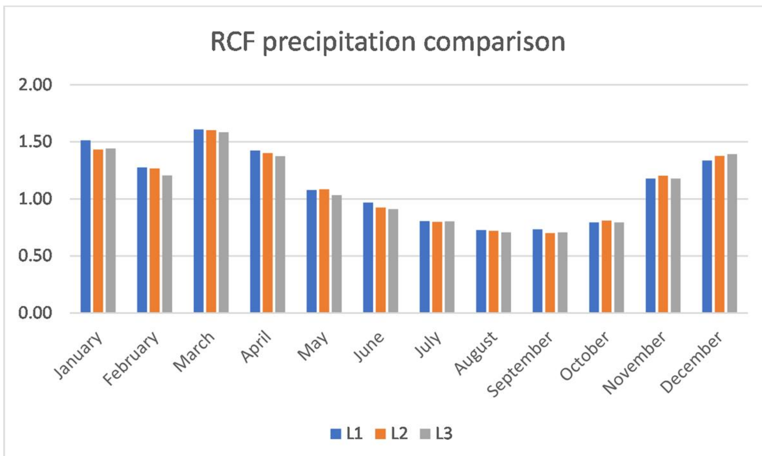


Figure 3.1: RCF comparison for precipitation

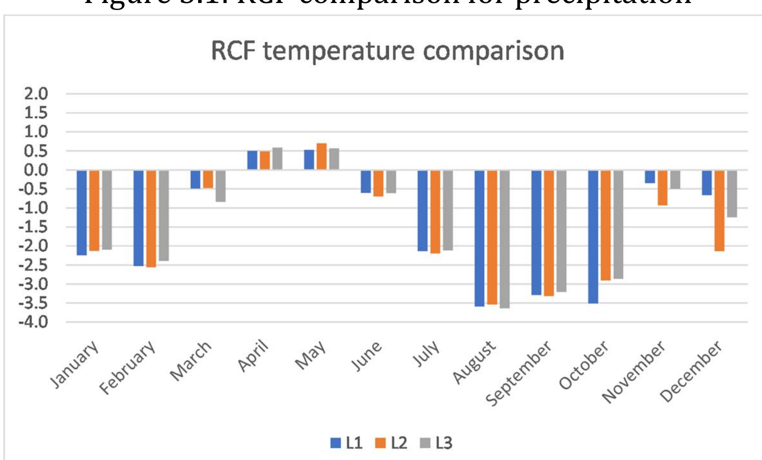


Figure 3.2: RCF comparison for temperature

We have also evaluated the standard deviation of differences (monthly observed precipitation or temperature model data (2002-2016) is subtracted from forecast precipitation or temperature data (2002-2016)) and the findings are as given in Table 3.3 and 3.4 for precipitation and temperature, respectively.

	January	February	March	April	May	June	July	August	September	October	November	December
L1(SD)	0.5	0.7	1.0	0.8	0.96	1.16	0.87	0.72	0.95	0.92	0.86	0.61
L2(SD)	0.5	0.8	0.9	0.8	0.86	1.25	0.95	0.79	1.04	0.82	0.86	0.73
L3(SD)	0.5	0.8	0.9	1.0	0.91	1.24	0.95	0.72	0.95	0.89	0.92	0.50

Table 3.3: Standard deviation table for precipitation

For precipitation, the standard deviation seems similar and less than 1 and which indicates that those historical data are clustered around mean. This may be one reason why tuning is less effective for precipitation.

	January	February	March	April	May	June	July	August	September	October	Novembe	December
L1(SD)	2.9	3.2	2.4	1.4	1.8	1.1	1.4	1.0	1.3	2.7	1.7	2.4
L2(SD)	3.3	3.1	2.8	1.8	1.8	1.2	1.3	1.0	1.3	1.6	3.0	2.4
L3(SD)	3.4	3.0	2.4	1.6	1.7	1.0	1.5	1.1	1.2	1.4	1.7	3.1

Table 3.4: Standard deviation table for temperature

For temperature, the standard deviation seems higher in colder months which indicates that those historical data have more variability in winter than summer. These spread out data makes the tuning process for temperature is more variable during colder months and less variable in warmer months than tuning process of precipitation.

As a part of our forecasting method, first of all, we download the monthly and daily forecast data from the ECHAM model provided by the FUNCEME. Thereafter, we mask out data from the global data to our domain and spread out masked data using weighted average parameter to our locations of interests as well. After masking out, we compare the nesting (grid to grid) ECHAM4p5 data with GPCC and CRU precipitation and temperature data (upscaling the resolution of both temperature and precipitation data) respectively if they are available, or with ECCC station data if not. Then we compute area weighted average daily precipitation or daily temperature of the desired region and sub-regions. Finally, we tune up climate model data by applying regional correction factors from the tables provided above.

We have used the online data computing source with Software developed by IRI (International Research Institute for Climate and Society), Columbia University, USA. The averaged daily and monthly model data are then fed into IRI online software using RCF factors to get tuned up output results. Output data are calculated as temporal distributions of temperature and precipitation.

3.2.1 Regional Correction Factor (RCF)

The Regional Correction Factors (RCF) or Bias factors are what we need to tune up forecast data. These factors are calculated using 2002 to 2016 historical forecast data (precipitation or temperature) and observed data (precipitation or temperature) which are fed into MATLAB with codes to get output as a table containing the RCF factors. We have two sets of tables, one for precipitation and another for temperature. In tables 3.1 and 3.2, we have 36 different factors in each RCF table where 12 columns represent each month and 3 rows represent each lead time upto three months.

These RCF factors are used to divide by/subtract from the gridded forecast data that we get from the ECHAM model. The tuned data can then be compared with observed data from GPCC, CRU or ECCC weather stations. RCF =1 (precipitation) or 0 (temperature) implies no bias, RCF > 1/0 implies over-forecasting the weather parameter and RCF < 1/0 implies under forecasting the weather parameter.

3.3 Forecast verification method

The first approach of verification is to produce time series plots of forecasts and observations which provide a tentative idea between forecast and observed data distributions and which further reveal outliers in either forecast or observation data-sets. So initially we will use time series plots to compare tuned forecast data with observation stations data. This gives a clear picture of deviation of forecast from the true state of the observed weather. The resolution of numerical models should be equal to the observed data resolution otherwise it leads to a verification dilemma while the horizontal scale difference between observations and forecasts can easily cause problems. The verification of precipitation and temperature provides basic statistics on how much the forecast values differ from the observations. One aspect of their behavior is that temperature may behave relatively smoothly in space and time while the precipitation may behave less smoothly.

4 Findings and discussion

4.1 Monthly precipitation

As a test of the method we compared ECHAM ensemble forecasts, direct and tuned with both GPCP and ECCC monthly precipitation measurements between July 2019 and June 2020. The monthly precipitation for Southern Ontario reveals that our forecast precipitation throughout the year is missing the heavy precipitation during October and January while our forecast is doing better to some extent during spring and summer. In order to have a better picture of precipitation for entire months, we decide to work on daily precipitation forecast.

	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	March	April	May	June
ECCC	84.3	75.7	60.2	141.6	44.0	60.1	104.2	39.9	80.2	59.5	64.0	60.8
Forecast_1_Tuned (L1)	82.3	71.6	73.3	78.8	58.7	69.6	31.0	52.2	41.3	46.9	19.6	33.3
Forecast_2_Untuned (L2)	N/A	50.3	48.0	66.7	95.0	81.8	65.6	56.5	54.8	69.0	81.1	25.3
Forecast_3 _Untuned(L3)	N/A	N/A	48.5	52.3	83.4	96.5	61.5	64.5	53.0	62.2	93.3	94.1
GPCP	78.0	71.1	72.9	131.1	61.1	84.3	121.0	55.8	83.3	61.1	69.8	N/A

Table 4.1: Monthly precipitation table (values in mm)

In Table 4.1, Forecast 1 Tuned (L1) represents current month forecast with correction, L2 and L3 are leading months forecast from earlier months without correction and note that for the month of September, 60.2 mm is the observed monthly precipitation from Environment Canada weather stations, 73.3 mm is forecast done for the same month, 48.0 mm is the forecast done on August for September, 48.5 mm is forecast done on July for September and 72.9 mm is monthly observed precipitation analyzed by GPCP. The N/A for rows 3 and 4 indicates that we have started working on forecast from July and no earlier forecast data available. The N/A for fourth row tells that GPCP data for the month of June was not available at the GPCP official site and later when data was officially available, data could not be post processed due to google drive authentication conflict between IRI and google.

4.2 Daily precipitation and temperature

The daily observations and forecasts of precipitation and temperature will give us in depth knowledge of how much daily precipitation and surface temperature varied over the month. We cannot expect perfect forecasts of what happened on a particular day but might hope to match amplitudes and patterns of variability as well as simple monthly means.

4.2.1 Daily precipitation using ensemble means

We have analyzed one year (July, 2019 - June, 2020) of precipitation and temperature data for this thesis. Initially, we took the mean of all 20 ensemble members and started comparing with observations data taken from 27 weather stations data.

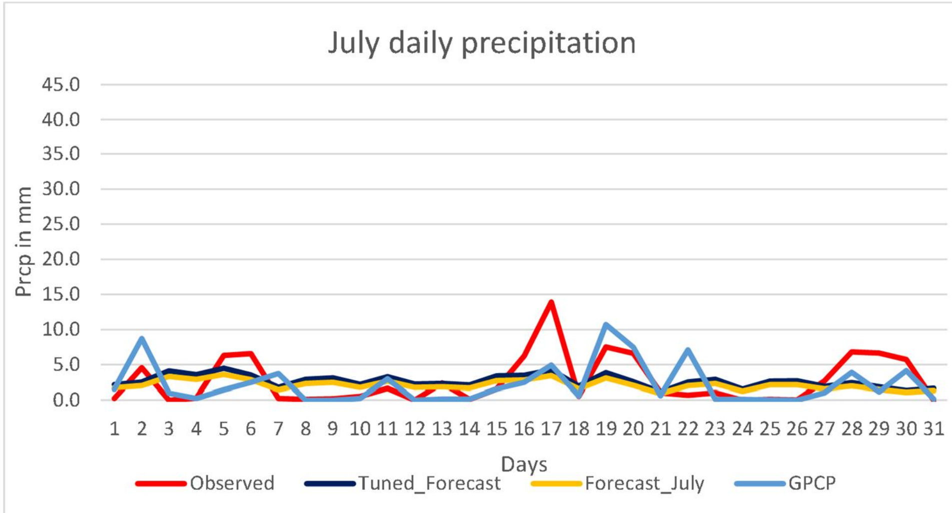
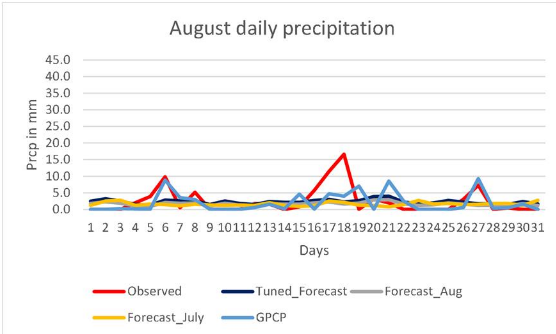


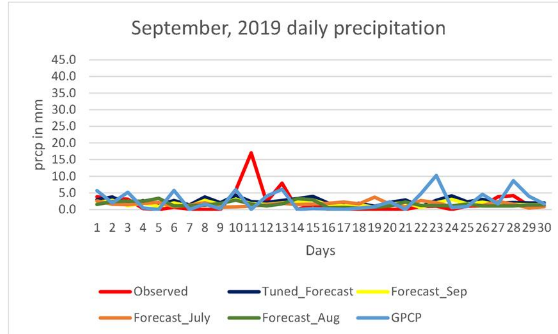
Figure 4.1: July, 2019 daily precipitation

In figure 4.1, the red line represents the observed data averaged over 27 ECCC weather stations, the light blue represents the observed data for the region from GPCP, the dark blue line represents the tuned ensemble mean forecast for precipitation and the yellow line represents the untuned forecast from the ECHAM 4p5 model. From those figures, we can see that both observed data GPCP and ECCC have substantial variability could be due to inclusion of land lake in GPCP data but not in ECCC stations data while forecast data is giving a more average precipitation without the day to day variability shown in the observed data. We have used tuned forecast for one month out of three months to simplify the figure. The tuned _ forecast means tuning is applied only on the respective month in each figure, for instance, in Figure 4.1, tuning is applied to July only. To clarify, in Figure 4.2b,

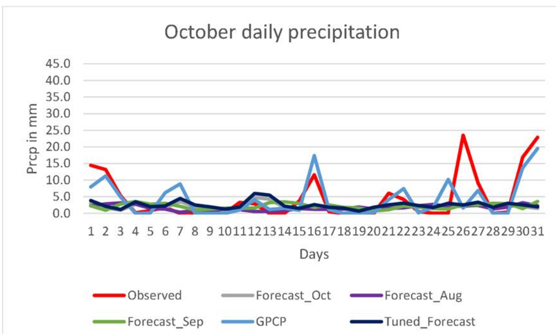
Forecast Sept represents L1, first leading month on September and Forecast Aug represents L2, second leading month from August and Forecast _July represents L3, third leading month from July.



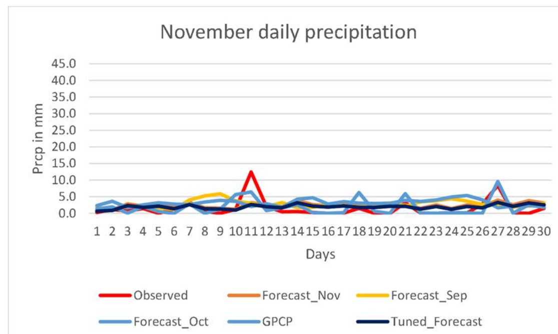
(a) August, 2019 daily precipitation



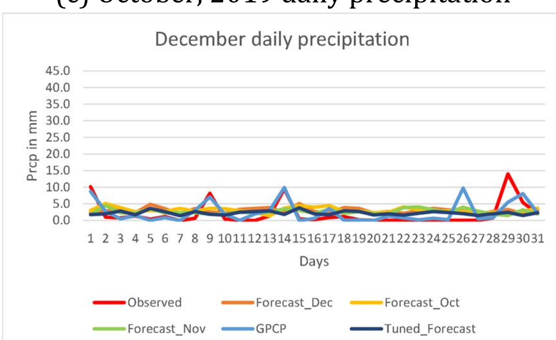
(b) September, 2019 daily precipitation



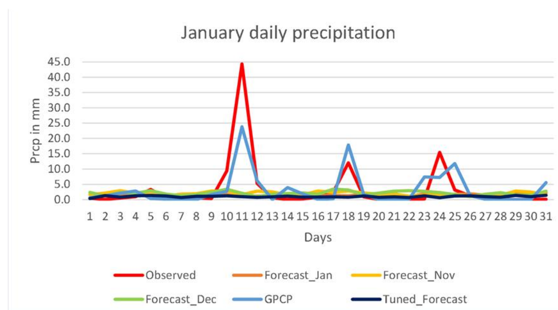
(c) October, 2019 daily precipitation



(d) November, 2019 daily precipitation

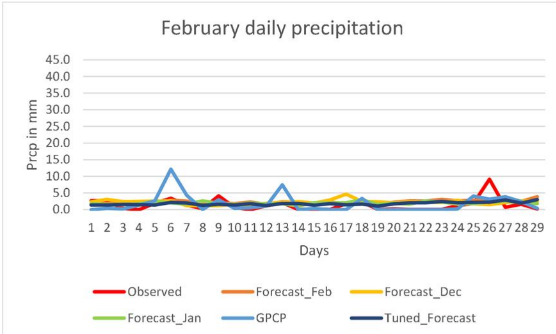


(e) December, 2019 daily precipitation

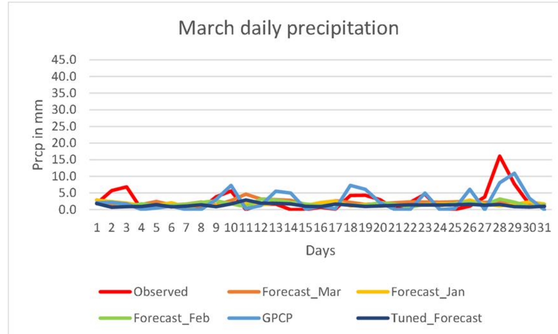


(f) January, 2020 daily precipitation

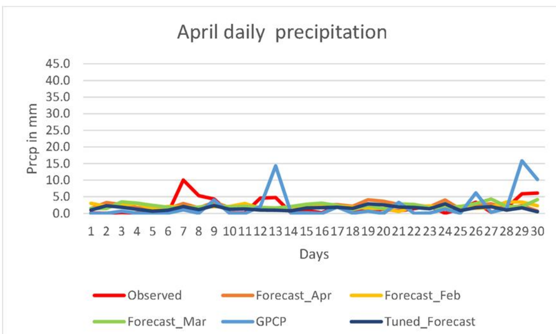
Figure 4.2: Daily precipitation



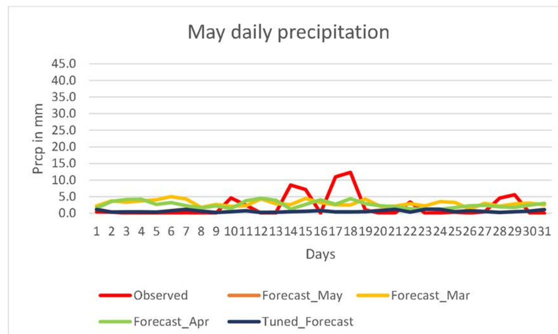
(a) February, 2020 daily precipitation



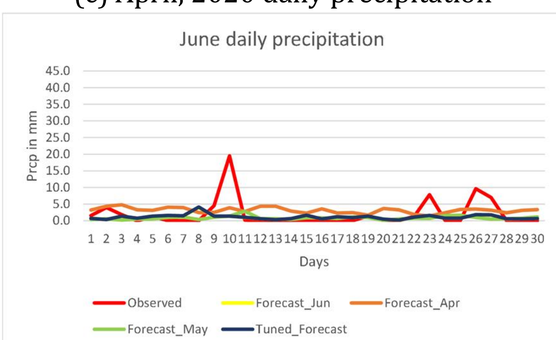
(b) March, 2020 daily precipitation



(c) April, 2020 daily precipitation



(d) May, 2020 daily precipitation



(e) June, 2020 daily precipitation

Figure 4.3: Daily precipitation

In Figure 4.3, May and June plots do not have GPCP data due to their unavailability at that time officially. Precipitation is highly variable, between measurement stations and between ensemble members. We can see that the observed precipitation pattern is variable while the forecast is more or less accurate. Here, we have used the mean of 20 ensemble members which misses the variability exist among the members because while taking the mean of ensemble members, it erases information of all extreme values from the original model data. This inspired us to to check the variation among all the ensemble members.

Variation among ensemble members with different statistical measures for September precipitation is also studied.

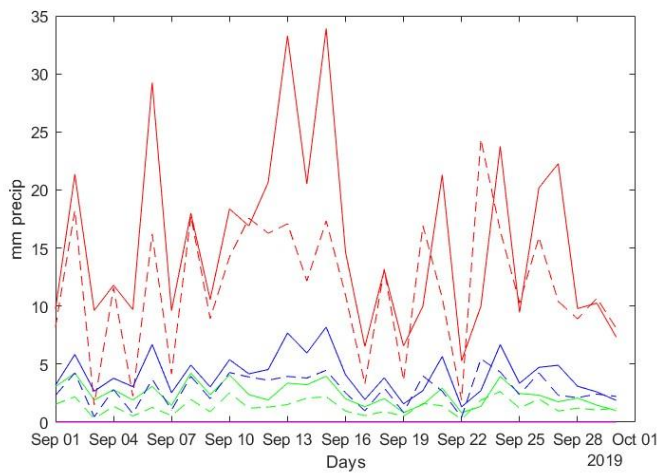
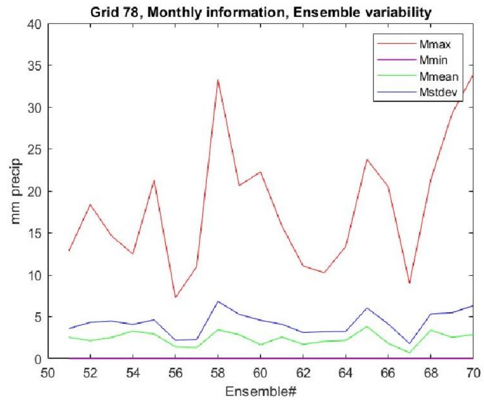
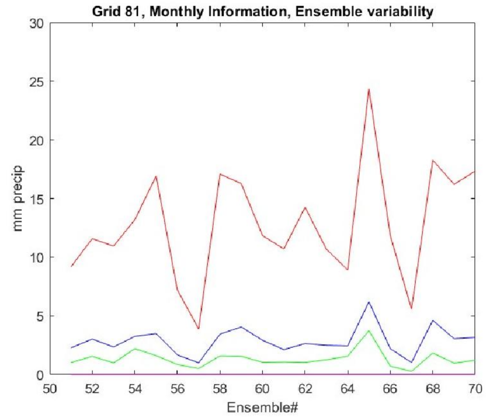


Figure 4.4: Variation among ensemble members with different statistical measures, September, 2019 daily precipitation

In Figure 4.4, the solid line represents grid point 78 and dashed line represents grid point 81 ; red line represents max, green line represents means, maroon line represents min and blue line represents standard deviations among ensemble members. The maroon line is zero in the figure.

Monthly variation among ensemble members with different statistical measures for September daily precipitation were also studied and it was found that daily precipitation among ensemble members ranges from 0 to 35 mm.





(a) Monthly variation of daily precipitation of September at grid point 78(78.25W, 43.254N)

(b) Monthly variation of daily precipitation of September, 2019 at grid point 81(81.5625W, 43.254N)

Figure 4.5: Monthly variation of different statistical measures at default grid points.

In Figure 4.5, red line represents max, blue line represents standard deviation, green line represents mean and maroon line represents min which is zero.

The variation among 20 ensembles members at two default grid points which we have named 78 (centered on 78,25W, 43.254N) and 81 (81.5625W, 43.254N) provided by model data is provided in the following figures.

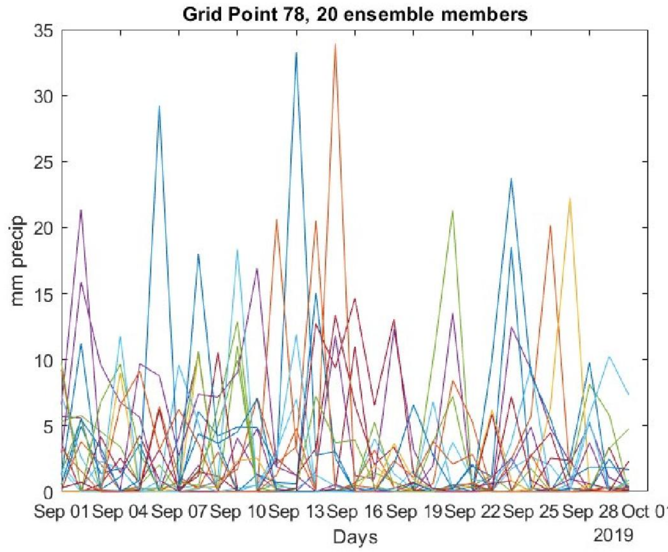


Figure 4.6: Variation at grid point 78, September, 2019 daily precipitation (78,25W, 43.254N)

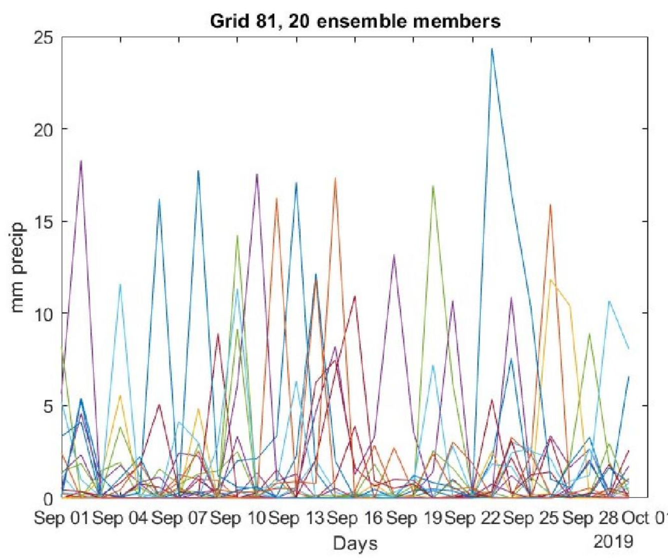


Figure 4.7: Variation at grid point 81, September, 2019 daily precipitation (81.5625W, 43.254N)

As we can see, there is huge variation among all ensemble members from nearly zero to 35 mm in Figure 4.6.

Generally, a forecast is made using the mean of all members in a model, but unknown perturbations among the ensemble members lead us to study individual ensemble members as an alternative. The next section will show the difference of forecast between a few ensemble members vs mean of 20 members. Those results from the comparison of the few members and means of 20 members could provide new forecasting insight over the region.

We found that there is huge variation among ensemble members at default grid points, we want to find whether there is similar variation among ensemble members over SW Ontario

region.

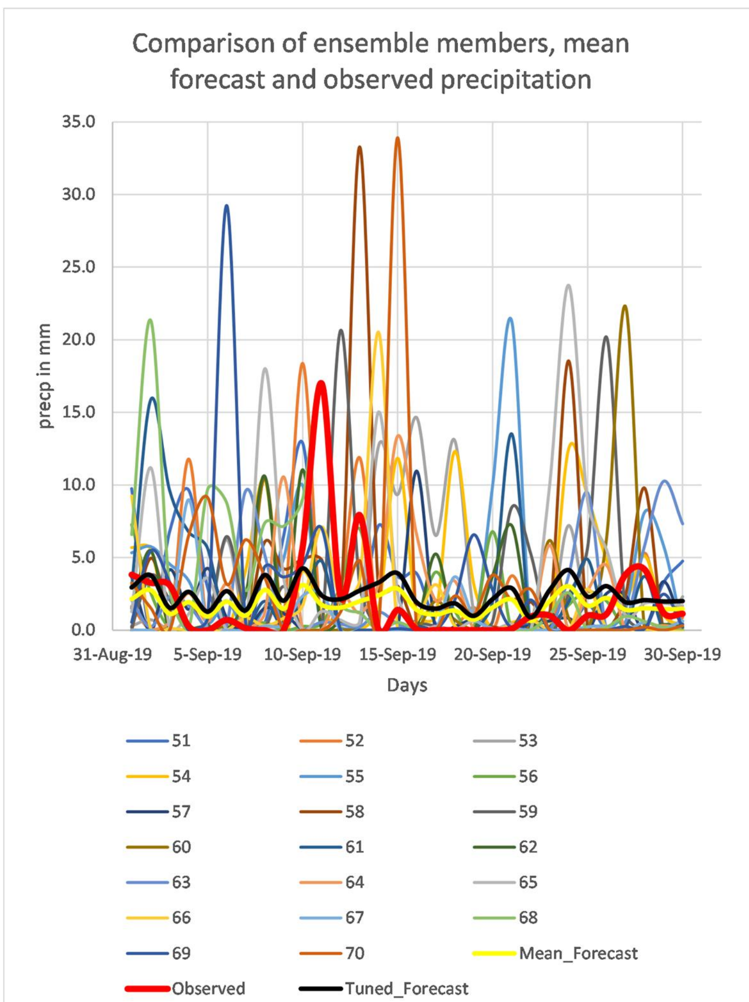


Figure 4.8: Comparison of all members with mean forecast and observed data for September precipitation over SW Ontario, 2019

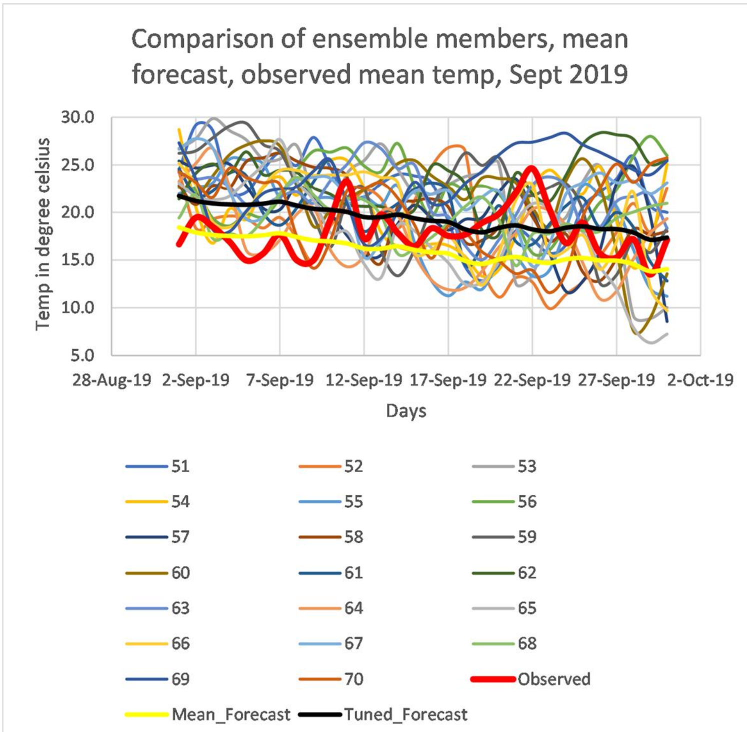


Figure 4.9: Comparison of all members with mean forecast and observed data for September mean temperature over SW Ontario, 2019

In Figures, 4.8 and 4.9, both figures look complicated but we can focus only on black line (Tuned Forecast), yellow line (Mean Forecast) and red line (Observed) rather than all other colors which represent ensemble members variation only. In these figures, we can see that those variations of ensemble members get canceled out while taking mean of them. Furthermore, we can see ensemble mean forecast(Yellow line) misses those variability. In addition to this, if we look carefully, some of the ensemble members follow closely the observed data(red line).

4.2.2 Daily precipitation using individual ensembles

In ECHAM data, there are 20 ensemble members and their numbering starts from 51, 52, 53 to 70. 20 individual ensemble members have variability more similar to the observation data than the mean of all 20 members. In order to illustrate this further, we have used first two ensemble members 51 and 52 out of 20 ensemble members.

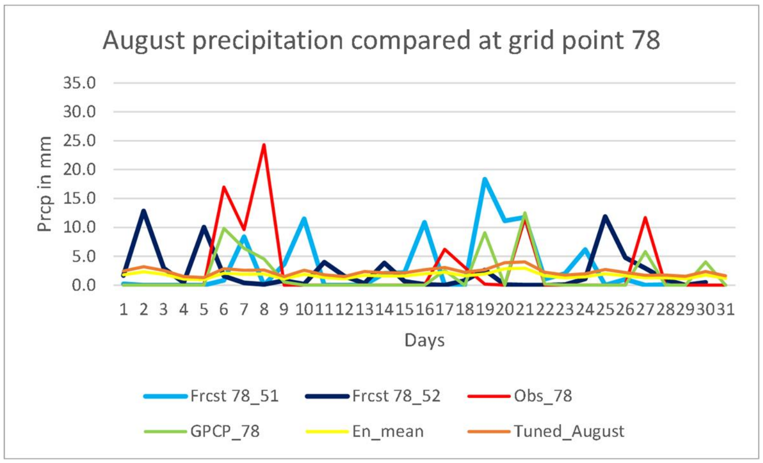


Figure 4.10: August precipitation, 2019 comparison at grid point 78

We have used only two ensemble members out of 20 ensemble members. We chose first two (51, 52) out of 20 (51, 52, 53, ..., 70) for the sake of convenience. In figures 4.10 and 4.11, observed data from Environment Canada in red line (Obs _78), another observed data from GPCP in green line (GPCP 78) are compared with forecast data having two individual ensemble members 51 and 52 (Frcst78 51 and Frcst78 52) in light blue and dark blue respectively and mean of 20 ensemble members in yellow line (En mean). In addition to this, we also included the tuned forecast for the respective month in orange color (Tuned August). The forecast data for the month of August in the Figures 4.10 and 4.11 at two default grids 78 and 81 respectively are compared to earlier Figure 4.2a. The individual member forecasts are more interesting in the sense that they show some features of the observed data while in Figure 4.2a, forecast data misses all the variability. We have also shown ensemble means in both 4.10 and 4.11 colored in yellow to get the idea of why taking mean of ensembles earlier was not working well.

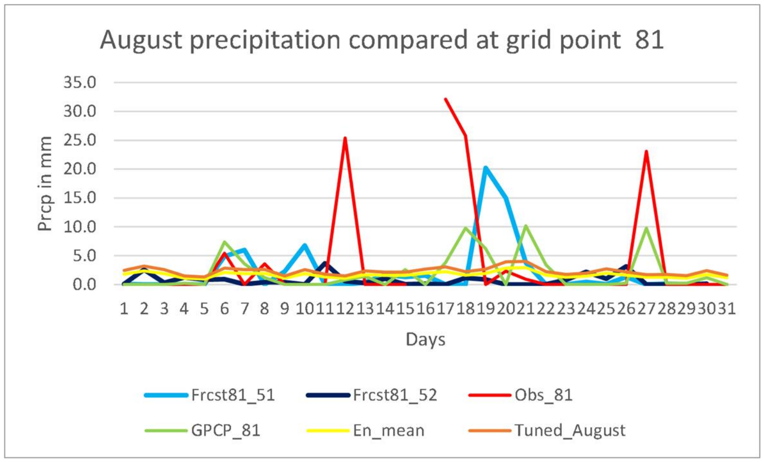


Figure 4.11: August precipitation, 2019 comparison at grid point 81

The forecast data for the month of September in the Figures 4.12 and 4.13 at two default grids 78 and 81 respectively are compared to earlier Figure 4.2b and it is found that individual ensemble members are following observed data shown in the red line. In addition to this, in Figures 4.12 and 4.13, the means of 20 ensembles in yellow color misses all variability producing less agreeable results.

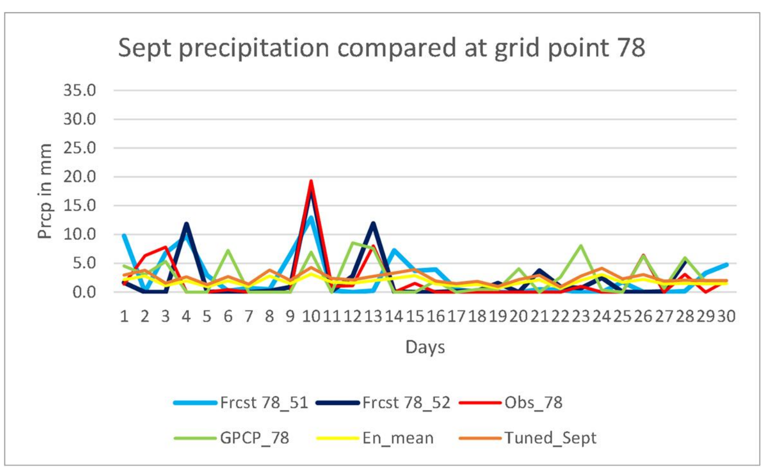


Figure 4.12: September precipitation, 2019 comparison at grid point 78

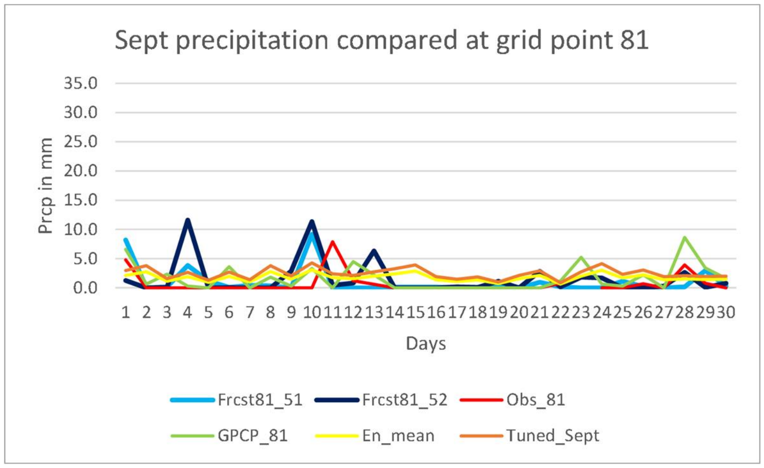


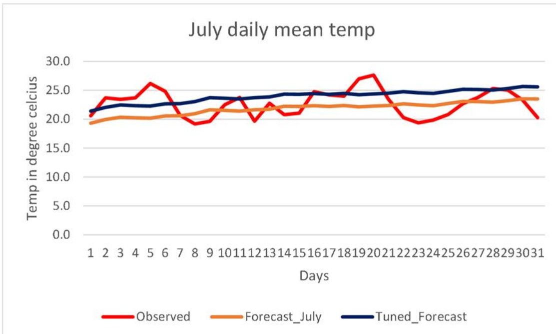
Figure 4.13: September precipitation, 2019 comparison at grid point 81

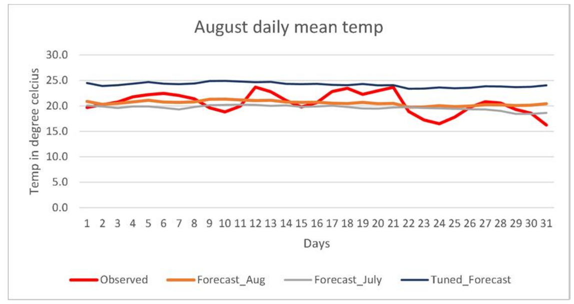
4.2.3 Daily temperature results

4.2.3.1 Daily mean temperature using ensemble means

As with precipitation, we have compared one year (July, 2019 - June, 2020) daily average, maximum and minimum temperature data for South-Western Ontario in this thesis. Initially, we took the mean of all 20 ensemble members and started comparing with observations data taken from 27 weather stations data as CRU data were unavailable at that time. The data for all three parameters like average, maximum and minimum were available so we wanted to see broader outlook for temperature. The forecasting for temperature should be of higher confidence than the precipitation forecast.

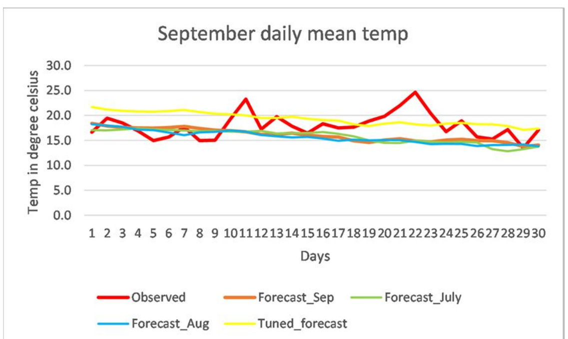
In Figures, 4.14 and 4.15, the red line represents the observed data averaged across from 27 weather stations, the orange line represents the untuned forecast for mean temperature from the ECHAM 4p5 model. The mean temperature forecast misses the variability found in observed data and the tuned forecast data in dark blue is higher among all. In all other months and figures below, there are two or three forecast months, for example Forecast July, Forecast Aug, Forecast Sept which were compared with observed September data from Environment Canada in red line. We have also tuned and added the forecast for the current month only (otherwise for three months figure looks messier), for example, Tuned forecast in the figure in blue line.

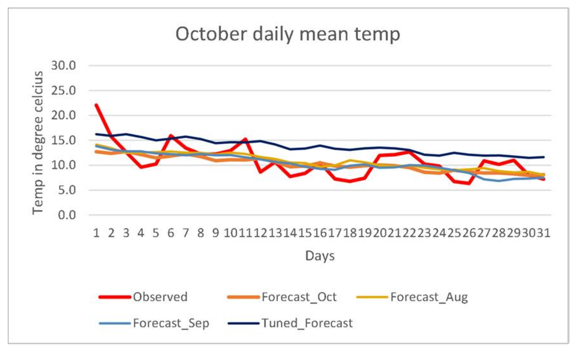




(b) August, 2019 daily mean

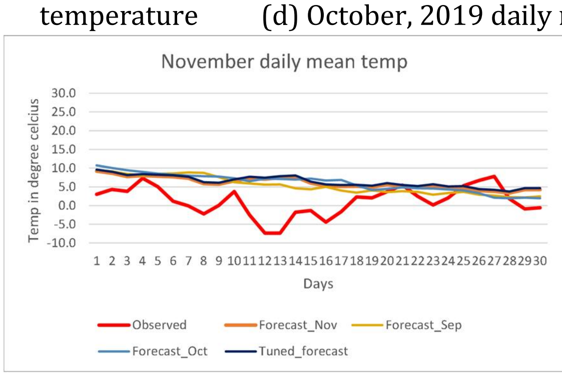
temperature(a) July, 2019 daily mean temperature

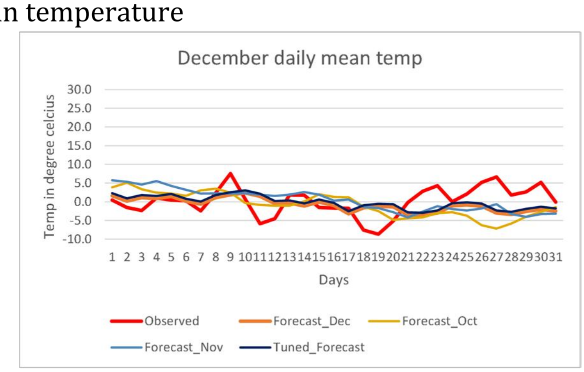




(c) September, 2019 daily mean

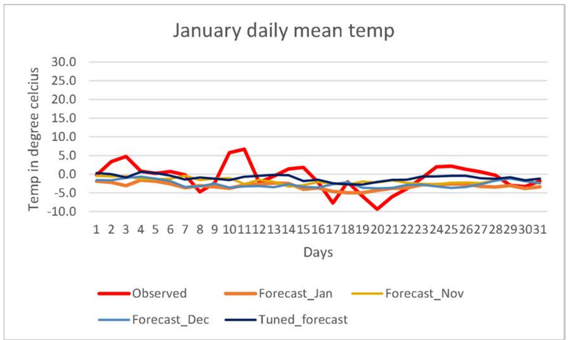
temperature (d) October, 2019 daily mean temperature



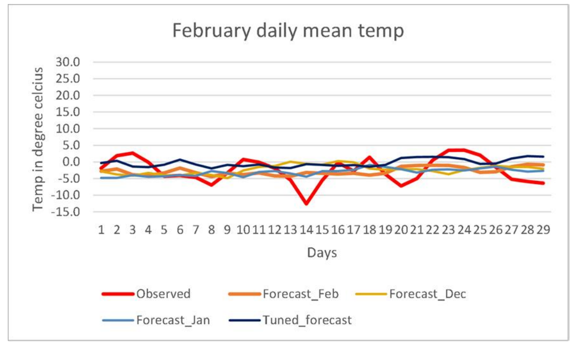


(e) November, 2019 daily mean temperature (f) December, 2019 daily mean temperature

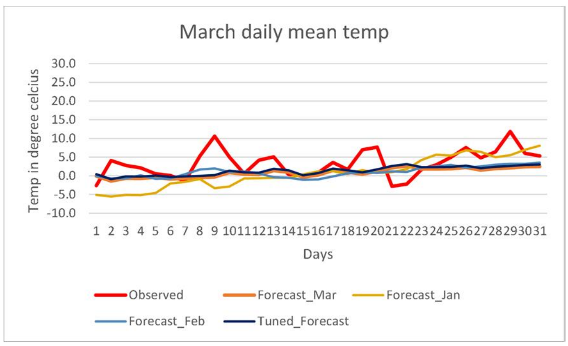
Figure 4.14: Daily mean temperature



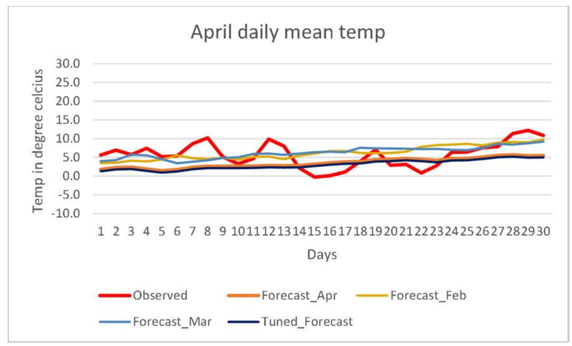
(a) January, 2020 daily mean temperature



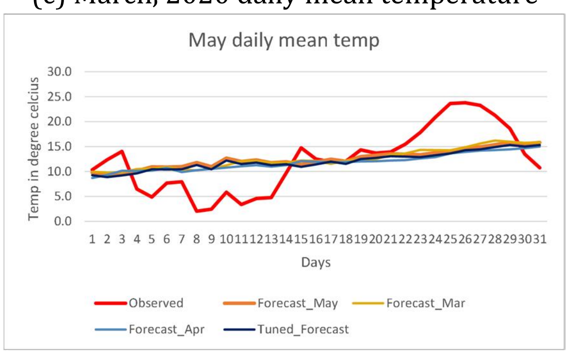
(b) February, 2020 daily mean temperature



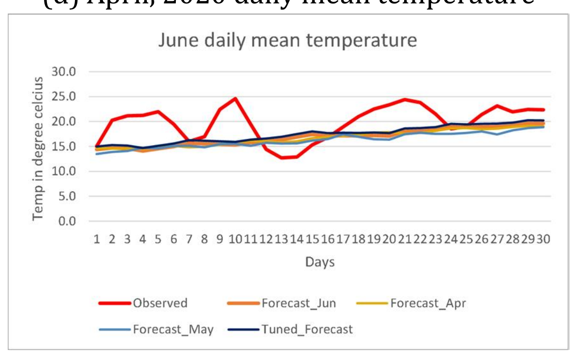
(c) March, 2020 daily mean temperature



(d) April, 2020 daily mean temperature



(e) May, 2020 daily mean temperature



(f) June, 2020 daily mean temperature

Figure 4.15: Daily mean temperature

4.2.3.2 Daily mean temperature using individual ensembles

In an earlier section, we found that individual ensemble members (like 51, 52 etc) follow the variability of observation data more closely than the mean of all 20 members in most months.

One reason could be, the mean solely average out the data and gives an average result as compared to individual ensemble members.

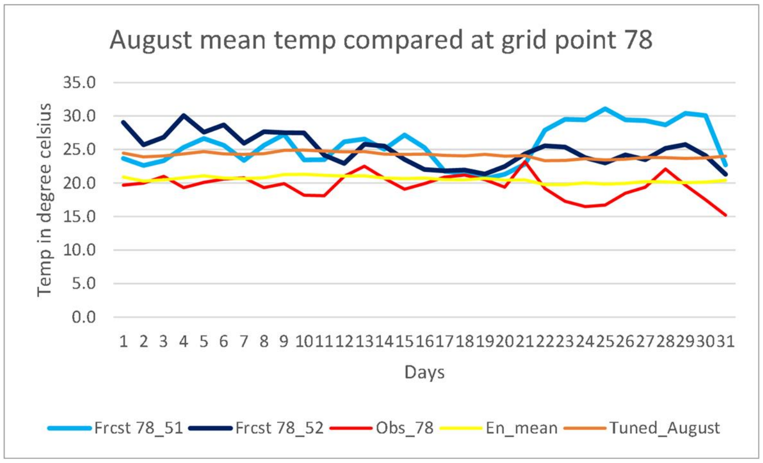


Figure 4.16: August, 2019 mean temperature comparison at grid point 78

In Figures 4.16 and 4.17, we have used only 2 ensemble members out of 20. The forecast data in the Figures 4.16 and 4.17 when compared to earlier 4.14b are found encouraging as it is giving variability but still misses the actual variability found in the observed data in Figure 4.14b where ensemble mean forecast misses all variability found in observed data.

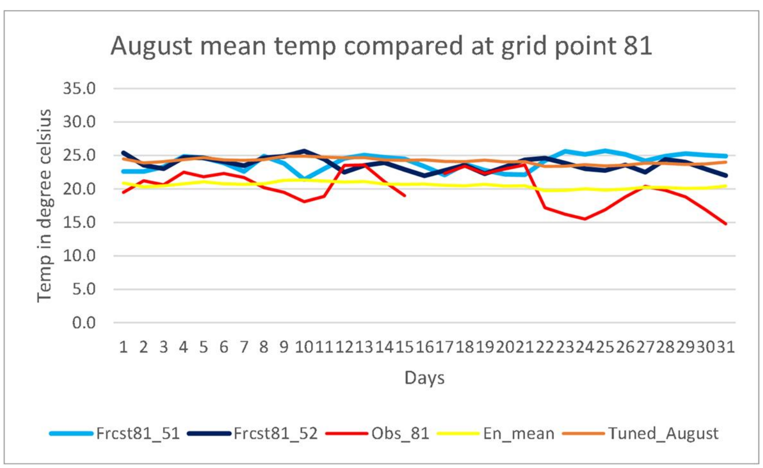


Figure 4.17: August, 2019 mean temperature comparison at grid point 81

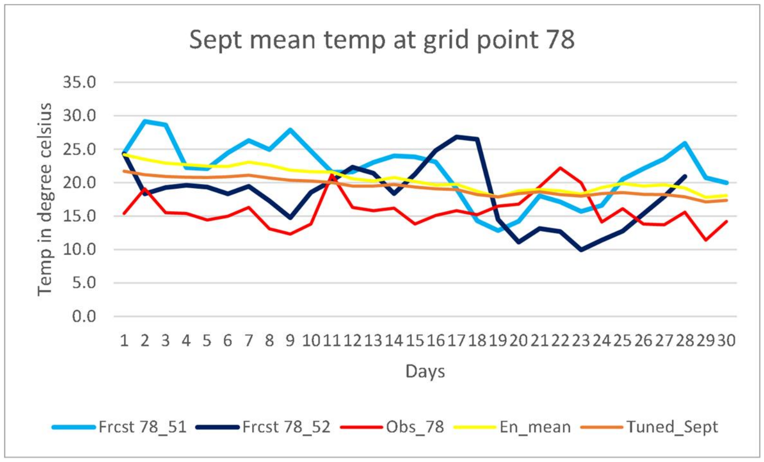


Figure 4.18: September, 2019 mean temperature comparison at grid point 78

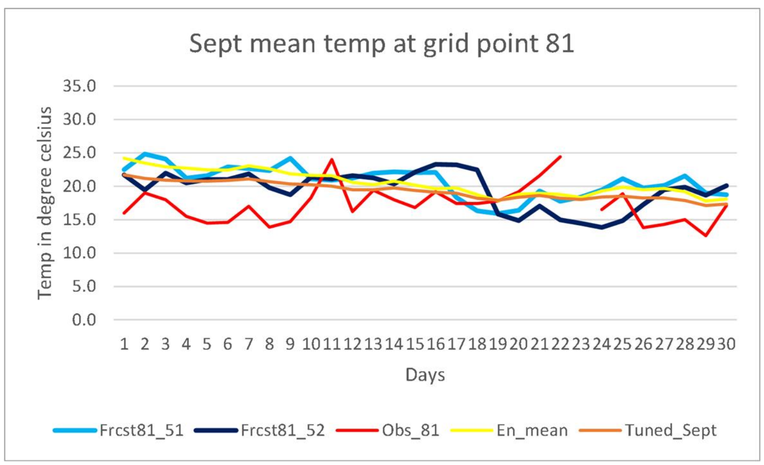
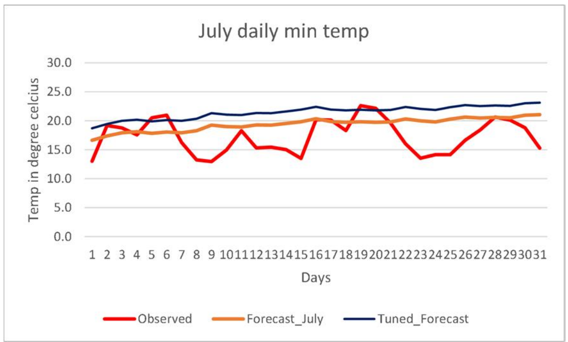


Figure 4.19: September, 2019 mean temperature comparison at grid point 81

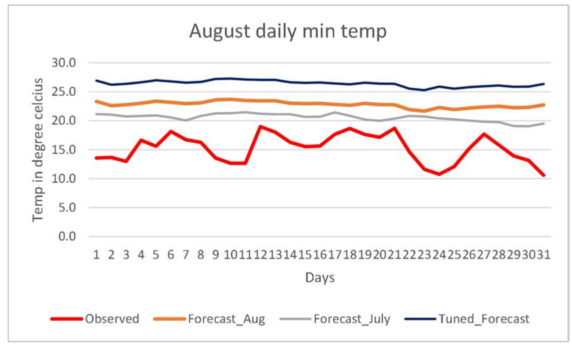
Here, in Figures 4.18 and 4.19, similar results are found as above and the yellow line represents the mean of 20 ensembles which gives an average results missing all crest and troughs compared to others as found in Figure 4.14c.

4.2.3.3 Daily minimum temperature using ensemble means

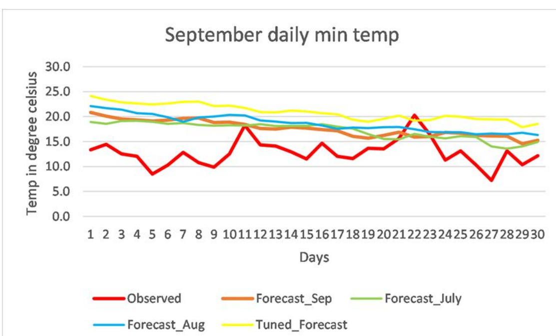
Similarly, we took the minimum temperature of all 20 ensemble members and started comparing with observations data taken from 27 weather stations data across South-Western Ontario.

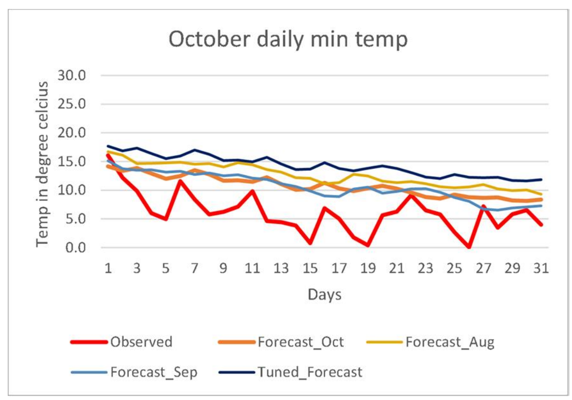


(a) July, 2019 daily minimum temperature

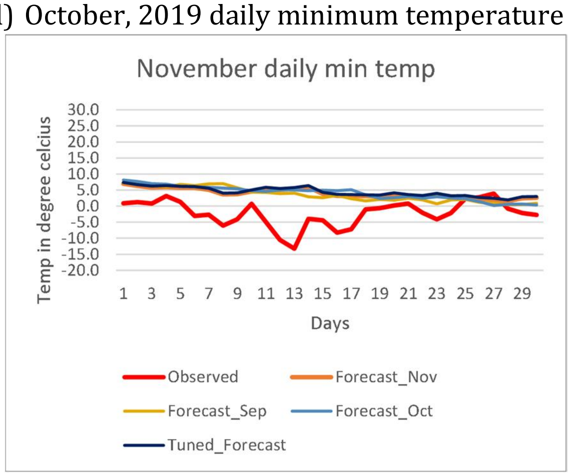


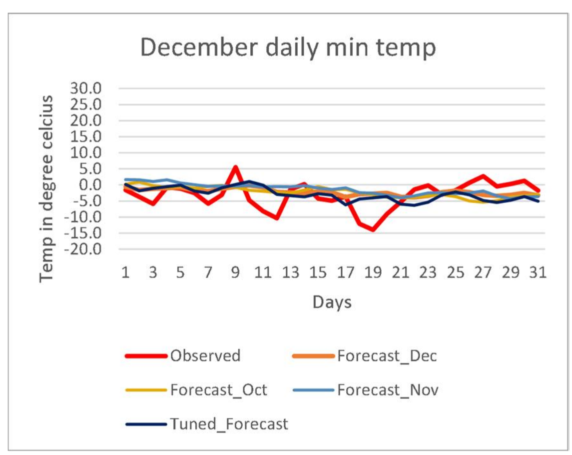
(b) August, 2019 daily minimum temperature





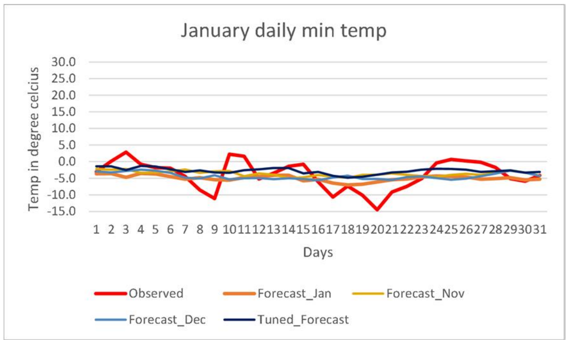
(c) September, 2019 daily minimum temperature
(d) October, 2019 daily minimum temperature



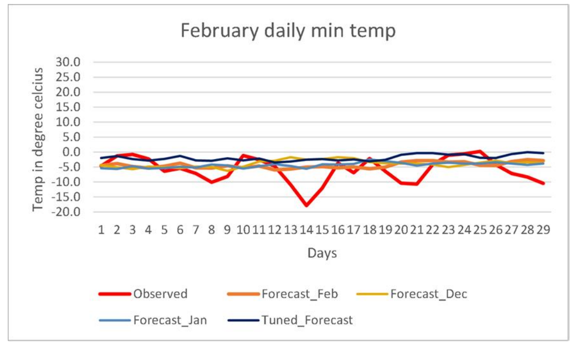


(e) November, 2019 daily minimum temperature (f) December, 2019 daily minimum temperature

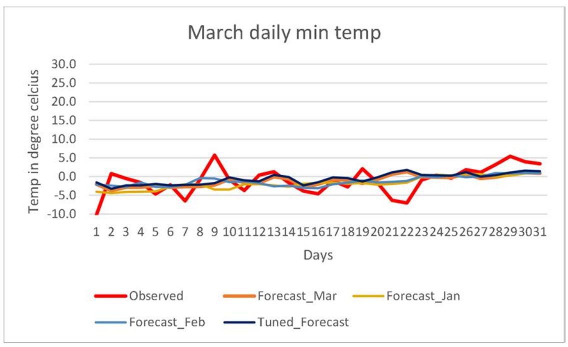
Figure 4.20: Daily minimum temperature



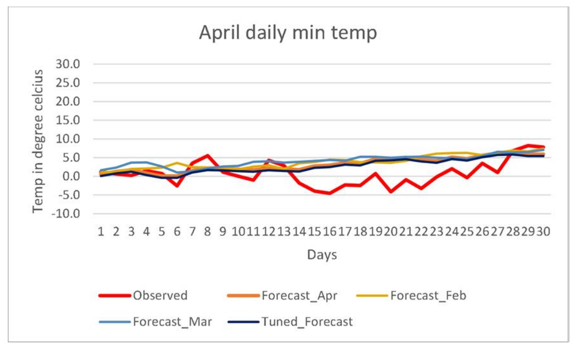
(a) January, 2020 daily minimum temperature



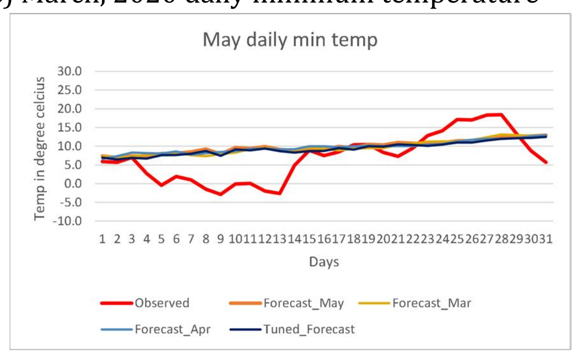
(b) February, 2020 daily minimum temperature



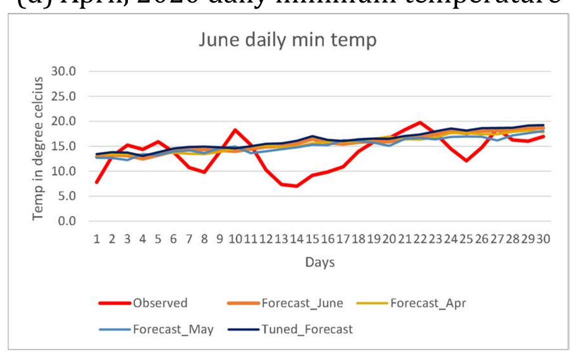
(c) March, 2020 daily minimum temperature



(d) April, 2020 daily minimum temperature



(e) May, 2020 daily minimum temperature



(f) June, 2020 daily minimum temperature

Figure 4.21: Daily minimum temperature

The red line represents the observed data taken from 27 weather stations, the orange line represents the untuned forecast for minimum temperature from ECHAM 4p5 model and the blue line represents the tuned forecast. The minimum temperature forecast gives the plain results as compared to the variability found in observed data and most of the months have higher minimum temperature values than observed one. The tuned forecast is below than the Model forecast and misses the variability of observed data.

4.2.3.4 Daily minimum temperature using individual ensembles

The individual ensemble member which follows the variability of observation data more closely than the mean of all 20 members in the most months are 51, 52 etc.

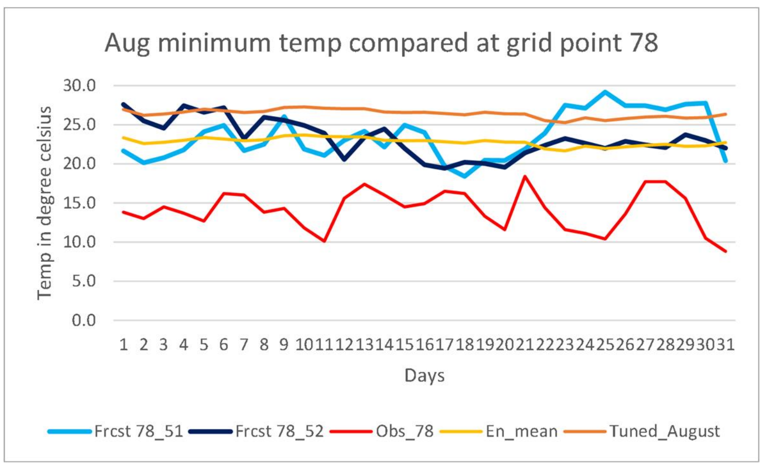


Figure 4.22: August, 2019 minimum temperature comparison at grid point 78

In Figures 4.22 and 4.23, we have used only 2 ensemble members out of 20 for August. The forecast data in the Figures 4.22 and 4.23 when compared to earlier Figure 4.20b are found similar in the sense that the minimum values predicted from forecasts are significantly higher than the observed values. Here, ensemble means misses the actual variability compare to individual ensemble members and observed data as in Figure 4.20b .

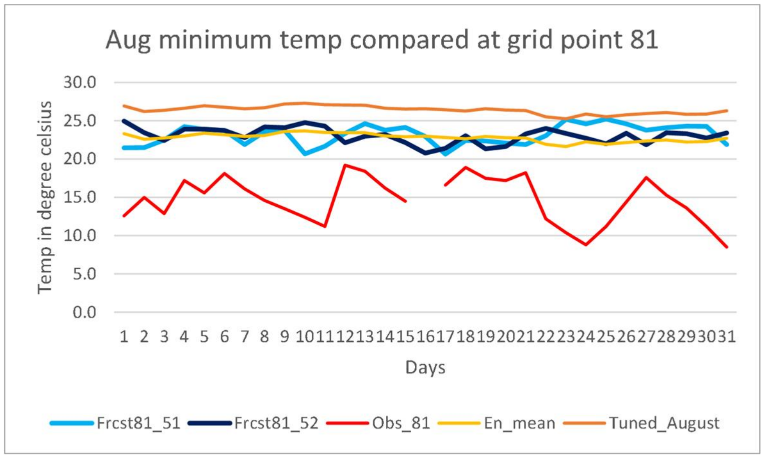


Figure 4.23: August, 2019 minimum temperature comparison at grid point 81

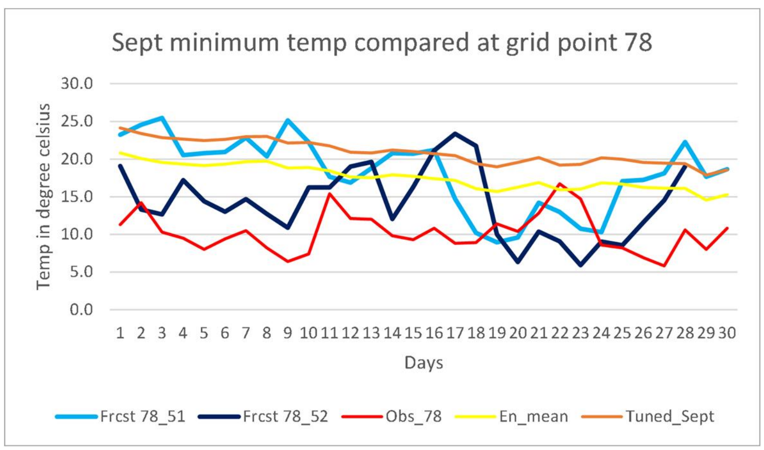


Figure 4.24: September, 2019 minimum temperature comparison at grid point 78

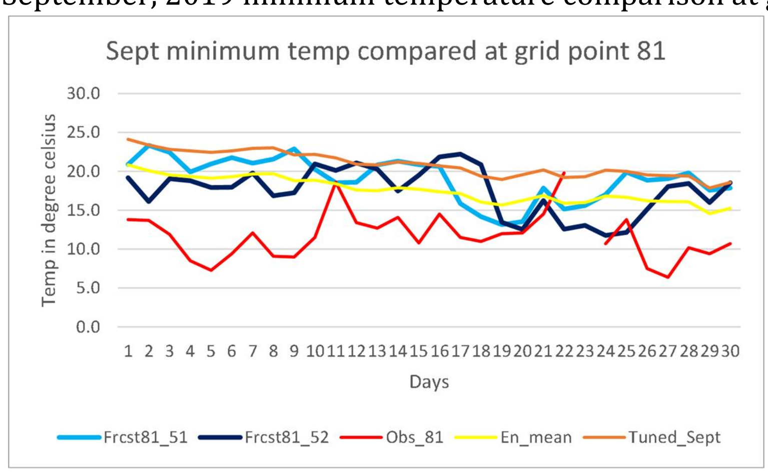
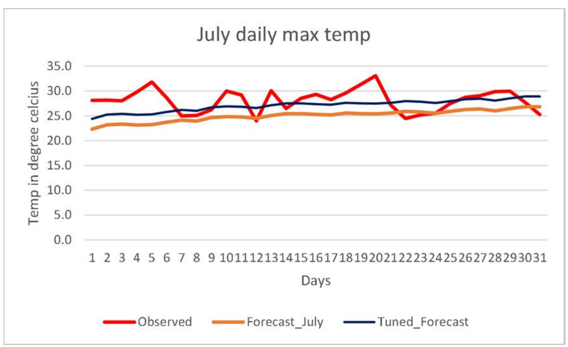


Figure 4.25: September, 2019 minimum temperature comparison at grid point 81

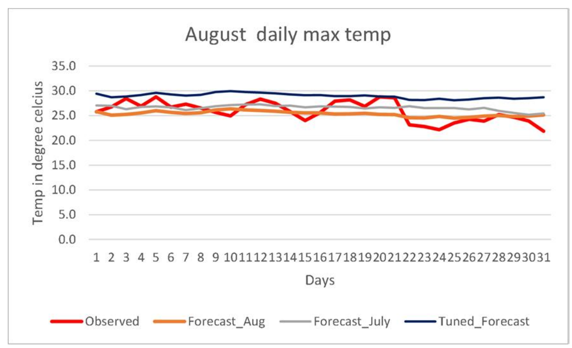
Here, Figures 4.24 and 4.25represents the month of September 2019. The individual ensemble members in dark blue and light blue are following the variability but still have higher values than the red line, the observed one. The yellow line represents the mean of 20 ensembles which gives less variable results compared to others as found in Figure 4.20c.

4.2.3.5 Daily maximum temperature using ensemble means

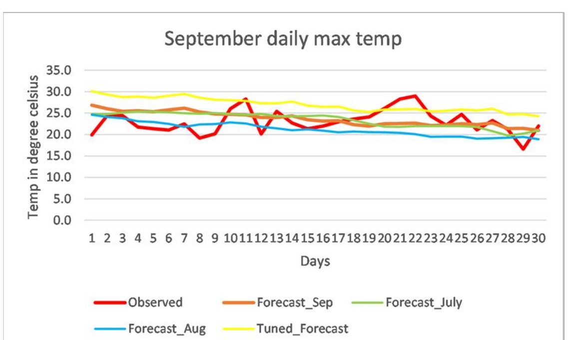
Finally, we took the maximum of all 20 ensemble members and compared with observational data taken from 27 weather stations.



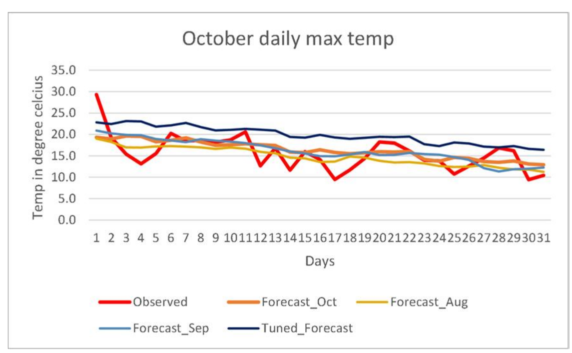
(a) July, 2019 daily maximum temperature



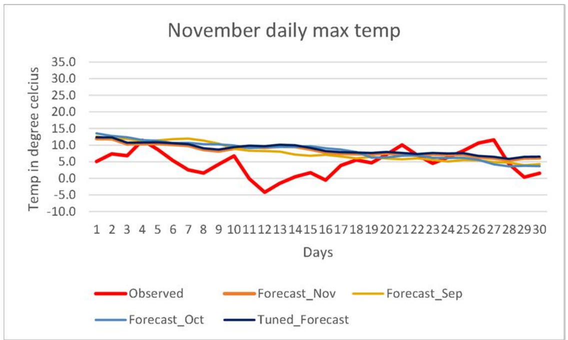
(b) August, 2019 daily maximum temperature

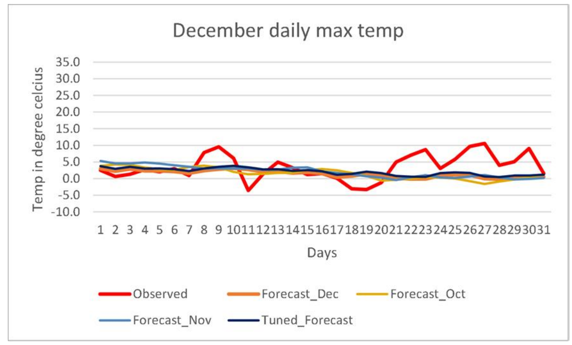


(c) September, 2019 daily maximum temperature



(d) October, 2019 daily maximum temperature

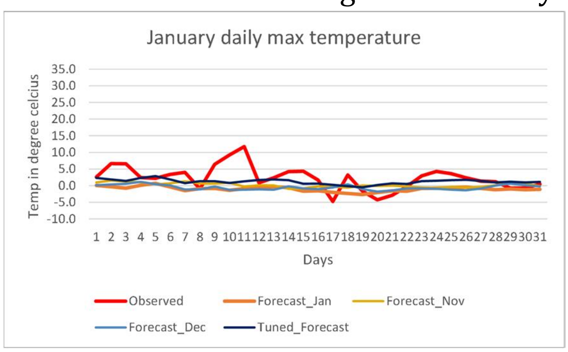


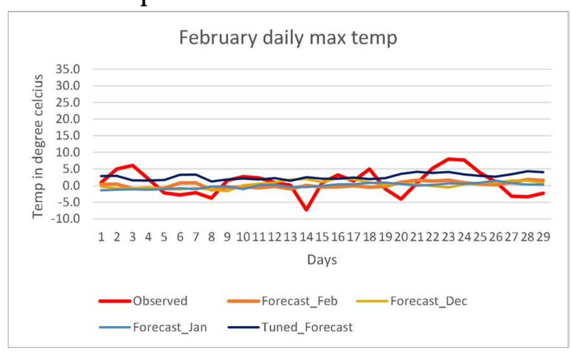


(e) November, 2019 daily maximum temperature

(f) December, 2019 daily maximum temperature

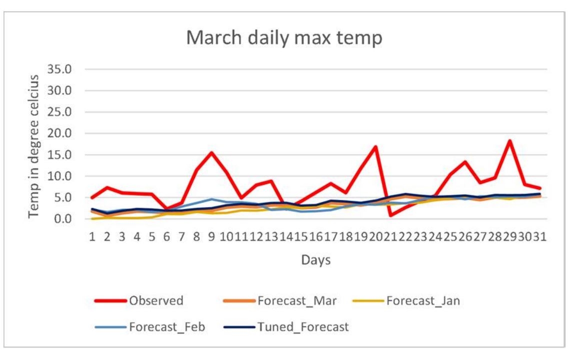
Figure 4.26: Daily maximum temperature

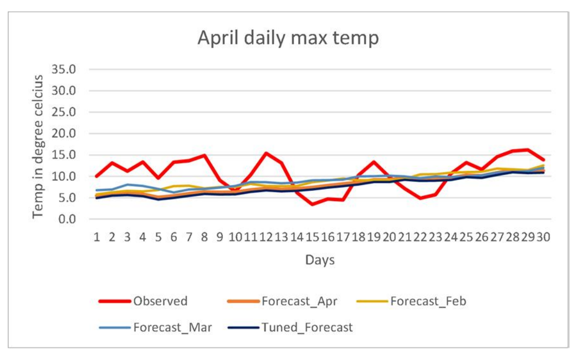




(a) January, 2020 daily maximum temperature

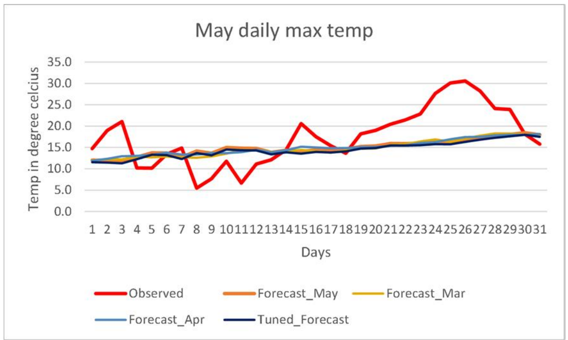
(b) February, 2020 daily maximum temperature



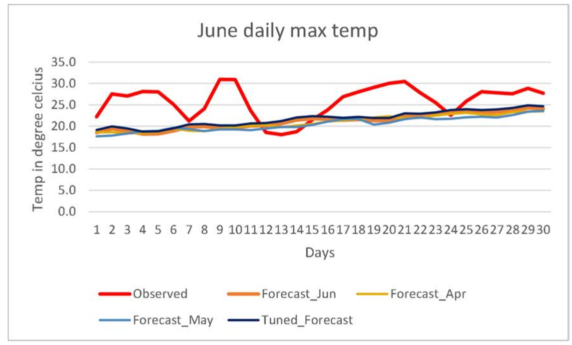


(c) March, 2020 daily maximum temperature

(d) April, 2020 daily maximum temperature



(e) May, 2020 daily maximum temperature



(f) June, 2020 daily maximum temperature

Figure 4.27: Daily maximum temperature

The red line represents the observed data taken from 27 weather stations, the orange line represents the untuned forecast for maximum temperature from ECHAM 4p5 model and the blue line represents the tuned forecast. Here also, the maximum temperature forecast misses the variability found in observed data and the tuned forecast is far below both observed and forecast values.

4.2.3.6 Daily maximum temperature using individual ensembles

The individual ensemble member which follows the variability of observation data closely than the mean of all 20 members in the most months are 51, 52 etc.

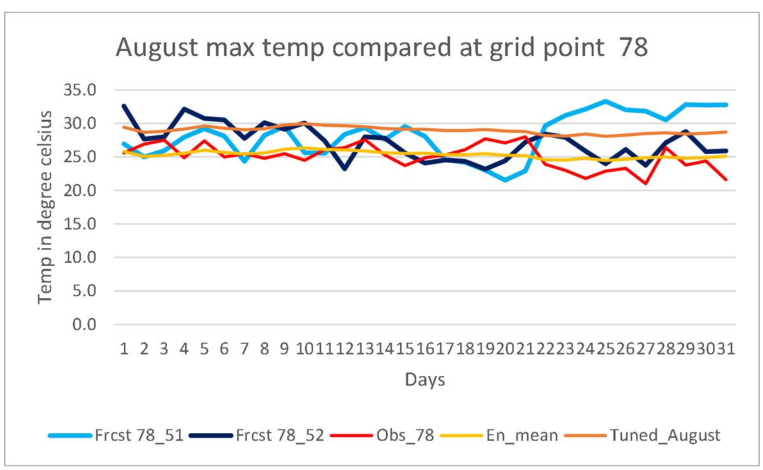


Figure 4.28: August, 2019 maximum temperature comparison at grid point 78

In Figures 4.28 and 4.29, we have used only 2 ensemble members out of 20. The forecast data in these Figures 4.28 and 4.29 when compared to earlier Figure 4.26b are found more interesting in the sense that it is giving variability but still misses the actual variability found in observed data as in Figure 4.26c where forecast data misses all variability found in observed data. The yellow lines in Figures 4.28 and 4.28 represent the ensemble means from Figure 4.26b which is giving less variable results compared with individual ensembles.

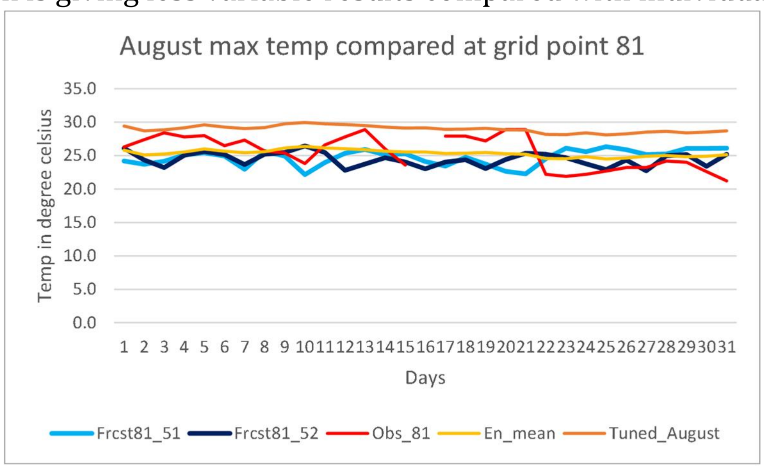


Figure 4.29: August, 2019 maximum temperature comparison at grid point 81

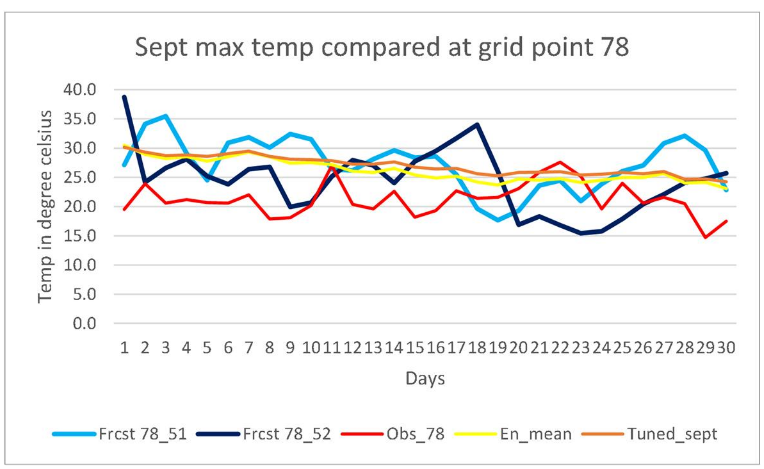


Figure 4.30: September, 2019 maximum temperature comparison at grid point 78

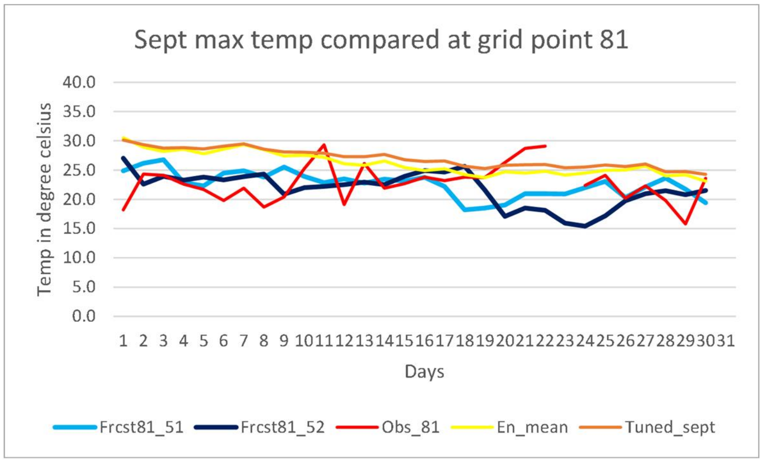


Figure 4.31: September, 2019 maximum temperature comparison at grid point 81

Here, as we can see in Figures 4.30 and 4.31, there is some variability if we consider individual ensembles but still not following the observed data and the yellow line represents the mean of 20 ensembles which gives less reliable results as found in Figure 4.26c.

4.2.4 Explanation of individual ensemble doing better on long term forecasting

The individual members that appeared to perform better than the mean of all 20 ensemble members in most instances were 51 and 52 (when compared 20 ensemble members data to observed data). In general, forecast are done using the mean of all members in a model but as in our case their mean misses all the variability when it is compared with observed data. One of the reasons of few members doing better than mean of all 20 members could be some vital data information gets removed while averaging out all in the case when there is huge variations among individual ensemble members.

We wanted to see what happens to those huge variations if we take monthly average of daily precipitation for the whole year 2019-2020.

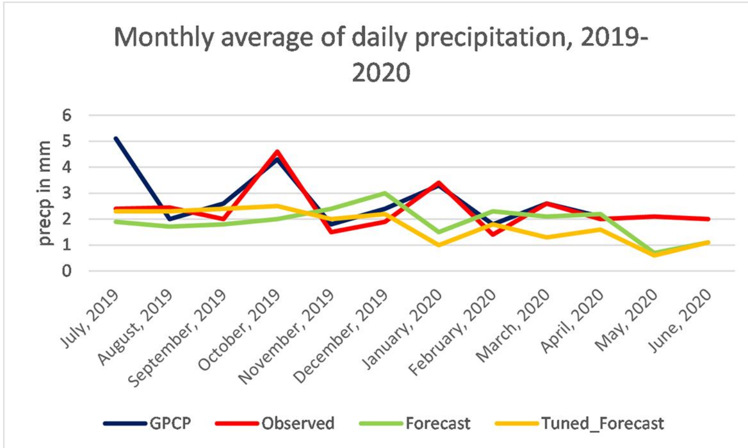


Figure 4.32: Monthly average of daily precipitation, 2019-2020

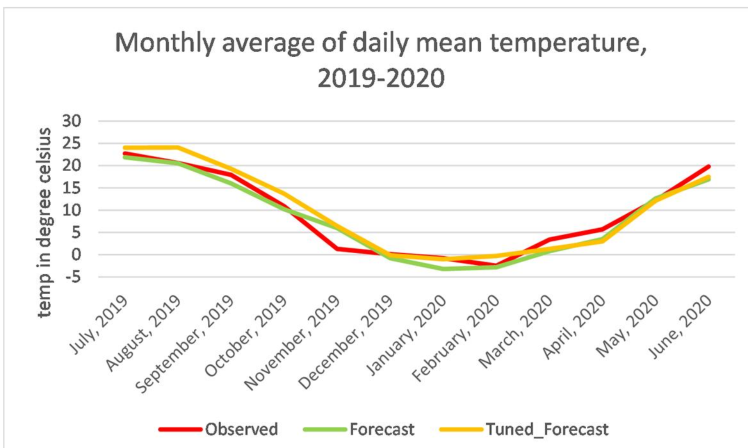


Figure 4.33: Monthly average of daily mean temperature, 2019-2020

In Figures, 4.32 and 4.33, the monthly average of daily mean temperature is doing better as observed, forecast and tuned forecast are following more closely than that of monthly average of daily precipitation. Monthly average of daily mean temperature figure also reveals that accuracy of forecasting temperature is higher than precipitation.

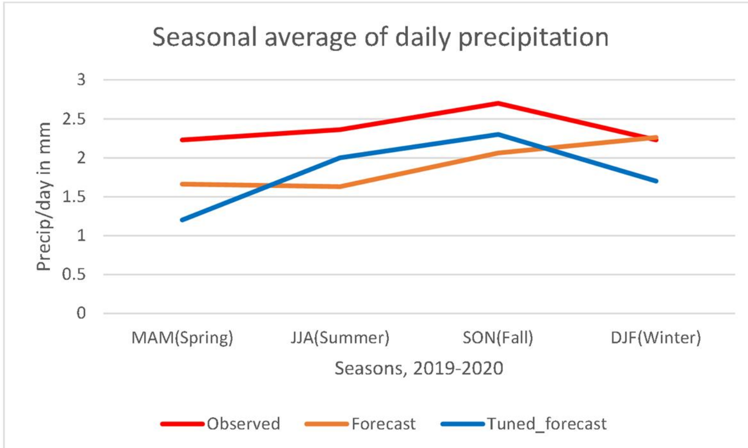


Figure 4.34: Seasonal average of daily precipitation, 2019-2020

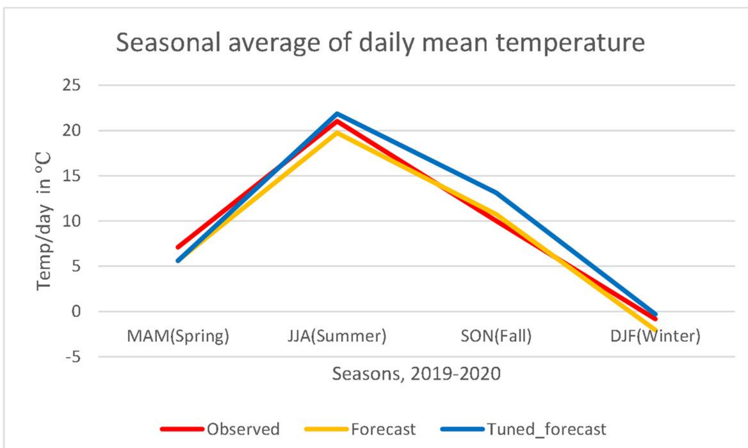


Figure 4.35: Seasonal average of daily mean temperature, 2019-2020

In Figures, 4.34 and 4.35, the tuning process seems better performing for precipitation than for temperature during summer and fall. In Figure 4.34, the tuning process does not seem reliable during winter and spring.

4.2.5 Weather outlook for larger domain, Western Canada

We have been working on a small domain i.e. South-western Ontario. Weather forecasting in small domain has lesser (Song et al., 2018) topography related errors. In our case the smaller domain missed a lot of default grid points as suggested by the ECHAM model (South-

Western Ontario region has only two default grid points) and results were not encouraging. In order to account this problem, we have also compared ECHAM model precipitation forecast and GPCP precipitation data in the Western Canada region as a larger domain with significant variations in terrain and Land use/Land cover than in SW Ontario. The ensemble model result also has degradation of forecasting accuracy, as with the smaller domain though ECHAM for Western Canada (July) seems to have more day to day variation than for South-Western Ontario region (July). The unreliable results using larger domain could be due to coarse resolution used by ECHAM model as larger domain can give reliable forecast only when model uses finer spatial resolution data.

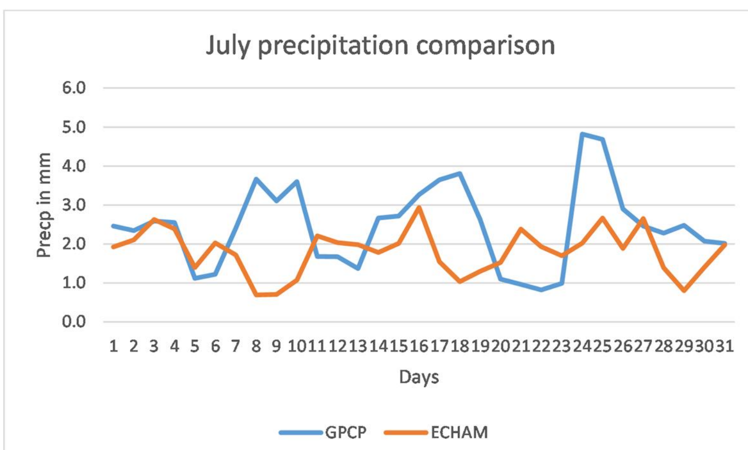


Figure 4.36: July, 2019 precipitation compared for Western Canada

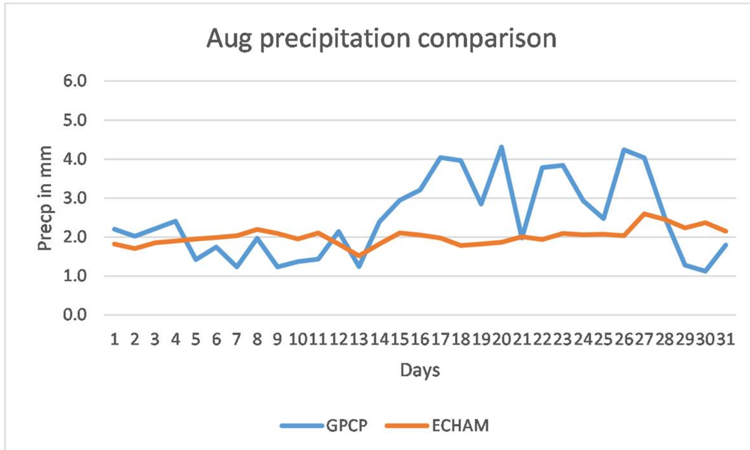


Figure 4.37: August, 2019 precipitation compared for Western Canada

In Figures 4.36 and 4.37, we can see that model forecast is predicting less precipitation than the observed precipitation and August forecast has less variability compared to July forecast.

5 Conclusion

Ensemble member means forget the variability among ensemble members as variation among ensembles can be significant, hence, we need to take into consideration of this information while evaluating the forecasts. Moreover, we have been focused on precipitation from the very beginning and precipitation is the more difficult, more spatially variable quantity. One reason of the discrepancy in the results between forecast and observed could be the default grid of ECHAM4p5 model which contains which contains both land and lake, while observed stations are based on land stations only. Another reason could be coarse resolution used by the model.

The RCF factors for both precipitation and temperature used in this thesis vary month to month and its effect on daily precipitation and temperature was found to have no effect.

The temporal features of the observed daily precipitation and temperature did not completely match with the features that we get from any of the 20 ensemble members forecast or with the patterns of the mean of all 20 members forecast. However, for some individual members like 51 and 52 the forecast patterns had some promising similarities with the observations. For future work we are trying to replace this ECHAM4p5 with CanSIPS model run by Environment Canada having data resolution of $1^{\circ} \times 1^{\circ}$. CanSIPS depends on two versions of CCCma's coupled climate model (Merryfield et al., 2011) to produce an ensemble of forecasts from 1 to 12 months. The two CanSIPS models, CanCM3 and CanCM4, share the same ocean component which is coupled to versions 3 and 4 of CCCma's global atmospheric model. Gridded atmospheric temperatures, humidities and winds, ocean temperatures, and sea ice data are assimilated into separate coupled assimilation runs for each ensemble member to produce initial conditions for the forecasts. Once we looked through the variation among ensemble and tuned up accordingly even for temperature, we are planning to move to CanSIPS model output where we do not get land/lake issues and have finer resolution than the ECHAM model.

We are also thinking to go for shorter range forecast using Weather Research and Forecasting (WRF) or other forecasts models in future work.

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