

Spatiotemporal Evaluation of Reanalysis and In-situ Surface Air Temperature over Ethiopia

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Abstract: Water resources management and modelling studies are often constrained by the scarcity of observed data, especially of the two major variables i.e., precipitation and temperature. Modellers, hence, rely on reanalysis datasets as a substitute; though its performance heavily vary depending on the data availability and regional characteristics. The present study aims at examining the ability of frequently used reanalysis datasets in capturing the spatiotemporal characteristics of maximum and minimum surface temperatures over Ethiopia and to highlight the biases, if any, in these over Ethiopian region. We considered ERA-Interim, NCEP 2, MERRA and CFSR reanalysis datasets and compared these with temperature observations from 15 synoptic stations spread over Ethiopia. In addition to the long term averages and annual cycle, a critical comparison of various extreme indices such as diurnal temperature range, warm days, warm nights, cool days, cool nights, summer days and tropical nights are also undertaken. Our results indicate that, the performance of CFSR followed by NCEP 2 is better in capturing majority of the aspects. ERA-Interim suffers a huge additive bias in the simulation of various aspects of minimum temperature in all the stations considered; while its performance is better for maximum temperature. The inferior performance of ERA-Interim is noted to be only because of the difficulty in simulating minimum temperature.

Key words: ERA Interim; NCEP Reanalysis; MERRA; CFSR; Diurnal temperature range; reanalysis performance.

1. INTRODUCTION

The absence of representative climatic variable datasets for conducting extensive analyses in various hydrologic and climatic simulations, prompted the development of alternate data sources. Reanalysis is an approach that uses a widespread collection of observational data from various sources to appraise a modelling process to produce a temporally and spatially continuous global (or regional) best estimate of numerous atmospheric, terrestrial and oceanographic parameters. An advantage of reanalyses is that they provide data that cover the entire world or a region of interest (in the case of regional reanalysis). Reanalysis data are classified into three major phases corresponding to the advancements in the observing system: the 'early' period from 1940 to 1957, when the first upper air observations were established; the 'modern radiosonde network' era from 1958 to 1978; and the era of 'modern satellite' from 1979 to present (Kistler et al. 2001). Most frequently used reanalysis datasets are: European Centre for Medium-Range Weather Forecasts (ECMWF's) ERA-40 (Uppala et al. 2005) and ERAinterim (Dee et al. 2011), NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al. 2011), Japanese Meteorological Agency's JRA-55 (Ebita et al. 2011; Kobayashi et al. 2015), NOAA National Center for Environmental Prediction's NCEP/NCAR Reanalysis I (Kalnay et al. 1996), NCEP-DOE Reanalysis 2 (Kanamitsu et al. 2002) and NCEP Climate Forecast System Reanalysis (CFSR) (Saha et al. 2010; Saha et al. 2014). Two variables of prime importance are precipitation and temperature. Our previous study on reanalysis precipitation had established the superiority of ERA-Interim and CFSR datasets in simulating the spatiotemporal characteristics of Ethiopian daily precipitation (Tewodros et al., unpublished manuscript, 2016). Usage of CFSR is also recommended by Dile and Srinivasan (2014) through hydrological modelling of data scarce upper Blue Nile basin. In this study, we focus on the performance of reanalysis datasets in simulating daily surface temperature over Ethiopia.



Studies have reported consistent warming trends in the maximum and minimum temperatures over Ethiopia, in the past decades. Minimum temperature has been increasing faster than the maximum temperature, which is an indication of warmer nights over this region (Mengistu and Lal 2014). This is consistent with the global increase of minimum and maximum temperatures (Easterling et al. 1997; Vose et al. 2005). While global minimum temperature increased around 0.01°- 0.02°C year-1, global maximum temperature increased around 0.01 -0.015°C year-1 over the last two decades. Gebrehiwot and Veen (2013) reported that the northern part of Ethiopia is warming faster than the national average of 0.02°C year-1. At the same time, an increase of about 0.037°C year-1 over Ethiopia is also reported by McSweeney et al. (2010), considering the data over the period 1957-2005. Another aspect of temperature, the diurnal range, has decreased worldwide for the last four to five decades (Dai et al. 1999). Decrease in the diurnal temperature range (DTR) is approximately equal to the increase of mean temperature (Karl et al. 1993). In most of the regions, the decrement in DTR is due to the higher rate of increase in night time minimum temperature when compared that of maximum temperature (Easterling et al. 1997; Horton, 1995; IPCC, 2013). Spatially, high diurnal temperature variations are observed in arid areas and low diurnal temperature variations are characteristic of low lying humid areas. Contrary to other East Africa countries, Ethiopia experiences relatively cool temperatures due to the highland areas (Washington et al. 2012). Hence, elevation is an important element in determining the climate of Ethiopia, with temperature dropping about 6.5°C for every 1 km rise. In addition, favourable wind directions and cloud cover further lowers the temperatures in daytime, at higher elevations, even during dry season.

In addition, continent in compliance with the global average surface temperature rise in the range of 2°C to 4.5°C had reported an increase more than 3°C over African. This will result in an increase in frequency of hot days and decrease in frequency of cold days (IPCC, 2013). Global Climate Model historical projections over east Africa also replicated a warmer future (Washington et al. 2012). Future projected increase in surface temperature is found to be consistent irrespective of the emission scenarios considered.

In climatic research, examination of extreme temperature is far more important than the mean. East Africa is characterized by a diverse natural vegetation and varied topography. Temperature and rainfall, hence, widely vary from place to place within a short extent and with the temperature increasing and precipitation fluctuations, water availability and crop production are likely to decrease in the future (Khan, 2009). The extreme temperature fluctuations result in reduction in crop yields. The increase in temperature has an effect on physiology, biochemistry and gene regulation pathways of plants (Bita and Gerats, 2013). Crops able to resist to higher temperature will be favoured and those that resist cooler temperature will be affected. Under this context, it is worthwhile to note the recent reporting of increase in warm extremes and decrease in cold extremes (Omondi et al. 2014). It is further shown that the frequency of warm days and nights are increased, with a significant increase in the number of warm nights per year. As discussed above, while a few studies have investigated the climate change impact assessment and future temperature scenarios, the performance of reanalysis datasets in simulating different aspects of temperature and increasing trend of extremes have not been analysed over the region. Past studies over this region had either not focussed on the simulation of extremes as a performance criterion or had considered a short period of time (Mekasha et al. 2014).

Realizing the importance of availability of reliable climatic datasets which effectively simulates the extreme episodes, in the present study, it is aimed to investigate the performance of frequently used reanalysis datasets in simulating different aspects of daily minimum and maximum temperature over Ethiopia. Hence, the objective of the study is to identify the best reanalysis dataset that provides a realistic representation of observed in situ surface minimum and maximum temperatures. The efficacy of reanalysis datasets is examined by investigating its long term performance in simulating various aspects of minimum and maximum temperatures and also in capturing the spatiotemporal characteristics of extremes over Ethiopian region.

2. STUDY REGION AND DATA

2.1 Study Region Characteristics

Ethiopia is situated in East Africa, located between latitudes 2.9°N to 15.3°N and longitudes 32.7°E and 48.3°E. Ethiopia's topography is distinct with altitudes varying from as much as 116 m below m.s.l. in the Danakil depression to more than 4,600 m above mean sea level in the Ras Dashen. Country experiences highest mean maximum temperature in north-east regions, about 45°C in the months of April to September and around 40°C in the months of October to March. North-western lowlands also experience a mean maximum temperature of 40°C



in June, while the western and south-eastern lowlands experience mean maximum temperatures of 35°C to 40°C during April. The lowest mean temperatures, of 4°C or lower, are recorded at night in highland areas in the months of November and February (National Meteorological Services Agency, 1989; Ethiopian Mapping Authority, 1988).

2.2 Observed and Reanalysis Datasets

2.2.1 Synoptic Data

Minimum and maximum daily temperature are obtained for 15 stations, namely, Debre Zeit, Awassa, Neghele, Mekele, Nekemte, Combolcha, Debre Markos, Gore, Arba Minch, Gondar, Bahir Dar, Gode, Dire Dawa, Jimma, and Addis Ababa. The stations are well-spread across the country and capture the spatial heterogeneity of the region. About 5% missing data in the observations are filled through climatological daily temperature (Henn et al. 2013).

2.2.2 Reanalysis Data

ERA-Interim; MERRA; NCEP/NCAR Reanalysis-II and CFSR Reanalysis data are used. Since, the four reanalyses datasets differ in their spatial resolution, an interpolation technique is employed to obtain the temperature values corresponding to the 15 station locations. Ideally an interpolation at regional/station scale may need any statistical and dynamical downscaling techniques, since the reanalysis data are of coarser resolution. However, considering the homogenous structure of temperature, in this study interpolation is done by adopting a simple procedure of regridding through a nearest neighbour method.

3. RESULTS AND DISCUSSION

Spatio-temporal characteristics of four reanalysis datasets are examined for its efficacy in reproducing minimum and maximum temperature values across Ethiopia. Various aspects of minimum and maximum temperature such as the diurnal temperature range, the frequency of 90th (10th) percentile of minimum and maximum temperature, number of cool nights, cool days, warm nights, warm days, summer days and tropical nights are compared for 15 locations. However, for the demonstration purpose, characteristics of only six stations, namely, Awassa, Mekele, Gore, Bahir Dar, Dire Dawa and Addis Ababa are shown in this section.

3.1 Performance of Reanalysis Data in Simulating Long Term Statistics

3.1.1 Minimum temperature

The comparison of ERA-Interim, MERRA, NCEP and CFSR datasets with the observational data for 15 stations is carried out by estimating various moments and performance measures. While ERA fails in all the stations, the performance of NCEP 2, CFSR and MERRA is relatively better with minimum bias in standard deviation, correlation and root mean square error.

The long term behaviour of reanalysis datasets are further analysed by comparing annual mean and annual cycle variation. ERA, MERRA and NCEP 2 exhibit a hot bias in simulating the annual mean minimum temperature of most of the stations. An exception is CFSR, which either underestimates or lie very closely to the observed data. Similar behaviour is observed in annual cycle comparison, where the inferior performance of ERA is highlighted. While MERRA, NCEP 2 and CFSR simulates the annual seasonal fluctuations, the superiority of CFSR in capturing the long-term averages are distinguishable here. The significantly higher hot bias in ERA-Interim, hot bias in MERRA & NCEP 2 and cold bias in CFSR are also distinct over all stations. Further, the quality of reanalysis is analysed in simulating the overall distribution and various percentile values. While, the empirical cumulative density functions are distinctly different, ERA's overestimation of minimum temperature intensities are evident; whereas CFSR lies very close to the observed distribution in most of the stations.



3.1.2 Maximum temperature

Performance comparison was done by using a Taylor diagrams (Taylor, 2001) for six selected stations and the averaged maximum temperature over the region. The analysis shows that ERA and NCEP 2 are superior with maximum correlation, least RMSE and minimum bias in standard deviation of maximum temperature, for most of the stations and also for the area average. While CFSR closely follow NCEP 2, evidently, MERRA fails to simulate these statistics. While, ERA performs worse in simulating minimum temperature characteristics, it is seemingly superior in simulating maximum temperature relatively better.

The spread of annual mean maximum temperature reveal the inconsistency among the reanalysis datasets and the spatial heterogeneity displayed by them. None of the reanalysis can be pointed out as the best in capturing the long term statistics of maximum temperature. Nevertheless, the annual cycle and its seasonality is simulated by CFSR, ERA and to an extent NCEP 2 also. The contradictory behaviour of MERRA in simulating the climatological annual cycle averaged over the period 1981-2013 in few stations is noteworthy.

Further analysis of empirical cumulative density functions display a similar behaviour as that of annual mean, with no consistently accurate simulation from any reanalysis over all stations. On an average, CFSR and NCEP 2 perform relatively better in simulating the distribution of maximum temperature. Interestingly, quantile-quantile plots display strong relationship between the observed and the reanalysis datasets, though it also reveal consistent hot or cold bias in some stations. The biases towards the extremes are far less when compared to the Q-Q plots of minimum temperature.

3.2 Performance of Reanalysis in Simulating the Extremes

European Climate Assessment Indices such as diurnal temperature range, warm days, warm nights, cool days, cool nights, summer days and tropical nights are used (Klein Tank et al. 2002; Zhang et al. 2011) for the analysis.

3.2.1 Minimum temperature

The 10th and 90th percentile of daily minimum temperature for all 15 stations shows that for both these extremes, CFSR closely follow the observed percentiles. All other reanalysis datasets are found to be overestimating both these percentiles. The frequency of observed cool nights is almost constant for all the stations. While ERA-Interim has null value for all the examined stations, confirming its inability in simulating various aspects of minimum temperature, MERRA and NCEP 2 underestimated the cool nights. CFSR, though was superior in simulating the 10th percentile, it overestimates the frequency of cool nights, indicating more dense left tailed distribution. A similar analysis of frequency of warm nights reveals that except CFSR, all other reanalysis overestimate the high minimum, with ERA being the worst. CFSR, either slightly underestimates or remain close to the observed warm night frequency. Another index, tropical nights, which is better captured by CFSR and overestimated by other reanalysis. ERA seems to have a definite additive bias in simulating minimum temperature over Ethiopian region.

3.2.2 Maximum temperature

The extreme indices related to maximum temperature are investigated. The performance of reanalysis in simulating 10th and 90th percentiles indicate that though CFSR can be pointed out as the better among the four datasets, its performance is not consistent for all stations. Similar performances can be noticed in the simulation of other extreme indices such as frequency of cool days, warm days and summer days. To conclude, in simulating the extreme characteristics of maximum temperature, though CFSR does perform well, all four reanalysis more or less exhibit same characteristics. It is worthwhile to note the absence of any definite additive bias in ERA simulations in the case of maximum temperature statistics.



3.2.3 Diurnal temperature range

The monthly average diurnal temperature range is computed. The superiority of CFSR, followed by MERRA and NCEP 2 is evident from the boxplots of diurnal range. Quite expectedly, ERA failed to capture the observed diurnal range (both mean and spread). Though the performance of ERA is satisfactory for maximum temperature, the underperformance can be attributed to the huge additive bias in ERA's minimum temperature.

4. CONCLUSIONS

Observed temperature datasets are often scarce, discontinuous and frequently contain discrepancies. Holistic spatial variability of temperature is not available over a data sparse country like Ethiopia. The topography of the country has also an effect in creating a non-uniform spatial distribution in temperature variables. Often, this compel the hydrological and climatological modelling studies to rely on proxy data, which frequently are reanalysis datasets. The performance of four reanalysis temperature data is evaluated and compared with observed station temperature data.

Various aspects of minimum and maximum temperature from reanalysis are compared with the 15 synoptic station data. The present study shows no single reanalysis datasets capture the spatio-temporal variation of temperature over the Ethiopian region. The bad performance of the reanalysis products could be due to the weak parameterization of the boundary layer, simulation of surface soil moisture, and coupling of the land to the atmosphere (Koster et al. 2004; Pitman and Perkins 2009). However, among the four reanalysis datasets considered, CFSR and NCEP 2 follow the observed variations closely, when compared with MERRA and ERA. It is worthwhile to point out the huge additive bias suffered by ERA, irrespective of the station, in simulating all the aspects of minimum temperature. However, its performance is reasonably good in the case of maximum temperature statistics. These results would be beneficial to various regional hydrological modellers and practitioners in selecting a suitable proxy dataset that better represent the region under consideration.

ACKNOWLEDGEMENT

We would like to acknowledge the following organizations for providing the datasets free of charge: National Metrologic Agency (NMA) of Ethiopia for synoptic station surface temperature data; ECMWF for ERA-Interim data; NASA for MERRA, NCEP/NCAR for Reanalysis II datasets and Climate Forecast System Reanalysis (CFSR).

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