Evaluating winter precipitation over the western Himalayas in a high-resolution Indian regional reanalysis using multi-source climate datasets

Article

Accepted Version

Evaluating Winter Precipitation over the Western Himalayas in a High-Resolution Indian Regional Reanalysis using multi-source climate datasets

Nischal[1], Raju Attada[1*], Kieran M. R. Hunt[2]

[1]Department of Earth and Environmental Sciences, Indian Institute of Science Education and Research Mohali, Punjab, India

[2]National Centre for Atmospheric Science, Department of Meteorology, University of Reading, UK

Revision Submitted to

Journal of Applied Meteorology and Climatology

***Corresponding author:**

Raju Attada
Department of Earth and Environmental Sciences,
Indian Institute of Science Education and Research Mohali, India.
Email: rajuattada@iisermohali.ac.in

ABSTRACT

Considerable uncertainties are associated with precipitation characteristics over the western Himalayan region (WHR). These are due to typically small-scale but high intensity storms caused by the complex topography which are und-er-resolved by a sparse gauge network. Additionally, both satellite and gauge precipitation measurements remain subject to systematic errors, typically resulting in underestimation over mountainous terrains. Reanalysis datasets provide prospective alternative but are limited by their resolution, which has so far been too coarse to properly resolve orographic precipitation. In this study, we evaluate and cross-compare Indian Monsoon Data Assimilation and Analysis (IMDAA), the first high-resolution (12 km) regional reanalysis over India, against various precipitation products during winter season over WHR. We demonstrate IMDAA's efficiency in representing winter precipitation characteristics at seasonal, diurnal, interannual scales, as well as heavy precipitation associated with western disturbances (WDs). IMDAA shows closer agreement to other reanalyses than to gauge-based and satellite products in error and bias analysis. Although depicting higher magnitudes, its fine resolution allows a much closer insight into localized spatial patterns and diurnal cycle, a key advantage over other datasets. Mean winter precipitation over WHR shows a significant decreasing trend in IMDAA, despite no significant trend in the frequency of WDs tracked in either IMDAA or ERA5. The study also exhibits the potential use of IMDAA for characterizing winter atmospheric dynamics, both for climatological studies and during WD activity such as localized valley winds. Overall, these findings highlight the potential utility for IMDAA in conducting monitoring and climate change impact assessment studies over the fragile western Himalayan ecosystem.

Keywords: Precipitation, Western Himalayas, IMDAA reanalysis, Western Disturbances

1. Introduction

North India receives one-third of its annual precipitation (Dimri *et al.,* 2016; Hunt *et al.,* 2018) during the winter season (December through March), in the form of snowfall and rainfall, primarily associated with synoptic-scale extra-tropical cyclonic systems, known as western disturbances (WDs) (Lang and Barros, 2004; Dimri and Mohanty, 2009; Yadav *et al.*, 2013; Dimri, 2013). These extra-tropical cyclonic storms typically originate over the Mediterranean region and travel eastward along the subtropical westerly jet (Dimri *et al.,* 2016, Hunt *et al.,* 2018). Moreover, winter WDs are further known to contribute to approximately 40-50% of the total annual precipitation over the western Himalayas (Madhura *et al.*, 2015; Cannon *et al.,* 2015; Krishnan *et al.,* 2019). Winter precipitation is an important source of irrigation for Rabi crops and plays a critical role in recharging the water resources in the northern plains as well as maintaining the snow cover of the western Himalayan glaciers, which feed major north Indian rivers (Yadav *et al.*, 2013; Dimri *et al.,* 2015). Accurate and precise measurement of precipitation is essential for studies involving monitoring and assessing climate change impacts (Hussain *et al.,* 2017). Most products, including gauge-based, satellite, and reanalysis datasets, often face difficulty estimating orographic precipitation over the Himalayas (Sun *et al.*, 2018), since the complex and steep orography of the Himalayas substantially modulates the spatio-temporal variability of regional precipitation on fine scales (Andermann *et al.*, 2011). Thus, reliable precipitation measurements for such complex and heterogeneous landscapes demand high-resolution datasets.

Conventionally, in-situ observational data – i.e. gauges – are considered to be one of the most reliable and accurate measurements for precipitation fields at a point scale (e.g. Wang *et al.*, 2019). However, uncertainties resulting from measurement errors (e.g. Ye *et al.*, 2004), missing data, insufficient spatial and temporal coverage, etc. (Dahri *et al.,* 2021) offer significant challenges for station-based data analysis. Furthermore, underestimation of precipitation is a key issue associated with rain gauges (e.g. Immerzeel *et al.,* 2015). This can be caused by instrument wetting, pre-measurement evaporation (WMO, 2008), and wind-driven under-catchment, which enhances up to 50 % during snowfall (Dahri *et al*., 2018, Baudouin *et al.*, 2020). In addition, the network of in-situ observations over the WHR is quite sparse due to varying topography and land cover such as bare rocky surfaces where the possibility of natural hazards including rock falls, avalanches or glacial lake outburst floods create difficulties for gauge installation (e.g. Juen 2006; Carey 2010). Moreover, the spatial distribution of snow cover increases over the region during the winter season and data is missing when stations are buried under snow (e.g. Joshi and Ganju, 2010; Escher-Vetter *et al*., 2012; Cullen and Conway, 2015; Choudhury et al. 2021). Moreover, conventional rain gauges struggle to measure snowfall accurately (Strangeways 2004). Such adverse conditions combined with large orographic variability make it difficult to set up and maintain a dense precipitation-gauge network. As a result, these gauges are generally placed at the foot of the mountains or in valleys, which are relatively drier than elevated regions (Singh and Kumar, 1997; Winiger et al. 2005; Dimri and Ganju 2007; Immerzeel *et al.,* 2015; Dahri *et al.,* 2018), thus introducing additional uncertainties into gridded datasets, apart from the ones added due to interpolation. Overall, the discontinuity and insufficiency of available observational data reduces the representativeness of gridded observational precipitation products over the region and hinders the production of accurate precipitation estimates and subsequent climate change impact assessment studies over the area.

Various remotely sensed and reanalysis precipitation products have been used to compensate for these disadvantages. Often, however, these datasets differ considerably in their spatiotemporal resolution, making intercomparison challenging (Andermann *et al.*, 2011). Satellite precipitation estimates are indirect and often associated with a large degree of variability (Sun *et al.*, 2018). Although precipitation retrieval techniques in satellite products have evolved a lot in recent decades (Maggioni *et al.*, 2016), the reliability and degree of precision for these datasets in mountainous regions are still questionable (e.g. Meng *et al.,* 2014; Xia *et al.,* 2015, Xu *et al.,* 2017). An underestimation of orographic precipitation is quite common in infrared (IR) retrievals, given their inability to capture light precipitation events. Detection of cold season orographic precipitation is also challenging for passive microwave retrievals (e.g. Derin and Yilmaz, 2014). In addition, satellite-based microwave retrievals of precipitation rates are inaccurate above snow cover (Derin *et al.,* 2016). Moreover, errors associated with sampling, geo-referencing, and applied algorithms lead to various uncertainties and affect the accurate estimation of precipitation at higher elevations (Hussain *et al.,* 2017). Besides, these products require rain-gauge calibration implying a dependence on the quality and density of station data (Baudouin *et al*. 2020), and thus associated discrepancy gets enhanced over orographic regimes like WHR, where station coverage is quite sparse. In addition, these gridded datasets are typically available only at relatively coarse resolutions, where the leeward and windward sides of mountain areas are generally embedded into a single gridbox, exacerbating the unrepresentative nature of and uncertainties associated with these measurements.

Reanalysis datasets provide prospective alternatives for estimating precipitation. These are produced by assimilating observations from a wide range of sources into numerical weather prediction models to generate atmospheric and surface fields. They provide significant advantages in terms of data consistency, homogeneity and coherency, which makes them suitable for atmospheric and climate research (Dee *et al.,* 2014). Globally, reanalysis datasets have been extensively used in precipitation studies owing to their homogeneous nature (Trenberth and

Guillemot, 1998; Bengtsson *et al.,* 2004; Bao and Zhang, 2013; Murakami 2014). However, the spatial resolution (more than tens of kilometres) of global reanalysis datasets is often inadequate for effectively capturing localized and regional precipitation distribution, specifically over complex topography, and thus relatively high-resolution regional reanalysis datasets are required to adequately represent regional hydroclimate (Wang *et al.*, 2019; Ashrit *et al.*, 2020).

High-resolution data is particularly important in regions with complex topography due to large spatial variability (Gampe *et al.*, 2017). Various studies have highlighted the enhancement of temporal and intensity-related variability associated with WDs over the Himalayan regions due to increased baroclinicity with adverse implications in terms of increased frequency and duration of extreme precipitation events (e.g. Madhura *et al.*, 2015; Midhuna *et al.*, 2020). Such events are often a result of supportive synoptic and mesoscale atmospheric conditions prevailing over the region and the interaction of other processes, including intraseasonal oscillations, local convective dynamics (Gouda *et al.*, 2018) and orographic forcing. The localized nature of these events hinders their accurate assessment in coarse resolution datasets. Therefore, high resolution datasets are crucial for precise understanding of extreme weather related hydrometeorological hazards such as landslides, avalanches and floods over complex topography.

Recently, the first high resolution (12 km) regional atmospheric reanalysis dataset, Indian Monsoon Data Assimilation and Analysis (IMDAA), focusing on the South Asian region, has been released (Rani *et al.,* 2021). This state-of-the-art reanalysis is generated by the National Centre for Medium Range Weather Forecasting (NCMRWF) in collaboration with the India Meteorological Department (IMD) and UK Met Office under the National Monsoon Mission project, Government of India. The reanalysis spans the modern meteorological satellite era (1979–present) and outputs atmospheric data at 63 vertical levels. This is now one of the highest resolution regional reanalyses available over India, providing the important advantage of improved representation of orographic features. Ashrit *et al.* (2020) and Aggarwal *et al.* (2022) explored the efficiency of IMDAA in representing precipitation characteristics as well as atmospheric thermodynamics and circulation during the Indian summer monsoon, but wintertime precipitation characteristics are yet to be evaluated using IMDAA.

Some validation studies of different multi-source datasets have been carried out previously over the Himalayan region. Andermann *et al.* (2011) evaluated various precipitation datasets along the Himalayan front and reported a significant variation in performance among the evaluated datasets along the orography, however, the datasets show higher consistency, with respect to each other, along with the lower relief realms. Palazzi *et al.* (2013) showed that various category gridded precipitation datasets adequately captured the interannual variability of precipitation over the Hindukush-Karakoram region. Dahri *et al*. (2018) reported underestimation in the rain gauge measurements in the high-altitude Indus basin during the winter season and underpinned the necessity of bias adjustment to reduce errors. A cross-validation for different categories of precipitation datasets in the Indus River basin was performed by Baudouin *et al.* (2020), reporting a large difference in average precipitation between the rain gauge and the reanalyses, most likely resulting from opposite biases from both dataset types and not only from the reanalysis, as often suggested. While precipitation in ERA-Interim (ERAI) is found to be well correlated with observational data across the Karakoram (Immerzeel *et al.*, 2015; Dahri *et al.*, 2016), Hussain *et al*. (2017) reported a poor spatial correlation for TRMM-3B42 with in-situ observations, however, an increase in the correlation was observed with decreasing temporal resolution from daily to monthly scale. Furthermore, it was found that the estimation of summer precipitation compared to winter precipitation in TRMM-3B42 was more accurate in the Hindu Kush-Karakoram Himalayan region. The effect of elevation on the performance of gridded precipitation datasets has also been observed (Andermann *et al.*, 2011; Hussain *et al.*, 2017). A statistical performance evaluation study for different precipitation gridded datasets was conducted by Kanda *et al.* (2020), which highlighted the need for bias correction in different datasets over the WHR.

The present study focuses on evaluating winter precipitation variability using high resolution Indian reanalysis (IMDAA, 1979-2018) over diurnal, subseasonal, seasonal and interannual timescales across the WHR. In this study, we will cross-compare and validate the performance of IMDAA against a range of different precipitation datasets from various sources, including gridded observational data, satellite-based and reanalysis products. The results will then be contextualised by comparing the western Himalayan atmospheric dynamics in IMDAA and the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA5) dataset (Hersbach *et al.,* 2018) during the winter monsoon, with an additional focus on the trend and variability of WDs.

2. Data and Methods

a. Data

Our study focuses on the validation of IMDAA using different categories of gridded precipitation datasets, discussed below, and summarized in Table 1, for the respective periods of their availability from 1979-2018 during the winter season (December to March) over the WHR (29°N-37.5°N and 72.5°E-80.5°E, see Figure 1a). The selection criteria for different categories of datasets in this evaluation study are the availability of long-term (~20 years) precipitation estimates, and at least daily temporal resolution, which is consistent with the availability period of IMDAA. The types of datasets evaluated in the present study include reanalysis products, satellite and gridded observational datasets, as well as combinations thereof. We also use various atmospheric fields from IMDAA and ERA5 for the assessment of wintertime meteorological conditions.

1) Gauge-based Datasets

Three commonly used daily precipitation datasets generated through the interpolation of only rain-gauge measurements have been utilised in our study. IMD precipitation data (0300 UTC-0300 UTC) provides daily gridded rainfall (Pai *et al.*, 2014) generated from a dense network of 6955 rain gauge stations with varying periods of availability. Daily rainfall estimates are interpolated from gauges to a 0.25°×0.25° grid, following Shepard (1968). However, the station network suffers from low spatial coverage of gauges over the western Himalayan belt, with almost non-existent stations over the rugged terrains of the upper Himalayan and Karakoram ranges. We selected another gauge-based daily precipitation product (0000 UTC-0000 UTC) provided by the Climate Prediction Centre (CPC) of the National Oceanic and Atmospheric Administration (NOAA) which is constructed from a global gauge-network of around 30,000 stations (Xie *et al.,* 2007; Chen *et al.,* 2008). However, limited rain-gauge stations have been considered from the WHR. Covering an extended period of over 50 years, the Asian Precipitation Highly-Resolved Observational Data Integration towards Evaluation of Water Resources (APHRODITE) dataset provides long-term daily precipitation data (0000 UTC-0000 UTC) generated from a dense network of in-situ rain gauges (5000–12000 stations), interpolated at a resolution of 0.05° with an orographic correction for precipitation, and further re-gridded to 0.25°×0.25° resolution using area-weighted mean (Yatagai *et al.,* 2012). Our study combines APHRO_V1101 (1951–2007) and its extended version APHRO-V1101EX_R1 (2007–2015) to obtain long term precipitation records over the region, following previous literature (Ji *et al.,* 2020; Guan *et al.,* 2020; Lalande *et al.,* 2021; Liaqat *et al.,* 2021; Phung *et al.,* 2021).

2) Reanalysis Datasets

Precipitation estimates in different reanalyses can vary from each other based on the assimilation scheme used, the underlying model (including parameterizations) and assimilated observations. The Indian Monsoon Data Assimilation and Analysis (IMDAA) is a high resolution (12km) regional atmospheric reanalysis over the South Asian region, developed by NCMRWF in collaboration with UK Met Office and IMD. IMDAA obtains lateral boundary conditions from ERAI and precipitation estimates are generated by the Unified atmospheric model and the four-dimensional variational (4D-Var) data assimilation technique, which assimilates various conventional and satellite observations from the ECMWF, NCMRWF and IMD archives, including surface observations (land and ocean), aircraft data, upper air observations from radiosondes and pilot balloons. However, no precipitation measurements are assimilated in IMDAA. For further information, the reader is referred to Rani *et al*. (2021). Our study utilizes IMDAA-generated precipitation at 0000 UTC. The dataset provides advantages in better representation of orographic features owing to its high resolution.

We also used a state-of-the-art global reanalysis dataset, ERA5 (0000 UTC-0000 UTC), developed by ECMWF with a new version of their NWP model (IFS Cycle 41r2; Hersbach *et al*., 2020). Using 4D-Var, ERA5 assimilates observations from the ECMWF data archive, National Centers for Environmental Prediction (NCEP), as well as other conventional datasets such as ISPD and ICOADS, satellite observations, and precipitation measurements. ERAI, an older ECMWF reanalysis product (Dee *et al.,* 2011) and predecessor of ERA5 has also been used in this study, but only for tracking WDs since it is used to provide lateral boundary conditions in IMDAA. In addition, NCEP's Climate Forecast System Reanalysis (CFSR, 0000 UTC-0000 UTC) is used, which provides precipitation estimates using a coupled atmosphere–ocean model comprising the

Global Forecast System and the Geophysical Fluid Dynamics Laboratory Modular Ocean Model (Saha *et al*., 2010, 2014).

Another reanalysis used for validation is the Modern-Era Retrospective Analysis for Research and Applications version-2 (MERRA-2, 0000 UTC-0000 UTC), published by the National Aeronautics and Space Administration (NASA)'s Global Modeling and Assimilation Office. This reanalysis is generated using the Goddard Earth Observing System Model-5, which assimilates various land surface and satellite observations. The advanced data assimilation techniques used in MERRA-2 provide an advantage over topographic regions with sparse gauges, though an underestimation for winter seasonal precipitation has been reported (Hamal *et al*., 2020).

3) Satellite and Merged Datasets

Our study also utilises five satellite datasets. The widely used Tropical Rainfall Measuring Mission (TRMM)-Multi-Satellite Precipitation Analysis (0300 UTC-0300 UTC), is developed through a collaboration between NASA and Japan's National Space Development Agency. It combines precipitation data from various satellite instruments (TRMM Microwave Imager, Precipitation Radar, Visible and IR Scanner, Special Sensor Microwave Imager), blended with geostationary IR data, with further calibration using monthly gauge data (Huffman *et al*., 2007).

We also used the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) developed by NOAA in collaboration with the Centre for Hydrometeorology and Remote Sensing, University of California, Irvine. The precipitation estimates (0000 UTC-0000 UTC) are generated by applying the PERSIANN algorithm on GridSat-B1 IR satellite data followed by a training of the artificial neural network using NCEP Stage IV hourly precipitation data and finally calibrating and adjustment of biases is done using the Global Precipitation Climatology Project (GPCP) monthly precipitation dataset (GPCPv2.2). Daily precipitation records are also produced by GPCP Version 1.3 (0000 UTC-0000 UTC), from the World Climate Research Programme, by merging estimates from IR, microwave, and sounder data of precipitation-related satellites and gauge-based analyses.

A merged high-resolution satellite product, Integrated MultisatellitE Retrievals (V3) for Global Precipitation Measurement (GPM), generates precipitation estimates (0000 UTC-0000 UTC) by the day-1 IMERG algorithm, through intercalibrating, merging, and interpolating microwave and IR estimates of GPM satellite constellation with gauge-based observational data (Huffman *et al*., 2015). The data is specifically useful over regions with a lack of ground-based precipitation-measuring instruments.

Lastly, we also use the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). This is a merged, daily, land-only precipitation product (0000 UTC-0000 UTC) by the U.S. Geological Survey in association with Earth Resources Observation and Science Centre and is prepared by merging 0.05°×0.05° and 0.25°×0.25° resolution satellite IR cold cloud duration measurements with in-situ gauge observations.

b. Methodology

1) EVALUATION INDICES

Generally, precipitation datasets are utilised without any modifications or prior adjustments for analysing localized precipitation patterns, and it has been now established that the spatial resolution strongly affects dataset performance (Zandler *et al.,* 2019). Moreover, interpolation techniques can generate substantial variations and uncertainties in the computed statistical metrics, especially when precipitation is considered over a complex region. Therefore, we choose to include this information in our evaluation, since the focus is on whether there are advantages offered by the high resolution of IMDAA. We thus compare different datasets in their native resolutions without any interpolation, similar to previous literature (e.g. Dinku *et al.,* 2008; Liu *et al.,* 2015; Beck *et al.,* 2017; Bayissa *et al.,* 2017; Zandler *et al.,* 2019). Different statistical metrics, including mean, standard deviation, coefficient of variation and pattern correlation coefficient (PCC), have been computed to understand how the representation of regional precipitation varies between datasets. All the metrics have been calculated for a common time period (2000–2015), using regionally averaged seasonal mean precipitation at the native spatial resolution of each product, except PCC, for which datasets have been re-gridded using bilinear interpolation to IMDAA's resolution. We also investigate the total number of heavy precipitation events per year exceeding selected percentile (90^{th}, 95^{th} and 99^{th}) thresholds in each dataset. The number of events has been counted by considering precipitation estimates from all grids between the period 2000-2015, therefore, the datasets have been re-gridded here to a common resolution of 0.25°, to avoid additional counts from higher resolution datasets.

To quantify IMDAA's skill, we further computed different skill scores of the model agreement with the data, using area-averaged (though at original spatial resolution) daily time series of precipitation in different datasets for a common time period 2000-2015. The definitions for commonly known evaluation indices such as correlation coefficient, root mean square difference (RMSD), mean absolute difference (MAD) and BIAS have been summarized in the Appendix, except for less widely used metrics including index of agreement (IOA), adjusted R-squared, and pattern correlation coefficient (PCC), which are discussed below.

(i) Index of agreement

Index of agreement (IOA) is widely used to measure how well model-produced estimates simulate observed data (Willmott 1981) and thus has been used here to quantify the similarity between IMDAA and other datasets (Gebregiorgis *et al.,* 2018). It is defined as:

$$IOA = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(|y_i - \bar{x}| + |x_i - \bar{x}|)^2)} ,$$

Where, n is the total number of observations (daily time series of precipitation), y_i are the values for target dataset (i.e., IMDAA) and, x_i and $\underline{x}$ are the values and mean for the corresponding evaluation dataset, respectively.

(ii) Adjusted R-squared

Adjusted R-squared is a statistical measure to indicate the amount of variance in the dependent variable by the regression model in the population by replacing biased estimators with their unbiased counterparts (Karch 2020). It considers the number of variables in the predictor (IMDAA) and penalizes the supplementary explanatory variables by adjusting the degrees of freedom while estimating the error variance. It provides the statistical quantification of variability amounts associated with a dataset compared to a reference dataset with an adjustment for bias. Additional details have been provided in the Appendix.

(iii) Pattern Correlation Coefficient (PCC)

PCC is the Pearson product-moment coefficient of linear correlation between two variables with values at corresponding locations on two different maps (Anand *et al.*, 2018).

2) CLIMATOLOGY, VARIABILITY AND TRENDS

The spatial distribution of seasonal (DJFM) winter precipitation climatology and variability in all datasets, considering their respective native spatial resolution and temporal availability between 1979–2018 over the study region has been investigated. Full available time periods for each dataset between 1979-2018 have been considered for the evaluation of the geographical distribution of precipitation estimates, since spatial patterns of precipitation tend to be less affected by the averaging period. We further analysed spatial patterns of seasonal mean precipitation differences in IMDAA with respect to different datasets, after rescaling all datasets to the grid used in IMDAA. The spatial patterns on trends of seasonal mean precipitation are computed through seasonal mean precipitation series at each grid point for different precipitation products for a common period of 35 years (1984–2018), at their native spatial resolutions, using the non-parametric Mann-Kendall test (Roxy *et al.,* 2015). The datasets with at least an available time period of 35 years have been selected for spatial trends considering that at least 30 years or more is a minimal period to provide considerable climatological trend information. To investigate the interannual variability of the seasonal mean precipitation, standardized precipitation anomalies over the WHR have been utilized to categorize excess and deficit precipitation years, considering the standardized anomalies exceeding ±0.5, respectively.

3) IDENTIFICATION OF WDs

The tracking of WDs over the study region was carried out using the WD tracking algorithm from Hunt *et al.* (2018). The algorithm involves the computation of mean relative vorticity in the 450–300 hPa layer followed by filtration of short-wavelength noise using the desired spectral truncation (T63 and T42) and further identification of positive-definite vorticity regions to determine the centroid locations for each candidate WD. The linkage of these centroids in time, with steering wind-biased distance constraints, allows the identification of potential WD tracks. Lastly, the database is refined by rejecting those tracks which do not pass-through north India (20°N–36.5°N, 60°E–80°E), last less than 48 hours, or dissipate at a point westward of their genesis. WDs were tracked in IMDAA (1980–2018) and ERA5 (1979–2018) at spectral truncations of T42 and T63 and in ERAI (1979–2015) at T63. The interannual frequency of identified winter WDs was compared for IMDAA (T42 and T63), ERA5 (T42 and T63) and ERAI to analyse the interannual variability of WDs at seasonal scale. ERAI is used as a lateral boundary condition in both IMDAA (Rani *et al.,* 2021) thus, ERAI tracks have also been considered to analyse the frequency of WDs. The T63 ERAI tracks are identical to those used in Hunt *et al.* (2018).

4) WINTER ATMOSPHERIC DYNAMICS

In order to evaluate the performance of IMDAA in capturing the mean circulation features during the winter season, the climatology of various atmospheric variables such as upper-level winds (200 hPa), outgoing longwave radiation (OLR), geopotential heights (200 hPa, 500 hPa, 850 hPa) and 2-m air temperature have been compared with ERA5. Further, the fidelity of IMDAA in simulating localized dynamics associated with WD activity over the WHR has been examined through a case study for an intense WD which affected WHR during 16–19 February 2003 and caused widespread precipitation over the region.

3. Results and Discussion

a. Climatology and Variability

The spatial distribution of multi-year seasonal mean precipitation in different gridded datasets over WHR is presented in Figure 1 and regionally averaged seasonal precipitation estimates, including mean and variability for a common temporal period (2000–2015) are provided in Table 2. Table 2 also details the pattern correlations and the number of heavy precipitation events (exceeding the 90th, 95th, and 99th percentiles) during the common period. Considerable heterogeneity for mean winter precipitation amounts and variability is evident among different categories of datasets (Table 2), with all reanalyses (IMDAA, ERA5, CFSR, MERRA-2) showing higher magnitudes than the satellite products (GPCP, TRMM, PERSIANN, CHIRPS, IMERG) and gauge-based datasets (IMD, CPC, APHRODITE). IMDAA, with a mean of 2.38 mm/day and standard deviation of 0.74 mm/day (Table 2), shows a good agreement overall with the other reanalyses ERA5 and CFSR, albeit with a slightly higher magnitude. Among the reanalyses, MERRA-2 has the lowest mean and largest variability, which might be associated with the use of dry-biased CPC data for surface precipitation flux (Reichle *et al.*, 2017; Baudouin *et al.,* 2020). The realistic representation of the mean amounts of winter precipitation of IMDAA is evident through its observed similarity to the ERA5 reanalysis, which has been revealed to perform best with observations in the surrounding upper Indus Basin in previous studies (Baudouin *et al*., 2020; Dahri *et al*., 2021). It is evident that all reanalyses, including IMDAA, are wetter and exhibit large spatial variability compared to other types of datasets. Among the observational datasets, mean precipitation in IMDAA is closest to IMD, followed by APHRODITE (Table 2), whereas it shows largest differences compared to CPC. Insufficient observations and uncertainties arising from interpolation techniques generally lead to dry biases in observational datasets (e.g. Dahri *et al*., 2021). An overall general agreement within the satellite data category can be observed. However, IMDAA shows an overestimation compared to satellite products, the exception being IMERG with higher resolution. The precipitation amount and variability for IMERG is highest among satellite datasets, much closer to IMDAA. As satellite observations generally exhibit higher accuracy for convective precipitation over flat terrains (Ebert *et al.,* 2007; Baudouin *et al.,* 2020), their usefulness is limited over the elevated western Himalayan terrain that typically receives more stratiform precipitation (Fig. S2).

Wide discrepancies in the geographical seasonal mean precipitation patterns (Fig. 1) among the different categories of datasets can be seen, though with an agreement across the regions of the highest precipitation – the lower Himalayas and foothills. As indicated by the statistics (Table 2), IMDAA stands much closer to all reanalyses compared to other data categories in depicting regional spatial precipitation patterns (Fig. 1), having lower spatial precipitation differences with IMDAA (Fig. 2). The IMD observational dataset shows a similar spatial distribution of precipitation magnitude in the lower Himalaya and the western Karakoram range, but considerable discrepancies are noticeable along the foothills and in eastern Ladakh (Fig. 1), where the IMD data set has a marked positive difference compared to all other data sets (Fig. 2). Since IMD includes almost no measurements over these locations (Kishore *et al.,* 2016), the precipitation estimates here are derived from extrapolation of higher values downslope, resulting in higher precipitation estimates. Relatively wetter patterns (Fig. 1) and a large positive difference are seen in IMDAA (Fig. 2) compared to APHRODITE and CPC, both of which rely on the WMO Global Telecommunication System, which covers few observations in WHR, generally collected from stations present over dry valley locations in the study region, thus, additionally suffering from under-catchment of solid precipitation at higher altitudes (Palazzi *et al*., 2013; Dahri *et al*., 2018). This makes the validation of IMDAA precipitation over this region using gauge-based datasets challenging. IMDAA exhibits a larger magnitude of precipitation than all the satellite datasets (Table 3, Fig. 2), with the smallest differences over the foothills in IMERG, which has a similar resolution to IMDAA. However, it can be noted from the previous studies (Dahri *et al.*, 2021; Baudouin *et al.*, 2020) that precipitation from satellite products exhibit drier biases over the region. Various uncertainties in terms of interpolation algorithms, calibration limitations due to poor coverage of rain-gauge measurements, and inability to accurately retrieve orographic precipitation have been denoted as causes for the same (Hussain *et al.*, 2017). However, differences in precipitation magnitude are mainly found over lower Himalayas and foothills in IMDAA with all datasets (Fig. 2). These regions receive maximum precipitation during winter, thus, such differences highlight discrepancies and limitations associated with available data over the region.

Higher pattern correlations (Table 2, Fig. 1) between IMDAA and all other datasets are observed, least being for GPM-IMERG, indicating an agreement on the spatial patterns of seasonal mean precipitation for IMDAA with other datasets, even though significant differences in magnitudes are present. Additionally, the spatial patterns of solid precipitation distributions in IMDAA are similar to independent MODIS-satellite snow cover fractions (Fig. S6).

Summing up, the gridded products provide inconsistent precipitation amounts over the region, but agree on the areas with the highest precipitation. Since different dataset categories are generated with different input data and dissimilar developmental methods, presence of such similar signals relates to the depiction of actual situation (Baudouin et al., 2020). Unlike satellite and gauge-based products, reanalysis products are developed with different data assimilation techniques and distinct atmospheric models (Ghodichore *et al*., 2018) and are known to provide a better depiction of frontal system precipitation in the winter season, specifically over high elevations (Dahri et al., 2021; Beck at al., 2019), compared to other two product categories which generally underestimate precipitation in such cases. IMDAA performs well in simulating regions with precipitation maxima and allows a much closer look at the localized precipitation distribution over the region. However, reanalyses generally tend to produce higher precipitation magnitudes along with a depiction of larger variability, which in fact is highest in IMDAA, highlighting a key limitation of the current IMDAA reanalysis.

Adjusted-R^2 values (Table 3) are computed for area-weighted daily precipitation values during 2000-2015 and significance has been tested using Mann-Kendall test at a confidence level of 95%. These also underpin the observed discrepancies among different datasets over the study, with large variation for values observed over the panels of different datasets. Here, we carry out a cross-validation by examining the association between individual datasets by using each dataset as a reference. Highest agreements are observed within the reanalyses; however, MERRA-2 shows lesser association supporting the negative differences observed earlier (Table 2). Observational datasets IMD and CPC also show good agreement with each other, however, APHRODITE diverges from the group and is also the dataset showing the least association with all other categories too. Satellite products are in good agreement with each other and generally with datasets from other categories too, except for MERRA-2 and APHRODITE; both of which also have lower fitness magnitudes with all other datasets. The reanalyses, IMDAA, ERA5 and CFSR, depict a significant relationship with all the datasets, specifically with each other and IMD. Considering that reanalyses and observations generally rely on different data sources and developmental methods, a significant relationship among these is a sign of quality of the datasets (Baudouin *et al.,* 2020), thus, implying the reliability of their precipitation estimates.

The total number of heavy precipitation events per winter season exceeding the 90^{th}, 95^{th}, and 99^{th} percentiles (considering the wide range of discrepancies for precipitation amounts across different datasets) considering all grid locations for each dataset during the period 2000-2015 have also been evaluated (Table 2). For each dataset (re-gridded to common resolution of 0.25˚), the precipitation values during the common period are collapsed into a single vector to which the percentile thresholds computed from area-averaged daily precipitation time series (2000-2015) are applied and totals counts exceeding the thresholds are selected. It is to be noted that since large uncertainties remain over the region regarding precipitation amounts, we use the percentile thresholds rather than actual values. Overall, the obtained counts indicate close agreement of IMDAA with all reanalyses. However, the number of events in MERRA-2 have lower counts compared to other reanalyses at all three thresholds. An overall agreement can be observed within the satellite category among TRMM, CHIRPS and PERSIANN-CDR, exceptions being IMERG and GPCP (highest and lowest resolution data among satellite products, respectively), though slight overestimation in IMDAA with respect to all satellite datasets (except IMERG) can be observed. However, gauge-based datasets exhibit a sharp disagreement among each other and with respect to other data categories too for all percentiles, with APHRODITE showing a sharp overestimation as compared to all the evaluated datasets, including IMDAA.

The wintertime precipitation over the WHR comprises both snowfall and rainfall, with snowfall constituting almost 80% of the total observed precipitation (e.g. Krishnan *et al.,* 2019). Therefore, the differences between mean rainfall and snowfall in IMDAA and ERA5 have also been analyzed. Compared to ERA5, IMDAA shows higher amount of snowfall (~3 mm/day) over the Greater Himalayas and some regions of the Lower and Karakoram Himalayas (Fig. S1). The variation in rainfall between IMDAA and ERA5 shows larger variations in IMDAA over some regions of lower Himalayas. Along the foothills, the differences in rain and snow often have different signs, implying that local temperature differences play a role.

The analysis of interannual variability patterns of seasonal mean winter precipitation in different datasets has been used to identify pluvial and dry years (Fig. 3). IMDAA is able to reproduce the pluvial and deficit precipitation years, corresponding well with other datasets. All reanalyses as well as PERSIANN-CDR and IMD datasets depict an enhancement in the frequency of dry periods in recent years. IMDAA, along with other datasets, agrees that 2001 was one of the driest years. Decadal variability is evident in most of the analyzed datasets, which might be attributable to forcing by large scale tropical climate drivers such as Arctic Oscillation, North Atlantic Oscillation and Pacific Decadal Oscillation (e.g. Roy 2006). Overall, the interannual variability of wet and dry years in IMDAA is in good agreement with the other datasets, particularly IMD and ERA5.

b. Trends

Seasonal mean precipitation trends over the study region as a whole (Fig. 4i-k) reveals close agreement among reanalyses, depicting similar values of mean and decreasing trend – although IMDAA is the only one among them in which that trend is significant at the 95% confidence level (Mann-Kendall test). IMDAA agrees with the gauge-based dataset IMD, with a significant negative trend, but the trends for remaining gauge- and satellite-based datasets are not significant and disagree with each other even on their sign. The spatial patterns of these trends computed over a common period of 35 years (1984–2018) for eight datasets (Fig. 4a-h) corroborate the area-weighted trends in the region. Most of the datasets agree on a negative trend over WHR, which is strongest in IMDAA, IMD, and CFSR, but there is disagreement in terms of regional trends in both the CHIRPS and CPC datasets, which are both predominated by positive trends. It is worth noting that the observed negative trend for seasonal winter precipitation in most of the datasets well agrees with the station based decreasing trends by Shekhar *et al*. (2010, 2017) who found decreasing precipitation rates at different point stations over the region, confirming the reliability of IMDAA data for trend analysis studies. The trend is statistically significant along the foothills and lower Himalayan belt in IMDAA; mostly over western Jammu and Kashmir and western Ladakh in CFSR; and in IMD, over eastern Himachal Pradesh and eastern and central Ladakh. ERA5 agrees strongly with IMDAA on the spatial focus of negative trend, but without any statistical significance. In contrast, positive precipitation trends observed in CPC and CHIRPS show disagreement on where those trends are significant, and PERSIANN-CDR and MERRA-2 have regions of both significant positive and negative precipitation trends but disagree with each other on the sign of those trends. A strong positive and statistically significant precipitation trend is visible in CPC over Himachal Pradesh and Uttarakhand, whereas CFSR shows a strong yet statistically insignificant trend is observed over some regions of eastern Jammu and Kashmir. The decreasing spatial and temporal trends in the majority of the evaluated datasets support the earlier observed increasing frequency of dry periods in recent years. Earlier, Dimri and Dash (2012) observed a decreasing trend of winter precipitation over the WHR, and a decrease in the winter snowfall has also been reported by Shekhar *et al*. (2010). Overall, the diversity in winter precipitation trends among datasets is largely due to methodological constraints associated with respective dataset development.

c. Seasonal cycle of Precipitation

A fine representation of seasonal variability in any dataset holds key significance as the seasonal cycle of precipitation has important dynamical implications. Therefore, we also investigated the seasonal cycle of winter precipitation over the study region by comparing area-averaged daily climatology in all datasets for a common period of 2000-2015 for their individual spatial resolutions (Figure 5). All reanalyses, including IMDAA, are in close agreement with each other on the seasonal evolution of precipitation, with very little differences observed at daily climatological scales. However, although gauge-based observations show differences in magnitude, the representation of subseasonal variability is quite similar, with a notably stronger agreement between IMD and IMDAA, compared to other gauge products. IMDAA overestimates the magnitude of the seasonal cycle relative to all the satellite products, with least differences with respect to IMERG, however, they do agree with each other on the form of the seasonal cycle.

Summarising so far, IMDAA is in agreement with all other reanalysis datasets, particularly ERA5. All datasets agree that the heaviest precipitation falls in February and the weakest is in December. Furthermore, the results reveal that all reanalyses and the gauge-based IMD dataset produce similar patterns of regional daily precipitation variability.

d. Skill Scores

Various statistical skill scores (Table 4) have been computed for area-weighted daily time series of precipitation for statistical evaluation of IMDAA in comparison to other datasets. IMDAA shows a good correlation with all the datasets (r>0.6), with the highest correlations found among the reanalysis products (r>0.9), followed by gridded observational datasets IMD, CPC and satellite datasets (r>0.7). IMDAA again depicts the lowest correlation with APHRODITE among all datasets, in agreement with earlier computed statistics. Higher correlations among independent datasets with different data sources and generation methods, are indicators of better precipitation estimates in both the datasets (Baudouin *et al.,* 2020), thus good correlations obtained for IMDAA highlight the reliability of its area-mean precipitation estimates. Overall, IMDAA has IOA values closer to 1 with most datasets, with the highest values among reanalyses, supported by low RMSD, MAD and bias with respect to ERA5 and CFSR, but MERRA-2 again diverges from the group. IMDAA has an index of agreement greater than 89% with all reanalyses, around 71% with satellite products, and greater than 70% with gridded gauge-based datasets. IMDAA shows relatively larger positive differences (following Fig. 2) and higher error magnitudes with the gauge-based and satellite datasets. A strong agreement between IMDAA and IMD is evident through all indices, including highest correlation (0.90) and lowest RMSD, MAD and mean difference (bias). Indeed, IMDAA shows positive differences in comparison to all the datasets, supporting the earlier observed higher magnitudes of precipitation in IMDAA over other datasets (Fig. 2).

Fig. 6 shows the spatial maps of observed point-to-point correlation for daily precipitation climatology between IMDAA and each of the other datasets for 2000–2015 at each grid point, after regridding all datasets to a common spatial resolution of IMDAA. We see a high degree of point-to-point correlation for all reanalyses over the majority of the region, with slightly lower correlation with MERRA-2 over the Himalayan foothills. IMDAA shows a comparatively weak pointwise correlation with many of the satellite datasets – TRMM, IMERG and GPCP; however, the pointwise correlation is better between with PERSIANN-CDR and CHIRPS over the upper Himalayan ranges. Among the observational products, IMDAA has a good correlation with IMD and CPC over most of the study region, although some divergence from the group is evident in APHRODITE, verifying the earlier obtained statistical metrics. It is promising that the region of greatest agreement, especially among the reanalyses, is along the western Himalayas – implying the existence of a common dynamical source of precipitation (e.g. WDs) in this region to which the reanalyses respond relatively robustly; although it is also possible that this agreement is due to common sources of biases between the reanalyses, such as the interaction between parameterised convection and the orography.

e. Diurnal cycle of Precipitation

The diurnal cycle of different types of precipitation is one of the fundamental aspects of variability but it is often neglected in validation studies. For those datasets with hourly data, we can also compare their representation of the diurnal cycle of winter precipitation over the study region (Fig. 7). Realistic representation of the diurnal cycle of precipitation in reanalyses is often challenging due to their reliance on convective parameterization, which typically causes precipitation to occur too early in the day (Dirmeyer *et al.,* 2012). Among the four reanalyses considered here, IMDAA performs best when compared with IMERG, capturing the early morning maximum along much of the western Himalayas and relatively consistent late afternoon peak over the plains south of the Himalaya, both of which are missed to at least some degree by the other reanalyses. IMDAA struggles to simulate the correct diurnal cycle over Tibetan Plateau, with the peak occurring near local midnight rather than the local noon seen in IMERG or mid-afternoon in the other reanalyses.

This is a region where much of the precipitation occurs in the form of stratiform from the underlying model (Fig. S2), and thus generated by the microphysics scheme. Given, however, that the peaks in both stratiform and convective precipitation (Fig. S3) appear mistimed here (at least compared with ERA5), this may be a result of IMDAA assimilating far fewer observations outside of India, rather than problems with the model physics. Analysis of precipitation contribution by convective and stratiform fractions reveal a dominance by stratiform precipitation over the Karakoram and Greater Himalayas in both IMDAA and ERA5, whereas the lower Himalayas experience a mixed proportion of both types of precipitation (Fig. S2). The Himalayan foothills and the plains observe more contribution through convective precipitation.

f. Western Disturbances

WDs are upper-level synoptic-scale cyclonic perturbations in the subtropical jet and are the primary contributors of wintertime precipitation over the WHR. About 80% of observed winter precipitation here occurs during days when a WD is active (Midhuna *et al.,* 2020), with the remaining 20% typically being contributed by local scale convective systems. Given the general agreement (Fig. 4) among datasets, including IMDAA, that winter precipitation is declining, and that a large majority of winter precipitation occurs on WD days, we might ask whether the two are linked by a decline in WD frequency. To test this, WDs were tracked in both ERA5 and IMDAA datasets, using two values of spectral truncation (T42 and T63) to account for potential differences in feature size. The trends of tracked WD frequency in these four datasets, along with an additional set of T63 tracks computed using ERAI for Hunt *et al.* (2018), are shown in Figure 8(a). All datasets show a weak and insignificantly increasing trend of winter WDs in the recent decades. An agreement in the pattern of timeseries is observed for coarser grid resolution (T42), but with differences in respective magnitude. The comparatively finer resolution truncation (T63) shows a similarity in patterns for most years but IMDAA generally has more interannual variability compared with ERA5. ERAI also has a similar interannual pattern, but with a reduced count compared to the higher resolution reanalyses. The weaker, insignificant increase for WD frequency indicates that seasonal occurrences of WDs has been almost constant during the last few decades, or that the effect of interannual variability in WD frequency is much higher than the long-term trends. Generally, the trend significance is measured against internal variability, the fact that the trend fails a significance test indicates that the linear trend is weak compared to interannual variability. Moreover, the standard deviation of the seasonal totals is clearly larger than the trend. However, significant decreasing trend of seasonal mean precipitation has been observed (Fig. 4). Similar results have been reported by Shekhar *et al.* (2010), concluding that seasonal (November-April) occurrences of WDs (1984/85-2007/08) have less effect on snowfall patterns over the western Himalayas, however, a decreasing trend for number of snowfall days was observed in their study. On the contrary, Cannon *et al*. (2015) reported an increase in WD occurrences in the region, while Madhura *et al*. (2015) highlighted an increase in the interannual variability of WD frequency in recent decades. Our results highlight the challenges that remain in determining recent trends in WD activity, a fact which is highlighted by disagreement between earlier studies.

Further, we carried out the analysis of WD-day precipitation composites (Fig. 8b-p) which show that IMDAA performs well in capturing spatial precipitation details when compared with ERA5, though the two reanalyses have higher magnitudes when compared with IMD. IMD shows slight variations in terms of precipitation amount and location, which could be a result of the sparse gauge density over the Himalayas. There is some variation across the season, with all three datasets agreeing that February sees the heaviest WD-day precipitation and December the lightest, in agreement with the results for the climatology discussed earlier.

WD-associated seasonal and monthly precipitation fractions have been plotted by dividing the total precipitation observed during WD-days by the total seasonal precipitation over the study region. The results reveal that 60–90% of wintertime precipitation over the Himalayan region can be attributed to WD activity (Fig. 9), in agreement with previous studies (e.g. Hunt *et al.*, 2019). IMDAA shows a strong agreement with IMD and ERA5, but the higher resolution of IMDAA provides the advantage of a more detailed look into the localized precipitation fractions over the domain, revealing elongated structures orientated northwest-southeast. These features are parallel to the orography and have maximum values on the southern side of local ridges, consistent with WDs bringing moisture flux from the southwest and orographic forcing from regional topography. The attributable fractions for rain and snow (Fig. S4) in IMDAA and ERA5 reveal the dominance of snowfall over the Greater and Karakoram Himalayas, whereas rainfall being the main observed form of precipitation during wintertime over the lower Himalayas and foothills. IMDAA is able to capture the localized variations in WD attributed precipitation percentages owing to its high resolution, whereas ERA5 shows a comparatively homogeneous pattern.

g. Evaluation of dynamical and thermodynamic conditions

As we have seen, winter precipitation over the WHR is primarily associated with WDs. As they are embedded in the large scale sub-tropical westerly jet (200 hPa), WD activity depends significantly on its position and intensity (Krishnan *et al.,* 2019). A comparison of winds at 200 hPa for IMDAA with ERA5 shows that IMDAA is realistic in capturing the wintertime subtropical westerly jet (SWJ) over the region (Fig. 10g-i). However, IMDAA produces a weaker SWJ over WHR (Fig. 10i). An assessment of winter-mean climatological conditions of 2-m air temperature (Fig. 10a-c), OLR (Fig. 10d-f) and geopotential heights (Fig. S5) in IMDAA compared to ERA5 has been carried out. IMDAA captures the spatial patterns of temperature and OLR over WHR and shows potential in finely representing these dynamical features compared to ERA5. However, IMDAA shows warmer temperatures (statistically significant differences) over the lower Himalayas and foothills extending up to northeastern Himalayas and slightly colder temperatures over some western regions of Greater Himalayas, central Tibetan plateau and WHR compared to ERA5 (Fig. 10c). During winter, low OLR values are noticeable over WHR in both IMDAA (Fig. 10d) and ERA5 (Fig. 10e). Generally, lower magnitudes of mean OLR are observed over the region during winter as compared to other seasons owing to the influence of convective activity and cloud formation, although climatological mean OLR is also lower here due to the higher underlying orography. IMDAA exhibits slightly higher OLR magnitudes than ERA5 along the south-eastern Ladakh region and over the Himalayan foothills, extending up to the northeastern Himalayas. The patterns of mean geopotential height (Fig. S5) at different pressure levels over the WHR during the winter season seem to be well represented in both IMDAA and ERA5 with slightly higher magnitudes in IMDAA over WHR. To sum up, IMDAA is capable of representing seasonal mean dynamical and large-scale circulation patterns during winter.

h. Case Study for western disturbance over WHR

As one of the potential major advantages of the higher resolution of IMDAA is its ability to better capture local orographically-driven dynamics, we also explore the representation of such dynamics during the passage of WD over WHR. Here, this is accomplished through analysis of a case study for an intense WD that occurred during 16-19 February 2003, which affected WHR and caused widespread precipitation over the region. Overcast skies and enhanced cloud cover associated with deeper convective activity are key features observed during the passage of WD over WHR (e.g. Rao and Rao 1971), which is noticeable in satellite imagery from NASA EOSDIS (Fig. 11a-d). IMDAA is realistically representing the daily evolution of the total cloud cover associated with the intense WD over WHR (Fig. 11e-h), further supported by abrupt negative OLR anomalies (Fig. 11i) during the period indicating increased atmospheric convection. This convective activity plays an essential role in developing secondary circulations during the propagation of WDs and results in heavy localized precipitation over the WHR (e.g. Dimri *et al.*, 2016; Hunt *et al.,* 2019). Our results demonstrate the ability of high resolution IMDAA in representation of realistic evolution of the WD induced cloud cover patterns compared to remotely sensed observations.

Furthermore, the analysis of regional valley wind systems during the given period has been carried out to validate the representation of local scale circulation patterns in IMDAA compared to ERA5, which highlights the advantages offered by its high resolution. Figure 12 shows the spatial and temporal patterns of local scale 10-m wind patterns at two different valley sites (the Suru valley in Jammu and Kashmir and the Spiti Valley in Himachal Pradesh) before, during, and after the passage of WD over WHR. IMDAA (Fig 12b) shows high fidelity in capturing the local scale circulation features at the two valley sites, correctly capturing the maximum intensity of winds during the in contrast to the more spatially homogeneous ERA5 wind speed.

The temporal evolution of these valley winds during the passage of WD is shown for both valley sites in Fig. 12g-h, where an abrupt increase in magnitudes of valley wind speed is observed on 16 February at both locations. This variability is captured in IMDAA, but not in ERA5 where the wind speed is roughly constant during the passage of the WD. Additionally, the effect of the WD passing over the study region is dynamically characterized by an increase of the local minimum temperature (Fig. 12i-j) and a drop in the surface pressure (Fig. 12k-l), which corroborates previous studies (e.g. Rao and Rao, 1971; Singh *et al.,* 2019). Overall, it is clear that IMDAA shows high fidelity in representing local scale wind responses associated with WD activity over WHR, a key advantage offered by its high resolution.

4. Summary and Conclusions

This study evaluated winter precipitation and its variability and trends in the recently introduced high resolution reanalysis IMDAA using various gridded, satellite, and reanalysis datasets over the western Himalayan region between 1979–2018, as per their respective period of availability. Based on the findings, the following conclusions can be made:

1. IMDAA captures the spatial variability of winter precipitation over the western Himalayas well, on both seasonal and interannual scales, and has climatological precipitation statistics that are very similar to the other reanalyses considered. However, it shows higher precipitation amounts compared to other datasets along the lower Himalayas and foothills.
2. IMDAA agrees with the other reanalysis datasets in showing a slight decline in winter precipitation over the western Himalayas over recent decades, though it is the only reanalysis dataset in which that trend is significant, in accordance with trends reported in earlier studies in individual station data (Shekhar *et al*., 2010, 2017). The IMD gauge-based precipitation dataset also has a significant decline over the same period, but no other gauge-based or satellite products have significant trends when averaged over the whole western Himalayan region.
3. Tracking of WDs carried out in both ERA5 and IMDAA reanalyses showed a weak insignificant increase in frequency over the study period (1979–2018). This agrees with previous reanalysis-based studies; however, several observation-based studies have reported a recent decline in WD frequency. Our results, thus, highlight the challenges that remain in determining recent trends in WD activity over the region, making it an important area of further work.

4. IMDAA shows potential in reproducing climatological winter circulation patterns and surface conditions. However, the validation of high-resolution features such as valley wind speeds and local dynamics during the passage of WDs over the region strongly emphasizes advantages offered by IMDAA's high resolution compared to ERA5. The dataset showed high potential in representing more localized ridge- and valley-scale features, offering a better characterization of regional dynamics.

In summary, we acknowledge that low density of gauges and complex orography leads to high discrepancies and uncertainties in the available data products over WHR. Overall, reanalyses – including IMDAA – suffer from precipitation overestimation likely owing to errors in the representation of parameterized convection. However, the findings in this study emphasize the benefits provided by the high-resolution model and output of IMDAA, including understanding the complex interplay between terrain and mountain meteorology over WHR, even with its higher precipitation magnitudes. The reanalysis shows high fidelity in simulating local-scale dynamics as well as large scale circulation features responsible for winter precipitation over the region. Such findings strongly underpin the capabilities of IMDAA in exploring the winter monsoon and its variability and in analysing the meteorological precursors of precipitation extremes. Overall, IMDAA, despite its amplified magnitudes, is useful for precipitation climatology, interannual variability and synoptic meteorology over WHR, however, is still unable to capture diurnal peak precipitation realistically over the Tibetan Plateau. Even with a resolution of 0.12° (~12 km), IMDAA still does not adequately resolve regional orography, and this is likely to continue to result in discrepancies in precipitation magnitude over the region.

Moreover, large uncertainties remain in understanding the spatio-temporal precipitation in the WHR due to limited observations and thus, it becomes hard to obtain benchmark precipitation trends, as well as verification of spatial precipitation amounts in IMDAA. Further work is needed to constrain historical trends in winter precipitation in this region and link those trends to changes in synoptic-scale activity, such as western disturbances. Finally, we note that high-resolution simulations cannot replace ground-based in-situ observations and the lack of gauge data over such terrains with high spatial variability adds challenges for accurate precipitation measurements, which can be tackled through increased coverage of in-situ stations over the region.

Acknowledgments.

This research work was supported by Science and Engineering Research Board, Department of Science and Technology, Government of India under the "Start-up Research Grant (SRG) scheme" (Grant reference: SRG/2020/001857). Authors gratefully acknowledge NCMRWF, Ministry of Earth Sciences, Government of India, for IMDAA reanalysis. IMDAA reanalysis was produced under the collaboration between UK Met Office, NCMRWF, and IMD with financial support from the Ministry of Earth Sciences, under the National Monsoon Mission programme. Nischal gratefully acknowledges the financial assistance from the Prime Minister's Research Fellowship (PMRF), Ministry of Education, Government of India. KMRH is supported through the Weather and Climate Science for Service Partnership (WCSSP) India, a collaborative initiative between the Met Office, supported by the U.K. Government's Newton Fund, and the Indian Ministry of Earth Sciences (MoES). The authors acknowledge and appreciate the editor and anonymous reviewers for their constructive feedback, which helped in improving the quality of our work.

Data Availability Statement

All the data used in this study is publicly available and accessible. IMDAA data is available on the RDS NCMRWF portal at https://rds.ncmrwf.gov.in/datasets. ECMWF fifth generation (ERA5) data can be accessed through https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5. NCEP Climate Forecast System data is provided at https://cfs.ncep.noaa.gov/cfsr and MERRA-2 is available at https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2. The gauge-based datasets can be accessed from https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html (IMD), https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html (CPC) and http://aphrodite.st.hirosaki-u.ac.jp/products.html (APHRODITE). GPCP satellite data is available at https://www.ncei.noaa.gov/products/climate-data-records/precipitation-gpcp-daily and TRMM-3B42 at https://disc.gsfc.nasa.gov/datasets/. The remaining datasets used in the study are publicly accessible at https://www.chc.ucsb.edu/data (CHIRPS), https://gpm.nasa.gov/data/directory (GPM-IMERG) and https://chrsdata.eng.uci.edu/ (PERSIANN-CDR), respectively. WD days during DJFM over the study region are quantified based on Indian Daily Weather Reports (IDWR) issued by the IMD.

APPENDIX

Evaluation indices

The quantitative assessment of IMDAA in comparison to different datasets was carried out using a series of statistical indicators and skill scores for the daily time series of winter precipitation. The indices used for statistical evaluation of the performance of IMDAA with other datasets are discussed below where n is the total number of observations (daily time series of precipitation), x_i depicts the value for respective evaluation dataset, y_i depicts the value for IMDAA dataset, $\underline{x}$ is the mean for evaluation dataset values and $\underline{y}$ is the mean for IMDAA dataset values.

Pearson's correlation coefficient (r) is a quantitative measure of strength of linear agreement between two datasets which ranges from -1 to +1, with positive values indicating a positive correlation and vice versa.

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

The Root Mean Square Difference (RMSD) is a measure of overall difference associated with residuals in a predictor dataset in comparison to the validation dataset, whereas relative RMSD (rRMSD) is a normalized variant of RMSD with respect to the mean of the validation dataset. Lower values of RMSD and rRMSD indicate stronger association between datasets.

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \qquad (2)$$

$$RMSDrel = \frac{RMSD}{\bar{x}} * 100 \qquad (3)$$

Mean Absolute Difference (MAD) is a measure of the accuracy of a predictor dataset in terms of average magnitude of errors present in the predictions in comparison to the validation dataset. rMAD is a normalized variant of MAD.

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \qquad (4)$$

$$rMAD = \frac{MAD}{\bar{x}} * 100 \qquad (5)$$

BIAS is the quantitative measure to define the tendency of underestimation or overestimation in a dataset with respect to a validation dataset where the negative values indicate underestimation and vice versa.

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i) \tag{6}$$

$$rBIAS = \frac{BIAS}{\underline{x}} * 100 \tag{7}$$

Adjusted R-squared is defined as:

$$Adj. R^2 = 1 - (1 - R^2)\frac{n-1}{n-k-1}$$

where, k is the number of independent variables and n is the number of observations.

REFERENCES

Aggarwal, D., R. Attada., K.K. Shukla, R. Chakraborty, and R.K. Kunchala, 2022: Monsoon precipitation characteristics and extreme precipitation events over Northwest India using Indian high-resolution regional reanalysis. *Atmos. Res.,* 267, 105993, https://doi.org/10.1016/j.atmosres.2021.105993.

Anand, A. S. K. Mishra, S. Sahany, M. Bhowmick, J.S. Rawat, and S. K. Dash, 2018: Indian summer monsoon simulations: Usefulness of increasing horizontal resolution, manual tuning, and semi-automatic tuning in reducing present-day model biases. *Sci. rep.,* **8(1),** 1-14.

Andermann, C., S. Bonnet, and R. Gloaguen, 2011: Evaluation of precipitation data sets along the Himalayan front. *Geochem. Geophys. Geosyst.*, **12(7)**, Q07023.

Ashrit, R., and Coauthors, 2020: IMDAA Regional Reanalysis: Performance Evaluation during Indian Summer Monsoon Season. *J. Geophys. Res. Atmos.*, **125(2)**, e2019JD030973, https://doi.org/10.1029/2019JD030973.

Bao, X., and F. Zhang, 2013: Evaluation of NCEP-CFSR, NCEP-NCAR, ERA-Interim, and ERA-40 Reanalysis Datasets against Independent Sounding Observations over the Tibetan Plateau. *J. Climate,* **26(1)**, 206-214.

Baudouin, J. P., M. Herzog, and C. A. Petrie, 2020: Cross-validating precipitation datasets in the Indus River basin. *Hydrol. Earth Syst. Sci.*, **24(1)**, 427-450, https://doi.org/10.5194/hess-24-427-2020.

Bayissa, Y., T. Tadesse, G. Demisse and A. Shiferaw, 2017: Evaluation of Satellite-Based Rainfall Estimates and Application to Monitor Meteorological Drought for the Upper Blue Nile Basin, Ethiopia. *Remote Sens.*, 669.

Beck, H. E. and Co-authors, 2017: Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrol. Earth Syst. Sci.*, **21**, 6201–6217.

Bengtsson, L., S. Hagemann, and K. I. Hodges, 2004: Can Climate Trends be calculated from Re-Analysis data?. *J. Geophys. Res. Atmos.*, **109(D11111)**.

Cannon, F., L. M. Carvalho, C. Jones, and B. Bookhagen, 2015: Multi-annual variations in winter westerly disturbance activity affecting the Himalaya. *Climate Dyn.*, **44(1-2)**, 441-455.

Carey, M., 2010: In the Shadow of Melting Glaciers. Climate Change and Andean Society; Oxford University Press: Oxford, UK, 288.

Chen, M., P. Xie, and Coauthors, 2008: CPC Unified Gauge-based Analysis of Global Daily Precipitation. *Western Pacific Geophys. Meeting*, Cairns, Australia, 29 July-1 August, 2008.

Choudhury, A., A. C. Yadav, and S. Bonafoni, 2021: A response of snow cover to the climate in the northwest himalaya (NWH) using satellite products. *Rem. Sens.*, **13(4)**, 655.

Cullen, N. J. and J. P. Conway, 2015: A 22-month record of surface meteorology and energy balance from the ablation zone of Brewster Glacier, New Zealand. *J. Glaciol.*, **61**, 931–946.

Dahri, Z. H., and Co-authors, 2021: Spatio-temporal evaluation of gridded precipitation products for the high-altitude Indus basin. *Int. J. Climatol*., **41(8)**, 4283-4306.

Dahri, Z. H., E. Moors, F. Ludwig, S. Ahmad, Khan, A. Khan, I. Ali, and P. Kawat, 2018: Adjustment of measurement errors to reconcile precipitation distribution in the high-altitude Indus basin. *Int. J. Climatol.,* 38.

Dahri, Z. H., F. Ludwig, E. Moors, B. Ahmad, A. Khan, and P. Kabat, 2016: An appraisal of precipitation distribution in the high-altitude catchments of the Indus basin. *Sci. Total Environ.*, **548**, 289-306.

Dee, D. P., M. Balmaseda, G. Balsamo, R. Engelen, A. J. Simmons, and J.-N. Thépaut, 2014: Toward a consistent reanalysis of the climate system. *Bull. Amer. Meteor. Soc.,* **95**(8), 1235–1248.

Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, and F. Vitart, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.*, **137(656)**, 553-597.

Derin, Y., and K. K. Yilmaz, 2014: Evaluation of multiple satellite-based precipitation products over complex topography. *J. Hydrometeor.,* **15(4),** 1498-1516.

Derin, Y., E. Anagnostou, A. Berne, M. Borga, B. Boudevillain, W. Buytaert, and K. K. Yilmaz, 2016: Multiregional satellite precipitation products evaluation over complex terrain. *J. Hydrometeor.*, **17(6)**, 1817-1836.

Dimri, A. P., 2013: Intraseasonal oscillation associated with the Indian winter monsoon. *J. Geophys. Res. Atmos.*, **118**, 1189– 1198.

Dimri, A. P., and A. Ganju, 2007: Wintertime seasonal scale simulation over Western Himalaya using RegCM3. *Pure Appl. Geophys.*, **164(8)**, 1733-1746.

Dimri, A. P., and S. K. Dash, 2012: Wintertime climatic trends in the western Himalayas. *Climate Change*, **111(3)**, 775-800.

Dimri, A. P., and U. C. Mohanty, 2009: Simulation of mesoscale features associated with intense Western Disturbances over western Himalayas. *Meteorol. Appl.,* **16(3)**, 289-308.

Dimri, A. P., D. Niyogi, A. P. Barros, J. Ridley, U. C. Mohanty, T. Yasunari, and D. R. Sikka, 2015: Western Disturbances: A review. *Rev. Geophys.*, **53(2)**, 225– 246.

Dimri, A. P., T. Yasunari, B. S. Kotlia, U. C. Mohanty, and D. R. Sikka, 2016: Indian winter monsoon: Present and past. *Earth Sci. Rev.*, **163(2)**, 297-322.

Dinku, T., S. J. Connor, P. Ceccato, and C.F. Ropelewski, 2008: Comparison of global gridded precipitation products over a mountainous region of Africa. *Int. J. Climatol*., **28**,1627–1638.

Dirmeyer, P. A., and Coauthors, 2012: Simulating the diurnal cycle of rainfall in global climate models: resolution versus parameterization. *Climate Dyn.,* **39(1)**, 399-418.

Ebert, E. E., J. E. Janowiak, and C. Kidd, 2007: Comparison of near-real-time precipitation estimates from satellite observations and numerical models. *Bull. Amer. Meteor. Soc.*, **88(1)**, 47-64.

Escher-Vetter, H., and Co-authors, 2012: Hydrological and Meteorological Records from the Vernagtferner Basin—Vernagtbach Station, for the Years 1970 to 2001. PANGAEA: Bremen, Germany.

Forsythe N., S. Blenkinsop, and H. J. Fowler, 2015: Exploring objective climate classification for the Himalayan arc and adjacent regions using gridded data sources. *Earth Syst. Dyn.,* **6(1)**, 311–326.

Funk, C., and Coauthors, 2015: The climate hazards infrared precipitation with stations-a new environmental record for monitoring extremes. *Sci. Data,* **2,** 150066.

Gampe, D., and R. Ludwig, 2017: Evaluation of gridded precipitation data products for hydrological applications in complex topography. *Hydrology*, **4(4),** 53.

Gebregiorgis, A. S., and Co-authors, 2018: To what extent is the day 1 GPM IMERG satellite precipitation estimate improved as compared to TRMM TMPA-RT?. *J. Geophys. Res.: Atmos.*, **123(3)**, 1694-1707.

Gelaro, R., and Coauthors, 2017: The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA2). *J. Climate*, **30(14)**, 5419-5454.

Ghodichore, N., R. Vinnarasi, C. T. Dhanya, and S.B. Roy, 2018: Reliability of reanalyses products in simulating precipitation and temperature characteristics over India. *J. Earth Syst. Sci.,* **127(8**), 1-21.

Gouda, K. C., S. Nahak, and P. Goswami, 2018: Evaluation of a GCM in seasonal forecasting of extreme rainfall events over continental India. *Wea. Climate Extrem.*, **21**, 10-16.

Guan, X., and Co-authors, 2020: Evaluation of Precipitation Products by Using Multiple Hydrological Models over the Upper Yellow River Basin, China. *Remote Sens.,* **12(24),** 4023.

Hamal, K., and Coauthors, 2020: Evaluation of MERRA-2 Precipitation Products Using Gauge Observation in Nepal. *Hydrology*, **7(3)**, 40, https://doi.org/10.3390/hydrology7030040.

Hersbach, H., and Coauthors, 2020: The ERA5 global reanalysis. *Quart. J. Roy. Meteor. Soc.*, **146(730)**, 1999-2049. https://doi.org/10.1002/qj.3803.

Huffman, G. J., and Coauthors, 2007: The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales. *J. Hydrometeor.*, **8(1)**, 38-55.

Huffman, G. J., and Coauthors, 2015: NASA Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG). Algorithm Theoretical Basis Document (ATBD) Version, **4**, 26.

Huffman, G. J., R. F. Adler, M. M. Morrissey, D. T. Bolvin, S. Curtis, R. Joyce, B. McGavock, and J. Susskind, 2001: Global precipitation at One-degree Daily Resolution from Multi-satellite Observations. *J. Hydrometeor.*, **2(1)**, 36-50.

Hunt, K. M. R., A. G. Turner, and L. C. Shaffrey, 2018: The evolution, seasonality and impacts of western disturbances. *Quart. J. Roy. Meteor. Soc.*, **144(710)**, 278-290.

Hunt, K. M. R., A. G. Turner, and L. C. Shaffrey, 2019: Representation of Western Disturbances in CMIP5 Models. *J. Climate,* **32(7)**, 1997-2011.

Hussain, S., X. Song, G. Ren, I. Hussain, H. Dongmei, and M. H. Zaman, 2017: Evaluation of gridded precipitation data in the Hindu Kush–Karakoram–Himalaya mountainous area. *Hydrol. Sci. J.*, **62(14)**, 2393-2405.

Immerzeel, W. W., N. Wanders, A. F. Lutz, J. M. Shea, and M. F. P. Bierkens, 2015: Reconciling high-altitude precipitation in the upper Indus basin with glacier mass balances and runoff. *Hydrol. Earth Syst. Sci.*, **19(11),** 4673-4687.

Ji, X., and Co-authors, 2020: Evaluation of bias correction methods for APHRODITE data to improve hydrologic simulation in a large Himalayan basin. *Atmos. Res.,* **242**, 104964.

Joshi, J. C., and A Ganju, 2010: Use of objective analysis to estimate winter temperature and precipitation at different stations over western Himalaya. *J. Earth Syst. Sci.*, **119(5)**, 597-602.

Juen, I., 2006: Glacier Mass Balance and Runoff in the Cordillera Blanca, Peru. Ph.D. Thesis, University of Innsbruck, Innsbruck, Austria.

Kanda, N., H. S. Negi, M. S. Rishi, and A. Kumar, 2020: Performance of various gridded temperature and precipitation datasets over Northwest Himalayan Region. *Environ. Res. Commun.*, **2(8)**, 085002, https://doi.org/10.1088/2515-7620/ab9991.

Karch, J., 2020: Improving on Adjusted R-Squared. *Collabra:Psychology,* **6(1)**, 45.

Kishore, P., S, Jyothi, G. Basha, S. Rao, M. Rajeevan, I. Velicogna, and T.C. Sutterley, 2016: Precipitation climatology over India: validation with observations and reanalysis datasets and spatial trends. *Climate Dyn.*, **46(1-2)**,541–556.

Krishnan, R., T. P. Sabin, R. K. Madhura, R. K. Vellore, M. Mujumdar, J. Sanjay, S. Nayak, and M. Rajeevan, 2019: Non-monsoonal precipitation response over the Western Himalayas to climate change. *Climate Dyn.*, **52(7)**, 4091-4109.

Lalande, M., M. Ménégoz, G. Krinner, K. Naegeli, and S. Wunderle, 2021: Climate change in the High Mountain Asia in CMIP6. *Ear sys. dyn.,* **12(4),** 1061-1098.

Lang, T. J., and A. P. Barros, 2004: Winter storms in Central Himalayas, *J. Meteor. Soc. Japan,* **82(3)**, 829–844.

Liaqat, M. U., G. Grossi, S. ul Hasson, and R. Ranzi, 2022: Characterization of Interannual and Seasonal Variability of Hydro-Climatic Trends in the Upper Indus Basin. *Theor. Appl. Climatol.,* **147,** 1163–1184, https://doi.org/10.1007/s00704-021-03850-3.

Liu, M. and Co-authors, 2015: Evaluation of high-resolution satellite rainfall products using rain gauge data over complex terrain in southwest China. *Theor. Appl. Climatol.* 119, 203–219.

Madhura, R. K., R. Krishnan, J. V. Revadekar, M. Mujumdar, and B. N. Goswami, 2015: Changes in western disturbances over the Western Himalayas in a warming environment. *Climate Dyn.*, **44**, 1157-1168.

Maggioni, V., Meyers, P., & Robinson, M. (2016). A review of merged high resolution satellite precipitation product accuracy during the Tropical Rainfall Measuring Mission (TRMM)-Era. Journal of Hydrometeorology, 17(4), 1101–1117.

Meng, J., L. Li, Z. Hao, J. Wang, and Q. Shao, 2014: Suitability of TRMM satellite rainfall in driving a distributed hydrological model in the source region of Yellow River. *J. Hydrol.,* **509**, 320-332.

Midhuna, T. M., P. Kumar, and A. P., Dimri, 2020: A new Western Disturbance Index for the Indian winter monsoon. *J. Earth Syst. Sci.*, **129**, 59, https://doi.org/10.1007/s12040-019-1324-1.

Murakami, H., 2014: Tropical cyclones in reanalysis data sets. *Geophys. Res. Lett.,* **41(6)**, 2133-2141.

Nguyen, P., and Coauthors, 2019: The CHRS Data Portal, an easily accessible public repository for PERSIANN global satellite precipitation data. *Sci. Data*, 6(1), 180296.

Nitu, R. and, Co-authors., 2018: WMO Solid Precipitation Intercomparison Experiment (SPICE) (2012–2015). Instruments and Observing Methods Report No. 131, World Meteorological Organization, Geneva. https://www.wmo.int/pages/prog/www/IMOP/publications-IOM-series.html.

Pai, D. S., L. Sridhar, M. Rajeevan, O. P. Sreejith, N. S. Satbhai, and B. Mukhopadhyay, 2014: Development of a new high spatial resolution (0.25° × 0.25°) long period (1901-2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam*, **65(1)**, 1-18.

Palazzi, E., J. V. Hardenberg, and A. Provenzale, 2013: Precipitation in the Hindu-Kush Karakoram Himalaya: Observations and future scenarios. *J. Geophys. Res.: Atmos.*, **118(1)**, 85-100.

Phung, D., T. Nguyen-Huy, N.N. Tran, D.N. Tran, S. Nghiem, N.H. Nguyen, and T. Bennett, 2021: Hydropower dams, river drought and health effects: A detection and attribution study in the lower Mekong Delta Region. *Clim. Risk Manag.,* **32**, 100280.

Rani S. I., T. Arulalan, J. P. George, E. N. Rajagopal, R. Renshaw, A. Maycock, D. M. Barker, and M. Rajeevan, 2021: IMDAA: High-Resolution Satellite-Era Reanalysis for the Indian Monsoon Region, *J. Climate*, **34(12)**, 5109-5133, https://doi.org/10.1175/JCLI-D-20-0412.1.

Rao, B. V., and Rao, T. S., 1971: A theoretical and synoptic study of western disturbances. *Pure Appl. Geophys.*, **90(1),** 193-208.

Reichle, R. H., Q. Liu, R. D. Koster, C. S. Draper, S. P. Mahanama, and G. S. Partyka, 2017: Land surface precipitation in MERRA-2. *J. Clim.*, **30(5),** 1643-1664.

Roxy, M., K. Ritika, P. Terray, R. Murtugudde, A. Karumuri and B. N. Goswami, 2015: Drying of Indian subcontinent by rapid Indian Ocean warming and a weakening land-sea thermal gradient. Nat. Commun., 7423 (2015).

Roy, S. S., 2006: The impacts of ENSO, PDO, and local SSTs on winter precipitation in India. Phy. Geog., 27(5), 464-474.

Saha, S., and Coauthors, 2010: The NCEP Climate Forecast System Reanalysis. *Bull. Amer. Meteor. Soc.*, **91(8)**, 1015-1058.

Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System Version 2. *J. Climate*, **27(6)**, 2185-2208.

Shekhar M. S., H. Chand, S. Kumar, K. Srinivasan, and A. Ganju, 2010: Climate change studies in the western Himalaya; *Ann. Glaciol*., **51(54)**, 105–112.

Shekhar, M. S., N. N. Rao, S. Paul, S.C. Bhan, G. P. Singh, and A. Singh, 2017: Winter precipitation climatology over Western Himalaya: Altitude and Range wise study. *J. Ind. Geophys. Union*, 21(2),148-152.

Singh, D., A. Kumar, M. S. Shekhar, and S. Garg, 2019: The impacts of the approaching western disturbances (WDs) on the surface meteorological variables over the north-west Himalaya (NWH), India. J. Earth. Syst. Sci., 149.

Singh, P., and N. Kumar, 1997: Effect of orography on precipitation in the western Himalayan region. *J. Hydrol.*, **199(1-2)**, 183-206.

Strangeways, I., 2004: Improving precipitation measurement. *Int. J. Climatol*., **24(11)**, 1443–1460.

Sun, Q., C. Miao, Q. Duan, H. Ashouri, S. Sorooshian, and K.-L. Hsu, 2018: A Review of Global Precipitation Data Sets: Data Sources, Estimation, and Intercomparisons. *Rev. Geophys.*, **56(1)**, 79-107.

Trenberth, K. E., and C. J. Guillemot, 1998: Evaluation of the atmospheric moisture and hydrological cycle in the NCEP/NCAR reanalyses. *Climate Dyn.,* **14(3)***,* 213-231.

Wang, Y., J. Chen, and D. Yang, 2019: Bayesian Assimilation of Multiscale Precipitation Data and Sparse Ground Gauge Observations in Mountainous Areas. *J. Hydrometeor.*, **20(8)**, 1473-1494.

Willmott, C. J., 1981: On the validation of models. *Phys. geo.,* **2(2)**, 184-194.

Winiger, M. Y., M. Gumpert, and H. Yamout, 2005: Karakorum–Hindukush–western Himalaya: assessing high-altitude water resources. *Hydrol. Process.,* **19(12)**, 2329-2338.

Xia, T., Z. J. Wang, and H. Zheng, 2015: Topography and Data Mining Based Methods for Improving Satellite Precipitation in Mountainous Areas of China. *Atmos.*, **6(8)**, 983-1005.

Xie, P., A. Yatagai, M. Chen, T. Hayasaka, Y. Fukushima, C. Liu, and S. Yang, 2007: A gauge-based analysis of daily precipitation over East Asia, *J. Hydrometeor*., **8**, 607-626.

Xu, R., F. Tian, L. Yang, H. Hu, H. Lu, and A. Hou, 2017: Ground validation of GPM IMERG and TRMM 3B42V7 rainfall products over southern Tibetan Plateau based on a high-density rain gauge network. *J. Geophys. Res.: Atmos.*, **122(2)**, 910-924.

Yadav R. K., D. A. Ramu, and A. P. Dimri, 2013: On the relationship between ENSO patterns and winter precipitation over North and Central India. *Glob. Planet. Change,* **107**, 50-58.

Yadav, R. K., R. Kumar, and M. Rajeevan, 2009: Increasing influence of ENSO and decreasing influence of AO/NAO in the recent decades over northwest India winter precipitation. J. Geophys. Res.: Atmos., 114(D12).

Yatagai, A., K. Kamiguchi, O. Arakawa, A. Hamada, N. Yasutomi, and A. Kitoh, 2012: APHRODITE: Constructing a Long-Term Daily Gridded Precipitation Dataset for Asia Based on a Dense Network of Rain Gauges. *Bull. Amer. Meteor. Soc.*, **93(9)**, 1401-1415.

Ye, B., D. Yang, Y. Ding, T. Han, and T. Koike, 2004: A bias-corrected precipitation climatology for china. *J. Hydrometeor.*, **5(6)**, 1147–1160.

Zandler, H., I. Haag, and C. Samimi, C., 2019: Evaluation needs and temporal performance differences of gridded precipitation products in peripheral mountain regions. *Nature:Sci. rep.,* **9(1)**, 1-15.