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Article

Accepted Version

Nischal, Attada, R. and Hunt, K. M. R. ORCID: https://orcid.org/0000-0003-1480-3755 (2022) Evaluating winter precipitation over the western Himalayas in a high-resolution Indian regional reanalysis using multi-source climate datasets. Journal of Applied Meteorology and Climatology, 61 (11). pp. 1613-1633. ISSN 1558-8432 doi: 10.1175/JAMC-D-21-0172.1 Available at https://centaur.reading.ac.uk/106218/

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To link to this article DOI: http://dx.doi.org/10.1175/JAMC-D-21-0172.1

Publisher: American Meteorological Society

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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

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

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

109 Recently, the first high resolution (12 km) regional atmospheric reanalysis dataset, Indian
110 Monsoon Data Assimilation and Analysis (IMDAA), focusing on the South Asian region, has been
111 released (Rani *et al.,* 2021). This state-of-the-art reanalysis is generated by the National Centre for
112 Medium Range Weather Forecasting (NCMRWF) in collaboration with the India Meteorological
113 Department (IMD) and UK Met Office under the National Monsoon Mission project, Government
114 of India. The reanalysis spans the modern meteorological satellite era (1979–present) and outputs
115 atmospheric data at 63 vertical levels. This is now one of the highest resolution regional reanalyses

116 available over India, providing the important advantage of improved representation of orographic
117 features. Ashrit *et al.* (2020) and Aggarwal *et al.* (2022) explored the efficiency of IMDAA in
118 representing precipitation characteristics as well as atmospheric thermodynamics and circulation
119 during the Indian summer monsoon, but wintertime precipitation characteristics are yet to be
120 evaluated using IMDAA.

121 Some validation studies of different multi-source datasets have been carried out previously
122 over the Himalayan region. Andermann *et al.* (2011) evaluated various precipitation datasets along
123 the Himalayan front and reported a significant variation in performance among the evaluated
124 datasets along the orography, however, the datasets show higher consistency, with respect to each
125 other, along with the lower relief realms. Palazzi *et al.* (2013) showed that various category gridded
126 precipitation datasets adequately captured the interannual variability of precipitation over the
127 Hindukush-Karakoram region. Dahri *et al*. (2018) reported underestimation in the rain gauge
128 measurements in the high-altitude Indus basin during the winter season and underpinned the
129 necessity of bias adjustment to reduce errors. A cross-validation for different categories of
130 precipitation datasets in the Indus River basin was performed by Baudouin *et al.* (2020), reporting
131 a large difference in average precipitation between the rain gauge and the reanalyses, most likely
132 resulting from opposite biases from both dataset types and not only from the reanalysis, as often
133 suggested. While precipitation in ERA-Interim (ERAI) is found to be well correlated with
134 observational data across the Karakoram (Immerzeel *et al.*, 2015; Dahri *et al.*, 2016), Hussain *et*
135 *al*. (2017) reported a poor spatial correlation for TRMM-3B42 with in-situ observations, however,
136 an increase in the correlation was observed with decreasing temporal resolution from daily to
137 monthly scale. Furthermore, it was found that the estimation of summer precipitation compared to
138 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

253 without any interpolation, similar to previous literature (e.g. Dinku *et al.,* 2008; Liu *et al.,* 2015;
254 Beck *et al.,* 2017; Bayissa *et al.,* 2017; Zandler *et al.,* 2019). Different statistical metrics, including
255 mean, standard deviation, coefficient of variation and pattern correlation coefficient (PCC), have
256 been computed to understand how the representation of regional precipitation varies between
257 datasets. All the metrics have been calculated for a common time period (2000–2015), using
258 regionally averaged seasonal mean precipitation at the native spatial resolution of each product,
259 except PCC, for which datasets have been re-gridded using bilinear interpolation to IMDAA's
260 resolution. We also investigate the total number of heavy precipitation events per year exceeding
261 selected percentile (90^{th}, 95^{th} and 99^{th}) thresholds in each dataset. The number of events has been
262 counted by considering precipitation estimates from all grids between the period 2000-2015,
263 therefore, the datasets have been re-gridded here to a common resolution of 0.25˚, to avoid
264 additional counts from higher resolution datasets.

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

272 *(i) Index of agreement*

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

276 $$IOA = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(|y_i - \bar{x}| + |x_i - \bar{x}|)^2)} ,$$

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

280 *(ii) Adjusted R-squared*

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

288 *(iii) Pattern Correlation Coefficient (PCC)*

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

291 2) CLIMATOLOGY, VARIABILITY AND TRENDS

292 The spatial distribution of seasonal (DJFM) winter precipitation climatology and variability in all
293 datasets, considering their respective native spatial resolution and temporal availability between
294 1979–2018 over the study region has been investigated. Full available time periods for each dataset
295 between 1979-2018 have been considered for the evaluation of the geographical distribution of
296 precipitation estimates, since spatial patterns of precipitation tend to be less affected by the

297 averaging period. We further analysed spatial patterns of seasonal mean precipitation differences
298 in IMDAA with respect to different datasets, after rescaling all datasets to the grid used in IMDAA.
299 The spatial patterns on trends of seasonal mean precipitation are computed through seasonal mean
300 precipitation series at each grid point for different precipitation products for a common period of
301 35 years (1984–2018), at their native spatial resolutions, using the non-parametric Mann-Kendall
302 test (Roxy *et al.,* 2015). The datasets with at least an available time period of 35 years have been
303 selected for spatial trends considering that at least 30 years or more is a minimal period to provide
304 considerable climatological trend information. To investigate the interannual variability of the
305 seasonal mean precipitation, standardized precipitation anomalies over the WHR have been
306 utilized to categorize excess and deficit precipitation years, considering the standardized anomalies
307 exceeding ±0.5, respectively.

308 3) IDENTIFICATION OF WDs

309 The tracking of WDs over the study region was carried out using the WD tracking algorithm from
310 Hunt *et al.* (2018). The algorithm involves the computation of mean relative vorticity in the 450–
311 300 hPa layer followed by filtration of short-wavelength noise using the desired spectral truncation
312 (T63 and T42) and further identification of positive-definite vorticity regions to determine the
313 centroid locations for each candidate WD. The linkage of these centroids in time, with steering
314 wind-biased distance constraints, allows the identification of potential WD tracks. Lastly, the
315 database is refined by rejecting those tracks which do not pass-through north India (20°N–36.5°N,
316 60°E–80°E), last less than 48 hours, or dissipate at a point westward of their genesis. WDs were
317 tracked in IMDAA (1980–2018) and ERA5 (1979–2018) at spectral truncations of T42 and T63
318 and in ERAI (1979–2015) at T63. The interannual frequency of identified winter WDs was
319 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

342 of 0.74 mm/day (Table 2), shows a good agreement overall with the other reanalyses ERA5 and
343 CFSR, albeit with a slightly higher magnitude. Among the reanalyses, MERRA-2 has the lowest
344 mean and largest variability, which might be associated with the use of dry-biased CPC data for
345 surface precipitation flux (Reichle *et al.*, 2017; Baudouin *et al.,* 2020). The realistic representation
346 of the mean amounts of winter precipitation of IMDAA is evident through its observed similarity
347 to the ERA5 reanalysis, which has been revealed to perform best with observations in the
348 surrounding upper Indus Basin in previous studies (Baudouin *et al*., 2020; Dahri *et al*., 2021). It is
349 evident that all reanalyses, including IMDAA, are wetter and exhibit large spatial variability
350 compared to other types of datasets. Among the observational datasets, mean precipitation in
351 IMDAA is closest to IMD, followed by APHRODITE (Table 2), whereas it shows largest
352 differences compared to CPC. Insufficient observations and uncertainties arising from
353 interpolation techniques generally lead to dry biases in observational datasets (e.g. Dahri *et al*.,
354 2021). An overall general agreement within the satellite data category can be observed. However,
355 IMDAA shows an overestimation compared to satellite products, the exception being IMERG with
356 higher resolution. The precipitation amount and variability for IMERG is highest among satellite
357 datasets, much closer to IMDAA. As satellite observations generally exhibit higher accuracy for
358 convective precipitation over flat terrains (Ebert *et al.,* 2007; Baudouin *et al.,* 2020), their
359 usefulness is limited over the elevated western Himalayan terrain that typically receives more
360 stratiform precipitation (Fig. S2).

361 Wide discrepancies in the geographical seasonal mean precipitation patterns (Fig. 1) among
362 the different categories of datasets can be seen, though with an agreement across the regions of the
363 highest precipitation – the lower Himalayas and foothills. As indicated by the statistics (Table 2),
364 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

480 statistically insignificant trend is observed over some regions of eastern Jammu and Kashmir. The
481 decreasing spatial and temporal trends in the majority of the evaluated datasets support the earlier
482 observed increasing frequency of dry periods in recent years. Earlier, Dimri and Dash (2012)
483 observed a decreasing trend of winter precipitation over the WHR, and a decrease in the winter
484 snowfall has also been reported by Shekhar *et al*. (2010). Overall, the diversity in winter
485 precipitation trends among datasets is largely due to methodological constraints associated with
486 respective dataset development.

487 *c. Seasonal cycle of Precipitation*

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

499 Summarising so far, IMDAA is in agreement with all other reanalysis datasets, particularly
500 ERA5. All datasets agree that the heaviest precipitation falls in February and the weakest is in
501 December. Furthermore, the results reveal that all reanalyses and the gauge-based IMD dataset
502 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.

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

558 *f. Western Disturbances*

559 WDs are upper-level synoptic-scale cyclonic perturbations in the subtropical jet and are the
560 primary contributors of wintertime precipitation over the WHR. About 80% of observed winter
561 precipitation here occurs during days when a WD is active (Midhuna *et al.,* 2020), with the
562 remaining 20% typically being contributed by local scale convective systems. Given the general
563 agreement (Fig. 4) among datasets, including IMDAA, that winter precipitation is declining, and
564 that a large majority of winter precipitation occurs on WD days, we might ask whether the two are
565 linked by a decline in WD frequency. To test this, WDs were tracked in both ERA5 and IMDAA
566 datasets, using two values of spectral truncation (T42 and T63) to account for potential differences
567 in feature size. The trends of tracked WD frequency in these four datasets, along with an additional
568 set of T63 tracks computed using ERAI for Hunt *et al.* (2018), are shown in Figure 8(a). All
569 datasets show a weak and insignificantly increasing trend of winter WDs in the recent decades. An
570 agreement in the pattern of timeseries is observed for coarser grid resolution (T42), but with
571 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.

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

609 *g. Evaluation of dynamical and thermodynamic conditions*

610 As we have seen, winter precipitation over the WHR is primarily associated with WDs. As they
611 are embedded in the large scale sub-tropical westerly jet (200 hPa), WD activity depends
612 significantly on its position and intensity (Krishnan *et al.,* 2019). A comparison of winds at 200
613 hPa for IMDAA with ERA5 shows that IMDAA is realistic in capturing the wintertime subtropical
614 westerly jet (SWJ) over the region (Fig. 10g-i). However, IMDAA produces a weaker SWJ over
615 WHR (Fig. 10i). An assessment of winter-mean climatological conditions of 2-m air temperature
616 (Fig. 10a-c), OLR (Fig. 10d-f) and geopotential heights (Fig. S5) in IMDAA compared to ERA5
617 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

641 the intense WD over WHR (Fig. 11e-h), further supported by abrupt negative OLR anomalies (Fig.
642 11i) during the period indicating increased atmospheric convection. This convective activity plays
643 an essential role in developing secondary circulations during the propagation of WDs and results
644 in heavy localized precipitation over the WHR (e.g. Dimri *et al.*, 2016; Hunt *et al.,* 2019). Our
645 results demonstrate the ability of high resolution IMDAA in representation of realistic evolution
646 of the WD induced cloud cover patterns compared to remotely sensed observations.

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

655 The temporal evolution of these valley winds during the passage of WD is shown for both
656 valley sites in Fig. 12g-h, where an abrupt increase in magnitudes of valley wind speed is observed
657 on 16 February at both locations. This variability is captured in IMDAA, but not in ERA5 where
658 the wind speed is roughly constant during the passage of the WD. Additionally, the effect of the
659 WD passing over the study region is dynamically characterized by an increase of the local
660 minimum temperature (Fig. 12i-j) and a drop in the surface pressure (Fig. 12k-l), which
661 corroborates previous studies (e.g. Rao and Rao, 1971; Singh *et al.,* 2019). Overall, it is clear that
662 IMDAA shows high fidelity in representing local scale wind responses associated with WD
663 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

752 discussed below where n is the total number of observations (daily time series of precipitation), x_i
753 depicts the value for respective evaluation dataset, y_i depicts the value for IMDAA dataset, $\underline{x}$ is
754 the mean for evaluation dataset values and $\underline{y}$ is the mean for IMDAA dataset values.

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

758 $$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (1)$$

759

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

764 $$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \quad (2)$$

765 $$RMSDrel = \frac{RMSD}{\bar{x}} * 100 \quad (3)$$

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

769 $$MAD = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \quad (4)$$

770 $$rMAD = \frac{MAD}{\bar{x}} * 100 \quad (5)$$

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

774 $$BIAS = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i) \quad (6)$$

775 $$rBIAS = \frac{BIAS}{\underline{x}} * 100 \quad (7)$$

776 Adjusted R-squared is defined as:

777 $$Adj.R^2 = 1 - (1 - R^2)\frac{n-1}{n-k-1}$$

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

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