Title: 'ERA5-based database of Atmospheric Rivers over Himalayas'

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Note: The Reviewer comments are copied below verbatim in black color, along with our point-by-point responses in blue color.

Reviewer 1

Dear Reviewer:

Thank you for giving your time to review our work and for your insightful comments and suggestions that have significantly improved the quality of our manuscript.

General comments:

The manuscript is well written and provides an interesting topic of detecting atmospheric rivers (ARs) over Himalayas. However, I think the manuscript is more suitable for a climate research journal (e.g., Journal of climate, International journal of climatology) rather than a data journal. Because Atmospheric river is a character of water vapor transport in the atmosphere, like an index, can be calculated from different data (reanalysis, simulations) and difficult to evaluate the accuracy. And data quality is one of the key standard of the current journal.

Response:

We thank the Reviewer for his/her comment. Although vertically integrated vapor transport (IVT) is calculated using reanalysis data, we do not believe ARs are "calculated", rather they are "detected" i.e., "identified" or/and "tracked". This difference is important in differentiating an index from a dataset. Unlike an index, (e.g., Standardized Precipitation Index or Normalized Vegetation Index, which has one fixed value for a particular day or month, ARs at each timestep form a dataset; at each timestep it includes many characteristics, e. g., its major axis, location, the intensity at each location, its track, its structure, etc. Therefore, we respectfully disagree in labelling an AR as an "index", and strongly believe that our developed dataset of ARs is well suited for ESSD. In fact, since the inception of ARs dataset development, the manuscript has been designed specifically for ESSD.

While replying to Reviewer's other comments below, we provide more details for understanding and recognizing the challenges in AR dataset.

This work calculates the ARs only based on ERA5, i would like to know how it differs if calculated based on other reanalysis data, e.g. MERRA, NCEP, JRA. Do they got the similar results? Which is the best? Such questions need to be answered if the data aims to practical use.

Response:

Several studies have noted that AR detection based on different reanalysis products generally produces similar results in identifying ARs (such as the frequency, length, duration, etc.). We highlight the relevant conclusions from three recent works below.

Nayak & Villarini, (2017), after comparing six reanalysis products (20CRV2, NCEP-NCAR, JRA-55, MERRA, ERA-Interim and NCEP-DOE), concluded that all the reanalysis products generally provided robust identification of AR frequency, along with their characteristics. Similar results were obtained by Brands et al., (2017), who compared ARs from NOAA-CIRES Twentieth Century Reanalysis v2 (NOAA-20C) and ECMWF ERA-20C (ERA-20C) over multiple regions of the globe. They noted that though the difference (using bias and correlation) between the frequency of ARs based on the two products is significant in the early 20th century, it approaches almost zero towards the end of the century, and the correlations between the frequencies are near 1 (see their Figures 7 and 8). Over multiple regions of the globe, Bin Guan & Waliser, (2015) noted that ERA-Interim reanalysis-based and MERRA reanalysis-based ARs showed similar characteristics, with more than 91% temporal matching in their occurrences (see their Figure 5J and L).

Having said that, we believe and agree with the reviewer that studies on comparing ARs based on different reanalysis and detection algorithms can be valuable for forwarding the AR science. However, such inter-comparison analysis needs dedicated studies. As a matter of fact, this is the main goal of the Atmospheric River Tracking Method Project (ARTMIP).

Following the Reviewer's concern, we have added the below text in revising the manuscript on intercomparison of AR data based on different reanalysis and different identification algorithms.

"It may of interest to compare the present ERA5-based AR dataset with ARs from other different reanalysis products and identified using different algorithms, a major objective the Atmospheric River Tracking Method Project (ARTMIP, https://www.cgd.ucar.edu/projects/artmip/). However, since many recent studies have concluded a robust identification of ARs (Nayak & Villarini, (2017), Brands et al., (2017), Guan & Waliser, (2015), Lora et al., 2020, Rutz et al, 2019), we believe the comparison may not help in improving the quality of the dataset and may deviate the reader from the main objective of the manuscript."

Further, ERA5 has hourly resolution, why you use six hourly data? This has disadvantages: 1, it will reduce the accuracy of detecting durations of ARs. 2, if you use instantaneous wind speed to calculate u*q, four times a day could largely differs from 24 times a day, because the atmospheric vapor transport has strong diurnal cycle, especially during monsoon season.

Response:

We thank the Referee for her/his comment. We have used 6-hourly ERA5 datasets because of four main reasons:

(1) This temporal resolution is commonly used in AR-detection algorithms when using global reanalysis products (Nash & Carvalho, 2020; Waliser & Guan, 2017). It is worth mentioning that most climate model simulations for ARs are also archived at this temporal resolution.

(2) Our main goal is to identify ARs in the Himalayas and provide a ready-to-use and easily manageable AR database for AR studies over this region for a sufficiently long period i.e., 37 years. We realize that for such a lengthy duration (including all the seasons) to reduce the data

volume, 6-hourly analysis is sufficient to produce a distinct and manageable database that can be loaded in most of the software on a home desktop machine. In contrast, 1-hourly AR data will consume more RAM due to larger size, thereby reduce the system performance, while only adding marginal information than 6-hourly data. If we carefully assess the benefits of hourly ARs versus 6-hourly ARs, we notice that there are no significant advantages in using hourly observation. For example, since we compute the integrated water vapor transport (IVT) at 4-time steps i.e., 00UTC, 06UTC, 12UTC, and 18 UTC a day, if an AR is identified at any of these time steps say at 06 UTC, five hours before 06 UTC (01, 02, 03, 04, 05 UTC) is considered in the AR duration, but if no AR is identified for one-time step, we will only miss 5-hour analysis in the worst-case scenario.

(3) 6-hourly datasets provide sufficient temporal information to show the gradual evolution of AR over time (Nash et al., 2018; Ramos et al., 2015), rather than abrupt changes.

(4) A previous study (Rutz et al., 2014) has found similar results in mean AR duration when 6-hourly ERA-Interim IVT dataset is used compared to 1-hourly observational-based dataset used by an earlier study (Ralph et al., 2013) for the same study area in Bodega Bay, US West Coast. Another study (Dettinger, 2011) also observed similar results in AR duration when daily observations are used instead of 1-hourly in northern California. Other studies (Guan & Waliser, 2017; Bin Guan & Waliser, 2015; Rutz et al., 2014; Shields et al., 2018) have also shown small differences in AR characteristics (frequency, duration, length, etc.) when temporal resolution of datasets are varied from 6-hourly to 1-hourly or from 6-hourly to 3-hourly or from 6-hourly to 12-hourly.

We have added more information in the revised manuscript (Data Section) to justify the choice of temporal resolution. The text there reads as:

"The 6-hourly interval is chosen for four main reasons 1.) it is a common denominator among AR detection algorithms using atmospheric reanalysis datasets (Brands et al., 2017; Bin Guan & Waliser, 2015; Mundhenk et al., 2016; Rutz et al., 2014), 2) it provides sufficient temporal information on AR events and captures the gradual changes of AR characteristics (Nash & Carvalho, 2020; Ramos et al., 2015), 3.) many studies have found minor differences in ARs based on differing the temporal resolutions (Guan & Waliser, 2017; Guan & Waliser, 2015; Rutz et al., 2014; Shields et al., 2018), and 4.) as compared to 1-hourly data, it is easily-manageable on a

desktop machine with small random access memory (RAM), while marginally compromising on the extent of information available on AR characteristics".

Yes, we agree that atmospheric vapor transport, along with local temperature, exhibits diurnal cycles (Fletcher et al., 2020). With ARs, however, this cycle is generally only marginal, because the source of moisture is most often non-local and related to synoptic-scale features, such as extratropical cyclones and low-level jets. In Ramos et al., (2015), for example, we notice that during all the timesteps of an AR, IVT intensity remained above $300\ kg.m^{-1}.s^{-1}$ and varied consistently between $800-1000\ kg.m^{-1}.s^{-1}$ in the core of the AR (See Figure 6 in Ramos et al., (2015)). Similar observations can be made in other studies (see, for example, Nash & Carvalho, 2020).

The atmospheric vapor transport in ARs is captured reasonably well using 6-hourly intervals, as these time intervals produce maps that show the gradual transformation of AR intensity over time (changes in AR intensity i.e., broadening or weakening or dissipation) (Neiman et al., 2008).

There are many methods to calculate ARs, which will lead to multiple different results when calculating ARs. The method in your manuscripts itself also has some empirical treatments. For example, line 222, why you use 15 days moving average instead of 10 or 20? Is it physical mechanism dependent? The methods and the based data source selected could lead to large uncertainties in the ARs data.

Response:

We agree with the Reviewer that there are indeed many algorithms available to detect ARs. Two recent reviews on comparison of AR algorithms (Lora et al., 2020; Rutz et al., 2019) have highlighted that all AR algorithms provide robust identification of AR features and good agreement in the detection of moderate ($IVT{\sim}500\ kg\ m^{-1}\ s^{-1}$) and strong ($IVT{\sim}700\ kg\ m^{-1}\ s^{-1}$) AR events. These reviews, based on the ARTMIP (Atmospheric River Tracking Method intercomparison Project), also included the algorithm by (Lavers et al., 2012), a modified version of which is adopted in the present study. The major differences among these algorithms come from the exclusion or inadequately identifying “weak” AR features ($< 250\ kg\ m^{-1}\ s^{-1}$); however, $IVT < 250 kg.m^{-1}s^{-1}$ may not be considered “weak” depending on the season and region of interest. The “weak” or less intense ARs are usually found in cold regions like Antarctica, Arctic, and the western Himalaya, or when ARs are just forming or dissipating. These ARs are the ones that account for the major differences among the AR detection algorithms (Lora et al., 2020). Weak ARs are generally excluded by high threshold detection algorithms like Sellars et al., (2017) and Mahoney et al., (2016). For the Himalayan region, we want to identify and include weak ARs in our database as many authors have reported the importance of weak ARs in modulating the hydroclimate of cold regions like Antarctic and Artic (Gorodetskaya et al., 2014; Mattingly et al., 2018; Nash et al., 2018; Wille et al., 2019).

We do not believe that the Lavers et al., (2012) (Lavers) is unique for use over the Himalayas; however, it has a few advantages that appear appealing in the present context. Lavers algorithm is region-specific i.e., a detection transect can be defined precisely at the location required, which will help detect only those ARs that penetrate the Himalayan base. Many algorithms, for example, the Pan & Lu, (2019), require defining a rectangular region and ARs detected within the region may not necessarily impact or cross a specific location of interest. Another advantage of the Lavers algorithm is that it uses a climatology-based threshold, dependent on location and season, which can account for the smaller saturation capacity of ARs in cold season over the Himalayas. Many algorithms, such as Sellars et al., (2017) and Liang & Yong, (2020), use a fixed threshold, $e.g.,$ 750 or 500 $kg.m^{-1}.s^{-1}$, regardless of season and location, which is too extreme to identify “weak” ARs, most likely present in the Himalayas. Many algorithms (Gershunov et al., 2017; Mahoney et al., 2016; Sellars et al., 2017), which track the life cycle of ARs, are complex, and are not suited for the present work, since our aim is provide a database of ARs, not necessarily their origin, moisture sources, and life cycle. In summary, we preferred the Lavers algorithm mainly for its conceptual and computational simplicity.

We have added more information in the revised manuscript. The text there reads as:

“Many algorithms are available to identify or track ARs. The AR Tracking Method Intercomparison Project (ARTMIP) was initiated to compare different AR algorithms using a common reanalysis dataset (Shields et al., 2018). Rutz et al., (2019) found differences among

algorithms when compared in their native configuration (setup), but highlighted the agreements on AR distribution across latitudes in US and Europe when normalized. Lora et al., (2020) then expanded this study globally and found robust agreements among algorithms in identifying "strong" and "moderate" ARs but considerable differences for "weak" ARs. They attributed the disagreement mainly to the high-threshold algorithms that only detect "strong" ARs or identify only the core regions of ARs, while low-threshold algorithms capture overall ARs intensities at different locations, even outside the widely accepted extratropical regions. Here, we modified the algorithm developed by Lavers et al., (2012) to identify ARs over the Himalayas, since the algorithm is conceptually and computationally simple. The algorithm is region-specific and allows for the use of space and time varying thresholds. The algorithm has been successfully employed in many AR studies over the US West Coast (Barth et al., 2017), Europe (Lavers & Villarini, 2015a, 2015b), and the central US (Lavers & Villarini, 2013; Nayak et al., 2016; Nayak & Villarini, 2017). For the Himalayas, we want to identify and include "weak" ARs in our database, as they may have important impacts on regional precipitation, as observed by various studies in cold regions like Antarctic and Artic (Gorodetskaya et al., 2014; Mattingly et al., 2018; Nash et al., 2018; Wille et al., 2019)."

We would like to highlight that all AR-identification algorithms have empirical parameters, see the table below adapted from Rutz et al., (2019) and Shields et al., (2018).

AR-Identification Algorithm name	Parameters	References
AR Detection Methodology (ARTD) Goldenson	Absolute IVT threshold: $250\ kg\ m^{-1}s^{-1}$ Absolute IWV threshold $> 15\ mm$ Length $\geq 1500\ km$ 18 hours (3-time steps for 6-hourly)	(Gershunov et al., 2017)
Guan_Walis	Relative IVT threshold: latitude dependent 85th percentile threshold. Absolute minimum IVT threshold: $100\ kg\ m^{-1}s^{-1}$ for polar locations Length: >2000 km, Length/Width ratio: >2	(Bin Guan & Waliser, 2015)

	IVT direction within 45° of AR shape orientation, poleward direction	
Lavers	Relative IVT threshold: latitude dependent 85th percentile threshold. 4.5° latitude movement allowed	(Lavers et al., 2012)
Ramos	Relative IVT threshold: Latitude dependent 85th percentile Length $\geq 1500\ km$ $<$ 4.5° latitude movement allowed Persistent ARs: 18 hours	(Ramos et al., 2016)
Payne & Magnusdittir	Relative IVT threshold: 85th percentile of maximum IVT Absolute IWV threshold: >2cm Persistent AR: $\geq 12\ hour$ 850 hPa, zonal and meridional winds should be positive and $> 10\ m\ s^{-1}$ Length: $2000\ km$ (the central AR axis) in the zonal direction for landfalling only	(Payne & Magnusdottir, 2015)
Pan & Lu	Dual threshold (relative): Regional: 80% quantile IVT Local threshold: spatially smooth 85% quantile IVT using Gaussian Kernel density technique Length: $> 2000\ km$ Length/Width ratio: > 2	(Pan & Lu, 2019)
Mundhenk	Relative: Latitude dependent IVT percentiles Length: $> 1400\ km$ Aspect ratio: 1:4 Latitudinal limit: 16 N/S	(Mundhenk et al., 2016)

Now, regarding the 15-day-based IVT threshold, we would like to note that the 15-day moving average is considered only to obtain the threshold for a particular day. This 15-day moving average, based on the previous study by Nayak & Villarini, (2017), is used to smoothen the IVT data against any short-term fluctuations, i.e., to exclude the effect of any outlier and/or noise before computing the daily- varying threshold (smooth threshold). We noted that the choice of 10 or 20-day instead of the 15-day moving average threshold does not significantly impact the threshold as shown in Figure R1. Many other studies have used moving averages to remove small-scale perturbations in the data before AR analysis (Dettinger, 2016; Komatsu et al., 2018; Matthews et al., 2018; Payne & Magnusdottir, 2014; Xu et al., 2020).

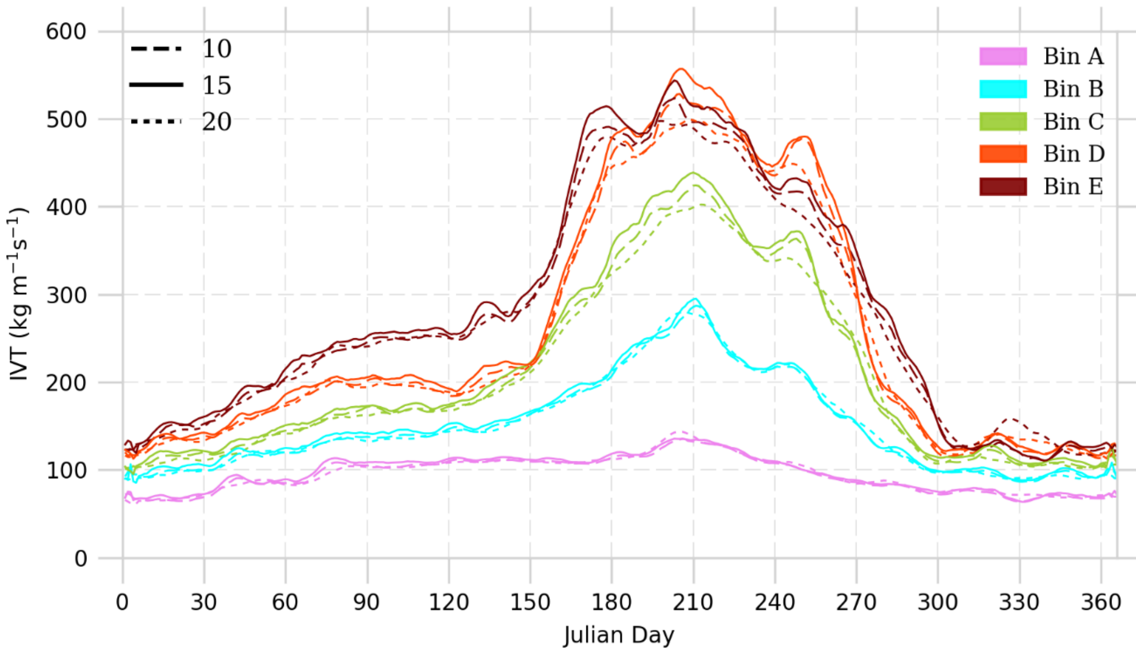

Figure R1: The daily 85th percentile threshold for each bin is shown by different colors (legend on top right) using different moving average constant i.e., 10, 15 and 20-day moving average which is shown by different linestyle (legend on top left).

Why is the threshold of IVT set to different values for different seasons? This will has disadvantages for practical application during disaster research. In such circumstance, for example, you will likely exclude some ARs that will leads to flood in wet season but include some ARs that may not leads to flood in dry season.

Response:

We understand the Reviewer's concern. We have used a time-varying threshold as it provides a meaningful estimate of a points of change (seasonality) in the natural system, with respect to the local climatology, which can have socio-economic impacts and in general influence the regional weather. Since ARs are anomalous moisture transports beyond the regional climatology, the use of time-varying and location-dependent threshold is strongly advocated in the AR literature (Brands et al., 2017; Guan & Waliser, 2015; Lavers et al., 2012; Lavers & Villarini, 2013; Mundhenk et al., 2016), mainly due to large inter-seasonal variability in IVT (Figure R1). By using a large, fixed threshold, adopted in some "strict" algorithms such as Sellars et al., (2017)., we may not find ARs in any season over the Himalayas, except in summer. As in many previous studies over other regions (see for Example Lavers & Villarini, (2013)), we reveal the existence of ARs in winter over the Himalayas, and we note their potential in causing extreme precipitation events. We believe a time-varying threshold is reasonable and required for the Himalayas, since it allows the detection of "weak" to "moderate" ARs (Lora et al., 2020) that can be of importance in the complex Himalayan terrain.

typing error

Line 31:Driver-like => should it be 'river-like'

Response

Yes, it is "river-like", thank you for pointing it out. We have corrected this in the revised submission.

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