Interannual Variability and Seasonality of Precipitation in the Indus River Basin[Ⓢ]

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ABSTRACT

The Indus River basin is highly vulnerable to water scarcity due to increasing population, unsustainable management practices, and climate change. Yet the regional hydroclimate and precipitation dynamics remain poorly understood. Using running trend and spectral analysis with multiple gauge-based, remote sensing, and reanalysis precipitation datasets, this study analyzes precipitation temporal variability, its subregional variations, and the main seasonal drivers, particularly the South Asian monsoon. The results uncover remarkable alternation of long-term positive and negative interdecadal precipitation trends in the basin over the past half century. These trends have led to substantial changes in water input over the region at the time scales comparable to climate assessment periods (30 years), and therefore this high intrinsic variability must be accounted for in climate change adaptation studies. This study also reconstructs onset and withdrawal dates of the South Asian monsoon that exhibit interdecadal variability, but their dominant modes differ from that of annual precipitation. The findings hypothesize that higher-frequency variability in El Niño–Southern Oscillation is likely to have a pronounced impact on monsoon onset and duration in the studied region.

1. Introduction

The Indus River, located in the western and sub-Himalayan region of South Asia, originates in the Tibetan Plateau and flows through the Himalaya–Karakoram–Hindu Kush (HKH) ranges and fertile alluvial plains before discharging into the Arabian Sea. The trans-boundary Indus basin is shared between Pakistan, India, China, and Afghanistan, where the water supply from the surface and groundwater sources serves a population of over 300 million with rapidly growing density and feeds one of the largest irrigation systems in the world (Fowler and Archer 2006; Gilmartin 2015; Immerzeel et al. 2015; Winiger et al. 2005). However, despite its immense significance in sustaining the local economies and societies, the future of water security here is uncertain and unpredictable. Understanding of

the regional hydroclimate—in terms of spatial distribution of precipitation and surface–subsurface hydrology—is inadequate and exacerbated due to the transient climate dynamics observed in the region, where the signals of the change are spatially complex and heterogeneous (Bolch et al. 2012; Immerzeel et al. 2010; Immerzeel et al. 2013; Kargel et al. 2011; Miller et al. 2012; Scherler et al. 2011; Soncini et al. 2015; Yao et al. 2012). Moreover, geo-political, social, and economic challenges result in difficulties in operation of a comprehensive climate monitoring network, poorly established data and information sharing practices, and mismanagement of water resources (Laghari et al. 2012; Shrestha et al. 2014) that introduce further barriers in understanding the local hydroclimate and subsequently addressing water security issues. Yet, there are few regions in the world where the potential impacts of climate change on societies, economies, and environment can be as severe (Chaudhary and Bawa 2011; Qiu 2016; Shrestha et al. 2014). In an overview commentary, Immerzeel and Bierkens (2012) highlighted that for the Indus basin “the vulnerability to water scarcity is the highest in Asia”: climate change,

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accelerated population growth, and unsustainable exploitation of water resources are all expected to impact hydrologic fluxes of the basin in profound ways.

Water resources in the Indus basin depend on complex interactions of various processes including precipitation, evapotranspiration, surface runoff, groundwater, and snow and ice melt. The two main climate drivers, the winter westerlies and the summer South Asian monsoon (SAM), result in significant regional differences in the seasonal hydroclimate (Bolch et al. 2012; Kaab et al. 2012). While the westerlies prevail in the Hindu Kush and western regions of the basin, the South Asian monsoon predominantly governs the Indus Plains and the Himalayas. Previous assessments for the remote Karakoram mountains have qualitatively indicated the significance of both the westerlies and the monsoon but there is a lack of consensus on the seasonal distributions of precipitation (Bolch et al. 2012; Fowler and Archer 2006; Hewitt 2011; Janes and Bush 2012). Furthermore, the near absence of gauges in HKH and the generally poor quality of available in situ data sources have generated inconsistencies in regional precipitation interpolations (Bolch et al. 2012; Hewitt 2005; Palazzi et al. 2013; Winiger et al. 2005). The existence of the markedly different hydroclimates within the basin have often been neglected in past basinwide studies (Rana et al. 2015; Sorí et al. 2017). Previous precipitation trend analyses made conclusions dependent on specific intervals (Archer and Fowler 2004; Palazzi et al. 2013; Singh et al. 2014) that have limited applicability to regional and global change. Moreover, synoptic-scale teleconnections with phenomena such as El Niño–Southern Oscillation (ENSO) have traditionally focused on the larger East and South Asia region (Annamalai et al. 2007; Goswami and Xavier 2005; Li et al. 2018; Stolbova et al. 2016; Sun et al. 2017; Xavier et al. 2007), obscuring the vital details of its effects on SAM arrival, duration, and withdrawal in the Indus basin. The anomalous behavior of hydrometeorological characteristics due to ENSO events exhibit regional differences (Byshev et al. 2012), further emphasizing the need to consider the behavior of monsoon in specific relation to the Indus basin.

In the agrarian section of the basin, where economies and everyday life are driven by seasonal precipitation, understanding its drivers, spatial patterns, and interdecadal trends is a key component for managing and planning water resources (Karki et al. 2011; Lieven 2012). Likewise, understanding the variability and precursors of the “rainy season” associated with the SAM is crucial for agricultural planning, cultivation and harvesting of major crops, and disaster management related to floods and droughts. Building on this need to understand the regional precipitation, the

primary objective of this study is to address precipitation temporal variability over the Indus basin, its subregional variations, and uncertainties—all representing crucial information for the development of robust inferences on the present hydroclimatic regime of the basin and its future. Specifically, the study aims to provide insights into key questions including precipitation variability at meso/subbasin spatial scales and characteristic differences in seasonal cycles over these subregions; the existence of short- (decadal and subdecadal) and long-term (multi-decadal) variability and trends in annual and seasonal precipitation; the temporal dynamics of monsoon onset and withdrawal date as well as its duration; and the existence of detectable links between annual and seasonal precipitation metrics and ENSO. The study also assesses the performance of commonly used precipitation products and their commonalities in terms of how they represent spatiotemporal precipitation distribution, especially in the high-altitude regions of the basin. The approach employs a novel running trend method that covers the entire dataset duration to assess both variability and decadal to interdecadal trends in seasonal and annual precipitation. Furthermore, two new methods are used to extract monsoon onset and withdrawal dates, one based on precipitation thresholds with criteria specific to the Indus basin, and a Bayesian inference approach that detects seasonal changepoints of atmospheric moisture content. In this context, this study aims to provide a more comprehensive overview of precipitation in the basin and improve on the past methods used to analyze trends and derive monsoon arrival/departure dates.

2. Data and methods

a. Indus basin regionalization and datasets

The basin is partitioned into five subregions based on a set of combined topographic, hydrologic, and climatic criteria (Fig. 1a). These regions include the low-lying Indus Plains; the Himalayas, Karakoram, and Hindu Kush ranges which together form the Upper Indus Basin (UIB); and the Hindu Kush Extension mountainous area [the Sulaiman–Kirthar ranges; not further included in the analysis because of the extreme aridity of its environment (Mani 2012) and therefore difficulty in carrying out precipitation variability analysis].

The study uses 12 openly available precipitation datasets including gauge-, satellite-, reanalysis-based, and observation–reanalysis merged precipitation products that are commonly found in the past literature for this region. All datasets have daily or finer temporal resolution and span a minimum of 15 years. The two gauge-based

FIG. 1. Spatial distribution and monthly climatology of precipitation over the Indus River basin. (a) Geographic location and topographic, hydrologic, and glaciological features of the basin. The watershed is delineated into five regions: I, Indus Plains; II, Himalayas; III, Hindu Kush; IV, Karakoram; and V, Hindu Kush Extension. UIB is defined as the region encompassing the Himalayas (II), Hindu Kush (III), and Karakoram (IV) ranges. Precipitation is averaged over the climatological standard normal and period averages for (b) APHRODITE (1981–2007), (c) GPCP 1DD (2001–10), (d) PERSIANN-CDR (2001–10), (e) TRMM (2001–10), (f) CMORPH (CRT) (2001–10), (g) CMORPH (RAW) (2001–10), (h) MERRA-2 (PRECTOT) (1981–2010), (i) MERRA-2 (CORR) (1981–2010), (j) CPC-Unified (1981–2010), (k) ERA-Interim (1981–2010), (l) CFSR (1981–2010), and (m) GMFD (1981–2010). Monthly precipitation climatology is averaged over the same periods for (n) Indus Plains, (o) Himalayas, (p) Hindu Kush, and (q) Karakoram.

products are APHRODITE V1101R1 (Yatagai et al. 2012), which is specific to the monsoon Asia region with a spatial resolution of $0.25^\circ \times 0.25^\circ$ and available from 1951 to 2007, and CPC-Unified (Xie et al. 2007) available from 1979 to 2015 ($0.5^\circ \times 0.5^\circ$). Four satellite or satellite-gauge merged products are used including GPCP (1DD V1.2, from 1997 to 2014, $1^\circ \times 1^\circ$; Huffman et al. 2001); CMORPH V1.0 (Joyce et al. 2004), both raw (RAW) and bias-corrected (CRT) versions (from 1998 to 2015, $0.25^\circ \times 0.25^\circ$); TRMM (TMPA V7 3B42, from 1998 to 2015, $0.25^\circ \times 0.25^\circ$; Huffman and Bolvin 2015); and PERSIANN-CDR (from 1983 to 2014, $0.25^\circ \times 0.25^\circ$; Ashouri et al. 2015). To add further verification on precipitation from products that rely on constraints imposed by the physics of atmospheric dynamics, four reanalysis products are also utilized including ERA-Interim (from 1979 to 2015, $0.25^\circ \times 0.25^\circ$; Dee et al. 2011); NCEP CFSR (from 1979 to 2010, $0.312^\circ \times \sim 0.312^\circ$; Saha et al. 2010); both bias-corrected (PRECTOTCORR, subsequently referred to as CORR) and model generated (PRECTOT) precipitation for NASA MERRA-2 (from 1980 to 2015, $0.5^\circ \times 0.625^\circ$; Bosilovich et al. 2015); and the observation–reanalysis merged Global Meteorological Forcing Dataset for Land Surface Modeling (also known as Princeton Global Meteorological Forcing Dataset, subsequently referred to as GMFD; from 1948 to 2010, $0.25^\circ \times 0.25^\circ$; Sheffield et al. 2006). In addition to precipitation products, the time series of the Oceanic Niño Index (ONI) from Climate Prediction Center (CPC) of NOAA (from 1950 to 2015; Huang et al. 2017) are used as a proxy for ENSO activity to explore its relationship with annual and seasonal precipitation as well as monsoon onset and withdrawal dynamics.

These multiple data sources are characterized by intricate interdependencies, inconsistencies (Sun et al. 2018), and other limitations. Specifically, precipitation products have intrinsic biases due to sparsity of the ground gauge network (in situ observations) because the rugged terrain and hazardous climatic conditions prevent comprehensive monitoring in the UIB; gauges located in valleys that do not capture high-altitude precipitation (Hewitt 2011; Immerzeel et al. 2015; Soncini et al. 2015); inadequate quantification of snowfall and snow water equivalent by ground gauges, satellite retrievals, and model estimates (Kneifel et al. 2010; Mei et al. 2014; Palazzi et al. 2013; Rasmussen et al. 2012); and methodological issues of data assimilation, length time biases, and imperfect physics of models in reanalysis products (Dee et al. 2014). Consequently, the choice of a single representative data product is difficult, and our analysis relies on several datasets. Additional details for the datasets, their shortcomings, and commonalities are presented in the online supplemental material.

b. Precipitation trend analysis

Climatological standard normal and period averages, based on World Meteorological Organization's technical specifications, are used for the subsequent spatio-temporal analysis in the Indus Plains, Himalaya, Hindu Kush, and Karakoram regions. Period averages from 2001 to 2010 are calculated for the four satellite-based products, the period average from 1981 to 2007 is used for APHRODITE due to its available time series ending in 2007, and the climatological standard normal from 1981 to 2010 is used for the remaining products. Trends are determined using a robust nonparametric regression, Theil–Sen estimator (Theil 1950; Sen 1968), in conjunction with the Mann–Kendall test (Mann 1945; Kendall 1948) to determine the significance of monotonic trend at a p value less than 0.1. We study seasonal trends for the two periods corresponding to impact of prominent regional weather systems: the westerlies in winter months, from January through April (JFMA), and the South Asian monsoon in summer months, from June through September (JJAS). Since the precipitation datasets used in the study have different temporal coverages, the analysis is in a format that permits comparisons among the products, also allowing one to differentiate between short- (decadal and subdecadal) and long-term (multidecadal) climate variability in the analyzed series. A running trend approach, based on Brunetti et al. (2012), is used to estimate trends over different periods and assess their significance using consecutive years of the dataset as the starting (x axis in Fig. 4) and ending points (y axis in Fig. 4) of a given interval. For our study objectives, we have imposed a minimum “trend” duration of 10 years to enable use of datasets that have shorter periods of availability (e.g., satellite-based products), while adding to the information pool that exposes short-term variability in the region. However, in general, the running trend analysis removes the need to place a fixed threshold on the length of time series, and the threshold can be tailored to the study objectives, data availability, climate parameters, and/or region-specific challenges.

c. Monsoon onset and withdrawal

Given unavoidable tradeoffs in any identification method, this study explores two approaches to determine the monsoon onset and withdrawal dates for the combined Indus Plains and the Himalayas regions. The Karakoram and Hindu Kush ranges are excluded in this analysis due to the subdued imprint of monsoon precipitation in these regions (Miller et al. 2012). The first method is a precipitation-based approach (based on Zhang et al. 2002), defining a

threshold as the representative value for the winter (JFMA) mean precipitation over the climatological standard normal or period average for the given dataset. The monsoon onset date (between 1 June and 15 August) is defined as the day on which the 5-day running mean precipitation exceeds this threshold and persists for seven consecutive days. Accounting for precipitation variability that can lead to false identification, a second criterion requires that at least 20 days, in any 30-day consecutive period following the onset, must have the running mean precipitation greater than the threshold. Similarly, we define the monsoon withdrawal date (between 15 August and 15 October) as the day on which the 5-day running mean precipitation drops below this threshold and persists for 10 days, without a gap of greater than 5 days between the first two consecutive 10-day spells.

This method eliminates the pitfalls of a fixed threshold value [e.g., 5 mm day⁻¹ in [Ashfaq et al. \(2009\)](#), [Kajikawa et al. \(2012\)](#), [Wang and LinHo \(2002\)](#), [Zhang et al. \(2002\)](#), etc.] and gives due consideration to the spatial differences in precipitation magnitude within the different subregions, accounts for the temporal changes in precipitation due to climate variability as the threshold will change over subsequent climatological standard normal, and allows for compatibility across datasets with different bias characteristics. This approach, relying on the regional changes in precipitation intensity and frequency, is applied for 9 of the 12 data products: APHRODITE, CMORPH-CRT, CPC-Unifed, ERA-Interim, GMFD, GPCP, MERRA-2 (CORR), PERSIANN-CDR, and TRMM datasets. Due to the differences in the data product availability from 1951 to 2015, there are between two and nine product-based estimates of monsoon onset and withdrawal dates. We exclude the uncorrected versions (CMORPH-RAW and MERRA-2 PRECTOT) and the CFSR product due to the issue of well-pronounced inconsistency of estimates for years with well-defined onset and withdrawal transitions (presented in subsequent analysis).

The second approach is a Bayesian inference methodology that detects changepoints of atmospheric moisture content. This approach relies on the regional atmospheric moisture and cloud dynamics using time series of two variables, total cloud cover (TCC) and total column water (TCW), from ERA-Interim reanalysis for the period of 1979–2015. The product of TCC and TCW is used as a proxy of the characteristic atmospheric regime for the Indus Plains and the Himalayas regions. Since the South Asian monsoon advects a significant amount of moisture and alters cloudiness process, the proxy typically exhibits sharp, drastic changes during onset and withdrawal. The Bayesian “changepoint” algorithm of [Ruggieri \(2013\)](#) is

used to compute the corresponding days of the year (DOY). The approach identifies an average linear regression model for piecewise time intervals, locating changepoints when transitions in the mean, trend, and/or variance take place in the analyzed series. As multiple plausible changepoints can be detected within the period of interest, the identified onset and withdrawal dates are set to correspond to the maximum posterior probability within intervals of DOY 152–227 (1 June–15 August) and 244–288 (1 September–15 October) for onset and withdrawal respectively. During the few years when the algorithm results in equal magnitude probabilities, or flat/zero changepoint posterior probabilities, the dates are set as “undefined” (“NaN” in Tables S4 and S5 in the supplemental material).

The results obtained with the two approaches to determine the monsoon onset and withdrawal dates yield estimates that may have varying degrees of agreement in different years. Observed data to validate the computed dates for the specified regions are unavailable and therefore the overall agreement of estimates from the different products and methods, that is, their “convergence,” is used as the criterion to obtain a single, likeliest estimate of onset/withdrawal date. To do that, the Bayesian averaging approach developed by [Tebaldi et al. \(2005\)](#) and modified by [Xu et al. \(2019\)](#) is used to yield a method that accounts for estimate convergence only. Specifically, for each calendar year from 1951 to 2015, individual estimates are assumed to follow Gaussian distribution with identical mean and variances that are specific to each product/method, representing the likelihood distributions. The mean and individual variances are assumed to follow uninformative priors [as in [Tebaldi et al. \(2005\)](#), uniform density on the real line for the mean, and the Gamma distributions for the inverse of square root of variance]. The resultant joint posterior density cannot be integrated analytically, and therefore the Markov chain Monte Carlo (MCMC) method is used to estimate the posterior distribution for the date of monsoon onset or withdrawal [the same MCMC parameters as in [Tebaldi et al. \(2005\)](#) are used in this study]. To address the issue of possible cross dependency of estimates from the various products (and the two methods) on factors that may compound the estimation of monsoon onset and withdrawal transitions, we carried out bootstrapping. One-hundred samples with replacement are drawn from product estimates for the period of 1979–2015 (i.e., when more than three estimates are available), and each of these samples is used in the abovementioned Bayesian averaging procedure. Medians of 100 posterior probability density functions are used to construct 25% and 75% confidence intervals for the date estimate (taken as the median of 100 pdf

medians). Prior to 1979 only two estimates of dates were available and therefore no bootstrapping was carried out.

d. Cross-correlation and spectral analysis

We estimate cross-covariance, cross-correlation, smoothed sample power spectrum and spectral density function, and smoothed coherency spectrum following the algorithms outlined in [Watts and Jenkins \(1968\)](#). To remove the impact of long-term trends in spectral analysis, low frequency variability in the series is filtered through differencing as $y_t = x_t - x_{t-1}$ and the text refers to y_t as the “differenced series.” Parzen lag window ([Parzen 1961](#)) is used to reduce the variance of spectral estimators, leading to smoothed spectral estimates. The lag window size L , the corresponding spectral window bandwidth ($1.86/L$; [Watts and Jenkins 1968](#), p. 256), and 80% confidence intervals ([Watts and Jenkins 1968](#), p. 255) are indicated in all relevant spectrum plots. We also added 95% confidence intervals in plots for cross correlation to offer a more conventional level of correlation magnitude assessment. For spectral analysis, we further exclude the TRMM dataset as short series durations result in wide confidence bounds and thus unreliable estimate of the power spectra. Cross-spectral analysis includes only the two longest datasets: APHRODITE and GMFD.

3. Results

a. Precipitation spatial distribution and seasonality

The spatial distribution of annual precipitation over the basin ([Figs. 1b–m](#)) exhibits a region of sharp gradient that delineates the areas of low ($<300 \text{ mm yr}^{-1}$, Indus Plains and Karakoram) and high ($>700 \text{ mm yr}^{-1}$, Himalayas) precipitation (Table S3). Multiple datasets [including APHRODITE, CMORPH (CRT), CPC-Unified, GMFD, GPCP, MERRA-2 (CORR), PERSIANN-CDR, and TRMM] show a rather similar spatial pattern. However, noticeable differences in the annual (Table S3) and seasonal ([Fig. S2](#)) magnitudes are present. The GPCP 1DD and PERSIANN-CDR ([Figs. 1c,d](#)) precipitation products exhibit spatial and magnitude similarity despite the coarser resolution of GPCP, likely because the latter uses the GPCP product for bias correction ([Ashouri et al. 2015](#); [Dimri et al. 2015](#)). PERSIANN-CDR and GMFD ([Fig. 1m](#)) products show smoothing of spatial features as compared to TRMM ([Fig. 1e](#)), CMORPH ([Fig. 1f](#)), and APHRODITE ([Fig. 1b](#)) that all feature relatively higher spatial variability within the Himalayas. There is a strong correlation between the gauge-based CPC-Unified ([Fig. 1j](#)) and the reanalysis MERRA-2 (CORR) ([Fig. 1i](#)) products due to

the CPC-Unified bias-correcting scheme applied to MERRA-2 (PRECTOT; [Bosilovich et al. 2015](#); [Reichle et al. 2017](#)). The uncorrected MERRA-2 product shows high precipitation zones in the western Karakoram ([Fig. 1h](#)), which is uncharacteristic of the region. ERA-Interim precipitation distribution over the Himalayas has larger magnitudes than any of the other products [3.48 mm day^{-1} averaged over the region as compared to 3.11 mm day^{-1} for CFSR and 3.07 mm day^{-1} for MERRA-2 (PRECTOT), not shown], also extending into adjacent regions ([Fig. 1k](#)), while the CFSR product exhibits spurious undulations in the precipitation pattern ([Fig. 1l](#)).

The relative seasonality in the four subregions is illustrated in [Figs. 1n–q](#). The various datasets exhibit highest consistency for the relatively topographically uniform Indus Plains ([Fig. 1n](#)). In this lowland area, precipitation falls predominantly during the summer monsoon (JJAS), contributing nearly 66%–77% of the annual total. A much lower fraction during the winter (JFMA) months constitutes nearly 16%–20% (Table S3). Overall, there is an agreement in the seasonal distribution across the products and the fractional composition is nearly invariant. The satellite-based estimates tend to be higher, followed by reanalysis estimates that have higher magnitudes in JJAS months but resemble the gauge-based products in the remaining months ([Fig. 2a](#)). The annual magnitudes also show consistency among the datasets, where satellite-based products (GPCP and PERSIANN in particular), show relatively higher magnitudes ([Fig. 3a](#)).

The Himalaya region is evidently the wettest among considered, with an average annual precipitation of approximately 600–1270 mm (Table S3). The precipitation of the region exhibits a dominance of the monsoon contribution to the annual precipitation ([Fig. 1o](#)) but with a larger spread of estimates: 51%–63% is during summer months compared to 20%–34% of winter precipitation, except for the CFSR product that shows marginally higher winter contribution (41.2%) compared to summer precipitation (40.3%). Reanalysis estimates generally form the upper envelope of the seasonal cycle, with distinctly higher magnitudes in winters, as compared to the gauge- and satellite-based averages ([Fig. 2b](#)). While nearly all the products associate maximum precipitation in the monsoon period with the month of July, the winter precipitation is resolved differently depending on the product family: satellite-based products show winter peak in February, whereas gauge-based and reanalysis datasets show the peak in March. The magnitudes are consistent with past studies in the region; for example, [Palazzi et al. \(2013\)](#) determined July peak at $\sim 5 \text{ mm day}^{-1}$ for APHRODITE and TRMM, $5.5\text{--}6 \text{ mm day}^{-1}$ for GPCP, and a much higher estimate of 10 mm day^{-1} for ERA-Interim.

FIG. 2. (a)–(d) Monthly precipitation climatology specific to a product family. Gauge-based average (dark blue) is the mean of APHRODITE and CPC-Unified; satellite-based average (red dotted) is the mean of GPCP 1DD, PERSIANN-CDR, TRMM, and CMORPH (CRT); and reanalysis product average (green dashed) is the mean of CFSR, ERA-Interim, and MERRA-2 (CORR). The time series are averaged over the period specified in Fig. 1.

CFSR and ERA-Interim have higher annual magnitudes, while the bias-corrected MERRA-2 and GMFD are closer in magnitudes to the gauge-based products (with MERRA-2 CORR practically overlapping CPC trendline; Fig. 3b).

For Hindu Kush (Fig. 1p), there is an agreement among the datasets in terms of significance of the westerlies (except for CMORPH RAW and CRT): nearly 43%–58% of the annual precipitation falls during the winter months, while 14%–35% during JJAS. However, the spread of both the absolute magnitudes and fractional estimates is larger than for the two previously considered regions with the summer precipitation and annual totals in this region showing higher coefficient of variation (at 0.22 and 0.42, respectively; Table S3). ERA-Interim has the highest annual magnitude while CPC (and similarly MERRA-2 CORR) and CMORH-CRT with the smallest annual precipitation magnitude (Fig. 3c). Like the Himalayas, the reanalysis products show higher magnitudes, especially in the winter months, than the gauge- and satellite-based datasets. The winter peak is estimated either in February (satellite-based) or March (gauge-based and reanalysis; Fig. 2c).

Annual precipitation estimates for the Karakoram highlight the large uncertainty of existing data products

for this region with the coefficient of variation of annual estimates 0.64 (Table S3). This vast disparity is also visible in Fig. 3d where ERA-Interim and CFSR show much higher annual precipitation magnitudes as compared to other products, while the gauge-based products (and MERRA-2 CORR) have smaller magnitudes. CMORPH-CRT has an atypical behavior with inconsistent pattern as compared to the other products and the lowest precipitation values. The monthly climatology of the region (Fig. 1q) also shows higher variation among the data products, especially during the winter months (e.g., for the month of March, the precipitation magnitude ranges between $0.057 \text{ mm day}^{-1}$ for CMORH-CRT and 3.64 mm day^{-1} for CFSR, not shown). The satellite- and gauge-based products show higher fractional precipitation during JJAS (41%–69%), while the seasonality inferred from the reanalysis products exhibits nearly equal or somewhat larger contribution during the winter months (34%–48%; Table S3). The reanalysis products show higher magnitudes in winter months, as compared to the satellite- and gauge-based products that are smaller by more than 50% (Fig. 2d), an observation that is consistent with previous studies (Immerzeel et al. 2015; Lutz et al. 2014). The differences in terms of absolute magnitude and peak timing matches those observed for the other regions.

FIG. 3. Annual precipitation time series for (a) Indus Plains, (b) Himalayas, (c) Hindu Kush, and (d) Karakoram. The uncorrected versions of MERRA-2 (PRECTOT) and CMORPH (RAW) are not included.

From the initial set of 12 products, we select five for the trend analysis: APHRODITE, ERA-Interim, GMFD, PERSIANN-CDR, and TRMM. Specifically, because of the spurious spatial irregularities in the CFSR (Fig. 1l) and MERRA-2 uncorrected (Fig. 1h) products, and inconsistent climatology of the CMORPH datasets with gross underestimation of magnitudes (Mei et al. 2014), especially in the Karakoram and Hindu Kush regions (Figs. 1p,q), we exclude these products from the subsequent analyses. Furthermore, the bias-corrected version of MERRA-2 is analogous to CPC-Unified at monthly scale (Figs. 1i,j), both grossly underestimating precipitation as compared to the other products especially in the UIB (Fig. 3 for CPC/MERRA-2 CORR and Table S3). GPCP exhibits similar spatial characteristics (Figs. 1c,d) and approximate magnitudes (Table S3) to PERSIANN-CDR but has a lower spatial resolution and a shorter record. Based on our observations of similarity or limitations of these datasets, we exclude them from further analysis and proceed with the selected subset of the five products.

b. Annual trends

The long-term annual precipitation series reveal alternating interdecadal positive and negative trends (Fig. 4). The dominant contributions to precipitation variability for the Indus Plains and the Himalayas are low-frequency

oscillations of 15–20-yr periods as well as high-frequency modes of 2.5–3-yr periods (Figs. 5a,b). This explains the observed interdecadal and interannual variability and what can be perceived as short-term trends (this can also be qualitatively observed in the 10-yr moving average plots in Fig. S6). For the Indus Plains, a maximum positive trend of $0.27\text{--}0.51\text{ mm day}^{-1}\text{ decade}^{-1}$ (depending on the data product) started during mid-1980s and lasted through mid to late 1990s (Fig. 4a), when a short-term reversal led to a period of precipitation decrease (from -0.89 to $-0.48\text{ mm day}^{-1}\text{ decade}^{-1}$) before another increase in precipitation magnitudes in late 1990s/early 2000s. A similar temporal pattern can be observed for the Himalayas (Fig. 4b), with $0.41\text{--}0.97\text{ mm day}^{-1}\text{ decade}^{-1}$ increase from the mid-1980s to mid-1990s (with relatively fewer windows of statistical significance) and a strong reversal in the 1990s that resulted in the maximum decline from -1.68 to $-1.13\text{ mm day}^{-1}\text{ per decade}$ (particularly pronounced in the ERA-Interim and PERSIANN products). The Hindu Kush region exhibits a somewhat different pattern of interannual dynamics: the dominant contributions to long-term precipitation variability are low-frequency oscillations of 20–25-yr period and 3.5-yr modes (Fig. 5c), with nearly equal contributions of fluctuations of shorter periods (higher frequencies). A statistically significant long-term positive trend for this region started in the 1960s and lasted through the 2000s, with

FIG. 4. Running trend analysis of annual precipitation for (a) Indus Plains, (b) Himalayas, (c) Hindu Kush, and (d) Karakoram. The x axis is the starting year, while the y axis is the ending year of the analyzed trend period (a minimum assessment duration of 10 years is imposed). The circle color represents the sign of the slope (red is a negative trend and blue is a positive trend); color shading represents the magnitude of the slope ($\text{mm day}^{-1} \text{ decade}^{-1}$; the darker the color, the steeper the trend slope). The larger circles indicate statistically significant slopes at $p < 0.1$.

the maximum rate of $0.53\text{--}0.96 \text{ mm day}^{-1} \text{ decade}^{-1}$. Like other regions, a reversal in the pattern took place in the 1990s, resulting in precipitation decrease at the rate from -1.42 to $-0.78 \text{ mm day}^{-1} \text{ decade}^{-1}$ (Fig. 4c). ERA-Interim shows somewhat different behavior than other products where the negative trend extends further back (starting from 1979 when the ERA-Interim time series starts, as is also the case for Himalayas in Fig. 4b). As before, the Karakoram region exhibits the highest disparity among the products: while the features of the time series resemble the other regions, the analysis indicates mostly nonsignificant trends; ERA-Interim shows a significant (decreasing) trend starting from the

1980s to mid-1990s and ending in the 2000s (Fig. 4d), with the maximum rate of $-0.59 \text{ mm day}^{-1} \text{ decade}^{-1}$, while PERSIANN-CDR also shows few windows of statistically significant decreasing trend.

A prevalent feature observed in the Plains and Hindu Kush is a pronounced rise in annual precipitation starting in the early 2000s, reaching the maximum of $0.53\text{--}0.96$ and $0.66\text{--}1.1 \text{ mm day}^{-1} \text{ decade}^{-1}$, respectively. Both the Himalayas and Karakoram regions show sparse windows of statistically significant positive change (the respective maxima are $0.38\text{--}0.5$ and $0.25\text{--}0.45 \text{ mm day}^{-1} \text{ decade}^{-1}$ visible for PERSIANN and TRMM in Figs. 4b and 4d). This behavior follows a short-term, subdecadal period

FIG. 5. (a)–(d) Smoothed spectral density function of annual precipitation (original series). Original (i.e., non-differenced) time series are used in all subplots. The lag window size of 16 was used in the estimation of all spectra. Parzen window bandwidth (identical for all spectra) and confidence intervals (different for all products) are indicated in (d). Confidence intervals are shown at 80%.

of strong decline in annual precipitation that commenced in 1997/98 (visible in Fig. 3, particularly in the Indus Plains for all products; Fig. 3a).

c. Seasonal trends

To better understand the role of seasons in the identified interdecadal trends, we separate winter (JFMA, Fig. S4) and summer (JJAS, Fig. S5) seasons. Monsoon precipitation is the dominant component in the annual budgets of the Indus Plains and the Himalayas regions (Figs. 1n,o) and thus the covariation between summer and annual variability is high (the cross correlation between JJAS and annual precipitation is 0.88–0.95 for the Indus Plains and 0.69–0.89 for Himalayas, maximum at lag zero, not shown). The positive incline in JJAS precipitation beginning in the 2000s is present across all the datasets in the Indus Plains (Fig. S5a), although interannual variability for the Himalayas introduces substantial noise (mostly nonsignificant trends). This post-2000 significant wetting behavior in the summer precipitation has also been observed in north-central India by Jin and Wang (2017). It is noteworthy that in the Indus Plains winter precipitation also exhibits an increase over the past decade and half (Fig. S4a), contributing to the sharp increase of annual totals. This shift in precipitation magnitudes in the 2000s, preceded by the strong post-1997/98 decline, points to the possibility

that one of the strongest ENSO events in recorded history (Karl et al. 2015; Wolter and Timlin 1998) might be responsible for both annual and seasonal precipitation variability in the Plains, while for UIB the signals of change are more difficult to interpret perhaps because of high-mountain climate and orographic precipitation or data limitations in representing precipitation structure in such areas (explained in “Dataset shortcomings” in the supplemental material). Our analysis reveals relatively moderate cross correlations between the ONI and summertime precipitation series (Figs. 6a,b): as low as -0.42 at zero lag, and as high as $+0.42$ at positive lag 1, implying negative covariation within the same year and 1-yr forward positive correlation of summer precipitation for both Indus Plains and Himalayas with ENSO activity. Overall, the influence of ENSO on precipitation in this region appears to be confined to a frequency band corresponding to short-term oscillations of 2.5–4-yr periods (Fig. 7a).

In the Hindu Kush region, trends in the annual precipitation are explained by the dynamics of winter precipitation as the dominant component (with cross correlation between JFMA and annual precipitation at lag zero varying between 0.73 and 0.86, not shown). For the Karakoram region, annual precipitation exhibits a wider range of cross correlations with winter (0.66–0.87) or summer (0.55–0.81, not shown) totals, reflecting again

FIG. 6. Correlation analysis of JJAS precipitation over the (a) Indus Plains and (b) Himalayas regions with ENSO activity and JFMA precipitation over the (c) Hindu Kush and (d) Karakoram regions with ENSO activity using the differenced annual time series. “CI” refers to confidence intervals: 80% (inner whiskers) and 95% (outer whiskers).

either a greater uncertainty of the data or mixed contributions of the two seasons to the annual total. Winter precipitation in Hindu Kush (Fig. S4b) yet again shows a prominent positive trend post-2000. A noteworthy feature for the latter two regions is the

presence of positive cross correlations of up to +0.5 (depending on product) between ENSO intensity (ONI) and winter precipitation (JFMA) at positive lag of one year (Figs. 6c,d). As above, such a relation signifies positive carryover effect of ENSO anomalies,

FIG. 7. Spectral and correlation analysis of ONI index and monsoon onset date and duration for the combined Indus Plains–Himalaya region. (a) Smoothed coherency spectrum between ENSO ONI series and annual/JJAS precipitation for APHRDITE (green) and GMFD (blue). (b) Smoothed spectral density estimates for monsoon onset and duration (both differenced and non-differenced series) with 80% confidence interval. (c) Smoothed coherency spectrum between ENSO ONI series and monsoon onset/duration. (d) Sample cross-correlation function between ENSO ONI series and monsoon onset/duration. Panels (b)–(d) use monsoon onset and duration series (Fig. 8) for the combined Indus Plains and Himalayas regions. Detailed spectral and correlation analysis is provided in Fig. S7.

FIG. 8. Trend analysis of monsoon onset dates, withdrawal dates, and duration for the combined Indus Plains-Himalaya region. (left) Time series and (right) running trend analysis for the 1951–2015 period for (a) onset, (b) withdrawal, and (c) duration. On the left-hand side of (a) and (b), the y axis is DOY; the black lines show the median onset/withdrawal DOY, and the shaded region is the 5%–95% region of posterior estimates. On the left-hand side of (c), monsoon duration is calculated as withdrawal date less onset date (Tables S4 and S5). On the right-hand side of (a) and (b), shades of red indicate trends of earlier monsoon onset/withdrawal, while shades of blue represent trends of delayed onset/withdrawal. On the right-hand side of (c), shades of red indicate shortening monsoon duration (delayed onset and/or early withdrawal) and shades of blue indicate increasing monsoon duration (early onset and/or delayed withdrawal). For all three plots, the slope unit is in days per year, and the large circles indicate statistically significant slopes at p value < 0.1 .

confined to a frequency band corresponding to 3–4-yr oscillations (not shown).

d. Monsoon analysis

Understanding the dynamics of the monsoon system is of high importance because of its key role in the basin's precipitation budget, where even minor changes in the onset and withdrawal of precipitation can have pronounced impacts on the water resources of the region. However, the analysis of trends of the monsoon onset

and withdrawal dates is difficult due to their interannual and interdecadal variability, typical of climates with well pronounced seasonality (Fatichi et al. 2012). The derived 1951–2015 time series of monsoon onset dates (Fig. 8a and Table S4) illustrates this behavior: stationary (in the mean) periods alternate with intervals of positive and negative trends, with the overall interannual variability reaching approximately 48 days. The analysis of Fig. 8a indicates the presence of alternating trend periods that have statistical significance: the

first period (positive, blue color) starts in the 1950s and ends in 1970, the second (positive) starts in the early 1970s and ends in early 1990s, and the third period (negative, red color) starts in the late 1970s and continues through 2015. These three periods exhibit the respective maximum rates of 2, 2.8, and $-2.83 \text{ days yr}^{-1}$. In between the first and the second trend periods, there is a negative interdecadal trend. The third period starting in the late 1970s is prominent because it extends over much longer duration resulting in the early onset of monsoon, and approximately coincides with the beginning of a period of abrupt increase in global (land and ocean) surface temperatures (Hansen et al. 2010; Karl et al. 2015; Ruggieri 2013). Prior to the 2000s, the onset patterns moderately correlate with annual and seasonal precipitation for the Indus Plains with cross correlations of the series reaching -0.34 and -0.46 at lag zero (annual and JJAS respectively, not shown), implying that a delayed onset also had the tendency to be associated with lower annual and JJAS precipitation. However, the dominant contributions to the onset date variability are rather different from those characteristic of precipitation variations: one can infer the presence of low-frequency oscillations of 25–30-yr periods and contributions of ~ 4 -yr and higher (~ 2.5 years) frequency modes (Fig. 7b). The maximum (zero lag) cross correlation between the ONI and monsoon onset date series is ~ 0.4 and for duration series is -0.4 , that is, stronger El Niño causes onset delay and shorter duration (Fig. 7d). Coherent oscillations are pronounced in the frequency bands corresponding to cycles of ~ 2.5 – 4 -yr periods, and larger than 30-yr periods (Fig. 7c). This implies that while ENSO variability contributes to short- and longer-term variations of monsoon onset dates in the Indus basin, other drivers, yet to be identified, have impacted nearly bidecadal trends of the onset and its year-to-year variations (Thapa et al. 2018).

Monsoon withdrawal date series also exhibits nearly 48-day (Table S5) variation over the analyzed period. The withdrawal dynamics appear to be mostly “decoupled” from the analyzed series of monsoon onset and summer precipitation over the region, showing mostly nonsignificant trends, and potentially implying different mechanistic causes. Starting from the late 1990s through 2015, the withdrawal trends show an earlier departure of the monsoons from the region by a maximum rate of $-1.2 \text{ days yr}^{-1}$ (Fig. 8b). The general pattern of monsoon duration trends matches that of monsoon onset; an earlier onset tends to correspond with a prolonged duration and vice versa (Fig. 8c). Periods starting from the late 1970s to early 1990s and ending from the 2000s to 2010s showed significant increase in monsoon duration with a maximum of 3.4 days yr^{-1} .

4. Discussion and conclusions

This study highlights the complex region- and time-dependent dynamics of precipitation in the Indus River basin. Specifically, we investigated the contributions from the two main drivers of spatial and seasonal variability in precipitation: the winter precipitation and the South Asian monsoon. To do so, we analyzed commonly used precipitation products available for the region and discussed the observable issues of individual data products, especially in the high-mountain regions. We subsequently carried out a running trend analysis that reduces the dependence of conclusions on the availability interval of a specific product or a set duration. Finally, we carried out a novel reconstruction of regional monsoon onset and withdrawal dates to understand the interannual and interdecadal changes in the commencement and duration of monsoon and its effects on the seasonal precipitation. The analysis of ENSO activity targeted the exploration of its impact on monsoon temporal dynamics.

We uncovered strong, alternating positive and negative interdecadal precipitation trends in various parts of the basin, which have resulted in substantial changes in water input. These trends are expressed over the time scales of 20–30 years, making them comparable to the periods used in climate assessment studies. They likely represent an outcome of internal (frequently referred to as intrinsic) climate variability and highlight the sensitivity of precipitation signal analysis when it is confined to a specific time interval (Fatichi et al. 2016). We therefore stress the need to account for variability in climate change studies in this region. While the reasons for these multidecadal trends are yet to be fully understood, there is an apparent contribution of ENSO variability to higher frequency oscillations in the precipitation totals. Further, the impacts of 1997/98 extreme El Niño episode appear to have triggered similar type of precipitation response in the region: a subdecadal decrease and a subsequent increase of precipitation over the Indus Plains, where the South Asian monsoon has the most dominant seasonal contribution. Given the current projections of increasing frequency of extreme El Niño events (Cai et al. 2014), future precipitation in the region is likely to exhibit even higher variations. The analysis of interdecadal trends in the monsoon onset and withdrawal dates in the Indus Plains and the Himalayas regions show their relative decoupling from each other. Onset dates exhibit interannual variations coherent with higher frequency ENSO. However, longer-period variability of monsoon dates is yet to be understood. A connection between the monsoon onset/duration and the strength of ENSO had been

hypothesized earlier for the entire South Asian monsoon region (Goswami and Xavier 2005), and we made a connection here by observing coherent oscillations in the frequency bands corresponding to cycles of ~2.5- and 4-yr periods. The spatial and seasonal analysis of precipitation over the four regions present a compelling case for giving due consideration to spatial differences when basinwide studies are carried out. We found considerable differences in both the seasonal structure and magnitudes, which would have been otherwise masked were the analysis carried out at a larger spatial scale. Furthermore, a cursory examination of precipitation datasets also yielded interesting conclusions. Specifically, we found that the Karakoram region shows the highest spread in annual precipitation estimates among the various products, with gauge- and satellite-based products showing higher fractional precipitation during the summer months, while reanalysis products showing larger contribution during the months of January–May. Additionally, interdependent products have nearly identical spatiotemporal features (e.g., MERRA-2 CORR and CPC-Unified, GPCP and PERSIANN-CDR), while certain datasets have quite uncharacteristic behavior (e.g., both the raw and corrected versions of CMORPH and CFSR, in particular), where they fail to adequately capture the spatial and/or seasonal patterns of precipitation.

The study relies on multiple precipitation products and methods that, nonetheless, have limitations. From the analysis of dataset sources and their interdependencies as well as features of seasonal distributions, we conclude that caution should be exercised in interpretation of any given product, especially for regions such as HKH with complex orography and climatology. Based on the results and the lack of ground-truth data of high accuracy, we believe there is no “single best” precipitation data product that can represent precipitation in the region adequately. Therefore, budget estimates can be strongly biased when a sole dataset is used for water input assessments. All precipitation products are likely to have large biases in the high-altitude areas of UIB and the disparity of estimates for these regions was illustrated here. Moreover, observational network changes over time may also manifest in trend analysis, introducing spurious shifts and uncertainties (Beck et al. 2017), as indicated in studies for other regions (Ferguson and Villarini 2012; Ferguson and Mocko 2017; Hamlet and Lettenmaier 2005). Improvement of quality and reliability of datasets necessitates densification of the gauge network at the higher altitudes of the HKH region or representation of orographic precipitation in models. The identification of monsoon onset and withdrawal dates through Bayesian averaging of multiproduct,

two-method estimates yielded small variance of the posterior probability density functions for most years. Some years, however presented challenges because of inconspicuous transitions to/from the monsoon. Monsoon withdrawal dynamics may exhibit gradual subsiding nature, making date determination challenging.

There are intricate linkages between economic sustainability, livelihood security, and water resources in the Indus basin and its neighboring watersheds. Precipitation plays a critical role in agricultural practices and dynamics of surface and groundwater resources. Therefore, an improved understanding of this variable provides crucial insights for water and climate policy measures. A refined analysis accounting for uncertainties in these main drivers is therefore necessary for climate vulnerability assessments, hydrometeorological disaster management, and questions of regional water and food security. This study has important implications for understanding the spatiotemporal behavior and patterns of precipitation in the Indus basin, which feeds into variability assessment for water resources in the region. Furthermore, the analysis framework in this study can also be used for other basins in the larger Himalaya–Karakoram–Hindu Kush region to construct a synoptic-scale hydroclimate characterization of the westerlies and the monsoon precipitation.

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