Dominant Controls of Cold-Season Precipitation Variability Over the High Mountains of Asia

Moetasim Ashfaq (✉ mashfaq@ornl.gov)

Oak Ridge National Laboratory <https://orcid.org/0000-0003-4106-3027>

Shahid Mehmood

Academia Sinica <https://orcid.org/0000-0002-0963-526X>

Sarah Kapnick

Geophysical Fluid Dynamics Laboratory,

Subimal Ghosh

Indian Institute of Technology Bombay

Muhammad Adnan Abid

Abdus Salam International Centre for Theoretical Physics <https://orcid.org/0000-0002-7389-7977>

Fred Kucharski

Abdus Salam International Centre for Theoretical Physics

Fulden Batibeniz

Institute for Atmospheric and Climate Science, ETH <https://orcid.org/0000-0002-1751-3385>

Anamitra Saha

Indian Institute of Technology Bombay

Katherine Evans

Oak Ridge National Laboratory

Huang-Hsiung Hsu

Academia Sinica <https://orcid.org/0000-0001-9919-4404>

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1 Dominant controls of cold season precipitation variability over the high mountains of Asia

2 Shahid Mehmood^{1,2,3}, Moetasim Ashfaq^{*1}, Sarah Kapnick⁴, Subimal Gosh⁵, Muhammad Adnan Abid⁶, Fred
3 Kucharski⁶, Fulden Batibeniz^{1,7}, Anamitra Saha⁸, Katherine Evans¹, Huang-Hsiung Hsu²

4
5 ¹ Computational Sciences and Engineering Division (CSED), Oak Ridge National Laboratory, Oak Ridge, TN, USA

6 ² Earth System Science Program, Taiwan International Graduate Programme, Research Center for Environmental Changes
7 (RCEC), Academia Sinica, Taipei, Taiwan

8 ³ Institute of Atmospheric Physics, College of Earth Science, National Central University, Zhongli, Taiwan.

9 ⁴ Geophysical Fluid Dynamics Laboratory, Princeton, NJ, USA

10 ⁵ Department of Civil Engineering, Indian Institute of Technology Bombay, India

11 ⁶ Earth System Physics, Abdus Salam International Centre for Theoretical Physics, Trieste, Italy

12 ⁷ Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland

13 ⁸ Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA
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33 *Corresponding Author

34 Moetasim Ashfaq

35 mashfaq@ornl.gov
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Abstract

A robust understanding of the sub-seasonal cold season (November–March) precipitation variability over the High Mountains of Asia (HMA) is currently lacking. Here, we identify dynamic and thermodynamic pathways through which natural modes of climate variability establish their teleconnections over the HMA. First, we identify evaporative sources that contribute to the cold season precipitation over the HMA and surroundings areas. The predominant moisture contribution comes from the mid-latitude regions including Mediterranean/Caspian Seas and Mediterranean land. Second, we establish that several tropical and extratropical forcing display a sub-seasonally fluctuating influence on the cold season precipitation distribution over the region, and given that many of them varyingly interact with each other, their impacts cannot be explained exclusively or at seasonal timescales. Lastly, a single set of evaporative sources cannot always be identified as the only determinant in propagating a remote teleconnection, because nature of moisture anomalies and its sources depend on the pattern of sub-seasonally varying dynamical forcing in the atmosphere.

Introduction

The High Mountains of Asia (HMA) include mountain ranges of Himalayas, Karakoram, Hindukush in South Asia, and Pamir and Tian Shan in Central Asia, which are home to over 100 mighty peaks that reach the sky over 7000 meters above the sea level. Except for the eastern and central Himalayas, a significant fraction of the annual precipitation over these mountains and surrounding valleys is received during the cold season (November–March), which regulates the largest non-polar glacial mass, also known as the Water Towers of Asia. The meltwater from these mountains serves as one of the major sources of river recharge for several river basins in Asia, including; Brahmaputra in eastern Himalayas^{1,2} (>65%), Ganges in central Himalayas^{1,3} (~48%) Indus in western Himalayas and Karakoram^{4,5} (>60%), and Amu-darya and Syr-darya in Pamir (>70%)⁶. The region encompassing the HMA is quite susceptible to high inter-annual climate variability^{7,8}. To this end, while the runoff through meltwater is relatively more sustainable source for river flows as glaciers partially buffer extreme dry conditions in year-to-year precipitation variability⁹, this source of freshwater is now considered threatened due to a persistent rise in global temperatures¹⁰. Consequently, economies in the downstream regions of Asian mountains that heavily depend on the irrigated agriculture through meltwater dependent river flows^{11,12} and the hydropower generation⁹ are now considered vulnerable due to the uncertainty surrounding the future of seasonal snow accumulation and overall glacial mass in the coming decades. Therefore, a clear knowledge towards processes dictating climate variability and change over the HMA is imperative for the sustenance and sustainability of regional social-ecological systems.

Most of the winter precipitation over the HMA comes through the eastward moving extratropical cyclones, known as the Western Disturbances (WDs)¹³. Given that the HMA are in a landlocked region, WDs are the key mechanism that transport moisture from distant water bodies and terrestrial areas. They interact with the Indian subcontinent warm air mass and topography to produce precipitation that falls as rain over the lower elevations and valleys, and as snow over the higher elevations. The trajectories and the strength of WDs, which determine the amount of moisture that is distributed as precipitation across the mountains in Central and South Asia^{14,15}, are influenced by the positioning and strength of the subtropical westerly jet over the region. Several earlier studies establish that natural climate forcing, including El Niño-Southern

Oscillation (ENSO) and North Atlantic Oscillation (NAO), have a positive influence on the winter precipitation variability over this region^{16,17,18,19,20}, linking it to enhanced moisture transport from surrounding water bodies (Arabian, Mediterranean and Caspian Seas)^{21,22} into the region during the positive phase of NAO^{23,24,25} and ENSO^{22,23,24,26}. However, recent studies demonstrate a lack of spatiotemporal robustness in these teleconnections²². For instance, one study suggests a dipolar pattern of NAO influence with negative association over the Pamir Mountains and a positive association over the Karakorum and Himalayas²⁷. Another study determines that direct ENSO teleconnection over this region lacks sub-seasonal persistence, and that tropical Indian Ocean plays a key role in regulating the positive ENSO forcing via inter-basin interactions²². A role of contemporaneous atmospheric wave activity in the Atlantic and Eurasian regions that, in addition to NAO, gives rise to several recurrent atmospheric circulation patterns such as East Atlantic Mode (EAM), East Atlantic/West Russia pattern (EAWR), Scandinavian pattern (SCAND), has also been suggested in precipitation variability over the region comprising of the HMA²⁸. Likewise, Siberian High (SH), which is a semipermanent feature in the Northern Hemisphere, is also known to have influence on the precipitation distribution over the HMA²⁹. However, a clear understanding of the collective influence of these modes of climate variability is currently lacking. In fact, these complementary and/or competing paradigms reflect knowledge gaps that need to be bridged for more rigorous understanding towards the cold season precipitation variability over the HMA.

One important aspect of the cold season climate over the HMA that has received relatively less attention is the identification of complementary moisture sources that contribute to the regional precipitation. Only very recently, a couple of studies have taken on this topic using Eulerian water-source tagging capability in a Global Climate Model (GCM)³⁰ or by employing a Lagrangian modeling approach on a few years of reanalysis data³¹. However, method-based uncertainties in moisture source identification, such as those arising from the use of single simulated or reanalyzed data, different water vapor tracking approaches, and relatively short analysis periods warrants the need for further studies to establish comprehensive understanding in this regard. Moreover, these studies have primarily focused on Central Asia and do not fully cover the region encompassing the HMA. More importantly, no study thus far has systematically evaluated thermodynamic pathways through which abovementioned modes of natural climate exert influence on precipitation variability over the HMA. A reevaluation of remote teleconnections over this region is also necessary due to the lack of consensus among previous studies regarding their influences.

Therefore, the major aims of this study are 1) to establish more robust understanding of evaporative sources that contribute to the cold season precipitation over the HMA and surroundings areas, 2) to reevaluate remote teleconnections that exert an influence on precipitation variability over the HMA during the cold season, and 3) to explain remote teleconnections in terms of anomalies in atmospheric circulations and moisture transport. For this purpose, this study employs a Lagrangian moisture tracking algorithm to identify major evaporative sources and examines their intra-seasonal variability over the HMA at climatological scale in multiple reanalysis datasets. Furthermore, a multi linear regression analysis is used to elucidate relative influences of various modes of natural climate variability on the cold season precipitation over the HMA, and to unravel dynamic and thermodynamic pathways through which their teleconnections are established.

Results

Moisture Sources

Most of the cold season precipitation over the HMA is distributed in the western Himalayas, Karakoram, Hindukush, and Pamir Mountain ranges (Fig. S1). The evaporative source domain of this study (Fig. 1a) provides up to 97% of the moisture for this precipitation, which is shown as the recycling ratio or the fraction of moisture falling as precipitation in a specific grid cell that originated as evapotranspiration from the entire source region (Fig. 1b). Note that these estimates are based on the averages of ERAI, ERA5, and MERRA2, while their individual magnitudes are shown in Figure S2 which display close correspondence. The average recycling ratios based on regional contributions are shown in Figure 2 for the most prominent sources, and Figure S3 shows the individual contributions from all regions separately for ERAI³², ERA5³³ and MERRA2³⁴. Every sub-region provides moisture, but the major contribution comes from the Mediterranean/Caspian Seas, Mediterranean land, local recycling, North Atlantic and Indian Ocean. The strongest influences of the Mediterranean/Caspian Seas, Mediterranean land and North Atlantic are displayed in the west-northwest where each of these three regions contribute up to 42%, 36% and 14% to the total seasonal precipitation respectively. The contribution from these three regions gradually decreases down to 5% going from west to east. On the other hand, the strongest footprint of local recycling is seen over eastern Nepal (up to >50 % of the seasonal total) with a gradual decrease in contribution to 25% and less while going west over the Hindukush mountains and beyond. The Indian Ocean contribution is the strongest over relatively dry regions in southwestern Pakistan and Uttar Pradesh region in India where it contributes up to 35% of the total seasonal precipitation. The spatial distribution of regional contributions displays close correspondence across three reanalyses with most of their differences within $\pm 5\%$. The most noticeable disagreement exists in the case of local recycling where its relative contribution is >10% lower in MERRA2 than that in ERAI and ERA5 over the Himalayas and Karakoram (Fig. S3).

Moisture contributions from individual sources exhibits intra-seasonal variations (Fig. 3). Some disagreements in the sub-seasonal magnitudes of regional contributions also exist across the reanalysis datasets. More than half of moisture comes from the Mediterranean/Caspian Seas and Mediterranean land throughout the cold season. The amount of moisture from the Mediterranean/Caspian Seas reduces to almost half (~20%) of what they contribute in the early part of the season (~35%). In contrast, an increase of 15–20% is seen from the Mediterranean land by the end of the season. Up to 50% decline in contribution from the Indian Ocean is also witnessed from its peak in January (~14%). The local recycling is also the strongest towards the end of the season (~18%) while moisture contribution from North Atlantic remains steady throughout the season (~10%). Noticeable disagreements among reanalysis are present for moisture contributions from the Mediterranean/Caspian Seas and local recycling (up to $\pm 4\%$). Nonetheless, all datasets display similar pattern of relative contributions and intra-seasonal variability from each source region (Fig. 3). Given that there is no consequential disparity among the reanalysis (Figs. 3, S2, S3), we perform rest of the analyses using the average of three datasets.

Influence of natural modes on precipitation variability

Several natural modes of climate variability (see *Methods*) exert influences on year-to-year variations in monthly precipitation amounts during the cold season, as the R^2 magnitudes and areas with significant F-test statistics predominantly display gradual improvements throughout the season, highlighting the importance of each predictor in elucidating the drivers of precipitation

variability over the study region (Fig. S4). However, the explained variance is relatively low in February and to some extent in January over most of the study area. In the MLR model for total recycled precipitation, the relative comparison of standardized partial regression coefficients across predictors and months reveals several important details (Fig. 4). First, TWEIO is the most prominent and persistent forcing throughout the cold season that exhibits statistically significant positive influence on precipitation variability in several months with the strongest teleconnection in December. Only exception is in March where TWEIO influence over parts of the Tien Shan mountains is significantly negative. SCAND is the other forcing that exhibits relatively persistent (though not always significant) positive influence throughout the season with exceptions over the parts of Hindukush mountains in November and central Himalayas in January. The strongest, widespread, and statistically significant negative influences are exerted by EAM in December and January over most of the region. Except for Himalayas, EAM teleconnection is also negative in February. SH footprints are conspicuously comparable to EAM though relatively subdued during these three months, with exceptions over the Himalayas in February. Other modes also exhibit sparingly noticeable but spatiotemporally varying influences on the recycled precipitation. Among them, statistically significant negative influences are displayed by ENSO over parts of the Hindukush and Pamir Mountains in November and December, and by EAWR (NAO) over the central Himalayas in January (November). Similarly, statistically significant positive influences come from NAO over the Karakoram, Hindukush, and Pamir Mountains in November, from EAWR over the Hindukush and Pamir Mountains in December, and from SH over the parts of Karakoram, Hindukush, and Pamir Mountains in March. Overall, the mix of spatiotemporally varying tropical and extratropical influences on the precipitation distribution over the HMA highlights inherent complexity of precipitation teleconnections that perhaps is one of the causes for the limited seasonal predictability skill over this region³⁵.

Dynamical and thermodynamical pathways of remote teleconnections

The intra-seasonal thermodynamical and dynamical pathways through which tropical and extratropical forcings exert their influences can be explained by examining related monthly anomalies in moisture contributions from individual evaporative sources and overlying circulation anomalies that facilitate anomalous moisture transport. Note that the key feature of atmospheric circulations over the HMA during the cold season is the presence of subtropical westerly jet^{36,37} that guides the movement of WDs over the region. The changes in the strength or positioning of the Jetstream can be manifested using the anomalies in atmospheric winds and geopotential height at 200 mb while changes in the moisture contribution from source regions can be explained using the anomalies in regionally recycled precipitation. Therefore, to provide physical explanation of intra-seasonally and/or spatially varying influences exerted by each mode of natural climate variability, we construct separate MLR models for 200 mb geopotential height, zonal winds, and meridional winds, and for recycled precipitation from individual source regions, using same set of predictors employed in the total recycled precipitation MLR (see *Methods*). The complete analysis of the standardized partial regression coefficients is shown in the supplementary information (Figs S5-S12) while we focus on only a few prominent cases in the main figures (Figs.5-7) to elucidate the major findings.

Across all the modes and months, TWEIO exhibits the strongest influence in December. A statistically significant strengthening of subtropical westerly jet (Fig. 5a; negative geopotential height anomalies) is witnessed in December with anomalous center located over the study region that stretches in semi northwest-southeast orientation. The pattern of anomalous atmospheric wave

train also intensifies the eastward moisture flow over the midlatitudes. As a result, these atmospheric anomalies lead to a statistically significant increase in moisture supply from the midlatitude source regions including the Mediterranean/Caspian Seas, Mediterranean land, and northern Eurasia, in addition to enhanced moisture advection from the Indian Ocean. The local recycling also exhibits an increase due to excessive precipitation (Fig. 5b-g). The strengthening of subtropical westerly jet is also present in January but with anomaly center now located on the west of the study region that stretches diagonally over the Arabian Peninsula and northern Africa (Fig. 5h). However, it is now accompanied by a weak atmospheric ridge over the midlatitude source regions east of Atlantic which undermines the eastward moisture flow from the western Mediterranean Sea. Overall, such atmospheric anomalies limit the statistically significant increase in moisture advection from the mid-latitude source regions to the western flank of the low pressure, while favoring enhanced moisture transport from the tropical Atlantic, Indian Ocean and Africa (Fig. 5i-n; S5). Particularly, the enhanced moisture transport from the African land is spatially widespread and mostly statistically significant (Fig. 5n). Perhaps what is most striking to note in these results is that no single set of moisture source regions can be identified as the key driver of TWEIO influence over the HMA, as it is the pattern of atmospheric anomalies that dictates where the excess moisture would come from. The atmospheric anomaly pattern varies month to month (Figs. 5, S6) and so does the anomalies in moisture from individual source region (Figs. 5, S5), which in turn dictate the spatiotemporal variability in the TWEIO influence.

The strongest and widespread negative influence is displayed by EAM in December and January (Fig. 4). In January, two statistically significant high-pressure centers emerge, one over the study region and one over the central Europe, which is zonally elongated over the Atlantic sector Fig. 6a). These EAM-induced atmospheric anomalies mutually limit moisture advection over the HMA from all source regions (Fig. 6b-g), leading to a significant reduction in monthly precipitation (Fig. 4e3). A similar but slightly shifted and less strong pattern of atmospheric anomalies also emerges in December (Fig. S6), causing a significant but relatively less precipitation reduction (Fig. 4e2). While the overall structure of EAM-induced zonally elongated high-pressure cell over Europe persists throughout the cold season, the strength and location of atmospheric high over the study region substantially varies during rest of the season, leading to insignificant or spatially heterogeneous precipitation responses in other months (Figs. 4, S6-S7). The pattern of SH teleconnection in January exhibit peculiar similarity with that of EAM (Fig.4), which is a result of correspondence in the dynamic and thermodynamic anomalies induced by these two modes of climate variability (Figs. S7-S8).

As previously noted, SCAND is the only other forcing after TWEIO that exhibits relatively persistent (weak positive) influence throughout the season. The atmospheric anomalies induced by SCAND tend to strengthen westerly flow all the way from the Mediterranean Sea to Russia, which diagonally transverses western parts of the study regions (Figs. 6f, S6). This pattern of circulation anomalies fundamentally persists throughout the season with some variations in magnitude that explains relative persistence of SCAND teleconnection. Considering the SCAND influence in February, two zonally connected low pressure cells, one over the east Atlantic and one over the northwest of the HMA (Fig. 6f) increase moisture advection from midlatitude evaporative sources over the Hindukush and Pamir Mountains through the eastern flank of the atmospheric low (Fig. 6g-j), leading to a positive teleconnection of SCAND over those regions. Alternatively, moisture intrusion from the subcontinent land and Indian Ocean is limited over the western flank of the atmospheric low. Given the northwest location of the SCAND-induced atmospheric low during the cold season over the study region, its positive influence is less noticeable over the Himalayas

(Figs. 4, S9). Likewise, EAWR teleconnection over the HMA is relatively more significant over the Karakoram, Hindukush, and Pamir Mountains (Fig. 4). The only exception is in January where it exerts significant negative influence over the Himalayas. The main features of EAWR-induced atmospheric anomalies exhibit a southeast-northwest dipole of high- and low-pressure cells over the study region that display spatiotemporal variability in their patterns and strength (Fig. S6). Interestingly, unlike other natural modes variability where sources of moisture anomalies may vary sub-seasonally, the EAWR influence propagates relatively persistently over the HMA through the climatologically leading moisture source regions (Mediterranean/Caspian Seas, Mediterranean land; Fig. S10).

The most prominent influences of NAO and ENSO are displayed in November (Fig. 4), which are also spatially counteracting. During the positive NAO phase, a trough (ridge) forms over Central Asia (India) (Fig. 7a) in November that facilitates enhanced (reduced) moisture transport from the Indian Ocean, East Africa, and mid-latitude regions to the north-northwest parts (central Himalayas) (Fig. 7b-g), while an opposite pattern of atmospheric and moisture anomalies appears during the positive phase of ENSO (Fig. 7h-n). With few exceptions, the ENSO and NAO influences are relatively unremarkable during the rest of the cold season (Figs. 4, S11, S12). Overall, the remote teleconnections over the HMA are a combination of compounding or counteracting influences that are often spatiotemporally superimposed on each other.

Discussion

The interplay of tropical forcing and several internal modes of climate variability in the Northern Hemisphere plays a key role in precipitation variability over the HMA. Throughout the cold season, statistically significant positive correlation exists between the two tropical forcing i.e., ENSO and TWEIO (Table 1). Note that TWEIO reflects the strength of east-west precipitation anomaly dipole in the tropical Indian Ocean in response to disruption in the Walker circulation in the Indian sector^{22,38}. It should not be confused with the Indian Ocean Dipole (IOD) that represents the dipole pattern of sea surface temperature anomalies in the Indian Ocean and is mostly active during the summer and fall seasons. A significant relationship between TWEIO and sea surface temperatures anomaly in the equatorial central Pacific has been reported in recent studies²², suggesting that TWEIO is likely an outcome of ENSO forced inter-basin interactions via atmospheric link. Such interannual modality of tropical climate variability induces anomalous diabatic heating in the atmospheres over equatorial central Pacific and the tropical Indian Ocean, as precipitation distribution deviates from its mean in these parts of oceanic basins. As a result, eastward propagating Rossby waves are generated with origins in equatorial central Pacific and tropical Indian Ocean that have an impact on extratropical circulations^{38,39}. These waves not only interact with each other but also with the internal atmospheric modes of variability such as NAO, EAM etc²⁸. These interactions during the Northern Hemisphere winter are reflected in the statistically significant monthly correlations between tropical forcing (ENSO, TWEIO) and several of these modes used in this study. When monthly sea level pressure anomalies are regressed onto the ENSO and TWEIO indices, the spatial patterns shows that ENSO projects on NAO in November, EAM in November–January and EAWR in December. Similarly, TWEIO also projects on these modes in several months (Fig. 8). Note that sea level pressure regressions show close resemblance between ENSO and TWEIO for all months, as they exhibit persistent high correlations. These patterns reveal that there are several pathways through which ENSO can exert its influence over a distant region. In the case of HMA, ENSO teleconnection is a combination of

direct and indirect influences, where indirect influences come through inter-basin connection (TWEIO) and interactions of ENSO and TWEIO with internal modes of variability in the Northern Hemisphere, including NAO, EAM and EAWR.

The influences of SH over the HMA also comes through multiple pathways, as it exhibits interplay with other internal atmospheric modes of variability in the Northern Hemisphere. Apparently, the two tropical forcings and SH operate quite independently, as their indices lack significant correlations (Table 1). However, strong interactions between SH and other internal modes of variability (EAM, EAWR and SCAND) are displayed through statistically significant correlations in several months. Monthly patterns of sea level pressure regressions onto EAM and EAWR (Fig. S13) reveal a low-pressure pattern over Mongolia and Siberia – the vicinity of SH maxima – that explains significant out of phase relationships of SH with these modes in several months. The sea level pressure regression onto SH also shows that it negatively projects on EAM and EAWR throughout the cold season (Fig. 8). A weak (significant) positive projection of SH on NAO (SCAND) is also displayed in November (December). Given the spectacle of interactions within the extratropics and interactions between the tropics and extratropics, it is anything but clear that the impacts of tropical forcings and internal atmospheric modes of northern hemisphere climate on the HMA precipitation cannot be explained exclusively. What makes it even more intriguing is the fact that several of these modes of climate variability can co-exist at seasonal scales²⁸, and when superimposed, can either compound or compensate each other's impact.

The lack of spatiotemporal persistence in several teleconnections also points towards the fact that previously established scientific perspectives on the role of natural modes of climate variability, such as ENSO and NAO, in seasonal precipitation variability over the HMA are largely equivocal. The analyses described in this study amply demonstrate not only that an individual mode can have opposing influences within a season, but also that its teleconnection may be a combination of multiple varying pathways. Moreover, a single set of evaporative sources, such as climatologically prominent moisture sources, cannot always be identified as a key determinant in propagating a remote teleconnection through excess or inadequate moisture transport over the HMA, because nature of moisture anomalies and its sources depends on the pattern of sub-seasonally varying dynamical forcing in the atmosphere. While moisture anomalies form the two most prominent sources (Mediterranean/Caspian Seas and Mediterranean land) are undoubtedly key to the establishment of these relationships, oftentimes, complementary or contrasting contributions from other moisture sources also play an important role. For instance, note that moisture from Africa, tropical Atlantic and northern Eurasia contributes only ~5% to the total at climatological scale over the parts of Karakorum, Hindukush, and Himalayas, but their relative roles in propagating remote influences in several months over these regions are reasonably remarkable when compared to those of climatologically prominent moisture sources (Figs. 4, S5-S12).

An important aspect that may not be ignored is the existence of relatively large unexplained variance in February (Fig. S4). While our analyses are limited in what can be inferred from them in this regard, they provide notable clues that may be useful for more targeted analyses in future research endeavors. A large portion of the explained variance during the cold season comes from tropical forcings which is largely absent in February, as ENSO and TWEIO display little influence on the precipitation variability over the HMA²². Also, note that February is the only month with no significant correlation between tropical forcings and mid-latitude atmospheric modes of northern hemisphere, suggesting the importance of tropical-extratropical interactions in the propagation of planetary scale teleconnections.

Nonetheless, our analyses provide more comprehensive evaluation of sub-seasonal precipitation variability over the HMA during the cold season. Specifically, we establish robust understanding of the terrestrial and oceanic moisture sources over the HMA during the cold season and demonstrate a key role of moisture recycling over the midlatitude regions, which is also partly supported by findings in recent studies²⁸. Further, we note that several natural modes of climate variability have a sub-seasonally fluctuating influence on the cold season climate over the HMA and given that a number of these modes varyingly interact with each other, their impacts should not be studied exclusively or at seasonal timescales. In fact, an individual mode can have opposing influences within a season, and that its teleconnection may be a combination of multiple varying pathways. The dynamic and thermodynamic pathways dictating the variability of cold season precipitation over the HMA are admittedly as complex as the region itself, and while our analyses partly unravel their complexity, further analytical and modeling studies are needed to fully characterize the underlying mechanisms. The fact that half of the moisture recycles from the terrestrial sources during the cold season (Figs. 2, 3, S3) highlights the potential importance of land-atmosphere interactions that should be systematically explored in future studies.

Methods

Datasets

We use three reanalysis datasets: the European Center for Medium-Range Weather Forecast (ECMWF), Reanalysis (ERA-Interim)³², available at $0.75^\circ \times 0.75^\circ$ horizontal grid spacing, the National Aeronautics and Space Administration-Global Modeling and Assimilation Office (NOAA) Modern-Era Retrospective Analysis for Research and Application Version 2 (MERRA-2)³⁴, available at $0.5^\circ \times 0.625^\circ$ horizontal grid spacing, and the European Reanalysis version 5 (ERA5)³³ available at $0.25^\circ \times 0.25^\circ$ horizontal grid spacing. The ERA5 and MERRA2 are remapped to the ERA-Interim horizontal grid before their use. For moisture back trajectory analyses, we obtained four variables from each reanalysis: daily evapotranspiration, daily precipitation, six-hourly vertically integrated eastward moisture flux, and six-hourly vertically integrated northward moisture flux. For the rest of the analyses, we obtain six monthly variables from each reanalysis: precipitation, sea level pressure, geopotential height, zonal winds, meridional winds, and sea surface temperature. All datasets cover 1980–2018.

Note that the use of reanalyzed precipitation in moisture back trajectory analysis is necessary for it to be consistent with the reanalyzed moisture fluxes and evapotranspiration used in the determination of evaporative sources, as observed precipitation is often not well aligned with the reanalysis at daily timescale. An inaccurate understanding of the relative contribution from various evaporative sources may be established if large disparities exist between reanalyzed and observed precipitation. The use of multiple reanalyses minimizes the possibility of such inaccuracies. Apart from that, most of the HMA region is infamous for very low density of ground stations network⁴⁰ and poor satellite-based enhancements in precipitation estimates⁴¹. Therefore, there is no way to conclude that gridded daily observations are superior to the reanalyzed precipitation over the HMA. In fact, the three datasets that provide observed daily precipitation for this region have less agreement among themselves relative to the agreement among the reanalysis (Fig. S1).

Moisture back trajectory analyses

We use a modified version of the Dynamic Recycling Model (DRM) – a Lagrangian moisture tracking algorithm– to determine the moisture sources that contribute to the cold season precipitation over the HMA. Previously, we have employed it in several studies over South Asia⁴², Mediterranean⁴³ and Arabian Peninsula. The model was originally developed by Dominguez et al (2006)⁴⁴, which was modified to remove reliance on parameterization^{44,45,46}. The version used in the current study is detailed in Mei et al (2015)⁴². It assumes a well-mixed atmosphere and therefore makes use of vertically integrated zonal and meridional moisture fluxes. This assumption is reasonable over regions with low atmospheric shear, such as the HMA during the cold season. Note that the use of data assimilation in reanalysis may lead to a violation of moisture conservation assumption, however, Dominguez et al (2006)⁴⁴ note that it does not have noticeable impact on the results. The moisture back trajectory analyses have been performed from 1 October through 31 March continuously. The month of October is discarded to account for the residence time of moisture vapor in the atmosphere. Our analyses span over 38 seasons, starting with the cold season from 1 November 1980 to 31 March 1981 and ending with the cold season from 1 November 2017 to 31 March 2018.

For this study, we make use of evaporative source region between 60°W–90°E along the longitudes and 0°N–60°N along the latitudes, which is divided in Nine exclusive but complementary moisture sources (Fig. 1a). The sub-division broadly separates known oceanic basins and large water bodies to ensure relatively accurate attribution of precipitation over the study region to remote sources. Most subdivision of terrestrial regions are based on the homogeneity of precipitation seasonality within a sub-region during the November to March season. The 9 subdivisions are defined as: 1) Study region – land in Central and South Asia that receive significant amount of cold season precipitation, 2) Indian Ocean – grids between 30°E–90°E and 0°N–30°N that include Indian Ocean, Arabian Sea, Bay of Bengal, Persian Gulf and Red Sea, 3) tropical Atlantic – Atlantic ocean between 0°N–20°N and 60°W–30°E, 4) Mediterranean/Caspian Seas – water grids that cover Mediterranean Sea, Black Sea, Caspian Sea and Aral Sea, 5) Mediterranean land – land between 25°N–40°N and 20°W–60°E, 6) Africa– land between 0°N–25°N and 20°W–60°E, 7) Subcontinent land – land grid points in India and Pakistan that are not part of the study region, 8) northern Eurasia – land grids up to 60°N, covering Europe (excluding Mediterranean land region), Russia and China, and 9) North Atlantic – ocean grid points between 20°N–60°N and 60°W–20°E.

Multi linear regression analyses

We use seven internal and/or inter-annual modes of natural climate variability in a multi linear regression model (MLR) to investigate the variability of cold season recycled precipitation. These modes are defined as: 1) ENSO –the standardized Nino 3.4 index, which is the area averaged detrended sea surface temperature anomaly over the equatorial Pacific Ocean (5°S–5°N, 170°–120°W), 2) Tropical Western/Eastern Indian Ocean precipitation dipole (TWEIO)^{22,38} – the standardized differences of detrended area averaged precipitation over the tropical western (40–80°E; 10°S–10°N) and eastern (90–140°E; 10°S–10°N) Indian Ocean, 3) SH – the standardized area averaged detrended sea level pressure over 40–65°N; 80–120°E, 4–7) the standardized indices of NAO, EAM, EAWR and SCAND from the Climate Prediction Center (<https://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml>), which are based on the rotated principal component analyses of mean standardized 500-mb geopotential height anomalies over

20–90° N latitudinal band. The spatial pattern of the last four indices is shown in Figure S2 using the monthly sea level pressure regression onto each of these indices. All variables used in these analyses are based on the average of ERAI, ERA5 and MERRA2. We employ Variance Inflation Factor (VIF) analysis to determine the multicollinearity in the model and note that the MLR model does not suffer from this issue as VIF corresponding to all independent variables remains less than 1.5. The importance of each of the seven predictors is determined by comparing coefficient of determination (R^2) and F-test statistics (Fig. S3).

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose

Author Contributions

M.A. supervised the research. S.M. collected data. S.M. and M.A. performed analyses. All authors were involved in discussions of the results. M.A. and S.M. prepared the manuscript with contributions from all co-authors.

Data Availability

The reanalysis and observations data used in this study is freely available.
ERA5: <https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5>
ERAI: <https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-interim>
MERRA2: <https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/>
PERSIANN: <https://www.ncei.noaa.gov/products/climate-data-records/precipitation-persiann>
CHIRPS: <https://www.chc.ucsb.edu/data/chirps>
APHRODITE: <https://www.chikyu.ac.jp/precip/english/downloads.html>

Figures Captions

Figure 1. The evaporative source region, seasonal (November–March) recycling ratio and recycled precipitation. (a) The evaporative source region with its subdivisions. (b) Seasonal fraction (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapotranspiration (filled contours) over the evaporative source region (recycling ratio), and corresponding recycled seasonal precipitation (mm/day; line contours). This analysis is shown as an average of results from ERA5, MERR2 and ERAI over 1981–2018.

Figure 2. **Seasonal (November–March) recycling ratio and recycled precipitation from individual source region.** Seasonal fraction (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapotranspiration (filled contours) over the individual evaporative source subregions, and corresponding recycled seasonal precipitation (mm/day; line contours). a) Mediterranean/Caspian Seas, b) Mediterranean land, c) local recycling, d) Indian Ocean, and e) North Atlantic. This analysis is shown as an average of results from ERA5, MERR2 and ERAI over 1981–2018.

Figure 3. **Climatological Intra-seasonal variability of the recycled precipitation from individual source regions.** Percent contribution from individual source regions to the total recycled precipitation at intra-seasonal (5-day running mean) timescale. The lines represent average of three reanalyses and shaded area represents range across them. Only regions with contributions exceeding >6% during the season are shown.

Figure 4. **Monthly standardized partial regression coefficients associated with the natural modes of climate variability (independent variables) in the multi linear regression model.** Each coefficient describes monthly standardized anomaly in the total recycled precipitation per unit monthly anomaly in the corresponding standardized natural mode of climate variability while holding all other modes constant.(a1–a5) ENSO, (b1–b5) TWEIO, (c1–c5) SH, (d1–d5) NAO, (e1–e5) EAM, (f1–f5) EAWR, (g1–g5) SCAND. Stippling represents statistical significance at 90% confidence level.

Figure 5. **Standardized partial regression coefficients associated with the TWEIO in the multi linear regression models.** Standardized partial regression coefficients of geopotential height, zonal and meridional winds (a), and regionally recycled precipitation (b–e) on TWEIO index for December. Four selected evaporative source regions are shown that exhibit most prominent statistically significant relationship. (f–j) Same as in (a–e) but for January. Standardization of regionally recycled precipitation is with respect to the total recycled precipitation. Stippling represents statistical significance at 90% confidence level.

Figure 6. Same as in Figure 5 but for EAM in January (a–e) and for SCAND in February (f–j).

Figure 7. Same as in Figure 5 but for NAO (a–e) and ENSO (f–j) in November.

Figure 8. **Linear regression of sea level pressure anomalies onto the natural modes of climate variability.** Regression of the monthly detrended sea level pressure anomalies onto the standardized indices of ENSO (1st column), TWEIO (2nd column), SH (3rd column). Stippling represents statistical significance at 95% confidence level. All regression coefficients are standardized.

Table 1. Pearson simple cross correlations between indices at lag 0. Note that four EOF-based indices (NAO, EAM, EAWR and SCAND) are orthogonal to each other.

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Figure 1. **The evaporative source region, seasonal (November–March) recycling ratio and recycled precipitation.** (a) The evaporative source region with its subdivisions. (b) Seasonal fraction (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapotranspiration (filled contours) over the evaporative source region (recycling ratio), and corresponding recycled seasonal precipitation (mm/day; line contours). This analysis is shown as an average of results from ERA5, MERR2 and ERAI over 1981–2018.

[Recycling Ratio and Precipitation]

Figure 2. **Seasonal (November–March) recycling ratio and recycled precipitation from individual source regions.** Seasonal fraction (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapo-transpiration (filled contours) over the individual evaporative source subregions, and corresponding recycled seasonal precipitation (mm/day; line contours). a) Mediterranean/Caspian Seas, b) Mediterranean land, c) local recycling, d) Indian Ocean, and e) North Atlantic. This analysis is shown as an average of results from ERA5, MERR2 and ERAI over 1981–2018.

Figure 3. **Climatological (1981–2018) intra-seasonal variability of the recycled precipitation from individual source regions.** Percent contribution from individual source regions to the total recycled precipitation at intra-seasonal (5-day running mean) timescale. The lines represent average of three reanalyses and shaded area represents range across them. Only regions with contributions exceeding >6% during the season are shown.

Figure 4. **Monthly standardized partial regression coefficients associated with the natural modes of climate variability (independent variables) in the multi linear regression model.** Each coefficient describes monthly standardized anomaly in the total recycled precipitation per unit monthly anomaly in the corresponding standardized natural mode of climate variability while holding all other modes constant. (a1–a5) ENSO, (b1–b5) TWEIO, (c1–c5) SH, (d1–d5) NAO, (e1–e5) EAM, (f1–f5) EAWR, (g1–g5) SCAND. Stippling represents statistical significance at 90% confidence level.

Figure 5. **Standardized partial regression coefficients associated with TWEIO in multi linear regression models.** Standardized partial regression coefficients of geopotential height (colors), zonal and meridional winds (contours) (a), and regionally recycled precipitation (b–g) on TWEIO index for December. Six selected evaporative source regions are shown that exhibit most prominent statistically significant relationship. (f–n) Same as in (a–g) but for January. Stippling represents statistical significance at 90% confidence level.

Figure 6. **Standardized partial regression coefficients associated with EAM and SCAND in multi linear regression models.** Same as in Figure 5 but for EAM in January (a–g) and for SCAND in February (h–n).

Figure 7. **Standardized partial regression coefficients associated with NAO and ENSO in multi linear regression models.** Same as in Figure 5 but for NAO (a–g) and for ENSO in November (h–n).

Figure 8. **Linear regression of sea level pressure anomalies onto the natural modes of climate variability.** Regression of the monthly detrended sea level pressure anomalies onto the standardized indices of ENSO (1st column), TWEIO (2nd column), SH (3rd column). Stippling represents statistical significance at 95% confidence level. All regression coefficients are standardized.

Index-1	Nov	Dec	Jan	Feb	Mar	Index-2
ENSO	0.59	0.68	0.61	0.55	0.46	TWEIO
ENSO	0.29	-0.15	-0.15	-0.15	0.19	SH
ENSO	0.39	0.18	-0.05	-0.17	0.06	NAO
ENSO	0.50	0.32	0.36	0.28	0.28	EAM
ENSO	0.11	0.49	0.25	0.15	-0.07	EAWR
ENSO	0.28	0.14	-0.18	0.06	0.04	SCD
TWEIO	-0.07	-0.08	-0.09	0.06	-0.24	SH
TWEIO	0.38	0.15	-0.04	-0.17	-0.12	NAO
TWEIO	0.40	0.45	0.24	0.20	0.32	EAM
TWEIO	0.39	0.43	0.31	0.01	0.11	EAWR
TWEIO	0.29	0.20	-0.15	-0.07	-0.05	SCAND
SH	0.30	-0.00	-0.05	-0.08	0.02	NAO
SH	0.17	-0.34	-0.55	-0.38	-0.10	EAM
SH	-0.35	-0.14	-0.26	-0.64	-0.44	EAWR
SH	0.23	0.45	-0.03	0.17	0.26	SCAND

Table 1. Pearson simple cross correlations between indices at lag 0. Note that four EOF-based indices (NAO, EAM, EAWR and SCAND) are orthogonal to each other.

Supplementary Material

Dominant controls of cold season precipitation variability over the high mountains of Asia

Shahid Mehmood^{1,2,3}, Moetasim Ashfaq¹, Sarah Kapnick⁴, Subimal Gosh⁵, Muhammad Adnan Abid⁶, Fred Kucharski⁶, Fulden Batibenz^{1,7}, Anamitra Saha⁸, Katherine Evans¹, Huang-Hsiung Hsu²

¹ Computational Sciences and Engineering Division (CSED), Oak Ridge National Laboratory, Oak Ridge, TN, USA

² Earth System Science Program, Taiwan International Graduate Programme, Research Center for Environmental Changes (RCEC), Academia Sinica, Taipei, Taiwan

³ Institute of Atmospheric Physics, College of Earth Science, National Central University, Zhongli, Taiwan.

⁴ Geophysical Fluid Dynamics Laboratory, Princeton, NJ, USA

⁵ Department of Civil Engineering, Indian Institute of Technology Bombay, India

⁶ Earth System Physics, Abdus Salam International Centre for Theoretical Physics, Trieste, Italy

⁷ Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland

⁸ Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA

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Figures Captions

Figure S1. **Comparison of seasonal (November–March) precipitation in observations and reanalysis.** Climatological seasonal mean precipitation (mm/NDJFM) in three observations (top row) and three reanalysis (bottom row) datasets for 1981–2018. Only those observations are considered that provide daily data.

Figure S2. **Seasonal (November–March) recycling ratio and recycled precipitation from evaporative source region.** Seasonally fraction of moisture (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapotranspiration (filled contours) over the evaporative source region, and corresponding recycled seasonal precipitation (mm/day; line contours) in (a) ERAI, (b) MERRA2, (c) ERA5. This analysis is shown as an average of results over 1981–2018.

Figure S3. **Seasonal (November–March) recycling ratio and recycled precipitation from individual source region.** Seasonally averaged fraction (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapotranspiration (filled contours) and corresponding recycled seasonal precipitation (mm/day line contours) from individual evaporative sources. (1st column) ERAI, (2nd column) MERRA2, (3rd column) ERA5. The analyses are based on the averages over 1981–2018.

Figure S4. The amount of variation in monthly recycled precipitation that is explained by the (multi; row 2–7) linear regression model, expressed as coefficient of (multiple; row 2–7) determination (R^2), with the addition of each independent variable. The stippling represents F-statistics significance at 90% confidence level.

Figure S5. **Monthly Standardized partial regression coefficients associated with TWEIO in the individual multi linear regression models for recycled precipitation from each source.** Each coefficient describes standardized monthly anomaly in the recycled precipitation from each region per unit monthly anomaly in the standardized TWEIO index while holding all other modes constant. (1st column) November, (2nd column) December, (3rd column) January, (4th column) February, (5th column) March. Standardization of regionally recycled precipitation is with respect to the total recycled precipitation. Stippling represents statistical significance at 90% confidence level.

Figure S6. **Monthly Standardized partial regression coefficients associated with the natural modes of climate variability (independent variables) in the multi linear regression models.** Each coefficient describes monthly standardized anomaly in the 200mb geopotential height (contours), and zonal and meridional winds (vectors) per unit monthly standardized anomaly in the corresponding natural mode of climate variability while holding all other modes constant. (1st row) ENSO, (2nd row) TWEIO, (3rd row) SH, (4th row) NAO, (5th row) EAM, (6th row) EAWR, (7th row) SCAND. Columns (left to right) represent November to March. Stippling represents statistical significance at 90% confidence level.

Figure S7. Same as in Figure S6 but for EAM.

Figure S8. Same as in Figure S6 but for SH.

Figure S9. Same as in Figure S6 but for SCAND.

Figure S10. Same as in Figure S6 but for EAWR.

Figure S11. Same as in Figure S6 but for NAO.

Figure S12. Same as in Figure S6 but for ENSO.

Figure S13. **Linear regression of sea level pressure anomalies onto the natural modes of climate variability.** Regression of the monthly detrended sea level pressure anomalies onto the standardized indices of NAO (1st column), EAM (2nd column), EAWR (3rd column), and SCAND (4th column). The stippling represents statistical significance at 95% confidence level. All regression coefficients are standardized.

[Seasonal Mean Precipitation: 1980–2018]

Figure S1. **Comparison of seasonal (November–March) precipitation in observations and reanalysis.** Climatological seasonal mean precipitation (mm/NDJFM) in three observations (top row) and three reanalysis (bottom row) datasets for 1981–2018. Only those observations are considered that provide daily data.

Figure S2. **Seasonal (November–March) recycling ratio and recycled precipitation from evaporative source region.** Seasonally fraction of moisture (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapotranspiration (filled contours) over the evaporative source region, and corresponding recycled seasonal precipitation (mm/day; line contours) in (a) ERAI, (b) MERRA2, (c) ERA5. This analysis is shown as an average of results over 1981–2018.

Figure S3. **Seasonal (November–March) recycling ratio and recycled precipitation from individual source region.** Seasonally averaged fraction (expressed in %) of moisture falling as precipitation at each grid cell that originated as evapotranspiration (filled contours) and corresponding recycled seasonal precipitation (mm/day line contours) from individual evaporative sources. (1st column) ERAI, (2nd column) MERRA2, (3rd column) ERA5. The analyses are based on the averages over 1981–2018.

Figure S4. The amount of variation in monthly recycled precipitation that is explained by the (multi; row 2-7) linear regression model, expressed as coefficient of (multiple; row 2-7) determination (R^2), with the addition of each independent variable. The stippling represents F-statistics significance at 90% confidence level.

Figure S5. **Monthly Standardized partial regression coefficients associated with TWEIO in the individual multi linear regression models for recycled precipitation from each source.** Each coefficient describes standardized monthly anomaly in the recycled precipitation from each region per unit monthly anomaly in the standardized TWEIO index while holding all other modes constant. (1st column) November, (2nd column) December, (3rd column) January, (4th column) February, (5th column) March. Standardization of regionally recycled precipitation is with respect to the total recycled precipitation. Stippling represents statistical significance at 90% confidence level.

Figure S6. **Monthly Standardized partial regression coefficients associated with the natural modes of climate variability (independent variables) in the multi linear regression models.** Each coefficient describes monthly standardized anomaly in the 200mb geopotential height (contours), and zonal and meridional winds (vectors) per unit monthly standardized anomaly in the corresponding natural mode of climate variability while holding all other modes constant. (1st row) ENSO, (2nd row) TWEIO, (3rd row) SH, (4th row) NAO, (5th row) EAM, (6th row) EAWR, (7th row) SCAND. Columns (left to right) represent November to March. Stippling represents statistical significance at 90% confidence level.

Figure S7. Same as in Figure S5 but for EAM.

Figure S8. Same as in Figure S5 but for SH.

Figure S9. Same as in Figure S5 but for SCAND.

Figure S10. Same as in Figure S5 but for EAWR.

Figure S11. Same as in Figure S5 but for NAO.

Figure S12. Same as in Figure S5 but for ENSO.

Figure S13. **Linear regression of sea level pressure anomalies onto the natural modes of climate variability.** Regression of the monthly detrended sea level pressure anomalies onto the standardized indices of NAO (1st column), EAM (2nd column), EAWR (3rd column), and SCAND (4th column). The stippling represents statistical significance at 95% confidence level. All regression coefficients are standardized.