

Association of Atmospheric River Frequency over the Western Himalayas with Large Scale Modes of Climate Variability

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Key Points

- Climate modes and their interactions show potential for predicting winter atmospheric rivers over the Western Himalaya.
- Two climate patterns and one interaction explain interannual winter atmospheric river frequency over the Western Himalaya.
- A generalized additive model matches a linear model's skill for winter atmospheric river frequency using three climate modes instead of eight.

Abstract

Winter atmospheric rivers (ARs) contribute substantially to precipitation in the Western Himalaya, but how large-scale climate modes jointly influence their frequency remains unclear. Using 19 climate modes and their interactions over 39 winters (1980-2018), we combine correlation, phase-composite analysis of integrated vapor transport (IVT), and linear, generalized linear (GLM) and generalized additive (GAM) models. The Pacific/North American (PNA) and East Atlantic/Western Russia (EA-WR) patterns are strongly associated with winter AR frequency and show consistent IVT composite signals, whereas East Pacific-North Pacific (EPNP) acts mainly through its interaction with PNA. Notably, several modes show significant IVT changes in the phase analysis like Arctic Oscillation and PNA, but are not prominently retained in models with least error metrics. No single mode explains AR variability, and models with interaction terms outperform a simple linear model. The GLM and GAM show comparable predictive skill, but the GAM utilizes three climate modes against eight for the

GLM. EA-WR and the EP-NP $\times$ PNA interaction are retained in both models, and EP-NP also enters the GAM as a nonlinear main effect. These results indicate that winter AR frequency depends on the combined and partly nonlinear effects of several climate modes, providing a statistical basis for predicting seasonal AR frequency and water resource planning in this data-limited region.

Plain Language Summary

Atmospheric rivers contribute substantially to the water budget of the Western Himalayas, so their prediction is beneficial for water resource management of the area. The number of these events varies from one winter to the next. We tested how large-scale climate patterns are linked to this variation over a period of 39 years. No single climate pattern could explain the annual variability in the number of winter atmospheric rivers on its own. However, three patterns, one of which acts through its combination with another, together explained a large part of the variation in winter atmospheric rivers.

Keywords

Atmospheric Rivers; Climate Modes; Himalayas; Generalized Linear Models; Generalized Additive Models

1. Introduction

Atmospheric rivers (ARs) are long and thin bands of concentrated water vapour in the lower atmosphere and are an important factor in local precipitation (Zhu & Newell, 1998; Payne et al., 2020). The occurrence of ARs is closely connected with climate modes, which are recurring, though not perfectly periodic, large-scale patterns of atmosphere–ocean variability that oscillate over months to years (McGregor, 2024; Guan & Waliser, 2015). Research has shown that the frequency and occurrence of ARs vary considerably according to the phase of the climate mode, thus affecting regional rainfall and the water cycle (Guan & Waliser, 2015; Nash et al., 2022;

Yang et al., 2024). The effects of a climate mode are not confined to its area of origin; for instance, the El Niño–Southern Oscillation (ENSO) starts in the tropical Pacific but can affect the weather a long way away, a phenomenon known as teleconnection. Depending on its phase, a climate mode can either increase or decrease the likelihood of AR activity, and this impact can vary from one region to another. It is common for several climate modes to be active at the same time and for them to interact in order to determine AR patterns (McGregor, 2024; Wallace & Gutzler, 1981).

Research at global scale indicates that large-scale climate patterns can have a strong impact on the frequency and intensity of ARs, as well as on their routes and the amount of rainfall they bring. Nevertheless, the strength and direction of these effects differ according to region and season. Guan & Waliser (2015) found that ENSO, the Madden–Julian Oscillation (MJO), the Arctic Oscillation (AO), and the Pacific–North American pattern (PNA) all contribute significantly to the nature of winter AR activity on a global scale. For instance, El Niño generally leads to an increase in the frequency of ARs in a number of subtropical and extratropical regions, whereas the MJO, AO, and PNA affect AR occurrence linked to the large-scale circulation anomalies.

Studies at a regional level offer a more detailed examination of this subject. In western North America, Guan et al. (2012) discovered that the phase of the MJO has a strong effect on high-impact AR landfalls in the Sierra Nevada region. Mundhenk et al. (2018) demonstrated that combining the states of the MJO and the Quasi-Biennial Oscillation (QBO) can be used to predict landfalling ARs on a subseasonal basis. Other research carried out in the North Pacific and western North America has associated ENSO and Pacific decadal variability with year-by-year changes in AR activity (Gershunov et al., 2017; Xu et al., 2023). More recently, Yang et al. (2024) stated that the AO, QBO, ENSO, MJO, the Pacific Decadal Oscillation (PDO), and the PNA all influence AR clustering and orientation in the western United States, the main

factors varying between early and late winter. With regard to the Atlantic side, Li et al. (2022) found that ENSO and the North Atlantic Oscillation (NAO) together determine when and where cold-season ARs take place.

Nash et al. (2022) discovered that large-scale climate patterns also have an effect on High Mountain Asia (HMA), since tropical storms over western and northwestern HMA occur more frequently during El Niño, positive AO, and negative Siberian High (Sib-H) conditions. This trend is not confined to HMA; for instance, in Northern California regional climate patterns such as the AO, PNA, Western Pacific Oscillation (WPO), and Eastern Pacific Oscillation (EPO) have a greater influence on precipitation from landfalling ARs than ENSO and can either enhance or reduce the effects of ENSO according to how they align (Guirguis et al., 2019). Generally, these studies indicate that variability in ARs is closely linked to the wider climate system, but the impact of each mode and the way they interact can differ considerably from region to region (Xu et al., 2023).

Not only do climate modes have an effect on the times at which ARs occur, but they also influence how well the ARs can be forecasted. DeFlorio et al. (2018) observed that the skill of subseasonal AR forecasts increased during El Niño in the North Pacific and in the western United States, as well as during negative AO conditions in the North Atlantic and in the United Kingdom. The greatest improvements in forecast skill occurred when the phases of ENSO and PNA were aligned. These 'forecasts of opportunity' indicate that large-scale climate information could make AR prediction frameworks more effective. Taken together, the findings show that climate modes provide valuable insights into AR variability and could enable climate information to move from being a diagnostic tool to being a means of predicting regional AR frequency.

Statistical methods have already demonstrated this potential in a number of fields. For example, Lavers et al. (2012) applied a Poisson regression model to examine the number of winter AR events in the British Isles by means of large-scale climate indices and found that count-based statistical models can be used for measuring the variability in AR frequency. Subsequent research has since extended climate-based forecasts to other areas and different time scales: Zhou & Kim (2018) investigated the prediction of winter AR frequency over the North Pacific in relation to ENSO, Castellano et al. (2023) developed a statistical subseasonal forecasting tool for AR activity in California based on MJO and QBO conditions, and Dong et al. (2024) demonstrated that monthly and seasonal predictions of AR frequency over the eastern United States were possible using the PNA. Altogether, these studies verify the predictive value of large-scale climate information and indicate that the main factors responsible for AR activity can vary considerably regionally.

It is clear from the evidence that climate modes have an impact on the occurrence of ARs in High Mountain Asia (Nash et al., 2022), but it is still not known how various large-scale climate modes together affect the frequency of ARs in the Western Himalayas. Findings from broader regions cannot be directly applied in this case since the influence of climate modes on AR activity differs regionally. Moreover, although some other areas have observed nonlinear effects of climate modes on ARs (Xu et al., 2023), we still do not know how the frequency of ARs in the Himalayas responds to different climate modes, either in a linear or nonlinear way. Since climate modes can jointly influence AR activity, it is necessary to investigate their interactions, as the effect of one mode may depend on that of another (Guan et al., 2012; Mundhenk et al., 2018; Li et al., 2022; Xu et al., 2023). In order to address these uncertainties, this study develops a statistical framework to model and predict the number of winter ARs in the Western Himalayas by making use of several large-scale climate indices. A generalized linear model (GLM) with a log link is employed to examine linear relationships between the climate indices

and AR counts (McCullagh & Nelder, 2019). A generalized additive model (GAM) is also used, as it enables to capture nonlinear responses, such as thresholds or non-monotonic patterns, that a GLM cannot represent (Hastie & Tibshirani, 2017; Wood, 2017). Interactions of climate modes like Sib-H $\times$ AO and PNA $\times$ Niño4 have been established in the past, hence both models are tested with various interaction terms between the climate modes (Gong et al., 2001; W. Li & Forest, 2014). Interaction terms are retained only where they improve on the additive models. By comparing the linear and nonlinear effects and by looking at the interactions between these modes, we hope to determine which climate signals are most closely associated with variability in ARs in the Western Himalayas and how well they predict the frequency of winter ARs. To our knowledge, this is the first study to apply and compare both GLM and GAM to the frequency of winter ARs in the Western Himalayas, using several large-scale climate indices and directly testing their linear, nonlinear, and interactive effects.

2. Data

The study focuses on winter ARs in the western Himalayan area, covering latitudes from 29°N to 37°N and longitudes from 72°E to 81°E. It makes use of meteorological data from ERA5, which is the fifth-generation atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 has a horizontal resolution of $0.25^\circ \times 0.25^\circ$ (approximately 31 km worldwide), includes 37 vertical pressure levels, and provides data on an hourly basis. For this research, data were gathered at six-hour intervals (00, 06, 12 and 18 UTC) during the winter period (from December to February) between the years 1980 and 2018. The integrated vapor transport (IVT; in $\text{kg m}^{-1} \text{s}^{-1}$) was computed from the ERA5 data by employing 20 pressure levels ranging from 1000 to 300 hPa, in accordance with the formula given below:

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$$IVT = \sqrt{\left(\frac{\int_{1000}^{300} qu dp}{g}\right)^2 + \left(\frac{\int_{1000}^{300} qv dp}{g}\right)^2}$$

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In this context, q denotes specific humidity (in kg kg^{-1}), u and v represent the zonal and meridional wind components (in m s^{-1}), p is the pressure level (in hPa), and g stands for gravitational acceleration (in m s^{-2}). Table S2 gives the number of winter atmospheric rivers over the Western Himalayas for each year from 1980 to 2018 (Nayak et al., 2021). Each winter, defined as December-January-February (DJF), is named according to the year in which January and February take place.

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The study looks at 19 climate modes in order to evaluate their possible influence on the frequency of winter AR occurrences in the Western Himalayas. The monthly index values for Niño3, Niño4, the Southern Oscillation Index (SOI), the Dipole Mode Index (DMI), the PDO, and the Atlantic Multidecadal Oscillation (AMO) were obtained from the NOAA Physical Sciences Laboratory climate indices archive. The monthly values for NAO, AO, WP, EPNP, PNA, the East Atlantic pattern (EA), the East Atlantic–Western Russia pattern (EA-WR), the Antarctic Oscillation (AAO), and the Scandinavian pattern (SCAND) were sourced from the NOAA Climate Prediction Center teleconnection indices. The Tropical Western–Eastern Indian Ocean (TWEIO) index, the Equatorial Indian Ocean Oscillation (EQ) and the Siberian High (Sib-H) index were calculated using the approaches outlined by Abid et al. (2020), Gadgil et al. (2004), and Panagiotopoulos et al. (2005), respectively.

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In each case, we calculated the average of the monthly index values for December, January, and February (DJF) in order to arrive at one DJF value. We then correlated these seasonal climate-index values with the frequency of AR occurrences in the winter over western Himalayas.

3. Methods

The study uses a multi-stage statistical method to identify the climate patterns that affect winter AR activity in the Western Himalayas and to develop a predictive model for AR frequency, as described in the sections below.

3.1 Analysis using the Pearson Correlation

To identify which climate modes and interactions are most relevant to winter AR activity in the Western Himalaya, we computed Pearson correlations between each of them and winter AR frequency. For each winter (DJF) season, we calculated the mean value of each climate mode index and compared it with the AR events that occurred during that winter, using the AR frequency dataset for the Himalayan region for 1980–2018 (Table S2). Correlations were tested for significance with a t-test, and modes with $p < 0.13$ were retained for the phase-wise analysis (Section 3.2).

3.2 A composite analysis of the phases of the climate mode (using Welch's t-test)

Although the Pearson correlation (Section 3.1) can show whether a climate mode is statistically linked to the frequency of winter ARs, the correlation coefficient alone does not prove this association reflects a genuine and physically meaningful change in the atmosphere's moisture-transport environment. It may instead reflect a few exceptional years rather than a consistent physical mechanism. To investigate this, a phase-wise and grid cell-wise composite analysis of the IVT was carried out for each significant climate mode identified in Section 3.1. This checked whether the positive and negative phases correspond to a clear and spatially coherent difference in the amount of moisture transported into the study area, since this is the physical variable through which a climate mode could plausibly affect AR frequency.

The climatic indices are adjusted to have a mean of zero and a standard deviation of one. Winters were considered in the positive phase if the index was above +0.5 standard deviations

and in the negative phase if below -0.5 standard deviations. At each grid cell across the study area, we calculated the mean DJF IVT separately for positive- and negative-phase winters. This enabled us to determine differences in the strength and spatial coverage of AR-favorable moisture transport conditions between the two phases.

In order to find out whether there was a statistically significant difference in the mean IVT between the two phases, we carried out a two-sample t-test (Welch's t-test for unequal variances) at each grid cell, comparing the IVT distributions for the positive and negative phases at the 5% level of significance.

3.3 Using GLM and GAM to Predict AR Frequency

Before building the multivariate models, we first ran a simple linear regression of winter AR frequencies on each significant climate mode. This showed how well each mode predicted AR frequency on its own and provided a baseline for comparison. Even though AR counts are discrete and not normally distributed, this step gave us an estimate of how much AR frequency changes with each climate index. Neither the correlation analysis (Section 3.1) nor the phase composites (Section 3.2) provide this information. We used a t-test to check whether each regression coefficient differed significantly from zero, indicating a linear relationship between the climate mode and AR frequency. We also measured predictive performance using leave-one-out cross-validation (LOOCV) with root mean squared error (RMSE) to compare these results with the GLM and GAM models discussed later.

Although single-predictor linear regression is a useful baseline, it has two main drawbacks for our study. First, it assumes the response is continuous and normally distributed, but AR frequency is actually count data. Second, it examines each climate mode separately and cannot show how multiple modes might work together. GLMs and GAMs solve both problems by

216 letting us model count data with the right distribution and include multiple modes and their
217 interactions in one model.

218 **GLM**

219 The general form of a GLM is given by:

$$220 \quad g(\mu_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in}$$

221 where $\mu_i = E(y_i)$ is the expected value of the response variable, $g(\cdot)$ is the link function,
222 $x_{i1}, \dots, x_{in}$ are the predictor variables for observation i , and $\beta_0, \dots, \beta_n$ are the coefficients
223 estimated via Maximum Likelihood Estimation.

224 In this study, since the response variable (number of winter ARs) represents count data, a
225 Poisson distribution with a log link function was used, giving:

$$226 \quad \log(E(ARs)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

227 In this case, each x stands for a climate mode or interaction that has been found to be statistically
228 significant as described in Sections 3.1. The model was fitted by taking into account all of the
229 significant modes and interactions at the same time, which enabled the combined and joint
230 effects of several climate drivers on the frequency of AR events to be measured in a single
231 equation, a point that the single-predictor regression is unable to address.

232 **GAM**

233 The general form of a GAM extends the GLM by replacing the linear predictor terms with
234 smooth, non-parametric functions:

$$235 \quad g(\mu_i) = \beta_0 + f_1(x_{i1}) + f_2(x_{i2}) + \cdots + f_n(x_{in})$$

236 where each f_i is a smooth function of a predictor, estimated from the data using basis splines
237 rather than assumed to follow a fixed linear form:

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$$f_i(x_i) = \sum_{k=1}^{K_j} \beta_{jk} b_{jk}(x_j)$$

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Again using a Poisson distribution with a log link (consistent with the GLM), this becomes:

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$$\log(E(ARs)) = \beta_0 + f_1(x_1) + f_2(x_2) + \dots + f_n(x_n)$$

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In this study, GAM was employed to determine whether the relationships between climate

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modes and the frequency of winter AR events are nonlinear, since the GLM is unable to do so

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as it assumes that the effect of each predictor must be a straight line in log-space. The smooth

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terms were fitted using a certain number of basis splines (k) and a smoothing parameter (λ),

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and it is these two elements that decide how flexible or smooth the resulting curve is; a smaller

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λ results in greater wiggleness, whereas a larger λ leads to a smoother and more linear-like fit.

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The basis dimension was set to $k = 4$ for each main-effect smooth and $k = 3$ per margin for the

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interaction term, and λ was estimated by restricted maximum likelihood (REML)

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Evaluation of the models

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GLM and GAM were evaluated on the basis of RMSE, the Akaike information criterion (AIC),

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and the pseudo R^2 . The log-likelihood shows the probability of the observed data given the

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fitted model, higher (less negative) values meaning that the fit is better. The AIC includes the

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log-likelihood and imposes a penalty for extra parameters, so that lower AIC values indicate a

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more optimal balance between fit and complexity. Pseudo R^2 measures the improvement in

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model fit compared with a null model that contains only an intercept, analogous to R^2 in linear

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regression.

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We applied both the GLM and the GAM using the same set of significant climate modes and

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their interactions so that a direct comparison could be made. The GLM examined whether a

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linear combination of the predictors (in log-space) was able to account for AR frequency. The

GAM investigated whether nonlinear and flexible relationships would lead to an improvement in the results. The models were assessed using LOOCV across 39 winters and were compared with one another and with the linear regression baseline using RMSE, AIC, and Pseudo R-squared.

4. Results

This section shares the results of the multi-stage statistical analysis described in Section 3. The goal is to find the climate modes that influence winter AR variability over the Western Himalayas and to develop a model to predict AR frequency.

4.1. Identification of Significant Climate Modes

We performed a Pearson correlation (r) analysis between the winter frequency of ARs over the Western Himalaya (1980–2018) and each of the 18 climate mode indices, as well as all pairwise interactions between them. This helped identify which modes and interactions have a significant relationship with AR activity. Table S3 shows the r and p -values for all eighteen climate modes analysed in this study. Using a relaxed significance level of $\alpha=0.13$, which fits the small sample size ($n=39$ winters) and the exploratory purpose of this step, AO, PDO, PNA, EA-WR, and Sib-H showed significant correlations with winter AR activity in individual climate modes and for interaction terms from a total of 171 combination terms 22 interaction were found significant (Table1). This suggests they could be useful predictors in the modeling framework. The other climate modes and interactions had non-significant correlations ($p>0.13$) and were not included in further analysis.

Table 1. Pearson correlation (r) between annual winter AR frequency and significant climate modes and interactions over the Western Himalayas, with corresponding statistical significance (p -values), 1980–2018.

Interaction	r	p	Interaction	r	p	Interaction	r	p
AO	0.273	0.093	Sib-H	-0.249	0.127	EA-WR	0.337	0.036
PNA	-0.311	0.054	PDO	-0.318	0.049	SCAND × Sib.H	0.267	0.100
EP.NP × PNA	0.425	0.007	NAO × EA.WR	0.418	0.008	AO × Sib.H	-0.404	0.011
AMO × NAO	-0.392	0.013	EP.NP × EA	-0.390	0.014	NAO × Sib.H	-0.389	0.015
SCAND × TWEIO	-0.375	0.019	AMO × AO	-0.363	0.023	NAO × EQ	0.348	0.030
SCAND × EQ	-0.340	0.034	NAO × AAO	-0.321	0.046	AO × TWEIO	0.317	0.049
EP.NP × Sib.H	0.294	0.069	NAO × TWEIO	0.290	0.073	AMO × SCAND	0.287	0.077
AO × WP	0.282	0.082	SOI × NAO	-0.279	0.086	AO × EA.WR	0.273	0.092
AO × EQ	0.273	0.093	Nino4 × PNA	0.272	0.094	PDO × PNA	0.271	0.095

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283 4.2. Climate Mode Phase Attribution

284 In order to investigate the relationship between different climate modes and the frequency of
285 winter AR occurrences, we compared the DJF-mean IVT for the positive and negative phases
286 of the AO, PDO, PNA, and EA-WR patterns from 1980 to 2018. Since Nash et al. (2022) had
287 previously shown the link between Sib-H and AR-favorable moisture transport over High
288 Mountain Asia, we decided not to include Sib-H. They found that ARs happen more frequently
289 when the Sib-H phase is negative, which is in agreement with the negative correlation that we
290 have observed (Table 1). By using the phase-composite method, we examined whether the
291 statistical association between each of the remaining modes and AR frequency also exhibited a
292 consistent difference in moisture transport between its two phases. A Welch's two-sample t-test

was carried out at the 5% significance level, and only those grid cells that showed statistically significant phase differences ($p < 0.05$) were included in the composite difference maps.

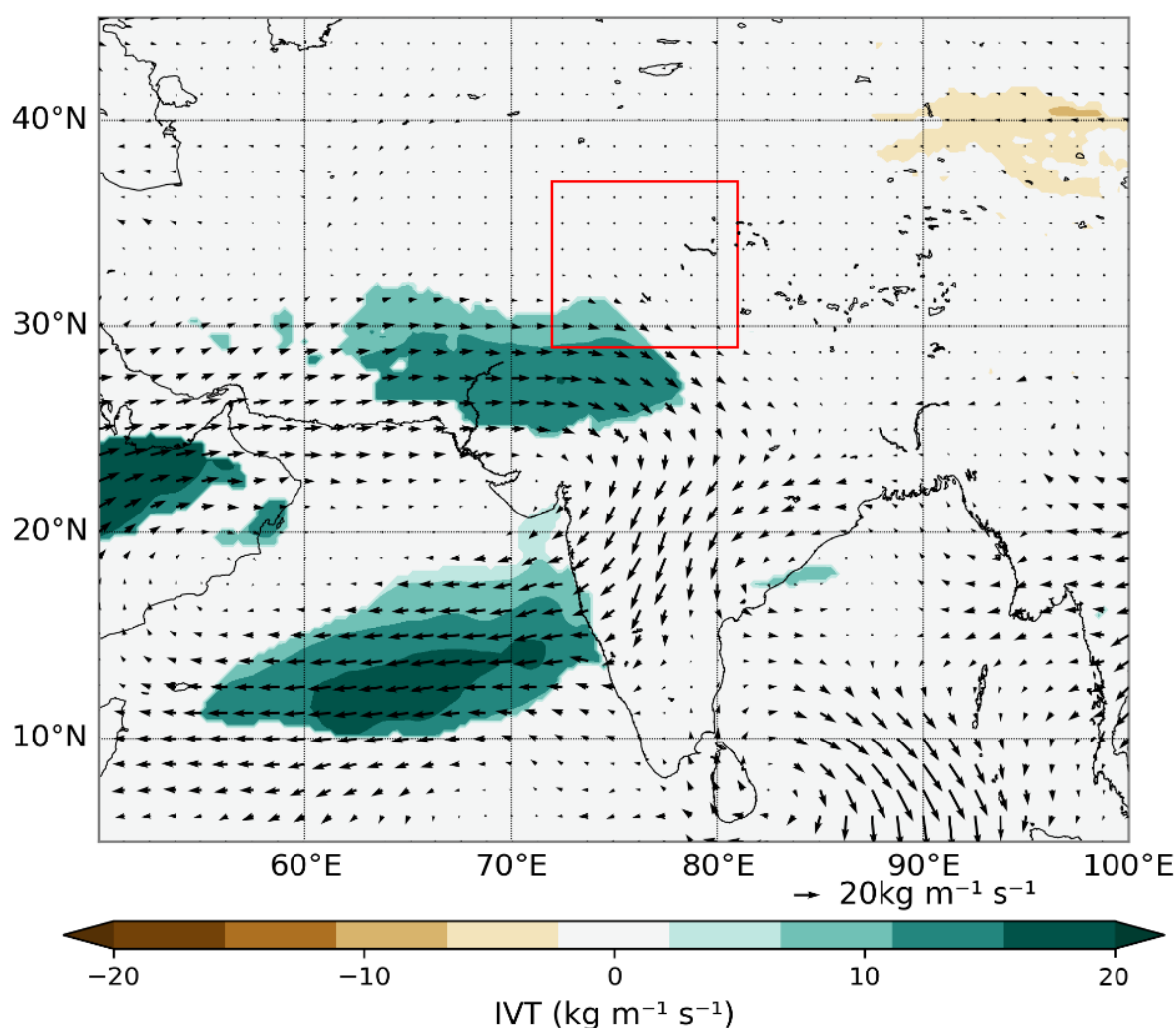


Figure 1. Composite differences in IVT between AO+ and AO- phases over the Western Himalayas from 1980 to 2018. Only differences statistically significant at or above the 95% confidence level (Welch's two-sample t-test, $p < 0.05$) are shaded.

Figure 1 shows the combined difference in the DJF mean IVT between the AO+ and AO- phases, but only for grid cells where this difference is found to be statistically significant according to Welch's t-test at the 5% level. In the AO+ phase, significantly higher IVT appears as a zonally extended band near 27–30°N, stretching across the area just south of the study region and extending all the way to its southern boundary (indicated by the red box). Nash et al. (2022) recorded a similar increase in IVT during AO+ minus AO- over southwest Asia, this being linked to an anticyclonic anomaly over the Arabian Sea, in the case of ARs affecting High

Mountain Asia. Although the significant signal does not reach within the entire study box, its position just upstream of it implies that there is an enhanced moisture-transport pathway during AO+. Such conditions are conducive to ARs occurring over the Western Himalayas.

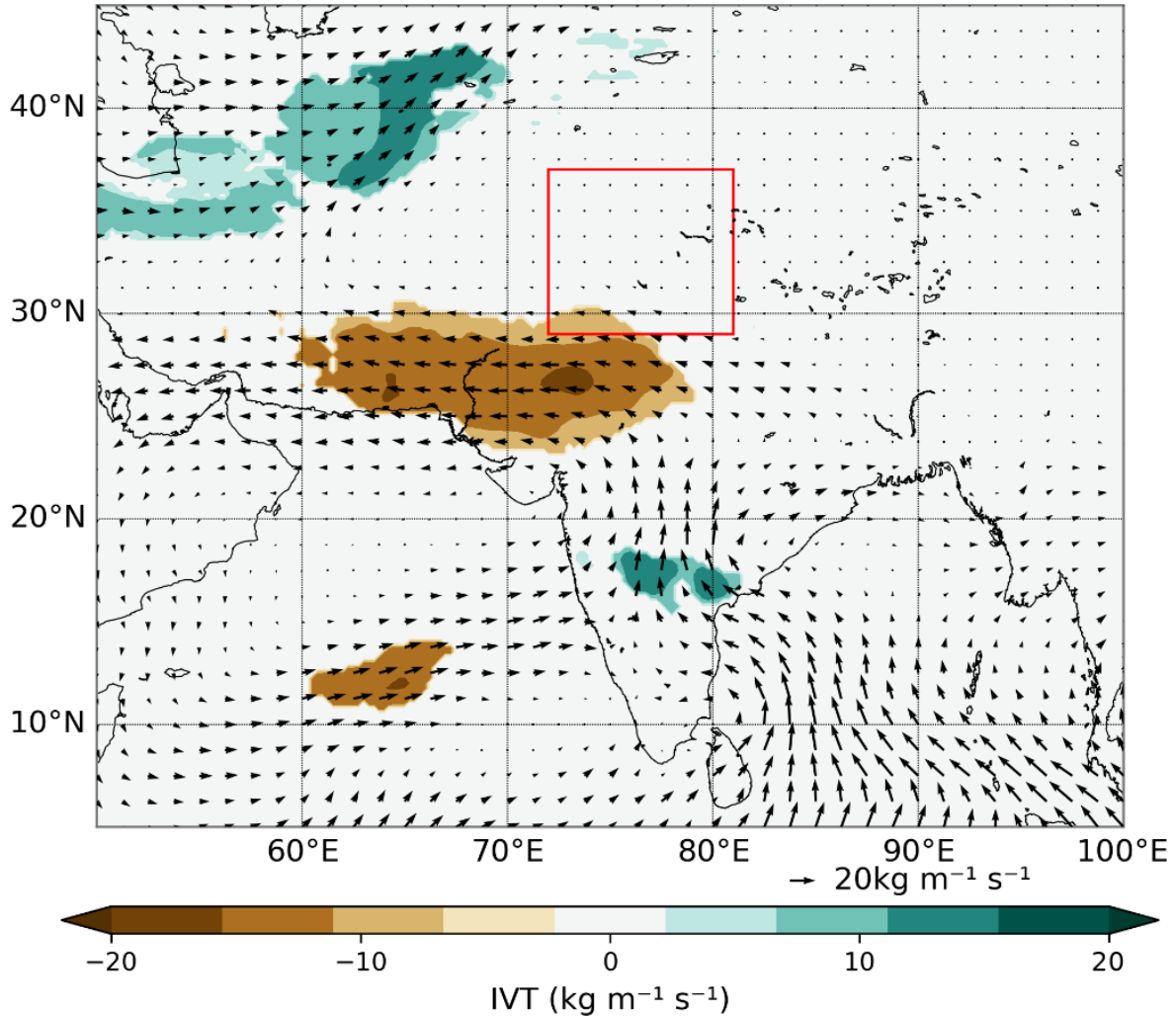


Figure 2. Composite difference in IVT between PDO+ and PDO- phases over the Western Himalayas.

As with AO, DJF-mean IVT was compared between the positive and negative phases of the PDO. Figure 2 shows the composite difference (PDO+ minus PDO-) at grid cells passing Welch's t-test at the 5% significance level. The dominant significant signal is a zonally elongated band of negative difference along roughly 25–30°N, located to the south and southwest of the study domain (red box), indicating higher IVT during the negative phase of the PDO. Positioned immediately upstream of the domain, this band of enhanced moisture transport represents conditions favourable to AR development and propagation toward the

Western Himalayas during PDO-. This is consistent with the negative correlation between the PDO and winter AR frequency found at the screening stage (Table 1, $r = -0.318$), supporting the retention of PDO as one of the stronger predictors carried into the modelling stage.

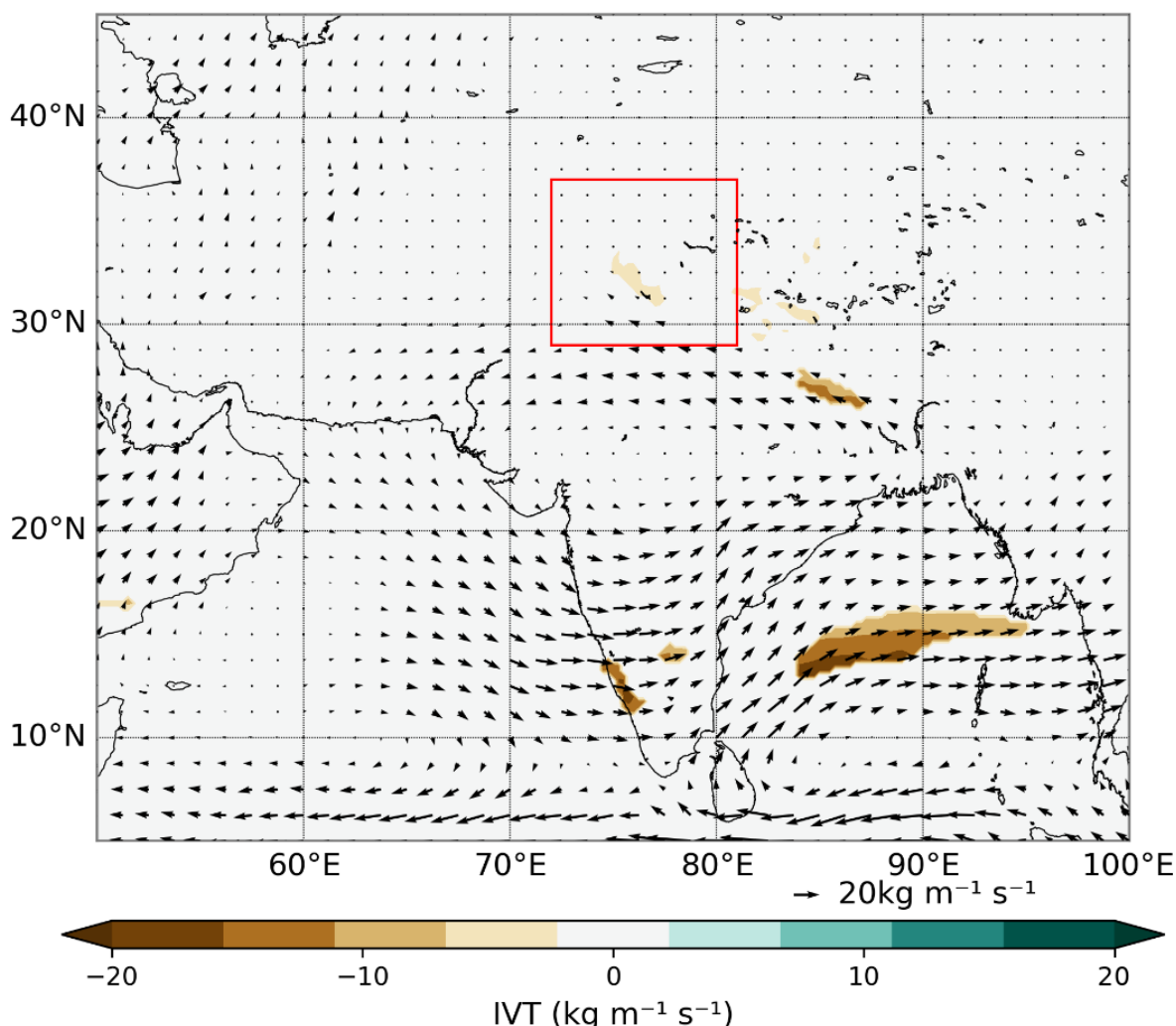


Figure 3. Composite difference in IVT between PNA+ and PNA- phases over the Western Himalayas.

In comparison with AO and PDO, the PNA displays a weaker and more diffuse signal in Figure 3, with only a small region showing a significant IVT difference in the Western Himalayas. In the cases where there is a significant difference, it is negative, indicating that IVT is greater during the negative phase (PNA-). This is in agreement with the negative correlation between PNA and winter AR frequency that was previously found (Table 1, $r = -0.311$) and is similar to the direction observed for PDO, which is positively associated with PNA (Chen et al., 2023). Although the PNA does not produce a clear and large-scale moisture transport pattern like AO

and PDO, its consistent relationship with AR frequency and its presence in the interaction terms of the multivariate models show that it still contains useful information regarding winter AR variability in the Western Himalayas.

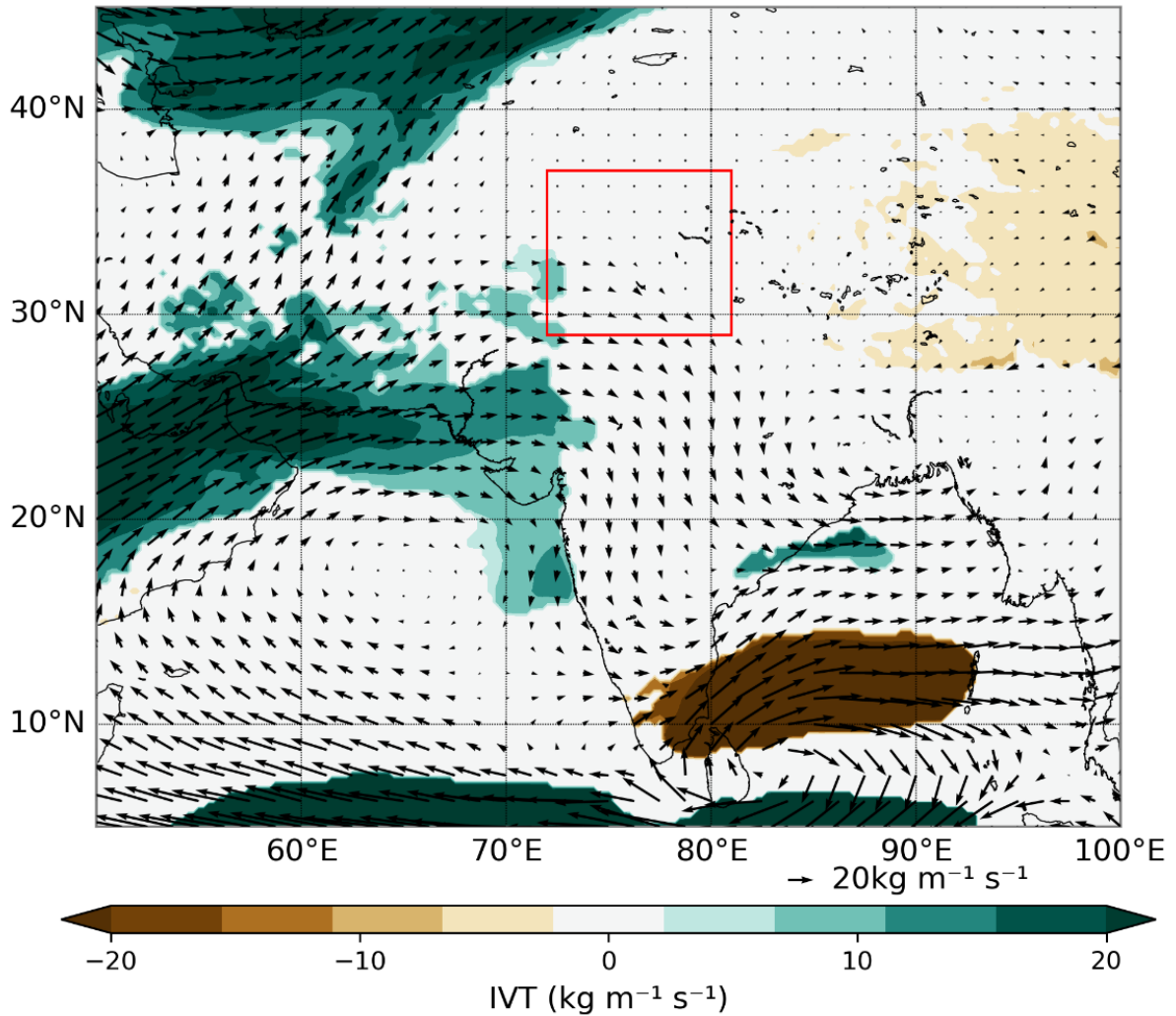


Figure 4. Composite difference in IVT between EA-WR+ and EA-WR- phases over the Western Himalayas.

A similar analysis was carried out for the EA-WR pattern (Figure 4). Significant positive differences dominate the western part of the domain, indicating higher IVT during the positive phase (EA-WR+), with the signal extending into the western edge of the study box (red box). This band of enhanced moisture transport, situated across and immediately upstream of the domain, represents conditions favourable to AR occurrence over the Western Himalayas during EA-WR+. This is consistent with the positive correlation between EA-WR and winter AR

frequency found at the screening stage (Table 1, $r=0.337$ and $p=0.036$), the strongest positive correlation among the modes tested.

Taken together, the phase-composite analysis shows that the sign of the IVT response matches the correlation found at the screening stage for every mode examined: AO+ and EA-WR+ are associated with enhanced moisture transport, while PDO- and PNA- show higher IVT over the Western Himalayas. This agreement between two independent lines of evidence, one based on discrete AR counts and the other on a continuous atmospheric IVT field, indicates that these modes are not only statistically related to AR frequency but also correspond to real differences in the moisture-transport environment in which ARs develop. The analysis therefore provides physical support for retaining these modes as predictors in the statistical modelling of winter AR frequency that follows.

4.3. Multivariate Model Performance (GLM and GAM)

In supplementary Text S1 we examined how well individual climate modes predict winter AR frequency using single-predictor linear models. EA-WR emerged as the strongest standalone predictor (LOOCV RMSE 2.27, $p=0.036$), but RMSE values clustered narrowly between 2.27 and 2.33 across all five modes, and in every case the cross-validated predictions spanned a much narrower range than the observed AR counts. This indicates that no single climate mode captures a substantial share of the year-to-year variability in AR frequency. Here we build on that baseline by developing multivariate GLM and GAM frameworks that incorporate several climate modes together with their interactions, and we use the single-predictor RMSE range as a reference against which the multivariate models are compared.

GLM

The GLM was constructed using the climate modes and their interactions which were found to be statistically significant in Section 4.1. Since AR activity is influenced by the combined state

of several climate modes, not merely one (Nash et al., 2022; Guirguis et al., 2019; Soulard et al., 2019), we experimented with different combinations of predictors and interaction terms. Some of the equations analysed are given in Table S4, the final model was selected on the basis of the lowest AIC and RMSE values in order to achieve a balance between fit and complexity, resulting in the following equation:

$$\log(E(ARs)) = \beta_0 + \beta_1(EA - WR) + \beta_2(PDO) + \beta_3(EPNP \times PNA) + \beta_4(NAO \times Sib.h) + \beta_5(SCAND \times TWEIO)$$

GAM

The GAM was fitted between the number of winter ARs and the statistically significant climate modes and their interactions, using a Poisson distribution with a log link function. Some of the equations analysed are given in Table S4, the final fitted model with lowest AIC and RMSE is given by:

$$\log(E(ARs)) = \beta_0 + f_1(PNA) + f_2(EA-WR) + f_3(EPNP) + f_4(PNA \times EPNP)$$

In this equation the interaction entered the GAM linearly (effective degree of freedom (edf)= 1), as did PNA and EA-WR. EPNP is the only nonlinear response in the equation (edf = 2.4).

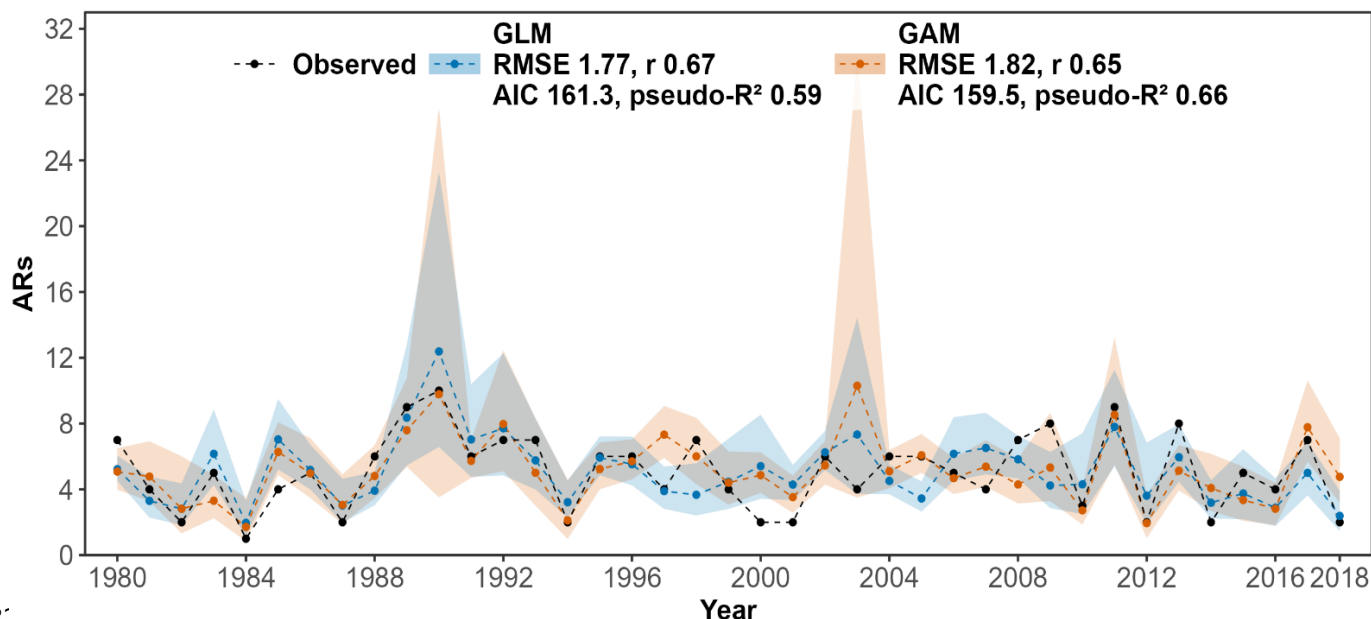


Figure 5. LOOCV results for the GLM (blue colour) and the GAM (orange colour), showing observed (black colour) and out-of-sample predicted winter AR counts over 1980–2018. Shaded bands indicate 95% confidence interval. The values of RMSE, Pearson correlation (r), AIC, and pseudo R^2 are shown in the legend.

Figure 5 compares the LOOCV predictions of both models with the observed AR data. The GLM and GAM show comparable skill, with similar RMSE (1.77 vs 1.82), correlation ($r = 0.67$ vs 0.65) and AIC ($\Delta\text{AIC} = 1.8$), indicating no clear difference in predictive performance. The GAM has a higher in-sample pseudo- R^2 (0.66 vs 0.59), but this does not imply better out-of-sample predictive skill (LOOCV $R^2 = 0.37$ vs 0.41). Neither model is consistently superior across years. For example, the GAM reproduces the 1990 peak more closely (about 10 vs 12.4 predicted for roughly 10 observed), whereas the GLM performs better in 1997 and 2003, when the GAM overestimates AR counts. The single-predictor linear models have LOOCV RMSE values between 2.27 and 2.33 (Table S1), these are much higher than GLM and GAM RMSE values, 1.77 and 1.82 respectively. The variation demonstrated by GLM and GAM in the variability of AR frequency year by year is much better than single modes as is depicted in Figure 5 and Figure S2. Thus, it is evident that overall, both models captured the interannual fluctuations of winter AR frequency from a small set of climate modes and interactions, explaining about 40% of out-of-sample variance.

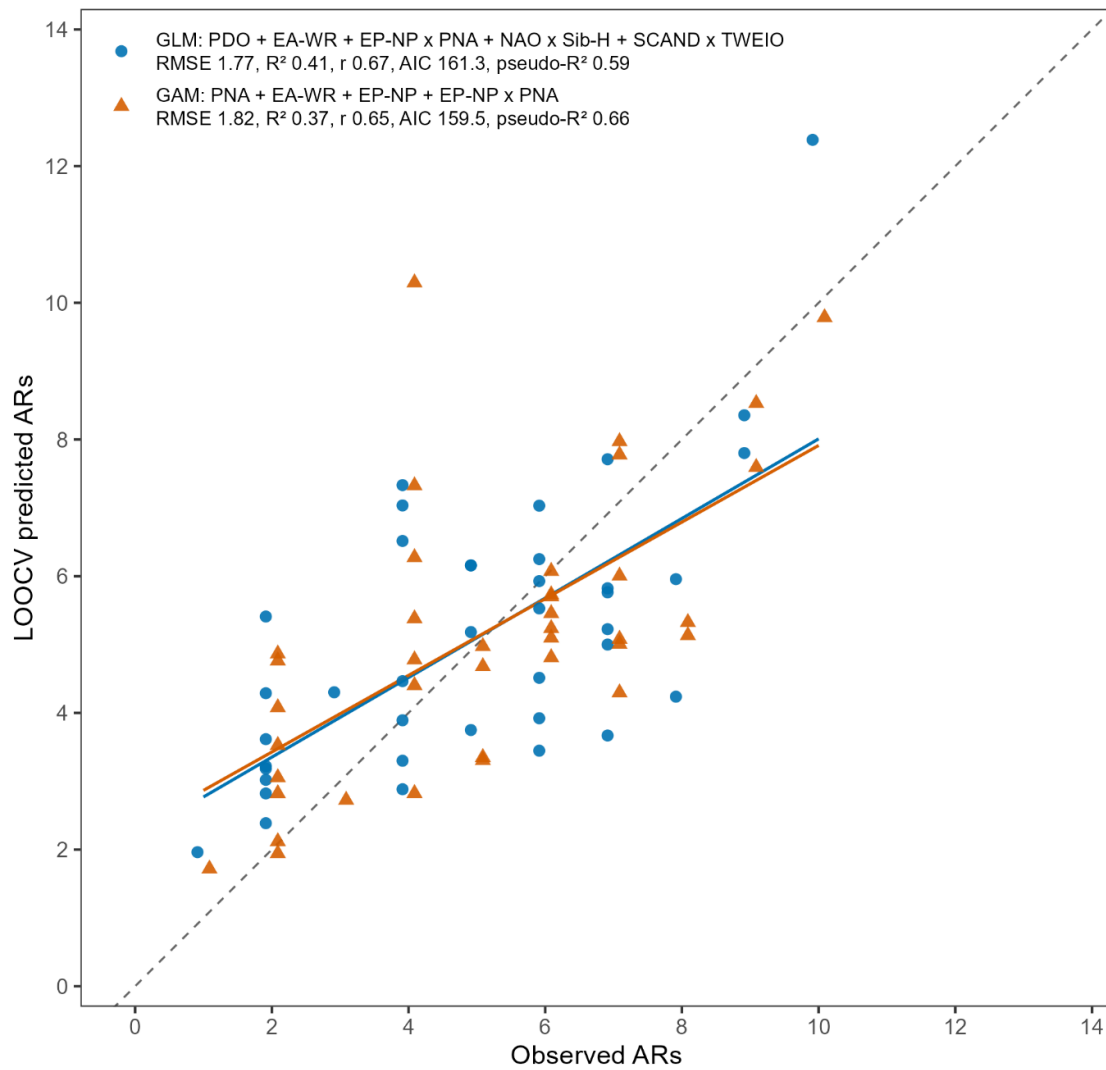


Figure 6. Scatter plot of LOOCV predicted ARs by GLM (blue colour) and GAM (orange colour) versus observed ARs.

In Figure 6 we can observe both models overestimate AR frequency in low-AR years and underestimate it in high-AR years. The regression lines of both models overlap indicating comparable skill, consistent with their comparable RMSE, R^2 and r . The 2003 winter had the largest effect on the GAM's RMSE: 4 ARs were observed against about 10 predicted by the GAM and about 7 by the GLM. This single year contributed 31% of the GAM's RMSE, compared with 9% for the GLM. When it was excluded, RMSE fell from 1.82 to 1.53 for the GAM and from 1.77 to 1.71 for the GLM, so this year largely contributes to the GAM's slightly higher RMSE.

Given this comparable skill, the GAM is preferable because it achieves similar performance with fewer terms (4 terms and 3 climate modes, compared with 5 terms and 8 modes in the GLM). EA-WR and the EP-NP $\times$ PNA interaction were retained in both models, indicating that these are most significant for winter AR frequency over the Western Himalaya consistent with Table 1 high r and p values. EA-WR and the EP-NP $\times$ PNA interaction were retained in both models, indicating that these are the most significant climate modes for modelling winter ARs over the Western Himalaya. This is consistent with Table 1, where EA-WR ($r = 0.337$, $p=0.036$), EP-NP $\times$ PNA ($r = 0.425$, $p=0.007$) show the strongest correlations with AR frequency.

5. Discussion

The application of Poisson regression to link the frequency of winter ARs with climate indices agrees with previous studies in other midlatitude areas. Lavers et al. (2012) used an AIC-based stepwise selection procedure, similar to the one employed in this study, to associate winter AR occurrences over Britain with climate variability and found that one predictor the SCAND was enough to account for the interannual variation in ARs, there being more ARs when the SCAND was in its negative phase. In contrast, no single mode was dominant in controlling AR variability over the Himalayas; several modes (PDO, PNA, AO, EA-WR) exhibited similar predictive power, and in order to make a meaningful improvement in predictive ability interaction terms proved to be a pivotal, indicating a more complex multi-mode circulation control than that seen over the North Atlantic.

The significant climate modes identified here are consistent with those reported for the wider High Mountain Asia region. Nash et al. (2022) found ARs reaching western and northwestern HMA to be significantly more frequent during positive AO and negative Siberian High conditions, matching the directions obtained in this study from the correlation and phase-

437 composite analyses. The present study extends that set of modes, with PDO, PNA and EA-WR
438 also emerging as relevant predictors over the Western Himalayas specifically, none of which
439 was examined by Nash et al. One difference concerns ENSO, which they found to be significant
440 across HMA during which more ARs occur but no significant relationship with winter AR
441 frequency was established in our study. One reason could possibly be that their analysis spans
442 DJFMAM rather than DJF alone.

443 Nash et al. (2022) noted that it is difficult to separate the effects of individual modes because
444 they rarely act alone, and they suggested that future research should look at their combined
445 influence. Our models address this by including interaction terms. For example, EPNP is not
446 significant as a direct predictor but is included through the PNA $\times$ EPNP term, even though
447 EPNP by itself has only a weak correlation with AR frequency ($r = -0.009$). Both the GLM and
448 the GAM include interaction terms, and the EP-NP $\times$ PNA interaction was the strongest term
449 in each. The GAM predicts the annual ARs with fewer climate modes (three modes in four
450 terms, compared with eight modes in five terms for the GLM). The interaction entered the GAM
451 linearly, and the only nonlinear response was that of EP-NP. Although both models show
452 comparable skill but GAM has an advantage as it uses less modes and interactions. These results
453 suggest that winter AR variability over the Western Himalaya is associated with the combined
454 state of several climate modes, and in part with a nonlinear dependence on EP-NP, and not with
455 any single mode alone.

456 Since the dataset includes only 39 winters, there is limited statistical power to screen climate
457 modes. To keep physically reasonable predictors, a more relaxed significance threshold ($\alpha =$
458 0.13) was used. Both the GLM and GAM were fitted with relatively few observations compared
459 to the number of parameters and interaction terms, so overfitting remains a concern, even
460 though leave-one-out cross-validation was applied. The high pseudo R-squared for the models
461 should be considered in this context. The interaction terms in the models were not analysed on

their own with the phase-composite analysis used for individual modes in Sections 4.2. As a result, their direct relationship with moisture-transport field is not fully described. Finally, the results are based on a single reanalysis dataset, which could influence the findings, as shown in other multi-reanalysis studies (Lavers et al., 2012).

A natural extension of this work would be to apply the phase-composite approach used in Section 4.2 to the significant interaction terms themselves, compositing IVT on the joint phase states of interacting mode pairs, for example EP-NP+/PNA+, EP-NP-/PNA-, EP-NP+/PNA-, EP-NP-/PNA+. The composites presented here characterise each mode individually and therefore cannot show how the moisture-transport field responds when two modes are in reinforcing or opposing states. This will help in understanding whether the improvement in predictive skill from these terms corresponds to identifiable changes in the spatial structure of moisture transport, and whether those changes are consistent with the circulation mechanisms reported in the studies, and this would provide a physical basis for interaction effects that the statistical models currently capture only implicitly.

The analysis presented here covers 1980–2018, but ERA5 extends to the present, so the record can be lengthened immediately by several additional winters. This would increase the statistical power of the screening stage and reduce the need for a relaxed significance threshold, and would also enlarge the sample available for fitting the multivariate models, where the ratio of observations to estimated parameters is currently a limitation. Applying the same framework across several reanalysis products, as Lavers et al. (2012) did, would further test the robustness of the identified relationships to reanalysis uncertainty.

6. Conclusion

The study developed and compared a hierarchy of statistical methods, comprising correlation screening, phase-composite analysis, linear regression, GLM, and GAM, in order to identify

the climate patterns that determine the frequency of winter AR events in the Western Himalayas and to evaluate their predictive capacity. Previously, more extensive studies had not dealt with this issue.

When we first examined the nineteen climate mode indices, we found that AO, PDO, PNA, EA-WR, and Sib-H had the strongest connections to winter AR frequency in individual climate modes, and in interactions several interactions were found significant. Later, a phase-composite analysis of individual climate modes confirmed these statistical links. In every case, the phase that led to higher IVT matched the direction of the mode's correlation with AR frequency. This means the associations show a real and consistent change in moisture transport, not just a random link. Both the AR count and the continuous atmospheric field back up these results, which makes us more confident in the physical basis of the predictors, not just their statistical correlation.

Linear regressions based on a single predictor showed that no one climate mode accounted for a large share of the variability in AR, RMSE values remaining very close within the range of 2.27 to 2.33 for all five modes. EA-WR was the most effective predictor on its own. When a multivariate GLM and GAM was employed with interaction terms, there was a significant gain in out-of-sample predictive accuracy. Both GAM and GLM demonstrated comparable performance. However, GAM has an advantage over GLM as it utilizes few modes and interactions in comparison to GLM. This finding shows that employing predictors and interaction terms together to these models improve predictive ability for this dataset.

In both the modes EA-WR emerged as the strongest single term predictor and, among interactions $EP-NP \times PNA$ was pivotal. For non-linear predictor in GAM EPNP reinforced the model, although its not significant on its own but due to interaction effect it comes into the

GAM equation. Thus, only three modes EA-WR, PNA, EPNP, and one interaction EP-NP $\times$ PNA could predict the winter AR frequency.

Putting the results together it becomes clear that the frequency of winter AR events in the Western Himalayas is the result of the combined and in part nonlinear influence of a number of climate patterns and is not controlled by any one single factor, unlike in places such as the British Isles where it was found that a single mode could account for the variability in winter ARs (Lavers et al., 2012). To our knowledge, this is the first direct comparison of linear and nonlinear multivariate models for predicting winter ARs in the Western Himalayas. The GAM's skill, despite a 39-year record, suggests that climate modes and their interactions have potential of forecasting ARs, which could support water-resource management in this sparsely observed and hydrologically important region.

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8. Open Research

All data used in the study are publicly available and their sources are mentioned in Data section of the paper.

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