ISSN 0354-8724 (hard copy) | ISSN 1820-7138 (online)

Investigating the impact of El Niño Southern Oscillation and North Atlantic Oscillation on Temperature regime in the Republic of Azerbaijan

Tamerlan Mehdiyev[A1], Asgar Mammadov[A], Anar Nuriyev[A]

[A] Baku State University, Academic Zahid Khalilov street-33, Baku, Azerbaijan; ORCID TM: 0009-0000-5574-4048; AN: 0000-0002-5052-860X

Received: February 7, 2026| Revised: April 1, 2026| Accepted: April 13, 2026

doi: 10.5937/gp30-64738

Abstract

The study aims to investigate recent changes in the climate of Azerbaijan and climate drivers behind these changes. To reveal the combined influences of multiple climate oscillations, it was decided to employ regression models with climate teleconnections of North Atlantic Oscillation (NAO) and El Niño Southern Oscillation (ENSO). Prior to these, Statistical analysis such as Mann – Kendall test and extreme value tests were applied to identify statistically significant trends. The findings revealed that temperature persistence dominates the local climate in the country. Overall, the impact of North Atlantic Oscillation is small, while El Nino – Southern Oscillation shows little to no impact.

Keywords: Azerbaijan; North Atlantic Oscillation; Climate Teleconnections; El Nino – Southern Oscillation; Climate Variability in Azerbaijan

Introduction

Climate change is a popular topic in the Republic of Azerbaijan for multiple reasons. Many are concerned with water resources, particularly glaciers as it is believed that it will add more challenges to already under stress water management sector (Huseynov et al., 2025a). Another concerning environmental issue is sea level change in Caspian Sea. There are different schools of thought on what is behind this trend. Some point out that hydroclimatic processes can be the main driver behind it (Jorissen et al., 2020). Others attribute this phenomenon to the anthropogenic influence (Ataei et al., 2018). Regardless of cause, it is expected that discussion around these matters will be even more frequent. Especially considering that countries located along the Caspian Sea are seeking ways to increase maritime transportation with the plans to establish middle corridor, such challenges remain to be main sources of discussion (Palu & Hilmola, 2023).

Several studies and reports from various international organizations note that Azerbaijan is among the countries that are most vulnerable to the climate change (World Bank Group, 2023). How the climate in Azerbaijan is changing has been the main subject of several studies. However, existing studies are mostly confined to analysing linear trend changes and frequently lack the application of robust methodologies. Accessibility to data, limited collaboration among data providers and academia remain to be constraining factor for elaborate studies (Blois, 2021). One way

1 Corresponding author: Tamerlan Mehdiyev; e-mail: tamerlan.mehdiyev@bsu.edu.az, +994 55 813 95 47

to get around the data scarcity problem is to rely on previously published materials or secondary datasets. Luckily, some local articles contain valuable station datasets (Mammadov, 2015). Secondary datasets like these can improve the depth and scope of the analysis in a scarce data environment. However, another important limitation of use of these datasets is that they along with methodological frameworks have mostly been pre-processed with the specific objectives in mind (Huseynov et al., 2025b). This can restrict their reusability and make it very hard for researchers to extract raw information suitable for independent analysis. Generally, by looking at literature related to climate change studies for Azerbaijan, several issues can be highlighted. First, the coverage of meteorological observation network is questionable, and temporally limited (Ebinger et al., 2010). Access to national dataset is very restricted if none existing. Although, law of the Republic of Azerbaijan on the right to obtain information is adopted in 2002, and constitute regulation on data sharing, yet mechanisms seem to be not working properly. State Hydrometeorological service does not have open-access online database which researchers can inquire about data for access. This hinders direct access and fast data access options for researchers. Furthermore, most of the physical studies exclude assessments for sectoral impact, keeping many aspects out of equation (World Bank Group, 2023). Last but not least important, the limited depth of literature focusing on how the climate forces, drivers, and conditions affect the local climate remains to be the main constraint. Caspian Sea in this sense remains an interesting case. It can be noted that ongoing sea level change amidst increased efforts to develop sea transport might have allured researchers to study Caspian Sea thoroughly. On the topic of climate dynamics, especially wind regime of Caspian Sea, and complex interlinkages with climate, more collaborative research is observed (Safarov et al., 2025).

The main objective of this research is to enhance the understanding of climate interlinkages affecting Azerbaijan. The conventional literature on Azerbaijan's climate mostly underlines the impact of the northern high-pressure (Siberia) systems, the soothing effect of the Caspian Sea, and Greater Caucasus (Khromov, 2005). Nonetheless, less attention has been given to understanding the possible role of large-scale atmospheric oscillations in contributing local climatic conditions. Most of the work have been done largely depict Azerbaijan's climate as being mainly confined by geographic factors, yet evidence from the literature focusing on other parts of world, demonstrates that the influence of external climate drivers are too strong to be disregarded (Velichkova et al., 2025). There are several atmospheric oscillations that can directly or indirectly affect regional climate variability. Among them the North Atlantic Oscillation (NAO) and the El Niño–Southern Oscillation (ENSO) are very influential and can be considered as predominant for climate of Caucasus too.

Even though NAO and ENSO originate far away from land, they still can substantially influence weather patterns across Europe, Mediterranean coast and the Caucasus. NAO is defined by the pressure difference between the Icelandic Low and the Azores High. It has multiple phases and any change in its phases can largely impact the winter weather in big parts of northern hemisphere. When it is in positive phase, a strong pressure gradient forms, and it strengthens westerly winds which steer warm, moist Atlantic air into Europe, resulting in green winter for the lands. Conversely, when it is in the negative phase, it weakens these winds and thus opportunity emerges for cold Arctic air to enter southward, bringing freezing temperatures and dry conditions to Northern Europe. However, due to the moderating effect of Mediterranean sea, winter becomes relatively colder in southern Europe and Caucasus.

ENSO on the other hand, is a complex form of ocean-atmosphere dynamics. Being one of the most dominant climate drivers, ENSO is a natural cycle in Pacific Ocean temperature, wind and cloud regimes. It is considered that influence of ENSO can be felt anywhere around the globe. ENSO has three phases, namely: La Nina, Neutral, and El Nino phases. During the neutral phase, steady trade winds blow across the tropical Pacific from the east to west. These winds accumulate warm water in the western part of Pacific. In exchange, the eastern part of pacific gets colder water through upwellings. Temperature gradient between east and west gets higher and thus rising air in the west move and descent in the east which creates cycle called Walker circulation. In this phase, west part of the ocean gets milder weather. In the case of La Nina, trade winds blow harder and western part of ocean gets warmer. Eastern part on the other hand gets colder and thus temperature gradient gets bigger. El Nino is completely opposite of La Nina. Trade winds get slower, allowing warmer water to drift back towards the east. This causes Walker circulation to break down, ending in multiple smaller circulations.

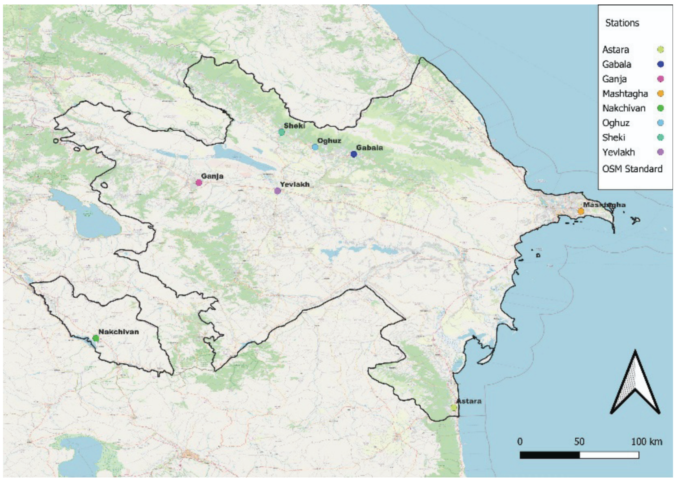

Figure 1. Map of the locations of stations

For our study, eight representative stations were selected from various climatic zones across Azerbaijan: Shaki, Oguz, Gabala, Astara, Nakhchivan, Mashtagha, Yevlakh, and Ganja (Figure 1). Sheki and Oguz both located in the north-west of Azerbaijan, on the southern slopes of the Greater Caucasus Mountains have similar climate types. They both experience a moderately humid climate with relatively cool conditions compared to lowland areas of Azerbaijan. Summers are warm, and winters are usually cold (temperatures usually vary around 0 °C in winter) and snowy. Gabala is neighboring city to Oguz, and its climate bears similarities with Sheki and Oguz's. But the city is located on relatively higher plateau, which results in relatively more snowfall. Astara, located on the southern Caspian Sea coast is distinctive with one of the most humid climates in Azerbaijan. It has humid subtropical climate and experiences more precipitation in autumn and winter. Its summers are warm, and winters are quite mild.

Nakhchivan has a strong continental and semi-arid climate. It holds both records of highest and lowest temperature in Azerbaijan. Mashtagha, located on Absheron peninsula, has a semi-arid climate with a strong maritime influence. Summers are very hot but moderated by sea breezes, with strong wind. Winters on the other hand are mild, rarely experience snowfall. Yevlakh is located in the Kura-Araz lowland, an extensive plain that cover more than half of Azerbaijan. It is mostly characterized by semi-arid climate. Summers are very hot, and winters are mild, with little precipitation. Ganja, located on the northern foothills of Lesser Caucasus Mountains has a continental climate. Summers are hot, and winters are cool.

Material and Methodology

Data used for this study comes from various sources. The data which is the main core of our study mostly acquired from State Hydrometeorological Service of Republic of Azerbaijan as it is the government body responsible for measurements of climate variables. But as we already discussed, access to the data for researchers is very challenging. For this reason, it becomes necessary to look for other sources. A portion of the data used in this study was obtained directly from this service, while other parts were extracted from international organizations. These external sources include the National Centers for Environmental Information (NCEI), World Meteorological Organization (WMO) and the U.S. National Oceanic and Atmospheric Administration (NOAA). It is important to note that this data was originally provided to these organizations by the National Hydrometeorological Service of Azerbaijan under international agreements and obligations. Another key resource is Climatic Research Unit TEMperature (CRUTEM), a global collection of station data created by the Climatic Research Unit at the University of East Anglia. The specific version we used for our research is CRUTEM 5.0.2.0 (Osborn, 2020). Combination of these datasets makes up our base climate data for analysis. For calculations related to teleconnections, other sources were used.

The Niño-3.4 sea surface temperature (SST) index, extracted from NOAA's Extended Reconstructed Sea Surface Temperature version 5 (ERSSTv5) dataset, was employed to represent ENSO values (Huang et al., 2017). Another teleconnection that was used in this study, The North Atlantic Oscillation (NAO) is considered to be very important, heavily affecting the winter in northern hemisphere. It basically defines normalized pressure difference between a station on the Azores and one on Iceland. The index we used was obtained from the Climatic Research Unit (CRU), University of East Anglia (Jones et al., 1997). It is worth noting that all the datasets acquired for the study are monthly datasets.

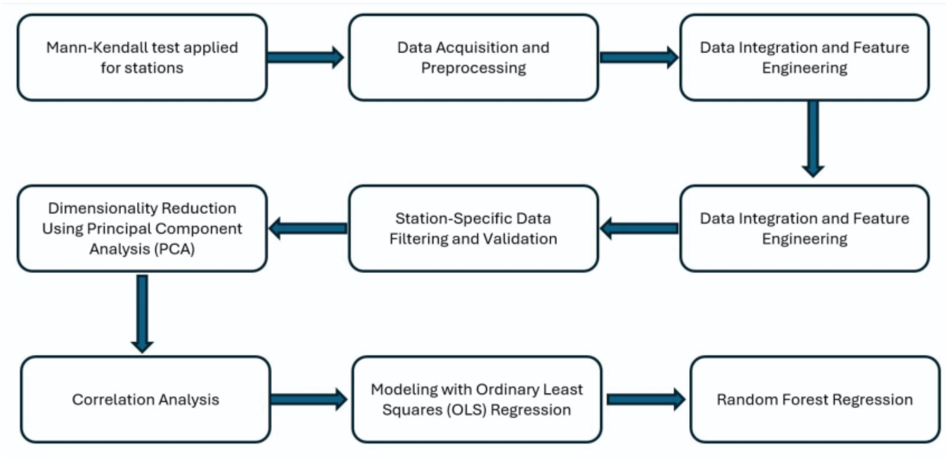

Figure 2. Workflow of methodological framework applied in this study

Figure 2 sums up what have been done for this study. But it does not reflect all the details. We have started our work with Mann-Kendall (MK) statistical test to identify trends that are statistically significant. MK test is a non-parametric test that is very popular in atmospheric and climate sciences. It is robust to outliers and can handle missing values which makes it very effective in identifying trends. In our research we applied MK prior to modelling steps because we wanted to identify trends before we examined relationship between temperature and indices. Teleconnections like NAO and ENSO often exhibit cycles of various timespans, short-term, long-term, etc. Prior studies identified NAO cycles around 7, 13, 20, 26, and 34 years (Seip et al., 2019). We can argue that any statistically significant trend can contain impact of these cycles. Similar things can be said about ENSO as well. Some studies showed strong ENSO teleconnection under warming trends identified by MK test (Vu Duy et al., 2022).

It should be noted that prior to each stage of analysis, preprocessing was conducted to ensure quality and uniformity. Only minimal preprocessing was required for the statistical analysis, specifically Mann-Kendall and Sen's Slope analysis as the temperature data were mostly complete with few occasional null values. The more extensive preprocessing was applied to the subsequent analysis which mostly involve data cleaning, structuring, and parsing. Data cleaning is a foundational step in any data analysis, involving detecting and correcting errors, inconsistencies, missing values, duplicates. Missing values were addressed using forward and backward filling. Additionally, disparate datasets were merged using a standardized date column to unify different time formats. Only after these preprocessing steps were completed were subsequent analysis conducted.

Then we created lagged values for temperature, NAO and ENSO. For time-series analysis using lagged features is very common and useful. For temperature analysis, effect of predictor is not directly reflected on temperature. Past states influence current temperatures. Due to delayed dynamics, introduction of lagged features became a necessity. After the basic diagnostics were performed, we moved on with next phase which is to apply Principal Component Analysis (PCA). PCA is a widely used statistical technique to reduce dimensionality of dataset. It transforms a set of variables that might be correlated into uncorrelated variables that are called principal components. Due to high temporal autocorrelation and persistent nature of ENSO, the values of ENSO, NAO, and temperature became highly multicollinear. That makes models fail to differentiate variables that are too similar to each other. Thus, to eliminate this problem PCA was applied. By applying PCA, we were able to reduce dimensionality through changing correlated variables into uncorrelated parts, therefore enhancing model stability and interpretability. We acquired various groups of PCA which expressed combination of drivers. After introducing PCA to our analysis we witnessed serious decrease in multicollinearity. To break down how each climate driver contribute to temperature variance, a Block Principal Component Analysis (Block PCA) was introduced. What it does differently than PCA is that it organizes predictors into theoretically defined blocks and applies dimensionality reduction within each block independently. To further assess multicollinearity among predictor blocks Variance Inflation Factor (VIF) was employed. With the help of VIF it is possible to quantify how much the variance of a regression coefficient is inflated because of linear relationship with other predictors. VIF values under 1 mean that there is complete independence from other predictors while VIF range 1 to 5 means modest to moderate correlation. Any value above 10 indicate severe multicollinearity.

To investigate how different components relate to current temperatures at each station in Azerbaijan, regression analysis were employed. To have concise results we used two models: one that's straightforward (Ordinary Least Squares, or OLS), and another, named Random Forest is better suited for dealing complex, non-straight-line relationships. This machine learning technique creates decision trees from various samples of data and then averages their predictions to forecast monthly temperatures.

The primary linear model applied in this research is OLS regression. It was implemented using the statsmodels library in Python. For each station, the dependent variable is the observed monthly temperature values (y), with the independent variables consist of PCA components written and grouped as PC1, PC2, PC3 (PC4 for two stations) and the NAO features. A constant was added to the predictor matrix for each station. These were applied station by station along with diagnostic checks that include model summaries. To solve potential non-linearities, Random Forest regression is employed using scikit-learn's RandomForestRegressor with 100 estimators and a fixed random seed for reproducibility. The same predictor matrix which includes PCA components along with NAO features and observed temperature are used, enabling direct comparison possible.

Results

As mentioned in our workflow, we started our analysis with statistical tests. The ultimate purpose was to differentiate the stations with statistically significant trends. To accomplish this goal, we used pymannkendall library of Python programming language. We analyzed 8 stations, using monthly datasets gathered from various sources. With testing we identified P, Z, and Kendall tau values. Aside from these, we also uncovered Sen's slope values for our stations. Mann-Kendall values give us statistical significance of trends with percentage. We set alpha level (threshold) for significance as $p < 0.05$ (95% confidence level) since most of the time climate analysis employs this level.

Table 1. Results of Mann-Kendall test and Sen's Slope analysis

Station	Trend	P-value	Z-stat	Kendall Tau	Sen's Slope (°C/year)
Astara	no trend	0.056	1.913	0.07	0.007
Gabala	no trend	0.073	1.793	0.064	0.008
Ganja	increasing	0.007	2.699	0.099	0.012
Mashtagha	no trend	0.163	1.396	0.051	0.005
Nakchivan	no trend	0.245	1.163	0.043	0.006
Oguz	increasing	0.0	6.074	0.218	0.029
Sheki	increasing	0.0	6.104	0.22	0.029
Yevlakh	no trend	0.118	1.565	0.057	0.007

Looking at the results of Mann-Kendall test and Sen's Slope analysis (Table 1), we can see that only three stations have statistically significant trends. Those stations are Ganja, Oguz, Sheki. Sheki and Oguz located in same geography, and relatively close to each other showed very similar results. Interestingly, both stations illustrate increase of 0.030 °C per year, equal to ~1.5–3°C of warming over 50–100 years, which aligns with the global climate change predictions for the given time span (50–100 years). For other stations, we see that they also show increase in temperature though the trends are not statistically significant.

Next, the processes of data cleaning, structuring were applied to temperature, ENSO and NAO data. After preprocessing, further analysis were conducted to examine the relationships between monthly temperature data from selected weather stations and climatic teleconnection indices (ENSO and NAO). Along with lagged features, correlation matrixes were applied. The findings indicated high multicollinearity in the matrix (Figure 3).

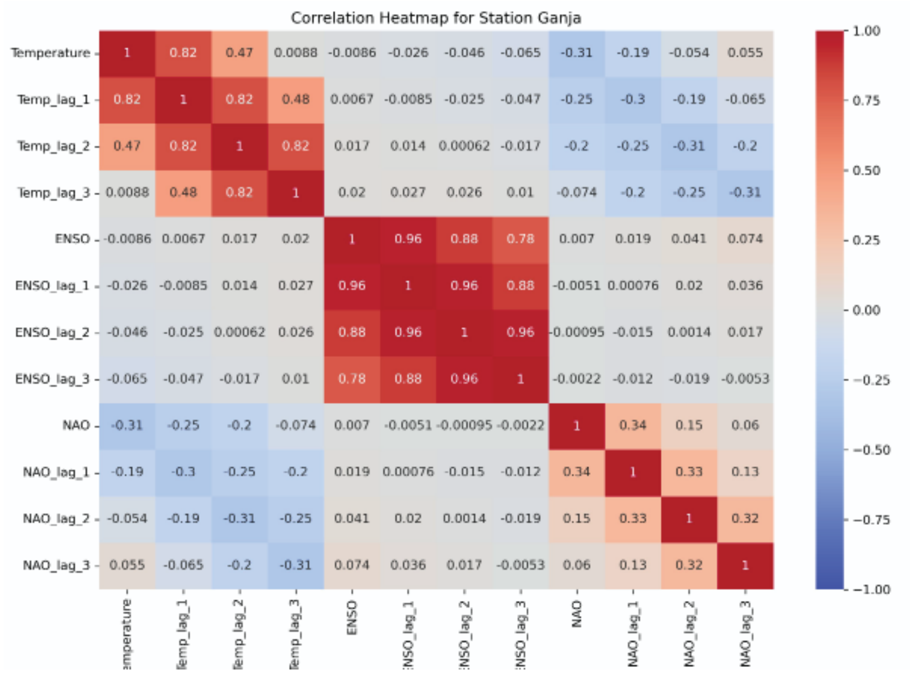

Figure 3. Correlation heatmap for Ganja station

In Figure 3 we see that multicollinearity of one of stations (Ganja) is substantially high and it is especially reflected among ENSO lags. Other stations also had same issue, showcasing high multicollinearity among lags. To solve multicollinearity and enhance our model, Principal Component Analysis were employed.Principal Component Analysis made a direct impact decreasing multicollinearity levels significantly (Figure 4).

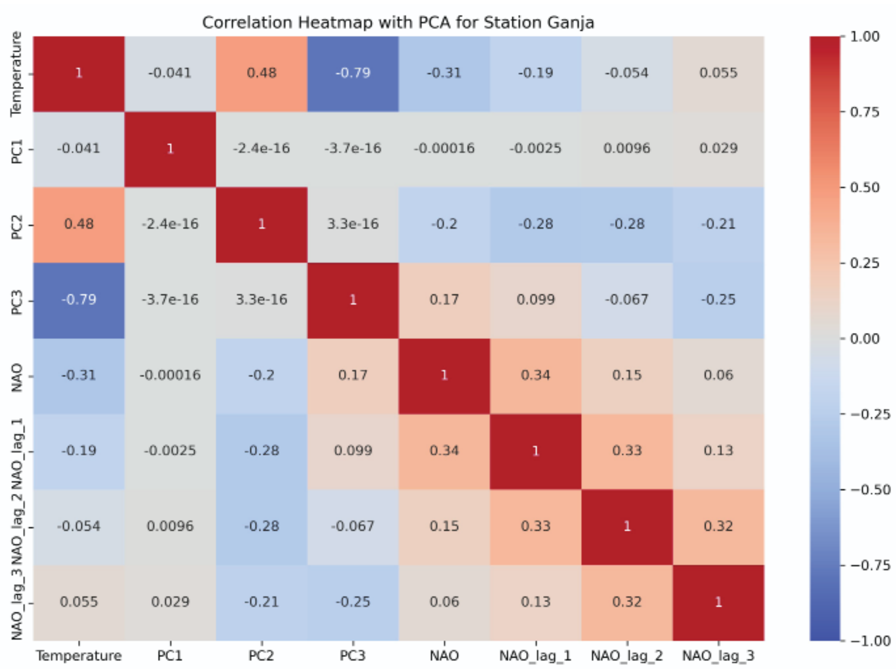

Figure 4. Correlation heatmap for Ganja station after the application of PCA

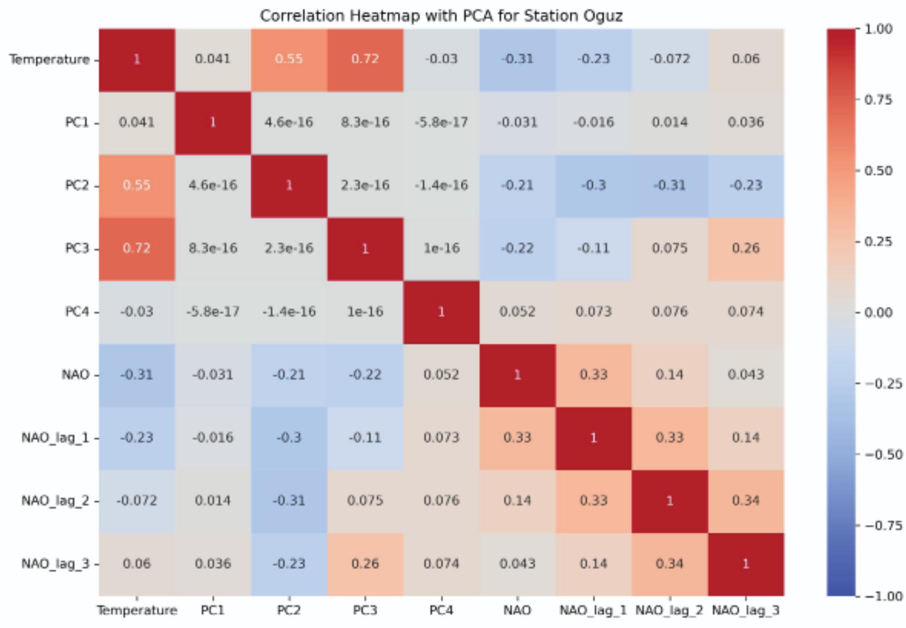

Figure 4b. Correlation heatmap for Oguz station after the application of PCA

Application of PCA showed that PC1 mostly correlated to ENSO and its lags while PC2 and PC3 mostly represented temperature lags. Some stations (Nakchivan, Oguz) appeared to have 4 PCs (Figure 4b). The variation in the number of PCs across stations is because of differences in variance of each station dataset. PC loadings from those stations with 4 PCs point out that PC4 mostly represent ENSO for those stations.

After the application of PCA, the application of Ordinary Least Square (OLS) regression models were introduced for each station. To avoid redundancy, outputs for a single representative station (Ganja) were showcased since there is consistency of results across stations. Results indicate relatively stable models for each station. Just to give an example, looking at OLS regression results of one of stations (Ganja), value of 0.868 for R-squared can be seen, which means OLS regression model for Ganja is very stable and explains 86.8% of the variance. The values for F-statistic and Prob (F-statistic) on the other hand are 191.3 and 3.06e-133 respectively. These values prove that the model is statistically significant and the relationship we found is not because of random chance. Durbin-Watson value of 2.306 is not an ideal value but it is generally accepted (Abdulhafedh, 2017). This value suggests that there is no major problem with autocorrelation. We got value of 9.021 for Kurtosis which indicates that our data has heavy outliers (Figure 5). Similar results were observed on the other stations too.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            Temperature   R-squared:                       0.868
Model:                            OLS   Adj. R-squared:                  0.864
Method:                 Least Squares   F-statistic:                     191.3
Date:                Fri, 06 Feb 2026   Prob (F-statistic):          3.06e-133
Time:                        14:41:36   Log-Likelihood:                -841.62
No. Observations:                 331   AIC:                             1707.
Df Residuals:                     319   BIC:                             1753.
Df Model:                          11
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          6.9722      0.442     15.787      0.000       6.103       7.841
Temp_lag_1     0.9792      0.046     21.232      0.000       0.888       1.070
Temp_lag_2     0.1193      0.071      1.683      0.093      -0.020       0.259
Temp_lag_3    -0.5616      0.046    -12.098      0.000      -0.653      -0.470
ENSO          -0.3123      0.864     -0.361      0.718      -2.012       1.388
ENSO_lag_1     0.1874      1.547      0.121      0.904      -2.857       3.232
ENSO_lag_2     0.8113      1.546      0.525      0.600      -2.231       3.854
ENSO_lag_3    -0.8103      0.873     -0.929      0.354      -2.527       0.906
NAO           -0.8231      0.177     -4.645      0.000      -1.172      -0.474
NAO_lag_1      0.3942      0.188      2.092      0.037       0.023       0.765
NAO_lag_2      0.3331      0.189      1.759      0.080      -0.040       0.706
NAO_lag_3     -0.3589      0.181     -1.980      0.049      -0.715      -0.002
==============================================================================
Omnibus:                       53.229   Durbin-Watson:                   2.306
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              502.482
Skew:                           0.210   Prob(JB):                    7.71e-110
Kurtosis:                       9.021   Cond. No.                         366.
==============================================================================
```

Figure 5. OLS Regression results for Ganja

In the coefficients section present in Figure 5, NAO values that look comparable in magnitude are observed. These values can be misleading because NAO and temperature persistence values operate on completely different scales. Temperature persistence values mostly vary by around 20 to 25 whereas NAO typically varies roughly between -3 and 3. To interpret physical impact of NAO in figure 5, one should consider the coefficient along with standard deviation. Since NAO has a much smaller range of variation, it requires a steep slope to produce a modest temperature effect.

This is where partial and semi partial correlations can be very helpful. To move beyond the raw coefficients and investigate contribution of drivers we introduced scale-free partial and semi-partial correlations (Figure 6).

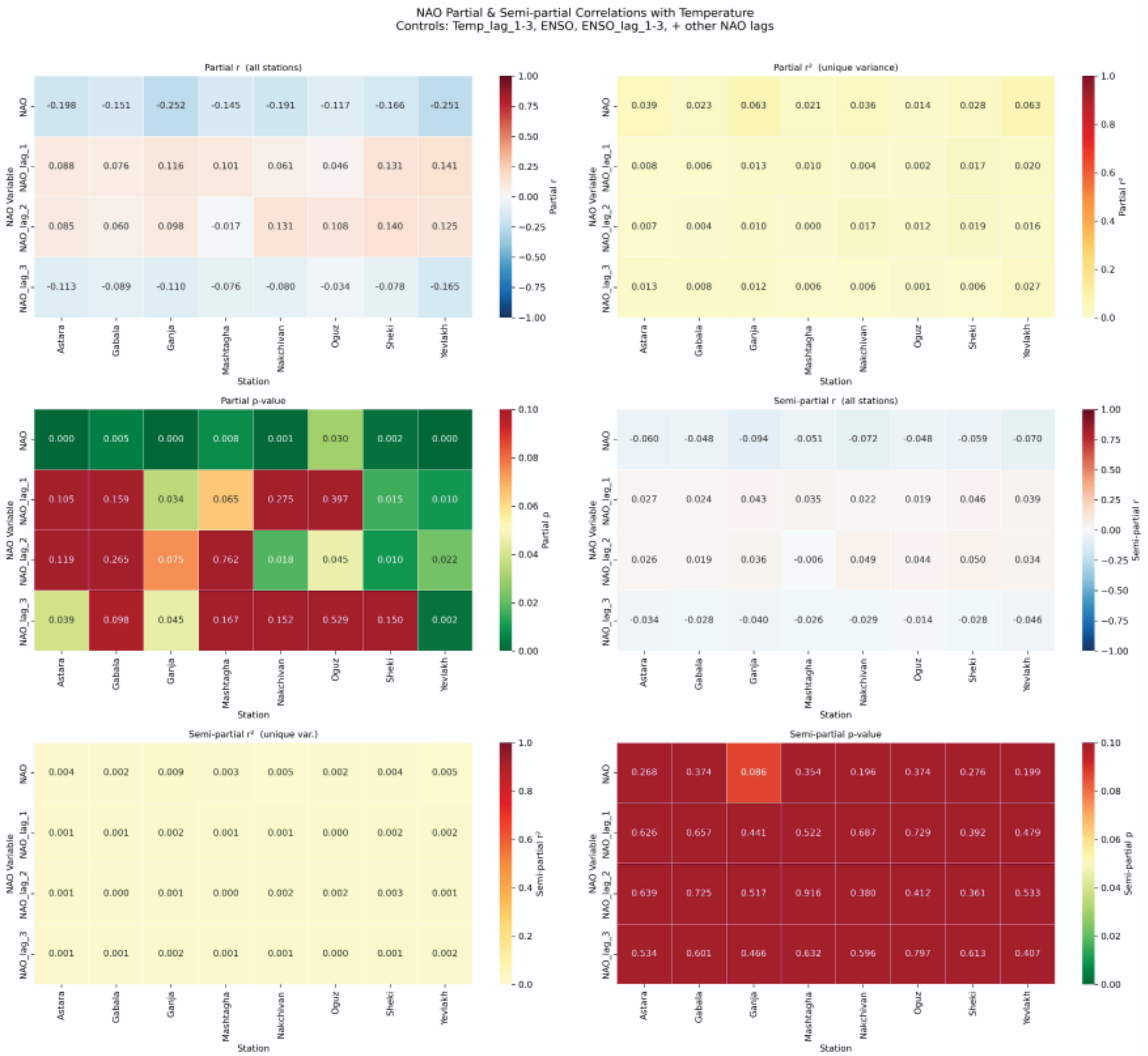

Figure 6. Partial and semi-partial correlations with temperature

Partial correlation basically strips away the effects of all the other predictors from both NAO and Temperature and what remains is the pure, isolated link between the two. The semi-partial correlation on the other hand only removes the effects of other predictors from NAO only, while temperature stays as it is. When squared, this value gets the exact percentage of total temperature variance that NAO only accounts for. Partial and semi-partial correlation analysis showed that among NAO terms, only the contemporaneous index (NAO) retained consistent independent significance across the stations. Others showed various results mostly indicating multicollinearity.

Figure 7 shows the OLS regression coefficients for our predictors across all the stations. According to the Figure 7, PC2 and PC3 are the largest coefficients across all stations, reflecting the dominant role of temperature persistence in temperature variability. By contrast, NAO lags and ENSO (PC1) display coefficients that are small and mostly non-significant.

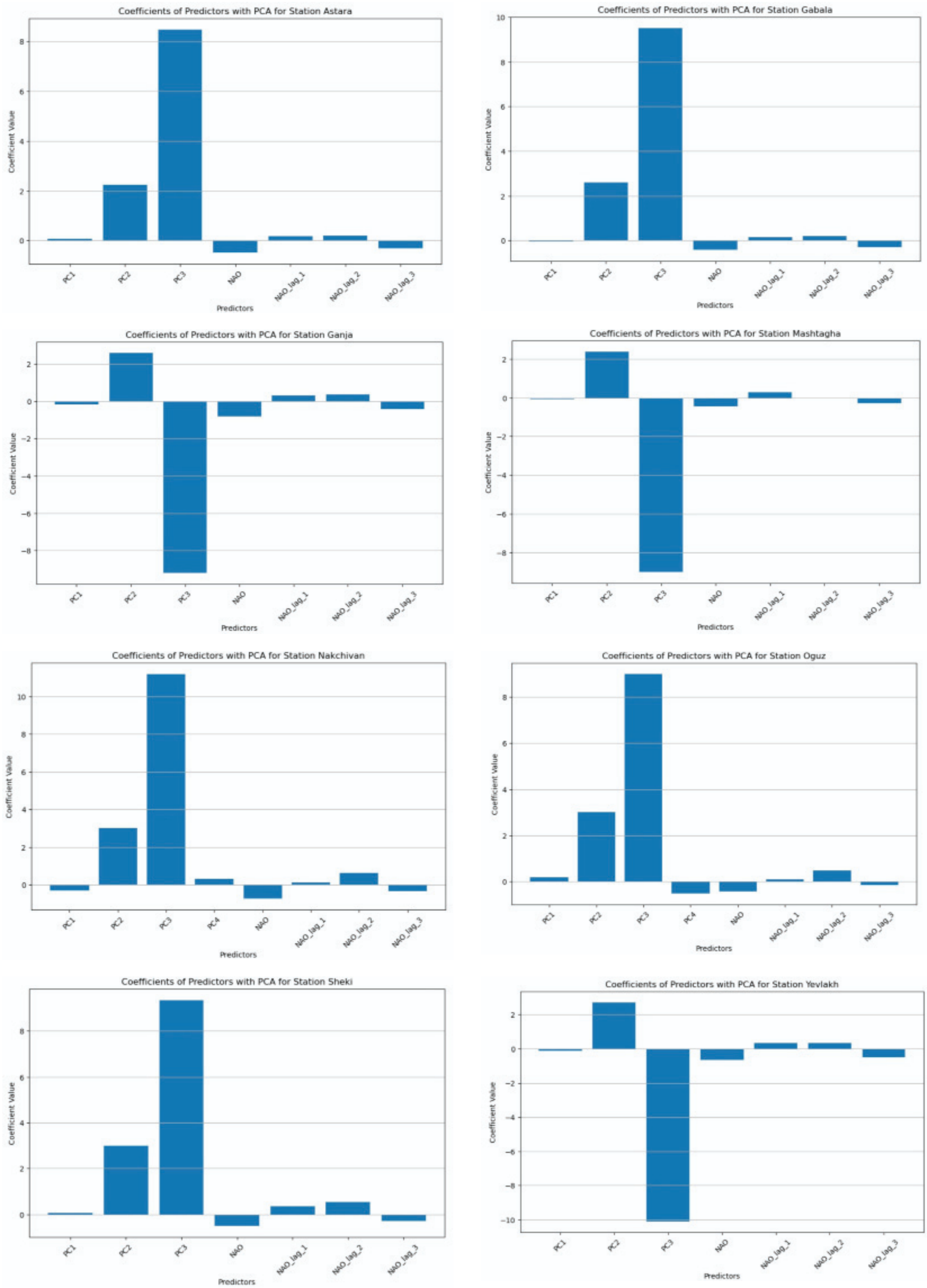

Figure 7. Coefficients of predictors with PCA for stations

Generally, all the stations show that PC3 is overwhelmingly stronger compared to other predictors (Figure 7). All of them indicate similar patterns with little differences. However, when comparing feature importances from Random Forest Regression models we see relatively bigger differences. There can be multiple reasons behind these differences. The divergence most probably stems from fundamental differences between OLS and RF modelling. The coefficients of predictors are extracted from OLS model. This means that they assume linear relationship between predictors and temperature. Minor differences can arise due to random noise and interactions with lags and PCs.

Table 2. Extracted feature importances for all the stations

STATIONS	TEMPERATURE P	NAO	ENSO
Astara	95.75%	2.51%	0.98%
Gabala	95.63%	2.78%	0.84%
Ganja	92.46%	6.44%	1.10%
Mashtagha	94.78%	4.34%	0.88%
Nakchivan	94.51%	3.73%	1.10%
Oguz	90.35%	6.42%	1.85%
Sheki	93.07%	5.69%	1.24%
Yevlakh	97.07%	2.31%	0.61%

RF importances show that among all the stations, only Ganja, Oguz, and Sheki experienced relatively higher values for NAO and ENSO (Table 2). These are also the only stations that have statistically significant trends according to Mann-Kendall non-parametric test.

To get an overview of relative strength of temperature persistence and teleconnections in explaining temperature variance, a variance decomposition analysis was conducted using a block principal component analysis (Block PCA) framework (Figure 8). These analyses do not just focus on whether each driver connects statistically to temperature, but it digs deeper, asking how much of the total temperature variance each driver accounts for on its own.

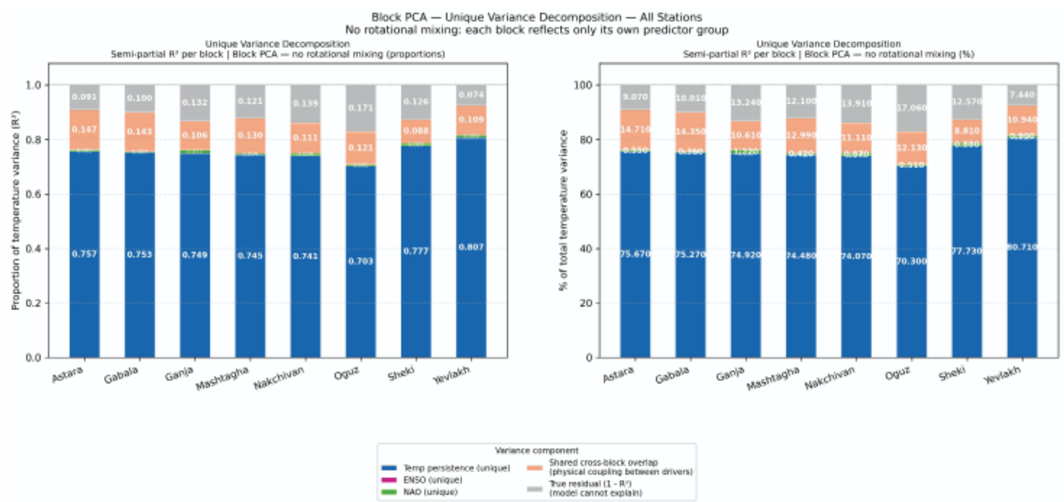

Figure 8. Unique variance decomposition for all stations

Figure 8 presents two panels. The left panel represents each driver's unique variance as a fraction of the total variance, demonstrating the relative dominance of temperature persistence, NAO, and ENSO among themselves. In this case the segments represented by bars add up to 1. The right panel on the other hand depicts each driver's contribution as a percentage of the total temperature variance. It should be noted that both panels take shared overlap and residuals into account.

One of the big methodological challenges in this type of analysis is multicollinearity. Multicollinearity can inflate regression coefficients and making it almost impossible to pin down the independent contribution of any single driver. To overcome this challenge, Variance Inflation Factor (VIF) diagnostics were applied to the blocks (Figure 9).

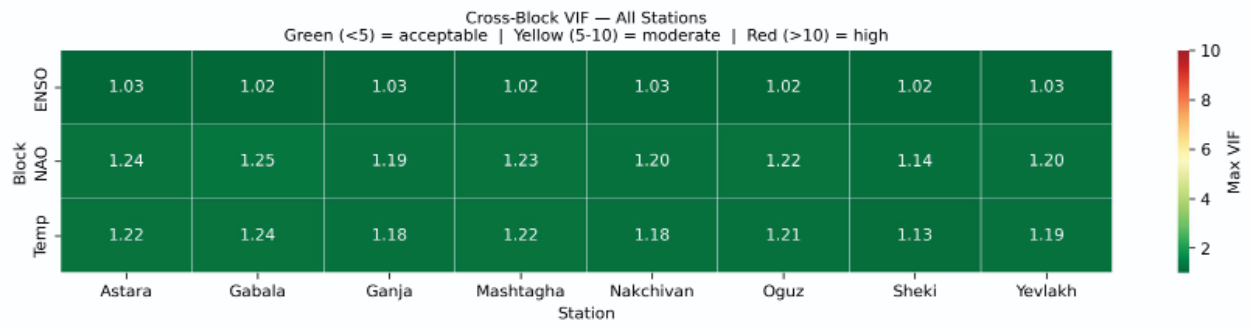

Figure 9. Cross-Block VIF diagnostics

A Variance Inflation Factor (VIF) of 1 usually means no correlation or no multicollinearity. Values between 1 and 5 indicate a moderate correlation. As Figure 9 indicates our values are well below the conventional threshold of 5. This indicate that our unique variance decomposition using block PCA (Figure 8) retains statistically significant predictors.

Another important finding was about the temporal changes occurred over the years. To examine whether the relative contributions of the three blocks (Temperature persistence, NAO, ENSO) changed or remained stable, unique variance decomposition using the Block PCAs was repeated independently for two time periods with the equal length: 1991–2004 and 2005–2018 (Figure 10).

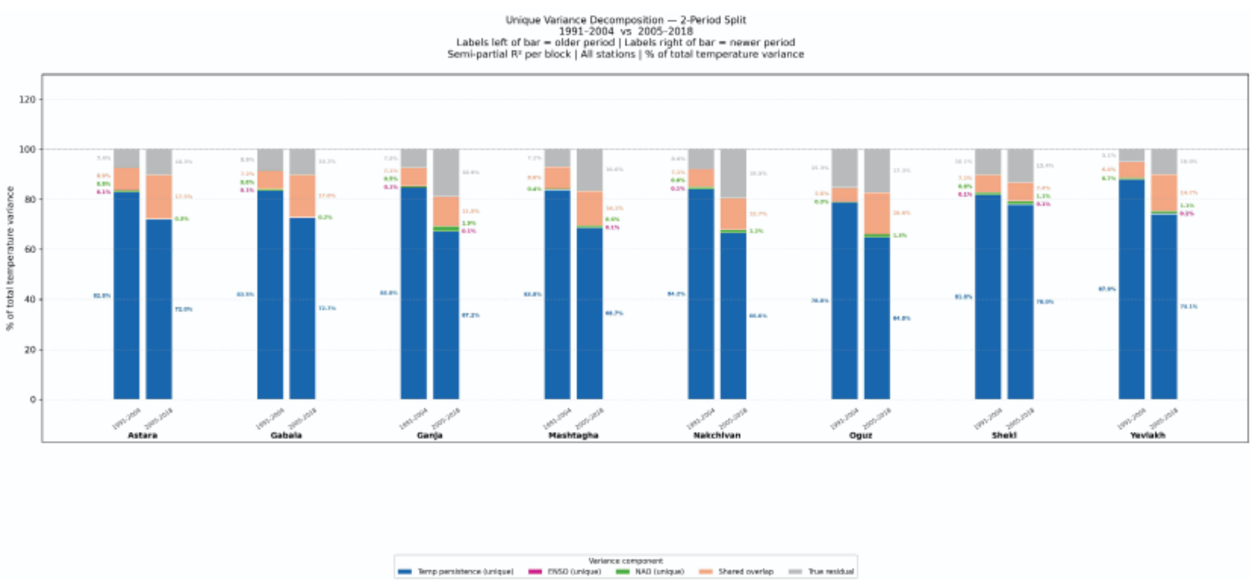

Figure 10. Temporal change of unique variance decomposition for all stations for two periods; 1991 – 2004 and 2005 – 2018.

With the approach given in Figure 10, the methodological consistency of analysis using block structure was preserved. Each period contains approximately 168 months of observations per station, making sure a statistically acceptable sample for reliable Block PCA estimation. Prior to application of unique variance decomposition, VIF diagnostics were recomputed and results ranged from 1.0 to 1.3.

To further analyse the changes, another unique variance decomposition using the Block PCAs was applied only this time with three time-periods: 1992 – 2000, 2001 – 2009 and 2010 – 2018 (Figure 11).

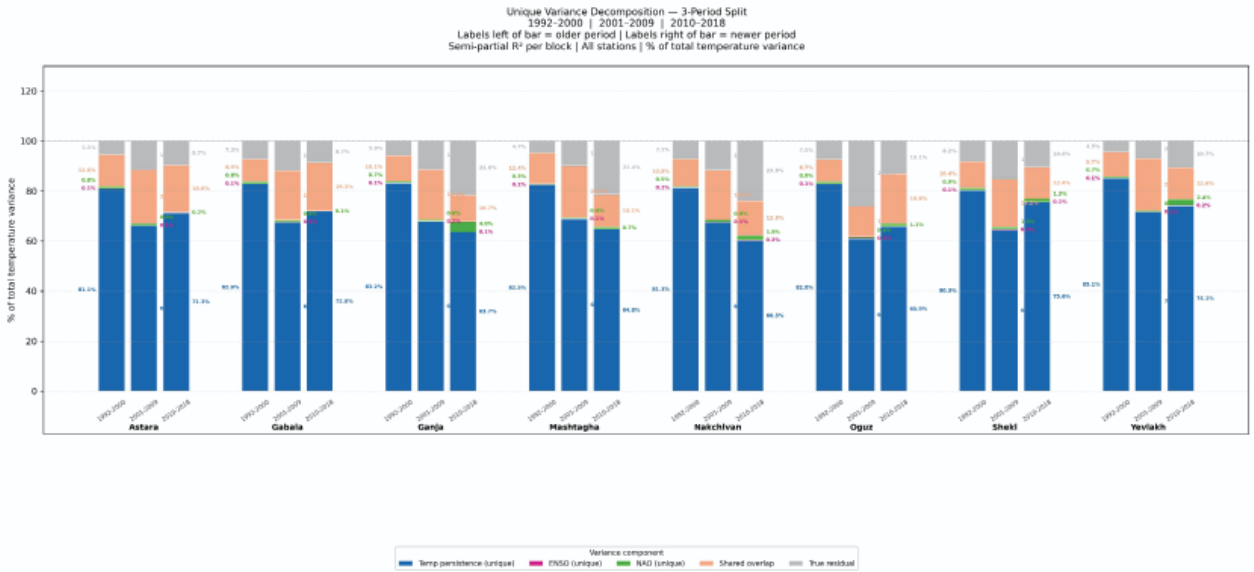

Figure 11. Temporal change of unique variance decomposition for all stations for three periods; 1992 – 2000, 2001 – 2009 and 2010 – 2018.

Figure 11 represents 3 time periods. The figure accounts for unique variance components of temperature persistence, NAO, ENSO along with shared cross block overlap and true residual. The three comparison points lets better scrutinization on the direction of trends and their consistency.

Discussion

The choice of applying the lag structure method was a deliberate one. Considering that climate drivers mostly do not show immediate impact and it takes some time to be reflected on temperature regime, it was decided to adopt lag structure to capture delayed effects.

Partial and semi-partial correlation analysis demonstrated that out of all the NAO terms, only the contemporaneous NAO contained significant, independent link with temperature across all the stations. The lags on the other hand exhibited unstable signs and yielded largely insignificant partial and semi-partial correlations. Figure 8 further revealed that temperature persistence is the dominant driver of month-to-month temperature variability across all eight stations in Azerbaijan. It accounts for 70.3% to 80.7% of total temperature variance and it does this independently of external climate forcing. The dominance of temperature persistence suggests that it is the local thermodynamic memory that governs interannual and seasonal temperature variability in the country. NAO, on the other hand, contributes a small but consistent unique share of temperature variance at every station, with values ranging from 0.360% to 1.220%. By contrast, ENSO barely contributes, confirming that ENSO's impact has been negligible in the given period. The shared cross block overlap accounts for values ranging from 8.8% to 14.7% at different stations. It represents portions that cannot be attributed to any single driver along with physical coupling between external forcing and temperature persistence.

Results of temporal change analysis offer different perspective on climate drivers. Figure 10 reveals striking findings about the temperature persistence. It shows sizable decline for the contribution of temperature persistence, a reduction of around 8 to 18 percentage across stations. Interestingly this decline was accompanied by increase in the shared cross-block overlap. This overlap explains joint variance of temperature persistence and other climate drivers. As demonstrated in Figure 6, there is significant overlap of NAO lags with temperature persistence. Therefore, we can assume that this shared overlap in Figure 10 include effects of NAO as well. This pattern points out an increasing physical entanglement among temperature persistence and external drivers. Although contribution of NAO still remains small, it showed a modest increase in 6 out of 8 stations. ENSO on the other hand remained as negligible over the years. Obvious increase in true model residual might be due to model's inability to capture growing temperature variability which is connected to more frequent extreme weather events in the second period.

While two period let us to see shift, it provides only single point comparison. To address this limitation, Block PCA decomposition with three time periods was employed (Figure 11). It offers better temporal resolution and easier tracking of changes. Figure 11 reveals that identified change across stations is not a gradual linear trend but rather a stepwise transition. The contribution of temperature persistence saw an abrupt decrease in 2001 – 2009 while in third period, it fluctuated. Another important detail is the consistent and, in some stations, strong increase of NAO in the third period.

Initially negligible contribution of ENSO might seem inconsistent with few regional studies which highlights the significance of ENSO to Caspian Sea basin. Safarov et al. (2025) showed that Southern Oscillation Index (SOI) which is one of several indices used to measure ENSO has a stronger impact to Caspian Sea level changes than NAO does. However, ENSO influences the Caspian basin through wind patterns and evaporation rather than direct thermodynamic forcing on surface temperature. That is an important point because the index can convey a meaningful hydrological signal at the basin scale but barely leave a mark on local temperature especially in places like Azerbaijan where temperature persistence dominates variability as observed in the study. Thus, the findings of our study reinforce rather than contradict the work of Safarov et al. (2025), implying that the influence of ENSO and NAO in Azerbaijan works through dynamical pathways that are not reflected by direct temperature analysis at the station level.

To sum up our analysis revealed that changes in temperature persistence was abrupt one rather than being gradual, especially reflecting itself time period between 2001 and 2009. Second, over the years, we witnessed continuous growth in shared overlap and true residuals. This suggests that the regional climate has entered a phase of increased complexity which calls for deeper research with methods that can tackle changing patterns.

Reference

Abdulhafedh, A. (2017). How to detect and remove temporal autocorrelation in vehicular crash data. *Journal of Transportation Technologies, 7*(2), 133–147. https://doi.org/10.4236/jtts.2017.72010

Ataei, S. H., Khakpour, A. M., Adjami, M., & Neshaei, S. A. (2018). Investigation of Caspian Sea level fluctuations based on ECMWF satellite data. *International Journal of Coastal, Offshore and Environmental Engineering, 3*(2), 21–30. https://doi.org/10.29252/ijcoe.2.2.21

Blois, C. L. (2021). *Examining well-being and vulnerability in data-poor nations: Azerbaijan and Kyrgyzstan*.

Ebinger, J., Hancock, L., & Tsirkunov, V. (2010). *Weather and climate services in Europe and Central Asia: A key tool for energy sector adaptation to climate change*. World Bank Group.

Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T., Chepurin, G., Lawrimore, J. H., Menne, M. J., Smith, T. M., Vose, R. S., & Zhang, H. (2017). Extended reconstructed sea surface temperature, version 5 (ERSSTv5): Upgrades, validations, and intercomparisons. *Journal of Climate, 30*(20), 8179–8205. https://doi.org/10.1175/JCLI-D-16-0836.1

Huseynov, J., Tagiyev, A., & Ismayilova, M. (2025). Characteristics of the contemporary spatiotemporal distribution of atmospheric precipitation in the southern and southeastern parts of the Greater Caucasus region. *Visnyk of V. N. Karazin Kharkiv National University Series: Geology, Geography, Ecology, 62*, 360–371. https://doi.org/10.26565/2410-7360-2025-62-27

Huseynov, N., Huseynov, J., & Guliyev, Z. (2025). The conceptual model of climate change in the Republic of Azerbaijan. *GeoJournal of Tourism and Geosites, 61*, 1875–1886. https://doi.org/10.30892/gtg.61345-1555

Jones, P. D., Jónsson, T., & Wheeler, D. (1997). Extension to the North Atlantic Oscillation using early instrumental pressure observations from Gibraltar and south-west Iceland. *International Journal of Climatology, 17*(13), 1433–1450. https://doi.org/10.1002/(SICI)1097-0088(19971115)17:13<1433::AID-JOC203>3.0.CO;2-P

Jorissen, E. L., Abels, H. A., Wesselingh, F. P., Lazarev, S., Aghayeva, V., & Krijgsman, W. (2020). Amplitude, frequency and drivers of Caspian Sea lake-level variations during the Early Pleistocene and their impact on a protected wave-dominated coastline. *Sedimentology, 67*(2), 649–676. https://doi.org/10.1111/sed.12658

Khromov, S. (2005). *Meteorology and climatology*. Baku State University.

Mammadov, A. (2015). *Azərbaycanda müasir iqlim dəyişmələri və onun proqnozlaşdırılması [Climate change and its forecasting in Azerbaijan]*. MBM.

Osborn, T. J., & Jones, P. D. (2020). Land surface air temperature variations across the globe updated to 2019: The CRUTEM5 dataset. *Journal of Geophysical Research: Atmospheres, 125*(6). https://doi.org/10.1029/2019JD032352

Palu, R., & Hilmola, O.-P. (2023). Future potential of Trans-Caspian corridor: Review. *Logistics, 7*(3). https://doi.org/10.3390/logistics7030039

Safarov, E., Bayramov, E., Safarov, S., Neafie, J., & Hedjazi, A. (2025). Impact of changes in the wind regime on the Caspian Sea level fluctuation and its relationship with SOI and NAO. *Scientific Reports, 15*. https://doi.org/10.1038/s41598-025-20346-6

Seip, K. L., Grøn, Ø., & Wang, H. (2019). The North Atlantic Oscillations: Cycle times for the NAO, the AMO and the AMOC. *Climate, 7*(3). https://doi.org/10.3390/cli7030043

Velichkova, T., Kilifarska, N., & Mokreva, A. (2025). Study of the North Atlantic Oscillation influence on the climate of Europe and the Balkan Peninsula. *Proceedings of the Bulgarian Academy of Sciences, 78*(6), 862–872. https://doi.org/10.7546/CRABS.2025.06.09

Vu Duy, V., Ouillon, S., & Nguyen Minh, H. (2022). Sea surface temperature trend analysis by Mann–Kendall test and Sen's slope estimator: A study of the Hai Phong coastal area (Vietnam) for the period 1995–2020. *Vietnam Journal of Earth Sciences, 44*(1), 73–91. https://doi.org/10.15625/2615-9783/16874

World Bank Group. (2023). *Azerbaijan country climate and development report*. https://openknowledge.worldbank.org/entities/publication/8dd535d5-126a-4181-8ffe-c0fa49b2599f