Weather types and their frequencies over Central Asia – an ERA-Interim based analysis of monthly climate variability and change for the boreal cold season

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Abstract
Climate research in Central Asia is usually based on the analysis of meteorological observations. However, data scarcity in mountain regions causes uncertainties and, thus, the magnitude of climate change and variability in Central Asia is still under debate. Furthermore, the investigation of observations does only allow an assessment of the near surface climate. Since the meteorological conditions in the upper troposphere are generally unknown, the atmospheric mechanisms leading to observed climate changes remain unexamined. Here, the authors present a study of climate change and variability in Central Asia based on the ERA-Interim reanalysis, which provides gridded data-sets of various meteorological parameters for 60 atmospheric levels. In order to investigate the climatic conditions during the boreal cold season, the authors apply an objective weather type classification to 500hPa geopotential height fields. The results show that warm and wet conditions in Central Asia are associated with an anticyclonic anomaly over South Asia or a southward shift of the westerly jet stream. Dry conditions are accompanied by a cyclonic anomaly over South Asia. The authors show that the WT composition strongly affects the monthly and seasonal temperature and precipitation characteristics and that prevailing climatic trends are partially triggered by changing WT frequencies. About 50% of the seasonal temperature trend and 60% of the trend in March can be explained by WT frequency changes. While the observed seasonal precipitation trends cannot be explained by WT frequency changes, a positive trend in November seems to be accompanied by a decreasing frequency of high pressure over Central Asia.

Keywords: Climate Change, climate variability, weather types, precipitation, temperature

Paper type: Research paper

1. Introduction

Central Asia, consisting of the five former Soviet Republics Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan, is located between the Caspian Sea in the west, the
Ural Mountains as well as Russia in the north and the high mountain systems Hindu Kush, Tien Shan and Altai Mountains in the south and east (De Pauw 2007; Mirzabaev 2013). The area is characterized by a semi-arid to arid and extreme continental climate and represents a transition zone between temperate and subtropical climates (Böhner 2006; Schiemann et al. 2008; Bothe et al. 2011). The annual precipitation sums are low over most parts of Central Asia. About 90% of the region receives 400 mm or below (De Pauw 2007; Shiemann et al. 2008). More than 50% of the annual precipitation totals are detected between November and March (cold season) and fall as snow in the Tien Shan and Pamir (Syed et al. 2006; Barlow and Tippett 2008; Schiemann et al. 2008; Apel et al. 2018; Gerlitz et al. 2018). Snow and ice in the headwater catchments are essential for more than 70 million inhabitants of Central Asia, since melt water in spring and summer allows irrigation and hydroelectricity production during the warm season (Unger-Shayesteh et al. 2013; World Bank 2018). Agriculture is one of the most important economic sectors in Central Asia and heavily depends on irrigation water. These circumstances result in a high vulnerability to droughts (Dukhovny 2010; Unger-Shayesteh et al. 2013). The regional warming in Central Asia distinctly exceeds the global average, with projected trends up to 4.8°C until the end of the century (Giorgi 2006; Intergovernmental Panel on Climate Change (IPCC) 2014). Projected climatic changes will lead to higher water demand for irrigation due to increasing evapotranspiration. Furthermore, progressive glacier melt and decrease of snow coverage in cold mountain areas are projected (Gerlitz et al. 2018, Sommer et al. 2013). The combination of high water demand for agriculture and the high warming rates will most likely result in an increase of water related vulnerability and risks. Therefore, a profound understanding of the regional climate system and its change is essential to support sustainable water management and to protect the population from water related hazards (Shiemann et al. 2008; Unger-Shayesteh et al. 2013; Gerlitz et al. 2018).

In order to investigate climate conditions and trends in Central Asia, robust and reliable data sets are needed. Climatological records from observational stations are scarce in the study area and often exhibit inhomogeneities. Climate reanalysis products represent a promising alternative data basis for regional climate studies, as they provide spatially and temporally complete data. The ERA-Interim reanalysis is one of the most widely used global atmospheric reanalysis products. The gridded data set has been positively evaluated for China, Central and High Asia (Dee et al. 2011; Gerlitz et al. 2014; Bao and Zhang 2012; Wang and Zeng 2012).

Climate reanalysis include large amounts of data, as they consider both, near surface climate characteristics and the overlying atmospheric circulation, and provide fields of various atmospheric variables, such as temperature, pressure, humidity, etc. Thus, the investigation of reanalysis products requires software tools and algorithms, which structure large data sets and extract its most important features.

Suitable approaches to obtain the major atmospheric modes from reanalysis products are weather type (WT) classifications. They allow to compress complex data sets into a small number of classes, which are clearly structured and easy to interpret. A commonly used classification technique is the k-mean cluster analysis (K-MCA), which allows an automated
separation of a data set into a specific number of groups. Since this traditional classification technique has been shown to be unsuitable for WT classification, due to the necessity of a pre-defined number of clusters and the dependence of the cluster solution to the initial definition of cluster seeds, various improvements of the classification methodology have been suggested (Michelangeli et al. (1995), Roller et al. (2016)). Gerlitz et al. (2018) have already successfully implemented the first WT classification for Central Asia based on an improved K-MCA and investigated the relationship between the WT composition and the near surface climate at the seasonal scale. In the presented follow up study, the authors apply the same WT classification method to 500 hPa GPH fields and particularly focus on the investigation of climate variability and change at the monthly scale. The resulting WTs allow to study the regional atmospheric circulation over Central Asia and to investigate relationships between WTs and near surface temperature and precipitation. Therefore, mean temperatures and precipitation totals are reconstructed based on the WT composition and related to corresponding observations. A trend analysis of observed and reconstructed temperature and precipitation fields is conducted at seasonal and monthly scales aiming at an investigation with a higher temporal resolution compared to Gerlitz et al. (2018). Climatic trends are calculated grid-wise and spatially averaged for each Central Asian country, in order to assess the climate change impact at the national scale and to support political decisions.

The aim of the presented study is two-fold: (1) the authors introduce climate reanalysis data as a promising source for the investigation of regional climate variability and change in Central Asia. The authors recommend to utilize reanalysis data in the field of applied climatology in order to reduce the uncertainty of climate change assessments. (2) the study advances the investigation of Gerlitz et al. (2018) by focusing on the analysis of the monthly climate variability during the boreal cold season. Monthly temperature and precipitation trends are derived from observed and reconstructed data sets, and compared with WT frequency changes in order to study the proportion of climate variability and change which can be explained by trends of WT occurrences.

Section 2 provides an overview of the topographical characteristics and climate conditions in Central Asia. A brief description of the ERA-Interim reanalysis data and the data pre-processing is given in Section 3.1. The classification algorithm of the K-MCA and the techniques for the analysis of weather types and the reconstruction of temperature and precipitation fields are described in this chapters 3.2 and 3.3. In Section 4, the temporal and spatial characteristics of the WTs as well as the influence of WT compositions on temperature and precipitation anomalies are summarized. In Section 5 relevant results are discussed.

2. Study area and data

An extent between 20° and 60° North and from 50° to 90° East is chosen as the study area. Politically Central Asia consists of the five former Soviet Republics Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan (Figure 1, upper panel) and covers an area of approximately 4 million km², which represents 10% of the Asian continent (Dukhovny and de
Schutter 2011). The Central Asians landscape consists of vast plains with elevations below 500m. In the east, the Altai, the Tien Shan, the Pamir and the Hindu Kush mountain regions border the study area. The mountains of Central Asia exceed elevations of 5000 m with some peaks higher than 7,000 m (De Pauw 2007).

In general, seasonal air temperatures decrease from southwestern to northeastern and eastern Central Asia (Figure 2, upper panel) due to the following reasons: The solar intensity decreases from lower to higher latitudes and the elevations increases from the Turanian Plain to the Altai mountains in eastern Central Asia and to the Hindu Kush, Pamir and Tien Shan mountains in the southeastern parts of the study area. Most parts of Kazakhstan, Uzbekistan and Turkmenistan as well as eastern Kyrgyzstan receive very low seasonal precipitation amounts below 110mm (Figure 2, lower panel). In particular, very dry conditions are observed over Turkmenistan and Southwest Kazakhstan. Higher seasonal totals with values between 350 and 650 mm are observed at the western slopes of the Hind Kush, Pamir and Tien Shan mountains, which are exposed to moist westerly winds.

The annual cycle of precipitation and temperature is mainly influenced by the position and intensity of the westerly jet stream over Central Asia (e.g. Chanysheva et al. 1995; Bothe et al. 2011). Due to the intense heating of surfaces in summer, strong heat lows are generated, so that the entire target domain is characterized by dry conditions. In autumn the westerly jet stream migrates gradually south and transports moist air masses from the Mediterranean and Arabic Sea to the study area. In winter the jet stream moves further south and is now located over Iran and Pakistan. The northern part of Central Asia is dominated by the Siberian High resulting in dry and cold conditions, whereas the southern half is characterized by mild temperatures and higher precipitation amounts.
Figure 1. Upper panel: Political map of Central Asia. Lower panel: Physical map of Central Asia. Data on cities, countries and natural features are obtained from Natural Earth (2019). Elevation is based on SRTM 30m (SRTM 2019). The maps are produced with the open source geographic information system (QGIS 2019).
Mariotti (2007), Trigo et al. (2010), Dimri (2013) and Gerlitz et al. (2018) show that temperature and precipitation are influenced by a tropical inflow into Central Asia, which is related to the El Niño Southern Oscillation (ENSO). During an El Niño warm phase, southwesterly winds transport heat and moist air masses into the target domain, caused by positive pressure and sea surface temperature (SST) anomalies over the West Indian Ocean. An El Niño cold phase (La Niña) is accompanied by an anticyclonic anomaly over Central Asia and northeasterly winds, which transport dry air masses into the target domain. Relationships between severe droughts in Central Asia, for example during the years 1989, 1999 to 2001 and 2008, and El Niño cold phases are mentioned by Barlow et al. (2002; 2016), Hoell et al. (2014) and Gerlitz et al. (2016; 2018). Barlow et al. (2002) found relationships between the drought period from 1998 to 2001 in Central Asia with La Niña conditions as
well as very high SSTs in the West Pacific. Gerlitz et al. (2018) show that the influence of the ENSO on the Central Asian climate is much more persistent than the northern hemispheric contribution.

Besides of the tropical ENSO, the state of the westerly circulation has been found to influence the Central Asian winter climate. Syed et al. (2006; 2010) illustrate that positive precipitation anomalies over Central South West Asia are associated with a positive North Atlantic Oscillation (NAO) phase and an El Niño warm phase. These events are related to an intensification of a Rossby trough over Central and South West Asia. La Niña and negative NAO phases are accompanied by negative winter precipitation anomalies. Barlow and Hoell (2015) mention that the drought between November 2013 and April 2014 in the Middle East and Southwest Asia is linked to a positive NAO phase, cold central Pacific and warm western Pacific SSTs.

A link between an increased moisture influx into western parts of Central Asia and the positive manifestation of the East Atlantic/Western Russia (EA/WR) pattern as well as the Polar/Eurasian pattern is emphasized by Yin et al. (2014). Similar relations are described by Gerlitz et al. (2018). Positive phases of the Arctic Oscillation (AO) and EA/WR pattern are associated with an increased advection of cold and moist air masses into the study area. An opposite mode of the EA/WR pattern results in negative precipitation anomalies over the target domain due to a shift of the westerly jet stream towards North. Gerlitz et al. (2018) further identified a relationship between negative temperature anomalies over Central Asia and a positive state of the Scandinavian pattern associated with a northerly transport of cold polar air masses.

3. Methodology

3.1. Data and preprocessing

The ERA-Interim reanalysis product is used for the investigation of atmospheric and near surface climate conditions. ERA-Interim is provided by the European Center for Medium-Range Weather Forecasts (ECMWF 2016) and is one of the most widely used global atmospheric reanalysis products (Dee et al. 2011). It can be freely downloaded at https://apps.ecmwf.int/datasets/data/interim-full-daily. Each data set is obtained as a raster layer and exhibits a spectral resolution of about 80km (or 0.75° in x- and y-direction). 500hPa GPH fields with a time resolution of 6 hours serve as a basis to derive WTs. WTs are analyzed with respect to their spatio-temporal characteristics of the near surface temperature, precipitation, wind speed and direction at the 500 hPa level. While air temperature and wind fields are 6-hourly averages, precipitation values are summed to 12 hourly precipitation totals. In order to apply the improved K-MCA according to Michelangeli et al. (1995) and adjusted by Roller et al. (2016) for the WT classification (see section 3.2), all gridded data are prepared in a few steps. At first, the raster layers are cut to the extent of Central Asia and are averaged to daily means (GPH heights, 2m temperatures and wind components) or daily sums (precipitation totals).
The classification is applied to standardized GPH fields. The seasonality is kept in the data set in order to investigate the seasonal cycle and intra-seasonal variability of atmospheric conditions over Central Asia (Gerlitz et al. 2018). Daily GPH fields are standardized grid-wise by subtracting the mean from the GPH values and dividing results by the standard deviation. With the aim to investigate the influence of WTs on near surface climate anomalies, temperatures and wind components are converted standardized in the same way. Precipitation fields are converted in a slightly different way, because the values are highly skewed. Anomalies are calculated grid-wise in percent by subtracting the overall mean from the values and dividing the results by the overall mean.

3.2. WT classification approach
Classifications are widely used in climate studies, because they allow to group complex data sets into a relative small number of discrete patterns. The results are clearly structured so that the relevant findings can be easier interpreted (Huth et al. 2008; Jacobeit 2010; Käsmacher and Schneider 2011).

The aim of K-MCA clustering is to group a data set into k clusters, whereby all objects with similar statistical characteristics are allocated to one group and remaining data, which feature large statistical dissimilarities to that group, are excluded and assigned to one of the other groups. In order to achieve these objectives, the k-mean algorithm conducts three major steps. In a first step, k different points are randomly selected as initial centroids. In a second step, all objects of the data set are assigned to their nearest centroids and new clusters are generated (Figure 3, top left). In the third step, the centroids are recalculated from the current clusters (Figure 3, top right). Step two and three are repeated (Figure 3, bottom left) until the centroids do not change anymore (Figure 3, bottom right). At the end of the algorithm, each cluster is characterized by maximum internal homogeneity with maximum dissimilarities to the other groups (Forgy 1965; MacQueen 1967; Lloyd 1982).

However, the result of the partition is sensitive to the number of clusters (Figure 4), which has to be predefined in classical clustering approaches (e.g. Forgy 1965; Mac-Queen 1967; Lloyd 1982), and the random selection of the centroids at the beginning of the algorithm (Huth et al. 2008; Jacobeit 2010). If an unsuitable number of k is chosen or the centroids are poorly distributed, the K-MCA might lead to a solution that does not represent the best partition of the data set (Bradley et al. 1998; Gerlitz et al. 2018).
Figure 3. K-means clustering process. Top left: Choose a number of clusters (step 1) and assign each point to the nearest centroid (step 2). Top right and bottom left: Recalculate the centroids (step 3). Repeat step 2 and step 3. Bottom right: Until the centroids do not change anymore (TUM 2018).

Figure 4. An example for the sensitivity of the results to the predefined number of clusters. Left: A correct number of clusters allows to identify the natural clusters. Center and right: To choose a too low (left) or high (right) number of clusters leads to an unsuitable partition (modified after TUM 2018).

To avoid these shortcomings in weather type classification, some improvements of the K-MCA approach have been suggested by Michelangeli et al. (1995) and Roller et al. (2016): The first processing step applies an S-mode PCA to reduce data size and to remove colinearity from the data set (Huth et al. 2008). Moreover, this technique filters local GPH fluctuations, for example low-pressure cells (Gerlitz et al. 2018). Data reduction is realized by an Empirical Orthogonal Function (EOF). This method is used to extract only few variables from the high dimensional data set (principal components), which explain a large proportion of the variance.
In this study 9 principal components (95% of the total variance) serve as input data for the classification. The dynamical k-means cluster algorithm serves as the basis for the improved K-MCA. An optimum number of clusters is automatically derived by means of a repeated separation of the 9 PCs and virtual data sets. For each k, the data set is partitioned into k clusters and the robustness of the clustering results is subsequently evaluated. At first, 100 cluster separations are calculated for k=2 to 20, whereby every partition is computed with 1000 iterations. The anomaly correlation coefficient (ACC) is then calculated for each cluster combination of two partitions with the same number of clusters. The ACC is a measure which describes the degree of correlation between patterns. It ranges from -1 (completely different distributions) to 1 (identical patterns). All ACC values are computed for each realization with k classes and averaged to an ACC score. The cluster solution with the highest ACC score, represents the best partition of the data into k classes (see Gerlitz et al. (2018) for details).

With the aim of identifying the optimum number of k, a classifiability index (CI) is defined as the average of ACC scores for each k. The CI value of 1 indicates that all 100 clusters solutions are completely identical and the data set is well classifiable into k classes. Low CI values indicate, that the cluster solutions are different depending on the random distribution of the seeds. In order to estimate the CI significance, CI values are also derived from 100 red-noise data sets using the identical processes. The red-noise data have exact the same statistical properties as the 9 PCs (standard deviation, mean and lag -1 (day) autocorrelation). Based on the CI values of the red-noise data, a two sided 5% - 95% confidence interval is calculated for each k. If a CI value, derived from the PCs is higher than the upper bound of the confidence interval for a specific number of k, the classifiability of the atmospheric data is assumed to be significantly higher than the classifiability of the synthetic records. Larger numbers of k usually show with higher CI values, but produce clusters featuring low external dissimilarities. Thus, the optimum number of clusters is defined as the lowest k that exhibits a higher CI value than the upper bound of the confidence interval (Michelangeli et al. 1995; Roller et al. 2016; Gerlitz et al. 2018).

3.3. Analysis of WT characteristics

In order to investigate the influence of WTs on the near surface conditions over Central Asia and the atmospheric circulation over Eurasia, GPH fields, 2m air temperature, precipitation and wind fields are averaged for each WTs. U and v wind components are merged into wind fields featuring the wind directions and speeds.

With the aim to analyze the influence of the WT composition on the near surface climate anomalies, seasonal and monthly temperature and precipitation estimates (reconstructions hereafter) are derived from the WTs and their frequencies of occurrence. This approach is based on the assumption, that the spatial manifestation of the daily temperature and precipitation data for each WT remains stable during the whole investigation period. Reconstructions are calculated grid-wise by multiplying seasonal or monthly frequencies of each WT with corresponding temperature means or precipitation totals. The partial results are
then summarized to monthly or seasonal values. Reconstructed and observed seasonal and monthly patterns of temperature and precipitation are then correlated in order to quantify the skill of the WT classification in reproducing the variability of the near surface climate over Central Asia.

Trends are derived from observed and reconstructed temperature and precipitation fields and for the WT frequencies based on a Sen's slope approach for the period between 1979 and 2016. A significance level of 0.1 is selected for the correlation and trend analysis in this study.

4. Results

4.1. Temporal and spatial characteristics of the WTs

The comparison of the CI confidence interval of the synthetic data with the CI values of original GPH data for k varying from 2 to 20 (Figure 5, top left), indicates that k=9 represents the optimum number of clusters. Relative frequencies of the WTs are similar at the seasonal scale and vary between 8.5% for WT5 to 13.3% for WT8 (Figure 5, top right). At the monthly scale, WT frequencies are strongly different (Figure 5, middle panel). Lowest monthly frequencies are below 5%, highest frequencies exceed 20% for each WT. The major WT characteristics (GPH, temperature and precipitation fields) are shown in Figures 6 to 8. The results indicate that monthly WT frequencies reflect the seasonal cycle of the insolation. The 9 WTs clearly display the influences of westerly winds and the tropical circulation on the near surface climate.

Particularly the warm patterns (WT3 to 5) are associated with high GPH and anticyclonic circulation anomalies over South Asia. This leads to southwesterly winds (Figure 6 and 7), which transport warm tropical air masses from the Red and Arabian Sea into the target domain. WT5 exhibits by far the highest positive air temperature and GPH anomalies and is accompanied by the most pronounced anticyclonic anomaly that stretches almost over the entire area of Eurasia. In contrast, WT9 and 7 are associated with the strongest negative temperature anomalies and are characterized by northwesterly winds over Kazakhstan and Uzbekistan, which advect polar air masses into the study area. A strong cyclonic anomaly over South Asia distinctly weakens tropical inflow. This constellation leads to negative temperature anomalies over the target domain. WT6 represents a weakened variation of WT9 with neutral to moderately negative air temperature anomalies. The anticyclonic anomaly over Russia is shifted southward and the cyclonic anomaly over South Asia is less pronounced.
Figure 5. Top left: The classifiability index (CI) for 2 to 20 numbers of clusters (blue line) and the 90% confidence interval based on the CI values of the 100 red-noise data sets (gray shading). Top right: Relative frequencies of the resulting 9 WTs for the entire boreal cold season from 1979 to 2016. Middle panel: Boxplots of the relative frequencies. Bottom panel: Relative frequencies of the resulting 9 WTs for each month.
Figure 6. First three rows: Daily ERA-Interim 500hPa GPH [m] fields over Eurasia for each WT and associated 500 hPa wind fields (arrows). Last three rows: Corresponding standardized GPH and wind anomalies. The grey box illustrates the study area Central Asia, which is used for the WT classification.
Figure 7. Left half: Daily ERA-Interim 2m air temperatures [°C] over Central Asia for each WT and associated 500hPa wind fields (arrows); Right half: Corresponding standardized 2m air temperatures and wind anomalies for each WT.
Figure 8. Left half: Daily ERA-Interim precipitation totals [mm] over Central Asia for each WT and associated 500hPa wind fields (arrows). Right half: Corresponding precipitation [%/100] and wind anomalies.

WT1 shows a transition state between very cold and warmer conditions. The westerly jet
stream is shifted southward and northwesterly winds transport polar air masses into the western and southwestern parts of Central Asia. Contemporaneously, a pronounced anticyclonic anomaly is located over southern Asia, resulting in a southwesterly inflow of tropical air masses into the east of Central Asia. This leads to weak positive temperature anomalies over the Hindu Kush, Tien Shan and Altai Mountains. WT8 is characterized by slightly positive air temperature anomalies. The pattern features a cyclonic anomaly over Europe and West Asia and an anticyclonic anomaly over eastern Central Asia and eastern Russia. This leads to northward meridional winds, which advect warm tropical air masses. WT2 features inverse circulation conditions. A southward meridional wind anomaly over Central Asia transports polar air masses into the whole study area resulting in negative temperature anomalies.

A southward shift of the westerly jet stream results in a northwesterly inflow of moist air masses, in particular at the eastern side of a Rossby trough (Figure 6, upper panel). Additionally, the southwesterly flow of tropical air masses from the Caspian Sea, the Red Sea and the Persian Gulf leads to an enhanced moisture supply, if an anticyclonic anomaly is located over South Asia. The patterns WT1 and 3 feature both, a southward shift of the westerly jet and an anticyclonic anomaly over South Asia. As a result, they are characterized by the highest positive precipitation anomalies (Figure 8, right panel). Likewise, WT7 is associated with a Rossby trough over Central Asia, but the vast cyclonic anomaly over Eurasia and South Asia leads to a reduced tropical moisture supply, which results in slightly reduced, but still strongly positive, precipitation anomalies.

Very dry conditions are associated with an anticyclonic circulation anomaly over Central Russia and northern Central Asia and a cyclonic anomaly over South Asia. This combination results in a northward shift of the jet stream, a weakened transport of moist air masses into the target domain and hence in lower precipitation amounts (WT4, 6 and 9). Likewise, WT5 features a cyclonic anomaly over South Asia, but the westerly jet is located over Northern Kazakhstan, which leads to slightly positive precipitation anomalies in the north of the target domain, while the south is characterized by dry conditions.

The zonal displacement of the western jet stream with a Rossby trough over western Central Asia and a Rossby ridge over Mongolia in WT8 leads an intensified moisture supply from the Arabian Gulf and thus to positive precipitation anomalies over western Kazakhstan, Uzbekistan and Turkmenistan. WT2 features, an inverse circulation and precipitation pattern.

4.2. Evaluation of WT-based temperature and precipitation reconstructions
Seasonal and monthly correlations between observed and WT-based reconstructed air temperatures are mostly above 0.4 and statistically significant over the whole study area (Figure 9, right columns and Table I). The high correlations indicate, that the seasonal and monthly temperature variability is strongly influenced by the WT compositions. This shows that the consideration of reanalysis based assessments of the upper tropospheric conditions provide essential information for the interpretation of observed climate variability and change. There are nearly no differences between the average reconstructions and observations on the
seasonal scale and in November and February (Figure 9, left columns). However, reconstructed monthly air temperature means are around 2°C higher in December and January and 2 to 5°C lower in March. Correlations between observed and WT-based reconstructed seasonal and monthly precipitation means are mainly positive. But the values are often not statistically significant and in general much lower and spatially more heterogeneous distributed than correlation coefficients of air temperatures.
Figure 9. First and second column: Spatial distribution of observed and WT-based reconstructed seasonal (WS) and monthly (Nov. - Mar.) temperature means [°C]. Third and fourth column: Spatial distribution of correlations and the corresponding significance values (p-values) between the observations and reconstructions.
Figure 10. Line charts: Time series of the seasonal observed (dashed black lines) and reconstructed temperatures [°C] (dashed red lines) and trends of observations (black lines) and reconstructions (red lines) for each Central Asian state. The captions above include the trend slope and the p-value for observations (S(Obs), P(Obs)) and reconstructions (S(Rec), P(Rec)) as well as the correlation between observed and reconstructed temperatures (Cor). Bar chart: Time series of seasonal relative WT frequencies. Trend slopes (S) and the corresponding significance value (P) are provided for each WT.
Table I. Correlations between observed and reconstructed 2m air temperature means over each Central Asian state and the whole study area for the boreal cold season and each month between November and March from 1979 to 2016.

<table>
<thead>
<tr>
<th>Countries</th>
<th>November</th>
<th>December</th>
<th>January</th>
<th>February</th>
<th>March</th>
</tr>
</thead>
<tbody>
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<td>0.51</td>
<td>0.55</td>
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</table>

At the seasonal scale, correlations for temperature are significant over entire domain and amount to values between 0.2 and 0.8 with maximum values over western and southeastern Kazakhstan. The correlations at the national scale are above 0.6 for all Central Asian countries.

The highest correlations at the monthly scale are observed in November and March. Values are statistically significant and above 0.6 over most parts of Central Asia. From December to March, correlations are highly significant over North Kazakhstan and slightly decrease towards the southwestern and southeastern parts of the study area. Thus, Kazakhstan features the highest correlation values. Uzbekistan and Turkmenistan are associated with lower correlation values compared to Kyrgyzstan and Tajikistan, however correlations are always exceed r=0.5.

Monthly and seasonal precipitation patterns are characterized by high spatial and temporal variations (Figure 11, left columns and Figure 12, line charts) and the correlation between reconstructions and observations is not always significant. The absolute differences between the monthly means of observations and reconstructions are marginal. However, the low and non-significant correlations for Uzbekistan, Turkmenistan and Northeast Kazakhstan illustrate that variations of the precipitation anomalies are only explained to some extent by the WT composition (Figure 11, right columns and Table II). This result is additionally confirmed by very low magnitudes of the reconstruction time series.
Figure 11. First and second column: Spatial distribution of observed and WT-based reconstructed seasonal (WS) and monthly (Nov. - Mar.) precipitation sums [mm] over Central Asia. Third and fourth column: Spatial distribution of correlations and the corresponding significance values (p-values) between the observations and reconstructions.
Figure 12. Line charts: Time series of the seasonal observed (dashed black lines) and reconstructed precipitation sums [°C] (dashed red lines) and trends of observations (black lines) and reconstructions (red lines) for each Central Asian state. The captions above include the trend slope and the p-value for observations (S(Obs), P(Obs)) and reconstructions (S(Rec), P(Rec)) as well as the correlation between observed and reconstructed precipitation sums (Cor). Bar chart: Time series of seasonal relative WT frequencies. Trend slopes (S) and the corresponding significance value (P) are provided for each WT.
Table II. Correlations between observed and reconstructed precipitation sums for each Central Asian state and the whole study area for the boreal cold season and each month between November and March from 1979 to 2016.

<table>
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<td>0.44</td>
<td>0.24</td>
<td>0.47</td>
<td>0.24</td>
</tr>
<tr>
<td>Turkmenistan</td>
<td>0.23</td>
<td>0.65</td>
<td>0.44</td>
<td>0.06</td>
<td>0.22</td>
<td>0.17</td>
</tr>
<tr>
<td>Central Asia</td>
<td>0.34</td>
<td>0.69</td>
<td>0.47</td>
<td>0.39</td>
<td>0.42</td>
<td>0.26</td>
</tr>
</tbody>
</table>


4.3. Air temperature, precipitation and WT frequency trends

Trends of observed seasonal air temperatures are positive over almost the entire study area and vary in average between 0.025°C/y in Tajikistan and 0.047°C/y in Turkmenistan (Figure 10, line charts, Figure 13 and Table III). Trends are statistically not significant over Kazakhstan, Tajikistan and Uzbekistan. March is associated with very high and strongly significant air temperature trends (Figure 14, left columns). Averaged trends vary from 0.096°C to 0.147°C per year over Kazakhstan, Uzbekistan, Turkmenistan and Kyrgyzstan and reach 0.25°C/y over Central Kazakhstan (Table III). The trend over Tajikistan is less pronounced (0.059°C/y) and not statistically significant. The maximum value of 0.25°C per year corresponds to an air temperature increase of more than 8°C during the period from 1979 to 2016. Such a high trend is most likely influenced by extreme values at the beginning or the end of the time series and is certainly overestimated. However, a distinct air temperature increase is apparent in the observed time series.
Figure 13. Spatial distribution of trends of the seasonal observed (left column) and reconstructed (right column) 2m air temperature means [°C/y] (WS Trends) and the corresponding significance values (WS P-Values) over Central Asia for the boreal winter season from 1979 to 2016.

Table III. Trends of the observed (black values) and reconstructed (red values) air temperature means per decade [°C/decade] for each Central Asian state for the boreal cold season and each month between November and March from 1979 to 2016. Statistically significant trends are highlighted (*).

<table>
<thead>
<tr>
<th>Country</th>
<th>Season</th>
<th>Nov</th>
<th>Dec</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kazakhstan</td>
<td>S(Obs)</td>
<td>0.43</td>
<td>0.53</td>
<td>-0.25</td>
<td>0.12</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.19</td>
<td>-0.11</td>
<td>-0.07</td>
<td>0.04</td>
<td>0.21</td>
</tr>
<tr>
<td>Kyrgyzstan</td>
<td>S(Obs)</td>
<td>0.41*</td>
<td>0.3</td>
<td>-0.35</td>
<td>0.2</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.2*</td>
<td>-0.05</td>
<td>0.04</td>
<td>0.1</td>
<td>0.24</td>
</tr>
<tr>
<td>Tajikistan</td>
<td>S(Obs)</td>
<td>0.25</td>
<td>0.15</td>
<td>-0.27</td>
<td>0.06</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.2*</td>
<td>-0.05</td>
<td>0.05</td>
<td>0.09</td>
<td>0.24</td>
</tr>
<tr>
<td>Uzbekistan</td>
<td>S(Obs)</td>
<td>0.33</td>
<td>0.09</td>
<td>-0.4</td>
<td>0.2</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.2*</td>
<td>-0.1</td>
<td>-0.05</td>
<td>0.04</td>
<td>0.21</td>
</tr>
<tr>
<td>Turkmenistan</td>
<td>S(Obs)</td>
<td>0.47*</td>
<td>-0.04</td>
<td>-0.15</td>
<td>0.66</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.19*</td>
<td>-0.09</td>
<td>-0.03</td>
<td>0.05</td>
<td>0.18</td>
</tr>
</tbody>
</table>
Figure 14. Spatial distribution of trends of the monthly observed (first column) and reconstructed (second column) 2m air temperature means [°C/y] and the corresponding significance values (P-Values Observations, P-Values Reconstructions) over Central Asia November to March (1979 to 2016).

The air temperature trends during the boreal cold season and in March are most likely triggered by increasing frequencies of the warm patterns WT3 to 5, which are associated with
an anticyclonic anomaly over South Asia and a southwesterly advection of warm tropical air masses into Central Asia (Table V). The cold patterns WT7 and 9, which are accompanied by a strong cyclonic anomaly over South Asia and an advection of polar air masses, exhibit negative frequency trends. The colder patterns WT2 (featuring a southward meridional wind) and WT6 likewise show negative frequency trends in March. Although the reconstructed temperatures feature lower trends than the observations (Figure 14), about 50% of the seasonal trend and 60% of the trend in March can be assigned to the WT frequency changes. Notably, negative and partially significant temperature trends are detected over Uzbekistan, Northeast Kazakhstan and southeastern Central Asia in December. The cooling trend is related to an increasing frequency of the colder patterns WT1 and 2 (Table V), i.e. an increasing occurrence of polar outbreaks. In January, negative (and partially significant) trends between -0.02°C and -0.15°C per year are detected for northeastern Kazakhstan, however, positive trends are apparent for the rest of the target domain. In November, positive trends between 0.05°C and 0.1°C per year are observed for entire Central Asia. Temperature trends in January and November cannot be explained by WT frequency changes (Figure 14).

Table IV. Trends of the WT frequencies per decade [%/decade]. The WTs are sorted by their air temperature anomalies over Central Asia from strongly positive (dark red) to strongly negative (dark blue). Statistically significant trends are highlighted (*).

<table>
<thead>
<tr>
<th>Temperature Anomalies</th>
<th>WS</th>
<th>Nov</th>
<th>Dec</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
</tr>
</thead>
<tbody>
<tr>
<td>WT5 Strong positive</td>
<td>1</td>
<td>-2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>WT3 Positive</td>
<td>1.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.4*</td>
</tr>
<tr>
<td>WT4 Positive</td>
<td>1.2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0*</td>
<td>2.9*</td>
</tr>
<tr>
<td>WT8 Positive</td>
<td>-0.5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-0.4</td>
<td>0</td>
</tr>
<tr>
<td>WT1 Mainly negative</td>
<td>1.1</td>
<td>0</td>
<td>2.1</td>
<td>0</td>
<td>2.4*</td>
<td>0</td>
</tr>
<tr>
<td>WT6 Mainly negative</td>
<td>-0.9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-1.4</td>
<td>-2.5*</td>
</tr>
<tr>
<td>WT2 Negative</td>
<td>0.9</td>
<td>0</td>
<td>3.2*</td>
<td>2.2</td>
<td>0</td>
<td>-3.1*</td>
</tr>
<tr>
<td>WT7 Strong negative</td>
<td>-2.3*</td>
<td>0</td>
<td>0</td>
<td>-3.4</td>
<td>-2.1</td>
<td>0</td>
</tr>
<tr>
<td>WT9 Strong negative</td>
<td>-1.1</td>
<td>0</td>
<td>0.0*</td>
<td>0</td>
<td>-1.2</td>
<td>0</td>
</tr>
</tbody>
</table>

The results of the trend analysis for seasonal precipitation amounts indicate a slight drying tendency for the most regions of Central Asia. Negative precipitation trends range from -0.01% to -1.5% per year, but are statistically significant over Tajikistan and Kyrgyzstan only. East Kazakhstan features positive trends between 0.01%/y and 1.5%/y (Figure 12, line charts, Figure 15 and Table VI). Trends of precipitation reconstructions show a similar spatial pattern, particularly over Kazakhstan, but the small scale features of varying precipitation trends are not reproduced by the reconstructions. This indicates a limited skill of the WT classification in explaining the observed precipitation changes.
Figure 15. Spatial distribution of trends of the seasonal observed (left column) and reconstructed (right column) precipitation sums [%/y] (WS Trends) and the corresponding significance values (WS P-Values) over Central Asia for the boreal winter season from 1979 to 2016.

Table V. Trends of the observed (black values) and reconstructed (red values) precipitation sums per decade [%/decade] for each Central Asian state for the boreal cold season and each month between November and March from 1979 to 2016. Statistically significant trends are highlighted (*).

<table>
<thead>
<tr>
<th>Country</th>
<th>Season</th>
<th>Nov</th>
<th>Dec</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kazakhstan</td>
<td>S(Obs)</td>
<td>-0.85</td>
<td>-1.92</td>
<td>3.05</td>
<td>-6.58</td>
<td>2.01</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.87</td>
<td>1.03</td>
<td>-1.75</td>
<td>-0.59</td>
<td>1.4</td>
</tr>
<tr>
<td>Kyrgyzstan</td>
<td>S(Obs)</td>
<td>-5.37</td>
<td>9.97</td>
<td>-1.38</td>
<td>-8.61</td>
<td>3.78</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>1.63</td>
<td>1.02</td>
<td>-1.61</td>
<td>-1.2</td>
<td>2.76</td>
</tr>
<tr>
<td>Tajikistan</td>
<td>S(Obs)</td>
<td>-3.49</td>
<td>13.75*</td>
<td>2.51</td>
<td>-8.62</td>
<td>5.13</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.32</td>
<td>1.76</td>
<td>-0.23</td>
<td>-1.43</td>
<td>0.54</td>
</tr>
<tr>
<td>Uzbekistan</td>
<td>S(Obs)</td>
<td>-2.76</td>
<td>13.93</td>
<td>0.35</td>
<td>-6.7</td>
<td>4.39</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.31</td>
<td>0.54</td>
<td>-0.21</td>
<td>-0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>Turkmenistan</td>
<td>S(Obs)</td>
<td>-3.97</td>
<td>15.87</td>
<td>-1.3</td>
<td>-12.02</td>
<td>4.81</td>
</tr>
<tr>
<td></td>
<td>S(Rec)</td>
<td>0.31</td>
<td>0.03</td>
<td>-0.24</td>
<td>0.23</td>
<td>-1.07</td>
</tr>
</tbody>
</table>
Table VI. Trends of the WT frequencies per decade [%/decade] over Central Asia from 1979 to 2016. The WTs are sorted by their precipitation anomalies from strongly negative (dark red) to strongly positive (dark blue). Statistically significant trends are highlighted (*).

<table>
<thead>
<tr>
<th>Precipitation Anomalies</th>
<th>WT4</th>
<th>WT9</th>
<th>WT6</th>
<th>WT2</th>
<th>WT5</th>
<th>WT8</th>
<th>WT7</th>
<th>WT1</th>
<th>WT3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Strong negative</td>
<td>Strong negative</td>
<td>Strong negative</td>
<td>Mainly negative</td>
<td>SE: positive / NW: negative</td>
<td>Mainly positive</td>
<td>Positive</td>
<td>Strong positive</td>
<td>Strong positive</td>
</tr>
<tr>
<td></td>
<td>1.2</td>
<td>-1.1</td>
<td>-0.9</td>
<td>0.9</td>
<td>1</td>
<td>-0.5</td>
<td>-2.3*</td>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3.2*</td>
<td>-2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2.2</td>
<td>0</td>
<td>0</td>
<td>-3.4</td>
<td>2.1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>-1.2</td>
<td>-1.4</td>
<td>0</td>
<td>0</td>
<td>-0.4</td>
<td>0</td>
<td>2.4*</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.0*</td>
<td>0</td>
<td>0</td>
<td>-3.1*</td>
<td>0</td>
<td>-2.1</td>
<td>0</td>
<td>4.4*</td>
</tr>
</tbody>
</table>

In November, positive and significant trends between 0.01% and 3.5% per year over southern Central Asia are apparent in both, observations and reconstructions. This precipitation increase seems to be accompanied by a decreasing (non-significant) frequency trend of the dry WT5 (Figure 16, Table VII). December features a dipole, with negative precipitation trends in the north and positive trends in the south of the target domain, which are likewise well reproduced by the WT based reconstruction. In January, decreasing trends between -0.1%/y and -1.5%/y are detected over Tajikistan and Kyrgyzstan and Kazakhstan and Turkmenistan. Negative trends are most likely related to increasing and decreasing frequencies of the dry and wet patterns WT2 and WT7, respectively (Table VI).
Figure 16. Spatial distribution of trends of the monthly observed (first column) and reconstructed (second column) precipitation sums [%/y] and the corresponding significance values (P-Values Observations, P-Values Reconstructions) over Central Asia for November to March from 1979 to 2016.
5. Discussion and conclusion

Based on methods suggested by Gerlitz et al. (2018), this study investigates the atmospheric circulation and its influence on temperature and precipitation over Central Asia during the boreal cold season at seasonal and monthly scales. A WT classification is conducted based on an improved k-means cluster analysis. The resulting 9 WTs reflect the seasonal cycle of the insolation and the southward shift of the polar frontal zone during the core winter season. While the core winter months are influenced by patterns featuring negative GPH and 2m temperature anomalies (WT7 and 9), the warm patterns with positive GPH anomalies (WT3 to 5) mainly occur at the beginning and the end of the boreal cold season.

Temporal and spatial characteristics of the 9 WTs reflect findings of other studies (e.g. Martyn 1992; Mariotti 2007; Schiemann et al. 2008; 2009; Bothe et al. 2011; Gerlitz et al. 2018), stating that the following three factors considerably influence the air temperatures and precipitation amounts over Central Asia: the position and strength of the westerly jet stream, the manifestation of the pressure anomalies over North as well as South Asia and the topography of the study area.

Positive air temperature anomalies are triggered by anticyclonic circulation anomalies over South Asia leading to southwesterly winds, which transport warm tropical air masses from the Red and Arabian Sea into the target domain. Cold WTs are associated with a northwesterly inflow of polar air masses over Kazakhstan and Uzbekistan and a cyclonic anomaly over South Asia. A southward shift of the westerly jet stream intensifies the transport of moist air masses into the target domain. An anticyclonic anomaly over South Asia leads to a southwesterly advection of moist tropical air masses from the Caspian Sea, Red Sea and Persian Gulf into southern and eastern parts of Central Asia. WTs featuring both, a southward shift of the westerly jet and an anticyclonic anomaly over South Asia, are characterized by strongly positive precipitation anomalies (WT1 and 3). The highest precipitation totals are observed at the windward slopes of the Tian Shan, Pamir and Altai mountains, which are exposed to the north- and southwesterly flow. Very dry conditions are associated with anticyclonic anomalies over Central Russia and northern Central Asia and cyclonic anomalies over South Asia (WT4, 6 and 9).

The high correlations between observed and WT-based reconstructed temperature fields show that the applied WT classification is able to reproduce the temperature variability over Central Asia at the seasonal scale and for each month. In contrast, correlations between precipitation observations and reconstructions feature much lower seasonal values. Correlation coefficients at the monthly scale vary strongly but are positive in most cases. In a next step, a validation with other data types, for example with meteorological data from observational stations, would enable a more profound test.

The detected seasonal temperature trends are in agreement with findings by Gerlitz et al. (2018). A significant trend of ERA-Interim observations is detected over almost the entire target domain during the period from 1979 to 2016. The values range in average between 0.025°C/y in Tajikistan and 0.047°C/y in Turkmenistan. About 50% of the increasing trend
can be assigned to WT frequency changes. While the frequencies of the cold patterns WT7 and 9 feature a negative trend, the frequencies of warm patterns WT3, 4 and 5 increase during the winter season.

At the monthly scale, highest temperature trends are detected in March. Observed trends amount to 0.059°C/y in Tajikistan and 0.147°C/y in Kazakhstan. Maximum values of 0.25°C/y have been observed in Central Kazakhstan, which corresponds to a temperature change of 5°C between 1979 and 2016. This trend is certainly overestimated, e.g. due to the limited length of the time series or extreme values at the beginning or end of the data record. Besides these shortcomings, a strong air temperature increase is apparent in the observed and reconstructed time series during the whole period. More than 60% of positive temperature trend in March can be assigned to frequency changes of the WTs. The frequencies of the three coldest patterns WT2, 7 and 9 exhibit a negative trend, whereas frequencies of the warm patterns WT3, 4 and 5 increase. The high air temperature trends in March strongly contribute to the temperature trends at the seasonal scale. Seasonal and monthly precipitation trends are often associated with a high degree of uncertainties. Seasonal trends indicate a slightly drying tendency over West Kazakhstan and the other four states of Central Asia. Solely East Kazakhstan features a positive trend. In spite of the above-mentioned limitations of the trend analysis, our results are in agreement with previous studies on temperature and precipitation changes in Central Asia (see e.g. Giese and Mossig 2004; Chen et al. 2009; IPCC 2014; Barlow and Hoell 2015).

Overall, the combination of increasing air temperatures and slightly decreasing precipitation amounts during the boreal cold season will enhance water related risk in Central Asia. Hence, to obtain deep insights into the relationships between WT frequencies, near surface parameters and large-scale circulation modes is urgently necessary for Central Asia, which is highly vulnerable to water related hazards. Therefore, the results of the presented study might support the development of short-term predictions of water availability.

Besides its specific findings, this study underlines the great value of climate reanalysis products for regional climate investigations in data scarce Central Asia. Such spatially and temporally complete data sets of the near surface climate and the overlying atmospheric circulation enable an analysis of climatic conditions at the regional scale and, particularly, allow to investigate the fundamental meteorological processes, which are responsible for observed climate variability and change. The authors, thus, recommend to utilize reanalysis data for a comprehensive analysis of the regional climate, its variability and change in Central Asia. While meteorological observations are an important basis for the investigation of the near surface climate, reanalysis data sets allow to additionally examine the corresponding conditions in the upper troposphere. The detected relationships between observed temperature and precipitation anomalies and the large-scale atmospheric conditions allow to better understand the climatic system and to interpret observed changes in a broader context.
6. References


