The changing extreme values of summer relative humidity in the Tarim Basin in Northwestern China

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Abstract Relative Humidity (RH) in the arid region of the Tarim Basin is crucial for many reasons. The Tarim Basin has experienced a tendency to become wetter in recent decades, and the RH here also shows an increase over the past decade. However, there has been little examination of these RH changes and especially the changes to the extremes. This study investigates the changes in extreme values and the probability distribution function (PDF) of summer RH using quantile regression during 2006-2018 to understand the possible reasons for the increase in the summer RH anomaly. We find that extremely high values of RH show a consistent significant increase, while extremely low values have no regionally consistent tendency. The overall average value of RH in the Tarim Basin becomes higher, driven by the upper half of the PDF. To explore the physical mechanism for these changes, we examine the corresponding regional meteorological anomaly patterns. The patterns indicate that the anomalous southwesterly airflow at 500hPa brings ample moisture into the basin and the ground in the middle of the basin significantly cools down when an extreme wet event occurs, promoting the occurrence of the extreme high RH. In this process, the contributions of water vapor transport and temperature are of equal significance though with different relative timing. These corresponding regional meteorological patterns occur more of-
ten in the most recent decade, which coincides with the recent increase in RH extremes in this region.

**Keywords** Relative humidity · Extreme wet · Quantile regression · Regional meteorological anomaly patterns · Tarim Basin · Asia

1 Introduction

Relative humidity (RH), describing the distribution of water vapor in the atmosphere, is of great importance for multiple fields. The Tarim Basin is the major source of dust aerosols affecting East Asian countries, and its RH is closely associated with the formation of sandstorms and sand transmission (Mao et al, 2011; Li et al, 2019a; Yang et al, 2019). RH directly affects the formation of dew, which is the most important water source for plants and animals’ survival in the desert (Chen et al, 2020; Gong et al, 2019; Gerson et al, 2014). The changes of RH are associated with the response of the ecological system in desert areas and water cycle to global warming (Held and Shell, 2012; Wright et al, 2010). Understanding changes in RH can also provide a deeper understanding of changes in extreme events in this area (Tao et al, 2014; Sun et al, 2014; Zhang et al, 2012).

In the past decade, some researchers have shown that RH over land should have a downward trend with global warming, since the more rapidly increasing temperature over land than the ocean leads to a faster increase in saturated vapor pressure with global warming, while vapor pressure over land cannot increase as rapidly (Sherwood and Fu, 2014; Collins et al, 2013; Simmons et al, 2010; Byrne and O’Gorman, 2016, 2018). This trend will lead to a drier climate in the future (Fu and Feng, 2014). However, in contrast to the overall situation over the continents, an upward variation of RH in the South Xinjiang, including the Tarim Basin region, has been observed in recent decades (Chen et al, 2020). Some more observations indicate that in Northwest China, a large region including the Tarim Basin, the precipitation has increased and the climate has become wetter in recent decades (Shi et al, 2007; Han et al, 2019; Peng and Zhou, 2017; Wang et al, 2017; Chen et al, 2015; Li et al, 2016). Wetness over the Tarim Basin has shown a decadal change, i.e., specifically an increase in recent decades (Tao et al, 2014, 2016). This decadal variability suggests that large-scale theoretical analysis over land cannot simply be used to understand changes in regional-scale RH. So what causes the increase of RH in recent decade? Water transport in some form must be part of the story in such an arid region, but this has not been explored in detail.

To better understand RH changes with global warming, the local conditions must be considered. Analyzing the probability distribution function (PDF) of RH locally provides a good perspective for interpreting the changes in RH distributions more broadly. This study focuses on summer RH over the Tarim Basin, since the majority of the precipitation falls in summertime (Huang et al, 2015), and the increase in wetness is mainly concentrated in summer (Li et al, 2016; Peng and Zhou, 2017). The change in the mean of the
time series has a close connection with its PDF and extreme values (Huybers et al., 2014; McKinnon et al., 2016). For example, in some areas, the increase in mean temperature is mainly manifested as the effect of either a decrease in extremely low values or an increase in extremely high values (Franzke, 2013, 2015). This indicates that understanding changes in summer RH extremes can also help to understand the mean RH change and to explore the associated physical mechanism. However, to our knowledge, no studies have focused on the full PDF of RH over the Tarim Basin. The changes to the PDF and particularly to the extreme values of summer RH are the subject of this study.

In this study, we analyze daily summer RH data over the Tarim Basin in order to gain a more complete picture of changes in summer RH. We focus on the most recent decade and explore the mechanisms of changes in RH and the RH probability distribution function. Existing studies generally agree about the remarkable increase in summer precipitation in this region, but there is no consensus regarding changes in the RH distribution and physical reasons for the changes. Is this an intensification of the hydrological cycle or a change in the regional weather patterns? We study the changes in RH extreme events and the regional anomalous meteorological patterns corresponding to the extreme events to provide a way to better understand the physical mechanisms.

This paper is organized as follows: Section 2 describes the data used in this study. In section 3, we examine the decadal change of RH. In section 4 we present the statistical examination of recent changes in RH, including analysis of extremes and probability distribution function changes. We examine the corresponding regional anomalous meteorological patterns in section 5. We then present discussion and conclusions in section 6.

2 Data

In this study, observed daily mean RH data from meteorological stations in the Tarim Basin area are obtained from the China Meteorological Administration (http://data.cma.cn/) for 1979 to 2018 (as shown in Fig. 1). The quality of the data has been controlled, and after removing stations that are missing data for 7 or more continuous days during the whole period (1979.1.1-2018.12.30), 19 stations remain for this analysis. Linear interpolation has been used to fill periods of missing data less than 7 days.

In addition to the observed RH records, the 2-meter temperature, 2-meter dewpoint temperature (from which RH can be calculated) and precipitation from the ERA5-Land hourly reanalysis dataset over 1981-2018 (Copernicus Climate Change Service (C3S), 2019; Hersbach et al, 2020) with the resolution 0.1° × 0.1° are used. We also use 500-hPa geopotential height (Z500), 850-hPa geopotential height (Z850), and zonal (u) and meridional (v) wind speed on 500hPa and 850hPa from the ERA5 hourly dataset on pressure over 1981-2018 (Copernicus Climate Change Service (C3S), 2017; Hersbach et al, 2020), with resolution 0.25° × 0.25°. In this study, all data from the ERA5 and ERA5-Land datasets except precipitation are processed into daily data, which
is obtained by the average value of 4 time points (0:00, 6:00, 12:00, 18:00) per day. This averaging procedure is not necessary for precipitation because daily accumulated precipitation is directly available in the ERA5-Land data set. The summer in this study is defined as June, July and August, and all anomalies are obtained by removing the seasonal cycle, similar to previous studies (Koscielny-Bunde et al, 1998): the climatological seasonal cycle is calculated as the long-time average for each day between 1981 and 2018.

3 Increasing local tendency of summer RH during the recent decade

We first examine the summer RH anomaly by calculating the mean in each year averaged over the 19 stations, shown in Fig. 2(a). From the previous studies, it is clear that RH may show interannual variability (Du et al, 2012), and in our analysis we see distinct interannual and decadal variability of summer RH over the Tarim Basin (Fig. 2a). The recent decade can be easily identified as having an upward tendency (consistent with the “becoming wetter” mentioned in section 1). But we want to understand how RH has changed beyond just the change in the mean.

If we understand the recent decadal-scale trend towards higher RH, we may be able to better understand the mechanisms causing interannual variability in RH. To determine the beginning of the increasing variation, the Sequential Mann-Kendall (SQMK) method (Nasri and Modarres, 2009) is used to check for the location of a change point in the summer RH anomaly time series. The method is described in the Appendix. The result shows that the transition point year is around 2006 and so we chose 2006-2018 as the period of interest for this study. The spatial distribution of the linear slope in the Tarim Basin is examined in Fig. 2(b). It shows that most stations have a tendency towards higher RH, which matches the results in previous studies (Han et al, 2019; Peng and Zhou, 2017; Wang et al, 2017).

4 Statistical examination of recent changes in RH

4.1 Tendencies of the extreme high and extreme low RH anomaly using Quantile Regression

To understand changes in extreme values of summer RH anomaly during the past decade, a non-parametric technique to estimate the slope in any percentile of a distribution, quantile regression, is employed (Koenker and Bassett Jr, 1978; Cade and Noon, 2003; Gao and Franzke, 2017; Huybers et al, 2014). Linear slopes in quantiles from the 5th, 50th and 95th percentiles of the summer RH anomaly time series at station 51639 are shown as examples (Fig. 3). This method can effectively show the year-by-year local trend of a specific percentile value. (For the total 92 days in the summer of each year, there is
no impact from the day-to-day ordering on the quantile slopes.) The different
slopes of the 5th and the 95th percentiles imply a change in $RH$ intraseasonal
variability.

A block bootstrap is used here for the estimation of significance of the
sign of the linear slopes, following McKinnon et al (2016). The fitted linear
slope in the data is removed first and then the residuals are resampled with
replacement using a 92 day block, which is chosen based on the assumption
the $RH$ is correlated within any given summer, but has negligible interannual
correlation. After adding these values back to the linear trend removed in the
first step, the trend is re-estimated. The process is repeated 1000 times. As in
McKinnon et al (2016), the resulting distribution of bootstrap trends is used to
determine whether the trend is significant, with a somewhat unusual definition
of significant as when 95% of the bootstrap slopes are of the same sign as the
observed trend (regardless of the magnitude of the bootstrap slopes). This
method will determine whether there is a detectable non-zero linear slope in
the interannual change.

The quantile regression method is applied at all 19 stations in the Tarim
Basin to investigate the changes in the summer $RH$ extreme values. The ex-
treme dry and wet days are defined when the corresponding $RH$ is lower than
the 5th percentile and higher than the 95th percentile for each summer, re-
spectively. Figure 4 shows that there is an increasing local tendency of the
95th percentile of summer $RH$ anomaly across nearly the entire Tarim Basin
area (Fig. 4c) and a weaker trend that is nevertheless largely spatially coher-
ent in the 50th percentile (Fig. 4b). (Of course this is very similar to Fig.
2a.) There is no equivalent positive tendency for the 5th percentile (Fig. 4a);
the extreme dry values of $RH$ anomaly demonstrate a complex distribution
of changes with few significant tendencies. In general, the high values become
higher, while the low values have no uniform tendency. The average value of
$RH$ in the Tarim Basin increases, which is driven by increases in the upper
half of the distribution. We thus expect that the intraseasonal variance of $RH$
has also increased, and we analyze the PDF in the next section.

4.2 Changes in the probability distribution function

The PDF provides a more compute picture of summer $RH$ variability and its
changes. In order to observe the changes of extreme values and mean values, it
is necessary to study the change of the PDF over time. We divide the data of
the past 13 years into two time periods (2006-2012 and 2012-2018), and then
qualitatively examine the PDF in both periods. Figure 5a shows a case study
(station 51639), and the PDF of 2012-2018 is wider than the PDF during the
previous time period. This case study suggests an increase in the variance of
$RH$ variability over time. To test whether it is the case in the entire region,
the year-by-year standard deviation of $RH$ anomalies are calculated. Figure
5b shows that the mean standard deviation of each year (that is, the average
of the annual standard deviations of 19 stations) increasing in the past decade, as we expected from Figure 5a.

The PDF of summer $RH$ anomaly in the Tarim Basin is non-Gaussian with a long wet side and a short dry side. Because the changes of non-Gaussian distributions are more complicated than those of normal distributions, the changes of extreme value are not necessarily simply a shift with the mean (Huybers et al., 2014; McKinnon et al., 2016; Loikith and Neelin, 2019). Compared with the PDF in the previous period, the long tail on the wet-side of the PDF during 2012-2018 obviously moves towards the higher value, while there is little change on the dry-side (Fig. 5a). A slight shift in the distribution peaks can also be observed (Fig. 5a). Although they differ in some details, the PDFs of the other 18 stations show similar and significant movement across the two periods, which corresponds to the results of the mean change (Fig. 2) and quantile regression (Fig. 4). There is only one station where the deviation of the second period is not obvious. Combined with the analysis above, the 95th percentile of $RH$ anomaly demonstrates a consistent increasing trend in the past decade. This increase exhibits remarkable regional consistency, implying that more extreme wet events have occurred throughout this arid area over 2006-2018. In the next section, we aim to understand this extremum change.

5 Meteorology associated with recent changes in extreme high RH

The previous analyses demonstrate that the changes in the mean are driven by the upper part of the distribution, and there is an increase in the wet extremes of summer $RH$ over the Tarim Basin during the recent decade. We now examine the large-scale meteorological conditions associated with the increase in extremes.

To analyze the weather associated with extreme events, one useful method is to make composites of the atmospheric fields (Gao and Franzke, 2017). Since the distribution of meteorological station data is uneven, reanalysis data has great advantages for investigating the spatial pattern of climate variables.

5.1 Comparison between ERA5 reanalysis and observed records over the Tarim Basin

We use ERA5 reanalysis data to examine the conditions of the weather patterns when extremely high $RH$ occurs in the observations. To verify that this is providing an adequate representation of the moisture, we first compare the summer $RH$ anomalies in observations with those in ERA5 data, as shown in Figure 6. The mean value for each summer averaged over all grid boxes in the research area using ERA5 data shows similar variability to that from 19 meteorological stations, especially in the recent decade (Fig. 6a). We also compare extremely high values of summer $RH$ in ERA5 data to those in the observations, similar to the temperature analysis done by Mao et al (2010).
We find that values of 95th percentile RH for each summer averaged over the research area using ERA5 data agree reasonably well with those averaged from 19 meteorological stations (Fig. 6b). Thus, ERA5 data shows a good coincidence with the observations not only for the mean values but also for extremely high values, and so it can provide a relatively reliable analysis for extreme wet days. This result is not surprising, because ERA5-Land assimilates near-surface temperature and humidity data (Hersbach et al, 2020).

5.2 Dry and hot climatology of the Tarim Basin

Before analyzing the possible causes of extreme RH events, we show the climatology in the Tarim Basin region to help contextualize the mechanism for extreme events. The Tarim Basin maintains high-temperature climatology in summer (Lu et al, 2019), an extremely arid desert area where drought occurs often (Zhang et al, 2015; Wang and Qin, 2017). Water is extremely scarce in this area, with annual precipitation less than 200 mm (Wang and Qin, 2017). The center of the basin is the vast Taklimakan Desert, located in northwestern China. The climatological seasonal cycle’s shown in Fig. 7a, showing that the RH of this region in summer is relatively low (Wang and Gaffen, 2001), and the soil is relatively drier than other seasons (Su et al, 2016). All these indicate that summer is a dry season. In this case, the climatological 2-m temperature of the entire basin in summer is above 300K and the climatological daily accumulated precipitation for JJA is less than 0.1mm (Fig. 7). Hot and dry conditions are the normal state in JJA for the Tarim Basin, corresponding to low RH. It is difficult for moisture to be transported into the desert region. The 38-year climatological mean wind in summer shows the prevailing westerlies, with weak southwesterly airflow entering the basin at 500 hPa and leaving the west side of the basin without penetrating the center of the desert (Fig. 7). Furthermore, near the surface, the airflow from the southwest is mainly blocked by the Himalaya Mountains, as well as the Kunlun Mountains at the south edge of the basin, which is one of the reasons for the formation of this desert (Hartmann, 2015). Tianshan Mountains are also important for the formation of the climatological characteristics in this region (Baldwin and Vecchi, 2016). The climatology at 850 hPa demonstrates a dry and hot current bypassing the Tianshan Mountains and entering the basin area from the northeast, where the Gurantunggüt Desert is located. The mountains to the north and south of the basin inhibit the transport of humid air. We seek to understand the extremely high RH condition in such an arid area.

5.3 Regional anomalous meteorological patterns for extreme wet events

An detailed study of the evolution of the local weather system when extreme events occur will provide a way to better understand the underlying physical mechanism, as is commonly done to study extreme events in the extratropics
We look at composites of regional anomalous meteorological patterns during and leading up to extreme wet events, defined as those exceeding the 95th percentile of an averaged RH anomaly time series. This time series is defined during summer over 2006-2018 as an average over 4 stations along the edges of the Tarim Basin (red stars shown in Figs. 1 and 8), thus minimizing the effects of the uneven the distribution of meteorological stations. For simplicity, only day 0 (when extremes happen), day -2 and day -4 are shown (Fig. 8), but days -3 and -1 have no surprising features.

Figure 8 shows composites of anomalies in precipitation, temperature, 500 hPa geopotential height (Z500), 850 hPa geopotential height (Z850) and the corresponding anomalous wind vector over the Tarim Basin for the extreme wet days (day 0), two days preceding the extreme wet days (day -2), and four days preceding the extreme wet days (day -4). Before extreme events occur, at day -4, a small amount of anomalous precipitation occurs in the oasis and mountains on the edge of the desert. Although the desert area in the center of the basin is relatively dry (Fig. 8a), the surrounding atmosphere is getting wet. At this time, temperature anomalies are weakly negative over the basin. A low pressure anomaly appears on the western side of the basin (with the weak airflow from the south at 500 hPa). Z850 anomalies do not change within the basin, but negative changes can be seen around the Tianshan Mountains on the southern edge of the basin (Fig. 8a). Approaching the day when the extreme event occurs, these phenomena become more pronounced. At day -2, positive precipitation anomalies and negative temperature anomalies take place in the basin (Fig. 8b), and the temperature decreases rapidly in the area of cold anomalies, coinciding with high pressure appearing near the surface of the Tarim Basin at 850 hPa. High vapor pressure and relatively low temperature are the conditions for high RH. The declining temperature and increasing moisture in the area suggest a change towards high RH conditions for this region.

The changes in temperature and precipitation are exacerbated at day -2. A large-scale cyclone centered at the west of the Tarim Basin has its east half over the desert (Fig. 8b). Compared with the composites of the Z500 anomalies and wind vector anomalies at day -4, Z500 anomalies have decreased substantially as a low pressure center has developed on the west of the Tarim Basin at day -2 (Fig. 8b). In this case, the relatively humid air current enters the basin from the south with strong winds. We note how unusual this pattern is by recalling that the mean wind pattern is just westerly (Fig. 7d).

The extreme wet day composite shows positive precipitation anomalies throughout the basin (Fig. 8c). The cold temperature anomalies have developed, with not only a strong reduction, but also an extension of the area anomalies to the entire basin. These strong negative temperature anomalies also coincide with high pressure developed at 850 hPa near the surface. At day 0, the cyclone at 500 hPa amplifies considerably with the center moving eastward, increasing Z500 anomalies over the west of the Tarim Basin to the
east, implying stronger wind from the direction of the Indian Ocean entering
the basin region. We note that upper-level moisture transport from the south
plays an important role in causing heavy precipitation in the summer (Huang
et al, 2015), and this transport has happened more with the recovery of the
Indian monsoon beginning in the early 2000’s (Jin and Wang, 2017; Huang
et al, 2020). Although the increase in the RH that we observe begins in 2006
and not the early 2000’s, the strengthening of the Indian summer monsoon is
conducive to more water vapor transport into the Tarim Basin. This mecha-
nism may contribute to the increase in the value of extreme RH in the past
decade. These conditions work together to cause the extreme wet events.

5.4 Contribution of moisture transport and temperature for extreme wet
events

Since RH is controlled by both water vapor transport and temperature, we
further explore their separate evolution during the development of this regional
weather system for extreme wet events. The definition of RH is

\[ RH = \frac{e}{e_s}, \]  

where \( e \) is vapor pressure, and \( e_s \) is saturation vapor pressure. \( e_s \) is a function
of temperature \( T \) (e.g. by the Teten formula, Xu et al (2012)). Assuming that
the air pressure is constant, \( e \) is a function of specific humidity \( q \), which is
deﬁned as the mass of water vapor in a unit mass of moist air. For efﬁcient
decomposition, the logarithmic form is adopted:

\[ \ln RH = \ln e - \ln e_s. \]  

To calculate the anomaly, we use \( \ln RH = \ln RH' + (\ln RH)' \), \( \ln e = \ln e' + (\ln e)' \)
and \( \ln e_s = \ln e_s' + (\ln e_s)' \). \( \ln RH' \) is the logarithmic climatological average of
RH, and similarly for \( \ln e' \) and \( \ln e_s' \). Then the local derivative to analyze the
change of \( (\ln RH)' \) in time using Eq. (2) is calculated:

\[ \frac{\partial}{\partial t} (\ln RH)' = \frac{\partial}{\partial t} (\ln e)' + (\ln e_s)' \]  

Using daily data, the daily tendency term, \( \frac{\partial}{\partial t} (\ln RH)' \), represents the daily
change of RH anomaly. (The use of daily data avoids the influence of unwanted
diurnal signals.) Using Eq. (3), daily change of RH anomaly, \( \frac{\partial}{\partial t} (\ln RH)' \),
(computed as a ﬁnite difference according to \( \frac{\partial}{\partial t} (\ln RH(t))' = \ln RH(t) - \ln RH(t-1) \)),
can be represented as the contribution of water vapor (the ﬁrst
term on the right side) and temperature (the second term on the right side).

Figure 9 shows the composites of the local daily change of \( (\ln RH)' \), \( -(\ln e_s)' \)
and \( (\ln e)' \) for extreme wet days (day 0) and 1-4 days prior to the extreme wet
days (days -1, -2, -3, and -4). \( \frac{\partial}{\partial t} (\ln RH)' \) increases incrementally until day -1
(Fig. 9b-e), when changes in the regional anomalous meteorological patterns
are similar between day -1 and day 0 than between any other two days (not shown). This reveals a more rapid development of the weather system at the beginning, approaching its mature state on day -1, then the rate of changes slows down, with the anomalies reaching their maximum size on day 0. Compared with $\frac{\partial}{\partial t} (\ln e)'$, the contribution of $\frac{\partial}{\partial t} (\ln e)'$ exhibits stronger growth at day -4, providing a considerable contribution of 70% to the total growth rate and thus suggesting a fairly important role of water vapor transport in the initial development. Then the vapor pressure contribution becomes almost the same as that of $\frac{\partial}{\partial t} (\ln e)'$ at day -3, indicating the equal importance for water vapor transport and temperature at this time. Subsequently, the contribution of $\frac{\partial}{\partial t} (\ln e)'$ is comparable with $\frac{\partial}{\partial t} (\ln e)'$ at day -2, becoming considerably more important at day -1 to day 0 and reaching 96% at day 0. This progression shows that the impact of temperature grows gradually with the increasing contribution of daily changes in saturation vapor pressure. Evaporation after precipitation will cool the surface, and along with the increased water vapor in the air, these conditions favor the increase of RH. The relationship between precipitation and surface cooling over desert is complex (Knippertz et al, 2009), however, and more observation and analysis is needed over the Tarim Basin in the future.

5.5 Frequency of the regional anomalous meteorological patterns

In the analysis above, we identified regional anomalous meteorological patterns associated with extreme wet events in the Tarim Basin. These patterns may also lead to many wet days that do not have RH as high as the 95th percentile. The increase in frequency of high RH events is not guaranteed to be due to an increase in the occurrence of this pattern. The intensifying hydrological cycle could potentially explain the change without any change to the statistics of the weather patterns. To determine if the weather pattern we identified above is related to the increase in high RH events, we look to see if the pattern is happening more often in later years of our time series.

To identify the specific regional anomalous meteorological patterns over the whole period, we first define the patterns for the extreme wet days (i.e., day 0) shown in Figure 8c as the featured patterns. In Figure 8, the study area is 70°E-100°E and 30°N-50°N, and there is a pattern of cooling, which shows distinct differences from the climatological mean state. Anomalous structure is also visible in the Z500 and Z850 fields. For efficient comparison and identification of days with similar patterns, the Pearson correlation is checked between the featured patterns and each day of summers 1981-2018. Due to the small amount of precipitation, only temperature, Z500 and Z850 are used. Correlation significance is determined using a t-test. Days that meet the requirement of all three fields being significantly correlated (at 99% confidence level) with their counterparts in the composite extreme wet day are considered to have the same regional anomalous meteorological patterns as the extreme wet day. (Note that similar results can be obtained by choosing a threshold value for the
The number of effective days per year is counted as the number of occurrences of the specific regional anomalous meteorological patterns (Fig. 10). There is a large amount of interannual variability in the occurrence of this pattern during the whole period, but nevertheless, the frequency of occurrences has a roughly increasing tendency in the recent decade (Fig. 10). This is in line with our conjecture. In the past ∼ 10 years, as the 95th percentile of RH has increased, the regional anomalous meteorological patterns that occur simultaneously have also appeared more frequently. Comparing Figures 6a and 10, we see that the increasing summer RH tendency coincides with an increasing number of the regional anomalous meteorological patterns during 2006-2018, which suggests that the regional anomalous meteorological patterns are not only associated with extreme wet days, but also play an important role in maintaining the seasonal mean RH. The decadal-scale variability occurs both in the mean summer RH time series and in the frequency of the regional anomalous meteorological patterns.

6 Discussion and Conclusions

In the past half century, the impact of global warming has greatly increased the water holding capacity of the atmosphere (Dai, 2006). Correspondingly, the atmosphere over land is drying, since the speed of water vapor transport from ocean to land cannot keep up with the speed of the increase in temperature over land (Byrne and O’Gorman, 2018). This large-scale behavior is a clear example showing that global warming can impact the interannual change of RH over land. The magnitude of the internal variability within the Earth’s climate system is important for understanding interannual variability and trends in RH. In addition, the regional behavior may in cases be quite different from the overall expectation of drying over land.

We analyzed daily summer RH data over the Tarim Basin, which is an extremely arid region dominated by a large desert. Over the record at the stations in the Tarim Basin, the RH has exhibited a large amount of decadal-scale variability, including an upward tendency in the summertime mean of RH during 2006-2018. In light of the large-scale, long term drying trend predicted, it is important to understand the internal variability that can cause regional deviations. The desert provides a relatively simple case study, and as moisture is critical in this region, it is also an important area for predicting local environmental and economic impacts.

Studies exploring why the Tarim Basin is getting wetter (whether measured by precipitation or humidity) find different results (Huang et al, 2015; Wang et al, 2017; Li et al, 2019b; Peng et al, 2020), and this disagreement implies that more work needs to be done. We provide a novel perspective on the recent increase in RH. We studied the changes in the PDF and extreme values of summer RH. The results using quantile regression show that there was an increasing trend for the 95th percentile during 2006-2018, while there is
no consistent regional tendency for the 5th percentile. This coincides with 
increasing variance and PDF changes of the summer RH anomalies during 
the most recent decade. High values become higher, while the low values do 
not have a consistent change. The average value of RH in the Tarim Basin 
becomes higher, likely driven by the upper half of the PDF.

To explore why the 95th percentile is increasing, we distinguished the re-
gional anomalous meteorological patterns that occur at the same time as ex-
treme wet events. The corresponding regional anomalous meteorological pat-
terns show abnormal southwesterly airflow at 500 hPa that transports water 
vapor into the basin and abnormal low temperature and high pressure near 
the surface with local precipitation. These processes cause the water vapor 
pressure to increase with more atmospheric water vapor and the saturated 
water vapor pressure to decrease with low surface temperature, resulting in 
an extremely high RH. The contributions of water vapor pressure and tem-
perature show equal importance to the mechanism. In the development of this 
regional anomalous meteorological pattern, water vapor transmission has a 
greater impact in the early stage, and temperature has a greater impact in the 
later stage.

In addition to examining the progression of the events themselves, we 
identify the regional anomalous meteorological patterns associated with the 
extreme events. We find the occurrence of the regional meteorological pat-
tern has increased over the past decade, providing a reasonable qualitative 
explanation for the increase of summer RH extreme wet days. This and the 
asymmetric changes to the distribution both suggest that dynamical changes 
are important for the recent change and that the changes are not simply a 
thermodynamically-driven intensification of the water cycle.

The Tarim Basin is a clear demonstration of large interannual variability 
in RH that complicates the detection of any forced trend without much longer 
time series. The decadal-scale variability in RH extremes in this specific re-
gion is not consistent with the overall expectation for drier land areas with 
climate change. This recent change is likely dynamical in nature, and we see 
an increase in variance as well as an increase in the mean. We have focused on 
the most recent period as an example, and more research is needed to identify 
the mechanisms for the inter-decadal variability in summer RH in the Tarim 
Basin. More regional studies of the variability and tendency of RH in different 
areas are also necessary to investigate the nuances in predictions of decreased 
RH over land in the future.

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viding the code for quantile regression.
A Methods used to detect the starting point of the recent trend in RH

A.1 Sequential Mann-Kendall test

To identify the change point in the summer RH time series, the Sequential Mann-Kendall (SQMK) test is adopted. Based on Mann-Kendall test, Sneyers (1991) introduced sequential values to help determine the approximate year of the beginning of a significant trend. This method calculates forward and backward sequences of the test statistic and enables detection of the approximate change point of a trend from the intersection point of the two sequences. The SQMK method is frequently used to identify trend start points (Yang and Tian, 2009). For more details and calculation see Nasri and Modarres (2009).

A.2 Standard Normal Homogeneity test

We also use another method, the Standard Normal Homogeneity test (SNHT), to check the change point. The result shows that the change point year is 2005 (Other results are not sensitive to this distinction; selecting 2005 as the starting year yields similar patterns and tendencies.) The SNHT was first applied in climate science by Alexandersson (1986). SNHT is a popular and effective way to detect a change point with its nonparametric variant (Salehi et al, 2020). Under the null hypothesis, the annual means of summer RH are assumed independent and identically distributed and thus the series is homogeneous. Then the test can detect the year where break occurs (Kang and Yusof, 2012). The details of this method can be found in Pohlert (2020).

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Fig. 1 Location and distribution of observation stations in the Tarim Basin. The red stars indicate the four stations located on the four edges of the desert (station 51639, shown in Fig. 3, is an edge station at the north edge). The center of the basin is the Taklimakan Desert, with tall mountains in the north and south. The map is created from the geographical information using the Google Maps API (http://code.google.com/apis/maps/) with the M_Map mapping package (Pawlowicz, 2020) and Matlab code (Bar-Yehuda, 2020).
Fig. 2 (a) JJA (June, July, August) mean value of RH averaged over the 19 stations for 1981-2018, the error bar shows the standard deviation of this spatial mean value; (b) the tendency of RH in JJA over 2006-2018 for each station. The black circle indicates stations with a significant trend at 95% confidence based on a two-sided t-test. The blue shaded area represents the period 2006-2018. Most stations show the increasing tendency over the Tarim Basin reflected in the mean (not shown).
Fig. 3 Quantile regression example for RH anomalies in JJA at station 51639 in the Tarim basin. Daily RH anomaly data is shown as a function of year (black circles). The dashed lines are the trends in the different percentiles, with red corresponding to the 95th percentile, blue corresponding to the 5th percentile, and green corresponding to the 50th percentile.
Fig. 4 Quantile regression trends of (a) 5th, (b) 50th and (c) 95th percentile of RH over JJA in the Tarim Basin during 2006-2018. The black-outlined circles show stations where the trends are found to be significant based on a bootstrap analysis (see text), whereas the circles without outlining show stations with insignificant trends. The 95th percentile shows a consistent and increasing tendency during this period, while the 5th percentile does not have a consistent tendency.
Fig. 5 (a) Probability distribution function (PDF) of RH anomaly in JJA at station 51639 for two periods, where the red line is for 2012-2018, and the blue line is for 2006-2012. The dashed line is a normal distribution with the same mean and standard deviation as the JJA RH anomaly PDF during 2012-2018. (b) Mean standard deviation of RH anomaly each year during summertime (JJA), computed by averaging each year’s standard deviations over all 19 stations. The error bar shows the standard deviation of each year’s collection of 19 station standard deviations. The blue shaded area indicates the period 2006-2018, which is the period that this study focuses on. It clearly shows that the standard deviation started to increase around 2006.
Fig. 6 (a) JJA (June, July, August) mean of RH anomaly in each year averaged over the study area (74°E-90°E, 35°N-43°N) using ERA5 data over 1981-2018 (black line). JJA mean of RH anomaly calculated from the observations is shown as a gray line, which indicates good agreement between the two sets of data. The blue shaded area indicates the period 2006-2018. (b) The Tarim Basin-averaged 95th percentile value of JJA RH anomaly for each year. The red line is calculated by averaging the observed station-level 95th percentiles over the 19 stations and the black line is calculated by averaging the ERA5 grid box-level 95th percentiles over the whole study area. There is good agreement between the observations and ERA5 data for these extremely high values of JJA RH anomaly. The error bars in both panels show the (spatial) standard deviations of the individual station (OBS) or grid box (ERA5) values.
Fig. 7  (a) The climatology of RH averaged over 1981-2018. The climatological mean in JJA for (b) 2-m Temperature (K), (c) precipitation (cumulative daily amount; mm), (d) 500-hPa geopotential height (m) (Z500), (e) 850-hPa geopotential height (m) (Z850). The red vector arrows indicate the climatological wind speed (m/s) at 500 and 850 hPa, respectively. The wind speed intensity is indicated in the upper right corners of (d) and (e). For Z850, the area where the surface pressure is lower than 850-hPa is set to white to avoid attempting to interpret data on underground pressure surfaces. Note that the 500 and 850 hPa wind vectors have different scalings. Overall, these climatological fields show that the Tarim Basin maintains a dry and hot climate.
Fig. 8 Composite time-evolution maps for (a) day -4 (the first column), (b) day -2 (the second column) and (c) day 0 (the third column) for extreme wet days exceeding the 95th percentile of the distribution of an averaged RH anomaly, which is computed from 4 stations (51639, 51810, 51839, 51765, shown as red stars) at the edges of the Tarim Basin, during JJA (local summer). Composites are for anomalies of climate variables: total precipitation anomalies (Precipitation, mm); 2-m temperature anomalies (T2m, K); 500-hPa geopotential height anomalies (Z500, m) and 500-hPa wind anomalies (vectors, m/s); 850-hPa geopotential height anomalies (Z850, m) and 850-hPa wind anomalies (m/s; vectors). For Z850, the area where the surface pressure is lower than 850-hPa is set to white. The wind speed intensity is indicated in the upper right corner of the relevant panels.
Fig. 9 Composite time-evolution maps for (a) day 0, (b) day -1, (c) day -2, (d) day -3 and (e) day -4 for the extreme RH events (same definition as in Fig. 8). The study region is 74°E-90°E and 35°N-43°N. The three columns of composites describe the local tendency changes of \((\ln RH)'/t\), \(-\ln (es)'/t\) and \((\ln e)'/t\), respectively. Non-dimensionalization has been applied before transforming to the log form of these climate variables. Daily data are used here and the units are 1/day for all local tendencies. These local tendencies also can be regarded as the daily change of \((\ln RH)'/t\), \(-\ln (es)'/t\) and \((\ln e)'/t\) before the extreme wet events. The ratio of the shaded-region averages of \(-\ln (es)'/t\) and \((\ln RH)'/t\) are shown in the upper right corner of each middle-column panel. Similarly, the ratio between \(\frac{\partial}{\partial t}(\ln e)'/t\) and \(\frac{\partial}{\partial t}(\ln RH)'/t\) shown in the upper right corner of each right-column panel. These ratios roughly show the contributions of the two components of \(\frac{\partial}{\partial t}(\ln RH)'/t\) each day before the extreme wet days.
Fig. 10 Frequency of occurrence of the regional anomalous meteorological pattern corresponding to the 95th percentile extreme wet events each year from 1981 to 2018. The blue shaded area represents the period 2006-2018. We see that during 2006-2018 the anomalous weather pattern tends to occur more frequently over time.