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Stability and long-range correlation of air temperature in the Heihe River Basin

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Abstract: Air temperature (AT) is a subsystem of a complex climate. Long-range correlation (LRC) is an important feature of complexity. Our research attempt to evaluate AT's complexity differences in different land-use types in the Heihe River Basin (HRB) based on the stability and LRC. The results show the following: (1) AT's stability presents differences in different land-use types. In agricultural land, there is no obvious variation in the trend throughout the year. Whereas in a desert, the variation in the trend is obvious: the AT is more stable in summer than it is in winter, with T_a ranges of [8, 20]°C and SD of the AT residual ranges of [0.2, 0.7], respectively. Additionally, in mountainous areas, when the altitude is beyond a certain value, AT's stability changes. (2) AT's LRC presents differences in different land-use types. In agricultural land, the long-range correlation of AT is the most persistent throughout the year, showing the smallest difference between summer and winter, with the *Hs* range of [0.8, 1]. Vegetation could be an important factor. In a desert, the long-range correlation of AT is less persistent, showing the greatest difference between summer and winter, with the *Hs* range of [0.54, 0.96]. Solar insolation could be a dominant factor. In an alpine meadow, the long-range correlation of AT is the least persistent throughout the year, presenting a smaller difference between summer and winter, with the *Hs* range of [0.6, 0.85]. Altitude could be an important factor. (3) Usually, LRC is a combination of the T_a and SD of the AT residuals. A larger T_a and smaller SD of the AT residual would be conducive to a more persistent LRC, whereas a smaller T_a and larger SD of the AT residual would limit the persistence of LRC. A larger T_a and SD of the AT residual would create persistence to a degree between those of the first two cases, as would a smaller T_a and SD of the AT residual. In addition, the last two cases might show the same LRC.

Keywords: Heihe River Basin; air temperature; long-range correlation; stability; geographical environment

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1 Introduction

Understanding the features and complexity of the air temperature (AT) has important implications for the development of ecosystems and climate change (Solomon *et al.*, 2009). AT is arguably the most important component of climate (Zhang *et al.*, 2003). It influences a broad range of ecosystem processes, including evapotranspiration, photosynthesis, decomposition, and carbon fixation (Running, 1987). Through these processes, AT affects vegetation dynamics and the distribution of biota. The spatial-temporal patterns of AT are particularly complex due to its interactions with components (Rind, 1999; Held, 2014) such as land cover, terrain, latitude, longitude, and vegetation (Cheng *et al.*, 2008; Shao *et al.*, 2012; Shiflett *et al.*, 2017). Lorenz is the first to explicitly note the nonlinear dynamics of the atmosphere. Recently, Li (2014) also stressed that AT variance was spatially and temporally non-uniform. Xu *et al.* (2013) cited a few concepts and methods that have been used to reveal the complexity of the climate change process, with a focus on understanding the complexity of temperature dynamics in Xinjiang, China.

Diurnal temperature is one of the climate change characteristics. On the one hand, research on it would be helpful to know local climate (Pike *et al.*, 2012), plant growth (Orlandini *et al.*, 2006), local ecology (Armbruster *et al.*, 2007), and earth surface processes. For example, diurnal temperature variation is an important index for urban heat island effect (Mathew *et al.*, 2018); it has an impact on proanthocyanidin accumulation in grape skins (Cohen *et al.*, 2012); and it is also used to estimate pore water fluid flux then further infer vertical groundwater-surface water exchange (Irvine *et al.*, 2017). On the other hand, diurnal temperature could improve fine weather forecast. Yang *et al.* (2013) concluded general rules and seasonal characteristics of daily extreme temperature and the speed of temperature change in Beijing. This conclusion they proposed could serve as a background for fine weather forecast.

While considerable research was on AT complexity, they focused on decadal or century scale (Franzke, 2012; Gil-Alana, 2012; Østvand, 2014). Complexity research on AT's time series at finer temporal scale should also be enhanced, and be expected to have some new discovery. Long-range correlation (LRC) is one of the complexity characteristics. It is distinguished from long-term range (Wu *et al.*, 2013), which describes the amplitude and duration of evolution trends based on the autocorrelation structure of the time series (Michael, 2012). It is also known as long-range dependence, long memory, or long-range persistence (Shen *et al.*, 2018). The LRC index reflects intensity of persistence or antipersistence (Zhang *et al.*, 2018). This index on AT would show AT in certain time has much influence on future AT. It should be stressed that LRC evaluation depends on higher demand for data. The data should be high frequency and continuous.

Our research shows the AT's complexity based on data at the scale of 10 minutes to evaluate complexity differences of different land-use types in Heihe River Basin (HRB) in 2014. AT's complexity is detected by AT's stability and LRC. Complexity in each month is calculated, and then the variations throughout the year are analyzed. Sections 2.1 and 2.2 show data description. Sections 2.3 and 2.4 show AT's complexity. To describe the stability from different perspectives, monthly stability is qualitatively determined by the average daily temperature range (T_a) and standard deviation (SD) of the AT residual. Adaptive fractal analysis (AFA) is used to analyze AT's LRC. Section 3 evaluates differences of AT's complexity in different land-use types. Section 4 discusses the differences, and shows the relationship between AT's stability and LRC. Section 5 gives some main conclusions.

2 Data and methods

2.1 Study area

The Heihe River Basin (HRB) is the second largest inland river basin in northwest China and central Eurasia, and it covers an area of approximately 128,000 km^2, as shown in Figure 1. Administratively, the basin includes part of Qilian County in Qinghai Province, some counties and cities in Gansu Province, and part of Ejin Banner in Alxa League of Inner Mongolia.

Research on HRB will be of ecological significance. Because of HRB's relatively abundant water resource (mean annual runoff is 37.3×10^8 m^3), the area is an important commodity grain base in northwest China. It covers diverse agricultural lands, including wheat, corn and Chinese tamarisk. However, it has recently experienced rapid socioeconomic development and an increase in population density (Song *et al.*, 2017). Extensive exploitation of the water and land resources in the upper and middle parts of the basin has led to a sharp decrease in water resources in the lower reaches of the Heihe River. This has resulted in a severe deterioration of the eco-environment in the Ejin Banner Oasis, which is located in the downstream sections of the basin.

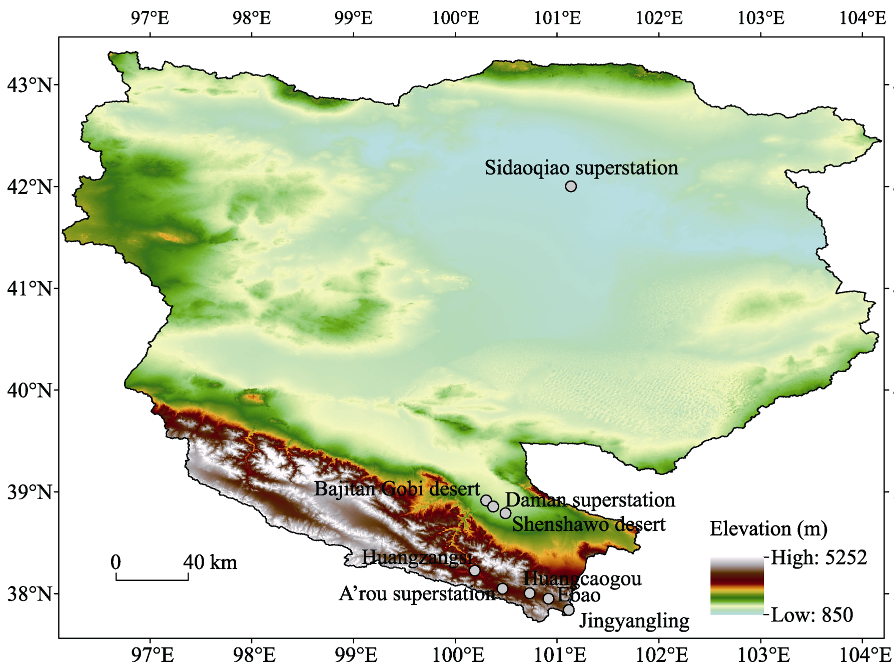

Figure 1 Location of stations in the Heihe River Basin in this study

It is thus an optimal experimental area for understanding the variance of AT based on the geographical environment. Geographical differentiation is evident in the basin. From south to north, there are three major geomorphological units: the southern Qilian Mountains, the middle Hexi Corridor and the northern Alxa High-plain. The southern Qilian Mountains, with a remarkable vertical zonal gradient, is the water source area. The elevation of the area ranges from 2000 to 5500 m, and the mean annual precipitation increases from approximately 250 mm in the low-mountain or hilly zone to approximately 500 mm in the high-mountain zone. The middle Hexi Corridor is located between the Qilian Mountains and the Beishan Mountains. The elevation of the area decreases from > 2000 m to 1000 m, and the mean annual precipitation decreases from 250 mm to < 100 mm from south to north. The northern Alxa High-plain is mainly occupied by bare Gobi and Chinese Tamarisk, with a mean altitude of approximately 1000 m and a mean annual precipitation of < 50 mm.

2.2 Data

The dataset is from the "Heihe Watershed Allied Telemetry Experimental Research (HiWATER)" project (Liu *et al*., 2011; Kang *et al*., 2015). Data is recorded every 10 minutes, and 144 records are ensured every day. Each record corresponds to a moment. The AT data used in this research are obtained at a height of 5 m in 2014. AT data at a 5 m height are the most complete and cover most stations. Additionally, the data are concentrated in 2014.

This paper obtained AT data from nine stations, as shown in Figure 1 and Table 1. In addition to the completeness of data, different geographical environments were considered when selecting stations. These environments span a broad range of altitudes, latitudes and land-use types. The altitudes of the stations vary from 873 m to 3750 m, and the latitudes range from 37.8384° to 42.001°. The land-use types include alpine meadow, deserts and agricultural lands. From higher altitude to lower altitude and lower latitude to high latitude, the stations were JYL_U, EB_U, HCG_U, AR_U, HZS_U, SSW_M, DM_M, BJT_M and SDQ_L. Alpine meadow areas include JYL_U, EB_U, HCG_U and AR_U. Agricultural lands include HZS_U, DM_M and SDQ_L. Deserts include SSW_M and BJT_M. The subscript letter in the abbreviations (U, M and L) corresponds to different reaches. For example, JYL_U means that the station is in the upper reaches of HRB.

Table 1 List of stations used in this study

	Station	Abbreviation	Latitude (°)	Longitude (°)	Altitude (m)	Land-use type
Upper reaches	Jingyangling	JYL_U	37.8384N	101.116E	3750	Alpine meadow
	Ebao	EB_U	37.9492N	100.9151E	3294	Alpine meadow
	Huangcaogou	HCG_U	38.003N	100.7312E	3137	Alpine meadow
	Arou superstation	AR_U	38.0473N	100.4643E	3033	Alpine meadow
	Huangzangsi	HZS_U	38.2254N	100.1918E	2612	Wheat
Middle reaches	Shenshawo desert	SSW_M	38.7892N	100.4933E	1594	Desert
	Daman superstation	DM_M	38.8555N	100.3722E	1556	Corn
	Bajitan Gobi desert	BJT_M	38.915N	100.3042E	1562	Gobi mesert
Lower reaches	Sidaoqiao superstation	SDQ_L	42.001N	101.137E	873	Chinese tamarisk

*The subscripts in the abbreviation (U, M and L) correspond to different reaches. For example, JYL_U indicates that Jingyangling is in the upper reaches of HRB.

2.3 Qualitative estimation of AT's *s* stability

To describe the stability of AT from different perspectives, monthly stability is qualitatively estimated by the T_a and SD of the AT residuals. The monthly T_a is calculated using formula (1):

$$T_{ai} = \frac{1}{n}\Sigma_{k=1}^{n}[\max\{T_i(k,j)\} - \min\{T_i(k,j)\}](j=1,2\ldots,144;\ k=1,2\ldots,n) \tag{1}$$

Firstly, we calculated the daily temperature range, which is shown with $\max\{T_i(k,j)\} - \min\{T_i(k,j)\}$ in formula (1); then monthly T_a is average daily temperature range in a month. In the formula, i indicates which month is calculated and n is the number of days in month i and could be 28, 29, 30 or 31. k indicates which day is calculated in month i; j is a moment in a day, corresponding to one of 144 records; $T_i(k,j)$ is temperature at moment j, day k, and month i; and T_{ai} is the average daily temperature range in month i.The monthly SD of AT residuals is also used to measure AT's stability, as shown in Figure 2. First, the original AT series should be smoothed to get the trend, as shown by the red line in the figure. After many experiments, a period of 4 hours was considered an optimal interval for smoothing data to distinguish the stations' stability. The smoothing method is the same as step (1) in AFA, which is introduced in the method of calculating LRC. Then, AT residuals are calculated as step (2) in AFA. Finally, the monthly *SD* is calculated.

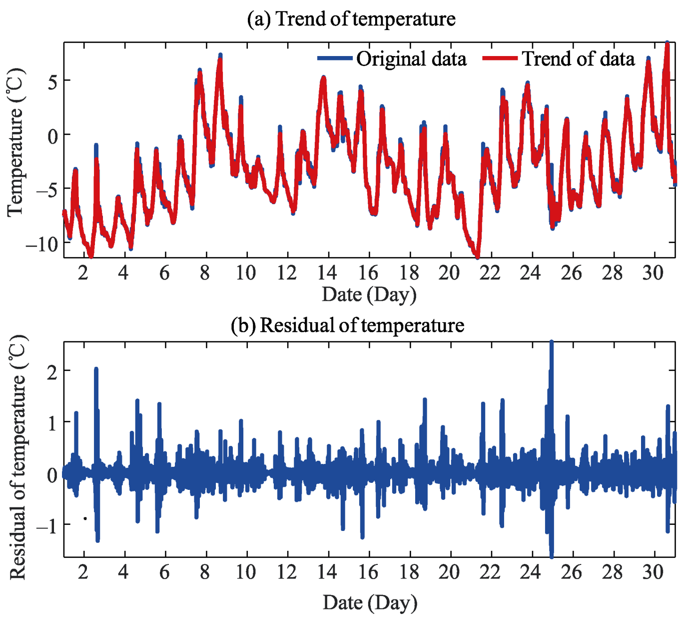

Figure 2 Residual of air temperature in Heihe River Basin from January 2014 to December 2014

2.4 Method for long-range correlation

After the qualitative estimation of AT's stability, this paper quantifies the LRC of AT's complexity. LRC is a way to express the "memory" or serial correlation in a time series. It is often called the Hurst exponent and is denoted as H. Usually, it is composed of 3 degrees: long-range correlation, negative long-range correlation and uncorrelated process. Anti-persistent and persistent processes contain structures that distinguish them from truly random sequences of data. $0.5 < H < 1$ indicates a correlated process, or what is termed a persistent process. In this case, increases in the time series are likely to be followed by further increases, and decreases are likely to be followed by decreases. In addition, a finding of $0 < H < 0.5$ indicates an anti-correlated or anti-persistent process, which means that increases in data series are likely to be followed by decreases (and decreases are likely to be followed by increases). $H = 0.5$ indicates that the process is random and that the data points are uncorrelated with each other.

In this paper, to effectively remove the trends of time series, adaptive fractal analysis (AFA) (Gao *et al.*, 2019) is used to measure LRC. In some ways, it is similar to detrended fluctuation analysis (DFA). However, in addition to sharing many of the same advantages as DFA, AFA can deal with arbitrary and strong nonlinear trends by constructing overlapped sliding fitting windows (Gao *et al.*, 2007; Riley *et al.*, 2012). This method has been successfully used for chaos and fractal analysis of bio-signals (Gao *et al.*, 2012). Its method of analysis is as follows:

(1) The first step in AFA is to identify a globally smooth trend that is created by patching together local polynomial fits to the time series. A global trend is a synthetic time series $\{v_i\}$, $i = 1, 2, ..., N$, where N is length of the original time series. The fit to overlapping regions is created by taking a weighted combination of the fits of two adjacent regions. It ensures that the concatenation of local fits is smooth, according to formula (2) (Gao *et al.*, 2007):

$$y^{(c)}(l) = w_1 y^{(i)}(l+n) + w_2 y^{(i+1)}(l) \tag{2}$$

where $w_1 = \left(1 - \frac{l-1}{n}\right)$ and $w_2 = \frac{l-1}{n}$.

(2) The next step is to detrend the data by removing the global trend signal that was just created. Then, the residual of the original data is $\{u_i - v_i\}$, where $\{u_i\}$ is the original data.

(3) The last step is to quantify the Hurst exponent, H, based on the relation between the variance of the magnitude of the residuals, $F(w)$, and the window size, w, as formula (3) shows (Gao *et al.*, 2007):

$$F^{(2)}(w) = \left[\frac{1}{n}\sum_{i=1}^{n}\left(u_i - v_i\right)^2\right]^{1/2} \sim w^H \tag{3}$$

H can be quantified through the slope (obtained using simple linear regression) of a linear relation in a plot of $\log_2 F(w)$ as a function of $\log_2 w$.

3 Results

3.1 Qualitative estimation of AT's stability

To analyze the differences in stability at each station, the monthly stability of these stations is now determined. Taking the SD of the AT residual as the x-axis and T_a as the y-axis, a month at a station corresponds to a point in the coordinate system. For every station, we may draw a direction line from January to December. The stability of each station is shown in Figure 3. AT presents a smaller range of fluctuation when the point is closer to the origin, which indicates that AT is more stable. In contrast, AT presents a larger fluctuation range when the point is farther from the origin, which indicates that AT is more unstable.

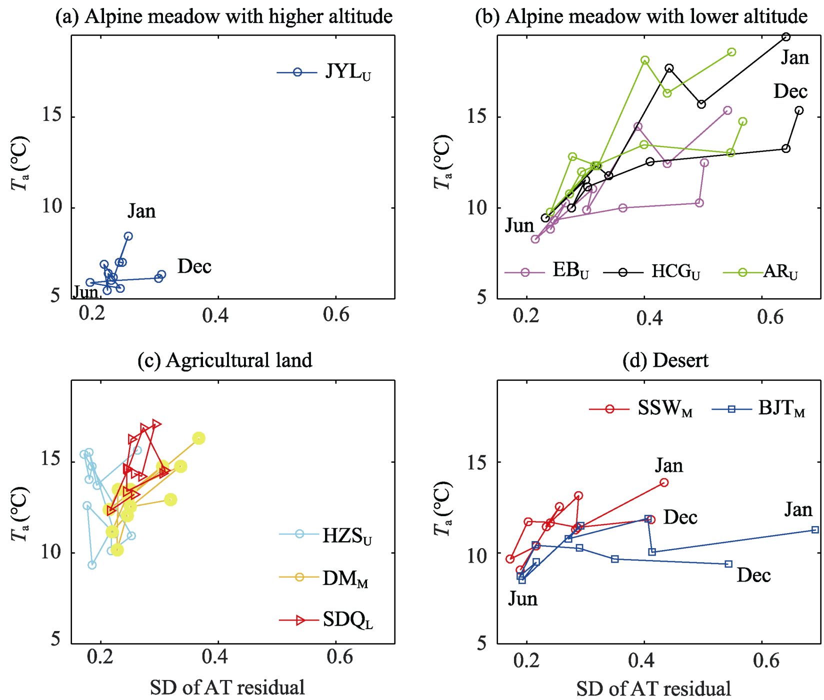

Figure 3 Stability of AT based on T_a and SD of AT Residual in Heihe River Basin from January 2014 to December 2014. Categories (a) and (b) are alpine meadow area, but the altitude of category (a) is higher than category (b); Category (c) is agricultural land area; and Category (d) is desert area.

Besides JYL_U, AT's stability presents differences in different land-use types. Nine stations are classed into four categories based on the lines of all stations: (1) AT of JYL_U is stable throughout the year. Moreover, the difference in stability between summer and winter is the smallest at all stations. Both the T_a and SD of the AT residual are the lowest throughout the year, within 5℃ and 0.3, respectively. (2) AT of EB_U, HCG_U and AR_U are more stable in summer than in winter. Moreover, the difference in stability between summer and winter is the greatest. Both the T_a and SD of the AT residual show obvious differences between winter and summer, with a range of [8, 20]℃ and [0.2,0.7], respectively. (3) There are no obvious variations in the trend of AT's stability across the year in HZS_U, DM_M and SDQ_L. Their T_a ranges are greater than the SD of the AT residual, with ranges of [9, 18]℃ and [0.1, 0.4], respectively. (4) AT of SSW_M and BJT_M are more stable in summer than it is in winter. Moreover, the difference in stability between summer and winter is lower than that observed for category (b). In contrast to category (c), the range for the SD of the AT residual in these stations is greater than that of T_a, with [8, 14]℃ and [0.1, 0.7], respectively.

3.2 Quantified estimation of AT's long-range correlation

This part quantitatively describes AT's LRC. The variation of LRC with month is shown in Figure 4. Taking the month as the x-axis and the LRC as the *y*-axis, a month of a station's data corresponds to a point in the coordinate system. For every station, we can draw a line from January to December.

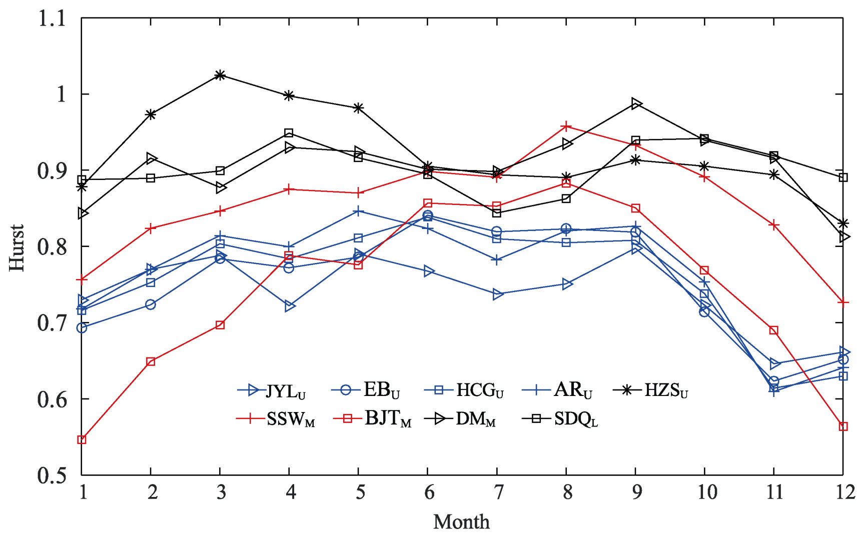

Figure 4 Monthly LRC in each station in Heihe River Basin from January 2014 to December 2014. Different line colors correspond to different categories and to different land-use types. A black line is agriculture land, red is desert, and blue is alpine meadow.

There is a long-range correlation for all stations. The monthly *H* of each station is far greater than 0.5, and some of them even approach 1. This result indicates that ATs all behave as a persistent process, which means further increases (decreases) in AT are likely to occur in the next sampled moment. For example, in this paper, AT's trend in the next 10 minutes is likely to be the same as that observed for the previous 10 minutes.

AT's long-range correlation presents differences in different land-use types. According to the observed variation trend of LRC, the 9 stations are classified into three categories, which correspond to the different colors in Figure 4. The first category includes HZS_U, DM_M, and SDQ_L, which is shown with black lines. Their *Hs* are all greater than 0.8 and are among the highest in all categories throughout the year. Additionally, their fluctuations are not well pronounced. The second category includes SSW_M and BJT_M, which is shown with red lines. Although their values are more varied, they share a similar variance in monthly *H*. Their LRCs vary significantly between summer and winter. *H* is lower in winter months and higher in summer months, with ranges of [0.7, 0.96] and [0.54, 0.88], respectively. The last category includes JYL_U, EB_U, HCG_U, and AR_U, which is shown with blue lines. Their *Hs* are all lower than 0.85, and they generally remain lower throughout the year. In addition, they do not fluctuate significantly, except in November and December.

4 Discussion

4.1 Analysis on differences of AT's stability

4.1.1 Impact of altitude on AT's stability

First, altitude could be an important factor in AT's stability, as categories (1) and (2) show. In mountainous areas, when the altitude lies beyond a certain value, the characteristics of AT's stability could change. For categories (1) and (2), aside from their altitudes, their geographical environments are similar, including land-use type and latitudes. The altitude of JYL_U is 3750 m in category (1). It is higher approximately 456 m than that of EB_U, which is the highest station in category (2). Wang *et al*. (2011) stressed that altitude is an important factor in a climate system. When the altitude is beyond a certain value, the influence of altitude could be more significant than that of other climate components. This was similar to what Dobrowski *et al*. (2009) mentioned, i.e., when one component loses its explanatory power, the other is prevalent. In addition, owing to the high altitude, AT is closely coupled to atmospheric circulation. Thus, low-stature vegetation (Alpine Meadow) can effectively decouple from free convection (to create aerodynamic resistance to heat exchange) (Körner, 2007).

4.1.2 Impact of land-use type on AT's stability

Land-use type has a good relation with AT's stability. In the same land-use type, similar seasonal trends of T_a and SD of AT residuals could be observed. As shown in categories (3) and (4), the stations share the same land-use type, i.e., agricultural land or desert. In agricultural land, there is no obvious variation trend in AT's stability across the year. Moreover, their T_a ranges are greater than those of the SD of AT residuals. In desert, the AT of the stations is more stable in summer than in winter. In contrast to agricultural land, the ranges of these stations' SD of AT residuals are greater than the ranges of T_a. There is evidence indicating that AT affected land-use type by affecting phenology of organisms, the range and distribution of species, and the composition and dynamics of communities (Walther *et al*., 2002). Considering earth is a complex system with interactive components, land-use type could affect AT in turn. For example, rain falling on the Earth contributes to plant growth, and plant growth transpires the moisture back to the atmosphere during the process of growing. In addition, the atmospheric water vapor can form clouds, thereby affecting the solar radiation, which influences how plants grow (Rind, 1999).

4.2 Analysis on differences of AT's long-range correlation

Land-use type has a good relation with AT's LRC. In the three categories mentioned above, different categories correspond to different land-use types. They are agricultural land (category 1), desert (category 2) and alpine meadow (category 3).

In agricultural land, the long-range correlation of AT is the most persistent across the year in all land-use types. Additionally, it shows the least difference in LRC between summer and winter, possibly due to the influence of vegetation, which could have a positive influence on climate dynamics (Shiflett *et al*., 2017). These areas include wheat, corn and Chinese tamarisk. In summer, vegetation roots continually absorb water from the soil, and air maintains stable humidity levels. Dense vegetation reduces the wind speed, reduces airflow, and finally maintains AT's stability. In winter, time lag could be an important factor for climate–vegetation interaction (Wu *et al.*, 2015). Vegetation influences AT not only in real time but also for longer periods. In other words, this low level of complexity provides a suitable living environment for vegetation.

In deserts, the long-range correlation of AT is less persistent. Additionally, the greatest difference in LRC between summer and winter is observed in these stations. Solar insolation could be a dominant influencing factor. Because of the high H in summer, AT shows a more persistent process than it does in winter. This also means that AT's variance trend in the next 10 minutes is more likely to be the same as in the previous 10 minutes in summer than it is in winter. Therefore, the AT in summer is less complex than winter. Solar radiation is strong in summer and weak in winter (Guo *et al.*, 2012). Therefore, it could have a positive influence on AT in summer (Ricke *et al.*, 2010; Held, 2014).

In alpine meadows, the long-range correlation of AT is the least persistent throughout the year. Additionally, compared with desert, it presents a smaller difference in LRC between summer and winter but has a greater difference than agricultural land does. On the one hand, high elevation could be a dominant influencing factor for complexity in these areas. The areas are in southern Qilian Mountains, whose elevations range from 3000 to 4000 m. Usually, AT in mountainous areas is especially complex due to the high elevations (Ørbæk, 2007). On the other hand, similar to the agricultural land, alpine meadows could play an important role in the difference in AT's LRC between summer and winter.

4.3 Comparison of AT's stability and long-range correlation

Usually, LRC is the combination of the T_a and SD of AT residuals. It includes three cases. First, a larger T_a and smaller SD of the AT residual would be conducive to a more persistent LRC, as observed for the agricultural land in this research, which has the best LRC throughout the year due to its larger T_a and smaller SD of AT residual. Second, a smaller T_a and larger SD of the AT residual would limit a persistent LRC, as observed in the desert. BJT_M has with the smallest LRC in winter among all stations throughout the year, which corresponds to a smaller T_a and a larger SD of the AT residual. Because of the similar variation in stability, the variation of SSW_M's LRC is very similar to that of BJT_M. Third, a larger T_a and SD of the AT residual would lead to a persistent LRC that falls between those observed for the first two cases, as would a smaller T_a and SD of the AT residual. In addition, the last two cases might show the same LRC, as observed in alpine meadows. The stability differs greatly between JYL_U and the other three stations in alpine meadow, but their LRCs are similar. JYL_U has the smallest T_a and SD of the AT residual. The other three stations have either the largest T_a and SD of AT residual or a smaller T_a and SD of AT residual.

5 Conclusions

The purpose of this research is to evaluate AT's complexity differences of different land-use types in the HRB. Our research focuses on AT's differences in different geographical environments based on dataset with 10 minutes. Nine stations are selected in the experiment and span a broad range of altitudes, latitudes and land-use types. AT's complexity is deduced from stability and LRC. First, to describe the AT's stability from different perspectives, stability is evaluated by using the T_a and SD of the AT residuals, which vary with different geographical environments. Second, to effectively remove the trend of time series, LRC is evaluated by the AFA method. Third, both AT's stability and LRC in different land-use types are analyzed. Finally, the paper reveals the relationship between AT's stability and LRC.

Some of our main conclusions are as follows:

(1) Land-use type has a good relation with AT's stability. However, for the same land-use type, altitude could be another important factor in AT's stability, when it reaches a certain height. In agricultural land, there is no obvious variation trend throughout a year, with T_a ranges of [9, 18]℃ and SD of the AT residual ranges of [0.1, 0.4], respectively. But in desert, the variation trend is obvious: the AT is more stable in summer than it is in winter, both the T_a and SD of the AT residual show obvious differences between winter and summer, with a range of [8, 20]℃ and [0.2, 0.7], respectively. In addition, in mountainous areas, when altitude is beyond a certain value, the characteristics of AT's stability could change. In this research, the stability is very different among alpine meadows. The range for the T_a and SD of the AT residual are [8, 14]℃ and [0.1, 0.7], respectively. Altitude could be an important influencing factor.

(2) Land-use type has a good relation with AT's LRC. In agricultural land, the long-range correlation of AT is the most persistent in all land-use types, with *Hs* range of [0.8, 1]. Additionally, they show the least difference in LRC between summer and winter, possibly due to the influence of vegetation. In desert, the long-range correlation of AT is less persistent. Additionally, the greatest difference of LRC between summer and winter is observed at these stations, with *Hs* range of [0.54, 0.96]. Solar insolation could be a dominant influencing factor. In alpine meadows, the long-range correlation of AT is the least persistent throughout the year, with *Hs* range of [0.6, 0.85]. Additionally, compared with desert, they present a smaller difference in LRC between summer and winter but a greater difference than agricultural land does. Altitude could be an important factor.

(3) Usually, LRC is a combination of the T_a and SD of the AT residual. A larger T_a and smaller SD of the AT residual would be conducive to a more persistent LRC. A smaller T_a and larger SD of the AT residual would limit the persistence of LRC. In addition, a larger T_a and SD of the AT residual would lead to persistence at a level between the first two cases, as would a smaller T_a and SD of the AT residual. In addition, the last two cases might show the same LRC.

In summary, this research could be an effective way for managing agricultural activities and understanding the local ecology. As an important component in the climate system, AT influences a broad range of ecosystem processes, including evapotranspiration, photosynthesis, decomposition, and carbon fixation. Additionally, analyzing the time series of AT would be conductive to understanding AT's internal variability and externally forced components. The spatial-temporal patterns of AT are particularly complex due to its interactions with many components. Using a more complex method could be an effective way to discover the features of AT.

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