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# Using Quantile Regression to Evaluate Human Thermal Climates in China

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Studies of how climate influences humans have long been a major interest in climatology and other disciplines. Many different thermal comfort indices have been developed to measure the combined atmospheric effects on human bodies. Using different indices, studies have been conducted to examine the spatial variations of human thermal comfort in various countries (e.g. Terjung, 1966, 1968; Green, 1967; Auliciems and de Freitas, 1976; de Freitas, 1979, 1985; Auliciems and Kalma, 1979, 1981; McGregor, 1993). These human bioclimatic studies have important implications on human health, migration patterns, retirement decisions, tourism development, energy requirements, etc.

Yan (2005) used the CLO (clothing insulation) index of Gagge, Burton and Bazett (1941), which provides a rough measure of the amount of clothing required to maintain comfort, to examine the human thermal climates and spatial patterns of extreme thermal stress in China. The CLO index has the advantage that it synthesizes the interaction between thermo-physiological processes of the body with the atmospheric variables to provide a dynamic energy balance model as compared to traditional empirical indices that are only based on exterior climatic elements that affect human comfort. Similar to the studies of de Freitas (1979) and McGregor (1993), Yan (2005) investigated the human thermal climates of China through the examinations of seasonal *average* isoline maps of CLO requirements.

Information on *average* clothing needs in a specific region obtained from the *average* CLO maps is very useful. However, the *average* CLO maps have a severe deficiency in informing tourists of the physio-climatic comfort when planning for a visit or retirees in choosing the “ideal” climatic location for retirement. They only provide information on the center of the distribution of climate variation of a region. Other information, like the shape and variation of the CLO index will provide a more complete picture of human comfort. For example, knowing that the *average* CLO index for a particular month of a particular destination is 1.0 (which represents the clothing ensembles of briefs, broadcloth, long-sleeved shirt, single-breasted suit jacket, tie, straight fitted trousers, calf-length socks and hard-soled shoes) is not very helpful when 25% of the time in the month the CLO index is 2.6 or above (which requires a clothing ensembles of long underwear, shirt, fitted trousers, gloves, socks, hat and heavy coat) while another 25% of the time the CLO index is 0.3 or below (representing a clothing ensembles of briefs, shorts, open-neck short-sleeved shirt, light socks and sandals).

This extra information on the variation of the CLO index can be obtained by using bivariate quantile regression of He, Ng and Portnoy (1998) or Koenker and Mizera (2004) to generate various “quantile (percentile)” CLO isoline maps, e.g. the $0.25^{th}$ and $0.75^{th}$ (25th and $75^{th}$) quantile (percentile) CLO isoline maps. The main objective of this study is to provide a more complete picture of the amount of clothing requirement to maintain comfort in various regions of China by generating a broader range of

CLO isoline maps. Tourists, retirees, policy makers and planners can then use the isoline maps in planning their vacation trips, retirement relocation, urban/regional allocations of energy resources, etc., and helping them better prepare for the unpleasant "surprises".

## Methodology and Data

### *CLO Index*

As explained in Yan (2005), the CLO index is computed as

$$I_{cl} = \frac{(33 - t_a)}{0.155H} - \frac{H + R_0 \cos\alpha p^m (1 - C^x) a_r b}{(0.62 + 0.19V^{0.5})H} \text{ clo} \tag{1}$$

where $I_{cl}$ is resistance to thermal transfer through clothing measured in clo unit ($0.155\text{m}^2\text{KW}^{-1}$), 33 is skin temperature at optimal comfort and $t_a$ is air temperature both measured in Celsius, $H$ is the rate of dry heat transfer to the surrounding environment ($\text{Wm}^{-2}$), $R_0$ is solar constant (1370 $\text{Wm}^{-2}$), $\alpha$ is solar angle, $p$ is atmospheric transmissivity, $m$ is optical air mass, $C$ is cloud cover in tenths, $x$ is cloud transmission related to optimal air mass, $a_r$ is the proportion of surface area receiving radiation, $b$ is absorptivity of clothing, *and* $V$ is wind speed (cm $\text{s}^{-1}$). Following Yan (2005), the rate of dry heat transfer $H$ is chosen to be 87 W $\text{m}^{-2}$ which is 75% of the metabolic rate (116 W $\text{m}^{-2}$) of the lower limit of light class of work. The solar angle in degrees is calculated as $\alpha = \sin^{-1}(\sin\phi \sin\delta + \cos\phi \cos\delta \cos h)$ where $\phi$ is latitude reading, $\delta$ is solar declination which is set to the declination on the fifteenth of each month as representative of the month, and $h$ is hour angle which is set to 45 degrees. The atmospheric transmissivity $p$, which is depletion of solar radiation by gases, water vapor and dust particles, is set to 87.5% (de Freitas, 1979). The cloud transmission related to optimal air mass $x$ is estimated to be 1.4 (Hay, 1970) and the absorptivity factor $a_r b$ is estimated by the mean value of 0.4. Negative CLO values were set to zero in Yan (2005) but in this study, we chose to retain the negative values to signify heat stress that is more severe than just the requirement of a nude clothing ensemble.

### *Quantile Regression*

After almost three decades of development, quantile regression (as invented by Koenker and Bassett in1978) is gradually emerging as a fundamental tool of applied statistics as more and more commercial software has started to incorporate this methodology into its toolbox. The conventional least-squares regression method provides an estimate of the relationship between the *average* of the dependent variable and the explanatory variable. However, other aspects of the relationship, e.g., variation and skewness of the distribution, are also pertinent and important information. Quantile regression is designed specifically to provide a more complete picture of this relationship. A concise introduction to quantile regression can be found in Koenker and Hallock (2001).

In this study, the nonparametric version of quantile regressions proposed in Koenker and Mizera (2004) was used to estimate the various CLO quantile surfaces because the CLO surface, which is heavily influenced by topographic features in China, is obviously too complex to be reasonably modeled by some parametric functions. We chose to use Koenker and Mizera's (2004) penalized triogram instead of the bivariate quantile smoothing splines of He, Ng and Portnoy (1998) because the prior has the nice property of orthogonal equivariance, which means that the fitted quantile surfaces will not have the tendency to line up along the axes. This is an advantage in our study when the domain of the observations, like the longitude and latitude weather station data we have, do not fall nicely on a regular rectangular grid (Figure 1).

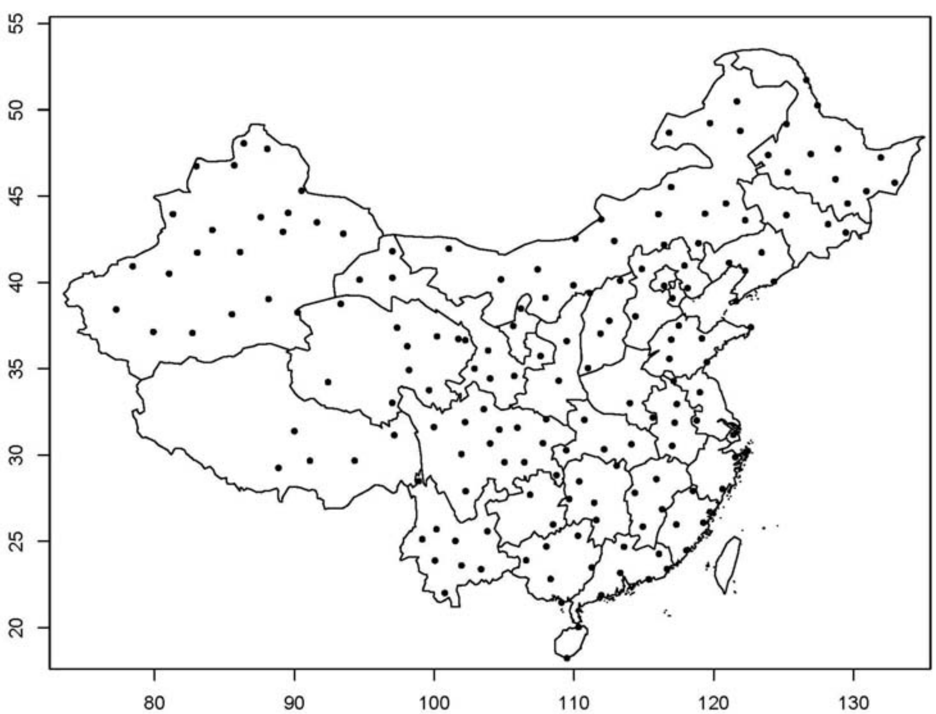


**Figure 1** Map of China with provincial borders and locations of the 172 stations.

The penalized triogram minimizes the following objective function:

$$\sum_{i=1}^{n}\left\{\tau\left[z_i - g\left(x_i, y_i\right)\right]^{+} + \left(1-\tau\right)\left[z_i - g\left(x_i, y_i\right)\right]^{-}\right\} + \lambda J\left(g\right) \tag{2}$$

where $n$ is the total number of observations, $z_i$ is the CLO index, $x_i$ and $y_i$ are the longitude and latitude readings of the $i^{\text{th}}$ observation, $\tau$ which has a value between 0 and 1 determines the desired quantile surface, $\left[r_i\right]^{+}$ and $\left[r_i\right]^{-}$ are the positive and negative residuals $r_i = z_i - g\left(x_i, y_i\right)$ (distances from the actual CLO index to the estimated quantile surface), $J(g)$ measures the roughness of the estimated quantile surface, and $\lambda$ is the smoothing parameter which controls the balance between the fidelity of the estimated quantile surface $g$ to the CLO values measured by the first part of equation (2) and the roughness $J(g)$ of the fitted surface $g$.

Notice that the objective function assigns a weight of $\tau$ to positive residuals and $(1-\tau)$ to negative residuals. When $\tau = 0.5$, the median (0.5-th quantile) regression surface minimizes the objective function which assigns the same weight to both the negative and positive residuals so that half of the CLO values fall above the median regression surface while the other half of them fall below it. Similarly, twenty-five percent of the CLO values will fall below the 1st quartile (0.25-th quantile) regression surface and seventy-five percent above it when $\tau = 0.25$. Hence, by varying the value of $\tau$ between 0 and 1, we can obtain the various CLO quantile regression surfaces.

The smoothing parameter $\lambda$ controls the smoothness of the fitted surface. When $\lambda$ approaches infinity, a huge penalty is exerted on the roughness of the fitted surface and, hence, the quantile regression surface becomes a plane, which is the smoothest among all possible types of surfaces. When $\lambda$ equals 0, no penalty is imposed on the roughness of the quantile regression surface and the surface will attempt to interpolate every CLO value if there is only one CLO index at each station. However, with the repeated CLO measurements at each station in our data set, the quantile surface will attempt to interpolate the $\tau$ –th sample quantile of the CLO values at each station. The choice of the smoothing parameter which determines the degrees of smoothness in any nonparametric smoothing problem is always a delicate issue. However, the decision is made easy in our study. Since there are thousands of CLO measurements (in the neighborhood of 1,400 for a monthly window and 4,500 for a seasonal window) at each station, the asymptotic theory of a nonparametric smoother suggests that the chosen $\lambda$ should approach zero and we choose to compute the interpolating quantile surface with $\lambda$ equals to 0 to reveal useful local features of CLO. In fact, the seasonal average CLO estimates in Yan's (2005) were rather overly smoothed to the extent that many of the local characteristics of the CLO requirements being affected by geographic variations were lost.

*Data analysis*

Data on daily air temperature and wind speed for 172 climate stations in China from 1960 to 1998, obtained from the Chinese Academy of Meteorological Sciences, were used in this study (Figure 1). The daily temperature and wind speed data for these stations from 1999 to 2004 were downloaded from the US National Climatic Data Center (NCDC) (http://www.ncdc.noaa.gov/oa/ncdc.html). Cloud cover was omitted in the computation of the CLO index. This omission had no practical significance; the simulation that we had performed using 1960 to 1998 data revealed that only 3.6% of the observations had resulted in a difference in CLO values of larger than 0.3 between including and not including the cloud coverage data.

Daily CLO values were calculated using equation (1) and the quantile regression estimates were then computed using the algorithms that are available in the **quantreg** and **cobs** package available in ***R*** (a language and environment for statistical computing and graphics that can be freely obtained from http://www.r-project.org via the GNU General Public License.) Spatial distribution of stations was not optimal. There was no station located in the western half of the Tibet Autonomous Region. There was no data on Mongolia either but the isolines that were generated in the various contour plots below showed the convex hull of the weather station and included a large part of Mongolia. That portion of the isolines should be ignored because they were merely an extrapolation of the data information.

## Results and Discussions

*Spatial Variation of Annual Thermal Climates*

Figure 2(a) – 2(c) are the annual quantile regression surfaces of CLO requirements for $\tau$ = 0.1, 0.5, and 0.9, respectively. They are estimated using all CLO values of the 172 stations from 1960 to 2004. Figure 2(d) is the estimated annual average CLO surface computed by interpolating the average CLO values across all the stations over the 45-year period. Both the average CLO surface and the median regression surface ($\tau$ = 0.5) provide measures of central tendency of CLO requirements at the various stations. However, the median regression surface has the additional advantage of not being sensitive to outliers in CLO values. The $0.1^{th}$ regression surface provides the upper limit for the bottom 10% of CLO requirements while the $0.9^{th}$ regression surface is the lower bound of the top 10% of CLO requirements at the various stations.

In general, the CLO requirements gradually increase from the south towards the north with the northeast having the highest CLO values that reflect the influence of latitude. This is particularly prominent in the $0.9^{th}$ quantile regression surface in Figure 2(c) which is primarily determined by the generally higher CLO values in winter. This result is very similar to the finding in Yan's (2005) figure for average CLO requirements in winter. Also similar to Yan's (2005) figure for the average clo requirements pattern in summer, our $0.1^{th}$ regression quantile surface in Figure 2(a), which is strongly affected by lower CLO values in summer, are more meridional in eastern China where heat stress is caused by the warm moist tropical air masses and the summer monsoon. When comparing Figure 2(b) and 2(d), which summarize the center part of the CLO distribution across the stations, we see a very similar pattern that resembles Yan's (2005) figures for spring and for fall. We will address the seasonal variation in more detail in the next section.

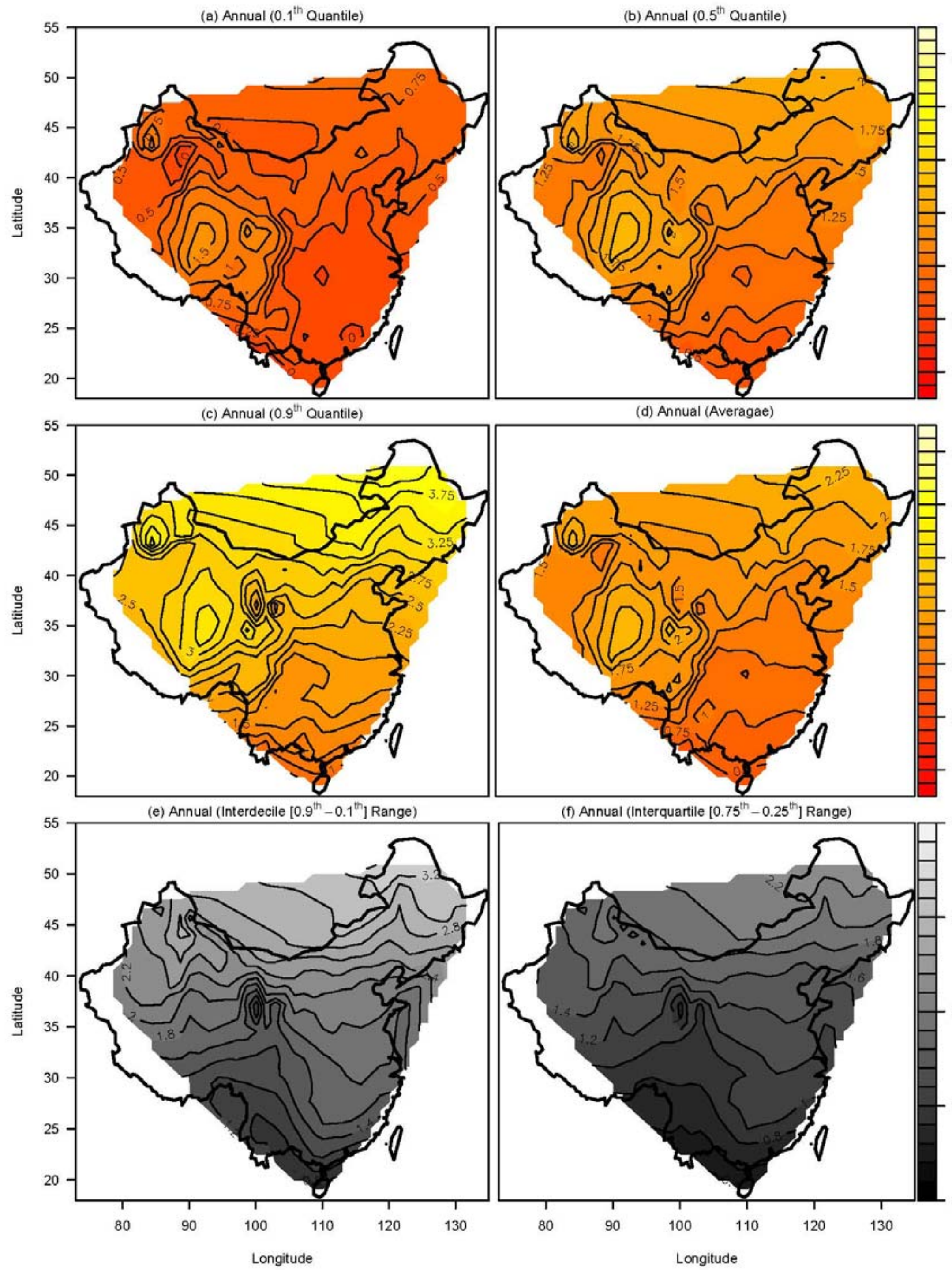


**Figure 2** Panels (a), (b), and (c) present the $0.1^{th}$, $0.5^{th}$ and $0.9^{th}$ quantile regression surfaces, respectively, estimated using all CLO values of the 172 stations from 1960 to 2004 while panel (d) contains the average regression surface. Panels (e) and (f) show the interdecile ($0.9^{th} – 0.1^{th}$ quantile regressions) and interquartile range, respectively.

In the Qinghai-Tibetan Plateau area, altitude contributes to the high CLO requirements even though it is at lower latitude than Xinjiang in the northwest, Inner Mongolia in northern central and Heilongjiang in northeast China. On the other end, the relatively low CLO values in the Sichuan Basin compared to its surrounding areas is the result of the mountains in western Sichuan and Qinghai blocking the northerly cold air which is also prominent in all three quantile regression surfaces and the average CLO surface. There is also a region in the eastern part of the Qinghai province centered at Qinghai with lower CLO values as revealed by the $0.5^{th}$, $0.9^{th}$ quantile regression surfaces and the average CLO surface. The mountain ranges (Qilian Shan and Altun Shan) to the north have moderated the severe cold stress in winter. However, this lower CLO pattern has disappeared in the $0.1^{th}$ quantile regression surface since the combination of high latitude and altitude has ameliorated the severe heat stress in summer.

To investigate the annual variation of the CLO requirements at the various locations, we constructed the interdecile ($0.9^{th} - 0.1^{th}$ quantile) range in Figure 2(e). It reflects the vertical distances in CLO values between the $0.9^{th}$ quantile regression surface in Figure 2(c) and the $0.1^{th}$ quantile regression surface in Figure 2(a) at each location. It shows that the higher the latitude reading, the larger the variation in CLO requirements with the exception of Qinghai that has an interdecile range of 1.2, which is as low as those in the southern part of China. The moderated cold stress in winter due to the mountain range in the north discussed above and the alleviated heat stress in summer caused by high latitude together contribute to the low variation among the middle 80% of the CLO values in the Qinghai area. The interquartile ($0.75^{th} - 0.25^{th}$ quantile) range in Figure 2(f) also shows similar pattern.

*Seasonal Patterns of Thermal Climates*

To study the seasonal variation of thermal climates in China, we divide the data into winter (December, January and February), spring (March, April and May), summer (June, July and August) and fall (September, October and November). Figure 3(a) – 3(d) contain the seasonal quantile regression surfaces of CLO requirements and the average CLO surface in winter. The contour patterns of these figures are very similar to that in Figure 2(c). This is no surprise because the $0.9^{th}$ quantile regression surface in Figure 2(c) is primarily determined by the top 10% of the CLO values in each region so that 10% of the data points lie above the regression surface while 90% of them fall below it. Winter, in general, has the highest CLO requirements in all regions. The less oppressive cold stress located in the Sichuan Basin is very conspicuous in the $0.1^{th}$ quantile regression surface and the average CLO surface but not in the median quantile regression surface. This demonstrates the sensitivity of the average CLO surface to the abnormally low CLO values that occur in 10% of the days in winter in the Basin.

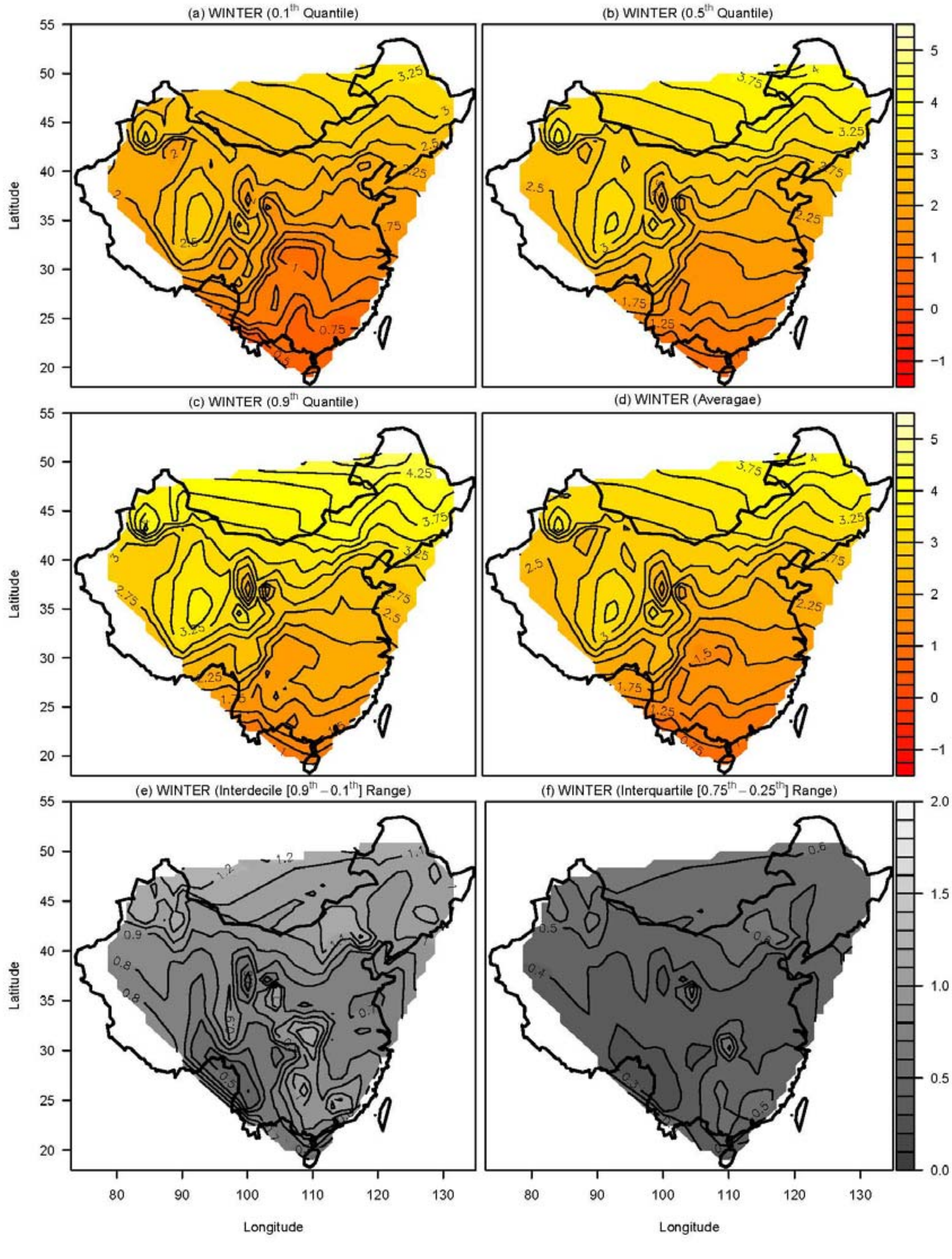


**Figure 3** Panels (a), (b), and (c) present the $0.1^{th}$, $0.5^{th}$ and $0.9^{th}$ quantile regression surfaces, respectively, estimated using CLO values of the 172 stations in winter of 1960 to 2004 while panel (d) contains the average regression surface. Panels (e) and (f) show the interdecile ($0.9^{th} – 0.1^{th}$ quantile regressions) and interquartile range, respectively.

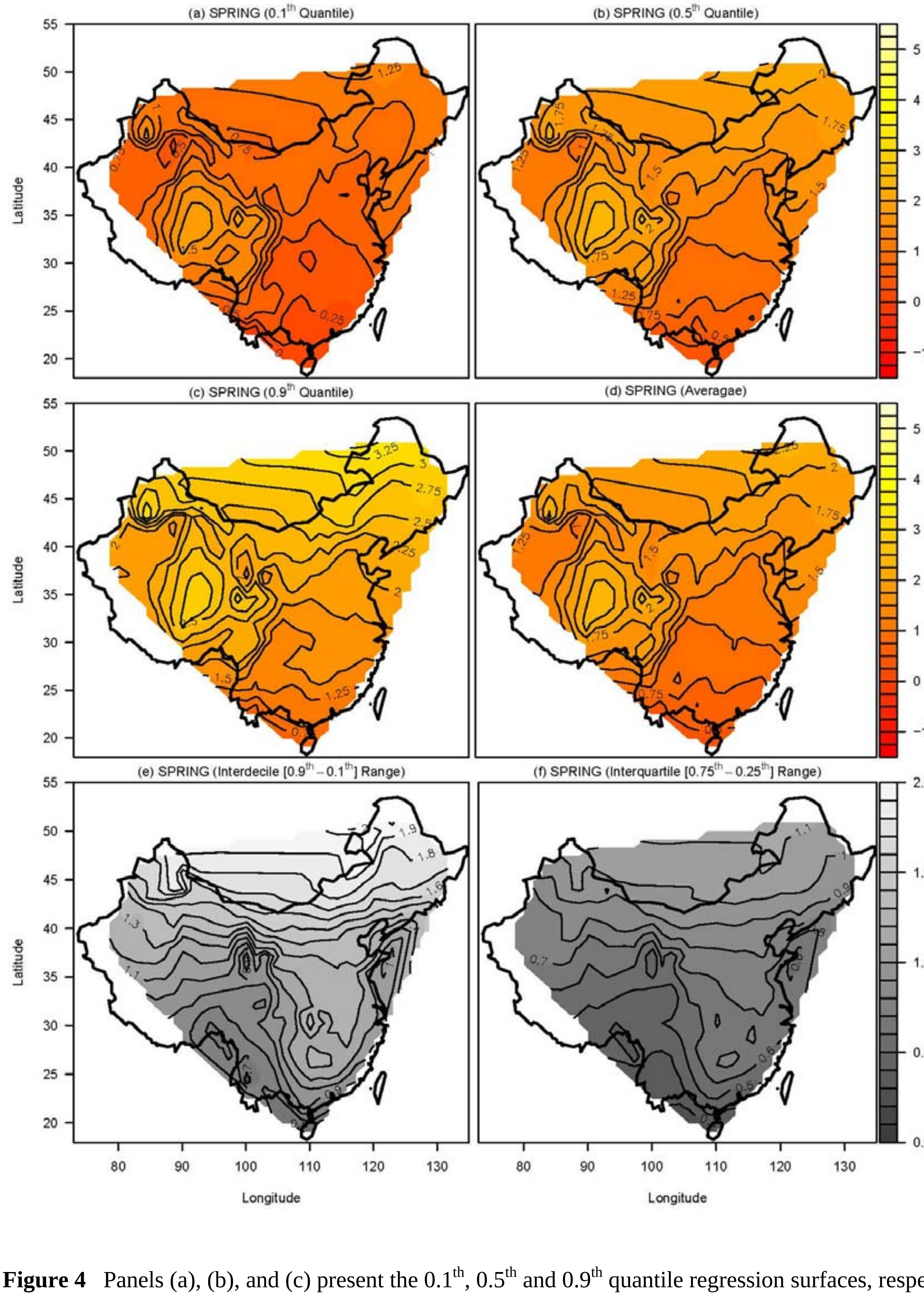


**Figure 4** Panels (a), (b), and (c) present the $0.1^{th}$, $0.5^{th}$ and $0.9^{th}$ quantile regression surfaces, respectively, estimated using CLO values of the 172 stations in spring of 1960 to 2004 while panel (d) contains the average regression surface. Panels (e) and (f) show the interdecile ($0.9^{th} – 0.1^{th}$ quantile regressions) and interquartile range, respectively.

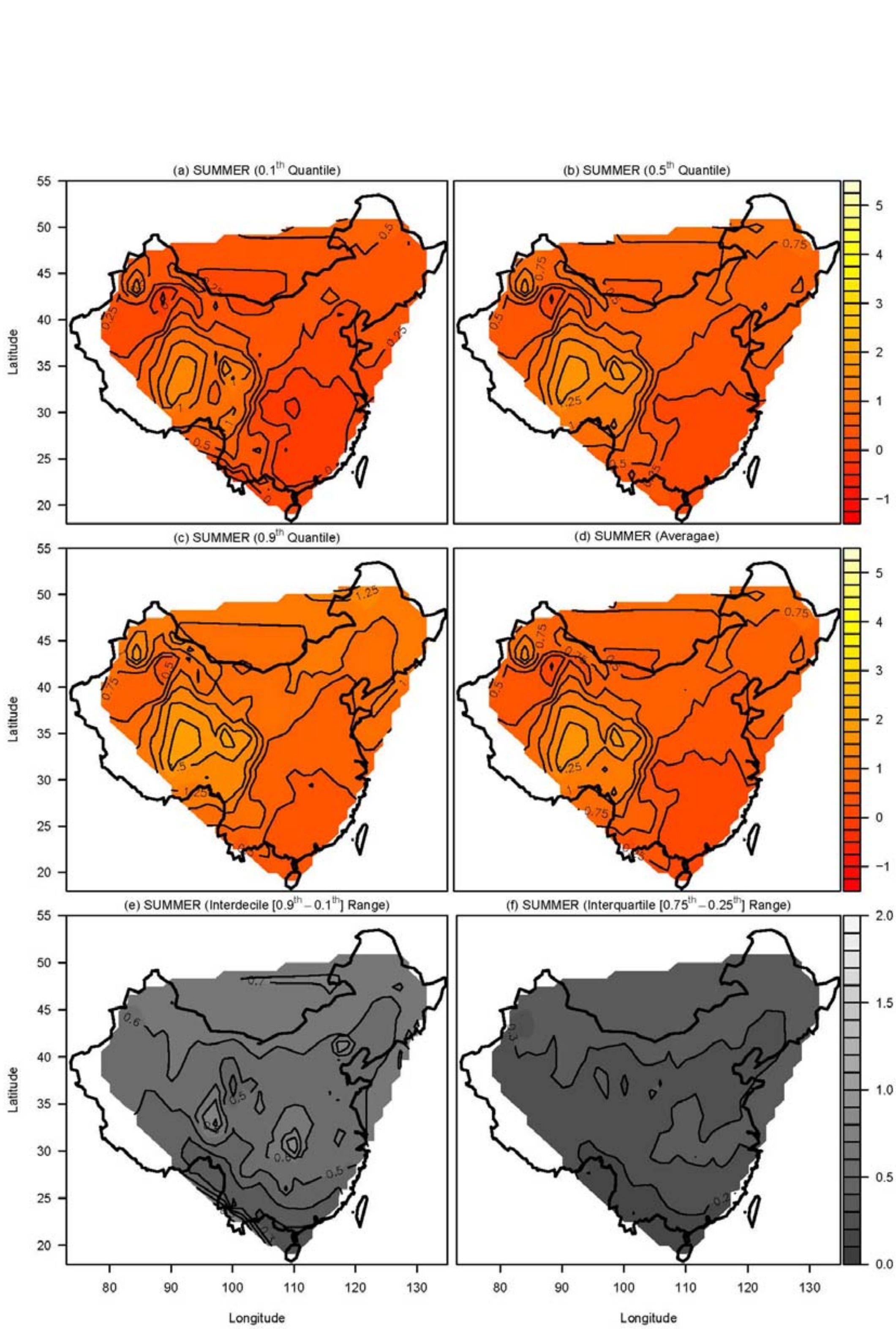


**Figure 5** Panels (a), (b), and (c) present the $0.1^{th}$, $0.5^{th}$ and $0.9^{th}$ quantile regression surfaces, respectively, estimated using CLO values of the 172 stations in summer of 1960 to 2004 while panel (d) contains the average regression surface. Panels (e) and (f) show the interdecile ($0.9^{th} – 0.1^{th}$ quantile regressions) and interquartile range, respectively.

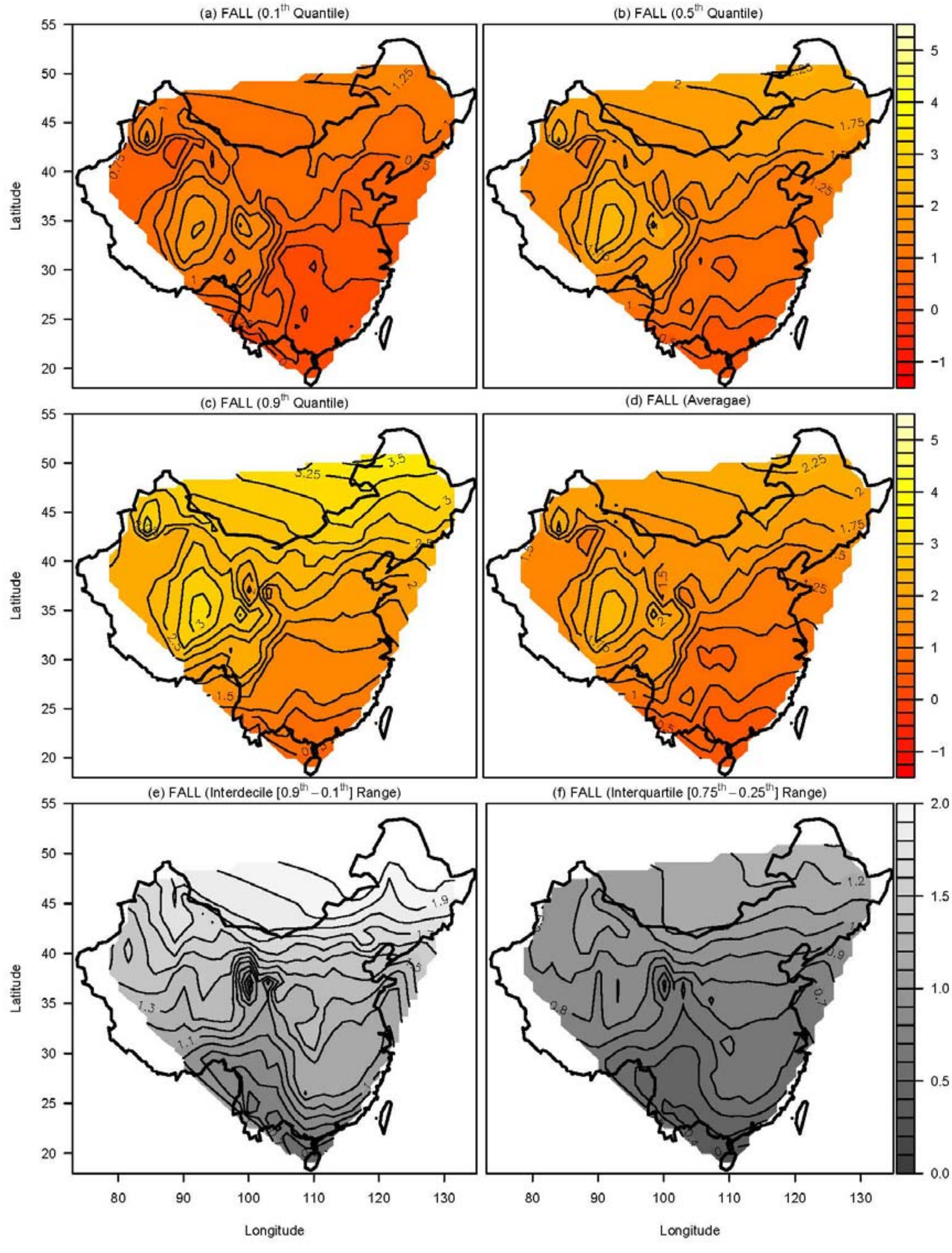


**Figure 6** Panels (a), (b), and (c) present the $0.1^{th}$, $0.5^{th}$ and $0.9^{th}$ quantile regression surfaces, respectively, estimated using CLO values of the 172 stations in fall of 1960 to 2004 while panel (d) contains the average regression surface. Panels (e) and (f) show the interdecile ($0.9^{th} - 0.1^{th}$ quantile regressions) and interquartile range, respectively.

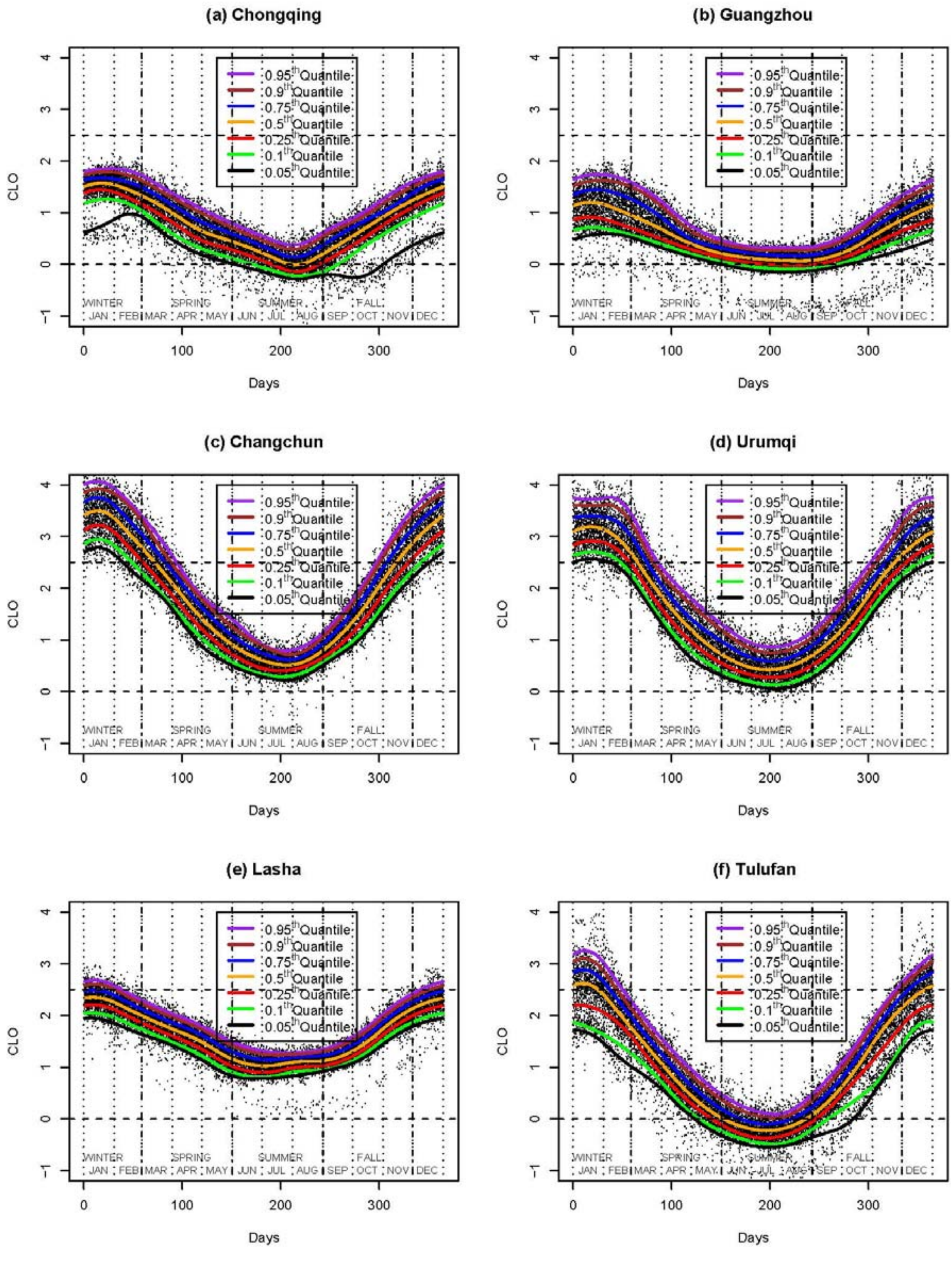


**Figure 7** From the bottom to the top in each panel are the 0.05th, 0.1th, 0.25th, 0.5th, 0.75th, 0.9th, 0.95th quantile regression fits of CLO requirements on the days of the year for 6 different cities.

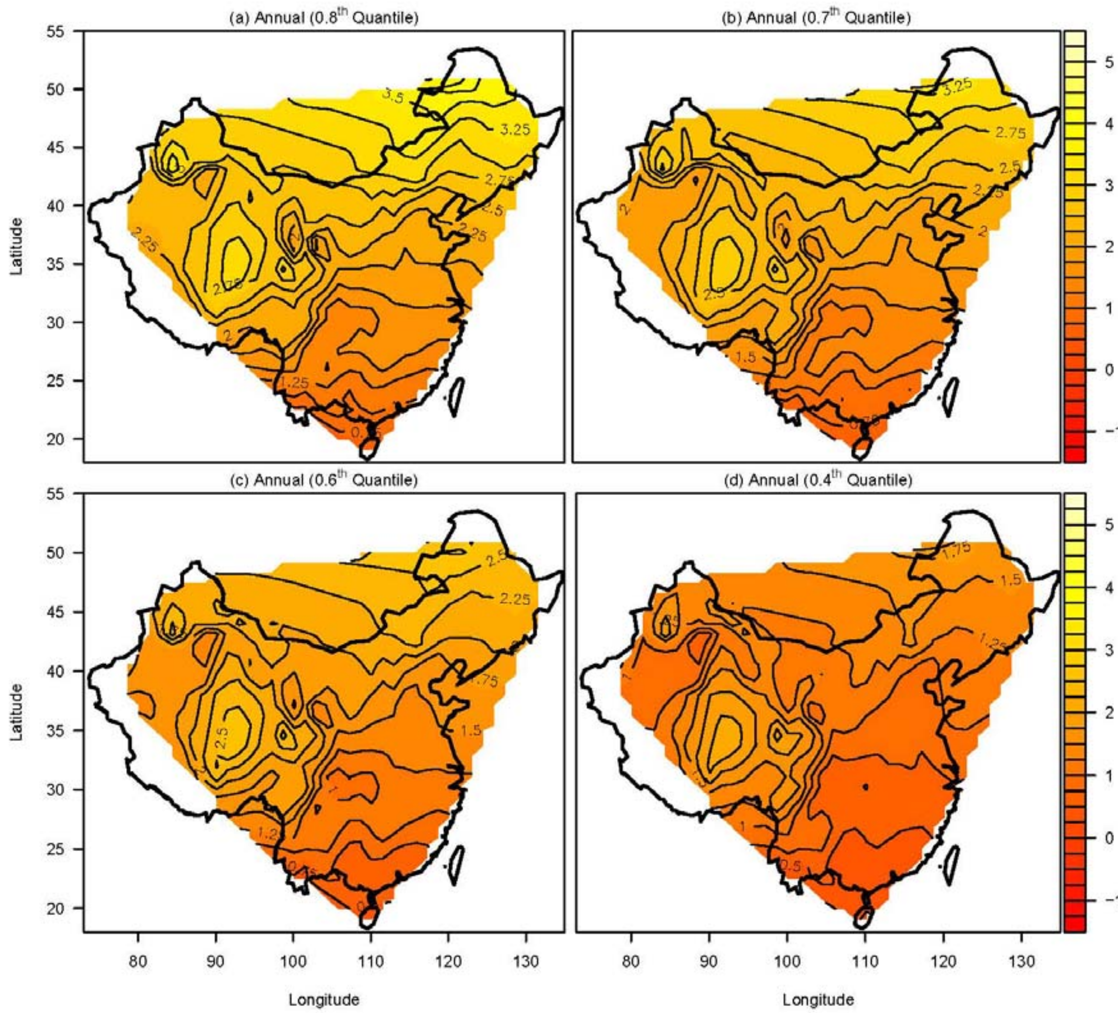


**Figure 8** The $0.8^{th}$, $0.7^{th}$, $0.6^{th}$, and $0.4^{th}$ quantile regression surfaces estimated using all CLO values of the 172 stations from 1960 to 2004.

To investigate the variation of the CLO requirements in winter, we constructed the interdecile ($0.9^{th} - 0.1^{th}$ quantile) range in Figure 3(e). Even though the Sichuan Basin has less oppressive cold stress in winter as compared to its surrounding region in the east and west, it does have one of the highest CLO variations between the lowest and highest 10% of the CLO values. Other regions of high variation in CLO requirements above 1.0 are the northern sector of the Guangxi autonomous region, the central part of Guangdong province around Guangzhou, the central part of Inner Mongolia, northern part of China in Heilongjiang and Jilin provinces, and the northwest region of Xinjiang. These high variations of CLO requirements are important information for tourists, retirees and policy makers when planning their travel, retirement migration or resource allocation decisions so that they will not be caught by any "surprises". This information will not be revealed by just investigating average CLO contour plots. In general, there is not much variation in CLO requirements among the middle 80% of the data in winter.

The general isoline patterns for spring and fall are similar to those of winter but with lower CLO requirements. However, the interdecile range contour map for spring presented in Figure 4(e) reveals two regions of anomalously high interdecile range in Hunan, one is centered around Zhangjiajie City (with an interdecile range of 1.3 CLO) in the northwest part of the province and the other around Yongzhou City (with an interdecile range of 1.2 CLO) in the south. This high interdecile range in Hunan can be attributed to its inland location in central south China and local topography. Hunan is surrounded by low mountains and hills, with Wuling Mountain to the northwest, Xuefeng Mountain to the west, Nanling to the south and Luoxiao Mountain to the east. Thus the province is influenced by the impact of continentality and receives less onshore winds, and results in higher temperatures.

Summer sees a very different contour pattern with more meridional isoline alignment similar to that being observed in Yan's (2005) study. Even high latitude in the northeast does not provide much relief on the severe heat stress while the high elevation in the Qinghai-Tibetan Plateau area does provide moderate alleviation, which results in higher CLO requirements of 1.25 half of the time in summer (Figure 5(b)) and also on average (Figure 5(d)). The small cell of anomalously severe heat stress in the intramontane basins in Xinjiang is the effect of continentality, which has the characteristic of receiving large amount of radiation heat and results in very high temperature in the summer. The interdecile range in Figure 5(e) shows that there is not much variation between the $0.1^{th}$ and $0.9^{th}$ quantile surfaces across the whole country. In general, the interdecile range for spring (Figure 4(e)) and fall (Figure 6(e)) is higher than that in winter (Figure 3(e)) and summer (Figure 5(e)) and it increases with latitude.

To gain further insight into the relatively high interdecile range in the Sichuan Basin in winter, we constructed in Figure 7(a) the various nonparametric univariate quantile regression lines (Ng and Maechler (2007)) of the CLO values on the days of the year for Chongqing, which is located at the center of the Sichuan Basin. It provides another view of the variability of CLO requirements that focuses on variability over every day of a year rather than the spatial variation over a yearly or seasonal window as presented in all the quantile regression surfaces so far. From the figure, Chongqing does have high variability in CLO values in both winter and fall but lower variation in spring and summer. In addition, the CLO values are skewed towards the lower end in winter and fall while staying pretty symmetric in spring and summer. The cluster of outliers in the lower tail of the CLO distribution in winter pulls the $0.1^{th}$ quantile regression surface down and, hence, explains why it shows up as one of the regions with high interdecile range in winter even though its general CLO requirements in winter are not as high as those in the Qinghai-Tibetan Plateau area, Xinjiang, Inner Mongolia or the north-east provinces.

Figure 7(b) contains the various univariate quantile regression lines for Guangzhou. Similar to Chongqing, Guangzhou also experiences high variability in CLO requirements in winter and lower variation in summer, and there is no single day with CLO value that rises above 2.5. Like Chongqing, even though Guangzhou does not experience severe cold stress in winter, it does have one of the highest spreads in the middle 80% of the CLO requirements. Moreover, its CLO distribution is a lot more symmetric compared to that in Chongqing. Again, this variation of CLO requirements across time is revealed only with the help of quantile regressions, albeit a univariate quantile regression lines instead of the bivariate regression quantile surfaces. This additional information provides better insights into the influence of both geographic factors and the annual cycle of large scale atmospheric circulation on thermal climates, and the choice of appropriate clothing ensembles for maintaining comfort.

*Patterns of Severe Thermal Stress*

Yan (2005) constructed contour plots for the average percent of time with severe cold stress (CLO > 2.5) and severe heat stress (CLO = 0) to study patterns of severe thermal stress. The various regression quantile surfaces are natural candidates for studying severe thermal stress. From the $0.9^{th}$ quantile regression surface in Figure 2(c), for example, it is noted that the whole region north of about $37^{o}$N and almost all of the Qinghai-Tibetan Plateau area experience severe cold stress with CLO > 2.5 for 10% of the time in a year. At $40^{o}$N, $43^{o}$N and $47^{o}$N, and a consecutively smaller portion of the Plateau suffers from severe cold stress for at least 20%, 30%, and 40% of time according to the $0.8^{th}$, $0.7^{th}$ and $0.6^{th}$ quantile regression surface in Figure 8(a), 8(b) and 8(c), respectively. According to the $0.5^{th}$ quantile regression surface in Figure 2(b), none of China suffers from severe cold stress for more than half of the time in a year. On the other hand, severe heat stress is observed 10% of a year at Guangzhou in the southeast, Zhangjiajie east of the Sichuan Basin and Tulufan City in the intramontane basins according to Figure 2(a).

The univariate quantile regression plots for the various cities also contain information on the percentage of time a city undergoes severe cold stress or heat stress for the various days of the year. For example, Chongqing does not have any day with a CLO higher than 2.5 from Figure 7(a). Looking at where the $0.1^{th}$ quantile regression line crosses the 2.5 CLO threshold in Figure 7(c), we can see that Changchun in northeast China has at least 90% of the time (from the last two-third of December to the middle of February) in winter under severe cold stress. Likewise, Urumqi also experiences severe cold stress for at least 90% of the time from mid December to mid February (Figure 7(d)). Even though at high altitude of 3649 meters, Lasha in the Tibeten-Qinghai Plateau experiences severe cold stress for no more than 10% of the time from the second half of December through January according to where the $0.9^{th}$ quantile regression line crosses the 2.5 CLO boundary in Figure 7(e). Investigating Figure 7(f), we see that Tulufan experiences severe heat stress for at least half of the time in June, July and most of August according to where the median regression line intersects the 0 CLO line. This is the result of continentality. As observed above, Guangzhou goes through severe heat stress for at least 10% of the time from early summer to as late as early fall according to Figure 7(b). It has higher CLO variation in the winter, early spring and late fall, and much lower variation in summer.

**Conclusion**

The application of nonparametric version of quantile regressions to evaluate the human thermal climates in China using the CLO index has facilitated better insights into both the spatial characteristics and information on the spread and variations of the clothing requirements. Hence a more complete picture of the human bioclimates of the various regions in China is produced. Results of the present study are consistent with Yan's (2005) findings. Furthermore, the quantile regression surface plots reveal more local characteristics of CLO distribution patterns affected by topographic variations. The interdecile range surface plots expose details in spatial CLO variability that cannot be uncovered by examining average CLO values.

Quantile regression is most commonly used in economics and financial mathematics, and recently it is being used in ecology (Koenker and Schorfheide, 1994), meteorology (Bremnes, 2004) and climatic changes (Chamaillé-Jammes, 2007). It has the ability to detect variation and skewness of a distribution. To our knowledge, this is the first utilization of nonparametric quantile regression in human biometeorology. Technically, quantile regression is fairly easy to apply, as programs are available free. We suggest that quantile regression should be considered more often as a tool to examine various climatic patterns.

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