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E-mail: kfang@fjnu.edu.cn**Keywords:** tree ring, boosted regression trees, nonlinearity, climate change, drought, Tibetan PlateauSupplementary material for this article is available [online](#)**Abstract**

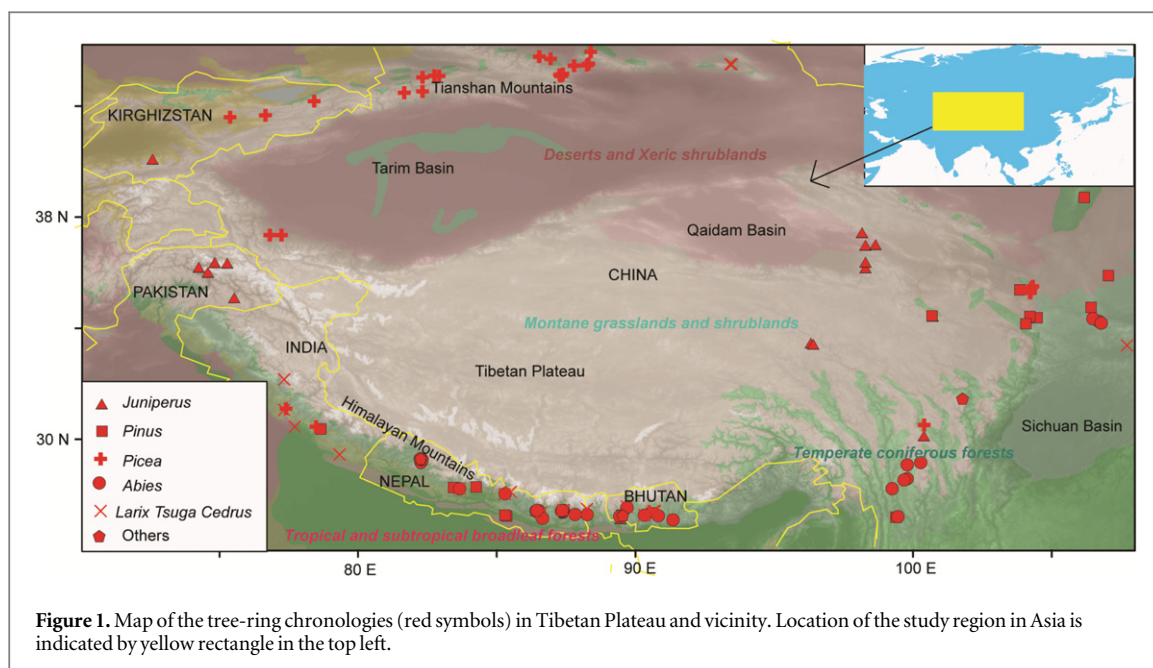
Investigations of climate–growth interactions can shed light on the response of forest growth to climate change and the dendroclimatic reconstructions. However, most existing studies in the climatically important Tibetan Plateau (TP) and surrounding regions focus on linear growth responses to environmental variation. Herein we investigated both the linear and the nonlinear climate–growth interactions for 152 tree-ring chronologies in the TP and vicinity. We introduced the boosted regression tree (BRT) technique to study the nonlinear climate–growth relationships by pooling several sites with similar climate–growth relationships to mitigate potential biases due to the shortness of the instrumental records. Across most of the TP and surroundings, tree growth is stressed by drought. The warming induced drought has been evidenced by the strong interactions between temperature and precipitation in the BRT analyses. The drought stress on forest growth is particularly conspicuous for a hydrological year over much of the Northern TP and surroundings. The BRT analyses indicate the compensation effect of moisture prior to the growing season for the moisture deficit in the early growing season in May to July, when most of the ring-width formation occurs.

1. Introduction

The heating and blocking of the world's highest Tibetan Plateau (TP) has a crucial role in modulating the Asian climate, such as the Asian summer monsoon (Broccoli and Manabe 1992, Wu *et al* 2007). Forests in TP and surroundings are of particular importance in the context of the on-going climate change as the vegetation can rapidly modulate the heating effect of TP by modulating its albedo (Betts 2000) and evapotranspiration (Swann *et al* 2010). Additionally, forest growth in TP can strongly influence the agro-economic livelihood of the regional populations. This highlights the significances of investigations on the interactions between climate and forest growth, including possible nonlinear responses, which can

shed light on the impact of future climate change on the vegetation. The modifications in forest productivity and the impacts of climate are imprinted in the annual growth of tree rings. Thus, tree-ring based climate–growth relationships (Fritts 1976, Cook and Pederson 2011) can shed light on the response of forest growth to climate change (Foley *et al* 2003, Andreu-Hayles *et al* 2011) and provide the basis for tree-ring based reconstructions (Fritts 1976, Jones *et al* 2009, Frank *et al* 2010).

Although several investigations have been conducted on the tree-ring based climate–growth relationships in the TP and surrounding areas (Yuan *et al* 2003, Zhang *et al* 2003, Sheppard *et al* 2004, Shao *et al* 2005, Liu *et al* 2006, Esper *et al* 2007, Li *et al* 2008, Liang *et al* 2008, Cook *et al* 2010, Gou *et al* 2013, Yang



et al 2014), these studies were generally limited to a moderate number of sites. Thus a comprehensive investigation of the climate–growth relationships in the region is still needed. In addition, the previous studies generally identify the climate determinants for tree growth by checking the climate–growth relationships in a few months or seasons. This study attempts to investigate the climate determinants by checking the climate–growth relationships for all possible combinations of the monthly climate variables of precipitation and temperature from the previous to current growing seasons, i.e. 666 climate variables. We found tree rings in much of the TP and surroundings showing the highest correlations with moisture of a hydrological year (detailed below). This indicates a nonlinearity in climate–growth relationships caused by the interactions between different climate variables. For example, abundant moisture in the early growing season can supply moisture during the late growing season to facilitate tree growth even when the moisture level is low late in the season (Fang *et al* 2012b). Thus, our study paid special attention to the nonlinearity of the climate–growth relationships for tree rings in responses to moisture of a hydrological year, which is distinguished from previous studies.

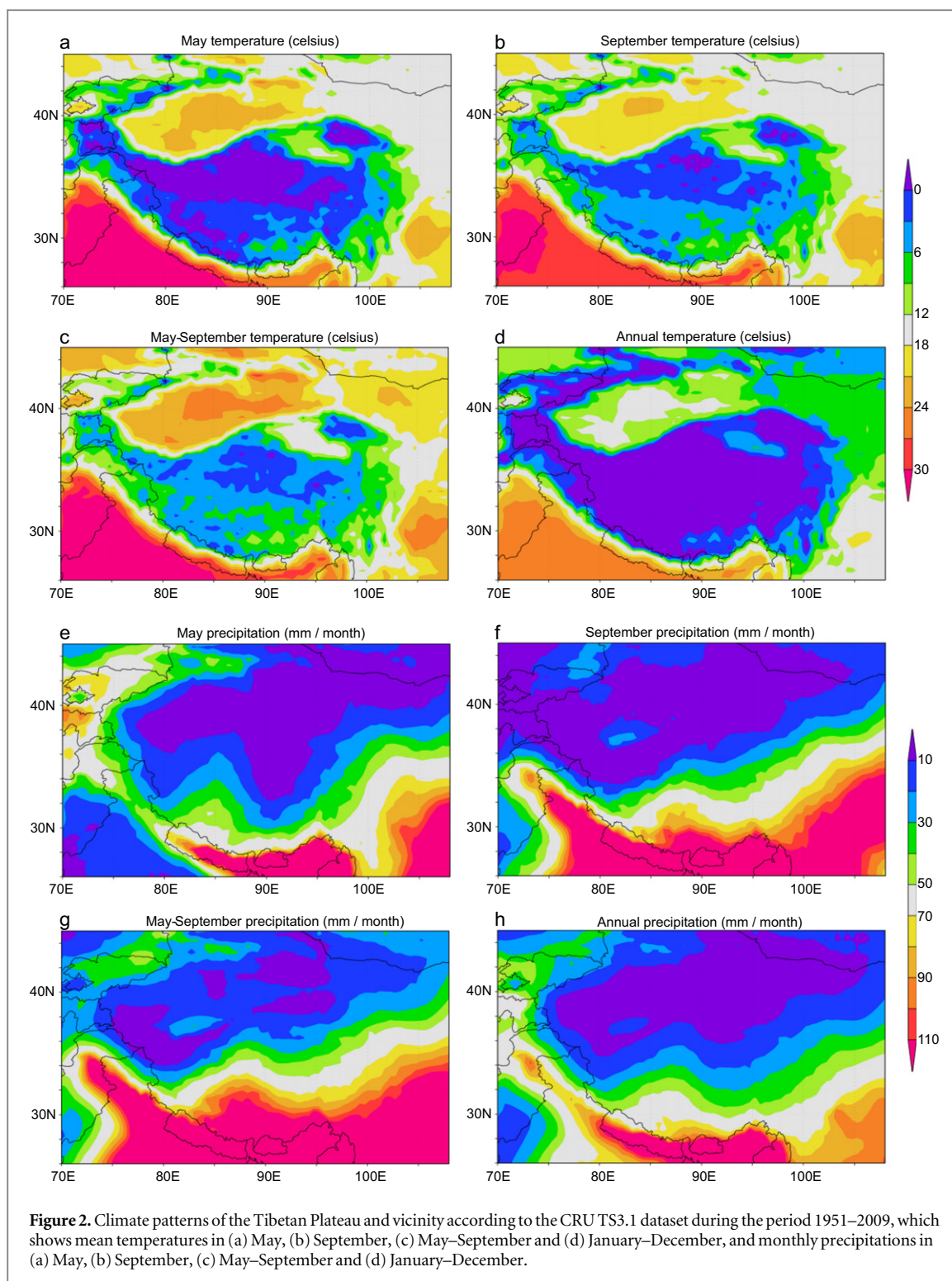
The nonlinearity in climate–growth relationships in dendroclimatology have been investigated using machine learning (ML) methods, such as the artificial neural network (ANN) analyses (Woodhouse 1999, Zhang *et al* 2000, Moffat *et al* 2010, Fang *et al* 2012b). These ML methods are black-box methods and are difficult to statistically assess the relative contribution of each variable. The boosted regression trees (BRTs) technique, a modern ML method, is an advanced regression method in which the simple regression trees are fitted in a forward, stage-wise regression model (boosting) (Friedman 2001, Elith *et al* 2008). In

BRT, the regression trees are built via recursive binary splits and then the boosting adds a new tree to each step to fit the regression residuals from earlier trees and minimize the modeling deviance (Hastie *et al* 2001). This novel non-parametric ensemble method combines the advantages of both conventional statistical and ML methods and can interpretably explore nonlinear climate–growth relationships, the interactions between climate variables and the relative contribution of each variables (Elith *et al* 2008, Leathwick *et al* 2008). The BRT method has been widely used to detect nonlinearity in ecological systems (Salonen *et al* 2012, Zhao *et al* 2012). However, to the best of our knowledge, this technique has not been applied to dendroclimatic studies. The focuses of this study are to (1) find the key climate determinant of tree growth in TP and the surrounding regions, (2) explore the nonlinearity in climate–growth relationships for tree rings showing most conspicuous responses to moisture of a hydrological year, and (3) evaluate the efficiency of the BRT technique in dendroclimatic studies.

2. Data and methods

2.1. Tree-ring and climate data

The TP covers an area of 2 500 000 km² in central and Eastern Asia with an average elevation of more than 4500 m. The elevations increase sharply from the Southern rim of the TP to the Himalaya Mountains and the interior of the TP (figure 1). Most of the TP is characterized by a highland continental climate with a long, dry winter, a cool, wet summer and a large diurnal range of temperatures (figure 2). The growing season starts in May along the Southern rim of the TP, across most of the Eastern TP, and also the



neighboring regions East and North of the TP. The boundary between annual mean temperatures that are above and below zero mirrors the boundary of the TP (figure 2). It is relatively wet over the Southern and Eastern rims of the TP and dry over the Northern and Western TP and neighboring regions. Spring precipitation makes up a larger portion of the annual precipitation in the Northwestern TP (more than 1/4) than in the Southeastern TP (less than 1/5) (figure 2). The low-lying regions in Southeastern TP are

dominated by tropical and subtropical broadleaf forests. Temperate broadleaf and mixed forests are found on the Southern slope of the Himalaya Mountains. Coniferous forests are seen in Eastern part of the TP, particularly the river valleys, and the surrounding mountain ranges (e.g., the Tianshan Mountains) (figure 1).

We compiled a network of 152 tree-ring chronologies in the TP and the surrounding regions from the International Tree Ring Data Bank (ITRDB; <http://>

www.ngdc.noaa.gov/paleo/ftp-treering.html), the Chinese Tree Ring Data Center (CTRDC; <http://ctrdb.ibcas.ac.cn/index.asp>) and additional sources (figure 1, and table S1 in the supplementary data, available at stacks.iop.org/ERL/10/034010/mmedia). Among them, 55 chronologies are from China to the Eastern and Northern TP and most of the remainders are from Southern Himalaya. The mean length of the tree-ring chronologies is 455 years. Most of the tree-ring chronologies span from 300 to 400 year (figure S1). The majority of the tree-ring chronologies is from the coniferous species such as *Picea* (46 chronologies) and *Juniperus* (32). Most of the tree-ring sites are located along the Southern and Eastern rims of the TP, where sufficient heat and moisture allow old-growth forests to grow (figure 1 and table S1). A limited number of tree-ring samples are available from the cold and dry interior TP. Only few tree ring samples were taken from the humid and hot regions, such as the low-lying areas of the Southeastern rim of the Himalayan Mountains.

Only raw tree-ring measurements were available at several sites, such as those in the ITRDB; these were treated by fitting an age-related growth curve with a cubic smoothing spline with a 50% cutoff at approximately 67% of the mean segment length to remove the growth trends. The tree-ring chronologies were indexed as ratios between raw measurements and the fitted growth values, which were averaged to produce a chronology using a robust mean methodology with the program ARSTAN (Cook 1985). The precipitation and temperature data were taken from the $0.5^\circ \times 0.5^\circ$ gridded CRU TS3.1 dataset, which covers the period from 1901 to 2009 (Mitchell and Jones 2005). We only used precipitation and temperature data since 1950, which is when the most of instrumental records became available (Cook *et al* 2010).

2.2. Correlation and response analyses

Linear climate–growth relationships for TP and surroundings can be detected using correlation and response functions. The multi-collinearity amongst monthly climatic parameters was reduced by extracting their principal components (PCs) in the response function analysis (Fritts 1976). The eigenvectors with relatively low values calculated from the monthly climate variables are excluded for the response analyses. The relationships between tree rings and the PCs of the monthly variables were back transformed to relationships with the monthly climate variables, i.e. the coefficient of response function analyses. The response function analysis was performed using the program DendroClim2002 (Biondi and Waikul 2004). This program evaluates the significance of the correlation and response functions using a bootstrap procedure. Because climate of both the previous and current years can influence tree growth, we used the precipitation and temperature from the start of previous

growing season (the previous May) to the end of the current growing season (the current October). The monthly correlation values were subjected to hierarchical clustering analysis (Ward 1963) to identify groupings of climate–growth relationships. For the grouping analysis, the variables for the grouping refer to individual tree-ring sites and the observations are the monthly correlation values.

In addition, we also calculated correlations between tree rings and all combinations of monthly variables from previous May to current October (666 variables) to identify the key climate determinant for regional tree growth. We paid special attention to the tree rings with strongest responses to the moisture of a hydrological year if the highest climate–growth correlation found for a period of 11, 12 or 13 months. This is because a hydrological year may not exactly start at the beginning of a month and thus may include moisture conditions from adjacent months. Seven sites showing the second highest correlations (less lower than the highest correlation for 0.05) with the moisture of a hydrological year were also considered for these analyses.

2.3. BRTs technique

We applied the BRT method to investigate the nonlinearities only for those sites that have the highest correlations with the moisture of a hydrological year as tree rings in such sites tend to show strong nonlinearity in climate–growth relationships due to the interactions among climate variables. Although the responses of tree growth to moisture of a hydrological year are observed over much of TP and the surroundings, this study only showed BRT analyses for the marginal areas of Northeastern TP, where the drought stress of a hydrological year is most conspicuous (detailed below). The application to dendroclimatology is composed of algorithms for the regression trees representing the climate–growth relationships and the boosting that adaptively combines the simple regression trees to improve the predictive performance. The BRT analyses were implemented in R version 2.15.2 (Team 2008) using the GBM (DISMO) package 1.6-3.1 (Elith *et al* 2008, Ridgeway 2010). The number of trees (nt) is determined by iteratively increasing the number until a minimum predictive deviance is reached (herein approximately 8000). The optimized parameters were determined using the ten-fold cross-validation method, which tested the model on the withheld portion of the data using the Gaussian response function (Elith *et al* 2008, Ridgeway 2010). To increase the model accuracy, randomness is included using a bagging fraction of 0.5. The maximum level of interaction is determined by the tree complexity (tc), with higher values indicating a higher maximum limit of interactions, which is set to 5 herein. The learning rate (lr), which determines the contribution of each tree to the model, is set to 0.005.

The relative influence of the climate variables on tree-growth in the BRT is averaged from all the trees based on the numbers of binary splitting and squared improvements to the model of each splitting (Friedman 2001). The marginal effects of the individual climate variables are determined using partial dependence functions by setting the average effects of the other variable. However, these partial responses can be biased when strong interactions between climate variables exist (Friedman 2001). The interaction between any possible pair of climate variables is quantified by forming predictions of the predictors at fixed intervals within their ranges with the other predictors at their respective means (Elith *et al* 2008).

One major difficulty for this application of the BRT method in dendroclimatic analysis is the short (a few decades) overlap period between tree rings and climate data. The size of the samples has the strongest influence on the predictive performance for the BRT analyses (Elith *et al* 2008). We attempted to mitigate the potential bias due to the brevity of the samples by performing the BRT analysis on a dataset pooled from different sites. However, as spatial autocorrelation between the tree-ring chronologies can occur for neighboring sites, we only select tree rings from the sites with similar climate–growth relationships but relatively different growth variations from remote areas. For the marginal areas of Northeastern TP, we divided the tree-ring chronologies into three groups based upon their proximity to the three provincial capital cities, which are relatively far away from each other. These three regional datasets have low spatial autocorrelation and provide a total sample size of 194 years. The tree-ring indices of the three regions are again normalized by dividing its mean to generate the dimensionless indices with the mean of 1. We additionally conducted the BRT analyses for individual dataset to examine whether the pooled dataset can reflect the key features of each dataset.

On the other hand, controlling the number of predictors can simplify the BRT model and improve the predictive performance (Elith *et al* 2008), particularly when the sample size is small. As revealed in the previous monitoring studies in marginal areas of Northeastern TP (Gou *et al* 2013), the ring-width formation generally occurs in the early growing season from May to July and the cell wall thickening occurs in the late growing season from August to October. We thus set the early growing season for ring-width formation from May to July and the late and non-growing seasons with limited ring-width formation from the previous August to the current April. Accordingly, our study uses six predictors to model tree growth: the temperature and precipitation of the previous early growing season (previous May to July), the late and non-growing seasons (previous August to current April) and the current early growing season (current May to July).

3. Results

3.1. Linear climate–growth relationships

In Northeastern TP, significantly negative correlations and responses are found between tree growth and temperatures of the previous May and the current June and August. Positive correlations are found between tree growth and precipitation in the current spring (May–June). This indicates a drought-stressed pattern in the previous and current growing seasons in Northeastern TP (figure 3 and table 1), which is also observed over its marginal areas. Similar drought-stressed growth patterns are observed in the Tianshan Mountain and Southwestern TP (figure 3 and table 1), except for that the negative relationships with temperature in the non-growing season are less significant. In the Southeastern TP, we observed positive correlations between tree growth and temperatures in the previous and current growing seasons. In Northern India, negative correlations with temperature and positive correlations with precipitation are only found during the current growing season. The climate–growth responses in Nepal and Bhutan did not have consistent patterns. We therefore plotted the individual climate–growth relations for each site instead of calculating the regional mean climate–growth relationships (figure S2). Most of the sites in Nepal and Bhutan have the general negative correlation with precipitation.

We found tree rings from 48 sites showing highest correlations with the moisture of a hydrological year. Among these chronologies, 46 chronologies are located in the cold and arid regions of the Northeastern TP (7 sites), the marginal areas of Northeastern TP (11), the Tianshan Mountains (10) and the Southwestern TP (18) (figure 4 and table S2). The strongest responses for hydrological years were typically observed for seasons starting in previous August (table S2).

3.2. Nonlinear climate–growth relationships

In the BRT analyses, we found that only the chronologies on the marginal areas of Northeastern TP have the highest responses to the moisture of a hydrological year. However, 37 tree-ring chronologies from other regions showing highest linear correlations with moisture of a hydrological year only have moderately high nonlinear correlations. We thus only apply the BRT analyses for tree rings on the marginal areas of Northeastern TP, where the responses to moisture of a hydrological years are observed in both the linear and nonlinear analyses. Partitioning the precipitation influences on growth into late and non-growing seasons (previous August–current April), early growing season (current May–July), and previous early growing season (previous May–July) revealed the strongest responses from the late and non-growing seasons (39.9% of the variance) and current early growing season (38.3%) (figure 5). The fitted growth

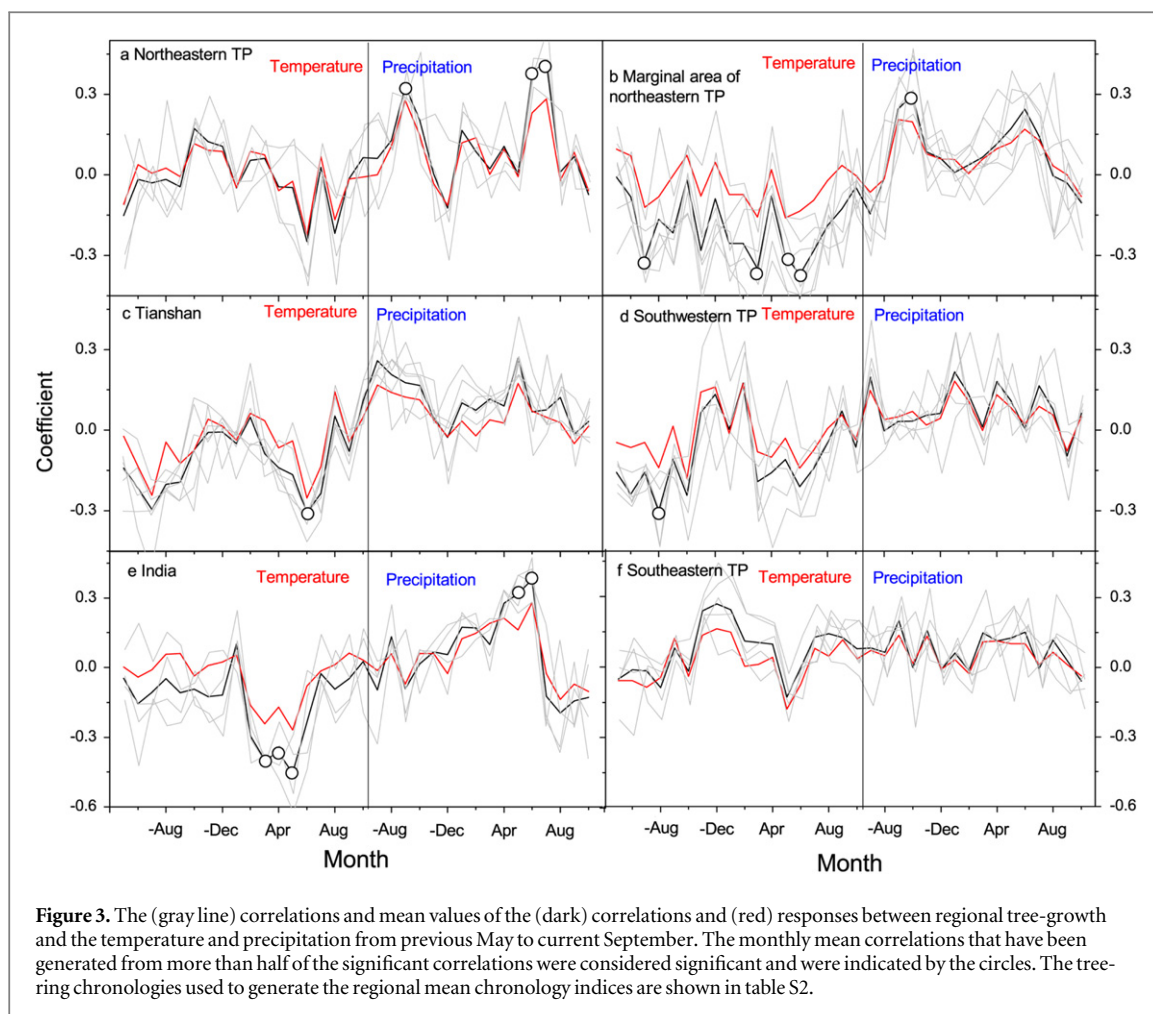
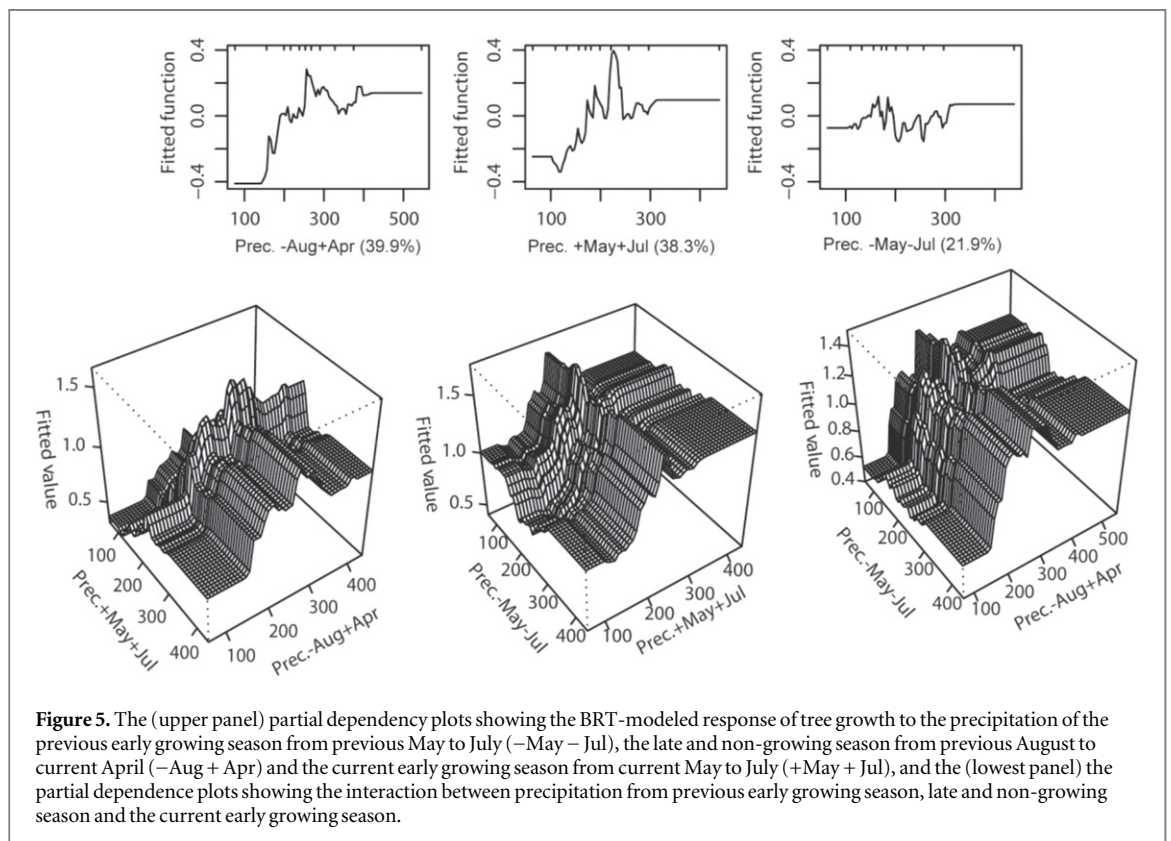
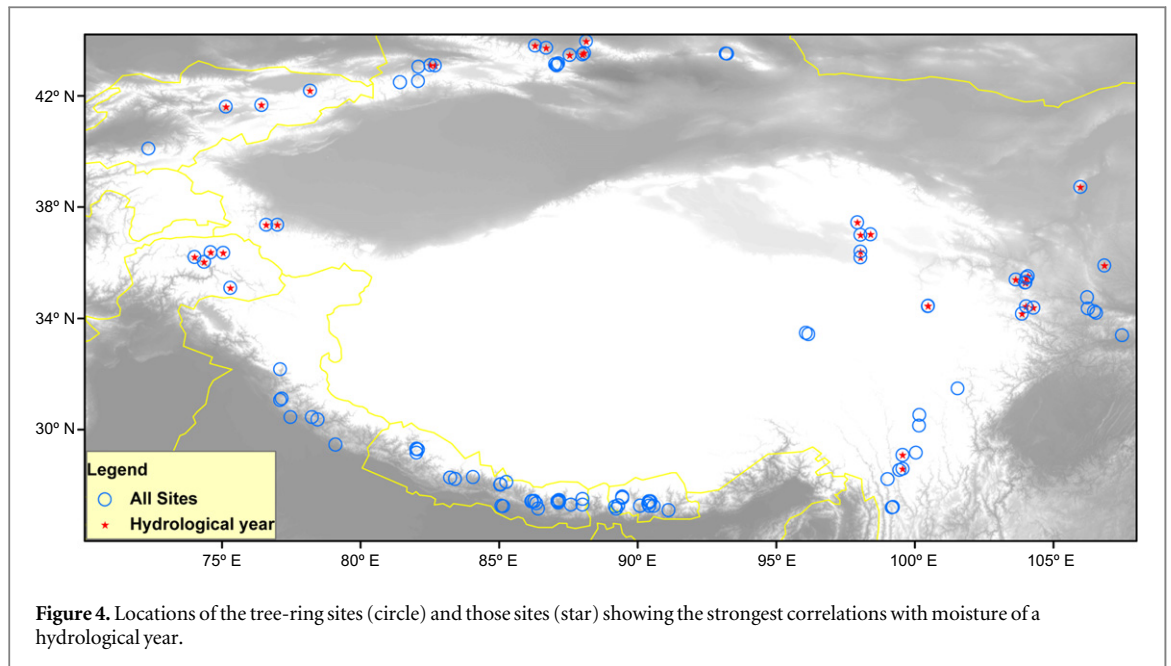


Figure 3. The (gray line) correlations and mean values of the (dark) correlations and (red) responses between regional tree-growth and the temperature and precipitation from previous May to current September. The monthly mean correlations that have been generated from more than half of the significant correlations were considered significant and were indicated by the circles. The tree-ring chronologies used to generate the regional mean chronology indices are shown in table S2.

Table 1. Classification the tree-rings sites with similar climate–growth correlations and responses. The codes are shown in table S1.

Region	Sub-region	Sites	Sites with different responses
Northeastern TP and vicinity	Northeastern TP	DELINH, DULAJP-SHENJP-DUSHJP, WULANJ, DEZQIN-GOUQIN	QUMAJP-ZHIDJP
	Chinese Loess Plateau	XML002-XML003-XML004-XML005, SYKRWL-BSIRWL, GANNAN, SONGMI, ZHANGX, KONGTO, LAZIKO	SANGTS, XIAOLO, ANGRWL-LENRWL-ZHARWL
Tianshan and South-western TP	Tianshan	MIQAPS-MIQBPS, TIANPS-BAIRWL, XIARWL-SHIRWL, KUERPS-QIARWL, RUS152e-RUS152i-RUS152l-RUS152n-RUS152t-RUS152w-RUS152x, RUS150e-RUS150i-RUS150l-RUS150n-RUS150t-RUS150w-RUS150x, RUS164e-RUS164i-RUS164l-RUS164n-RUS164t-RUS164w-RUS164x	BLKALS-BLKBLS, BIGKPS, KENGPS, JIALPS, BEQURU-HXBURU-XGSURU-ZEDURU, BONKJT-GEFKJT-GRAKJT-HOCKJT-MURKJT
	Southwestern TP	YCHAPS-YCHBPS, PAK001-PAK002-PAK003-PAK004, PAK005-PAK006-PAK007, PAK009-PAK010-PAK011-PAK012, PAK014-PAK015-PAK016	
India		IND010, IND012, IND019-IND020, IND021	IND013, IND017
Southeastern TP		XINSIC, TANSIC, DAOSIC, WXYIUN-PTCYUN-WEXYUN, SHANGR	XCHSIC-MAXSIC, XIANGC, BAWSIC



curves in climate conditions in the BRT analyses indicate the sensitivity of tree growth to climate. The nonlinear response has a sigmoid shape with the steepest gradient for precipitation levels around 200 mm for the late and non-growing seasons and 125 mm for the current early growing season, respectively (figure 5), indicating the strongest response in these climate conditions. The strongest interaction are found between the precipitation of the late and non-growing seasons and that of the current early growing

season (figure 5, lower left), which are particularly strong as indicated by the steepest gradients in the late and non-growing seasons precipitation is around 250 mm and the growing season precipitation is around 170 mm. When considering the influences of both temperature and precipitation, we again found that precipitation in the late and non-growing seasons has the highest influence explaining 28.5% of the total variance, which is followed by the precipitation of the current early growing season (figure 6). The three

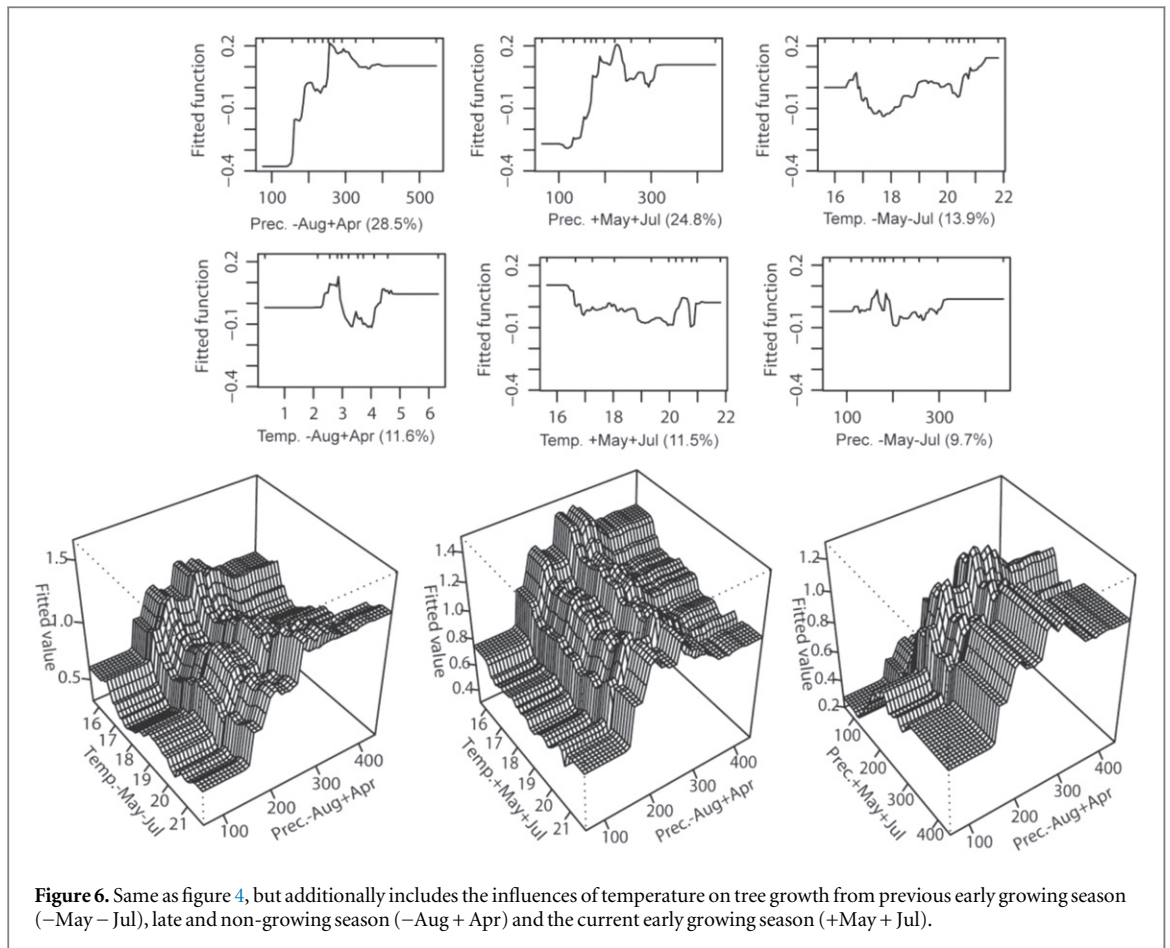


Figure 6. Same as figure 4, but additionally includes the influences of temperature on tree growth from previous early growing season (–May – Jul), late and non-growing season (–Aug + Apr) and the current early growing season (+May + Jul).

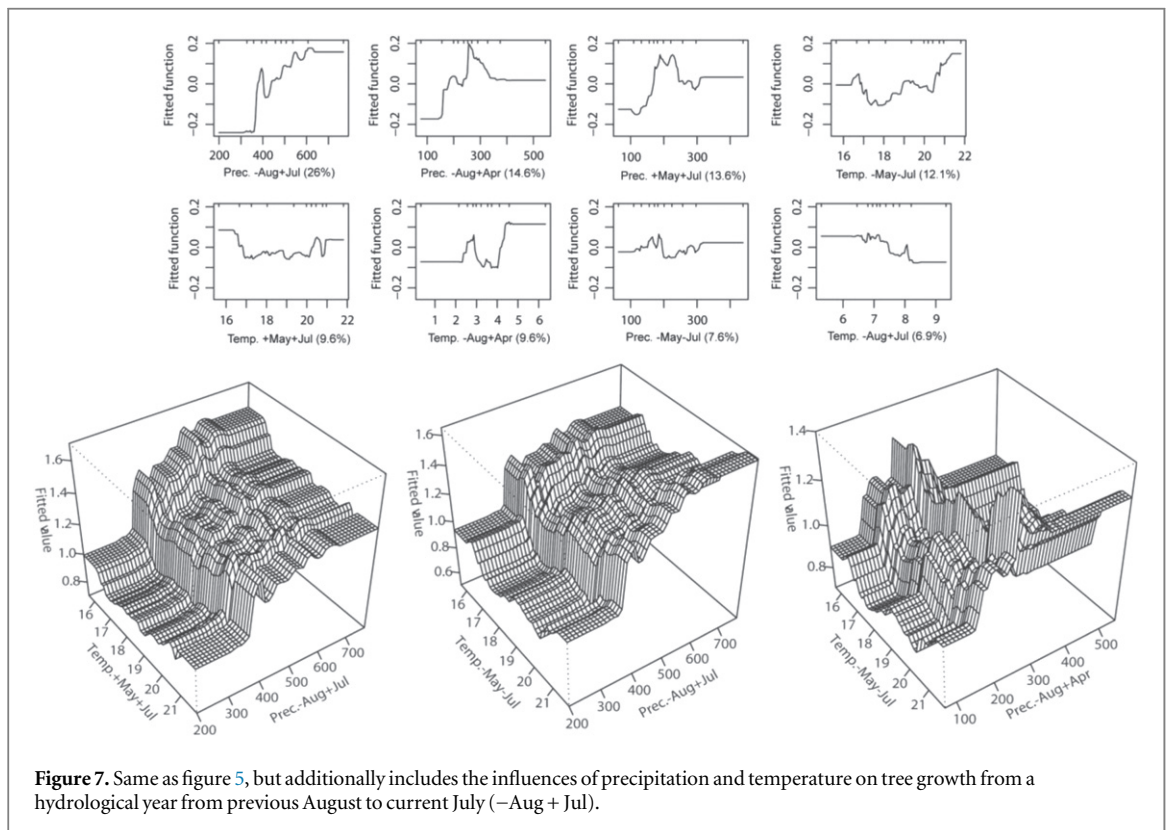


Figure 7. Same as figure 5, but additionally includes the influences of precipitation and temperature on tree growth from a hydrological year from previous August to current July (–Aug + Jul).

strongest interactions are seen between the precipitation of the late and non-growing seasons and (i) the temperatures of the previous and (ii) current early growing seasons, and (iii) the precipitation of the current early growing season. The interactions are particularly strong when the late and non-growing seasons precipitation is ~ 250 mm. When the influences of the precipitation and temperature of the hydrological year are also included, the precipitation of the hydrological year has the highest influence (26%), followed by the precipitations of the late and non-growing seasons and the current early growing season (figure 7). The influences of moisture of a hydrological year on tree growth is most conspicuous when the hydrological year precipitation is from ~ 380 to ~ 600 mm as indicated by the steep gradient of the sigmoid shape response curve. The two strongest interactions are found between the precipitation of the hydrological year from ~ 380 to ~ 600 mm and the temperatures of the current and previous growing seasons, followed by the interactions between the precipitation of the late and non-growing seasons and the temperature of the previous early growing season.

4. Discussion

4.1. BRT in dendroclimatology

The ML feature in BRT method does not assume *a priori* knowledge on climate–growth relationships, which is particularly useful for datasets where such knowledge is not adequately developed or does not exist. The advantages of BRT-based modeling contains not only statistical features (Elith *et al* 2008, Salonen *et al* 2012), but also is immune to overfitting, which is a common challenge of ANNs (Friedman *et al* 2000). In addition, the interactions between climate variables are automatically included in BRT modeling because the responses are determined by the input values in the regression trees (Elith *et al* 2008). Traditional climate–growth analyses, based upon the widely used correlation coefficient, can face difficulties in reveal the real climatic influences on growth of the climate variables are strongly correlated (Fritts 1976, Cook and Pederson 2011). The response function can remove the multi-collinearity among the climate variables, but the climate variables with real interactions may not be considered in the response function analysis (Fang *et al* 2012a). The BRT technique differs from the correlation and response functions that are used to produce a single ‘best’ model and differs from the ANN method by having better expressions of the fitting process (De’ath 2007, Elith *et al* 2008). This is more efficient in detecting the interactions between the predictors. Another advantage of the BRT method is that it can calculate the relative influences of the individual climate variables on tree growth, which are not available in many other methods such as the ANN.

One major difficulty in using the BRT method in dendroclimatology is the potential for erroneous modeling due to noisy or insufficient data because the overlap period between the climate and tree ring datasets is relatively short (approximately 60 years in the TP and vicinity). When pooling tree-ring chronologies from different sites, special attention should be paid to the autocorrelation and the discrepancies between these sites (Salonen *et al* 2012). It also should be noted that tree rings from remote areas may contain low autocorrelation with different growth variations but their climate–growth relationships may be different from each. There is a tradeoff between reducing the similarity in growth variations and keeping the similarity of the climate–growth relationships among sites. In dendroclimatology, the tree-ring indices are often normalized series with the same mean value over their entire spans but can have different mean values over the instrumental period because different series often have different time spans. The site discrepancies result from different mean values can cause systematic biases in BRT analyses. Thus it is necessary to keep the same mean values for both the tree-ring indices and climate data from different sites. One still needs to be in mind that the variability of the tree-ring data can be different across sites, which can also cause considerable biases. It would be helpful to compare the results from the pooled dataset to the BRT analyses for individual datasets. We found that the BRT analyses for individual datasets also indicate the strong influences of the late and non-growing season moisture (figure S3). The shape of the nonlinear dependencies identified in BRT often has irregular surfaces as shown before (Elith *et al* 2008, Salonen *et al* 2012), yet this does not severely hinder the interpretations.

In addition, the interactions inferred from BRT analyses can help selecting of the target climate variables for reconstructions, which should be the major climate determinant and no other climate variables have ‘secondary’ but significant impacts on tree growth (Juggins 2013). The interactions we observed (e.g., figures 5–7) between the target climate variable and the other climate variables violate this assumption. One can avoid reconstructing the climate variables with significant interactions or can alternatively combine these climate variables to produce a more comprehensive variable of climatic or even biological relevance (Williams *et al* 2013). The temperature interacts with precipitation to influence tree growth as indicated by the highest interaction between temperature and precipitation instead of having a direct influence on tree growth. It is thus more reliable to reconstruct a comprehensive drought indices from tree rings instead of temperature or precipitation only when tree rings show significant relationships with both temperature and precipitation (Cook *et al* 2010). For tree rings at sites that show strong responses to the moisture of the late and non-growing and current early growing seasons, the reconstruction of moisture

for a hydrological year should be more robust than reconstructions of moisture in either the non-growing or the growing seasons (Sheppard *et al* 2004).

On the other hand, this BRT model can be used to reconstruct the paleoclimate by using tree rings as predictors. This is particularly useful if conspicuously nonlinear climate–growth relationships are observed. For example, 37 tree-ring chronologies showing highest linear correlations with moisture of a hydrological year only show moderately high relationships with moisture of a hydrological year in the BRT analyses. These indicate that the linear correlation analysis may not fully model the nonlinear climate–growth relationships for these sites. The nonlinear method are expected to better reveal the climate extremes relative to the linear method as the nonlinearity in climate–growth relationships often increases towards the climate thresholds (Fang *et al* 2012b). For the BRT based reconstruction, one expected difficulty is the low sample size, which requires for pooling tree rings from different sites. Thus, it is appropriate for the BRT method to be used for climate reconstructions of large areas including several different sites but less proper for reconstructions of a single point or a small area.

4.2. A drought stress on tree growth in the TP and surrounding regions

Although temperature shows higher linear correlation with tree growth than precipitation, both the response and the BRT analyses indicate that the precipitation plays a more important role. The strongest interaction between temperature and precipitation in BRT analyses further indicate that the temperature is more likely to play an indirect role on tree growth by modulating the soil moisture via evaporation. For this area, the moisture availability is the major determinant for tree growth. High temperatures in the TP and surroundings can be associated with enhanced drought and reduced tree growth, except for the tree growths in Southeastern TP where sufficient water is available. The decline in tree growth is typically seen for trees on the marginal areas of Northeastern TP associated with the warming trend and the reduced precipitation due to the decay of the Asian summer monsoon (Cook *et al* 2010, Fang *et al* 2012b, 2012c). Similar warming-induced growth decline was also observed in the arid inner Asia area (Mongolia and Northern China) (Liu *et al* 2013). Although the current warming have enhanced the local water cycle in the past decades, resulting in more precipitation and increased tree growth in Northeastern TP (Yang *et al* 2014). However, the long-term warming trend has been found to have different impacts, such as the associated retreat of mountain glaciers across the TP, suggesting long-term opposing changes in the regional water balance. Because these glaciers form an important water resource for the lower catchment regions, glacial retreat can reduce the available moisture and

decrease tree growth in the future scenarios of global warming. The arid areas, including the study region, appear quite sensitive to current warming trend (Ji *et al* 2014). Accordingly, if the future warming trend continues, the forests in the arid parts of the TP and surroundings could be highly vulnerable because of their negative effects on forest growth.

4.3. Effects of moisture of the hydrological year on tree growth

Trees in this arid region often form pure forests with little competition for moisture and nutrients. Such trees may adapt to this arid environment by utilizing the moisture of a whole hydrological year, which has also been revealed in other arid regions, such as Mongolia (Pederson *et al* 2001). In the early growing season, the intense photosynthesis activities that result in most of the ring-width formation require large amount of moisture (Gou *et al* 2013). However, the monsoon front does not reach this area in the start early growing season. The snowmelt from the non-growing season makes up a large portion of the moisture for the early growing season. Thus higher relative influence of moisture on tree growth are observed for the late and non-growing season but not the current early growing season for many regions. Since the spring precipitation in Northwestern TP and surroundings is relatively more abundant than the marginal areas of Northeastern TP, the responses to moisture of a hydrological years is not that conspicuous in Northwestern TP and surroundings in the BRT analysis. The strong interaction between the moisture from the late and non-growing season and the current early growing season shown by the BRT analysis supports the hypothesis that moisture in the late and non-growing season is retained for tree growth in the following growing season, which has also been revealed in previous studies (Fang *et al* 2012b). Temperature on the marginal areas of Northeastern TP generally peaks in July, which can result in drought stress due to warming-induced evaporation (Cook *et al* 2010), which might be contribute to the completion of the ring-width formation in the early growing season. In the late-growing season after August or July, moisture is used for lignification and to produce nutrients for tree growth of the following year (Gou *et al* 2013). Therefore, moisture is not significantly correlated with tree growth in the late growing season but significantly correlated with tree growth in the following year.

The strongest influences of moisture of a hydrological year on tree growth further indicates the special importance of soil for forest growth in this region due to its important role in retaining the moisture. Therefore the ‘forests islands’ on the treeless marginal areas of Northeastern TP are often found in sites with rocky base, which can better retain the soil moisture relative to the porous loess (Fang *et al* 2012b, 2012c).

Accelerated settlement of the black carbon aerosol due to the enhanced industrial activities, particularly high in winter, since the 1980s in the TP and surroundings, has observed to accelerate the snowmelt in the non-growing seasons by lowering down the albedo of the snow (Huang *et al* 2011). In China, there have been projects to utilize the non-growing snowfall for agricultural activities of the lower reaches of the rivers for this area by facilitating snowmelt via adding carbon dusts on the snow, which acts similarly as the black carbon aerosols. We strongly suggest not doing this as the non-growing season precipitation are highly useful for the growth of the local forests. In addition, deforestation can enhance the soil erosion, which makes the forest growth in this area more stressful. Apart from the marginal area of Northeastern TP, it is suggested to pay attention to the water and soil conservation in other areas of the Northeastern TP, the Tianshan Mountains and the Southwestern TP that show less conspicuous but also strong relationships to moisture of a hydrological year.

5. Conclusions

Using a network of 152 tree-ring chronologies, we investigated the linear and nonlinear climate–growth relationships in TP and surroundings. The major difficulty in applying the BRT method to dendroclimatology is the short overlap period between tree rings and climate datasets. We therefore pooled tree-ring chronologies with similar climate–growth relationships but different growth patterns from remote regions into one BRT application. Drought stress induced by a warm climate is the major climatic determinant for tree growth. Temperature is indirectly related to tree growth by reducing the soil moisture via warming induced evaporation as suggested by the strong interactions between temperature and precipitation in this area. Continuous warming and potential drying due to the retreat of the mountain glaciers may cause a growth decline in the future. Tree rings in many drought-stressed sites show significant relationships with the moisture of a hydrological year, which is particularly significant on the marginal areas of Northeastern TP. Soil moisture retained prior to the start of the early growing season in May can strongly contribute to the ring width formation because the most of the ring-width formation occur in this period while the monsoon front does not reach this area yet. It is thus the late and non-growing season moisture has high relative influence on tree growth in the current early growing season. It is therefore highly important for soil protection in these seriously eroded areas as the soil is important to retain the late and non-growing water. From the late growing season since August, the moisture is used for cell wall thickening and producing nutrients for the tree growth of the next year. Thus moisture of the late growing season is more significantly correlated with ring width of the following year.

The strong interactions between temperature and precipitation and between moisture prior to and the current early growing seasons demonstrate the utility in reconstructing a composite climate variable that incorporates these climate signals.

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