



Influences of Climate Extremes on NDVI (Normalized Difference Vegetation Index) in the Poyang Lake Basin, China

Zhiqiang Tan^{1,2} · Hui Tao¹ · Jiahu Jiang¹ · Qi Zhang¹

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Abstract Based on long-term NDVI (Normalized Difference Vegetation Index) derived from Global Inventory Modeling and Mapping Study (GIMMS) and daily meteorological observations from 14 stations in the Poyang Lake Basin, this study investigated the relationship between vegetation variation and climatic extremes during 1982–2006. Ten typical indices were adopted to describe climatic extreme, including two precipitation-related and eight temperature-related indices. Correlation analysis shows that monthly averaged NDVI variations are generally determined by temperature but not precipitation extremes. Positive correlations appear between NDVI and temperature indices, and the correlations are more significant in spring and autumn. Significant negative correlations are found in summer and winter between NDVI and precipitation-related indices. In addition, spatial heterogeneity analysis shows that NDVI is more vulnerable to climate change for the middle basin than other regions. Finally, we demonstrate that NDVI can currently responds to temperature extremes or with a lag of 1 month. With respect to precipitation extremes, the strongest response may occur 2 months later. Our study highlights the role of climate extremes to the NDVI, and is helpful to improve the understanding of vegetation vulnerability to climate fluctuations.

Keywords Climate extremes · Monthly · NDVI · Poyang Lake Basin

Introduction

There is a general agreement that global warming and related changes in the water cycle are likely to enhance the frequency and severity of extreme climate events (Holmgren et al. 2006; Wallace et al. 2014; Tao et al. 2014), which have already caused more severe floods and droughts (Kerr 2003; Schuster et al. 2012; Woodward et al. 2014; Kim et al. 2014), and subsequent significant impacts on natural ecosystems and human societies (Hasson et al. 2009; Rocklov and Forsberg 2009; Frank et al. 2015). A current view is that extreme climate events trigger vegetation shifts, as these events can induce generalized mortality disrupting a situation in which vegetation would either remain stable or follow successional replacement in equilibrium under stable climate conditions. There are important challenges imposed by the need of long-term studies, but a research agenda focused on the condition and inertia of vegetation under extreme events is well suited to understand the variety of responses (Lloret et al. 2012). Recently, long-term remote sensing data on spatial scales of sub-meter (LiDAR) to kilometers (AVHRR) provide a consistent and repeatable measurement for capturing the effects of many processes causing vegetation changes (Hui et al. 2008; Verbesselt et al. 2010). The Normalized Difference Vegetation Index (NDVI) is a widely used index characterizing vegetation growth conditions due to its close correlation with the fraction of photosynthetically active radiation absorbed by plant canopies, the Leaf Area Index (LAI), the potential photosynthesis and the biomass amount. Vegetation can be differentiated from water, cloud, snow and other objects by the reflectivity differences of the near-infrared

✉ Hui Tao
htao@niglas.ac.cn

¹ State Key Laboratory of Lake Science and Environment, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing 210008, China

² University of Chinese Academy of Sciences, No. 19 Yuquan Road, Beijing 100049, China

and red wave bands (Liu et al. 2012). It can also reduce most irradiance changes relative to instrument calibration, sun angle, terrain, cloud shadow and atmospheric conditions (Tucker, 1979; Crippen 1990). Thus, the NDVI is a good proxy for evaluating the potential links of the variability in regional ecosystems and local ecotones with the spatio-temporal variability to climate conditions (e.g., Tourre et al. 2008; Koepke et al. 2010; Zhang et al. 2013; Frost et al. 2014).

Accordingly, increasing concern on extreme climatic events has triggered extensive research on vegetation dynamics, especially the relationship of the NDVI to climatic indices (e.g., Wang et al. 2010; Van Asch and Hoek 2012; Shevymogov et al. 2013). Actually, the impacts of climate changes on vegetation growth are diverse and not constant. Numerous studies have validated the responses of NDVI to climatic changes, and concluded that they differed among vegetation types (Breda et al. 2006; John et al. 2013). For example, Li and Tao (2000) demonstrated that correlation between annual NDVI and annual precipitation stronger over grasslands than over areas covered with shrubs and forests. Reichstein et al. (2013) also proposed that there were specific anticipated effects of climate extremes on forests, peatlands, grasslands, and croplands depending on the type of ecosystem. Liu et al. (2013) analyzed vegetation extremes of eight biomes in Amazonia, and found that extreme low precipitation shows the strongest correlation with declines in temperate broadleaf forest and temperate grassland.

Previous studies found that the vegetation type is an important factor in the strength of the correlations between the NDVI and climate indices. The sensitivity of different biomes to climatic changes has been proven to have different response times which might be the consequence of a more lasting or even profound impact after a certain time lag. Valladares et al. (2007) claimed that physiological and developmental responses to temperature shift of the vegetation (organism) from normal acclimation required a few days to weeks. Cavender-Bares and Bazzaz (2000) proposed that adult trees had a suit of morphological and physiological traits that could attenuate the impact of severe conditions. Miriti et al. (2007) believed facilitative interactions varied throughout the different life-history stages, which in turn might exhibit different sensitivity to extreme climatic events. Knowledge of dominant time lag between vegetation and climate extremes might be helpful to assess the resistance and resilience of vegetation and improve our understanding of vegetation vulnerability to climate change. However, the delayed responses of vegetation to climate extremes variation and the mechanisms are poorly understood.

Despite several efforts to evaluate changes in the climate indices and their impacts on NDVI, climate conditions of regions unobserved are usually predicted using limited meteorological datasets in previous studies. Interpolation methods are always used based on the hypothesis of spatial homogeneity. But climate conditions generally bear high uncertainty,

because they are jointly affected by complicated topography, land use, human activity and other factors. Moreover, most former studies concentrated on several common climate indicators. How the changes in climate extremes affect NDVI remains unknown and require further investigation.

The Poyang Lake Watershed is one of the most frequently affected areas by a variety of flood and drought events in China, and is well known for its ecological and economic importance (Guo et al. 2008; Zhang et al. 2012). The Poyang Lake Basin is located in Jiangxi Province, which is the center of China's rice growing region. During severe flood events, around 10,000 km² of farmland and rural areas are still inadequately protected by levees (Shankman et al. 2006). Some 10 million people are at risk of being affected by floods and droughts. Historical severe drought and flood events have caused huge economic losses, numerous fatalities, and serious damages to rural and urban areas surrounding Poyang Lake. The Poyang Lake Basin is famous for abundant biomes, which, for example, provide sufficient bait and natural habitat for hundreds of thousands of migrating birds. The dramatic changes in precipitation and temperature over the Poyang Lake Basin play an important role in shaping the vegetation ecosystem (Kanai et al. 2002). The knowledge of the severity and spatial patterns of such ecological impacts becomes crucial (Seneviratne et al. 2012). The Poyang Lake Basin has experienced historical changes in climate conditions and vegetation cover, and thus provides an excellent study site.

At present, the temporal and spatial patterns of the responses of the NDVI to climate extremes have not been investigated for the Poyang Lake Basin. Therefore, the three objectives of this research are to: (1) investigate the dominant effects of monthly climate extremes on the NDVI for the period 1982–2006; (2) estimate the temporal and spatial heterogeneity of the relationship between typical climate extremes and the NDVI; and (3) analyze if “lag effects” between climate extremes and the NDVI exist.

Datasets and Methodology

Study Area

The Poyang Lake is located in the northern parts of Jiangxi province, China, and connected to the south bank of the middle and lower reaches of the Yangtze River (Wang et al. 2012). Poyang Lake is fed by the inflows of five tributaries (Ganjiang, Fuhe, Xinjiang, Raohe and Xiushui) and discharges into the Yangtze River through a narrow outlet located in Hukou (Fig. 1). The lake has a drainage basin area of 162, 225 km², about 97 % of Jiangxi province (Shankman and Liang 2003). The wide alluvial plain is surrounded by hills and mountains with a maximum elevation of around 2200 m above mean sea level. In recent decades, the lake and the

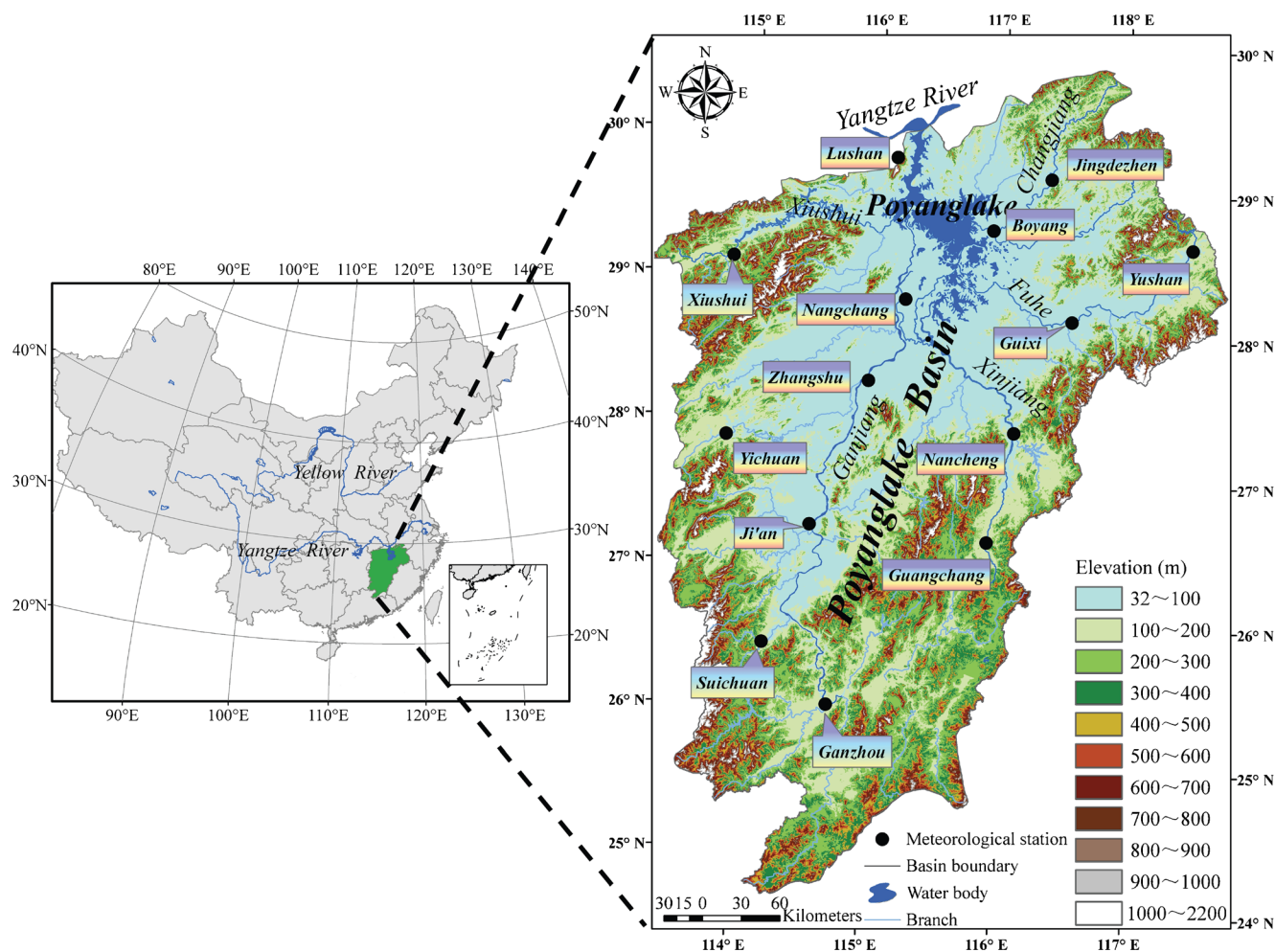


Fig. 1 Topography, location of the 14 meteorological stations, and the river network (containing five main tributaries: Ganjiang, Fuhe, Xinjiang, Raohe and Xiushui) of the Poyang Lake Basin

surrounding catchments have suffered from frequent occurrences of droughts and floods, especially in the 1990s and 2000s (Wang et al. 2008; Min et al. 2011).

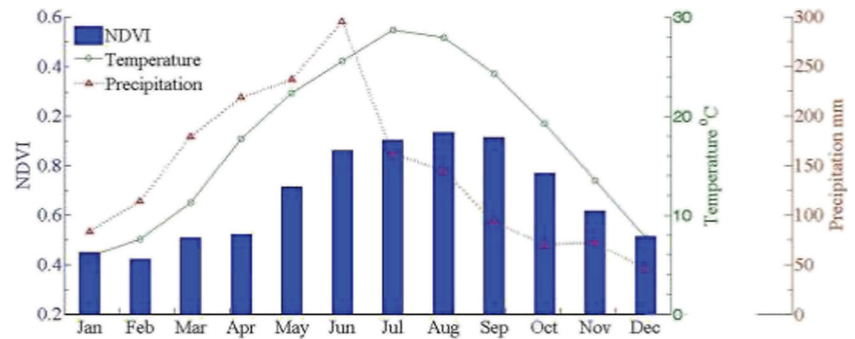
Located in the core area of the Poyang Lake Basin is the Poyang Lake Wetland, which has been registered as a Ramsar wetland site of international importance, in 1992 (Zhang et al. 2012). There exists abundant wetland vegetation in and around the area, while the hills and mountains in the east, west, and south are covered by subtropical forest. The central area of the Poyang Lake Basin is relatively flat and mainly used for farming (mainly crops are rice and oilseed rape) or for urban dwellings. Hence, the vegetation in this area is often affected by human activities. Usually, shrubs and perennial or annual grasses (e.g. *Carex cinerascens*, *Triarrhena lutarioriparia* and *Phragmites australis*) cover the floodplains around the lake. The amount of biomass in the flood prone areas is often affected by the water level fluctuation of the lake (Liao et al. 2013). According to the generalized NDVI, the plants start growing rapidly in May, and the biomass peaks in August and September (Fig. 2).

The major growth period of the vegetation in the Poyang Lake Basin takes place in spring and summer with influences from the subtropical monsoon. The monthly average temperature ranges from 5.8 °C in January to 28.7 °C in August (Fig. 2). The annual average precipitation is about 1712 mm. There is a significant transition of monthly precipitation in June, when it decreases dramatically after that. With respect to the annual cycle, about 54.2 % of the total precipitation falls in March to June, but only 15.9 % occur from October to the next January.

Datasets

Monthly characteristics of the plants are closely related to characteristics of the annual cycle of weather patterns, therefore changes in plant phenological events may signal important year-to-year climatic variations. The land surface conditions (1982–2006) of the Poyang Lake Basin are derived using the remote sensing data from the Advanced Very High Resolution Radiometer (AVHRR), provided by the Global Inventory Modeling and Mapping Study (GIMMS) group of

Fig. 2 Inner-annual cycle of the NDVI, mean temperature and precipitation in the Poyang Lake Basin, 1982–2006



NASA (Tucker et al. 2005). The final output have been screened for large-view angles and clouds, and partially corrected for atmospheric effects (Gurgel and Ferreira 2003). It is worthy noting that GIMMS NDVI provides biweekly composite NDVI, by applying a maximum value compositing (MVC) algorithm. It is believed that MVC algorithm can largely reduce effects of atmosphere and land anisotropy.

The monthly NDVI has been generated from the processed biweekly NDVI composites. The MVC procedure was used to minimize the effects of cloud contamination and to reconstruct the NDVI to a monthly time series. In this study, the monthly NDVI dataset with a spatial resolution of 8 km for a time period from January 1982 to December 2006 is used to investigate the vegetation characteristics. There are usually two ways to match remote sensing data and site observations. The first way is to extract remote sensing data according to site coordinates. The second way is to interpolate site observations with resolution of remote sensing data. Since interpolation may introduce extra uncertainty, site-centered mean value of 3×3 NDVI pixels was calculated to represent site NDVI. Mean NDVI values around meteorological sites were

presented in Table 1. Applying this averaging method seems more reliable, as it reduces (i.e. smoothers) the spatial error and keeps the condition of the underlying surface vegetation at each weather station as uniform as possible.

Considering the continuity and validity of the datasets, 14 meteorological stations of Jiangxi province were chosen for research, each of which has a long-term data from 1982 to 2006. Detailed information of 14 stations as well as statistical information of precipitation and temperature is summarized in Table 1. For each station, the China Meteorological Data Sharing Service System (<http://cdc.cma.gov.cn/>) has provided daily maximum air temperature (Tmax), daily minimum air temperature (Tmin) and 24 h precipitation (PRCP) for the time period of 1982–2006.

In the present study, crucial indices (2 precipitation indices and 8 temperature indices) of climate extremes are selected and calculated using the software RCLimDex (Version 1.0) as developed and maintained by Zhang Xuebin and Yang Feng at the Climate Research Branch of the Meteorological Service of Canada (Hyndman and Fan, 1996; Zhang et al. 2005). All indices have been recommended by the CCI/CLIVAR

Table 1 Geographic information of 14 meteorological stations and their mean monthly precipitation, average annual temperature, and average annual NDVI for 1982–2006. The mean monthly precipitation and average annual temperature are calculated from daily meteorological data. The average annual NDVI is calculated using biweekly remote sensing data

ID	Stations	Longitude degree	Latitude degree	Altitude m	Precipitation mm/month	Temperature °C	NDVI
58506	Lushan	115.9833	29.5833	1164.5	173.53	11.84	0.35
57598	Xiushui	114.5833	29.0333	146.8	135.82	16.71	0.53
58527	Jingdezhen	117.2000	29.3000	61.5	151.79	17.75	0.51
58519	Boyang	116.6833	29.0000	40.1	138.20	17.87	0.35
58606	Nanchang	115.9167	28.6000	46.7	136.73	17.92	0.35
58608	Zhangshu	115.5500	28.0667	30.4	144.76	18.06	0.41
58715	Nancheng	116.6500	27.5833	80.8	144.28	17.96	0.48
57793	Yichun	114.3833	27.8000	131.3	136.03	17.46	0.47
57799	Ji'an	114.9667	27.1167	76.4	129.23	18.60	0.37
58813	Guangchang	116.3333	26.8500	143.8	147.69	18.42	0.48
57896	Suichuan	114.5000	26.3333	126.1	123.51	18.70	0.47
57993	Ganzhou	114.9500	25.8500	123.8	122.84	19.52	0.44
58626	Guixi	117.2167	28.3000	51.2	160.23	18.61	0.43
58634	Yushan	118.2500	28.6833	116.3	153.48	17.67	0.46

Table 2 Descriptions of the selected ten extreme climate indices

ID of Index	Name of Index	Definitions	Unit
RX1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
RX5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm
TMAXmean	Daytime temperature	Monthly mean value of TX (daily maximum temperature)	°C
TMINmean	Nocturnal temperature	Monthly mean value of TN (daily minimum temperature)	°C
TXx	Max Tmax	Monthly maximum value of daily maximum temperature	°C
TXn	Min Tmax	Monthly minimum value of daily maximum temperature	°C
TNx	Max Tmin	Monthly maximum value of daily minimum temperature	°C
TNn	Min Tmin	Monthly minimum value of daily minimum temperature	°C
TN10	Cool nights	Percentage of days when TN < 10th percentile	Days
TN90	Warm nights	Percentage of days when TN < 90th percentile	Days
TX10	Cool days	Percentage of days when TX < 10th percentile	Days
TX90	Warm Days	Percentage of days when TX < 90th percentile	Days

Expert Team for Climate Change Detection Monitoring and Indices (ETCCDMI). The precipitation and temperature data have been quality controlled before the selected indices have been computed in advance. The details of the ten selected indices are shown in Table 2.

Methodology

In this study, correlations between climate indices and NDVI were estimated by the Pearson correlation coefficient. Pearson’s R measures the strength and direction (decreasing or increasing, depending on the sign) of a linear relationship between two variables. It ranged from –1.0 to 1.0, with higher values indicating better agreement, and is given by

$$R = \frac{\sum_{i=1}^N (O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_{i=1}^N (O_i - \bar{O})^2 \right]^{0.5} \left[\sum_{i=1}^N (P_i - \bar{P})^2 \right]^{0.5}} \tag{1}$$

where O_i and P_i denote the monthly value of the two variables, and \bar{O} and \bar{P} denote the means of the two variables, respectively. In general, this paper addresses the comparison of climate indices (P) with the NDVI (O) based on the same set of conditions (i.e., a pairwise comparison) for a 25-year period with N time increments for an arbitrary duration (here: at seasonal and monthly time scale).

Results

Relations Between NDVI and Extreme Indices on a Monthly Basis

According to the annual cycle of climate extremes, TXn (Minimum Tmax), TNn (Minimum Tmin) and TXx (Maximum Tmax) all increased by about 0.05 °C·year⁻¹, less than the increase of TX90p (Warm days, 0.38 °C·year⁻¹) and TN90p (Warm nights, 0.36 °C·year⁻¹). Precipitation indices of RX1day (Maximum 1-day precipitation amount) and RX5day (Maximum 5-day precipitation amount) increased by about

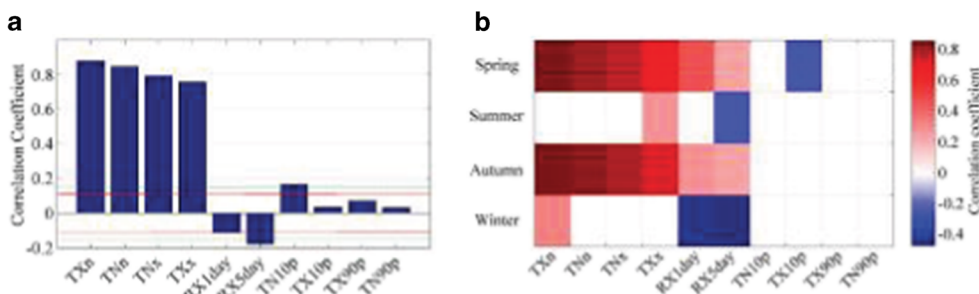


Fig. 3 Correlation coefficient between the selected ten climate indices and the NDVI on monthly time scale, 1982–2006: **a** whole year (N = 300, r_{0.05} = 0.11, r_{0.01} = 0.15), the horizontal dashed lines (green) denote the 95 % confidence interval, solid line (red) denote the 99 % confidence

interval; **b** four seasons (N = 75, r_{0.05} = 0.23, r_{0.01} = 0.30), blank denotes no significant correlation between climate indices and NDVI (at the 95 % confidence level)

0.21 mm·year⁻¹ and 0.44 mm·year⁻¹, respectively. However, the increase of annual temperature and precipitation did not lead to a significant increase or decrease in NDVI (rate of change was smaller than 0.01 %).

Correlation analysis using deviation from the value of normal year (monthly average of the 25 years data) for

every climatic variable and NDVI will give the more exact information on direct effects of climate extremes on vegetation. Accordingly, relations between NDVI and extreme indices on a monthly basis were investigated using deviation of long term dataset (Fig. 3a). Figure 3a shows a decreasing strength of the monthly NDVI response

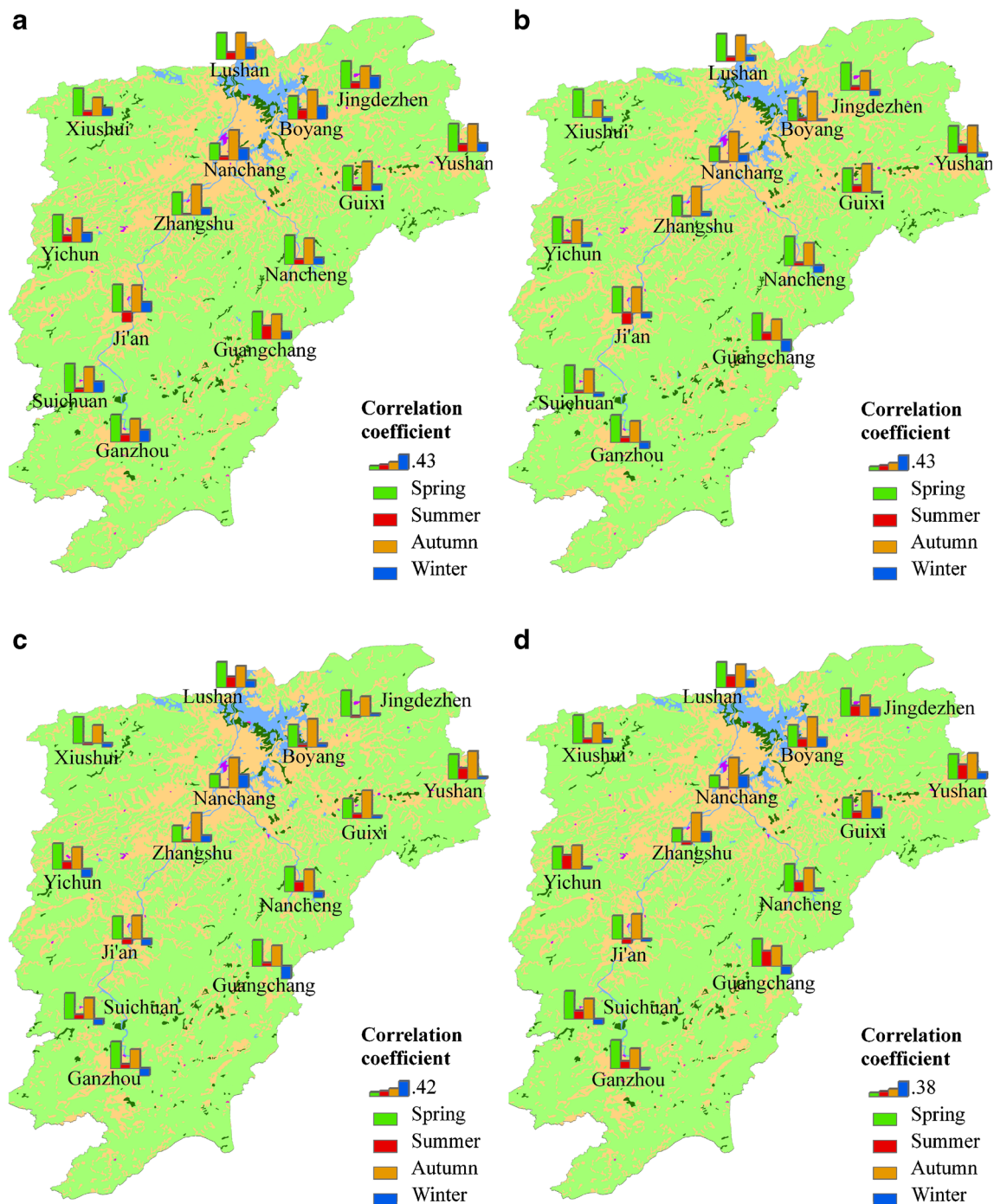


Fig. 4 Spatial patterns of correlation coefficients between monthly mean NDVI and extreme climate indices (a: TXn (°C); b: TNn (°C); c: TNx (°C); d: TXx (°C); e: RX1day (mm); f: RX5day (mm)) in different seasons. The height of each bar presents the value of correlation

coefficient relative to the reference value in each legend, respectively. Bars above the bottom denote positive values, bars below the bottom denote negative values. $N = 75$, $r_{0.05} = 0.22$, $r_{0.01} = 0.30$

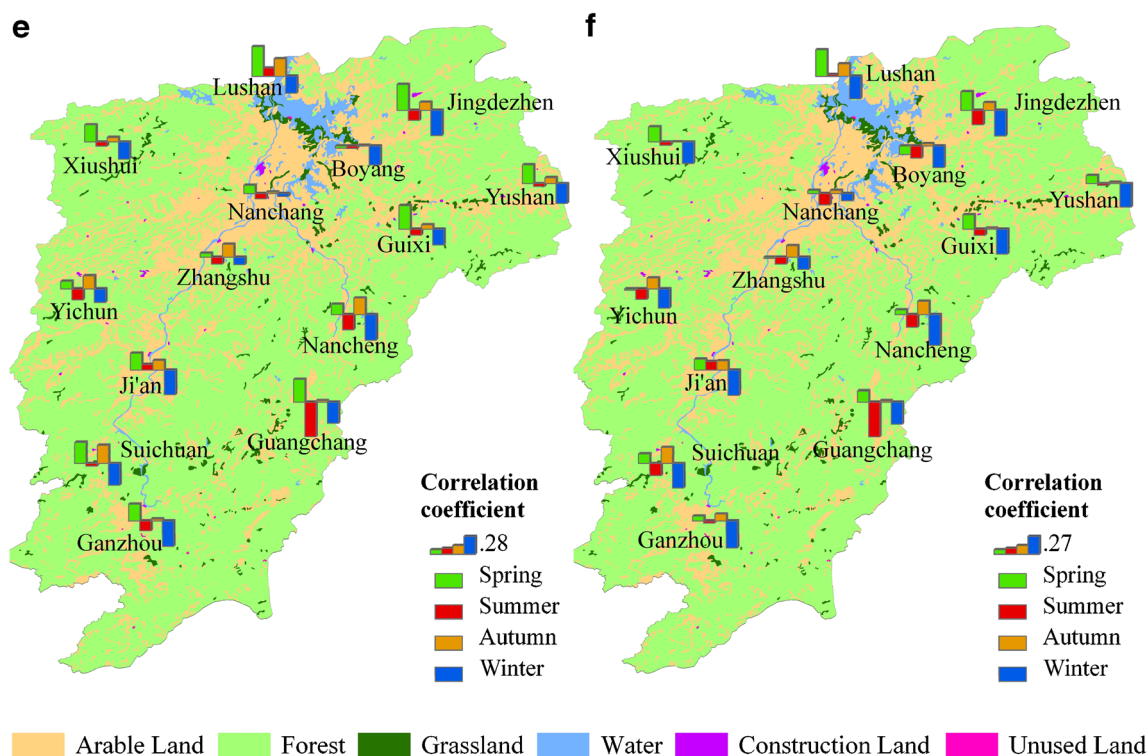


Fig. 4 (continued)

to extreme indices in order of TXn, TNn, TNx (Maximum Tmin), TXx, RX5day, RX1day, TN10p (Cool nights), TX10p (Cool days), TX90p and TN90p. Correlations between NDVI and all the former seven indices are significant (at the 95 % confidence level). Namely, NDVI in the study region was mainly dominated by the extreme minimum night-time and day-time temperatures indices. Monthly NDVI generally responds positively to temperature indices and negatively to precipitation indices.

Meanwhile, relations between monthly NDVI and extremes indices in different seasons were evaluated and presented in a color image (Fig. 3b). The former six climate indices (TXn, TNn, TNx, TXx, RX1day, and RX5day) show significant positive correlations with NDVI in spring and autumn (at the 95 % confidence level). However, correlations between NDVI and the former four temperature indices (TXn, TNn, TNx and TXx) are not significant in summer and winter. On the other hand, NDVI presents very significant negative response to RX1day ($R_{\text{mean}} = -0.37$, $p < 0.01$) and RX5day ($R_{\text{mean}} = -0.47$, $p < 0.01$) in summer and winter.

Because TN10p does not impact NDVI significantly in either season (Fig. 3b), the former six indices (TXn, TNn, TNx, TXx, RX1day and RX5day) were chosen according to the value of correlation coefficients in Fig. 3a to evaluate the spatial heterogeneity of relations between NDVI and climate extremes.

Spatial Distribution of the Correlation Coefficients of NDVI and Extreme Indices

For simplicity, temperature indices of TXn, TNn, TNx and TXx, precipitation indices of RX1day and RX5day were selected here as typical extreme climate indices. Spatial patterns of relations between NDVI and typical indices were investigated among different seasons on a monthly time scale (Fig. 4).

The authors find that in spring and autumn, NDVI variation responses to TXn, TNn, TNx and TXx positively and significantly (Fig. 4a, b, c and d). But relations are much weaker in summer and winter, they also vary in sign.

Moreover, the impacts of RX1day and RX5day on NDVI differed among seasons (Fig. 4e, f). Positive correlations were detected between NDVI and the two extreme precipitation indices in spring and autumn for almost all meteorological stations, while most of the correlations were negative in summer and winter.

According to the spatial heterogeneity of relations between NDVI and climate extremes in specific season, we can conclude that, NDVI in the middle basin is less correlated to climate variation than NDVI in other regions of the study area. These variances are much more apparent for RX1day and RX5day (Fig. 4e, f). For instance, the mean value of absolute correlation coefficients between spring NDVI in meteorological stations of the middle basin (Boyang, Nanchang and Zhangshu) and RX1day is 0.08. The

Table 3 Cartogram of multiple correlation coefficients between the basin averaged NDVI and monthly climate extreme indices with different time lags

Climate indices	Correlation coefficient			
	0	1	2	3
TXn	0.90	0.88	0.63	0.22
TNn	0.87	0.91	0.69	0.30
TNx	0.82	0.89	0.71	0.34
TXx	0.81	0.85	0.67	0.32
RX1day	0.40	0.64	0.68	0.56
RX5day	0.28	0.53	0.64	0.57

0 means climate indices and NDVI were collected over the same period ($N = 300$, $r_{0,01} = 0.15$); 1–3 indicates NDVI lag behind climate indices for 1–3 months

significance level is much lower than that of other stations for the same period ($R_{\text{mean}} = 0.31$, $P < 0.01$). Distribution of relations between NDVI and other indices also presents the similar patterns.

Delayed Responses of NDVI to Extreme Climate Indices

In order to recognize lag effects of climate extremes, the authors calculated the correlation coefficients between monthly NDVI and climate extremes with different time lags (Table 3). It is easy to conclude that TXn without time lags (or with a lag less than 1 month) have the most significant effects on monthly NDVI. Strongest relations between NDVI and other temperature indices of TNn, TXn and TXx were found with a lag of 1 month. On the other hand, NDVI exhibited the strongest responses to precipitation indices of RX1day and RX5day with a lag of 2 months.

Discussion and Conclusion

Monthly analysis of relations between NDVI and climate extremes proposed that extreme temperature indices (TXn, TNn, TNx and TXx) have stronger impacts on NDVI than precipitation indices (RX1day and RX5day) in Poyang Lake Basin. This conclusion is consistent with the hypothesis that for southern humid vegetation, where water is not a limiting factor for vegetation growth, higher temperature rather than increased precipitation is associated with the increase of NDVI (Zhang et al. 2010; Piao et al. 2014). This weak correlation between NDVI and precipitation indices may be attributed to the coincident reduction of incoming solar radiation during wet period (Beer et al. 2010; Piao et al. 2003).

Actually, relations between NDVI and climate extremes vary in different seasons. The correlations of NDVI with temperature indices are weaker in summer and winter than in

spring and autumn. High temperature increases the efficiency of plant photosynthesis and water use efficiency, and promotes the growth of vegetation in spring. By contrast, in autumn, metabolism of vegetation weakens with the decrease of available energy. On the other hand, high temperature may lead to increase of evaporation and decline of soil moisture in summer. The vegetation fraction of annual herbaceous plants, as well as deciduous forests decreased due to the phenological feature of vegetation rather than climate change in winter (Chen et al. 2006).

Compared to extreme temperature indices, significant negative correlations between monthly NDVI and extreme precipitation indices (RX1day and RX5day) in summer and winter implied that increased precipitation may lead to a decline of NDVI during these two seasons. As discussed above, there are intensive river network and robust irrigation system in southern plains of China. Meanwhile, precipitation in this region concentrated mainly in summer, more rainfall might cause soil supersaturation and decrease bioactivity in the wet season. Landslide caused by big flood and excessive precipitation is one of the biggest threatens of mountain vegetation. Inundation of vegetation in lowland areas, especially in the areas around the Poyang Lake by flood can also lead to the decrease of NDVI. In addition, much cloud in rainy day also reduced the solar radiation and inhibited photosynthesis of plants. In winter, much precipitation might result in a decrease in soil temperature, and decreased soil temperature would probably become the key factor for restraining vegetation growth, according to Liebig's law of the minimum (Zhang et al. 2013; Von Liebig 1842).

Furthermore, relations between NDVI and typical extreme climate indices exhibited spatial heterogeneity among different meteorological stations. Vegetation in middle basin was less sensitive to climate change than other regions (Fig. 4). To the best of the authors' knowledge, the flat middle basin covered with more arable lands is more likely to be affected by artificial factors. Farming processes such as seed, weeding, fertilization and harvest, and so on would possibly change the greenness of plants. These changes were not controlled by climate conditions exactly. Moreover, concentrated constructing lands (urban land, factory and mine, road, oil field and airport, and so on) in middle area would not respond to the climate changes either.

It is noteworthy that vegetation ecosystems adapt to climate change attributes to physiological, anatomical, and functional strategies. These strategies are mainly reducing water loss, respiration costs, photosynthetic activity, and growth rate. But it takes a certain time lag (Potter and Brooks 1998; Vicente-Serrano et al. 2013). In the present study, a notable discovery was that extreme temperature indices with a lag of 1 month (or less than 1 month) had the strongest impacts on NDVI. Meanwhile, most significant response of NDVI to extreme precipitation indices was observed with a lag of

2 months. Delayed responses of monthly NDVI in Poyang Lake Basin to climate extremes were detected in this study, but the specific reasons and the differences of response patterns need further investigation and discussion.

The authors' investigation of relationship between climate indices and vegetation, as well as the lag effects of temperature and precipitation on NDVI are consistent with other studies (Gu et al. 2009; Zhang et al. 2011). Different scholars diverged in their climate change impact assessments because multiple processes at different temporal, spatial, and organizational scale could influence ecosystem dynamics in conflicting directions. Biotic and abiotic factors not explicitly dealt with in the authors' study include the competition and adaptation among species, soil properties, soil moisture content, topography, fire occurrence, grazing management and urbanization, all of which could be important in affecting vegetation activity at the site-specific level (Yang et al. 1998). Estimating change from remotely sensed data however was not straightforward, since time series contained a combination of seasonal, gradual and abrupt ecosystem changes occurring in parallel (Verbesselt et al. 2012).

Our present works together with previous studies highlighted the role of climate extremes to the NDVI and confirmed the high vulnerability of ecosystem in the Poyang Lake Basin. Understanding the characteristics of climate extremes and the mechanisms how they affect vegetation is crucial for improving the knowledge of vegetation vulnerability to climate fluctuations and climate change.

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References

- Beer C, Reichstein M, Tomelleri E, Ciais P, Jung M, Carvalhais N, Papale D (2010) Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. *Science* 329(5993):834–838
- Breda N, Huc R, Granier A, Dreyer E (2006) Temperate forest trees and stands under severe drought: a review of ecophysiological responses, adaptation processes and long-term consequences. *Annals of Forest Science* 63(6):625–644
- Cavender-Bares J, Bazzaz F (2000) Changes in drought response strategies with ontogeny in *quercus rubra*: implications for scaling from seedlings to mature trees. *Oecologia* 124(1):8–18
- Chen P, Yu S, Zhan Y, Kang X (2006) A review on plant heat stress physiology. *Chinese Agricultural Science Bulletin* 22(5):223–227
- Crippen R (1990) Calculating the vegetation index faster. *Remote Sensing of Environment* 34(1):71–73
- Frank D, Reichstein M, Bahn M, Thonicke K, Frank D, Mahecha MD, et al. (2015) Effects of climate extremes on the terrestrial carbon cycle: concepts, processes and potential future impacts. *Global Change Biology*. doi:10.1111/gcb.12916
- Frost G, Epstein H, Walker D (2014) Regional and landscape-scale variability of landsat-observed vegetation dynamics in northwest siberian tundra. *Environmental Research Letters* 9(2). doi:10.1088/1748-9326/9/2/025004
- Gu T, Zhou S, Shao B, Li Q (2009) Interactions between vegetation cover change and precipitation in poyang lake region. *Chinese Journal of Ecology* 28(6):1060–1066
- Guo H, Hu Q, Jiang T (2008) Annual and seasonal streamflow responses to climate and land-cover changes in the poyang lake basin, China. *Journal of Hydrology* 355(1–4):106–122
- Gurgel H, Ferreira N (2003) Annual and interannual variability of NDVI in Brazil and its connections with climate. *International Journal of Remote Sensing* 24(18):3595–3609
- Hasson A, Mills G, Timbal B, Walsh K (2009) Assessing the impact of climate change on extreme fire weather events over southeastern Australia. *Climate Research* 39(2):159–172
- Holmgren M, Stapp P, Dickman C, Gracia C, Graham S, Gutiérrez J, Hice C, Jaksic F, Kelt D, Letnic M (2006) Extreme climatic events shape arid and semiarid ecosystems. *Frontiers in Ecology and the Environment* 4(2):87–95
- Hui F, Xu B, Huang H, Yu Q, Gong P (2008) Modelling spatial-temporal change of poyang lake using multitemporal landsat imagery. *International Journal of Remote Sensing* 29(20):5767–5784
- Hyndman R, Fan Y (1996) Sample quantiles in statistical packages. *The American Statistician* 50:361–367
- John R, Chen J, Ou-Yang Z, Xiao J, Becker R, Samanta A, Ganguly S, Yuan W, Batkhishig O (2013) Vegetation response to extreme climate events on the Mongolian plateau from 2000 to 2010. *Environmental Research Letters* 8(3). doi:10.1088/1748-9326/8/3/035033
- Kanai Y, Ueta M, Germogenov N, Nagendran M, Mita N, Higuchi H (2002) Migration routes and important resting areas of siberian cranes between northeastern siberia and China as revealed by satellite tracking. *Biological Conservation* 106(3):339–346
- Kerr R (2003) Climate change: a perfect ocean for four years of globe-girdling drought. *Science* 299(5607):636
- Kim C, Park M, Lee J (2014) Analysis of climate change impacts on the spatial and frequency patterns of drought using a potential drought hazard mapping approach. *International Journal of Climatology* 34(1):61–80
- Koepke D, Kolb T, Adams H (2010) Variation in woody plant mortality and dieback from severe drought among soils, plant groups, and species within a northern Arizona ecotone. *Oecologia* 163(4):1079–1090
- Li B, Tao S (2000) Correlation between AVHRR NDVI and climate factors. *Acta Ecologica Sinica* 20(5):898–902
- Liao J, Shen G, Dong L (2013) Biomass estimation of wetland vegetation in poyang lake area using ENVISAT advanced synthetic aperture radar data. *Journal of Applied Remote Sensing* 7(1):073579–073579
- Liu Y, Song P, Peng J, Ye C (2012) A physical explanation of the variation in threshold for delineating terrestrial water surfaces from multitemporal images: effects of radiometric correction. *International Journal of Remote Sensing* 33(18):5862–5875
- Liu G, Liu H, Yin Y (2013) Global patterns of NDVI-indicated vegetation extremes and their sensitivity to climate extremes. *Environmental Research Letters* 8(2):025009
- Lloret F, Escudero A, Iriondo J, et al. (2012) Extreme climatic events and vegetation: the role of stabilizing processes. *Global Change Biology* 18(3):797–805

- Min Q, Shi J, Min D (2011) Characteristics of sediment into and out of poyanghu lake from 1956 to 2005. *Journal of China Hydrology* 31(1):54–58
- Miriti M, Rodríguez-Buritica S, Wright S, Howe H (2007) Episodic death across species of desert shrubs. *Ecology* 88(1):32–36
- Piao S., Fang J., Zhou L., Guo Q., Henderson M., Ji W., & Tao S (2003) Interannual variations of monthly and seasonal normalized difference vegetation index (NDVI) in China from 1982 to 1999. *Journal of Geophysical Research: Atmospheres* (1984–2012), 108(D14)
- Piao S, Nan H, Huntingford C, Ciais P, Friedlingstein P, Sitch S, Chen A (2014) Evidence for a weakening relationship between interannual temperature variability and northern vegetation activity. *Nature Communications* 5. doi:10.1038/ncomms6018
- Potter C, Brooks V (1998) Global analysis of empirical relations between annual climate and seasonality of NDVI. *International Journal of Remote Sensing* 19(15):2921–2948
- Reichstein M, Bahn M, Ciais P, Frank D, Mahecha M, Seneviratne S, Zscheischler J, Beer C, Buchmann N, Frank DC, Papale D, Rammig A, Smith P, Thonicke K, van der Velde M, Vicca S, Walz A, Wattenbach M (2013) Climate extremes and the carbon cycle. *Nature* 500(7462):287–295
- Rocklov J. and Forsberg B. (2009) The attributed effect of climate extremes, climate related epidemics or outbreaks on health is largely dependent on the choice of approach—a case study comparing four approaches for estimating excess hospital admissions during a record warm summer in south Sweden. *Epidemiology* 20(6):S68–S68
- Schuster Z, Potter K, Liebl D (2012) Assessing the effects of climate change on precipitation and flood damage in Wisconsin. *Journal of Hydrologic Engineering* 17(8):888–894
- Seneviratne S., Nicholls N., Easterling D., Goodess C., Kanae S., Kossin J., Luo Y., Marengo J., McInnes K., Rahimi M. (2012) Changes in climate extremes and their impacts on the natural physical environment: An overview of the IPCC SREX report. In: EGU General Assembly Conference Abstracts (p. 12566)
- Shankman D, Liang Q (2003) Landscape changes and increasing flood frequency in China's Poyang lake region*. *The Professional Geographer* 55(4):434–445
- Shankman D, Keim B, Song J (2006) Flood frequency in China's Poyang lake region: trends and teleconnections. *International Journal of Climatology* 26(9):1255–1266
- Shevyrnogov A, Chernetskiy M, Vysotskaya G (2013) Multiyear trends of normalized difference vegetation index and temperature in the south of Krasnoyarsk krai. *Izvestiya Atmospheric and Oceanic Physics* 49(9):1047–1056
- Tao H, Fraedrich K, Menz C (2014) Trends in extreme temperature indices in the poyang lake basin, China. *Stochastic Environmental Research and Risk Assessment* 28(6):1543–1553
- Toure Y, Jarlan L, Lacaux J, Rotela C, Lafaye M (2008) Spatio-temporal variability of NDVI-precipitation over southernmost south America: possible linkages between climate signals and epidemics. *Environmental Research Letters* 3(4):044008. doi:10.1088/1748-9326/3/4/044008
- Tucker C (1979) Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* 8(2): 127–150
- Tucker C, Pinzon J, Brown M, Slayback D, Pak E, Mahoney R, Vermote E, El Saleous N (2005) An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data. *International Journal of Remote Sensing* 26(20):4485–4498
- Valladares F, Gianoli E, Gómez J (2007) Ecological limits to plant phenotypic plasticity. *The New Phytologist* 176(4):749–763
- Van Asch N, Hoek W (2012) The impact of summer temperature changes on vegetation development in Ireland during the weichselian lateglacial interstadial. *Journal of Quaternary Science* 27(5): 441–450
- Verbesselt J, Hyndman R, Newnham G, Culvenor D (2010) Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment* 114(1):106–115
- Verbesselt J, Zeileis A, Herold M (2012) Near real-time disturbance detection using satellite image time series. *Remote Sensing of Environment* 123:98–108
- Vicente-Serrano S, Gouveia C, Camarero J, Begueria S, Trigo R, Lopez-Moreno J, Azorin-Molina C, Pasho E, Lorenzo-Lacruz J, Revuelto J, Moran-Tejeda E, Sanchez-Lorenzo A (2013) Response of vegetation to drought time-scales across global land biomes. *Proceedings of the National Academy of Sciences of the United States of America* 110(1):52–57
- Von Liebig J (1842) *Die organische chemie in ihrer anwendung auf physiologie und pathologie*. Verlag von Friedrich Vieweg und Sohn
- Wallace J, Held I, Thompson D, Trenberth K, Walsh J (2014) Global warming and winter weather. *Science* 343(6172):729–730
- Wang F, Wu D, Li R (2008) Analysis on flood disaster characteristic in lake Poyang region. *Journal of Lake Science* 20(4):500–506
- Wang T, Kou X, Xiong Y, Mou P, Wu J, Ge J (2010) Temporal and spatial patterns of NDVI and their relationship to precipitation in the loess plateau of China. *International Journal of Remote Sensing* 31(7): 1943–1958
- Wang L, Dronova I, Gong P, Yang W, Li Y, Liu Q (2012) A new time series vegetation-water index of phenological-hydrological trait across species and functional types for Poyang lake wetland ecosystem. *Remote Sensing of Environment* 125:49–63
- Woodward M, Kapelan Z, Gouldby B (2014) Adaptive flood risk management under climate change uncertainty using real options and optimization. *Risk Analysis* 34(1):75–92
- Yang L, Wylie B, Tieszen L, Reed B (1998) An analysis of relationships among climate forcing and time-integrated NDVI of grasslands over the US northern and central great plains. *Remote Sensing of Environment* 65(1):25–37
- Zhang X, Hegerl G, Zwiers F, et al. (2005) Avoiding inhomogeneity in percentile-based indices of temperature extremes. *Journal of Climate* 18(11):1641–1651
- Zhang L, Chen X, Cai X, Habib A (2010) Spatial-temporal changes of NDVI and their relations with precipitation and temperature in Yangtze river basin from 1981 to 2001. *Geo-Spatial Information Science* 13(3):186–190
- Zhang G, Xu X, Zhou C, Zhang H, Ouyang H (2011) Responses of vegetation changes to climatic variations in hulun buir grassland in past 30 years. *Journal of Geographical Sciences* 66(1):47–58
- Zhang L, Yin J, Jiang Y, Wang H (2012) Relationship between the hydrological conditions and the distribution of vegetation communities within the Poyang lake national nature reserve, China. *Ecological Informatics* 11:65–75
- Zhang Y, Gao J, Liu L, Wang Z, Ding M, Yang X (2013) NDVI-based vegetation changes and their responses to climate change from 1982 to 2011: a case study in the koshi river basin in the middle Himalayas. *Global and Planetary Change* 108:139–148