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Contributions of natural and human factors to increases in vegetation productivity in China

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Abstract. Increasing trends in vegetation productivity have been identified for the last three decades for many regions in the northern hemisphere including China. Multiple natural and human factors are possibly responsible for the increases in vegetation productivity, while their relative contributions remain unclear. Here we analyzed the long-term trends in vegetation productivity in China using the satellite-derived normalized difference vegetation index (NDVI) and assessed the relationships of NDVI with a suite of natural (air temperature, precipitation, photosynthetically active radiation (PAR), atmospheric carbon dioxide (CO_2) concentrations, and nitrogen (N) deposition) and human (afforestation and improved agricultural management practices) factors. Overall, China exhibited an increasing trend in vegetation productivity with an increase of 2.7%. At the provincial scale, eleven provinces exhibited significant increases in vegetation productivity, and the majority of these provinces are located within the northern half of the country. At the national scale, annual air temperature was most closely related to NDVI and explained 36.8% of the variance in NDVI, followed by afforestation (25.5%) and crop yield (15.8%). Altogether, temperature, total forest plantation area, and crop yield explained 78.1% of the variance in vegetation productivity at the national scale, while precipitation, PAR, atmospheric CO_2 concentrations, and N deposition made no significant contribution to the increases in vegetation productivity. At the provincial scale, each factor explained a part of the variance in NDVI for some provinces, and the increases in NDVI for many provinces could be attributed to the combined effects of multiple factors. Crop yield and PAR were correlated with NDVI for more provinces than were other factors, indicating that both elevated crop yield resulting from improved agricultural management practices and increasing diffuse radiation were more important than other factors in increasing vegetation productivity at the provincial scale. The relative effects of the natural and human factors on vegetation productivity varied with spatial scale. The true contributions of multiple factors can be obscured by the correlation among these variables, and it is essential to examine the contribution of each factor while controlling for other factors. Future changes in climate and human activities will likely have larger influences on vegetation productivity in China.

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INTRODUCTION

Numerous studies have examined the dynamics of vegetation productivity over the last two to three decades at regional to global scales (Zhou et al. 2001, Ichii et al. 2002, Xiao and Moody 2004a, 2005, Beck and Goetz 2011, Xiao et al. 2013a). Many studies have identified increasing trends in vegetation productivity in many parts of the world, particularly in the northern hemisphere (Zhou et al. 2001, Xiao and Moody 2005). Climate change, particularly elevated air temperature, is believed to be the dominant driver (Zhou et al. 2001, Ichii et al. 2002, Xiao and Moody 2005). The effects of human activities on the increases in vegetation productivity have received less attention (Song et al. 2008, Li et al. 2012), and the relative effects of environmental factors and human activities also remain unclear (Evans and Geerken 2004, Seaquist et al. 2009, Li et al. 2012).

Many studies on vegetation dynamics are based on the normalized difference vegetation index (NDVI) derived from the advanced very high resolution radiometer (AVHRR) instrument onboard the National Oceanic and Atmospheric Administration (NOAA) satellites. These studies used NDVI as a proxy for vegetation productivity and identified increasing trends in vegetation productivity in many parts of the world, including Eurasia (Jeyaseelan et al. 2007), North America (Beck and Goetz 2011), and Australia (Donohue et al. 2009) as well as globally (Ichii et al. 2002, Xiao and Moody 2005, de Jong et al. 2012). A number of studies have examined the changes in vegetation productivity in China (Xiao and Moody 2004a, Park and Sohn 2010, Li et al. 2012, Xiao 2014). For example, Xiao and Moody (2014a) used AVHRR-derived leaf area index (LAI) to analyze the trends of vegetation productivity in China and their responses to temperature and precipitation from 1982 to 1998. Park and Sohn (2010) used NDVI data to examine the recent trends in vegetation cover for northern China and other parts of East Asia, and found a pronounced positive trend in NDVI for northern and northeastern China. Other approaches such as ecosystem models have also shown increased vegetation productivity in many regions (Hicke et al. 2002, Cao et al. 2003, Nemani et al. 2003), many of which were in

agreement with with the increasing trends of vegetation productivity inferred from NDVI (Hickler et al. 2005).

The identified increases in vegetation productivity have coincided with rising air temperatures. The global average land surface air temperature has been systematically increasing during the last three to four decades with the greatest changes witnessed in the northern middle and high latitudes (IPCC 2013). Elevated air temperature can increase plant growth by lengthening growing season (Nemani et al. 2002), enhancing photosynthesis, and altering nitrogen availability by accelerating decomposition or mineralization (Melillo et al. 1993). The enhancement of vegetation productivity has been mainly attributed to elevated air temperature (Zhou et al. 2001, Ichii et al. 2002, Xiao and Moody 2005). Precipitation is only the dominant controlling climatic factor in water-limited, semi-arid, and arid regions such as the Sahel (Herrmann et al. 2005, Hickler et al. 2005, Xiao and Moody 2005), Australia (Donohue et al. 2009), and northern China (Xiao et al. 2013a, Zhang et al. 2014a). Rising atmospheric carbon dioxide (CO_2) concentrations and nitrogen (N) deposition can also enhance plant growth (Ainsworth and Long 2005, Fleischer et al. 2013, Wang et al. 2014a, b), and these two factors have been linked to increased plant productivity in parts of China (Mao et al. 2012).

Besides multiple environmental factors, human activities can also increase vegetation productivity at the landscape scale. For example, internal migration had a negative influence on vegetation growth in China during the last two decades of the twentieth century (Song et al. 2008). In contrast, forest plantations have increased aboveground biomass carbon stocks during this period (Fang et al. 2001, Wang et al. 2007). Policy-driven conversions of croplands to forests and grasslands (i.e., the "Grain-for-Green" Program) have led to increased plant productivity on the Loess Plateau in China since 2000 (Lu et al. 2012a, Su and Fu 2013, Xiao 2014). Mu et al. (2013) showed that the total net primary productivity (NPP) of the Inner Mongolia grassland increased from 2001 to 2009 mainly because of human activities (land conversion from desert and cropland to grassland). Compared with climate change, the effects of human activities

such as agricultural management and afforestation have received less attention (Li et al. 2012). The relative effects of multiple environmental and human factors on the increases in vegetation productivity remain unclear.

Here we combined NDVI observations, climate data, atmospheric CO_2 concentrations, N deposition data, and provincial-level agricultural and forestry statistics to examine the effects of multiple natural factors and human activities on the increases in vegetation productivity in China. Increases in vegetation productivity at the national and provincial scales result from both enhanced plant growth and increases in vegetation cover. Potential drivers of NDVI trends include temperature, precipitation, photosynthetically active radiation (PAR), atmospheric CO_2 concentrations, and N deposition. Human activities that alter landscapes mainly include cultivation, afforestation, deforestation, and urbanization as well as improved agricultural management practices (fertilization, irrigation, and substitution of higher-yield crops for lower-yield crops). Our study focused on the period from 1982 to 2006 during which the data for the natural and human factors were all available. The objectives of this study were to analyze the trends of vegetation productivity using the long-term NDVI record at the national and provincial scales and to assess the relative contributions of the natural and human factors to increases in vegetation productivity by combining NDVI, climate data, atmospheric CO_2 concentrations, N deposition data, and agricultural and forestry statistics.

DATA AND METHODS

AVHRR NDVI

The normalized difference vegetation index (NDVI) is perhaps the most widely used vegetation index derived from satellite observations. NDVI captures the contrast between the visible-red and near-infrared reflectance of vegetation canopies. The NDVI typically ranges from about 0.1 to 0.75 for vegetation and from about −0.2 to 0.1 for snow, inland water bodies, deserts, and bare soils (Tucker et al. 1986), although sparsely vegetated areas can have NDVI values lower than 0.1.

NDVI is closely related to the fraction of photosynthetically active radiation (fPAR) absorbed by vegetation canopies and is indicative of the abundance and activity of chlorophyll pigments (Asrar et al. 1984). NDVI has been widely used to approximate vegetation productivity at various spatial scales (Zhou et al. 2001, Xiao and Moody 2004b, 2005). Although admittedly NDVI is only a proxy for vegetation activity and has various sources of uncertainty, this index, particularly the AVHRR-derived record, provides perhaps the best empirical device for examining the dynamics of vegetation productivity at large spatial and temporal scales (Xiao and Moody 2004b, 2005).

We used annual gross primary productivity (GPP) data from a synthesis flux database of the United States-China Carbon Consortium (USCCC) (Xiao et al. 2013b) to test the efficacy of NDVI for approximating GPP. This synthesis database consists of flux data from 22 eddy covariance flux sites across China and has been used to assess the spatial patterns and climatic controls of ecosystem carbon fluxes at the national scale (Xiao et al. 2013b). We used annual GPP to assess how well NDVI from the 250 m vegetation index data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) could approximate GPP in China for the period 2006–2010. We tested MODIS NDVI rather than AVHRR NDVI because the flux tower data were mainly available for the period that overlapped with that of MODIS NDVI. We obtained the MODIS ASCII Subsets for each of the eddy covariance flux sites from Oak Ridge National Laboratory (ORNL)'s Distributed Active Archive Center for Biogeochemical Dynamics (DAAC; http://daac.ornl.gov/MODIS/), and calculated total annual NDVI by summing 16-day NDVI values throughout the year. There was a strong linear relationship between annual GPP and annual NDVI across the sites (Fig. 1; $y = 127.20x − 295.48$, $R^2 = 0.70$, $p < 0.0001$), demonstrating that NDVI is a good proxy for vegetation productivity at the annual scale.

We obtained the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI dataset (Tucker et al. 2004, 2005) from the Global Land Cover Facility (http://www.landcover.org). The GIMMS dataset consists of NDVI data at the global scale for the study period from 1982 to 2006. This dataset is based on observations from
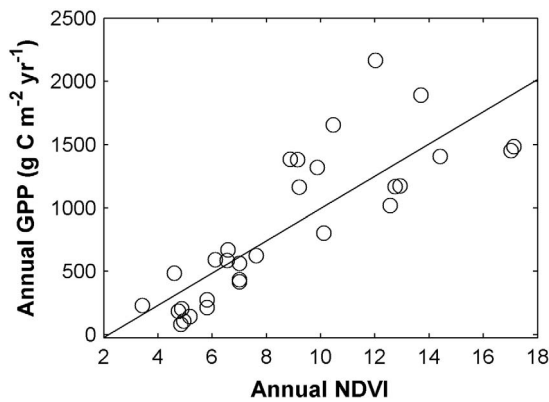
Fig. 1. Relationship between annual GPP and annual NDVI across eddy covariance flux sites in China.

the AVHRR instrument onboard the NOAA satellite series 7, 9, 11, 14, 16, and 17 (Tucker et al. 2004). It has a spatial resolution of 8 km, and consists of two 15-day composites for each month aggregated from the daily NDVI images within the 15-day period to minimize the effects of cloud contamination. It is well known that the NDVI signals from the AVHRR instruments can be biased by sensor calibration, view geometry, volcanic aerosols, and other effects. These effects are not related to vegetation change and have been corrected in the GIMMS dataset (Tucker et al. 2004).

We extracted the AVHRR NDVI data for China from the GIMMS dataset. For each pixel, we calculated the total annual NDVI by summing up all the 15-day NDVI values throughout the year. Negative NDVI values were not included in the summation as they are indicative of non-vegetation. We produced spatially averaged time series of annual NDVI for the entire nation for the period of 1982–2006. We also produced spatially averaged NDVI time series for each province, municipality, or autonomous region for the study period. Provinces, municipalities, and autonomous regions are referred to as provinces for simplicity hereafter.

MERRA reanalysis data

We used air temperature, precipitation, and PAR data from the Modern Era Retrospective-Analysis for Research and Applications (MERRA) reanalysis dataset (Rienecker et al. 2011) obtained from the Global Modeling and Assimilation Office

(GMAO; http://gmao.gsfc.nasa.gov/). The spatial resolution of the MERRA dataset is 0.5 degree × 0.667 degree. We extracted air temperature, precipitation, and PAR data for China from the global MERRA dataset. For each pixel, we calculated the annual mean temperature, annual precipitation, and annual mean PAR for each year from 1982 to 2006. Monthly mean air temperature and monthly PAR were averaged throughout each year to calculate annual mean air temperature and annual mean PAR. We calculated spatially averaged time series for temperature, precipitation, and PAR at both the national and provincial scales.

Atmospheric CO_2 concentrations

We obtained atmospheric CO_2 concentrations measured at Mauna Loa Observatory, Hawaii from the Global Greenhouse Gas Reference Network (http://www.esrl.noaa.gov/gmd/ccgg/trends/). The Mauna Loa CO_2 data, measured as the mole fraction in dry air, constitutes the longest record of direct measurements of CO_2 in the atmosphere. The monthly measurements were started by C. David Keeling of the Scripps Institution of Oceanography in March of 1958 (Keeling et al. 1976). The seasonal cycle has been removed to generate the annual mean CO_2 concentrations over the duration of this study (http://www.esrl.noaa.gov/gmd/ccgg/trends/).

N deposition

We used N deposition data from a gridded N deposition dataset (Lu and Tian 2007, Lu et al. 2012b) for the study period. This dataset was interpolated from sampling data of precipitation chemistry and ambient air concentration from site-network observations across China using the Kriging interpolation technique (Lu and Tian 2007). Aqueous NO_3^- and NH_4^+ were included for the estimation of wet deposition, and ambient NO_2 was involved in the prediction of dry deposition (Lu and Tian 2007). Precipitation concentration was multiplied by 20-year mean precipitation amounts to generate wet deposition fluxes, while dry deposition fluxes were products of the interpolated ambient CO_2 concentration and deposition velocities modeled for the main vegetation types (Lu and Tian 2007). The resulting gridded dataset is currently available at annual time step (kg N ha NO_3^{-1} yr NO_3^{-1})

and 10 km spatial resolution for the period from 1901 to 2006 (Lu and Tian 2007, Lu et al. 2012b). For each 10 km grid cell, total N deposition (kg N ha NO_3^{-1} yr NO_3^{-1}) was calculated by summing wet and dry N deposition for each year over the period 1982–2006. As with NDVI, temperature, precipitation, and PAR, we averaged total N deposition spatially to generate spatially averaged N deposition for the entire nation and for each province.

Agricultural and forestry statistics

We used agricultural statistics to assess the effects of improved agricultural practices on vegetation productivity. In China, the Rural Socio-Economic Survey Division of the National Bureau of Statistics conducts annual surveys of planted area, crop yield, management practices, and many other agricultural variables (e.g., livestock, farm machinery, household income). Crops include grains (e.g., rice, wheat, corn, millet, and sorghum), beans, potatoes, and sweet potatoes. For each province, we obtained annual agricultural statistics on cropland area, crop yield, irrigated area, fertilizer use, and pesticide use for each year from 1982 to 2006 from the *Compilation of Agricultural Statistics for the 30 Years since the Reform and Opening-up* (National Bureau of Statistics of China 2009). Among these variables, crop yield was chosen as the metric of agricultural intensity for assessing the influence of improved management practices on cropland productivity.

We also used forestry statistics to assess the influences of forest plantations on the dynamics of vegetation productivity. The State Forestry Administration of China conducts national forest inventories every five years, and reports forest cover (%), forest volume, total plantation area, plantation volume, and other forestry variables. To date, China has accomplished a total of seven national forest inventories: 1973–1976 (1st), 1977–1981 (2nd), 1984–1988 (3rd), 1989–1993 (4th), 1994–1998 (5th), 1999–2003 (6th), and 2004–2008 (7th). We obtained data on forest area, forest volume, total plantation area, and plantation volume for each province from the seven inventories (State Forestry Administration of China 1977, 1983, 1989, 1994, 2000, 2005, 2009). Among these variables, total plantation area was chosen as the afforestation metric for assessing

the influence of afforestation on forest productivity. For the national scale, we obtained the annual forest plantation area for each year from 1953 to 2006 from the 2011 *China Forestry Statistics Yearbook* (State Forestry Administration of China, 2012).

Data analysis

The linear trends of the annual NDVI were determined by linearly regressing NDVI as a function of time on a per-pixel basis (Zhou et al. 2001, Xiao and Moody 2005). We also analyzed the trends of NDVI at the national and provincial scales. Similarly, we analyzed the linear trends of the three climate variables (annual mean temperature, annual precipitation, annual mean PAR) and total N deposition at both spatial scales. The linear trends of crop yield and total forest plantation area were also analyzed at both spatial scales.

We examined the statistical relationships between NDVI and the environmental factors over the 25-year period at both the national and provincial scales. We conducted our analyses at both scales because the agricultural and forestry statistics were only available at the provincial scale, which allowed us to examine the relative effects of both natural and human factors on vegetation productivity. For the correlation of NDVI with each controlling variable, if both time series exhibited increasing or decreasing trends over the 25-year period, we detrended both time series prior to the correlation analysis, following previous studies (Wang and You 2004). Two variables can be correlated with each other simply because they both increase (or decrease) over time, leading to "spurious correlation." For each variable, we determined the linear fit between the variable and time and then removed the linear fit from the variable. The detrended time series is essentially the residuals from the linear fit.

Agricultural and forestry statistics were used to assess the effects of improved agricultural and forestry management practices on vegetation dynamics. We analyzed the changes of cropland area, total crop yield, crop yield per unit area, irrigated area, chemical fertilizer use, and pesticide use for both the national and provincial scales over the 25-year period. The statistical relationships between annual NDVI and crop

yield were then analyzed at both national and provincial scales. The annual NDVI was integrated from all vegetated areas, while the crop yield statistics represent the productivity of croplands only. Therefore, the relationship between annual NDVI and crop yield reflects how much variance in NDVI is explained by crop yield, and the proportion of the variance explained is measured by the coefficient of determination (R^2). We also assessed the changes in total forest cover, total forest volume, total forest plantation area, and total plantation volume. The statistical relationships between annual NDVI and total plantation area were examined at both national and provincial scales. Similarly, NDVI, crop yield, and total plantation area were detrended prior to the correlation analysis to avoid spurious correlation.

The natural (temperature, precipitation, PAR, atmospheric CO_2 concentrations, and N deposition) and human (crop yield and afforestation) factors can be correlated with each other. For a given factor, its correlation with NDVI can be influenced by other factors. Therefore, we also conducted partial correlation analysis (Kim 2014) for all the factors to assess the true contribution of each factor to NDVI while controlling for other factors. Partial correlation analysis measures the degree of association of two random variables, independent of other random variables. We regressed annual NDVI against all the environmental and human factors together and calculated the partial R^2 value for each factor. Partial correlation analysis was conducted for both national and provincial scales.

RESULTS

Trends in vegetation productivity

The mean annual NDVI sums over the period 1982–2006 varied substantially over space across China, and generally exhibited a decreasing gradient from the southeast to the northwest (Fig. 2A). The highest annual NDVI values (~6.0–8.0) were observed in a large part of the southeast and a part of the southwest. The remainder of the southwest and the majority of the northeast exhibited intermediate NDVI values (~3.5–5.0). The semi-arid and arid northwest and the majority of the Qinghai-Tibet Plateau had low NDVI values (~0.5–2.0).
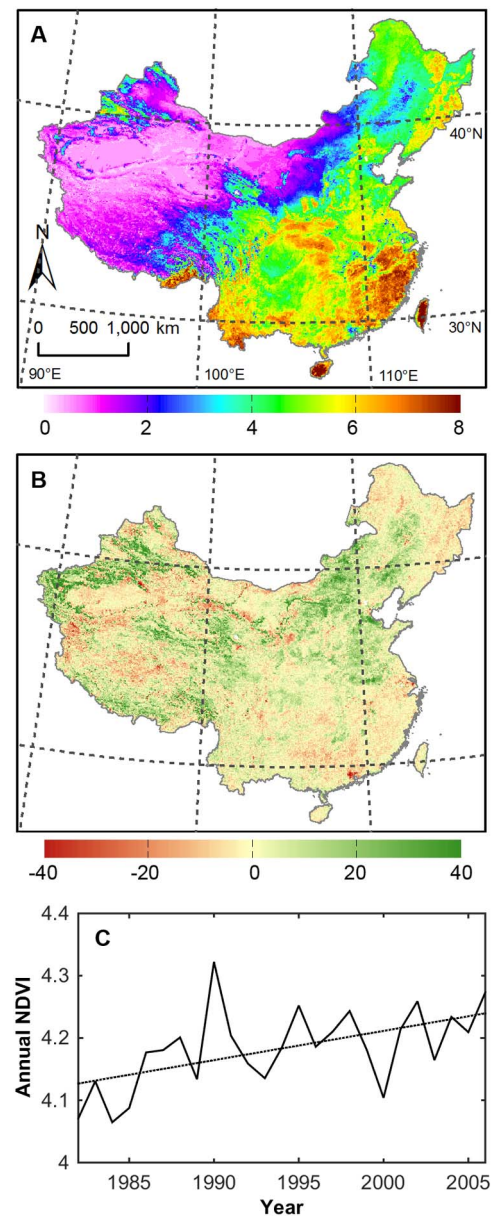

Fig. 2. Magnitude, spatial patterns, and trends of annual NDVI in China over the period 1982–2006: (A) magnitude and spatial patterns of annual NDVI averaged over the 25-year period; (B) trends of the annual NDVI on a per-pixel basis; and (C) trend of the annual NDVI averaged across China. The values of the trends in (B) are given by percentages (%) with positive values indicating increases in NDVI and negative values indicating decreases in NDVI. The solid and dashed lines in (C) stand for annual NDVI and its linear trend, respectively.

The magnitude of the trends in annual NDVI over the 25-year period also varied over space across China (Fig. 2B). Many areas in the north and northwest and parts of the northeast and the Qinghai-Tibet Plateau exhibited increasing trends in annual NDVI, and some areas in these regions also exhibited decreasing trends. Notably, the majority of the south and southeast and a large part of the southwest did not exhibit increases in annual NDVI and, instead, many areas in these regions showed decreasing trends.

At the national scale, the spatially averaged annual NDVI varied from year to year with a particularly high value in 1990 and particularly low values in 1984 and 2000 (Fig. 2C). Overall, the annual NDVI exhibited an increasing trend over the period of 1982–2006 (Fig. 2C; $y = 0.0047x - 5.14$, $R^2 = 0.29$, $p < 0.01$). At the national scale, the annual NDVI slightly increased over the 25-year period with an increase of 2.7% (or an absolute value of 0.11). At the provincial scale, increasing trends in annual NDVI were observed for a total of 11 provinces (Fig. 3). A decreasing trend in annual NDVI was observed for Shanghai (Fig. 3). The remaining 20 provinces exhibited no significant trends in NDVI ($p > 0.05$).

Effects of climate change, rising atmospheric CO_2, and N deposition

The annual mean temperature averaged across China exhibited a moderate increasing trend over the period 1982–2006 (Fig. 4A; $y = 0.03x - 57.01$, $R^2 = 0.44$, $p < 0.001$). In contrast, the annual precipitation exhibited a slight downward trend, although not statistically significant (Fig. 4B; $p = 0.66$); annual mean PAR exhibited no significant trend ($p = 0.19$). At the national scale, there was a significant relationship between annual NDVI and annual mean temperature over the 25-year period ($y = 0.13x + 3.21$; $R^2 = 0.51$, $p < 0.01$). We detrended the two times series (Fig. 4C) and examined the statistical relationship between these two variables again. There was still a significant relationship between these two variables (Fig. 4D; $R^2 = 0.31$, $p < 0.01$). Annual NDVI was not significantly correlated with annual precipitation or PAR at the national scale.

The atmospheric CO_2 concentrations had been dramatically rising and exhibited a strong increasing trend over the period 1982–2006 (Fig. 5A; $y = 1.63x - 2892.79$; $R^2 = 0.99$, $p < 0.001$).
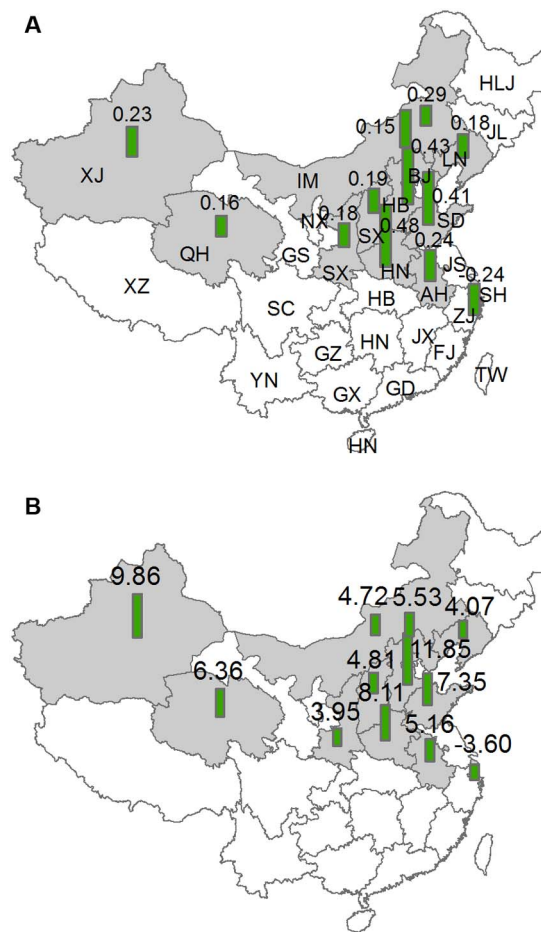

Fig. 3. Trends of annual NDVI at the provincial scale over the period 1982–2006: (A) absolute changes in annual NDVI and (B) relative changes (%) in annual NDVI. The shaded areas are provinces (municipalities, autonomous regions) with significant trends in annual NDVI. All of these provinces except Shanghai have positive trends. The following provinces were assessed in this study: Heilongjiang (HLJ), Inner Mongolia (IM), Xinjiang (XJ), Jilin (JL), Liaoning (LN), Gansu (GS), Hebei (HB), Beijing (BJ), Shanxi (SX, *east*), Tianjin (TJ), Shaanxi (SX, *west*), Ningxia (NX), Qinghai (QH), Shandong (SD), Xizang (XZ), Henan (HN, *north*), Jiangsu (JS), Anhui (AH), Sichuan (SC), Hubei (HB), Shanghai (SH), Zhejiang (ZJ), Hunan (HN, *south*), Jiangxi (JX), Yunnan (YN), Guizhou (GZ), Fujian (FJ), Guangxi (GX), and Guangdong (GD). Taiwan (TW), Hainan (HN), Chongqing (CQ), Hongkong, and Macau were not included in this study due to lack of data.
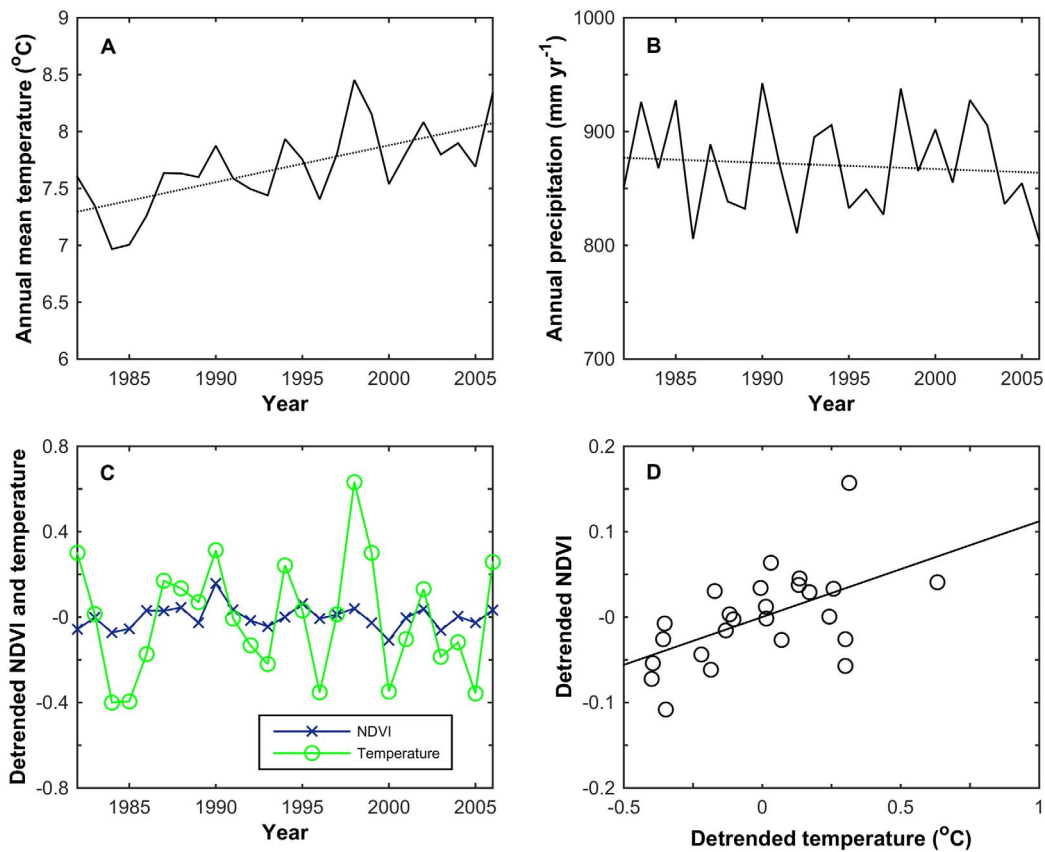
Fig. 4. Trends of annual mean temperature and annual precipitation and the relationships of these two climate variables with annual NDVI over the period 1982–2006: (A) trend of annual mean temperature ($R^2 = 0.44$, $p <$ 0.001); (B) trend of annual precipitation ($p = 0.66$); (C) detrended NDVI and detrended temperature; and (D) relationship between detrended NDVI and detrended temperature ($R^2 = 0.31$, $p < 0.01$). For (A) or (B), the solid line stands for annual mean temperature or annual precipitation, and the dashed line stands for the trend line.

There was a significant relationship between annual NDVI and atmospheric CO_2 concentrations prior to detrending (Fig. 5B; $R^2 = 0.29$, $p <$ 0.01). However, the detrending of both time series eliminated the relationship and the detrended NDVI was not significantly correlated with the detrended CO_2 (Fig. 5C; $p = 0.83$). Similarly, total N deposition showed a strong increasing trend during the 25-year period (Fig. 5D; $y = 0.21x - 394.49$; $R^2 = 0.94$, $p < 0.001$). Although there was a significant relationship between annual NDVI and N deposition prior to detrending (Fig. 5E; $R^2 = 0.29$, $p < 0.01$), the detrended NDVI was not significantly correlated with the detrended N deposition (Fig. 5F; $p = 0.76$).

At the provincial scale, annual mean temper- ature exhibited an increasing trend for the majority of the provinces; annual precipitation exhibited an increasing trend for four provinces (Xinjiang, Gansu, Ningxia, and Sichuan) and a decreasing trend for Heilongjiang; PAR exhibited an increasing trend for Heilongjiang, Inner Mongolia, Zhejiang, Hunan, and Jiangxi and a decreasing trend for Gansu, Ningxia, and Si- chuan (Fig. 6). There was a significant relation- ship between detrended annual NDVI and detrended annual mean temperature for seven provinces: Gansu, Qinghai, Sichuan, Chongqing, Hubei, Yunan, and Hunan, with R^2 values ranging from 0.15 to 0.29 (Fig. 7A). There were no significant relationships between these two variables for the remaining provinces. Among the 11 provinces that exhibited increases in NDVI
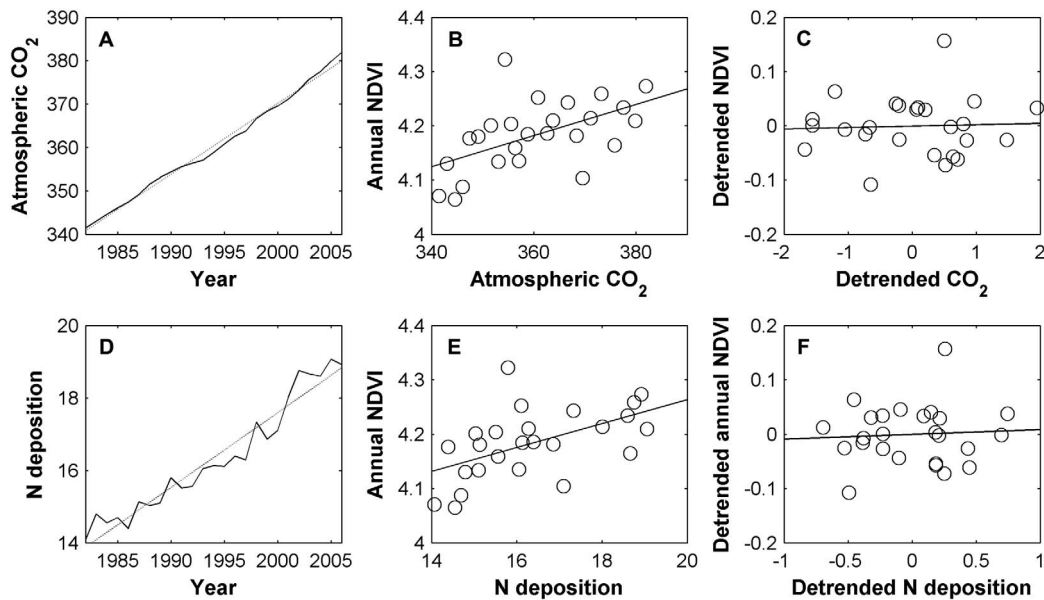
Fig. 5. Trends of atmospheric CO_2 concentrations and N deposition and the relationships of these two variables with annual NDVI over the period 1982–2006: (A) trend of annual mean CO_2 concentrations; (B) relationship between annual NDVI and atmospheric CO_2 concentrations prior to detrending ($R^2 = 0.29$, $p < 0.01$); (C) relationship between detrended NDVI and detrended CO_2 concentrations ($p = 0.83$); (D) trend of annual total N deposition; (E) relationship between annual NDVI and N deposition prior to detrending ($R^2 = 0.29$, $p < 0.01$); (F) relationship between detrended NDVI and detrended N deposition ($p = 0.76$). For (A) or (D), the solid line stands for annual mean atmospheric CO_2 concentrations or N deposition, and the dashed line stands for the trend line.

(Fig. 3), only two provinces—Qinghai and Henan exhibited significant relationships between NDVI and temperature (Fig. 7A). At the provincial scale, there was a significant positive relationship between detrended annual NDVI and detrended annual precipitation for Xinjiang (Fig. 7B). No province exhibited a significant relationship between detrended NDVI and detrended PAR.

At the provincial scale, there was a significant relationship between detrended annual NDVI and detrended atmospheric CO_2 concentrations for two provinces: Shandong and Sichuan, and there was no significant relationship between these two variables for the remaining provinces (Fig. 7C). Total N deposition exhibited an increasing trend for each province that we analyzed (Fig. 6). Detrended NDVI was correlated with detrended N deposition for four provinces: Beijing, Tianjin, Hubei, and Fujian with R^2 values ranging from 0.17 to 0.31 (Fig. 7D). The correlation between NDVI and N deposition was positive for Beijing, Tianjin, and Hubei and

negative for Fujian.

Effects of agricultural activities and afforestation

The trends in China's crop yield, cropland area, crop yield per unit area, irrigated area, and usage of both chemical fertilizers and pesticides from 1982 to 2006 are illustrated in Appendix: Fig. A1. The total crop yield of China exhibited a strong increasing trend over the 25-year study period, although the total cropland area exhibited a declining trend. The total crop yield was 4.98×10^8 tons in 2006, about 40.3% higher than that of 1982 (3.55×10^8 tons), while the total cropland area declined by 7.5% from 1982 (11.35×10^7 ha) to 2006 (10.50×10^7 ha). In the meanwhile, the crop yield per unit area exhibited a strong increasing trend from 1982 to 2006 and was elevated from 3.12 tons/ha to 4.75 tons/ha with an increase of 52.2%. The total irrigated area of China also strongly increased during the 25-year study period. The total irrigated area increased by 26.2% from 1982 (4.42×10^7 ha) to 2006 (5.58×10^7
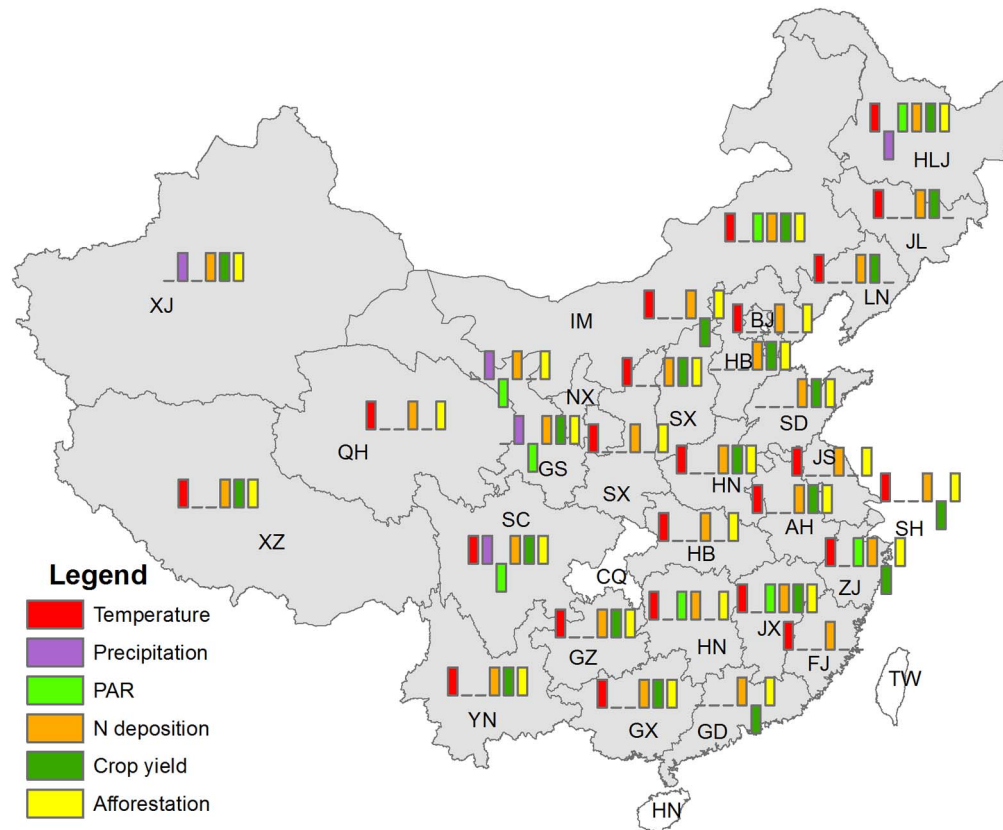
Fig. 6. Trends in annual mean temperature, annual precipitation, PAR, N deposition, crop yield, and afforestation at the provincial scale over the period 1982–2006. Upward bars indicate significant increasing trends, downward bars indicate decreasing trends, and no bars indicate insignificant trends.

ha). Similarly, the total usage of both chemical fertilizers and pesticides in agriculture had dramatically increased. The total fertilizer use increased by 226.5% from 1982 (1.51×10^7 tons) to 2006 (4.93×10^7 tons) and the total pesticide use increased by 100.0% from 1991 (0.77×10^6 tons) to 2006 (1.54×10^6 tons).

The changes in China's forest plantation area, total forest area, total plantation volume, and total forest volume are illustrated in Appendix: Fig. A2. The annual forest plantation area ranged between 1.0 and 9.2×10^6 ha per year since 1953, and was above 4.0×10^6 ha per year for most years. According to the seven national forest inventories, the total forest area had systematically increased from 1973 to 2008. From the first (1973–1976) to the seventh (2004–2008) inventory, the total forest area increased by 0.73×10^8 ha (59.8%). The total plantation volume elevated

from 1.64×10^8 m^3 in 1973–1976 to 19.61×10^8 m^3 in 2004–2008 with a 12-fold increase. Within this time domain, the total forest volume increased from 86.56×10^8 m^3 to 137.21×10^8 m^3 with an increase of 58.5%.

At the national scale, there was a significant relationship between annual NDVI and total crop yield over the period 1982–2006 (Appendix: Fig. A3; $y = 0.03x + 3.82$, $R^2 = 0.33$, $p < 0.01$). However, the detrending of the two time series eliminated the relationship between the two variables (Appendix: Fig. A3; $p = 0.17$). Similarly, at the national scale, there was a significant relationship between annual NDVI and the total forest plantation area over the period 1982–2006 (Appendix: Fig. A4; $y = 0.085x + 4.02$, $R^2 = 0.30$, $p < 0.01$). The detrending of the two time series also negated the relationship between detrended NDVI and detrended plantation area (Appendix:
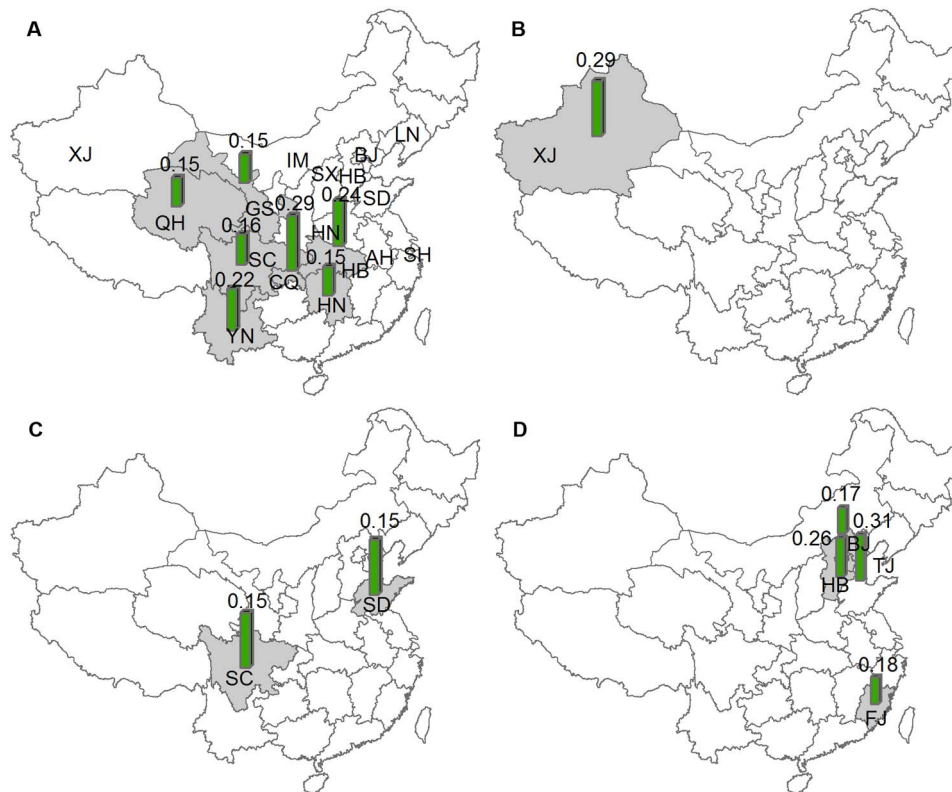
Fig. 7. Relationships of annual NDVI with annual mean temperature (A), annual precipitation (B), atmospheric CO_2 concentrations (C), and N deposition (D) at the provincial scale in China over the period 1982–2006. The shaded areas stand for provinces (municipalities, autonomous regions) with significant relationships between NDVI and temperature (or precipitation, atmospheric CO_2 concentrations, N deposition). The numbers stand for the R^2 values. All the relationships are positive except the relationship between annual NDVI and N deposition for Fujian (FJ).

Fig. A4; $p = 0.49$).

At the provincial scale, crop yield exhibited an increasing trend for 17 provinces and a decreasing trend for three provinces (Beijing, Shanghai, Zhejiang); total forest plantation area exhibited an increasing trend for the majority of the provinces (Fig. 6). The relationship between detrended NDVI and detrended crop yield varied by province (Fig. 8). Detrended NDVI was correlated with detrended crop yield for seven provinces: Inner Mongolia, Heilongjiang, Jilin, Liaoning, Shanxi, Ningxia, and Gansu, and all these provinces exhibited positive correlations. Among the 11 provinces with significant increases in NDVI (Fig. 3), three of them exhibited significant relationships between annual NDVI and total crop yield: Inner Mongolia, Liaoning, and Shanxi (Fig. 8). We also examined

the relationship between detrended annual NDVI and detrended total forest plantation area at the provincial scale, and there was no significant relationship between these two variables for any province.

Relative contributions of natural and human factors

We calculated the partial correlation for each of the environmental (temperature, precipitation, PAR, atmospheric CO_2 concentrations, and N deposition) and human (crop yield and afforestation) factors with annual NDVI at the national scale while controlling for other environmental and human factors. The partial R^2 values and the associated p values are summarized in Table 1. At the national scale, temperature made the greatest contribution to annual NDVI; afforestation made
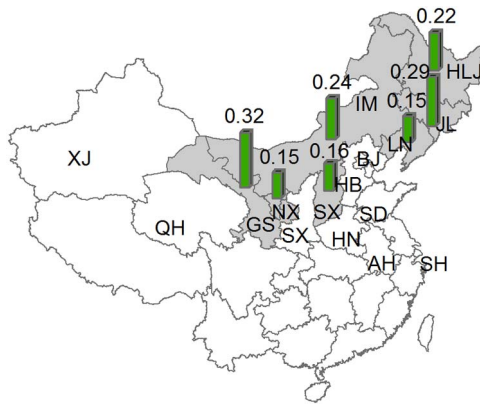
Fig. 8. Relationship between annual NDVI and crop yield at the provincial scale in China over the period 1982–2006. The numbers stand for the R^2 values. The shaded areas stand for provinces (municipalities, autonomous regions) with significant relationships between annual NDVI and crop yield.

moderate contribution to increased NDVI; crop yield made a minor contribution. Precipitation and PAR were statistically significant but their partial R^2 values were nearly 0. Atmospheric CO_2 concentrations and N deposition were not statistically significant.

We also calculated the partial correlation for each of the environmental and human factors with annual NDVI at the provincial scale while controlling for other factors (Fig. 9). A total of 23 provinces had partial $R^2 \geq 0.14$ for at least one factor. Temperature and precipitation exhibited partial $R^2 \geq 0.14$ for six provinces each, with partial R^2 values ranging from 0.14 to 0.18 and from 0.14 to 0.40, respectively. Atmospheric CO_2 concentrations, N deposition, and afforestation had partial $R^2 \geq 0.14$ for 4 provinces each. PAR and crop yield exhibited partial $R^2 \geq 0.14$ for 10 and 11 provinces, respectively. Crop yield had relatively high partial R^2 values with most values ranging from 0.25 to 0.49. Three or more of the environmental and human factors all exhibited

$R^2 \geq 0.14$ for seven provinces: Xinjiang (temperature + precipitation + afforestation), Beijing (precipitation + PAR + CO_2), Tianjin (CO_2 + N deposition + crop yield), Hebei (CO_2 + N deposition + crop yield + afforestation), Shandong (PAR + CO_2 + crop yield), Anhui (temperature + precipitation + PAR + N deposition), and Hunan (PAR + crop yield + afforestation).

DISCUSSION

Effects of natural factors on vegetation productivity

The overall increasing trend in vegetation productivity for China over the period 1982–2006 was generally consistent with previous NDVI-based studies (Xiao and Moody 2005, Park and Sohn 2010). Several studies showed that vegetation productivity exhibited increasing trends in China at the national scale (Xiao and Moody 2004a, Park and Sohn 2010), and some studies showed increasing trends in different parts of the country such as northwestern China (Ma et al. 2003, Xiao et al. 2013a), Loess Plateau (Xiao 2014), and Inner Mongolia (Brogaard et al. 2005). The increases in vegetation productivity inferred from NDVI were also generally consistent with results based on other approaches. For example, the analyses of national forest inventories and crop yield statistics showed that the total forest biomass carbon stocks and cropland NPP increased nationally during the 1980s and 1990s (Fang et al. 2001, Huang et al. 2007). Modeling studies have also indicated that the NPP of China's terrestrial ecosystems increased during the two decades (Cao et al. 2003, Wang et al. 2007).

At the national scale, air temperature was the leading climatic factor driving the increases in vegetation productivity. Previous studies showed similar findings (Zhou et al. 2001, Xiao and Moody 2005, Xiao et al. 2013a). Elevated air temperature can advance the leaf-out (or green-

Table 1. Partial correlation coefficients, R^2, and p-values of the environmental and human factors with annual NDVI at the national scale for China over the period 1982–2006.

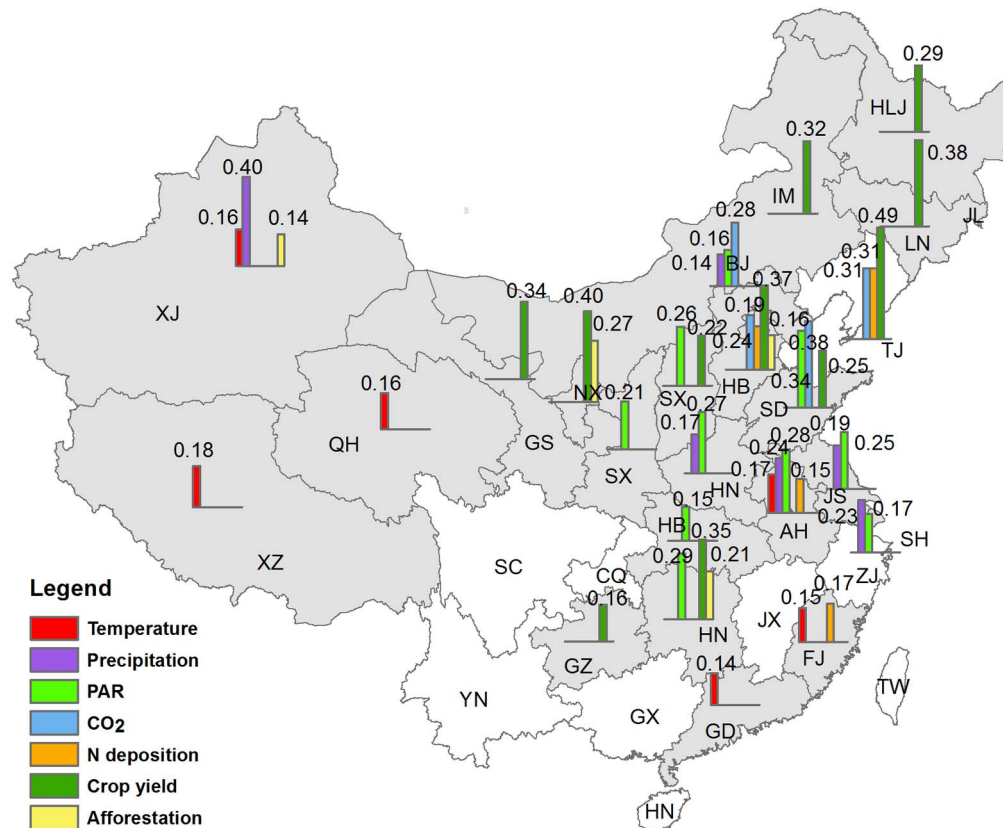| Statistics	Temperature	Precipitation	PAR	CO_2	N deposition	Crop yield	Afforestation
R	0.61	−0.09	−0.01	0.13	0.11	0.40	0.50
R^2	0.37	0.01	0.00	0.02	0.01	0.16	0.25
p-value	<0.01	<0.01	<0.001	0.58	0.65	0.07	0.01

Fig. 9. Partial R^2 of annual mean temperature, annual precipitation, PAR, atmospheric CO_2 concentrations, N deposition, crop yield, and afforestation with annual NDVI at the provincial scale in China over the period 1982–2006. All time series were detrended prior to correlation analysis. The numbers stand for the R^2 values. The shaded areas are provinces (municipalities, autonomous regions) with significant relationships between NDVI and at least one factor.

up) date and/or delay the senescence date, thereby lengthening the growing season in China (Song et al. 2010), and a longer growing season can in turn increase annual GPP and NPP (Zhang et al. 2008). A recent synthesis study based on eddy covariance flux observations across China demonstrated that the growing season length is one of the key factors controlling the spatial patterns of carbon and water fluxes for China's terrestrial ecosystems (Xiao et al. 2013b). At the provincial scale, however, air temperature only made a significant contribution to the increases of NDVI for a very limited number of provinces while controlling for other factors. At the national scale, annual precipitation exhibited a downward trend and made no significant contribution to the increases in vegetation produc-

tivity. Previous studies showed that the effects of precipitation on increases in vegetation productivity are likely limited to certain water-limited areas (Dan et al. 2007, Yan et al. 2009). However, our results showed that precipitation not only enhanced vegetation productivity in Xinjiang, a semi-arid and arid region, but also contributed to the increases in NDVI in humid provinces in eastern China while controlling for other factors likely because the increase in precipitation reduced the duration of drought over the growing season.

PAR alone was not correlated with NDVI at both national and provincial scales; while controlling for other factors, PAR was significantly correlated with NDVI for 10 provinces in the eastern half the country. PAR did not significant-

ly increase in most of these provinces where annual average surface-level PM2.5 concentrations were relatively high (de Sherbinin et al. 2014). Diffuse radiation exhibited an increasing trend in China (Ren et al. 2013) likely due to air pollution and the increase in aerosols (PM2.5). Diffuse radiation can result in higher light use efficiency by plant canopies and therefore have advantages over direct radiation (Gu et al. 2002). The increase in diffuse radiation is likely responsible for the enhancement effects of PAR on plant growth at the provincial scale. Atmospheric CO_2 concentrations and N deposition made no significant contribution to the increases in vegetation productivity at the national scale, while they significantly contributed to the increases in vegetation productivity for several provinces in northern, eastern, and southeastern China while controlling for other factors. Rising atmospheric CO_2 concentrations can enhance vegetation productivity locally or regionally. For example, the Free-air CO_2 enrichment (FACE) experiments showed that elevated atmospheric CO_2 enhanced photosynthesis, and trees were more responsive than other plant functional types (Ainsworth and Long 2005). A previous modeling study showed that rising atmospheric CO_2 made a significant contribution to the increase in carbon storage in China (Tian et al. 2011). The discrepancy between our results and these previous studies can be partly attributed to the differences in the spatial scales and to the fact that our results showed the effects of atmospheric CO_2 on GPP as approximated by NDVI, while other studies examined net carbon uptake or carbon storage

The effects of N deposition on the carbon cycle at broad scales have been controversial (Nadelhoffer et al. 1999, Magnani et al. 2007). One of these two studies showed that N deposition made a minor contribution to the carbon sink (Nadelhoffer et al. 1999), while the other concluded that the forest carbon sink was overwhelmingly driven by N deposition (Magnani et al. 2007). Another recent modeling study showed that atmospheric CO_2 and N deposition enhanced China's land carbon sink for the period 1961–2005 (Tian et al. 2011). Our results showed that despite the widespread increase in N deposition in China, its enhancement effects on vegetation productivity at the provincial scale were limited to some regions with large increases in N deposition (Lu et al. 2012b).

Effects of human activities on vegetation productivity

Besides multiple environmental factors (climate change, atmospheric CO_2 concentrations, and N deposition), human activities including afforestation and agricultural management also increased productivity across the landscape. Afforestation and reforestation have been nationwide efforts in China since the early 1950s. More recently, the "Grain for Green" program launched in 1999 converted agricultural lands on steep slopes to forests and grasslands. According to the national forest inventories, the persistent, nationwide efforts on forest plantations led to the increase in total forest area by ~60%. China now has the largest area of forest plantations in the world. Afforestation has contributed to the increases in vegetation productivity inferred from NDVI. Previous studies showed that the conversions of farmlands to forests and grasslands have increased plant productivity as approximated by NDVI and enhanced vegetation index (EVI) (Chen et al. 2007, Li et al. 2011, Lu et al. 2012a, Xiao 2014) and enhanced NPP, biomass, and carbon sequestration (Wang et al. 2007, Su and Fu 2013, Liu et al. 2014). At the national scale, afforestation explained 25.5% of the variance in NDVI while controlling for other factors, although forest plantation alone was not significantly correlated with NDVI after detrending. At the provincial scale, afforestation contributed to the increases in NDVI for some provinces while controlling for other factors. Our results showed that forest plantations were partly responsible for the increases in vegetation productivity inferred from NDVI.

At the national scale, crop yield explained 15.8% of the variance in NDVI, although crop yield alone was not significantly correlated with NDVI after detrending. At the provincial scale, crop yield was significantly correlated with NDVI for most provinces with increasing NDVI. Agriculture is one of the most important sectors of the economy in China and tremendous efforts have been made to improve agricultural productivity. For example, China has built more than 80,000 reservoirs across the country since the foundation of the People's Republic of China in

1949 (Ministry of Water Resources of China 2013). The improvement of irrigation infrastructures led to the substantial increase in irrigated area, which has facilitated the development of agriculture and the growth of crop productivity (Li et al. 2011). Meanwhile, the application of chemical fertilizers and pesticides in agriculture has dramatically increased. Moreover, higher-yield crop types gradually replace lower-yield crop types. As a result, the crop yield per unit area increased by ~50% because of these improved management practices. Therefore, China's crop yield had considerably increased although the total cropland area declined due to urbanization and conversions of cropland to forests and other land uses. The analysis of crop yield statistics showed that the total cropland NPP increased in China (Huang et al. 2007). Our results show that elevated crop yield contributed to the increases in vegetation productivity at both national and provincial scales.

Relative contributions of natural and human factors

Although numerous studies have used satellite-derived NDVI to examine vegetation dynamics, most of these studies only analyzed the contribution of climate change (Zhou et al. 2001, Ichii et al. 2002, Xiao and Moody 2005). Few studies also examined the influence of rising atmospheric CO_2 concentrations (Tian et al. 2011) or N deposition (Mao et al. 2012) at regional scales. The relative effects of environmental factors and human activities remain unclear (Evans and Geerken 2004, Seaquist et al. 2009, Li et al. 2012). We assessed the relative effects of multiple environmental (climate change, rising atmospheric CO_2 concentrations, and N deposition) and human (improved agricultural practices and afforestation) factors on vegetation productivity in China. Our results showed that their effects varied by spatial scale. At the national scale, temperature was the leading driver, followed by afforestation and crop yield. Altogether, temperature, plantation area, and crop yield explained 78.1% of the variance in vegetation productivity as approximated by NDVI, indicating that the increasing productivity in China was mainly driven by elevated air temperature, afforestation, and improved agricultural management practices. At the national

scale, precipitation, PAR, rising atmospheric CO_2 concentrations, and N deposition played no significant role in enhancing productivity.

At the provincial scale, the effects of the environmental and human factors varied not only by province but also by factor for several reasons. First, the magnitude and direction of long-term trends in each factor varied with province. Second, different vegetation types may exhibit different responses to these natural and human factors, while the distribution of vegetation types substantially varied with province. Third, the importance of some factors, particularly crop yield and afforestation, varied across provinces. Although crop yield and afforestation exhibited increasing trends for many provinces, cropland and total forest plantation area may only account for small percentages of the vegetated area. Finally, the influences of these factors may cancel each other, complicating the assessment of their relative contributions to increases in vegetation productivity. Previous studies have examined the effects of one or more factors on vegetation productivity for different regions in China (Xiao and Moody 2004a, Dan et al. 2007, Yan et al. 2009, Tian et al. 2011), and taken together, these studies also showed that the influences of the controlling factors vary with space. Our results show that each factor explained a part of the variance in NDVI for some provinces, and the dynamics of NDVI for some provinces could be attributed to the combined effects of three or more factors. At the provincial scale, PAR was positively correlated with NDVI in more provinces than temperature or precipitation, indicating that PAR was the leading climatic factor at this scale; temperature and precipitation were equally important at the provincial scale. Crop yield was correlated with NDVI for more provinces than was temperature, precipitation, rising atmospheric CO_2 concentrations, N deposition, or afforestation at the provincial scale. Overall, crop yield and PAR significantly contributed to increased productivity for more provinces than other natural and human factors.

Our results showed that the effects of natural and human factors on vegetation productivity varied with spatial scale, and the dominant factors of increased vegetation productivity differed at the national and provincial scales.

Our results also indicated that it is important to remove the potential "spurious correlation." Moreover, assessing the partial correlation of each driving factor with NDVI while controlling for other driving factors can better quantify the true contribution of each factor to increases in vegetation productivity.

Challenges and limitations

Disentangling the relative effects of environmental and human factors on vegetation dynamics remains a challenge. First, these factors influence vegetation productivity at different spatial and temporal scales. Second, the increases in vegetation productivity at the national and provincial scales include both enhanced plant growth and increase in vegetation cover that are challenging to differentiate from each other at these scales, although their controlling factors are likely different. Third, detailed information on human activities is not as readily available as climate data. Fourth, the gridded information on land use change is typically too coarse to capture the types of land use conversions. Finally, the datasets on climate change and human activities are characterized by different spatial units and formats. Unlike climate data, which are typically point-based or gridded, agricultural and forestry statistics are typically based on administrative units (e.g., provinces) and provide no information on the exact magnitude and locations of the variables such as crop yield, fertilizer use, and forest plantations within those units.

Our statistical approach combined gridded satellite observations, climate data, atmospheric CO_2 concentrations, N deposition data, and provincial statistics on agriculture and forestry. This approach allowed us to examine the effects of environmental factors and human activities on the increases in vegetation productivity inferred from NDVI and to assess the relative contribution of these factors from the provincial to the national scale. Despite its effectiveness, our approach has several limitations. First, NDVI is a proxy for GPP and cannot measure NPP or NEP well, while the translation from GPP to NPP (and/or NEP) is important for carbon cycling studies (Huang et al. 2007, Xiao et al. 2009). Second, the attribution of NDVI increases to enhanced plant growth or increase in vegetation cover remains challenging. Third, our statistical

approach lacks mechanistic understanding of ecosystem function and processes. Finally, each province typically spans a large land area, and the effects of the climatic and human factors could cancel out over space and mask the variability of productivity within each province. Spatially explicit information on agricultural management and afforestation that is more detailed than the provincial scale is essential for better understanding of the responses of increased vegetation productivity to agricultural management and afforestation.

Ecosystem models have also been used to assess the effects of climate change and human activity in China (Tian et al. 2011, Mu et al. 2013). Ecosystem models can provide a mechanistic understanding of ecosystem function and processes and conduct "experiments" to test the relative effects of different drivers on plant productivity (Xiao et al. 2009, Tian et al. 2011). Ecosystem models can explicitly the effects of climate change (Zhang et al. 2014b, Huang et al. 2015, Thorn et al. 2015) and disturbance (Wang et al. 2014, Zhang et al. 2015). Despite their complexity and mechanistic nature, ecosystem models can lead to substantial uncertainty in plant productivity (Schaefer et al. 2012, Raczka et al. 2013, Xiao et al. 2014). Remote sensing proxies (e.g., NDVI) and data-driven, statistical approaches can have similar or slightly higher performance than process-based ecosystem models for simulating GPP (Raczka et al. 2013, Verma et al. 2014). In addition, it is still a challenge for process-based ecosystem models to simulate the effects of human activities because of the lack of spatially explicit, gridded data on agricultural and forest management practices. Further efforts are needed to further disentangle the effects of climate change and human activity. Empirical and process-based approaches are complementary approaches, and can provide independent, alternative perspectives on the attribution of increased vegetation productivity. The future intercomparison of these different methods can also lead to improvement to both approaches.

Conclusions

We assessed the effects of multiple natural and human factors on vegetation productivity as approximated by NDVI in China. The contribu-

tions of these factors to increases in vegetation productivity varied with spatial scale. At the national scale, elevated air temperature made the greatest contribution (36.8%) to increases in vegetation productivity, followed by afforestation (25.5%) and crop yield (15.8%); the remaining factors made no significant contribution. Altogether, temperature, afforestation, and crop yield explained 78.1% of the variance in NDVI. At the provincial scale, crop yield and PAR were correlated with NDVI for more provinces than other factors, indicating that elevated crop yield resulting from improved agricultural management practices and increasing diffuse radiation associated with air pollution and high concentrations of aerosols were more important than other factors in increasing vegetation productivity. Each factor explained a part of the variance in NDVI for some provinces, and the increases in NDVI for many provinces could be attributed to the combined effects of multiple factors. The true influences of the natural and human factors can be obscured by the correlation among these variables, and it is essential to examine the contribution of each factor while controlling for other factors.

Climate is expected to continue to change in China during the remainder of the 21st century (IPCC 2013). Meanwhile, human activities such as improved agricultural management practices, forest plantations, urbanization, and policy-driven land use conversions and ecological restoration are also expected to rapidly occur. These projected changes will likely have larger influences on vegetation productivity in China. Future efforts are needed to further disentangle the effects of environmental factors and human activities by improving empirical and modeling approaches and developing more fine-scaled and more accurate datasets on vegetation dynamics and the associated environmental and human factors.

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SUPPLEMENTAL MATERIAL

ECOLOGICAL ARCHIVES

The Appendix is available online: http://dx.doi.org/10.1890/ES14-00394.1.sm