Positive Associations of Vegetation with Temperature over the Alpine Grasslands in the Western Tibetan Plateau during May

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(Manuscript received 13 July 2021, in final form 28 January 2022)

ABSTRACT: The Tibetan Plateau (TP) has undergone extreme changes in climatic and land surface conditions that are due to a warming climate and land-cover changes. We examined the change in vegetation dynamics from 1982 to 2015 and explored the associations of vegetation with atmospheric variables over the alpine grasslands in the western TP during May as an early growing season. The linear regression analysis of area-averaged normalized difference vegetation index (NDVI) over the western TP in May demonstrated a 7.5% decrease of NDVI during the period from 1982 to 2015, an increase of NDVI by 11.3% from 1982 to 1998, and a decrease of NDVI by 14.5% from 1999 to 2015. The significantly changed NDVI in the western TP could result in the substantial changes in surface energy balances as shown in the surface climatic variables of albedo, net solar radiation, sensible heat flux, latent heat fluxes, and 2-m temperature. The land and atmosphere associations were not confined to the surface but also extended into the upper-level atmosphere up to the 300-hPa level as indicated by the significant positive associations between NDVI and temperatures in both air temperature and equivalent temperature, resulting in more than a 1-K increase with NDVI. Therefore, we concluded that the increasing or decreasing vegetation cover in the western TP during May can respectively increase or decrease the temperatures near the surface and upper atmosphere through a positive physical linkage among the vegetation cover, surface energy fluxes, and temperatures. The positive energy processes of vegetation with temperature could further amplify the variations of temperature and thus water availability.

SIGNIFICANCE STATEMENT: The Tibetan Plateau (TP) is an important landmass that plays a significant role in both regional and global climates. This study aims to examine the vegetation change in the TP during May as an early growing season to examine the changes in the near-surface and upper-level climatic conditions associated with vegetation change and to identify the plausible physical processes of the vegetation effects on atmosphere. The satellite-derived vegetation index showed a 7.5% decrease from 1982 to 2015 in the western TP during May. This study identified the positive associations of vegetation activity with temperature and proposed a positive energy process for land–atmosphere interactions over the alpine grasslands in the western region of TP during the transition period from winter to spring.

KEYWORDS: Atmosphere; Asia; Atmosphere–land interaction; Heat budgets/fluxes; Sensible heating; Surface temperature; Temperature; Vegetation; Vegetation–atmosphere interactions

1. Introduction

The long-term atmospheric conditions exert a significant impact on the terrestrial ecosystem. Similarly, the terrestrial ecosystem influences climate through vegetation cover and soils and mediates energy and water balances at the land surface (Foley et al. 2003). Vegetation plays a vital role in carbon exchange between the land and atmosphere, making it a key component of the terrestrial ecosystem (Cleland et al. 2007; Liu et al. 2015). Changes in vegetation can impact not only the carbon cycle but energy and water cycles and have significant and broad implications on hydrology and climatology (Nemani 2003; Zhang et al. 2016). Any alteration of the vegetation dynamic, therefore, can alter the exchange of heat and moisture properties between the land and atmosphere (Lee et al. 2009; Mahmood et al. 2014; Niyogi et al. 2010; Pielke 2005; Snyder 2010).

The impact of land-cover change on climate have been extensively studied using observed as well as modeled data (Pielke et al. 2011; Mahmood et al. 2014). Numerous studies have shown that even a small change in land surface conditions can affect local as well as regional climates (e.g., Cao et al. 2015; Chase et al. 1996; Foley et al. 2005; Pielke 2005). Understanding and modeling land and atmosphere coupling relating to land-cover change and regional climate continues to be a major research need in land–atmosphere interaction studies and studying these processes is inherently challenging and complex (e.g., Santanello et al. 2018). In an early study,
Charney (1975) first presented a theory of how a reduction in vegetation might feedback to produce a decrease in rainfall through land–atmosphere interactions. Changes in land cover can modify surface roughness and impact heat and moisture exchange between the land surface and atmosphere and eventually can modulate temperature and precipitation (Boyaj et al. 2020; Chen et al. 2020; Pielke et al. 2016; Pielke and Niyogi 2009; Ahmad et al. 2020). For instance, Boyaj et al. (2020) examined the impact of urbanization on rainfall in peninsular India and observed that increased surface temperatures, sensible heat flux, planetary boundary layer height, water vapor mixing ratio and convective available potential energy, resulting in the increased rainfall. Chen et al. (2020) studied land-use/land-cover change impact on hydroclimate using the Weather Research and Forecasting (WRF) Model simulations and identified the intensified precipitation over the downwind areas of urban and built-up lands in central Taiwan. Further, Pielke et al. (2016) revealed that changes in land cover impact climate at local and regional scales and can produce significant spatial variation in climate-system fluxes that can influence weather pattern of distant through teleconnections. Over the past several centuries, the globe has witnessed the unprecedented changes in the pace, magnitude, and spatial extent of changes in the land surface, which could result in changes in surface energy and water budgets and thus regional as well as global climates. As a result, changes in land variables and their impacts on land–atmosphere interactions, and ultimately on climate, have been investigated throughout the world at various spatial and temporal scales (Bonan 2008).

Land–atmosphere interactions encompass two key biogeo-physical processes that have significant implications on the thermal, hydrological, and aerodynamical characteristics of the planetary boundary layer (Mahmood et al. 2014). The first process constitutes energy feedback through albedo and the partitioning of radiation into sensible and latent heat fluxes (Pielke et al. 1998). Land surface characteristics, such as soil and vegetation properties, can alter the exchange of heat and moisture between the land and atmosphere through energy, momentum, and moisture exchanges (Foley et al. 2005; Niyogi et al. 2010). Therefore, any perturbation in land surface characteristics due to urbanization, agriculture intensification, grassland degradation, deforestation, or afforestation can result in shifting the albedo and turbulent heat flux regimes. For instance, the removal of vegetation may increase albedo, resulting in less energy available for transferring to the lower atmosphere and a disturbance of the balance between sensible heat flux and latent heat flux. This further induces atmospheric subsidence thereby reducing rainfall (Charney 1975). This results in a positive feedback loop, as the drier conditions cannot sustain the vegetation. These perturbations can further reduce vegetation cover and increase albedo, resulting in a decrease in precipitation, drier conditions, and further reduction through the positive feedback (Charney 1975; Lee et al. 2015).

The second feedback mechanism, moisture feedback, occurs through a change in moisture content driven by evapotranspiration. Such processes have been described and quantified in several prior studies (Douglas et al. 2006, 2009; Koster 2004; Lee et al. 2009). Soil moisture plays a crucial role in land–atmosphere interactions and modulation of the water cycle (Bao et al. 2010; Betts et al. 1996) through the modification of latent heat flux and atmospheric moisture flux convergence (Foley et al. 2005; Sud et al. 1996). The water availability in the soil regulates evapotranspiration, which in turn modulates air temperature and humidity in the lower atmosphere (Erdenebat and Sato 2018). For instance, the elevated soil moisture inducing greater evaporation provides an increased moisture source for enhanced precipitation, which further increases soil moisture (Dirmeyer et al. 2006; Mehl 2004). At the same time, soil moisture can also enhance cooling effects through the partitioning of radiative heat flux into latent heat, inducing negative effect on temperature. However, the preexisting environmental conditions, which vary over spatial scales, determine the feedback mechanism. For instance, Yang et al. (2018) observed a predominant positive soil–precipitation feedback over land surfaces and a contrasting negative feedback across dry and wet regions. The interaction between soil moisture and precipitation is often complex and involves confounding factors (Tuttle and Salvucci 2016).

Interrelations of energy and moisture feedbacks govern the land–atmosphere interactions and vary among different land-cover types. For example, conversion of natural vegetation to croplands can increase or decrease temperature depending on whether conversion occurs in tropical, temperate, or boreal areas and can increase or decrease humidity depending on the type of natural vegetation replaced and the type of crops established (Bounoua et al. 2002). These changes can impact the thermodynamic conditions and the general circulation of air masses far from the original surface forcing (Snyder et al. 2004). A review of dominant forcing in three different vegetation type, tropical forests, boreal forests, and temperate forests, was proposed by Bonan (2008). According to Bonan’s study, tropical forests are dominated by moisture (cooling) feedback, whereas boreal forests are dominated by energy (warming) feedback due to low surface albedo that leads to the absorption of incoming solar radiation. However, the land and atmosphere feedback in the temperate region, especially over the highland plateau, is still complex and currently undecided.

The Tibetan Plateau (TP), with its unique topographical and physiographical characteristics, is an important landmass that plays a significant role in both regional and global climate (Wu et al. 2012). The mechanical and thermodynamic forcing of the TP is crucial in influencing the regional climate and the Asian monsoon systems (Duan et al. 2012). Because of its location and elevation, the TP has a significant and globally unique impact on the atmosphere (e.g., Wu et al. 2016). The complex interactions of land surface processes and conditions, linked to vegetation, surface energy balance, snow cover, soil moisture, and frozen soil, with the atmosphere play an important role in modulating the local, regional, and global climates (Gao et al. 2016). Therefore, the land–atmosphere interactions over the TP can influence the large-scale atmospheric circulations not only in Asia but across the entire globe by...
absorbing a large amount of incoming solar radiation with marked seasonal variations (Duan et al. 2011, 2012). The complicated boundary layer processes resulting from differences in land surface variables over the TP could lead to frequent rainfall and flooding in eastern China during summer (Tao and Ding 1981). The strong surface heating over the TP is also a fundamental factor in producing interannual variability of the East Asian summer monsoon (EASM), and numerous studies have observed a strong correlation between winter TP snow cover and the EASM (Wu et al. 2016; Zhang et al. 2004).

In recent decades, the environmental systems of the TP have undergone extreme changes due to climatic change and variability (Yang et al. 2014). The plateau has warmed significantly, and the surface temperature has increased by 1.8°C since the 1980s, which has had a significant impact on the transfer of heat, moisture, and momentum from the ground to the atmosphere (Yang et al. 2014), which could further exaggerate the changing climates over the TP region through the land–atmosphere feedback mechanisms. Additionally, anthropogenic activities such as stocking of livestock, land-cover change, over grazing, urbanization, highway construction, deforestation and desertification, and unsustainable land management practices have greatly increased over the TP (Cui and Graf 2009; Harris 2010). As a result, grasslands have undergone rapid degradation since the 1980s due to the dual effect of climate change and human activities (Harris 2010; Cao et al. 2019). Babel et al. (2014) indicated that there is reduction in transpiration and increase in evaporation due to pasture degradation over the TP. The study conducted by Wu et al. (2015) revealed that there was increase in near-surface temperature because of grassland degradation in Inner Mongolia. Cao et al. (2015) suggested increase in winter temperature and subsequent decrease in summer temperature through the modification of surface energy budge due to land-cover changes from croplands to grasslands and grasslands to barren land in the agropastoral transitional zone of North China. On the other hand, Shen et al. (2015) showed an evapotranspiration induced cooling effect due to increase in vegetation activity in the growing season from May to September over the TP, resulting in negative feedback between climate and vegetation. The TP soil temperature and number of thawing days have also significantly increased from 1980 to 2005, resulting in drying of soil and a reduction in precipitation (Xue et al. 2009). These changes can further modify the ecosystem and consequently affect the regional, and potentially Asian, climates (Cao et al. 2018; Wu et al. 2016), which could threaten billions of people’s lives downstream (Hua and Wang 2018; Wang 2016).

Gaps still exist in our knowledge of land–atmosphere interactions in the TP, and their impacts on the weather and climate around the TP, however, which makes it difficult to understand the complete energy and water cycles over the TP. The previous studies have focused on the variabilities of either atmospheric conditions (e.g., Jin et al. 2011; Yan et al. 2020; Zhao et al. 2020) or land surface conditions (e.g., Ma et al. 2020; Sun et al. 2017; Zhong et al. 2019). However, relatively less studies examined the integrated associations between land surface and atmosphere over the highland plateau (e.g., Babel et al. 2014; Liu et al. 2020; Shen et al. 2015). Additionally, there are only a few studies on the associations between climatic and land surface conditions over the alpine steppe grasslands in the western TP, as compared with the eastern TP (Gong et al. 2017; Zhang et al. 2011). Therefore, this study aimed to examine the changes in vegetation dynamics from 1982 to 2015 and to explore its effect on vegetation and climate interactions over the alpine grasslands in the western TP during May as an early growing season. The growing season of grasslands in the TP starts in early May and ends in late September (Wang et al. 2016; Gao and Liu 2013).

The normalized difference vegetation index (NDVI) has been widely used as an indicator of vegetative index due to its capability to measure energy absorption and photosynthesis activity and help to acquire vegetation change information (Tucker and Sellers 1986; Xu et al. 2012; Zhu et al. 2013). The NDVI products derived from the Global Inventory Modeling and Mapping Studies (GIMMS) of the Advanced Very High Resolution Radiometer (AVHRR) developed by the National Oceanic and Atmospheric Administration (NOAA) has been excessively used in climate study (e.g., Ibrahim et al. 2015; Zhu et al. 2013; Lee and He 2018; Shull and Lee 2019; He et al. 2018; Lee et al. 2008). Relative to its previous version (i.e., NDVIg), the AVHRR/2 to AVHRR/3 NDVI bias has been attenuated in the third-generation NDVI3g, which greatly enhances the possibility to detect climate-related nonstationary seasonal and interannual variabilities (Pinzon and Tucker 2014). Thus, the objectives of this study are, to examine the spatiotemporal distribution of vegetation in the TP during an early growing season using the satellite-based vegetation index NDVI from GIMMS3g, to examine the changes in the near-surface and upper-level climatic conditions associated with the vegetation change in May, and to identify the plausible physical processes of the vegetation effects on climate in the western TP to depict the land and atmosphere interactions over the alpine grasslands.

2. Data and methods

a. Study area

The Tibetan Plateau is the largest continental plateau on Earth and is therefore known as the “roof of the world.” The TP is situated in the central and eastern Asia (Fig. 1) with an average elevation of 4000 m (Huang et al. 2016; Kuang and Jiao 2016). It is a sensitive and ecologically fragile area that plays a vital role in global climate conditions and change (Gao et al. 2016; Liu and Chen 2000). Because of its complex topography and sensitive climate, it is regarded as one of the hot spots in climate change study and served as indicator area for climate change (Peng et al. 2014; Yao et al. 2012). The mean annual temperature of the plateau varies from −5°C to 10°C (Huang et al. 2016) with mean annual precipitation of approximately 100–1000 mm with high spatial variability from high in the southeast to low in the northwest (Wang et al. 2015). The climate is warm and humid in the southeast and cold and arid in the northwest, with marked wet and dry
The TP monsoon climate is mainly controlled and influenced by a complex interaction of the Indian monsoon, the westerlies, and to a lesser extent by the East Asian monsoon (Yao et al. 2012). The summer monsoon accounts for 60%–70% of the total annual precipitation in the TP, whereas winter accounts for only 10% (Bookhagen and Burbank 2010; Tong et al. 2014) and the snow accounts for a large portion of precipitation on the TP (Maussion et al. 2014).

There is spatial difference in vegetation types both horizontally and vertically due to difference in hydrothermal environment in the TP (Huang et al. 2019). The high altitudes are cold, whereas low altitudes are hot and humid in the TP. Therefore, land cover on the TP varied greatly and included forests, grasslands, permanent snow and ice, croplands, and bare land (e.g., Cheng et al. 2018; Wang et al. 2020; Zhou et al. 2020), with grasslands as a prevailing type. The deciduous, evergreen, and mixed forests were mainly in the eastern and southeastern region of the TP (Huang et al. 2019). Around 70% of the TP was covered by permafrost with moisture content, and thus supported more vegetation growth in comparison with seasonally frozen soil regions (Wang et al. 2017). The alpine steppe and meadow were the dominant grassland type covering around 50%–60% of the area, making alpine grasslands the principal vegetation of the TP (e.g., Liu et al. 2017; Wang et al. 2015; Wei et al. 2019). The vast grassland ecosystems of the TP have been used by Tibetans for grazing and sustaining their pastoral livelihood and culture for thousands of years (Wei et al. 2019). The western TP mainly consists of alpine steppe along with alpine meadows and deserts as shown in Fig. 1, based on International Vegetation Classification grassland types and the map of Terrestrial Ecoregions of the World, as suggested by Dixon et al. (2014).

The study area of this study was mainly alpine steppe areas in the western TP, as indicated with the dotted box in Fig. 1 (i.e., 30°–35°N and 80°–90°E), in which rare study focused on the associations between vegetation and climate. According to vegetation map of the TP (Chen et al. 2015), the study area was in the transition zone of the alpine meadows to alpine steppe. We examined the vegetation dynamics during the month of May as our study period because May was the start of the growing season as well as the premonsoon season. The climatic condition over the TP in the premonsoon season has tremendous implications on the Asian monsoons (Zhang et al. 2011). Therefore, the vegetation dynamics in May is of great significance not only for local climate but also for the regional climate. Also, the linear regression trend of May NDVI over the TP revealed overall a significant decreasing trend of NDVI from 1982 to 2015 with a decrease in the NDVI by 7.5% for the 34 years (see Fig. 4). Thus, the change of vegetation dynamic in May from 1982 to 2015 was selected to study the association of vegetation...
variability with the surface fluxes and upper atmosphere over the alpine grasslands in the western TP.

b. Data sources

1) Vegetation Data

The remotely sensed NDVI has been extensively used to quantitatively assess vegetation dynamics and health (Eckert et al. 2015; Huang et al. 2019). The NDVI was a key indicator of vegetation cover and structure, photosynthetic activity, and other vegetation traits (Tucker and Sellers 1986). The index was a good indicator of net primary productivity, vegetation coverage, leaf area index, and biomass. Therefore, any changes in NDVI reflect an increasing or decreasing in vegetation coverage (Morawitz et al. 2006). NDVI has been extensively used in climate and atmosphere interaction studies in Asia (e.g., Lee and He 2018; He et al. 2018). The NDVI computed from the red (RED) and near-infrared (NIR) ratio of vegetation reflectance in the electromagnetic spectrum [i.e., NDVI = (NIR – RED)/(NIR + RED)] (Prince et al. 2009) and its values range from −1.0 to +1.0, with positive values representing high greenness or photosynthetic activity and negative values representing snow or no vegetation (Gillespie et al. 2019; Tucker et al. 2005).

In this study we used the GIMMS NDVI3g from 1982 to 2015, with a pixel scale of 1/128 (Tucker et al. 2005; Pinzon and Tucker 2014). Temporally, the NDVI3g comprised bimonthly (15 days) composites generated using the maximum value composite (Holben 1986). It is a source of the longest time series of global imagery available for land-cover change, vegetation phenology, and dynamic studies (Peng et al. 2012; Wu et al. 2015). The GIMMS NDVI3g has been shown to effectively remove artifacts caused by changes in factors such as orbital drift, cloud cover, volcanic aerosols, and solar zenith angle (Pinzon and Tucker 2014). The dataset used for this study was obtained from the Global Land Cover Facility at the University of Maryland, which comprises bimonthly values for the time span from July 1981 to December 2015 at a grid increment of 0.08° with WGS84 datum. Figure 2 shows annual and May climatology of the NDVI distribution in the TP based on the GIMMS NDVI3g dataset from 1982 to 2015. The NDVI value in the study area of western TP during May is up to 0.2 with increasing from northwest to southeast (Fig. 2b).

2) Atmospheric Data

We used reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF, hereinafter ERA5; Hersbach et al. 2020). ERA5 is the fifth generation of ECMWF atmospheric reanalysis of the global climate. It is the latest data from ECMWF with a horizontal grid increment of 0.25° × 0.25° on a regular latitude–longitude grid stratified by 37 pressure levels for atmospheric variables (i.e., ERA5) and 0.1° × 0.1° for land variables (i.e., ERA5-Land). The data were available from 1979 for ERA5 and from 1981 for ERA5-Land. To be consistent with the GIMMS NDVI3g, data from 1982 to 2015 were used. The land variables from ERA5-Land were used to investigate the effects of vegetation dynamics on near-surface climate using albedo, net solar radiation, sensible heat flux, latent heat flux, 2-m air temperature (K), and mean sea level pressure. The effects of vegetation dynamics on the upper atmosphere were examined with ERA5 using temperatures (K) and specific humidity (kg kg⁻¹) from 500- to 100-hPa levels. The units of surface net solar radiation, sensible heat flux and latent heat flux, which were in joules per meter squared, and mean sea level pressure, which was in pascals, were converted to watts per meter squared and hectopascals, respectively. We calculated the annual means of equivalent temperature $T_E$ using the ERA5 variables of air temperature (K) and specific humidity (kg kg⁻¹) from 500- to 100-hPa levels. The $T_E$ includes both dry and moist heat contents, which correspond to moist enthalpy, and thus provides a more complete measure of changes in the energy budget (Davey et al. 2006; Fall et al. 2010; Younger et al. 2019; Zhang et al. 2019). In this study, we calculated $T_E$ using (Zhang et al. 2019)

$$T_E = T + T_M,$$

where $T$ is the air temperature and $T_M$ is the moisture content of the air temperature, which is given by

$$T_M = L*v/C_p;$$

FIG. 2. (a) Annual and (b) May NDVI climatology over the TP using the GIMMS NDVI3g datasets from 1982 to 2015. The study area is indicated with the dash-outlined rectangle.
In Eq. (2), \( L_v \) is the latent heat of vaporization \((2.5 \times 10^6 \text{ J kg}^{-1})\), \( q \) is the specific humidity \((\text{kg kg}^{-1})\), and \( C_p \) is the specific heat of air \((1005 \text{ J kg}^{-1} \text{ K}^{-1})\). Therefore, we can calculate the \( T_e \) by using the following expression:

\[
T_e = T + L_vq/C_p. \tag{3}
\]

Further, to evaluate the performance of ERA5, we selected observed data from 110 meteorological stations from the China Meteorological Data Service Center from 1982 to 2013 (Meng et al. 2014). We also chose additional reanalysis data, including National Centers for Environmental Prediction Reanalysis-2 (NCEP-2) (Mesinger et al. 2006), Japanese 55-year Reanalysis (JRA-55) (Kobayashi et al. 2015), and Climate Research Unit (CRU; Harris et al. 2020) global gridded atmospheric data, to assess their performance against the weather-station data.

c. Statistical methods

1) COMPARISONS OF GLOBAL GRIDDED DATA WITH WEATHER-STATION DATA

While the meteorological station data could provide most accurate climatic information in the TP, they have limited spatial coverage and their coverage varies over time. In addition, because of the complex terrain and extreme environmental conditions, most surface observational stations were situated in the lower parts of the eastern and central TP, often in valley locations. Global gridded atmospheric data, including reanalysis data, provide a promising alternative that is homogeneous in both time and space. The reanalysis datasets are produced using coupled numerical models in which the past and present state of our climate system is represented by incorporating a large amount of observation data (Martens et al. 2020). Additionally, reanalysis datasets are temporally and spatially homogeneous data (Colston et al. 2018). Previous studies have suggested that reanalysis data is more appropriate to use in the TP due to lack of sufficient observational data that hinders our understanding of the interactions between land surface conditions with the atmosphere (Mazhar et al. 2021; Ma et al. 2020). In the TP, the reanalysis dataset has been widely used to study climate variability because of its spatial and temporal homogeneity (Shi and Liang 2014). In this study, we compared three reanalysis data (ERA5, NCEP-2, and JRA-55) and CRU with Chinese weather-station data to select the best gridded dataset among the four datasets to be used in the TP climate study. We selected daily temperature from 110 Chinese meteorological ground stations in the TP. The data was then converted to monthly data. The temporal correlations analysis of the global gridded data with the Chinese meteorological data at the 110 weather stations were performed for annual and May mean temperatures using Pearson correlation. Nonparametric correlation analysis was also assessed by using Kendall rank and Spearman’s rank correlations. Kendall and Spearman’s rank correlations were used to measure the degree of association between two variables without any assumptions about the distribution of the data (Lehmann 1975).

2) LINEAR REGRESSION ANALYSIS

Linear regression analysis is a statistical method used to analyze the functional relationship between two or more variables (Freund et al. 2006). Specifically, the relationship between the two variables is determined by evaluating the degree to which one variable can be predicted or explained by the others. We performed linear regression trend analysis to determine the spatial characteristic of vegetation (i.e., NDVI in this study) over the plateau. We showed the linear regression trends of May, as an early growing season, over the three periods of 1982–98, 1999–2015, and 1982–2015, respectively. We also estimated the NDVI change in percent over the three different periods, respectively. The slope of the regression line was utilized to determine how NDVI changed over time. Its significance was tested by a Student’s \( t \) test at the 10% level.

3) DETRENDED CORRELATION ANALYSIS

The correlation analysis was performed to examine the associations between the climate variables and the time series of May NDVI, area averaged only over the region with significantly changed NDVI in the western TP. Pearson’s correlation coefficient \((r)\) was calculated at each grid point for all climatic variables to quantify the strength and direction of relationship with the alpine vegetation. The climatic variables include albedo, net solar radiation, sensible heat flux, latent heat flux, 2-m air temperature, and mean sea level pressure in the early growing season of May. To reduce the impacts from global warming, we removed the trend of NDVI and the climatic variables by subtracting \( n \times \) slope from the original NDVI, and climatic variables \((n = 1, 2, 3, \ldots, 34)\), where the slopes were estimated by the ordinary least squares method (Hurley and Boos 2013). The vertical cross sections of the detrended correlation for both air temperature and equivalent temperature were calculated using zonally averaged values over the western TP (80°–90°E) to explore the effects of vegetation on the upper-level temperatures. Further, the significance of the correlation coefficient was tested by using Student’s \( t \) test at the 10% level. The detrended correlations for the periods of 1982–98 and 1999–2015, respectively, were analyzed and shown in the online supplemental material.

4) DETRENDED COMPOSITE DIFFERENCE ANALYSIS

We used a detrended composite analysis to evaluate the potential physical processes observed in the correlation analysis by examining climatic variables of albedo, net solar radiation, sensible heat flux, latent heat flux, 2-m temperature, and mean sea level pressure. Composite analysis is a sampling technique based on the conditional probability of a certain event occurring (i.e., change in vegetation in the study area) (NOAA 2021). The same process for detrending in the correlation analysis was performed for composite difference analysis. The detrended May NDVI time series of 1982–2015, area averaged only over the region with significantly changed NDVI in the western TP, were then used to identify the eight years of the highest May NDVI (approximately top 25th percentile) and the corresponding eight of the lowest May NDVI.
The composite differences of the surface and atmospheric variables between the eight years of the highest May NDVI and the eight years of the lowest May NDVI were calculated. The composite analysis was applied to each grid cell. The vertical cross sections of the detrended composite for both air temperature and equivalent temperature were also calculated over the western TP of 80°–90°E. A t test for a two-sample difference of means (Walpole et al. 1993) was applied to examine statistical significance of the composite differences with rejection of null hypothesis with zero difference between the means of two variables at the 10% level. The detrended composite differences for the periods of 1982–98 and 1999–2015, respectively, were analyzed with the four years of the highest May NDVI and the corresponding four years of the lowest May NDVI. The results were shown in the online supplemental material.

3. Results

a. Evaluation of global gridded datasets over the TP

The scatterplot with correlation between weather station and global gridded datasets were presented in Fig. 3. The Pearson coefficients (r values) for CRU, ERA5, JRA-55, and NCEP-2 were found to be 0.805, 0.808, 0.748, and 0.629, respectively, with weather station data at the annual scale and, for May, they were 0.814, 0.867, 0.753, and 0.605 for CRU, ERA5, JRA-55, and NCEP-2, respectively. The results obtained from nonparametric correlation were similar with those from parametric correlation (Table 1). The nonparametric correlation indicated the Kendall tau and Spearman’s rho correlations of 0.618 and 0.801 were for CRU on annual basis and 0.616 and 0.792 for May. For ERA5, the Kendall and Spearman correlations of 0.622 and 0.810 were found on annual basis and 0.685 and 0.862 for May. For JRA-55, the Kendall and Spearman correlations were 0.546 and 0.732 on annual basis and 0.555 and 0.730 for May. For NCEP-2, the Kendall and Spearman correlations of 0.430 and 0.591 were on annual scale and 0.414 and 0.60 for May. Additionally, all the correlation values were significant at the 1% level, considering the degree of freedom of 108 (=110 – 2). In summary, among CRU, ERA5, NCEP-2, and JRA-55 dataset, annual mean, and May temperatures from ERA5 showed the highest correlations with those from the Chinese weather station data in the TP. The correlation values of the CRU were similar to those of the ERA5. CRU provided data for temperature and precipitation but lacked for other atmospheric variables, which restricted its use for the analysis of the land and atmosphere interactions. Therefore, ERA5 was used to examine the associations of vegetation changes with the climate in subsequent analyses.

b. NDVI changes during early growing season

In the study area of western TP, the trends of May NDVI were distinct between the first half and the second half over the 34 years of 1982–2015 (Fig. 4b). To completely understand the vegetation variation in the TP, the study duration was divided into three periods: the full 34 years from 1982 to 2015, the first 17 years from 1982 to 1998, and the last 17 years from 1999 to 2015. We conducted the linear regression trend analyses of May NDVI over the periods of 1982–2015, 1982–98, and 1999–2015, respectively. The spatial patterns of linear regression trends over the plateau with the three study periods were shown in Fig. 4a. The time series of NDVI (Fig. 4b) were area averaged in the western region of the plateau only over the region with significantly changed NDVI during the specific study periods. The percentage changes of May NDVI, which were estimated by the slope over the mean of linear regression lines, were 7.5% decrease, 11.3% increase, and
14.5% decrease during 1982–2015, 1982–98, and 1999–2015, respectively. Also, the percentage change of NDVI at each grid point over the plateau with significantly increased and decreased NDVI during the three specific periods were shown in Fig. 4c. The analyses revealed a significant decreasing trend of NDVI in the southwestern TP during the month of May over the period from 1982 to 2015 for the 34 years. A significantly increasing trend of May NDVI during 1982–98 was observed in the western and eastern TP and, during 1999–2015, a significantly decreasing trend was in the western and central plateau as shown in Fig. 4c.

c. Associations of vegetation activity with near-surface atmospheric conditions

To examine the impact of vegetation activity in the western plateau on the surface energy balance and thereby near-surface conditions during May, we used the climate variables, including albedo, net solar radiation, sensible heat flux, latent heat flux, and 2-m temperature, and also mean sea level pressure as a dynamic variable. Figure 5 showed the detrended correlation between time series of NDVI, area averaged only over the region with significantly changed NDVI in the study area, and each gridded atmospheric variable in May during the period of 1982–2015. The detrended correlation results showed strong positive associations of NDVI with net solar radiation, sensible heat flux, and 2-m temperature with an r value exceeding 0.5 in each case in the western plateau (Figs. 5b,c,e). In contrast, statistically significant negative correlations were observed between NDVI and albedo, latent heat flux, and mean sea level pressure (Figs. 5a,d,f). As for the spatial patterns of the western TP, the positive correlation of 2-m temperature with NDVI (Fig. 5e) was associated with

|                | Annual temperature | May temperature |
|----------------|--------------------|-----------------|
|                | Pearson  | Kendall | Spearman | Pearson  | Kendall | Spearman |
| CRU and OBS    | 0.805    | 0.618   | 0.801    | 0.814    | 0.616   | 0.792    |
| ERA5 and OBS   | 0.808    | 0.622   | 0.810    | 0.867    | 0.685   | 0.862    |
| JRA-55 and OBS | 0.748    | 0.546   | 0.732    | 0.753    | 0.555   | 0.730    |
| NCEP-2 and OBS | 0.629    | 0.430   | 0.591    | 0.605    | 0.414   | 0.60     |

FIG. 4. (a) Linear regression trends of May NDVI (per decade), (b) time series of the May NDVI, area averaged only over the region with significantly changed NDVI in the western plateau, and (c) percentage change of May NDVI for the three study periods of (top) 1982–2015, (middle) 1982–1998, and (bottom) 1999–2015. In (a) and (c), statistically insignificant grid points were masked out at the 10% level and the study area is indicated with the dash-outlined rectangle.
the negative correlation of albedo (Fig. 5a) and the positive correlation of net solar radiation (Fig. 5b). Assuming NDVI increased, it could result in decreased surface albedo and increased net solar radiation at surface and thus air temperature at 2 m. The increased net solar radiation induced more sensible heat transfer from surface to the atmosphere (Fig. 5c). The corresponding decrease in the latent heat flux was in response of increasing sensible heat flux (Fig. 5d). Additionally, the negative association of mean sea level pressure with NDVI (i.e., lower pressure with higher NDVI) was observed in response to the thermodynamic process over warmer surface with increased vegetative cover (Fig. 5f). The results of detrended correlation analyses for the periods of 1982–98 and 1999–2015, respectively, were consistent with those for the period of 1982–2015 (Figs. S1 and S2 in the online supplemental material).

The composite analyses further confirmed the associations between vegetation and near-surface climatic variables (Fig. 6). The detrended composite patterns of the land surface variables were generally consistent with the detrended correlation results. Figure 6 showed the composite differences of climate variables between the eight years of highest and of lowest May NDVI in the western TP. Albedo was significantly decreased during the years of high NDVI values and the spatial extent (Fig. 6a) was consistent with that in the correlation pattern (see Fig. 5a). The detrended composite analysis results showed a statistically significant increasing net solar radiation of more than 0.8 W m$^{-2}$ over the significantly different regions of the western plateau during the years of high NDVI values (Fig. 6b). A significantly positive difference in sensible heat flux (Fig. 6c) was found in the northwestern region of TP when subtracting the sensible heat flux of the eight lowest years of May NDVI from the eight highest years. Correspondingly, the composite differences indicated statistically significant positive temperature anomaly in the western region during the eight highest years of May NDVI (Fig. 6e). The negative composite differences of mean sea level pressure (MSLP; i.e., weakened MSLP) during the high May NDVI years (Fig. 6f) was consistent with significantly positive differences of 2-m temperature. Further, a negative composite difference of

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**FIG. 5.** Correlation patterns of detrended time series of May NDVI, area averaged only over the region with significantly changed NDVI in the western plateau, with detrended (a) albedo, (b) net solar radiation, (c) sensible heat flux, (d) latent heat flux, (e) 2-m temperature, and (f) MSLP at each grid cell in May from 1982 to 2015. The green contour is the 10% significance level. The study area is indicated with the dash-outlined box.
latent heat flux was observed that was consistent with significantly positive differences of sensible heat flux (Fig. 6d). The composite patterns of the climate variables with the high and low NDVI years during the period of 1982–98 indicated the consistent patterns (Fig. S3 in the online supplemental material), as depicted for the 1982–2015 period, and those for the 1999–2015 period were also consistent (Fig. S4 in the online supplemental material).

d. Positive associations of vegetation with the upper-level temperatures

The modified energy balance due to vegetation variability was not just concentrated over the surface, but further influenced from lower to upper atmospheres. At the lower atmosphere, which is 500 hPa over the plateau, there were positive relationships of the NDVI with temperature at the 10% significant level in the western plateau in May during 1982–2015 (Fig. 7a). The positive relationships over the western TP, spreading both horizontally and vertically and reaching to the upper troposphere at 300-hPa level in the western TP as shown in the vertical cross sections of detrended correlation, zonally averaged temperatures over 80°–90°E (Fig. 7b). There was a greater than 1 K increase in the temperature at the 500-hPa level (Fig. 7c) and extending to the 400-hPa level with a significant composite pattern over the latitudinal domain of the study area (i.e., 30°–35°N) during the eight years with highest NDVI in the western TP (Fig. 7d). Additionally, the results of vertical cross sections using equivalent temperature revealed the similar vertical patterns of correlation and composite difference between the temperature and NDVI (Fig. S5 in the online supplemental material). The analyses of the depth-layered temperatures in the troposphere using both air temperature and equivalent temperature supported that the positive associations of NDVI with
temperatures are not only near the surface but also in the troposphere over the western plateau.

e. Proposed a positive energy process for land–atmosphere interaction

The results of this study revealed the significant associations of surface energy fluxes with vegetation changes occurred during the early growing season of May in the western region of the TP. Lower albedo with the increased NDVI was observed, which further influenced the surface energy balance, resulting in increased net solar radiation at the surface and, subsequently, sensible heat flux. Further, our results documented a statistically significant positive correlation between NDVI and 2-m temperature. The 2-m temperature significantly increased with more thermal energy transfer from the surface, which was obtained from reduced albedo. The corresponding decrease in mean sea level pressure was in response to increasing 2-m temperature. The spatial pattern of the detrended composite differences supported the correlation results and indicated a tight physical linkage among the vegetation cover, surface energy, and temperature. In addition, the areas with significant energy processes extended beyond the significantly changed NDVI area horizontally and vertically. The detrended correlation results demonstrated a statistically significantly positive associations of detrended area-averaged time series of May NDVI, area averaged only over the region with significantly changed NDVI in the western TP, with detrended temperature at 500-hPa level. At 500 hPa, which is the lower atmosphere for the TP, the significant positive correlation patterns occurred over the western TP and extended to the upper-atmospheric level of 300 hPa. The composite difference patterns of vertical cross sections supported the upper-level positive associations of vegetation with temperatures over the western TP. Based on the identified positive effects of vegetation on temperature associated with increased/decreased NDVI in the western region of the TP,
we proposed a positive energy process for land–atmosphere associations as shown in Fig. 8.

4. Discussion and conclusions

The positive energy process identified in this study is comparable to the studies in the alpine grasslands of the TP (e.g., Babel et al. 2014; Wu et al. 2015; Shen et al. 2015). Our result suggested that positive process of vegetation cover with temperature is dominant during the early growing season of May. However, Shen et al. (2015) used WRF mesoscale modeling simulations to demonstrate the cooling effect of the enhanced vegetation growth on the weather in the TP. The study indicated the negative feedback between vegetation and temperature leading to the cooling effect during the entire growing season from May to September, as compared with the Arctic region where a warming effect was found. This could result from competing effects in the energy and moisture processes that produce complex mechanisms of climatic responses to vegetative change. For example, Babel et al. (2014) used eddy covariance and observations data along with modified land surface and atmospheric models and revealed that pasture degradation induced a shift in evapotranspiration timing and a decrease in incoming solar radiation that could have a significant influence on the larger-scale climate of the highland area of the TP. In contrast, Cao et al. (2015) used a WRF Model to study the impact of land-cover and land-use change (LCLUC) on the regional climate in the agropastoral transitional zone of North China and found that change in LCLUC led to decline of summer temperature with local cooling of 1°C, along with increase in winter temperature of 0.8°C with local warming effect. Similarly, He et al. (2020) identified near-surface cooling effect due to cropland expansion during the late growing season from August to September in northeastern China by using several statistical approaches and observation and remote sensing data. Moreover, the resulting cooling effect due to cropland expansion extended atmospheric column reaching up to upper troposphere influencing its circulation.

Depending on land heterogeneity, the response of vegetation change has impact on the regional circulation pattern resulting in various response of temperature and precipitation (Pielke 1974). For example, Ahmad et al. (2020) depicted positive relationship between NDVI and precipitation and negative relationship between NDVI and maximum and minimum temperature in the hilly areas of Pakistan using observation and remote sensing datasets. Several studies have illustrated a difference in surface energy partition into sensible heat flux and latent heat flux affecting the total surface energy distribution over the TP due to difference in vegetation types (e.g., Xie et al. 2017; Zuo and Zhang 2016). As a result, pronounced differences in the energy exchange processes throughout the TP was found (Hu et al. 2018). Further, Wen et al. (2020) used a high-resolution assimilation dataset of the water-energy cycle in China and found that the sensible heat flux was mostly higher in barren land region over the western TP, resulting in a higher net radiation in this region. Similarly, Ma et al. (2020) used hourly land–atmosphere interaction in situ observation data from high-elevation and cold-region observation network and illustrated that sensible heat flux dominates surface energy balance in the TP during premonsoon season, followed by the latent heat fluxes in the monsoon season. In another study, Han et al. (2019) evaluated surface heat fluxes data from ERA-Interim reanalysis and concluded that from March to May, sensible heat flux dominates most of the TP, which is high in the west. Further, Xie et al. (2019) implemented empirical orthogonal function analysis to study sensible heat flux from 1981 to 2013 by using ERA-Interim, JRA-55, and the MERRA reanalysis and demonstrated that there is a marked spatiotemporal differences of sensible heat flux in the TP. In recent study by Ma et al. (2021), the sensible heat flux was found to be decreasing from 2001 to 2018 in the western TP based on a number of satellite images such as SPOT/VGT (i.e., vegetation), Terra/MODIS, geostationary satellite (FY-2C) data and observational data from the Third Pole Environment (TPE) Observation and Research Platform (TPEORP).

As a major component of the surface energy balance, latent heat flux plays an important role transferring moisture from the surface to atmosphere (e.g., Ma et al. 2017). In the TP, latent heat flux shows heterogeneous spatial variation and largely depends on the local soil moisture condition, which is
in turn affected by precipitation, glacier, and permafrost distribution (Li et al. 2020). The study conducted by Ge et al. (2017) confirmed that precipitation and air temperature are the major factors, affecting the latent heat in the alpine grasslands of the TP including meadow and steppe using dynamic composites and statistical analyses. Further, Wu et al. (2016) also noted difference in feedback processes for the sensible heat flux and latent heat flux over the TP. Song et al. (2017) observed a decreasing trend of actual evaporation from 2001 to 2010 from meteorological observation and satellite remote sensing data. Similarly, Li et al. (2020) calculated latent heat flux employing the maximum entropy production model from three reanalysis datasets (ERA5, JRA-55, and MERRA-2) forced by the net radiation, surface temperature, and soil moisture and noticed decreasing trend of latent heat flux from 1980 to 1991. However, there is lack of consensus about the trend and distribution of latent heat flux over the TP. Various studies indicated that the premonsoon period, sensible heat flux is greater than the latent heat flux making sensible heat flux as a major source for delivering heat to the atmosphere, whereas in the monsoon season latent heat flux is greater than sensible heat flux (Ma et al. 2020; Shi and Liang 2014). In addition, topography, location, and land-cover type also affect the land and atmosphere interactions with seasonal variation. Besides the energy and moisture processes, permafrost degradation, glacier melting due to climate warming, thawing–freezing process, and their combined effects have significant impact on the vegetation dynamic and spring phenology (Chen et al. 2011; Yao et al. 2012), producing complex pattern of land interactions. Additionally, human activities and socio-economic factors interact with the environment, complicating the energy exchange process (Wang et al. 2017). Overall, climatic and environmental factors affecting the long-term change of latent heat flux in the western TP are unclear and uncertainties exists.

Based on the findings of this study, positive associations of vegetation with temperature over the alpine grasslands were observed in the western TP that can extend to the upper atmosphere, resulting in 1-K increase in the temperature at the 500-hPa level. Although energy and moisture feedbacks and processes compete in the temperate region as identified by Bonan (2008), our findings implied a dominant energy process in the western TP during May. According to Bonan (2008), the moisture feedback is predominant in the summer while the albedo feedback is prevalent in the winter in the temperate region, resulting in positive radiative forcing because of radiation absorption with a lower albedo (Snyder et al. 2004). Based on the findings of this study, we suggest that the positive energy processes of vegetation with temperature could be dominant in the May, which is the transition period from winter to spring in the high-altitude grasslands on the TP. Since May is the transition season from dormancy to growing season in the study region of western TP, which is the temporally and spatially marginalized region, the identified energy processes help to better understand the energy process and association of vegetation with atmospheric variables and explore land–atmosphere interactions in the region. Also, many studies have recognized the importance of the western TP surface condition in global climate system (e.g., Wu et al. 2016; Xiao and Duan 2016).

The identified positive association between vegetation and temperature in the western TP is based on the remotely sensed vegetation data and the near-surface atmospheric variables from the ERA5 reanalysis data by undertaking various statistical methods. However, to study detailed feedback mechanism an idealized simulation using a coupled land–atmosphere climate model is required to identify more robust relationship between vegetation activity and climate in the TP (Eastman et al. 2001). Additionally, future explorations using observational data rather than reanalysis data are also needed to exclusively identify the land–atmosphere interactions in the TP. As the TP with its rugged topography and high altitude plays a key role in the modulation of climate at the local, regional, and global scales, any changes in the land surface can have serious implications on climate characteristics, impacting millions of people not only downstream but also remote regions through atmospheric teleconnection. Besides, a warming climate is expected to have a profound impact by melting glaciers, thawing the permafrost, and modifying hydrological and carbon cycles, and complicating feedback mechanisms. Therefore, it is important to acknowledge heterogeneous land surface characteristics in the TP associated with permafrost degradation and glacial loss because of surface warming while studying effect of land-cover change on the atmosphere in the TP, which can help to improve our understanding of land-cover change and its impact on local as well regional atmospheric conditions.

The linear regression trend analysis indicated a changing trend of NDVI in the western region of the plateau from increasing of 1982–98 to decreasing of 1999–2015. Both increased and decreased NDVIs showed the consistent biogeophysical associations with near-surface and atmospheric variables. As a result, increased or decreased NDVI was respectively linked to decreasing or increasing albedo and subsequently increasing or decreasing, respectively, net solar radiation at the surface, the result of which was a statistically significant respective increase or decrease in sensible heat flux and thereby 2-m temperature. The changes in the near-surface climatic conditions further induced changes in the lower- and upper-atmospheric conditions. The biogeophysical processes during the early growing season, which is “positive associations of vegetation with temperature,” were consistent between the two periods with distinct trends of vegetation over the alpine grasslands of western TP (i.e., 1982–98 vs 1999–2015). The increasing or decreasing vegetation cover in the western plateau can modify the surface energy balance, hydrological balance, and the carbon cycles, thus complicating the responses and feedbacks of the alpine steppe to global climate change. The positive energy processes of vegetation with temperature in the highland plateau proposed by this study could further impact soil moisture and water availability, affecting millions of people downstream.

Acknowledgments. We thank Dr. Lei Meng from Western Michigan University for providing Chinese Meteorological Data. We thank Dr. Aaron Maxwell for his constructive
comments and suggestions to improve the paper. We are thankful to two anonymous reviewers for their constructive and insightful suggestions to improve the paper. Eungul Lee was supported by a grant from Kyung Hee University in 2019 (Grant KHU-20192773) and a National Research Foundation of Korea (NRF) grant funded by the South Korean government (MSIT) (NRF-2020R1F1A1048886).

Data availability statement. The GIMMS NDVI3g are available from the Global Land Cover Facility at the University of Maryland (https://www.nasa.gov/nex) as cited in Pinzon and Tucker (2014). The climate data are available online for the ERA5 (https://cds.climate.copernicus.eu), the JRA-55 (https://rda.ucar.edu/datasets/ds628.0), the NCEP-2 (https://psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html), and the CRU (https://lre1.uea.ac.uk/cru/data).

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