

Large discrepancies among remote sensing indices for characterizing vegetation growth dynamics in Nepal

Decheng Zhou^a, Liangxia Zhang^{a,*}, Lu Hao^a, Ge Sun^b, Jingfeng Xiao^c, Xing Li^d

^a Key Laboratory of Ecosystem Carbon Source and Sink, China Meteorological Administration (ECSS-CMA)/Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), College of Applied Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China

^b Eastern Forest Environmental Threat Assessment Center, Southern Research Station, USDA Forest Service, Research Triangle Park, NC 27709, USA

^c Earth Systems Research Center, Institute for the Study of Earth, Oceans, and Space, University of New Hampshire, Durham, NH 03824, USA

^d Research Institute of Agriculture and Life Sciences, Seoul National University, Seoul 151742, South Korea

ARTICLE INFO

Keywords:

Vegetation index
Vegetation cover
Vegetation productivity
Mountain ecosystem
Vegetation growth
MODIS

ABSTRACT

Mountain ecosystems provide multiple ecosystem services and are “natural laboratories” to understand ecosystem responses to global change. Because of the inaccessibility and the high cost of field surveys, remote sensing indices are the major and sometimes the only measures to monitor the vegetation growth dynamics in mountains. However, there are large discrepancies in those indices that should be quantified in mountainous regions. This case study in Nepal, a highly mountainous region, explores the consistency and inconsistency of six widely used remote sensing indices in monitoring vegetation growth from 2000 to 2020. The study considers three greenness indices of normalized difference vegetation indices (NDVI), enhanced vegetation index (EVI), and near-infrared reflectance of vegetation (NIR_v), one cover index of leaf area index (LAI), and two productivity indices of gross primary productivity (GPP) and solar-induced chlorophyll fluorescence (SIF). We find high spatial consistency in the multiyear means ($r = 0.79\sim 1$, $N = 4300$, $p < 0.01$), especially in the highlands and between EVI and NIR_v, and a logarithmic relationship between greenness indices or GOSIF and LAI or GPP. In contrast, the long-term trends differ substantially by index and space. Only 7% of the lands show synchronized significant increase though all the indices show a widespread increasing tendency (77~87% of the lands). The prevalent non-significant changes of all the indices primarily contribute to the trend uncertainties, especially in the highlands. The inconsistencies between greenness and productivity indices and in them further exaggerate the uncertainties. Our results emphasize the large discrepancies of remote sensing indices in quantifying mountain vegetation growth dynamics. Larger inconsistency is expected if we consider disparities among the quality-control schemes, study seasons, remote sensing models, satellite platforms, and sensors. Reinforced remote sensing data, model improvements and/or new indices are needed for an accurate quantification of the vegetation growth dynamics in mountain regions.

1. Introduction

Vegetation in mountains often differs substantially in a very short horizontal distance due to the large variability of elevation, climate, and nutrient availability (Gao et al., 2019). Ecosystems in mountains are known to be more sensitive to environmental perturbations than those in the lowlands, and therefore have been widely acknowledged as “natural laboratories” to study vegetation responses to global change (Gottfried et al., 2012; Zhou et al., 2019). Meanwhile, mountains offer essential ecosystem services such as freshwater resources and hydro-power to more than half of global population though they occupy only

one-fourth of global land surface (Locatelli et al., 2017). The symbolic term “water towers” is a good example to stress the importance of mountains for providing fresh water resources (Viviroli et al., 2007). Changes in vegetation growth can significantly influence ecosystem services through modulating the land-atmosphere exchanges of carbon, water, and energy (Chapin et al., 2011; Frankenberg et al., 2011; Sellers et al., 1997). Therefore, an accurate quantification of the vegetation growth dynamics in mountains is not only crucial for a better understanding of the climate change effects on terrestrial ecosystems, but also a premise for a scientific evaluation of the ecosystem service provisions.

Field surveys are the most accurate method to quantify vegetation

* Corresponding author.

E-mail address: zhanglx@nuist.edu.cn (L. Zhang).

<https://doi.org/10.1016/j.agrformet.2023.109546>

Received 25 July 2022; Received in revised form 19 April 2023; Accepted 5 June 2023

Available online 8 June 2023

0168-1923/© 2023 Elsevier B.V. All rights reserved.

growth. However, they are time-consuming and labor intensive, particularly in mountainous regions, and therefore usually cover very limited geographic areas and time periods (Pan et al., 2011). By contrast, remote sensing indices have been increasingly used as proxies to quantify vegetation growth due to multiple advantages such as global coverage, repeatability, consistency, and low cost (Xiao et al., 2019; Zeng et al., 2022). Those indices can be generally grouped into three broad types: greenness, cover, and productivity (Ding et al., 2020). The greenness indices such as normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) are most widely used since they are easy to calculate from surface reflectance of the optical spectral bands (Camps-Valls et al., 2021; Zhang et al., 2017a). Near-infrared reflectance of vegetation (NIR_v), a newly-developed greenness index, has gained considerable research interests recently since it can isolate the vegetated signal from the soil background (Badgley et al., 2017; Zeng et al., 2022; Zhang et al., 2022). The vegetation cover indices, usually represented by a canopy structure parameter of leaf area index (LAI), is also preferred in many studies since it is believed to be more relevant to photosynthetic capacity (Street et al., 2007; Xiao and Moody, 2004). Productivity, a direct indicator of vegetation growth, can be represented by gross or net primary productivity (GPP or NPP)—a major component of the ecosystem carbon cycle (Chapin et al., 2011). At the same time, solar-induced chlorophyll fluorescence (SIF), the re-emission of energy from plants during photosynthetic activity (Baker, 2008), has been widely used as a direct proxy of productivity in recent decade (Chen et al., 2022; Doughty et al., 2021; Frankenberg et al., 2011; Guanter et al., 2014; Li and Xiao, 2019; Li et al., 2018; Pierrat et al., 2022; Wang et al., 2022a, 2020). Despite the unparalleled advantages of remote sensing indices, the resulting patterns and dynamics of vegetation growth may differ greatly among indices due to the different definitions and certain inherent errors caused by sensors and/or atmospheric conditions (Ding et al., 2020; Yang et al., 2022a; Zeng et al., 2022). For example, though the widespread greening trend revealed by greenness indices is expected to enhance ecosystem carbon uptake though photosynthesis in recent decades (Chen et al., 2019; Piao et al., 2020; Zhu et al., 2016), increasing evidence hints that increase in greenness may not necessarily benefit ecosystem productivity (Ding et al., 2020; Liu et al., 2021; Sarmah et al., 2021; Wei et al., 2022). Therefore, there is an urgent need to identify the consistency and inconsistency of different indices in monitoring vegetation growth for a more holistic view of the advantages and disadvantages of remote sensing applications.

Currently, a systematic comparative study of remote sensing indices in mountains is limited. Numerous studies have compared the vegetation dynamics revealed by different remote sensing indices at regional and global scales (Doughty et al., 2021; Fang et al., 2019; Fensholt and Proud, 2012; Jiang et al., 2017; Liu et al., 2021; Lyapustin et al., 2014; Sarmah et al., 2021; Wang et al., 2022b; Zhang et al., 2022, 2017a). However, they primarily focused on the disparities among different vegetation types and latitudinal regions or among different satellite sensors for one kind of remote sensing indices. Ding et al. (2020) compared the growth trends of vegetation greenness, cover, and productivity globally, but did not explore the altitudinal patterns specifically and include the two recently-flavored indices of NIR_v and SIF. Liu et al. (2022) evaluated the vegetation dynamics in high mountains, but focused on the consistency of different sensors in estimating NDVI. A recent study by Yang et al. (2022a) explored the consistencies among different vegetation products in the Tibetan Plateau, but mainly concentrated on the performances in characterizing land surface phenology. Considering the large elevation gradients, remote sensing data are expected to have large discrepancies in mountains due to the complex climate-vegetation conditions and poor data quality (Doughty et al., 2021; Huete et al., 2002). For example, Krakauer et al. (2017) indicated overall browning of vegetation in western Nepal from 2000 to 2016 based on Moderate-resolution Imaging Spectroradiometer (MODIS) LAI, while Baniya et al. (2018) reported significant greening

trends in the whole Nepal from 2000 to 2017 using NDVI. However, it remains unclear how the inconsistency among different remote sensing indices differs by altitude and whether vegetation growth has been enhanced or degraded in mountains by a warming climate and increasing human disturbances.

Using Nepal as an example, this study explores the consistency and inconsistency of six widely used remote sensing indices in monitoring vegetation growth dynamics in mountains including NDVI, EVI, NIR_v, LAI, GPP, and SIF. Nepal is ideal for such a comparative study since it covers a large altitude range (60–8000 m in elevation) and a nearly complete spectrum of vertical vegetation zone worldwide. Our objectives are to (1) compare the spatial distributions of the multiyear means and long-term trends of vegetation growth as revealed by different remote sensing indices, and (2) identify the possibility of long-term vegetation growth enhancement or degradation and the inconsistency in terms of greenness, cover, and productivity. We mainly focused on the discrepancies among different kinds of remote sensing indices in characterizing vegetation growth dynamics. Inconsistencies of the same indices between different remote sensing platforms, sensors, and model algorithms were also discussed briefly though they are beyond the scope of the present research. These efforts can not only improve our understanding of the vegetation dynamics and the uncertainties in mountains but also provide references for decision-making of climate change adaptation and mitigation strategies in Nepal.

2. Data and methods

2.1. Study area

Nepal is a mountainous and landlocked country in South Asia bounded by an Indian foothill of the Himalaya to the south, east and west, and the Chinese Tibetan Plateau to the north (Fig. 1). It covers a land area of 147,181 km² with extremely large altitudinal gradients ranging from about 60 m in the southeast to more than 8000 m (Mt. Everest) in the north. The topography is dominated by Terai in plains (< 200 m), hills in lowlands (200 ~ 1000 m) and midlands (1000 ~ 3000 m), and mountains in high lands (> 3000 m). The complex topography results in a complete vertical climate zone, with a mean annual precipitation from 200 mm in some northern regions to more than 5000 mm in the south and a mean annual temperature ranging from -10 °C in the north to more than 30 °C in the south (Baniya et al., 2018; Koju et al., 2020; Krakauer et al., 2017). Forest, including needle-leaved forests located in highlands and broad-leaved forests situated in low and mid-lands, is the main vegetation type in Nepal, followed by crop and grass (FRTC, 2022).

2.2. Datasets

The collection 6.1 Nadir bidirectional reflectance distribution function (BRDF)-Adjusted Reflectance (NBAR) product (MCD43A4) from MODIS (Schaaf and Wang, 2021) was used to calculate the NDVI, EVI, and NIR_v at a 500 m scale and daily timescale. MCD43A4 provides a BRDF-adjusted surface reflectance for seven MODIS spectral bands (1–7) to remove the view angle effects. LAI data were obtained from an 8-day composited MODIS LAI product (MOD15A2H, Version 6.1, and 500 m) (Myneni et al., 2021). The GPP and NPP data were obtained from the version 6.1 gap-filled MODIS GPP (MOD17A2HGF, 8-day composite, 500 m) and NPP (MOD17A3HGF, yearly) products (Running and Zhao, 2021). The two products have excluded the poor-quality inputs and filled the missing values through linear interpolation. The SIF data were obtained from the global, OCO-2 based SIF product (GOSIF) product (Li and Xiao, 2019), which has a spatial resolution of 0.05° and temporal resolution of 8 days. The dataset was developed based on discrete OCO-2 SIF observations, MODIS data, and reanalysis climate data. For each pixel, the LAI, GPP, and SIF data were aggregated to a monthly timescale by the maximum value composite (MVC) method (Huete et al., 2002),

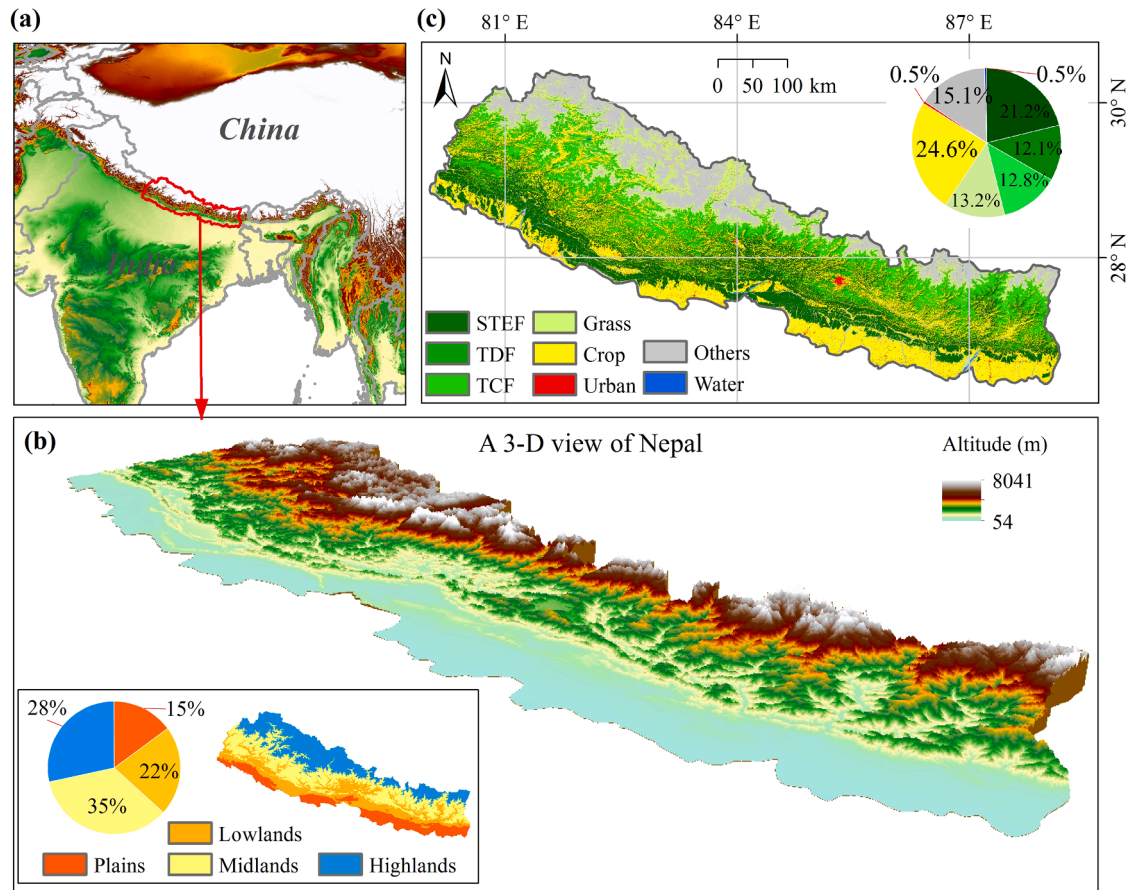


Fig. 1. Topographical map and the land cover map in 2019 of Nepal. The forests include Sub-tropical Evergreen Forest (STEF), Temperate Deciduous Forest (TDF), and Temperate Coniferous Forest (TCF). The elevation data were obtained from the NASADEM data product (NASA JPL, 2020). The land cover data was provided by the International Centre for Integrated Mountain Development (ICIMOD) (FRTC, 2022).

and then the mean value during the growing season was estimated for each year. Given the large variability of vegetation growing season along elevation gradients, we loosely defined the growing season as the months from April to October following a global-scale study (Piao et al., 2015) to make the number of observations consistent across the space. The associated uncertainties were discussed by quantifying the vegetation dynamics in summer season only (see discussion later).

Land cover maps in 2000 and 2019 at a spatial resolution of 30 m were obtained from the International Centre for Integrated Mountain Development (ICIMOD). The maps have been developed by the Forest Research and Training Centre (FRTC) of Nepal through the National Land Cover Monitoring System (NLCMS) (FRTC, 2022). The dataset was generated using freely available Landsat data in Google Earth Engine (GEE) platform, with an overall accuracy larger than 90% (FRTC, 2022). We regrouped the raw land cover types into forest (forest and other wooded land), grass (grassland), crop (cropland), urban (built-up land), water (water body), and others (glacier, snow, riverbed, bare soil, and bare rock with sparsely vegetation). Therein, forest alone occupies approximately 46% of the total land area in 2019 (Fig. 1b). Given a lack of forest subtypes in the raw land cover dataset, we loosely divided the forest into Sub-Tropical Evergreen Forest (STEF, ≤ 1200 m), Temperate Deciduous Forest (TDF, $1200 \sim 2100$ m), and Temperate Coniferous Forest (TCF, ≥ 2100 m) basing on altitude (<https://www.imnepal.com/forests-nepal/assessed> on June 21, 2022). The elevation data (Fig. 1a) were obtained from the NASADEM data product at 1 arc second resolution (NASA JPL, 2020). Both the land cover and elevation data were resampled to a 500 m resolution by the majority method to keep consistent with the MODIS-based products. Land pixels experiencing land cover change between 2000 and 2019 (accounting for

approximately 10% of the total) were excluded when we compared the vegetation growth dynamics across land covers.

2.3. Methods

2.3.1. Calculating NDVI, EVI, and NIR_v

The NDVI, EVI, and NIR_v were calculated as:

$$NDVI = \frac{B_2 - B_1}{B_2 + B_1} \quad (1)$$

$$EVI = 2.5 \times \frac{B_2 - B_1}{B_2 + 6 \times B_1 - 7.5 \times B_3 + 1} \quad (2)$$

$$NIR_v = (NDVI - C) \times B_2 \quad (3)$$

where B_1 , B_2 , and B_3 represent the surface reflectance of red (band 1), near-infrared (band 2), and blue (band 3) bands, respectively. The values for B_1 , B_2 , and B_3 range from 0 and 1 (Huete et al., 2002). The parameter C was set to 0.08 (Badgley et al., 2017). We calculated these indices at a daily time scale and aggregated them to a monthly scale by the MVC method and then calculated their growing-season mean values.

2.3.2. Identifying the discrepancies among different remote sensing indices

Discrepancies of the six indices in characterizing vegetation growth dynamics in Nepal were analyzed from three perspectives.

First, we calculated multi-year means in the period from 2000 to 2020, and then compared the spatial distributions of the six indices across altitudes and land covers, and the space on a per-pixel basis. To reduce the impacts of spurious vegetation signals, land pixels with NDVI

< 0.1 were removed following the convictions (Ding et al., 2020; Liu et al., 2022; Pan et al., 2018).

Second, we estimated the long-term trend from 2000 to 2020 on a per-pixel basis by a linear regression model and then compared the spatial distributions of the vegetation growth trends as revealed by the different remotely sensed indices. The trends were grouped into four types basing on the linear changing slope and two-tailed significance test: significant increase (slope > 0, $p < 0.05$), significant decrease (slope < 0, $p < 0.05$), increase (slope > 0, $p \geq 0.05$), and decrease (slope < 0, $p \geq 0.05$).

Last, we analyzed the possibility of vegetation growth enhancement or degradation by combined uses of the long-term trends in all the six remote sensing indices. The possibilities were divided into seven categories as defined in Table 1. In addition, we compared the long-term trends of greenness, cover, and productivity following previous experiences (Ding et al., 2020). Change of vegetation cover was represented by LAI dynamics directly. Change of productivity was defined as “significant” if both GPP and GOSIF changed significantly in the same direction. Otherwise, their trends were defined as “non-significant or uncertain”. Given that vegetation indices (NDVI, EVI, and NIR_v) are integrated indicators that are closely related to both vegetation cover and productivity (Zeng et al., 2022), they were termed as “greenness” in this study in order to examine their consistencies with the other vegetation indicators. Change of greenness was considered as “significant” when the changes for NDVI, EVI, and NIR_v were significant and in the same direction.

To keep more spatial details, the GOSIF results were resampled to the pixel size (i.e., 500 m) of MODIS datasets (NDVI, EVI, NIR_v , LAI, and GPP) when we compared the spatial variability of those indices by altitude and land cover. However, the MODIS-based estimates were resampled to the pixel size of GOSIF product (0.05°) by a mean method when we performed correlation analysis among different indices across the space on a per-pixel basis.

3. Results

3.1. Spatial patterns of the multiyear mean values

The spatial patterns of vegetation growth are overall consistent among the six remote sensing indices in Nepal (Fig. 2). Vegetation growth peaks around 2500 m and decreases dramatically by the rise of elevation, with a clear “cliff” between the hills of midlands and mountains of highlands regardless of the indices (Fig. 3a–c). However, large discrepancies are observed in the plains and lowlands. The multiyear means of all the greenness indices (NDVI, EVI, and NIR_v) in the lowlands and plains are similar to and slightly lower than those in the midlands, respectively, with an obvious “plateau” between 200 and 2500 m. The LAI also exhibits similar estimates in the mid- and low-lands, but much

lower values in the plains. The two productivity indices of GPP and GOSIF exhibit highly contrasting patterns along with altitudes. Specifically, spatial distributions of GOSIF are consistent with those of greenness indices, yet GPP declines rapidly and gradually by the decrease of elevation from the midlands to the plains. The large spatial variability of vegetation growth can be also seen from a perspective of different vegetation types, as indicated by the maximum in forest, followed by crop and grass for all the remote sensing indices (Fig. 3d–f). In addition, GPP was clearly lower in the STEF than in the other two forests, while all the other indices show similar multiyear mean estimates among all the forest types. Note that vegetation growth in urban land is close to that of cropland since most of the current urban land is covered by forests or croplands in early years (e.g., urban land tripled from 2000 to 2019 in Nepal), therefore leading to relatively high mean estimates across the whole study period.

On a per-pixel basis, all the indices, especially the vegetation greenness indices and GOSIF ($r = 0.95\sim 1$), are strongly related to one another ($r = 0.79\sim 1$, $N = 4300$, $p < 0.01$) (Fig. 4). The correlations are slightly weaker between GPP and all the other remote sensing indices ($r = 0.79\sim 0.81$). However, the correlations differ greatly by land cover and elevation (Fig. 5). The TDF or the low- and mid-lands show relatively weaker correlations than the highlands where are dominated by grasslands and others. The GPP is more closely related to GOSIF than to the greenness indices in the TDF and grasslands, but the opposite happens in the STEF, TCF, crop, and others. Among the greenness indices, a closer relationship of GPP with NIR_v than with NDVI and EVI is only found in STEF. In addition, a logarithmic relationship is shown between the greenness indices or GOSIF and GPP or LAI (Fig. 4).

3.2. Spatial patterns of the long-term trends

All the remote sensing indices, in particular the indices of greenness and cover, show an upward tendency in Nepal from 2000 to 2020 (Fig. 6). Specifically, about 77–87% of the land pixels experience an enhancement in vegetation growth. Nevertheless, the area percentages of “significant increase” vary substantially by the indicator, ranging from 20% in GPP to 45% in GOSIF. Additionally, the altitudinal patterns differ greatly by the index (Fig. 7a–f). According to the greenness indices, vegetation growth increases in more than 80% of the lands around the 1000–1500 m zone, and the percentage declines dramatically by the rise or decrease of elevation but a peak in the plains. The high-elevation regions (around 4000 m) also show a small peak of vegetation growth enhancement, but mostly in a non-significant form. By contrast, the vegetation growth enhancement mainly occurs in the plains and lowlands based on LAI and GPP. GOSIF shows two evident peaks of vegetation growth enhancement in both the low and high-altitude regions. By land covers, all the indices show the most prevalent vegetation growth enhancement in croplands and the most widespread vegetation degradation (“significant decrease”) in urban lands (Fig. 7g). Comparatively, vegetation growth increases or decreases insignificantly in more than four-fifths of the TCF and grasslands.

The linear change rates are highly consistent across the space for the three greenness indices ($r = 0.94\sim 0.99$) (Fig. 8). By contrast, weak relations are observed between the GPP and all the other indices ($r = 0.36\sim 0.44$). In general, NIR_v shows slightly stronger relations to LAI and productivity indices than NDVI and EVI. Similar to the multiyear mean estimates, we find large discrepancies among those six indices in monitoring vegetation growth dynamics across land covers or elevations (Fig. 5). For example, there are negative relationships between GPP and the other indices in the TDF and STEF. GOSIF in general presents much weaker connections with the other indices, particularly with GPP and in the highlands. Overall, NIR_v is marginally more closely related to GPP in terms of long-term trends than the other indices.

Table 1
Defining the possibility of vegetation growth enhancement or degradation.

Possibility	Definition
Very likely increased	Significant increase in all the six indices
Likely increased	Significant increase in three to five indices and insignificant change in the others
Probably increased	Significant increase in two indices and insignificant change in the others
Very likely decreased	Significant decrease in all the six indices
Likely decreased	Significant decrease in three to five indices and insignificant change in the others
Probably decreased	Significant decrease in two indices and insignificant change in the others
Uncertain	Significant change in none or only one index or both significant increase and significant decrease have been observed among the six indices

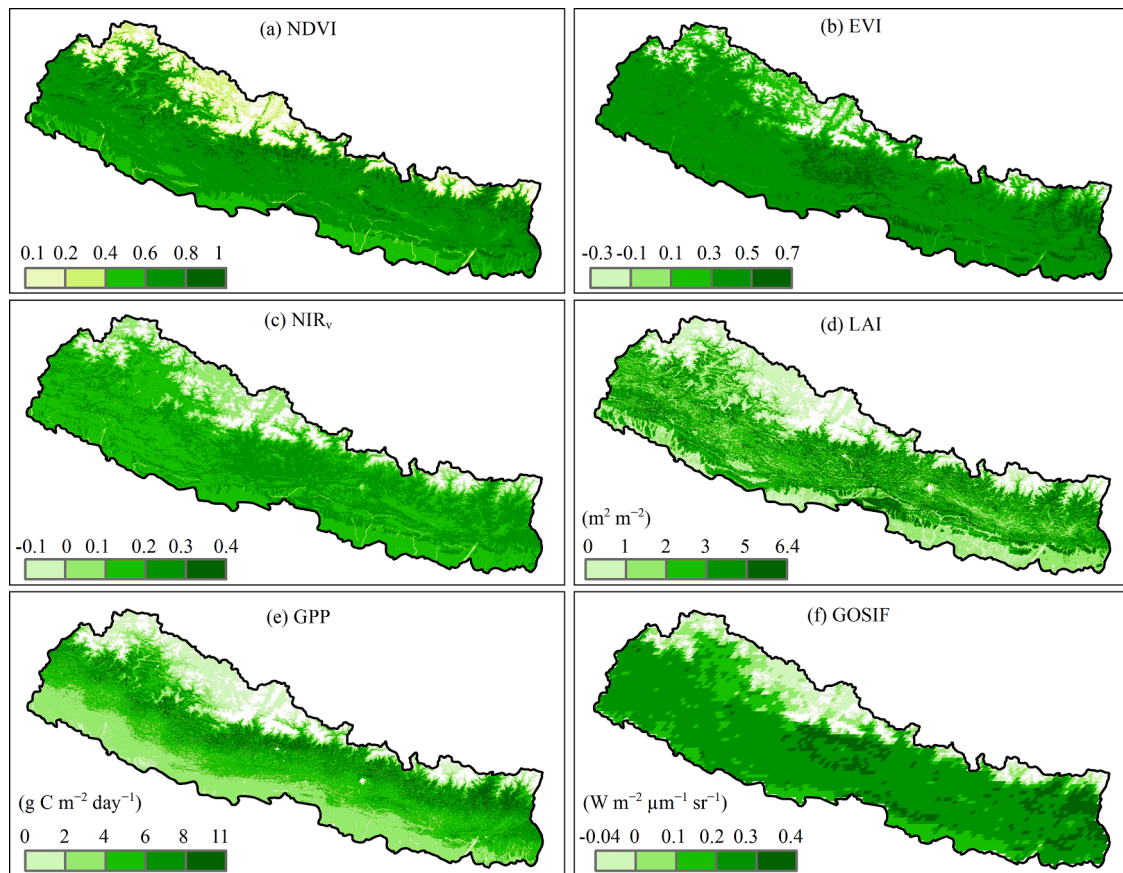


Fig. 2. Spatial distributions of the multiyear mean values in Nepal according to six remote sensing indices during the period from 2000 to 2020. The white colored areas mean no data (hereafter). Normalized difference vegetation indices, NDVI; Enhanced vegetation index, EVI; Near-infrared reflectance of vegetation, NIR_v ; Leaf area index, LAI; Gross primary productivity, GPP; OCO-2 solar-induced chlorophyll fluorescence, GOSIF.

3.3. Possibilities of vegetation growth enhancement or degradation

Considering the large discrepancies of different indices, change of vegetation growth is “uncertain” in nearly half of the study area from 2000 to 2020 (Fig. 9a), and the discrepancies increases sharply as elevation increases in the mid- and high-lands, with a clear “cliff” around 1500–2000 m (Fig. 9b). Indeed, vegetation growth likely or very likely increases in 41% of the total lands, with the greatest possibility in the plains and the second in the lower altitudinal bins of the midlands (Fig. 9b). Further, the consistency differs greatly by the land cover (Fig. 9c). More than 60% of croplands likely or very likely experiences vegetation growth enhancement, closely followed by the TDF and STEF, whereas the percentage is less than 20% in the TCF, grass, urban, and the others. Note that vegetation growth likely or very likely decreases in very few areas (<1%) of Nepal (Fig. 9a) that mainly occurs in urban lands (Fig. 9c).

By further distinguishing the inconsistency types, more than half of the study area exhibits non-significant trends in greenness, cover, and productivity, in particular over the high altitudinal regions, and only 7% of the lands show consistent increases in all the indices (Fig. 9d–f). About 36% of the remaining portion of the study area experiences significant increases in greenness and/or cover but non-significant change in productivity. By contrast, only 5% of the land witnesses significant increase in productivity and non-significant change in greenness or cover. Around 40% of croplands likely experience significant vegetation growth enhancement (Fig. 9e), but mainly in terms of greenness and/or cover (Fig. 9f). Such inconsistent trends also occur in the other land covers.

4. Discussion

4.1. Consistency and inconsistency of the multiyear mean estimates of vegetation growth

Our results show overall consistent altitudinal patterns of the multiyear mean estimates, suggesting the robustness of remote sensing indices in capturing the general picture of vegetation growth patterns in mountains. This is because vegetation greenness indices are integral indicators that not only relates to canopy structure (Carlson and Ripley, 1997), but also links to chlorophyll abundance in leaves (Running et al., 2004), while LAI is a robust indicator of leaf area increment (Fang et al., 2019). All of them may eventually be linked to photosynthetic capacity and plant growth potential (Myneni et al., 1997). The consistency is particularly high between EVI and NIR_v because they both represent vegetation greenness and can largely reduce the impact of background soil on vegetation signal (Badgley et al., 2017; Doughty et al., 2021; Zhang et al., 2022). Overall, vegetation growth peaks in the mid- and low-lands because forests are mainly situated there.

However, the relative magnitudes of vegetation growth in the plains and lowlands differ greatly by the index, especially between greenness or cover and productivity. This might be caused by (1) the different definitions and ecological meanings of those indices (Ding et al., 2020) and (2) the different vegetation types in the plains and lowlands (Fig. 1). On one hand, vegetation greenness and cover can determine the potential light absorption capacity, and thus photosynthetic potential, but not necessarily the actual photosynthetic rates. The actual vegetation growth is further modulated by the vegetation-specific potential light use efficiency, incident photosynthetically active radiation, and multiple environmental stresses such as air temperature stress and soil water

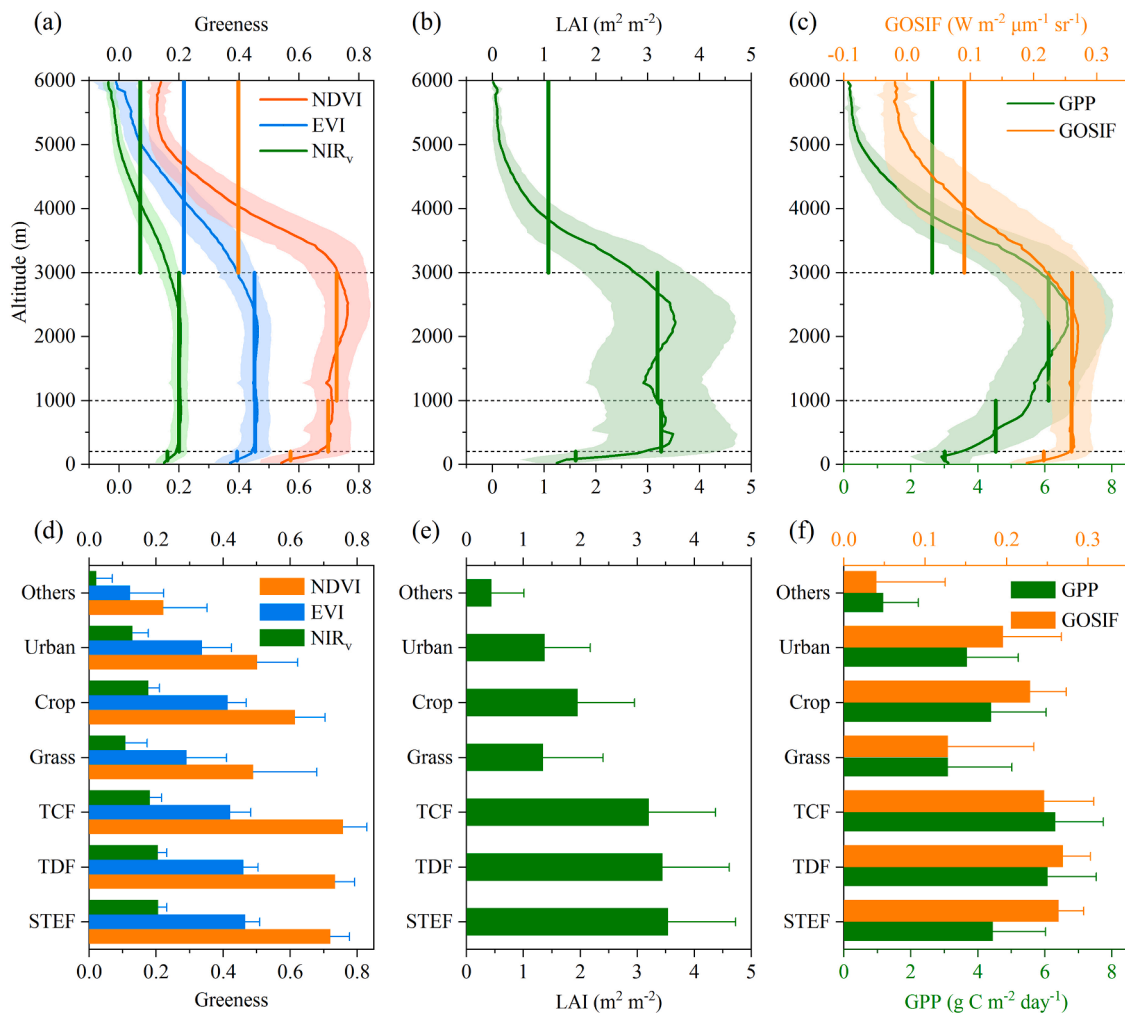


Fig. 3. Variations of the multiyear mean estimates of the six remote sensing indices by the 50-m altitude bin and land cover type in Nepal.

availability (Chapin et al., 2011; Piao et al., 2020; Zhang et al., 2019). In fact, vegetation indices were proved to be poor indicators of actual photosynthetic rates when all vegetation types and seasons were considered (Gamon et al., 1995). On the other hand, the plain areas are dominated by croplands, the biome-specific properties (e.g., efficiency in using sunlight) of which were highly different from the forests in the hills according to the MODIS GPP algorithm (Running and Zhao, 2021).

Contrary to previous studies (Doughty et al., 2021; Jeong et al., 2017; Zhang et al., 2022), we find no clear advantages of SEIF and NIR_v than NDVI and EVI in characterizing MODIS GPP in mountains. Indeed, we find highly consistent spatial distributions of those indices in Nepal. The phenomenon can be attributed to the diverse correlations by land cover (Fig. 5), therefore overshadowing the superiority of these two indices in some ecosystems. For example, the representativeness of GOSIF to MODIS GPP is poorest in STEF (Li and Xiao, 2019; Zhang et al., 2022), most likely due to more serious cloud and aerosol contamination in the tropical or subtropical areas (Samanta et al., 2012). It should be noted that the MODIS GPP product have substantial uncertainties (Zhao et al., 2006) and there are no regional-scale GPP reference data for evaluating SIF and NIR_v. The MODIS data were reported largely underestimate the cropland GPP (Guanter et al., 2014), which at least partially contribute the large discrepancy between the multiyear mean GPP and GOSIF in the low- to mid-latitude regions (Fig. 3c). Reinforced remote sensing data and ground-based experiments are needed to assess the accuracy of MODIS GPP and the effectiveness of other indices in monitoring the vegetation growth patterns in mountainous regions.

4.2. Consistency and inconsistency of the long-term trends of vegetation growth

All the indices show a widespread vegetation growth enhancement in Nepal during the past two decades though the area percentages with a “significant change” are different. This agrees well with numerous findings that Earth’s surface is greening up due to climate change, CO₂ fertilization, and/or land management (Piao et al., 2020). However, our results emphasize the large discrepancies of the vegetation growth trends in mountains when evaluated statistically on a per-pixel scale. Our findings correspond well with a recent study by Ding et al. (2020), who suggest that the vegetated areas with simultaneous increases in NDVI, EVI, LAI, GPP, and NPP accounted for only 5.4% of the global total. The disparities are largely contributed by the non-significant changes of all those indices in more than half of the total land area, especially in the highlands, hinting that impacts of climate change and land use activities on vegetation growth might be ignorable or have been cancelled each other in the most lands of Nepal. For example, Zeng et al. (2017) suggested that warming is not always occurring faster at higher elevations, and Gao et al. (2019) found no general rules controlling the vegetation phenology in mountains.

In addition, we confirm more prevalent enhancement in greenness indices than in productivity, which constitutes the second major source of the disparities. The concurrent increases in ecosystem respiration and productivity (Ding et al., 2020; Liu et al., 2021) have been considered as the major reason for the inconsistency between greening and productivity in previous studies. However, it cannot explain the inconsistency

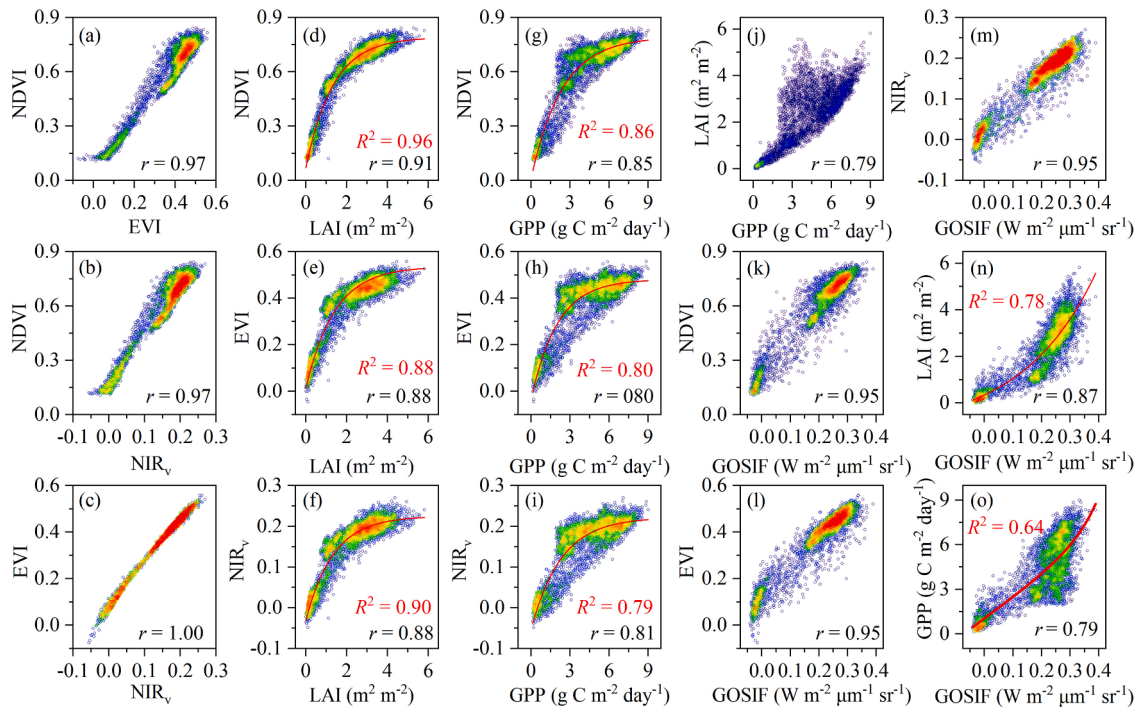


Fig. 4. Correlations among the six remote sensing indices across the space. The blue- to red-colored points represent increasing point density. All the Pearson's correlation coefficients (r) are significant at the 0.01 level ($N = 4300$, two-tailed test). Red line shows the possible non-linear fitted curve, with R^2 indicating the coefficient of determination.

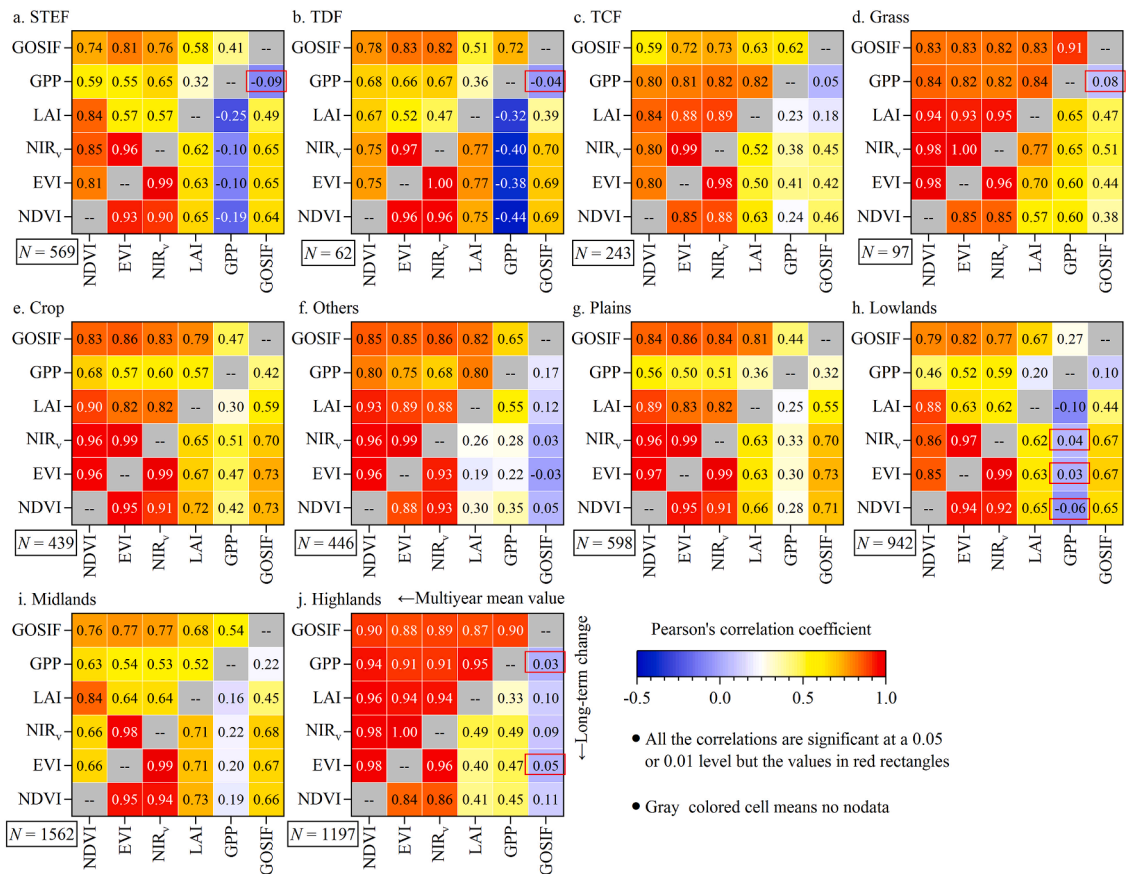


Fig. 5. Pearson's correlation coefficients among the six indices over different land covers (a–f) and elevation-regions (g–j). The correlations were calculated at a grid scale of 0.05° to keep accordance to the pixel size of GOSIF. Only grid cells dominated by relatively pure land covers (area percentage $> 2/3$) were screened to estimate the correlation coefficients for each land cover type. The urban lands were not included due to the scarcity of urban-dominated grid cells.

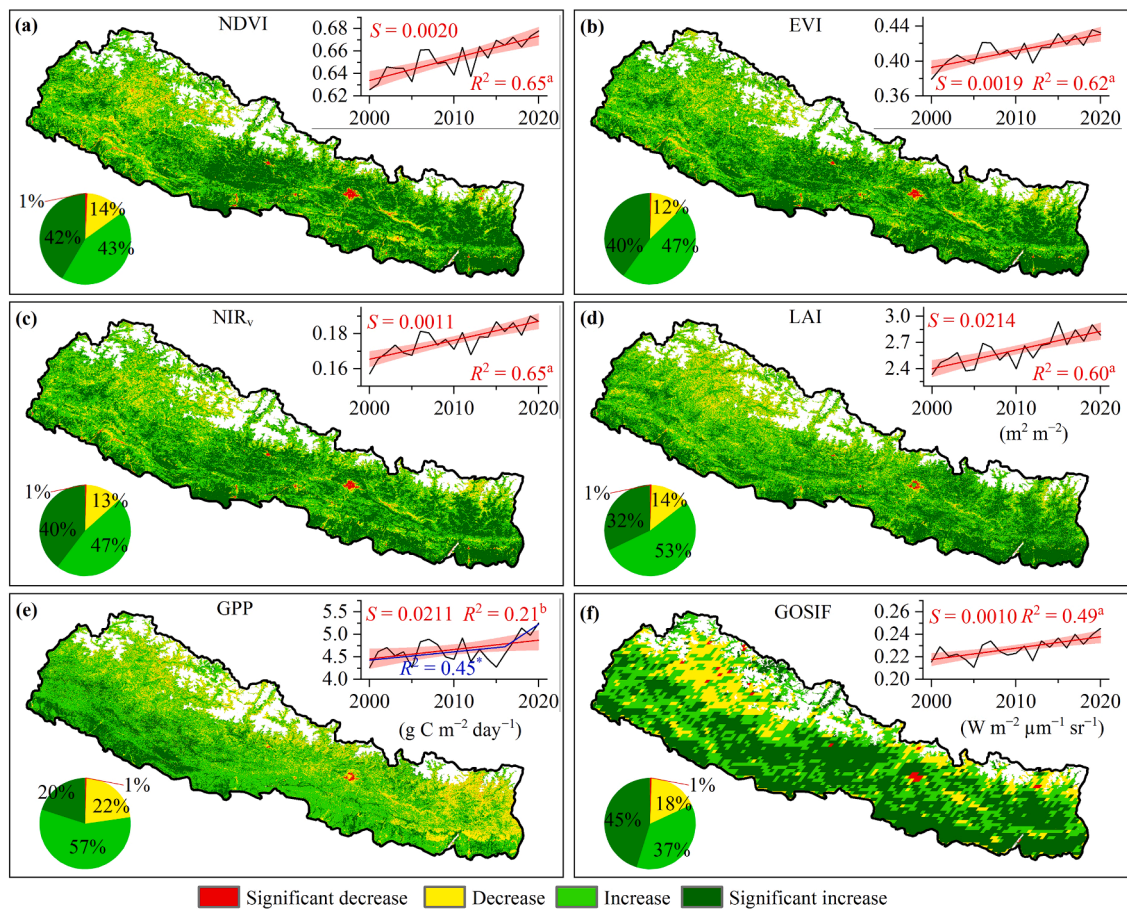


Fig. 6. Spatial distributions of the long-term change trends of the six remote sensing indices. Inserted line and pie charts show the trends of the mean value for the whole Nepal, and the area percentages of different trends.

with GPP. We argue that other factors may play more important roles. First, photosynthesis of green tissues may end under extreme conditions and non-green leaves may also contribute to the photosynthesis (Hubau et al., 2020). For example, a recent study by Hu et al. (2022) show that the relationship between GPP and LAI were highly coupled in arid grasslands, but were fully decoupled in humid evergreen broadleaf forests. This at least can partially explain the negative relationship between greenness or LAI and GPP in the STEF and TDF over Nepal. Second, increasing leaf growth may enhance self-shadowing, which in turn reduce productivity (Street et al., 2007). Third, human disturbances such as cropland (Chen et al., 2019; Sarmah et al., 2021) and forest (Oldekop et al., 2019) management practices may impact the carbon uptake. For example, we find that though croplands have the largest possibility of vegetation growth enhancement among all the land cover types, most of the “likely increased” areas are caused by the synchronized increases in greenness, cover, and SIF (Fig. 9). Oldekop et al. (2019) found a decrease in deforestation due to decentralized community-based forest management in Nepal, which certainly enhanced the vegetation productivity. It is worthwhile noting that increasing ecosystem respiration may further underscore the benefits of greening for carbon sequestration in mountains. For example, we compared the long-term trends of MODIS NPP with those of GPP and others (Fig. 10). As expected, NPP increases in fewer areas than GPP (65% vs. 77%) and around 15% the lands exhibit a decrease in NPP but an increase in GPP. Also, the correlations of the other indices with NPP are much weaker than that with GPP. These together suggest the possible overestimation of the greening benefits for mitigating climate change and promoting the other ecosystem services by using the indices of greenness, cover, and gross primary productivity.

Furthermore, the different proxies to vegetation greenness, cover, or productivity also contribute to the disparities. For example, only 69% of the lands show consistent long-term trends (in both the change directions and significance levels) for the three greenness indices, and the percentage reduces to 35% for the two productivity indices (Fig. 11). This should be mainly caused by the different sensitivities of the spectral bands to vegetation signal, which in turn lead to different responses of the indices to environmental perturbations (Huete et al., 2002; Liu et al., 2022). In general, the TCF and grassland in highlands present larger discrepancies than the other lands if viewed from the change directions and significance levels. This is a little different from the general latitudinal patterns of vegetation growth that the inconsistency was relatively higher in tropical forests, grasslands, and croplands (Wang et al., 2022b). The probability of vegetation growth enhancement is highest in the plains where are dominated by croplands, most likely due to intensive agricultural activities such as irrigation and fertilizer uses (Chen et al., 2019; Sarmah et al., 2021).

As advocated elsewhere, SIF (Jeong et al., 2017), NIR_v (Badgley et al., 2017; Dechant et al., 2022), and LAI (Glenn et al., 2008; Myneni et al., 1997) are better than NDVI and EVI in tracking the change of vegetation productivity. Nevertheless, we do not find clear advantages of all of them in mountains. On the contrary, we demonstrate relatively lower consistency between GOSIF and MODIS GPP in the highlands where are dominated by grasslands and others. The phenomenon might be closely related to the poor data quality of all the remote sensing data in mountainous regions and the uncertainties of MODIS GPP product (see discussion later). Concurrently, the GOSIF may fail to capture the spatial details of vegetation growth in highly heterogeneous regions like mountains due to its coarse spatial resolution. In addition, the

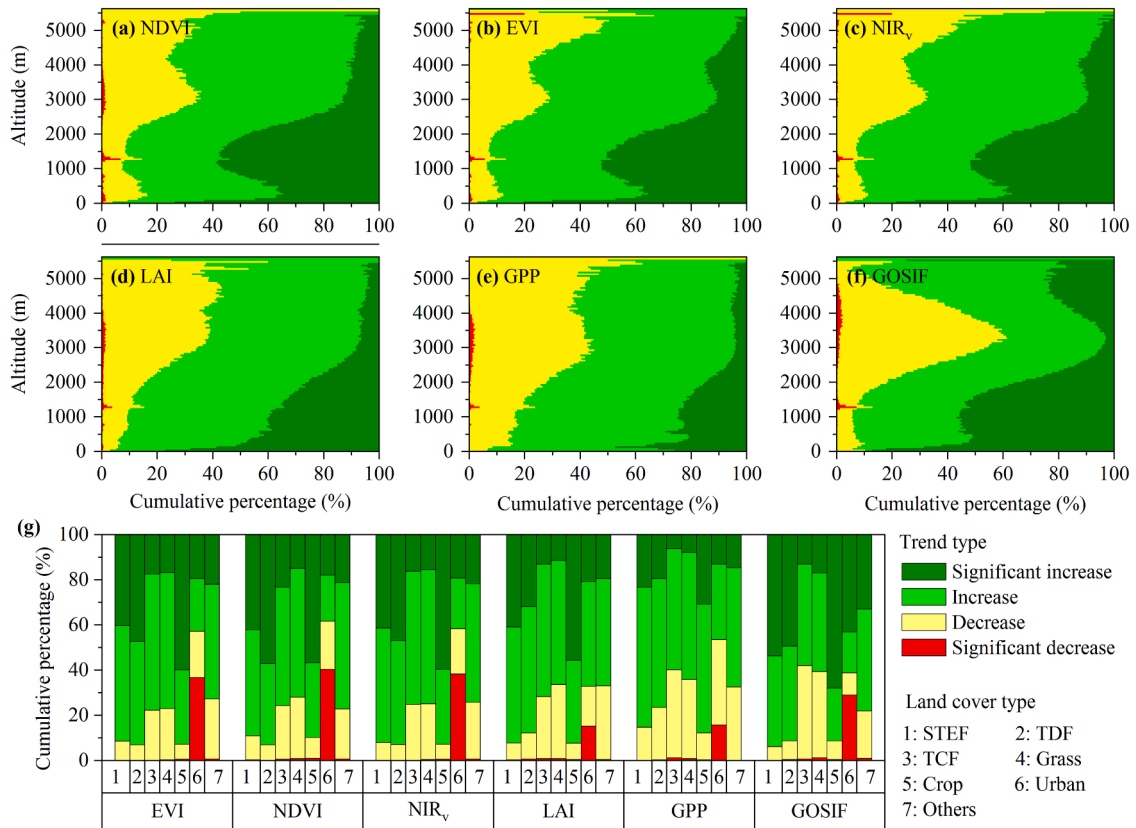


Fig. 7. Area percentages of the different long-term trends for the six remote sensing indices by the 50-m altitude bin and land cover type.

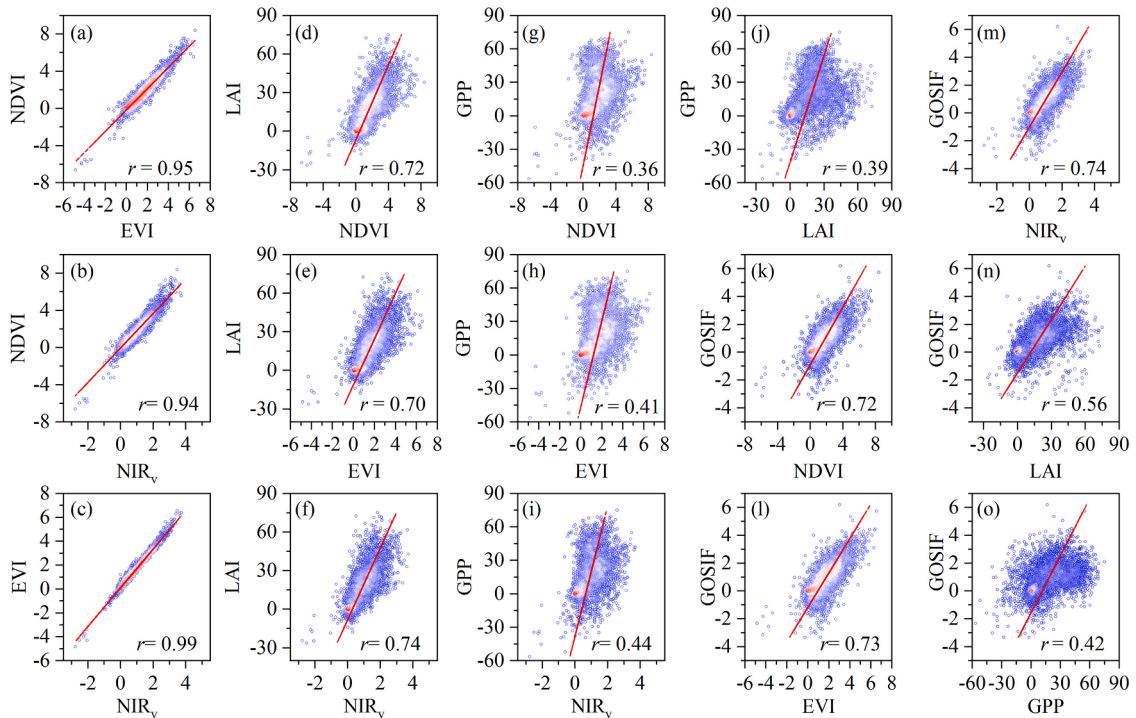


Fig. 8. Correlations of the long-term linear changing rates (scaled by 1000 times) among different remote sensing indices across the space. All the r values are significant at the 0.01 level ($N = 4300$, two-tailed test). Red line shows a linear fitted curve.

contrasting sensitivities of GPP and SIF to environmental drivers (Song et al., 2018; Yang et al., 2022b) could also contribute to the discrepancies in their long-term trends. Our results show more increases in

GOSIF than MODIS GPP in Nepal (Fig. 6e and f), agreeing well with previous findings at a global scale (Li and Xiao, 2019).

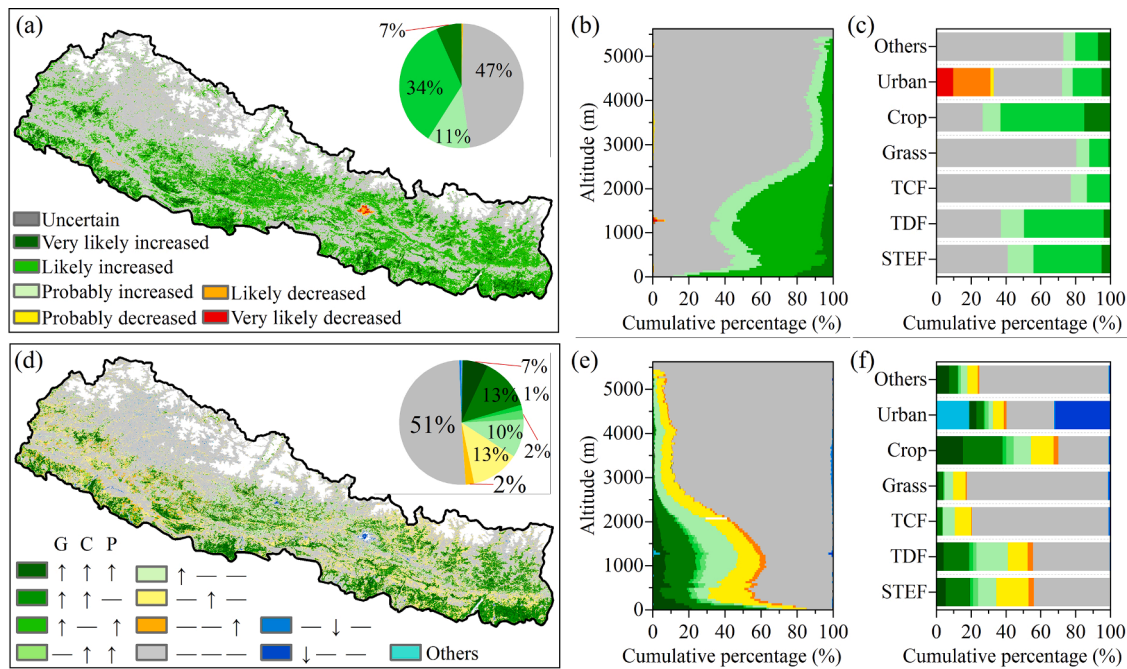


Fig. 9. Possibility of vegetation growth enhancement or degradation according to the long-term trends of the six remote sensing indices (a–c), and the long-term vegetation growth trends in terms of vegetation greenness (G), cover (C), and productivity (P) (d, e, f). “↑”, “↓”, and “—” in panel d indicate “significant increase”, “significant decrease”, and “non-significant or uncertain”, respectively.

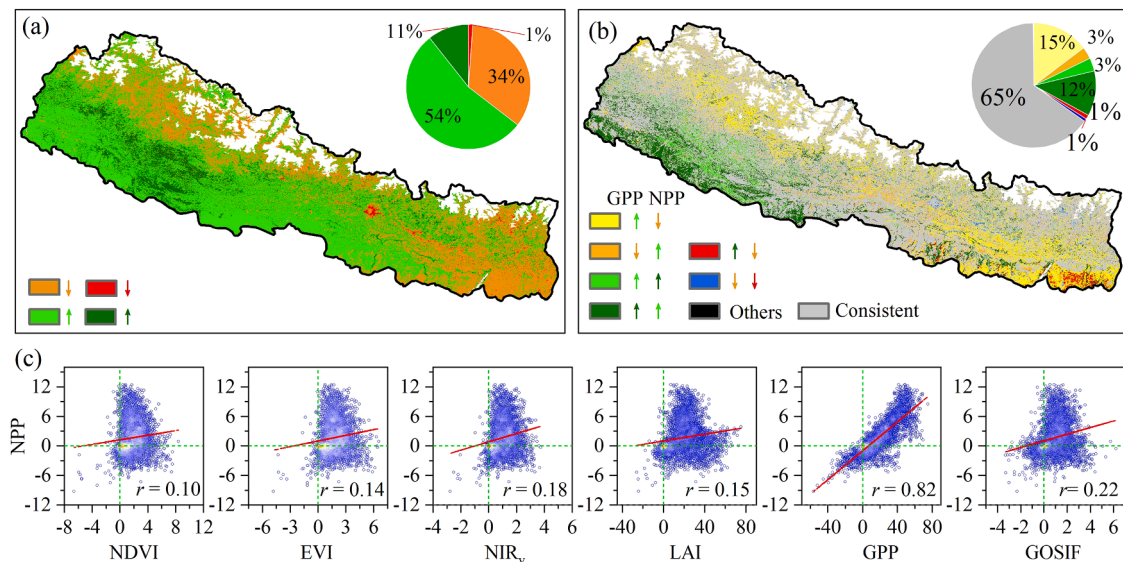


Fig. 10. Comparison of the long-term trends in net primary productivity (NPP) with those in the six remote sensing indices. (a) Trend of NPP. (b) Consistency between the trends of NPP and GPP. (c) Correlations between the NPP ($\text{kg C m}^{-2} \text{ year}^{-1}$) and the six remote sensing indices across the space. The red- and orange-colored down arrows represent significant ($p < 0.05$) and non-significant decreases, respectively. The up arrows in dark and light green colors indicate significant ($p < 0.05$) and non-significant increases, respectively.

4.3. Other potential causes of the discrepancies in remote sensing data

The discrepancies listed above can be further manifested. Data-quality control is of utmost importance to an effective application of remote sensing in mountains. For example, we summarized the data quality of the MODIS products being used in this study and find that the number of available data on average reaches 135 for the daily MCD43A4 product during the growing season, which only accounts for 64% the total time periods. The data missing problem is overall more serious in the mid- to high-lands (Fig. 12a). Worse still, only 46% of the available

data have good-quality values and the percentages decrease in a linear form with increasing altitudes. Though the number of data is nearly the same across the space for the gap-filled LAI and GPP products (Fig. 12b and c), the percent of good-quality data fluctuates greatly by the latitude, with relatively smaller percentages in the latitudinal bins from 2000 to 2600 m or above 5500 m. By further distinguishing the causes of the poor-quality data, we find that clouds (especially in the high-elevation regions) and aerosols (especially in the lowlands) are the two major noises in the LAI products (Fig. 12d). Similarly, the cloud contamination is also mainly responsible for the poor-quality GPP

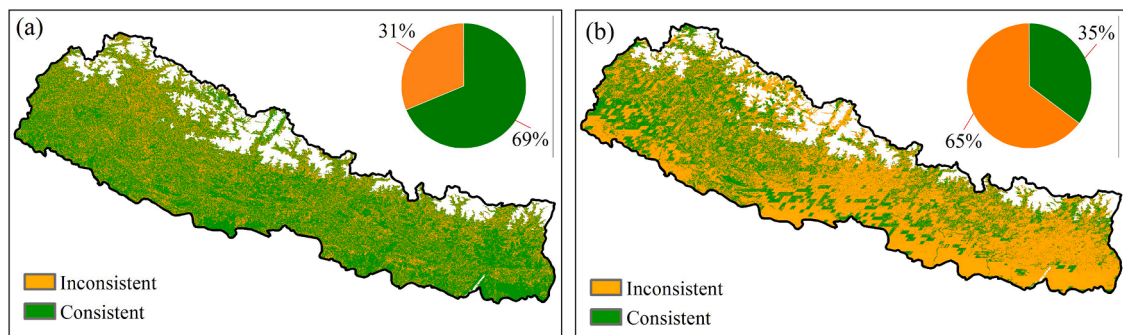


Fig. 11. Consistency among the three greenness indices (i.e., NDVI, EVI, and NIR_v) (a) or between the GPP and GOSIF (b). The trend was assumed to be “consistent” if all the indices changed in the same directions and significance levels. Otherwise, the trends are “inconsistent”.

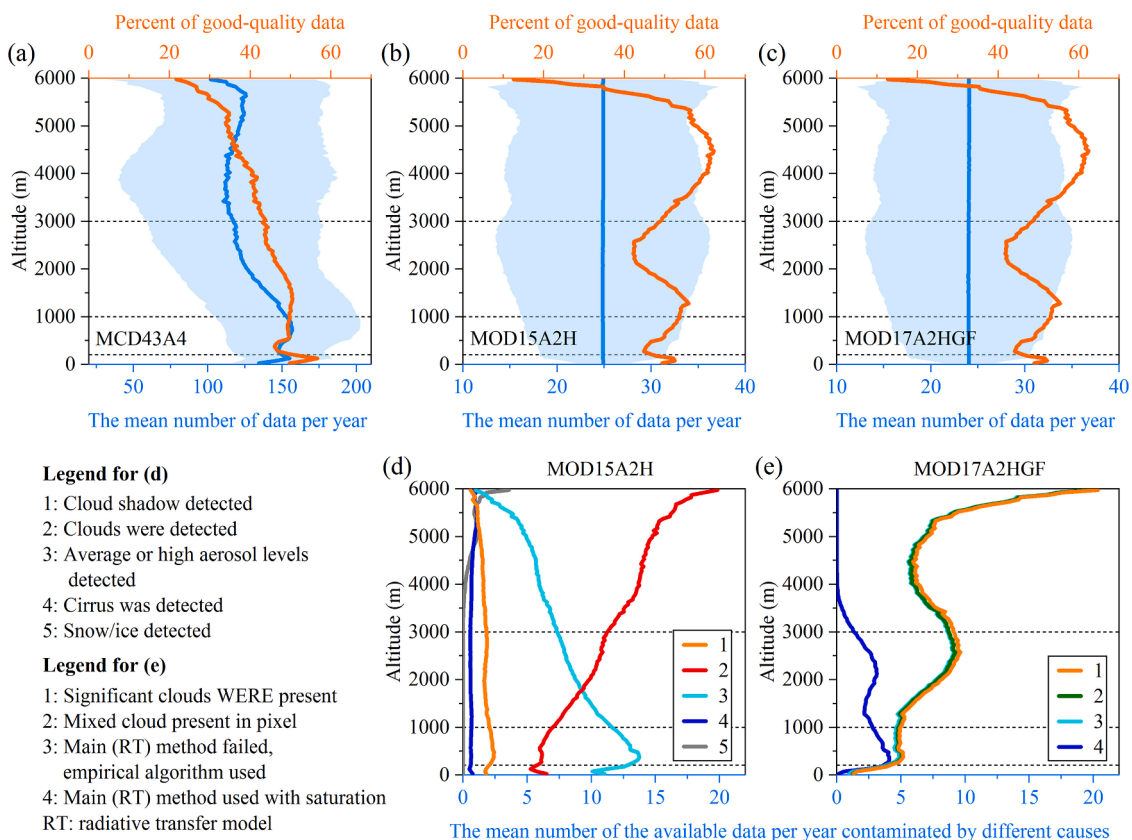


Fig. 12. Variations of the MODIS data quality by the 50 m altitude bin during the growing season averaged from 2000 to 2020. (a–c). The number of data and the percentage of “good quality” flagged data. (d, e) The number of the data contaminated by different noises. Since the data quality are nearly uniform for the red, near-infrared, and blue bands of MCD43A4 products, only the red band was shown in figure panel a.

estimates since it leads to the failure of radiative transfer equation in generating the Look-up-Table (LUT) for the MODIS FPAR (Fraction of Photosynthetically Active Radiation) algorithm (Fig. 12e) — a main parameter of the MODIS GPP model. Though the poor-quality data have been cleaned and determined by linear interpolation in the year-end gap-filled products (Running and Zhao, 2021), the filled values can never represent the actual GPPs under cloudy sky conditions. The GOSIF data should have the same data quality problems because MODIS data were the key inputs for the GOSIF model (Li and Xiao, 2019). The poor data quality of certain largely contributes to the discrepancies among different indices in mountains, especially in STEF and TDF, and the highlands. However, it remains a debate whether we should use all or only “good quality” flagged pixels. Taking NDVI as an example, we show that about 13% of the study area would have no data for the entire growing season in one or more years if using only “good quality” data

(Fig. 13a and b). The quality control has little impacts on the spatial distributions of the multiyear means (Fig. 13c), but strongly impacts the long-term trends. For example, only 46% of the total land pixels show the same change trends in terms of directions and significance levels (Fig. 13d–f). Appropriate filtering and reconstruction methods are recommended in future efforts to reduce the impacts of data quality, but caution should be paid to the possible new errors introduced by the gap-filling algorithms themselves (Liu et al., 2017).

Choices of seasonal scales and remote sensing-based models could also largely contribute to the inconsistency. On one hand, increases in greenness and cover can enhance growing-season carbon uptake, but not necessarily the annual total carbon storage (Linscheid et al., 2021). The relation between SIF and GPP is also proved to be seasonal-dependent (Pierrat et al., 2022). As a result, the consistency among different indices may differ by the seasonal scale. For example, we examined the

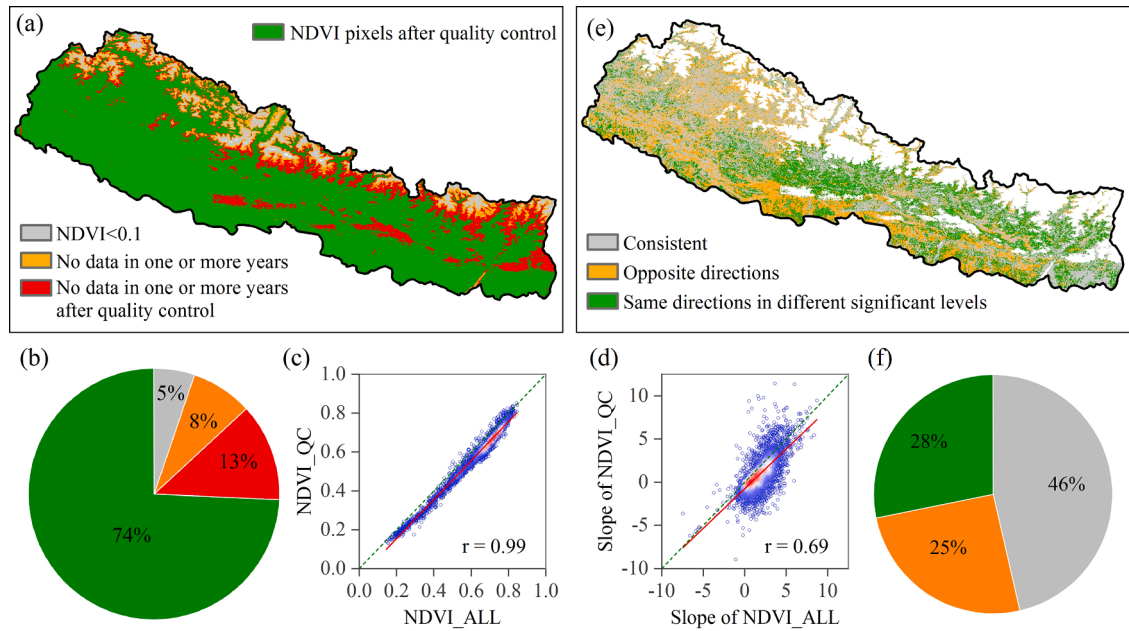


Fig. 13. Comparison of the long-term NDVI trends with and without quality control. (a, b) Data availability with and without quality control. (c, d) Correlations of the multiyear means or long-term changes of NDVI after quality control (NDVI_QC) with those without quality control (NDVI_ALL) across the space. (b, f) Consistency between the NDVI trends with and without quality control.

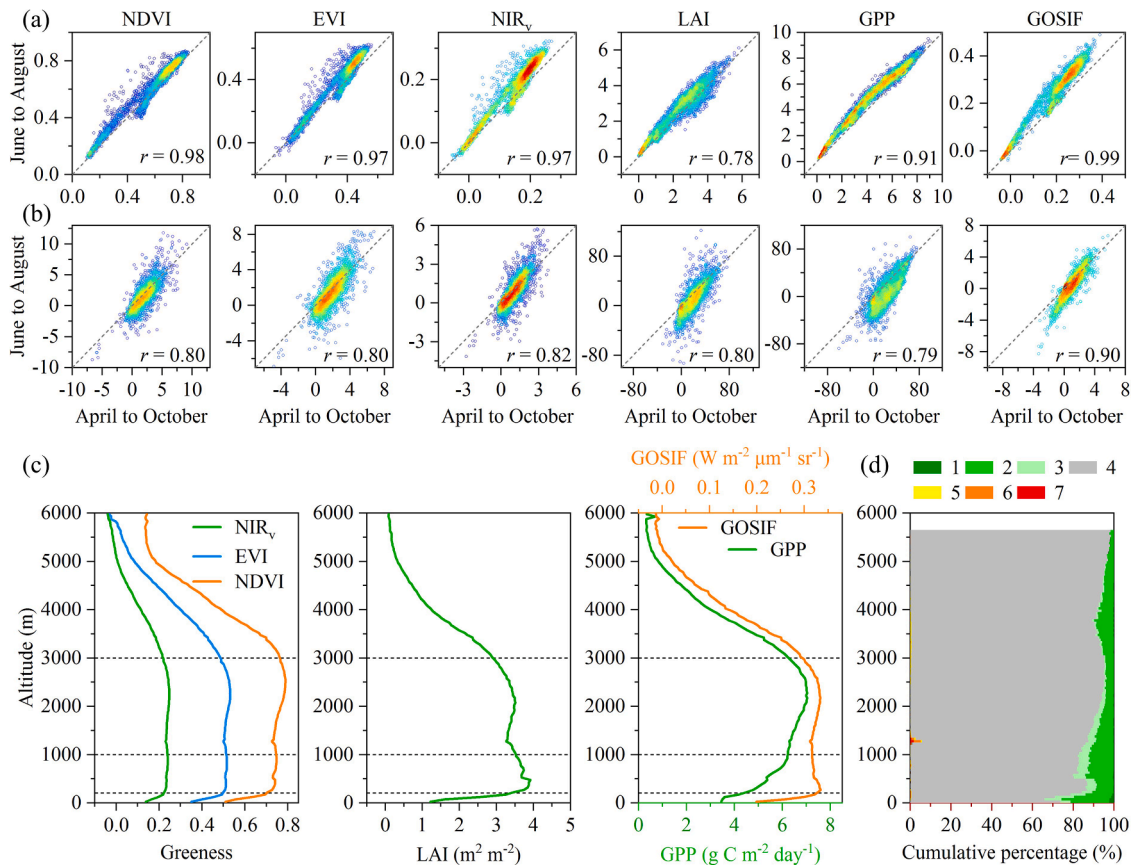


Fig. 14. Comparison of the vegetation growth dynamics between the growing season defined in this study (April to October) and the summer season (June to August). (a, b) Correlations of the multiyear means (the units of those indices are the same as that shown in figure panel c) and long-term change rates (scaled by 1000 times) between the two seasonal scales. (c) Variations of the multiyear mean estimates of the six remote sensing indices by the 50-m altitude bin in the summer season. (d) Possibility of vegetation growth enhancement or degradation according to the long-term trends of the six remote sensing indices in the summer season (1, very likely increased; 2, likely increased; 3, probably increased; 4, uncertain; 5, probably decreased; 6, likely decreased; 7, very likely decreased).

spatial-temporal patterns of all the indices in summer (June to August) (Fig. 14). Results show that although the spatial distributions of the multiyear means (Fig. 14a and c) and long-term change rates (Fig. 14b) are overall consistent in different seasonal scales ($r = 0.79 \sim 0.99$, $p < 0.001$), the percentage of the lands with “likely or very likely” vegetation growth enhancement (23%) in summer (Fig. 14d) is much lower than that (41%) in the growing season (April to October) defined in this study. On the other hand, large discrepancies might exist in the same kind of remote sensing index such as GPP (Pei et al., 2022; Zhang et al., 2019, 2015) and LAI (Fang et al., 2019) due to the disparities in model inputs and structure. To illustrate, we compared the GPP patterns revealed by MODIS product with that by three other GPP products including vegetation photosynthesis model (VPM) (Zhang et al., 2017b), two-leaf light use efficiency model (TL-LUE) (Bi et al., 2022), and a upscaled eddy covariance dataset created by Japanese National Institute for Environmental Studies (labeled as NIES) (Zeng et al., 2020) during their overlapping period from 2000 to 2016. We find large discrepancies of the GPP patterns, especially in the long-term trends (Fig. 15). The multiyear means from MODIS is overall lower than the other three products, particularly over the lower latitude regions (Fig. 15a and d). The lower estimates of MODIS GPP might be due to the poor representativeness of the environmental stresses of soil moisture (Koju et al., 2020; Stocker et al., 2019). The long-term change rates of MODIS GPP are weakly linked to that of all the other three products ($r = 0.03 \sim 0.21$) (Fig. 15b and d) on a per-pixel basis and on average even show an opposite tendency to some other products (Fig. 15c).

In addition, vegetation growth patterns might differ greatly by data collections, satellite sensors, and platforms though they are beyond the

scope of present research. For example, the version 5 MODIS data may underestimate the greening trend caused by the sensor degradation (Zhang et al., 2017a), while version 6 MODIS data may overestimate the greening trend due to the overcorrection in some regions (Lyapustin et al., 2014). A recent study by Liu et al. (2022) suggests that inconsistent pixels among three widely-used NDVI products (GIMMS (Global Inventory Modelling and Mapping Studies), SPOT/VEGETATION, and MODIS) account for three-fifths of the vegetated area in the High Mountain Asia due to the contrasting characteristics (e.g., band center and bandwidth, sensitivity of sensors, satellite orbit, and resolution) of different satellite sensors. To illustrate, we compared the vegetation growth dynamics revealed by the AVHRR (Advanced Very High Resolution Radiometer) based GIMMS (Pinzon and Tucker, 2014), SPOT/VEGETATION and PROBA-V based CGLOPS-1 (Copernicus Global Land Operations “Vegetation and Energy”) (Smets et al., 2020), and MODIS-based (calculated in this study) NDVI products in Nepal during the overlap time periods of 2000–2015 (Fig. 16). Results show overall consistent spatial distributions of the multiyear means (Fig. 16a, e–g), but large inconsistencies in the long-term trends. The CGLOPS-1 products present much more “significant increase” (accounting for 51% of the total lands) than the other two products (23–29%), and there are relatively low spatial consistencies between different NDVI products on a per-pixel basis ($r = 0.12 \sim 0.50$, $N = 1752$). Discrepancies can be also found in the same sensor onboard different satellite platforms. For example, we compared the growing-season MODIS NDVI estimates from Terra (MOD13A1) (Didan, 2021b) and Aqua (MYD13A1) (Didan, 2021a) satellites during 2003 and 2020 and found some differences in both the multiyear means and long-term trends, especially over the

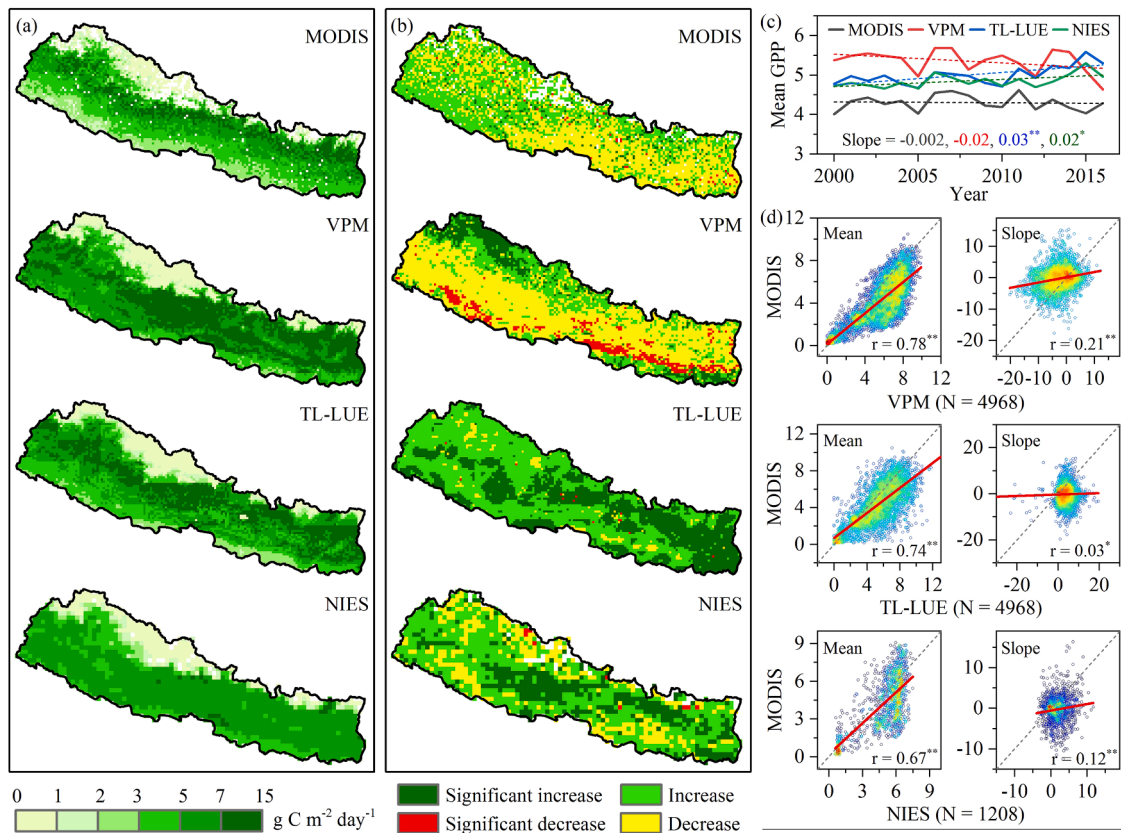


Fig. 15. Comparison of the vegetation growth dynamics in term of GPP revealed MODIS with that by vegetation photosynthesis model (VPM, monthly, $0.05^\circ \times 0.05^\circ$) (Zhang et al., 2017b), two-leaf light use efficiency model (TL-LUE, monthly, $0.05^\circ \times 0.05^\circ$) (Bi et al., 2022), and a upscaled eddy covariance dataset (labeled as NIES, 10-day, $0.1^\circ \times 0.1^\circ$) (Zeng et al., 2020) during the period from 2000 to 2016. (a, b) Spatial distributions of the multiyear mean values and long-term trends. (c) Long-term trends of the mean GPP in Nepal. (d) Correlations of the multiyear means and long-term changing slopes derived from MODIS data with that from the other three products. The MODIS data were aggregated to the same grid scales of the other three GPP products by a mean method when performed the comparison analysis. ** and * mean the trends or correlations are significant at the 0.01 and 0.05 levels, respectively.

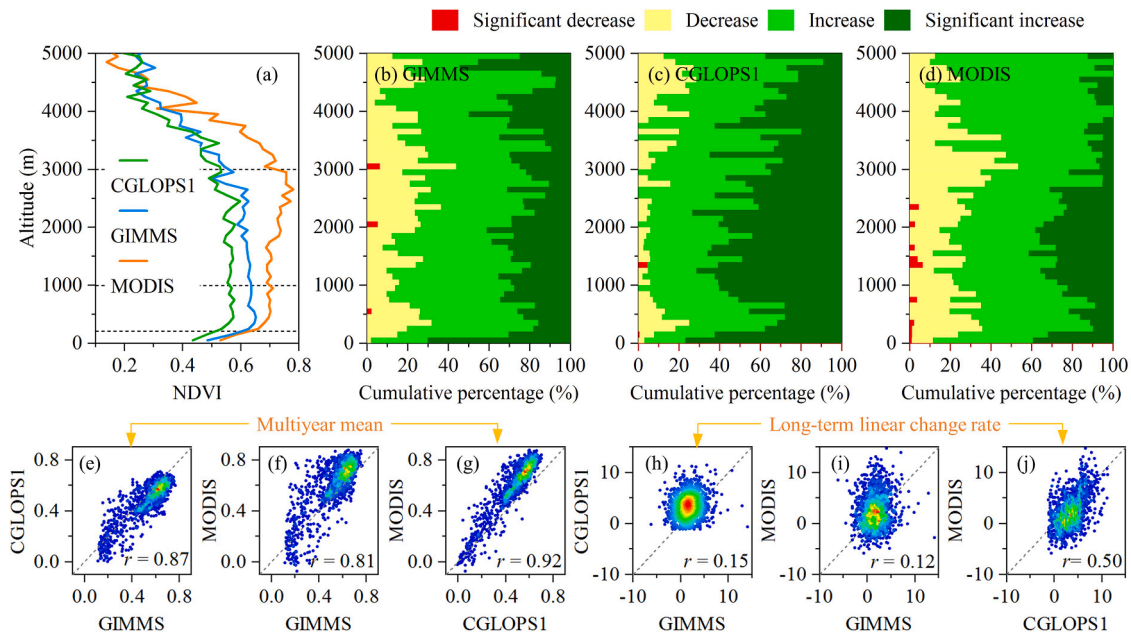


Fig. 16. Comparison of the growing-season vegetation growth dynamics revealed by the AVHRR based GIMSS NDVI3g (8 km, half-month), the SPOT/VEGETATION and PROBA-V based CGLOPS-1 NDVI (1-km, 10-days), and the MODIS NDVI calculated in this study (500 m, daily). (a-d) Multiyear means and long-term trends by 100 m altitude bins. (e-j) Correlations of the multiyear means and long-term linear change rates across the space among different products. The long-term linear change rates are scaled by 1000 times. All the correlations are significant at the 0.01 level. The CGLOPS-1 and MODIS data are aggregated to a cell size of 8 km by a mean method to keep consistent with GIMMS data.

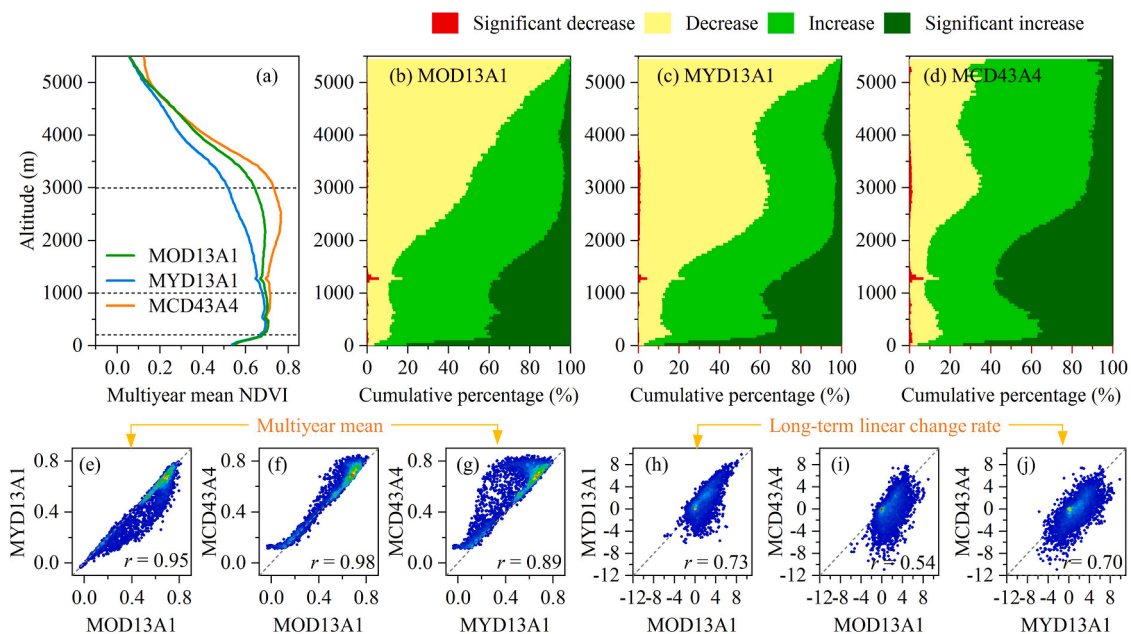


Fig. 17. Comparison of the growing-season vegetation growth dynamics revealed by the NDVI data from Terra/MODIS (MOD13A1, 500 m, 16-days), Aqua/MODIS (MYD13A1, 500 m, 16-days), and that calculated from the combined reflectance products of both satellites (MCD43A4, 500 m, daily). (a-d) Multiyear means and long-term trends along the 50 m altitude bins. (e-j) Correlations among different NDVI data in terms of the multiyear means and long-term linear change rates (scaled by 1000 times) across the space.

middle to high lands (Fig. 17). In addition, they both exhibit smaller multiyear means (0.55~0.59 vs 0.62) and fewer “significant increase” (31~32% vs 42%) than the NDVI data calculated from the combined reflectance products (MCD43A4) in this study. These together highlight the importance of improving the remote sensing indices, model algorithms, and satellite sensors/platforms, and the necessity of combined uses of multiple indices when the better data are not yet available for monitoring mountainous vegetation dynamics.

5. Conclusions

This study provides a systematic comparison of six widely used remote sensing indices in characterizing the vegetation growth in a typical mountainous region. Our results indicate overall high consistency, especially between the EVI and NIR_v , in capturing the spatial variations of the multiyear mean vegetation growth in mountains. The consistency differs by the altitude and land cover type, with the largest

consistency in the highlands which are dominated by grass and sparsely vegetation. Also, we find prevalent non-linear relationships between greenness indices or GOSIF and LAI or GPP. In contrast, large inconsistencies exhibit in the long-term trends of vegetation growth across the space, though all the indices show a widespread greening tendency. The fraction of the lands in an “uncertain” trend increases sharply by the rise of elevation in the mid- to high-lands, with a clear “cliff” between 1500 and 2000 m. The non-significant changes of all the indices in the study period mainly contribute to the trend uncertainties, especially in the highlands. The inconsistency between greenness and productivity indices (particularly in the lowlands which are dominated by the STEF and TDF) and in them (particularly between the productivity indices of GPP and SIF) further increase the discrepancies. Those discrepancies will be further cascaded when considered the quality-control methods, seasonal scales, product models, data collections, and satellite sensors/platforms. Although this study emphasizes the inconsistency, the synchronized changes of all the remote sensing indices in few areas echo the strong impacts of agriculture (increase) and urbanization (decrease) on the vegetation growth in Nepal. Future efforts should be tailored to explore the mechanisms behind the inconsistencies, apply reinforced remote sensing data or ground-based experiments to determine which indicator is more accurate, improve model algorithms of existing indices, and/or develop new remote sensing indices in mountainous regions.

CRedit authorship contribution statement

Decheng Zhou: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft. **Liangxia Zhang:** Methodology, Writing – review & editing, Supervision. **Lu Hao:** Writing – review & editing. **Ge Sun:** Writing – review & editing. **Jingfeng Xiao:** Writing – review & editing. **Xing Li:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (#42061144004) and the National Key R & D Program of China (#2021YFB2600100), and the Natural Science Foundation of Jiangsu Province (#BK20220055). J.X. was supported by University of New Hampshire.

References

- Badgley, G., Field, C.B., Berry, J.A., 2017. Canopy near-infrared reflectance and terrestrial photosynthesis. *Sci. Adv.* 3 (3), e1602244.
- Baker, N.R., 2008. Chlorophyll fluorescence: a probe of photosynthesis *in vivo*. *Annu. Rev. Plant Biol.* 59, 89.
- Baniya, B., Tang, Q., Huang, Z., Sun, S., Techato, K.A., 2018. Spatial and temporal variation of NDVI in response to climate change and the implication for carbon dynamics in Nepal. *Forests* 9 (6), 329.
- Bi, W., et al., 2022. A global 0.05° dataset for gross primary production of sunlit and shaded vegetation canopies from 1992 to 2020. *Sci. Data* 9 (1), 1–13.
- Camps-Valls, G., et al., 2021. A unified vegetation index for quantifying the terrestrial biosphere. *Sci. Adv.* 7 (9), eabc7447.
- Carlson, T.N., Ripley, D.A., 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sens. Environ.* 62 (3), 241–252.
- Chapin, F.S., Matson, P.A., Vitousek, P.M., 2011. *Principles of Terrestrial Ecosystem Ecology*. Springer New York, NY, XV, p. 529.
- Chen, A., Meng, F., Mao, J., Ricciutto, D., Knapp, A.K., 2022. Photosynthesis phenology, as defined by solar-induced chlorophyll fluorescence, is overestimated by vegetation indices in the extratropical Northern Hemisphere. *Agric. Forest Meteorol.* 323, 109027.
- Chen, C., et al., 2019. China and India lead in greening of the world through land-use management. *Nat. Sustain.* 2 (2), 122–129.

- Dechant, B., et al., 2022. NIRVP: a robust structural proxy for sun-induced chlorophyll fluorescence and photosynthesis across scales. *Remote Sens. Environ.* 268, 112763.
- Didan, K., 2021. MODIS/aqua vegetation indices 16-day L3 global 500m SIN grid V061 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2023-04-10 from 10.5067/MODIS/MYD13A1.061.
- Didan, K., 2021. MODIS/terra vegetation indices 16-day L3 global 500m SIN grid V061 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2023-04-10 from 10.5067/MODIS/MYD13A1.061.
- Ding, Z., Peng, J., Qiu, S., Zhao, Y., 2020. Nearly half of global vegetated area experienced inconsistent vegetation growth in terms of greenness, cover, and productivity. *Earth Futur.* 8 (10) e2020EF001618.
- Doughty, R., et al., 2021. Global-scale consistency of spaceborne vegetation indices, chlorophyll fluorescence, and photosynthesis. *J. Geophys. Res. Biogeosci.* 126 (6) e2020JG006136.
- Fang, H., Baret, F., Plummer, S., Schaepman-Strub, G., 2019. An overview of global leaf area index (LAI): methods, products, validation, and applications. *Rev. Geophys.* 57 (3), 739–799.
- Fensholt, R., Proud, S.R., 2012. Evaluation of earth observation based global long term vegetation trends—comparing GIMMS and MODIS global NDVI time series. *Remote Sens. Environ.* 119, 131–147.
- Frankenberg, C., et al., 2011. New global observations of the terrestrial carbon cycle from GOSAT: patterns of plant fluorescence with gross primary productivity. *Geophys. Res. Lett.* 38 (17), L17706.
- FRTC, 2022. National Land Cover Monitoring System of Nepal. Forest Research and Training Centre (FRTC), Kathmandu, Nepal.
- Gamon, J.A., et al., 1995. Relationships between NDVI, canopy structure, and photosynthesis in three Californian vegetation types. *Ecol. Appl.* 5 (1), 28–41.
- Gao, M., et al., 2019. Divergent changes in the elevational gradient of vegetation activities over the last 30 years. *Nat. Commun.* 10 (1), 1–10.
- Glenn, E.P., Huete, A.R., Nagler, P.L., Nelson, S.G., 2008. Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. *Sensors* 8 (4), 2136–2160.
- Gottfried, M., et al., 2012. Continent-wide response of mountain vegetation to climate change. *Nat. Clim. Chang.* 2 (2), 111–115.
- Guanter, L., et al., 2014. Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence. *Proc. Natl. Acad. Sci.* 111 (14), E1327–E1333.
- Hu, Z., et al., 2022. Decoupling of greenness and gross primary productivity as aridity decreases. *Remote Sens. Environ.* 279, 113120.
- Hubau, W., et al., 2020. Asynchronous carbon sink saturation in African and Amazonian tropical forests. *Nature* 579 (7797), 80–87.
- Huete, A., et al., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sens. Environ.* 83 (1–2), 195–213.
- Jeong, S.J., et al., 2017. Application of satellite solar-induced chlorophyll fluorescence to understanding large-scale variations in vegetation phenology and function over northern high latitude forests. *Remote Sens. Environ.* 190, 178–187.
- Jiang, C., et al., 2017. Inconsistencies of interannual variability and trends in long-term satellite leaf area index products. *Glob. Chang. Biol.* 23 (10), 4133–4146.
- Koju, U.A., et al., 2020. Analysis of spatiotemporal dynamics of forest net primary productivity of Nepal during 2000–2015. *Int. J. Remote Sens.* 41 (11), 4336–4364.
- Krakauer, N.Y., Lakhankar, T., Anadón, J.D., 2017. Mapping and attributing normalized difference vegetation index trends for Nepal. *Remote Sens.* 9 (10), 986.
- Li, X., Xiao, J., 2019. A global, 0.05-degree product of solar-induced chlorophyll fluorescence derived from OCO-2, MODIS, and reanalysis data. *Remote Sens.* 11 (5), 517.
- Smets, B., Tavares, J.L., Toté, C., Wolters, E., 2020. Copernicus global land operations “Vegetation and Energy” CGLOPS-1. Product User Manual. https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_PUM_NDVI1km-V3_I1.10.pdf.
- Li, X., et al., 2018. Solar-induced chlorophyll fluorescence is strongly correlated with terrestrial photosynthesis for a wide variety of biomes: first global analysis based on OCO-2 and flux tower observations. 24(9): 3990–4008.
- Linscheid, N., et al., 2021. Time-scale dependent relations between earth observation based proxies of vegetation productivity. *Geophys. Res. Lett.* 48 (24) e2021GL093285.
- Liu, R., Shang, R., Liu, Y., Lu, X., 2017. Global evaluation of gap-filling approaches for seasonal NDVI with considering vegetation growth trajectory, protection of key point, noise resistance and curve stability. *Remote Sens. Environ.* 189, 164–179.
- Liu, X., et al., 2021. European carbon uptake has not benefited from vegetation greening. *Geophys. Res. Lett.* 48 (20) e2021GL094870.
- Liu, Y., et al., 2022. Evaluation of consistency among three NDVI products applied to High Mountain Asia in 2000–2015. *Remote Sens. Environ.* 269, 112821.
- Locatelli, B., Lavorel, S., Sloan, S., Tappeiner, U., Geneletti, D., 2017. Characteristic trajectories of ecosystem services in mountains. *Front. Ecol. Environ.* 15 (3), 150–159.
- Lyapustin, A., et al., 2014. Scientific impact of MODIS C5 calibration degradation and C6 + improvements. *Atmos. Meas. Tech.* 7 (12), 4353–4365.
- Myneni, R., Knyazikhin, Y., Park, T., 2021. MODIS/aqua leaf area index/FPAR 8-day L4 global 500m SIN Grid V061 [Data set]. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MODIS/MYD15A2H.061. Accessed 2022-04-15.
- Myneni, R.B., Keeling, C., Tucker, C.J., Asrar, G., Nemani, R.R., 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature* 386 (6626), 698–702.
- NASA JPL, 2020. NASADEM Merged DEM Global 1 arc second V001 [Data set]. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MEaSUREs/NASADEM/NASADEM_HGT.001. Accessed 2022-04-15.

- Oldekop, J.A., Sims, K.R., Karna, B.K., Whittingham, M.J., Agrawal, A., 2019. Reductions in deforestation and poverty from decentralized forest management in Nepal. *Nat. Sustain.* 2 (5), 421–428.
- Pan, N., et al., 2018. Increasing global vegetation browning hidden in overall vegetation greening: Insights from time-varying trends. *Remote Sens. Environ.* 214, 59–72.
- Pan, Y., et al., 2011. A large and persistent carbon sink in the world's forests. *Science* 333 (6045), 988–993.
- Pei, Y., et al., 2022. Evolution of light use efficiency models: Improvement, uncertainties, and implications. *Agric. For. Meteorol.* 317, 108905.
- Piao, S., et al., 2020. Characteristics, drivers and feedbacks of global greening. *Nat. Rev. Earth Environ.* 1 (1), 14–27.
- Piao, S., et al., 2015. Detection and attribution of vegetation greening trend in China over the last 30 years. *Glob. Chang. Biol.* 21 (4), 1601–1609.
- Pierrat, Z., et al., 2022. Diurnal and seasonal dynamics of solar-induced chlorophyll fluorescence, vegetation indices, and gross primary productivity in the boreal forest. *J. Geophys. Res. Biogeosci.* 127 (2), e2021JG006588.
- Pinzon, J.E., Tucker, C.J., 2014. A non-stationary 1981–2012 AVHRR NDVI3g time series. *Remote Sens.* 6 (8), 6929–6960.
- Running, S., Zhao, M., 2021. MODIS/terra gross primary productivity gap-filled 8-day L4 global 500m SIN grid V061 [Data set]. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MODIS/MOD17A2HGF.061. Accessed 2022-04-15.
- Running, S.W., et al., 2004. A continuous satellite-derived measure of global terrestrial primary production. *Bioscience* 54 (6), 547–560.
- Samanta, A., Ganguly, S., Vermote, E., Nemani, R.R., Myneni, R.B., 2012. Why is remote sensing of amazon forest greenness so challenging? *Earth Interact.* 16 (7), 1–14.
- Sarmah, S., et al., 2021. Mismatches between vegetation greening and primary productivity trends in South Asia—a satellite evidence. *Int. J. Appl. Earth Obs. Geoinf.* 104, 102561.
- Schaaf, C., Wang, Z., 2021. MODIS/terra+ aqua BRDF/albedo nadir brdf adjusted ref daily L3 global - 500m V061 [Data set]. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MODIS/MCD43A4.061. Accessed 2022-04-15.
- Sellers, P., et al., 1997. Modeling the exchanges of energy, water, and carbon between continents and the atmosphere. *Science* 275 (5299), 502–509.
- Song, L., et al., 2018. Satellite sun-induced chlorophyll fluorescence detects early response of winter wheat to heat stress in the Indian Indo-Gangetic Plains. *Glob. Chang. Biol.* 24 (9), 4023–4037.
- Stocker, B.D., et al., 2019. Drought impacts on terrestrial primary production underestimated by satellite monitoring. *Nat. Geosci.* 12 (4), 264–270.
- Street, L., Shaver, G., Williams, M., Van Wijk, M., 2007. What is the relationship between changes in canopy leaf area and changes in photosynthetic CO₂ flux in arctic ecosystems? *J. Ecol.* 95 (1), 139–150.
- Viviroli, D., Dürr, H.H., Messerli, B., Meybeck, M., Weingartner, R., 2007. Mountains of the world, water towers for humanity: typology, mapping, and global significance. *Water Resour. Res.* 43 (7), W07447.
- Wang, X., et al., 2022a. Satellite solar-induced chlorophyll fluorescence and near-infrared reflectance capture complementary aspects of dryland vegetation productivity dynamics. *Remote Sens. Environ.* 270, 112858.
- Wang, X., Chen, J.M., Ju, W., 2020. Photochemical reflectance index (PRI) can be used to improve the relationship between gross primary productivity (GPP) and sun-induced chlorophyll fluorescence (SIF). *Remote Sens. Environ.* 246, 111888.
- Wang, Z., et al., 2022b. Large discrepancies of global greening: indication of multi-source remote sensing data. *Glob. Ecol. Conserv.* 34, e02016.
- Wei, F., et al., 2022. Divergent trends of ecosystem-scale photosynthetic efficiency between arid and humid lands across the globe. *Glob. Ecol. Biogeogr.* 31 (9), 1824–1837.
- Xiao, J., et al., 2019. Remote sensing of the terrestrial carbon cycle: a review of advances over 50 years. *Remote Sens. Environ.* 233, 111383.
- Xiao, J., Moody, A., 2004. Trends in vegetation activity and their climatic correlates: China 1982 to 1998. *Int. J. Remote Sens.* 25 (24), 5669–5689.
- Yang, J., et al., 2022a. TROPOMI SIF reveals large uncertainty in estimating the end of plant growing season from vegetation indices data in the Tibetan Plateau. *Remote Sens. Environ.* 280, 113209.
- Yang, J.C., et al., 2022b. Gross primary production (GPP) and red solar induced fluorescence (SIF) respond differently to light and seasonal environmental conditions in a subalpine conifer forest. *Agric. For. Meteorol.* 317, 108904.
- Zeng, J., et al., 2020. Global terrestrial carbon fluxes of 1999–2019 estimated by upscaling eddy covariance data with a random forest. *Sci. Data* 7 (1), 313.
- Zeng, Y., et al., 2022. Optical vegetation indices for monitoring terrestrial ecosystems globally. *Nat. Rev. Earth Environ.* 1–17.
- Zeng, Z., et al., 2017. Climate mitigation from vegetation biophysical feedbacks during the past three decades. *Nat. Clim. Chang.* 7 (6), 432–436.
- Zhang, J., et al., 2022. NIRv and SIF better estimate phenology than NDVI and EVI: effects of spring and autumn phenology on ecosystem production of planted forests. *Agric. For. Meteorol.* 315, 108819.
- Zhang, L., et al., 2019. Contrasting the performance of eight satellite-based GPP models in water-limited and temperature-limited grassland ecosystems. *Remote Sens.* 11 (11), 1333.
- Zhang, L., Zhou, D., Fan, J., Hu, Z., 2015. Comparison of four light use efficiency models for estimating terrestrial gross primary production. *Ecol. Model.* 300, 30–39.
- Zhang, Y., Song, C., Band, L.E., Sun, G., Li, J., 2017a. Reanalysis of global terrestrial vegetation trends from MODIS products: browning or greening? *Remote Sens. Environ.* 191, 145–155.
- Zhang, Y., et al., 2017b. A global moderate resolution dataset of gross primary production of vegetation for 2000–2016. *Sci. Data* 4 (1), 1–13.
- Zhao, M., Running, S.W., Nemani, R.R., 2006. Sensitivity of moderate resolution imaging spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. *J. Geophys. Res. Biogeosci.* 111 (G1), G01002.
- Zhou, D., et al., 2019. Potential impacts of climate change on vegetation dynamics and ecosystem function in a mountain watershed on the Qinghai-Tibet Plateau. *Clim. Chang.* 156 (1), 31–50.
- Zhu, Z., et al., 2016. Greening of the Earth and its drivers. *Nat. Clim. Chang.* 6 (8), 791–795.