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Satellite view of seasonal greenness trends and controls in South Asia

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Abstract

South Asia (SA) has been considered one of the most remarkable regions for changing vegetation greenness, accompanying its major expansion of agricultural activities, especially irrigated farming. The influence of the monsoon climate on the seasonal trends and anomalies of vegetation greenness is poorly understood in this area. Herein, we used the satellite-based Normalized Difference Vegetation Index (NDVI) to investigate various spatiotemporal patterns in vegetation activity during summer and winter monsoon (SM and WM) seasons and among irrigated croplands (IC), rainfed croplands (RC), and natural vegetation (NV) areas during 1982–2013. Seasonal NDVI variations with climatic factors (precipitation and temperature) and land use and cover changes (LUCC) have also been investigated. This study demonstrates that the seasonal dynamics of vegetation could improve the detailed understanding of vegetation productivity over the region. We found distinct greenness trends between two monsoon seasons and among the major land use/cover classes. Winter monsoons contributed greater variability to the overall vegetation dynamics of SA. Major greening occurred due to the increased productivity over irrigated croplands during the winter monsoon season; meanwhile, browning trends were prominent over NV areas during the same season. Maximum temperatures had been increasing tremendously during the WM season; however, the precipitation trend was not significant over SA. Both the climate variability and LUCC revealed coupled effects on the long term NDVI trends in NV areas, especially in the hilly regions, whereas anthropogenic activities (agricultural advancements) played a pivotal role in the rest of the area. Until now, advanced cultivation techniques have proven to be beneficial for the region in terms of the productivity of croplands. However, the crop productivity is at risk under climate change.

1. Introduction

Vegetation is a vital component of terrestrial ecosystems and land cover with great variability over time and space. Rapid variations in vegetation provide valuable information about ecological responses to climate changes [1, 2], crop status [3] and land use and cover changes (LUCC) [4]. A substantial attention has been given to the spatiotemporal changes in vegetation activity and their driving factors. Previous studies suggested that an extensive part of the world is experiencing dramatic changes in photosynthesis [5], among which South Asia (SA) is significant [6–8].

SA is one of the most vulnerable regions to climate change in the world; it is home to approximately 1.7 billion people and includes three rich biodiversity hotspots: the eastern Himalayas in Nepal, northeastern India and Bhutan; the Western and Eastern Ghats of India and Sri Lanka; and the Indo-Burma hotspot in India and Myanmar [9]. Numerous studies have recognized the well-connected relationship between vegetation growth and climate in this region [10–14].

94% of the land in SA, suitable for agriculture, is already being cultivated [15,16]. As an agriculture dominant zone, the interaction between cropland productivity and climate has been the main research
interest in this region [17–19]. Studies have revealed that the summer and winter crop production in India has increased by four times and six times, respectively, over the last five decades [20]. However, disasters, including droughts, floods, heat waves, etc. have been increasing since the past century [21, 22], putting the vegetation at risk. An accurate quantification of the South Asian vegetation response towards changing climate would have fundamental implications for our understanding of regional food security.

Numerous studies have used the Normalized Difference Vegetation Index (NDVI) to quantify the vegetation greenness changes, both globally and regionally [23–25]. NDVI has been correlated with different climatic parameters for trend analysis to examine the vegetation ecosystem dynamics [26–28]. However, previous studies have not investigated how vegetation trends differed among the seasons or the seasonal sensitivity of the vegetation to climate change over SA. The spatial patterns of NDVI trends and their drivers may vary significantly in different regions and seasons due to distinctive inter-annual variability [7,29,30], which needs to be understood. Annual trends often cannot explain the details of the vegetation growth patterns. The trends also depend on the method used to define a particular time that best reflects a season [31–33], which could affect conclusions about the trends in specific regions. In this study, we considered summer monsoon (SM, June–September) and winter monsoon (WM, December–April) seasons as these are the two significant periods governing the vegetation dynamics in SA [9].

Land use and land cover changes (agriculture advancements, deforestations, urban expansion, etc.) are continually occurring over SA [5,34–36]. Investigating the prominent areas of vegetation changes for different land use/cover categories would improve our understanding of the linkage between LUCC and vegetation dynamics. In this study, three key land use categories, namely, irrigated cropland (IC), rainfed cropland (RC) and natural vegetation (NV) have been considered. Studying the coupled effects of LUCC along with the climate system influences would help in comprehending the long-term impacts on vegetation productivity.

Our main focus is to understand how the vegetation trends vary across different seasons and regions and to examine the controls behind these observed variations over South Asia.

The main objectives of this study were:

1. To characterize the spatiotemporal distribution of vegetation over SA in the two monsoon seasons (SM and WM) using 32 years of NDVI time series.
2. To better understand the heterogeneous responses of vegetation greenness to inter-annual trends and seasonal dynamics in monsoon climates within the study area.
3. To illustrate the vegetation trends and variability in different land use/cover categories (irrigated cropland, rainfed cropland and natural vegetation) to see the LUCC impacts on the trends and seasonality of vegetation greenness.

2. Datasets

2.1. NDVI time series data

The updated version (version 3) of the Advanced Very High-resolution Radiometer (AVHRR) based Global Inventory Monitoring and Modeling Systems (GIMMS) NDVI time series (GIMMS3g) [37] was acquired for the period of 1982–2013. The spatial and temporal resolutions are 0.083° and 15 day, respectively. This dataset is the longest available NDVI time series, suitable for monitoring long-term vegetation changes. GIMMS3g accurately characterizes vegetation responses to climate variability [38,39].

2.2. Climate data

The temperature and precipitation datasets were obtained from the Climate Research Unit (CRU), version TS3.23 [40], spanning from 1982–2013 with a spatial resolution of 0.5°. All of the climate datasets were thoroughly evaluated and applied in global/regional climate studies. The climate parameters utilized were monthly total precipitation (P) and the monthly average minimum (T_{mn}), maximum (T_{mx}) and mean (T_{mp}) temperatures.

2.3. Land use/land cover (LULC) and topographic data

Moderate Resolution Imaging Spectroradiometer (MODIS) LULC data (MCD12Q1) (supplementary figure S1 available at stacks.iop.org/ERL/13/034026/mmedia) and the Global Cropland data (GCE) version 1 [41] (supplementary figure S2) (available at http://e4ft101.cr.usgs.gov/provisional/MEaSUREs/GFSADCM1KM/02-data/) were used to extract the natural vegetation and cropland areas in the region. The spatial resolutions of MCD12Q1 and GCE are 500 m and 1 km, respectively. All the natural forests and grasslands from MCD12Q1 data of 2013 were considered as natural vegetation areas. Both the MCD12Q1 (2013) and GCE datasets were resampled to GIMMS3g resolution and the cropped areas (irrigated and rainfed) were extracted (figure 1(a)) from them. The MCD12Q1 data for 2001 were also used to compare with 2013 data for change analysis.

The topography data were the 30 arc second spatial resolution GMTED 2010 (Global and Multi Resolution Terrain Elevation Data 2010) DEM (digital elevation model) data (figure 1(b)) [42].
3. Methods

3.1. Processing of the time series data
From the GIMMS3g time series, NDVI values flagged as 'good quality' were extracted for the analysis. We derived the maximum value composites (MVC) for each month of each year from the bimonthly NDVI data. The MVC method was adopted to remove the influence of atmospheric noise. Even after applying MVC, the dataset contained residual noise and produced erroneous results. To further remove these biases, we applied Savitsky–Golay filter [43] to the dataset. We masked out areas where the mean annual NDVI (1982–2013) was less than or equal to 0.15, considering these as extremely arid, bare ground/desert or permanent snow cover to avoid the signals from non-vegetative areas [44].

We calculated the monthly and seasonal standardized anomalies (Std. anomaly) for NDVI, precipitation, and temperature from 1982–2013 using the following equation

\[
\text{Std. anomaly} = \left( \frac{X - \overline{X}}{\sigma} \right)
\]

where \(X\) is the parameter value at a particular time (month/season), \(\overline{X}\) and \(\sigma\) are the average (monthly/seasonal) and standard deviation (monthly/seasonal), respectively, over the studied time period (1982–2013) [45]. For seasonal anomaly detection of precipitation, \(X\) represented the cumulative precipitation of each season, while for NDVI and temperature, \(X\) was calculated as the seasonal average for each year (in equation 1). Subsets of the CRU dataset were resampled to make them compatible with the NDVI data. 5 monthly and 10 seasonal (summer monsoon and winter monsoon) anomaly datasets were prepared for NDVI, precipitation, and temperature \((T_{\text{mn}}, T_{\text{mx}}, T_{\text{mp}})\) from 1982–2013.

In the discussion to follow, monthly standardized anomalies in NDVI, precipitation, and temperature will be referred to as SGA (standardized greenness anomaly), SPA (standardized precipitation anomaly), \(ST_{\text{mn}}A\) (standardized minimum temperature anomaly), \(ST_{\text{mx}}A\) (standardized maximum temperature anomaly), and \(ST_{\text{mp}}A\) (standardized mean temperature anomaly). The seasonal anomaly dataset for NDVI will be labelled as SGA_{SM}/SGA_{WM} (SM/WM). Similarly, seasonal precipitation anomaly dataset will be labelled as SPA_{SM}/SPA_{WM} (SM/WM), while \(ST_{\text{mn}}A_{SM}/ST_{\text{mn}}A_{WM}\), \(ST_{\text{mp}}A_{SM}/ST_{\text{mp}}A_{WM}\), and \(ST_{\text{mx}}A_{SM}/ST_{\text{mx}}A_{WM}\) will represent the seasonal anomaly datasets of \(T_{\text{mn}}, T_{\text{mp}}, T_{\text{mx}}\) for summer monsoon and winter monsoon, respectively.

3.2. Trend analysis
The linear trends in each of the time series (NDVI, precipitation, and temperature) were calculated using the least squares linear regression method for each pixel, reflecting the spatial characteristics of the rate of change per time step (e.g. for monthly data: rate of change per month) at the pixel level. The slope \((a)\) of the regression showed the mean temporal change: \(a > 0\) denoted increasing trends/greening and \(a < 0\) indicated decreasing trends/browning. The significance was tested by the nonparametric Mann–Kendall significance test. The slope pixels with the 95% confidence levels \((p < 0.05)\) were highlighted for subsequent analysis.

We computed the inter-annual NDVI trends for irrigated cropland, rainfed cropland and natural vegetation, taking the average values across pixels for each year located in each LULC class. For all other parameters, the average anomalies across the pixels were considered to calculate the inter-annual trends. Recent studies indicated that vegetation trends are rarely monotonic but rather include periods with different trends. Transitions between trends occurred more frequently in the
2000s than in the 1980s [46]. Therefore, we segmented the inter-annual trends into two parts (1982–1999 and 2000–2013) to focus more on the latest trend (2000–2013) for all the vegetation and climate parameters.

3.3. Connection to key drivers

To comprehend the possible roles of climatic drivers (rainfall and temperature) on vegetation variability, Pearson’s correlation method was applied between monthly anomaly datasets of vegetation and climate parameters. Lagged correlations were computed to evaluate the potential delay of vegetation response to rainfall, where the SPA time series were shifted one month (lag 1), two months (lag 2) and three months (lag 3) prior to the SGA time series in both the seasons. As suggested in previous literatures, the STmnA, STmpA and STmxA time series were correlated with the SGA considering 0 lag for each season.

For LUCC exploration, we applied change detection analysis to 2001 and 2013 land use classifications. We detected the conversion of each land use category using Arc GIS software.

4. Results

4.1. Seasonal characteristics of the spatiotemporal patterns of greenness trends

Although greening was apparent for both the summer (SM) and winter monsoons (WM), a high degree of spatial heterogeneity was found in SGA trends that varied seasonally over SA (figure 2 and supplementary table 1). The study area showed extensive greening, with an NDVI growth rate of 0.24% per year ($R^2 = 0.49$, $p < 0.05$) over the period. Approximately 37% of the study area showed greening and 4% showed browning over the entire time period. During the WM season, almost 38% of the total area showed significant changes, while during the SM season, the significantly changed area was 23%. Greening was much stronger during WM (slope > 0.04, $p < 0.05$) than the SM season, with positive slopes covering 33% of the study area. This result demonstrated that the winter monsoon contributed greater variability to the vegetation greenness over SA.

Greenness significantly increased in the agricultural fields of the Gangatic plain, the Indus valley in Pakistan, the Deccan plateau, and Bangladesh (figure 2(b)), with a steeper (>0.04) slope during the WM season. Meanwhile, browning (~5%) occurred mostly in the natural vegetation areas of the Himalayan foothills, northeastern India, parts of the Western Ghats and parts of northeastern Sri Lanka (figure 2(b)) during the same season. In the SM season, SGA trend displayed a fragmented pattern, slightly increasing in the Deccan plateau, the Indus valley in Pakistan, part of Myanmar and the Gangatic plain (figure 2(a)). There was no significant browning during the SM season.

The spatial correlation of the NDVI trends with elevation data revealed that the most evident browning occurred in the foothills (200–500 m). The NDVI also decreased in the high elevation (>1000 m) areas with high percentages (figure 3). Out of the 3636 decreasing pixels, 2428 occurred at elevations of more than 1000 m (supplementary table 2).

4.2. Spatial variability of seasonal greenness and climatic factor correlation

Our correlation analysis largely demonstrated the impacts of climate dynamics on NDVI anomalies. Precipitation did not show any significant trend (supplementary figure S5). However, temperature
Figure 3. Counts of browning pixels along the elevation gradient over South Asia in the winter monsoon season.

Figure 4. Spatial distribution of the minimum ($T_{mn}$), mean ($T_{mp}$) and maximum ($T_{mx}$) temperature linear trends during the summer monsoon season (a)–(c) and winter monsoon season (d)–(f) from 1982–2013.

significantly increased in the last 32 years (figure 4). $T_{mn}$, $T_{mx}$ and $T_{mp}$ displayed substantial increasing trends prominently in the Himalayan region, northeastern India and northwestern semi-arid regions in both SM and WM seasons. Temperature showed a seasonal variation in the spatial distribution of its trends over the study area. During the SM season, $T_{mp}$ and $T_{mn}$ increased in most of the areas ($\sim55\%$), while during WM, $T_{mx}$ increased significantly in almost 69.4% of the total area (supplementary table 1).

There was a distinct spatial pattern in the seasonal response of vegetation greenness to the rainfall anomaly (figure 5 and supplementary table 3). During the SM season, the xeric vegetation correlated positively to rainfall, while during WM, the positive correlation was visible in the southern and eastern India. Lags of one
month and two months were significant during the SM (19.1% area) and WM (20.4% area) seasons, respectively. During SM, 20.16% of the vegetation exhibited a significant positive response toward precipitation anomaly and approximately 3.4% showed a negative response. During WM, 14.2% of the total area displayed positive correlations to rainfall anomalies, and 7.6% showed significant negative correlation.

Like precipitation, the temperature parameters also showed significant spatial variability in their correlation with NDVI in both seasons (figure 6 and supplementary table 3). During the SM season, the arid western areas displayed a negative correlation with temperature anomaly; however, during the WM season, the negative correlation shifted toward the southern and eastern parts of the region. The eastern part of the central India showed a positive relationship to temperature anomaly during SM, while during WM, the association was negative. The Indus valley in Pakistan demonstrated a negative correlation with temperature during SM while the correlation was positive during the WM season. Vegetation in the Indian Gangatic plain was positively correlated to temperature during the WM season, while in the SM season, there was no any significant correlation between them. During SM, $T_{mx}$ had an impact on vegetation growth in most of the regions (32.7%), whereas during WM, $T_{mp}$ showed the highest percentage (29%) of vegetated area under its impact. $T_{mn}$ showed the highest negative impact (19%) and $T_{mx}$ showed the highest (14%) positive impact on vegetation growth during the WM season. During SM, $T_{mn}$ demonstrated the highest (~20%) negative impact and $T_{mp}$ showed the highest positive impact (13.4%).

4.3. LUCC impacts on the vegetation trends

The greenness trends in both seasons varied greatly among the major LULC categories. The key greening areas were the croplands, while major browning trends were found mostly over natural vegetation areas. We investigated the linear trends of the NDVI in IC, RC and NV in different seasons to understand the specific relationship of the LUCC with the long-term vegetation trends (figure 7). RC and IC both showed conspicuous increasing trends in the WM season, but the trends were less significant in the SM season. IC demonstrated more significant and stronger increasing trends (Slope = 0.06, $R^2 = 0.7$) than RC (slope 0.03, $R^2 = 0.43$) during the WM season.

NV was showing an obviously increasing trend (slope = 0.03) until 2000; however, since 2000, NV started to decline at a significant rate (~0.03) during the WM season. Furthermore, the IC and RC NDVI trends were much lower during 2000–2013 than during 1982–1999 in both seasons.

We also calculated precipitation (supplementary figure S6) and temperature (supplementary figures S7 and S8) inter-annual trends over these LULC categories. For NV, the temperature displayed a very strong
Figure 6. Spatial distribution of the correlation between standardized greenness anomaly and (a) standardized minimum temperature anomaly, (b) standardized mean temperature anomaly, (c) standardized maximum temperature anomaly, (d) standardized minimum temperature anomaly, (e) standardized mean temperature anomaly, and (f) standardized maximum temperature anomaly. (a)–(c) and (d)–(f) represent the summer and winter monsoon seasons, respectively.

Figure 7. Inter-annual trends of NDVI in irrigated cropland (IC), rainfed cropland (RC) and natural vegetation (NV) classes during (a)–(c) summer monsoon and (d)–(f) winter monsoon. Trends from 1982–2013, 1982–1999 and 2000–2013 are shown in black, red and green colors, respectively.
and significant increasing trend in both the seasons. During SM, $T_{mn}$ increased significantly over RC; however, $T_{mp}$ and $T_{mx}$ trends were not significant. During WM, the overall trends of $T_{mn}$, $T_{mp}$ and $T_{mx}$ were significant and strong (slope > 0.03) in all of the LULC categories. Since 2000, all the 3 temperature parameters over NV and IC while only $T_{mp}$ and $T_{mx}$ over RC displayed decreasing trends during the WM season, although they were not significant. There was an overall positive correlation ($R = 0.32$) between the maximum temperature and NDVI anomaly over irrigated cropland during WM, though the correlation was weak (0.05 < $p$ < 0.1) (supplementary figure S9). Precipitation exhibited a significant increasing trend since 2000 over croplands during SM; however, the overall trends in both seasons were non-significant.

The inter-annual NDVI trends also revealed that the vegetation cover was much reduced during the periods of 1991–1994, 1999–2000, 2004, and 2007. These reductions were largely linked to various extreme climate events and disturbances, such as drought, the El Niño-Southern Oscillation (ENSO) and the eruption of Mount Pinatubo. During SM, these events were distinct in all the 3 categories; during WM they were only prominent in NV, except for the 1991–1994 event, which was noticeable in croplands too.

The LUCC analysis from 2001–2013 demonstrated the visible changes in the Himalayan foothills, the eastern part of central India and Western Ghats (figure 8). These areas are predominantly natural forest where the conversions occurred mostly from forest to either croplands or urban areas. Some also degraded to open shrub lands or bare lands.

5. Discussion

This study utilized satellite-derived NDVI time-series data to characterize seasonal trends in vegetation growth over South Asia as well as to understand the drivers behind the observed changes. Linear regression was performed for every pixel to obtain the spatial patterns of linear trends and correlation was computed among those trends. The differences in the resolutions of the compared datasets (NDVI and climate) probably caused the low correlation ($R < 0.5$) value. Additionally, the spatial variability of correlations between NDVI and climatic factors resulted in an overall low correlation significance ($p > 0.05$) in all the LULC classes and especially in the natural vegetation. This study is consistent with other reports of significant greening across South Asia [5–7]. The most interesting findings of this study were the striking differences of the greening/browning between seasons and among the LULC categories. Distinctly, this study showed that the overall greenness trend over SA was largely contributed by the winter monsoon season.

Our study revealed that a large portion of SA experienced greening throughout the period of 1982–2013 in both the SM and WM seasons. However, the slope magnitude was much higher for the WM season than that of the SM season. Most of the greening areas fell within the cropland category, showing a strong positive slope during the WM season, which corroborates other studies where winter crop intensification has been described [3, 20]. Those previous studies were mostly concerned with small regions of the Indian subcontinent, whereas our study demonstrated that winter
crop productivity increased over the entire region. In contrast to the greening, browning was predominant in the natural vegetation areas, particularly during the WM season since 2000.

To understand the spatial and seasonal variations in the NDVI trends, we analyzed the relationships of the vegetation growth with climatic factors and tried to figure out the linkage with prominent LUCCs. Our study revealed that although NDVI had been increasing over both rainfed and irrigated croplands, irrigated croplands showed much stronger NDVI slope magnitudes during the WM season, indicating the significant role of the winter monsoon irrigation on the greening of SA. The WM season produces less rainfall than the SM season; therefore, the irrigation has increasingly been used to supplement precipitation, resulting in the increasing NDVI shown by this study. This also indicates the importance of soil moisture for the vegetation growth as the croplands are generally (mostly for irrigated and partially for rainfed) maintained by moisture supply during the WM season.

In general, the climate variability over SA could be characterized by the increasing trends of air temperatures, specifically during the WM season when precipitation trend was not significant, showing agreement with some of the recent studies [47, 48]. Moreover, our research demonstrated that rainfall had a substantial role in the NDVI trends during the SM season, while temperature was crucial during the WM season for explaining the NDVI variability over SA. Increasing temperature played a pivotal role in influencing winter crops in India, according to Mondal et al. [20]. Consistent with this study, besides the impact of irrigation, we found a temperature ($T_{	ext{mn}}$ and $T_{	ext{mx}}$) linkage to vegetation growth over the croplands of the Gangatic plain in India and the Indus valley in Pakistan during the WM season. Previous studies also described that CO$_2$, a major factor for anthropogenic warming, has the potential to impact plant phenology [49]. Therefore, CO$_2$ could be another possible factor for the greening of SA, likely lengthening the growing season of the crops, which eventually could result in higher NDVI during the WM season. However, the study of CO$_2$ and phenology as potential drivers goes beyond the scope of this research.

This study revealed typical characteristics of vegetation responses to precipitation anomalies in South Asia. The vegetation anomalies were found to be more strongly correlated to the cumulative precipitation over a period of time than to instantaneous precipitation. Therefore, the magnitude of the correlation between precipitation and NDVI anomalies considering lag months was much higher. In both the seasons, the semi-arid and dry sub humid areas where rainfed cropland is a predominant source of livelihood, vegetation activity was affected by rainfall with lags of one month (in SM) and two months (in WM), again implying the importance of soil moisture availability in those regions. Even slight variations in temperature and precipitation can lead to soil moisture differences, which in turn, can negatively affect the crop productivity making those regions vulnerable. A lag of one month between rainfall and the NDVI anomaly in the SM season has been demonstrated by various global and regional studies [11, 27, 50]; however, we found a significant correlation with a lag of two months between these two components during the WM season. It is understandable that in the southern part of SA (water limited areas), rainfall is essential in the two months prior to vegetation growth, as the rainfall amount is very low (<40 mm) during the WM season over those areas (supplementary figure S3). This understanding could improve the existing climate models’ abilities to predict the vegetation dynamics.

The eastern part of central India showed contrasting relationships between NDVI and temperature in different (positive during the SM and negative during the WM) seasons. Furthermore, NDVI in this region was positively correlated to precipitation during the WM season. These results indicate that some other factors, such as radiation, CO$_2$ or other human activities, could be the dominant factors for vegetation growth in this region.

The observed browning trends in the Himalayan foothills and northeastern India from our study were similar to the patterns that have been reported for the tropical mountain and forest regions over SA by previous studies [51, 52]. However, we found that those trends were conspicuous, especially during the WM season. Browning in natural vegetation was likely to be associated with rising temperature and/or decreasing precipitation resulting in larger net evapotranspiration deficits [53] and decreased NPP [54], as temperature had a strong increasing trend over those areas during the WM season, while rainfall did not show any discernible trend. Greater warming rates at higher elevations could cause intense browning due to moisture stress [55]. This could possibly be the reason behind the increased browning at higher (>1000 m) altitudes during the WM season found in our study, as the Himalayan region showed a strong warming trend in that season.

The reason behind the winter monsoon temperature decrease in all the LULC categories post 2000 could be explained by the warming hiatus revealed by recent studies [56], although the overall trends since the past three decades show a strong significant increase. The negative relationship between winter monsoon NDVI and temperature anomaly during 2000–2013 over croplands showed that the alarming warming during the WM season likely threaten the future cropland productivity over SA, as groundwater is limiting in those areas [57]. Until now, due to advanced cultivation techniques, croplands have managed to show a high NDVI trend; however, this would not be sustainable in the near future under the current climate change risks in SA. Recent studies revealed that SA is one of the global hotspots for heat stress on croplands due to
climate change [58]. With increasing heat stress and very little room for large scale irrigation expansion in SA, this rate of change seems likely to be unsustainable in the future. Intensive irrigation could also pose many other threats to environment including degradation and unsustainable use of natural resources [59]. Severe land degradation due to agricultural mismanagement is common in Sri Lanka (>50%), India (>50%), Pakistan (20%) and Bangladesh (>25%) [57]. The cultivated Himalayan mountain belt is also vulnerable to various disasters [35]. The reduced trend in the latest (2000–2013) cropland NDVI has demonstrated the vulnerability of those regions under recent climate changes. The decline in summer and winter crop yields in India during the recent decades demonstrated by Milesi et al [3] using statistical data was consistent with our results. Our research revealed that inter-annual variability of both precipitation and temperature have a collective effect on NDVI variability over SA. This study used only precipitation and temperature as the climatic variables, limiting the research on the other driving factors behind the vegetation growth over SA.

Along with climate variability, LUCC had a significant role in the browning of the Himalayan foothills as well as northeastern India and Western Ghats. Agricultural expansion was visible at higher elevations (1800–2600 m) with medium slopes (10–30°) [35]. It was reported that the overall browning of NV in the Himalayan foothills was attributed to the LUCC due to the clearance of forests for urban development and agricultural expansion [34, 60]. An analysis of the deforestation rates in northeastern India during the period from 1972–1999 indicated a substantial reduction in the total forest cover due to the conversion of forests to cropland and uncontrolled exploitation [19, 61]. Deforestation also threatens Western Ghats [36]. In agreement with all these studies, we also found conspicuous conversion of forest cover to cropland and urban areas mainly in the Himalayan foothills up to northeastern India, Western Ghats and the eastern part of central India. LUCC in these areas likely caused the partial browning in NV. From our results, we could also expect that browning had been intensified since 2000 considering the development scenario in recent decade. Because of the combined effect of climate and LUCC, the overall NDVI of the NV areas showed browning trends during WM season, even though the temperature had a decreasing trend in recent decade (2000–2013). Hence, several factors actually interacted with and influenced the vegetation dynamics in NV.

The impact of drought years (1987, 2000, 2004, 2007) [62] along with other mechanisms, such as the Mt Pinatubo aerosols in 1991 [6] and the large-scale atmospheric phenomena such as ENSO [63] (1997–1998) were reflected in the time series of NDVI, overlying the inter-annual trends. These kinds of extreme events could affect the overall greenness, but may not alter the overall trends unless those extreme events are too frequent and go beyond the threshold of ecosystem resilience [64]. In the semi-arid and dry subhumid zones, the extreme variability of rainfall with high intensities, poor spatiotemporal distribution of rainfall, few rainfall events and dry spells are the main limiting factors for vegetation production rather than the total amount of rainfall [65]. Short term or agricultural drought can cause reductions in yield; however, this can be mitigated through proper management techniques [66]. NV areas responded intensely to the short term events which could gradually change the NDVI or cause an abrupt change [67].

Evidently, the spatial and seasonal heterogeneity of NDVI trends resulted from regional climate variations and vegetation structures, though the LUCC played a major role as well.

6. Conclusions

The focus of this research was to analyze the seasonal rather than annual dynamics of the vegetation in order to illustrate the significance of the seasonal influences on long term vegetation patterns. We also explored the climate and LUCC as the drivers of the seasonal and long term NDVI variations over the study area. By analyzing the spatiotemporal changes in vegetation activity, we found major differences in the greenness trends between the two monsoon seasons and among the key land use/cover (croplands and natural vegetation) classes. This study showed that nearly one quarter of all the pixels increased in greenness during 1982–2013 over the region. The winter monsoon contributed larger variability to the overall vegetation changes in South Asia, which is the major finding of this study. The increased productivity over irrigated croplands contributed to the greening of South Asia during the winter monsoon season. Meanwhile, significant browning occurred in the Western Ghats, northeastern India and the Himalayan foothills since 2000, and changes were observed during the same season. Natural vegetation areas, especially those at higher altitudes, were likely to be at risk because of the significant winter warming and loss of forest cover. This study revealed that in South Asia, climate variability and LUCC had a synergistic impact on NDVI changes in natural vegetation areas, while anthropogenic activities (advanced agricultural activities) played a crucial role in the rest of the region. In the future, warm and dry winter monsoons may limit the crop productivity by restricting the water available through surface irrigation, especially to those areas where ground water is limited. While our analysis may improve the understanding of the seasonality of greenness trends and the roles of climate and LUCC over South Asia, future finer resolution observations of vegetation productivity could further strengthen the research. Additionally, identifying the influences from the other
factors, such as phenological changes, CO₂ fertilization, nitrogen deposition, etc., could further reveal the mechanisms that are driving the vegetation growth patterns found in this study.

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