ORIGINAL ARTICLE

Climatic Change and Human Activities Link to Vegetation Dynamics in the Aral Sea Basin Using NDVI

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Abstract
The rural and urban areas of Central Asia underwent substantial land cover changes which has escalated the water scarcity condition in the Aral Sea, during past decades. In this article, we analyzed spatial variation of the vegetation based on GIMMS NDVI (Global Inventory Modelling and Mapping Studies) and its correlation with climatic variables (temperature, precipitation and soil moisture) in the Aral Sea Basin (ASB) for growing and non-growing seasons over two different periods, i.e., 1982–1999 and 2000–2015. For this purpose, NDVI was obtained from GIMMS and climatic variables from datasets on the CRU (Climatic Research Unit). The results showed a weak positive correlation between NDVI and climatic variables during the growing season for both the study periods. The analysis revealed 0.08/10 years and 0.04/10 years of vegetation trends during growing and non-growing periods, respectively. During the growing season of 2000–2015, the spatial vegetation trend decreased by 7.84% area coverage as compared to 1982–1999. The small regions that showed only slight vegetation increase were observed over cropland and mountain regions in the northeastern and southeastern parts of basin. The impacts of human activities on the growing NDVI season were further investigated using residual trend analysis. The results revealed that in the growing season of 1982–1999, the human impact on NDVI changes was significant, with a positive residual trend accounting for 37.03% of the total area. For the period 2000–2015, a positive residual trend of 2.22% was found in the basin.

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1 Introduction

Comparative regional analysis of Central Asian countries showed that the air temperature has continuously risen over the past several decades. As demonstrated in a previous study, the near surface temperature rose by 18–28 °C in the region during the twentieth century (Hu et al. 2013). Among the arid and semi-arid ecosystems of CA, vegetation is highly related to local climatic variations (Yin et al. 2016). Similarly, the carbon cycle plays a major role in vegetation increase which has suffered transformations due to climate change in the CA region (Li et al. 2015). The dependency of vegetation on carbon cycle and other geochemical cycles is imperative to study as vegetation provides an important source of food to human population. Sustainable development of the Aral Sea Basin (ASB) is a challenge due to the progressing problems in the region such as the decline of the ASB water extent and rising temperatures (Micklin 2000) which gravely influences the vegetation dynamics of the region. Monitoring and analysis of the regional land and vegetation cover changes can aid in informed

decision-making for ensuring sustainable and responsible use of natural resources. Normalized Difference Vegetation Index (NDVI) dataset, linked to vegetation biomass, can be employed for studying the vegetation dynamics and changes in different regions as it provides data for historical vegetation trend analysis along with monitoring for different land surfaces.

Vegetation variability in response to climate change is still poorly studied and understood in CA (Yuan et al. 2017). Previous studies investigated the relationship between Normalized Difference Vegetation Index (NDVI) and different factors such as localized, annual and seasonal climate changes (Peng et al. 2013; Piao et al. 2006; Potter and Brooks 1998; Yuan et al. 2017). The results highlighted vegetation as one of the key factors to control the terrestrial ecosystem carbon cycle. A positive correlation between NDVI and precipitation in arid and semi-arid areas has been presented in the CA region (Ichii et al. 2002; Jiang et al. 2017; Yin et al. 2016). Yin Gang and other researches showed a weak increasing trend of NDVI in CA over the period 1982–2012, with a significant positive trend between the years 1982 and 1994 but a decreasing NDVI trend after the year 1994. The influence of drought on vegetation in the CA region has also been analyzed demonstrating a positive correlation between the vegetation and the SPEI drought index (Standardized Precipitation Evapotranspiration Index) in most regions from 2000 to 2012 (Deng et al. 2020; Xu et al. 2016). First study illustrated that the vegetation vulnerability towards drought was higher from July to September except for shrublands, while another study showed the extensive vegetation degradation was due to the summer water deficit (Deng et al. 2020; Xu et al. 2016). The reduction of NDVI was induced by the decreased amount of precipitation (Yin et al. 2016). During the recent years, it has been reported that the increased thermal stress and continuously declining soil moisture in the region has resulted in a drought stress impacting vegetation health severely (Guo et al. 2018). Another study showed that the vegetation decreased per decade during the growing season in the Central Asia region based on the trends. observed through the aridity index for the region (Deng et al. 2020). The results from other researchers reported that the natural vegetation trend in CA intensified by 0.004 per decade from 1982 to 2013, and the shrublands vegetation continues to increase in the region along with that of the grasslands (Li et al. 2015). Jiang et al. analyzed the human impact on vegetation change in CA, with the focus on the rapid development of oil and natural gas extraction in the southern part of the Kara-Kum Desert and the Southern Ustyurt Plateau, mainly through Google Earth software (Jiang et al. 2017).

Vegetation dynamics depends on numbers of factors like temperature, precipitation, evapotranspiration and water availability within a respective region. During the 1960s, the water volume in the ASB, which posed a major impact on CA climate, began to decline revealing extensive variations in surface inundation (Ilyas et al. 2019). There are several reasons for the water level reduction like inefficient management of the water resources of two major trans-boundary rivers within the region, Amu Darya and Syr Darya; rapid increase of population; intensive cropland exploitation; and construction of hydropower and irrigation structures. All of these factors were marked as the sources of environmental threat (Glantz 1999; Glazovsky 1995; Micklin 1998) to the ASB. In addition to this, the moisture supply in the region is contributed by the midlatitude westerlies which has presented severe dryness dominated by upstream standing wave patterns from the North Atlantic (Bothe et al. 2011). This atmospheric teleconnection predominantly defines the moisture influx in the regions based on the seasonal atmospheric flow.

Vegetation intensity and dynamics varies in response to atmospheric thermal and moisture fluctuations; hence, it is imperative to study the association and dependency between these variables and vegetation among different land cover types (Garzelli et al. 2018; Jiang et al. 2017; Sun et al. 2015). Based on available literature, we can say that several studies on vegetation changes and factors affecting the CA region were carried out (Jiang et al. 2017; Yin et al. 2016; Zhou et al. 2015). However, long-term studies analyzing the variations of NDVI within different vegetation seasons in the ASB region are limited; hence, this study examines long-term time-series linkages between vegetation dynamics and climatic and anthropogenic variables. This study aims at analyzing and evaluating the impacts of climatic and human-driven changes on vegetation dynamics within the Aral Sea Basin. Based on the objective, this study investigates the climatic variables (air temperature, precipitation, and surface soil moisture) and human activity (land use) changes and the association of these variations on vegetation density changes in the ASB, during two different periods (1982–1999 and 2000–2015) using NDVI datasets.

2 Study Area, Materials and Methods

2.1 Study Area

In this paper, the concerned study area is the ASB (Fig. 1). The ASB, located in CA, has seen significantly influenced by anthropogenic load since the mid-twentieth century, leading to the desiccation of the basin (Berdimbetov et al. 2020; Micklin, 2000; Zavialov et al. 2003). The Aral Sea is a closed basin with a watershed area of almost 1.8 million square kilometers including the Amu Darya and Syr Darya river systems (Micklin 2007; Zmijewski and Becker 2014). The percentage share of the basin belonging to different countries is the Republic of Kazakhstan (36.4%),
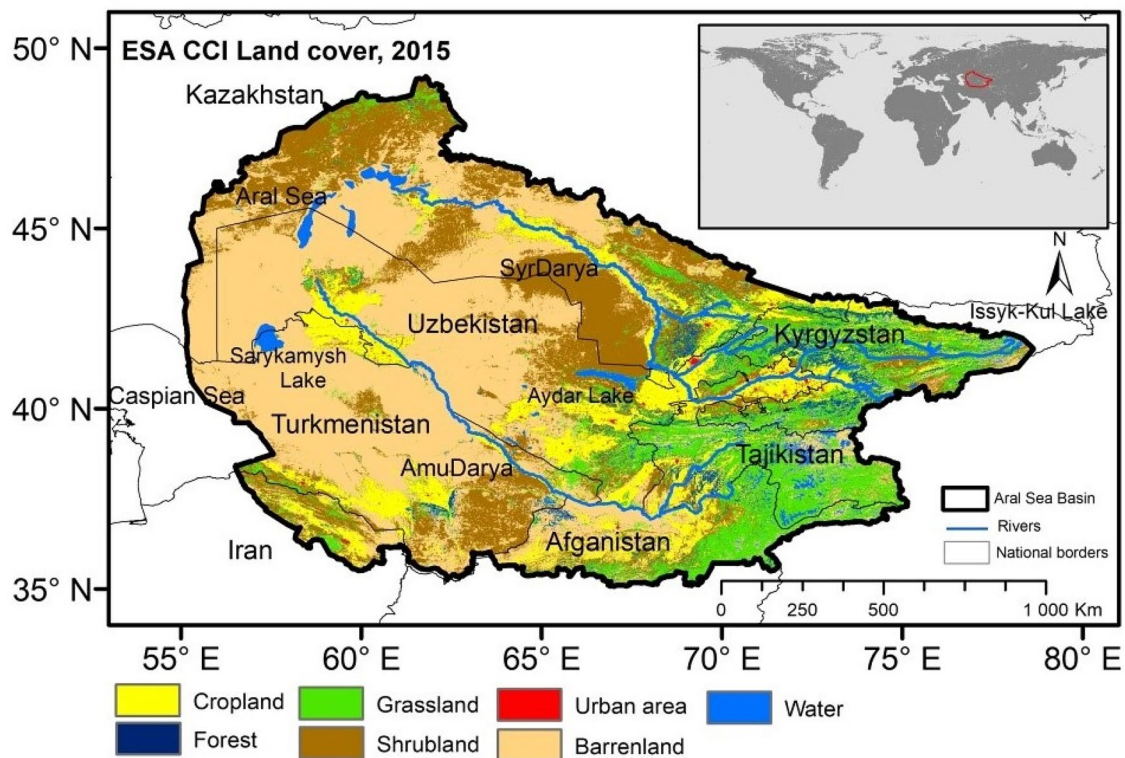
Fig. 1 Study area: ASB's land use land cover map

Turkmenistan (20.2%), Uzbekistan (18.5%), Kyrgyzstan (8.2%), Afghanistan (7.5%), Tajikistan (5.9%), and Iran (3.4%). The land cover change distribution in the region, based on AVHRR and ESA-CCI data, was analyzed for the period between 1982 and 2015. The main parts constituting the basin include desert area (42.79%) and the shrubland (27.25%), in the land cover change as of 2015 (Fig. 1). In addition, the grassland (13.54%), cropland irrigated (11.12%), forest (1.06%), water area (2.31%), natural vegetation cropland (1.57%) and urban area (0.36%) were identified.

The territory of Central Asia falls under the temperate climate and with desert area found predominantly in the western parts of the Aral Sea Basin (Guo et al. 2019). It is characterized by high temperature and low rainfall. Summer is very hot with an average temperature in July at 25.5 °C with a maximum temperature range of 40–45 °C. The winter months are very cold. The absolute minimum temperature is − 30 (to − 35 °C). After a cold winter, warm spring and hot summer begin quickly (Abdurahimov and Kurbanov 2015; Berdimbetov et al. 2021). The cold period lasts for 180–200 days. Climatic conditions of the desert zone, occupied by the territory, are characterized by extreme drought, summer heat, cloudlessness accompanied by low rainfall. The annual precipitation is about 100–400 mm (Gessner

et al. 2013; Guo et al. 2019), and in some places, it is 50 mm or less.

The region's water resources mainly consist of glaciers, lake water, runoff, and soil moisture. High altitudes, Tian-shan, Pamir, and the glaciers in the Tibetan Plateau are the main sources of fresh water. Pamir glaciers play a significant role in the CA water balance (Unger-Shayesteh et al. 2013) and form the basis of the Amu Darya and the Syr Darya river flow. There are several large and small water bodies in the CA area, including the Aral Sea (1.176×10^4 km^2 in 2004), Sarygamysh Lake (0.5×10^4 km^2), and Aydar Lake (0.3×10^4 km^2). Aydar Lake (40°55' N, 66°48' E) was formed based on the Soviet plan in the late 1960s, due to the excessive precipitation in 1969, in the part of the Syr Darya river (21 km^3) through Shardara reservoir and Arnasay. It flowed to Aydar Lake because the water flow to the Aral Sea did not fit into the Syr Darya River. It is probable that Aydar Lake volumes impacted significantly on the Aral Sea shrinkage. In the region, agriculture is the largest source of water resource consumption, accounting for nearly 90% of the annual amount of water in this sector (Unger-Shayesteh et al. 2013). Water consumption in agriculture, along with the decline of the Aral Sea, caused serious environmental problems. From 2002 to 2009, the Aral Sea area fell by 62% (Singh et al. 2012).

2.2 Datasets

We obtained the NDVI dataset; GIMMS (Global Inventory Modelling and Mapping Studies) based on the daily data record from the NOAA's Advanced Very High-Resolution Radiometer (AVHRR; a spatial resolution of 1/12° based on which we calculated the monthly averages of NDVI from 1982 to 2015; (https://ecocast.arc.nasa.gov). The GIMMS dataset is a series of NDVI matrices over 34 years. The GIMMS dataset was originally created to study biophysical changes as part of the International Satellite Land Surface Climatology Project (ISLSCP). According to a previous study (Gallo et al. 2004), AVHRR and MODIS derived NDVI showed over 90% correlation; hence, AVHRR has been used in this study.

NDVI is a relative index of the state of vegetation that can be used in climatic and biogeochemical models for calculating photosynthesis (Bilal et al. 2019), carbon dioxide exchange between the atmosphere and the surface of the earth, evaporation, transpiration, absorption, and emission of energy from the earth's surface. This data set is an improved version of the AVHRR data, with the necessary adjustments by taking into account the image geometry, volcanic aerosols, and other effects not related to the change of vegetation itself (Beck and Goetz 2011; Tucker et al. 1985). The recently released annual land cover maps of the European Space Agency Climate Change Initiative (ESA-CCI, https://maps.elie.ucl.ac.be) from 1992 to 2015 partially overcame these resolution problems with a 300 m and long and consistent annual time series for all major land cover transitions (i.e., maps, including grasses, crops, and urban areas; ESA 2017). Moreover, we used climate factors such as temperature, precipitation, and soil moisture datasets from the Climatic Research Unit (CRU TS 4.0), University of East Anglia (https://crudata.uea.ac.uk/cru/data). The CRU dataset covers all land areas (except Antarctica) from 1901 to 2015 (at a spatial resolution of 0.5°) and is based on monthly observational data from land meteorological stations across the world (Harris et al. 2014). This article uses soil moisture data from the Global Land Data Assimilation System (GLDAS, https://disc.gsfc.nasa.gov). Its resolution is 0.25° degree with layer depth 0–10 cm (Rodell et al. 2004). The spatial resolution of the CRU and GLDAS datasets was resampled to 1/12° using Resampling tool (Environment setting) from ArcMap 10.3 raster toolset to achieve the same resolution as that of the GIMMS NDVI.

2.3 Methods

Long-term trends in NDVI data were computed using linear regression method for annual and seasonal analysis at growing (April–September) and non-growing (October–March) scales. Interdependence between NDVI and climate factors

(temperature, precipitation, soil moisture) is represented by the correlation coefficients. We used the spline interpolation method to interpolate average climate variables for each grid cell in total area (Duulatov et al. 2019; Xu et al. 2016). Based on Pettitt's non-parametric method, we determine the change point in NDVI and climate factors.

2.3.1 Determination of Change Point

This study investigates the climatic variations and their impacts on vegetation by analyzing the changes in temperature, precipitation, and soil moisture with NDVI along with the human effects from 1982 to 2015. Based on the previous studies, Central Asia region has known to shown significant variations in climate during the last few decades. For this, a hypothesis was tested to determine the change point for the Aral Sea Basin based on the time series of NDVI, temperature, precipitation and soil moisture. First, based on Pettitt's test (1979), we employed a non-parametric method to determine the change point of NDVI, temperature, precipitation, and soil moisture. The test was confirmed with the change point found in all 4 variables, mostly for the year 2000 or later (Fig. 2).

To understand the spatial and temporal changes in the vegetation trends with respect to climatic and anthropogenic variations, it was important to study the disturbances before and after the change point. So, we divided the study period into two parts based on the change point test, marking the first study period between 1982 and 1999 and the second study period between 2000 and 2015.

2.3.2 Linear Regression Analysis

Linear trend analysis has been performed to observe vegetation trend change over the ASB where we analyzed the slope of vegetation change for each pixel. Linear regression trend analysis is performed using RStudio software, which can simulate trends in each grid (Tong et al. 2018). In this study, the relative slope in formula (1) is used to indicate the relative change in NDVI in each pixel (Liu et al. 2019).

$$R_{slope} = \frac{n \times \sum_{i=1}^{n} i \times NDVI_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} NDVI_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2}, \qquad (1)$$

where i is the annual number; n the monitoring period (cumulative number of years); NDVI as the average $NDVI_i$ year; the slope of each pixel is the trend of the NDVI slope, if $R_{slope} > 0$, then the NDVI value of the pixel in n years increases, otherwise it decreases (Hu et al. 2019). Moreover, linear regression is the key function in the process of computing residual trend analysis.
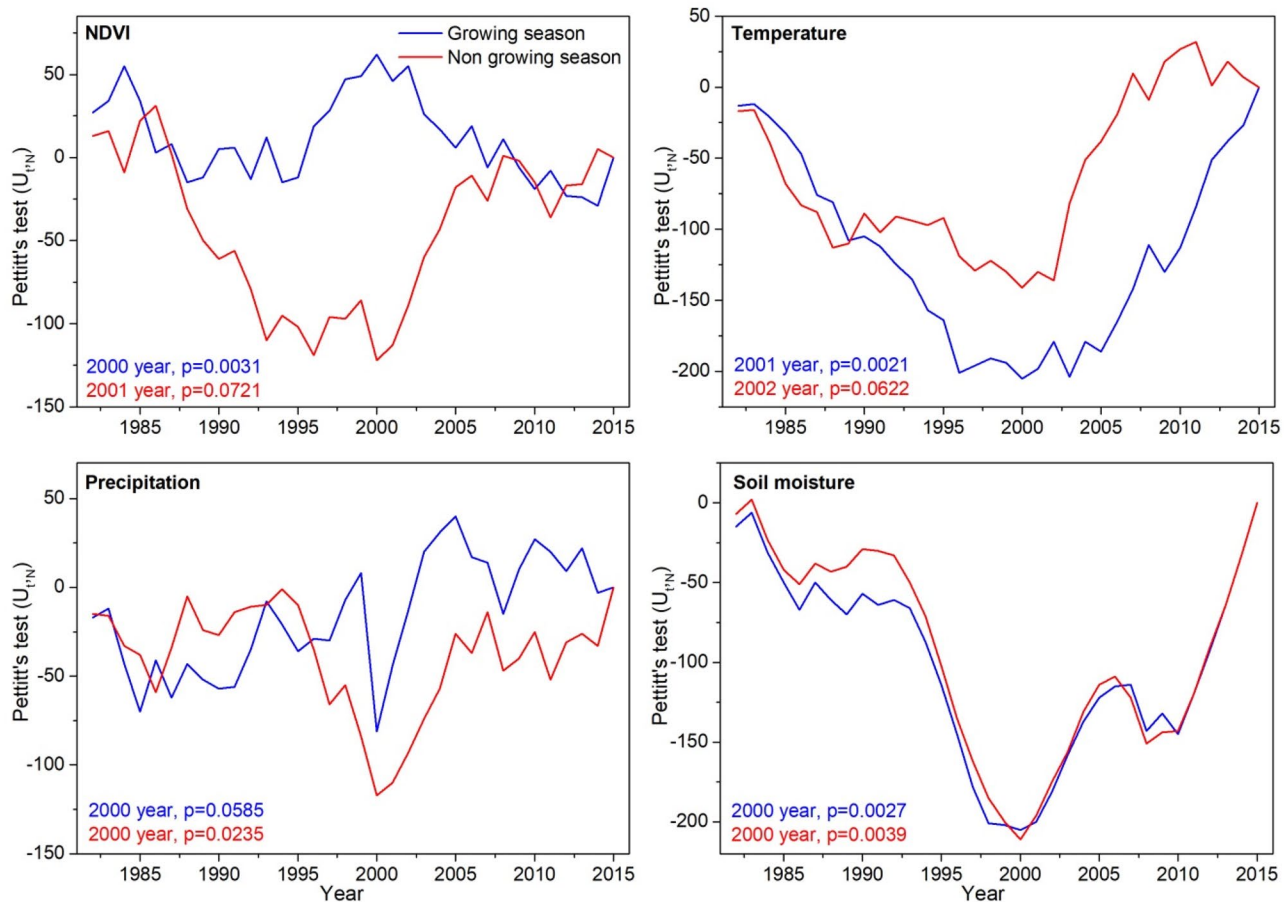
Fig. 2 Change-point detection by NDVI, temperature, precipitation, and soil moisture using the Pettit test for the period 1982–2015 over ASB

2.3.3 Residual Trend

In this study, residual trend analysis has been considered for using phenological information to enhance the accuracy of detecting changes in agricultural areas (human-driven land use) while not considering the impacts of other variables. The residual trend is introduced by Evans and Geerken (2004). First, a regression model between the observed NDVI and climate variables (temperature, precipitation, and soil moisture) is calculated for each pixel. Secondly, the residual difference between the observed NDVI and the predicted NDVI from the linear regression model is calculated (Ibrahim et al. 2015). This method helps to differentiate between climate variation and the effects of human activities on vegetation changes. The equation is as follows (Luo et al. 2018):

$$NDVI_{res} = NDVI_{act} - NDVI_{pre}, \qquad (2)$$

where: $NDVI_{res}$ is a residual error value, $NDVI_{act}$ is actual value and $NDVI_{pre}$ is predicted annual value. If a residual trend is positive, then we can assume that human activity

influences the increase of NDVI in selected pixels, and if the residual trend is negative, the effects of NDVI change are destructive.

3 Results

3.1 Distribution of Vegetation Along Vegetation Types

Figure 3 shows the spatial distribution of NDVI variability in two different periods (1982–1999 and 2000–2015) and seasons (growing and non-growing). Most of the eastern stretching from northeast to southeast parts of the ASB showed moderate to high vegetation cover (Fig. 3a, c) for the growing season during both the study periods. Desert or no vegetation showed a high spatial coverage of 38.11% by area for the first period (1982–1999), while low vegetation presented the highest spatial area coverage of 40.40% for the same period under growing season. The spatial distribution kept declining for moderate and high vegetation with only 16.50% and 2.5% area coverage, respectively, for
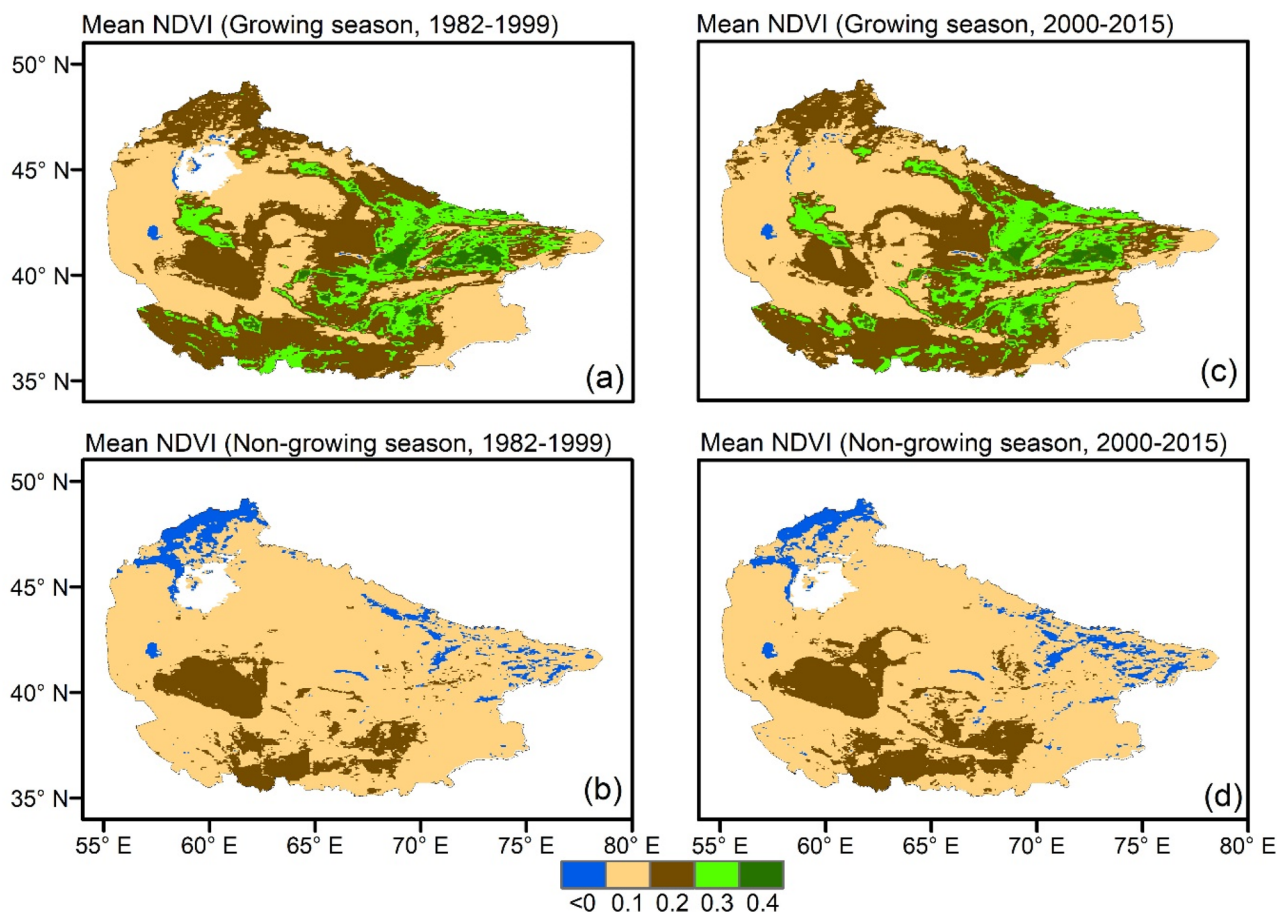
Fig. 3 Spatial distributions of average NDVI at different periods and different seasons in ASB. Growing season (**a** 1982–2015, **b** 2000–2015) and non-growing season (**c** 1982–1999, **d** 2000–2015)

the growing season during the earlier period (Table 1). We defined several vegetation classification (no vegetation, low and high vegetation types) according NOAA AVHRR vegetation data use guide (NOAA 2018).

During the non-growing season, both the study periods showed no distinct spatial distribution of moderate or high vegetation. Most of the low vegetation areas were observed in the southern, southwestern and northwestern and fewer parts of eastern regions of the ASB (Fig. 3b, d). The non-growing months showed smaller vegetation regions which can be attributed to the permafrost period of the winter months. The results also showed that most of the area during

the non-growing season, based on NDVI values, fell under the category of no and low vegetation with 75.23% and 13.27% for an earlier period and 72.76% and 12.56% for later period, respectively (Table 1). While moderate vegetation only sparsely covered an area of 6.46% and 6.68% for earlier and later periods, respectively.

The comparison of vegetation conditions over the two periods during the growing season showed that the earlier study period (1982–1999) had low area coverage for no and moderate vegetation and high coverage for low and high vegetation. This suggested that the area coverage increased during 2000–2015 under the category of no vegetation and

Table 1 Area proportion of average NDVI range on different periods and different seasons in ASB

| Vegetation types	NDVI range	Growing season		Non-growing season	
		1982–1999 (%)	2000–2015 (%)	1982–1999 (%)	2000–2015 (%)
No vegetation	0–0.1	38.11	39.47	75.23	72.76
low vegetation	0.1–0.2	40.10	38.94	13.27	12.56
Moderate vegetation	0.2–0.3	16.50	16.82	6.49	6.68
High vegetation	> 0.4	2.50	1.99		

moderate vegetation although the percentage increase was little.

3.2 Spatial and Temporal Trend Change of NDVI

Based on linear regression analysis, the NDVI changes (Fig. 4a) indicated a slightly rising trend in the northeastern, south, and southwestern parts of ASB during the growing season of the 1982–1999 period. A low positive trend at 0.005 change rate, accounting for 49.09% of the basin, was observed during this period (Table 2). A high positive trend was only observed in 2.08% of the area. A declining trend in vegetation over 27.83% of the total area during the growing season, with an average trend value of -0.005 has been observed. Moreover, no vegetation change was noticed in 20.87% for the earlier growing season. Furthermore, during.

During the growing season of 2000–2015, the positive NDVI trend distribution was reduced as compared to the 1982–1999 period. The spatial distribution showed clear declining rates of vegetation over most parts of the
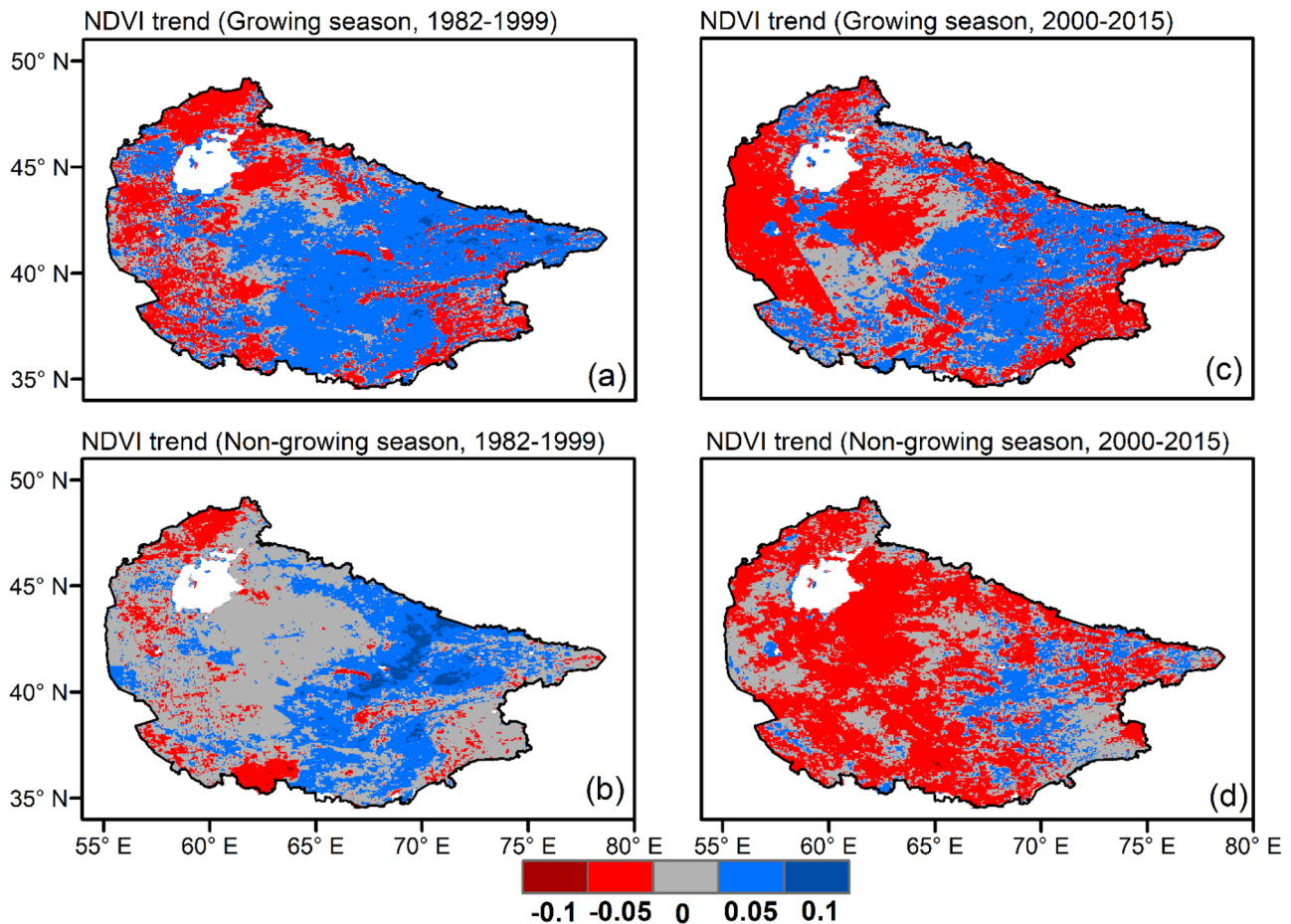
Fig. 4 Spatial trend distributions of mean NDVI at different periods and different seasons in ASB. Growing season (**a** 1982–2015, **b** 2000–2015) and non-growing season (**c** 1982–1999, **d** 2000–2015), blue color positive trend, red color negative trend, and gray color no trend

Table 2 Area proportion of NDVI trends on different periods and different seasons in ASB

NDVI trend types	NDVI trend value	Growing season		Non-growing season	
		1982–1999	2000–2015	1982–1999	2000–2015
High negative trend	− 0.1	0.12	0.05	0.11	1.12
Low negative trend	− 0.05	27.83	42.72	11.27	57.24
No trend	0.00	20.87	24.21	56.55	31.08
Low positive trend	0.005	49.09	31.91	32.08	10.56
High positive trend	0.1	2.08	1.10	–	–

northwestern and southwestern parts of the basin (Fig. 4b). Both low and high positive trends suffered declines with the total area coverage of 31.91% and 1.10%, respectively. Conversely, the low negative trend increases sharply with the highest area coverage of 42.72% of the basin (Table 2).

During the non-growing season, most of the eastern and southeastern parts of the basin presented increasing vegetation trends, while most of the northwestern and southwestern regions showed no change trends in the basin for 1982–1999 (Fig. 4b). In this period, the highest area coverage fell under no vegetation change accounting for more than half of the basin area (56.55%), while the second highest was found for a low positive trend with 32.08% of the area and none for high positive change (Table 2). While for the later study period (Fig. 4d), low negative vegetation change covered most of the northwestern, southwestern and central parts of the basin. The analysis showed that low negative vegetation covered more than half of the basin followed by no change accounting for (31.08%) (Table 2). The areas with the unchanged vegetation trends were mainly in large desert areas in the southeast and southwest parts of the basin. The results clearly indicated that the period of 2000–2015 suffered severe vegetation decline compared to 1982–1999.

3.3 Relationship Between NDVI and Climate Factors

Climate change in its turn had a considerable impact on vegetation (Hu et al. 2015; Peng et al. 2013; Piao et al. 2006). To understand the climatic impacts, we studied the relationship between NDVI changes in the ASB along with temperature, precipitation, and soil moisture, over two timescales (growing and non-growing). Between 1982 and 1999, trend values for NDVI and all climate variables increased during the growing season (Table 3). Study results demonstrated that the NDVI, temperature, precipitation, and soil moisture showed slight increasing trends during the first period; while for the later period, precipitation showed slight but declining rate; while the rest of the variables showed slightly increased rates and soil moisture showed a strong increasing trend during the growing season of later period. Based on the observed slope values for different variables, precipitation showed the highest magnitude of change for the growing season during the earlier period; while for the later period, soil moisture showed the highest magnitude of change (Table 3). During the non-growing season of 1982–1999, precipitation and soil moisture showed negative trends, while vegetation and temperature showed slightly increasing trends. From 2000 to 2015, temperature showed a negative trend and vegetation, and temperature showed slightly increasing trends while soil moisture showed a high increasing trend. For the earlier period, based on slope calculations the highest magnitude of change was observed for precipitation which

Table 3 Change rates and mean values of NDVI and climate parameters at different periods and different seasons in ASB

Period	Season	NDVI			Temperature			Precipitation			Soil moisture		
		Slope (10^{-1})	Mean	R^2	Slope	Mean (°C)	R^2	Slope	Mean (mm)	R^2	Slope	Mean (mm)	R^2
1982–1999	Growing	0.008	0.134	0.165	0.041	18.362	0.107	0.217	16.854	0.128	0.061	92.428	0.162
	Non-growing	0.004	0.086	0.127	0.009	−1.117	0.156	−0.106	22.515	0.170	−0.082	91.709	0.224
2000–2015	Growing	0.002	0.129	0.158	0.050	19.094	0.248	−0.099	16.915	0.153	0.820	97.397	0.738
	Non-growing	0.002	0.086	0.163	−0.073	−0.250	0.196	0.101	24.096	0.155	0.745	96.611	0.642

showed a declining trend; while for the later period, the highest magnitude of change was observed for soil moisture (Table 3).

For a more accurate determination of the spatial correlation distribution between the NDVI and climate parameters, we calculated the correlation variation for each pixel. First, we categorized the correlation coefficient change as: high positive > 0.2, moderate positive 0.1–0.2, low positive 0–0.1, low negative 0–(−0.1), moderate negative–0.1–(−0.2), and high negative. < −0.2 correlation. The relationship between NDVI and climate parameters at different periods and two seasons is given in Fig. 5.

During the growing season (1982–2015), a large part of the area between NDVI and temperature was covered by negative correlation (Fig. 5a), especially in the north, northeast, and southwest of the basin. In contrast, the NDVI precipitation and soil moisture were recorded with a positive correlation across most parts of the basin except for some regions in the south and southeast (Fig. 5c, e). It was also observed that spatially precipitation and soil moisture with vegetation showed a similar distribution of negative and positive correlation over the basin area.

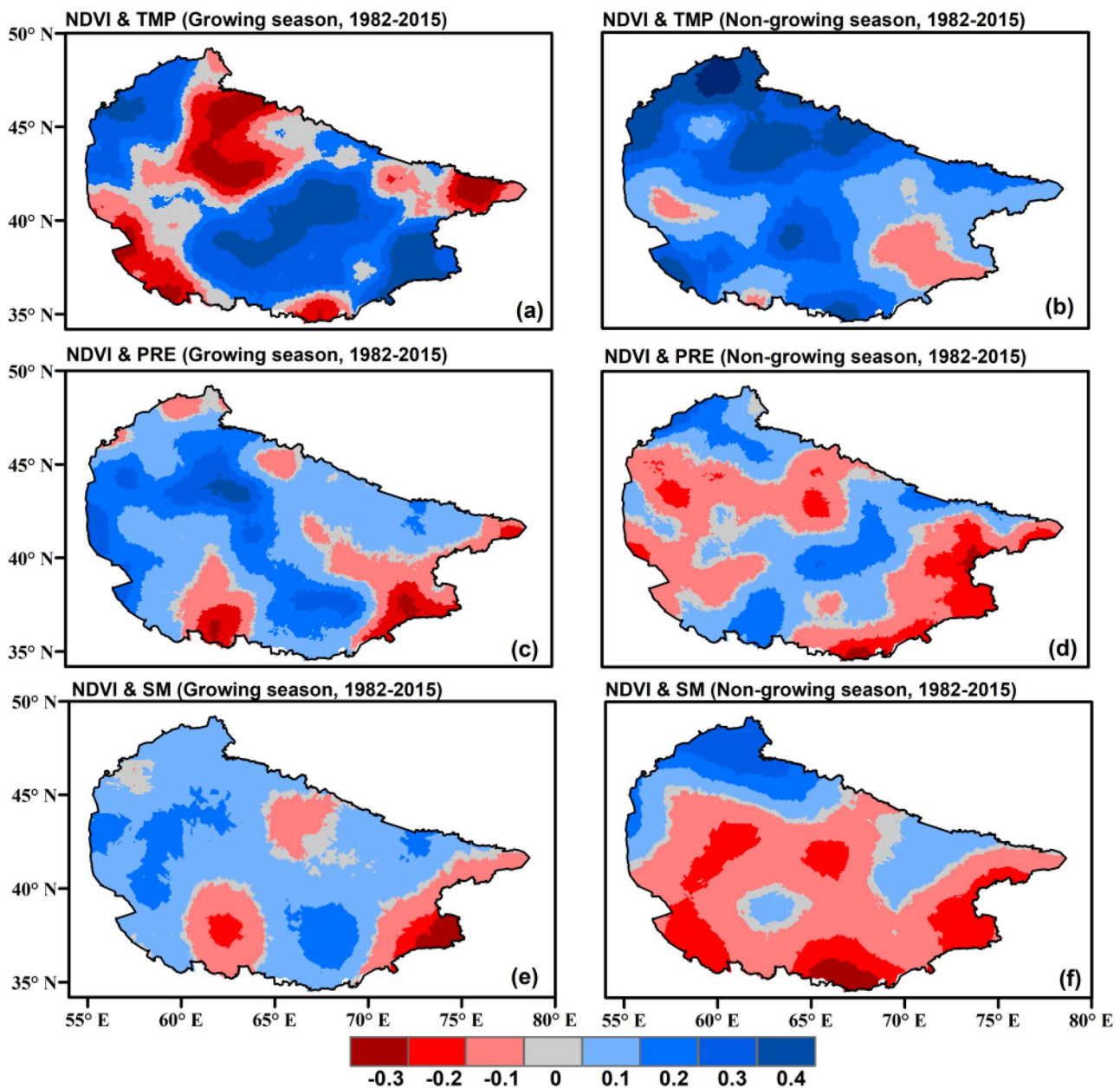Vegetation and temperature showed a positive correlation spatially covering most parts of the basin with only

Fig. 5 Spatial distribution of correlation coefficients between NDVI and climate parameters in ASB at different periods and different seasons

southwest and a small region in the east as an exception (Fig. 5b). NDVI showed a positive correlation over small regions stretching from the northeast down towards south and also in northeastern parts of the basin while the stretch from north to northwest and southeast showed negative correlation (Fig. 5d). Likewise, soil moisture showed a negative correlation with vegetation for most parts of the basin covering from east to central and southwestern parts of the basin with the northwestern and southwestern patch as an exception (Fig. 5f).

During the growing season of 1982–1999, the NDVI mainly changed while precipitation and soil moisture was controlled in most parts of the basin. The results found that 23.8% (428.4×10^3 km^2) had high positive, 19.3% (347.4×10^3 km^2) moderate positive and 25.7% (432.6×10^3 km^2) had low positive correlation making up to a total of 68.2% (1227.6×10^3 km^2) of the total area had a positive correlation between NDVI and precipitation where the rest of the 22% marked no/negative correlation. During the growing season 2000–2015, the effect of precipitation and soil moisture on the NDVI variation was relatively reduced, with the increased temperature effects, which is almost identical based on three parameters with NDVI–precipitation at 48.6% (474.8×10^3 km^2) and NDVI–soil moisture at 51.9% (934.2×10^3 km^2) and NDVI–temperature at 52.4% (975.6×10^3 km^2).

During the non-growing season, the NDVI changed under the influence of temperature showed a positive correlation in the larger parts of the basin between 1982–1999 and 2000–2015, at 87.5% (1575×10^3 km^2) and 78.8% (1418.4×10^3 km^2) respectively. A high positive correlation between NDVI and precipitation covered almost 45% (810×10^3 km^2) in both study periods. NDVI and soil moisture for the non-growing season showed a negative correlation of 56.9% (1024.2×10^3 km^2) between 2000 and 2015, with 20.3% (365.4×10^3 km^2) of high negative and 15.2% (273.6×10^3 km^2) of moderate negative correlation. There was no interconnected correlation between NDVI and soil moisture and precipitation between 2000 and 2015 and approximately 5.2% (93.6×10^3 km^2) of the area.

We calculated the correlation coefficient distribution between mean seasonal NDVI and climate parameters over two time periods for different vegetation categories according to Fig. 2 (low, moderate, and high vegetation). During the growing season of 1982–1999, it was observed that low NDVI showed a negative correlation with all three of the climatic parameters but with precipitation, only the correlation was found significant ($P < 0.05$), while it showed a low significant positive correlation with temperature during the non-growing period. Moderate vegetation showed a negative but non-significant correlation with precipitation during the growing period while it showed a low significant positive correlation ($P < 0.005$) and negative correlation ($P < 0.05$) with temperature and precipitation, respectively, during the non-growing period. Intense vegetation showed a significant negative correlation with temperature for both growing (-0.24) and non-growing seasons (-0.58) (Table 4).

During the second half of the study (2000–2015), the results revealed that temperature showed more influence on different vegetation categories as compared with other climatic variables over both growing and non-growing seasons. High NDVI showed a strong negative association with temperature for the growing season while low and moderate NDVI showed significant positive correlations with temperature for the non-growing seasons. Precipitation appeared to have a strong negative effect on high NDVI during the growing season. Soil moisture showed a negative but non-significant correlation with all three vegetation categories during non-growing and with high NDVI for the growing season (Table 5).

3.4 Impacts of Human Activities on the Aral Sea

Our analysis showed that climate change is one of the main drivers influencing vegetation cover in the ASB besides human activity, which is also an important factor (Tong

Table 4 Correlation coefficients between the mean NDVI and climatic variables for different vegetation types between 1982 and 1999

Vegetation types	Period	NDVI	Temperature		Slope	Precipitation		Slope	Soil moisture		Slope
		Slope	Corr. NDVI&TMP			Corr. NDVI&PRE			Corr. NDVI&SM		
			R	P value		R	P value		R	P value	
Low NDVI	Growing	0.0011	-0.116	0.108	0.084	-0.265	0.006	-0.014	-0.015	0.882	0.060
	Non growing	0.0004	0.103*	0.000	0.072	-0.169	0.08	-0.272	-0.101	0.308	0.057
Moderate NDVI	Growing	0.0003	0.027	0.778	0.111	0.335	0.719	-0.027	0.338	0.702	0.060
	Non growing	0.0016	0.44*	0.000	0.080	-0.193	0.045	-0.231	-0.127	0.197	0.057
High NDVI	Growing	-0.0001	$-0.24*$	0.000	0.091	0.171	0.077	-0.005	0.401	0.916	0.088
	Non growing	-0.0002	0.578*	0.000	0.080	0.011	0.988	-0.062	0.021	0.83	0.097

*Mean significance at $P < 0.005$

Table 5 Correlation coefficients between the mean NDVI and climatic variables for different vegetation types between 2000 and 2015

Vegetation types	Period	NDVI Slope	Temperature		Slope	Precipitation		Slope	Soil moisture		**Slope**
			Corr. NDVI&TMP			Corr. NDVI&PRE			Corr. NDVI&SM		
			R	P value		R	P value		R	P value	
Low NDVI	Growing	0.0011	0.097	0.348	0.014	0.613	0.972	− 0.193	0.154	0.606	0.027
	Non growing	0.0004	0.456*	0.000	− 0.084	0.115	0.278	0.215	− 0.021	0.84	0.019
Moderate NDVI	Growing	0.0003	0.066	0.522	0.056	0.176	0.464	− 0.168	0.126	0.805	0.026
	Non growing	0.0016	0.492*	0.000	− 0.120	0.169	0.1	0.359	− 0.102	0.332	0.018
High NDVI	Growing	−0.0001	0.522*	0.000	0.102	− 0.319*	0.000	− 0.369	− 0.073	0.487	0.013
	Non growing	−0.0002	0.126*	0.000	− 0.162	− 0.108	0.294	0.051	− 0.077	0.461	0.041

*Mean significance at $P < 0.005$

et al. 2018). We applied the residual trend of NDVI to analyze the extent of human-driven impacts on vegetation within the basin. The overall significant increase in NDVI residuals indicated that vegetation growing in these areas cannot only be explained by climatic factors. For instance, over the cropland areas, the NDVI change reflected the impact of human activities, which has shown to depend strongly on irrigation. We deduced that if the NDVI residual trend is positive, human activities must have played a larger role in increased NDVI values, while a negative slope indicated no contribution from humans (Kang et al. 2017; Tong et al. 2018).
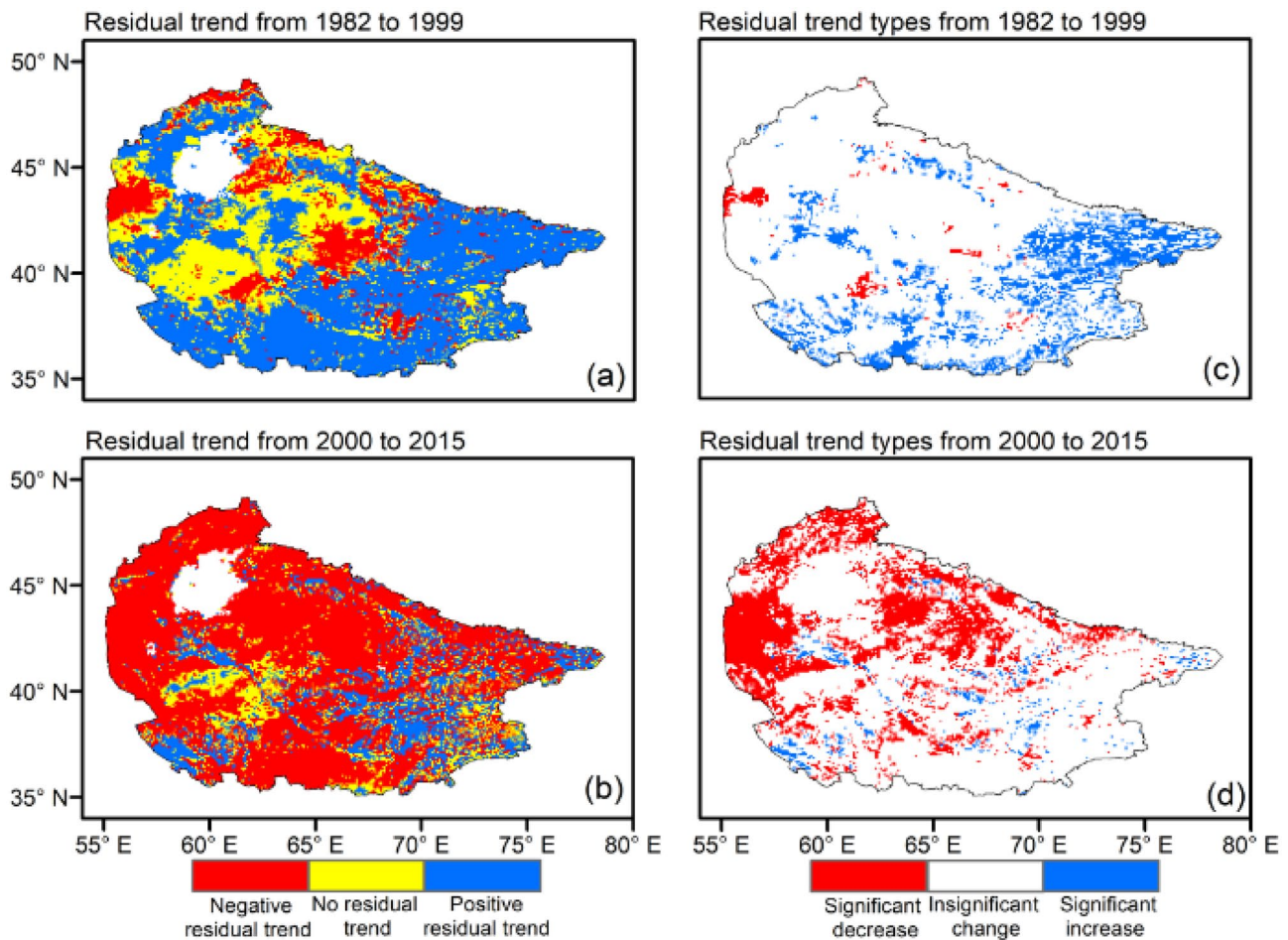
The spatial distribution of residual trend from 1982 to 1999 (Fig. 6a) presented areas with significant changes in vegetation. The increase observed in significant residual trend showed enhanced vegetation predominantly stretching from over the eastern to southern parts of the basin while declining vegetation has only been observed in the western most part of the basin covering small area. From this, it can be conferred that the increasing trend has been observed where located cropland areas and density of population is high (Fig. 6c). The area of the significant increasing residual trend of NDVI occupied 37.03% of the total area from 1982 to 1999.

Between 2000 and 2015 years, the area with that showed a significant increase in vegetation based on the residual trend of NDVI declined and accounted only for 2.22% of the basin area (Fig. 6d). In this study period, it was visible that the significant negative residual trend covered larger regions of the basin with a total of 39.36%. Clear indications of decreased vegetation through negative residual trend were observed in the north and northwest part of the basin especially along the large desert and shrublands located near the Aral Sea. So, it can be reasoned that the impact of human activity on vegetation change was increasingly positive between 1982 and 1999 but, these human activities started destructively affecting it after the 1999 year of change point.

4 Discussion

In this article, we have analyzed the seasonal NDVI changes in the ASB area, the effects of climate (temperature, precipitation, and soil moisture), and the human factors over the two time periods (1982–2015, 2000–2015). In the growing season, the ASB region experienced a significant increase in temperature and soil moisture content during the study period with the precipitation levels increased during the pre–1999 period but decreased after 1999.

In the growth season, the positive vegetation trend stretches mainly from the northeast part of the basin towards the northwest. These areas make up the urban, cropland, and mountainous regions of Uzbekistan, Kyrgyzstan, and Tajikistan. Similarly, along the Amu Darya and the Syr Darya rivers, i.e., the northern and southern parts of Uzbekistan, there has been increased vegetation in small areas with smaller patches around the Aral Sea, especially in the post-2000 era. From 2000 to 2012, the area of vegetation in Turkmenistan, which lies in the lower reaches of the Amu Darya, increased significantly as compared to the previous period (Xu et al. 2016). Decreasing vegetation trends during the growing season were observed mainly in the desert areas of the basin, including the Ustyurt Plateau, in the southwest parts of the Kara-Kum and the Aral Sea. No change in the NDVI trend was observed in the shrublands of the Kyzyl-Kum steppe between 1982 and 1999, and a negative trend has been reported since 2000. In the non-growing season, the two study periods showed an opposite process. In the 1982–1999 period, most of the area was covered by improved vegetation activity while the later period showed a negative trend in vegetation. This is attributed to continuous declines in precipitation and enhanced potential evapotranspiration resulting in persistent summer droughts in Central Asian region (de Beurs et al. 2015). The results showed heterogeneous distribution of vegetation trends during the two time scale between growing and non-growing periods attributing to the climatic fluctuations like thermal stress and moisture budget

Fig. 6 Spatial distribution of residual NDVI based on Linear Regression of growing season NDVI with climate factors. **a** Residual NDVI 1982–1999, **b** residual NDVI 2000–2015, **c** residual NDVI types 1982–1999, and **d** residual NDVI types 2000–2015

contributed through the midlatitude westerlies in the region (Bothe et al. 2011).

In the growing season, according to the results of the spatial correlation of NDVI with temperature, precipitation, and soil moisture, NDVI formed a positive correlation with precipitation and soil moisture. In 1982–1999, NDVI recorded a positive correlation with 68.2% precipitation and 57.6% soil moisture. Vegetation changes were observed in cropland, grassland, shrub, and mountain areas, except desert areas in the southeast of the basin, which are affected by precipitation and soil moisture. A study of 1960–1990 revealed that the climate change also impacted positively for obtaining high crop yield like wheat (Sommer et al. 2013a) till 1990 until the moisture deficit from Aral Sea has not been so grave. The correlation between NDVI, precipitation, and soil moisture during the post-1999 period shows a completely different scenario, with a negative correlation in the cropland and mountain areas of the basin and a positive correlation in the desert areas to the south of the basin. During this growing season, the temperature effect was also significantly

increased with a positive correlation in cropland and mountainous areas in the north of the basin (52.4%). During the non-growth season, NDVI varied mainly in temperature control during both the study periods.

Our results indicated that the human effect has also played a considerable role in the change of NDVI, especially before 1999. There is a significant positive residual trend in the northeast and northwest parts of the basin. This territory is mainly the most densely populated and developed region for agricultural activity. Similarly, human impact on NDVI changes was observed in large and small cropland areas along the Amu Darya and Syr Darya rivers. During this period, 37.03% of the area was affected by NDVI. In the post-1999 period, the scale of human impact was significantly reduced. Our results are in part consistent with previous researches. Irrigated arable lands, mainly cotton monocultures, increased by 60% from 1962 to 2002 (Lioubimtseva et al. 2005). Only in 1992–2002, the total irrigated area increased by half a million hectares (Lioubimtseva and Cole, 2006). In a small part of Turkmenistan, the

irrigated area grew by 59% and covered 300,000 hectares (Glazovsky 1995). Using available data from the Food and Agriculture Organization of the United Nations (FAOSTAT) database, agricultural area on the territory of Turkmenistan and Uzbekistan, from 2000 to 2015, decreased by 4.68% and 2.3%, respectively.

The climatic and human-driven changes on vegetation would translate into the economic disturbances like short-term gains and long-term losses for farm holders in Uzbekistan region, with Kyrgyzstan at the higher production risk and positive gains for Kazakhstan (Sommer et al. 2013b). The reduction of human impact on vegetation changes in the period after 2000 was also related to the reduction of irrigated areas and of the Amu Darya and Syr Darya water levels. Also, the ecosystems' Water Use Efficiency has shown negative relationship with drought episodes and positive association during post drought period which reveals that the ecosystem responses like vegetation health gets impaired during water deficit periods (Zang et al. 2020; Zou et al. 2020). In the last few years, the river area in the region has decreased, and this process is mainly influenced by the short-term drought episode of 2000–2001 in the lower reaches of the Amu Darya river (Aitekeyeva et al. 2020). According to statistic data from Chatly hydro-station downstream of the Amu Darya river, during the growing season, the average annual water volume was 350 m^3/s in 1982–1999 and 203.75 m^3/s in 2000–2015, compared to only 8.61 m^3/s in 2000–2001 constitute water. Another negative effect of human activities on the development of vegetation is related to the poor irrigation system. This has resulted in increased soil salinization in cropland areas of Turkmenistan and Uzbekistan, respectively, to 90% and 60% for the regions (Akramkhanov et al. 2012; Djanibekov et al. 2016).

From 1960 to 2015, the salinity of water within the Aral Sea rose from 10 to 97–100 g/l (Micklin 2014). The open field, formed in the seabed, is covered with fine salt and soil particles. As the wind blows, dust extends far into the air (Gaybullaev et al. 2012), which, in turn, has not only increased the salinity of irrigated areas in the seaside region but also projected serious repercussions on the health of the population living in those areas (Ataniyazova, 2003). According to our analysis, the Aral Sea forest area increased by 5.2% over the period from 1982 to 2015 that now covers a total area of 432.7 km^2. Due to the extensive human-driven activities in the region of Aral Sea, the basin underwent irreversible ecological destruction attributing to immense water withdrawals needed for large-scale reclamation of irrigation in the Central Asian countries (Wang et al. 2020). The continuous withdrawals for irrigation led to unprecedented shrinkage in Aral Sea volumes which due to the multiple interconnected factors such as global and regional atmospheric circulations patterns and its associated hydrological and hydrometeorological variations resulted in fluctuations

in mountain-glacial melting and dry spells in the regions along with frequent and intensified drought episodes (Micklin, 2007).

This study revealed that the timely monitoring and analysis of the regional land use and vegetation cover changes can aid in informed decision-making for ensuring sustainable and responsible use of natural resources. This study can also contribute to assessing the impacts of climate change on sustainable livelihoods and in monitoring the Sustainable Development Goals. This study can be utilized for scientific monitoring of SDG 1—No poverty, SDG 12—Responsible consumption and production, along with SDG 15—Life on land to report the climate and human-driven impacts on the available livelihood resources and economic set up within the ASB with differential effects on vegetation growth. The study has used remotely sensed data and hence there lies a limitation of not fully demonstrating the connection between ground data sources which can be considered for future studies to enhance the validation of the study results.

5 Conclusion

This study showed that during the growing season, the NDVI distribution was much better in 1982–1999 compared to 2000–2015, with the vegetation coverage area of 51.17% and 33.01% of the total area, respectively. This showed that the vegetation trends only increased slightly over the two study periods, with 0.008/10 years recorded for 1982–1999 and 0.004/10 years for 2000–2015. The positive trend is mainly in cropland and grassland areas. The non-growing season recorded a steady vegetation trend of 56.6% of the area in 1982–1999 and a negative vegetation trend of 57.24% of the area in 2000–2015. The distribution of negative and stable trends is mainly attributed to the dessert and shrub regions. Growing season NDVI in 1982–1999 was mainly controlled by precipitation and soil moisture in most cropland, grassland and mountain areas. During the growing season 2000–2015, cropland and grassland were predominantly temperature controlled. In the non-growing season, almost the entire region formed a positive correlation between NDVI and temperature than other factors. Although the climatic variations projected evidently yet no conspicuous impacts could be seen on the vegetation dynamics due to these variations within the ASB region. The human impact on vegetation changes during the growing season was significant during the study period up to 2000, whereas the human impact was significantly reduced during the subsequent study period. The residual NDVI trend in 1982–1999 was significant in 37.03% of the region, with an increase of 2.22% in the study period after 2000. The residual trend was found to be mainly distributed along densely populated areas in the irrigated cropland. This study aims to improve

our understanding of vegetation dynamics of the ASB to assess the impacts projected by climatic and anthropogenic drivers affecting the vegetation conditions within the region. This study can also be implicated with food security challenges of the Aral Sea Basin as it can be used as a baseline by decision-making authorities and land managers to understand the drivers and dynamics determining the vegetation changes within the basin.

Declarations

Conflicts of Interest The authors declare no conflicts of interest.

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