Temporal Responses of Vegetation to Climatic Factors in Kazakhstan and Middle Asia

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Key words: NDVI; Climate variability, Vegetation Response, Correlation analysis.

SUMMARY

Normalized Difference Vegetation Index (NDVI) is generally recognized as a good indicator of terrestial vegetation productivity. Understanding climatic influences, in particular precipitation and temperature, on NDVI enables prediction of productivity changes under different climatic conditions. We combined a NOAA/AVHRR NDVI dataset and a gridded climate dataset to analyse inter-annual and within-season relationship between NDVI and two ecoclimatic parameters (precipitation and temperature) in Kazakhstan and Middle Asia for the time-period 1981-1998. Evaluation of within-season relationship was based on monthly values of NDVI and climatic parameters during the growing season (April-October), while for evaluation of inter-annual relationship were taken either mean growing season values or mean values over the individual seasons (spring, summer, autumn). The results indicate that a strong correlation exists between NDVI and the two climatic parameters at inter-annual and within-seasonal scales. Temperature was the leading climatic factor controlling both inter-annual and within-season NDVI dynamics. The dynamic of vegetation activities over the period 1982-1998 was found to be strongly predicted by dynamic of annual precipitation and mean temperature over spring. For semi-desert and steppe vegetation, the inter-annual NDVI-precipitation correlation was higher when precipitation was accumulated over the current year with one-two preceding years, while the within-season dynamic displays a response time of NDVI to precipitation of 1-2 months. The correlation coefficients between NDVI-rainfall and NDVI-temperature exhibit a clear structure in terms of spatial distribution. The results indicate that the response of vegetation to climatic factors increases in order from forest, to semi-desert and steppe, to desert and shrubs vegetation. The correlation coefficients associated with cultural vegetation, especially in areas of irrigation agriculture, as well as the correlation coefficients associated with degrading regions depend on a number of other factors such as type and intensity of irrigation or cropping practice.

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1. INTRODUCTION

Since the early 1980th many studies of vegetation distribution and vegetation conditions at both global and regional scales were based on the using of data time-series of NOAA AVHRR sensor. The sensor gave a continuous spatial cover on a regular frequency of the photosynthetic activity, which can be expressed by indices such as Normalized Difference Vegetation Index (NDVI*)*. The vegetation absorbs a great part of incoming radiation in the visible portion of the spectrum (VIS=220-680 nm) and reaches maximum reflectance in the near-infrared channel (NIR=730-1100 nm). The NDVI, defined as ratio (NIR-VIS)/(NIR+VIS), represents the absorption of photosynthetic active radiation and hence is a measurement of the photosynthetic capacity of the canopy (Tucker & Sellers, 1986). Negative NDVI values indicate non-vegetated areas such as snow, ice, and water. Positive NDVI values indicate green, vegetated surfaces, and higher values indicate increase in green vegetation.

The correlation between NDVI and above-ground biomass is well established (Justice *et al.*, 1985; Tucker *et al*, 1985; Tucker & Sellers, 1986). Temporal and spatial correlations between NDVI and climatic factors are investigated in many research works. Particularly good correlation in the arid regions, both spatial and temporal, show NDVI and rainfall (Richard & Poccard, 1998; Tateishi & Ebata, 2004; Li *et al*, 2004), the relationship between NDVI and temperature are reported to be weaker but also significant (Kowabata *et al*, 2001; Schultz & Halpert, 1995; Wang *et al*, 2001; Wang *et al.*, 2003). Some scientists derived also high correlation between NDVI and potential evapotranspiration (Yang *et al*, 1998), between NDVI and soil moisture (Farrar *et al*, 1994). However, there were studies indicated opposite results: the studies conducted by Li *et al*. (2002) and Xiao & Moody (2004) for China found a leading role of temperature by controlling vegetation patterns, and Eklundh (1998) reported to find no significant correlation between NDVI and rainfall in East Africa.

Numerous studies have suggested a linear relationships between NDVI and climate predictors. Theoretically, NDVI can be considered as climatic recorder, mainly as a rainfall recorder. This assumption was used in various drought watching and drought early warning systems (Kogan, 1997; Song *et al*, 2004). However, the relationship is linear only in a limited range of rainfall conditions. The upper thresholds for the linear relationship between NDVI and rainfall were reported to be approximately 500 mm/yr for semi-arid Botswana (Nicholson & Farrar, 1994), 700-800 mm/yr for Senegal (Li *et al*, 2004), and 500-700 mm/yr for China (Li *et al*, 2002). Above these limits, NDVI increases with rainfall only at a slower rate.

The response of NDVI to rainfall and temperature is dependent on vegetation types and varies by geographical region. Woodland and forest vegetation shows a lesser correlation between NDVI and climate factors. Shrubs and desert vegetation patterns are reported to higher correlate with temporal and spatial variations of climate factors. Vegetation patterns in steppe grassland and savanna evident the highest correlation with that of rainfall and temperature (Li *et al*, 2002; Wang *et al*, 2001, Li *et al*, 2004). Nicholson & Farrar (1994) reported for Botswana the response of NDVI to rainfall to be more dependent on soil types than on vegetation types.

Many studies proved a high sensitivity of NDVI to inter-annual rainfall anomalies. Thus, NDVI can be used as a good proxy for the study of inter-annual climate variability on regional and global scales or for identification of climatic signal by evaluation of land degradation (Richard & Poccard, 1998, Kuwabata *et al*, 2001; Evans & Geerken, 2004). However, there are limits of rainfall amounts under which only a weak NDVI sensitivity to inter-annual rainfall anomalies can be found. This rainfall limits varies by geographical region, but generally, a minimum of 200-300 mm/yr seems necessary to induce the NDVI sensitivity to rainfall anomalies (Nicholson *et al*, 1990). Temperature deviation from average reported to have no correlation with NDVI deviation from average (Wang *et al.*, 2001).

In this study, we present an analysis of dynamics of vegetation activity and their associations with dynamics of climate factors, rainfall amounts and temperature in Kazakhstan and the Middle Asia for all vegetated pixels, and for each vegetation type as well as for the whole region. Our research based on using of a NDVI dataset that have been retrieved from Advanced Very High Resolution Radiometer (AVHRR) and a gridded climatology dataset (New *et al.*, 2000).

2. DATA AND METHODS

2.1 Noaa Avhrr Ndvi Data Set

We used 10-day maximum NDVI composites of the AVHRR sensor with a spatial resolution of 8 km. The data cover the period of growing season (April-October) from 1982 to 1998. Data were derived from NASAs Distributed Active Archive Center. Using a method described by Los (1993) NDVI data were calibrated against three time invariant desert targets located in the Big Arabian Desert, Nubia Desert and Taklamakan Desert. This method removes effects of sensor degradation and corrects drift between different sensor systems. In addition to that, we removed noisy pixel areas characterized by exceptionally low NDVI values relatively to their pixel neighbourhood. This pixels represented large cloud areas and were replaced by a mean value calculated from the temporal neighbouring NDVI layers.

2.2 Climate Data

For our study we used a global monthly climatology dataset (New *et al.*, 2000). This gridded dataset is interpolated from climate station records and has a spatial resolution of 0.5°. We used two variables, precipitation and temperature. To match the 8-km NDVI dataset, the monthly precipitation and temperature data were resampled to 8-km resolution.

2.3 Land-Cover Data

The land cover data in the study area were taken from the digital land-cover map derived from Moderate Resolution Imaging Spectroradiometer (MODIS) that have been accessible in the U. S. Geological Survey (USGS) archive centre. Originally, this map has 1 km spatial resolution and was resampled to 8 km resolution. There are 10 mean land cover types in the study area (Figure 1, Table 1).

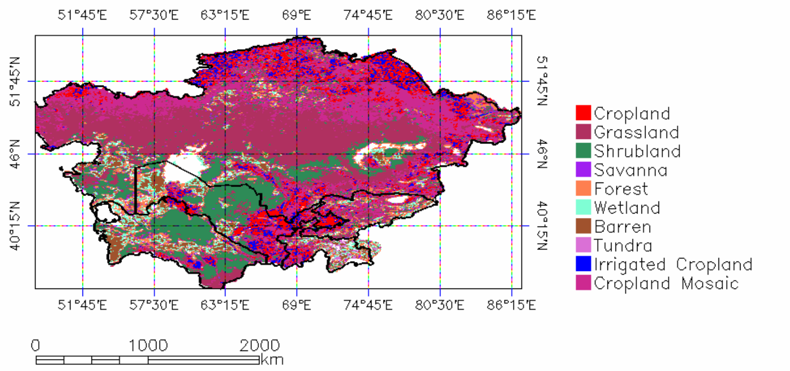

Fig. 1 Land-cover distribution in Kazakhstan and the Middle Asia based on the USGS land-cover map.

Table 1. Land-cover types in the study area (after USGS land-cover map).

Land-cover type	Number of Pixels	Area, million km²	Percentage, %
Cropland	9008	1.763	26.15
Irrigated cropland	4163	0.266	3.95
Cropland mosaic	18535	1.186	17.60
Grassland	26951	1.725	25.59
Shrubland	13186	0.844	12.52
Savanna	2077	0.133	1.97
Wetland	3135	0.201	2.97
Forest	6616	0.423	6.28
Tundra	332	0.021	0.32
Barren or sparsely vegetated (BSV)	2771	0.177	2.63
Total	**86774**	**6.740**	**100**

2.4 Analysis Methods

We then analysed the correlations between NDVI and climate data for each vegetation type as a homogeny area. Since spatial averaging hides the geographically variability of NDVI, we also analysed the spatial patterns of NDVI-climate correlations on a per-pixel basis. The strength of correlations were mapped and analysed.

We examined temporal relationship between NDVI and each of the climate factors - precipitation and temperature. Analyses examined both inter-annual relationship (between years) and intra-annual relationship (within-season). Within season analyses compared equivalent monthly time-series within the same growing season. Seasonal analysis compared time-series of mean growing season values over the study period 1982-1998. Significance at the 5% confidence level was used as the test criteria for all correlation calculations.

As first, we analysed within-season relationships. Analysis of within-season relationships was based on comparing time-series of monthly NDVI values, monthly rainfall amounts and mean monthly temperature. The growing season in the study region dues approximately from the beginning of April to the end of October. There is a time lag between precipitation events and the response of vegetation to such events. The time interval can vary from 1 to 12 weeks depending on vegetation type (Li *et al.*, 2002; Wang *et al*, 2001; Nicholson & Farrar, 1994; Tateishi & Ebata, 2004). Therefore, correlation analyses of within-season relationships were performed using NDVI and climate variables in two ways. First, correlation coefficients were calculated between the time-series of monthly NDVI and each climate variable over the same period (synchronous data). Second, the same type of correlation analysis was conducted with time lags being imposed to each climate variable. In order to account for time lag, we calculated NDVI-rainfall correlation coefficients using time lags of 1, 2, and 3 months.
By analysing inter-annual relations, evaluation of temporal relationships between NDVI and climate predictors was done through calculating correlation coefficients between corresponding pairs of NDVI and climate time-series over the whole study period from 1981 to 1998. Input data were mean values of NDVI and temperature, and total sums of rainfall over the growing season for every year. In order to evaluate the time period over with precipitation most strongly influences vegetation productivity, a series of analyses were performed using maps of precipitation totalled over 2 and 3 years too. Analysis of inter-seasonal relationships was made on the same way but with the data of separate seasons: spring, summer, and autumn. For analysis the NDVI-climate relationship for individual vegetation type, we generated spatially averaged time-series of the data.

3. RESULTS

3.1 Within-Season Relationships

3.1.1 <u>General trends of NDVI, precipitation and temperature during the growing season</u>

Considerable uniform time-series behaviour among the vegetation types during the growing season exists each year (Figure 2). The duration of the growing season is approximately from April to October. All land-cover types have the lowest NDVI values at the begin of the growing season, in April. Generally, all land-covers display increases in NDVI from April into June-July, peak during these both months and decrease permanent in August-October.
The 17-year average NDVI time-series of the vegetation types generally show uniform behaviour through the growing season (data not shown). NDVI curves for shrubland showed a peaking time in May, while the curves for grassland, savanna and cropland peak later, in June or July.

The peaking time for forest and wetland is in July-August. Through the growing season, NDVI values of forest and wetland were always highest, cropland and grassland values were intermediate and shrubland lowest among the vegetated lowland areas. Tundra areas are located in the mountainous regions at the high between 2600-3500 meter. This land-cover type shows a contemporary low NDVI values over the growing season with a maximum in

August. Barren or sparsely vegetated areas in lowland does not have any recognizable muster of NDVI curves and show values about zero (0-0.04) through the growing season.

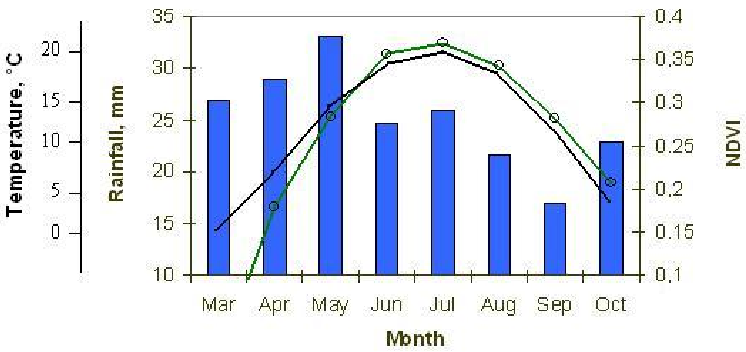

Fig. 2. Average monthly values of precipitation (blue pillars), temperature (black line) and NDVI (green line) during growing season.

Reasons for a large discrepancy in NDVI temporal patterns of individual land-cover types is a large difference in moisture and temperature conditions over the territory of the study area and differential responses of vegetation cover to summer climate conditions such as responsiveness to precipitation or limitations from high temperatures. In the next section we investigate the influence of climatic predictors on vegetation development during the phenological cycle. We carried out a detailed investigation of temporal relationships between NDVI and eco-climatic parameters during the growing season and highlighted how this relationship changes in the space over the study area.

3.1.2 Within-season correlations between NDVI and climatic factors

The previous studies have shown presence of a time-lag between a weather event, especially rainfall, and the vegetation response to it (Yang *et al.*, 1998; Wang *et al.*, 2003; Richard & Poccard, 1998). Figure 2 illustrates that there is a time-lag of approximately two months between precipitation and NDVI time-series averaged over the whole study area. On the contrary, the profiles of NDVI and temperature are synchronous. Therefore, by analysing NDVI-precipitation relationship for individual land-cover classes, we calculated correlation coefficients imposing different time-lags from 0 to 2 months. For NDVI-temperature relationship, we calculated calculations only on a synchronous basis (no lag). All computed correlations are significant at the 95% level.

On the level of land-cover type, the maximum r-values for NDVI-precipitation were obtained with either 1 time-lag or 2 time-lag correlations (Table 2). Thus, for cropland, cropland mosaic, grassland, shrubland, savanna and sparsely vegetated areas, the highest correlation coefficient was derived by imposing 1 lag, while for wetland, forest and the average over all pixels, the strongest relationship was obtained by imposing 2 lag between data. Vegetation cover of irrigated cropland and tundra exhibits only weak response to precipitation. With regard to land-cover type, the results of NDVI-precipitation correlation analysis indicate that r-values increase as one moves from irrigated cropland, tundra and wetland (r = 0.03, -0.05

and 0.34 respectively), to forest, savanna, cropland and cropland mosaic (r = 0.82, 0.79, 0.82 and 0.86), then to grassland, shrubland and barren or sparsely vegetated land (r = 0.93, 0.94 and 0.92). This seems best explained by the diversity that exists between the different vegetation types associated with each land-cover. The results of correlation analysis of our study are in agreement with the research results obtained by for others dry regions (Li *et al.*, 2004; Nicholson & Farrar, 1994; Li *et al.*, 2002; Wang *et al.*, 2003). In accordance with the results, the higher correlation coefficient between NDVI and precipitation is observed in treeless landscapes with natural grassland or shrubland vegetation cover. This indicates the strong control rainfall as a limiting factor on NDVI in these areas. Vegetation cover of agriculturally used land such as cropland exhibit a lower response to precipitation, while forested areas the lowest.

Table 2. Within-season correlation coefficient between NDVI and climatic variables within each land-cover type and for all pixels.

Land-cover	NDVI-pre correlation			NDVI-tem correlation
	0 lag	1 lag	2 lag	
Cropland	0.57	**0.82**	0.02	0.97
Irr. Cropland	-0.87	-0.55	**0.03**	0.86
Cropland Mosaic	0.67	**0.86**	-0.10	0.92
Grassland	0.64	**0.93**	0.37	0.86
Shrubland	0.21	**0.94**	0.61	0.90
Savanna	0.73	**0.79**	-0.31	0.95
Wetland	-0.70	-0.30	**0.34**	0.94
Forest	-0.32	0.67	**0.82**	0.95
Tundra	-0.93	-0.59	**-0.05**	0.89
BSV	0.38	**0.92**	0.70	0.76
All pixels	-0.16	0.45	**0.81**	0.92

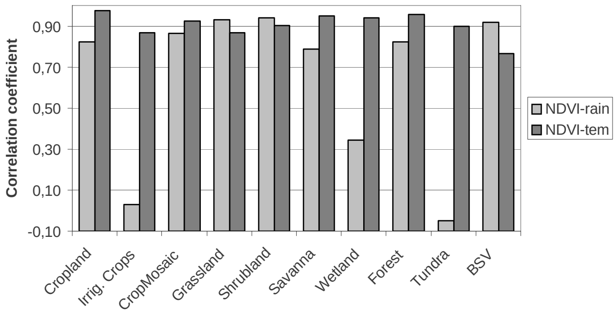

Fig. 3. Comparison of within-season correlation coefficients between NDVI-precipitation and NDVI-temperature for different land-cover types.

The calculated NDVI-temperature correlation coefficients indicate that for all land-cover types there is a significant correlation between NDVI and temperature monthly time-series. The 17-years average r-value between NDVI and temperature was very strong ranging from 0.76 to 0.97 for different land-cover types. The results of NDVI-temperature correlation analysis, as might be expected, indicate that this relationship is very strong since temperature often serves as an indirect measure of available energy for plant growth. Above a certain base temperature, a plant's rate of growth is found to be proportional to temperature. From Figure 3 we can see that for the most land-cover types, within-season NDVI-temperature correlation coefficient was higher than the NDVI-precipitation correlation coefficient with exception of grassland, shrubland and BSV. That agrees with the results of the research works obtained by Li *et al.* (2002) for China, by Yang *et al.* (1997) for Nebraska, U.S.A., but disagree with the results of Wang *et al.* (2001 and 2003) obtained for the Great Plains, U.S.A.

3.1.3 Spatial patterns of within-season NDVI-climate relationships

The results of this study show that 75.76% of all pixels exhibited significant positive correlation ($r > 0.48$) between within-season monthly time-series of NDVI and rainfall. The pixels with high correlation coefficients ($r > 0.70$) are mainly distributed in the north, south-west and east portion of the study area (Figure 4). The total area of pixels varied substantially by land-cover type (Figure 5). The spatial patterns of pixels with either low positive ($r < 0.48$) or with negative correlation coefficients are found of three location types: first, areas of irrigated cropland in river deltas and river valleys; second, mountainous areas in the south; third, areas with degrading vegetation cover in the west and central parts of the study region. For NDVI-rainfall correlation, the total area of pixels that exhibit positive correlation ranged from 8.43 to 82.15% for tundra and shrubland, respectively. For cropland, grassland, forested areas and savanna, 79.65%, 81.70%, 75.04% and 79.63% of the pixels exhibited positive NDVI-rainfall correlation, correspondingly. For wetland, only 13.62% of the pixels responded positively to precipitation.
The percentage of pixels with significant positive correlation between NDVI and temperature was also high. Taken together, 79.62% of those pixels exhibited positive correlation coefficients. The pixels with high value of correlation ($r > 0.70$) are distributed over two broad swath of land in the north and south-east. The pixels with low (< 0.48) or negative r values are located in the mid and south-western parts of the region. These areas are mostly covered by shrubby or short grass vegetation. Around the Aral lake, there are pixels with negative correlation coefficients. These pixels represent severe degraded areas which are deprived of any vegetation cover. Positive NDVI-temperature correlations were observed for 98.10%, 96.58%, 96.49%, 90.87% and 88.67% of cropland, irrigated cropland, cropland mosaic, forested areas and wetland, respectively. Compared with temperature, precipitation plays a minor role in explaining the greening patterns in these land-cover types. For other land-cover types, precipitation makes a greater contribution to the greening patterns than temperature does. For grassland, shrubland, savanna and BSV, the total area of the pixels with positive NDVI-temperature correlation was 66.70%, 63.42%, 74.33% and 51.28%, accordingly. This is smaller than that of NDVI-precipitation.

3.2 Inter-Annual Relationship Between Ndvi and Climate Factors

Precipitation has a strong effect on inter-annual variability of vegetation. The relationship between precipitation and inter-annual variability of vegetation is shown by correlations

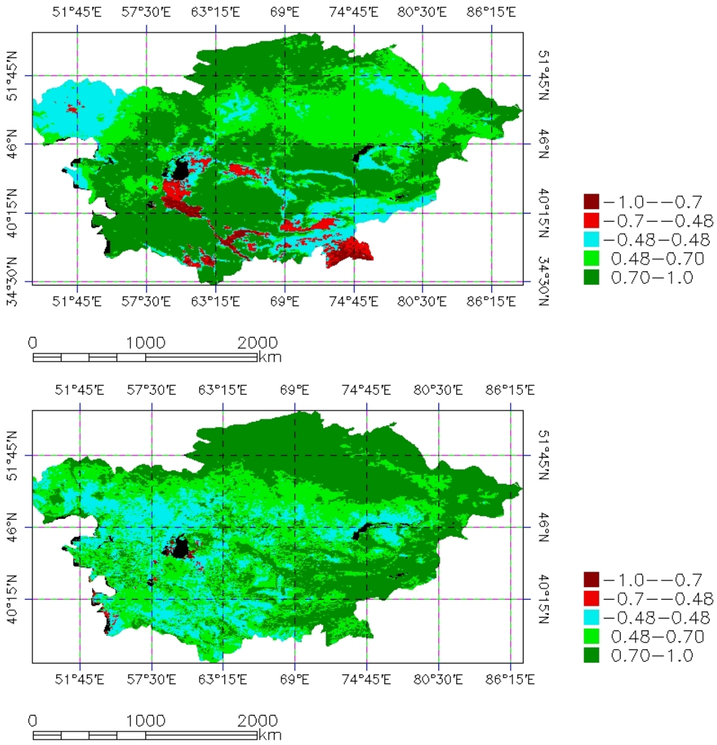

Fig. 4. Correlation coefficients, r, of the within-season relationship between NDVI and precipitation (upper panel), and NDVI and temperature (lower panel) on a per-pixel basis.

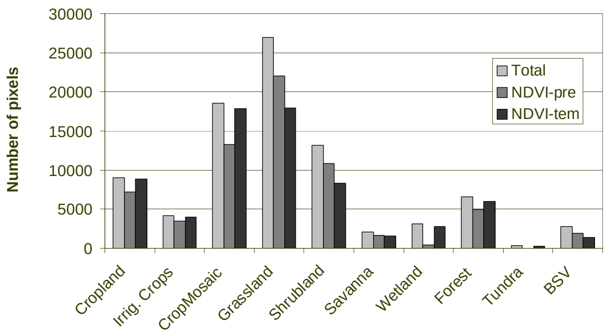

Fig. 5. Total number of pixels with significant NDVI-precipitation and NDVI-temperature correlations for each land-cover type.

between time-series of mean growing season values of NDVI and growing season precipitation amounts. For the study region as a whole, correlation between synchronous data of NDVI and precipitation was low (r = 0.21). But when we correlate the NDVI with precipitation totalled over a longer time, correlation coefficients increased and peaked when the time interval reached 2 years (r = 0.60). For the individual land-cover categories, the correlation coefficients were also stronger when we totalled precipitation over two-three years (Table 3). Thus, the correlation between NDVI and precipitation totalled over two years exhibited values of 0.62, 0.54, 0.63, 0.59 and 0.57 for cropland, irrigated cropland, cropland mosaic and BSV, respectively. The lowest values are observed in forested areas (r = 0.11) and in savanna (r = 0.26).

Correlation coefficients between time-series utilizing summer precipitation and summer NDVI values also varied depending upon combinations of time duration over which precipitation was totalled. For cropland, cropland mosaic, savanna and tundra, the highest correlation coefficients were achieved by utilizing precipitation amounts totalled over three summer seasons. The correlation coefficients equalled 0.79, 0.72, 0.76 and 0.51, respectively. For grassland, shrubland, forest and the average over all vegetated pixels, the strongest correlations were computed with precipitation totalled over two seasons, 0.63, 0.63, 0.34 and 0.80, respectively.

This result agree with the results obtained for others regions (Li *et al.,* 2002; Li *et al*., 2004; Wang *et al*., 2003) where woody areas exhibited low sensitivity to inter-annual precipitation variability. An explanation may be that tree root system is capable to hold a great deal of moisture that can be released over time. This makes possible trees to grow without to be immediately affected by precipitation shortage in a dry year. Grass and shrub vegetations have much smaller root systems and can not hold moisture over a longer time. Therefore, they are more significantly affected by the inter-annual variability of precipitation.

The NDVI versus temperature inter-annual correlations depict the degree to which the two parameters are related over the entire study period. We calculated correlations both using annual average growing season values and annual average seasonal values. Growing season correlations between NDVI and temperature were computed using data from the April-October period.

The results of these calculations exhibited for the most land-cover types very low values of correlation coefficient. Only for forested areas and tundra, correlation was notable with r value of 0.33 and 0.21, respectively. Inter-annual correlation with seasonal data were computed using data from different seasons. It means we used mean values over the periods April-May, June-August and September-October. We found strong positive correlation coefficients between the time-series of spring NDVI-temperature. For the most land-cover types with exceptions of shrubland and BSV, the correlation coefficients exhibited r values > 0.70. This results are in agreement with the other studies results suggesting that productivity in northern high latitudes is increasing in response to increased temperatures during spring (Tucker *et al.,* 2001; Xiao *et al.,* 2004). This increase of temperature during spring affects the spring NDVI values in two ways: first, through an earlier start of the growing season; and second, through a rapider climb of NDVI values during the spring months.

3.2.1 Spatial patterns of inter-annual relationships between NDVI and climatic factors

Over the entire study region, 45.42% of the vegetated pixels exhibited significant correlation between the 17-year time-series of growing-season NDVI and that of precipitation. These pixels build up two broad bands across the north and the south of the study area (Figure 5). Outside these bands, there are only small spots of pixels with significant positive correlation.

The largest NDVI-precipitation correlations (r > 0.70) occur in western, eastern and southern regions and take only about 11% of the whole area. The percentage of pixels with significant positive correlation varied broadly by land-cover type, ranging from 6.62% to 61.75% for tundra and cropland mosaic, respectively (Figure 6). As it was explained in the preceding

Table 3. Inter-annual correlation coefficient (r-value) between NDVI and climatic variables for every land-cover type. For the NDVI-precipitation relationship, correlation coefficients were computed not only between synchronous time-series but also when precipitation was totalled over the current year and one-two preceding years.

Land-covers	NDVI-precipitation			NDVI-temperature
	1 year	2 years	3 years	
Cropland	0.38* 0.69**	0.62 0.76	0.58 **0.79**	0.03 **0.83**
Irrigated Cropland	0.12 0.18	**0.54** 0.17	0.40 0.18	0.14 **0.83**
Cropland Mosaic	0.44 0.65	0.63 0.71	0.51 **0.72**	0.06 **0.76**
Grassland	0.58 0.43	**0.69** 0.63	0.36 0.57	0.12 **0.69**
Shrubland	0.52 0.47	0.47 **0.63**	0.44 0.61	0.01 **0.55**
Savanna	0.23 0.55	0.26 **0.76**	-0.17 0.36	0.08 **0.82**
Wetland	0.12 0.34	0.34 0.27	**0.41** 0.18	0.12 0.73
Forest	0.04 0.30	0.11 **0.34**	-0.30 0.31	0.33 0.79
Tundra	0.17 0.22	0.49 0.49	0.29 **0.51**	0.21 0.71
BSV	**0.57** 0.34	0.39 0.31	0.36 0.21	-0.08 0.39
All pixels	0.21 0.51	0.60 **0.80**	0.48 0.77	0.13 0.76

** in every cell, the upper number represents correlation coefficient derived from utilizing growing season NDVI and growing season precipitation or temperature data,*

*** the lower number represents correlation coefficient derived from utilizing seasonal NDVI and according climate variables: for NDVI-precipitation analysis, that is the summer value; for NDVI-temperature, that is the spring value.*

chapter over (see), the treeless land-cover types exhibit a higher dependence on inter-annual precipitation variability than the land-cover types with woody vegetation. This fact also appears when we compare the pixels percentage by land-cover type. Thus, for forested areas and savanna, the percentage of pixels with value of the correlation coefficients over 0.50 equal only 14.82 and 33.46. On the contrary, for shrubland, grassland and the three classes of cropland combined, respectively 41.7%, 46.02% and about 56% of all pixels manifested the correlation coefficients with values of over 0.50.

Generally, the spatial patterns of the NDVI-precipitation correlations for summer data correspond to that of growing season data, but the spatial extension of areas with significant positive correlation coefficients is smaller (Figure 6, central part). Over the entire study region, 33.36% of the vegetated pixels exhibited correlation coefficients with values > 0.50.

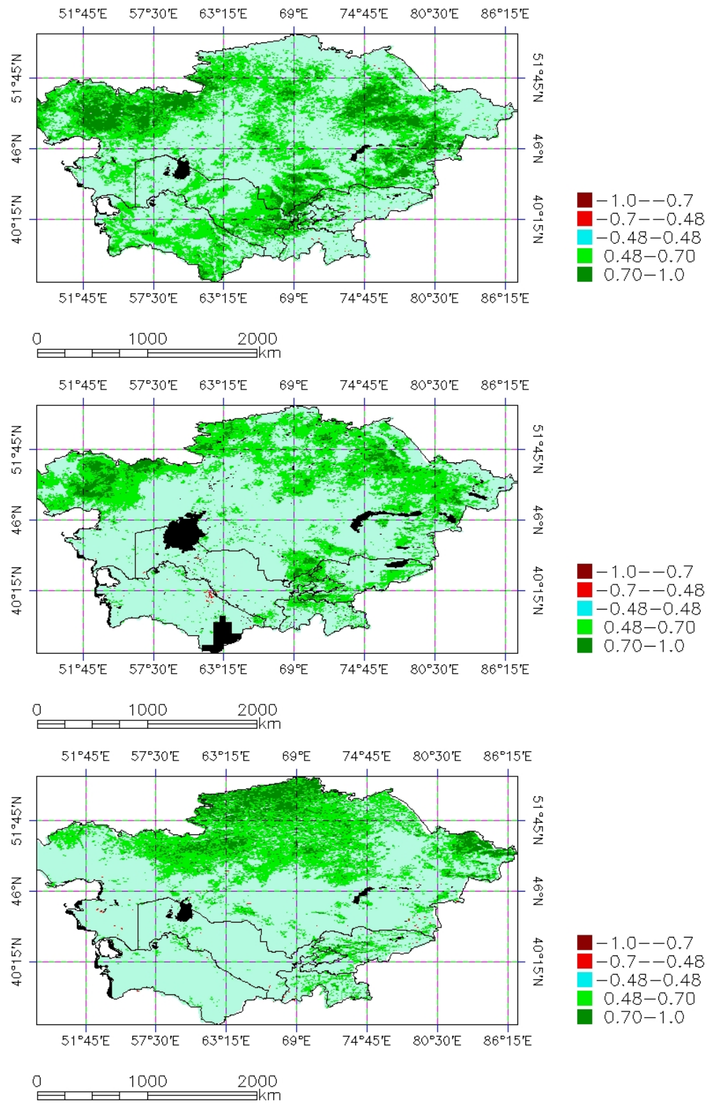

Fig. 6. Correlation coefficients, r, of the inter-annual relationship between NDVI and precipitation using data from growing season (upper part), from summer season (centre), and between NDVI and temperature using data from the April-May period (lower part) on a per-pixel basis.

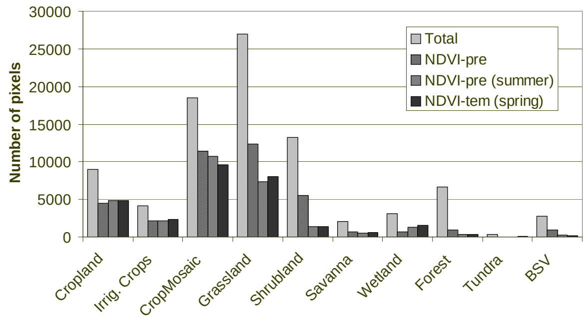

Fig. 7. Total number of pixels with significant inter-annual NDVI-precipitation and NDVI-temperature correlation for each land-cover type.

For all vegetated pixels, 33.56% exhibited positive NDVI-temperature correlations using data from the spring season. These pixels are mainly distributed in the northernmost portion of the study region (Figure 6, lower part). For cropland, irrigated cropland, cropland mosaic, grassland and savanna, 54.03%, 56.04%, 51.88%, 29.89% and 30.47% of pixels exhibited positive NDVI response to variability of spring temperatures, respectively. Low percentages of pixels showed significant NDVI-temperature correlations in shrubland, forest, tundra and BSV.

4. CONCLUSION

This study examined inter-annual and within-season relations between time-series of NOAA AVHRR NDVI and analogous series of climate variables for the 1982-1998 growing seasons in Kazakhstan and the Middle Asia. Strong temporal correspondence between NDVI-precipitation, and NDVI-temperature were observed. The strength of NDVI-climate associations depends on land-cover type but there are variations in the response of NDVI to climate factors within each land-cover class on the per-pixel basis. The correlation between NDVI and temperature was found to be higher than correlation between NDVI and rainfall both on within-season and inter-annual scales. The result is indicative of the available energy and heat on plant growth during the growing season.

The results indicated that the correlations between precipitation and NDVI for within-season and inter-annual relationships are always positive. Inter-annual analyses with growing season data and summer data demonstrated that NDVI values are most strongly correlated with the precipitation that has been integrated over two to three recent year periods. Different land-covers showed different strength of correlations between NDVI and precipitation. The response of vegetation to the inter-annual precipitation variability increases in order from forest, to savanna, to shrubland and to sparsely vegetated areas, to cropland, and to grassland. The results of the within-season NDVI-rainfall analysis exhibited that the correlations were stronger in areas dominated by natural vegetation such as grassland, shrubland, and sparsely vegetated areas. In cropped areas, however, the association was weaker due, probably, to crop irrigation and land management activities. This result is consistent with the observation of the relations between NDVI and precipitation in other dry regions (Wang *et al*. 2003; Yang *et al.,* 1997; Li *et al.,* 2002; Li *et al.,* 2004). For within-season relations, distinct time lags associated with NDVI's response to precipitation event were determined.

Our analyses also show that temperature is an important factor for plant growth but the correlation between NDVI and temperature is not always positive. Thus, the inter-annual correlation coefficients between growing season NDVI and temperature indices were negative. This may be because there is a strong negative relationship between precipitation and temperature. On the contrary, within-season analyses show strong positive correlation between NDVI and temperature indices, so does also inter-annual analysis with the data related to mean values of NDVI over spring and the corresponding temperature data.

The results of this study have contributed to a better understanding of the relations between AVHRR/NDVI and eco-climatic variables and the temporal characteristics of such relations in a dry inner region of the Eurasia, but should be considered preliminary. Many environmental factors are inter-related and interact in complex ways that are still inadequately understood. Stratification of observed NDVI-climatic relations according to land cover characteristics is suggestive of important relations, but other environmental factors (e.g., soil reflectance, human activities) need to be examined in order to assess their roles in monitoring vegetation conditions using NDVI. A full analysis requires a more mechanistic understanding of the interactions between temperature, precipitation and other factors as they determine evapotranspiration and influence energy balance.

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