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Spatial patterns of NDVI in response to precipitation and temperature in the central Great Plains

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Abstract. The Normalized Difference Vegetation Index (NDVI) has proven to be a robust indicator of terrestrial vegetation productivity. Among climatic factors, precipitation and temperature strongly influence both temporal and spatial patterns of NDVI. We examined spatial responses of NDVI to precipitation and temperature during a 9-year period (1989–1997) in Kansas. Biweekly climate maps (precipitation and temperature) were constructed by interpolation of weather station measurements. Maps of biweekly growing season (March to October) NDVI were constructed for Kansas using National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) NDVI images. Average precipitation is a strong predictor of the major east–west NDVI gradient. Deviation from average precipitation explained most of the year-to-year variation in spatial patterns. NDVI and precipitation covaried in the same direction (both positive or both negative) for 60–95% of the total land area. Minimum and average temperatures were positively correlated with NDVI, but temperature deviation from average was generally not correlated with NDVI deviation from average. Our results demonstrate that precipitation is a strong predictor of regional spatial patterns of NDVI and, by inference, patterns of productivity.

1. Introduction

Remotely sensed Normalized Difference Vegetation Index (NDVI), calculated as the difference between near-infrared and visible reflectance values normalized over the sum of the two (Eidenshink and Faundeen 1994), is a good measure of landscape patterns of green biomass (Rosental *et al.* 1985, Prince 1991), and can be used to estimate landscape patterns of primary productivity (Gausman 1974, Sellers 1985, 1987, Tucker and Sellers 1986, Goward and Dye 1987, Sellers *et al.* 1992), and to

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predict crop yields (Lee *et al*., in review). Wang *et al*. (in review) found that precipitation is strongly correlated with NDVI in the central Great Plains, when viewed at an appropriate temporal scale. In particular, total precipitation during a 15-month period (current growing season plus seven preceding months) was most strongly correlated with average growing season NDVI. In addition, Wang *et al*. found a strong linear relation between 15-month precipitation and growing season NDVI, except for the flood year of 1993, when exceptionally high rainfall was associated with decreased NDVI. Further work is required to understand spatial patterns of NDVI as it relates to climatic variation at a regional scale.

Many studies have used NDVI to monitor the temporal response of vegetation to climatic fluctuations in the USA (Di *et al*. 1994, Yang *et al*. 1997), in Africa (Tucker *et al*. 1983, 1985, Justice *et al*. 1986, Townshend and Justice 1986, Malo and Nicholson 1990, Davenport and Nicholson 1993, Nicholson and Farrar 1994, Anyamba and Eastman 1996), in India (Srivastava *et al*. 1997), and at a global scale (Schultz and Halpert 1993); but only a few studies have examined spatial patterns of NDVI as they relate to climate variation (Tucker *et al*. 1985, Nicholson *et al*. 1990, Farrar *et al*. 1994, Nicholson and Farrar 1994). We examined influences of precipitation and temperature on spatial patterns of NDVI in the state of Kansas on a biweekly basis over the course of 9 years (1989–1997).

2. Study area

This study was conducted for the state of Kansas, which is in the heart of the central Great Plains region of North America. The region has a temperate continental climate with a strong east–west precipitation gradient and a strong north-west–south-east temperature gradient. Mean annual precipitation ranges from less than 450 mm toward the west to more than 1200 mm toward the south-east; whereas mean annual temperature varies from less than 11°C toward the north-west to more than 15°C toward the south-east. Accordingly, vegetation ranges from tall-grass prairie and gallery forest in the east to short-grass prairie in the west (Kuchler 1974). Croplands now occupy over half of the land area (Whistler *et al*. 1996). Year-to-year variation in rainfall is high, with precipitation of wet years often as much as four times that of dry years, and the region is highly susceptible to drought (Warrick 1975, Bark 1978, Reed 1993). During the time period of our study, the state of Kansas experienced successive dry years from 1989 to 1991, and successive wet years from 1992 to 1997, except 1994, which was a dry year.

3. Data processing

3.1. *NDVI and climate data processing*

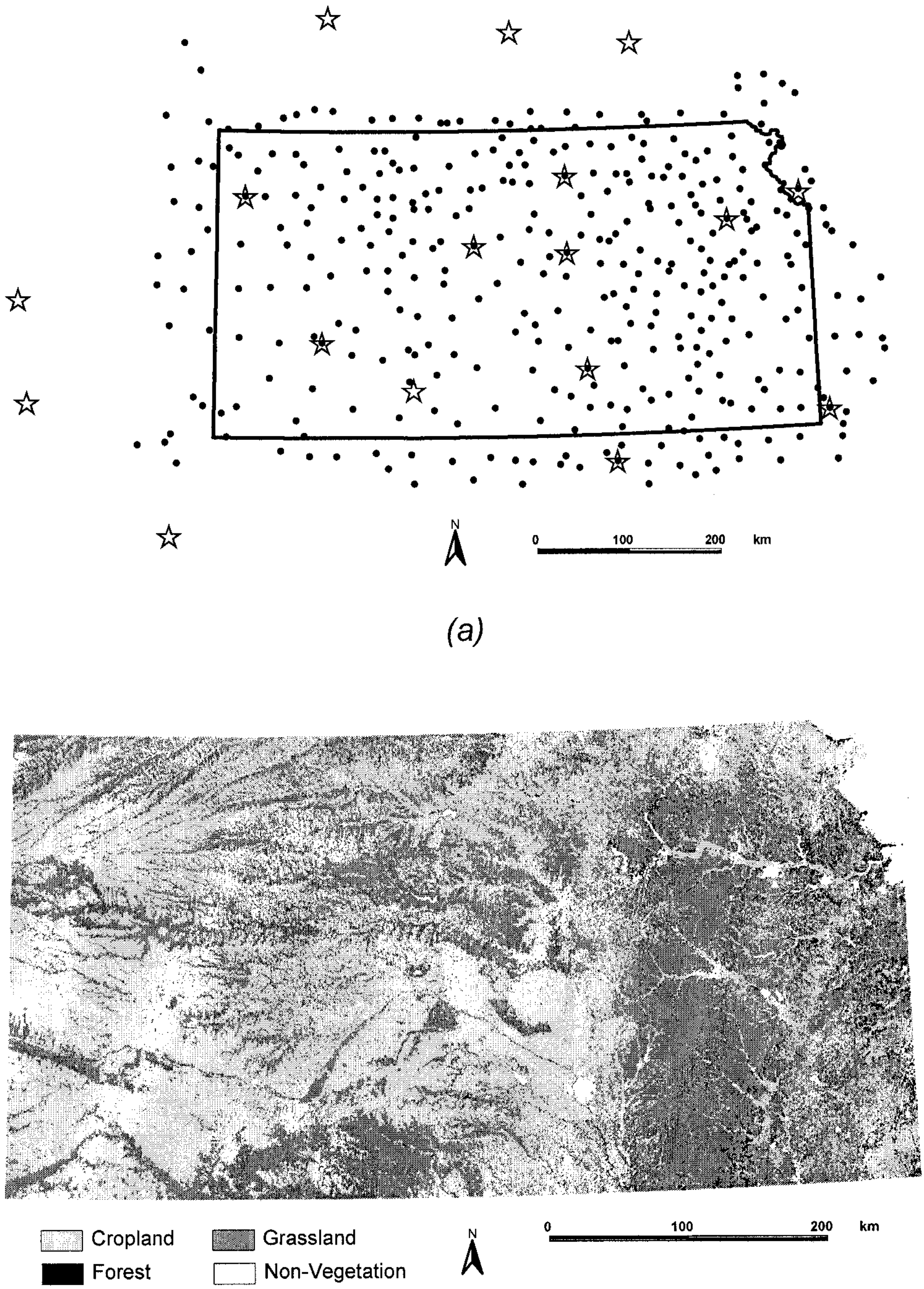
Biweekly digital maps of greenness (NDVI), precipitation and temperature were constructed for the entire state of Kansas over the course of 9 years (1989–1997) (Wang *et al*., in review) using ARC/INFO GRID GIS software version 7.1 (Environmental Systems Research Institute, Redlands, CA, USA). Biweekly NDVI images for the growing seasons (March to October) were derived using National Atmosphere Administration Advanced Very High Resolution Radiometer (NOAA AVHRR) satellite imagery. This imagery consists of 1 km Maximum Value Composite NDVI images, maximum values selected to eliminate cloud contamination, compiled by the United States Geological Survey (USGS) EROS Data Center, and further processed to remove cloud contamination and made available by the Kansas Applied Remote Sensing Program (KARS). Seasonal average NDVI images were generated by averaging the biweekly NDVI images from March to October. Precipitation maps (biweekly and monthly for each entire year) were derived from daily precipitation data (NOAA National Climate Data Center) from 410 weather stations in and around the state of Kansas (figure 1(*a*)). Biweekly temperature maps—maximum, minimum, average, and accumulated growing degree day (AGDD, Yang *et al.* 1997)—were constructed using daily maximum and minimum temperature data derived from 17 weather stations (figure 1(*a*)). All climate maps used simple distance-weighted interpolation. Analyses were stratified according to the categories of cropland, grassland, and forest (figure 1(*b*)) in the landcover map for Kansas (Whistler *et al.* 1996).

3.2. *Analysis of relations between climatic factors and NDVI*

We examined spatial relations between NDVI and each of the climate factors—precipitation, temperature (maximum, minimum, average and degree days) stratified according to landcover categories (cropland, grassland and forest). Correlation coefficients between NDVI and each climate factor were calculated for the state of Kansas by directly comparing corresponding spatial locations for pairs of NDVI and climate maps. The primary goal of the analyses was to evaluate the correspondence between NDVI spatial patterns and climate variation. Analyses examined relations both within growing seasons (within-season) and between seasons (seasonal). Within-season analyses compared different biweekly periods within the same growing season. Seasonal analyses compared NDVI and precipitation values between different years. For each year NDVI was averaged through growing season and precipitation was accumulated for the entire growing season plus 14 preceding months.

For each biweekly period in the growing season (March to October), NDVI–precipitation correlation coefficients were calculated, with precipitation summed over 14 different time durations (1–14 biweekly periods) and five different time lags (zero to four biweekly period lags), i.e. each biweekly NDVI image was compared with a total of 70 different precipitation patterns. This resulted in 32, 130 correlation coefficient values (17 periods $\times$ 70 combinations $\times$ 9 years $\times$ 3 landcover types). Thus, we were able to assess the time-scale (duration and lag) of precipitation that most strongly influences NDVI spatial patterns. In addition, to assess the correlation between NDVI variation and precipitation variation, we performed a similar analysis based on deviation of NDVI and precipitation from an 8-year average (1989–1997, excluding 1993, an anomalous flood year). In this case, NDVI deviation was compared with precipitation deviation for the same 70 different combinations of time duration and lag. We also calculated the correlation coefficients between each NDVI image and the 9-year average precipitation. For each year, within-season correlation coefficients between NDVI images and maps of temperature indices (maximum, minimum, average and AGDD) in the current and immediate preceding biweekly periods of the same growing season were calculated. Correlation coefficients for additional combinations of duration and lag were not calculated because preliminary analysis of a subset of combinations showed that only the current and preceding biweekly periods of temperature were significantly related to NDVI.

Correlation coefficients between growing season average NDVI images of each year and precipitation maps were calculated. In order to evaluate the time period over which precipitation most strongly influences overall productivity, a series of analyses were performed using maps of precipitation totalled over different time intervals, ranging from 8 to 22 months preceding the end the growing season (October), with a 1-month increment. Correlation coefficients between average NDVI



(b)

Figure 1. (*a*) Locations of weather stations used for precipitation (circles) and temperature (stars) map interpolation; and (*b*) land use/landcover map of Kansas used for stratification of analyses (Whistler *et al.* 1996).

of the year and average temperature indices (maximum, minimum, average temperatures and AGDD) were also calculated. Correlation coefficients between maps of growing season average NDVI deviation and precipitation deviation were calculated. The calculations of precipitation and NDVI deviation used an 8-year average (1989–1997, excluding 1993), since 1993 was an anomalous flood year when NDVI did not increase linearly with precipitation, but instead decreased (Wang *et al*., in review). In addition, we examined the proportion of land area where NDVI and precipitation deviations either covaried (i.e. where both positive or both negative) or varied in the opposite directions (i.e. one was positive and the other negative). Again, precipitation was calculated for each time interval ranging from 8 to 22 months.

4. Results

4.1. *Spatial patterns of NDVI, precipitation, and temperature*

Average precipitation increases markedly from west to east (figure 2(*a*)), average annual temperature decreased from south-east to north-west (figure 2(*b*)), and average NDVI increased from west to east (figure 2(*c*)).

4.2. *Within-season relations between precipitation and NDVI*

Based on systematic analyses correlation coefficients values, we found that spatial correlation coefficients between NDVI and precipitation were quite different for NDVI according to time of the growing season, time interval and lag over which precipitation was summed, and landcover type. Correlation coefficients were generally very small in March and April, increased in May as the NDVI increased. Generally, correlation coefficients remained high during June and July, except in 1989, a dry year in which coefficients dropped markedly starting in June. In some years correlation coefficients dropped off in August (1991, 1994, 1996, 1997), while others remained high until the end of the growing season (1990, 1992, 1993, 1995) (figure 3).

Generally, higher correlation coefficients were observed for longer time intervals over which precipitation was summed. For time intervals longer than six biweekly periods, however, the coefficient only increased slightly with increased interval (figure 4).

Overall, time lags (no time lag, one, two, three or four biweekly period lags) only had a weak influence on correlation coefficients (data not shown). For grassland and cropland, correlation coefficients were best with time lags of two to three biweekly periods during the summer. For forested land, correlations were best with time lags of two to three biweekly periods in early summer, and best with time lags of four biweekly periods in late summer. During the fall, correlation coefficients were best with no time lags for all landcover types.

High correlation coefficients were generally associated with discrete precipitation events, which were either preceded or followed by a relatively dry period (table 1). Among these precipitation events, three periods (23 August 1989, 17 July 1992, 3 May 1996) received much more precipitation than previous periods and were followed or accompanied by marked increases of NDVI. Two periods (15 June 1990, 10 August 1990) were followed by two periods with much less precipitation. Three other periods (25 September 1992, 24 September 1993, 26 August 1994) received more precipitation when NDVI values were dropping, and caused NDVI values to drop more slowly. The period 18 April 1997, however, was not associated with a

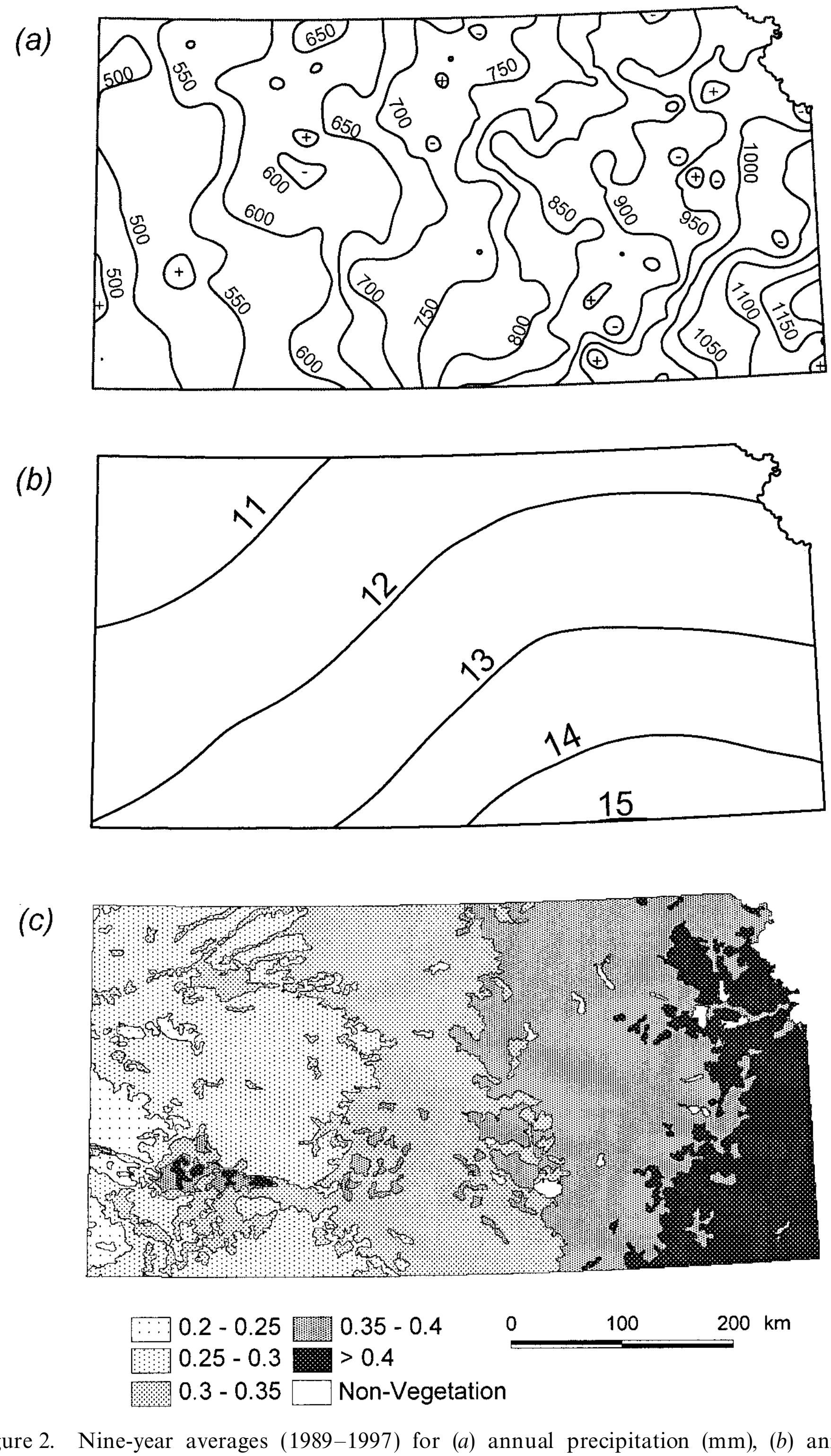


Figure 2. Nine-year averages (1989–1997) for (*a*) annual precipitation (mm), (*b*) annual average temperature (°C), and (*c*) growing season NDVI for Kansas.

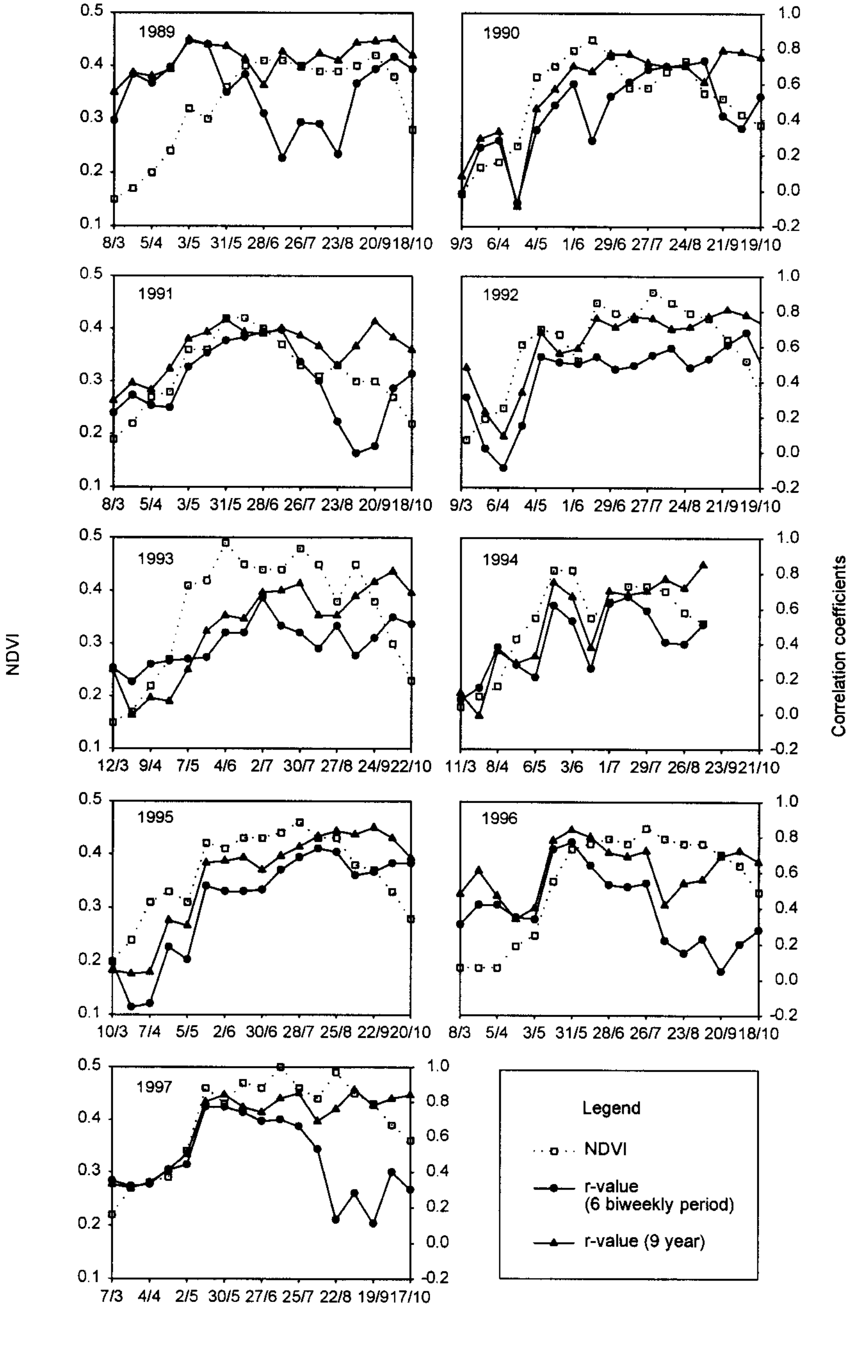


Figure 3. Biweekly NDVI (squares) and correlation coefficients between spatial distribution of biweekly NDVI and both precipitation (summed in six biweekly periods just before the NDVI period) (circles) and average precipitation (triangles).

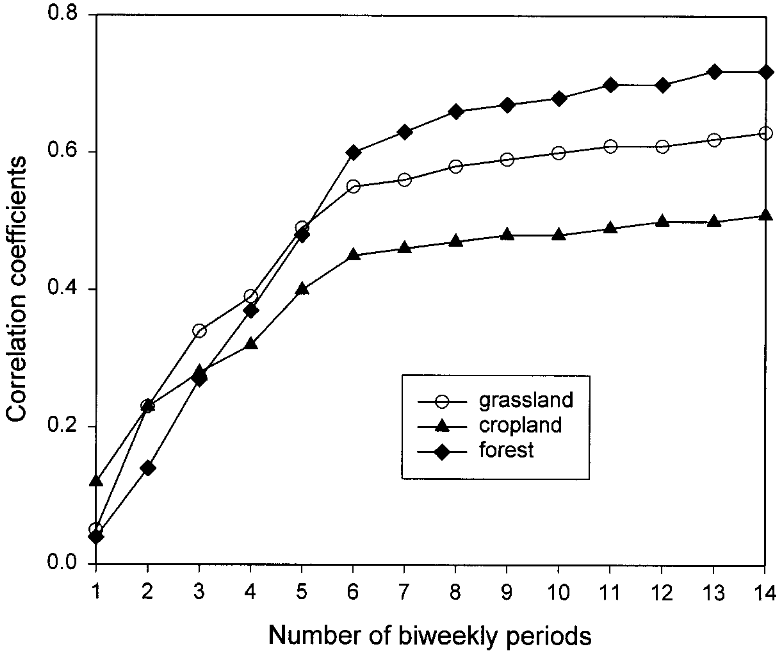


Figure 4. Correlation coefficients (9-year average) between spatial distribution of biweekly NDVI in early July and precipitation summed over 1–14 previous biweekly periods for each major landcover type.

Table 1. Correlation coefficients (*r* values) for relationship between biweekly precipitation and subsequent biweekly NDVI for discrete precipitation events for all landcover types. The numbers in the column headings indicate the time lag (number of biweekly periods) following the precipitation events. No correlation coefficients are given late in the growing season, when no NDVI images were available.

Precipitation event	0	1	2	3	4
22 March 1989	0.60	0.48	0.63	0.79	0.76
23 August 1989	0.64	0.73	0.68	0.68	0.56
18 May 1990	0.49	0.59	0.57	0.62	0.69
15 June 1990	0.58	0.62	0.71	0.72	0.69
10 August 1990	0.53	0.65	0.67	0.58	0.43
17 July 1992	0.58	0.61	0.61	0.60	0.65
25 September 1992	0.71	0.71	0.63	–	–
10 September 1993	0.53	0.64	0.69	0.67	–
24 September 1993	0.59	0.62	0.60	–	–
26 August 1994	0.50	0.71	–	–	–
3 May 1996	0.29	0.73	0.77	0.77	0.69
18 April 1997	0.19	0.31	0.65	0.72	0.73

discrete precipitation event. Furthermore, not all discrete precipitation events during the 9-year study period were associated with subsequent NDVI changes (e.g. 31 May 1991, 6 May 1992, 7 May 1993).

Very strong correlations were generally found between biweekly NDVI and 9-year average precipitation across all map locations. In addition, the correlation was generally stronger when the NDVI values were higher (figure 3). At the beginning of the season the correlation coefficients increased rapidly as the average NDVI value increased; then coefficients remained high, fluctuating only slightly during the summer; and finally coefficients typically increased during the late season.

4.3. *Seasonal relations between precipitation and NDVI*

When average growing season NDVI deviation was compared with precipitation deviation as a function of time interval over which precipitation was summed, the results were quite different and complicated in different years (figure 5). For 1989, a very dry year, correlation coefficients remained high for all precipitation time intervals. At the opposite extreme, for 1993, an extremely wet year, there was no significant correlation. For 1990, preceded by a very dry year, correlation coefficients started high, peaked at a 14-month interval, and dropped sharply to negative values. For 1994, a year following an extremely wet year, correlation coefficients started low, abruptly increased between 14 and 16 month time intervals, and remained high for longer time intervals. For different landcover types, grassland and cropland showed moderate correlations while forest showed weaker correlations. Side-by-side maps of growing season NDVI deviation and precipitation deviation (calculated for a

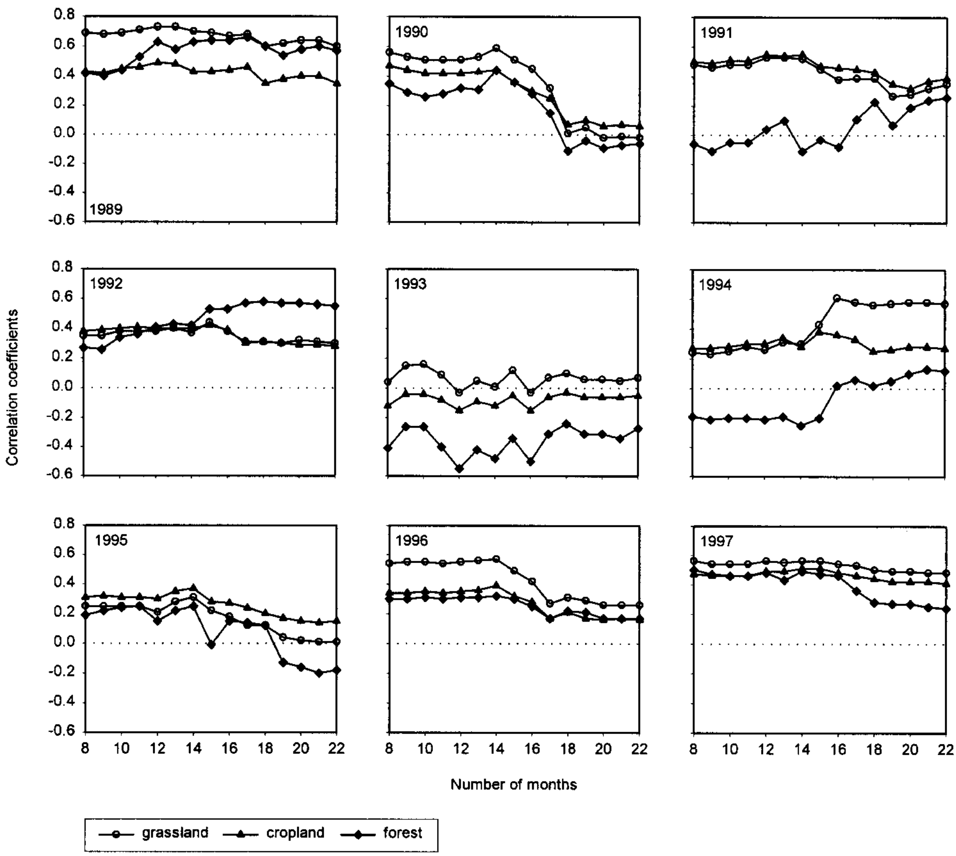


Figure 5. Correlation coefficients between spatial distribution of growing season (March to October) average NDVI deviation from 8-year average and precipitation deviation from 8-year average, as a function of time duration over which precipitation is summed (8–22 month period).

15-month interval) (figure 6) depict two major patterns. These maps clearly show that the regions with negative NDVI deviation correspond very well with regions of negative precipitation in all years. They also show that the regions with positive NDVI deviation correspond well with regions of positive precipitation deviation in all years except 1993. In 1993, the eastern part of Kansas was characterized by positive precipitation deviation and negative NDVI deviation, especially in the river valleys, which were flooded during much of the growing season.

NDVI and precipitation both increased or both decreased for the majority of land area, except in 1993 (figure 7). On average, NDVI and precipitation both changed in the same direction (both increased or both decreased together) for the largest percent land area when precipitation was summed over a 12–15 month time interval. Different years displayed different patterns as a function of time interval: (1) relatively constant (1991 and 1993); (2) increase followed by relatively constant (1989, 1997), (3) increase followed by decrease (1992), or (4) constant first then decrease (1990, 1994, 1995, 1996). In 1989, 1990, 1991 and 1994, both NDVI and precipitation decreased in most of the areas. Even in the areas where precipitation increased, percent area with decreased NDVI was slightly larger than the percent areas with increased NDVI. In 1992, 1993, 1995 and 1997, both NDVI and precipitation increased in most of the areas. Even in areas with decreased precipitation, the percent area with increased NDVI was approximately the same as the areas with decreased NDVI. For 1996, the percent area with increased NDVI was larger in the areas with increased precipitation, whereas the percent area with decreased NDVI was larger in the areas with decreased NDVI. For different landcover types, the NDVI deviations for grasslands and croplands closely followed the precipitation deviations, but NDVI deviations for forest followed precipitation deviations only in some years.

When precipitation was unusually high ($>20\%$ above average) or unusually low ($>20\%$ below average), NDVI in most areas changed in accordance with precipitation (both increasing or both decreasing). Precipitation in 1989, 1990 and 1991 were much lower than normal and NDVI in these years decreased in more than 97% of the total area where precipitation was unusually low. In 1994, a dry year that was preceded by one of the wettest years in history, NDVI decreased in 81% of the total area where precipitation was unusually low. The areas of unusually high precipitation during these 4 years were relatively small and were not typical. The years 1992, 1995 and 1997 were wetter than normal and NDVI increased in more than 89% of the total areas where precipitation was unusually high. In 1993, NDVI increased in only 63% of the total area where precipitation was unusually high. The areas for which precipitation was unusually low during 1992, 1993, 1995 and 1997 were very small and not typical. In 1996, which had near average precipitation, NDVI decreased in 93% of the total area where precipitation was unusually low and increased in 78.8% of the total area where precipitation was unusually high.

4.4. *Relations between temperature and NDVI*

The within-season relationship between NDVI and temperature were quite different for minimum, average and maximum temperatures (data not shown). For minimum temperature, correlation coefficients were almost all positive. Through the growing season, the coefficients were either high or low from March to May, peaked in June or early July, dropped to very low values afterwards, and generally increased again at the end of the growing season. Patterns for average temperature were

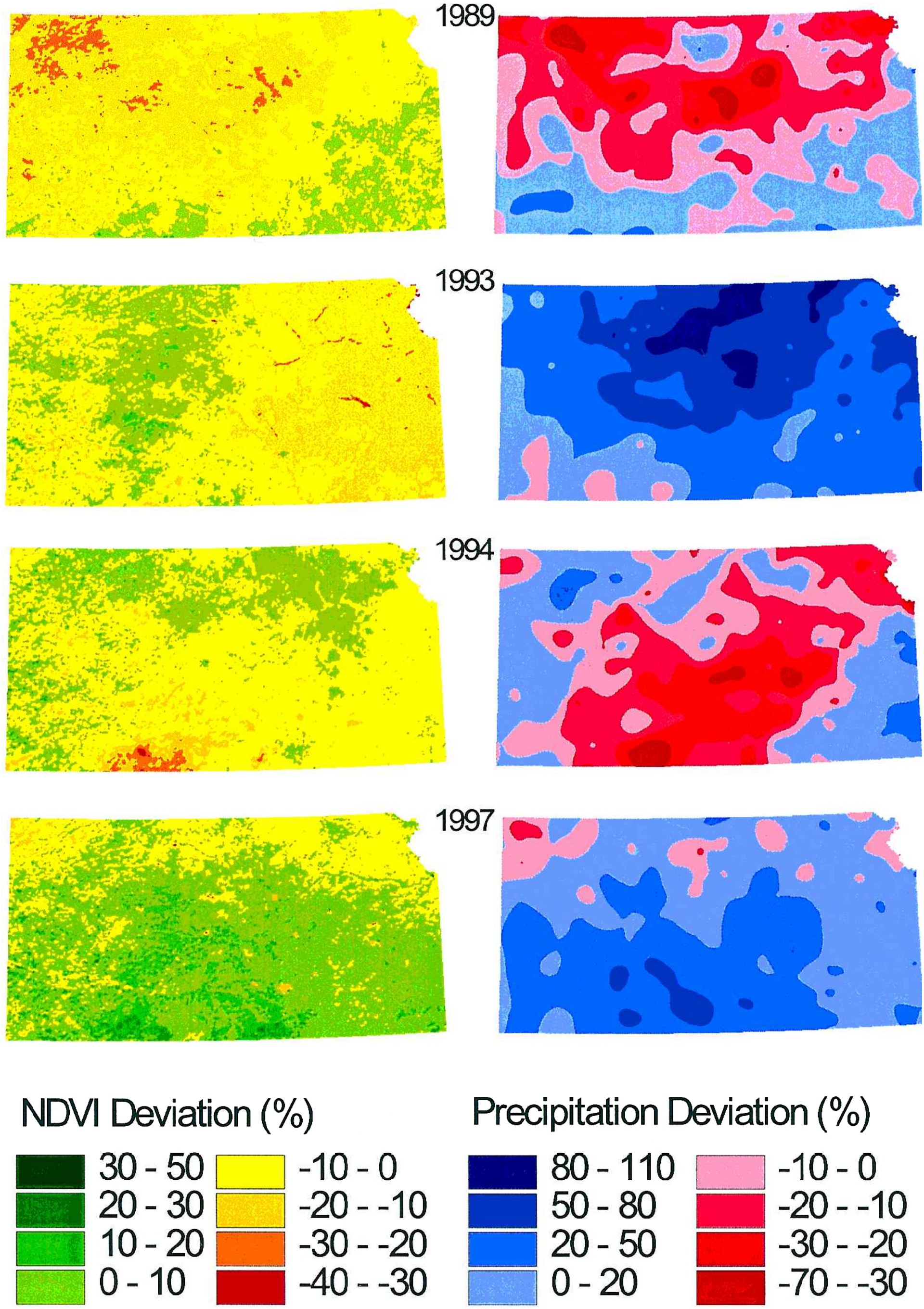


Figure 6. Spatial distribution of growing season NDVI deviation from 8-year average and 15-month precipitation deviation from 8-year average for selected years: 1989, a dry year; 1993, a wet year; 1994, a dry year after a wet year; and 1997, a high productivity year.

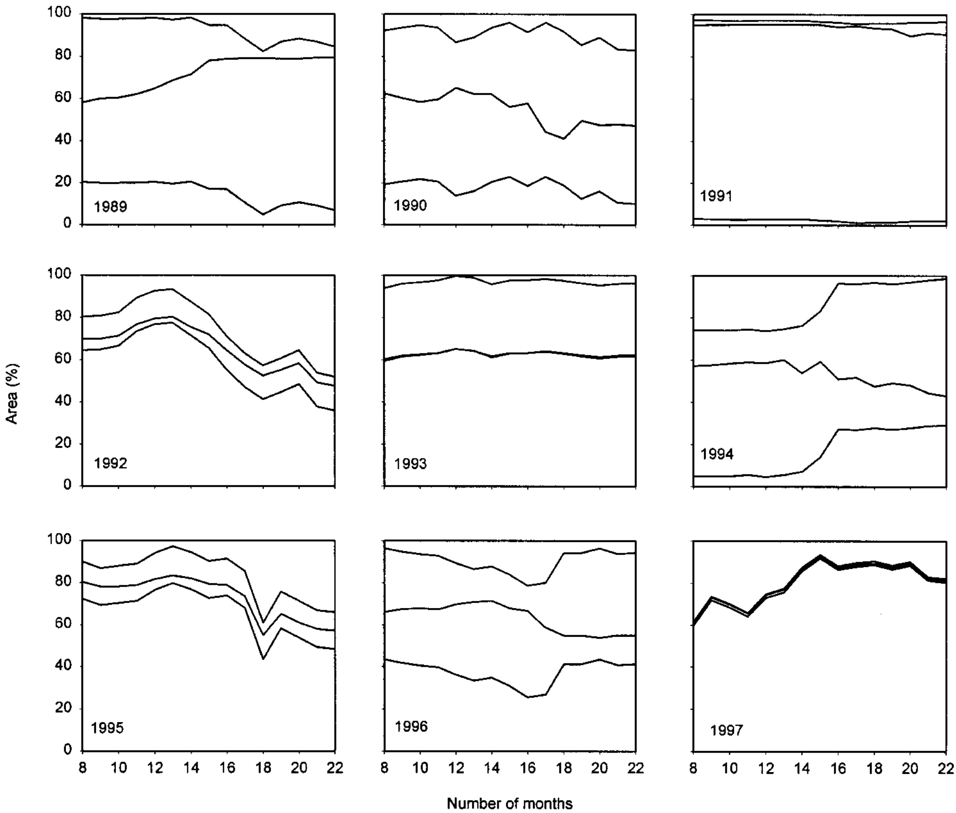


Figure 7. Percentage of total area for each combination of NDVI and precipitation deviation: both positive (below lowest curve), both negative (between lowest curve and second lowest curve), NDVI negative and precipitation positive (between second lowest curve and uppermost curve), NDVI positive and precipitation negative (above uppermost curve). Thus, the height of the second curve shows the percentage area for which NDVI and precipitation deviation co-vary. Curves are compressed for 1993, when both precipitation and NDVI decreased only for a very small area; and for 1997, when NDVI decreased only for a small area.

generally similar to those for minimum temperature, but the correlation coefficients were smaller and the magnitudes of fluctuation were larger. By contrast, maximum temperature correlation coefficients fluctuated from large positive numbers to large negative numbers, and were not easily interpreted. Results using one biweekly period time lag were quite similar to results using no time lag. The correlation coefficients between deviations of NDVI and deviations of temperature indices also showed no pattern that could be readily interpreted.

Growing season average NDVI showed strong correlations with minimum temperature, moderate correlations with average temperature, weak or no correlations with maximum temperature, and weak or negative correlations with AGDD (figure 8). NDVI deviation from normal showed a strong negative correlation with temperature deviation from normal only in 1989 and 1993, but very weak negative correlations for other years (data not shown).

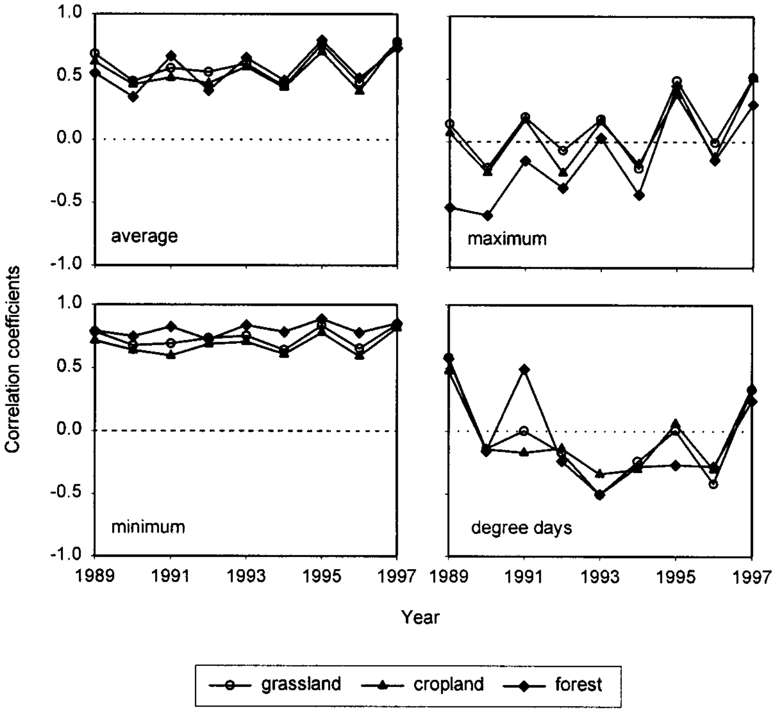


Figure 8. Correlation coefficients between spatial distribution of growing season (March to October) average NDVI and average, maximum, minimum temperatures and accumulated growing degree days for the growing season.

5. Discussion

5.1. *Spatial patterns of precipitation, temperature and NDVI*

Our results demonstrate that NDVI spatial patterns in the central Great Plains are primarily related to precipitation spatial patterns. Temporal variation of NDVI spatial pattern was largely explained by precipitation deviation from average. In agreement with our previous work, the current study demonstrates that NDVI at any given time is influenced by precipitation during a time interval that includes both the current growing season and part or all of the previous growing season. We observed considerable year-to-year variation in the details of exactly what time interval is best for predicting current NDVI, however typically a 13–15 month interval is the best predictor. The relative differences in NDVI according to spatial location are relatively constant, such that the gradient of NDVI from west to east is typically preserved no matter what the weather conditions may be in a particular year.

5.2. *Within-season responses of NDVI to precipitation*

Based on correlation analyses of biweekly precipitation and NDVI maps, we were able to assess the influence of precipitation on NDVI spatial patterns. NDVI spatial pattern for a given biweekly period is generally more strongly correlated with the average precipitation than with recent precipitation (figure 3). Short-term variation in precipitation patterns does not change the underlying spatial patterns of NDVI because the underlying gradients are controlled by long-term climate conditions

On average, correlation coefficients between NDVI and precipitation increased when precipitation was summed over longer time intervals (figure 4). While correlation values continued to increase for up to 14 biweekly periods, the rate of increase was small after six biweekly periods. Most of the influence of precipitation on NDVI is explained by the accumulated precipitation up to six biweekly periods prior to the NDVI biweekly period. Our results indicate that the influence of precipitation on NDVI depends upon the temporal pattern in which precipitation is received. NDVI is most strongly influenced by discrete precipitation events that are either preceded or followed by a relatively long period of much lower precipitation. In general, the strongest correlation between precipitation and NDVI are associated with such precipitation events, as is shown by most cases in table 1. Most of the time the influence of precipitation in a given biweekly period is combined with influences of proceeding and subsequent periods. This is direct evidence that precipitation after a dry period triggers rapid growth by plants. During dry periods after significant precipitation, those local areas with the highest precipitation stay green longer than areas with lower precipitation, presumably because of differences in soil moisture.

Discrete precipitation events influence the spatial distribution of NDVI for several subsequent periods and have a distinct time lag before the maximum influence. While there was an immediate response of NDVI change, correlation coefficients were typically highest after time lags of three biweekly periods (table 1). This time lag interval is in agreement with our previous analyses of temporal patterns (Wang *et al.*, in review). Also, significant precipitation events later in the growing season, particularly after mid-August, had less influence on NDVI, presumably because most plants are producing seed and investing less energy in the creation of additional biomass at this time of year. Exceptions were found in some areas that were probably dominated by cool season (C3) grasses, which were stimulated by increased soil moisture and cooler temperatures.

Different landcover types displayed different relations between precipitation and NDVI. All other factors being equal, we would expect the highest correlations for cropland, moderate correlations for grassland, and lower correlations for forest, based on greater response of annuals vs perennial and of herbaceous vs woody vegetation to differences in precipitation. Instead, we observed the highest correlations for forest and the lowest for cropland. Several factors contribute to these results. High correlation coefficients for forest probably result because the forest in Kansas is situated at the marginal limits of the range of eastern deciduous forest, and is especially sensitive to changes in the spatial distribution of precipitation. Furthermore, the total forest area is small and located along river valleys across a distinct gradient of precipitation. By contrast, cropland and grassland cover extensive land areas and include a wider variety of environmental conditions (soils, geomorphology, etc.), as well as a greater diversity in land use practices than do forests. Correlations between precipitation and NDVI were stronger for grasslands than croplands. Much of this difference may be because our current study did not distinguish between irrigated lands in the drier west and non-irrigated lands in the wetter east, and did not distinguish differences in crop types (winter wheat, sorghum, soybean, corn, etc.). Yang *et al.* (1997) also found that the correlation between NDVI and precipitation was stronger in areas of grassland than in areas with predominantly cropland due to extensive crop irrigation. Our previous research found that temporal correlation between precipitation and NDVI were higher for croplands than for grasslands (Wang *et al*., in review).

5.3. *Seasonal responses of NDVI to precipitation*

The spatial distribution of average NDVI values over the growing season in the study area was most strongly influenced by precipitation accumulated during the current growing season, the preceding winter, and part of the previous growing season. In most cases, the strongest relationships were between NDVI compared to accumulated precipitation for the current growing season, plus five to seven preceding months (13–15 months total).

Different years exhibited different patterns of correlation coefficients between average NDVI and precipitation spatial distribution as a function of time interval over which precipitation was summed. We, however, were not able to interpret reasons for these differences based on these analyses alone. By contrast, we can more readily interpret year-to-year differences in correlation coefficients between NDVI and precipitation deviations as a function of time interval over which precipitation was summed. The major year-to-year differences can be explained by the combination of precipitation during the current growing season and precipitation during the preceding winter and previous growing season. In particular, correlations between spatial patterns of NDVI and precipitation deviations were strong for 1989, which was a dry year preceded by another dry year, and very weak for 1993, which was one of the wettest years in recorded climate history. Correlation coefficients are generally highest during or immediately following dry periods. The year 1994 was preceded by a wet year, and displayed low correlation for short time intervals, but high correlation coefficients for time intervals greater than 15 months, which included precipitation from 1993. By contrast, 1990, which was preceded by a typical dry year, correlation coefficients were high for time intervals less than 15 months, but dropped off markedly for longer intervals. Preceding dry years lead to low soil moisture at the start of the growing season and therefore plants response to precipitation was more accentuated. Preceding wet years lead to high soil moisture and lower responsiveness of vegetation to precipitation.

In general, NDVI and precipitation co-vary over most of the study area. The percent land area over which NDVI and precipitation change in the same direction (both positive or both negative deviations) reached a maximum of 60–95% at a 12–15 month time interval over which precipitation was summed (figure 7). In general, from 78.8% to 99.8% of the land area with high precipitation (>20% above average) also had NDVI increases (table 2). The flood year of 1993 was an exception, with only 67.1% of the land area receiving high precipitation also having an increase in NDVI. Depending upon the year, from 81.6% to 99.7% of the area with low precipitation (<20% below average) also had NDVI decreases.

5.4. *Responses of NDVI to temperature*

In general, temperature was not strongly correlated with NDVI in our study area, either within season or across seasons. Within the growing season, NDVI was best correlated with minimum temperature, especially in early summer and towards the end of the growing season. This is consistent with minimum temperature limiting growth early and late in the growing season. For the growing season as a whole, we observed only weak correlations between temperature and NDVI, except for 1989

Table 2. Area and percentage of land in the categories of NDVI increase vs NDVI decrease for overall areas where precipitation was unusually high or low in a given year. Precipitation was calculated as the sum over a 13-month interval. High and low precipitation was defined based on an increase or decrease of 20% or more from the 8-year average. Area is reported in km^2. The % area is relative to the total land area with either high or low precipitation.

		High precipitation (>20% above average)		Low precipitation (>20% below average)	
Year		+NDVI	−NDVI	+NDVI	−NDVI
1989	area	3926	6181	84	28 335
	% area	38.8	61.2	0.3	99.7
1990	area	23	95	813	26 153
	% area	19.5	80.5	3.0	97.0
1991	area	1135	476	2036	119 587
	% area	70.5	29.5	1.7	98.3
1992	area	82 363	8591	1006	1946
	% area	90.6	9.4	34.1	65.9
1993	area	120 813	59 369	0	0
	% area	67.1	32.9	0.0	0.0
1994	area	136	127	15 395	68 223
	% area	51.7	48.3	18.4	81.6
1995	area	70 800	8115	318	494
	% area	89.7	10.3	39.2	60.8
1996	area	24 668	6639	757	10 822
	% area	78.8	21.2	6.5	93.5
1997	area	46 265	99	2057	805
	% area	99.8	0.2	71.9	28.1

and 1993. For 1989, strong negative correlations probably resulted because high temperatures worsened drought conditions. In 1993, NDVI deviation and minimum temperature deviation were strongly correlated. This correlation was probably spurious, because higher minimum temperatures in eastern Kansas were coincidental with flood conditions that lead to lower NDVI. Examinations of interactions between temperature and precipitation are beyond the scope of this study, and represent an important topic for future research.

6. Conclusion

Our analyses show that the general spatial distribution of NDVI in the central Great Plains corresponds directly with the spatial pattern of average annual precipitation, while year-to-year variation of NDVI depends largely on the variation of precipitation. Within the growing season, NDVI is greatly influenced by precipitation summed during the six preceding periods; while for the growing season as a whole, precipitation summed during the growing season (March to October) plus five to seven preceding months (13–15 months total interval) is a very good indicator of NDVI values throughout the study area. We only see influence of temperature on NDVI during the early and late growing season. The strong relationship between precipitation and NDVI, along with detailed characterization of spatial patterns for our study region, provides the basis for prediction of productivity at landscape scales under different climate regimes.

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