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Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA

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Abstract. Normalized Difference Vegetation Index (NDVI) is generally recognized as a good indicator of terrestrial vegetation productivity. Understanding climatic influences, in particular precipitation and temperature, on NDVI enables prediction of productivity changes under different climatic scenarios. We examined temporal responses of remotely sensed NDVI to precipitation and temperature during a nine-year period (1989–97) in Kansas. Biweekly (every two weeks) and monthly precipitation data were derived from 410 weather stations and biweekly temperature data were derived from 17 weather stations inside and around the borders of Kansas. Biweekly and monthly climate maps were derived by interpolation. Biweekly growing season (March–October) NDVI values for Kansas were calculated using National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) NDVI images. Average growing season NDVI values were highly correlated with precipitation received during the current growing season and seven preceding months (15-month duration); biweekly NDVI values were correlated with precipitation received during 2–4 preceding biweekly periods; and response time of NDVI to a major precipitation event was typical 1–2 biweekly periods (2–4 weeks). Temperature was positively correlated with NDVI early and late in the growing season, and there was a weak negative correlation between temperature and NDVI in the mid growing season. Precipitation has the primary influence on NDVI and, by inference, on productivity. The relationship between precipitation and NDVI is strong and predictable when viewed at the appropriate spatial scale.

1. Introduction

The Normalized Difference Vegetation Index (NDVI) is calculated as the difference between near-infrared (NIR) and visible (VIS) reflectance values normalized over the sum of the two (Eidenshink 1992):

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{VIS})/(\mathrm{NIR} + \mathrm{VIS}) \tag{1}$$

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NDVI is a good indicator of the ability for vegetation to absorb photosynthetically active radiation and has been widely used by researchers to estimate green biomass (Rosental *et al.* 1985, Tucker *et al.* 1985, Prince 1991), leaf area index (Asrar *et al.* 1984) and patterns of productivity (Goward and Dye 1987) because the internal mesophyll structure of healthy green leaves strongly reflects NIR radiation, and leaf chlorophyll and other pigments absorb a large proportion of the red VIS radiation (Gausman 1974, Tucker 1979, Sellers 1985, 1987, Tucker and Sellers 1986, Sellers *et al.* 1992). Environmental factors such as soil, geomorphology and vegetation all influence NDVI values. Variations in climatic factors, in particular precipitation and temperature, have a strong influence on variation in NDVI for a given site. Satellite imagery from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) enables derivation of daily NDVI values throughout most of the world. NDVI data are made available as biweekly (every two weeks) composite images, which are derived using the maximum NDVI value during the biweekly period. This compositing technique is used to remove most cloud coverage within a dataset. This consistent availability of biweekly NDVI imagery since 1989 presents the possibility for detailed analyses of the influence of climate factors on productivity.

During the past two decades, many studies have used NDVI to monitor the response of vegetation to climatic fluctuations 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), the US (Di *et al.* 1994, Yang *et al.* 1997) and at a global scale (Schultz and Halpert 1993). From these studies we conclude that temporal variations of NDVI are closely linked with precipitation and there is a strong linear (Malo and Nicholson 1990) or log-linear (Davenport and Nicholson 1993) relationship between NDVI and precipitation in cases where monthly or annual precipitation is within a certain range. If precipitation is greater than a particular threshold—e.g. 500 mm yr^{-1} or 50–100 mm $month^{-1}$ in Botswana in South Africa (Nicholson and Farrar 1994), 1000 mm yr^{-1} or 200 mm $month^{-1}$ in East Africa (Davenport and Nicholson 1993) and 1000 mm yr^{-1} in the Sahel of West Africa—moisture is no longer a limiting factor and NDVI increases only very slowly with increased precipitation (Nicholson and Farrar 1994). In Africa there is typically a lag between peak precipitation and peak NDVI response (Justice *et al.* 1986), and the best correlation is between NDVI and precipitation in the concurrent month plus two previous months (Malo and Nicholson 1990, Davenport and Nicholson 1993). Because relationships between NDVI and climatic factors depend upon location, more detailed analyses are needed for a variety of regions to better understand temporal variation of precipitation and temperature as they influence NDVI.

Precipitation and temperature directly influence water balance, causing changes in soil moisture regime which, in turn, influences plant growth. Thus, soil moisture is widely recognized as a key parameter that links precipitation, temperature and NDVI, though temperature also affects plant phenology and growth directly. Farrar *et al.* (1994), in studies of NDVI, rainfall and model-calculated soil moisture of Botswana, found that while the correlation between NDVI and precipitation is highest for a multi-month average, NDVI is controlled by soil moisture in the concurrent month. Temperature can also have a more direct influence on plant growth. Yang *et al.* (1997) studied relations between NDVI and temperature in Nebraska, USA, and observed strong correspondence between NDVI and accumulated growing degree days (AGDD), and between NDVI and soil temperature.

Our understanding of the mechanism and extent of the influence of weather on NDVI is far from complete. Most other studies have related NDVI curves with precipitation and temperature curves during the growing season to find the best correlations. They could not distinguish the influence of different climate factors at different times of the growing season. Across years, they also compared NDVI and precipitation of the growing season, so the influence of precipitation beyond the growing season was usually ignored. While it is widely recognized that both short-term and long-term variation in such meteorological variables as precipitation and temperature have a significant influence on NDVI, few studies have examined temporal patterns in great detail.

This study addresses three key questions. First, what climatic variables (e.g. precipitation, temperature) best explain variation in NDVI over time, both within and between years? Second, how quickly and over what time period does NDVI respond to different patterns of precipitation and temperature? And finally, how does NDVI respond to weather variation for different land cover categories, in particular grassland, cropland and forest? In this study, we examined influences of precipitation, soil moisture and temperature on temporal patterns of NDVI in the state of Kansas on a biweekly basis over the course of nine years (1989–97). A unique approach was used involving systematic and comprehensive examination of the importance of integrating NDVI and precipitation over different time intervals for within season, cross-season, and interannual analyses.

The cross-season analysis is new and unique, in that it distinguishes the influence of climate factors according to time during the growing season. This was accomplished by performing a series of correlation analyses across years using NDVI of each biweekly period of the growing season as one variable and the corresponding climate measurements as the other variable. Separate correlations were examined for climate measurements integrated over different time intervals (according to both duration and lag time).

For interannual analyses, we performed a similar series of correlation analyses using NDVI integrated for the entire growing season as one variable, and climate measurements as the other variable. Again, separate correlation analyses were performed for climate measurements integrated over different time intervals (according to both duration and lag time). This approach is different from approaches of other studies, in that we not only relate integrated NDVI with integrated precipitation of the same growing season, but also examine the importance of precipitation received before the growing season. We determined the importance of precipitation before the growing season by performing correlation analyses for a series of time intervals extending back to the preceding growing season.

In addition, although several studies have addressed the importance of soil moisture as the linkage between precipitation and NDVI (Farrar *et al.* 1994, Yang *et al.* 1997), soil moisture has generally been calculated from models rather than field data. We analysed long-term field measurements of soil moisture from Konza Prairie to better understand linkages between precipitation, soil moisture and NDVI for the central Great Plains.

This study represents the most comprehensive analysis to date, in terms of the number of weather stations used (410 for precipitation), in terms of the length of time analysed, and in terms of the systematic and complete design used to understand temporal patterns.

2. Methods

2.1. *Study area*

This study was conducted for the entire state of Kansas, which lies in the central Great Plains region of North America. A strong east–west precipitation gradient results in average annual precipitation increasing from less than 450 mm in north-west Kansas to more than 1200 mm in south-east Kansas (data provided by the NOAA National Climatic Data Center [NCDC] 1998). The precipitation in Kansas is highly variable, with precipitation of wet years often as much as four times that of dry years. For this reason, Kansas is one of the most vulnerable regions in the US with respect to drought (Warrick 1975, Bark 1978) and is representative of the drought-prone, mid-continental temperate environments found elsewhere in the world (Reed 1993). The annual average temperature decreases from 15°C at the south-eastern border to 10.5°C at the north-western border. Much of Kansas is classified as prairie; with short-grass prairie (grama–buffalograss) in the west, mixed prairie in the middle, and tall-grass prairie (bluestem with diverse forbs) in the east (Kuchler 1974). By landcover types, croplands (both irrigated and dryland) occupy 51.3% of the area, mainly distributed from central to west; grasslands occupy 39.5% of the area, mainly distributed in the east; and forests (1.2% of area) only found primarily as riparian or gallery forests along river valleys in the east (Whistler *et al.* 1996).

2.2. *NDVI and climate data processing*

First, digital maps of NDVI, precipitation and temperature for a nine-year period (1989–97) were constructed for the state of Kansas. These maps were constructed to examine temporal patterns of climatic influences on NDVI. ARC/INFO GRID GIS software version 7.1.1 (Environmental Systems Research Institute, Redlands, CA, USA) was used for all map construction and analyses. A landuse/landcover map for Kansas (Whistler *et al.* 1996) was adapted to enable stratification of analyses according to the categories of cropland, grassland and forest. In addition, data were compiled for Konza Prairie (Briggs and Knapp 1995) to enable analysis of relations between NDVI and *in situ* precipitation and soil moisture.

2.2.1. *Biweekly NDVI maps*

This study used NOAA AVHRR 1.1 km biweekly Maximum Value Composite NDVI images for growing seasons (March–October) during 1989–97. These images were compiled by the United States Geological Survey (USGS) EROS Data Center from NOAA/AVHRR satellite images. Data processing involved five steps: (1) radiometric calibration to account for sensor degradation; (2) atmospheric correction to adjust for influences of water vapour, aerosols, ozone and Rayleigh scattering; (3) computation of NDVI for all pixels; (4) geometric registration to transform the sensor-based projection to an Earth surface-based projection; and (5) maximum NDVI composition (Eidenshink 1992). NDVI values are in the range from −1.0 to 1.0, where increasing positive values indicate increasing green vegetation and negative values indicate nonvegetated features such as water, barren areas, ice, snow or clouds. NDVI composition involves pixel-by-pixel processing to determine the maximum value during each biweekly period, thus minimizing cloud-contaminated pixels and selecting those pixels illuminated from nearest to nadir. These data were further processed and made available by the Kansas Applied Remote Sensing (KARS) Program.

2.2.2. *Biweekly and monthly precipitation maps*

Daily precipitation data, supplied by the NOAA NCDC (1998), were derived for the entire years 1988–97 from 410 weather stations in and around the state of Kansas. The daily precipitation data for these 410 weather stations were accumulated into biweekly totals, corresponding to the biweekly periods of the NDVI data, and then interpolated into raster maps based on the longitude and latitude of the weather stations. Daily precipitation data were also accumulated into monthly totals throughout the entire year to enable convenient comparisons across years. Biweekly and monthly raster maps of precipitation for Kansas were constructed using a weighted distance interpolation method. To assess the accuracy of this interpolation, we randomly reserved 10 weather stations from the annual precipitation interpolation for 1995 and compared interpolated and recorded values (average error less than 8%). The interpolation approach worked effectively because of the relatively gentle topography and the large number of weather stations used for analysis.

2.2.3. *Biweekly temperature maps*

Biweekly average, maximum and minimum temperature maps for 1988–97 were derived from 17 weather stations in and around the state of Kansas. AGDD were calculated using the methods of Yang *et al.* (1997):

$$\mathrm{AGDD} = \Sigma\ [(T_{\max} + T_{\min})/2 - T_{\mathrm{base}}] \tag{2}$$

where $T_{\max}$ is the daily maximum temperature, $T_{\min}$ is the daily minimum temperature, and the base temperature (T_{base}) was set at 10°C. We applied a base temperature of 10°C if the minimum temperature was less than 10°C and a maximum temperature of 30.5°C if the maximum temperature was more than 30.5°C. We summed daily values into biweekly AGDD, corresponding with the periods of NDVI. Biweekly temperature maps for Kansas (maximum, minimum, average and AGDD were constructed using a weighted distance interpolation method.

2.2.4. *Landuse/landcover map*

A landuse/landcover map for Kansas, originally generated by KARS (Whistler *et al.* 1996), was obtained from the Kansas Geological Survey Data Access and Support Center (1999) online database.

2.2.5. *Biweekly precipitation and soil moisture for Konza Prairie*

Daily precipitation data and biweekly soil moisture data for 1988–97 at 25 cm depth for watershed N04D of Konza Prairie were obtained from the online database of Konza Prairie Long Term Ecological Research (1999) (Briggs and Knapp 1995).

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

We examined relations between each of the climate factors and NDVI. The raster maps of biweekly NDVI, precipitation and temperature (maximum, minimum, average and AGDD) were stratified according to landcover categories (cropland, grassland and forest) and correlation coefficients were calculated between each of the factors and NDVI for the entire pixels for each landcover category. Analyses examined relations within growing seasons (within-season), across growing seasons (cross-season) and across years (interannual). Within-season analyses examined different biweekly periods of the same growing season. In contrast, cross-season analyses examined the same biweekly period of different growing seasons. Interannual analyses examined data averaged or accumulated through each growing season, or in some cases for even longer time durations. A primary goal of these analyses was to evaluate the temporal scale of response of NDVI to climate variation.

2.3.1. *Within-season relations between climate factors and NDVI*

For each biweekly period in the mid growing season (mid-April–August), NDVI–precipitation correlation coefficients were calculated, with precipitation in five different time durations (1–5 biweekly periods) and five different time lags (0–4 biweekly period lags). This resulted in a total of 25 different combinations as shown in table 1. Thus, we were able to assess the time scale (duration and lag) of precipitation that most strongly influences current NDVI, as well as to assess whether precipitation is more highly related to NDVI in wet vs dry years.

Further explanation is needed to clarify the process used for within-season analyses. Starting with the first year used for analysis (1989), a correlation coefficient was calculated between the 18 biweekly NDVI values through the growing season and the corresponding 18 precipitation values for the same biweekly period. This process was repeated for each of the nine years and then an average correlation coefficient was calculated. Separate sets of calculations were performed for each of the three land cover types and for Konza Prairie. This calculation, with an interval of one biweekly period and no time lag, corresponds with time interval represented by the first cell of table 1. Next, another set of correlation coefficients were calculated in the same way, except the precipitation values were for the biweekly period before the NDVI period, with an interval of one biweekly period and a time lag of one biweekly period (column 1, row 2 of table 1). The process was continued, with calculation of coefficients for each of the 25 integrated precipitation values.

For each year, within-season correlation coefficients between NDVI and 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 analyses of a subset of combinations showed that only the immediate two periods of temperature were significantly related to NDVI.

2.3.2. *Cross-season relations between climate factors and NDVI*

For each biweekly period, we calculated cross-season correlation coefficients between NDVI of the various years and corresponding precipitation. As compared with the within-season analysis, this cross-season analysis allows us to distinguish at what time during the growing season NDVI is most influenced by precipitation.

Table 1. The design for analysis of temporal patterns (5 time durations × 5 time lags). The numbers in the cells indicate the time interval for which precipitation is accumulated (0 indicates the current biweekly period, 1 indicates the first previous period, 0–1 indicates from current period to first previous period, etc.).

	Duration				
Lag	1	2	3	4	5
0	0	0–1	0–2	0–3	0–4
1	1	1–2	1–3	1–4	1–5
2	2	2–3	2–4	2–5	2–6
3	3	3–4	3–5	3–6	3–7
4	4	4–5	4–6	4–7	4–8

Sets of correlation coefficients analyses were performed for NDVI and climate measurement pairs, with biweekly NDVI for a particular period for each year as one variable, and climate measurements of the corresponding year as the other variable. Separate analyses were performed for precipitation integrated over the same set of 25 precipitation intervals used for within-season analyses (5 durations $\times$ 5 lag times), as shown in table 1. This analysis design permits us to assess the time scale (duration and lag) of precipitation that most strongly influences current NDVI.

Further explanation is needed to clarify the process used for cross-season analyses. Starting with the initial biweekly period of the growing season (beginning on 1 March), first a separate correlation coefficient was calculated between the nine NDVI values (one from each year) and the corresponding nine precipitation values for the same biweekly period of the same year. This process was repeated for each of the biweekly periods through the growing season and then an average value of the correlation coefficients was calculated. Separate sets of calculations were performed for each of the three land cover types and for Konza Prairie. This calculation, with interval of one biweekly period and no time lag, corresponds with time interval represented by the first cell of table 1. Next, another set of correlation coefficients was calculated in the same way, except the precipitation values were for the biweekly period before 1 March, with an interval of one biweekly period and a time lag of one biweekly period (column 1, row 2 of table 1). The process was continued, with calculation of coefficients for each of the 25 integrated precipitation values.

Similarly, we also calculated cross-season correlation coefficients between biweekly NDVI and temperature. In this case, the analysis was somewhat less extensive in that only the temperature of the current period and immediate preceding period were used.

2.3.3. *Interannual relations between climate factors and NDVI*

Correlation coefficients between growing season average NDVI of each year and precipitation were calculated. In order to evaluate the time period over which precipitation most strongly influences overall productivity, a series of analyses was performed using precipitation totalled over various periods of time. These precipitation periods ranged from just the current growing season (eight months) to the growing season plus the period back to the beginning of the last calendar year (22 months), incremented at one-month intervals (8, 9, 10 … 22). Correlation coefficients between average NDVI of the year and average temperature indices (maximum, minimum, average temperatures and AGDD) were also calculated.

3. Results

3.1. *Relations between precipitation, soil moisture and NDVI*

3.1.1. *General trends of NDVI and precipitation during the growing season*

Nine-year average biweekly NDVI values (1989–97) increased rapidly during the spring (early March–mid-May), peaked during the summer months (mid-May–early September), and decreased rapidly during the fall (mid-September–mid-October). NDVI curves for both grassland and forest landcover categories showed only one peak, while NDVI curves for the croplands were bimodal, one for wheat and the other for corn, the two major crops in the state. Through the growing season, forest NDVI values were consistently highest, grassland values were intermediate and cropland lowest. The forest and cropland displayed similar patterns of greening up in the early growing season, while grasslands greened up approximately one half-biweekly period later (one week later). This pattern resulted in part from the distributions of the three landcover types: forest occurs along the eastern border where precipitation is highest; grassland occurs mainly in the east in areas where precipitation is intermediate; and most cropland occurs in the west where precipitation is lowest and irrigation prevails. During the autumn, greenness dropped off at similar times for all three landcover categories. NDVI curves typically mirrored the precipitation curves, which increased during the spring and decreased during the autumn.

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

During the nine years (1989–97), there was considerable year-to-year variation in precipitation and NDVI (figure 1). Correlation coefficients between NDVI and precipitation in grassland, cropland and forest (table 2) are high in specific combinations of time duration and lag. In terms of time duration, NDVI was more strongly related to the sum of precipitation in four or five biweekly periods than in one to three periods. In terms of time lag, NDVI was more strongly influenced by the second preceding biweekly period (four-week lag) though differences existed among different landcover types. In our analyses (data not shown), NDVI responded more rapidly to precipitation during 1990 and 1991, which were both dry years, and during 1992, a year immediately after four consecutive dry years. By contrast, NDVI responded more slowly to precipitation during 1997, which was a wet year, and during 1994, a year immediately after a wet year. The correlation coefficients were also different for the different landcover types. For grassland, correlation coefficients were mostly positive and maximum values for each year were between 0.70–0.96 with an average value of 0.85. For forest, correlation coefficients were also mostly positive and maximum values for each year were between 0.66–0.91 with an average value of 0.79. For cropland, correlation coefficients were positive for years 1989,

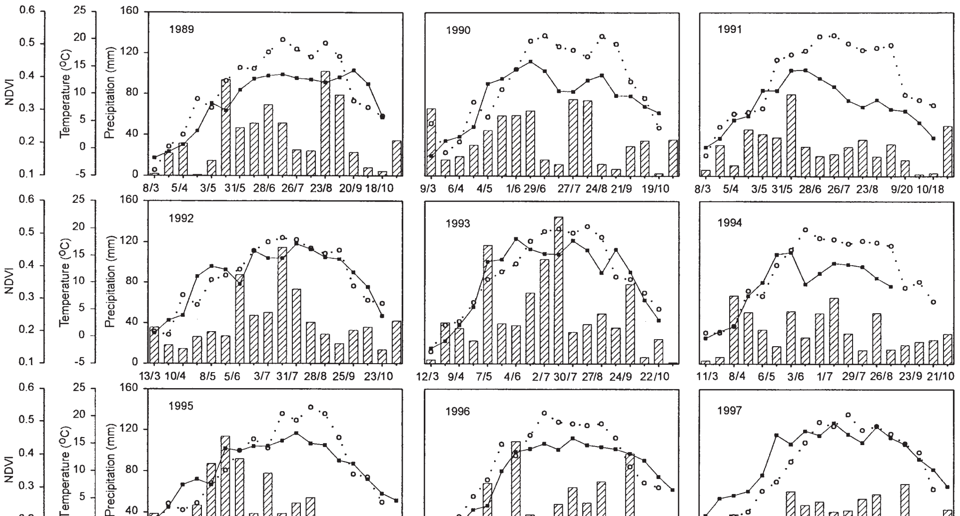

Figure 1. Precipitation, temperature, and NDVI for each biweekly period of each growing season (1989–97) for grassland within Kansas.

Table 2. Nine-year (1989–97) average within-season correlation coefficients (*r*-value) between precipitation and NDVI for grasslands, croplands and forests in Kansas and Konza Prairie). The numbers in the first column indicate the time interval for which precipitation is accumulated (0 indicates the current biweekly period, 1 indicates the first previous period, 0–1 indicates from current period to first previous period, etc.).

Periods	Grassland	Konza	Cropland	Forest
0	0.13	0.07	0.09	0.02
1	0.42	0.14	0.27	0.25
2	**0.53**	0.32	**0.28**	**0.43**
3	0.41	**0.38**	0.11	0.40
4	0.30	0.26	0.05	0.32
0–1	0.38	0.14	0.16	0.20
1–2	**0.63**	0.30	**0.30**	**0.45**
2–3	0.61	**0.50**	0.20	0.55
3–4	0.44	0.46	0.06	0.44
4–5	0.32	0.35	−0.03	0.36
0–2	0.61	0.29	**0.30**	0.42
1–3	**0.74**	0.52	0.28	**0.60**
2–4	0.61	**0.56**	0.11	0.58
3–5	0.42	0.52	0.02	0.45
4–6	0.38	0.47	0.06	0.46
0–3	**0.76**	0.48	0.27	0.58
1–4	0.73	0.54	**0.18**	**0.63**
2–5	0.56	0.56	0.05	0.56
3–6	0.44	**0.57**	0.07	0.51
4–7	0.41	0.50	0.10	0.50
0–4	**0.75**	0.52	0.17	0.63
1–5	0.66	0.56	**0.11**	**0.63**
2–6	0.56	**0.62**	0.09	0.61
3–7	0.46	0.58	0.10	0.54
4–8	0.17	−0.05	0.03	0.26

1992, 1996 and 1997 with maximum values of 0.93, 0.69, 0.93 and 0.76 respectively, but negative for the years 1990, 1991, 1993, 1994 and 1995 with maximum negative values of −0.78, −0.91, −0.69, −0.72 and −0.64 respectively.

For Konza Prairie, patterns of biweekly NDVI and precipitation (figure 2) and correlation coefficients between NDVI and precipitation were similar to those observed for the grassland at a statewide scale, but correlation coefficients were smaller, especially for single periods, and the correlation coefficients were negative for the year 1997.

3.1.3. *Cross-season relations between precipitation and NDVI*

Cross-season correlation coefficients between precipitation and NDVI varied depending upon combinations of time duration and time lag, and also early, middle or late growing season (tables 3 and 4). For both time duration and time lag, we found similar results for the analyses performed on a year-by-year basis (table 2). Correlations between precipitation and NDVI averaged through the growing season were strongest for longer durations (precipitation integrated over four or five biweekly periods) and for medium time lags (two biweekly period lags).

For different landcover categories, grasslands had the strongest correlations

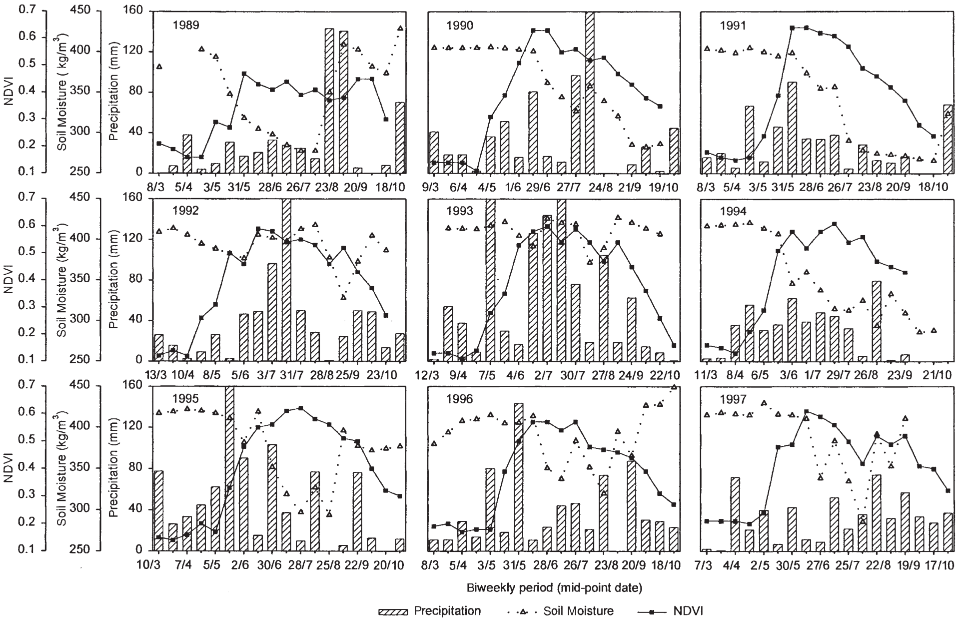

Figure 2. Precipitation, soil moisture and NDVI for each biweekly period of each growing season (1989–97) for Konza Prairie, Kansas.

between precipitation and NDVI; whereas cropland correlation coefficients were intermediate, and correlations for forests were weakest. Through the growing season, no significant correlations between precipitation and NDVI were observed during the early growing season for all landcover types, and only weak correlations were observed during early summer for croplands, and during late summer for forested areas. Moderate to strong correlations were apparent during the rest of the growing season.

In cross-season comparisons of soil moisture and NDVI in Konza Prairie, correlation coefficients were generally low through the season, except in June and late September (table 5). Thus, the strongest correlations occurred during June, when NDVI was approaching its peak and soil moisture began to decline. In September, correlations were again strong when NDVI began to decline and soil moisture began to increase.

3.1.4. *Response time of NDVI to major precipitation events*

A major precipitation event after a period of drought is almost always followed by a sharp increase in NDVI (figure 1). To evaluate the lag time between major precipitation events and increased NDVI, we selected seven precipitation events that met the following criteria: (1) no other major precipitation events occurred during the preceding two biweekly periods; (2) the event occurred toward the middle of the growing season, when temperature was relatively high; and (3) the event was sufficiently large (i.e. average precipitation was more than 50 mm during a biweekly period). Since NDVI values for a biweekly period could be recorded on any date during that period, we are not able to assign lag times more precise than 14-day intervals (table 6). In only one case did NDVI respond during the same biweekly period as a precipitation event—during 1991, a major precipitation on 24 and

Table 3. Average cross-season correlation coefficients between NDVI and precipitation in different combinations of time periods for grasslands, croplands and forests in Kansas and Konza Prairie ($n = 15$ biweekly periods, which define the growing season). The numbers in the first column indicate the time interval for which precipitation is accumulated (0 indicates the current biweekly period, 1 indicates the first previous period, 0–1 indicates from current period to first previous period, etc.).

Period	Grassland	Cropland	Forest	Konza
0	0.19	0.21	0.10	0.07
1	0.31	0.32	0.15	0.14
2	**0.34**	0.32	**0.19**	0.32
3	0.19	0.20	0.10	**0.38**
4	0.15	0.11	0.06	0.26
0–1	0.33	0.34	0.16	0.14
1–2	**0.44**	0.42	**0.24**	0.30
2–3	0.38	0.36	0.20	**0.50**
3–4	0.29	0.22	0.18	0.46
4–5	0.22	0.14	0.07	0.35
0–2	0.46	0.46	0.22	0.29
1–3	**0.47**	0.48	0.23	0.52
2–4	0.46	0.38	**0.26**	**0.56**
3–5	0.34	0.27	0.14	0.52
4–6	0.25	0.21	0.08	0.47
0–3	0.47	0.49	0.22	0.48
1–4	**0.50**	0.47	**0.27**	0.54
2–5	0.45	0.38	0.22	0.56
3–6	0.33	0.31	0.14	**0.57**
4–7	0.24	0.22	0.06	0.50
0–4	**0.50**	0.47	**0.25**	0.52
1–5	0.50	0.44	0.25	0.56
2–6	0.44	0.39	0.21	**0.62**
3–7	0.31	0.28	0.12	0.58
4–8	0.24	0.11	0.01	−0.05

25 May caused a sharp increase of NDVI in the biweekly period 24 May–6 June. In this case, we can infer that the time lag was less than 14 days. Based on the possible lag times in table 6, we conclude that the lag time for NDVI response to precipitation ranges from 8–26 days, with the most likely response time within 14 days. This lag time should be further analysed for different landcover types in future studies as different landcover types respond differently to precipitation.

3.1.5. *Relations between soil moisture and NDVI*

For Konza Prairie, the NDVI patterns apparently were influenced by the soil moisture patterns between late May and September of most years (figure 2). Correlation coefficients between soil moisture and NDVI, however, were only high during 1990 and 1991 (r-value equalled 0.74 and 0.85, respectively), but low in the other years due to different time lags.

3.1.6. *Interannual relations between precipitation and NDVI*

For Kansas as a whole, correlation between NDVI and precipitation was moderate for the growing season. When we correlate the NDVI with precipitation during a longer time, i.e. add more months of precipitation preceding the growing season,

Table 4. Maximum cross-season correlation coefficients (*r*-value) between precipitation and NDVI for grasslands, croplands and forests in Kansas. Time indicates the time during which precipitation is accumulated. For example, for grassland at the period mid-point date 6 June, NDVI was best correlated with the precipitation from second to fourth periods preceding the NDVI period.

	Period	4/6	4/20	5/4	5/18	6/1	6/15	6/29	7/13	7/27	8/10	8/24	9/7	9/21	10/5	10/19
Grassland	Time	1–3	0	2–6	2–6	2–4	0	0–2	1	0–4	0–3	0–2	1–5	0–4	3–4	4–6
	r-value	0.29	**0.55**	**0.75**	**0.81**	**0.82**	**0.61**	**0.57**	**0.55**	**0.82**	**0.83**	**0.62**	**0.87**	**0.78**	**0.81**	**0.73**
Cropland	Time	1–3	0–4	2–6	2–6	2–4	0	0–1	0–1	0–2	0–3	1	1–5	2–6	1–5	2–6
	r-value	**0.38**	**0.67**	**0.87**	**0.82**	**0.81**	**0.54**	**0.37**	**0.47**	**0.84**	**0.87**	**0.78**	**0.90**	**0.82**	**0.79**	**0.83**
Forest	Time	2–3	0	2–4	2–3	2	0–1	1–2	3	2–4	4–5	1–2	1–5	2–3	3	0–1
	r-value	0.29	**0.66**	**0.61**	**0.68**	**0.47**	**0.59**	**0.72**	**0.24**	**0.59**	**0.45**	**0.41**	**0.60**	**0.67**	**0.82**	**0.61**

Table 5. Cross-season correlation coefficients (*r*-value) between NDVI and soil moisture for Konza Prairie are only moderately high in early summer and early autumn. The first row indicates mid-point date of the biweekly NDVI period.

Date	4/20	5/4	5/18	6/1	6/15	6/29	7/13	7/27	8/10	8/24	9/7	9/21	10/5	10/19
r-value	−0.03	−0.49	0.36	0.13	**0.72**	**0.61**	0.15	0.37	0.56	−0.11	0.22	**0.71**	**0.52**	0.02

Table 6. NDVI responding time to precipitation event.

Year	Major precipitation event	Period when NDVI responded	Possible time lag (days)
1989	16–22 May	24 May–6 June	8–21
1989	19, 28 August	30 August–12 September	11–24
1990	21, 26 July	3–16 August	8–26
1991	24–25 May–6 June	24 May–6 June	<14
1992	1, 6, 10 June	12–25 June	11–24
1992	13, 15, 20, 21 July	24 July–6 August	11–24
1995	1, 7, 8 May	12–25 May	11–24

correlation coefficient increased steadily and peaked when the time interval reached 15 months. For the three landcover categories, the correlation coefficients were strong for cropland and grassland, and weaker for forest. We also calculated the same set of correlation coefficients, but excluded the year 1993, which was an exceptionally wet year, and found much stronger relations for all landcover categories (figure 3).

For interannual comparisons, average NDVI for the growing season increased linearly with precipitation received during the growing season plus seven preceding months (figure 4), except for 1993 (regression coefficients: $b_0 = 0.151$, $b_1 = 0.000207$; $r^2 = 0.85$, $p < 0.002$).

3.2. *Relations between temperature and NDVI*

3.2.1. *Within-season relations between temperature and NDVI*

Biweekly NDVI was strongly correlated with temperature indices of the same biweekly period in most years (table 7). In 1989 and 1996, however, the biweekly

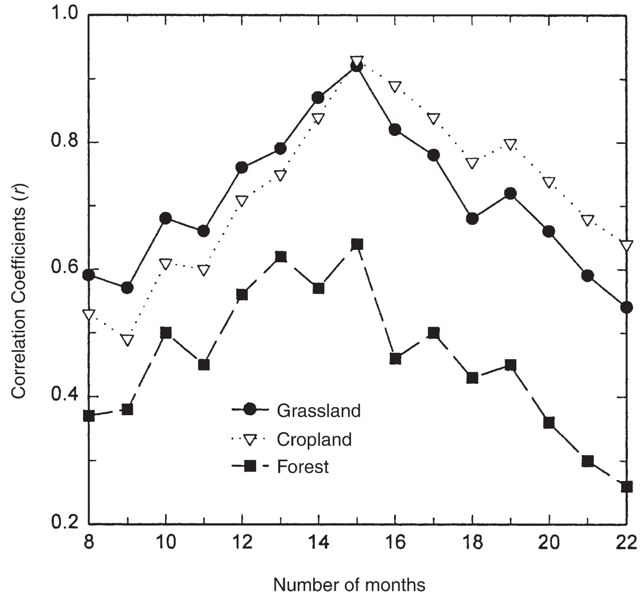

Figure 3. Correlation coefficients as a function of time duration over which precipitation was totalled, with separate curves for grassland, cropland and forest. Correlation coefficients were calculated using data for all years except 1993, which was an exceptionally wet year.

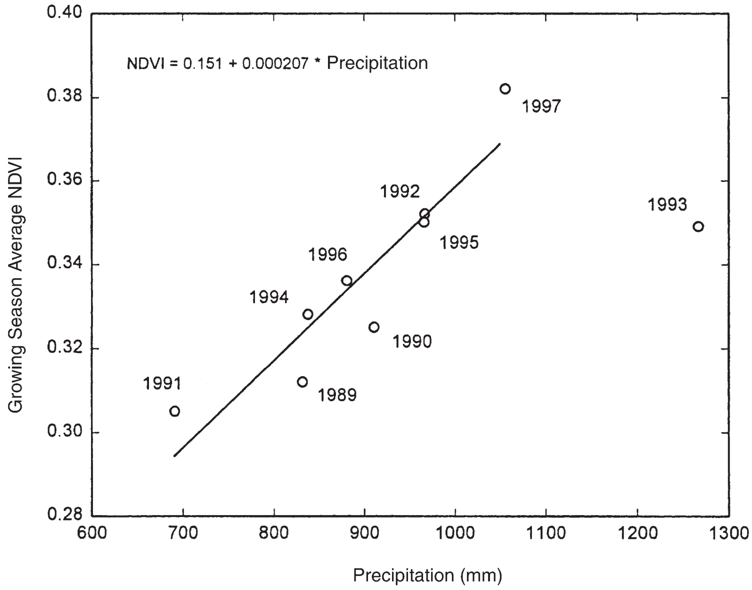

Figure 4. Average growing season NDVI as a function of precipitation received during the current growing season plus the seven preceding months (15-month total precipitation). The linear regression line was calculated using values for all years except 1993, which was an exceptionally wet year.

Table 7. Nine-year (1989–97) average correlation coefficients between NDVI and temperature of the concurrent and previous period. NDVI is best correlated to minimum temperature of the concurrent period for grassland and forest, but to average temperature of concurrent period for forest.

Time period	Curr. min.	Prev. min.	Curr. max.	Prev. max.	Curr. avg.	Prev. avg.	Curr. AGDD	Prev. AGDD
Grassland	**0.83**	0.78	0.79	0.70	0.82	0.74	0.82	0.76
Cropland	0.57	0.46	0.50	0.37	**0.62**	0.42	0.60	0.50
Forest	**0.87**	0.80	0.81	0.76	0.87	0.80	0.83	0.80

NDVI was most strongly correlated with temperature indices of the previous biweekly period. For forests, the strongest correlations were with minimum and average temperatures; for grassland, with minimum temperature; and for cropland, with average temperature. The correlation coefficients were highest for forest, intermediate for grassland, and lowest for cropland.

3.2.2. *Cross-season relations between temperature and NDVI*

Biweekly NDVI was weakly correlated with temperature of the concurrent period, but moderately related with temperature of the previous period at specific time of the growing season (table 8). NDVI was moderately correlated with minimum temperature of previous period in late March, early April, late September and early October. NDVI was also negatively correlated with the maximum temperature of the immediately preceding period during late May to early September.

Table 8. Cross-season correlation coefficients (*r*-value) between NDVI and minimum temperature of the previous period are moderately strong only in the early and end season; coefficients (*r*-value) between NDVI and maximum temperature of previous period are mostly negative in summer. The first column indicates the mid-point date of NDVI biweekly period.

	Previous minimum			Previous maximum		
Date	Grassland	Cropland	Forest	Grassland	Cropland	Forest
9 March	0.66	0.63	0.87	0.74	0.64	0.82
23 March	0.33	0.50	0.41	0.37	0.33	0.47
6 April	0.74	0.77	0.74	0.51	0.37	0.64
20 April	0.63	0.43	0.78	0.47	0.11	0.73
4 May	0.23	0.08	0.27	−0.13	−0.26	−0.10
18 May	−0.03	−0.02	−0.23	−0.42	−0.50	−0.47
1 June	0.01	−0.13	0.09	0.33	0.18	0.46
15 June	−0.61	−0.77	−0.46	−0.67	−0.72	−0.60
29 June	−0.48	−0.64	0.23	−0.42	−0.62	0.36
13 July	−0.40	−0.21	0.00	−0.55	−0.32	−0.16
27 July	−0.26	−0.36	−0.24	−0.58	−0.69	−0.41
10 August	0.03	0.11	0.13	−0.58	−0.48	−0.55
24 August	−0.04	−0.19	−0.04	−0.40	−0.56	−0.40
7 September	−0.25	−0.29	−0.11	−0.61	−0.64	−0.53
21 September	−0.39	−0.25	−0.27	−0.56	−0.57	−0.44
5 October	0.27	0.23	0.25	−0.18	−0.27	−0.04
19 October	0.59	0.46	0.64	0.18	0.11	0.38

3.2.3. *Interannual relations between temperature and NDVI*

We observed a negative correlation between temperature indices (minimum, maximum, average and degree–days) and average NDVI for the entire growing season (correlation coefficients of −0.61, −0.68, −0.67 and −0.72, respectively).

4. Discussion

The central Great Plains of North America is a region characterized by a long growing season (March–October) and a high degree of variability in weather conditions from year to year (figure 1). Weather in the state of Kansas is typical of the region. Our results show that, for the state of Kansas, precipitation is the primary factor limiting plant growth. This result is substantiated by the correlations between precipitation and NDVI for within-season, cross-season and interannual comparisons. Ultimately, precipitation influences NDVI through its influence on soil moisture (figure 2). By contrast, temperature is only positively correlated with plant growth in the early and late growing season and negatively influences plant growth during mid-summer (table 8). Our analyses integrate precipitation and temperature data over large areas using the entire pixels, and as such are not strongly influenced by variation in land management or other local level factors (e.g. pest outbreaks or fires). Our current study distinguishes major temporal patterns, but does not distinguish spatial patterns. Wang *et al.* (2001) demonstrate that the spatial patterning of NDVI is strongly related to the spatial patterning of precipitation.

4.1. *Within-season and cross-season responses of NDVI to precipitation*

Different landcovers showed different strength of correlations between NDVI and precipitation. We had expected a stronger correlation for croplands based on greater response of annual than perennial vegetation types. In contrast, we observed a stronger correlation for grasslands because we did not distinguish the irrigated and non-irrigated croplands. This result is consistent with our observation of the spatial relations between NDVI and precipitation (Wang *et al.* 2001) and also agrees with the research of Yang *et al.* (1997).

Our analyses enable us to evaluate temporal patterns of precipitation as they relate to NDVI. Within-season and cross-season analyses demonstrate that NDVI values are most strongly correlated with the precipitation that has been integrated over three to four recent biweekly periods. The strength of the relationship varied, however, depending on the landcover type that is being evaluated. For croplands, NDVI appears to respond more quickly to precipitation, with higher correlation coefficients over shorter durations and shorter time lags, than for grasslands. Forests display the slowest response time to precipitation, both in terms of duration and time lag. This is consistent with adaptive strategies used by plants to use water efficiently. For example, more deeply rooted annual and perennial plants (such as native warm-season grasses) are more buffered from climatic fluctuation than are more shallow-rooted annual crop plants. Forests are even more buffered from climatic fluctuation because of the predominance of deep-rooted woody perennials, and because forest trees in most parts of Kansas grow along drainages and water courses where soil moisture is higher.

NDVI of a single biweekly period was most strongly correlated with precipitation that occurred two biweekly periods before (four-week lag). After a major precipitation event, the response time of NDVI was typically about one biweekly period (two-week lag). These results generally agree with the findings of Justice *et al.* (1986), Malo and Nicholson (1990) and Davenport and Nicholson (1993); however, our study specifically differentiated the temporal scale of response of NDVI, because we examined correlations across all combinations of time duration and lag time. In addition, our study systematically distinguished relations according to landcover types.

Depending upon weather conditions for preceding time intervals, NDVI response can be quite different. For two different time scales, both for single biweekly periods and for the entire growing seasons, the response of NDVI to precipitation was quicker when conditions were drier. In the case of single biweekly periods, lag times were usually shorter when conditions were drier (figure 1), as can be observed by inspection of rainfall events and subsequent NDVI change. Although precipitation within the second preceding biweekly period was typically the most strongly correlated with NDVI (four-week lag time), the response time of NDVI to a major precipitation event after a long drought took only about one biweekly period (two-week lag time). Among years, for the single biweekly period analyses, NDVI was most highly correlated with precipitation of the immediate preceding period during dry years (1990–92), but with precipitation of the second or third preceding period during wet years (1993–97). This result agrees with the findings of Yang *et al.* (1997).

By analysing nine years of weather and NDVI data, we were able to identify when, within the growing season, NDVI was most highly correlated with precipitation (table 4). For grassland, NDVI was almost always correlated with precipitation, except in April. For cropland and forest, in contrast, NDVI was correlated with precipitation during most of the season. During early April neither cropland nor forest land responded to precipitation, which suggests that soil moisture is not generally a limiting factor at this time of year. In addition, cropland displayed weak correlation or a weak negative correlation with precipitation in the early summer, whereas forest displayed only a very weak correlation in the late summer. The low correlation for cropland in early summer probably results because of the winter wheat harvest. We do not have an explanation for the low correlation for forest in late summer.

The study of Farrar *et al.* (1994) showed that NDVI was controlled by soil moisture of the concurrent month. Our study narrowed the time duration to the concurrent biweekly period in most cases (figure 2) in Konza Prairie. During mid-summer we typically observed no time lag between soil moisture change and NDVI change, with NDVI tracking the decrease in soil moisture. However, there were time lags of one to two biweekly periods in some years.

4.2. *Interannual responses of NDVI to precipitation*

NDVI during an average growing season is influenced by precipitation of not only the current growing season, but also precipitation in the months preceding the growing season, as well as the growing season of the preceding year. The strongest correlation between NDVI and precipitation was found when precipitation was integrated over a 15-month period that included the entire current growing season (eight months) plus the seven preceding months (figure 3). Analysis of data for Konza Prairie shows that soil moisture levels at the beginning of the growing season determine the magnitude of the NDVI values (figure 2). NDVI values stop increasing or begin to decrease when soil moisture begins to decline and becomes a limiting factor (Price *et al.* 1993). Soil moisture levels are strongly influenced by precipitation accumulated over a relatively long period of time. Much of winter precipitation is stored as increased soil moisture because of low temperature and low evapotranspiration rates. In addition, precipitation during the previous growing season (especially towards the latter part of the season when plants are browning down) influences vegetation condition of perennial plants and overwintering crops (e.g. winter wheat), which in turn affects greenness of the current growing season.

We observed a strong linear relationship between 15-month accumulated precipitation and average growing season NDVI (figure 4). While various studies have observed relationships between NDVI and precipitation during the current growing season, we are unaware of any studies that show a linkage between NDVI and precipitation over such an extended time interval. Our study represents a comprehensive temporal analysis both in terms of analysis of appropriate time interval and in terms of the number of consecutive years analysed. Our study demonstrates a strong and distinct linear relationship between NDVI and precipitation. The 1993 growing season was a notable exception because it was one of the wettest years in recorded history for Kansas. During 1993 productivity was probably decreased by a combination of factors, in particular waterlogged and flooded soils, cooler temperature and increased cloudiness resulting in decreased solar radiation.

4.3. *Relations between NDVI and temperature*

Our analyses also show that temperature is an important factor for plant growth, but its variation is a contributing factor only at specific times of the growing season. Though within-season analyses show strong correlation between NDVI and temperature indices, cross-season analyses show that NDVI is strongly positively related to temperature only at the beginning and end of the growing season (table 8). During the summer, NDVI is negatively correlated to maximum temperature. Our analyses cannot distinguish whether this negative correlation results because of (1) direct inhibition of photosynthesis, (2) inhibition of plant growth due to water stress, or (3) covariance between temperature and precipitation, with lower temperatures associated with cloud cover during precipitation events.

Within-season relations between temperature and NDVI were different for different landcover types. As grasslands revive earliest, then forests, and croplands latest, minimum temperature is a more important limiting factor for grasslands, but a less important factor for croplands.

Yang *et al.* (1997) reported strong correspondence between AGDD and NDVI (average correlation coefficient $r=0.81$), and concluded that total energy accumulation most strongly influenced plant growth. By contrast, we found that NDVI was even better correlated with minimum temperature within the growing season than with AGDD. Further, we found that temperature was positively correlated with NDVI only at the beginning and end of the growing season, but negatively correlated during mid-season. High minimum temperatures during the early and late growing season are probably associated with lower levels of frost damage and overall better conditions for plant growth.

Interannual 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. Causal relationship cannot be directly determined from correlation analyses. In this case, we are unable to distinguish effects of temperature vs precipitation. A full analysis requires a more mechanistic understanding of the interactions between temperature, precipitation and other factors as they determine evapotranspiration, which is more closely related to within-season NDVI than precipitation (Srivastava *et al.* 1997). Thus, further studies are needed to examine temporal relations of temperature and precipitation as they influence energy balance, and in turn determine actual evapotranspiration.

5. Conclusion

This study demonstrates a strong relationship between precipitation and NDVI in the state of Kansas, and representative of the central Great Plains. Through systematic analysis of biweekly precipitation data, we were able to determine the temporal scales, defined by both time duration over which rainfall was integrated and time lags, that most strongly influence NDVI. Our analyses provide the basis for predicting changes in productivity that accompany changes in rainfall and temperature.

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