

Development of a Drought Detection Indicator using MODIS Thermal Infrared Data

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Abstract : Based on surface energy balance climatology, surface temperatures should respond to drying conditions well before plant response. To test this hypothesis, land surface temperatures (LST) derived from MODIS data were analyzed to determine how the data were correlated with climatic water balance variables and NDVI anomalies during a growing season in Western and Central Kansas. Daily MODIS data were integrated into weekly composites so that each composite data set included the maximum temperature recorded at each pixel during each composite period. Time-integrated, or cumulative values of the LST deviation standardized with mean air temperatures had significantly high correlation coefficients with SM, AE/PE, and MD/PE, ranging from 0.65 to 0.89. The Standardized Thermal Index (STI) is proposed in this study to accomplish the objective. The STI, based on surface temperatures standardized with observed mean air temperatures, had significant temporal relationships with the hydroclimatological factors. STI classes in all the composite periods also had a strong correlation with NDVI declines during a drought episode. Results showed that, based on LST, air temperature observations, and water budget analysis, NDVI declines below normal could be predicted as early as 8 weeks in advance in this study area.

Key Words : MODIS, Land Surface Temperature, NDVI, Water Budget Factor, Drought.

1. Introduction

Innovations in remote sensing technology have provided new solutions to environmental problems because remotely sensed data contain valuable information about the energy reflected and emitted by the earth's surface. Using a wide range of sensors and digital satellite image processing algorithms, important biophysical information can be extracted from these data. The main advantage of satellite remote sensing

imagery is that it covers a relatively large area regularly and has much finer resolution than most surface observations systems (e.g. weather stations). In natural hazard monitoring, remote sensing techniques have become crucial tools for timely decision making processes (Ungannai and Kogan, 1998). Therefore, it is recommended that meteorological data should be used in conjunction with remote sensing data to develop better solutions for drought monitoring.

It is well documented that vegetation dynamics are

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highly correlated with vegetation indices derived from satellite imagery. These indices are defined as dimensionless radiometric measures that indicate the activity of green vegetation, including the leaf area index, percent green cover, biomass, chlorophyll content, and absorbed photosynthetically active radiation. The most commonly used indicator of vegetation abundance and vigor is the *Normalized Difference Vegetation Index* (NDVI). Several studies have been conducted in the Great Plains region, showing the usefulness of the NDVI for bioclimatic research (Lozano-García *et al.*, 1995; Tao *et al.*, 1997; Rundquist, 1998; Rundquist *et al.*, 2000). Although NDVI has proven a good indicator of vegetation activity, it is not appropriate for “real-time” drought monitoring due to its lagged response to climatic conditions. Studies have shown that responses of NDVI to climatic factors lag behind by several weeks (Peters *et al.*, 1991; Seguin *et al.*, 1994; Lozano-García *et al.*, 1995; Wang *et al.*, 2001).

Quicker drought detection may be possible using thermal emission patterns from remote sensors. Land surface temperature is an important biophysical indicator because it is directly linked to both the net radiation flux received by the surface and the surface’s moisture conditions. It is believed that by using thermal emission patterns in combination with meteorological observations, relationships between the surface temperature and moisture regimes on the ground will predict drought areas before they are detected by the NDVI. With high radiometric and temporal resolution, thermal infrared data from MODIS (*Moderate Resolution Imaging Spectroradiometer*) may allow us to infer changes in surface thermal regimes more accurately and assist in better drought detection. The purpose of this study is to determine how MODIS thermal infrared data are coupled with surface moisture conditions and NDVI, and how early the thermal signals can indicate a drought episode in a central Great Plains region.

2. Methodology

1) Study Area

The study area covers western and central Kansas, which forms part of the central Great Plains region of North America (Fig. 1). This region has a distinct continental climate characterized by significant monthly, seasonal, and year-to-year variations in temperature and precipitation with a strong east-west precipitation gradient and a northwest-southeast temperature gradient. In southwest Kansas, mean annual precipitation is about 48cm, but in one out of three years, it is less than 35.4cm or more than 61cm. The variability tends to be greater in western and south-central Kansas compared to the more humid eastern region. This highly variable precipitation regime makes western Kansas one of the most drought-prone regions in the United States (Reed, 1993). The frequently occurring droughts and the extreme temperature seasonality result in a grassland-type ecosystem with shortgrass prairie in the west and mixed

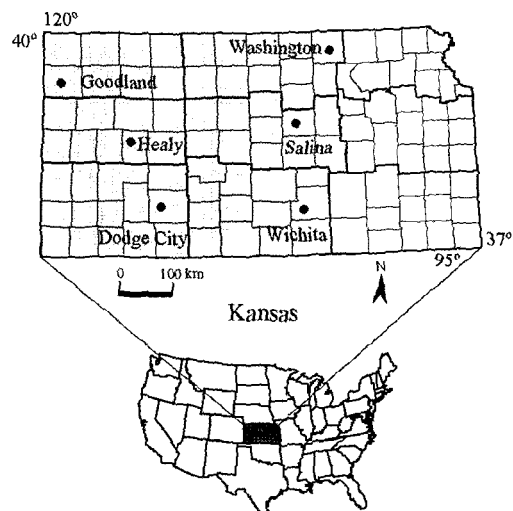


Fig. 1. Study area, showing locations of weather stations. The thin solid lines represent county boundaries, and the thick lines divide the state into nine climatic divisions.

prairie in the central region (Küchler, 1974). Droughts also have a substantial impact on the local agricultural economy and natural grassland/rangeland management practices. Water availability from the High Plains aquifer has transformed much of the semi-arid shortgrass prairie region into one of the largest irrigated agricultural regions in the U.S. (Kromm and White, 1992). Since this region has relatively flat topography and is mostly vegetated by grasses or crops, satellite-driven thermal signals from the surface may be relatively uncontaminated by slope, aspect, or shadows.

2) MODIS Data

Sixty-seven daily MODIS LST images were obtained from July to October, 2000. Most MODIS daytime LST pixels are observed between 10:00 and 12:00 in the morning in local time. Even though the difference of LST observation time of MODIS is within two hours throughout the imagery, LST could change significantly between 10:00 a.m. to 12:00 p.m. due to rapid energy flux into the land surface. Knowing that the increase of incoming radiation during the two-hour period could be a problem in comparing thermal infrared data from one place to another, the impact of the data acquisition time upon thermal signals as a drought indicator needs to be evaluated. Since LST may increase in proportion to incoming solar radiation, hourly solar radiation measurements recorded in the automated weather data network were used to standardize LST values for a single fixed time in each composite image. To compare all pixel values for a day against one fixed time, a reference time was selected in each day. The reference acquisition time of each image was decided based on the time when most image pixels were acquired. Then, the LST of each image pixel was adjusted for the reference time using an incoming solar radiation ratio between the reference time and the acquisition time of that pixel for each composite period. These time-corrected LST data were compared to the original data to see if the time

correction improved the representativeness of the data for the land surface conditions.

3) Climatic Water Budget

A hydroclimatological analysis is an effective methodology for drought monitoring because it focuses on fluxes of moisture between the land surface, vegetation and the atmosphere, taking into account soil properties. One specific methodology for monitoring drought and vegetation conditions is with the climatic water budget. The climatic water budget is a monthly, weekly, or daily comparison of water supply and climatic demands for water. Since water conditions in soil layers are closely tied to vegetation growth, knowledge of the water budget provides quantitative insights in biophysical research, especially on drought-vegetative response relationships. By comparing precipitation and potential evapotranspiration, it is possible to obtain values of soil moisture, water deficit, and water surplus. Empirical techniques, also called bookkeeping methods, have been widely accepted because they are simple to evaluate and require only limited climatic data (Mather, 1978). For daily water budget calculations, one weather station was selected for each climatic division in the study area. Since six climatic divisions exist in the study area, six weather stations were selected in total. Using an empirical water budget program, four important water budget factors were calculated from the daily meteorological data. They include percent soil moisture (SM), the actual/potential evapotranspiration ratio (AE/PE), moisture deficit (MD), and moisture deficit/potential evapotranspiration ratio (MD/PE). In most cases, these four factors indicate moisture conditions on the ground.

4) LST-Water Budget Factors Relationships

Daily LST data had to be compressed to weekly data for comparison with vegetation growth represented by weekly NDVI. To synchronize the LST data with

weekly NDVI data, the daily LST values were collapsed into weekly composite data with the same weekly intervals as the NDVI data set. In creating the composites, the highest land surface temperature in each weekly period was included in the composite because previous research had found that the maximum apparent temperature composite was most uniform with little apparent speckle or other image artifacts (Cihlar *et al.*, 1994; Park *et al.*, 2002).

Since LST deviations from air temperatures are influenced by moisture conditions on the ground, LST deviation from air temperature was used as an indicator of surface moisture conditions in this study:

$$\text{LST deviation} = \text{LST} - \text{Air Temperature (T}_{\text{air}})$$

LST minus air temperature has been known to be an adequate indicator for surface moisture conditions because it is known that the measure has a linear inverse relationship with vapor pressure deficit of air, and a positive relationship with sensible heat flux (Idso *et al.*, 1977; Jackson *et al.* 1981). The study hypothesis is that areas suffering from a water shortage have lower NDVI values and higher gradients between LST and air temperature compared to drought-free areas. Therefore, LST deviation is expected to have a negative correlation with SM and AE/PE, but a positive correlation with MD. Correlation coefficients between the LST deviation values in each of the maximum LST composites and the water budget factors were calculated to determine how well the LST data represented surface moisture conditions.

5) Drought Thermal Index and NDVI

Since it was hypothesized that warmer surfaces had greater NDVI deviations during drought periods than cooler surfaces, their thermal signals were expected to have significant positive relationships with the NDVI deviations. Oftentimes, however, LST data do not have a significant relationship with NDVI over short periods

of time because responses by plants to a change in land surface water regime may not be instantaneous. One of the important objectives of this study is to determine how early the LST signals may predict NDVI declines. Since the water budget factors and LST described above represent moisture conditions on the land surface, these factors were expected to have a significant, lagged correlation with NDVI.

The weekly maximum NDVI composite data for a growing season (March-October) in 2000 and ten-year mean (1990-1999) weekly NDVI data were obtained from archives in the Kansas Applied Remote Sensing (KARS) Program at the University of Kansas to measure NDVI deviations in each week. The NDVI deviation is defined as a target NDVI value minus the ten-year average NDVI for each week. To determine the relationship, LST deviations in each composite period were categorized into classes according to their levels. Then, correlation coefficients between these classes in each composite period and the NDVI deviations associated with each of the classes in a composite period whose NDVI values began to decline significantly (September 15-21) were computed. For LST deviation classes with the same interval, a "Standardized Thermal Index" (STI) is proposed in this study to rescale the land surface temperature standardized with mean air temperature from 0 to 1. The index is defined as the cumulative mean of land surface temperature standardized with mean air temperature ($[\text{LST} - \text{meanT}_{\text{air}}]_{\text{cum}}$) divided by the cumulative mean of the sum of the land surface temperature and the mean air temperature ($[\text{LST} + \text{meanT}_{\text{air}}]_{\text{cum}}$), which is given by

$$\text{STI} = [\text{LST} - \text{meanT}_{\text{air}}]_{\text{cum}} / [\text{LST} + \text{meanT}_{\text{air}}]_{\text{cum}}$$

If we assume that LST and mean air temperature are not lower than 0°C during the growing season, and the LST of maximum temperature composite data is not lower than air temperature, STI ranges from 0 to 1. Maps of STI scaled with 0.05 intervals were created in

each composite period, and each map was categorized with 7 different STI levels. The mean values of these STI classes were calculated, and correlation coefficients between these STI class values and the NDVI decline values were calculated to see if the thermal signals were significantly correlated with NDVI deviations.

3. Results and Discussions

1) LST vs. Water Budget Factor Relations

Solar radiation measured hourly in the automated weather data network showed that energy flux density increased rapidly from 10:00 a.m. to 12:00 p.m. by 52.4% on average. However, time correction for a reference time did not change the LST distribution of the data substantially because the variance in image acquisition times was very small. Most data acquisition times were concentrated around the mode of the data acquisition time. Time-corrected LST data improved their correlation with the water budget factors, SM, AE/PE, and MD/PE. However, the distribution of improvement varied spatially. The strength of correlation most significantly increased in the southwestern part of the state; it increased up to 20.8% in Dodge City and up to 11.2% in Healy, while the improvement was only 3~4% in Salina and Wichita, and minimal in Goodland and Washington. In general, the time-corrected LST data improved their correlations with water budget factors by 5.6% for SM, 6.3% for AE/PE, and 5.6% for MD/PE compared to the original non-corrected LST data. Since, in part of the study area, the standardization of data acquisition time had a significant impact on the representativeness of thermal signals for land surface conditions, it is believed that time-correction is an important procedure for the thermal surface analysis.

Correlation coefficients between LST deviations from air temperatures and four water budget factors were

calculated (Table 1, top). In all cases, LST-mean air temperatures ($LST\text{-}meanT_{air}$) had higher correlation coefficients with the water budget factors than those with maximum air temperatures. It is believed that this was because we standardized for variations in the atmospheric temperature that were not related to variations in surface moisture conditions. Relationships between the $LST\text{-}meanT_{air}$ and the water budget factors were further analyzed. SM, AE/PE and MD/PE had consistent significant relationships with $LST\text{-}meanT_{air}$, whereas MD had varied relationships from place to place. Among the former three factors, SM had the highest correlation coefficients, ranging from -0.40 to -0.73 with the mean of -0.56 (Table 1, top).

Time-integrated, or cumulative values of the $LST\text{-}meanT_{air}$, showed even stronger relationships with the water budget factors, increasing the correlation coefficients by 33.4% on average. The absolute values of their correlation coefficients ranged from 0.65 to 0.89 (Table 1, bottom). However, MD still did not show a meaningful relationship with cumulative $LST\text{-}meanT_{air}$ values, while the relationships for the other three factors were improved substantially. MD is merely the difference between PE and AE. Therefore, it does not indicate MD against the need for water, which is PE. This means relative water budget values based on water demand are more meaningful than absolute terms.

Seasonal patterns of the water budget factors in the six weather stations are represented in Fig. 2. Not surprisingly, AE/PE and MD/PE values showed a mirror-image pattern because they are complementary measures to each other in a water budget. AE/PE and MD/PE responded to precipitation more sensitively than did SM. As shown in the graph, abrupt peaks of AE/PE or drops in MD/PE, indicating rainfall events, were observed, whereas SM value changes were more gradual. This is because SM is a measure of moisture storage where AE has already been taken out. AE and MD were affected by minimal precipitation whereas SM

Table 1. Correlations between land surface temperature (LST) deviations from air temperature and climatic water budget factors. Relationships of LST- meanT_{air} and cumulative LST- meanT_{air} with the climatic water budget factors are compared for each weather station. On average, correlation coefficients increased by 33.4% when LST- meanT_{air} values were temporally integrated.

Relationships		Dodge City	Goodland	Healy	Salina	Washington	Wichita	Mean	
Current values	SM (%)	LST-maxT _{air}	-0.46*	-0.68**	-0.30	-0.51*	-0.11	-0.40	-0.41
		LST-meanT _{air}	-0.47*	-0.73**	-0.40	-0.69**	-0.47*	-0.57*	-0.56
	AE/PE	LST-maxT _{air}	-0.46*	-0.67**	-0.30	-0.48*	-0.12	-0.41	-0.40
		LST-meanT _{air}	-0.47*	-0.72**	-0.37	-0.68**	-0.48*	-0.58*	-0.55
	MD	LST-maxT _{air}	0.73**	-0.12	-0.28	0.61*	0.17	0.48*	0.26
		LST-meanT _{air}	0.75**	-0.17	-0.19	0.67**	0.08	0.63*	0.29
	MD/PE	LST-maxT _{air}	0.41	0.66*	0.32	0.48*	0.16	0.39	0.40
		LST-meanT _{air}	0.42	0.72**	0.38	0.68**	0.52*	0.57*	0.55
Cumulative values	SM (%)	(LST-maxT _{air}) _{cum}	-0.72**	-0.83**	-0.28	-0.85**	-0.10	-0.75**	-0.43
		(LST- meanT _{air}) _{cum}	-0.87**	-0.80**	-0.70**	-0.76**	-0.65**	-0.82**	-0.73
	AE/PE	(LST-maxT _{air}) _{cum}	-0.73**	-0.77**	-0.26	-0.84**	-0.11	-0.76**	-0.43
		(LST-meanT _{air}) _{cum}	-0.89**	-0.82**	-0.69**	-0.78**	-0.66**	-0.83**	-0.73
	MD	(LST-maxT _{air}) _{cum}	0.30	0.17	-0.29	0.15	-0.29	0.55*	0.05
		(LST-meanT _{air}) _{cum}	0.13	-0.04	-0.56*	-0.02	-0.38	0.43	-0.11
	MD/PE	(LST-maxT _{air}) _{cum}	0.71**	0.75**	0.30	0.84**	0.12	0.74**	0.42
		(LST-meanT _{air}) _{cum}	0.86**	0.82**	0.72**	0.77**	0.67**	0.83**	0.73

* Significant at the 0.05 level, ** Significant at the 0.01 level

did not increase with the previous weekly rainfall totals as high as 14 mm.

2) STI and NDVI Anomalies

Mean STI values for each STI class ranged from 0.03 to 0.31 during the study period. As expected, these STI class values had significant positive relationships with NDVI deviations in each composite period, and the correlation coefficients increased from 0.85 to 0.98 as time progressed. This result clearly showed that warmer LST was correlated with severer drought. In mid-July, the correlation coefficient reached over 0.9 very rapidly, and showed only small increases thereafter. This result indicated that NDVI responses to the thermal signals could lag behind by up to eight weeks in this area. Comparing class mean values of STI and NDVI deviations, the overall correlation between these variables was strong with the coefficient of determination (r^2) of 0.85. However, as shown in Fig. 3,

there was a noticeable break in the linear relationship, where as STI passed over 0.2, NDVI decline rates increased and it produced 15% or more of NDVI declines. One notable result was that the relationships were stronger in the western part of the state compared to the central portion. Correlation coefficients computed in the west, such as Dodge City, Goodland, and Healy, were as strong as 0.83 (STI:MD/PE), while those in the central part of the state, including Salina, Washington, and Wichita, were only as strong as -0.48 (STI:AE/PE). This result may indicate that thermal signals are more reliable in drier environments.

Temporal NDVI anomaly patterns were variable from place to place, but, generally speaking, there were at least two drought episodes during the growing season studied, one in mid-summer (June) and the other in late-summer (September). During these drought episodes, NDVI values dropped below their ten-year means. These NDVI declines were associated with continuous

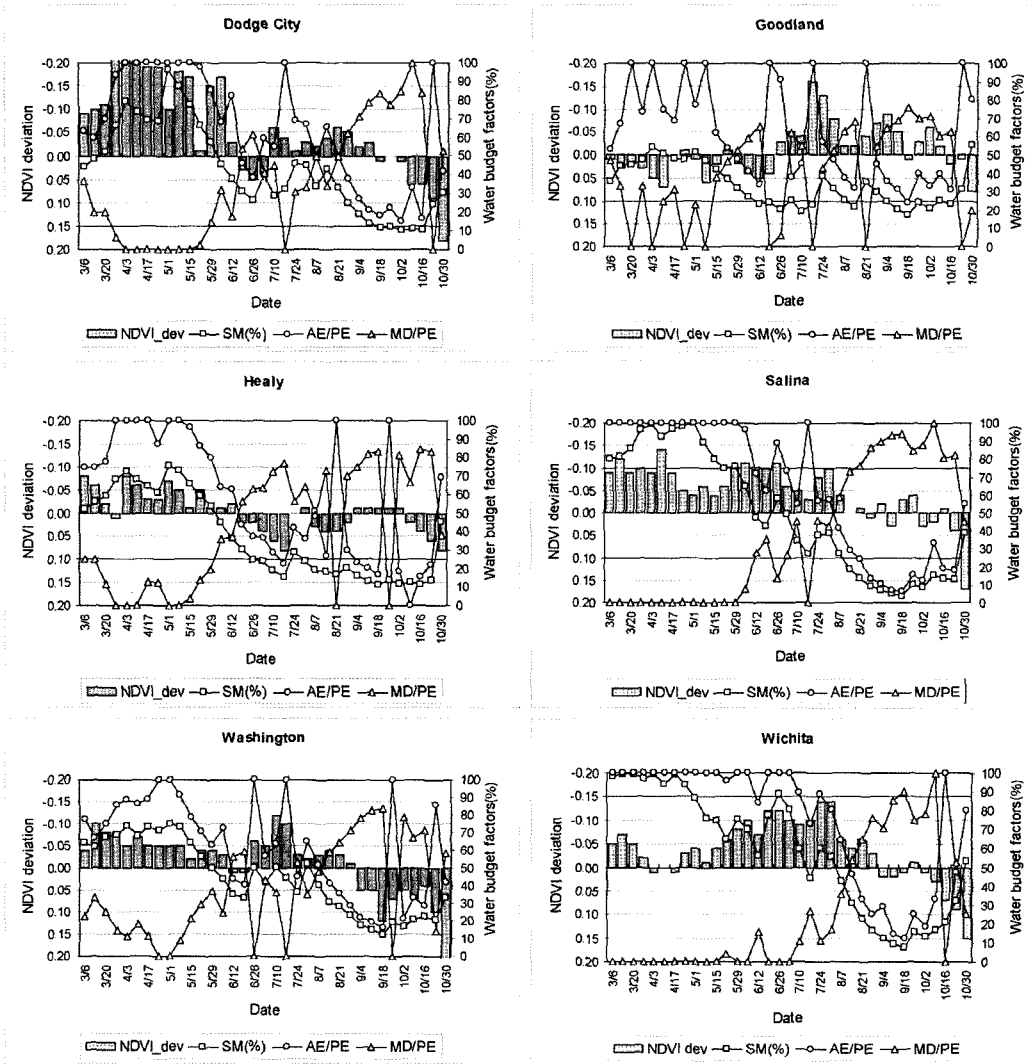


Fig. 2. NDVI deviations and water budget factors, including SM, AE/PE, and MD/PE, for the six weather stations.

decreases in SM, lasting from four to seven weeks. As shown in Fig. 2, if MD/PE values increased (or SM and AE/PE decreased) continuously for four or more weeks, the NDVI values dropped below the ten-year averages at the six weather stations. There was no significant biomass deterioration until late summer in Salina, but two drought spells were observed in other areas (mid summer and late-summer).

Three temporal characteristics were revealed in this analysis. First, in the mid-summer drought episode, it took longer for NDVI to decline below the ten-year mean after SM began to decrease. In the mid-summer drought spell, SM decreased continuously for 6.7 weeks on average until NDVI reached below-normal conditions, whereas this lag was reduced to 4.3 weeks for the late summer. Second, NDVI values during the

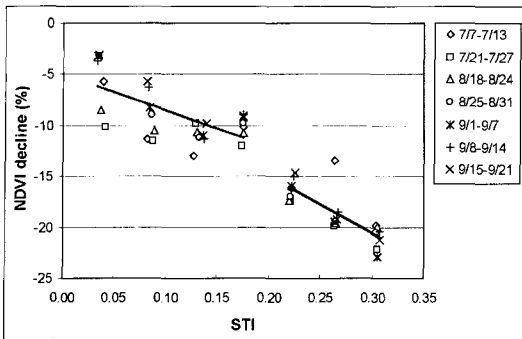


Fig. 3. Relationships between STI for each composite period and NDVI declines in mid-September. The overall r^2 value was 0.85, but as STI values became higher than 0.2, the rate of NDVI declines increased.

drought spells dropped close to 10-year-mean values several weeks prior to below-normal NDVI degradation. This may indicate a period of SM depletion, when plants are yet to be stressed. Third, SM decreased to less than 40% of field capacity in the late-summer drought spell before NDVI declined below average values. Since LST values reflect SM conditions well, it is believed that the LST signals can be a good indicator for biomass declines or deterioration. Although STI had strong correlation with eight-week lagged NDVI signals on average, point-based NDVI responses at the six weather stations varied. Considering the STI value of 0.2 and the SM of 40% as a threshold for drought detection, NDVI declines were detected as early as 2 to 8 weeks in advance depending on locations of the weather stations.

Since drought is a cumulative phenomenon, temporal distribution of precipitation is important. The prolonged absence of a significant amount of rainfall usually precedes NDVI degradation even though the response time of vegetation may vary depending on environmental conditions. It took more time to reach below-normal NDVI values in early summer than it did in late summer. This is because there was much more soil moisture available in early or mid-summer than in late summer, and evapotranspiration rates were much lower early on, typically, i.e. water demand is greater in

July/August, therefore increasing the drying rate. Across the state, NDVI values significantly decreased below the ten-year average in mid-September, especially in the western and upper central portions of the study area (Fig. 4A). These NDVI declines are depicted in STI maps.

Thermal signals signifying the drought phenomenon appeared in the western part of the state and moved eastward as time progressed. The STI maps showed early warm-up in the western part of the state as early as 8 weeks before the mid-September NDVI declines, and strong thermal signals were observed in the upper central portion of the study area by late August (Fig. 4B-C). However, the thermal indicator did not show strong signals for the eastern part of the study area even though the NDVI degradation appeared in this area in Fig. 4A. The eastern area is partly covered by the Flint Hill Uplands, where, for the most part, natural prairie grassland remains. Previous research conducted in Kansas and Nebraska has shown that the NDVI responses of native grasslands to precipitation were more sensitive than those of cropland or grassland-cropland mixed land uses (Yang *et al.*, 1997; Tao *et al.*, 1997). Therefore, one possible explanation for this result would be that NDVI for the Flint Hills declined significantly during the drought episode even though MD was not as great as in other areas to trigger strong thermal signals, or surface temperature increases.

4. Conclusions

This study aimed to develop a method for improving drought monitoring by integrating water budget analysis, NDVI, and MODIS daily thermal infrared data sets. From the study results, we can address two main problems in current drought monitoring schemes. First, accurate temperature observations from remotely sensed data can overcome the very coarse spatial resolution of

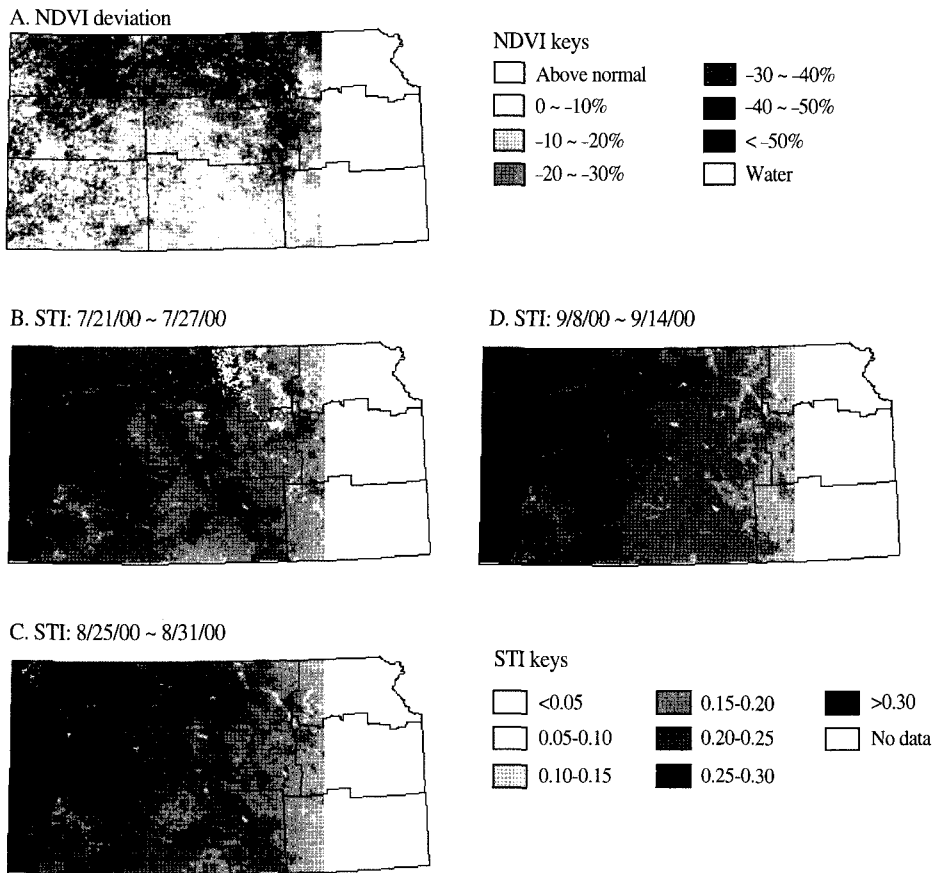


Fig. 4. Visual representation of the NDVI deviation (A) from the ten-year mean (1990-1999) and STI changes from July to September, 2000. The class interval was set to 0.05. The boundary lines represent climatic divisions.

weather stations at a relatively low cost. Second, it can be an appropriate tool for real-time drought monitoring, which current remotely acquired measures, such as NDVI, cannot accomplish due to a lagged vegetation response to drought. Results show that surface temperatures standardized with observed mean air temperatures had significant correlations with water budget factors, especially SM and AE/PE and MD/PE measures. The relationships were increased by 33.4% when the cumulative means of the surface temperatures were standardized with air temperature. These measures indicated NDVI deterioration as early as 8 weeks in advance based on six weather stations' observations.

STI, based on surface temperatures standardized with observed mean air temperatures, also had significant temporal relationships with the hydroclimatological factors. STI classes in all the composite periods had a strong correlation with NDVI declines during a drought spell. This suggests that STI can be a useful indicator, not only for real-time drought monitoring, but also for drought prediction. The analysis of the thermal infrared data gave a clear visual representation of early thermal signals for NDVI declines, which occurred in mid-September. Strong thermal signals appeared much earlier in the western part of the state than in the central areas. Knowing that environmental characteristics,

including temperature gradients and soil properties, are different from west to east, it is probable that the intensity of the thermal signals varied from place to place. The usage of the satellite-based thermal infrared and NDVI data combined with meteorological ground observations has excellent potential for improving current drought monitoring techniques to a large extent because it provides a higher spatial resolution and can indicate possible drought areas in advance.

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