2007

# Note on the NDVI-LST Relationship and the Use of Temperature-Related Drought Indices Over North America

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Recommended Citation
Sun, D., and M. Kafatos (2007), Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America, *Geophysical Research Letters*, 34, L24406. doi:10.1029/2007GL031485

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**Comments**
This article was originally published in *Geophysical Research Letters*, volume 34, in 2007. DOI:10.1029/2007GL031485

GEOPHYSICAL RESEARCH LETTERS, VOL. 34, L24406, doi:10.1029/2007GL031485, 2007



# Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America

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Received 26 July 2007; revised 6 September 2007; accepted 28 November 2007; published 28 December 2007.

[1] A comprehensive evaluation of the relationship between vegetation and Land Surface Temperature (LST) over the North America is presented. It is found that the correlations between LST and Normalized Difference Vegetation Index (NDVI) depend on the season-of-year and time-of-day. For winter, the correlation between NDVI and LST is positive. The strong negative correlations between LST and NDVI are only found during the warm seasons. Thus temperature-related drought indices may only be used in the warm seasons from May to October, and should be used with caution during cold seasons in North America. The cooling effect of vegetation on LST is stronger during daytime than nighttime. Moreover, the negative correlations between NDVI and LST are much stronger than those between NDVI and the brightness temperature. Therefore using daytime LST for drought monitoring should be more reasonable than using brightness temperature or nighttime LST. **Citation:** Sun, D., and M. Kafatos (2007), Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America, *Geophys. Res. Lett.*, *34*, L24406, doi:10.1029/2007GL031485.

## 1. Introduction

[2] Drought is one of the major environmental phenomena and has caused millions of deaths and cost hundreds of billions of dollars in damage. Satellite sensor data have been playing an increasingly important role in monitoring drought-related vegetation condition. Because of the close relationship between vegetation vigor and available soil moisture, especially in arid and semiarid areas, satellite derived Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) products have been used to evaluate drought conditions.

[3] *Kogan* [1990] suggested using the Vegetation Condition Index (VCI), utilizing NDVI derived from the NOAA-AVHRR (Advanced Very High Resolution Radiometer) for drought detection and tracking. *Kogan* [1995] also proposed the Temperature Condition Index (TCI). The TCI is derived from brightness temperature in the NOAA-AVHRR 11 $\mu$m channel, and its algorithm is similar to VCI except that the relevant formula was modified to reflect the opposite to the NDVI vegetation's response to temperature. Later *Kogan* [1995, 1997] developed a Vegetation Health Index (VHI) by combing the VCI and TCI to monitor drought and vegetation stress.

[4] *McVicar and Bierwirth* [2001] validated the ratio of land surface temperature and NDVI to assess drought conditions. *Wan et al.* [2004] used the MODIS LST and NDVI products to generate the Vegetation Temperature Condition Index (VTCI) for monitoring droughts in the southern Great Plain, USA. *Bayarjargal et al.* [2006] indicated that higher correlations exist between the vegetation drought indices, but less or no relationships are found between the temperature-related indices derived from the NOAA-AVHRR.

[5] All the above proposed vegetation and temperature condition indices for drought monitoring are based on the strong negative correlation between temperature (i.e., BT or LST) and NDVI. *Price* [1990] and *Carlson et al.* [1994] found that a scatter plot of LST and vegetation indices often result in a triangular shape. *Nemani et al.* [1993] found the slope of LST versus NDVI to be negatively correlated to crop-moisture index. *Prihodko and Goward* [1997] and *Boegh et al.* [1998] found the slope of LST/NDVI is related to the evapotranspiration rate of the surface. Increase in evapotranspiration caused by higher temperature results in decrease in soil moisture and a decline of NDVI, while dense vegetation induces more evapotranspiration and lowers the LST [*Price*, 1990; *Boegh et al.*, 1998; *Carlson et al.*, 1994] or the transpiring canopy is cooler [*Kogan et al.*, 2004]. However, a recent study by *Karnieli et al.* [2006] found that the northern ecosystems at high latitudes are characterized by positive correlations between LST and NDVI.

[6] Since the negative LST-NDVI relationship is the basis for temperature related drought indices, whether it holds or not is a fundamental issue to the applications of satellite-derived temperature related drought indices in drought monitoring. The objective of this paper is to further evaluate the NDVI-LST relationship and the effects of vegetation on LST as derived from a recently proposed split window algorithm for the GOES satellite [*Sun and Pinker*, 2003; *Sun et al.*, 2006a, 2006b].

## 2. Data

[7] The mean target brightness temperature and cloud cover fraction (CCF) derived from GOES-8 observations are available as by-products archived at the University of Maryland (http://www.meto.umd.edu/~srb/gcip) [*Tarpley et al.*, 1996; *Pinker et al.*, 2003]. They are hourly data at 0.5° resolution in the domain area 125°W to 70°W and 25°N to 50°N.

[8] The NDVI data are obtained from the Global Inventory Monitoring and Modeling Studies (GIMMS) (http://glcf.umiacs.umd.edu/data/gimms/) [*Zhou et al.*, 2003; *Tucker et al.*, 2005]. This bimonthly NDVI data at 8 km resolution

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0094-8276/07/2007GL031485$05.00

**Table 1.** Correlations Between Several Different Variables

| Variables | January | April | May | July | October |
|---|---|---|---|---|---|
| Samples, n | 4019 | 3993 | 4019 | 4017 | 3985 |
| r (Ta, NDVI) | 0.59[a] | 0.45[a] | 0.19[a] | −0.31[a] | 0.00 |
| r (BT, NDVI) | 0.55[a] | 0.35[a] | −0.18[a] | −0.19[a] | 0.00 |
| r ($LST_{max}$, NDVI) | 0.48[a] | 0.01 | −0.58[a] | −0.89[a] | −0.43[a] |
| r ($LST_{min}$, NDVI) | 0.52[a] | 0.38[a] | −0.01 | −0.26[a] | −0.00 |
| r ($LST_{mean}$, NDVI) | 0.50[a] | 0.29[a] | −0.27[a] | −0.61[a] | −0.20[a] |

[a]Correlation coefficients are statistically significant from zero at the 5% level.

are derived from the advanced very high resolution radiometers (AVHRR) on board the afternoon-viewing National Oceanic and Atmospheric Administration's (NOAA) series satellites (NOAA 7, 9, 11, and 14). It features reduced variations arising from calibration, view geometry, volcanic aerosols, and other effects not related to actual vegetation change.

[9] Monthly mean surface air temperature (Ta) data at 0.5° resolution are obtained from the University of Delaware [*Willmott et al.*, 1985].

## 3. Methodology

[10] The period 1996 to 2000 was selected for this study because improved information on clear sky radiances and cloud cover is available [*Li et al.*, 2007]. Clear conditions are selected to calculate skin temperature (LST) if cloud cover fraction (CCF) less than 10% is reported. The high temporal resolution (hourly here) of GOES makes it possible to calculate the daily maximum LST (mostly daytime), and the minimum LST (mostly nighttime). The 8 km NDVI data from the GIMMS are aggregated to the same 0.5° resolutions as LST and other data.

[11] To test for the quantitative relations from NDVI to the daily maximum, minimum, and mean LST, we estimate the following equation:

$$LST_{max}/LST_{min}/LST_{mean} = a + bNDVI \qquad (1)$$

Where $LST_{max}$, $LST_{min}$, and $LST_{mean}$ is the daily maximum, minimum, and mean LST, respectively. a and b are regression coefficients. Our main interests in this study are to understand the effects of vegetation (NDVI) on LSTs.

[12] Since there are in total only 5 years of data for each month, we use data of spatial points instead of time series analysis, and the regression coefficients were estimated using ordinary least squares. Correlation analyses were also performed with the monthly mean values of spatial points from 5-year (1996–2000) average over the North America.

## 4. Results and Discussion

[13] As shown in Table 1, the correlations between temperatures and NDVI vary with seasons. The correlations between NDVI and surface air temperature Ta are generally positive in winter and spring, negative in summer, and insignificant in autumn, this agrees with the regression results in North America in the study of *Kaufmann et al.* [2003]. The correlations between NDVI and brightness temperature (BT) at the 11 $\mu$m channel are similar to those between NDVI and surface air temperature, but become negative in late spring (May) as well as in summer. The correlations between NDVI and LST are generally positive in the winter and early spring (April). While the NDVI-LST relationships are generally negative in the warm months from May to October, at the same time, it is found that NDVI is more negatively related to the daytime maximum than the nighttime minimum LST. For autumn, the correlation between NDVI and LST is still negative, while the relationships between NDVI and BT or $T_a$ are insignificant.

**Table 2.** Regression Coefficients $a_1$ in Equation (1)[a]

| $a_{1(NDVI)}$ | January | April | May | July | October |
|---|---|---|---|---|---|
| $LST_{max}$ | 39.70 | 6.37 | −30.34 | −36.78 | −23.40 |
| $LST_{min}$ | 34.81 | 18.68 | −3.54 | −7.37 | −0.96 |
| $LST_{mean}$ | 29.81 | 15.99 | −10.31 | −20.81 | −7.00 |

[a]All the coefficients are statistically different from zero at the 5% level.

[14] The regression coefficients $a_1$ (Table 2) indicate that increases in NDVI lower $LST_{max}$ and daily mean LST in late spring (May), as well as in the summer and fall. During the warm months from May to October, the regression coefficients also indicate that the cooling effect of vegetation on LST is much stronger during daytime ($LST_{max}$) than nighttime ($LST_{min}$). Moreover, during summer, the negative correlations between NDVI and the daily mean LST (r = −0.61) are much stronger than those between NDVI and the brightness temperature (r = −0.19). As a result, using LST instead of brightness temperature should be more reasonable for drought monitoring.

[15] From Table 2, we can see that over the North America in early spring (April), the regression coefficient from NDVI to LST is positive and similar to that from NDVI to $T_a$ in the study of *Kaufmann et al.* [2003]. It is found that during early spring (April), the correlations between NDVI and nighttime minimum and mean LST are also positive, while the correlation between NDVI and daytime maximum LST is insignificant. It is found that in

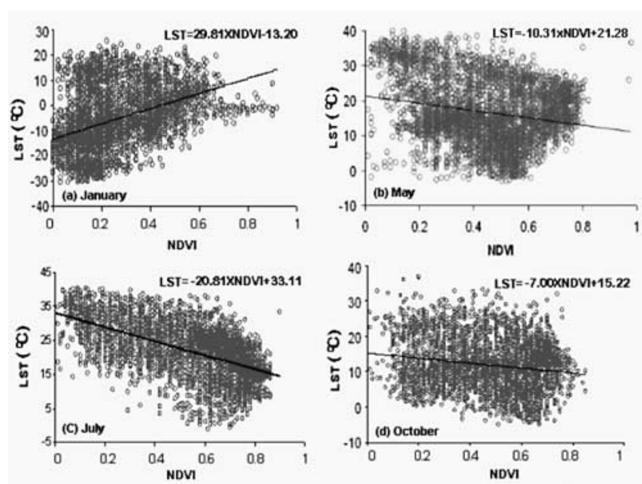


**Figure 1.** The scatter plots of 5-year (1996–2000) averaged monthly mean $LST_{mean}$ and NDVI during different months (a) January, (b) May, (c) July, and (d) October. The p-values for the linear regression lines in Figures 1a–1d are all less than 0.01.

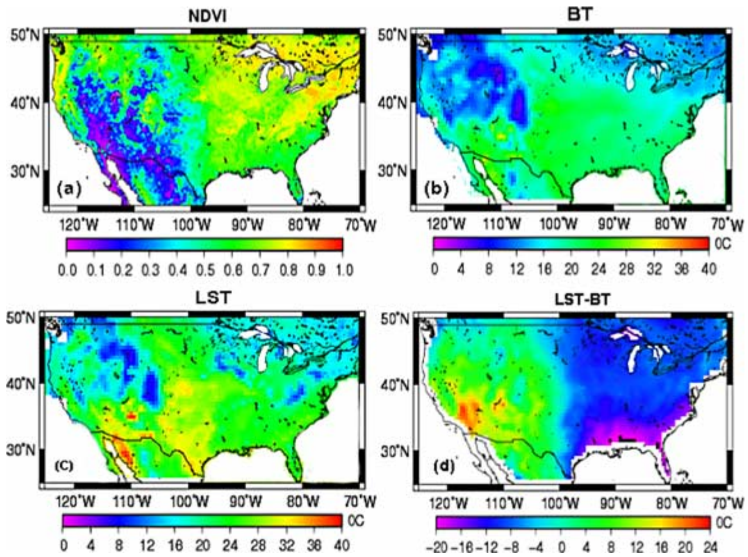


**Figure 2.** (a) Monthly (July) mean NDVI, (b) BT, (c) LST retrieved from Sun and Pinker split-window algorithm, and (d) the difference between LST and BT (LST-BT).

early spring (April), the LST-NDVI relationship is quite unlinear (not shown), when LST is less than about 15°C, it induces an increase of NDVI; however, if LST is above some critical value (>15°C), increase in evapotranspiration caused by higher LST may result in decline of NDVI. While during other months, the NDVI-LST relationship is close to linear. From Figure 1, we can see that LST almost linearly decreases with NDVI in warm months from May to October, but increases with NDVI in winter. The strong negative NDVI-LST relationship is only held in the warm seasons. Therefore, the temperature-related drought indices might only be used in the warm months from May to October and should be used with caution during other months in North America.

[16] Figure 2 further shows the spatial distribution of NDVI, brightness temperature (BT), the LSTs derived from the Sun and Pinker algorithm, and the difference between LST and BT (LST-BT) for five-year (1996–2000) mean in July. The LSTs show lower values at higher NDVI (dense vegetation) areas over the northeast United States (Figure 2c). This is because dense vegetation induces more evapotranspiration and cools the surface [*Price*, 1990; *Boegh et al. 1998*, *Carlson et al.*, 1994, *Kogan et al.* 2004]. As seen in Figure 2, during summer, LST can detect the negative NDVI-temperature relationship more clearly than brightness temperature, the correlation between LST and NDVI is −0.61, while the correlation between BT and NDVI is only −0.19. Strong negative correlations is found between the difference of LST and BT (LST-BT) and NDVI (r = −0.74). Therefore using LST, especially from geostationary satellites with high temporal resolution, for drought monitoring should be more reasonable than using brightness temperature.

[17] As shown in Table 1, even during warm seasons (late spring and fall), the correlations between NDVI and nighttime LST is insignificant. LSTs from the geostationary satellites (GOES here) with high temporal resolution may be better representative of surface conditions than those with lower temporal resolution (twice per day) from the polar orbiting satellites, such as the NOAA-AVHRR.

## 5. Summary

[18] In this study, it is found that the correlations between LST and vegetation depend on the season-of-year and time-of-day. For winter or cold season, the correlation between NDVI and LST and regression coefficient from NDVI to LST are positive. The strong negative correlation between LST and NDVI is only found in the warm months from May to October. The increases in NDVI lower daytime $LST_{max}$ and daily mean LST during spring, summer, and fall. The cooling effect of vegetation on LST is much stronger during daytime ($LST_{max}$) than nighttime ($LST_{min}$). Thus the hypothesis for temperature-related drought indices might only be true for warm seasons. During summer, the negative correlations between NDVI and the daily mean LST (r = −0.61) are much stronger than those between NDVI and the brightness temperature (r = −0.19). From this aspect, using daytime LST for drought monitoring should be more reasonable than using brightness temperature. Further investigations about using daytime LST derived from GOES for drought monitoring will be developed in a future work.

[19] **Acknowledgments.** This work was supported from the NASA grant NNX06AF30G.

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