Comparison of NOAA AVHRR Data to Meteorologic Drought Indices

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ABSTRACT: Evaluation of the AVHRR sensor on-board the NOAA-6 satellite shows that the spatial and temporal variations in drought conditions as defined by the Crop Moisture Index (CMI), Drought Severity Index (DSI), and the Hydrologic Deficit (HD) can be estimated by a combination of remote sensing vegetation indices. Multiple regression analysis explains 80, 57, and 44 percent of the variation in the CMI, DSI, and the HD, respectively, when regressed against AVHRR spectral channels and derived vegetation indices for four study periods extending from June through August, 1980. Regression R^2 values for a single selected study period range from 62 to 90 percent, 68 to 91 percent, and 51 to 88 percent of the variation in each of the nine Oklahoma climatic divisions for the CMI, DSI, and the HD, respectively.

INTRODUCTION

THE YEAR 1980 represented the most serious threat to agriculture in the last decade in the southern Great Plains of the United States. Not only was there a lack of summer moisture, but the event was coupled with daily maximum temperatures which exceeded 37°C for several weeks. By the end of June 1980, Oklahoma agriculture was in serious difficulty. Eventually, the drought cost the state agricultural community over ten million U. S. dollars. Federal disaster relief was sought for and received by many Oklahoma counties.

Agricultural drought is primarily determined by the moisture content of the soil and its availability for plant utilization throughout the growing season. Agricultural drought is a function of the interplay between rainfall, temperature, topography, evapotranspiration, and the ability of the soil to store moisture.

During periods of drought conditions, physiognomic changes within vegetation may become apparent on the landscape. When a rainfall event does occur during a period of drought, the "effectiveness" of the precipitation relative to vegetation change is related to such factors as soil type, terrain, vegetation type and condition, and antecedent soil moisture conditions. In addition, the amount, duration, and rate of precipitation enter into the measure of the "effectiveness " of the event. Satellite sensors are capable of discerning many of the changes in physiognomic characteristics of vegetation through spectral radiance measures and manipulation of such measures into vegetation indices. Curran (1980) indicates that indices are sensitive to the rate of plant growth as well as to the amount of growth. Such indices are also sensitive to the changes in vegetation affected by moisture stress. Tucker *et al.* (1983) report that the normalized difference green leaf vegetation index varies in close association with precipitation events. Precipitation amounts can affect vegetation productivity and, therefore, the spectral response from remote sensors sensitive to biomass and other vegetation characteristics.

This paper investigates the relationship between three meteorological drought measures, the CMI, DSI, and the HD, and vegetation characteristics assessed through remotely-sensed satellite sensor data acquired by the AVHRR (Advanced Very High Resolution Radiometer) on-board the NOAA-6 (National Oceanic and Atmospheric Administration) satellite. Multiple regression analysis is used to assess the level of explanation of each of the three meteorological drought indices through the use of remote sensing measures of vegetation conditions input as independent variables to the model building process. Four selected vegetation indices provide the principal model variables used to explain drought variation. In addition, cross-products and the 2nd, 3rd, and 4th powers of all variables were calculated and available for model inclusion in an attempt to introduce nonlinear variables.

AVHRR data are utilized in this study because of their applicability to large area analysis, high temporal resolution for evaluation of dynamic vegetation characteristics, computer compatibility of remotely-sensed data, and the extension of the sensitive spectral region into wavelengths which provide effective vegetation discrimination (Tucker *et al.*, 1984; Barnett and Thompson, 1983). The spatial and temporal character of the 1980 Oklahoma drought is evaluated through the acquisition of four AVHRR data sets extending from June through August, 1980. The severity of drought, its spatial position within the state, and its temporal progression are determined through the selected meteorological measures of drought and are related to AVHRR data through statistical models.

STUDY AREA

The state of Oklahoma covers over 180,000 square kilometers, is astride a forest/grassland ecotone, and is prone to substantial climatic inter-seasonal and intra-seasonal variations. Precipitation varies from a mean of 130 cm annually in the southeast to less than 40 cm in the northwest portion of the state. A period of maximum precipitation occurs in the spring with a second, lesser maximum occurring in the early fall. Precipitation in Oklahoma is strongly tied to the advection of moisture from the Gulf of Mexico. Without the southerly flow of maritime tropical air over the state, drought conditions will occur. In the summer of 1980, extreme drought was caused by an immense upper-tropospheric anticyclone which prevented the Gulf of Mexico moisture from entering the state for several weeks.

Temperatures vary less across the state than does percipitation. Mean annual temperatures range from 17.5°C at Idabel, in the extreme southeast corner of the state, to 12.0°C at Boise City, in the western part of the Oklahoma Panhandle. Average July temperatures range from 25°C in the Panhandle to 27.5°C in the southeastern quadrant of the state. January average temperatures range from 0°C in the Panhandle to 6.5°C in the southeast. Maximum temperatures of 37.8°C or higher may be expected in Oklahoma from June to September.

The vegetation of Oklahoma is quite varied due to differing precipitation regimes, elevation zones, and soil associations. Table 1 presents general vegetation types and basic soil information occurring by region throughout the state.

METEOROLOGIC DROUGHT MEASURES

The three meteorologic drought measures utilized in this paper represent three different measures of soil moisture conditions. Each are calculated for time and space comparisons of drought severity.

The Crop Moisture Index (CMI) calculates crop moisture conditions by examining the interrelationship between the deviations of precipitation levels from normal, soil moisture supplies,

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TABLE 1. GEOGRAPHIC REGIONS OF OKLAHOMA: SELECTED VEGETATION AND SOIL CHARACTERISTICS

GEOGRAPHIC REGION	VEGETATION TYPE	SOIL ORDER
Northeast (Ozark Biotic District)	Oak-hickory forest Oak-pine forest Bottomland forest Post oak-blackjack forest	ULTISOLS
Southeast (Ouachita Biotic District)	Oak-pine forest Oak-hickory forest Post oak-blackjack forest Bottomland forest	ULTISOLS
Southeast (Mississippi Biotic District)	Bottomland forest Loblolly pine forest Oak-hickory forest Cypress bottom forest	ULTISOLS ALLUVIUM
Northeast (Cherokee Biotic District)	Tall-grass prairie Post oak-blackjack forest Bottomland forest	MOLLISOLS
East (Osage Biotic District)	Post oak-blackjack forest Tall-grass prairie Oak-hickory forest Bottomland forest Oak-pine forest	ALFISOLS MOLLISOLS VERTISOLS
West (Mixed Grass (Biotic District)	Tall-grass prairie Mixed-grass eroded plains Sand-sage grasslands Mesquite grasslands Shinnery-oak grasslands Bottomland forest	ALFISOLS MOLLISOLS INCEPTI- SOLS
Northwest (Short Grass Biotic District)	Short-grass highplains Mixed-grass eroded plains Bottomland forest Sand-sage grasslands Pinon-juniper-mesa	MOLLISOLS ALFISOLS ENTISOLS

and evapotranspiration demands. The CMI considers surface as well as subsurface conditions when estimating a moisture availability index for agricultural crops (Palmer, 1968). The CMI is essentially a measure of evapotranspiration anomalies.

The Drought Severity Index (DSI) is designed to assess periods of anomolous precipitation or moisture deficits on, typically, a weekly or monthly basis. The DSI regards soil moisture only as an index of antecedent weather conditions (Palmer, 1965). Drought is defined as an interval of time in which the actual moisture received at a site significantly falls short of the expected or appropriate moisture supply for that climatic region. The severity of drought involves the interrelationship between the magnitude and duration of the moisture deficiency.

The Hydrologic Deficit (HD) uses soil moisture as an indicator of antecedent moisture conditions and describes the amount of moisture available for plant growth. The HD is calculated from an accounting model approach in which air temperature, precipitation, and plant available soil water capacity serve as inputs. The existing soil water status, weekly precipitation, and potential evapotranspiration are considered and moisture is either added or removed from the soil.

METHODOLOGY

Four AVHRR "Local Area Coverage (LAC)" data sets were acquired over Oklahoma for the time periods of 26 June, 14 July, 23 July, and 23 August 1980. These dates were chosen on the basis of cloud free conditions over the entire study area, nadir of the AVHRR data directly over central Oklahoma, and temporal coincidence with critical time periods during the Oklahoma drought. All four acquired data sets were displayed on an image processing system, and control points were selected in order to geographically reference the data to the Universal Transverse Mercator (UTM) coordinate system. A graphic digitizer was used to retrieve the UTM coordinates of the selected control points that were subsequently located on 1:24,000-scale topographic maps. All four satellite sensor data sets were georeferenced with an average root-mean-square error of 0.41 pixel. All data sets were aggregated to a 1609-m by 1609-m cell size. A nearest neighbor approach was utilized to georeference the data sets. The Earth Resources Laboratory Applications Software (ELAS), developed at the NASA National Space Technology Laboratories (NSTL), Mississippi, was utilized for all image processing and related data manipulations.

Figure 1 shows the areal distribution of the 181 Oklahoma cooperative weather stations utilized in this study. UTM coordinates for the weather stations also were obtained through use of a graphic digitizer. Meteorologic data collected at each station provided the basis for determining the CMI, DSI, and the HD for 32 study weeks extending from 24 February to 4 October 1980. Four weekly data sets were selected from the 32 weeks to coincide with the four satellite sensor data sets. A computer program was written to locate all 181 weather stations in the appropriate AVHRR cell for each of the four study weeks through use of the calculated UTM coordinates of both the satellite sensor data and the weather stations.

AVHRR spectral responses in channel 1 (0.58 to 0.68 micrometres), channel 2 (0.725 to 1.10 micrometres), channel 3 (3.55 to 3.93 micrometres), and channel 4 (10.50 to 11.50 micrometres) were extracted from the four satellite sensor data sets for those cells which approximated the location of the 181 meteorologic stations, plus or minus 0.4 cell. Using data from channels 1 and 2 of the AVHRR data, four vegetation indices were calculated for those cells extracted from the four satellite sensor data sets. The four calculated indices were the Gray-McCrary Index (GMI = Ch 2 − Ch 1), Transformed Vegetation Index (TVI = $\sqrt{(\text{Ch 2} - \text{Ch 1}/\text{Ch 2} + \text{Ch 1}) + 0.5}$), Normalized Difference Index (NDI = (Ch 2 − Ch 1)/(Ch 2 + Ch 1)), and the Difference Vegetation Index (DVI = 2.4 (Ch 2 − Ch 1)) (Perry and Lautenschlager, 1984). While these indices have been his-

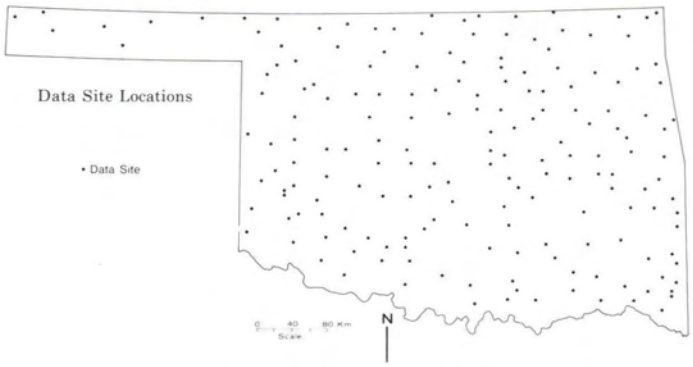

FIG. 1. Meteorologic stations in Oklahoma.

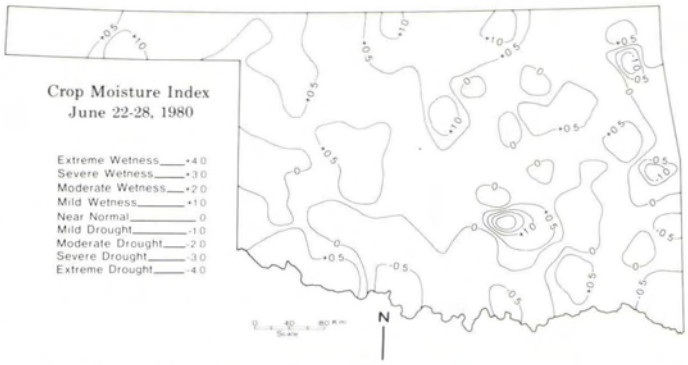

FIG. 2. Crop Moisture Index for Oklahoma (22-28 June 1980).

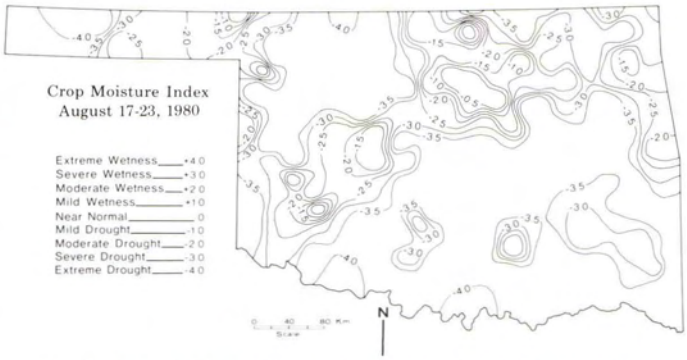

FIG. 3. Crop Moisture Index for Oklahoma (17-23 August 1980).

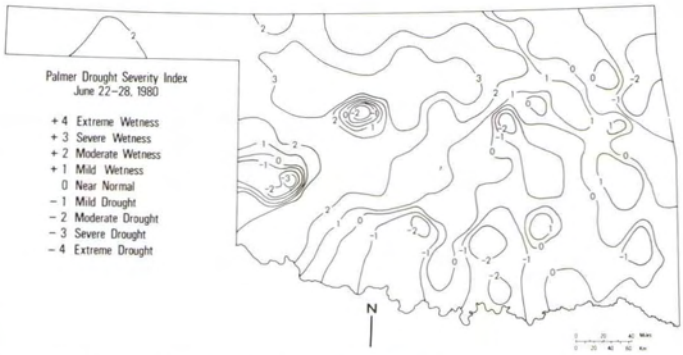

FIG. 4. Drought Severity Index for Oklahoma (22-28 June 1980).

applied to Landsat sensor data for land-cover assessment, they have been altered slightly for use with AVHRR data. Research by Norwine and Greegor (1983) and Brown and Bernier (1982) indicate that the results of vegetation analyses achieved through the use of the first two channels of AVHRR data are very similar to the results secured from the Landsat MSS channels 2 and 4. Leaf pigments and cell structure are the dominant factors controlling leaf reflectance in the visible and near infrared portions of the electromagnetic spectrum. Townshend and Tucker (1984) have shown that in three contrasting regions, AVHRR data represented approximately 70 percent of the variation in Landsat MSS bands 5 and 7 and over 50 percent of the variation in the normalized vegetation index. Gray and McCrary (1981) indicate that NOAA-6 AVHRR and Landsat MSS vegetation indices are in close agreement when compared over a primary crop growing region in South America. In addition to using the first two AVHRR channels for vegetation indice application, all AVHRR channels were used as variables in subsequent analyses.

Digital satellite sensor data are commonly analyzed by using the digital count values for each pixel recorded on computer-compatible tapes. This procedure may produce incorrect results if more than one image is used for mosaics or temporal overlays utilizing multiple satellite platforms because they require different calibrations of their multispectral scanners. Data acquired at different time periods also require corrections for different angles of solar illumination (Robinove, 1982). In this research, NOAA-6 satellite data were exclusively utilized to acquire data over a relatively short time period in 1980. The changing solar illumination conditions caused by the use of four different data sets extending from June to August was addressed by standardizing three AVHRR data sets to the 14 July 1980 data set. Following the application of atmospheric corrections and haze reduction algorithms, a large water body, located on all four data sets, was identified. Five 3 by 3 pixel groups were delineated within the water body. Digital count values within each of the five control areas were retrieved for each of the four AVHRR channels of the 14 July 1980 data set. These control values were compared to count values from the same pixel locations on the other three AVHRR data sets and adjustments were made in the count values to standardize their responses. The adjustments required to standardize all four AVHRR data sets were then applied to the 181 sample site locations within the study area.

In summary, three primary data sets were prepared for each of the four study periods. They contained the meteorologic drought measures, the AVHRR spectral responses in all four channels, and the calculated vegetation indices for each of the 181 meteorologic stations in Oklahoma.

ANALYSIS

The purpose of this research is to identify relationships between three selected spatial and temporal measures of drought characteristics and NOAA AVHRR spectral responses of landscape conditions (Thompson and Wehmanen, 1979). Figures 2 through 5 show a sample of the spatial and temporal variation in drought conditions within the state of Oklahoma at the beginning (26 June 1980) and the end (23 August 1980) of the study period for the CMI and DSI, respectively. Figures 2 and 4 show that, during the first study week (22-28 June 1980), moisture conditions were generally positive in nature, indicating above normal soil and crop moisture conditions. Slight to mild drought conditions, however, were occurring in the southern and extreme eastern portions of the state with isolated pockets in the west central portion. By 17-23 August 1980 (last study week), moderate to extreme drought had affected nearly the entire state. A small region occurring through the central portion of the state, oriented in a southwest to northeast direction, had experienced near normal to mild drought conditions (Figure 3). Figure 5 shows that severe drought (DSI) was prevalent throughout the south and southwest portion of the state with moderate to mild drought conditions generally throughout the remainder of the state. Figures 2 through 5 collectively indicate that drought conditions were becoming more severe with time and that the harsher, more severe drought conditions were becoming more widespread spatially.

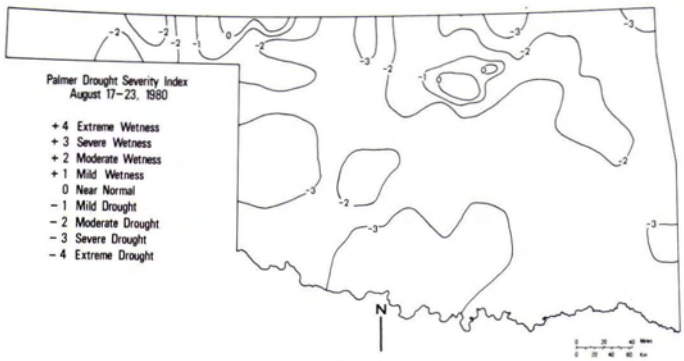

FIG. 5. Drought Severity Index for Oklahoma (17-23 August 1980).

To evaluate the utility of AVHRR data for assessing each of the three drought measures, remote sensing inputs (Table 2) were collected and regressed against each meteorologic drought measure in a multiple regression analysis. The meteorologic drought measures served as the dependent variables, while the remote sensing inputs served as the independent variables in the regression analysis. The 2nd, 3rd, and 4th powers of each variable, and the cross-product of all independent variable combinations, were calculated and also entered into the pool of variables for regression analysis. Powers and cross-products of the independent variables were calculated because of the non-linear relationship of the drought measures throughout the test period. Table 2 also presents the codes used to identify each of the independent variables during computer analysis.

Tables 3, 4, and 5 present the regression model for the Crop Moisture Index, the Drought Severity Index, and the Hydrologic Deficit, respectively, regressed against satellite sensor spectral variables for all four study weeks combined and for the entire state of Oklahoma. The models indicate that 80 percent, 57 percent, and 44 percent of the variation in the meteorologic drought indices, respectively, were explained by a 12-variable model derived through spectral response and time variables. While the regression models do relatively well in estimating the three drought indices, the R^2 values could be increased if a smaller geographic area having less diversity were tested and individual study weeks were evaluated separately.

Figure 6 shows the climatic divisions which comprise the state of Oklahoma. While the divisions are rather arbitrary data reporting and aggregation regions, they do more or less show basic climatic associations. The 181 meteorologic stations were sorted by the nine climatic divisions: approximately 20 stations per division. Table 6 shows that the variation in the drought indices are better explained (higher R^2) when the four study weeks are collectively modeled by climatic division (column indicated by "ALL") than when they were collectively modeled for the entire state. The R^2 values for the nine climatic divisions range from 55 to 87 percent for the Crop Moisture Index, 53 to 89 percent for the Drought Severity Index, and 42 to 86 percent for the Hydrologic Deficit. The increase in R^2 values occurred because the climatic divisions minimized variation in the location and degree of drought conditions over time and throughout the state. A single regression model for each meteorologic

TABLE 2. VARIABLES AND THEIR CODES UTILIZED IN REGRESSION ANALYSES

Variable Code	Variable Code Description
WK1	Week of observation
WK2	Week of observation^2
WK3	Week of observation^3
WK4	Week of observation^4
C1	AVHRR channel 1
C12	AVHRR channel 1^2
C13	AVHRR channel 1^3
C14	AVHRR channel 1^4
C2	AVHRR channel 2
C22	AVHRR channel 2^2
C23	AVHRR channel 2^3
C24	AVHRR channel 2^4
C3	AVHRR channel 3
C32	AVHRR channel 3^2
C33	AVHRR channel 3^3
C34	AVHRR channel 3^4
C4	AVHRR channel 4
C42	AVHRR channel 4^2
C43	AVHRR channel 4^3
C44	AVHRR channel 4^4
GMI	Gray-McCrary Index
GMI2	Gray-McCrary Index^2
GMI3	Gray-McCrary Index^3
GMI4	Gray-McCrary Index^4
TVI	Transformed Vegetation Index
TVI2	Transformed Vegetation Index^2
TVI3	Transformed Vegetation Index^3
TVI4	Transformed Vegetation Index^4
NDI	Normalized Difference Index
NDI2	Normalized Difference Index^2
NDI3	Normalized Difference Index^3
NDI4	Normalized Difference Index^4
DVI	Difference Vegetation Index
DVI2	Difference Vegetation Index^2
DVI3	Difference Vegetation Index^3
DVI4	Difference Vegetation Index^4
CIC2*	AVHRR channel 1 * channel 2
C12C23*	AVHRR channel 1^2 * channel 2^3

*The cross products of all possible variable combinations have been derived for inclusion into the pool of available variables for regression analysis.

TABLE 3. MULTIPLE REGRESSION ANALYSIS OF CMI AND SATELLITE SENSOR SPECTRAL RESPONSES FOR OKLAHOMA: SIGNIFICANT AT 0.05 CONFIDENCE LEVEL.

Dependent Variable	= Beta Value	Independent Variable
(all regions: state of Oklahoma) $R^2 = 0.800$		
	+554.71678	Intercept
	− 50.56171	WK
	+ 2.28389	C1
	− 0.43659	C4
	+ 0.10639	WK3
	− 0.00239	WK4
	− 0.00070	C43
	− 0.01799	WKC3
	− 0.01516	WKC4
	− 0.07269	C1C3
	+ 0.06272	C3C4
	− 1.00879	C3TVI
	+ 0.60887	C4ND

TABLE 4. MULTIPLE REGRESSION ANALYSIS OF DSI AND SATELLITE SENSOR SPECTRAL RESPONSES FOR OKLAHOMA: SIGNIFICANT AT 0.05 CONFIDENCE LEVEL.

Dependent Variable =	Beta Value	Independent Variable
(all regions: state of Oklahoma) $R^2 = 0.572$		
	+ 1.45414	Intercept
	− 4.41988	C1
	− 0.00374	WK2
	− 0.00040	C14
	+ 0.00023	C43
	− 0.00001	C44
	− 7.57115	ND4
	− 0.13576	WKC2
	+ 0.05988	WKDVI
	+ 7.24569	C1TVI
	− 7.18425	C1ND
	+ 0.02359	C1DVI
	− 0.00596	C2C3

TABLE 5. MULTIPLE REGRESSION ANALYSIS OF HD AND SATELLITE SENSOR SPECTRAL RESPONSES FOR OKLAHOMA: SIGNIFICANT AT 0.05 CONFIDENCE LEVEL.

Dependent Variable =	Beta Value	Independent Variable
(all regions: state of Oklahoma) $R^2 = 0.443$		
	−10.54493	Intercept
	+31.42846	TV1
	− 0.64061	DV1
	− 0.02148	WK2
	− 0.00019	C33
	+ 0.00087	C43
	− 0.00002	C44
	− 0.12718	GMI2
	+ 0.01174	GMI3
	+ 0.02783	WKC3
	+ 0.03264	WKGM1
	+ 0.04315	C2C4
	− 0.88492	C4TV1

TABLE 6. MULTIPLE REGRESSION ANALYSIS (R^2) OF THE CROP MOISTURE INDEX, DROUGHT SEVERITY INDEX, AND THE HYDROLOGIC DEFICIT VERSUS SATELLITE SENSOR SPECTRAL RESPONSES BY OKLAHOMA CLIMATIC DIVISIONS FOR *All* FOUR STUDY WEEKS, COLLECTIVELY, AND FOR *ONE* SELECTED STUDY WEEK, VIZ. 20-28 JUNE, INDIVIDUALLY. ALL REGRESSIONS ARE SIGNIFICANT AT THE 0.05 CONFIDENCE LEVEL.

	Crop Moisture Index		Drought Severity Index		Hydrologic Deficit	
Climatic Divisions	All (R^2)	One (R^2)	All (R^2)	One (R^2)	All (R^2)	One (R^2)
1	0.83	0.88	0.71	0.68	0.86	0.83
2	0.87	0.79	0.83	0.89	0.85	0.83
3	0.55	0.63	0.68	0.84	0.78	0.84
4	0.81	0.89	0.81	0.88	0.73	0.51
5	0.84	0.62	0.89	0.91	0.86	0.88
6	0.80	0.85	0.62	0.89	0.42	0.59
7	0.82	0.90	0.75	0.88	0.72	0.84
8	0.83	0.87	0.53	0.81	0.70	0.83
9	0.85	0.86	0.75	0.84	0.46	0.79

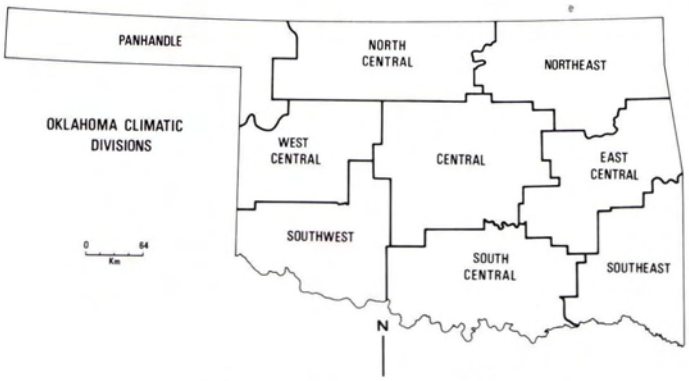

FIG. 6. Climatic divisions within Oklahoma.

drought index could not adequately explain all the variation present. By dividing the state into smaller geographic areas having similar climatic responses, the regression equation can better define a model which explains the reduced level of variation.

Table 6 also shows that the R^2 value for explaining the three drought indices is improved when individual study weeks are analyzed (column indicated by "ONE"). The first study week, 20-28 June, was randomly selected for analysis. The R^2 values for the Crop Moisture Index ranges from 62 to 90 percent, 68 to 91 percent for the Drought Severity Index, and 51 to 88 percent for the Hydrologic Deficit.

A stepwise "MAXR" technique was employed to derive the multiple regression models because numerous independent variables were to be considered during model building. The "MAXR" regression strategy attempts to identify the best one-variable model from the pool of derived variables which produces the highest R^2 value. Another variable, producing the greatest increase in R^2, is then added to the model. Once the two-variable model is obtained, each of the variables in the model are compared to each variable in the pool not included in the model. For each comparison, "MAXR" determines if the R^2 would increase if one variable was replaced by another selection. The appropriate substitution is made, if deemed necessary, to produce the largest increase in R^2. The comparison process continues until "MAXR" finds that no remaining substitution would increase the R^2. The user decides on the number of steps to be included in the regression, usually based on a minimal increase in R^2 with additional steps or a minimal decrease in the sum of squares error (Statistical Analysis System (SAS), 1985).

Curran and Hay (1986) reported that errors in the measurement of ground variables and in the measurement of remotely sensed variables can influence the accuracy of a simple regression model. If measurement errors exist in the independent variables, the estimate of the beta values can be biased. This study involves multiple regression analysis applied to a series of data sets in order to account for variability in a response variable. Variables are utilized to account for linear and nonlinear relationships. Vegetation indices derived through prior field studies and statistical testing serve as the independent variables. Every effort was taken to insure accuracy of ground variables: geo-referencing of satellite data; coordinate translation between the satellite data and the meteorologic stations; and satellite image to satellite image registration. Therefore, any error in the measurement or location of ground variables is considered minimal.

The term multicollinearity refers to the situation in which there are strong intercorrelations among the independent variables. Although multicollinearity makes it difficult to assess partial effects of independent variables, it does not hinder the assessment of their joint effects. If newly added variables are highly correlated with those variables in the model, then the Sum of Squares Error will not decrease very much, but the fit will not be poorer. So, the presence of multicollinearity does not diminish the goodness of the fit of the equation to the observed points. However, it may inhibit the ability to make predictions about the dependent variable, because the standard error of those predictions tends to become inflated (Agresti and Agresti, 1979). The multiple regression models developed in this research indicate marginal effects of collinearity. To reduce or eliminate undesireable collinearity, the following strategy was employed. When polynomial expressions are introduced into the analysis, the mean of the variable can be subtracted from the variable in order to provide "standardization" of that variable. In this way, the entrance of X^2 into the model is not predicted on X first entering the model. Collinearity further can be appraised by looking for large changes in the parameter estimates when an additional variable is added to the regression model. No significant fluctuations in the beta values were observed during model building. Correlation coefficients for the various combinations of independent variables were squared, thereby indicating the percent of variability in one variable explained by another variable in a linear model. Large intercorrelations between variables could be detected and inclusion of such variables into the regression models could be prevented. Changes in F and R^2 values produced by the inclusion of an additional variable into the model were evaluated since the relative "usefulness" of the variable in contributing to the accountability of the model can be assessed. Model building was terminated when F and R^2 fluctuations were insignificant. Finally, the multiple regression algorithm utilized in this analysis is not the standard stepwise regression procedure. During each iteration in the model building process, the entire model is re-evaluated and substitutions in the independent variables can be made if the effect on the R^2 value is replicated by a related

variable. The possibility of adding a variable to the model which is highly intercorrelated with a variable already in the regression is unlikely.

While the same 181 Oklahoma cooperative weather stations distributed throughout the state served as data points for the analysis of four time periods through the summer of 1980, environmental conditions occurred at each station from sample period to sample period which affected the satellite sensor spectral responses in a temporal and spatial context. Rainfall amounts, soil infiltration levels, wind velocities and durations, and vegetation types and their response within the senescent cycle are but some of the factors that affect the level of possible spatial autocorrelation within the multiple regression analyses. While the value of each observation on the independent variable is not strictly independent of prior sample periods because of the very nature of vegetation growth and development over time, the independent variables are independent of adjacent stations due to the coarseness of their distribution and the vagaries of environmental effects. Further, the independent remote sensing variables are being used to describe the variability in drought measures, not to predict changes in drought measures over time and space. Spatial autocorrelation can introduce bias into the regression coefficients (Johnston, 1978). This study does not attempt to build regression models based on models from prior study periods nor to suggest the relative importance of each variable in the regression model through use of variable coefficients. The models do contain variables to aid in explaining linear and non-linear relationships observed in the data for specific study periods.

CONCLUSION

The spatial and temporal variations in drought conditions presented in Figures 2 through 5 were derived through collected meteorologic inputs from a relatively dense network of recording stations. Spatial variability in the CMI, the DSI, and the HD can be seen throughout the state of Oklahoma for each of the four time periods evaluated. Part of the variability in the location and severity of drought conditions observed in the meteorologic-based drought indices can be explained by a combination of remotely sensed measures. The primary objective in developing regression equations was to learn which remotely sensed measures acting simultaneously accounted for the greatest percentage of the variation in each response variable. Cause and effect relationships are, at best, only implied. The remotely sensed measures, manipulated into various vegetation indices, are used as independent variables in the regression analyses. While the vegetation indices are not altogether unrelated and independent from a spectral perspective, they are evaluated for inclusion into the regression models as independent variables. This paper suggests that the integration of different vegetation indices, which measure different properties or attributes of vegetation, can be used to explain significant portions of the variation in drought characteristics evaluated by meteorological-based drought indices. Regression R^2 values for the AVHRR spectral channels and derived vegetation indices indicate that no single remote sensing variable utilized in the regression analyses explained a significant portion of the variation in the meteorologic drought indices. Collectively, however, remote sensing variables explained a meaningful amount of the variation in the tested drought measures.

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