6.2 IDENTIFYING TIME-LAG RELATIONSHIPS BETWEEN VEGETATION CONDITION AND CLIMATE TO PRODUCE VEGETATION OUTLOOK MAPS AND MONITOR DROUGHT

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1. INTRODUCTION

The temporal and spatial vegetation dynamics is highly dependent on many different environmental and biophysical factors. Among these, climate is one of the most important factors that influence the growth and condition of vegetation (Propastin et al., 2006). The complexity of the relationships between vegetation and climate; climate and oceanic dynamics; and the impacts of the combination of ocean-atmosphere interaction on vegetation result in a huge challenge in monitoring drought patterns and its temporal and spatial effects on vegetation.

Traditionally, climate-based drought indicators such as the Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI) have been used for drought monitoring (Wilhite, 2000; Hayes et al., 1999; Wells et al., 2004). However, most climate-based drought monitoring approaches have a limited spatial precision at which drought patterns can be mapped because the indices are calculated from point-based, meteorological measurements collected at weather station locations. In addition, weather stations are scarce in remote areas and not uniformly distributed. As a result, most climate-based drought indices maps depict broad-scale point-based data using statistical-based spatial interpolation techniques and the level of spatial detail in those patterns is highly dependent on the density and distribution of weather stations. Therefore, climate-based drought indices can be enhanced through integration with remote sensing data to be useful for local-scale drought planning and monitoring activities.

Remotely sensed data from the Advanced Very High Resolution Radiometer (AVHRR) have been widely used to monitor vegetation over large areas with relatively higher spatial resolution (e.g., 1-km, 4-km, and 16-km) than the climate data sets commonly used for drought monitoring (DeBeurs and Henebry 2004; Townshend et al. 1987; Tucker et al. 1985). Several studies indicated that remote sensing data has become a common process in quantitative description of vegetation cover that can be used to address temporal and spatial relationships between climate and vegetation including the eventual lagged relationships of climate (e.g., precipitation and temperature) to vegetation response (Camberlin et al., 2007; Groeneveld and Baugh, 2007; Anyamba and Tucker, 2005; Seaquist et al., 2005; Roerink et al.,2003). This quantitative description of vegetation can be used to identify and predict the vegetation stress during drought. In addition, satellite observations are a valuable source of timely, spatially-continuous information for monitoring vegetation dynamics and conditions. Thus, recent advances in remote sensing observations, improvements in the spatial and temporal coverage of weather stations, and improved computational capabilities and statistical analysis techniques have enhanced our capabilities to monitor drought and project its impact on vegetation conditions over large geographic areas.

Studying past and present droughts in relation to climatological, oceanic, and atmospheric parameters could help mitigate future drought impacts on society by improving our understanding of the drought hazard (Tadesse et al, 2005a). Improvements in short-, medium-, and long-range climate predictions enhance our capability to monitor vegetation conditions and develop better drought early warning and knowledge-based decision support systems. However, the complexities of drought characteristics, as well as the highly variable temporal and spatial relationships of climate-vegetation interactions, make the prediction of drought and its impacts on vegetation very challenging. Because of this, for better vegetation monitoring and more accurate assessment of the impacts of drought, a better understanding of how long it takes for a vegetation to respond after a precipitation event occurred is essential (Camberlin et al., 2007; Diodato, 2007; Foody, 2003; Goward and Prince, 1995). In addition, determining how this precipitation-vegetation response relationship varies both in space and time (i.e., geographically and across the growing season) is a fundamental research question to improving drought monitoring and prediction. The overall objective of the study was to assess the nature of temporal and spatial relationships between climate (e.g., precipitation and temperature), oceanic dynamics (e.g., sea surface temperature change in the Pacific and Atlantic ocean), and the vegetation condition, as measured by the satellite-derived standardized seasonal greenness (SSG) in the central United States (Figure 1) using 17 years of data (i.e., 1989 to 2005). Preliminary results of this study are presented in this paper.

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2. BACKGROUND

The National Drought Mitigation Center (NDMC) in partnership with the USDA Risk Management Agency

(RMA) is investigating to produce a new drought monitoring tool called the Vegetation Outlook (VegOut) that provides outlooks of general vegetation conditions based on prior climate and ocean index measurements, satellite-based observations of current vegetation conditions, and other environmental information. A data mining (regression-tree modeling) technique was used to analyze the time-lag relationships between vegetation conditions and the oceanic and climatic observations to predict future vegetation conditions at multiple time steps (Tadesse and Wardlow, 2007, Tadesse et al., 2005b). The VegOut utilizes the inherent time-lag relationship between climate and vegetation response and considers teleconnections between the ocean and climate patterns over the continental U.S. Current research is focusing on the development of 2-, 4-, and 6-week Vegetation Outlooks in the U.S. Great Plains (Figure 1). Alternative modeling techniques and new inputs into the current VegOut models are also being investigated in an effort to provide more accurate predictions of future vegetation conditions.

The overall objective of this study is to identify the best possible temporal and spatial correlation of the climate and oceanic variables that could improve the predictability of the general vegetation condition.

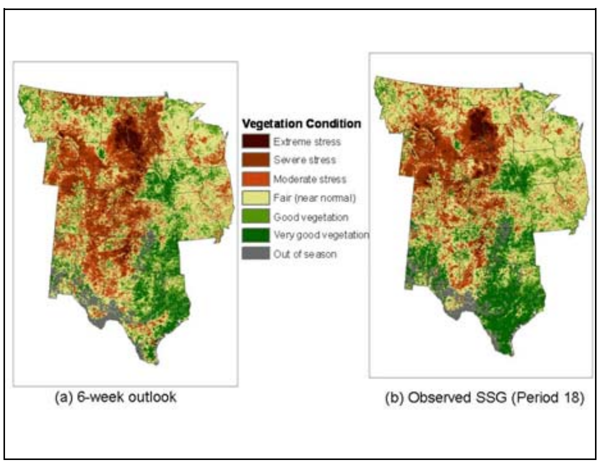

Figure 1. (a) Six-week Vegetation outlook (VegOut) map that was predicted for the period ending September 4, 2006; (b) Bi-weekly Standardized Seasonal Greenness (SSG) observed for the period ending September 4, 2006.

3. DATA

The specific climate, satellite, and oceanic data sets and the data for several static biophysical variables used to identify the relationships between the climate and vegetation; and oceanic indices and climate are briefly described below.

3.1 *Climate-based data*. Two commonly used climate-based drought indices, the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI), were used to represent the climatic variability that affects the vegetation condition. The SPI is based on precipitation data and has the flexibility to detect both short- and long-term drought. The PDSI is calculated from a soil water balance model that considers precipitation, temperature, and available soil water capacity observations at the station. Both indices were initially calculated at each weather station location and interpolated to create raster maps in producing a continuous 1-km^2 gridded surface of SPI and PDSI values across the entire study area.

3.2 *Satellite data*. The Standardized Seasonal Greenness (SSG) metric, which represents the general condition of vegetation, was calculated from 1-km^2 resolution NDVI data over the study area. The SSG is calculated from the Seasonal Greenness (SG) measure, which represents the accumulated NDVI through time from the start of the growing season (as defined from satellite) [Reed et al., 1994]. From the SG data, the SSG is calculated at 2-week time steps throughout the growing season using a standardization formula (i.e., the current SG minus the average SG divided by the standard deviation). The result is a series of SSG images (which have values ranging from -4.0 to +4.0) that show the vegetation condition at 1-km^2 spatial resolution that can be compared spatially to the other geospatial data sets.

3.3 *The oceanic indices*. Eight oceanic indices that may indicate ocean-atmosphere dynamics and teleconnections were used in this study. The indices include the Southern Oscillation Index (SOI), Multivariate El Niño and Southern Oscillation Index (MEI), Pacific Decadal Oscillation (PDO), Atlantic Multi-decadal Oscillation (AMO), Pacific/North American index (PNA), North Atlantic Oscillation index (NAO), Madden-Julian Oscillation (MJO), and Sea Surface Temperature anomalies (SST).

3.4 *Biophysical data*. The biophysical parameters used in this study included land cover type, available soil water capacity, percent of irrigated land, and ecosystem type. The dominant (or majority) value within a 9-km^2 window surrounding each weather station was calculated from the 1-km^2 images for each biophysical variable.

These climate, satellite variables (the bi-weekly historical records from 1989 to 2005), oceanic (2-week values extrapolated from monthly data), and biophysical variables were extracted for each weather station and organized into a database, which would be used in the finding the correlation and analyses to identify the time-lag relationships between the variables and vegetation condition.

4. CLIMATE-VEGETATION TIME SERIES RELATIONSHIPS

The correlation analysis between the climate data and vegetation indices have been carried out to identify the best suited period for the time-lag relationships. This correlation analysis explores the statistical connection between the vegetation condition and the occurrence of precipitation prior to the satellite based observation of vegetation. Computations were done for each period of the observed satellite index with the climate data by lagging 1 to 26 periods (bi-weeks) iteratively in time at each station to determine the maximum correlation. These iterative processes were conducted for a 15-state region (the total of 1420 stations) in the central U.S. resulted in the correlation values ranging from -0.68 to +0.81.

In this correlation analysis, it is observed that the correlation differs for each ecoregion. For example, Figure 2 (a) and (b) illustrate the climate-vegetation time-lag relationships and the differences between two ecoregions with sample size of 12 stations each in Nebraska and Kansas.

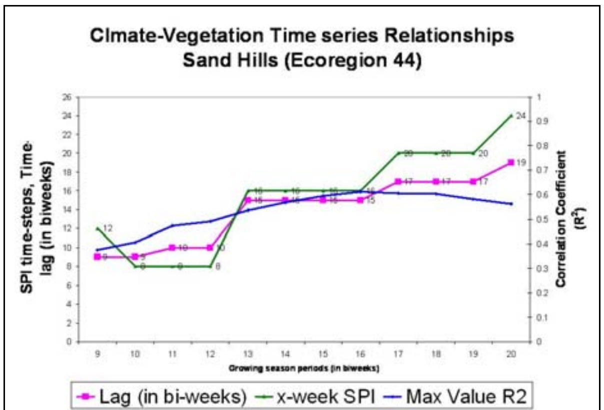

Figure 2 (a)

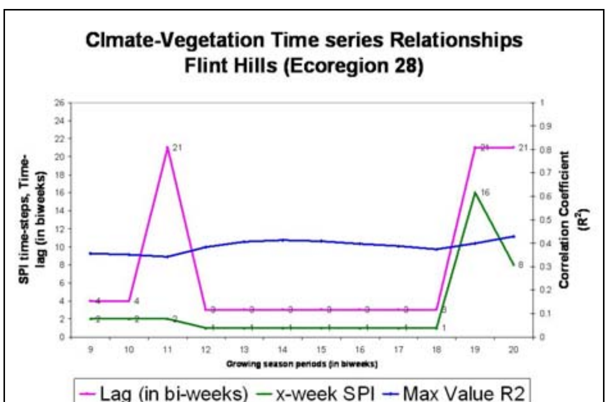

Figure 2 (b)

Figure 2. Climate-Vegetation Time Series Relationships for two ecoregions (a) Sand Hills, Nebraska (Ecoregion 44) and (b) Flint Hills, Kansas (Ecoregion 28). **X-week SPI represents the time interval considered to calculate the SPI.**

The Sand Hills (Nebraska) ecoregion (Figure 2 (a)) showed that the vegetation has a higher correlation with relatively longer-term period (x-week) SPI (i.e., 8-, 16-, and 20-week SPI) than the Flint Hills (Kansas) ecoregion, which was correlated with 1-week and 2-week SPI values in most part of the growing season. In addition, the lag time was also longer for Sand Hills (i.e., 20 to 34 weeks lag) as compared to Flint Hills (i.e., 6 to 8 weeks time lag) for most periods of the growing season. The other difference observed in this analysis was that the correlation coefficient values were higher (i.e., 0.37 to 0.61) for Sand Hills, whereas relatively lower for Flint Hills (i.e., 0.34 to 0.42). In both ecoregions, the correlation coefficient values were lower at the beginning of the season and improved as the season (vegetation condition) progressed.

5. OCEANIC-CLIMATE TIME-LAG RELATIONSHIP

A similar correlation analysis was done to identify the time-lag relationships between the climate and oceanic indices. Eight oceanic indices that were described in Section 2.3 were used in this study. To demonstrate the method, one of the oceanic indices (i.e., the MEI) is discussed in this paper.

Figure 3 shows the correlation coefficient of MEI and PDSI vs. growing season periods. This graph (Figure 3) showed an interesting and consistent time lag pattern of MEI with the PDSI values. It appears that the max R^2 for the lag between the PDSI and MEI (0.25 - 0.3) is about 12 bi-weeks (24 weeks) for the central U.S. This result suggests that MEI values at 6 months lead time may have a relatively better correlation with precipitation condition. This helps in determining which variables to integrate in modeling the VegOut.

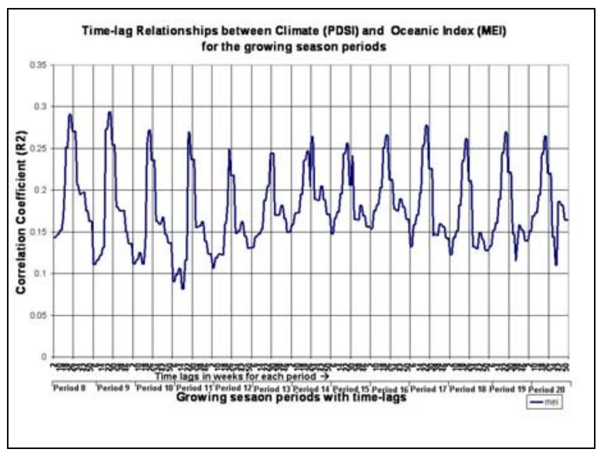

Figure 3. Time-lag relationships of climate (PDSI) and the MEI for the growing season of central U.S.

6. SPATIAL VARIABILITY: EMPIRICAL ORTHOGONAL FUNCTION (EOF) ANALYSIS

Multivariate analyses such as the Empirical Orthogonal Function (EOF) are widely used in many disciplines to identify spatial and temporal patterns among environmental variables. The main advantages of this analysis is to represent an overall statistical structure with fewer critical variables derived from all of the variables contained in the original data (Wilks, 2006). We make use of EOF analysis of the PDSI covariance matrix to identify the primary modes of drought variability in the Central United States. The spatial analysis (EOF) was also used to determine the spatial variability of the climate condition in each period during the growing season. The analysis of the covariance of climate condition was intended to reveal the spatial impact of drought in other years for this same time period. This helps in delineating areas that have similar climatic variability. Those areas with similar climate variability will then be used to delineate regions and investigate the influence of the teleconnection.

The eigenvalue analysis was utilized to retain an appropriate number of significant EOFs to represent a sufficient fraction of the variances in the data. Figure 4 illustrates the eigenvalues to show how each eigenvalue represent the variance of the data. As shown in the figure, the first 3-5 eigenvalues dominated the others in most of the PDSI values because the eigenvalues drop sharply. Note that only the first eigenvalue, representing 41% of total variance within the data set, was utilized in this study.

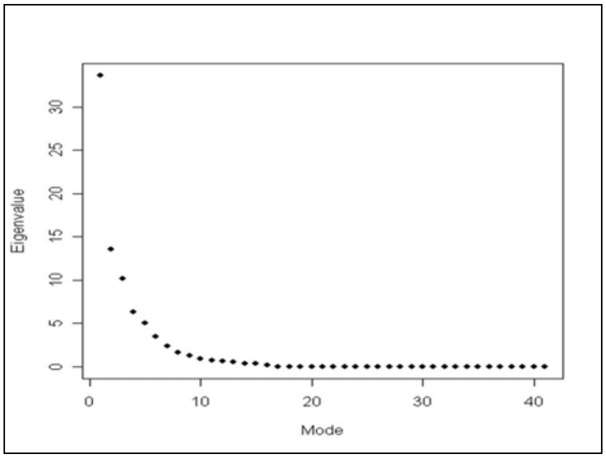

Figure 4. Eigenvalue spectrums of the PDSI values

Figure 5 shows the first EOFs of the PDSI corresponding to the first eigenvalue, which are the dominant mode of variation (i.e., more than 41% cumulative percentage of the total variance). The PDSI values used in this preliminary study were the bi-weekly PDSI values at each weather station in the 15-state study area during one of the summer growing biweekly periods (i.e., second-half of July)) to illustrate the methodology.

As shown in Figure 5, a distribution of strong negative values (-0.3 to 0.2) in the first mode starts in the Rocky Mountain region and encompasses much of the central Great Plains and into near Minnesota as well. Three distinct spatial patterns appear in the first EOF. This occurs in three broad regions, which are characterized by gradual increments of the first EOF found between the Rocky Mountains and south central United States (around Texas). These patterns show that strong negative values (e.g., severe to extreme drought) prevail over southern Montana, Wyoming, western part of North Dakota, western parts of South Dakota, the Sand Hills of Nebraska, eastern Nebraska; while less negative values (e.g., moderate drought) cover parts of the southeast regions, north Texas and the northeast in the study area. The third pattern may show near normal condition as compared to the other two patterns. Similar analysis cab be done for each biweekly periods of the growing season.

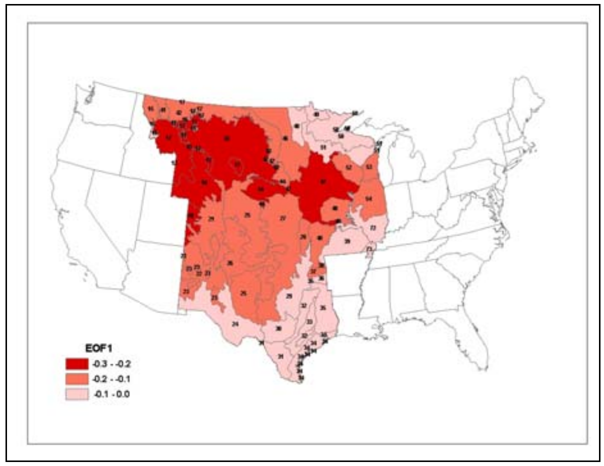

Figure 5. The first EOF of the PDSI values showing the possible spatial drought patterns.

7. FUTURE WORKS

In addition to the preliminary results presented in this paper, further thorough study is in progress to identify time lag relationships of vegetation conditions with climate, oceanic, and other environmental variables. Future research works are planned that include: i) continuing the study of temporal and spatial relationships between climate and vegetation based on not only specific ecoregion but also land cover type; ii) considering more oceanic indices to identify the best variable that correlates with vegetation and its time lag; and iii) selecting the best predictive variables based on the higher correlation values, and integrating the best climate and/or oceanic variables that correlate with vegetation condition to produce improved drought monitoring tool (i.e., the VegOut).

8. SUMMARY

Better understanding of temporal and spatial relationships of precipitation and vegetation conditions have been a fundamental research question in drought monitoring. In this study, it is attempted to address this research question. First, correlation has been done between the observed vegetation condition (i.e., satellite index value) in one period (bi-week) and 26 time-steps (i.e., 26 biweekly periods in a year) separately and iteratively. This correlation provides information that assists in determining the time-lag relationships between effective precipitation in time for vegetation growth or stress. The correlation coefficients in studying the climate-vegetation temporal relationships for the 15-state region are acceptably high for the intended purpose of comparing and determining the best time-lag period of precipitation that influences the vegetation conditions. Furthermore, there is a distinct progression in the level of the correlation (higher correlation coefficients) for specific ecoregions.

Second, the correlation between different oceanic indices and climate (drought) indices has been examined. Based on the correlation coefficient values, it is observed that all the selected oceanic indices do not show strong relationships with the climate and vegetation in the central United States. However, some indices (e.g., MEI) showed relatively significant correlation and interesting temporal pattern that may be helpful in analyzing and predicting vegetation conditions a few weeks ahead of time.

The other important result in this preliminary study was the identification of the spatial pattern (i.e. spatial covariance) of the climate data in the growing season. This may help in identifying the areas that have spatial relationships in intensity and duration of drought. It may also help in reginalizing the areas that have similar climate variation. The results of this relationships is expected to improve the accuracy of the VegOut that helps in drought monitoring. In addition, thorough study in the identifying the time lag relationships of vegetation condition with climate and other environmental variables have an advantage to predict the vegetation condition with better accuracy and higher spatial resolution.

9. AKNOWLEDGEMENTS

This study is supported in part by the U.S.D.A's Federal Crop Insurance Corporation (FCIC) through the Risk Management Agency (RMA) under USDA partnership (02-IE-0831-0228) with the National Drought Mitigation Center, University of Nebraska-Lincoln.

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