Historical Perspectives on AVHRR NDVI and Vegetation Drought Monitoring

Assaf Anyamba [1,2], Compton J. Tucker [2]

[1]Universities Space Research Association (USRA)

[2] Hydrological and Biospheric Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt,

Maryland

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1 INTRODUCTION

Satellite measurements of the biosphere have now become common place in various aspects of large-scale environmental monitoring including drought and crop monitoring. This was not the case until the launch of the Advanced Very High Resolution Radiometer (AVHRR) instrument in June 27, 1979 on board the National Oceanic and Atmospheric Administration (NOAA) first Advanced Television Infrared Observation Satellite (TIROS-N/ NOAA-6) polar orbiting satellite. Initially, the NOAA AVHRR satellites were designed to observe the Earth's weather patterns: primarily cloud dynamics, vertical soundings of the atmosphere, and sea surface temperatures. Early studies on remote sensing of vegetation were focused on understanding seasonality. The vernal advancement and retrogradation of vegetation (e.g., spring green-up, summer abundance, and fall dry-down) was first studied over the north-south expanse of the U.S. Great Plains using data from the Earth Resources Technology Satellite (ERTS) Multi-Spectral Scanner instrument (MSS) (Rouse et al., 1974a; b). Rouse et al (1974) and others demonstrated that biophysical characteristics of vegetation over this rangeland and cropland region could be inferred from satellite spectral measurements despite solar zenith angle differences across a long latitudinal gradient (Deering et al., 1975). Rouse et al. (1974) developed a difference ratio metric between the red and near-infrared (NIR) radiances over their sum to normalize the effects of the solar zenith angle. This derivation is based on the unique spectral response function of vegetated surfaces compared to other surface matter in the visible and NIR portion of the electro-magnetic spectrum as shown in **Figure 1**.

[Insert Figure 1 here]

Spectral reflectances and radiances of green vegetation canopies in the red region of the electromagnetic spectrum are inversely related to in-situ chlorophyll density due to photosynthetic chlorophyll absorption by vegetation in this band. In contrast, energy in the NIR region is scattered and reflected by the canopy structure of the vegetation and hence NIR reflectance is directly related to the green leaf density (Gates et al., 1965; Knipling, 1970; Woolley, 1971). These characteristics drive

the spectral response of plants in these two spectral regions, and the reflectances vary with seasonal changes in vegetation condition (phenology) and/or stress (e.g., drought). When captured remotely through time, such variations can be exploited for vegetation drought monitoring purposes. The ratio between red and NIR reflectances was named the *vegetation index (VI)*. There were other variants of the VI such as the Transformed Vegetation Index (square-root transformation of difference-sum ratio), the simple ratio (red/infrared), and the perpendicular vegetation index (Rouse et al., 1974; Deering et al., 1975; Richardson and Weigand, 1977). Eventually, researchers agreed upon the normalized difference vegetation index (NDVI) as the most efficient and simple metric to identify vegetated areas and their condition (Tucker, 1979). Normalization had many advantages including: minimizing directional reflectance and off-nadir viewing effects, reducing sun-angle, shadow and topographic variation effects and minimizing aerosol and water-vapor effects (Holben, 1986) This enabled large scale vegetation monitoring to be undertaken as normalization enabled different regions to be compared through time

The NDVI is computed as:

$$NDVI = (NIR\text{-}RED) / (NIR\text{+}RED) \qquad \text{(Equation 1)}$$

where RED and NIR are the spectral reflectance measurements in the red and near-infrared regions of the electromagnetic spectrum respectively. These spectral reflectances are ratios of reflected radiation to incoming radiation in each spectral band, with values ranging between 0.0 and 1.0. Theoretically, NDVI values can range between -1.0 and +1.0. However, the typical range of NDVI measured from vegetation and other earth surface materials is between about -0.1 (NIR less than VIS) for non-vegetated surfaces to as high as 0.9 for a dense green vegetation canopies (Tucker, 1979). The NDVI increases with increasing green biomass, changes seasonally, and responds to favorable (e.g. abundant precipitation) or unfavorable climatic-conditions (e.g., drought). This early research was based on National Aeronautic and Space Administration's (NASA) ERTS program, now known as the Landsat program. However, due to the low repeat cycle of the satellite (18 days) and persistent cloud cover

ERTS could not by itself provide the temporal frequency of measurements for systematic monitoring of the land surface. Such high temporal frequency measurements are required for operational applications like drought monitoring and other environmental applications that need cloud-free measurements.

2 A BRIEF HISTORY OF AVHRR

From 1980 to 1982, independent teams of researchers with an interest in land surface monitoring demonstrated that the visible channels on the NOAA AVHRR could be exploited for vegetation monitoring (Tucker et al., 1983). For the first time, vegetation could be monitored at a global scale from a satellite platform with a high temporal frequency of repeat observations (near daily global coverage). This meant that aspects of vegetation seasonality and health could be studied and monitored over time. However, measurements for land surface monitoring were not originally planned in the instrumental design of the NOAA Polar Orbiting Satellite program. The first ever AVHRR was flown on the Television Infrared Observation Satellite (TIROS-N) meteorological satellite in 1978. This AVHRR was configured with 4 spectral channels (0.55-0.90 μm, 0.73-1.1 μm, 3.5-3.9 μm, and 10.5-11.5 μm) customized for meteorological observations and applications. **Table 1** shows the spectral bandwidths of various AVHRR platforms and their possible uses and applications. Note that some channel bandwidths have changed over time with observational and technological requirements

[Insert Table 1 here]

After this pioneer mission, it became apparent that future AVHRR sensors required modifications to increase effectiveness for snow mapping and vegetation monitoring, primarily by narrowing the first channel in the red spectral region to 0.55-0.68 μm (Schneider et al., 1981). Since chlorophyll absorption of solar radiation is confined to these wavelengths, narrowing the first channel made detecting and mapping vegetation more effective, as opposed to the wider channel on the first TIROS, which constrained vegetation monitoring due to atmospheric attenuation. After the launch of the NOAA-6 platform in 1979, a new unintended measurement became possible from meteorological

satellites: the NDVI. A major advantage of AVHRR is its daily global coverage. Because of the

instrument's wide field of view (±55°) and polar-orbiting, sun-synchronous orbit, the AVHRR images

the Earth's land surface twice daily (day and night). Data collected over consecutive days minimize the

effects of cloud cover and other unfavorable atmospheric conditions. The high temporal resolution of

AVHRR, coupled with continual operational data acquisitions over many years, provides a historical

context for long-term monitoring and comparison of land surface conditions. Calculating anomaly

metrics through image differencing or other decomposition techniques can be used to show different

types of ecosystem anomalies that can be used for drought detection (Tucker et al., 1986; Tucker et al.,

1991; Eastman and Fulk, 1993; Tucker, 1996). At present, there is a 30-year history of global AVHRR

NDVI measurements (**Table 2**) that sets a climate-scale benchmark for land surface studies and

applications. (**Figure 2**). This long-term data set can be used to study aspects of drought frequency and

extent, as well as relationships between drought and climate variability.

<div align="center">

[Insert Table 2 Here: History of AVHRR sensors]

[Insert Figure 2 here: Image Series]

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3 NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI)

   3.1 NDVI Derived from AVHRR measurements

As previously defined in the introduction section for Landsat, the NDVI from broadband AVHRR data

is calculated from channels 1 (0.55-0.70 μm) and 2 (0.73-1.1 μm) using the following equation:

$$NDVI = (Channel\ 2 – Channel\ 1)/ (Channel\ 2 + Channel\ 1) \qquad (Equation\ 2).$$

Figure 1 shows comparison between AVHRR and Landsat TM spectral bandwidths for vegetation

mapping and their respective spectral responses. Often, AVHRR's channel 4 or 5 (10.3-11.3; 11.5-12.5

μm) is used as a thermal cloud mask. The thermal cloud mask eliminates NDVI data below a set

brightness temperature threshold, which is usually around 285K. In most tropical latitudes, it is

assumed that the surface brightness temperatures will be above the threshold value (even at high

elevations during the afternoon AVHRR overpasses). Since cloud pixels typically have brightness temperatures less than the land surface, the corresponding NDVI pixels are set to zero (Holben, 1986). Kimes (1983) and Holben and Fraser (1984) found that several factors unrelated to vegetation condition can affect NDVI over green vegetation including: atmospheric effects, cloud detection, and bi-directional reflectance effects. Different compositing techniques had to be investigated to form solutions to these issues (Kimes, 1983; Gatlin et al., 1984; Holben and Fraser, 1984; Kimes et al., 1984; Holben, 1986; Holben et al., 1986). One such technique was to form time-composite images of maximum NDVI values over periods of several days such as 7-, 10-, 15-day or monthly intervals (Holben and Fraser 1984; Holben, 1986). The use of a thermal cloud mask combined with maximum value compositing (MVC) reduces the effects of cloud contamination, atmospheric attenuation, view and illumination geometry, and surface directional reflectance. This is because maximum NDVI values are found to be associated with a clear atmosphere, while compositing tend to minimize other angular effects.

MVC was enacted as standard operating procedure in 1983 for the production of global AVHRR products generated by the Global Inventory Monitoring and Modeling Studies (GIMMS) group at the NASA Goddard Space Flight Center (GSFC). Reasons for enacting this as standard protocol were: a) the AVHRR channels 1 and 2 are spectrally very wide, b) channel 2 contains a water absorption band, c) directional effects were not well understood for broad-band sensors, and d) detailed atmospheric data were not available for explicit atmospheric correction. Therefore, since atmospheric conditions tend to suppress NDVI values in a non-clear atmosphere, MVC was the preferred solution.

3.2 Interpretation of NDVI

Radiation measurements of the Earth's surface from satellites are complex functions of not only the state and properties of the surface itself, but also the conditions and dynamics of the atmosphere

through which the reflected radiation is sensed. NDVI and other derived VIs are an attempt to provide the best estimates of the state and condition of vegetation while minimizing (or eliminating) the influence of other factors as mentioned in the previous section. Derived metrics have to be universal and reliable in time and space irrespective of these extraneous factors. A detailed analysis of the interpretation of VIs is given by Myneni et al. (1995), who concluded that NDVI represents the energy that drives photosynthesis. Over the past two decades, the NDVI has been widely used in many terrestrial applications. Some examples include: drought early warning, locust monitoring, vector disease risk assessment, estimation of forage, agricultural monitoring, land cover classification, and as an input to land surface and biophysical models. Early proof-of-concept studies showed NDVI to be a non-destructive measure of intercepted photosynthetically active radiation (PAR) (Hatfield et al., 1984; Asrar et al., 1984; 1985; Wiegand and Richardson, 1984), photosynthetic capacity, and primary production (Kumar and Monteith, 1982; Asrar et al., 1986; Sellers, 1985; 1987; Tucker and Sellers, 1986). Others studies used NDVI to study total biomass production for a wide range of vegetation types including grasslands, agricultural crops, and salt marshes (Steven et al., 1983; Tucker et al., 1983; 1985b; Hardisky et al., 1984). Intensive field studies using a combination of time-series AVHRR NDVI data and ground-based spectral measurements were used to estimate total biomass production in savanna ecosystems (Tucker et al., 1983; 1985b; Hiernaux and Justice, 1986; Prince and Tucker, 1986). Results from these studies showed that the cumulative NDVI was linearly related with the total above-ground dry biomass sampled at the end of the growing season over the Sahelian zone of Africa as shown in Figure 3.

[Insert Figure 3 here: NDVI vs. above ground biomass - Sahel]

3.3 Early Applications of NDVI

Researchers began to build on these early findings with large-scale studies using coarse-resolution AVHRR NDVI data to map regional to continental scale vegetation types (Norwine and Greegor, 1983;

Justice et al., 1985; Townshend et al., 1985; 1987; Tucker et al., 1985a; Dyer and Crossley 1986; Loveland et al., 1991; Tateishi and Kajiwara, 1992; Eastman and Fulk, 1993; Stone et al., 1994). These studies assumed that mapping the photosynthetic capacity of vegetation would lead to disaggregation of the land surface into land cover groupings based on vegetation function. Pertinent examples of such successful studies were: 1) land cover mapping, 2) investigating the relationship between photosynthetic capacity and rainfall in semi-arid lands (**Figure 4**) (Tucker et al.,1991; Nicholson et al.,1990), and 3) monitoring ecological conditions favorable for insect and birds in arid and semi-arid ecosystems (Tucker et al., 1985c; Hielkema et al.,1986). These studies led to the first use of AVHRR NDVI data in drought and desert locust monitoring through cooperation among NASA GSFC, Food and Agricultural Organization (FAO), and the U.S. Agency for International Development (USAID) (Tucker, 1996; Hutchinson, 1991).

[Insert Figure 4 here: NDVI and Rainfall]

4 AVHRR NDVI DROUGHT APPLICATIONS

The absence of reliable, continuous, and high-density time series of terrestrial weather and climate observations for most parts of the world made it difficult to monitor the spatial patterns of drought and other climate-related anomalies in the past (Janowiak, 1988; Nicholson, 1989). The 1983-1985 large-scale drought that affected the Sahel region of Africa was the signature event that eventually led to the use of coarse spatial resolution AVHRR NDVI data for drought monitoring (**Figure 5**).

[Insert Figure 5 here: Sahel Drought 1984]

High temporal resolution data is key factor for drought monitoring in order to capture the frequency of rainfall events (Tucker et al., 1986). During the early 1980s drought, most rainfall data records that were available through the World Meteorological Organization (WMO) and national meteorological services were compiled as weekly or 10-day cumulative records. Comparisons with near real-time rainfall data could be made by temporally sampling the AVHRR NDVI data to form weekly and

dekedal composites for drought monitoring, particularly with regard to agricultural conditions. Tucker et al. (1991) demonstrated that inter-comparisons of extended time series of NDVI data can provide useful information for drought monitoring in the Sahel region. Baseline vegetation conditions for the growing season (i.e., July to October) were defined as the mean NDVI calculated over several years, and the coefficient of variation in NDVI was used to represent variation between growing seasons. Drought and areas of high inter-annual vegetation variability were reflected in the multi-temporal AVHRR NDVI datasets, especially in the Sahel between the 1984-1985 drought years and the wet year in 1988 (Tucker et al.,1991). With a baseline established for vegetation (by month or growing season), current conditions could be assessed as above, below, or near normal; which is particularly important for monitoring agricultural conditions and determining agricultural production estimates. This was a pioneering first step towards using inter-annual and/or anomaly analysis of NDVI for drought monitoring of vegetation. Other related efforts that have applied NDVI for drought monitoring (Gallo, 1990; Kogan, 1990; 1995; Eidenshink and Hass, 1992; Burgan and Hartford, 1993; Burgan et al., 1996; Unganai and Kogan, 1998; among many others). Several NDVI-based indices developed for monitoring drought are discussed in the following section including vegetation condition conveyed by remotely sensed land surface temperature (LST).

4.1 Drought monitoring using NDVI

4.1.1 NDVI Anomalies

The simplest and most common NDVI-based methods of detecting and mapping drought use NDVI anomalies. Anomalies are calculated as the difference between the NDVI composite value for a specified time period (e.g., week, bi-week, or month) and the long-term mean value for that period. This isolates the variability in the vegetation signal and establishes a meaningful historical context for the current NDVI to determine relative drought severity. Anyamba and Tucker (2005) found that negative NDVI anomalies could identify and map the spatial extent of drought response in vegetation

with a baseline period of 20 years for the Sahel region (**Figure 5**). Other related studies have demonstrated strong relationships on an interannual time scale between NDVI anomalies and El Niño Southern Oscillation (ENSO) phenomena for east Africa (Anyamba and Eastman, 1996; Anyamba et al., 2001), southern Africa (Verdin et al.,1999; Martiny et al., 2006), southeast U.S. (Mennis, 2001), Brazil (Liu and Negron Juarez, 2001; Barbosa et al., 2006), the Northern Hemisphere (Lotsch et al., 2005), and globally (Myneni et al., 1996; Los et al.,2001). By understanding the relationship between ENSO events and drought occurrence, the dynamics of NDVI anomalies can be used to predict an oncoming drought (Liu and Negron Juarez, 2001).

4.1.2 *Standardized Vegetation Index (SVI)*

Building on the NDVI anomaly concept, the Standardized Vegetation Index (SVI) developed by Peters et al. (2002) describes the probability of variation from normal NDVI over multiple years of data (e.g., 12 years), on a weekly time step. The SVI is calculated as a z-score deviation from the mean in units of the standard deviation, calculated from the NDVI values for each pixel location of a composite period for each year during a given reference period. This is expressed in equation form as:

$$Z_{ijk} = \frac{NDVI_{ijk} - \overline{NDVI_{ij}}}{\sigma_{ij}}$$

(Equation 3)

where Z_{ijk} is the z-score, $NDVI_{ijk}$ is the weekly NDVI value, $NDVI_{ij}$ is the mean NDVI value, and σ_{ij} is the standard deviation in NDVI for pixel *i* during week j. The SVI was found to provide useful drought-related vegetation condition information over the U.S. Great Plains in near real-time (Peters et al., 2002). Due to the weekly time step of the SVI maps, this method can capture the rapidly changing patterns of drought and its severity during the growing season over a large area.

4.2 *Drought monitoring using NDVI and land surface temperature*

4.2.1 *Vegetation Condition Index (VCI)*

Kogan and Sullivan (1993) introduced a vegetation index-based drought metric called the Vegetation Condition Index (VCI) and developed a global drought-watch system using this index derived from AVHRR smoothed weekly NDVI data. The VCI is defined as:

$$VCI = (NDVI - NDVI_{min}) * 100 / (NDVI_{max} - NDVI_{min}) \text{ (Equation 4)}$$

where NDVI, $NDVI_{max}$, and $NDVI_{min}$ are values of the smoothed weekly NDVI, and the multiple-year NDVI maximum and minimum, respectively. The smoothed weekly data are scaled relative to the amplitude of their range at each given pixel location and then linearly scaled with a minimum of 0 and maximum of 100. Low values of VCI indicate poor/stressed vegetation-due to unfavorable weather conditions, and vice versa. The pixel-based normalization is performed to minimize the effect of spurious or short-term signals in the data and to amplify the long-term ecological signal. In a VCI study conducted by Liu and Kogan (1996), both NDVI anomalies and the VCI were shown to be correlated with rainfall anomalies. However, VCI was found to be more useful for seasonal and inter-annual comparisons of drought conditions over the South American continent. A study in India found that that the utility of the VCI for drought monitoring was improved when used in conjunction with the Temperature Condition Index (TCI) (Singh et al., 2003), which is calculated from AVHRR's thermal channels (10.3-11.3 µm). The TCI is defined as:

$$TCI = 100(BT_{max} - BT) / (BT_{max} - BT_{min}) \qquad \text{(Equation 5)}$$

where BT, $BT_{max,}$ and BT_{min} are the smoothed weekly, multiple-year maximum and minimum thermal brightness temperatures, respectively. Liu and Kogan (1996) found that the TCI performed better than NDVI and VCI especially in cases where there is excessive soil moisture due to heavy rainfall or persistent cloudiness. Under such conditions, NDVI is depressed and VCI values are low, which can be interpreted erroneously as drought. To address the issue of false positives for drought, a third Vegetation Condition Index (VHI) was developed by Kogan (1995) combining the VCI and TCI. VHI is expressed mathematically as:

$$VHI = \alpha * VCI + (1 - \alpha) * TCI \qquad \text{(Equation 6)}$$

where α is a coefficient determining the relative contribution of the TCI and VCI. Thus, VHI is a proxy characterizing vegetation health by combining estimation of both moisture and thermal conditions. Global maps of VCI, TCI, and VHI are routinely produced and distributed by NOAA-NESDIS at http://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_ftp.php.

4.2.2 *Temperature-NDVI ratio Index*

Another drought index called the Temperature-NDVI ratio was made by integrating land surface temperature and NDVI data. In a study to assess drought impacts over Papua New Guinea, McVicar and Bierwirth (2001) developed this drought index as a ratio of LST and NDVI, which they defined as T_s/NDVI. During a large-scale drought in 2007, the integral of this ratio over the period from January to December showed a strong positive correlation (r^2=0.82) with severe drought conditions in most of the provinces experiencing food shortages. Additionally, the index had an inverse relationship (r^2= 0.81) when plotted against cumulative rainfall from various meteorological stations in areas experiencing drought. The results from the study demonstrated that the composite AVHRR T_s/NDVI ratio provides an effective and rapid way to assess drought conditions. Under conditions of vegetation stress, T_s increases due to decreased transpiration rates, while it decreases at high NDVI values because of higher transpiration rates associated with increased photosynthetic activity.

4.3 LIMITATIONS OF NDVI AS A DROUGHT MONITORING TOOL

The studies previously described illustrate the wide range of applications of NDVI and NDVI-thermal based indices for drought-monitoring. They also bring to light some possible limitations and short-comings of using NDVI, NDVI-derived indices, and combined NDVI-thermal indices for drought applications. Of particular relevance are the limitations of NDVI over dense vegetation canopy areas. For example, in areas such as tropical forests and the boreal regions of the northern hemisphere, NDVI saturates and the relationship between NDVI and canopy dynamics will break down. In very wet

ecosystems, where soil moisture does not limit vegetation growth, the relationship does not hold at the peak of the growing season when NDVI reaches its maxima; although rainfall may still be increasing (Nicholson et al., 1990; Baret and Guyot, 1991; Wang et al., 2005). In such areas, the seasonal variation of NDVI is too small to discern significant drought events. Furthermore, many of these areas have persistent cloud cover throughout the year (Holben, 1986; Fensholt et al., 2006), which can lead to biases in anomaly analysis; this is because of the limited cloud-free observations available to calculate the NDVI and LST long-term means.

In semi-arid areas with sparse vegetation canopies, soil background conditions exert considerable influence on partial canopy spectra and the calculated VIs. Such soil background conditions include primary variations associated with the brightness of bare soil and secondary variations associated with 'color' differences among bare soils, as well as soil-vegetation spectral mixing. For example, a brighter soil background results in higher NDVI values than a dark soil background for the same quantity of partial vegetation cover (Huete et al., 1985; Huete, 1988; Huete and Tucker, 1991). In a study over the Sahel, secondary soil variance was responsible for the Saharan desert 'artifact' areas of increased VI response in AVHRR NDVI imagery. Some bare soil areas on the margins of deserts result in high NIR reflectance relative to the red reflectance, which artificially enhances the system NDVI. On the other hand, in Negev Desert, high NDVI values are shown to be associated with photosynthetic activity of microphytes (lower plants consisting of: mosses, lichens, algae, and cyanobacteria), which cover most of the rock and soil surfaces in this semi-arid region (Karnieli, 1996). Therefore, both soil characteristics and reflectance of lower plant communities may lead to misinterpretation of the vegetation dynamics and overestimation of ecosystem productivity and drought conditions in some semi-arid environments.

Indices that incorporate NDVI and LST, such as VHI and VTCI, rely on a strong inverse relationship

between NDVI and LST. Increasing LST is assumed to negatively impact vegetation vigor and consequently cause plant stress. However, this hypothesis does not hold across all global ecosystems. For example, in northern hemisphere and high altitude ecosystems, like Mongolia, where temperature is a limiting factor on vegetation growth, a positive correlation is found between these two variables. Therefore, neither of the two indices can truly indicate drought in such places (Karnieli et al., 2006; 2010). In these ecosystems, warmer temperatures usually mean more favorable rather than adverse growing conditions for vegetation. Furthermore, even in areas where this NDVI-LST relationship is assumed to be predominantly positive, it has been shown that the relationship varies with location, season, and vegetation type (Lambin and Ehrlich, 1996; Tateishi and Ebata, 2004). Therefore, the application of empirical NDVI-LST based indices such as VHI and VTCI must be restricted to areas and periods where negative correlations are observed and not on a global scale (Karnieli et al., 2010).

5. Operational NDVI-Based Drought Monitoring Systems

Ecosystems such as the grasslands of east Africa, the Sahel, and North America are excellent examples of where NDVI can be effectively used to monitor vegetation and drought conditions. This is because the phenology of vegetation closely reflects the seasonal cycle of rainfall (Nicholson et al., 1990; Justice et al., 1985; Ji and Peters, 2004). Using this knowledge, a drought-monitoring product was prototyped for the central United States. using AVHRR NDVI data as a primary input (Brown et al., 2002; Brown et al., 2008) with the purpose of providing vegetation-specific drought information. This product, known as the Vegetation Drought Response Index (VegDRI), has since been expanded to cover the rest of the continental United States (Wardlow et al., 2009). VegDRI integrates satellite-based observations of vegetation (AVHRR NDVI) with climate-based drought indices, as well as other biophysical information (such as land use/land cover type, soil characteristics, elevation, and ecological conditions). With this data, drought severity maps are produced to indicate any drought-related vegetation stress.

Another drought monitoring risk-based system was developed for East and South East Asia. The system analyzes current vegetation conditions (inferred from AVHRR NDVI) and precipitation data by comparing 10-day intervals to long-term means, in an effort to detect areas of drought and its effects on agriculture (Song et al., 2004). This and many other national early warning and drought monitoring systems (e.g. VegDRI, GIEWS) are based largely upon the pioneering efforts of the USAID to establish the Famine Early Warning System Network (FEWS NET) in 1985. FEWS NET brought together the U.S. government agencies NASA, U.S. Geological Survey (USGS), and NOAA to provide technical-expertise, data (including NDVI), and data systems integration for drought monitoring over Sub-Saharan Africa. This system has now grown to include Haiti, Central America, and Afghanistan. At the global level, the Food and Agriculture Organization (FAO) created the Global Information and Early Warning System on Food and Agriculture (GIEWS). GIEWS relies on FAO's Africa Real Time Environmental Monitoring Information System (ARTEMIS), which has been in existence since 1988. ARTEMIS provides analysis of near real-time AVHRR NDVI data and European METEOSAT satellite cold cloud duration (CCD) images (as a proxy for rainfall) over Africa every 10 days. With a historical satellite record since 1988, GIEWS analysts can pinpoint areas experiencing anomalously low rainfall. Around the world, several national and regional-level drought monitoring centers use NDVI data from AVHRR or other satellite systems as major input to their drought monitoring activities. Two such examples are 1) the AVHRR NDVI-based greenness products produced operationally for the continental U.S. by USGS EROS (http://ivm.cr.usgs.gov/) and 2) Australia's AVHRR NDVI based drought monitoring system (http://www.bom.gov.au/sat/NDVI/NDVI2.shtml).

6 RECENT DEVELOPMENTS IN NDVI ANALYSES

In earlier studies, a major impediment to using AVHRR NDVI in environmental and drought monitoring was the lack of a long-term time series of measurements to establish historically

meaningful baselines. By the early 1990s, a sufficiently long times series (~ 20 years) of NDVI

observations had been collected for research to start utilizing the dataset for large-scale drought

monitoring and studying the relationship between vegetation and large-scale climate variability. Such

long-term analysis studies have employed time series decomposition techniques such as principal

component analysis (PCA) (Eastman and Fulk, 1993), which decompose the NDVI image time series

into various spatial and temporal components (**Figure 6**). In general, the first four principal

components explain most of the variance in the data set and characterize long-term conditions and

different seasonality regimes. Lower order components, inter-annual climate events (such as El

Niño/La Niña- Southern Oscillation), localized patterns, and non-vegetation-related noise from changes

in different satellite platforms over time (Anyamba and Eastman, 1996). Fourier analysis is another

decomposition technique that can detect temporal variability patterns by breaking NDVI into phase and

amplitude components (Azzali and Menenti, 2000). However, Fourier analyses require stationary data,

whereby statistical parameters describing the data series (such as the mean and variance) do not change

over space or time. AVHRR NDVI data series, in particular, do not have these characteristics because

NDVI is subject to external factors like weather, climate, human influences (land cover

transformation), which change the nature of its statistics over time. Therefore, applying a Fourier

transform to non-stationary NDVI time series results in spurious signals. Such signals are not related to

ecosystem dynamics because the technique assumes harmonic behavior; the results are time-dependent

periodic signals, each defined by a unique phase and amplitude value. While regular events such as the

seasonality of vegetation can be extracted, interannual patterns (and hence long-term trends) like

drought are not easily resolved. As a result, the use of Fourier analyses on non-stationary NDVI data

should be performed with caution, with a focus on extracting patterns of seasonality.

A third technique is anomaly analysis, where departures from a base mean period are used to detect

periodic temporal patterns in NDVI. These types of analyses have been used to evaluate the

relationships between NDVI anomaly patterns and ENSO in different regions of the world (Anyamba and Eastman 1996; Myneni et al., 1996; Anyamba et al., 2002), linking vegetation response to variations in large-scale climate mechanisms (see **Figure 6** as an example). The understanding of such linkages or teleconnection patterns, especially the driving mechanisms, can be used in predicting areas that are likely to be impacted by drought (Verdin et al., 1999; Funk et al., 2008).

[Insert Figure 6 here: Principal Components-Analysis]

Unlike floods, drought is a creeping phenomenon and there are now attempts to use time-integrated NDVI data to represent the cumulative aspect of drought. As shown in the example for Australia in **Figure 7**, the impacts of drought (A and B) can be detected as increasing cumulative severity (negative NDVI anomalies) through the 2006-2007 growing season. This drought pattern is a sharp contrast to the period of excess moisture or inferred above normal rainfall (C and D) illustrated by the positive cumulative NDVI anomaly over the 2008-2009 growing season. Such comparisons are useful in examining drought severity from year to year across different regions and are especially useful in drought and agricultural real-time monitoring applications.

These and other studies have not only demonstrated the utility of AVHRR NDVI data in drought monitoring and mapping, but also illustrate the contribution that these time-series data have made towards a better understanding of the processes that lead to drought and the land-surface response to short-term and long-term climate variability.

[Insert Figure 7 here: Australia]

7 INSTRUMENTAL CHALLENGES AND NEXT GENERATION NDVI SENSORS

Although the AVHRR NDVI data have provided unprecedented information for drought and environmental monitoring, there remain challenges for data usage. First of all, the AVHRR has a large

pixel footprint ranging from 1 to 8-km spatial resolution (8 km for most available global data sets). Secondly, the instrument uses wide spectral bandwidths that are subject to atmospheric interference (specifically aerosols and water vapor) and are therefore not ideally suited for vegetation monitoring. Finally, given that AVHRR is an optical sensor, there remain major cloud contamination problems globally, especially in the tropical regions (Holben, 1986; Fensholt et al., 2009). For most areas of the world, the growing season is persistently cloudy with cloud cover present 30% or more of the time. As a result, it is not possible to monitor the dynamics of land-surface conditions at a high temporal frequency in such areas.

Presently, NDVI data from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board NASA's Terra (AM) and Aqua (PM) are now available and widely used in drought monitoring and agricultural applications (Becker-Reshef et al., 2010; Pittman et al., 2010; Gu et al., 2008). MODIS offers a generational improvement over AVHRR. The narrower spectral band widths for the 'red' band (band 1: 620-670nm), increase chlorophyll sensitivity, and the near infrared band (band 2: 841-876nm) has less water vapor absorption, which are marked advancements over AVHRR. Coupled with state-of-art atmospheric correction techniques, the MODIS spectral bands offer improved sensitivity to vegetation conditions/changes and provide data at several temporal (8, 16, and 32 days) and spatial (250-, 500-, and 1000-m) resolutions (Huete et al., 2002; Justice and Townshend, 2002). However, even with these improvements, cloud cover is still an impediment in some areas. Currently, there are various attempts to employ data from the geostationary Meteosat Second Generation (MSG) satellite to fill coverage gaps (Fensholt et al., 2006a), and to exploit radar/microwave systems (uninhibited by clouds) for alternative remote sensing observations of land surface conditions. The MSG can provide cloud-free imagery over cloud--contaminated areas in the tropics with a composite period less than 5 days due to high frequency imaging of the instrument (every 15 minutes) and therefore, cloud-free NDVI can be generated over areas with persistent cloud cover (e.g., West Africa) during the growing season (Fensholt et al., 2006b). Radar also provides cloud-free imaging capabilities that can be

particularly useful in studying vegetation dynamics of northern dense canopy forests (Ranson and Sun, 1994) and the Amazon (Hess et al., 1995). Some studies have begun to investigate the use of these data for drought and vegetation monitoring in a research mode, but have yet to transition the data and techniques to operational production and application. Another method of cloud screening uses Fourier analysis and empirical mode decomposition to derive cloud-free NDVI data by approximating NDVI values of cloudy pixels (Roerink et al., 2000; Pinzon et al., 2005). However, such techniques are better suited to long time-series research data sets than for real-time operational applications; because they require intensive analysis of baseline data for processing a corrected data set.

Another challenge is the inter-satellite instrument calibration among the series of AVHRR instruments that have been used over the past 29+ years to develop a historical NDVI time series. On average, the AVHRR sensors have a lifespan of 5 years (see **Figure 8, Table 2**). Therefore, the existing long-term NDVI dataset is made of a compilation of observations from several different AVHRR instruments with different calibration characteristics. The orbital decay and inter-sensor differences between these instruments introduces bias in the derived NDVI time series, which must be compensated for in order to develop a long-term data set appropriate for environmental monitoring. There have been several attempts to produce a coherent long-term NDVI time-series, including the GIMMS NDVI version **g** dataset (Tucker et al., 2005; Pinzon et al., 2005) (shown in **Figure 8**), and the Long-Term Data Records (LTDR) project (Pedelty et al., 2007). Biases that emerge in using AVHRR instruments from the different sensing platforms are apparent in **Figure 8** for two different land surfaces: the desert of the semi-arid Sahel and Congo forest. Following the uncorrected data series, the discontinuities or dramatic step-change (decrease or increase) in the NDVI time series at different points in time (e.g. 1984, 1988, and 1995) indicate the change from one AVHRR instrument to another. Each instrument has slightly different calibration characteristics; once in orbit it usually takes a couple months for a given instrument to be tested and cleared for operational use. Over time, the AVHRR is subject to

orbital drift (e.g. 1992 to 1994 Congo forest site) and hence, the degradation of sensor performance.

The GIMMS and LTDR data sets are attempts to remove and correct the effects of the aforementioned factors by creating a standardized and coherent time series, as shown in Figure 8. Using the lessons learned from MODIS (i.e., processing techniques, calibration, atmospheric correction, and directional effect determination), the LTDR Project applies these methods to the overlapping AVHRR and MODIS periods. The results gleaned from the overlap period are then applied to the AVHRR data preceding the MODIS instrument, to produce higher quality AVHRR data products. However, these datasets are more appropriate for historical, retrospective studies rather than near real-time operational activities (such as drought monitoring) because of the 1- to 3-year time lag between data updates.

[Insert Figure 8 here: EMD Correction Time Series Sahel and Congo Forest]

Although e MODIS data is available, delays in data processing render them inadequate for real time drought monitoring. MODIS is classified as a science mission and therefore its data processing chain was not designed for operational use. To help overcome this problem, the Land Atmosphere Near real-time Capability for EOS (LANCE) is providing near real-time (<less than 3 hours from observation) access to processed products such "eMODIS" from the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center that is used for drought monitoring (VegDRI: http://drought.unl.edu/vegdri/VegDRI_Main.htm) by FEWS and for VegDRI. In addition, MODIS data from LANCE is utilized for forest threat early warning (USFS Eastern Forest Environmental Threat Assessment Center: http://www.forestthreats.org/), and Global Land Agricultural Monitoring (GLAM: http://www.pecad.fas.usda.gov/glam.cfm), which is a joint project between GSFC and USDA Foreign Agricultural Service (FAS) to monitor global agricultural conditions.

8 CONCLUSIONS AND THE FUTURE

The AVHRR instrument was originally designed solely for meteorological applications. A significant

and unintended use for this data has been land-surface monitoring through use of the NDVI. The

AVHRR NDVI dataset from July 1981 to present has created a record of land-surface conditions that

has never been available before to the scientific and environmental monitoring communities. As

illustrated by the many examples in this chapter, and this book as a whole, these data will continue to

be important to a wide range of users including the drought monitoring community. In the short-term,

there will be continued availability of NDVI data from the NOAA series of satellites (NOAA-18 and

NOAA-19) and the Meteorological Operational polar-orbiting satellite (MetOp) AVHRR series from

the European community that also fly AVHRR instruments. In addition, the availability of data for

since 2001 from MODIS has ensured that there is a redundancy in NDVI data availability.

Additionally, MODIS provides a more spatially detailed global record of NDVI observations (250- and

500-m). These observations are better suited for a full suite of applications that require more landscape-

level observations than the AVHRR 1-km/8-km data could provide. The follow-on satellites in the

Joint Polar Satellite System (JPSS) with the Visible/Infrared Imager Radiometer Suite (VIIRS)

instruments (scheduled to launch in December 2011) will guarantee that the history of coarse- to

medium-scale global remote sensing data will continue to be available to support operational activities

such as drought monitoring. However, commitments by governments and space agencies to continue

these missions into the future, and lessen the turn-around time between science missions to applications

are of paramount importance to the drought monitoring community and other societal applications.

9 ACKNOWLEDGMENTS

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Figure captions

Figure 1. Spectral response curve of vegetation and the relative spectral response of LANDSAT and AVHRR bands in the visible and infrared portions of the electromagnetic spectrum. This characteristic response pattern of vegetation has defined the design of remote sensing instruments and the derivation of various metrics for vegetation monitoring. The AVHHR's wide spectral band widths are subject to atmospheric interference (specifically aerosols and water vapor).

Figure 2. Example of monthly NDVI time series data for Africa and the Middle East for a year. In general, areas of high NDVI or high vegetation density are represented in shades of green while areas of low NDVI/low vegetation density such as semi arid lands and Sahara and Arabian Deserts are show is shades of yellow to brown. The patterns change seasonally from January through December. Data produced by GIMMS Group at NASA/GSFC.

Figure 3. Summary figure for the NOAA AVHRR 1-km NDVI-Sahelian biomass relationship from 1981-1988. The figure represents the specific comparisons between ground sampled above ground total dry herbaceous biomass sampled at the end of the growing season and integrated NDVI data from the same growing season for these specific locations. From Prince (1991): [biomass (kg/ha) = -86+114*ndvi-days; Confidence Intervals: @3 ndvi-days, +/-61 kg/ha; @10 ndvi-days, +/-51 kg/ha). Source: Adapted from C.J. Tucker, *History of the Use of AVHRR Data for Land* Applications, in Advances in the Use of NOAA AVHRR Data for Land Applications (Dordrecht: Kluwer Academic Publishers, 1996), 1-19.

Figure 4. Comparison between average precipitation from 1982 to 1987 for 1794 stations from West Africa and coincident normalized difference vegetation index. Source: Data updated and adapted from C.J. Tucker, *History of the Use of AVHRR Data for Land* Applications, in Advances in the Use of NOAA AVHRR Data for Land Applications (Dordrecht: Kluwer Academic Publishers, 1996), 1-19.

Figure 5. Growing season (July to October) NDVI anomaly for the Sahel region showing the large areal extent of the Sahelian the drought in 1984. Before AVHRR NDVI data became available, such regional to continental mapping of drought extent and patterns was not possible. Source: Adapted from A. Anyamba and C.J. Tucker, "Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003," *J Arid Environ*, (2005) 63: 596-614.

Figure 6. Principal components analysis results of monthly NDVI anomaly time series for Southern Africa for the period 1986-1990 showing the drought spatial pattern in (a) and the associated temporal loadings in (b). This component accounts for 9.73% of the total variance of the anomaly time series. The temporal loadings (B) represent the correlation between each image in the time series with the component spatial pattern in (A). The component loadings show a positive correlation with the drought (negative) spatial component pattern in (A) between late 1986 and late 1987 and negative correlation (wetter or greener than normal conditions) between 1988 and 1990 with the spatial component pattern (A). This component patterm is related interannual variability rainfall associated with El Niño/La Niña-Southern Oscillation (ENSO) phenomenon. The temporal loadings are highly correlated ($r = 0.80$) with ENSO is represented by the Oceanic Nino Index (ONI). Reconstructed after Anyamba and Eastman (1996).

Figure 7. Cumulative NDVI anomalies (CVI) for Australia showing the cumulative nature of drought from December 2006 to 2007 (A) and the wetter/greener-than-normal conditions from December 2008 to February 2009 (C). Cumulative time series profiles of a drought location are shown in (B) and a wet location in (C).

Figure 8. Uncorrected (dotted line) and corrected (thick line) NDVI time series data plots for a Sahel

site and Congo Forest site. The empirical mode decomposition (EMD) method was applied to the

original NDVI data (un-corrected) and eliminates satellite discontinuities for example in 1984, 1988,

1994 and spurious trends (Pinzon et al., 2005).