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The Vegetation Outlook (VegOut): A New Method for Predicting Vegetation Seasonal Greenness

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Abstract: The vegetation outlook (VegOut) is a geospatial tool for predicting general vegetation condition patterns across large areas. VegOut predicts a standardized seasonal greenness (SSG) measure, which represents a general indicator of relative vegetation health. VegOut predicts SSG values at multiple time steps (two to six weeks into the future) based on the analysis of "historical patterns" (i.e., patterns at each 1 km grid cell and time of the year) of satellite, climate, and oceanic data over an 18-year period (1989 to 2006). The model underlying VegOut capitalizes on historical climate–vegetation interactions and ocean–climate teleconnections (such as El Niño and the Southern Oscillation, ENSO) expressed over the 18-year data record and also considers several environmental characteristics (e.g., land use/cover type and soils) that influence vegetation's response to weather conditions to produce 1 km maps that depict future general vegetation conditions. VegOut provides regional-level vegetation monitoring capabilities with local-scale information (e.g., county to sub-county level) that can complement more traditional remote sensing–based approaches that monitor "current" vegetation conditions. In this paper, the VegOut approach is discussed and a case study over the central United States for selected periods of the 2008 growing season is presented to demonstrate the potential of this new tool for assessing and predicting vegetation conditions.

INTRODUCTION

A plant's demand for water and thus general health is dependent on prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil (Wilhite, 2005). Agricultural drought, which is a situation in which the amount of soil moisture no longer meets the plants' needs, can cripple the economy and impact many sectors of society. For example, the 1988 drought, focused on the central and eastern United States, resulted

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in more than \$40 billion in losses to agriculture and related industries, and the wide-spread drought during the spring to early fall of 2002 that spanned large portions of 30 states was estimated to have produced more than \$10 billion in damages and losses (Lott and Ross, 2006). Because of the varied and potentially costly losses caused by drought events, better tools for monitoring and predicting general vegetation conditions are needed to more effectively deal with this natural hazard. The capability to map and monitor vegetation conditions over large geographic areas is critical for a wide range of applications in addition to drought monitoring, such as crop and range-land condition assessments, food security, and ecological studies.

   Satellite-based sensors such as the Advanced Very High Resolution Radiometer (AVHRR) and, more recently, the Moderate Resolution Imaging Spectroradiometer (MODIS) have been widely used for large-area monitoring of vegetation conditions (Tucker et al., 1985; Townshend et al., 1987; Reed et al., 1994; Myneni, et al., 1997; Jakubauskas et al., 2002; DeBeurs and Henebry, 2004). These imagers acquire near-daily global observations of the Earth's land surface, which provide continuous spatial spectral measures across the landscape. The analysis of vegetation index (VI) data calculated from the multispectral data collected by these instruments has been the standard for national- to global-scale vegetation mapping and monitoring for more than two decades.[2] NDVI is calculated from the data collected in the visible red and near-infrared spectral regions, which are responsive to changes in chlorophyll content and internal leaf structure (i.e., spongy mesophyll layer), respectively. NDVI has been found to be well correlated with biophysical parameters such as leaf area index (LAI) and green biomass (Asrar et al., 1989; Baret and Guyot, 1991) and has formed the basis for monitoring large-area vegetation conditions (Jakubauskas et al., 2002; Reed et al., 1996) and major phenological events (Reed et al., 1994). In addition, other VIs have been developed to improve on the NDVI for vegetation monitoring. These include the enhanced vegetation index (EVI) (Huete et al., 2006), the wide dynamic range vegetation index (WDRVI) (Gitelson, 2004), the normalized difference water index (NDWI) (Gao, 1996; Gu et al., 2007), and the vegetation condition index (VCI) (Kogan, 1990). This body of research illustrates the major emphasis that has been placed on improving our capabilities to monitor "current" vegetation conditions over large areas using satellite-based remote sensing.

   The development of methods to "predict" vegetation conditions from satellite-based observations and other ancillary information has been limited (Funk and Brown, 2006; Ji and Peters, 2003). Ji and Peters (2003) developed a vegetation greenness fore-casting model to predict future NDVI values for crops and grasslands in the U.S. Great Plains using 1 km AVHRR NDVI data and time-lagged precipitation and temperature information. Funk and Brown (2006) used AVHRR NDVI observations in combination with observed precipitation and relative humidity to project NDVI changes one to four months into the future for Africa. Considerable strides have been made by the climate community in the area of climate prediction (Kanamitsu et al., 2002; Reinbold et al., 2005; De Haan et al., 2007; Meinke et al., 2007), but the terrestrial community has yet to follow suit in the area of predicting vegetation conditions. The ability

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[2]VIs are calculated from the mathematical transformation of two or more spectral bands, with the most commonly used index being the normalized difference vegetation index (NDVI) (Tucker et al., 1985; Townshend et al., 1987; Reed et al., 1994; Myneni et al., 1997; Jakubauskas et al., 2002; DeBeurs and Henebry, 2004).

to provide outlooks of general vegetation conditions across large geographic areas remains relatively unexplored and the development of such a capacity would provide valuable information for early warning systems (e.g., drought) and a wide range of planning activities.

An integration of remotely sensed data with other relevant environmental variables that influence vegetation holds considerable potential for improving our capabilities to predict future vegetation conditions, as demonstrated in the work of Ji and Peters (2003) and Funk and Brown (2006). Various high-quality environmental data sets (e.g., climate, ocean, and remote sensing observations) with increasing length of records (i.e., > 20 years) are now available to develop new predictive techniques. For example, a more than 20 years historical time series of 1 km AVHRR NDVI observations has been established over the United States. These satellite observations could be coupled with longer records (e.g., ranging from 50 to 100 years) of climate and oceanic data to forecast vegetation conditions. In addition, the availability of advanced statistical data mining techniques such as regression tree analysis has allowed diverse sets of environmental variables to be effectively integrated into new vegetation-related models such as the Vegetation Drought Response Index (VegDRI) (Brown et al., 2008), upon which similar predictive models could be developed.

In this paper, we present a new approach called the Vegetation Outlook (VegOut), which provides future outlooks of general vegetation conditions based on climate and ocean data, satellite-based observations of vegetation conditions, and other general environmental information such as land cover, soils, and elevation. The goal of this new approach is predicting the vegetation condition based on the time-lag relationship between satellite-observed vegetation conditions and oceanic and climatic observations. The predicted (dependent) variable was the standardized seasonal greenness (SSG), which is explained in the following section of the paper. Testing was limited to three shorter-outlook periods (two-, four-, and six-week predictions) for three different periods of the growing season (i.e., early-, mid-, and late). The intent of this paper is to introduce the VegOut methodology and present initial results from a case study conducted for 2008 over a 15-state region centered on the Great Plains to demonstrate VegOut's utility for predicting vegetation conditions across the growing season at a regional scale.

MATERIALS AND METHODS

Study Area

The 15-state region of the central United States (Fig. 1) provides a diverse study area in terms of land cover types, land use practices, and climate across which to test the capability of the VegOut. Land cover varies from alpine forests along the Rocky Mountains in the west and the forested regions of northern Minnesota to the east–west transition of tallgrass to shortgrass prairie across the Plains states and the sparsely vegetated shrubland of southern Texas and New Mexico. In addition, many parts of the study area are intensively cultivated, including the corn- and soybean-dominated Corn Belt (central Nebraska eastward through Illinois), the Winter Wheat Belt (northern Texas, central Oklahoma, and south-central Kansas), and extensive tracts of irrigated and rain-fed cropland stretching the length of the Great Plains from North Dakota to
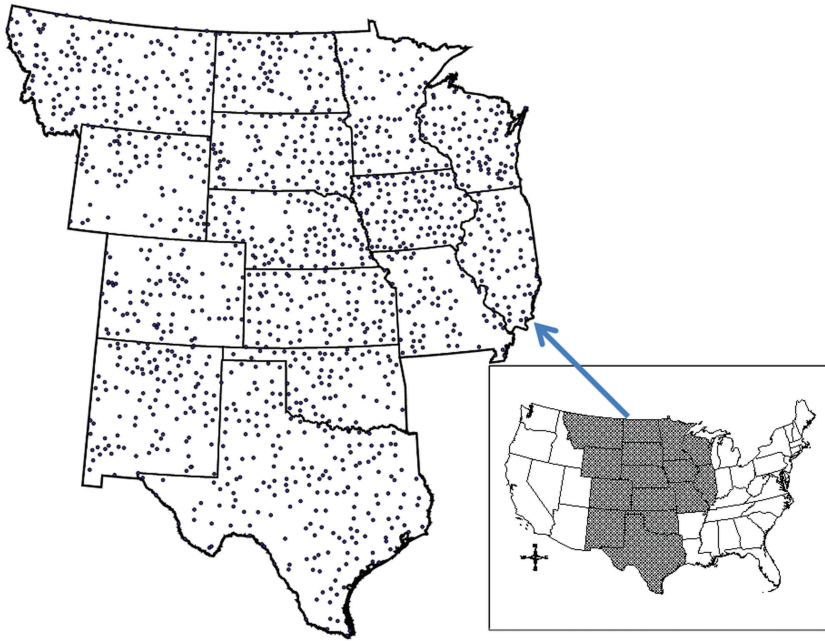
Fig. 1. The 1402 weather stations used for VegOut model development over the 15-state study area of the central United States.

Texas. The study area also has a marked precipitation gradient, ranging from 255 from 510 mm in the semiarid western locations to more than 1,020 mm in the east. Growing-season length is also highly variable, ranging from more than 250 days (late February to late November) in southern Texas to ~125 days (mid-May to late September) in the extreme northern part of the study area.

VegOut Model Inputs and Processes

Figure 2 shows the VegOut model inputs, processes, and final product generation, which are briefly described below.

Climate-based Drought Indicators. Climate is one of the most important factors influencing the growth and condition of vegetation (Braun et al., 2000; Propastin et al., 2006). Traditionally, climate-based drought indicators such as the Standard-ized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI) have been used for drought monitoring (Hayes et al., 1999; Wilhite, 2000; Wells et al., 2004). In this study, the SPI is incorporated to represent meteorological "dryness" during the growing season. Because this study is primarily interested in the effect of pre-cipitation deficits on the spatial patterns of vegetation health and vigor, the analysis has been restricted to a time period roughly aligned to the growing season. To gener-ate climate grids, based on weather station observations (i.e., point data), the inverse distance weight (IDW) interpolation method was used. The interpolation shows that most climate-based drought monitoring approaches have a limited spatial precision at which drought patterns can be mapped because the indices are calculated from
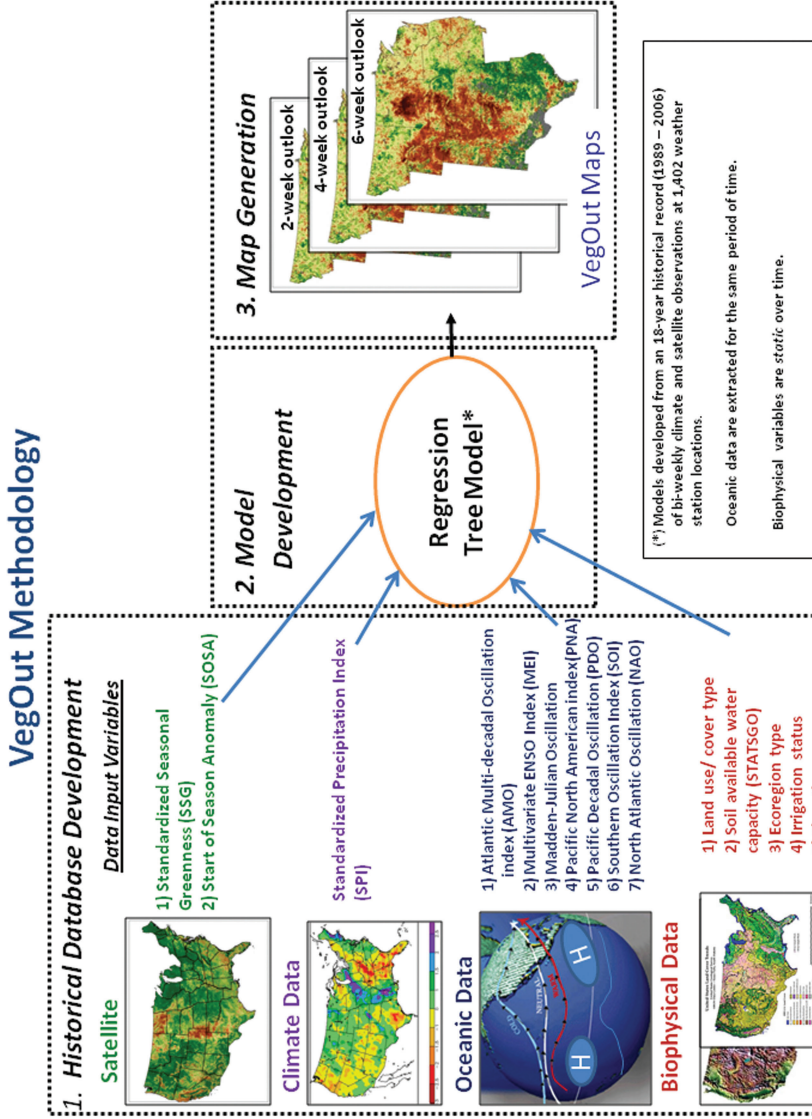
Fig. 2. VegOut database, process (regression-tree rules generation), and outlook map production.

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, the maps of most climate-based drought indices 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.

Satellite Vegetation Monitoring. An 18-year (1989–2006) time series of biweekly-composited 1 km AVHRR NDVI data (Eidenshink, 2006) was used to generate the SSG measure that is predicted by the VegOut model. This dataset was selected because it represents the longest complete time series of vegetation observations for the continental United States at this spatial resolution. In addition, the value of this dataset for acquiring vegetation information across the United States has been firmly established by a large body of research that has applied it to vegetation condition monitoring (Reed et al., 1996; Tieszen et al., 1997; Jakubauskas et al., 2002; Bayarjargala et al., 2006), land cover mapping (Loveland et al., 1995; Tieszen et al., 1997; Jakubauskas et al., 2002), and phenology studies (Reed et al., 1994; Schwartz et al., 2002, 2006).

Typically, for monitoring vegetation conditions, sequential NDVI values across the growing season are summarized to a metric such as seasonal greenness (SG) (also referred to as time-integrated NDVI), which can be considered a general proxy for vegetation performance (i.e., gross primary productivity [GPP]) (Reed et al., 1994; Brown et al., 2008). The SG represents the integrated (or accumulated) NDVI above a baseline "latent" NDVI value (representative of the non-vegetated background signal from soil and non-photosynthetic plant litter) from the start of the growing season (SOS) to a specified time during the year. High SG values reflect high green biomass conditions, whereas low SG values reflect lower biomass levels. For this study, SG values were calculated at the 1 km pixel level across the 15-state region for each biweekly period of the growing season in the 18-year time series using the following equation:

$$SG = \int_{(P1\,=\,SOS)}^{Pn\,=\,EOS} NDVI = \int_{P1}^{P2} (NDVI - NDVI_b) + \int_{P2}^{P3} (NDVI - NDVI_b) + \quad (1)$$

$$\ldots + \int_{Pn\,-\,1}^{Pn} (NDVI - NDVI_b),$$

where $P_1, P_2, P_3 \ldots P_n$ refer to the 14-day periods (i.e., bi-weeks); P_1 is the time period for the historical median SOS, and P_n is the time period for the historical median end of the growing season (EOS). The $NDVI_b$ is the NDVI value at a base line as defined by the median SOS day. Readers are referred to Reed et al. (1994) and Brown et al. (2008) for a more detailed description of the SG calculation from bi-weekly AVHRR NDVI data.

The pixel-level SG values were then converted to standardized seasonal greenness (SSG), which provided a measure of how the general vegetation conditions for a biweekly period in a specific year compare to historical average conditions for that same period in the growing season over the 18-year satellite data record. SSG values were calculated at two-week time steps during the growing season for each year using a standardization formula (Peters et al., 2002) that took the following form:

$$SSG = \frac{SG_i - \overline{SG}}{\sigma}, \tag{2}$$

where SG_i is the seasonal greenness at a particular period within a growing season for a specific year, $\overline{SG}$ is the 18-year historical mean seasonal greenness for the same period, and σ is the standard deviation of the historical record. The result was an 18-year time series of 1 km SSG images (with values ranging from –4.0 to +4.0) that provide standardized (both temporally and spatially) historical vegetation condition information. The empirically based VegOut models are developed using the historical SSG values in two ways. First, the SSG for the "current" period (i.e., date the series of vegetation outlooks are predicted [e.g., July 28]) was used as independent variable to set the "initial" vegetation conditions from which the three projected outlooks will be calculated into the future. Secondly, the SSG values for each of the three preceding outlook periods (e.g., two-week outlook on August 11, four-week outlook on August 25, and six-week outlook on September 8) for which predictions will be calculated were used as dependent variables to establish the historical patterns of vegetation condition evolution over these outlook intervals in the models. Thus, the actual observed values of the SSG are used to "initialize" the prediction of future values of the SSG. Similar approaches that use current observations to establish initial conditions (e.g., temperature on day 0) from which conditions are forecast into the future (temperature + 3 days) have been applied for numerical weather prediction (Neilley and Rose, 2005; Liu and Kalnay, 2008).

The other important satellite variable considered is the start of the season anomaly (SOSA) that represents the departure of the start of the growing season for a specific year from the historical average for a given space (i.e., grid or pixel). The SOSA is calculated at each pixel using the following equation:

$$SOSA_i = SOS_i - SOS_{med}, \tag{3}$$

where $SOSA_i$ is the departure of the start of the growing season for year i in number of days, SOS_i is the start of season (i.e., day of the year, DOY) for year 1, and SOS_{med} is the median start of season DOY from 1989 to 2006. The SOSA was included in the VegOut model to account for the different timings of emergence of natural and agricultural vegetation that can influence the seasonal vegetation performance in a given season.

Oceanic Indices and Teleconnections. The oceans play a significant role in shaping the complex nature of weather and climate, through interactions with the atmosphere. Because of the positions of high and low pressure centers over various parts of

the world, these interactions produce recognizable, repetitive, and alternative weather patterns (e.g., drought or excessive rainfall, and warm or cold temperatures) that affect vegetation conditions. These patterns can occur very far away from their oceanic triggers (i.e., teleconnection) and are a natural part of climate (Hanson, 2008). For example, El Niño–Southern Oscillation (ENSO) events have been associated with various natural events related to vegetation (such as recurring wildland fires and changes in tree-ring patterns) and they have been found to have a significant relationship with the climate in many regions of the world (Panu and Sharma, 2002).

Coupled global ocean–atmospheric models have demonstrated reasonable skill in predicting the sea surface temperature (SST) in the eastern and central Pacific (Barett, 1998; Goddard and Hoerling, 2003), which makes oceanic indices useful in climate and vegetation outlooks. Oceanic indices have been widely used in weather and climate forecasts because they collect quantitative data about current conditions that can be used to project how the complex relationships with climate and general vegetation conditions will evolve (Piechota and Dracup, 1996; Los et al., 2001). Thus, understanding such relationships improves drought and vegetation monitoring.

Atmospheric circulation patterns (high pressure and anticyclonic patterns) have been shown to exert influence on the occurrence of droughts (Stahl and Demuth, 1999). Studies have shown a direct link between the North American anomalous weather in the spring and early summer of drought years and SST anomalies that result from changes in storm tracks and moisture advection from the oceans to land (Trenberth and Guillemot, 1996; Stahl and Demuth, 1999). For example, Trenberth and Guillemot (1996) found that tropical Pacific SST changes and the La Niña event in 1988 had a significant role in establishing large-scale atmospheric circulation anomalies that were favorable for drought. These anomalies include the disruption in atmospheric heating patterns in the tropics by changing the location of the inter-tropical convergence zone (ITCZ), which could have initiated the circulation anomalies across North America responsible for the drought that year (Trenberth and Guillemot, 1996). Because vegetation monitoring is dependent on both precipitation and temperature, other studies (Smith et al., 1999; Trenberth and Caron, 2000; Larkin and Harrison, 2005a) indicated substantial anomalies in U.S. seasonal temperature and precipitation, providing a foundation for U.S. seasonal forecasts when they are statistically significant and robustly associated with El Niño (Larkin and Harrison, 2005b).

In predicting the vegetation condition, the overall assumption in this study is that each variable contributes to the complex nature of the vegetation growth. These variables alone may not be enough (separately) to explain the vegetation dynamics. Thus, the list of selected variables (though they are not an exhaustive list by themselves) to be integrated is considered to include the most important parameters for contributing to vegetation growth and predicting vegetation condition.

Seven oceanic indices are integrated into the predictions to account for the temporal and spatial relationships between ocean–atmosphere dynamics and climate–vegetation interactions (i.e., teleconnection patterns) that have been observed over the central United States (Barnston et al., 2005; Tadesse et al., 2005b; Los et al., 2001; Asner et al., 2000). These indices include the Atlantic Multi-decadal Oscillation Index (AMO), Madden-Julian Oscillation (MJO), Pacific Decadal Oscillation (PDO), Southern Oscillation Index (SOI), North Atlantic Oscillation (NAO), Multivariate ENSO Index (MEI), and Pacific North American Index (PNA). Table 1 provides the

Table 1. List of Variables, Update Cycles, and Data Sources for the VegOut Model

Data set name	Acronym	Type (update cycle)	Source	Data set name	Acronym	Type	Source
Standardized seasonal greenness	SSG	Satellite (continuous, 14-day)	AVHRR/NDVI	Atlantic Multidecadal Oscillation Index	SSG	Oceanic/atmospheric (same value for all sites, monthly)	CPC/NOAA
Start of season anomaly	SOSA	Satellite (continuous, annual)	AVHRR/NDVI	Madden-Julian Oscillation	SOSA	Oceanic/atmospheric (same value for all sites, 14-day)	BoM/Australia
Standardized precipitation index	SPI	Climate ASCII (at sites), 1 km raster surface (continuous, 14-day)	ACIS/HPRCC	Pacific Decadal Oscillation	SPI	Oceanic/atmospheric (same value for all sites, monthly)	JISAO/UW/NOAA
Ecological regions	ECO	Biophysical (categorical, static)	EPA/Ecoregions	Southern Oscillation Index	ECO	Oceanic/atmospheric (same value for all sites, monthly)	CPC/NOAA
Soil available water capacity	AWC	Biophysical (continuous, static)	STATSGO	North Atlantic Oscillation	AWC	Oceanic/atmospheric (same value for all sites, monthly)	CPC/NOAA
Digital elevation	DEM	Biophysical (continuous, static)	USGS-EROS	Multivariate ENSO Index	DEM	Oceanic/atmospheric (same value for all sites, monthly)	CPC/NOAA
Land cover	NLCD	Biophysical (categorical, static)	National Land Cover Database		NLCD		
Irrigated agriculture	IrrAg	Biophysical (continuous, static)	USGS-EROS	Pacific North American Index	IrrAg	Oceanic/atmospheric (same value for all sites, monthly)	CPC/NOAA

references (sources) for these indices. For each index, a 1 km grid is created for each monthly value and used twice in building the model to match the biweekly values of climate and satellite data.

Biophysical Parameters. Temporal and spatial vegetation patterns and their phenological dynamics are highly dependent on many environmental and biophysical factors in addition to climate. Most, if not all, climate-based global and regional prediction models assume that vegetation conditions are exclusively dependent on climate controls as opposed to the influence of other non-climatic factors such as topography, land use/land cover (LULC) type, and soil characteristics. Researchers have indicated that a comprehensive approach that includes not only the climate, but also soil, water (above and below the ground) and other environmental factors is necessary to build an integrated drought monitoring system (Svoboda et al., 2004). In developing a drought monitoring tool for vegetation stress, Tadesse et al. (2005a) and Brown et al. (2008) included a number of biophysical variables (ecoregion, elevation, LULC type, and soil available water holding capacity) that influence general vegetation performance. The present study builds on this work by integrating the same set of environmental variables into the VegOut model to be analyzed in combination with climate-, oceanic-, and satellite-related variables for vegetation condition predictions. To integrate the biophysical variables with other data (e.g., climate and satellite data), 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 and used for VegOut model development. These biophysical data are briefly explained below.

Digital Elevation Model (DEM). The DEM consists of a 1 km raster grid of regularly spaced elevation values that have been primarily derived from the U.S. Geological Survey's (USGS) 30 m DEMs, along with higher resolution data where available. The DEM was included in the VegOut models to account for the impacts of elevation on vegetation across the diverse 15-state study area, which includes mountains, plains, and coastal areas.

National Land Cover Data (NLCD). A 1 km land cover map was generated from the USGS 30 m National Land Cover Database 2001 (NLCD, 2001) (Homer et al., 2004) and incorporated into the VegOut model to reflect the different seasonal NDVI signals and climate-vegetation responses that are exhibited by different land cover types (e.g., cropland versus evergreen forest).The majority land cover class of the 30 m NLCD map contained within each 1 km The AVHRR pixel footprint was assigned as thematic class to each pixel in a 1 km land cover map.

Soil Available Water Capacity (AWC). AWC was extracted from the STATSGO soils database (USDA, 1994) [Authors: USDA, 1994 is not included in the references list. Please supply the missing reference] for each STATSGO soil map unit over the study area and converted to a 1 km raster grid. The AWC variable was included in the VegOut model to represent the potential of the soil to hold moisture and make it available to plants, which exerts control over plant growth (Churkina et al., 1999) and influences the sensitivity and response of vegetation to drought.

Irrigated Agriculture (IrrAg). The representation of irrigation in VegOut is critical because rainfed vegetation has much greater sensitivity and response to drought than irrigated vegetation. Geospatial irrigation status information across the United States was modeled by Brown et al. (2009). This model incorporated 2002 satellite-derived vegetation index data at a 250 m^2 resolution observed by MODIS (to identify the

annual peak of growing season productivity in a drought year), USDA county irrigation statistics (i.e., number of irrigated acres), and land cover categories. The percentage of irrigated farmland was calculated using the fraction of the area of irrigated land in a 1 km pixel. The land cover information was used based on the 2001 NLCD that was described above (Homer et al., 2004).

Ecoregions (ECO). A 1 km ecoregion grid was generated from the Omernik Level III ecoregion data (Omernik, 1987). The study area comprised 42 ecoregions that divide the regional landscape of 15 states into a series of geographic areas with similar ecosystems and environmental resources, which were identified using both abiotic (for example, climate, geology, hydrology, land use, and physiography) and biotic (for example, vegetation and wildlife) criteria (Omernik, 1995). Many environmental characteristics (for example, growing season length and plant species) exhibit considerable variability across the 15-state study area, which can influence the sensitivity of vegetation to climate. The ECO variable provided a geographic framework to help account for the diverse combination of biotic and abiotic factors encountered across the study area, which can influence the vegetative response of a general land cover type (e.g., grassland) in markedly different ways in this region.

Weather Station Selection and Development of the Training Database

For VegOut model development, a training database was built to extract historical climate and satellite information as well as the biophysical parameters (considered static over the 18-year record) at 1,402 weather station locations across the 15-state study area (Fig. 1). The selection of these specific stations from a pool of 3,000+ total stations was accomplished in a two-step process that involved: (1) quality assurance (QA) screening of the station's climate data record; and (2) removal of stations located in predominately urban areas in close proximity to large water bodies. At the initial QA screening stage, stations were eliminated if they were currently inactive, had a large proportion of missing observations (i.e., > 10% missing historical data), or had a historical record length that was too short (i.e., < 30 years of precipitation data and < 20 years of temperature data) to accurately calculate the SPI variable. The remaining stations were then screened by land cover criteria to remove stations that were surrounded by predominately urban areas or water (i.e., > 50% of total area) within a 9-km^2 area (i.e., 3 × 3 1 km pixel window centered on the station). The land cover screening was implemented because stations surrounded by these two land cover types often do not have a representative signal of natural vegetation conditions in the satellite observations because of the non-vegetated nature of the cover type's surface (i.e., water and densely built-up areas) or human activities such as municipal irrigation or lawns. As a result, the inclusion of such stations in the training data could result in signals observed from satellite that are representative of the surrounding vegetation, which could be under drought stress.

The historical time series of biweekly SPI values for each of the 1,402 stations was then generated for an 18-year period (1989 to 2006). For each oceanic index, the same value for a given bi-week was assigned to all stations. In addition, for oceanic indices reported on a monthly time step, the same monthly value was assigned to all bi-weeks where the majority of the 14-day windows occurred in that specific month. All the remaining satellite and biophysical variables were in a gridded raster format,

which required a geographic summarization of each variable across a window of grid cells (or pixels) that surrounded each station's location. A 3×3 window centered on the station's location was implemented for this study, whereby the mean of the 9 grid cells' values was calculated for continuous variables (e.g., average percentage of irrigated land or average soil water holding capacity) and the majority class for nominal or categorical variables (e.g., majority land cover type). This procedure was used to calculate an 18-year time series of biweekly SSG values to match the climate and oceanic variables. The SOSA metric was also summarized across a 9-cell window for each year, as it represents an annual measure. The station-based biophysical values were also calculated in the same fashion, but remained static over the 18-year data record.

VegOut Model Derivation Using Regression Tree Algorithm

For VegOut model derivation, an empirically based regression tree analysis technique was applied to the 18 years of historical data in the training data base for each of the targeted, seasonal bi-weeks being analyzed in this study. Regression tree approaches are increasingly being used for environmental modeling (De'ath and Fabricius, 2000; Yang et al., 2003; Zhang et al., 2007; Brown et al., 2008; Wylie et al., 2008) given their ability to effectively analyze large data volumes, identify complex relationships among variables, and handle non-parametric data distributions and a variety of data types (e.g., continuous, nominal, and ordinal). Regression tree techniques have the ability to identify complex historical relationships between the suite of climate-, oceanic-, and satellite-based parameters and static biophysical variables that can be used to predict future vegetation conditions (i.e., SSG). The basic concept is that this statistically based approach will search for and identify similar patterns in the climate, oceanic, and satellite records to those of a specific prediction date to base the vegetation condition (or SSG) predictions.

In this study, a commercial classification and regression tree (CART) algorithm called Cubist (Quinlan, 1993; Rulequest, 2009) was used to analyze the historical data in the training database and generate rule-based, piecewise linear regression VegOut models for each biweekly period. This CART algorithm performs a binary, recursive partitioning process that splits the initial set of training observations (root or parent node) into two child nodes that each contains a subset of more homogeneous training observations. This process is repeated, further subdividing the training data into pairs of child nodes until the partitioning process is terminated by user-defined criteria (e.g., minimum rule cover or percent of cases allowed to generate a rule) (Breiman et al., 1984; Yang et al., 2003). The CART algorithm produces a series of rule-based models from this partitioning. Each rule set has a corresponding multivariate linear regression equation that can be used to predict the value of the SSG measure for this study. Regression tree models can account for nonlinear relationships between predictive and target variables through a series of regression equations associated with different rule sets.

The VegOut models are composed of an unordered set of rules, with each rule having the syntax "if x conditions are met, then use the associated linear regression model." The following provides an example of the rules generated by the Cubist algorithm for VegOut:

Example Rule 1:

if:

ECO in {Western Corn Belt Plains, Central Great Plains}
LandCover in {Grassland, Pasture/Hay, Row Crops}
SPI ≤ –1.2
AWC ≤ 5.46
AMO < 0.6
PDO < –1.1
MEI < –2.0

then:

VegOut = –1.5 + 0.6SSG + 1.48SPI – 0.14 AWC + 0.25AMO – 0.5MEI + 0.14PDO.

If the data associated with a specific case meet the conditional statement for the ecoregion (i.e., located in the Western Corn Belt Plains and/or Central Great Plains) and the threshold criteria for the five continuous variables (i.e., SPI, AWC, AMO, PDO, and MEI), and are represented by one of the three land cover classes (i.e., grassland, hay/pasture, and row crops) identified by the Cubist regression algorithm, then the above multivariate linear regression equation is used to calculate a VegOut value (i.e., future SSG value) for a specific outlook period interval. If two or more rules in the Cubist model apply to the case, then the predicted values from each regression equation will be averaged to arrive at the final, predicted VegOut value.

To create a series of predicted maps, the VegOut rules for a given period (bi-week) model were applied to the gridded image (1 km raster) input data using *MapCubist* software developed at the USGS Center for Earth Resources Observation and Science (EROS). During the process of model implementation to the image data, the values of all the input variables (as listed in Table 1) for each pixel were considered to determine which rule(s) to select and then apply the corresponding linear regression equation(s) associated with the rule(s) to input data values in order to calculate the VegOut value for each pixel across the study area.

Model Validation

The predictive accuracy (or skill) of the VegOut model was validated using several different statistical measures: the mean absolute difference of a tree (MAD(T)), the relative error (RE), and Pearson's product-moment correlation coefficient (*R*). MAD(T) is expressed as:

$$\text{MAD(T)} = \frac{1}{N} \sum_{i=1}^{n} \left| O_i - f(\bar{x}_i) \right|, \tag{4}$$

where O_i is the function $f(\bar{x}_i)$, which represents the regression plane through the training set, and *N* is the number of samples used to establish the tree (Yang et al. 2003; Rulequest 2009). The RE is defined as:

$$RE(T) \;=\; \frac{MAD(T)}{R(\mu)},\qquad\qquad (5)$$

where $R(\mu)$ is the average error that would result from always predicting the mean value (ibid.). It is used to standardize the average error or mean absolute difference, MAD(T). For useful models, the relative error should be less than 1. In addition to the average error and relative error, Cubist also calculates Pearson's product-moment correlation coefficient (R) between actual and predicted values (ibid.). Then the coefficient of determination (R^2) was calculated to measure the agreement between the cases' actual values of the target attribute and those values predicted by the model. The evaluation of the models using the above statistical measures was done on the test data set (i.e., randomly selected 10% of the historical data over 18 years), which had not been seen in the 90% of the training data set used to train the prediction model.

RESULTS AND DISCUSSION

VegOut Model Performance across the Growing Season

A summary of the VegOut models' accuracy and error terms across 10 bi-weekly periods of the growing season is given in Table 2. The error terms (i.e., the MAD and RE values for each bi-week) shown in the table reveal that the MAD values range from 0.06 to 0.25, 0.1 to 0.33, and 0.15 to 0.35, for the two-, four-, and six-week outlook models, respectively. The relative error term (RE) also showed values ranging from 0.10 to 0.33, 0.14 to 0.49, and 0.21 to 0.51 for the two-, four-, and six-week outlook models, respectively. For the SSG values ranging between –4 and 4, these low MAD and RE values indicate higher accuracy of the predictive models. In addition, the coefficient of determination (R^2) values between the observed and predicted SSG values across the growing season ranged from 0.83 to 0.99, 0.72 to 0.98, and 0.71 to 0.94, for the two-, four-, and six-week outlooks, respectively.

An assessment of the intra-annual predictive accuracy of individual two-, four-, and six-week VegOut models for each 14-day period across the growing season showed that the lowest predictive accuracy (i.e., higher MAD and RE values and lower R^2) occurred in the early spring (late April and early May). Predictive accuracy improved and was relatively stable for the summer (peak growing season) and fall (senescence) periods (Table 2). The relatively lower predictive accuracy in the early spring may be due to low green biomass, resulting in greater fluctuation of the low SSG values in the early growing seasons and magnified by periods of unusually warm or cold temperatures, which is highly variable between years and within individual growing seasons.

### Longer Outlook Period (More than Eight Weeks) Testing

Longer outlook periods ranging from eight-week to 16-week SSG predictions were also preliminarily tested for period 12 (i.e., first half of June) to determine VegOut's performance over two- to four-month intervals. The early June period was selected because it allowed longer-duration SSG predictions to be made across the core of the growing season, with the testing terminating at the 16-week interval, which occurs in October when the majority of vegetation across the study is partially or fully

Table 2. Evaluation of the VegOut Model[a]

Period	Outlooks	Evaluation of test data			Period	Outlooks	Evaluation of test data		
		MAD(T)	RE(T)	R^2			MAD(T)	RE(T)	R^2
Period 9 (April 23–May 6)	Two-week	0.25	0.37	0.83	Period 14 (July 2–15)	Two-week	0.09	0.13	0.98
	Four-week	0.33	0.49	0.72		Four-week	0.16	0.23	0.92
	Six-week	0.35	0.51	0.71		Six-week	0.20	0.30	0.90
Period 10 (May 7–20)	Two-week	0.17	0.25	0.92	Period 15 (July 16–29)	Two-week	0.09	0.12	0.98
	Four-week	0.25	0.36	0.85		Four-week	0.14	0.20	0.94
	Six-week	0.31	0.45	0.77		Six-week	0.18	0.26	0.92
Period 11 (May 21–June 3)	Two-week	0.14	0.21	0.94	Period 16 (July 30–Aug 12)	Two-week	0.08	0.11	0.98
	Four-week	0.21	0.30	0.88		Four-week	0.13	0.18	0.96
	Six-week	0.28	0.41	0.81		Six-week	0.17	0.24	0.92
Period 12 (June 4–17)	Two-week	0.11	0.16	0.98	Period 17 (Aug 13–26)	Two-week	0.07	0.10	0.98
	Four-week	0.19	0.28	0.92		Four-week	0.11	0.16	0.96
	Six-week	0.26	0.37	0.85		Six-week	0.15	0.21	0.94
Period 13 (June 18–July 1)	Two-week	0.10	0.14	0.98	Period 18 (Aug 27–Sept 9)	Two-week	0.06	0.09	0.99
	Four-week	0.17	0.24	0.94		Four-week	0.10	0.14	0.98
	Six-week	0.22	0.32	0.88		Six-week	n.a.	n.a.	n.a.

[a]The mean absolute difference (MAD) values, relative error (RE), and coefficient of determination (R^2) between the observed and predicted SSG are shown for each period and the corresponding outlooks in all periods of the growing season.
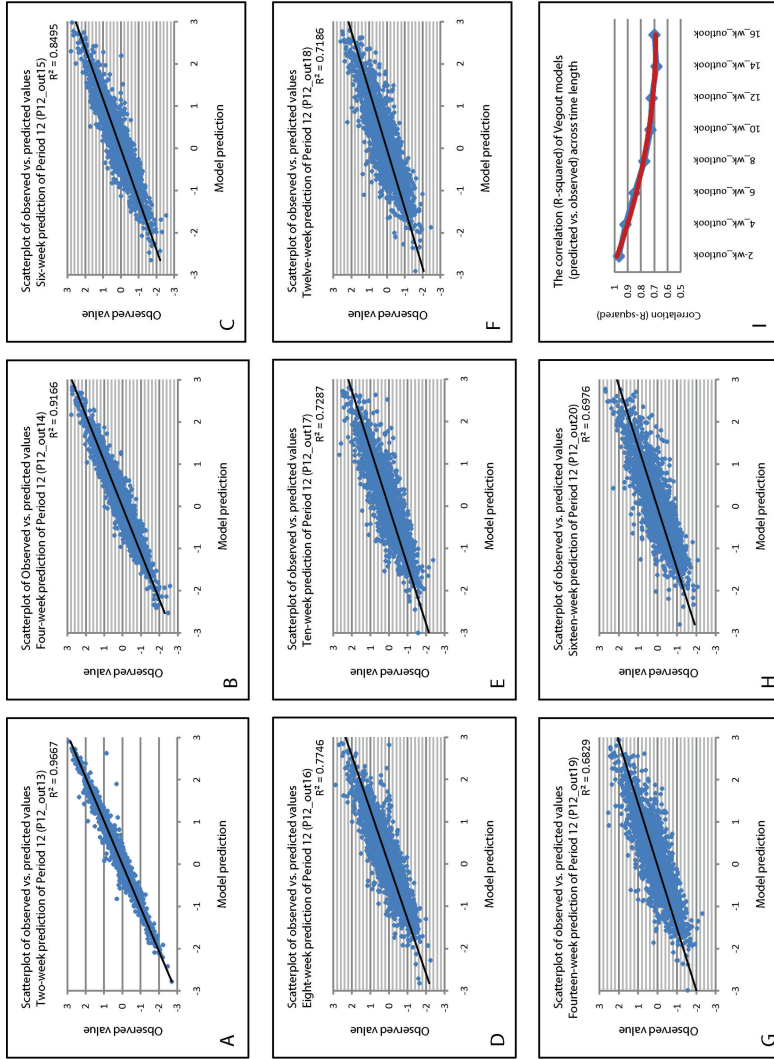
Fig. 3. Scatterplots of observed and predicted SSG values for period 12 (i.e., first half of June), and coefficient of determination (R^2) showing the accuracy of the prediction across the growing season. Figures 3A–H show the scatterplots of the observed and the two-, four-, six-, eight-, 10-, 12-, 14-, and 16-week predicted SSG values, respectively. Figure 3I shows the R^2 across the growing season.

senesced. Figures 3A–3H present the scatterplots of the predicted vs. observed SSG values from this testing. As might be expected, the two-week outlook had the highest R^2 value (0.97) and the least spread (i.e., lowest variability) between the observed and predicted values in the scatterplots. In general, the predictive accuracy of the shorter outlooks ranging between two and six weeks had relatively high R^2 values (> 0.85), with the least spread from the 1:1 line presented in the scatterplots in Figure 3. As the outlook periods lengthened, the VegOut models' performance decreased exponentially from an R^2 value of 0.78 for the nine-week outlook to 0.70 for the 16-week outlook. Although this paper focuses on the shorter, two- to six-week outlooks, which have been shown to have relatively high accuracies, the longer periods extending two or more months exhibit some potential that warrants further investigation.

Variable Contributions in the Outlooks

To understand the contribution of each individual variable in the rules, we have closely looked at the percentage of cases for which each input variable appeared in the conditional statement of the rules and in the regression model of applicable rules. Each "case" represents an observation (defined as a specific station/year combination for the bi-week being tested) in the historical database whose values for the various input variables meet the criteria of a specific conditional statement of a rule set. Table 3 presents the percentage contribution of each independent variable used to generate the two-, four-, and six-week VegOut models for period 15 (July 14–28) of the growing season. Since all the models in the growing season showed similar patterns, we present this period (July 14–28) to demonstrate the process and the outcomes. For this specific period, 18 rules (23,940 training cases), 28 rules (23,383 training cases), and 36 rules (23,021 training cases) were generated for the two-, four-, and six-week VegOut models, respectively. These rules are all generated based on the 18-year historical data for this specific period. The number of rules comprising the VegOut models progressively increased as the outlook period lengthened, illustrating the increasing complexity required in the modeling for the longer range outlooks.

The *conditional statement* column (the "*if …*" term) in Table 3 shows the approximate percentage of cases for which the input variables appear in a condition of an applicable rule. For example, the ecoregion variable was used most frequently (i.e., ranging from 86% to 99%) in the models' conditional statements for all three outlooks. In Table 3, the *Regression Model* column gives the percentage of cases for which the variables appear in the model of applicable rules. For example, the two satellite-derived variables (SSG and SOSA) were used in the regression tree model rules all the time (100%), which indicates that the satellite-based vegetation observations are the main drivers of predicting future vegetation conditions. The climate variable (SPI) was used in 58–76% of the regression models' conditional statements for the three outlook periods tested. The contribution of the oceanic indicators was more highly variable, ranging from 15% to 72%. The percentage of the use of these oceanic indicators differs in time (month to month) throughout the growing season. The values shown as <1% indicate that the variable was rarely or never used in that particular model. However, some variables (such as the NAO) in all three outlooks might not be used within the conditional statement of a regression tree but were used in the regression model calculation (Table 3). In general, Table 3 demonstrates that each variable typically had

Table 3. Percentage Contribution of Individual Variables (attributes) to the Period 15 (July 14–28) VegOut Models for Two-Week (A), Four-Week (B), and Six-Week (C) Outlooks, Respectively[a]

Data type	A. Two-week outlook: 18 rules; 23,940 cases			B. Four-week outlook: 28 rules; 23,383 cases			C. Six week outlook: 36 rules; 23,021 cases		
	Variable	Conditional statement	Regression model	Variable	Conditional statement	Regression model	Variable	Conditional statement	Regression model
Satellite data	SSG	58	100	SSG	39	100	SSG	55	100
	SOSA	55	76	SOSA	35	81	SOSA	62	78
Climate	SPI	<1	63	SPI	11	58	SPI	8	76
Oceanic/atmospheric	PNA	37	72	PNA	28	69	PNA	49	37
	PDO	52	67	PDO	30	71	PDO	32	56
	NAO	1	64	NAO	<1	72	NAO	<1	66
	MJO	7	43	MJO	<1	20	MJO	13	57
	MEI	<1	42	MEI	8	48	MEI	8	67
	SOI	<1	39	SOI	57	61	SOI	46	42
	AMO	<1	26	AMO	<1	11	AMO	19	29
Biophysical	DEM	7	15	DEM	7	34	DEM	<1	42
	AWC	<1	15	AWC	<1	13	AWC	<1	21
	IrrAg	<1	<1	IrrAg	<1	11	IrrAg	<1	18
	ECO	91	<1	ECO	86	<1	ECO	99	<1
	LCLU	<1	<1	LCLU	<1	<1	LCLU	<1	<1

[a]The top row of each table (A–C) shows the number of rules and cases for each individual model. The Conditional Statement column shows the approximate percentage of cases for which the input variable appears in the condition of an applicable rule, and the Regression Model column gives the percentage of cases for which the variables appear in the model of applicable rules. [Authors: How do the italicized variables in Table 3 differ from the others, i.e., what do the italicized variables signify?]
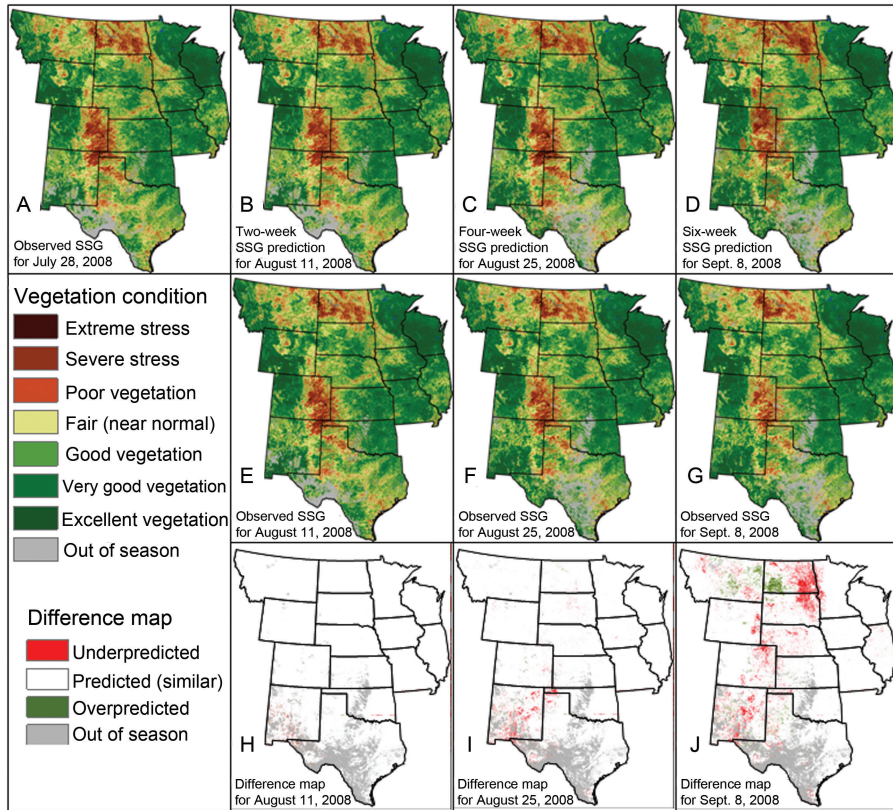
Fig. 4. A. Observed seasonal greenness (SSG) for July 28, 2008. B–D. Two-, four-, and six-week outlooks; E–G. Observed SSG for August 11, August 25, and September 8, respectively, that correspond to the two-, four-, and six-week outlooks, respectively. H–J. Change maps (the difference between the predicted and observed) for the two-, four-, and six-week outlooks, respectively.

a contribution of varying degrees in predicting the general vegetation conditions (i.e., SSG) at the two-, four-, and six-week intervals.

VegOut Maps

After regression tree rules were generated, 1 km VegOut maps were produced for the two-, four-, and six-week outlook intervals across the 2008 growing season. The 2008 growing season data were independent (unseen data) from the data used to develop the models, which were based on the 18 years of historical records between 1989 and 2006. Even though VegOut maps are produced for each 14-day interval (or bi-weeks) across the growing season, only the map results for the mid-summer period (bi-week) 15 (i.e., July 14–28) are presented in this paper to demonstrate the VegOut map results. Figure 4 shows the predicted two-, four-, and six-week VegOut SSG maps (Figs. 4B, 4C, and 4D, respectively) and the SSG patterns observed from satellite for the corresponding dates (4E, 4F, and 4G, respectively). The SSG values

Table 4. SSG Values Classified into Seven General Vegetation Condition Classes Based on the Standard Deviation (STDEV) of the SSG[a]

SSG values (STDEV)	Vegetation condition
–2.0 and less	Extreme stress
–1.0 to -2.0	Severe stress
–0.5 to –1.0	Poor vegetation
–0.5 to + 0.5	Fair (near normal)
+0.5 to +1.0	Good vegetation
+1.0 to +2.0	Very good vegetation
+2 and greater	Excellent vegetation

were classified into seven general vegetation condition classes based on the standard deviation (STDEV) of the SSG (Table 4). The first map (Fig. 4A) shows the satellite-observed SSG on July 28, 2008, which was the date that the series of VegOut maps was produced. The observed SSG data from the AVHRR instrument on July 28 provided the initial vegetation conditions at the time of the two-, four-, and six-week SSG predictions.

A visual comparison of the observed and predicted maps in Figure 4 shows good general agreement in their SSG patterns for the three outlook periods tested. Quantitative difference maps (i.e., the difference of the predicted minus the observed SSG maps) for the two-, four-, and six-week outlooks are presented in Figures 4H, 4I, and 4J, respectively to further illustrate the areas exhibiting the largest differences. Differences were categorized into three classes based on a one standard deviation threshold (in units of the SSG): (1) underprediction—if the SSG difference is less than –1 STDEV; (2) similar—if the SSG difference falls within the –1 to +1 STDEV range; and (3) overprediction—if the SSG difference is greater than +1 STDEV. For example, the SSG patterns depicted in the two-week VegOut map for August 11 (Fig. 4B) had a strong spatial agreement with the satellite-observed SSG patterns for the same period (Fig. 4E). The areal extent of overpredicted and underpredicted SSG values was minimal (Fig. 4H), with most of these differences limited to small, localized areas across the 15-state study area. The majority of differences occurred in southern New Mexico and southwest Texas, where SSG values tended to be underpredicted. The underprediction across these areas persisted in both the four- and six-week outlooks maps. However, a visual comparison of the predicted and observed SSG patterns for the two-week outlook over this area did not reveal a noticeable difference in the level of greenness on the SSG scale. The discrepancy between the visually observed differences in the SSG maps and those depicted in the difference map for these areas is likely a function of their sparsely vegetated landscapes, which are primarily composed of shrubs and sparse grasses. This discrepancy is due to the fact that the dynamic range of SSG values (i.e., range of values between the minimum and maximum SSG value range over the year) in sparsely vegetated locations is quite low and a minimal difference between the predicted and observed SSG values within this limited range will often exceed the 1 STDEV threshold used to flag major differences. As a result, the predicted and observed SSG values may be relatively similar for these locations.

Because of this performance, further study of VegOut is needed over sparsely veg-etated locations.

In the six-week outlook map, large areas of both overpredicted and underpre-dicted values were found in the northern Great Plains (North and South Dakota, as well as parts of Montana) and eastern Colorado (Figs. 4F and 4G). In most of these locations, with the exception of southwest North Dakota, the predicted SSG values for August 25 were much lower than those observed from the satellite-based AVHRR instrument. A review of precipitation maps[3] for July and August 2008 revealed that above-average rainfall (>130% of normal) was received across both eastern Colorado and eastern North and South Dakota over that time period. This above-average pre-cipitation likely resulted in a stronger greenness signal (higher SSG value) being observed from satellite on September 8 than the predicted SSG values, which were based on a drier scenario in the model because less precipitation has been typically received during July and August over the 18-year period used for model development. Further research is needed to better understand the role of extreme weather patterns (excessive rainfall or drought) on the predictive errors present in the maps generated by the VegOut models.

In general, the investigation of the spatio-temporal performance of VegOut across the growing season showed reasonably high predictive accuracy for the central United States, up to 6 weeks. In addition, the VegOut has finer spatial detail (1 km^2 resolution) that may help improve drought monitoring tools such as the U.S. Drought Monitor (USDM). Thus, this new vegetation monitoring tool is expected to have great potential for different types of users and purposes. For example, it may be used to justify sub-county declarations for the release of Conservation Reserve Program (CRP) lands for emergency grazing for parts of counties that might be severely impacted by drought or to gauge rangeland and haying conditions in neighboring states to determine locations to move cattle for grazing and purchase hay and other feed; it might also be used as an additional indicator of fire risk. Easier access to these products will allow for quicker assessments and decision-making at all levels. Feedback from users with specific needs (e.g., agricultural producers, university extension agents, and policy makers) is essential in improving the models so that the vegetation and prediction tools are truly useful to the sectors affected by drought.

Future Study and Planned Improvement of the VegOut Model

Advances in prediction of the vegetation conditions at finer resolutions (e.g., local scales) will depend on improvements in model structure and initialization, data assimilation, and selection of effective parameters that characterize vegetation growth. Efficient database development and improved analysis tools including data mining techniques allow for effective integration of a diverse set of input variables and identification of complex relationships between climate/oceanic variables and vegetation condition (i.e., satellite-based standardized seasonal greenness) related to drought.

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[3]Observed precipitation maps are available from High Plains Regional Climate Center, (http://www.hprcc .unl.edu/maps/current/).

More and better predictability studies are required to determine the regions, seasons, lead times, and processes necessary for improved predictive skill. In this study, the VegOut model included ecosystem and LULC data that contributed to deriving rules that reflected their effects. However, refining the model at a more local level may provide additional predictive skills. Improved and finer resolution satellite observations could help to fill this gap. For example, using MODIS data may improve spatial resolution, while using thermal data could help identify the patterns and influence of surface temperatures on vegetation. The development of a 250 m VegOut will be explored using 250 m MODIS data. A higher spatial resolution VegOut is expected to be more applicable to local-scale monitoring and decision making compared with the 1 km AVHRR. The limitation of using MODIS data at present is that the historical record is less than 10 years. Because of this, patterns and generated rules using short historical records may not be reliable for the model. However, work is in progress to "crosswalk" (transition) the MODIS data from AVHRR so that we may be able to use longer historical records. The initial research will rely on the shorter, nine-year MODIS historical record, which will be extended once the AVHRR–MODIS crosswalk activity is completed.

A new United States MODIS data delivery system called eMODIS has been created by the USGS-EROS to provide real-time and historical surface reflectance and NDVI products that are composited in seven-day intervals over the continental United States (ftp://emodisftp.cr.usgs.gov/eMODIS/). This data delivery system helps in acquiring "enhanced," "expedited," and "expandable" MODIS data. This will be very important in developing near-real time weekly and finer spatial resolution VegOut products in the future. Furthermore, incorporation of additional new variables such as remote sensing–based evapotranspiration (ET) and soil moisture (SM) products using MODIS may help improve the predictive accuracy of the VegOut. Testing the ET and SM variables to include in the VegOut model is expected to contribute to and complement the existing vegetation monitoring tools.

To assess and predict vegetation conditions, it is essential to identify different characteristics of the environment that influence climate–vegetation interactions. Because of this, the LULC type, irrigation, soil available water capacity, elevation, and ecological setting of the area have all been considered in the VegOut model. Furthermore, the ocean–atmosphere–vegetation interaction provides essential information in predicting vegetation condition. Thus, oceanic indices based on Pacific and Atlantic Ocean observations indicate that teleconnections with surface observations have been considered and integrated in the VegOut model. These oceanic indices help to predict the complex climate and vegetation conditions if they are used with other climate, satellite, and environmental variables rather than as stand-alone predictors. However, better understanding of land–atmosphere interactions and studying the impact of teleconnections at a local scale will most likely improve the modeling of antecedent conditions to climate and vegetation condition. In addition, model evaluation studies with enhanced ground observations are needed to improve models and to characterize and reduce uncertainties.

Other predictive techniques are being developed using different scenario-based (e.g., dry, normal, and wet) forecasts to provide vegetation outlooks. This method uses the same regression algorithm to identify the patterns and integrate several data inputs as described in this paper. The difference in this method will be using predicted

precipitation scenarios (e.g., what happens if 50% [150%] precipitation is received during the following six-week period for dry [wet] scenarios) and producing maps that reflect these scenarios. This approach will provide users with choices of particular scenario vegetation outlook maps based on what precipitation amounts they might expect.

CONCLUSION

Large-area outlooks of future vegetation conditions are important for a wide range of applications that include agricultural crop estimates, rangeland condition assessments, and drought monitoring. Such predictions are very challenging given the complexity of climate–vegetation interactions and diversity of land use practices across large geographic areas. However, potential advancements in this area are becoming possible with the availability of longer historical records of remote sensing observations and high-quality environmental data sets coupled with recent advancements in computing technologies and statistical data mining techniques.

VegOut is a new hybrid geospatial vegetation condition indicator that predicts the vegetation seasonal greenness based on historical satellite, climate, oceanic, and biophysical observations. The maps are designed to deliver a timely product (e.g., disseminating the maps every two weeks via the Internet) using current technological advances and algorithms. The VegOut maps are intended to provide the potential for national-level predicting capabilities with local-scale information (e.g., county to sub-county level) regarding the level of impacts of natural disasters such as drought stress on vegetation. In addition, VegOut capitalizes on historical climate–vegetation interactions and teleconnections between the ocean and climate (such as El Niño and the Southern Oscillation, ENSO) to generate these outlooks, while considering several static environmental characteristics (i.e., LULC type, irrigation status, soil characteristics, and ecological setting) that can influence vegetation's response to weather conditions.

The evaluation of the spatio-temporal performance of VegOut across the growing season showed reasonably high predictive accuracy across the 2008 growing season for the central United States and strong spatial agreement between the predicted and observed SSG patterns in the two-, four-, and six-week VegOut maps. The comparisons of the predicted and observed SSG patterns of the VegOut maps using independent year data (i.e., the 2008 growing season) in this study showed that major differences (both underprediction and overprediction) occurred primarily at a local scale. In addition, pronounced differences of both underpredicted and overpredicted SSG values persisted over sparsely vegetated locations of the study area, such as southwest New Mexico, for the three outlook periods tested. The performance of VegOut over sparsely vegetated locations and during excessively wet and dry periods needs further study. Moreover, longer outlook periods ranging from two to six months should be further investigated.

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