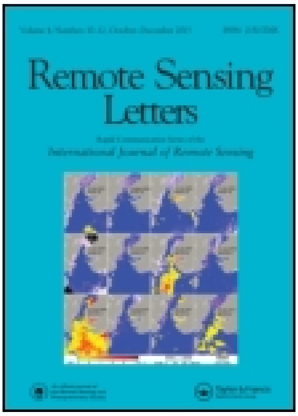

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Robert M. Rabin[ab], Marouane Temimi[cd], Jan Stepinski[c] & Phillip D. Bothwell[e]

[a] NOAA, National Severe Storms Laboratory, 120 David L Boren Blvd, Norman, OK 73072, USA

[b] Cooperative Institute for Meteorological Satellite Studies, University of Wisconsin-Madison, Madison, WI 53706, USA

[c] NOAA-CREST, City College, City University of New York, 160 Convent Avenue, New York, NY 10031, USA

[d] Institute Center for Water and Environment (iWater), Masdar Institute of Science and Technology, Abu Dhabi, UAE

[e] NOAA, NWS, Storm Prediction Center, 120 David L Boren Blvd, Norman, OK 73072, USA

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Monitoring surface dryness using geostationary thermal observations

Robert M. Rabin[a,b]*, Marouane Temimi[c,d], Jan Stepinski[c], and Phillip D. Bothwell[e]

[a]*NOAA, National Severe Storms Laboratory, 120 David L Boren Blvd, Norman, OK 73072, USA;* [b]*Cooperative Institute for Meteorological Satellite Studies, University of Wisconsin-Madison, Madison, WI 53706, USA;* [c]*NOAA-CREST, City College, City University of New York, 160 Convent Avenue, New York, NY 10031, USA;* [d]*Institute Center for Water and Environment (iWater), Masdar Institute of Science and Technology, Abu Dhabi, UAE;* [e]*NOAA, NWS, Storm Prediction Center, 120 David L Boren Blvd, Norman, OK 73072, USA*

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This study introduces an operational land dryness index (DI) developed by the National Oceanic and Atmospheric Administration (NOAA)/National Severe Storms Laboratory (NSSL) to assist mainly in wildfire risk assessment and forecasting. The index is developed based on observations of daytime rise of surface radiative temperature from the geostationary operational environmental satellites (GOES). Thermal measurements of heating rates are normalized using solar radiation, also from GOES, to account for spatial changes in solar time. Maps of the DI are developed systematically over the continental US on a daily basis from cloud-free pixels. In addition, anomalies of the DI are evaluated with respect to a 5-year mean to further classify the extent of dryness.

The DI is assessed using (1) the microwave-based soil moisture product from the National Snow and Ice Data Center (NSIDC), (2) estimates of soil moisture from the North American Land Data Assimilation System (NLDAS), that is based on the North American land surface model and (3) vegetation cover estimated from the normalized difference vegetation index (NDVI).

An overall agreement is found between the DI and microwave-based estimates of soil moisture. The peak absolute correlation, which reached around 0.6, is found in late summer over scrubland. The correlation between the products also shows a seasonal pattern that needs to be corroborated with further observations. The consistency of the developed product with other independent measures implies its reliability and its potential in wildfire forecasting.

1. Introduction

The moisture content of vegetation is of utmost importance for applications such as monitoring the potential for wildfires. Soil moisture is also a factor, but only because it affects the state of the vegetation. Direct measurements of soil moisture are limited to specific sites that may not be representative of larger areas. *In situ* measures of vegetation water content are practically non-existent. Qualitative products such as the US Drought monitor[1] are being developed to map drought conditions using a synthesis of multiple indices. Additionally, satellite observations of thermal and reflective properties from polar satellite data, such as the advanced very high-resolution radiometer (AVHRR), have have

*Corresponding author. Email: Bob.Rabin@noaa.gov

been applied to global monitoring of vegetative health and potential crop yields (Kogan 1990; Kogan 2001).

There have been many efforts to develop remote sensing techniques using microwave satellite data to estimate soil moisture. Some success has been achieved in quantifying surface moisture where the vegetation cover is not too dense using passive microwave measurements (e.g. Wang, Shiue, and McMurtrey 1980; Wilke and McFarland 1986; Choudhury et al. 1987; Neale, McFarland, and Chang 1990; Kustas et al. 1993; Basist et al. 2001). However, the presence of dense vegetation limits the ability to sense soil moisture. Recent algorithms include an estimate of vegetation moisture content. However, the horizontal resolution of these microwave measurements is about 40 km, which is relatively coarse as compared to the resolution of geostationary operational environmental satellites (GOES) data.

Infrared observations, in contrast, provide observations with a resolution of 4–10 km from geostationary platforms. Their major downside can be cloud obstruction. However, frequent image acquisition, about every 15 min, from geostationary satellites can alleviate this problem through compositing techniques. Temimi et al. (2011) have demonstrated, using observations from the Spinning-Enhanced Visible and InfraRed Imager (SEVIRI) radiometer aboard the Meteosat Second Generation (MSG) geostationary satellite, that daily compositing of geostationary observation can reduce the area obscured by cloud by 30% with respect to scenes acquired from polar orbiting satellites like the moderate-resolution imaging spectroradiometer (MODIS).

Remote thermal infrared measurements of land (radiative temperatures or their temporal change) have been largely used to estimate the surface's energy budget and soil moisture (e.g. Tarpley, 1988; Tarpley 1994; Brutsaert, Hsu, and Schmugge 1993; Hall et al. 1992; Anderson et al. 2007; Hain et al. 2011). The relationship between the observed daytime rise in surface radiative temperature, derived from the clear-sky data of the GOES sounder instrument, and modelled soil moisture, was explored over the continental United States (Rabin and Schmit 2006). The motivation was to provide an infrared (IR) satellite-based index for soil moisture or surface wetness, one that would have a higher resolution than possible from the microwave satellite. Higher (lower) heating rates are associated with drier (wetter) surfaces and higher (lower) Bowen ratios of sensible to latent heat flux. In areas of moderate-to-high vegetation cover, the satellite wetness index should be correlated with the Normalized Difference Vegetation Index (NDVI). This is because the amount of green vegetation tends to be related to available moisture.

The current study builds upon these previous attempts and proposes a dryness index (DI) for the purpose of identifying dry areas at risk of wildfires under favourable weather conditions. The DI is based on GOES imager data to provide higher-resolution information, as compared to microwave, on the relative moisture content of vegetation (or soil surface in the case of bare ground or partially covered soil). The imager provides data at 4 km horizontal resolution at nadir, which is twice than that of the sounder used in Rabin and Schmit (2006). The technique could be of enhanced value when applied to observations from the advanced baseline imager (ABI) aboard the GOES-R era of geostationary satellites, as these instruments will double the current resolution (providing 2 km IR measurements at nadir). Since the NDVI is related to vegetation cover and available moisture, the DI can be used together with NDVI to help assess dryness. Monitoring of vegetation cover from a geostationary satellite will become available for the first time with GOES-R, as the ABI sensor will include the channels required to estimate NDVI.

This study investigates the agreement between the developed DI and model-based and microwave-observation-based estimates of soil moisture.

2. Data and methodology

2.1. GOES dryness index

The GOES DI is influenced by the amount of available soil moisture and vegetation cover. The lack of (1) a green canopy with active evapotransporation or (2) near surface soil moisture in vegetation sparse regions, will lead to higher heating rates and values of the DI.

Specifically, the DI is based on the rise in surface temperature (T_s) between 10:00 and 13:00 local solar time. This value is normalized (divided by) the incoming solar radiation at the surface (S) to account for varying amounts of energy available for surface heating:

$$\mathrm{DI} = [T_s(2) - T_s(1)]/([S(2) + S(1)]/(2c)) \quad (1)$$

where 1 and 2 indicate the two observation times, and c is a scaling constant (500 W m^{-2}).

The values for T_s, S and cloud amount are obtained from hourly GOES Surface and Insolation Products (GSIP) produced at the National Environmental Satellite, Data, and Information Service (NESDIS) Center for Satellite Applications and Research (STAR): http://www.star.nesdis.noaa.gov/smcd/emb/gsip/index.htm

The horizontal resolution of the GOES DI is currently dictated by that of the GSIP products (1/8th$^\circ$). Furthermore, the DI is evaluated only where the sky is deemed to be clear. This is based on locations where the cloud fraction estimate included in the GSIP algorithm is zero. Separate estimates are made from the GOES-east (currently GOES-13) and GOES-west (currently GOES-15) satellites. Comparisons of the DI from the two GOES satellites over common geographical areas in the western United States revealed systematic difference in the values of DI. Values from GOES-west averaged l°C–2°C above those from GOES-east. The cause of this difference is unclear. Nevertheless, an arbitrary adjustment is applied to the GOES-west data to account for the systematic differences in the GOES-east heating rates. The results shown in this paper are from GOES-east.

The DI is computed for 2010 and 2011 on a daily basis with 7- and 14-day sliding averages. This compositing procedure reduces the number of cloudy pixels in each daily image and facilitates comparisons with the NDVI.

Finally, anomalies of the DI are calculated using deviations from 5-year monthly means (1996–2000). Those means were computed from GOES-based Surface Radiation Budget (SRB) outputs developed at the University of Maryland from the GEWEX Continental Scale International Project (GCIP): http://www.atmos.umd.edu/~srb/gcip/

2.2. Normalized Difference Vegetation Index (NDVI)

NDVI images are provided by the United States Geological Survey (USGS) Earth Resources Observation Systems (EROS) Data Center on a weekly basis. The values are derived from daytime measured reflectance in the visible (R_{vis}, 0.4–0.7 µm) and the near-IR (R_{NIR}, 0.7–1.1 µm) bands of the National Oceanic and Atmospheric Administration (NOAA) AVHRR instrument (NOAA-18) for clear sky regions:

$$\mathrm{NDVI} = (R_{\mathrm{NIR}} - R_{\mathrm{vis}})/(R_{\mathrm{NIR}} + R_{\mathrm{vis}}) \quad (2)$$

Typically, values of NDVI range between 0.0 and 1.0, providing a relative index of green vegetation cover (where photosynthesis is taking place). NDVI is based on the principle that plant leaves strongly absorb visible light for photosynthesis (chlorophyll), but reflect light in the NIR portion of the solar spectrum. Low values of NDVI can mean relatively bare ground or dry vegetation cover.

The change in NDVI on monthly time scales may be useful for identifying regions of increasing and decreasing vegetation coverage. Decreasing coverage may indicate less green biomass (i.e. harvested crops) or increased amounts of dry biomass (uncut, dry grasses, dry leaves below dormant trees, etc.).

2.3. Soil moisture from passive microwave data

Remote estimates of soil moisture from the Advanced Microwave Scanning Radiometer-Earth observing system (AMSR-E) are obtained from the National Snow and Ice Data Center (NSIDC) (Njoku 2004). The retrieved soil moisture is based on polarization ratios (PR) (normalized differences between the vertical and horizontal polarized brightness temperature) at 10.7 GHz and a vegetation/roughness parameter based on PR at 10.7 and 18.7 GHz. The estimates are valid in roughly the top 1 cm of soil on horizontal scales of about 60 km. They are most accurate where vegetation cover is low because vegetation attenuates the microwave signals received (Njoku et al. 2003; Njoku et al. 2004; Njoku and Chan 2006). It is worth noting that the horizontal resolution of this product is an order of magnitude less than the GOES observations. We have therefore resampled the microwave product to meet GOES spatial resolution for intercomparison purposes. The observations also end in October 2011, when the AMSR-E experienced a problem with its rotating antenna.

The AMSR-E product is projected onto an Equal-Area Scalable Earth grid (EASE) with a spatial resolution of 25 km, which is coarser than the grid of the GOES DI. Since a quantitative comparison can most readily be conducted between data sets on the same geographic projection, the DI and NDVI data described in the previous sections are resampled to match the EASE grid of the AMSR-E product.

2.4. Modelled soil moisture and moisture availability

An independent estimate of soil moisture modelled from precipitation and other meteorological data can be used to help gauge the accuracy of the GOES DI and the AMSR-E products.

Output from the North American Land Data Assimilation System (NLDAS), Mitchell et al. (2004), is used as an independent source of information about soil moisture and the availability of moisture to vegetation. The NLDAS uses precipitation data, satellite-based radiation data and numerical weather model output (such as temperature and wind) as input. We have obtained daily data archived over the 2010–2011 period on a 1/8° resolution grid from the NOAA National Centers of Environmental Prediction (NCEP).

3. Results and discussion

The agreement between the soil moisture products derived from microwave observations with those obtained using IR observations is assessed in this section.

Figure 1 shows maps of the 14-day average DI for early July 2011 and July 2010, respectively; missing values represent pixels that were cloudy at either time used to evaluate Equation (1). Despite persistent gaps, the maps provide the general pattern of dryness across most of the United States. They indicate that central regions in the United

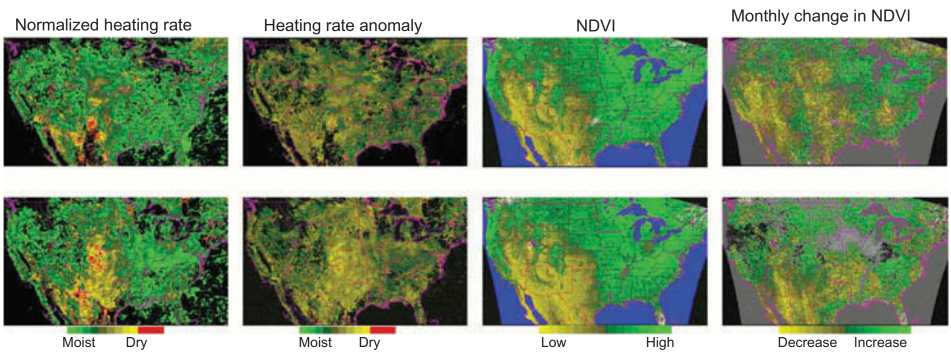

Figure 1. Example of the GOES-based DI (normalized heating rate), heating rate anomaly, NDVI and monthly change in NDVI estimated in July 2011 (lower row) and July 2010 (upper row).

States were dryer in 2011 than in 2010. Drought conditions began to develop in these regions in the summer of 2011 and persisted into 2012.

The 14-day NDVI composites from early July 2010 and 2011 are shown in the third column of Figure 1. Areas of green indicate dense, live vegetation, whereas areas of yellow indicate regions of dead, dry or no vegetation. Areas of white indicate regions where data is missing due to water or cloud cover. The contrasting monthly change in NDVI is shown in the fourth column of Figure 1 for early July 2010 and 2011. While the gross patterns of NDVI are similar for both years, July 2010 is characterized by more widespread decreasing NDVI in some regions of the southern plains.

A comparison of the DI and AMSR-E soil moisture product during years 2010 and 2011 reveals a negative correlation between the GOES DI and AMSR-E soil moisture index during the warm season months. The top row in Figure 2 presents maps of the GOES and AMSR-E products for August 20–26 (week 34) of 2010. Large-scale dry and moist regions are similarly depicted by both products. Noteworthy is the exceptional

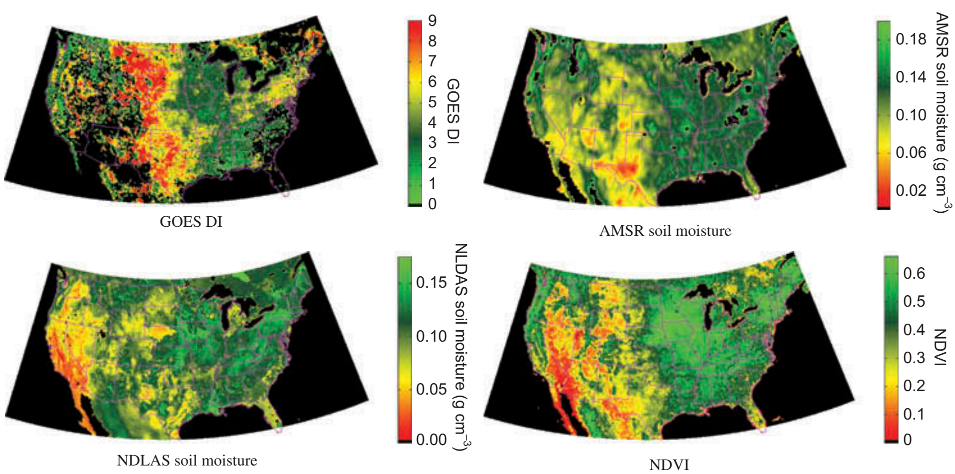

Figure 2. Spatial pattern of GOES-based DI (unitless), soil moisture estimates (g cm^{-3}) from the AMSR-E product and NDLAS model and NDVI 20–26 August 2010.

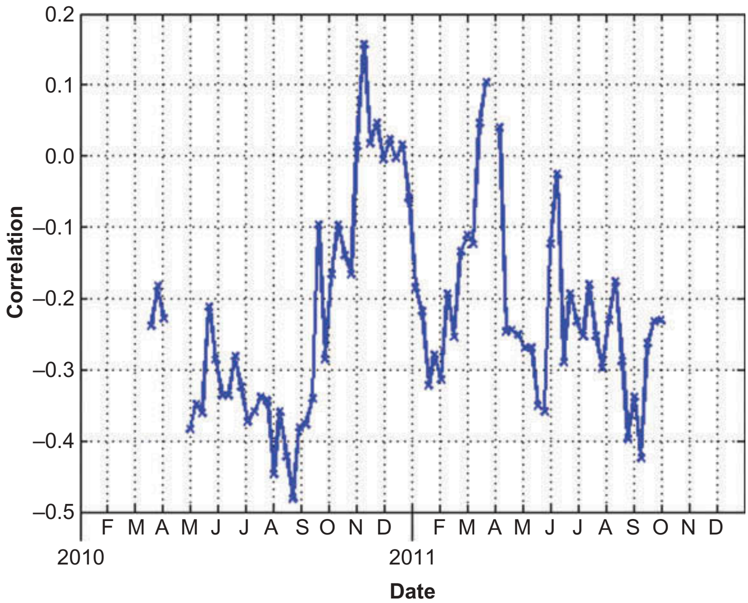

Figure 3. Correlation between GOES-based DI and AMSR-E soil moisture product, 2010–2011.

dryness in the US Great Plains and lower Mississippi Valley. The GOES product appears to be more spatially uniform than the AMSR-E product in most of that area. The correlation over the entire continental United States between both products at weekly intervals during 2010–2011 is given in Figure 3. It should be noted that a negative correlation exists between the GOES DI and soil moisture. The magnitude of the correlation appears to increase during the growing seasons (April–August), reaching a peak of roughly −0.5 during August in both years. It is worth noting that the correlation reached −0.6 over certain land cover types (not shown here) like scrubland, which implies that the agreement between IR- and microwave-based estimates of soil wetness depends on the land cover type. This might be expected because of varying properties of vegetation, such as density, stomata response to stress, wilting point and attenuation of microwave radiance from below.

A map of the NLDAS soil moisture corresponding to that of the GOES DI and AMSR-E product for August 20–26, 2010 is shown in Figure 2. Correlations of the GOES DI and the AMSR-E products with NLDAS soil moisture are given in Figure 4. During the warm months (April–September), the correlations of the GOES DI with the NLDAS soil moisture are generally −0.2 to −0.3 with no systematic change throughout the warm season. The correlation of the AMSR-E wetness index with NLDAS during the warm seasons is generally 0.4–0.6. However, the magnitude of correlation of AMSR-E with NLDAS exhibits an abrupt drop in June 2010 and a decreasing trend during the late summer of 2011.

The correlation of both the GOES and AMSR-E products with the NDVI is given in Figure 5. In the case of the AMSR-E soil moisture, the April–September trend in both 2010 and 2011 has a parabolic shape, which is roughly in phase with the magnitude of the NDVI during those time periods (not shown). For example, the NDVI peaks in July for most forests and in August for cropland and shrubland (western United States). The

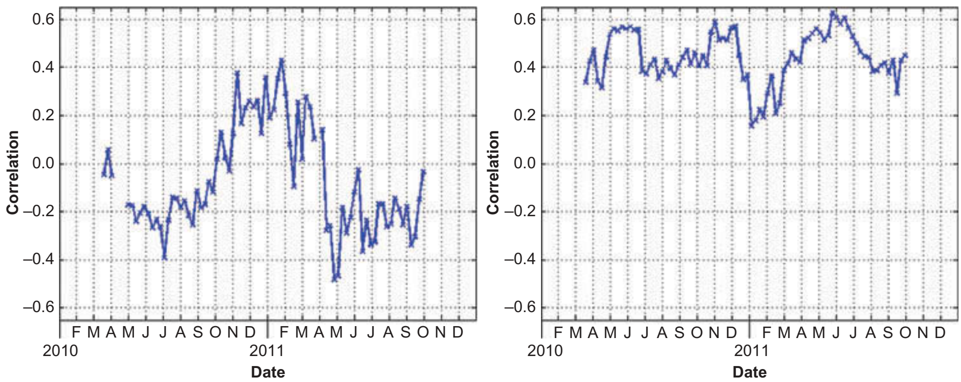

Figure 4. Correlation of NLDAS soil moisture and GOES-based DI (left), AMSR-E soil moisture product (right).

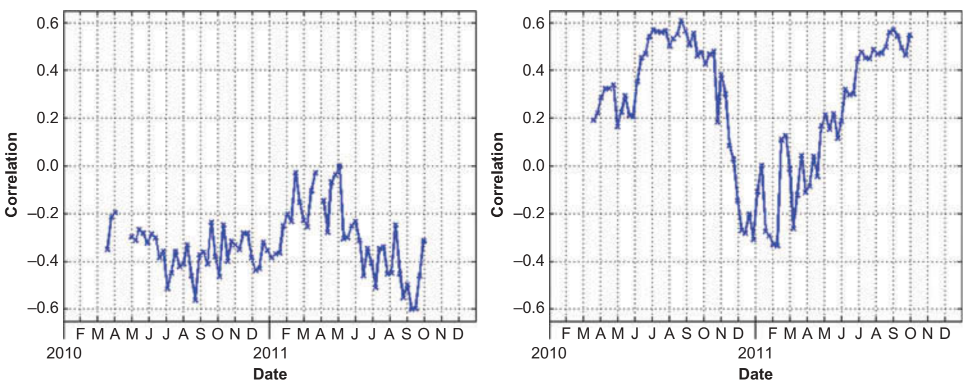

Figure 5. Correlation of NDVI and GOES-based DI (left), AMSR-E soil moisture product (right).

correlations of the GOES DI with NDVI have similar magnitudes to those of the AMSR-E soil moisture with NDVI (0.2–0.6). However, the correlations are more consistent during the course of the growing season for the GOES DI than for AMSR-E soil moisture.

In general, the characteristics of the GOES DI and the AMSR-E wetness index appear similar when compared to patterns of NDVI and modelled soil moisture, and to themselves. An exception is the abrupt drop in the correlation of AMSR-E soil moisture with modelled soil moisture during the summer of 2010 and the gradual decrease during the summer of 2011, while the GOES DI appears to perform more consistently. It is possible that the spatial variability of surface moisture becomes more obscured by the vegetation signal in the microwave during the course of the growing season, and/or that the enhanced resolution of the GOES IR data captures more of the soil moisture pattern during these periods.

Daily maps of the GOES DI are made available to fire weather forecasters at the NOAA Storm Prediction Center to help assess the extent of surface dryness in preparing outlooks for wild fire potential across the United States. They can be used to supplement other information on dry fuels and weather conditions favourable for wildfires, such as high wind, low relative humidity and high air temperature.

4. Conclusions

A new DI is proposed in this study. The index is determined using surface temperature and incoming surface solar radiation estimates from the geostationary satellites GOES-east and GOES-west. The index was assessed using ancillary sources of information, namely, the vegetation index NDVI, the AMSR-E soil moisture product and soil moisture estimates from NLDAS. The negative correlation between the determined DI and passive microwave soil moisture estimates from AMSR-E was persistent throughout most of the year, especially during the warm season. Similar behaviour was also noticed between the DI and soil moisture estimates from NLDAS. The consistency between the GOES DI and other measures confirms its reliability. Further work is underway to understand under which conditions (land cover and season), each product performs best.

These findings imply that the DI is suitable for applications like wildfire risk assessment, where vegetation and soil surface dryness are critical precursors. Ultimately, the findings of this work could lead to the development of a blended product to provide an estimate of surface dryness, which combines the superior resolution of the GOES IR observations with the microwave measurements that are less effected by cloud cover and highly sensitive to soil moisture.

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Note

1. National Drought Mitigation Center, University of Nebraska-Lincoln, US Dept. Agriculture, NOAA: http://droughtmonitor.unl.edu/

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