Drought monitoring in cultivated areas of Central America using multi-temporal MODIS data

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ABSTRACT

Drought is the most pressing problem facing farmers in Central America, and information on drought is thus crucial for agronomic planners to minimize impacts on crop production and food supply. This study assessed the cultivated areas affected by droughts using the Moderate Resolution Imaging Spectroradiometer (MODIS) data during 2001–2014, processed using a simple vegetation health index (VHI). The results, verified with the Advanced Microwave Scanning Radiometer 2 (AMSR2) precipitation data and TVDI (temperature vegetation dryness index), indicated that the correlation coefficients ($r$) between the VHI and AMSR2 precipitation data for 2013 and 2014 were 0.81 and 0.78, respectively, and the values between VHI and TVDI were $-0.68$ and $-0.61$, respectively. The largest area of severe drought was especially observed for the 2014 primera season (April–August) over the last 14 years. The drought mapping results were aggregated with the cultivated areas for crop monitoring purposes.

KEYWORDS

Drought; cultivated areas; remote sensing; Central America

1. Introduction

Drought is recognized as one of the most frequent and costly natural disasters, imposing devastating effects on human societies and ecosystems (Bruce 1994; Mishra & Singh 2010; Wilhite 2000). Drought can be grouped into four categories: (1) meteorological drought described as anomalies in accumulated rainfall, (2) agricultural drought reflecting reduced root-zone soil moisture and crop yields, (3) hydrological drought quantified by low stream flow, depleted groundwater, and reservoir level deficits, and (4) socioeconomic drought related to the inability to meet societal water demands (Choi et al. 2013; Dracup et al. 1980; Heim 2002; Heim & Brewer 2012; Wilhite & Glantz 1985). Climate change coupled with intensifying human activities, including urbanization, deforestation, water reservoir construction, has led to increased frequency and extreme drought events, causing significant impacts on water supplies, agriculture, issues of food, water, and energy security, and environmental ecosystems in all climatic regimes (Blenkinsop & Fowler 2007; Brunetti et al. 2002; Mishra & Singh 2009; Trenberth et al. 2014). The drought severity depends on its duration, intensity, spatial extent, and local socioeconomic conditions (Wilhite 2000). Identification of drought prone areas and drought prediction have thus received interests from an increasing number of researchers and policy makers because the results can help their responses to drought events to mitigate socioeconomic costs (Mishra & Singh 2011).

In Central America, millions of households are dependent on major food crops such as maize, beans, and sorghum for their daily subsistence. In recent years, impacts of climate change in the form of higher temperatures and lower precipitation have triggered intensive droughts and short
dry spells in the region (Field & Van Aalst 2014; Le Comte 1995; Le Comte 1998), profoundly impacting large areas of crop production and farm smallholders (Schmidt et al. 2012). Studies using historical climatic data have also indicated an increasing number of extreme weather events, leading to crop failure, reducing farmer resiliency, and threatening food security (IPCC 2007; Tucker et al. 2010). For instance, the severe and widespread rainfall deficits observed during the first half of 2014 in the study region delayed the start of the primera cropping season (April–August), and the situation was exacerbated by precipitation shortages during critical stages of crop growth. This phenomenon caused major crop production losses and increased market prices of food in the region, affecting approximately two million people suffering from food insecurity (WFP 2014). Thus, the need to investigate cultivated areas affected by drought in the study region is critical for producing a reliable geodatabase for drought and crop monitoring as well as irrigation scheduling.

Remote sensing provides an alternative approach for drought monitoring over large areas. Various satellite-based indices have been developed and widely applied for drought monitoring in the top few centimetres of soil: for example, the normal difference vegetation index (NDVI) and enhanced vegetation index (EVI) (Barbosa & Lakshmi 2016; Barbosa et al. 2015; Jain et al. 2009; Karnieli et al. 2010; Rahimzadeh et al. 2008), temperature dryness vegetation index (TVDI) (Keshavarz et al. 2014; Mallick et al. 2009; Sandholt et al. 2002; Son et al. 2012; Wan et al. 2004; Wang et al. 2010), vegetation health index (VHI) (Bokusheva et al. 2016; Choi et al. 2013; Kogan 1995b; Kogan 1997; Rojas et al. 2011; Seiler et al. 2007; Unganai & Kogan 1998), the normalized difference water index (NDWI) (Gao 1996), the normalized multi-band drought index (NMDI) (Chen et al. 2014; Gao 1996; Wang & Qu 2007; Wang et al. 2008), crop water stress index (CWSI) (Hatfield 1983; Idso et al. 1981; Jackson et al. 1981), and the modified perpendicular drought index (MPDI) (Ghulam et al. 2007; Jiahua et al. 2015; Li & Tan 2014).

Among these indices, TVDI is one of the most commonly used and is suggested for soil moisture assessment because it is based on the empirical analysis of NDVI, which provides little information about soil water content, and land surface temperature (LST), which is relatively related to water stress. The combination of NDVI and LST data can thus provide more complete information on soil moisture status (Carlson 2007; Nemani et al. 1993; Sandholt et al. 2002). The TVDI, however, has the disadvantage of being most often applied to arid or semi-arid regions (Rhee et al. 2010), and its use in the wet season is limited due to large disparities of NDVI and LST data, preventing us from forming an NDVI–LST triangle for derivation of dry and wet edges to associate LST with the soil moisture content and the vegetation cover. In this study, the VHI combining contribution of the vegetation condition index (VCI) and temperature condition index (TCI) measuring the increase in canopy temperature that occurs when plants undergo stress (Kogan 1995a; Kogan 1995b; Kogan 1997; Kogan et al. 2005) was applied for agricultural drought monitoring in the study region. The TCI is considered a thermal stress indicator to determine temperature-related drought phenomenon, assuming that a drought event will decrease soil moisture, causing temperature stress. The VCI normalizing NDVI/EVI values identify areas where vegetation is more or less dense than usual. Thus, VCI and TCI are averaged with uniform weighting to form the empirical VHI, which reflects both vegetation cover and temperature anomalies (Choi et al. 2013). This study used EVI to construct VCI because it can overcome limitations of NDVI related to soil background brightness and saturation problems at high biomass values (Bausch 1993; Carlson & Ripley 1997; Turner et al. 1999). The EVI, which is constructed by decoupling the canopy background signal and reducing atmospheric influences (Huete et al. 2002; Huete et al. 1997), is an effective index for assessing seasonal variations of crops, evergreen vegetation, and phenological events of crop growth (Gurung et al. 2009; Jiang et al. 2008; Potgieter et al. 2007; Son et al. 2014).

The main objective of this study was to assess droughts for cultivated areas in Central America using multi-temporal MODIS data during 2001–2014. The drought mapping results were spatially aggregated with the cultivated areas for drought and crop monitoring purposes.
2. Study region

The study region located in Central America includes five countries, Guatemala, Honduras, El Salvador, and Nicaragua, covering approximately 370,162 km² (Figure 1). The elevation in the region ranges from 0 to 4,189 m, and the terrain is rolling with occasional escarpments, with an estimated 7.4% land allocated for agriculture (Chen et al. 2015). The region has a tropical climate with two seasons: dry season (December–April) and wet season (May–November), which is interrupted by a short dry period (July–August). Maize is a dominant food crop among others (e.g. beans and sorghum). Crop cultivation is commonly practiced in sloping and hilly areas, heavily dependent on rain. There are typically three cropping seasons: primera (April–August), postrera (September–November), and apante (December–March) (Eitzinger et al. 2012).

The majority of maize and beans are planted during the primera and postrera seasons, and the length of the growing cycle of these crops is approximately four months. Due to climatic conditions, farmers mainly grow one maize crop per year, beginning in late April–June and harvesting in November (Olson et al. 2012). Beans and sorghum are inter-planted among maize in the second season, when maize matures and its stalk can be folded. In recent years, droughts have occurred more frequently in the region, creating detrimental impacts on crop production. For example, the delayed start of rains (April–May) across the region in 2014 led to rainfall deficits for the primera season (edo.jrc.ec.europa.eu) (Figure 2), followed by a more severe and extended dry spell in July and August into September in 2014 putting the first cropping season (primera) under serious threat and negatively impacting farming activities (Morel 2014). For the postrera season, the less precipitation for the planting month (September) caused by a prolonged period of dry spell (July–September) might be unfavourable for the establishment of beans especially in areas with sandy soils.

3. Data collection

3.1. MODIS data

The monthly EVI and LST MODIS data extracted from MOD13A3 and MOD11C3 products were collected from the U.S. National Aeronautics and Space Administration (http://reverb.echo.nasa.

Figure 1. Map of the study region showing spatial distributions of LUC classes constructed from Landsat data.
for the period from 2001–2014 to investigate droughts in the study region. The MOD13A3 EVI data are a level-3 data product with a spatial resolution of 1 km, computed from atmospherically corrected bi-directional surface reflectance that have been masked for water, clouds, heavy aerosols, and cloud shadows. In generating this product, the algorithm ingests all the 16-day 1-km products that overlap the month and employs a weighted temporal average if data are cloud free, or a maximum value in case of clouds. The data have been geometrically and radiometrically corrected and are ready for scientific publications (Vermote, Kotchenova, & Ray, 2015). The MOD11C3 LST product is a monthly composited average, derived from the MOD11C1 daily global product, and stored as clear-sky LST values during a month’s period in a 0.05°C, which has 1-degree (in Kelvin) accuracy for materials with known emissivity (Wan et al. 2002). The accuracy of MOD13A3 and MOD11C3 data have been assessed over a widely distributed set of locations and time periods via ground-truth and validation efforts (Solano et al. 2010; Vermote et al. 2015).

3.2. Ancillary data
The monthly precipitation data for 2013 and 2014 from the Advanced Microwave Scanning Radiometer 2 (AMSR2) onboard the sun synchronous satellite GCOM-W1 launched in 2012 were acquired from the Japan Aerospace Exploration Agency (https://gcom-w1.jaxa.jp) and used to verify the drought mapping results. The precipitation measurements taken at 6.9, 7.3, and 10.65 GHz were retrieved from brightness temperatures using the radiative transfer model. The data have been validated using in-situ observations or other satellite data, confirming the accuracy of the released product. The data are a level-3 product registered using the world geodetic system (1984), providing amount of surface rainfall (mm/hr.) with a 1-km spatial resolution, acquired in ascending pass. The 2010 global land-use/cover (LUC) map (30 m resolution) (Figure 1) was also collected from the National Geomatics Center of China (www.globallandcover.com) to spatially aggregate the cultivated areas with the drought mapping results. This map was primarily constructed using Landsat data based on two baseline years of 2000 and 2010 (Chen et al. 2015).

4. Methods
4.1. Drought detection with VHI
This study used VHI to investigate spatiotemporal variations of drought for cultivated areas in the study region during 2001–2014. The VHI can be expressed using the following equation:

\[ VHI = a \times TCI + b \times VCI, \]
where TCI and VCI were calculated as

\[
TCI = \frac{LST_{\text{max}} - LST}{LST_{\text{max}} - LST_{\text{min}}},
\]

\[
VCI = \frac{EVI - EVI_{\text{min}}}{EVI_{\text{max}} - EVI_{\text{min}}},
\]

where LST and EVI are the MODIS LST and EVI, \(LST_{\text{min}}\) and \(LST_{\text{max}}\) are the maximum and minimum LST, and \(EVI_{\text{min}}\) and \(EVI_{\text{max}}\) are the maximum and minimum EVI.

The moisture and temperature contributions to the crop cycle are currently unknown. Thus, an equal weight \((a, b = 0.5)\) was assigned to both indices. Because TCI and VCI characterize variations of moisture and thermal conditions of vegetation, respectively, the combination of these two indices represents an overall vegetation health. The VHI values range from 0 to 1, indicating changes in vegetation conditions from extremely unfavourable (vegetation stress) to optimal (favourable), respectively. Thus, VHI can be categorized into five classes to characterize drought levels: extreme drought (<0.1), severe drought (0.1–0.2), moderate drought (0.2–0.3), slight drought (0.3–0.4), and no drought (>0.4) (Kogan 1995a). Because this study focuses on cultivated areas, the persistent water pixels were masked out if \(EVI < 0.1\) during at least half year.

### 4.2. Aggregation of drought to cultivated areas

The 2010 LUC map (Figure 1) was spatially aggregated with drought maps to investigate the cultivated areas affected by drought across the study region for the primera and postrera seasons during 2001–2014, considering two classes of severe and moderate droughts that are associated with the reduction of crop yield (Kogan 1995a). The LUC map (30 m resolution) was first resampled to the same resolution with the drought maps (1-km resolution) derived from satellite data. The aggregation process was then carried out at a pixel level (1×1 km), considering only pixels covered by at least 20% of cultivated areas. In this study, although the LUC map was spatially resampled to the same resolution with drought maps, the information lost due to the resampling process of the high resolution data to lower resolution data and the resolution bias between the datasets could also introduce uncertainties due to the mixture of LUC elements.

Because drought had significant impacts on crop production during the most sensitive stages of crop growth, we performed an additional analysis of the probability of drought affecting portions of the cultivated areas of each administrative department. We assumed that when more than 20% of the cultivated area of an administrative unit affected by moderate and severe droughts, a large number of agricultural households experienced its consequences. The probability of a drought event \((p)\) considering June–July for the primera season and October–November for the postrera season that were the most sensitive periods for the crop growth (WFP 2014) was calculated as follows:

\[
\hat{p} = \frac{n}{N},
\]

where \(n\) is the number of years that the drought event occurs in a period of \(N\) (14 years), and the confidence interval for \(p\) is \(p \in \hat{p} \pm 2\sqrt{\hat{p}(1 - \hat{p})/N}\) (von Storch & Zwiers 1998).

### 4.3. Validation

Because ground reference data were unavailable for the entire period 2001–2014, we performed the assessment of drought mapping results only for 2013 and 2014 using the monthly AMSR2 precipitation data (10 km resolution). The VHI results (1 km resolution) were first resampled to the same resolution with the AMSR2 precipitation data; the linear regression was then used to examine the
significant correlation between the cumulated VHI data and the cumulated precipitation data for 2013 and 2014. We also performed the consistency verification of the VHI with TVDI calculated based on the empirical interpretation of VCI and TCI, using the following equation:

$$\text{TVDI} = \frac{TCI - TCI_{\text{min}}}{TCI_{\text{max}} - TCI_{\text{min}}},$$  \hspace{1cm} (5)$$

where TCI is the observed surface temperature condition at a given pixel, $TCI_{\text{max}}$ is the upper straight line in the triangle (dry edge) calculated from VCI–TCI scatterplot with small intervals of VCI ($TCI_{\text{max}} = a + b \cdot \text{VCI}$), and $TCI_{\text{min}}$ is the lower horizontal line of scatterplot (wet edge) calculated by averaging data points in the lower limits of the scatterplots (Figure 3). The TVDI values ranging from 0 to 1 characterize levels of soil moisture.

5. Results and discussion

5.1. Comparisons between VHI and AMSE2 precipitation and TVDI

The VHI results were compared with the accumulated AMSR2 precipitation data (derived from the monthly AMSR2 precipitation data) and the TVDI results to investigate the relationships between these datasets for 2013 and 2014. The comparison results between the VHI data, which were resampled to the same resolution with the AMSR2 precipitation data (i.e. 10 km resolution), indicated that although there were discrepancies between both datasets due to the resampling process, the VHI closely agreed with the real precipitation data measured from the C-band passive microwave radiometer, the AMSR2 on-board Aqua platform (Figure 4). The VHI values increased with increasing precipitation values or soil moisture content. The linear models achieved for the 2013 and 2014 data had correlation coefficients ($r$) of 0.81 and 0.78 and $F$-statistics of 5,049.3 and 4,324.6 with $p$-value $<0.001$, respectively, indicating that the relationship was significant at 95% confidence limit. The Durbin-Watson statistics were smaller than 2 in both cases, indicating that there was autocorrelation in the residuals or no significant correlation due to sequence of variable input in the analysis.

The correlation analysis between the VHI and TVDI results for April 2013 and April 2014 was also performed. The results showed significant negative correlations between these two datasets (Figure 5), indicating that the VHI value increased with decreasing TVDI values. The $r$ and $F$-statistics achieved for the 2013 data were $-0.68$ and $312,109.5$, while those for 2014 were $-0.61$ and

Figure 3. The scatterplot showing the relationship between TCI and VCI. The upper line and lower horizontal lines of the scatterplot are dry and wet edges: (a) Mar 2013 and (b) Mar 2014.
The fitted models with $p$-values lower than 0.001 and Durbin-Watson statistics lower than 2 indicated a significant relationship between two datasets at 95% confidence limit and the autocorrelation in the residuals due to sequence of variable input in the analysis, respectively. In general, lower results were observed for 2014 in both comparisons between VHI and AMSR2 precipitation data as well as TVDI data, probably due to the larger climatic variations in 2014 causing EVI and LST disparities.

5.2. Spatio-temporal evolution of droughts

The VHI values from 0 to 1 were regrouped into four categories to present different levels of drought: severe drought (0–0.2); moderate drought (0.2–0.3); slight drought (0.3–0.4); and normal (0.4–1). An example illustrating monthly spatial distributions of droughts for a normal year 2013 and abnormal year 2014 generally showed a large degree of variation of droughts over space and time (Figures 6, 7). The severe and moderate droughts were spatially scattered over the study region but were more common in areas along the Pacific coast, while the slight drought and normal conditions were more commonly distributed in forested areas in the middle region and along the Atlantic coast. The temporal evolution drought trends showed that the spatial distributions of moderate and serve droughts occurred from the early dry season (December) and returned to normal or wet conditions by the end of dry season (April) or the early rainy season (May) with the onset of rainfall.

![Figure 4](image1.png)

**Figure 4.** Correlation between accumulated VHI and AMSR2 precipitation for: (a) 2013 and (b) 2014.

![Figure 5](image2.png)

**Figure 5.** Correlation between the VHI and TVDI for: (a) March 2013 and (b) March 2014.
When investigating the total area of severe drought for a 14-year period (2001–2014), a larger area of severe drought was generally observed during the dry season (December–April) (Figure 8). The driest condition was especially observed for the 2014 first cropping season (primera) across the study region, which has been characterized by severe rainfall deficits during the last 14 years (Figure 9). The larger area of severe drought was clearly found during April–May, with dry conditions continuing until July. These results were consistent with the precipitation observations reported by the European Commission (edo.jrc.ec.europa.eu), which found that the late arrival of rainfall in 2014 caused a prolonged drought, consequently leading to issues of food security and nutrition for approximately 2.5 million people in the study region (UNOCHA 2014).

This finding drew attention to the plight of farmers in the study region. The region was not only delayed by the start of rains (April–May), but also by a pronounced rain deficit due to droughts during the most sensitive stages of crop development (Jun–July). The extensive rainfall deficits and irregular distribution followed by a more severe and extended dry spell could have a detrimental impact on crop production during the primera season, with the worst affected areas particularly observed for Nicaragua. The impacts of drought triggered increased market food prices in response to crop production shortages, leading to issues of food security and social concerns in the region.
Figure 7. Monthly spatial distributions of droughts in an abnormal year 2014.

Figure 8. Monthly severe drought areas achieved from the VHI classification for 2001–2014.
Thus, local authorities could evaluate this issue to avoid possible negative impacts on crop production and poor and vulnerable households.

5.3. Cultivated areas affected by drought

Because of the unavailability of LUC maps covering the study period (2001–2014), this study depended on the 2010 LUC map to perform the assessment of cultivated areas affected by drought. The cultivated areas extracted from this LUC map were overlaid on the drought maps (i.e. severe and moderate drought classes) to spatially delineate the areas of cultivation affected by drought during 2001–2014 (Figures 10, 11). The results indicated that approximately 49.7%–75.7% of the total cultivated area was affected by severe and moderate droughts in the primera season and approximately 19.8%–38.8% in the postrera season (Table 1). Larger areas of cultivation were affected by severe drought (in percentage) in the primera season, especially in 2001 (14.6%), 2009 (19%), and 2014 (14.2%), and secondarily in the postrera season in 2010 (1.9%) and 2013 (1.8%). Overall, such quantitative spatiotemporal information on the distributions of drought prone areas in cultivated areas could be useful for local agronomic officials to improve their crop management strategies to avoid possible impacts on crop production in the study region.

The results of the probability of drought affecting proportions of cultivated area of each administrative unit indicated that large clusters of departments having high probabilities of drought occurrence were especially observed for Nicaragua and Guatemala during June–July in the primera season (Figure 12a), and El Salvador and Guatemala during October–November in the postrera season (Figure 12b). In this study, a threshold of 20% of the total cultivated area of an administrative unit was applied because we assumed that a relatively large number of farmers in that unit was affected by drought. This threshold can be modified, however, depending on the goal of the study attributing to food security issues as well as economic losses due to the drought.

Eventually, impacts of climate change in the form of higher temperatures and less precipitation existing challenges for farmers in many parts of Central America significantly affected crop viability resulting in lower production and more unpredictable harvests (Eitzinger et al. 2012; Tucker et al. 2010). The drought probability for cultivated areas calculated in this study was based on a 14-year period, which was relatively short to relate it to climate change. Although there were still uncertainties in the probability calculation for a drought event due to the spatial resolution and the limited length of satellite data, this study presented useful information of possible droughts for cultivated areas in each administrative unit. The department with high drought probability should be closely monitored to reduce drought-related yield losses.
6. Conclusions

This study assessed the cultivated areas affected by agricultural droughts for 2001–2014 from MODIS data using VHI. Comparisons between VHI results and AMSR2 precipitation and TVDI data indicated significant relationships between these datasets. The spatial distributions of moderate and severe droughts were generally concentrated in areas along the Pacific coast. The drought began in the early dry season (December) and returned to normal conditions by the end of April or early
May with the onset of the rainy season. The largest area of severe drought was observed for the 2014 primera season, especially April–July. When relating drought to cultivated areas during 2001–2014, the total area affected by drought in the primera season was approximately 49.7%–75.7% of the total cultivated area, while that in the postrera season was approximately 19.8%–38.8%. The occurrence probability of a drought event (considering 20% of cultivated area affected by drought) at the department level during the sensitive stage of crop development indicated that large clusters of departments having high probabilities of drought occurrence were especially observed in Nicaragua and Guatemala during the primera season and El Salvador and Guatemala in the postrera season. This

Figure 11. Spatial distributions of cultivated areas affected by severe and moderate droughts for the postrera season (September–November) during 2001–2014.
Table 1. Total areas of cultivated areas affected by severe and moderate droughts for primera and postrera seasons during 2001–2014. The percentage refers to the total cultivated area of 27,239 km².

| Year | Severe drought km² | Moderate drought km² | Total km² | Severe drought km² | Moderate drought km² | Total km² |
|------|--------------------|----------------------|-----------|--------------------|----------------------|-----------|
|      | km²                | %                    | km²       | %                  | km²                  | %         |
| 2001 | 3,979              | 14.6                 | 10,859    | 39.9               | 14,838               | 54.5      |
| 2002 | 2,872              | 10.5                 | 13,149    | 48.3               | 16,021               | 58.8      |
| 2003 | 2,805              | 10.3                 | 12,990    | 47.7               | 15,795               | 58.0      |
| 2004 | 2,726              | 10.0                 | 10,818    | 39.7               | 13,544               | 49.7      |
| 2005 | 3,587              | 13.2                 | 15,313    | 56.2               | 18,890               | 69.4      |
| 2006 | 3,338              | 12.3                 | 12,871    | 47.3               | 16,209               | 59.5      |
| 2007 | 2,800              | 10.3                 | 13,298    | 48.8               | 16,098               | 59.1      |
| 2008 | 2,539              | 9.3                  | 12,125    | 44.5               | 14,664               | 53.8      |
| 2009 | 5,174              | 19.0                 | 15,449    | 56.7               | 20,623               | 75.7      |
| 2010 | 2,694              | 7.7                  | 13,387    | 49.1               | 15,481               | 56.8      |
| 2011 | 1,921              | 7.1                  | 12,760    | 46.8               | 14,681               | 53.9      |
| 2012 | 1,776              | 6.5                  | 12,985    | 47.7               | 14,761               | 54.2      |
| 2013 | 2,463              | 9.0                  | 14,517    | 53.3               | 16,980               | 62.3      |
| 2014 | 3,874              | 14.2                 | 11,902    | 43.7               | 15,776               | 57.9      |

Figure 12. Occurrence probability of having more than 20% of the cultivated area affected by severe and moderate droughts by administrative municipalities during: (a) primera season and (b) postrera season.

study demonstrates the use of MODIS data for drought monitoring in Central America. The results could be vital for policymakers to successfully conceive strategies to mitigate possible impacts of droughts on crop production to enhance food security in the region.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Barbosa HA, Lakshmi KTV. 2016. Influence of rainfall variability on the vegetation dynamics over Northeastern Brazil. J Arid Environ. 124:377–387.

Barbosa HA, Lakshmi KTV, Silva LRM. 2015. Recent trends in vegetation dynamics in the South America and their relationship to rainfall. Nat Hazards. 77:883–899.

Bausch WC. 1993. Soil background effects on reflectance-based crop coefficients for corn. Remote Sens Environ. 46:213–222.

Blenkinsop S, Fowler HJ. 2007. Changes in drought frequency, severity and duration for the British Isles projected by the Prudence regional climate models. J of Hydrol. 342:50–71.

Bokusheva R, Kogan F, Vitkovskaya I, Conradt S, Batyrbayeva M. 2016. Satellite-based vegetation health indices as a criteria for insuring against drought-related yield losses. Agric For Meteorol. 220:200–206.

Bruce JP. 1994. Natural disaster reduction and global change. Bull Am Meteorol Soc. 75:1831–1835.

Brunetti M, Maugeri M, Nanni T, Navarra A. 2002. Droughts and extreme events in regional daily Italian precipitation series. Int J Climatol. 22:543–558.

Carlson T. 2007. An overview of the “triangle method” for estimating surface evapotranspiration and soil moisture from satellite imagery. Sensors. 7:1612–1629.

Carlson TN, Ripley DA. 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sens Environ. 62:241–252.

Chen, CF, Valdez MC, Chen NB, Chang LY, Yuan PY. 2014. Monitoring spatiotemporal surface soil moisture variations during dry seasons in central America with multisensor cascade data fusion. IEEE J Sel Top Appl Earth Obs Remote Sens. 7:4340–4355.

Chen J, Chen J, Liao A, Cao X, Chen X, He C, Han G, Peng S, Lu M, Zhang W, Tong X, Mills J. 2015. Global land cover mapping at 30 m resolution: a POK-based operational approach. ISPRS J Photogramm Remote Sens. 103:7–27.

Choi M, Jacobs JM, Anderson MC, Bosch DD. 2013. Evaluation of drought indices via remotely sensed data with hydrological variables. J Hydrol. 476:265–273.

Dracup JA, Lee KS, Paulson EG. 1980. On the definition of droughts. Water Resour Res. 16:297–302.

Eitzinger A, Sonder K, Schmidt A. 2012. Tortillas on the roaster: Central American maize-bean systems and the changing climate. Baltimore, MD: Catholic Relief Services.

Field CB, Van Aalst M. 2014. Climate change 2014: impacts, adaptation, and vulnerability. New York, NY: Cambridge University Press.

Gao BC. 1996. NDWI – A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sens Environ. 58:257–266.

Ghulam A, Qin Q, Teyip T, Li ZL. 2007. Modified perpendicular drought index (MPDI): a real-time drought monitoring method. ISPRS J of Photogramme Remote Sens. 62:150–164.

Gurung RB, Breidt FJ, Dutin A, Ogle SM. 2009. Predicting enhanced vegetation index (EVI) curves for ecosystem modeling applications. Remote Sens Environ. 113:2186–2193.

Hatfield JL. 1983. Remote sensing estimators of potential and actual crop yield. Remote Sens Environ. 13:301–311.

Heim RR. 2002. A review of twentieth-century drought indices used in the United States. Bull Am Meteorol Soc. 83:1149–1165.

Heim RR, Brewer MJ. 2012. The global drought monitor portal: The foundation for a global drought information system. Earth Interact. 16:1–28.

Huete AR, Liu HQ, Batchiky K, van Leeuwen W. 1997. A comparison of vegetation indices over a global set of TM images for EOS-MODIS. Remote Sens Environ. 59:440–451.

Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ. 83:195–213.

Idso SB, Jackson RD, Pinter Jr PJ, Regina R, Hatfield JL. 1981. Normalizing the stress-degree-day parameter for environmental variability. Agric Meteorol. 24:45–55.

IPCC. 2007. Climate change 2007. Contribution of working groups I and II to the fourth assessment report of the intergovernmental panel on climate change. New York, NY: Cambridge University Press.
Jackson RD, Idso SB, Reginato RJ, Pinter PJ, Jr. 1981. Canopy temperature as a crop water stress indicator. Water Resour Res. 17:1133–1138.

Jain SK, Keshri R, Goswami A, Sarkar A, Chaudhry A. 2009. Identification of drought—vulnerable areas using NOAA AVHRR data. Int J Remote Sens. 30:2653–2668.

Jiahua Z, Zhengming Z, Fengmei Y, Limin Y, Cui H. 2015. Validating the modified perpendicular drought index in the North China region using in-situ soil moisture measurement. IEEE Geosci Remote Sens Lett. 12:542–546.

Jiang Z, Huete AR, Didan K, Miura T. 2008. Development of a two-band enhanced vegetation index without a blue band. Remote Sens Environ. 112:3833–3845.

Karnieli A, Agam N, Pinker RT, Anderson M, Imhoff ML, Gutman GG, Panov N, Goldberg A. 2010. Use of NDVI and land surface temperature for drought assessment: Merits and limitations. J Clim. 23:618–633.

Keshavarz MR, Vazifeoudsi M, Alizadeh A. 2014. Drought monitoring using a soil wetness deficit index (SWDI) derived from MODIS satellite data. Agric Water Manage. 132:37–45.

Kogan F. 1995a. Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. Bull Am Meteorol Soc. 76:655–668.

Kogan F. 1997. Global drought watch from space. Bull Am Meteorol Soc. 78:621–636.

Kogan F, Yang B, Wei G, Zhiyuan P, Xianfeng J. 2005. Modelling corn production in China using AVHRR-based vegetation health indices. Int J Remote Sens. 26:2325–2336.

Le Comte D. 1995. Highlights around the world. Weatherwise. 48:20–22.

Le Comte D. 1998. Weather highlights around the world. Weatherwise. 51:26–31.

Li Z, Tan D. 2014. A modified perpendicular drought index in NIR-Red reflectance space. IOP Conf Ser: Earth Environ Sci. 17:012040.

Mallick K, Bhattacharya BK, Patel NK. 2009. Estimating volumetric surface moisture content for cropped soils using a soil wetness index based on surface temperature and NDVI. Agric For Meteorol. 149:1327–1342.

Mishra AK, Singh VP. 2009. Analysis of drought severity-area-frequency curves using a general circulation model and scenario uncertainty. J Geophys Res. 114:1–18.

Mishra AK, Singh VP. 2010. A review of drought concepts. J Hydrol. 391:202–216.

Mishra AK, Singh VP. 2011. Drought modeling – a review. J Hydrol. 403:157–175.

Morel B. 2014. Drought hits Central America’s crops, cattle. Phys Org. [Internet]; [cited 2015 Apr 15]. Available from: http://phys.org/news/2014-08-drought-central-america-crops-cattle.html

Nemani R, Pierce L, Running SN, Goward SN. 1993. Developing satellite-derived estimates of surface moisture status. J Appl Meteorol. 32:548–557.

Olson MB, Morris KS, Méndez VE. 2012. Cultivation of maize landraces by small-scale shade coffee farmers in western El Salvador. Agric Syst. 111:63–74.

Potgieter AB, Apan A, Dunn P, Hammer G. 2007. Estimating crop area using seasonal time series of Enhanced Vegetation Index from MODIS satellite imagery. Aust J Agric Res. 58:316–325.

Rahimzadeh BP, Darvishsefati AA, Khalili A, Mahdoum MF. 2008. Using AVHRR-based vegetation indices for drought monitoring in the Northwest of Iran. J Arid Environ. 72:1086–1096.

Rhee J, Im J, Carbone GJ. 2010. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. Remote Sens Environ. 114:2875–2887.

Rojas O, Vrieling A, Rembold F. 2011. Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. Remote Sens Environ. 115:343–352.

Sandholt I, Rasmussen K, Andersen J. 2002. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. Remote Sens Environ. 79:213–224.

Schmidt A, Eitzinger A, Sonder K, Sain G, Rodriguez B, Hellin J, Fisher M, Läderach P, Vicente FS, et al. 2012. Tortillas on the roaster: Central American maize-bean systems and the changing climate. Geneva: UN Office for Disaster Risk Reduction (UNISDR).

Seiler RA, Kogan F, Wei G, Vinocur M. 2007. Seasonal and interannual responses of the vegetation and production of crops in Cordoba – Argentina assessed by AVHRR derived vegetation indices. Adv Space Res. 39:88–94.

Solano R, Didan K, Jacobson A, Huete A. 2010. MODIS vegetation indices (MOD13) C5 user’s guide [Internet]; [cited 2015 May 20]. Tucson, AZ: The University of Arizona. Available from: https://vip.arizona.edu/documents/MODIS/MODIS_VI_UsersGuide_01_2012.pdf

Son NT, Chen CF, Chen CR, Chang LY, Minh VQ. 2012. Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. Int J Appl Earth Obs Geoinf. 18:417–427.

Son NT, Chen CF, Chen CR, Minh VQ, Trung NH. 2014. A comparative analysis of multitemporal MODIS EVI and NDVI data for large-scale rice yield estimation. Agric For Meteorol. 197:52–64.

Trenberth KE, Dai A, van der Schrier G, Jones PD, Barichivich J, Briffa KR, Sheffield J. 2014. Global warming and changes in drought. Nature Clim Change. 4:17–22.
Tucker CM, Eakin H, Castellanos EJ. 2010. Perceptions of risk and adaptation: coffee producers, market shocks, and extreme weather in Central America and Mexico. Global Environ Change. 20:23–32.

Turner DP, Cohen WB, Kennedy RE, Fassnacht KS, Briggs JM. 1999. Relationships between leaf area index and Landsat TM spectral vegetation indices across three temperate zone sites. Remote Sens Environ. 70: 52–68.

Unganai LS, Kogan FN. 1998. Drought monitoring and corn yield estimation in southern Africa from AVHRR data. Remote Sens Environ. 63:219–232.

UNOCHA. 2014. Drought in Central America [Internet]. UN Office for the Coordination of Humanitarian Affairs; [cited 2015 Jun 17]. Available from: http://reliefweb.int/sites/reliefweb.int

Vermote EF, Kotchenova SY, Ray JP. 2015. MODIS surface reflectance user’s guide [internet]; [cited 2015 Apr 16]. Greenbelt, MD: NASA Goddard Space Flight Center. Available from: http://modis-sr.ltdri.org

von Storch H, Zwiers FW. 1998. Statistical analysis in climate research. New York, NY: Cambridge University Press.

Wan Z, Wang P, Li X. 2004. Using MODIS land surface temperature and normalized difference vegetation index products for monitoring drought in the southern Great Plains, USA. Int J Remote Sens. 25:61–72.

Wan Z, Zhang Y, Zhang Q, Li ZL. 2002. Validation of the land-surface temperature products retrieved from Terra Moderate Resolution Imaging Spectroradiometer data. Remote Sens Environ. 83:163–180.

Wang H, Li X, Long H, Xu X, Bao Y. 2010. Monitoring the effects of land use and cover type changes on soil moisture using remote-sensing data: A case study in China’s Yongding River basin. Catena. 82:135–145.

Wang L, Qu JJ. 2007. NMDI: A normalized multi-band drought index for monitoring soil and vegetation moisture with satellite remote sensing. Geophys Res Lett. 34:L20405.

Wang L, Qu JJ, Hao X. 2008. Forest fire detection using the normalized multi-band drought index (NMDI) with satellite measurements. Agric For Meteorol. 148:1767–1776.

WFP. 2014. Central and South America: the 2014 rainfall season [Internet]. World Food Program; [cited 2015 May 19]. Available from: http://documents.wfp.org/stellent/groups/public/documents/ena/wfp268824.pdf

Wilhite DA. 2000. Drought: a global assessment. London: Routledge.

Wilhite DA, Glantz MH. 1985. Understanding: the drought phenomenon: the role of definitions. Water Int. 10:111–120.