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The Microwave Temperature Vegetation Drought Index (*MTVDI*) based on *AMSR-E* brightness temperatures for long-term drought assessment across China (2003–2010)

Liyang Liu [a,h], Jishan Liao [a,1], Xiuzhi Chen [a,b,*], Guoyi Zhou [a], Yongxian Su [b,c,*], Zhiying Xiang [d], Zhe Wang [e], Xiaodong Liu [f], Yiyong Li [g], Jianping Wu [a,1], Xin Xiong [a], Huaiyong Shao [h,*]

[a] Key Laboratory of Vegetation Restoration and Management of Degraded Ecosystems, Guangdong Provincial Key Laboratory of Applied Botany, South China Botanical Garden, Chinese Academy of Sciences, Guangzhou 510650, China
[b] Laboratoire des Sciences du Climat et de l'Environnement, UMR 1572 CEA-CNRS UVSQ, 91191 Gif sur Yvette, France
[c] Key Lab of Guangdong for Utilization of Remote Sensing and Geographical Information System, Guangdong Open Laboratory of Geospatial Information Technology and Application, Guangzhou Institute of Geography, Guangzhou 510070, China
[d] School of Earth Sciences, Zhejiang University, Hangzhou 310027, China
[e] School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ, USA
[f] College of Forestry and Landscape Architecture, South China Agricultural University, Guangzhou 510642, China
[g] College of Forestry and Landscape Architecture, Anhui Agricultural University, Hefei 230036, China
[h] Key Laboratory of Geoscience Spatial Information Technology of Ministry of Land and Resources, College of Earth Science, Chengdu University of Technology, Chengdu 610059, China

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ABSTRACT

Satellite-based drought indices have been proved to be effective and convenient in detecting drought conditions at regional and global scales. However, most current drought indices are based on the visible/near infrared/thermal remote sensing, which might be influenced greatly by cloud, atmospheric water content and rain-fall. Microwave sensors can overcome the shortages of visible/near infrared/thermal remote sensing and show to be another important approach for drought monitoring due to its all-weather working advantages. But to date, the application of microwave vegetation drought indices in drought monitoring has not been thoroughly investigated. Here, for the first time we constructed a microwave derived Temperature Vegetation Drought Index (*TVDI*) - *MTVDI* based on the theory of optical *TVDI* using the brightness temperatures (*Tb*) from the Advanced Microwave Scanning Radiometer (*AMSR-E*) onboard Aqua satellite. Firstly, we built a new land surface temperature (*Ts*) inversion model based on the *AMSR-E* 18.7 GHz horizontal, 23.8 GHz and 89.0 GHz vertical polarized *Tb*, and then developed the Microwave Normalized Difference Vegetation Index (*MNDVI*) from the *AMSR-E* 23.8 GHz Microwave Polarization Difference Index (*MPDI*). After that, we constructed three versions of *MTVDI*: original *MTVDI* using *Ts* and *MNDVI*; *Imp-MTVDI* (Improved *MTVDI*) using the $Ts-T_{air}$ (the difference between land surface temperature and air temperature) to replace the *Ts*; and *NonL-MTVDI* (Nonlinear *MTVDI*) using nonlinear equation to fit the dry and wet edges, respectively. Finally, we used precipitation, soil moisture (*SM*) and *P/PET* (the ratio of precipitation to potential evapotranspiration) to validate the performances of *MTVDI*, *Imp-MTVDI*, *NonL-MTVDI*, *MODIS* derived *TVDI* and *iTVDI* (improved *TVDI*). The time-series drought assessments across China from 2003 to 2010 indicated that the trends of the proposed *MTVDI* showed the most negative correlations with the variations of precipitation, *P/PET* and *SM*, and showed best performances of significance test in most regions of China. Moreover, the MTVDI could better separate the drought levels in different degrees than MODIS-derived TVDI. However, the proposed *MTVDI* still has some uncertainties in regions widely covered by desert, Gobi and large water surfaces. In addition, this paper mainly focuses on large spatial scale and long term drought monitoring and only uses satellite data for model validation. Further studies are needed to develop a higher spatial- and temporal-resolution *MTVDI* for short-term and small spatial-scale drought monitoring.

1. Introduction

Droughts are broadly classified into four major types: meteorological (reduction of precipitation), agricultural (shortage of available water for plant growth), hydrological (deficiency of surface and

* Corresponding authors.
E-mail addresses: chenxz@scbg.ac.cn, xiuzhi.chen@lsce.ipsl.fr (X. Chen), suyongxian@gdas.ac.cn (Y. Su), huaiyongshao@163.com (H. Shao).
[1] Co-first authors.

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subsurface water supply), and socioeconomic drought (insufficient water supply to meet the demand of economic growth) (Wilhite, 2005; Zhang and Jia, 2013; AghaKouchak et al., 2015). It is the most costly natural disaster that poses significant water and food security concerns worldwide (Wilhite, 2005; Godfray et al., 2010; Zhang and Jia, 2013; AghaKouchak et al., 2015). It is also considered to be one of the most complex but least understood natural hazard (Hagman, 1984; Obasi, 1994; Wilhite, 2000). Given the serious impacts of droughts on economies, eco-environments and especially on the agricultures, it is vital and urgent to develop effective means for timely monitoring large spatial-scale drought events (Goddard et al., 2003; Tadesse et al., 2005).

In recent years, drought has been widely assessed based on observed changes in vegetation health and land cover from remotely sensed data (Tucker and Choudhury, 1987; Silleos et al., 2006; Nemani et al., 2009). Many drought indices based on visible/near infrared/thermal remote sensing data have been proposed to detect drought at the regional or global scales (Qin et al., 2006; Rhee et al., 2010; Escorihuela and Quintana-Seguí, 2016). They are mainly classified into three types: vegetation, temperature, and temperature-vegetation indices (Table.1).

The Normalized Difference Vegetation Index (*NDVI*) is the most frequently used vegetation index and the first visible/near infrared/thermal remote sensing-based measure used to monitor vegetation drought (Rouse et al., 1974; Jain et al., 2009; Ji and Peters, 2003; Karnieli et al., 2010; Bajgiran et al., 2008). Building on the original definition of *NDVI*, a number of vegetation indices were established in detecting droughts, such as the Transformed Vegetation Index (*TVI*) (Deering and Rouse, 1975; Tucker, 1979), Vegetation Condition Index (*VCI*) (Kogan, 1995a, 1995b) and Enhanced Vegetation Index (*EVI*) (Huete et al., 2002; Saleska et al., 2007). These indices describe the vegetation condition by combining spectral information from different parts of the electromagnetic spectrum that are sensitive to biophysical characteristics of vegetation, such as chlorophyll content, water content, and internal leaf structure (AghaKouchak et al., 2015). However, vegetation index is strongly correlated with the vegetation greenness (Sellers et al., 1992). It is often referred to a greenness index rather than a drought index (Jackson et al., 2004).

The land surface temperature (*Ts*) computed from thermal infrared bands has been found to provide valuable information on surface moisture conditions (Gutman, 1990). The most used temperature indices are the Normalized Difference Temperature Index (*NDTI*) (McVicar and Jupp, 1998) and Temperature Condition Index (*TCI*) (Bhuiyan et al., 2006; Jain et al., 2009). Compared with the vegetation index, the temperature indexis more sensitive to soil water stress due to the relationship between leaf temperature and transpiration (Goetz, 1997; Wang et al., 2004). Therefore, the temperature index might ignore the different drought-resistance of plants and thereby brought some inaccuracies in detecting the drought conditions of different vegetation types (Moran, 2004).

In recent years, various ways of combining *NDVI* and *Ts* information have been explored for drought monitoring and impact assessment (e.g., the Temperature Vegetation Drought Index (*TVDI*) combining *NDVI* and *Ts*) (Price, 1990; Nemani et al., 1993; Moran et al., 1994; Carlson et al., 1995). The *TVDI* method is an index based on the empirical interpretation of the *NDVI-Ts* triangle space (Fig. 3, in Section 3.3), relying on the relationship (typically, negative correlation) between *NDVI* and *Ts* (Lambin and Ehrlich, 1996; McVicar and Bierwirth, 2001; McVicar and Jupp, 1998; Karnieli et al., 2010). It has been widely applied in drought monitoring at the drainage basin scale (Son et al., 2012; Wang et al., 2010), regional scale (Chen et al., 2011a; Li et al., 2010; Liu et al., 2008; Cao et al., 2016; Zhang et al., 2016, July; Gao et al., 2011) and national scale (Liang et al., 2014; Wang et al., 2004). Studies showed that the combination of vegetation and temperature indices provides a more powerful tool for monitoring the drought conditions of vegetation than the individual vegetation and temperature indices (Sandholt et al., 2002; Singh et al., 2003).

Optical-based drought indicators are sensitive to cloud cover, atmospheric effects, aerosols, water vapor, and land cover condition and brings certain limitation for drought monitoring applications (Andela et al., 2013; Shi et al., 2008; Liu et al., 2011a). Unlike optical sensors, microwave sensors are less affected by atmospheric conditions and can penetrate into dense canopy, showed to be another important approach for drought monitoring due to its all weather working advantages (Zhang and Jia, 2013). Soil moisture derived from the microwave remote sensing is a sensitive index of drought, and was widely used to monitor water deficit (Andreadis et al., 2005; Cai et al., 2009; Chen et al., 2012; Yuan et al., 2015; Chen et al., 2016). But soil water deficit would much refer to the hydrological drought rather than the agricultural drought. Several studies investigated on microwave drought index for drought monitoring, such as the Microwave Integrated Drought Index (MIDI) (Zhang and Jia, 2013) and the Microwave Polarization Index (MPI) (Mao et al., 2010).

But to date, the application of microwave vegetation drought indices in drought monitoring has not been thoroughly investigated (Zhang and Jia, 2013). To integrate the advantages of both *TVDI* and microwave remote sensing in drought monitoring, this paper proposed a new drought monitoring index called the Microwave Temperature Vegetation Drought Index (*MTVDI*) based on the Aqua satellite advanced microwave scanning radiometer (*AMSR-E*) brightness temperatures (*Tb*) (Ashcroft and Wentz, 2000) of 89.0 GHz, 23.8 GHz and 18.7 GHz. The main objectives of this study are: 1) to construct the *NDVI-Ts* triangle using *AMSR-E* microwave *Tb* for drought monitoring, like the optical

Table 1
Drought indices based on visible/near infrared/thermal remote sensing data. α represented the weight of single index. $NDVI_{max}$ and $NDVI_{min}$ represent the maximum and minimum values of the Normalized Difference Vegetation Index, respectively. *LST* and *T* represent the Land Surface Temperature, T_{max}, LST_{max} and T_{min}, LST_{min} represent the maximum and minimum values of Land Surface Temperature, respectively. T_s represent the observed surface temperature, T_∞ and T_0 represent a modelled surface temperature with infinite and zero surface resistance, respectively. *TRMM* represent the precipitation based on Tropical Rainfall Measuring Mission satellite, and $TRMM_{max}$ and $TRMM_{min}$ represent the maximum and minimum values of the precipitation, respectively.

Drought Indices	Formula	Citation
NDVI	$(\rho858-\rho650)/(\rho858+\rho650)$	Rouse et al., 1974; Tucker, 1979; Kogan, 1991, 1995a
EVI	$2.5*(\rho858-\rho650)/(\rho858+6*\rho650-7*\rho469+1)$	Huete et al., 2002; Saleska et al., 2007
VCI	$(NDVI_i-NDVI_{min})/(NDVI_{max}-NDVI_{min})$	Kogan, 1995a
LSWI	$(\rho858-\rho1640)/(\rho858+\rho1640)$	Bajgain et al., 2015
TCI	$(T_{max}-T_i)/(T_{max}-T_{min})$	Kogan, 1995a
NDWI	$(\rho858-\rho1240)/(\rho858+\rho1240)$	Gao (1996); Chen et al. (2005)
NDDI	$(NDVI-NDWI)/(NDVI+NDWI)$	Gu et al., 2007
NDTI	$(T_\infty-T_s)/(T_\infty-T_0)$	McVicar and Jupp, 1998
NMDI	$(\rho860-(\rho1640-\rho2130))/(\rho860+(\rho1640-\rho2130))$	Wang and Qu, 2007
VHI	$\alpha*VCI+(1-\alpha)*TCI$	Kogan, 1995a, 1995b
SDCI[a]	$(1/4)*scaled\ LST+(1/2)*scaled\ TRMM$ $+(1/4)*scaled\ NDVI$	Rhee et al., 2010

[a] $Scaled\ LST=(LST_{max}-LST_i)/(LST_{max}-LST_{min})$, $scaled\ TRMM=(TRMM_i-TRMM_{min})/(TRMM_{max}-TRMM_{min})$, $scaled\ NDVI=(NDVI_i-NDVI_{min})/(NDVI_{max}-NDVI_{min})$.