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Integration of remote sensing datasets for local scale assessment and prediction of drought

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HIGHLIGHTS

- Phase relationships between rainfall and vegetation moisture conditions are observed
- Significant difference in response was observed between vegetation cover types
- An integrated approach for drought assessment is proposed

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ABSTRACT

Recent attempts to integrate remote sensing-based drought indices with precipitation data seem promising, and can compensate for potential uncertainties from image-based parameters alone, which may be unrelated to meteorological drought. However most remote sensing-based studies have been at regional or global scale and have not considered differences between different land cover types. This study examines a drought-prone region in Central Yunnan Province of China over a four-year period including a notable severe drought event in 2010. The study investigates the phase relationships between meteorological drought from image-based rainfall estimates from the Tropical Rainfall Measurement Mission (TRMM), and imaged drought from a remote sensing drought index, the Normalised Vegetation Supply Water Index (NVSWI) for different land cover types at local scale. The land cover types derived from MODIS and Landsat images were resampled to 250 m to match all datasets used. Significant differences between cover types are observed, with cropland and shrubland most highly correlated with 64 days' earlier rainfall and evergreen forest most responsive to rainfall 90 days earlier, indicating a need to consider detailed land cover information for accurate integrated drought indices. The finding that concurrent rainfall is only weakly correlated with observed drought, suggests that existing drought indices, which compute lowest weightings for the most distant lag period would be unrepresentative.

1. Introduction

Drought is a difficult condition to measure and quantify as it operates on many spatial and temporal scales, but a common feature is the deficiency of moisture resulting from abnormal weather patterns. Quantification of drought suffers from the observation that low rainfall and soil moisture levels resulting in lower agricultural productivity in one region may not be abnormal in another region with different crop types and farming practices. Remote sensing now freely provides many processed image products suitable for both global and local drought assessments.

Techniques for monitoring agricultural drought from remote sensing are indirect, as they depend on using image-based parameters to represent soil moisture status when the soil is often obscured by a vegetation cover. The techniques are mainly based on measuring vegetation health or greenness using vegetation indices, often in combination with canopy temperature anomalies using thermal infra-red wavebands. The most commonly used vegetation index, the Normalised Difference Vegetation Index (NDVI) (Tucker, 1979) is a ratio of highly reflective near infra-red (NIR) and highly absorptive red wavelengths in healthy vegetation, with stressed plants exhibiting decreased NIR and increased red reflectance. The temperature of vegetation under moisture stress is expected to increase due to closure of leaf stomata to reduce moisture loss by evapotranspiration. The main drawbacks of using image-based parameters alone to represent soil moisture arise from this indirect approach, since there may be other reasons than low soil moisture, for delayed greening or higher than normal canopy temperatures. For example the Vegetation Condition Index (VCI) developed for the Advanced Very High Resolution Radiometer (AVHRR) (Kogan, 2002) compares the observed NDVI to the range of values observed in previous years, but anything that stresses vegetation may cause reduced NDVI values such

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as disease, soil nutrient status or other climatic anomaly, and may not be related to soil moisture. The same applies to the Perpendicular Drought Index (PDI) (Ghulam et al., 2008) and the Modified Perpendicular Drought Index (MPDI) (Ghulam et al., 2007), which use the inverse relationship between the red and visible infra-red wavebands of Landsat ETM+ (Ghulam et al., 2007) and MODIS (Qin et al., 2008) to evaluate field moisture conditions under variable amounts of vegetation cover. Additionally, the NDVI has been found to give false 'greening' if seasonal canopy shadow effects are not removed (Morton et al., 2014). Similarly, the use of thermal infra-red wavebands in drought indices suffers from diurnal temperature and weather fluctuations at the image time which limit the ability of thermal images to represent soil moisture conditions. The Vegetation Supply Water Index (VSWI) (Carlson et al., 1990, 1994) combines a vegetation index (NDVI) with the thermal image-based parameter Land Surface Temperature (LST) (Eq. (1)) (Cai et al., 2011; Gao et al., 2008; Nemani et al., 2003) and is commonly used due to its simplicity and ability to represent two potential properties of vegetation stress in one index, but suffers from the mismatch in time scales, since vegetation greenness is fairly stable in the short to medium term but temperature fluctuates diurnally, and according to weather conditions as well as slope, aspect and terrain properties.

$$\mathrm{VSWI} = \mathrm{NDVI}/\mathrm{Ts} \tag{1}$$

The VSWI is also specific to the land cover type and measurement time of the image scene, and cannot be used as an absolute measure of drought severity. Thus, attempts to normalise the VSWI have contextualized the index within a defined period of available records (Gao et al., 2008; Abbas et al., 2014). This normalised VSWI can indicate present ground conditions compared with other periods on record i.e. drought severity on an absolute scale. For example, the NVSWI of Abbas et al. (2014) (Eq. (2)) portrays relative drought conditions across the years and between the years, with an NVSWI of zero indicating severest drought during the study period and NVSWI of 100 indicating wettest conditions.

$$\mathrm{NVSWI} = \frac{(\mathrm{VSWI}-\mathrm{VSWI}_{\min})}{(\mathrm{VSWI}_{\max}-\mathrm{VSWI}_{\min})} \times 100 \tag{2}$$

Since precipitation is the main direct causative factor of drought, an indirect, image-based drought index should benefit from the inclusion of rainfall data representing meteorological drought. This inclusion compensates for late sowing and harvesting of crops, plant disease or insect attack which may appear as relative drought stress on NVSWI images, or from false greening effects of the NDVI discussed above. This has been done by integration of image-based, with precipitation-based, drought indices, such as the Palmer Drought Severity Index (PDSI) (Palmer, 1965) or the Standardised Precipitation Index (SPI) (Guttman, 1999) which use only climate station precipitation data. Since drought is an abnormal phenomenon, these indices usually consider present precipitation in longer term context such as 24 months for SPI, and the PDI computes the probability of recording a given amount of rainfall over a period of one to 36 months. For integration with image-based drought indices the rainfall index at ground station points is spatially interpolated to interface with the image-based drought index (Qin et al., 2008; Gao et al., 2008). Since 1997 it has been possible to use image-derived rainfall estimates from the Tropical Rainfall Measuring Mission (TRMM) satellite in integrated drought indices (Almazroui, 2011; Du et al., 2013; Abbas et al., 2014). For example, Du et al. (2013) define a Precipitation Condition Index (PCI) to integrate with an image-based drought index, where TRMM daily precipitation data are amalgamated to monthly estimates and then normalised using minimum and maximum rainfall within a defined 10-year period (Eq. (2)). Thus their normalised precipitation index was combined with normalised, image-based temperature and vegetation indices for a holistic drought index.

$$\mathrm{PCI} = (\mathrm{TRMM}-\mathrm{TRMM}_{\min}/\mathrm{TRMM}_{\max}-\mathrm{TRMM}_{\min}) \times 100 \tag{3}$$

A major limitation of integrating precipitation data directly with image data is that image data indicate current ground conditions but concurrent rainfall data may be irrelevant, as drought is a response to rainfall in the recent past. Furthermore, it may possible that the absence of a particular period or event of rainfall can trigger a drought event, since some crops are very sensitive to a specified amount of moisture at specific growth stages. This limitation was considered by Gao et al. (2008) who described drought development as a "gradual process of ground drying" indicating an accumulative effect of precipitation deficit on response of vegetation to drought. Therefore they incorporated the effect of accumulative rainfall into their proposed VSWI by weighting eight 10-day backward periods with a regular decline to the most distant lag period having the lowest weight. Udelhofen et al. (2009) correlated an NDVI-based drought index with previous rainfall periods to understand the climatic processes affecting drought in agricultural areas in Spain. However, no previous study has quantitatively estimated the relevant lag periods for optimal incorporation of rainfall data into image-based drought indices. This is important because the use of a standard lag period, or one with regular decrease over time may be irrelevant for a particular study area (Nicholson and Farrar, 1994), soil type (Ji and Peters, 2003), or crop cover type (Wan et al., 2004). In addition, accurate knowledge of the response period of drought to previous rainfall can assist in the prediction of drought by several weeks or months, whereas existing drought indices can only estimate current drought.

The objectives of this research are to calculate and evaluate the phase relationships between image-observed drought and previous rainfall in different land cover types, in order to derive more accurate remote sensing-based drought indices as well as to predict drought onset using the lag time relationships.

The study made two assumptions: 1) The vegetation moisture response varies according to land cover type, and 2) correlation of vegetation response to earlier rainfall may not decrease regularly with time, but it may possible that two or more months' earlier rainfall affects vegetation moisture conditions more than current, or one month earlier rainfall.

2. Methodology

A study was undertaken in a drought-prone region of Central Yunnan Province of China to calculate and identify phase relationships between previous rainfall and image-observed drought over a 4-year period 2008–2011, including one notable severe drought in 2010 (Zhang et al., 2012). Spring droughts in the region have serious impacts on livelihoods as they come at the start of the growing season and these are dependent on rainfall from the previous November to February. The drought observations were based on image-derived NVSWI from MODIS images, using the MODIS NDVI standard product for 16-day intervals at 250 m resolution and the MODIS 8-day LST standard product at 1 km resolution. These were composited to 16-days and resampled to 250 m pixels to match the NDVI images. Rainfall estimates were derived from the TRMM (Abbas et al., 2014) as preferable to spatially limited climate station data, as a correlation coefficient between in situ station rainfall and TRMM, of 0.97 was observed (Abbas et al., 2014). The TRMM daily rainfall product was composited into 16-day intervals and resampled from the relatively coarse resolution of 0.5° to 250 m and used in the computation of PCI (Eq. (3)). Land cover types were mapped from two available global Land Use/Land Cover (LULC) products, the MODIS LULC at 500 m and GLC2000 LULC derived from Landsat at 30 m resolution, then resampled to 250 m, along with all other datasets. Three major LULC types together occupy approximately 96% of the