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Retrieving vegetation growth patterns from soil moisture, precipitation and temperature using maximum entropy

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ABSTRACT

This study employs entropy theory to evaluate the relation of vegetation cover to soil moisture, precipitation and temperature patterns in the Texas Gulf watershed. Over a 12-year period, we consider the Normalized Differential Vegetation Index (NDVI) of the growing season (May to September) for deciduous forest and grasslands, as well as precipitation, temperature, and soil moisture data at a biweekly time scale. Using three different vegetation growth metrics, we analyze patterns in vegetation responses. An entropy scaling of the system of vegetation-soil moisture-precipitation-temperature reveals trends toward maximum entropy and shows the relevance of coupling these atmospheric variables in vegetation dynamic analysis. Our analysis indicates that soil moisture is potentially efficient to use for vegetation dynamics monitoring at finer time scales compared to precipitation. The near-surface (5 cm) soil moisture series shows meaningful relationship with vegetation growth series. This seems interesting, as the recent satellite soil moisture monitoring projects are designed for estimating near-surface moisture. Month-wise, the vegetation response to atmospheric variables shows important dissimilarities. Therefore, we use an entropy-based clustering approach to discriminate the growing season. Later, we propose a nested statistical model for retrieving an estimate of NDVI. We find that the inclusion of soil moisture and temperature explains up to 68% and 62% of the variation of NDVI, respectively, for deciduous forest and grassland during June and July. However, these relationships appear weaker during the end of the growing season (August and September). The outcomes of the study are suitable for ecosystem monitoring under the realm of climate change. Likewise, the techniques employed may find useful applications for water resources management at the scale of large watersheds. Nevertheless, further studies on the topic are necessary and should involve diversified ecosystems and remote sensed products.

1. Introduction

The climate system is governed by complex interactions between the atmosphere, the hydroshepere, the lithosphere, the biosphere, and the cryosphere (Peixoto et al., 1991). Changes in vegetation cover are merely a response resulting from both environmental and biological conditions. However, it is a conundrum to accurately incorporate into vegetation and climate models all the interactions emanating from the biophysical components of the climate. Consequently, the real vegetation and ecosystem functionalities are commonly simplified (Reich et al., 2007; Sitch et al., 2003).

Several authors have reported significant relationships between precipitation, temperature, and remotely sensed vegetation indices (Brunsell and Young, 2008; Pettorelli et al., 2007; Kawabata et al., 2001). The choice of focusing on individual factors rather than all of them at the same time is guided by the aim to depict their influence separately. However, attempts at using solely precipitation or temperature for vegetation dynamics estimates have resulted in low efficiency, i.e., low overall correlation coefficients between Normalized Differential Vegetation Index (NDVI) and precipitation series (Liu et al., 2013; Nicholson et al., 1990). Ichii et al. (2002) found significant but weak relationships between vegetation growth and precipitation and pointed out insufficient long-term data. Outside of certain precipitation thresholds, Nicholson et al. (1990) reported weaker relationships between NDVI and precipitation, indicating non-linear overall relationships. At a global level, Kawabata et al. (2001) reported different scenarios of NDVI trends in relation to temperature and precipitation according to the location. However,

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efforts in retrieving NDVI from climate components poorly involved observed soil moisture data. Brunsell and Young (2008) emphasized the role of soil moisture in the short-term land surface response. Unfortunately, real observed soil moisture data are not consistently available in time and space (Seneviratne et al., 2006) and this has limited their use in large-scale vegetation dynamic studies.

Soil moisture is the water stored in the soil pores. Originally, this water is replenished by atmospheric water through infiltration but can also be recharged through capillary rise (Legates et al., 2011). The rate of each of these two processes of soil water recharge depends on environmental and geophysical factors (Wang et al., 2013; Legates et al., 2011). In contrast to precipitation, the water in the soil is the one directly available for plant roots. Compared to precipitation and temperature, land-based soil moisture measuring instruments are relatively more expensive and costly in terms of monitoring and maintenance. For that reason, historical land-based soil moisture measurements are not consistently available in time and space explaining why several studies have been conducted using model-generated soil moisture data (Seneviratne et al., 2006). Such an approach has led to model dependent conclusions, which clearly affect the uncertainty in model results. Meanwhile, moisture sensitivity to microwave represents a crucial alternative for deriving soil moisture using satellite images (Pellarin et al., 2009; Wagner et al., 2003). Hence, remote sensing of soil moisture has made possible the quantification of near-surface moisture by combining infrared remote sensing and vegetation index, i.e., the Advanced Microwave Scanning Radiometer of the Earth Observing System (AMSR-E) uses passive microwave signals to generate mean term soil moisture estimates at a 25 km spatial resolution (Njoku et al., 2003). Lately the National Aeronautics and Space Administration NASA's Soil Moisture Active Passive (SMAP) mission (Entekhabi et al., 2010) is proposing a high resolution (spatial = 9 km, temporal = 3 days) global soil moisture measurement (Das et al., 2011). Although the SMAP project offers promising application perspectives, the algorithm proposed for retrieving soil moisture from remote sensed signals imbeds a vegetation water content correction (Das et al., 2011).

A potential weakness of using remote sensed vegetation index in the algorithm utilized for deriving remote sensed soil moisture estimation is that once estimated in such a way it becomes questionable to reuse the estimated soil moisture in a vegetation growth model. Doing this may cause redundant information, which may lead to conflicting conclusions. Recently, Chen et al. (2014) used remote sensed soil moisture and concluded a significant relationship with NDVI. Note that both variables involved in Chen et al. (2014)'s analysis are derived from satellite images. That is a typical case of the concern regarding possible redundant information. Our approach departs from Chen et al. (2014), as we used land-based measurements of soil moisture. Indeed, our study aims to contribute to the understanding of relationships between vegetation growth patterns, soil moisture, precipitation, and temperature. A main point is to explore the relevance of coupling land-based records of soil moisture, temperature, and precipitation for vegetation growth analysis. However, further studies may be necessary to compare the inclusion of remotely sensed and land-based soil moisture in vegetation growth estimate.

Specifically in this study, we apply different statistical tools as well as entropy (Singh, 2013; Shannon, 1948). Actually, entropy-based models have been reported in several ecological studies (Pueyo et al., 2007; Austin, 2007; Phillips et al., 2006). For instance, Phillips et al. (2006) used the maximum entropy principle and devised a simplified ecological model capable of predicting reasonably the spatial distribution of species. Later, several studies evaluated the model's predictive performance in comparison with other statistical models and concluded on its consistency (Gastón and García-Viñas, 2011; Suárez-Seoane et al., 2008). However, this study emphasizes a joint entropy approach (Singh, 2013; Li et al., 2012). Along with remotely sensed vegetation index series, land-based historical records of precipitation, temperature, and soil moisture are considered to appraise patterns of vegetation growth in the Texas Gulf watershed. The watershed is dominated by a semi-arid climate with a westward drying gradient (Sohoulande Djebou et al., 2015). This moisture gradient seems to influence the spatial distribution of natural vegetation in the study area (Sohoulande Djebou et al., 2014). Despite a heterogeneous percentage of coverage, the vegetation types are diversified across the Texas Gulf where they play an essential ecological role (Sohoulande Djebou et al., 2015; Lowry et al., 2007; Webb and Leake, 2006).

We address the effectiveness of coupling soil moisture, precipitation, and temperature by performing an entropy scaling analysis on two types of vegetation cover: deciduous forest and grassland. We conducted a month-wise analysis of vegetation growth. Later, we apply an entropy-based clustering method to the growing season and the result is employed in a nested statistical model. Beside the introduction, this paper presents three main sections including: (i) the methodology section which describes the approach and the data employed in the study; (ii) the results and discussion section, which expounds and examines the main findings of the study; and (iii) the synthesis and conclusions section which capitulates the study and points out potential applications of the study outcomes.

2. Data and theory

2.1. Data and study domain

The spatial domain studied is the Texas Gulf watershed (Fig. 1) which spans approximately over 468,000 km^2. The watershed sustains important socioeconomic activities and encompasses diversified ecosystems (Jayakrishnan et al., 2004; Sohoulande Djebou et al., 2014). In this study, the period of 2000–2011 was considered and only the yearly vegetation-growing months of May, June, July, August and September (MJJAS) were targeted (Slayback et al., 2003). The NDVI data used are developed and released vegetation type wise, with a biweekly temporal resolution, by the United States Geological Survey's Earth Resources Observation and Science USGS-EROS. Actually, these NDVI data are estimated from the Advanced Very High Resolution Radiometer images with a 1.1 km spatial resolution (Eidenshink, 2006). However, the USGSG-EROS uses the National Land Cover Database 1991 and 2001, then provides NDVI series for various vegetation types (Homer et al., 2004). Daily land-based measured soil moisture series (5 cm and 25 cm depth) for the period 2000–2011 were obtained from the North American Soil Moisture Database NASMD (Ford and Quiring, 2013). We obtained daily precipitation and air temperature (maximum and minimum) data over the period 2000-2011 from the National Oceanic and Atmospheric Administration's National Climatic Data Center NOAA-NCDC. For consistency regarding the NDVI series, daily precipitation, temperature, and soil moisture series were rescaled to a biweekly temporal resolution. Finally, the study targeted height Landsat satellite scenes and their spatial domains (Fig. 1 and Table 1). Note that the Landsat satellite paths are preset in time and space. The location of the footprints are static and defined by the Worldwide Reference System 2 (Table 2). Each satellite scene spans in average 170 km north-southward and 185 km east-westward. We chose the eight Landsat scenes with respect to the spatial domain of the Texas Gulf watershed. Nevertheless, we avoided as much as possible overlapping scenes in order to prevent spatial redundancy. The land-based stations considered for the atmospheric variables (precipitation, temperature, soil moisture) are collocated within the spatial boundary of each of the satellite scene (Fig. 1). A range of vegetation types are identified by