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Vegetation response to precipitation across the aridity gradient of the southwestern United states

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ABSTRACT

Atmospheric water demand affects a variety of factors, including primary production and the terrestrial water balance. Precipitation gradients from arid to humid regions also impact the water balance and play a large role in vegetation dynamics. Focusing on a 23-year period (1989–2011), we examine precipitation during the growing season in conjunction with the Normalized Difference Vegetation Index (NDVI) series for 21 satellite scenes spanning across the southwestern United States. We classify the satellite scenes into three different groups, based on the United Nations Aridity Index (AI). Group 1 is categorized as relatively humid with $AI \geq 0.65$, group 2 is intermediate with $0.50 \leq AI < 0.65$, and group 3 is relatively dry with $AI < 0.50$. We target three types of vegetation covers: shrubland, pasture, and grassland. On a long-term basis, we find significant positive trends in the NDVI series for all types of vegetation in groups 1 and 2. The magnitude of the trend in NDVI decreases with the aridity level. However, neither the total precipitation nor the number of precipitation events (>3 mm and >13 mm) changed during this time. We also use cross-correlation analyses to establish the lagged behavior of the three types of vegetation in relation to precipitation amount and number of events. The vegetation response is similar between precipitation amount and number of precipitation events. However, in the arid region, we find distinct responses to precipitation depending on the vegetation type. The magnitude and significance of the vegetation response to precipitation patterns increase with environmental aridity. There is thus a meaningful disparity of vegetation behavior in time and space.

1. Introduction

Ongoing climate change is being attributed to multiple factors, and evidences of climate change impact are reported widely around the globe (Huntington, 2006). The increasing emission of greenhouse gases is recognized to be the main driver of climate warming. As a result, during the period of 1880–2012, IPCC (2014) reported a global increase in temperature of 0.85 °C. Furthermore, based on different greenhouse gases emission scenarios, IPCC (2014) projected the global mean surface temperature to rise by the end of the current century. Likewise, meaningful changes are projected in future precipitation regimes. Although the magnitude varies within the emission scenarios, changes in climate are expected to significantly impact arid ecosystems. However, the projected changes in precipitation amount vary widely, depending on the models and their underlying assumptions (O'Gorman, 2012). Any potential benefit from an increase in precipitation amount would likely be offset by an increase in evapotranspiration due to increased temperature (Maestre et al., 2012). This suggests complex perturbations in the hydrologic cycle in the future.

Water stress on vegetation is one of the ways of characterizing the amount of available moisture. Based on simulations from different multi-model ensembles, Seager et al. (2007) projected a consistently drier climate in the southwestern United States for the 21st century. In contrast, Maestre et al. (2012) reported several gaps in our knowledge regarding future impacts of climate change on drylands, and highlighted the need to consistently determine these impacts. Specifically for the southwestern United States, Weiss et al. (2004) emphasized the lack of studies addressing vegetation dynamics in relation to climate variability. Relying on model outputs

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to understand the future of climate and vegetation is clearly essential. However, no matter how sophisticated or robust any projection may appear, most models have uncertainties associated with their simulations. Therefore, it is necessary to consider first the observed trends to improve our observational understanding and hence refine our ability to interpret model simulations.

During the last two decades, the use of remote sensing has been essential for vegetation studies at large scales. The Normalized Difference Vegetation Index (NDVI) has been a successful and reliable tool in a variety of vegetation and precipitation studies (e.g., Rigge et al., 2013; Vicente-Serrano et al., 2006). Our study analyzes the influence of precipitation characteristics on vegetation during the growing season of May through September (Slayback et al., 2003) in arid and semi-arid regions. We make use of the NDVI and focus on the 23-year period from 1989 to 2011. Three different types of vegetation cover are considered, and their observational variability is investigated with particular focus on the southwestern United States, which spans a wide range in terms of aridity. NDVI has been frequently employed to address the influence of climatological components, such as temperature and precipitation on vegetation cover. However, the long-term impacts of precipitation patterns are still unclear at regional scales because of the temporal limitation of satellite data.

It is generally recognized that climate change will bring about a decrease in precipitation amount and a higher variability in precipitation events across arid and semi-arid regions (IPCC, 2014; Huntington, 2006). However, a timely supply of water via precipitation is critical for rain-fed vegetation. The expected future behavior of vegetation will be closely tied to the variability of precipitation, as driven by climate change. This study uses remotely sensed vegetation estimates across a strong moisture gradient in an arid and semi-arid region during the vegetation growing season to address how precipitation characteristics (number of events and precipitation amount) may relate to the growth patterns of different types of vegetation. As part of this main objective, we also estimate vegetation and precipitation trends, potential temporal lags of the vegetation response, as well as the effects of seasonality on vegetation growth.

2. Climate classification across the study domain

The southwestern United States is relatively dry, compared to the rest of the country. Water availability is already a critical issue and will become of heightened importance due to continued climate change. Because of the crucial role of vegetation in hydrological processes, it is paramount to understand its future variability in the southwestern United States. The study region encompasses the states of Louisiana, Arkansas, Oklahoma, Texas, New Mexico, and Arizona (Fig. 1). We classify this domain based on an aridity index, which is a useful indicator (Deniz et al., 2011) and describes the degree of dryness of the climate in a specific region.

Indeed, several indices have been developed and proposed for regional classification according to their aridity level (Sahin, 2012; Gao and Giorgi, 2008; De Martonne, 1926). However, the best known aridity index is defined by the United Nations Environmental Program (UNEP; Maestre et al., 2012). The UNEP aridity index (AI) is the ratio of annual precipitation (P, mm) to the annual potential evapotranspiration (PET, mm): AI = P/PET. This aridity index is widely accepted for characterizing dryland climatic boundaries (Maestre et al., 2012), and is employed here to characterize the degree of aridity across the spatial domain of our study. Based on AI, drylands are defined as regions where AI < 0.65. An extended UNEP classification identifies climate types (Maestre et al., 2012; Sahin, 2012) according to AI as: hyper-arid (AI < 0.05), arid (0.05 ≤ AI < 0.20), semi-arid (0.20 ≤ AI < 0.50), sub-humid (0.50 ≤ AI < 0.65), semi-humid (0.65 ≤ AI < 0.80), humid (0.80 ≤ AI < 1.0), and very humid (1.0 ≤ AI < 2.0). We assessed the UNEP AI across the study domain using the long-term average yearly Penman-Monteith potential evapotranspiration (PET) (Vorosmarty et al., 1998) and precipitation, provided by the Earth Observation System (EOS)-EarthData at the University of New Hampshire (http://eos-earthdata.sr.unh.edu). The original PET and precipitation data were gridded at a 0.5° resolution. Fig. 1 indicates that large parts of our study domain have an AI < 0.65 and can thus be classified as drylands. The dryness level gradually increases from east to west over the study region (Fig. 1). The local vegetation follows that trend in that it is much denser in the more moist east, and gets sparser westward (Homer et al., 2004).

For the vegetation dynamics analysis, we selected 21 Landsat satellite scenes (see details in the methodology section) across the domain. Each satellite scene has, on average, a footprint of 170 km × 185 km. For the purpose of this study, we classified the 21 satellite scenes into three groups (Table 1) based on the dryness of the climate. The first group (group 1), here designated as “moist,” is comprised of scenes 1 to 7 which span the relatively humid regions with AI ≥ 0.65. The second group (group 2), here designated

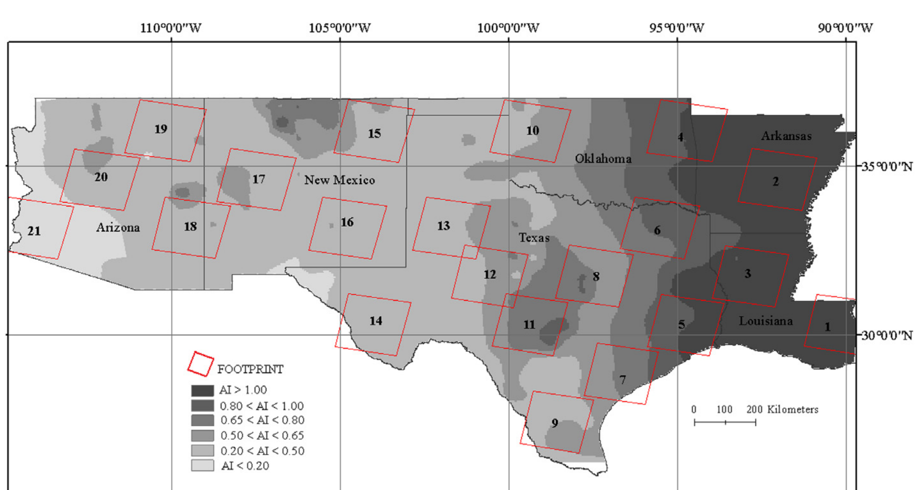

Fig. 1. UNEP Aridity Index variability and selected satellite scene (footprint) locations across the study region.