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Vegetation's role in controlling long-term response of near ground air temperature to precipitation change in a semi-arid region

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ABSTRACT

The response of near ground air temperature to changing precipitation regimes has received extensive attentions in climate change studies. In semi-arid and arid regions, the mean annual temperature correlates negatively with precipitation. However, it remains unclear to what extent one unit change of precipitation can trigger temperature change (i.e., the temperature sensitivity to precipitation). Taking a semi-arid region in Northwest China as a study area, we quantitatively investigated the temperature sensitivity to precipitation change. Further analysis shows that the temperature sensitivity correlates well with the Normalized Difference Vegetation Index (NDVI), indicating that vegetation plays an important role in controlling the long-term temperature sensitivity to precipitation change. Specifically, different land covers show significant differences in temperature sensitivity, with bare soil generally having a higher sensitivity while more densely vegetated areas such as forest and grassland having lower sensitivity values. This implies that vegetation contributes to reducing the temperature sensitivity to precipitation change through the land surface-atmosphere interaction in semi-arid and arid regions.

1. Introduction

Near ground air temperature (*T*) is a variable of the land surface energy transfer process controlled by various local properties including solar radiation, water availability, and land cover types. In semi-arid and arid regions where temperature is largely regulated by precipitation, special attentions have been paid to the high temperature associated with drought events (Yin et al., 2014). The response of temperature to precipitation change results from land surface-atmosphere interaction, in which vegetation plays an important role (Pielke et al., 1998); naturally, vegetation has been widely recognized as a key factor in regulating the near ground air temperature magnitude (Bonan, 1997; Peng et al., 2014). However, it remains unclear whether or not vegetation regulates the long-term temperature sensitivity to precipitation change. Moreover, we know little about the extent to which air temperature will increase/decrease in accordance with a given decrease/increase in precipitation in semi-arid and arid regions. Lacking such knowledge limits our ability to predict extreme temperature events in these regions, particularly at a time when global precipitation is projected to change in most parts of the world (Stott, 2016).

In semi-arid and arid regions, mean annual temperature correlates negatively with precipitation (Yin et al., 2014), with reduced evaporative cooling effect well explaining the relatively higher temperature during drought. Meanwhile, vegetation greening has been suggested to cool down local environment (Peng et al., 2014; Shen et al., 2015) through enhanced evaporative cooling, justifying the role of vegetation in regulating local energy balance (Findell et al., 2009; Wang and Dickinson, 2012). With land cover dynamic being widely recognized to regulate temperature, whether it controls the temperature sensitivity to precipitation change has rarely been explored, framing the purpose of this study. Considering the important role of vegetation plays in controlling the land surface-atmosphere interaction, we hypothesize that vegetation regulates the long-term temperature sensitivity to precipitation change in semi-arid and arid regions. To test this hypothesis, we use a temperature and precipitation dataset complemented with land cover maps and Normalized Difference Vegetation Index (NDVI) dataset in Northwest China mainly to: 1) estimate the sensitivity of near ground air temperature to precipitation change; and 2) investigate the role of land cover in determining the long-term response of near ground air temperature to precipitation change.

2. Materials and method

2.1. Study area and dataset

The study region is located in Northwest China, central Eurasia,

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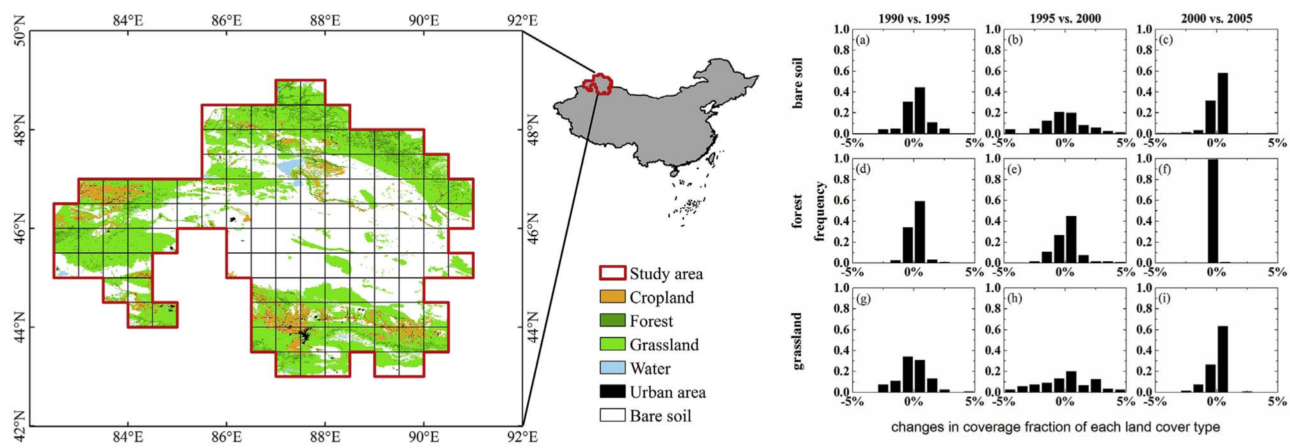

Fig. 1. The study region and the spatial distribution of land cover (left-hand panel); right-hand panel is the frequency distribution of land cover change evaluated by the difference of coverage fraction at pixel level for bare soil (a, b, and c), forest (d, e, and f), and grassland (g, h, and i); the three columns from left to right represent corresponding change of land cover between 1990 and 1995, 1995 and 2000, and 2000 and 2005.

stretching between 43.0–49.0 °N and 82.5–91.0 °E with an area of approximately 3.70×10^5 km^2 (Fig. 1, left-hand panel). The annual precipitation ranges from 110 mm to 550 mm, and the mean annual air temperature ranges from −7 °C to 7 °C. This region is classified as semi-arid with an aridity index below 0.5 according to Global Aridity and PET Database (http://www.cgiar-csi.org/data/global-aridity-and-pet-database). This is an ideal place to explore the temperature and precipitation relationship because it is less affected by the Arctic Oscillation or El Niño–Southern Oscillation (Adler et al., 2008).

To analyze the temperature sensitivity to precipitation, we used monthly mean air temperature observed at 2 m above the ground and monthly total precipitation from the period of 1982–2006 (China Meteorological Data Service Center, http://data.cma.cn/). These two datasets are at a spatial resolution of 0.5° × 0.5° interpolated by thin plate spline (TPS) in ANUSPLIN software based on 2, 472 site measurements and Global 30 Arc-Second Elevation (GTOPO30) data resampling. The assessment reports of precipitation and temperature (NMIC, 2012) showed that the monthly root-mean-square error (RMSE) varies from 0.2 mm to 0.8 mm for precipitation, and the annual RMSE ranges from 0.2 °C to 0.3 °C for temperature. In addition, the datasets have been widely evaluated for reliability and applied in numerous meteorological assessments and environmental impact studies (e.g., Wang et al., 2013; Wu et al., 2017).

Land cover maps of four years (i.e., 1990, 1995, 2000 and 2005) with a spatial resolution of 1 km × 1 km were obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The land cover types are classified at two levels, the first level contains 6 broad categories, i.e., cropland, forest, grassland, water body, urban area, and bare soil; the second level details the aforementioned 6 categories into 25 more specific land cover types (see Liu et al., 2003 for details). In the study region, forest, grassland and bare soil account for more than 90% of total area. Hence, in this study we only considered these 3 main land covers on the first level. The coverage fraction of each land cover, defined as the ratio of area between the specified land cover type and the pixel area, was calculated at the pixel level. Evaluations show that land cover did not change much in the past two decades (Fig. 1, right-hand panel). Therefore, we used the mean coverage fraction of the four years to represent the land cover conditions.

To account for the vegetation phenology, we used the continental Global Inventory Modelling and Mapping Studies NDVI dataset (http://glcf.umiacs.umd.edu/data/gimms) with a spatial resolution of 8 km × 8 km and an interval of 15 d (Tucker et al., 2005). We applied the maximum value composite method to generate a monthly NDVI dataset (Holben, 1986) to reduce noise mainly from clouds. The NDVI data were then spatially aggregated to a resolution of 0.5° × 0.5° so that they agreed, geographically, with the temperature and precipitation records.

2.2. Quantifying the temperature sensitivity to precipitation change

The monthly mean temperature and total precipitation were aggregated to the growing season (April through October, typical for Northwest China) at the pixel level (0.5° × 0.5°). We used a linear regression model (Yin et al., 2014) to detect the long-term temperature response to precipitation change,

$$\Delta T = a_0 + a_1 \Delta P \tag{1}$$

where ΔT and ΔP represent the annual mean temperature anomaly (°C) and total precipitation anomaly (mm) in the growing season, respectively; a_0 equals zero because both ΔT and ΔP are anomalies, while the linear regression slope a_1 (°C mm^{-1}) is determined by the least square method. In general, a_1 is negative for semi-arid and arid regions; we defined the sensitivity coefficient β (°C mm^{-1}) as the absolute value of a_1, in order to quantify the temperature sensitivity to precipitation change as,

$$\beta = |a_1| \tag{2}$$

Such correlation analyses were performed at each pixel.

2.3. Investigating the role of vegetation in determining the temperature sensitivity to precipitation change

To investigate how land cover type controls the temperature sensitivity to precipitation change, β was linearly correlated with coverage fraction of forest, grassland, and bare soil, respectively at pixel level,

$$\beta = b_0 + b_1 C_F \tag{3}$$

where b_0 and b_1 are fitting parameters, and C_F is the coverage fraction of the three major land cover types (i.e., forest, grassland and bare soil).

In addition to land cover type, we used NDVI as a surrogate of vegetation dynamics to numerically quantify how vegetation controls the temperature sensitivity to precipitation change; β was then linearly correlated with NDVI as,

$$\beta = c_0 + c_1 \mathrm{NDVI} \tag{4}$$

where c_0 and c_1 are fitting parameters.

The F-test was used throughout this paper to assess the significance of regressions.

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