NOTES AND CORRESPONDENCE

Interannual Covariability Found in Evapotranspiration and Satellite-derived Vegetation Indices over Northern Asia

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Abstract

Temporal variation in vegetation over a large area induces temporal variation in the land-atmosphere water budget through evapotranspiration activity. To examine this relationship interannually, normalized difference vegetation index (NDVI) and evapotranspiration (ET) values collected from 1982 to 2000 over northern Asia were investigated. Monthly global NDVI values were acquired from Pathfinder AVHRR land data. Monthly ET was estimated from NCEP/NCAR assimilated atmospheric data and CMAP global precipitation data. All calculations were made for 2.5×2.5 -degree grid boxes in the study region on a monthly basis. The correlation coefficient of the 19-year time series of ET and NDVI anomalies showed the annual maximum correlation in June, and high correlation generally distributed over the region except for southern arid areas and the most northern areas. Although interannual variations in temperature and precipitation anomalies also showed some relation to ET in the warm season, they did not exhibit high correlation in a specific month. Since the vegetation is probably most active in June, it is considered that vegetation variability contributed significantly to ET through its transpiration activity.

1. Introduction

Many studies have described how climate strongly dominates vegetation distribution and its temporal variability (Woodward 1987). Conversely, vegetation activity strongly influences the climate system (Eagleson 2002). For example, seasonal changes in the vegetation canopy modify the albedo and aerodynamic roughness of the land surface. In particular, evapotranspiration, which involves transpiration and evaporation of intercepted precipitation, from an extensive area of vegetation plays an important role in water and energy cycles. Therefore,

interannual or “long-term” change in vegetation may bring about climate system change.

Since the 1980s, the Advanced Very High Resolution Radiometer (AVHRR), an onboard sensor of the NOAA satellite, has allowed global vegetation monitoring through the normalized difference vegetation index (NDVI). The NDVI is computed as $NDVI = (Ch2 - Ch1)/(Ch2 + Ch1)$, where $Ch1$ (0.58–0.68 μm) and $Ch2$ (0.725–1.10 μm) are the reflectance measurements of AVHRR channels 1 and 2, respectively (Tarpley et al. 1984).

This study examined interannual NDVI variation and its relation to interannual variation in evapotranspiration (ET) in northern Asia. Northern Asia is seen as a key region in climatology and related sciences. A remarkable long-term temperature rise that may be related to global warming has been reported in the region, especially in winter (IPCC 2001). Long-

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term variation in snow cover has also been examined (Ye et al. 1998; Dye and Tucker 2003).

Recently, the use of decadal NDVI time series has improved the study of interannual variation in vegetation. A significant increase in vegetation at high latitudes in the Northern Hemisphere was reported by scrutinizing NDVI data from the 1980s (Myneni et al. 1997, 1998; Ichii et al. 2002). Furthermore, Tucker et al. (2001) found an NDVI increase from 1982 to 1991 and from 1992 to 1999 in higher northern latitudes. Interannual covariability between the NDVI and temperature over the Northern Hemisphere in the 1980s and 1990s has been discussed in relation to atmospheric circulation systems such as El Niño (Buermann et al. 2003; Gong and Ho 2003). Lotsch et al. (2003) examined vegetation-precipitation variability using NDVI from 1981 to 2000 and found positive correlations in arid areas. A net primary production increase, derived from NDVI data, has also been related to climatic factors (Nemani et al. 2003). Furthermore, Kondoh et al. (2002) have noted the relation of vegetation interannual change to atmospheric CO₂ content.

Suzuki et al. (1998) analyzed seasonal relationships between the NDVI and ET at the regional scale over Asia. The study found close covariability. However, no previous studies have targeted interannual relationships between the NDVI and ET. The present study sought to identify a vegetation-induced ET signal by examining time series NDVI and ET data from 1982 to 2000 over northern Asia. Since greater vegetation activity ought to induce a larger ET value, vegetation should have the potential to change ET interannually. This study helps clarify the role of vegetation in the climate system and provides a basic concept for climate change modeling.

2. Data and method

2.1 NDVI data

Monthly global NDVIs from 1982 to 2000 over northern Asia (30°E–150°E, 30°N–75°N) were obtained from the Pathfinder AVHRR Land (PAL) dataset (1° × 1-degree spatial resolution) (Smith et al. 1997). Initially, 10 days of daily AVHRR data were processed. The data were then composited by assigning each pixel a value based on its highest daily NDVI value. Monthly data were composited by choosing the

highest NDVI among the three 10-day datasets for each month. This process effectively removed cloud-contaminated observations.

Raw AVHRR measurements contain unfavorable temporal fluctuations due to non-vegetative factors such as satellite orbit drift, sensor degradation, and ozone concentration. The PAL data are adjusted for these factors and represent interannual variation in vegetation well (see Agbu and James (1994) for further information on the dataset). The NDVI data in the PAL dataset are particularly useful for studies of temporal and interannual vegetation behavior.

2.2 Evapotranspiration (ET)

Evapotranspiration from the land surface can be estimated from the atmospheric water budget (e.g., Peixoto and Oort 1983, 1992). ET from the bottom (i.e., land surface) of an air column, which vertically extends from the ground surface to the top of the atmosphere, can be expressed by the following atmospheric water budget equation:

$$ET = P + \frac{\partial W}{\partial t} + \nabla_H \cdot \vec{Q},$$

where t is the time, P is the precipitation at the bottom, W is the precipitable water in the air column, and $\nabla_H \cdot \vec{Q}$ is the horizontal flux divergence of water vapor integrated from the surface to the top of the atmosphere (so called aerial runoff).

This study assumed air columns above the 2.5×2.5 -degree grid cells and computed each term for each grid cell. The CPC Merged Analysis of Precipitation (CMAP) dataset (Xie and Arkin 1997) was used to determine monthly precipitation P . This global precipitation product is a composite of several kinds of data sources such as gauge observations, satellite estimates, and numerical model outputs. Gauge measurements are used primarily to estimate precipitation over the land. The spatial resolution is 2.5×2.5 -degree.

The terms $\nabla_H \cdot \vec{Q}$ and $\partial W / \partial t$ are computed from specific humidity and wind values. In the present study, these meteorological values were obtained from gridded 6-hourly atmospheric data (NCEP Reanalysis-2) provided by the National Centers for Environmental Prediction (NCEP) (Kanamitsu et al. 2002; Kalnay

et al. 1996). The land surface scheme of the assimilation system employs boundary condition climatologies from the Simple Biosphere Model (SiB) (Dorman and Sellers 1989). Although the scheme considers the vegetation seasonal cycle, no interannual change of vegetation is included. Therefore, this dataset is completely independent of NDVI interannual change.

Monthly $\nabla_H \cdot \vec{Q}$ from 1982 to 2000 for each grid cell (192×94) of the reanalysis model was estimated by integrating the flux divergence from the ground to 0 hPa (all 28 layers of the model). The estimated values were interpolated onto the same 2.5×2.5 -degree grid as the CMAP data. The monthly $\partial W / \partial t$ was calculated from the precipitable water difference between the beginning and end of each month.

2.3 Temperature

Additionally, surface temperature data were obtained from the CRU TS 2.0 dataset, which is comprised of monthly grids of observed climate data. The dataset spans the period from 1901 to 2000 and covers the global land surface at 0.5-degree resolution (http://www.cru.uea.ac.uk/~timm/grid/CRU_TS_2_0.html). Some dataset values were not suitable for long-term variation analysis, because interpolation and substitution of values occurred frequently in regions with sparse station networks, especially in the early years of the period. However, we regarded the temperature time series over northern Asia from 1982 to 2000 as representative for interannual temperature variation analysis, since northern Asia had a sufficiently dense surface station network during that period.

2.4 Calculation of monthly anomalies

First, to match the grid cells of NDVI (1×1 -degree) and temperature (0.5×0.5 -degree) data with NCEP Reanalysis-2 and CMAP data (2.5×2.5 -degree), NDVI and temperature values were re-sampled into 2.5×2.5 -degree grid cells by averaging. For instance, if a single 1×1 -degree NDVI grid cell extended over two or four 2.5×2.5 -degree grid cells, half or one-fourth of the single 1×1 -degree grid cell, respectively, was assigned to those 2.5×2.5 -degree grid cells. Next, the 19-year means of NDVI, ET, temperature, and precipitation were calculated for each grid box using monthly data. To extract the interannual variation for each month, monthly anomalies for each pa-

rameter were calculated by subtracting the 19-year mean from the original monthly value of each month. The 19-year time series of monthly ET anomalies was compared with the time series of the other parameters. Correlation coefficients were calculated using the 19-year values.

Insufficient solar illumination in high latitude regions in winter can create gaps in NDVI data. Thus, some grid boxes did not have the full nineteen samples in winter. All the grid boxes from September to December have one less sample due to missing NDVI data from September to December 1994.

3. Results and discussion

3.1 NDVI and ET distribution

Figure 1 presents a sample distribution of 19-year mean NDVI and ET values in June. High NDVIs are distributed around 60°N , corresponding to forest areas, while low NDVIs can be seen over southern arid and northern tundra areas. Estimated ET over the forest zone also shows high values, whereas values are low in the arid southern area. Some areas, for example around 100°E , 35°N , showed negative ET, which implies condensation of water vapor from the atmosphere to the land surface. Such unrealistic ET values tend to occur over complicated topography and are mainly due to insufficient horizontal resolution in the data. This study avoids discussing ET in such areas as much as possible.

3.2 Correlation between ET and the NDVI

Figure 2 presents frequencies of correlation coefficients between interannual variations of ET and NDVI anomalies for each month. Since the estimation accuracy of ET may be insufficient if ET from a single 2.5×2.5 -degree grid cell is adopted (e.g., Oki et al. 1995), ET was spatially smoothed by calculating a moving average for nine grid cells (i.e., the grid cell and eight surrounding grid cells). NDVI was also spatially smoothed by the same way. Because the earth surface area of a grid cell changes by latitude, each frequency was weighted by the area in the nine grid cells for the moving average.

From October to April, correlation coefficients are generally low. From May, correlation increases and reaches its annual maximum in June. The mean coefficient averaged over the

Fig. 1. Distribution of NDVI (a) and evapotranspiration (b) values in June averaged over the period 1982 to 2000. The unit of ET is mm/day.

area is 0.29. After July, the coefficient gradually decreases to the winter level.

Ohta et al. (2001) examined the seasonal variation of ET and transpiration from larch trees based on field observations at a larch forest near Yakutsk, Eastern Siberia, in 1998. According to their observations, transpiration from the trees reached a maximum rate, 1.7 mm/day, in mid-June; tree transpiration as a proportion of the total ET was also at a maximum in mid-June (70–80%). Other results have also demonstrated that the maximum photosynthetic rates, which are a proxy of transpiration, occur in the forest during early summer (Larcher 2003; Emmingham and Waring 1977). The present study found the highest correlation coefficient in June. Together the results of Ohta et al.'s, and the other studies, these findings suggest that the highest correlation between ET and NDVI is attributed to the greatest contribution of the vegetation transpiration to total ET in June.

Figure 3 shows the correlation coefficient

Fig. 2. Frequency of the correlation coefficient between interannual changes of ET and NDVI anomalies from 1982 to 2000 over the study region in each month. The ET and NDVI anomalies were smoothed by a moving average of nine grid cells. The frequency of each grid cell was weighted by the earth surface area within the grid cells. The mean correlation coefficient in each month is denoted by “ r ” in each panel.

distribution in June, the month with the highest total correlation coefficient using spatially smoothed ET and NDVI. There are positive correlation coefficients over most regions, suggesting that for most areas in Asia, interannual ET variation is affected by changes in vegetation. In arid and high altitude areas, small correlation coefficients (sometimes negative) are seen due to the very low NDVI in such areas. Negative coefficients are also found over a large area in northeastern Siberia (around 145°E, 65°N); the exact reason for this finding is unknown.

Three regions of high correlation coefficients shown in the map in Fig. 3 were selected: Western Siberia (50°E–90°E, 55°N–65°N; 64

Fig. 3. Distribution of the correlation coefficients between interannual changes of ET and NDVI anomalies in June from 1982 to 2000. Areas with negative ET relative to the 19-year June mean (see Fig. 1b) are shaded gray. Areas with no NDVI data (e.g., oceans) are also shaded gray. Three regions of analysis are denoted: A: Western Siberia, B: Eastern Siberia, and C: Kazakh.

grid cells), Eastern Siberia (80°E–130°E, 65°N–70°N; 40 grid cells), and Kazakh (50°E–60°E, 45°N–55°N; 16 grid cells). Figure 4 shows the mean correlation coefficients in these regions for each month. Annually, the highest correlation was found in June in all three regions. No significant coefficient relationships are evident between August and April in any of the three areas.

Figure 5 shows the interannual variations of the anomalies in June for the three regions. Very similar interannual changes can be seen in each region. Western Siberia has the highest coefficient ($r = 0.73$). Both the NDVI and ET anomalies have small values in 1982, 1985, and 1992, and large values in 1989, 1991, and 1997 to 2000. Moreover, an increasing trend can be seen both in the NDVI and ET anomalies. This trend of NDVI (0.062 per 19 years) seems consistent with Tucker et al.'s findings (2001). Interannual variation between ET and the NDVI anomalies is also very closely related in Eastern Siberia and Kazakh.

3.3 Correlation between ET-temperature and ET-precipitation

In addition to the transpiration component, ET also includes components of the evaporation from intercepted precipitation and other non-vegetation elements, such as ground surface. This study examined temperature (CRU TS2.0) and precipitation (CMAP) data in order to look into mechanisms other than transpiration that might induce variation in interannual ET. The interannual correlations between ET and temperature anomalies (referred to as ET-temperature), and between ET and precipitation anomalies (referred to as ET-precipitation), were calculated.

ET was estimated using CMAP precipitation data and other meteorological parameters. Parameters were produced by the assimilation system, which used temperature data. Due to these estimation methods, ET was not statistically independent of temperature and was, particularly, not independent of precipitation; thus, a careful interpretation of the meaning

Fig. 4. Mean correlation coefficients of the interannual changes of NDVI and ET anomalies from 1982 to 2000, averaged over the three study regions. The hatched area denotes values below the 99% significance level. The full 19-year time series has a value of 0.575. Time series with fewer than 19 samples have values greater than 0.575.

Fig. 5. Interannual variation of the NDVI and ET anomalies averaged in the three selected regions: (a) Western Siberia (50°E – 90°E , 55°N – 65°N), (b) Eastern Siberia (80°E – 130°E , 65°N – 70°N), and (c) Kazakhstan (50°E – 60°E , 45°N – 55°N). The correlation coefficient is denoted by “ r ” in each panel.

Fig. 6. Distribution of correlation coefficients between ET and temperature anomaly interannual variations (a) and ET and precipitation anomaly interannual variations (b) in June from 1982 to 2000.

of the resultant correlation coefficient is required. Therefore, this analysis focused on the relative relation of ET-temperature and ET-precipitation and their seasonal pattern.

Figure 6 shows the distribution of ET-temperature and ET-precipitation correlation

coefficients in June. There is a conspicuous difference in the ET-temperature and ET-precipitation differences. High positive correlations of ET-temperature are distributed primarily to the north of 55°N , while negative correlations are dominant over the southern area. In contrast, high positive correlations of ET-precipitation mainly cover the area south of 55°N , and negative correlations can be seen over the northern area. This finding suggests that temperature may contribute to variation in interannual ET in the northern area, while precipitation may induce variation in interannual ET in the southern area. If we consider temperature the dominant ET factor in the northern low-temperature area and aridity the dominant factor in the southern arid area, the results shown in Figure 6 are reasonable. Regional interannual variation in temperature and precipitation would contribute more or less to interannual ET variation by region.

Figure 7 illustrates variations of correlation coefficients in the three regions. Positive high correlations of ET-temperature are concentrated in the warm season in Western Siberia and Eastern Siberia. For ET-precipitation, positive high correlations are seen in the Kazakh region. However, these positive high correlations are not concentrated in a particular month. This feature is quite different from the relationship between ET and NDVI, for which the highest correlation is in June.

Fig. 7. Mean correlation coefficients between ET and temperature anomaly (open bar), and ET and precipitation anomaly (black bar) interannual change from 1982 to 2000, averaged over the three study regions. All coefficients were calculated from 19 samples (i.e., 19 years). The hatched area denotes values below the 95% (0.456) significance level.

The relationship among ET, vegetation, temperature, and precipitation in the climate system is complex. However, the present study suggests that interannual variation in vegetation significantly affects interannual variation in ET; a positive correlation is clearly evident in almost all vegetated areas but rarely evident in areas of sparse vegetation. In addition, the highest correlation of ET and NDVI is in June, when vegetation transpiration is usually most active. The ET-temperature and ET-precipitation relationships did not show this pattern. Thus, it is reasonable to attribute these results to vegetation transpiration activity.

4. Concluding remarks

A monthly time series of the NDVI, which is satellite-derived vegetation information, and the ET, which was estimated from gridded atmospheric data (NCEP Reanalysis-2 and CMAP), was examined at regional and continental scales from 1982 to 2000. Significant, positive correlations were found between NDVI and ET anomaly interannual variations over vegetated areas. The correlations were especially high in June, when vegetation is usually most active. Although temperature and precipitation probably also contribute to interannual variation in ET, the results of this study suggest that interannual variation in vegetation possibly makes a considerable contribution.

Climate change predictions should thus account for vegetation as a forcing factor of climate. The results of this study should help reveal relationships between the climate-vegetation system and its influence on ET.

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