Interannual Variability in Net Primary Production and Precipitation

Knapp and Smith (*1*) suggested that interannual variability in aboveground net primary production (ANPP) is not related to fluctuations in precipitation, based on analysis of data from 11 Long-Term Ecological Research sites across North America. This finding, if applicable to other regions, is crucial to climate change research, because it may necessitate revisions of projections of ecosystem responses to climate change (*2*, *3*). To examine the relationship between variability in net primary production (NPP) and precipitation at a broad scale, a long-term normalized difference vegetation index (NDVI) data set derived from the Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA), coupled with a historical climate data set, should constitute a useful and powerful data source, because NDVI data are strongly correlated with terrestrial NPP and are frequently used as NPP predictors (*4*, *5*).

We used an annual mean NDVI data set over China to quantify temporal NPP variability relative to precipitation variation, and used coefficient of variation (CV) to express the magnitude of interannual variability in NDVI and precipitation. We then calculated CVs of these two variables for each pixel, with a resolution of 0.1° latitude by 0.1° longitude, for five biome groups across China—forest, grassland, desert, alpine vegetation, and cropland (*6*)—using 1982 to 1999 NDVI and precipitation data compiled in China (*7*). We assumed that interannual variability in NDVI or NPP was related to temporal variability in precipitation if the correlation between CVs for NDVI or NPP and precipitation were identified as statistically significant.

The CV value of NDVI for these five biome groups showed a large spatial variation, with a mean CV of 8.3% for the forest biome group, 10.4% for grasslands, 24.6% for desert areas, 12.7% for alpine vegetation, and 9.3 % for cropland. The largest variation occurred in the desert biome, followed by herbaceous vegetation (grasslands and alpine meadows); forests were the least variable. These results agree with those of Knapp and Smith (*1*). However, our statistical analysis also showed a significant positive correlation between the CV of NDVI and that of precipitation for all five biome groups (Fig. 1, A to E). The coefficient of correlation (r) was 0.43 for forest, 0.56 for grassland, 0.37 for desert, 0.31 for alpine vegetation, and 0.39 for cropland, with a strong correlation between mean CV of NDVI and that of precipitation for these five biome groups [$r = 0.95$, $p = 0.012$ (Fig. 1F)]. Moreover, the relationship between CV of NPP estimated based on the Carnegie-Ames-Stanford Approach (CASA) model (*8*, *9*) and that of precipitation revealed trends similar to those implicit in Fig. 1. The r values were estimated at 0.53 for forest, 0.54 for grassland, 0.48 for desert, 0.37 for alpine vegetation, and 0.35 for cropland, with a highly significant correlation between mean NPP CV and mean precipitation CV for these five biome groups ($r = 0.97$, $p = 0.005$). These results are generally consistent with those of a previous study (*10*), but disagree with the conclusions of Knapp and Smith (*1*).

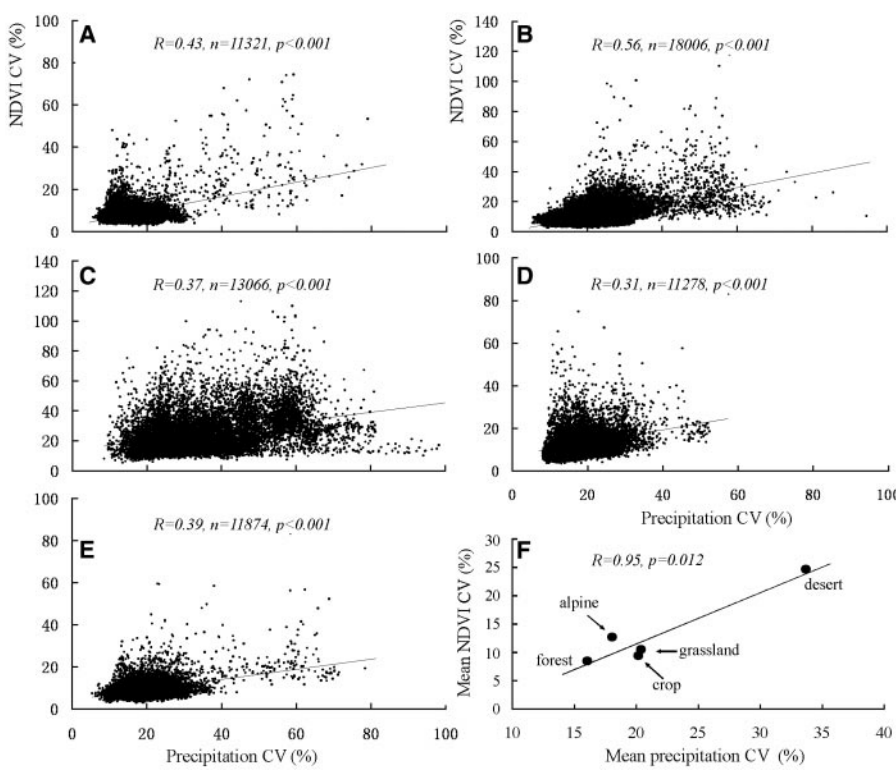

Fig. 1. Relationships between annual precipitation CV and NDVI CV across China for (**A**) forest, (**B**) grassland, (**C**) desert, (**D**) alpine vegetation, and (**E**) cropland; (**F**) relationship between mean NPP CV versus mean precipitation CV of all five biome groups. The relationship was significant for all groups.

Although the data used in the analysis by Knapp and Smith (*1*) were from the entirety of North America and included different terrestrial biomes, specifically forests, grasslands, and deserts, their study was limited to 11 sites. Considering the small sample size and the large spatial variation of NPP, we suggest that the conclusions of Knapp and Smith need broader investigation. Our results, which are based on remote-sensing approach, suggest that the relationship between interannual variability in NPP and precipitation across China is the opposite of the trends observed by Knapp and Smith (*1*) in North America.

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6. In (*1*), biomes were divided into forest, grassland, and desert. In our work, in addition to these three groups, the vegetation of the huge highland area of the Tibet-Qinghai Plateau was handled as a single group, termed alpine vegetation; cropland was also considered as a separate group, because it constitutes vegetation in a non-natural setting.
7. NDVI data for China were derived from the NOAA/NASA Pathfinder AVHRR land data set at 8 km spatial resolution and 10-day intervals from January 1982 to December 1999. Climatic data (monthly mean temperature and monthly precipitation) were compiled from the 1949 to 1999 temperature and precipitation data set of China at $0.1° \times 0.1°$ resolution, produced by interpolating data of monthly mean temperature and monthly precipitation from 682 climatic stations (*11*).
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Response: We appreciate the NDVI and NPP analyses performed by Fang *et al*. Additional exploration of the relationships between climate variability and important ecosystem processes such as NPP is certainly needed, and we agree that the large spatial extent and sample size available from satellite and climate data sets provides a real opportunity to robustly test predictions about those relationships. This is one of the recognized strengths of satellite data sets.

However, we are concerned by a key assumption of their analysis—that NDVI data can be used to quantify NPP dynamics with equal accuracy and sensitivity across all biomes. It has been well established that NDVI can be related to chlorophyll content, leaf area, and standing crop biomass in most biomes (*1*, *2*) and also NPP in some instances. Because standing crop biomass and NPP are positively related across broad spatial scales, it is common in the remote sensing literature for these very different ecosystem attributes to be treated as synonymous. It should be noted, however, that NDVI-based relationships typically are calibrated with standing crop biomass data, not NPP. Unfortunately, NDVI-NPP relationships are not robust under many conditions. In grazed grasslands, for example, where standing crop is low but NPP is high, NDVI can only accurately estimate standing crop (*3*, *4*). Worldwide, it is likely that a majority of the grasslands remotely sensed are grazed.

We are unaware of any studies that have demonstrated that interannual variability in NDVI is sufficiently sensitive to detect differences in NPP equally well across the range of biomes included in the analysis of Fang *et al*. Indeed, the sensitivity of NDVI to interannual rainfall variation has been shown to be low in both very wet and very dry regions of Southern Africa (*5*). Thus, we believe that the conclusions reported by Fang *et al*. should be viewed with interest, but also with caution. The final relationship they present (their figure 1F), which is most relevant to our study (*6*), is primarily driven by a single point for the desert biome, and background soil reflectance in arid regions further complicates NDVI-NPP relationship in deserts (*5*). Furthermore, a similar analyses for both North America and Africa found either no relationship or only a weak relationship between climate variation and vegetation activity as determined by NDVI values (*7*). Although Fang *et al*. have used an extensive data set in their analysis, the strength of our study (*6*) is that it was based on direct measurements of NPP using techniques specifically developed for each biome. Clearly, the two approaches are complementary, but the inherent trade-offs between data quality and spatial extent must be considered when comparing these relationships.

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