Supplementary Material

Discovering relationships in climate-vegetation dynamics

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1 Data sets description

Temperature data sets include seven different products, based on *in situ* data (Climate Research Unit (CRU) [7], University of Delaware (UDel) [5], NASA Goddard Institute for Space Studies (GISS) [6], Merged Land-Ocean Surface Temperature (MLOST) [19]), and satellite (International Satellite Cloud Climatology Project (ISCCP) [17], Land Parameter Retrieval Model (LPRM) [8]). We also included one reanalysis data set produced by ERA-Interim global atmospheric reanalysis (European Centre for Medium-Range Weather Forecasts (ECMWF) [3]).

Precipitation data sets consist of ten products. Specifically, four of them (Climate Research Unit (CRU) [7], University of Delaware (UDel) [5], Climate Prediction Center (CPC) [26], Global Precipitation Climatology Centre (GPCC) [18]) have been produced by *in-situ* data, three by satellite data (Climate Prediction Center morphing method (CMORPH) [10], Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) [20], (3B42RT) [9]) and the rest by a combination of the two of them (CPC Merged Analysis of Precipitation (CMAP) [25], ERA-Interim [3], Global Precipitation Climatology Project (GPCP) [1]).

For radiation two different products have been collected, the first one based on satellite data (NASA/GEWEX Surface Radiation Budget (SRB) [21]) and the second one on reanalysis data (ERA-Interim) [3]. The surface soil moisture products have been produced by satellite data (Global Land Evaporation - Amsterdam Methodology (GLEAM) [14], NASA [15], Climate Change Initiative (CCI) [11, 12, 24]). The three soil moisture products by CCI consist of a merged product created from all active data sets, a merged product created from all passive data sets as well as a product created from merged active and merged

[5] http://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html

Table 1: Data sources that are used in our experiments. The basic datasets' characteristics are provided, the variable name, the product name (abbrevation of the providers), the initial spatial and temporal resolution and the temporal coverage.

Variable	Product Name	Spatial Res.	Temporal Res.	Coverage
Temperature	CRU-HR	0.5°	monthly	1981-2011
	UDEL	0.5°	monthly	1981-2010
	ISCCP	2.5°	daily	1983-2009
	ERA	0.25°	daily	1981-2011
	GISS	2°	monthly	1981-2011
	MLOST	5°	monthly	1981-2011
	LPRM	0.25°	daily	2002-2011
Water	CRU-HR	0.5°	monthly	1981-2011
	CMORPH	0.25°	daily	1998-2011
	UDEL	0.5°	monthly	1981-2010
	PERSIANN	0.25°	daily	2001-2011
	CMAP	2.5°	monthly	1981-2011
	CPCU	0.25°	daily	1981-2011
	3B42RT	0.25°	daily	1998-2011
	GPCC	0.5°	monthly	1981-2010
	GPCP	2.5°	monthly	1981-2011
	ERA	2.5°	daily	1981-2011
	GLEAM	0.25°	daily	1981-2011
	NASA	0.25°	daily	2002-2011
	ESACCI-ACTIVE	0.25°	daily	1991-2011
	ESACCI-PASSIVE	0.25°	daily	1981-2011
	ESACCI-COMBINED	0.25°	daily	1981-2011
	GLOBSNOW	0.25°	daily	1981-2011
Radiation	SRB	1°	daily	1983-2007
	ERA	0.25°	daily	1981-2011
Greenness(NDVI)	GIMMS	0.25°	monthly	1981-2011

passive products. Finally, snow water equivalents data set includes a satellite-based product (GlobSnow project [13]).

For vegetation, we use the satellite remote sensed products of Normalized Difference Vegetation Index (NDVI). Data from the Global Inventory Modeling and Mapping Studies (GIMMS) data set has been used, which is one of the most commonly used NDVI data sets [22] covering a wide time interval of 30 years (1981-2011).

2 Construction of target variable

Before constructing those features, we first decompose the target and predictor time series into trends, seasonal cycles and anomalies. This is an important step, because the trend and seasonal component of the vegetation time series are not influenced by climatic features and thus we can search for interesting relationships between climate and vegetation time series.

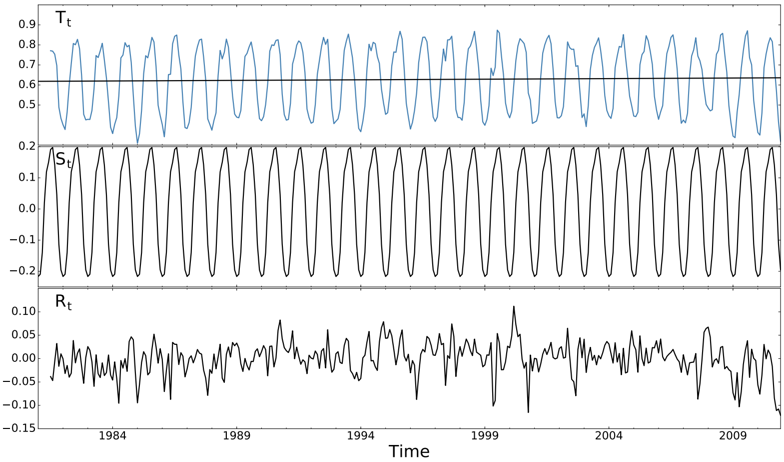

Fig. 1: The three components of the time series decomposition. On top, the linear trend fitted on the raw data, in the middle, the seasonal component and on the bottom the remaining anomalies of the NDVI time series. See text for details.

Many methods for decomposing time series have been proposed in the literature [2,23]. We decided to use an additive model without break-points, since it is conceptually-simple, while delivers satisfactory results in a reasonable amount of time. For the target time series, this decomposition looks as follows:

$$Y_t = T_t + S_t + R_t \tag{1}$$

with T_t the long-term trend, S_t the seasonal cycle and R_t the anomalies or residuals. The target time series is decomposed following three sequential steps. In a first step, time series Y_t is at every pixel de-trended linearly based on the entire study period, using a simple linear regression model:

$$Y_t \approx \beta_1 \times t + \beta_0 = T_t\,.$$

In this way we obtain the de-trended time series, $D_t = Y_t - T_t$. In a second step, the seasonal cycle S_t is estimated as a monthly expectation, taking the multi-year average for each month of the year. In a last step, the anomalies are calculated by subtracting the corresponding monthly expectation from the de-trended time series, $R_t = D_t - S_t$. The same time series decomposition method is followed for all predictor time series as well. Figure 1 shows for one particular

Table 2: Overview of the extreme indices. We apply the indices to raw (daily) data as well as to the (daily) anomalies (residuals with the trend). We also incorporate the lags and the cumulatives to investigate further their impact on vegetation response.

Name	Description
Spatial Heterogeneity [a]	Difference between max and min values within 1 degree box
STD	Standard deviation of daily values per month
DIR	Difference between max and min daily value per month
Xx/Xn	Max/Min daily value per month
Max5day/Min5day	Max/Min over 5 consecutive days per month
X99p/X95p/X90p	Num. of days per month over $99^{th}/95^{th}/90^{th}$ prc
X1p/X5p/X10p	Num. of days per month below $1^{th}/5^{th}/10^{th}$ prc
T25C/T0C [b]	Num. of days per month over 25C/below 0C
R10mm/R20mm [c]	Num. of days per month over 10mm/20mm
CHD (Consecutive High value Days) /CLD (Consecutive Low value Days)	Num. of consecutive days per month over 90^{th} prc/below 10^{th} prc
CDD (Consecutive Dry Days)/CWD (Consecutive Wet Days) [c]	Num. of consecutive days per month when precipitation <1 mm/≥ 1 mm

[a] Only for datasets with native spatial resolution $<1°$ lat-lon
[b] Only for temperature data sets
[c] Only for precipitation data sets

pixel a decomposition of the original time series, using the three-step procedure. The anomalies component (R_t) of the NDVI variable is the target variable that we use in our analysis.

3 Extreme indices

In our work, we have calculated different monthly indices on the raw data as well as on the residuals (including the trend) based on the recommended indices of [5,27]. Table 2 summarizes the extreme indices calculated for climate drivers. We also incorporate the time-lags and the cumulatives on the extremes in order to investigate the role of lagged responses to the past climate extremes (e.g. [4,16]) and the cumulated character of the extremes, respectively.

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