socioeconomic influences in potential adaptation efforts.

Study area
The Okavango, Kwando, and Upper Zambezi watersheds. The study area covers 681,545 km² in tropical and sub-tropical southern Africa: Zambia, Angola, Namibia and Botswana (Fig. 1). Mean annual precipitation (MAP) ranges from under 400 mm to 1400 mm yr⁻¹ and is strongly correlated with rainfall and elevation, with highest rainfall in the mountainous north.

Remote sensing data
Remote sensing data included ten years (2001-2010) of monthly NDVI data (response variable) and a suite of environmental variables used as candidate explanatory variables in the analysis, including precipitation (P), mean temperature (T), minimum temperature (Tmin), maximum temperature (Tmax), soil moisture (S), relative humidity (H), fire (F) and potential evapotranspiration rate (E). Time series of response and explanatory variables were aggregated from pixel-scale data by extracting mean values over areas defined by different precipitation intervals for each of the three drainage basins, producing 48 individual data polygons (Fig. 2).

Dynamic Factor Analysis (DFA)
DFA is a statistical exploratory tool built upon common patterns among, and interactions between, response and explanatory time series. Thus, no a priori understanding of interactions between response (NDVI) and explanatory variables (e.g., precipitation, fire etc.) is required. DFA models temporal variation in response variable as linear combinations of common trends, zero or more explanatory variables, a constant intercept parameter, and noise as:

\[ S(n,t) = \sum_{k=1}^{K} \beta_k \alpha_k(t) + \mu(t) + \sum_{i=1}^{n} \epsilon_i(t) + \epsilon_0(t) \]

where \( S(n,t) \) is a vector containing the set of N response variables (\( n=1:N \)); \( \alpha_k(t) \) is a vector containing the M common trends (\( m=1:M \)); \( \epsilon_i(t) \) are factor loadings or weighting coefficients, which indicate the importance of each of the common trends; \( \mu(t) \) is a constant level parameter; \( \epsilon_0(t) \) is a vector containing the K explanatory variables (\( k=0:K \)); and \( \beta_k \) are regression coefficients indicating the importance of each of the explanatory variable. Here, \( S_0 \) represents the 48 NDVI time series (each polygon in Fig. 2).

Results
NDVI was described by cyclic seasonal variation with distinct spatiotemporal patterns in different physiographic regions (Fig. 3). Incremental best models are shown in Fig 3 (in bold). Results support existing work emphasizing the importance of precipitation, soil moisture and fire on NDVI, but also reveal overlooked effects of temperature and evapotranspiration, particularly in regions with higher mean annual precipitation (MAP). Critically, spatial distributions of the weights of environmental covariates point to a transition in the importance of precipitation and soil moisture (strongest in grass-dominated regions with MAP < 750mm) to fire, potential evapotranspiration (PET), and temperature (strongest in tree-dominated regions with MAP > 950mm) (Fig. 4).

Conclusion
We quantified the combined spatiotemporal effects of a complete suite of environmental drivers on NDVI across a large and diverse savanna region. Results highlight the need for applying the DFA approach to remote sensing products for regional analyses of landscape change in the context of global environmental change. With the dramatic increase in global change research, this methodology augurs well for further development and application of spatially explicit time series modeling to studies at the intersection of biogeography, ecology and remote sensing.