Beyond precipitation: Physiographic thresholds dictate the relative importance of environmental drivers on savanna vegetation

R. Muñoz-Carpena [1], M. Campo-Bescós [1], D. Kaplan [2], J. Southworth [3], P.R. Waylen [3], Z. Likai [3], E. Keys [3], B. Child [3], M. Binford [3], C. Gibbes [4], and L. Rigg [5]

[1] Agricultural and Biological Engineering Dept., University of Florida, Gainesville, FL, USA; [2] Environmental Engineering Sciences Dept., University of Florida, Gainesville, FL, USA
[3] Geography Dept., University of Florida, Gainesville, FL, USA; [4] Geography and Environmental Studies Dept., University of Colorado, Colorado Springs, CO, USA; [5] Geography Dept, University of Northern Illinois, DeKalb, IL, USA

Abstract

Understanding the drivers of large-scale vegetation change is critical to managing landscapes and key to predicting how projected climate and land use changes will affect regional vegetation cover. In southern Africa, long-term changes in the ecosystem structure and productivity of savannas is thought to be driven by a combination of biotic and abiotic drivers, and may represent irreversible landscape degradation. We applied Dynamic Factor Analysis (DFA), a multivariate times series dimension reduction technique, to investigate the shared dynamics of spatially variable vegetation coverage across three large watersheds in southern Africa over ten years and to identify the most important physical drivers of vegetation change in the region. NDVI is described by a pattern of cyclic seasonal variation, with distinct spatio-temporal patterns in different physio-geographic regions. For the subregion in which Mean Annual Precipitation (MAP) < 750 mm N DVI was found to be most strongly influenced by soil moisture and precipitation, with much smaller effects of fire, evapotranspiration, and temperature. On the other hand, in regions with MAP > ~900 mm, fire and temperature began to dominate, followed in importance by evapotranspiration. While a number of previous studies of NDVI in southern Africa have focused on the relationship between NDVI and one or two explanatory variables, in this work we quantified the combined spatio-temporal effects of a suite of environmental drivers on NDVI across a diverse and sensitive savanna region. This expands our ability to understand landscape level changes in vegetation evaluated through remote sensing, and improves the basis for management of vulnerable regions like southern Africa savannas. Additionally, these methods also allow us to develop models of predicted surfaces, link to local level land use changes and develop spatially explicit change analyses at a monthly time-step. We can also use these developed models to predict this landscape out into the future under changing climatic conditions, and link to extreme events and highlight the role of socioeconomic institutions in potential adaptation efforts.

Study area

The Okavango, Kwando, and Upper Zambezi watershed. The study area cover 681,545 km^2 in tropical and sub-tropical southern Africa: Zambia, Angola, Namibia and Botswana (Fig. 1). Mean annual precipitation (MAP) ranges from under 400mm to 1400 mm yr-1 and is strongly correlated with latitude and elevation, with highest rainfall in the mountainous north.

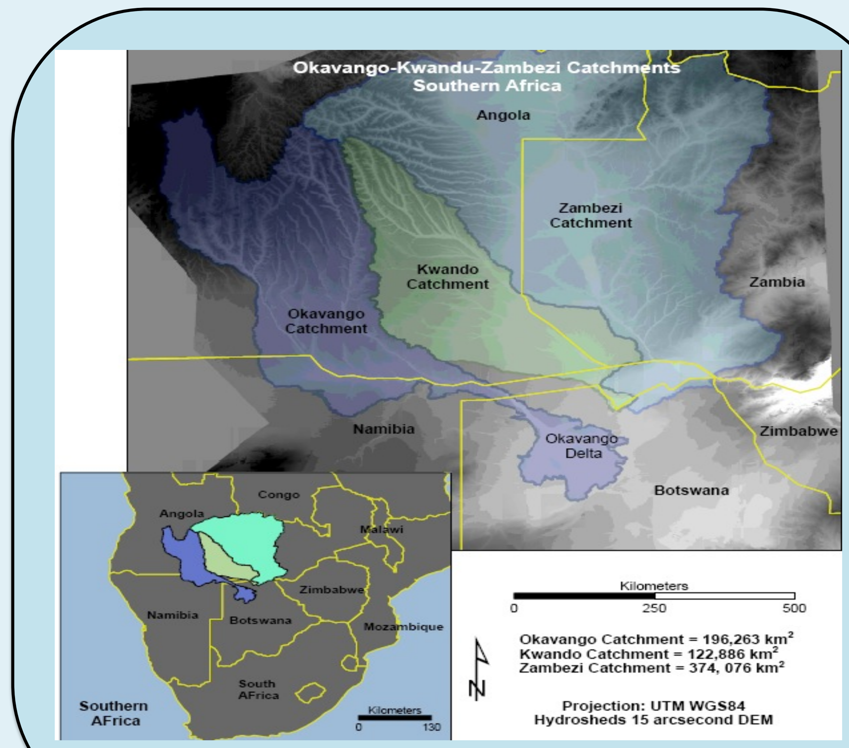

Figure 1. Study area

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).

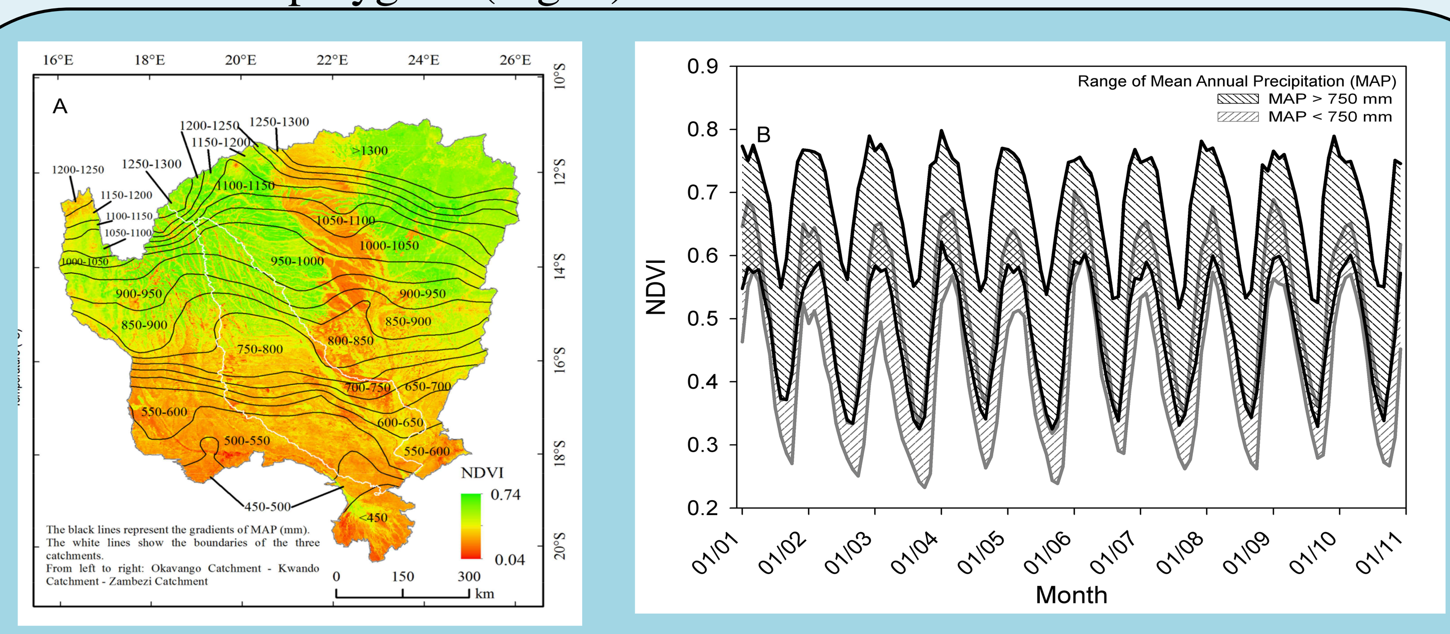

Figure 2. Spatial and temporal distribution of NDVI across the study area, derived from MODIS NDVI data from 2001 to 2010. A) Spatial pattern of mean annual NDVI. The subset polygons correspond to mean annual precipitation (MAP) intervals. B) Variability of observed NDVI for the study region for two MAP ranges.

Dynamic Factor analysis (DFA)

DFA is a statistical explanatory 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:

$$S_n(t) = \sum_{m=1}^{M} \gamma_{m,n}\alpha_n(t) + \mu_n + \sum_{k=1}^{K} \beta_{k,n}v_k(t) + \varepsilon_n(t)$$

$$\alpha_m(t) = \alpha_m(t-1) + \eta_m(t)$$

where $S_n(t)$ is a vector containing the set of N response variables ($n=1,N$); $\alpha_m(t)$ is a vector containing the M common trends ($m=1,M$); $\gamma_{m,n}$ are factor loadings or weighting coefficients, which indicate the importance of each of the common trends; μ_n is a constant level parameter; $v_k(t)$ is a vector containing the K explanatory variables ($k=0,K$); and $\beta_{k,n}$ are regression coefficients indicating the importance of each of the explanatory variable. Here, S_n represents the 48 NDVI time series (each polygon in Fig. 2).

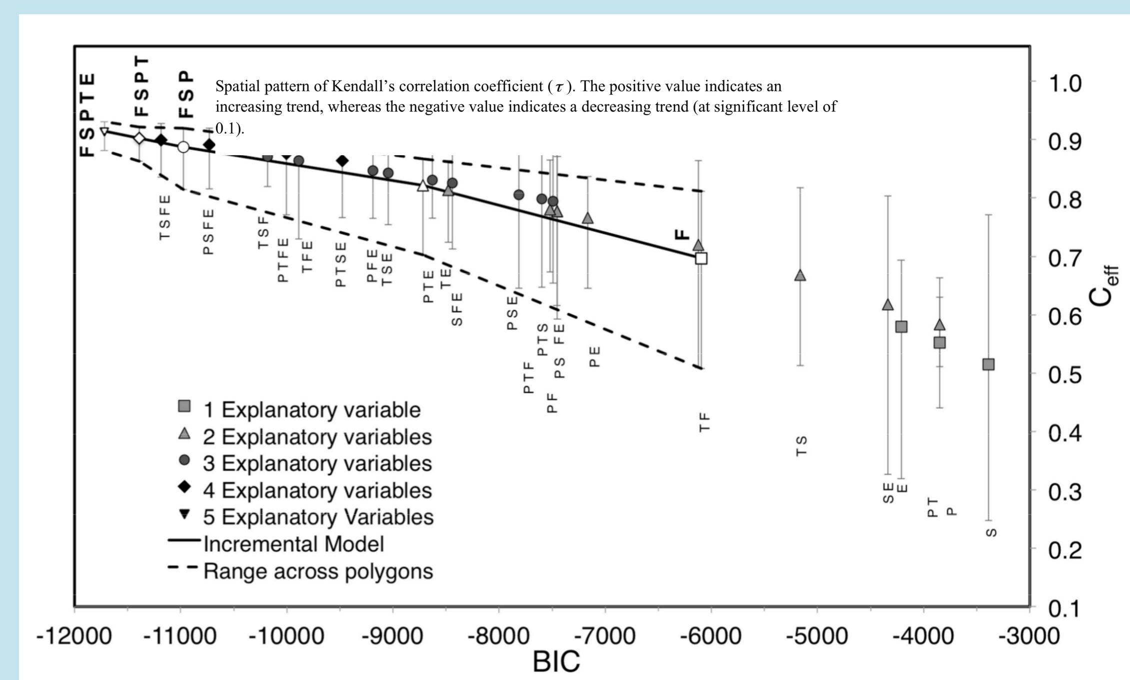

Figure 3. Incremental improvement of multi-linear regression performance with the addition of the explanatory variables: Precipitation (P), Temperature (T), Soil Moisture (S), Fire (F) and Potential Evapotranspiration (E). Incremental best models are shown in bold with white symbols with solid lines indicating the weighted average and dashed lines the range across the spatial domain. (Ceff: Nash-Sutcliffe Efficient Coefficient; BIC: Bayesian Information Criterion).

Results

NDVI was described by cyclic seasonal variation with distinct spatiotemporal patterns in different physiographic regions (Fig 2). 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).

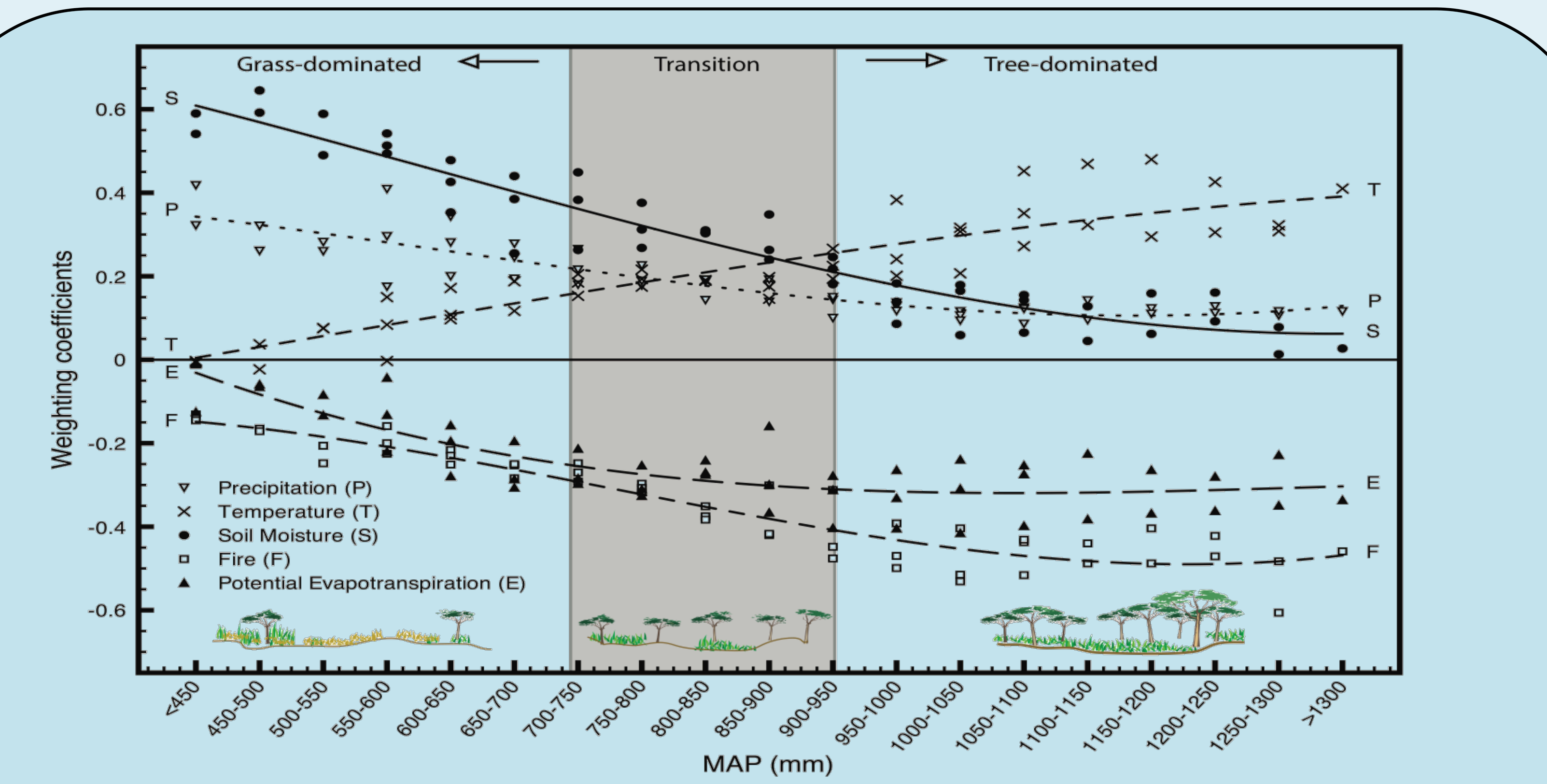

Figure 4. Model bk,n regression coefficients, illustrating the weight (or importance) of each explanatory variable for driving NDVI in savanna ecosystems as a function of MAP. Lines represent the main trajectories and highlight the change in the importance of environmental drivers along a gradient from grass- to tree-dominated landscape.

Using this developed model, we then modeled the predicted NDVI value for each precipitation polygon (for each month across the 10 years), and then subtracted each months actual NDVI. The resultant monthly coverages were then compiled and surface change significance determined. The seasonal Kendall's test was applied to detect the trends in the difference between the observed and the predicted NDVI. It is a non-parametric test which is more suitable when the normality and independence of variable is violated. If it is greater than zero and statistically significant, there is an increasing trend; if it is less than zero and statistically significant, there is a decreasing trend (Fig. 5a). The extent of the trend can be represented by the median of Sen's slopes for all months. The positive value indicates an increasing trend, and vice versa (Fig. 5b).

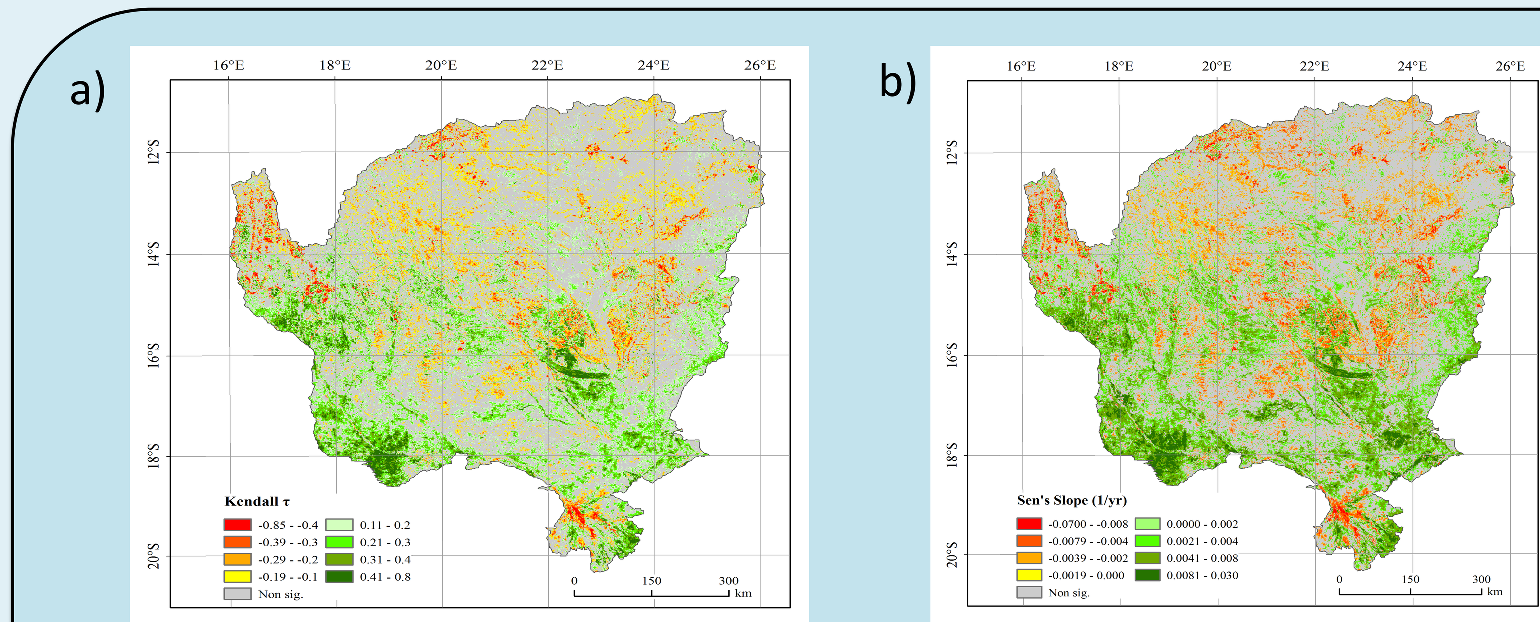

Figure 5. (a) Spatial pattern of Kendall's correlation coefficient (τ). The positive value indicates an increasing trend, whereas the negative value indicates a decreasing trend (at significant level of 0.1).; and (b) Spatial pattern of Sen's slope of the OKZ catchment. The positive value indicates an increasing trend, whereas the negative value indicates a decreasing trend

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 utility of 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.