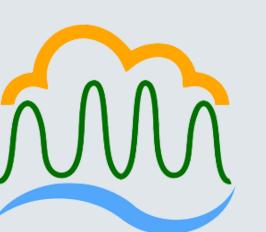
Measuring the Sensitivity and Stability of Vegetation in Response to the Hydroclimate Across East Africa with an Empirical Dynamic Modeling Approach





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Vegetative greenness is dynamic, shifting with seasonality and hydroclimatic factors across spatiotemporal scales. Emerging empirical methods provide a valuable perspective on the relationship between land and atmospheric systems and their collective behavior.

Climate-Vegetation Interactions



Evaluating the causal mechanisms between the land and atmosphere has been limited by high global spatiotemporal observation availability. Developing process-based climate-land surface model simulations has been the predominant path in the field, however, findings on directionality, temporal lag, and feedback processes vary widely across scale, ecosystems, model inputs, and statistical approaches.

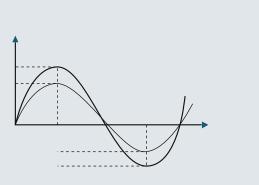
We investigate the spatial variation in predictability of vegetation condition across different land covers, uncovering the characteristics that strengthen or weaken predictability.

Empirical Dynamic Modeling



One such data-driven approach to uncover the inherent dynamics of complex, nonlinear systems is known as Empirical Dynamic Modeling (EDM). The non-parametric method is utilized across various fields including environmental and climate sciences to identify causal relationships, predict future system states and quantify predictability.

Interannual Variation of Vegetation Condition



- The stability of vegetation productivity (NDVI) can be depicted using time-delayed embedding. This technique, also known as Takens' embedding theorem, is a method for reconstructing the dynamics of a system from a single observed time series.
- We illustrate an example of the heteroscedasticity in the NDVI signal across years. An NDVI dekadal-averaged time series can be reconstructed into a manifold, or low-dimensional space, by a set of lagged embedding vectors.
- Knowledge of which areas experience high or low consistency in NDVI outcome at a certain time of the year can facilitate identification of regions or ecosystems that are less resilient to changes in climate or land management practices.

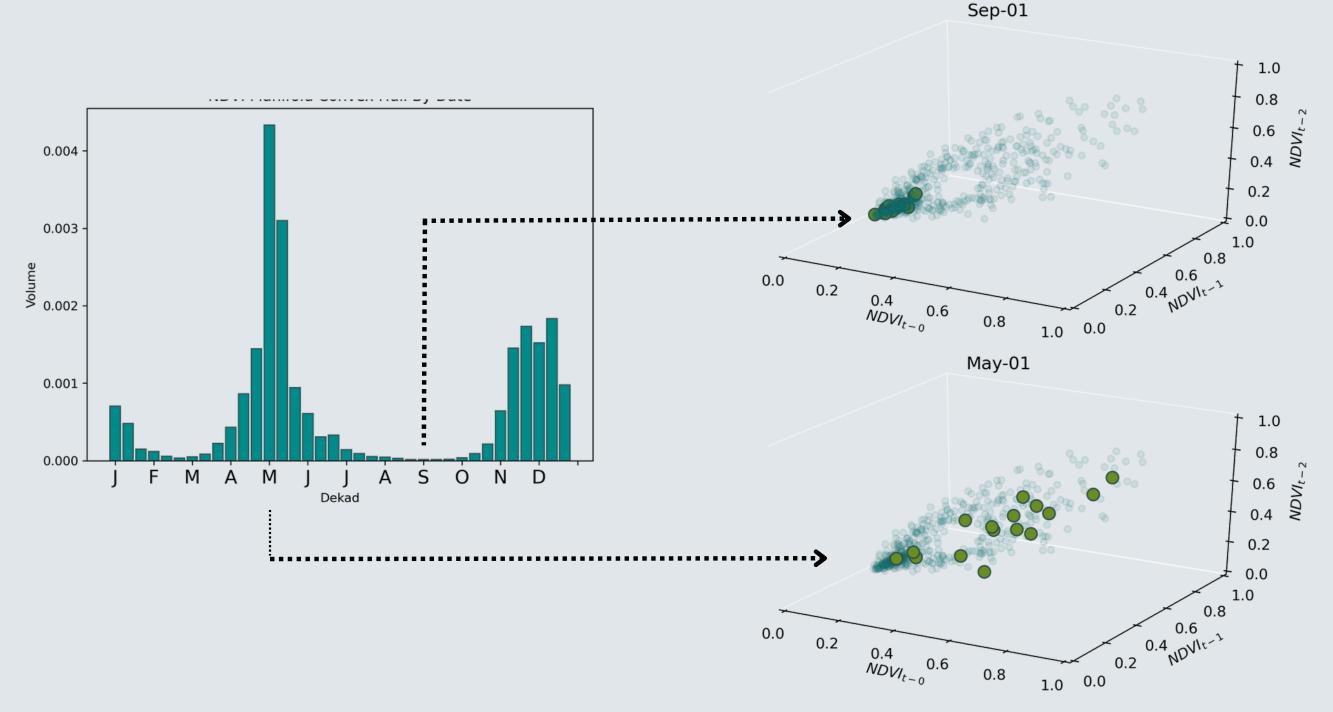


Figure 3. The NDVI within a season can vary substantially year to year. At an example location in the study region, we depict the convex hull volumes (a) of the time-delayed manifold for each dekad (b) across years (2002-2021).

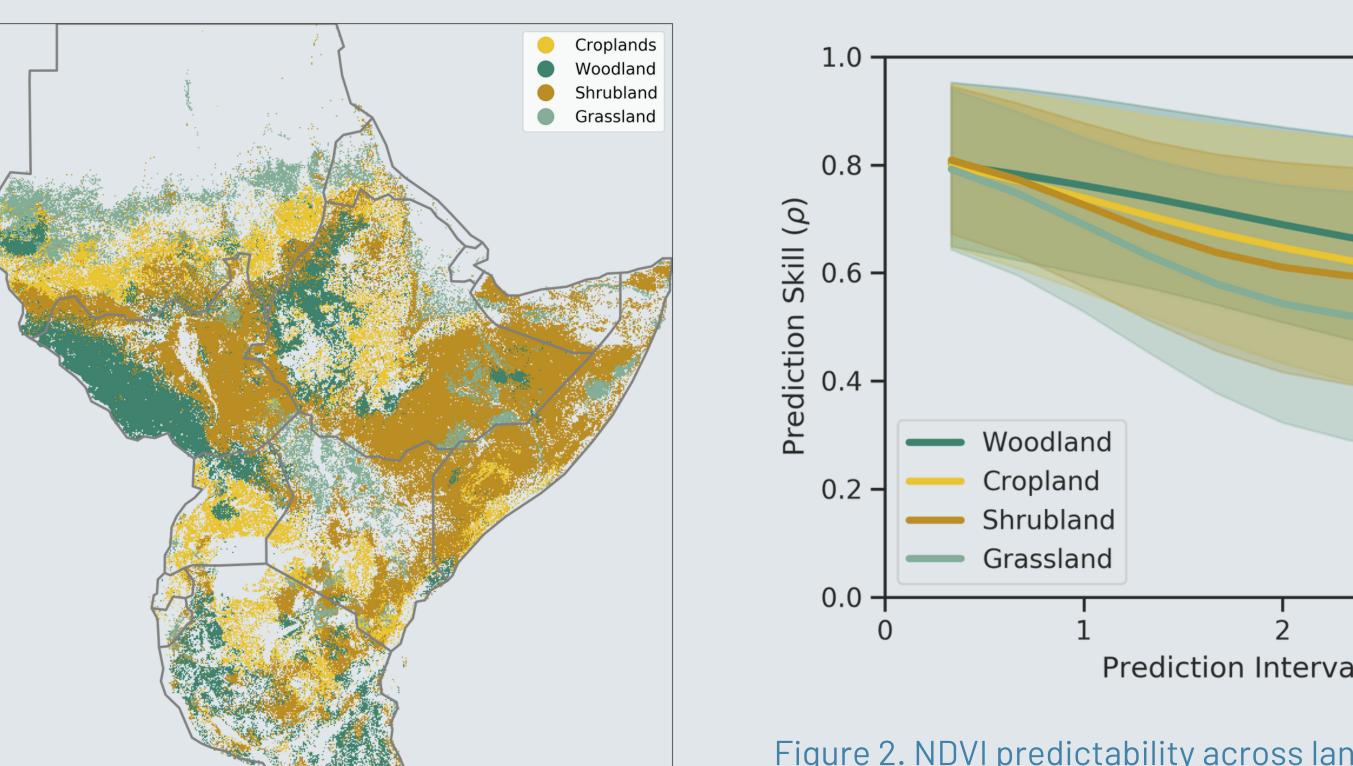


Figure 1. Primary vegetated land covers in East Africa - croplands, woodlands, shrublands, grasslands. Source: ESA-CCI

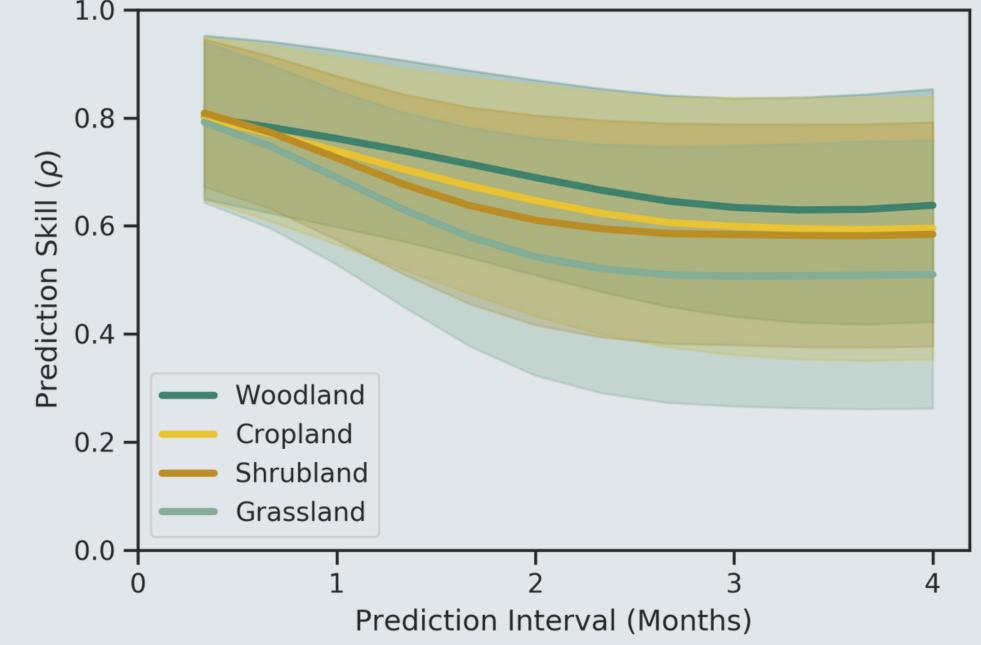
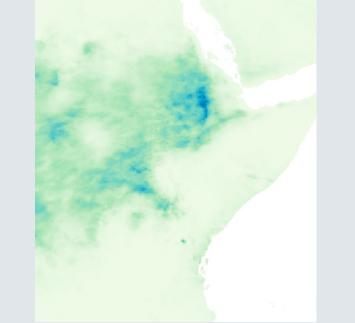


Figure 2. NDVI predictability across land covers. With increasing lead time (prediction interval), the skill will decrease until plateauing when seasonality starts to dominate the cycle. Woodlands may exhibit higher skill overall due to their structural complexity, deep rootings systems, and high levels of soil organic

By harnessing increasingly available long records of environmental remote sensing data, we can analyze the linkages between hydroclimatic variables that influence vegetation condition.

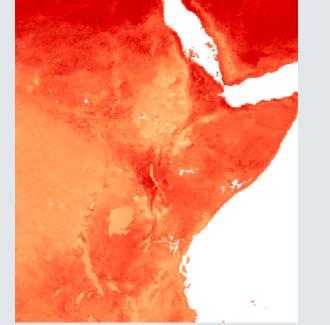
Characterizing the changes of drylands as a nonlinear and non-equilibrium dynamic problem, one approach is to analyze state dependent variables within the system to determine the response behavior.

To capture the intricate connections in the ecohydrological system across East Africa, we examined five critical components derived from remote sensing data.

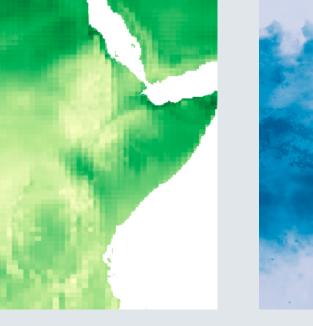


CHIRPS Precipitation

LST ↔ NDVI







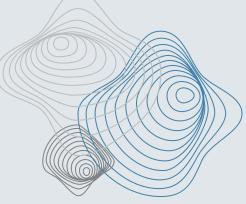


MODIS Land Surface USGS Reference

Temperature Evapotranspiration

eMODIS NDVI FLDAS Soil Moisture

Discovering Causal Relationships



- In order to identify relevant candidate variables for more robust and accurate NDVI predictions, we evaluate the relative strength of causal relationships in the hydroclimatic system using the Convergence Cross Mapping (CCM) technique.
- The process involves reconstructing the multidimensional state spaces from time-delayed embeddings and comparing the resulting manifolds of different variables. Causality is determined if the state space of one variable contains information about the other variable.
- The grouped bars for each variable pair offer insights into the directionality of causality. We quantify the amount by which external factors exert stronger forcing on NDVI rather than vice versa. The difference between skill in the precipitation and NDVI is the largest among pairings, confirming the importance of rainfall seasonality in this water limited region.

Measuring Predictability

SM ↔ NDVI refET ↔ NDVI

Figure 4. Causal (CCM) skill scores between NDVI and climate variables

directionality of their feedbacks. High bars indicate strong connections

across croplands in the study region reveal the strength and

while the leading bar in a pair has more influence on the other.

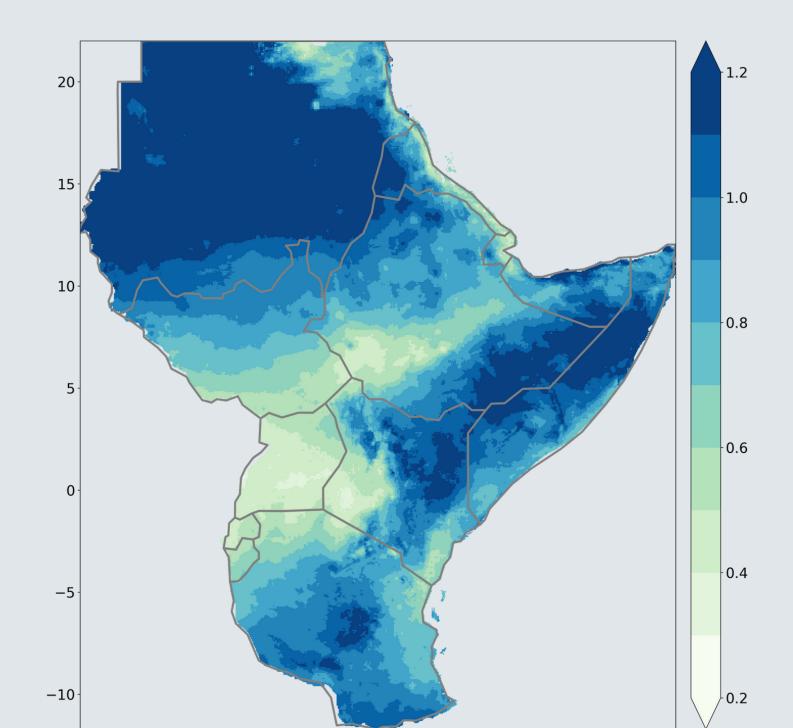


Figure 5. Rainfall seasonality according to the Walsh and Lawler Index where values < 0.19 indicate precipitation is spread throughout the year and values > 1.2 indicate extreme seasonality, with almost all precipitation occuring in 1-2 months.

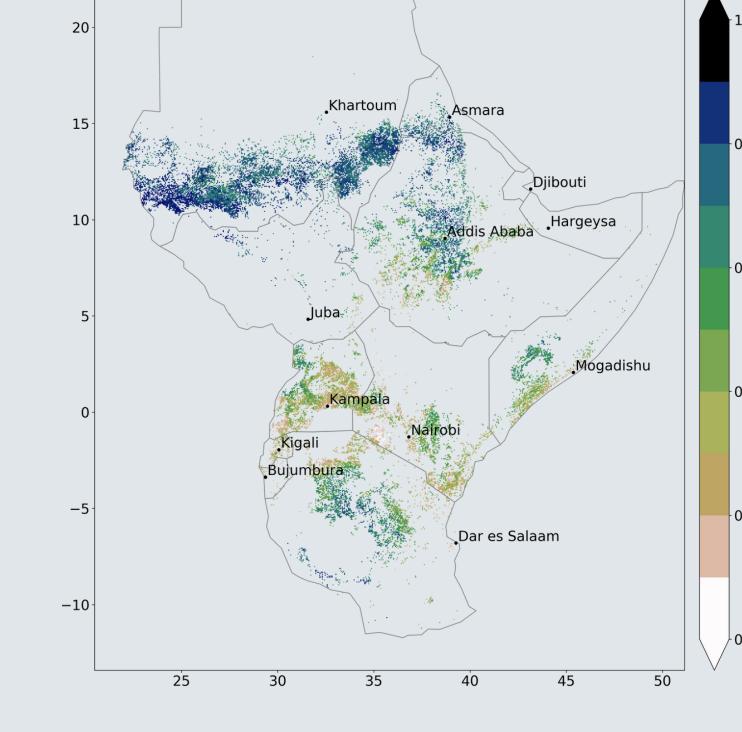


Figure 6. Four-month predictive skill of NDVI from historical land surface temperature and precipitation across croplands. Predictability is calculated with Simplex Projection and skill is measured by a correlation coefficient.

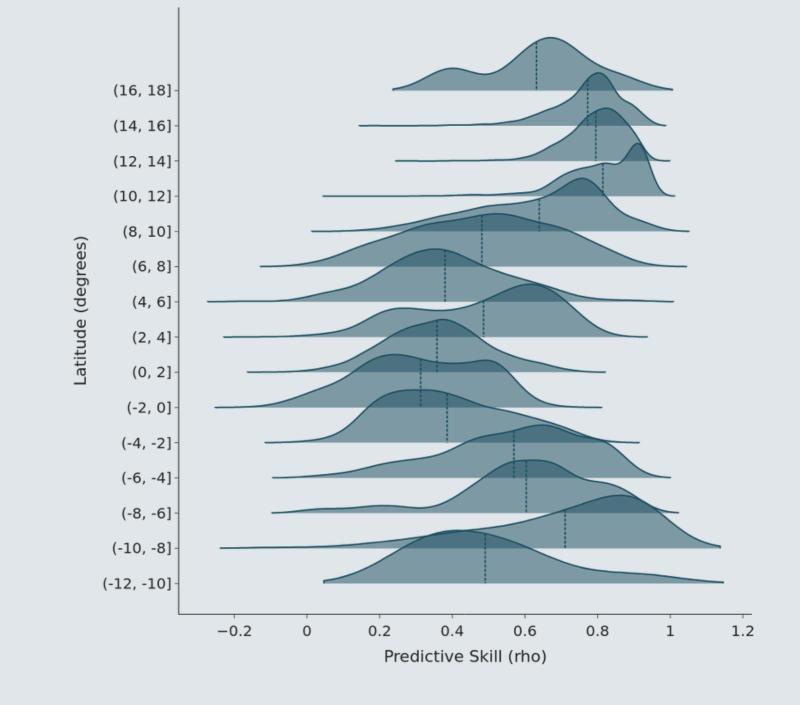


Figure 7. Distribution of four-month NDVI predictive skill across croplands by latitude. In midlatitudes of East Africa, where rainfall seasonality is more erratic and extreme, predictability is reduced.

Applying empirical dynamic modeling to the biogeosciences domain enables us to examine localscale environmental variability, generate spatially explicit maps of vegetation predictability given climatic scenarios, and deepen our understanding of how natural and managed lands are coupled with atmospheric conditions.