Short-Term Dry Season Forage Monitoring in Rangelands and Savannas of West Africa

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Presenter Information

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Abstract

Dry season plant biomass is critical for livestock production and hence livelihoods in rangeland communities. We have developed a cloud-based application that employs remote sensing data to provide weekly spatially explicit information on plant vegetation cover in West Africa during the dry season (typically October-June). In this paper, we discuss the data analysis steps and results that drive the application. Linear spectral mixture analysis is used to derive endmember samples of basic landcover primitives (active/green vegetation, non-active vegetation, and bare soil) from very high-resolution imagery that spans the spatiotemporal spectrum from wet/peak-green to dry/dormant conditions in Senegal. These samples are used to train and evaluate ensemble tree models for predicting proportional cover of the same land cover primitives at 500m scale, using MODIS derived NDVI, shortwave infra-red bands 3 and 2 (SWIR3 and SWIR2), and total 15-day antecedent precipitation as predictors. Our trained models can predict the fractional cover of green vegetation, non-green vegetation and bare soil across space and time with cross-validation root-mean square errors of 12%, 15% and 9% respectively. With a weekly cadence and low latency (~2-3 weeks), the tool can also provide timely information to support local decision making in the management of critical rangeland resources.

Introduction

Drylands (including rangelands and other savannas) are drought prone seasonal landscapes, with low average and unpredictable annual rainfall, and a combination of woody and herbaceous vegetation systems that provide distinct ecological functions (Bond & Midgley, 2000; Nicholson & Webster, 2007). Rangelands are also the domain of most agropastoral activity worldwide which places them firm firmly at the heart of the food and water security narrative.

Most of rangeland vegetation productivity occurs within a relatively short growing season (e.g. ~3 months in the West African Sahel) (Hiernaux et al., 2009). This can be reliably proxied using greenness indices such as NDVI (Tucker, 1979). The dry season period is however the most critical bottleneck for the survivability of rangeland livestock that rely on natural vegetation (woody or herbaceous) for forage. Tracking senescent/dormant vegetation conditions during the dry season requires narrow band reflectance in the short-wave infra-red (SWIR) part of the spectrum, where lignin/cellulose (normally present in greater amounts in non-active vegetation) have a higher absorption feature (Nagler et al., 2003; Serbin et al., 2013). These narrow band indices can be directly derived using hyperspectral remote sensing data, which is however not readily available on an operational scale. As such, scientists studying Australian savannas have shown that empirical relationships are needed between more commonly used multispectral reflectance (such as from MODIS) and these hyperspectral derived indices, to allow for operational mapping of dry vegetation conditions (Guerschman et al., 2009; Hill et al., 2017).

Building largely on the framework developed by Guerschman and Colleagues[1] for mapping fractional vegetation cover, but fine-tuned with local calibration/validation data and machine learning, we present a Google Earth Engine application[2] tailored specifically for monitoring of dry season vegetation in the West African arid and semi-arid lands. Our tool outputs weekly fractional cover estimates of active and non-active vegetation cover, and incorporates ancillary data (woody canopy cover, fire activity) for a more contextual assessment of dry season vegetation conditions, with a broader mandate to facilitate decision making in the management of rangeland forage resources. The rest of this paper discusses the data, methods and results that drive the application.

[1] https://data.csiro.au/collections/collection/CI42018
[2] https://savannalabnmsu.users.earthengine.app/view/forage-monitor

Methods and Study Site

We use Senegal, in West Africa, as the test case area for the development and implementation of the dry season rangeland vegetation monitoring application (Figure 1). Senegal extends from the very dry Sahel in the north, through a gradient of savanna/shrubland mosaics to the humid savanna/forest mosaics in the south. Most rural inhabitants in the country practice agropastoralism as the primary economic activity.

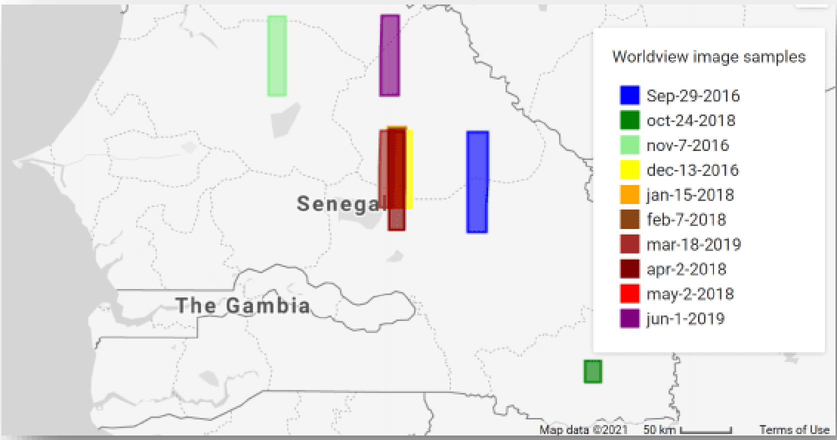

Figure 1 Senegal in West Africa used as test case area for dry season vegetation/forage monitoring application. Coloured rectangles are footprints of sampled Maxar's worldview 2 and worldview 3 imagery labelled by acquisition date. Worldview imagery is obtained courtesy of the NASA NextView License.

The following multi-source/multi-scale remote sensing data are used for mapping dry season fractional vegetation cover in Senegal: i) Daily MODIS Nadir Bi-directional Reflectance Distribution Function (BRDF) Adjusted Reflectance (NBAR, MCD43A4 Collection 6, 500m) (Schaaf & Wang, 2015); ii) Maxar's Worldview 2 and 3 (WV-2 and WV-3) imagery sampled across multiple locations and dates in the study area (Figure 1); and iii) Climate Hazards Infra-red Precipitation with Station (CHIRPS) data (Funk et al., 2015). The application also employs independent woody canopy cover maps for Senegal (Anchang et al., 2020), and Daily MODIS Thermal Anomalies and Fire (MOAD14A1, Collection 6, 1km) (Giglio & Justice, 2015), for end-use case purposes (see application demo).

Very high resolution (VHR) multispectral WV-2 and WV-3 image strips are sampled spanning the north-south gradient in Senegal, and with dates spanning the complete dry season cycle (September to June, Figure 1, Figure 2A). Linear spectral mixture analysis (SMA) is performed on VHR imagery to extract more accurate fractions of green vegetation, non-green vegetation and bare soil. SMA is preferred over pixel-based classification because of its greater efficiency for processing large volumes of VHR imagery; and the belief that, even at such high spatial resolution (~1.8m, non-sharpened bands), there is considerable spectral mixing among rangeland landcover types particularly in the dry season (e.g., likely mixtures between thin herbaceous vegetation and bare soil). Unmixed samples of VHR imagery are then aggregated to 500m as the main calibration/validation data source for predicting fractional cover.

MODIS NBAR reflectance is processed to derive 2 spectral indices: NDVI (near infrared – red / near infrared + red) and SWIR32 (ratio of SWIR bands 3/ SWIR band 2). These provide the 2-D spectral space for discriminating dry season fractional cover (Figure 2). The greenest (maximum NDVI) composite is obtained for the weeks corresponding to the exact date of worldview image acquisitions and combined with worldview derived fractional estimates (Figures 2B – 2C). For the same dates and locations, the sum of 15-day antecedent precipitation is derived from 0.05-degree CHIRPS data as a proxy for soil moisture conditions and to control models for reflectance (NDVI) differences imposed by vegetation canopy wetness.

The combined Worldview-MODIS sample data is used to train and evaluate independent gradient boosted regression tree models (Friedman, 2001) for predicting the fractional cover of green vegetation, non-green vegetation and bare cover. Model parameters (e.g., number of decision trees) are determined by simple trial and error. While the pre-existing framework for mapping vegetation fractional cover relies mostly on mixture models and linear regression (Guerschman et al., 2009; Hill et al., 2017), we choose the machine learning approach for 2 reasons: i) compared to traditional linear models, ensemble tree models have proven out-of-the-box performance at approximating linear and nonlinear functions and can better handle variable interactions, ii) it is challenging to obtain pure endmembers of landcover types of interest at MODIS scale (500m) for a coarse level SMA. Hence, we use SMA only on the very high-resolution imagery to derive accurate samples for calibration and validation.

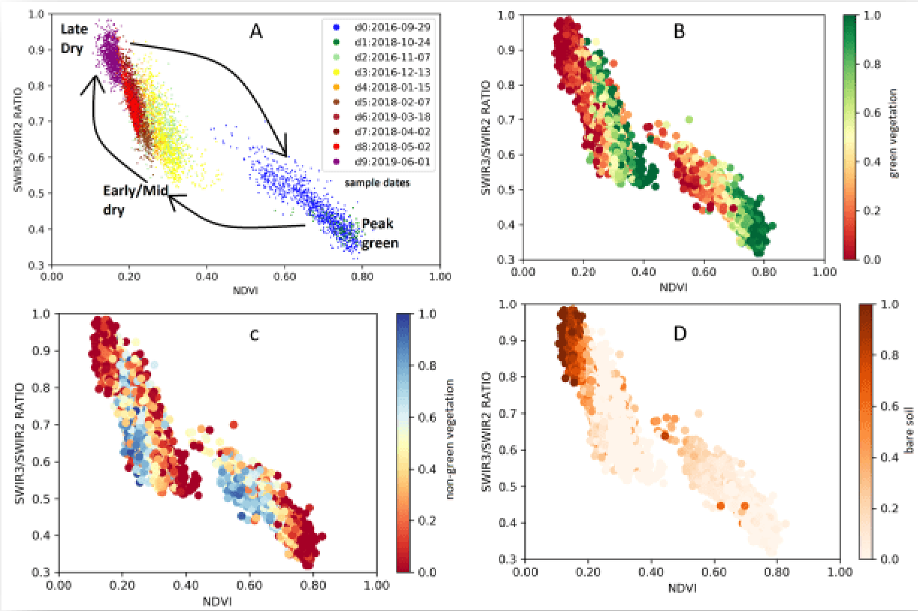

Figure 2 Theoretical framework for discriminating dry season vegetation fractional cover using a reduced 2-D spectral space that is controlled by dry season date (A) and correlates with the proportions of relevant land cover types derived from very high resolution imagery (B, C and D). Samples from the peak season (September-October) will generally have higher NDVI/higher fraction of green vegetation. As the dry season progresses, NDVI values will drop while SWIR32 (SWIR band 3/ SWIR band 2 ratio) values will steadily increase to reflect increasing non-active (dry or non-leaf) vegetation and bare soil conditions.

Results

Sample predictions of dry season fractional cover using gradient boosted regression tree models

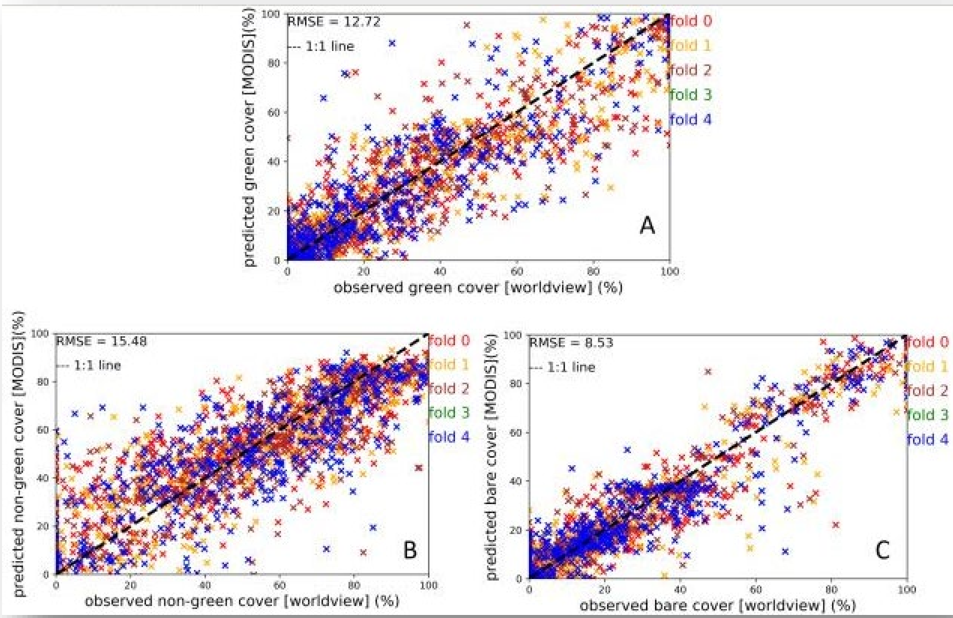

Figure 3 Model evaluations for predicting, A) green vegetation cover, B) non-green/non-active vegetation cover, C) bare soil cover, from MODIS NDVI , MODIS SWIR band ratio, and 15-day antecedent rainfall. Evaluation makes use of the k-fold validation

technique (k = 5) where 1/k of sample observations are sequentially withdrawn without replacement and used solely for test sample predictions and error estimates, while (k-1)/k of samples are used for training. The reported root mean square errors (RMSE) are pooled from out of sample predictions only. Most accurate predictions are obtained for bare soil cover which occupies the low extremes of NDVI and high extremes of SWIR32 (also see Figure 2). Meanwhile vegetation (especially non-green) cover suffers from less accurate predictions due to being less spectrally distinct.

Google Earth Engine Application

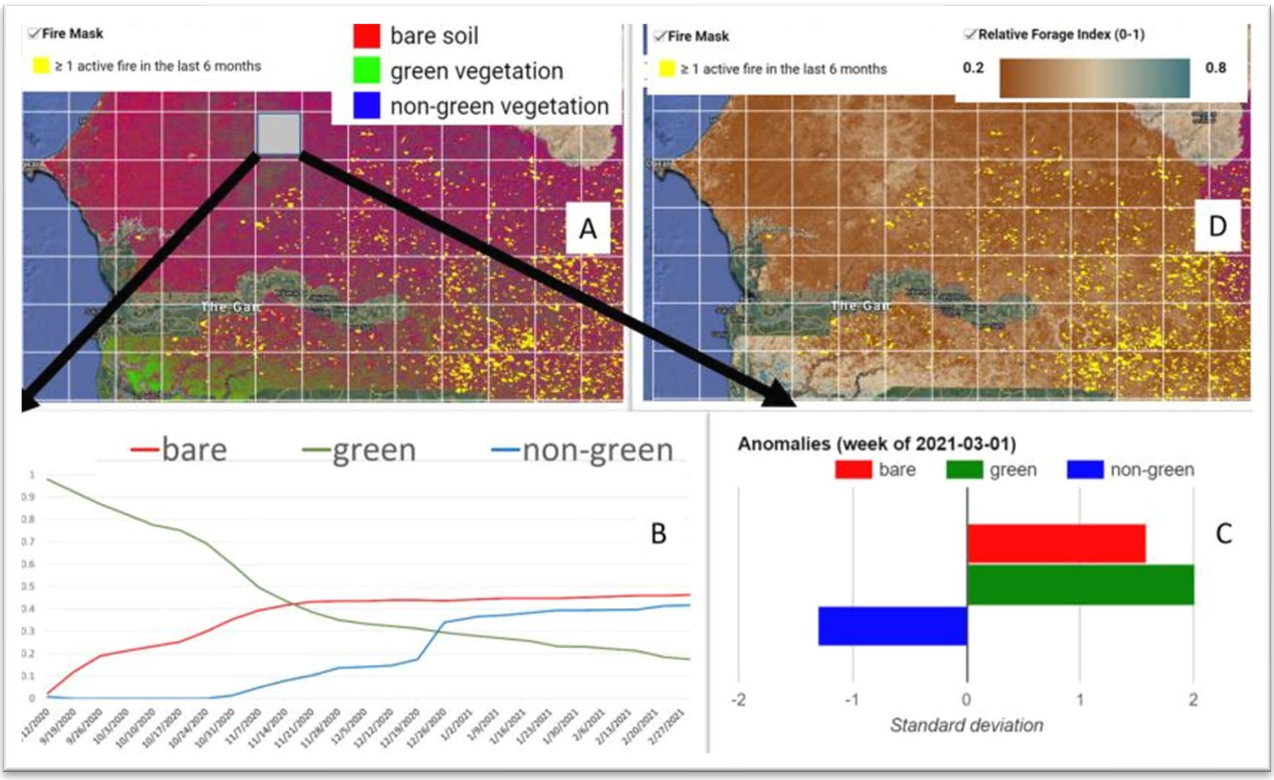

Figure 4 A demo of our Google Earth Engine application (https://savannalabnmsu.users.earthengine.app/view/forage-monitor) driven by the previously discussed analysis and models. The application outputs the most recent (A), 6 months (B), and 10-year anomalies (C), of weekly estimates of active (green) and non-active (non-green) vegetation and bare soil fractions for a selected location (period of September 2020 – March 2021 shown above). It also computes an arbitrarily weighted forage index (D) which assigns varying weights to areas based on the estimated fractional cover (green = most desirable, non-green = less desirable, and bare soil = non-desirable). The forage index also penalises areas that combine both higher fractions of non-green vegetation and woody canopy cover (not shown), as this may suggest a higher amount of non-leaf woody materials that are not very useful for foraging. Lastly, recent fire activity (yellow mask) is provided for more context as this may influence satellite reflectance (hence fractional estimates) as well as the practical interpretation of forage conditions.

Discussion, Conclusions and Implications

The framework for mapping of dry season fractional vegetation cover has long been established (Guerschman et al., 2009). However, it is challenged by the considerable differences in regional edaphic and bio-climatic conditions even within the broader context of rangeland and savannas. Our application builds on a solid concept and fine-tunes it to work for rangeland monitoring in the specific context of the West African savannas.

Our ensemble tree-based models trained locally can predict fractional cover in Senegal a with reasonably high accuracy. The relatively lower accuracy reported for non-active vegetation (~15% RMSE) is understandable and consistent with past studies (Hill et al., 2016). In our case, model calibration samples are obtained from VHR satellite imagery, and non-photosynthetically active vegetation is not a very spectrally distinct land cover type (as compared to low albedo green canopies and high albedo dry bare soil surfaces). Our end-user application heuristically compensates for this by subtracting the combined (and likely more accurate) estimates of green cover and bare soil from 1 (100%) to obtain non-green vegetation cover.

It is also important to note that the estimated non-green vegetation is not entirely dry/senescent plant material, which is relevant for foraging, but may also include non-forage materials such as woody plant tissue and burn scar/residue. We therefore include independent stable woody vegetation maps and recent fire activity as post-processing steps to enhance the interpretation of prevailing dry season forage conditions.

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