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Methods for Earth System Analysis in the West African Sahel: Land Cover and Climate Through Computational and Applied Sciences

by

Mollie M. Van Gordon

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Geography

and the Designated Emphasis

in

Computational Science and Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Associate Professor Laurel G. Larsen, Chair
Professor Emeritus Michael J. Watts
Professor Jeffrey Q. Chambers
Professor Inez Y. Fung

Fall 2018

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Abstract

Methods for Earth System Analysis in the West African Sahel:
Land Cover and Climate Through Computational and Applied Sciences

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Mollie M. Van Gordon

Doctor of Philosophy in Geography

Designated Emphasis in Computational Science and Engineering

University of California, Berkeley

Associate Professor Laurel Larsen, Chair

Precipitation and land cover in the West African Sahel have changed dramatically over the past 50 years. Region-wide data on land cover change in the Sahel, however, have been sparse or unreliable. I present a new 30 meter 2000-2016 annual resolution land cover dataset for the West African Sahel. The product is built from hand-classified land cover maps using random forest machine learning methods with Landsat, precipitation, and topography features. The resulting maps confirm the widespread extensification of agriculture in the region over this time period. Contrary to the common narrative of desertification, this increase in agriculture has not been accompanied by an increase in bare soil or sandy area. Land cover change volatility is shown to be spatially heterogeneous, both at local and regional scales. In addition to the new land cover dataset, I present spatial and temporal analyses of precipitation during the recent years of increased variability in the West African Sahel. I examine seasonal trends, interannual variability, and differences among datasets representing precipitation in the Sahel. Region-wide spatial organization of precipitation is identified using the self-organizing mapping pattern recognition technique. The number of days spent in the monsoon transition period is strongly negatively correlated with annual precipitation anomaly` indicating a tradeoff with the peak monsoon period, a result that supports the upped-ante hypothesis of precipitation in the Sahel.

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Acknowledgements.

First and foremost, deep appreciation to my partner David Gaffney-Rosenfeld. His intellectual, emotional, and logistical support is woven through every bit of this research and this dissertation.

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My thanks to everyone at the Center for Agriculture, Hydrology and Meteorology (AGRHYMET) in Niger, particularly Mamane Bako, Issifou Alfari, Abdou Ali, and Alkhalil Adoum. They have guided my research directions and offered their experience and their enthusiasm. Gratitude to Alisha Graves at the OASIS Initiative who gave me an introduction, a plane ticket, and an opportunity to keep my eyes on the wider context. Appreciation to Gray Tappan at the U.S. Geological Survey (USGS), who contributed invaluable context for the development of a successful land cover classification product.

The U.S. National Aeronautics and Space Administration (NASA) provided much crucial support for this work, both through an Earth and Space Sciences Fellowship (2015-2018) and through the SERVIR program. NASA-SERVIR and the United States Agency for International Development (USAID) have directly supported the land cover classification project and its hand-off to land cover researchers in West Africa. Special thanks to Dan Irwin, Emil Cherrington, Raymond French, and Rebekke Muench of the SERVIR team for their endless support, enthusiasm, and open invitations.

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2018 Commencement Address

When visiting schools to decide on a graduate program,
the chair of Geography at a different university
told me that the dissertation you write is not, in fact,
the definitive statement of you
as an individual or scholar.
Rather, the PhD is merely your ticket to play.
It is advice I have recalled many times over these past years.
When we begin this PhD program,
we cannot see the end or how to get there.
We pour ourselves into the work.
We flounder, we regroup, we wander, we refocus.
My first week here, an advanced grad student
advised the incoming cohort that everyone of us,
at some point in our graduate career, would
benefit from the free therapy at the health center.
He wasn't wrong. This is hard.
No PhD student is here in Geography
because this is a well-paying job full of
easy satisfaction and validation.
But we have the enormous privilege
of deciding what we study and how we study it.
We must care about what we do enough
to do it in depth and for a long time.
We also have to let go of our expectations
that we can do five PhD's worth of work
in our one dissertation.
And we have to lean on one another
and on the communities that surround us.
That is how we find the finish line.
And here we are. Game on.

Introduction.

My first experience in West Africa was in 2008. I studied reforestry efforts in Burkina Faso across scales: community organizations, local NGOs, national programs, multilateral development projects. In the ten years since, I have worked in the region in different capacities and in different sectors. These have included: grant proposal writing and grant management for water, sanitation, and hygiene projects; serving as a consultant on women's reproductive health projects; and most recently my work has been climate, land cover, and hydrology research. My collaborations have included local, national, regional, and international organizations.

The context, relationships, and experience I've gained along the way are invaluable to what I do, no matter the sector or geographic location. The work presented herein as the culmination of my graduate studies is fundamentally shaped by and rooted in West Africa. It is also, by design, a development of flexible and adaptable methods and perspectives applicable to many different questions, regions, and disciplines. My work and my perspectives are concurrently informed by active attention on the dynamic contexts, politics, and impacts of my science.

Background

Both land cover and climate in the West African Sahel have been sites of interaction, negotiation and contention since at least the early colonial era. These are arenas where science, development, and natural resource management all play a role. The concepts of drought, desertification and deforestation have been powerful narratives in the region, influencing colonial practices, national policies and international development efforts.

For the entirety of the 20th century, desertification has been a dominant narrative of past, current, and potential changes in climate, vegetation, and soil in the West African Sahel. Although there is no universal definition of desertification, the general idea is that the environment of the Sahel is becoming dryer, there is a trend toward less precipitation and reduced availability of surface moisture, and a reduction in vegetation that requires more water to thrive. This narrative is accompanied by a sense that the soil is becoming less fertile, less able to support vegetation and agriculture. The concept of desertification also expands beyond the purely physical characteristics of a landscape.

From its inception, the desertification narrative has held that land use and land management by humans, and particularly local people, are critical causal factors in the perceived or asserted trend toward environmental destruction or degradation. Human activity is seen as the driver behind the destruction of fragile dryland environments, and the changes are conceptualized as drastic and potentially irreversible. The relationships between human activity and the landscape is in reality much more nuanced and variable. In some areas, like the W Biosphere Reserve in Benin, the land use visions of agriculturalists, pastoralists and land managers have been at odds (Tamou et al. 2018). In the Maradi and Zinder regions of Niger and elsewhere, agricultural changes have been associated with restoration and increased tree growth (Boubacar 2016; Sendzimir et al. 2011). In northern Burkina, zai pits and stone bunds have been successful agricultural practices for the management of rainfall runoff (Roose et al. 2010).

In the later half of the 20th century, there was a shift in desertification discourse to include climate change as a causal factor. The 1994 convention text of the United Nations Conference to Combat Desertification (UNCCD) states: "Desertification is land degradation in arid, semi-arid and sub-humid areas resulting from various factors, including climatic variations and human activities." (UNCCD 1994). This institutionalization of the concept of desertification is vague enough to be all empassing, and available to be shaped for different contexts and different applications. This flexibility makes it a powerful concept in the political sphere, but hard to grapple with in a scientific or analytical context.

Although desertification of the Sahel has long been rejected by the scientific community, the narrative persists. Desertification, to the extent that it evokes visions of vegetation turning into dust and the sands of the Sahara marching southward, does not accurately describe observed land cover change in the Sahel (Behnke & Mortimore, eds. 2016; Mortimore 1989; Thomas & Middleton 1994; Warren & Agnew 1988; Swift 1996). Further, while desertification discourse tends to cast drylands as fragile vulnerable environments, current literature does not clearly support that hypothesis. (Behnke & Mortimore, eds. 2016; Shanahan 2016).

In recent decades, degradation has gained in popularity as an alternative or additional framework of land cover change. Where the desertification narrative envisions drastic step changes in land cover, the degradation approach captures a wider array of possible land cover dynamics. In the degradation framework, multi-directional, multi-dimensional, and more subtle land cover change is possible. Relevant characteristics for this conceptualization of land cover change include vegetation population distributions, hydrology, and land management practice. The valuation of land cover characteristics is of course subjective. Different agenda—for example ecosystem preservation or restoration, biofuel production, maximal agricultural yield, and pasture suitability—impose different criteria for optimal versus degraded land cover.

Recent debates over observations of regreening in the Sahel illustrate the significance of these finer grained understandings land cover change. As annual regional rainfall has been increasing in the past few decades after severe drought in the 1970s and 80s, satellite data for the Sahel has begun to show an increase in spectral indicators of vegetation. In many of these cases, however, co-located field studies do not find evidence of increasing vegetation (Herrmann & Sop 2016). This has generated an active debate on the significance of the contradictory observations. Studies increasingly support the idea that satellite detection of recent greening in the Sahel is related to herbaceous biomass, while woody vegetation has not exhibited an increase in prevalence (Spiekermann et al 2015; Brandt et al. 2017; Herrmann & Tappan 2013; Herrmann & Sop 2016). This distinction affects, for example, the suitability of the land for grazing. The potential roles and effects of anthropogenic land management are likewise an open topic of study (Bégué et al. 2011; Hiernaux et al. 2009; Olsson et al. 2005).

Degradation as a framework for understanding land cover change is an advance over desertification. Degradation, with its finer grained conceptualization of land cover change, allows a more nuanced understanding of land cover change, which can be used for a wider array of priorities (e.g. yield for food production). Relative to the desertification framework, degradation is less all-or-nothing alarmist, less threatening impending catastrophic and irreversible crisis. While not necessitated, the degradation framework can be more focused on farmer and land manager agency, although degradation frameworks tend to be still prejudiced against local land users as destructive. Nonetheless, for complex understandings of the landscape, such as in the regreening debate, neither desertification or degradation are sufficient frameworks.

Origins of Desertification

Desertification, a concept now well-entrenched at the global scale, traces its lineage back to European desiccation theory (Davis 2016). In the late 17th and early 18th centuries, western writers such as Edmund Halley (b.1656; d.1742), John Woodward (b.1665; d.1728), and Stephen Hales (b.1677; d.1761) developed the desiccation theory of land cover change (e.g. Woodward 1699). The theory suggested that the aridity of a landscape is causally connected to its level of vegetation. Land cover could be moved in either direction along a moisture gradient by forest management: deforestation led to aridification; afforestation to humidification (Grove 1996).

While early desiccation writing generally promoted the agricultural and health benefits of deforestation, this began to change toward the end of the 1700s (Davis 2016). In the 1760s and 70s, influential writing from colonial officials working in the tropics began to focus on deforestation as a threat to habitability and vitality (Grove 1996, 1997). Pierre Poivre (b.1719; d.1786) and Joseph Banks (b.1743; d.1820) were among those to warn that the lush Edenic environments of tropical islands could be lost to uninhabitable desert conditions under deforestation and overgrazing (e.g. Poivre 1797).

Western approaches to land management in the 18th and 19th centuries were further shaped by increasing capitalism, economic liberalization, and the agricultural improvement movement (Davis 2016). The growing agricultural improvement movement demanded a shift in the usage and governance of the commons. Peripheral lands managed in the commons, once considered a productive form of land use, became underutilized spaces, lost agricultural potential, and viewed as susceptible to misuse and degradation (Goldstein 2013). Proponents of the agricultural improvement movement in France worked for decades to change domestic land use and tenure rights, campaigning on the vilification of pastoral livelihoods, said to be hastening the demise of productive land by means of poor management and overgrazing. The prolonged battle for enclosure of the commons that played out in France over the 19th century left a widespread discourse of degradation, deforestation, overgrazing, and desiccation (Davis 2007; Whited 2000).

These domestic conceptualizations of landscape and land use were transferred to French colonial governance. Land cover types in the region were interpreted by Europeans, in lieu of historical data, in accordance with the imposed idea that the grasslands had once been full of dense forest (Benjaminsen 2016). These grassland ecosystems were labeled "derived savanna," that is, degraded from their "natural" forest climax vegetation (Fairhead & Leach 1998; Clements 1916). The French colonial forester Louis Lavauden, in his 1927 "Les Forets du Sahara," simultaneously coined the term "desertification" and ascribed the phenomenon to the ill-effects of nomadic people of the Sahara and the overgrazing by their animals (Lavauden 1927). Deforestation was often attributed to local agriculturalists and pastoralists, and colonial forest management and preservation governance served to dispossess local people of access to land and resources (Fairhead & Leach 1998). These coercive colonial policies carried through after independence in national environmental protection strategies (Boubacar 2016).

Desertification in Development Discourse

In the 1970s, the severe drought in West Africa brought widespread use and institutionalization of desertification language to national and international contexts. During the 1980s, however, climate change and biodiversity began to eclipse desertification as a priority concern for international development efforts. The creation of the UNCCD was seen by some as a concession made to African countries rather than a global commitment to the issue of desertification (Toulmin & Brock 2016). The UNCCD, ratified in 1996, holds a conference of the parties (COP) every two years to review progress. Their rhetoric supports local decentralized approaches, but program implementation is accomplished via National Action Programmes. The funding mechanism for the UNCCD, the "Global Mechanism," channels existing funding only. Any new funding comes through the Global Environment Facility, but there desertification projects are relatively underfunded compared to competing projects for biodiversity and climate change. As a result, project funding often comes from outside programs, such as the World Bank Sustainable Land Management Program (Toulmin & Brock 2016). Global attention, visibility, and narrative are of particular importance for the ability to secure funding for desertification projects.

Regardless, desertification remains embedded in the missions—and names—of international and regional cross-cutting institutions that exist based on the concept of desertification, such as the UNCCD and the Permanent Interstate Committee for drought control in the Sahel (CILSS). The institutionalization and fundamental embeddedness of desertification language within organizations working on land cover management and change constrains the flexibility to reconsider other land cover change narratives. In national and regional levels as well, desertification features prominently but is positioned in relation to drought and climate change issues. The close connections with international mechanisms are evident in the language incorporated into national policy documents. Niger's environmental management strategy, for example, echoes verbatim the definition of desertification used in the UNCCD (Boubacar 2016). In the most recent decades, desertification discourse has been coupled with the spectors of conflict, terrorism, and mass-migration. The Great Green Wall project was launched in 2007 by the African Union and supported by the European Union and the Food and Agriculture Organization of the United Nations (FAO). In its original conception, the project endeavored to plant a wall of trees across the continent east to west to fend off the advance of the Sahara desert (UNCCD 2016). The project was relaunched in 2013, backed by the UNCCD and the World Bank. The current semantics of the project emphasize reforestation benefits, including: "Growing a reason to stay to help break the cycle of migration" and "Growing a symbol of peace in countries where conflict continues to displace communities" (UNCCD 2016).

Overview

CILSS is the parent organization to a number of regional research institutes, including the regional center for research on agriculture, hydrology, and meteorology (AGRHYMET). Early in my graduate school career I found my way to Niamey, Niger to visit the institute. My conversations with researchers there about their work, progress and challenges were the germination of the land use land cover dataset presented in the first chapter. The dataset covers the West African Sahel at 30m resolution over the years 2000 to 2016, more than an order of magnitude increase in the land cover data available for land managers and decision-makers in the region. One of the tenets of my approach to science is the importance of applied research, and I embarked on this project in service of that goal. Knowing what questions to tackle required asking scientists in the region about the work already in progress. This kind of seeking and listening is crucial for producing useful, usable research.

I follow the presentation of the land use land cover dataset with details of its methodology development process. This work produced insights on spatial scale and factors affecting algorithm choice for machine learning classification of land cover from remote sensing data. Opening the methodology of the dataset to review, critique and adaptation promotes open science, strengthens the science itself, and fosters ethical, equitable research practices. I go on to lay out, in the service of open and collective effort, routes for future improvements of the dataset and methodology. Open presentation of possibilities for future work paves the way for continuing and nascent collaborations. Currently, development of the dataset is ongoing with collaborators at NASA and AGRHYMET. Further advances will be shaped by the involvement and ownership taken by scientists who are in and from the regions of study. I proceed from the land cover dataset and its methods to a demonstration of possibilities for rethinking approaches to spatio-temporal precipitation dynamics from a complex systems perspective. Exploring whether and how precipitation systems give rise to seasonal characteristics and trends provides an opportunity to explore inductive pattern recognition techniques and to question the representations of various precipitation datasets.

My portfolio of projects is, broadly speaking, an exploration of innovative methods, methods intended to offer new approaches to previously intractable questions. The interconnectedness of land cover, climate, humans, governance and science is a driving concept behind the work of this dissertation. In short: Chapter One presents a new 30 meter annual land use land cover dataset for the West African Sahel; Chapter Two discusses in more detail the methodology used to create the dataset and the insights gained in the process; Chapter Three describes promising directions and next steps for ongoing development of the land cover dataset; Chapter Four investigates precipitation dynamics in West Africa across spatial scales. Pattern recognition techniques are used to link synoptic scale regional precipitation patterns to annual rainfall characteristics; spatial organization of seasonal rainfall trends are compared across precipitation data products. Concluding remarks address some of the institutional contexts with which this research interacts and offer an alternative to the desertification narrative that has dominated discourse about land cover change in the region.

Chapter One.
A New High-Resolution LULC Dataset for West Africa
Building on visually classified maps

Introduction

This chapter presents a regionally-calibrated 30 m annual resolution (2000-2016) land use land cover (LULC) dataset for West Africa. Both the spatial and temporal resolution of this new dataset represent significant improvement over previously available LULC data. The process by which the dataset was created (discussed at length in the following chapter) enables: classification of future years of satellite observations; the creation of custom classifiers for the West African region; and future application of the methodology to other regions of the world. The dataset and these tools will be openly available, and are designed to be accessible regardless of local computing or internet connectivity capacity.

Global land cover products are notoriously unreliable for the Sahel, and accurate land cover data for the region are sparse (Leroux et al. 2014; Mbow et al. 2015). To address this gap, the U.S. Geological Survey (USGS) and the Regional Center for Agriculture, Hydrology and Meteorology (AGRHYMET) in Niger produced high-quality land cover maps for the region via hand-classification of Landsat images (Tappan et al. 2016). Classification of land cover by visual inspection of satellite images produces maps which are highly accurate, but the method is costly. The practical considerations of the time, labor, and money required constrain the spatial and temporal resolution of the end product. The advance presented here builds on these visually classified maps with machine learning techniques to successfully increase the resolution of available LULC maps by 1-2 orders of magnitude, from 2 km decadal resolution to 30 m annual resolution.

Classification of land cover for the entire West African Sahel can now be accomplished in a matter of hours and for free. The classification is carried out by a machine learning algorithm trained on the original hand-classified Atlas. The accuracy of the classification is stunning; case study validation has shown the machine learning classification matches or exceeds the accuracy of the hand-classified map.

The outputs from the project are three-fold: the completed 30 m annual time series of LULC for the entire region from 2000 to 2016; the methodology used to create the time series such that future years of data can be likewise classified; and the modular data pipeline itself, open source script that can be adapted for use with different inputs, different training datasets, different regions.

These high-resolution regionally calibrated land cover datasets, along with the classification algorithm developed to produce them, offer a foundation for major advances in the understanding of land surface processes in the region. These products can ultimately be used to provide more accurate inputs for food security modeling, hydrologic modeling, analyses of land cover change, and climate change adaptation efforts. The land cover classification tool presented here will be publicly available for use in creating additional West Africa land cover datasets with future remote sensing data, and can be adapted for use in other parts of the world.

Background

Land cover in the Sahel

The land cover of the West African Sahel has undergone drastic changes over the past fifty years. In the region, land cover is central to climate, demographic, and hydrologic changes, but data on regional land cover has historically been sparse. Field surveys of land cover are limited in spatial and temporal coverage, and global satellite products are notoriously inaccurate over West Africa. Land cover class schemas used in global products do not sufficiently represent the land cover types relevant in West Africa (Leroux et al. 2014; Mbow et al. 2015).

The land cover dataset from the Moderate Resolution Imaging Spectroradiometer (MODIS) is one of the best existing global land cover products (Channan et al. 2014; Friedl et al. 2010). It covers years 2001 to 2012 at 500 m resolution, and achieves a global accuracy of 72.3% to 77.4% overall, and 64.8% for agriculture (Herold et al. 2008). The 2013 MODIS map of land cover in West Africa is shown below. The five most common MODIS land cover classes in the Sahel collectively account for 98.75% of the area: grasslands; barren or sparsely vegetated; croplands; savannas; cropland/natural vegetation mosaic. Note that cropland appears spread across two land cover types in the MODIS dataset: cropland and vegetation/cropland mosaic.

Figure 1. MODIS 2013 land cover for West Africa.

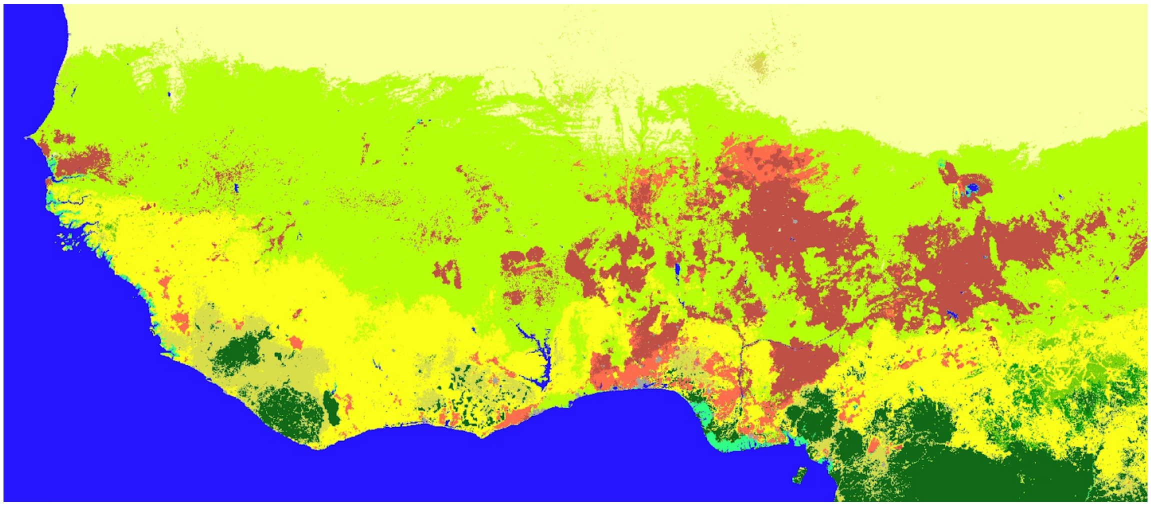


Table 1. MODIS land cover class legend.

The issue of class definitions aside, the land cover classes prevalent in West Africa are not easily distinguishable from one another by spectral signature alone. Traditional spectral land cover classification methods rely on land cover types having distinguishable characteristic patterns of reflectance across a number of different wavelengths. Without distinguishability in the characteristic spectra of different land cover types, algorithmic spectral classification breaks down. Examining the spectral signatures of land cover types present in the MODIS dataset for the West African Sahel offers insight into the difficulty with spectral classification.

Agriculture, for example, has been very challenging to reliably classify in West Africa using spectral data with algorithmic methods. It is perhaps the most important land cover type for understanding region-wide trends, targeting climate change adaptation measures, and planning food security measures. Differences in the appearance of agriculture over the course of the year and in different areas of the Sahel compound the issue of spectral separability. Variability in agricultural practices and changes across the region are influenced by national and multilateral agricultural extension programs and development initiatives and shaped by history, culture, and environment. Different staple crops are grown in different regions, and have different hydrological impacts (Ibrahim et al. 2014). Spatial organization of agriculture is not uniform across the region. Different trade offs are made between agricultural extensification (increasing the area under cultivation) and intensification (increasing the density of crops, reducing fallow periods, increasing intraseasonal crop cycles).

To date, efforts to monitor agriculture at a regional scale have depended on global land cover products produced with these methods. Despite being one of the highest performing products for agriculture worldwide, MODIS achieves only 51% accuracy for this class in West Africa (Leroux et al. 2014). With this level of accuracy, even the state-of-the-art MODIS product is largely useless for the study of agriculture in the region.

The plots below show the 2013 spectral signatures for different land cover classes in the West African Sahel, for two seasons: mid-September to mid-November; and mid-March to mid-May. The top row depicts the top five MODIS land cover classes in the Sahel, one column for each season. The second row depicts the top six land cover classes from the Atlas, a hand-classified land cover dataset, described in the next section. The top five land cover classes from MODIS account for 98.75% of the area of the Sahel; the top six classes from the Atlas dataset account for 88.50% of the area of the Sahel. Mean values of reflectance (y-axis) in the wavelengths captured by Landsat 7 bands (x-axis) are shown as solid lines. The shading indicates the standard deviation of each distribution.

Spectral signatures in both land cover datasets generally have at least some overlap, illustrating the challenge of spectral distinguishability between land cover classes in the Sahel. There are also some key differences to note between the two datasets. Relative to the Atlas data, the fewer classes in the MODIS dataset perhaps appear to have less overlap in their spectra. This is an indication that a spectra-based classification of land cover into the MODIS land cover types would be more successful than a spectral classification into Atlas land cover types. The question of the underlying accuracy of the two datasets, however, is key.

Under the assumption that a hand-classified locally-specific land cover dataset (Atlas) is generally more accurate and appropriate than a globally-tuned coarser resolution dataset

(MODIS, accuracy evaluation ibid.), the Atlas dataset is the indicator of spectral separability for accurate land cover classification into locally appropriate land cover types. Where the MODIS classification trades accuracy for separability, the consistent overlap in the Atlas land cover spectra illustrates the hurdle for spectral land cover classification in the Sahel.

Figure 2. Landsat 7 spectral signatures for MODIS (a & b) and Atlas (c & d) land cover classes in the Sahel, data from 2013. a & c) Spectral signatures in the fall season, mid-September to mid-November; b & d) Spectral signatures in the spring season, mid-March to mid-May. Season definitions are identical to those used as features in the AtlasV2 classifier (see Data & Methods section). Mean spectral signatures are plotted as solid lines, shaded with ± one standard deviation.

Figure 2.a) MODIS fall season spectral signatures.

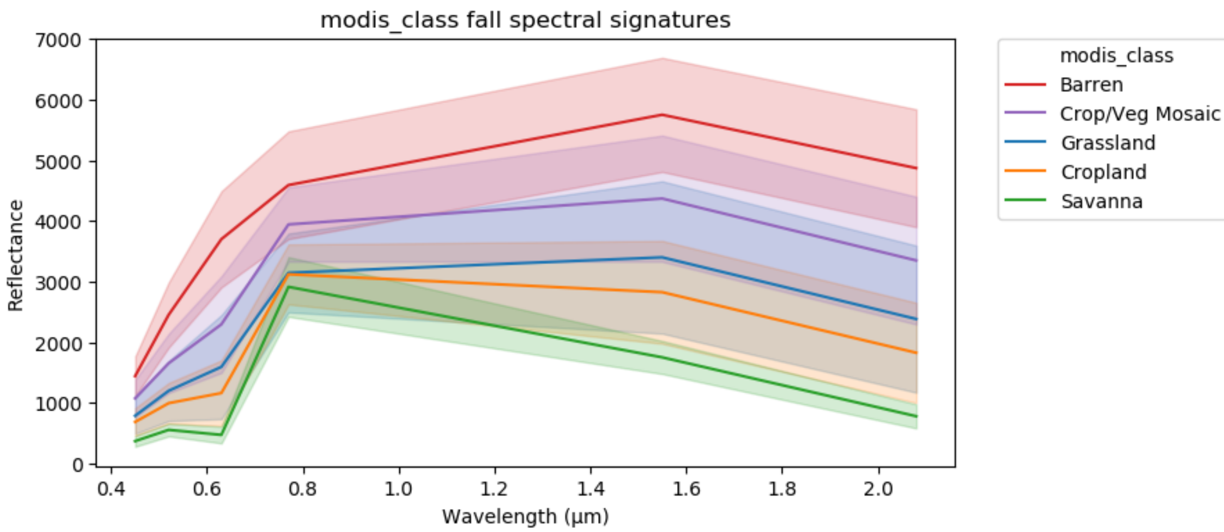


Figure 2.b) MODIS spring season spectral signatures.

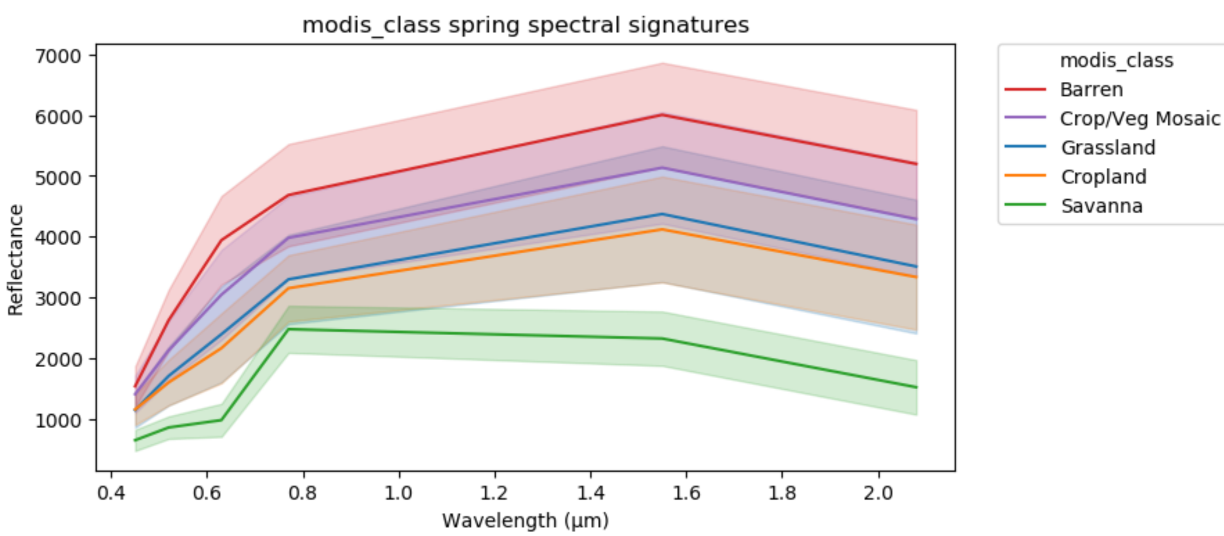


Figure 2.c) Atlas fall season spectral signatures.

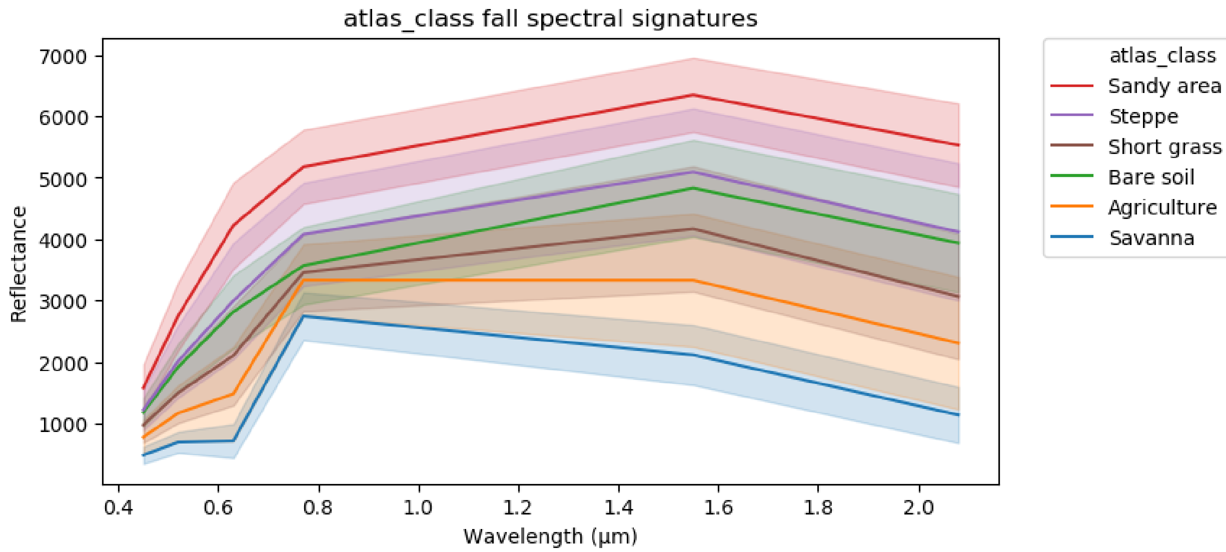
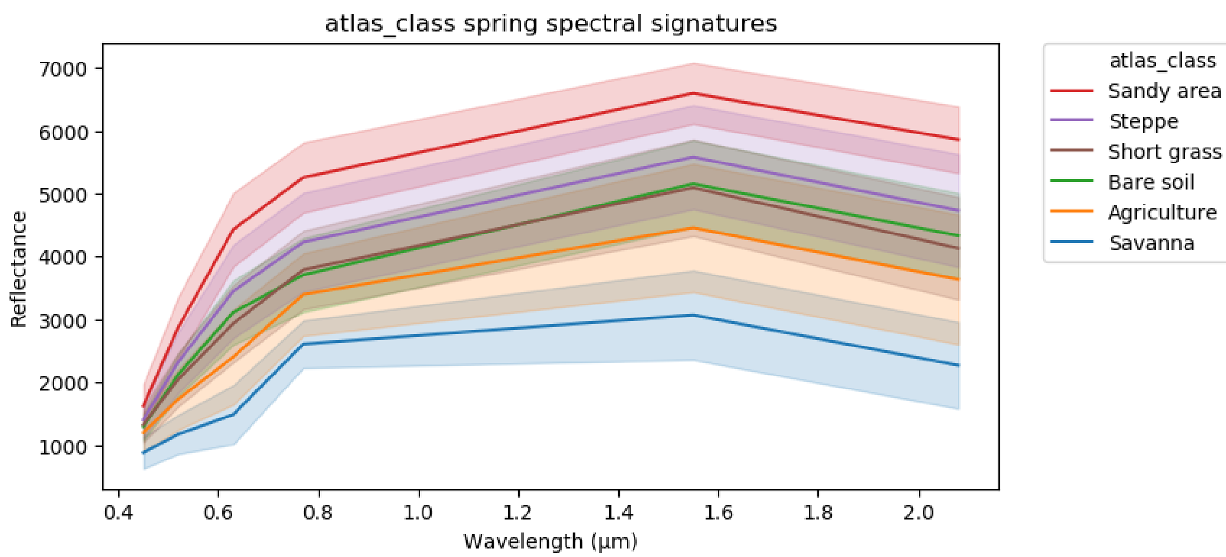


Figure 2.d) Atlas spring season spectral signatures.



The Atlas project

To address this dearth of accurate regional LULC datasets, CILSS, USGS, and USAID partnered to create three LULC maps specifically for West Africa for the years 1975, 2000, and 2013 (Tappan et al. 2016). Because spectral classification performs so poorly over the region, the Atlas project trained technicians to visually classify land cover from Landsat imagery. The LULC map construction occurred in three parts: Landsat scene selection, visual classification, and map post-processing. Landsat imagery used for the classification was drawn from three year spreads centered on each year of the final LULC maps to create quality images free from clouds. To produce a single map representing 2013 at 2 km resolution, technicians classified one 30 m pixel from Landsat imagery every 2 km. The choice to classify only one 30 m pixel every two km was forced by the sheer magnitude of the task: even at that limited density, a single map of the region requires classifying 1.2M land cover pixels by hand. The land cover class of each 30 m pixel was then assigned to the 2 km cell surrounding it, for an aggregate resolution of 2 km.

Every pixel of the resulting LULC map was visually inspected twice more to compare to Landsat imagery from 2000 and 1975, in order to produce maps for these two additional years. The maps were examined in workshops with regional experts, verified by field visit spot checks, and reviewed for quality control in post-processing. The final output of this monumental effort, which took 21 years to complete (1995-2016), was three hand-classified regional LULC maps for the years 2013, 2000 and 1975. They offer unprecedented accuracy and coverage for the region. However, with the visual classification approach scalability and resolution are limited.

Figure 3. Atlas 2013 land use land cover map with land cover class legend.

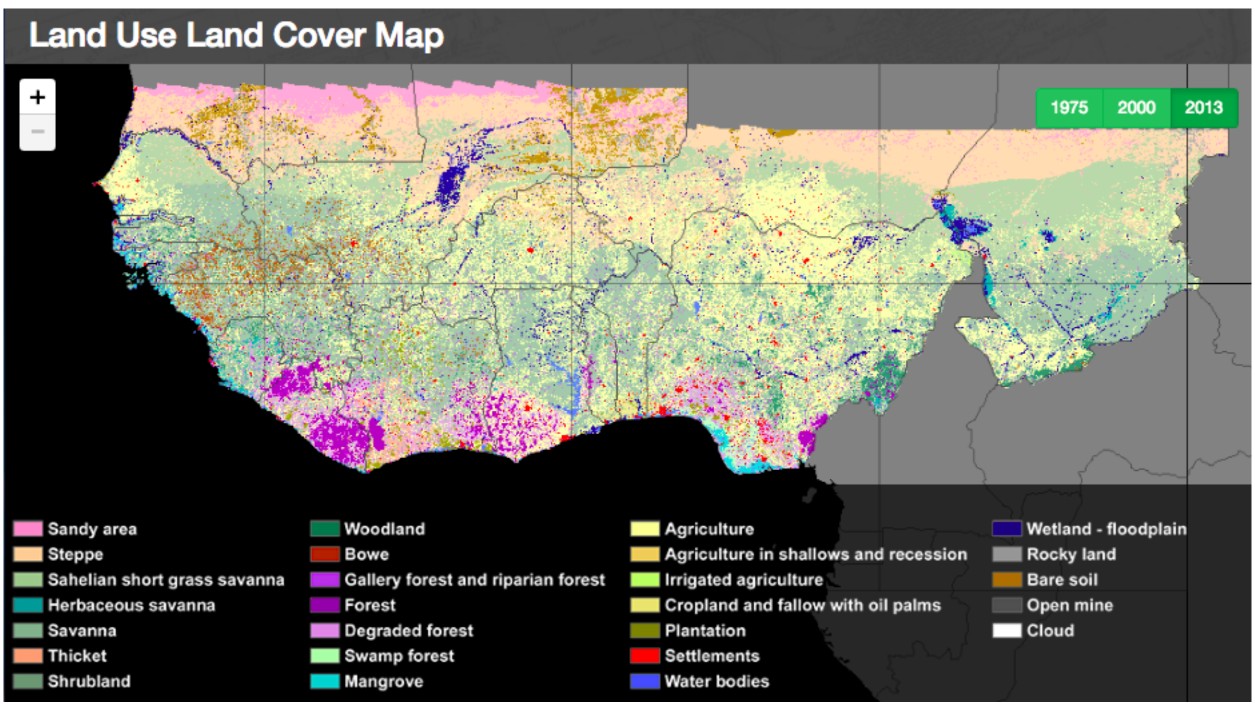


Image from online data viewer at https://eros.usgs.gov/westafrica/land-use-land-cover-map.

While purely spectral-based methods for LULC classification have been unsuccessful for the region, the visually classified maps present a unique opportunity to create a new blended approach. It was specifically the Atlas project's methodological choice to classify a single 30 m pixel and then scale up to 2 km that allowed this breakthrough. By taking advantage of the hidden 30 m data set embedded in the 2 km Atlas product, the resolution and scalability of

LULC mapping in the region can be drastically increased. Machine learning trained by the highly accurate visually classified Atlas map was used to develop a land cover dataset for the region at annual 30 m resolution, representing a two orders of magnitude increase in spatial resolution and an order of magnitude improvement in temporal resolution. This method produced maps with 73% accuracy overall. For the agriculture class, these maps have accuracies of 70.9%, drastically out-performing MODIS agriculture classification both in the region and globally.

Data & Methods

Input data construction

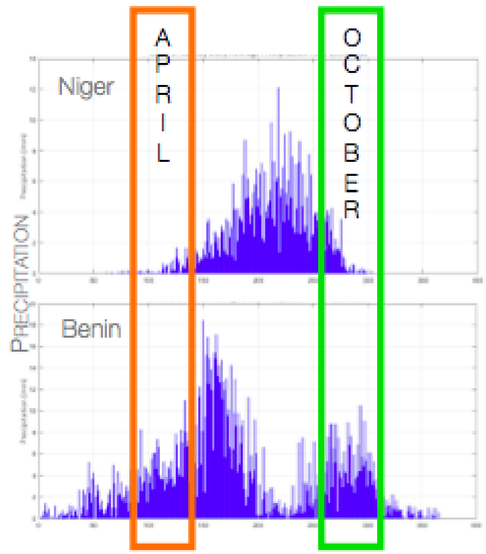
As seen in the previous section, spectral information alone does not provide an obvious separation between land cover classes. In light of that information, input data for training and classification were constructed from three different sources: Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) surface reflectance bands 1-5 and 7 (USGS 2018); Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) precipitation (Funk et al. 2015); and Shuttle Radar Topography Mission (SRTM) elevation with derived slope, aspect, and hillshade (Farr et al. 2007).

Landsat composites were constructed for each year, 2000-2016. Landsat 7 scenes only were used to maintain consistency across the time period. To ensure good coverage from which to create quality composites, Landsat scenes were pulled from a three-year spread around each year. This also served to smooth the Landsat time series. Cloudy and saturated pixels were masked using the Landsat quality band, and multiple observations of the remaining pixels were composited by choosing the median value for each pixel. Compositing by median value offers robustness to outlier observations. The choice of time of year for which to create composites was informed by the methodology used for the original Atlas classification.

Commonly, land cover classification is done with imagery from the season of peak greenness. The original Atlas project, however, used imagery from the time of year immediately after the end of the rainy season. The contrast between land cover types is highest during this time, skies are clear, and the fire season has not yet begun. In the Sahel, this time of year corresponds to mid-September to mid-November. The timing of the rainy season, however, is not the same everywhere in the region. Monsoon rains start in the coastal regions in March-April, move northward to the Sahel for peak northern rainfall in July-August, and then recede back to the coast to be followed by a dry season.

The northern Sahel receives as little as 200 mm of annual precipitation, with a single peak in August, while southern coastal regions of West Africa can receive 1500-2200 mm of rainfall per year, with peak rainfall in June and October, and clouds obscuring land surface for a much higher proportion of the year. To allow for differences in the seasonality of the rainy season throughout the region, and to capture more information particularly for regions with frequent cloud cover, two separate seasons were included as input data for the classifier training: a "fall" season from mid-September to mid-November; and a "spring" season from mid-March to mid-May. The inclusion of two seasons in the feature collection also potentially captures differences in annual phenological cycles between different land cover types, improving classification skill.

Figure 4. CHIRPS precipitation climatology with season selection.



To construct precipitation input data, CHIRPS pentad precipitation was scaled to 30 m resolution via nearest neighbors interpolation. Following the same protocol as for the Landsat data, precipitation for a given year is a composite of that year and one year before and after. Precipitation occurring in the spring season in all three years is summed to create the spring precipitation feature. Precipitation occurring in the fall season in all three years is likewise summed to create the fall precipitation feature. As with the Landsat data, this serves to smooth the precipitation time series. SRTM topography data was included as constant parameters.

The result of the input data construction process was a 30 m basemap of information to be used for algorithm training and land cover classification. Each 30 m pixel of this basemap contained, for any given year 2000-2016, 18 features:

(6 Landsat Bands + 1 Precipitation Total) * 2 Seasons + 4 Topography Features = 18 Basemap Features

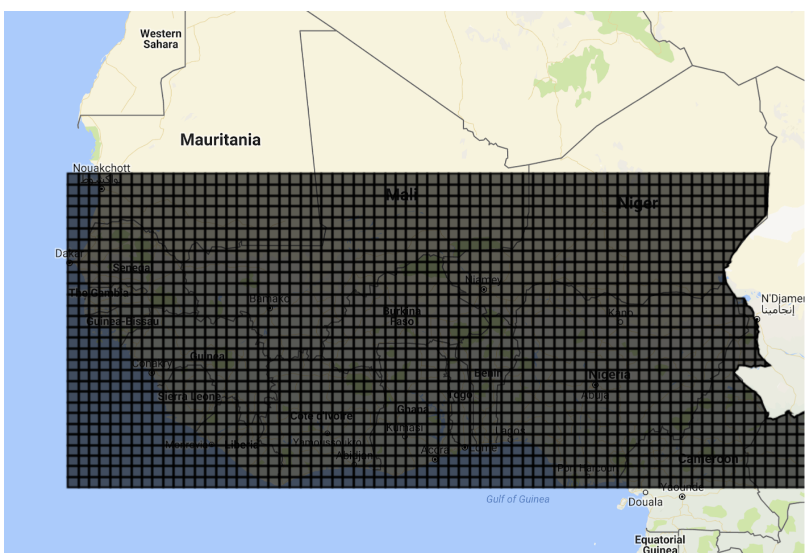
The Atlas data was then paired with the corresponding 30 m basemap pixel to create a training dataset for the classification algorithm. Because the random forest algorithm is not sensitive to data range or distribution, input data was not scaled. Random forests also tend to be robust to noise, which incentivizes inclusion of more features (Rodriguez-Galiano et al. 2012). The primary practical limitation in this case was the tractability of the dataset in terms of size: with two seasons of six Landsat bands plus precipitation, along with four SRTM features, each year of basemap data is 120 Gb.

Algorithm and parameters

The process by which the algorithm training methodology was developed, as well as the insights gained from these intermediate results are detailed in chapter two. The final optimized choices for the algorithm training procedures and parameterizations are as follows. The classification algorithm was trained on data from 2000 and 2013, using Atlas data from those years for model testing and validation.

The final land cover maps were classified using an array of geographically-specific random forest classifiers. The West Africa region was divided into 0.5 degree zones, and a separate random forest classifier was trained for each zone. In this particular case of algorithm-based classification, the smaller-scale classifiers outperformed larger regional classifiers trained on more data. This suggests that the effects of local variation in the appearance of land cover classes outweigh any classification skill gain from increasing the size and geographical extent of the training data. Such a result is in line with the existing hypothesis that local variation is one of the reasons that pure spectral classification has performed so poorly in West Africa.

Figure 5. Map of 0.5 degree zones over West Africa. A separate random forest classifier was trained for each of these zones. AtlasV2 includes zones only in the Sahel region of this map.



All random forest classifiers were given the same parameters. The subset of features available to each decision tree was sqrt(N features); minimum leaf split was one; there was no maximum tree depth. The choice of forest size was informed by the point of plateau in an accuracy vs. forest size plot tested on region-wide data. By qualitative evaluation, accuracy plateaued around a forest size of 60 trees. To capture any subsequent marginal accuracy gains, we increased the forest size to 100 trees with no loss in computational efficiency. The final classification algorithms were trained on the combined 2000 and 2013 Atlas data, holding 20% in reserve for validation. In order to smooth discrepancies in classification at zone boundaries, a nearest-neighbors kernel was implemented wherein 50% of the training data for each zone was taken from the surrounding eight zones and 50% of the training data was sampled from the central zone to which the algorithm was assigned.

Platforms for algorithm development

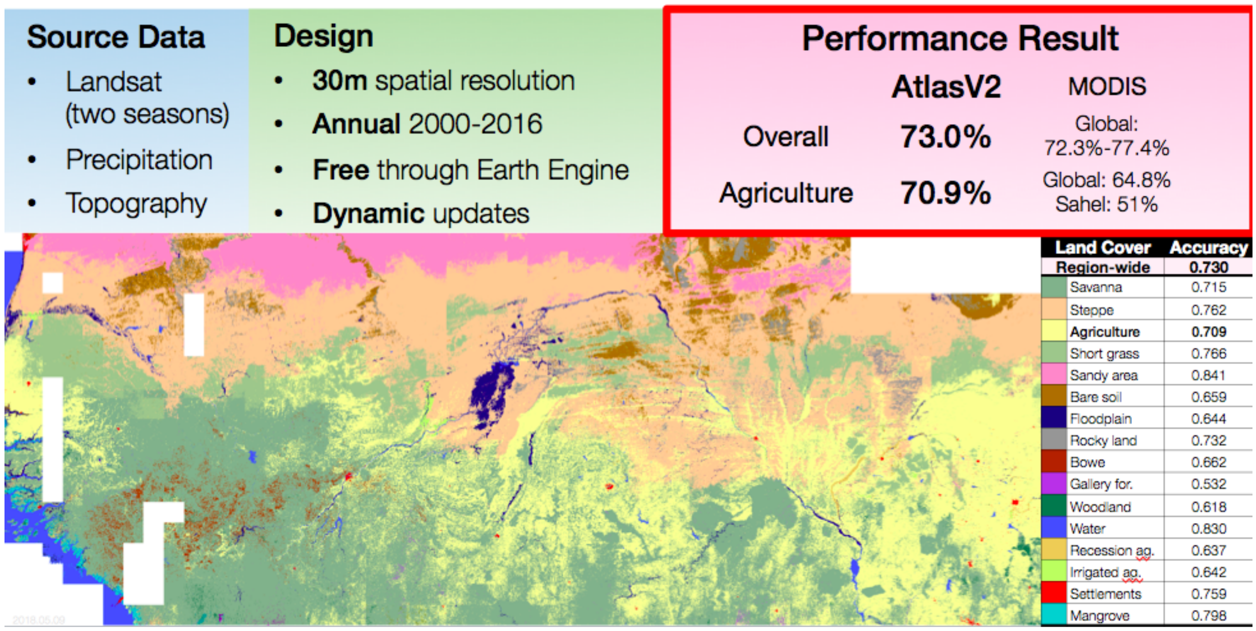
Two platforms were employed for algorithm development and map classification: Google's Earth Engine (Gorelick et al. 2017) and UC Berkeley's Savio computing cluster. Earth Engine is open access; when working on this platform data is stored, and computational operations are executed, on Google servers. This means access is independent of a user's local computational resources and does not require high capacity internet connectivity. Further, the platform offers a relatively approachable interface to high-powered computing for which specialized knowledge is not necessary. Earth Engine does have drawbacks, including the limited customizability of its machine learning routines, and limitations imposed on computational resource allocations.

While random forest training and classification software exists within the Earth Engine platform, working on UC Berkeley's Savio cluster allowed greater control over both algorithm implementation and use of computing resources. Input data was assembled and pre-processed within Earth Engine; subsequently composite images were exported and loaded onto Savio for training and classification. Algorithm development and final classification was conducted on Savio using the Scikit-learn toolbox (Pedregosa et al. 2011). Classified land cover maps were then uploaded to Earth Engine.

Results: AtlasV2

Overview

Figure 6. AtlasV2 map for the year 2016, overall accuracies, and dataset summary. The AtlasV2 map is bounded by (minLat, maxLat) = (9.0, 18.417); (minLon, maxLon) = (-17.542, 18.883); not including Chad, with ocean and bad data areas masked. Accuracy values presented are accuracies measured against the original Atlas classification for the years 2000 and 2013.



The figure above shows the AtlasV2 classified land cover map for the year 2016; years 2000-2015 not shown. Overall accuracy for the produced dataset, in terms of true positive rate, is 73.0%. This is comparable to MODIS global accuracy, at 72.3%-77.4%. For agriculture, AtlasV2 is 70.9% accurate, a vast improvement over MODIS accuracy for agriculture in the region (51%) and even over MODIS global agriculture accuracy (64.8%). The inclusion of precipitation in the AtlasV2 approach is of key importance for the classification accuracy, as detailed further in the feature importance section below. The accuracy improvements of the AtlasV2 accompany an increase in resolution over the original Atlas, from 2 km to 30 m in spatial resolution, and from decadal to annual temporal resolution. The data can be accessed, and custom analyses developed, through the Google Earth Engine platform, which is free to use. All data and computations are hosted on Google servers, which enables access regardless of local computational resources or internet connectivity.

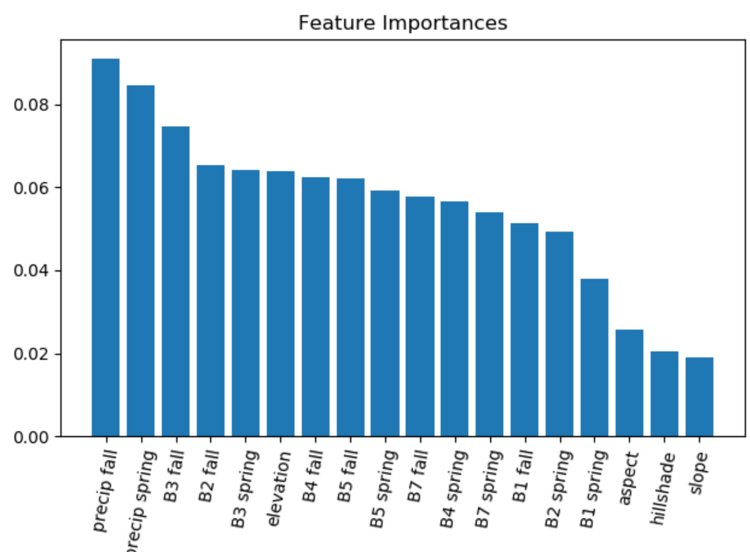
Feature importance

The feature importance plot below depicts the relative importance of all features to the classification algorithm. Results indicate that precipitation is important to the land cover classification, more than spectral bands alone. The inclusion of precipitation information is an important augmentation over algorithmic methods that rely on spectral information alone.

The feature importance metric is calculated with the Gini impurity index as follows. Each node of a decision tree contains a collection of samples with associated labels. The Gini impurity is a measure of false positive rate if a randomly selected sample is labeled with a randomly selected label from the node membership. For each node in a decision tree that splits on a given feature, the reduction in Gini impurity given the split is calculated and then weighted by node membership. These impurity reduction scores are accumulated by each feature over the entire decision tree. Feature importances are then averaged across trees to get the feature importance measures for the forest.

Most striking in the feature importance plot is the leading importance of precipitation. This is a strong indicator that precipitation information is necessary for a good classification; spectral classification alone would not perform as well. These results support the generally held knowledge that pure spectral land cover classification is not successful in the Sahel. Further, it demonstrates the advantage of AtlasV2 in the flexibility to include features beyond spectral information. Further exploration of the role of precipitation is detailed in the corresponding section that follows.

Figure 7. Relative feature importance values. Values are unitless and serve to indicate relative value across features. Feature importances are averaged across all zones within the AtlasV2 dataset. See chapter two for details of the random forest algorithm construction.



Among the other features in the library, Landsat 7 bands of both seasons are generally of equal importance. Topological features are generally least important, with the unexpected exception of elevation. A potential explanation for the importance of this feature is the plateau-lowland topography characteristic of much of the Sahel and the associated differences in land cover. In the area surrounding Niamey, for example, steppe is characteristic on the plateaus while agriculture occupies the lowlands. Further exploration of elevation and feature importances is warranted in future work, including examining relative feature importances with metrics other than Gini impurity such as permutation importance.

Case study: Niamey

Because high spatial resolution is one of the major advances of this new dataset, it is informative to look at a local case study (Figure 8). Niamey, on the banks of the Niger River, is the capital city of Niger and headquarters to AGRHYMET. The city is positioned in a zone of rapid geographical transition between more humid environments to the south and desert regions not far to the north. In this area, as in most of the Sahel, subsistence agriculture and pastoralism constitute a major part of the economy. As such, land cover is of critical importance; the difference between bare soil, steppe and agriculture has major implications for the population. Note the black circles on the MODIS and AtlasV2 highlight a crucial difference in the two LULC products. The reclassification of bare soil shown in MODIS to steppe or agriculture in the AtlasV2 tells a very different story about land cover changes in the region.

Time Series

In the period 2000-2016, the prevalence of savanna, steppe, and short grass savanna generally trended downward in the Sahel, while agriculture increased (Figure 9). While the Atlas maps for 2000 and 2013 offer a broad view of long-term trends, having only two data points can skew conclusions about the patterns or rate of change of different land cover types. The new AtlasV2 time series data allowed a finer investigation of how the prevalence of different land cover classes varies over this time period. Trends in the most common land cover classes (savanna, steppe, agriculture, short grass savanna, sandy area, and bare soil) were quantified with linear regression (Figure 10). The accompanying table details the estimated slopes, R^2, and p-values.

The trends in savanna, steppe, agriculture and short grass savanna dominate the time series of LULC in the region, all with p-values less than 0.024. Note also the trends in sandy area and bare soil: sandy area shows no significant trend over the period 2000 to 2016, and bare soil shows a significant if mild decrease in area. The agriculture and savanna classes in particular show strongly linear trends (high R^2, low p-value).

Figure 8. Land cover product comparison for Niamey case study.

Figure 8.a) Left: Location of Niamey in West Africa; Right: Land cover class legend

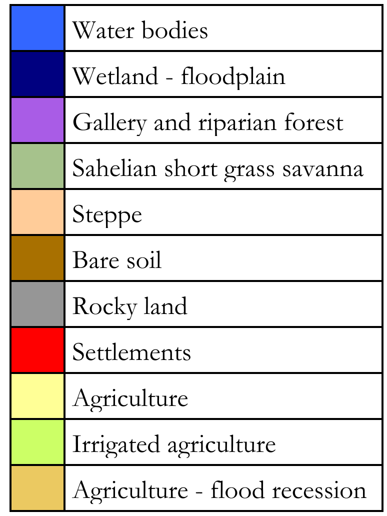


Figure 8.b) 2013 Niamey detail product comparison. Images are centered on the city; the Niger river bisects the map from northwest to southeast. All columns in a row show identical areas. Images in the second row are a zoomed in view of those in the first row. Columns are Landsat composite at 30 m resolution; Atlas at 2 km resolution; MODIS at 500 m resolution; and AtlasV2 at 30 m resolution. Black circles highlight differences in land cover classification between the MODIS and AtlasV2 products.

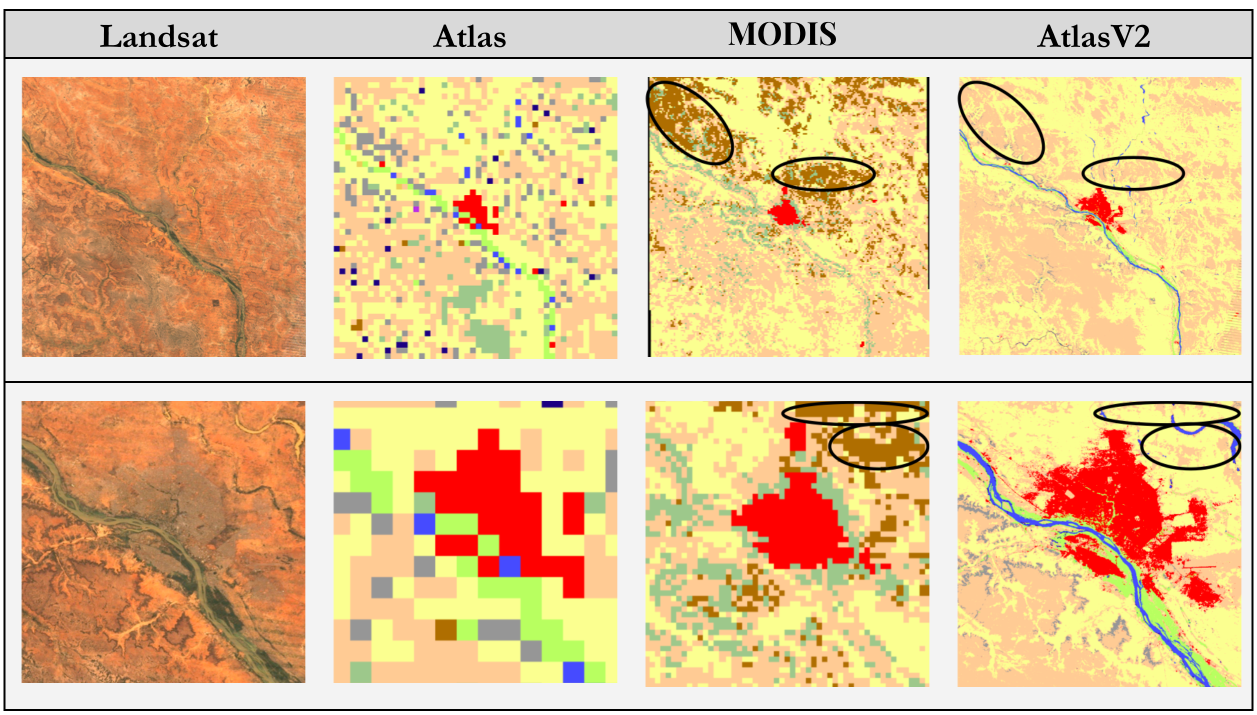


Figure 9. Land cover time series.

Figure 9.a) AtlasV2 time series of land cover change in the West African Sahel from 2000-2016 for the top six most prevalent land cover classes.

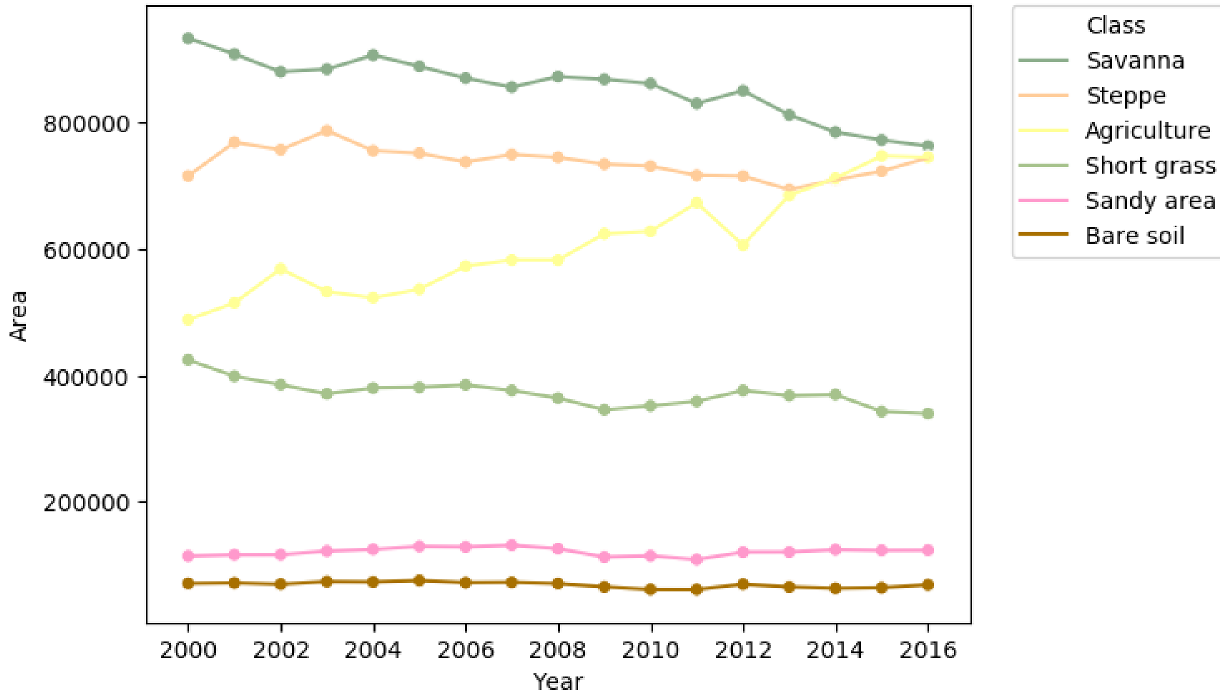


Figure 9.b) Comparison between AtlasV2 time series and original Atlas land cover class prevalence for 2000 and 2013.

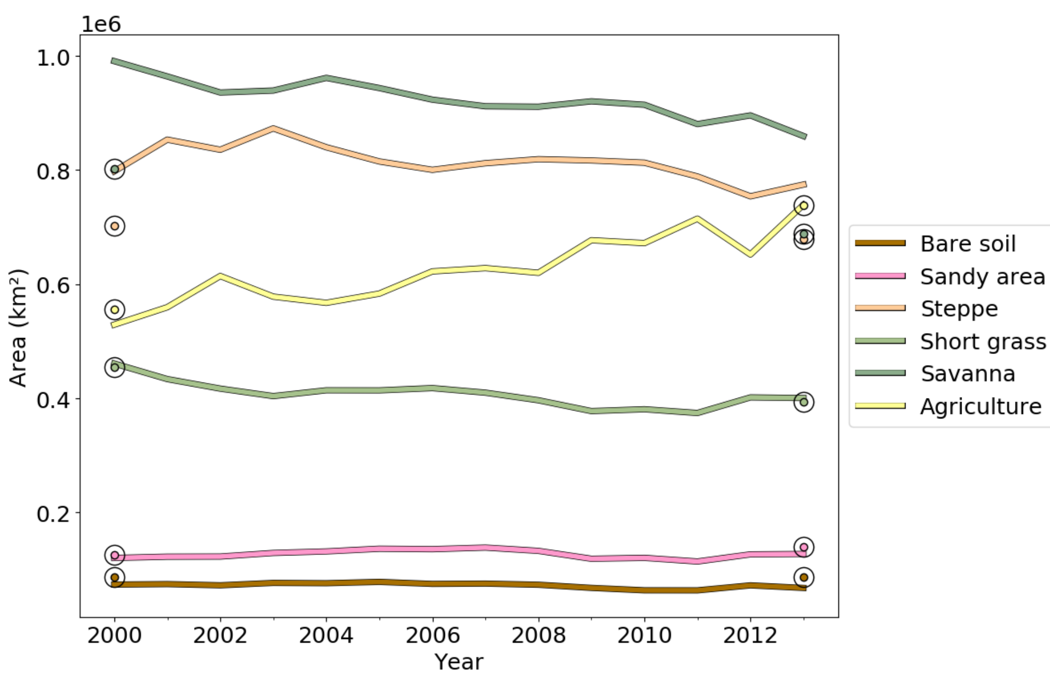


Figure 10. AtlasV2 time series of the six most common land cover classes, with linear regression lines of best fit. Shading indicates 95% confidence interval.

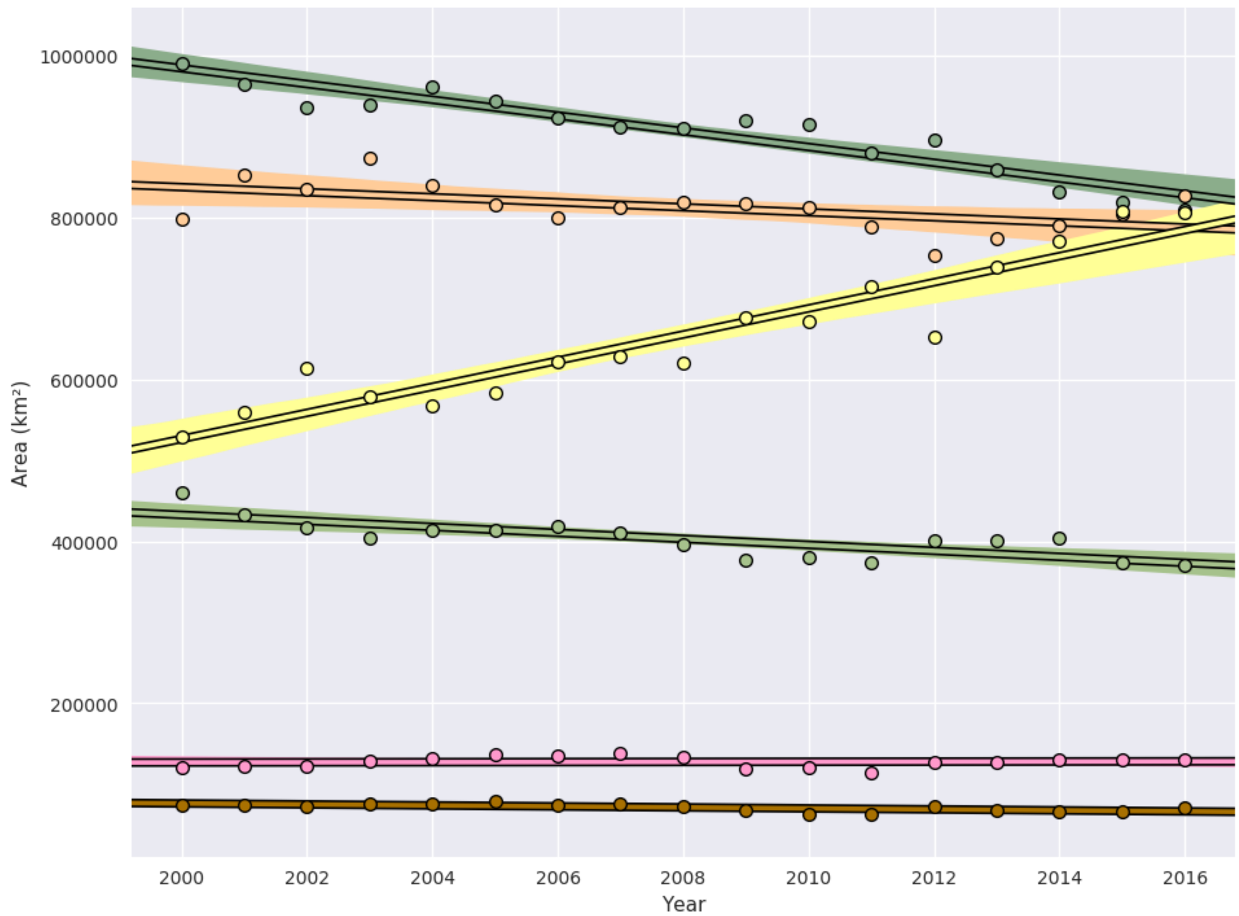


Table 2. Linear trend fits for top six land cover classes.

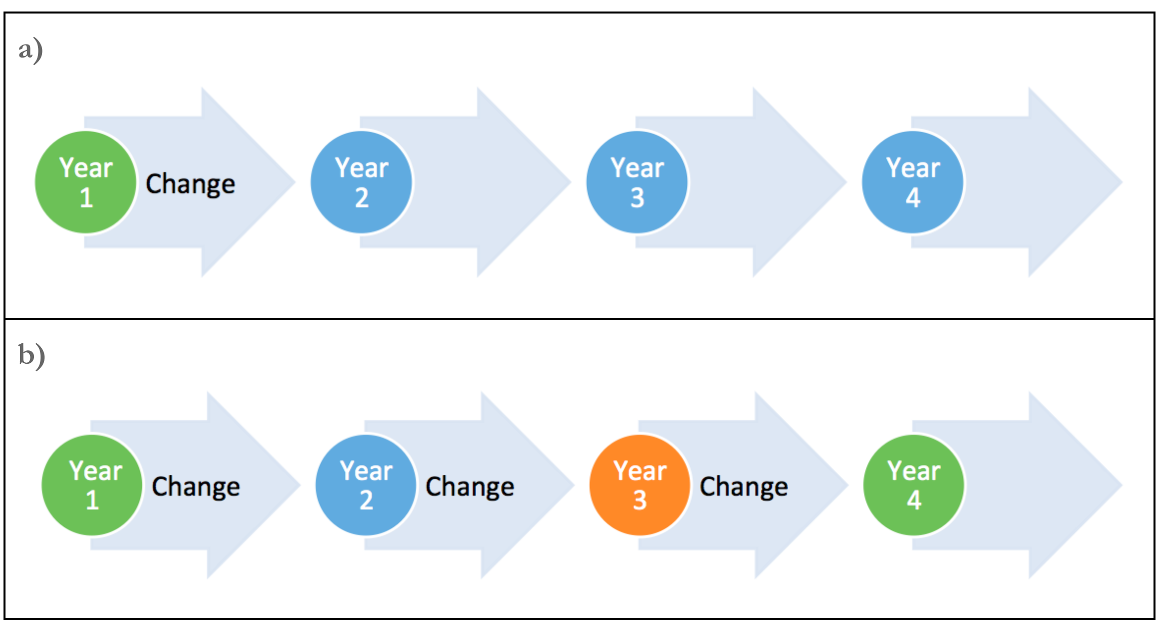
Linear Trend Fits		Slope (km^2/year)	R^2	p-value
	Savanna	-9721	0.8889	1.5E-08
	Steppe	-3108	0.2974	0.02357
	Agriculture	16127	0.8885	1.5E-08
	Short grass	-3700	0.6300	1.428E-04
	Sandy area	82	0.0037	0.8166
	Bare soil	-613	0.4352	3.961E-03

Conversion volatility and trends

Overview

Land cover in West Africa has gone through drastic changes over the past five decades. Climate, population trends and land use practices all contribute to land cover dynamics. Precipitation, for example, has exhibited increased variability, particularly in the last 25-30 years; during that time precipitation anomalies have often changed sign annually. Land use has also changed dramatically. Economic, climate and development factors have shaped the landscape in variable ways, including the extensification of agriculture, regreening through land management and changes in cultivation practices, and shifts in forest use and management. While these factors vary on an annual timescale, land cover data for the region has been limited to decadal resolution. Particularly in the current period of increased variability, this resolution is insufficient to understand land cover change dynamics.

Figure 11. Schematic illustrating the concept of conversion volatility and its interaction with observational time scale. The two rows illustrate two different scenarios for a pixel of land cover. The pixel, represented as a circle, is shown for each of four years. The pixel is assigned a land cover type, indicated by color. In the transition between years, the pixel can remain the same land cover type or it can change type. The pixel in scenario (a) is relatively stable, transitioning land cover type only once over the four years. The pixel in scenario (b) is more volatile, changing land cover type every year. If attempting to characterize the volatility of each pixel, the time resolution of observation will influence results. If, as in the original Atlas, one observes the pixels at only two time points, the first and fourth years, pixel (a) would appear to be volatile and pixel (b) would appear to be stable. At the annual time scale, however, the opposite behavior is evident.



Using the new annual LULC dataset, however, it is possible to look at annual conversion volatility. This advance from the two-year Atlas dataset is illustrated in the figure above. Using the AtlasV2 dataset to identify land cover conversion volatility hot spots can enable researchers to focus on possible mechanisms driving that volatility, as well as enable decision-makers and land managers to focus their efforts accordingly.

Region-wide

Conversion volatility is defined, for each 30 m pixel, as the number of conversions the pixel accrued during the period 2000 to 2016; the maximum number of conversions possible is 16. Every land cover classification decision is made by popular vote among the decision trees in the random forest algorithm. To exclude dubious conversions when the classification certainty is low, a user-defined threshold was imposed on the percent split in vote between the first and second most popular classes. A conversion arising from a classification with a vote split by less than the threshold was discounted from the total conversions accrued by the pixel over the time series. A lower bound for the number of conversions was calculated by assuming no change during any period of missing data.

The influence of classification uncertainty and the importance of thresholding the class vote split are illustrated in the figures below. Characteristic spectral signatures and precipitation features are plotted for all pixels and for only pixels with volatility scores ≥5 conversions for a 10% split threshold. These are the pixels more likely to be prone to erroneous class conversions as a result of poor feature separability. The difference in separability between the two columns is striking, reinforcing the importance of investigating higher split thresholds.

Figure 12. Spectral signatures and precipitation features of the top six classes in the AtlasV2 dataset. Plots a) and c) include all pixels; plots b) and c) include only pixels with volatility scores ≥5 conversions for a 10% split threshold. Plots a) and b) are the characteristic reflectance values in the Landsat 7 bands for the fall season, mid-September to mid-November. As previously, mean values are shown with a solid line; shading indicates one standard deviation. Plots c) and d) show the mean and one standard deviation of the seasonal precipitation features for the top six Atlas classes. Fall season defined as above and spring season, mid-March to mid-May. Class legend at right.

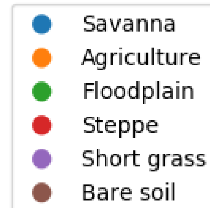


Figure 12.a)

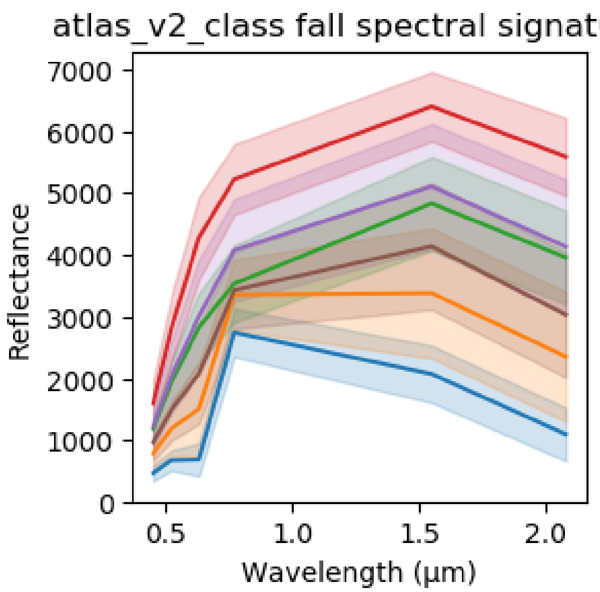


figure 12.b)

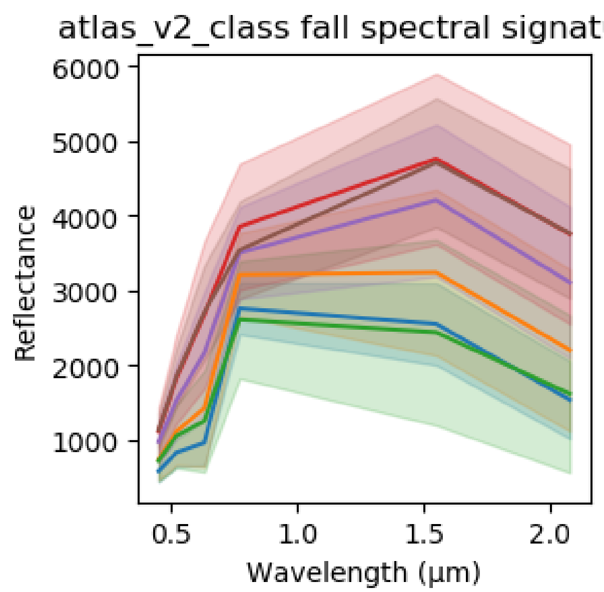


Figure 12.c)

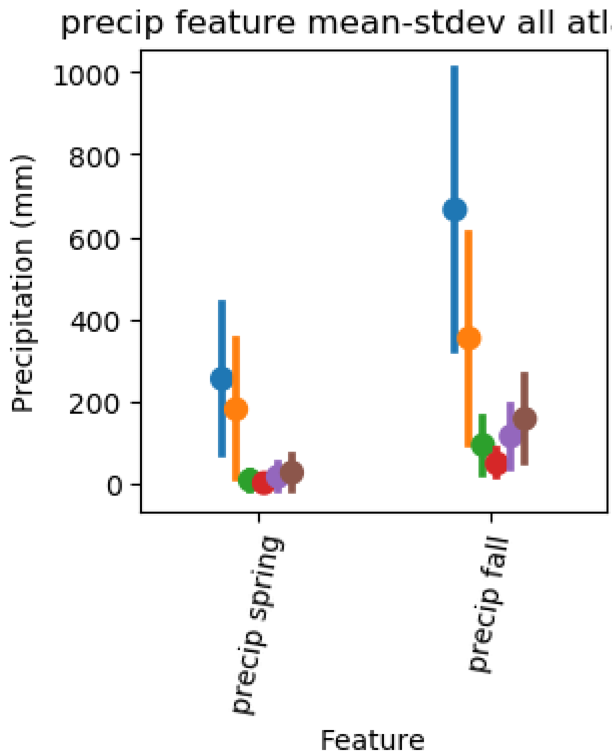
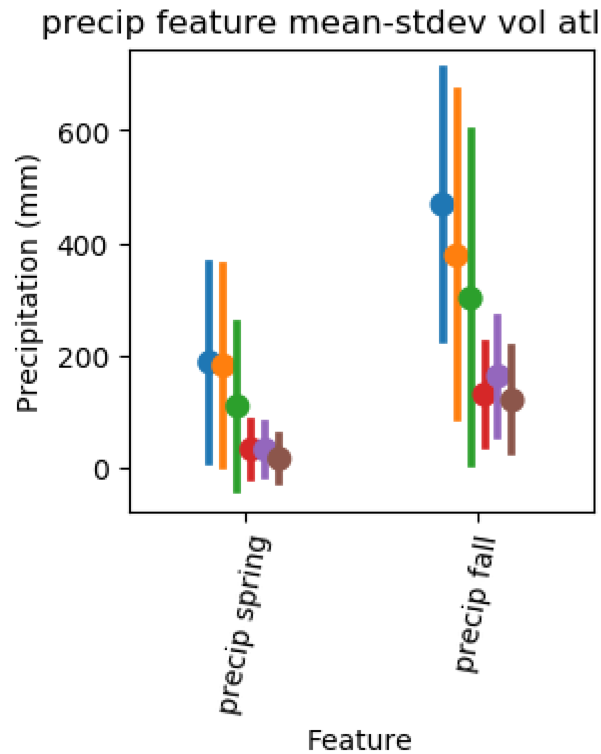


figure 12.d)



Four maps are shown below: the 2016 AtlasV2 land cover map for geographic reference; and three conversion volatility maps for different thresholds for the split of the conversion vote. With higher split thresholds, the volatility map is restricted to conversions made with higher agreement among the decision trees; total conversions for the overall map are reduced. Looking at a range of split thresholds provides information about the spatial structure of the underlying classification confidence in seemingly volatile areas.

Figure 13. Land cover and conversion volatility.

Figure 13.a) AtlasV2 land cover for 2016. Class legend at right.

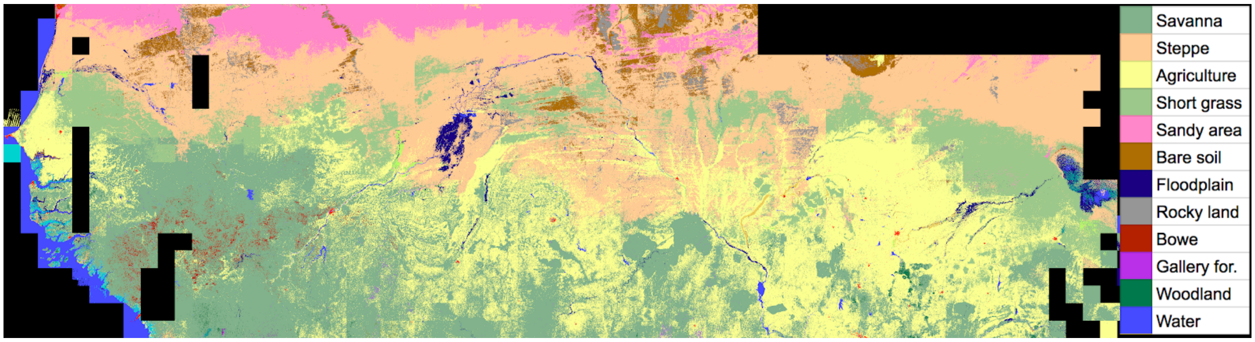


Figure 13.b) Conversion volatility for 10% split threshold.

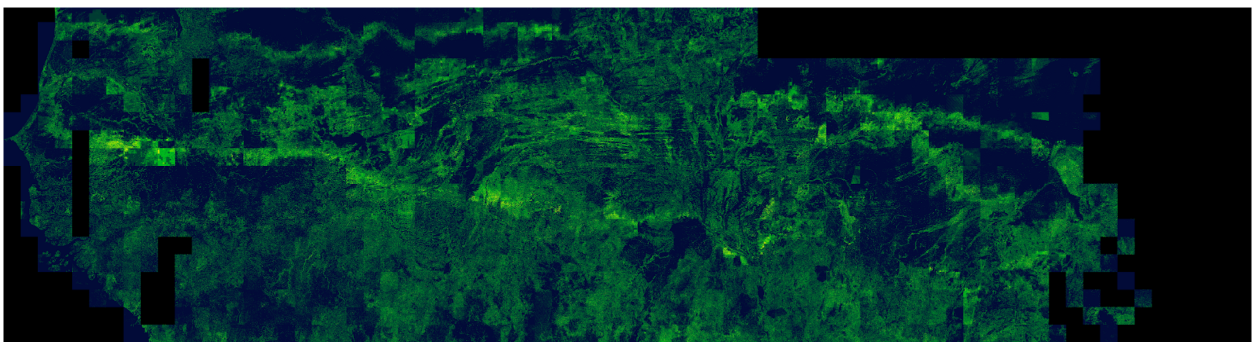


Figure 13.c) Conversion volatility for 20% split threshold.

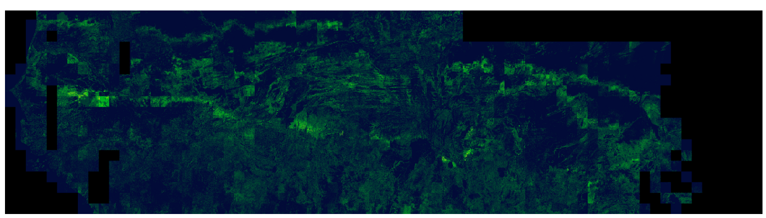


Figure 13.d) Conversion volatility for 30% split threshold.

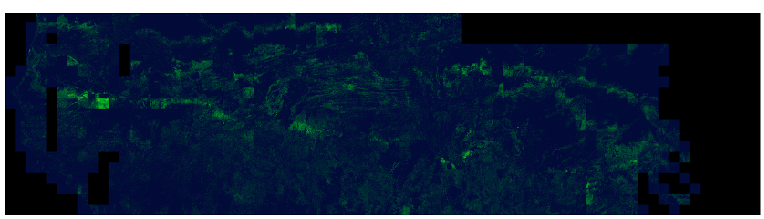
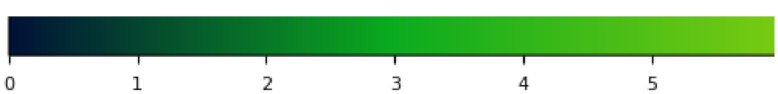


Figure 13.e) Color bar for conversion volatility in number of land cover class conversions from 2000 to 2016. Maximum number of transitions possible is 16; color bar truncated for readability.



Region-wide, there is great diversity in LULC volatility. Land cover types are stable in some places, undergoing few changes over the 17-year period 2000 to 2016. In other areas, land cover change frequently, flickering between different land cover types on an annual basis. At the boundaries between regions where land cover is largely homogenous (for example the steppe, short grass savanna and agriculture in southeastern Niger), land cover conversion is highly volatile. This indicates a flickering behavior as opposed irreversible conversions of land cover class that increase its contiguous area. A band of high conversion volatility sweeps across the Sahel, generally tracing the location where steppe meets a landscape of mixed agriculture and savanna. Even within this band, conversion volatility is not evenly distributed. Hotspots of conversion volatility appear in northwestern Burkina Faso and to the north of Bamako in Mali. Even at a split threshold of 30%, there is strong coherent spatial structure in the conversion volatility map. Possible influences of precipitation on conversion volatility at a regional scale are detailed in the next section.

Smaller scales

At the regional scale, some areas show intermediate volatility without much spatial structure. The thirty meter resolution allows closer examination, revealing that these areas are not characterized by intermediate volatility but instead by complex patterning of volatile and stable land cover at a much smaller scale. This highlights the importance of multiscale analysis and illustrates that different parts of the West African landscape exhibit conversion patterning at very different scales. Conversion volatility provides insight about landscape features that are not apparent from the land cover map. Within the AtlasV2 conversion volatility map, many examples of small-scale spatial patterning warrant future investigation.

In the area east of Bamako, an intricate small-scale labyrinth of stable-volatile patterning appears, following the spatial organization of the agriculture and savanna classes. Much of this patterning takes on a dendritic structure. In the detail view, the western area shows stable dendritic structures in a field of more volatile land cover. The eastern area, in contrast, shows volatile dendritic structures in a field of more stable land cover. In the 2016 land cover map, both the stable and volatile dendritic structures correspond to agriculture. It is only with the full time series and resulting conversion volatility that it is possible to see how different parts of this landscape, which appear identical in a land cover map, exhibit opposite conversion volatility behaviors. Further investigation of these areas could lead to insights on the different processes governing landscape changes in these different areas.

Figure 14. a) 2016 land cover map for Bamako and the surrounding area. The city of Bamako appears in bright red in the middle of the frame, cut through by the Niger River in blue, which runs diagonally southwest to northeast. Yellow area corresponds to agriculture; green corresponds to savanna; and dark red to the bowé land cover class. b) Conversion volatility map, spatially identical to the land cover class map in (a). Inset c) is a detail view of the conversion volatility map for the area east of Bamako. In the area at the western edge of the detail frame, stable agriculture (dark in the conversion volatility map) forms a dendritic spatial pattern distinct from the surrounding volatile savanna landscape. In the eastern part of the frame, the inverse is true. The dendritic structures are volatile and the surrounding savanna is stable. Legend for land cover classes and color bar for number of conversions, truncated.

Figure 14.a)

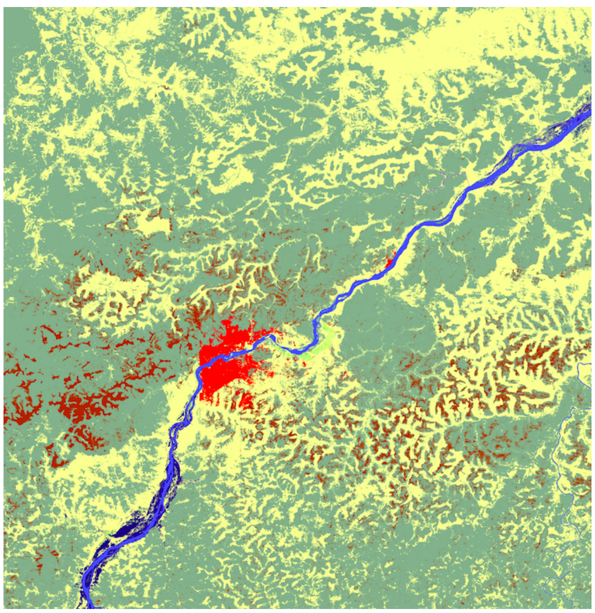


Figure 14.b)

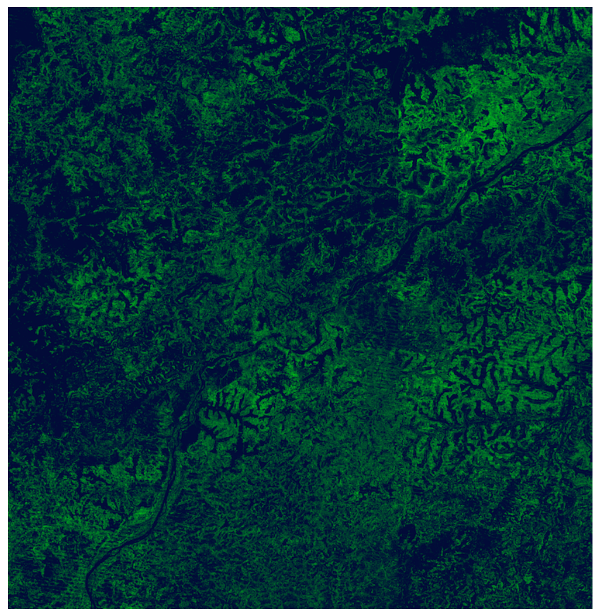
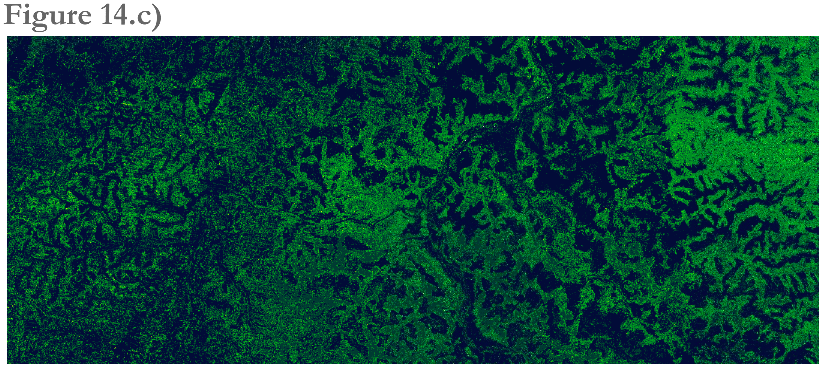
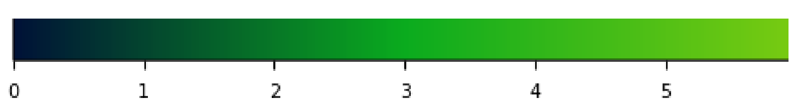


Figure 14.c)

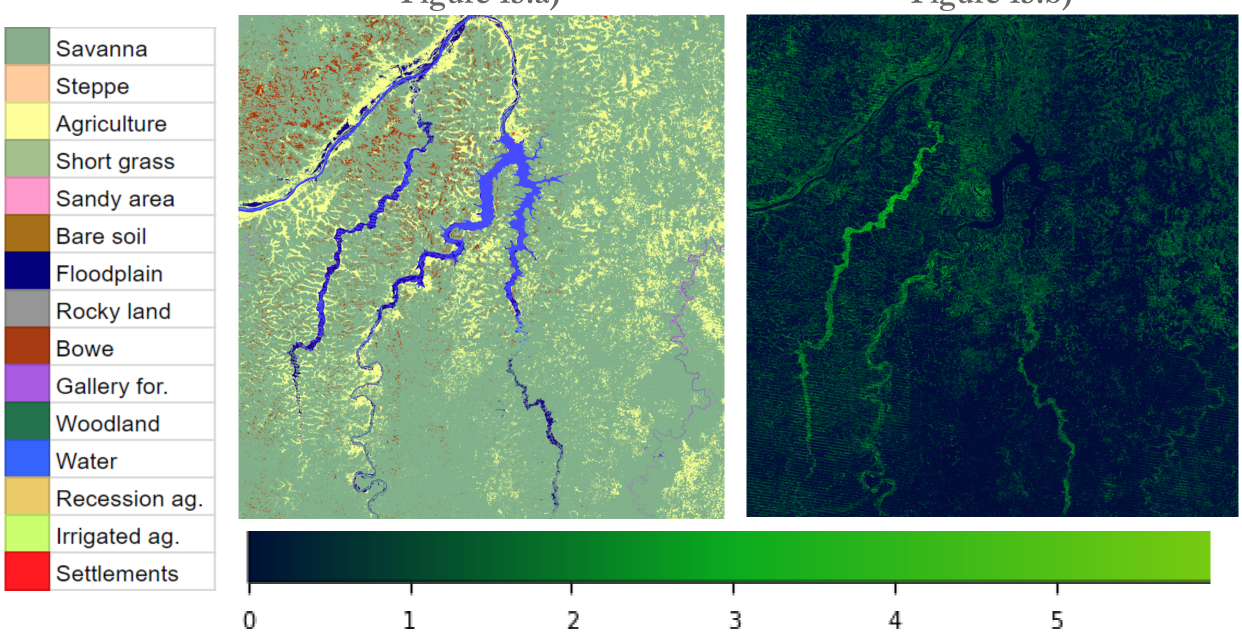




In the Guinean Highlands, among the headlands of the Niger River to the southwest of Bamako, there are three river branches that come together. These include, from west to east in the map above, the headland Niger River, the Fié River tributary, and the Sankaran River, which flows into a lake behind the Sélingué dam. The lake behind the dam shows the typical shape of a dammed reservoir. The other two branches show up on the land cover map as a mixture of water and floodplain. In the conversion volatility map, however, the three rivers show different behaviors. The Niger River shows a volatile floodplain around a stable central channel. The Fié River shows the entire floodplain as highly volatile. The lake shows expected stability surrounded with a more volatile edge, presumably where changes in the lake level affect the footprint of the lake. The Sankaran River flowing into the lake shows a similar floodplain-channel pattern as the Niger River, although at a much smaller scale and with much higher resolution in the braiding of the central channel.

Figure 15. Headlands of the Niger River, southwest of Bamako. (a) 2016 AtlasV2 land cover map. (b) Conversion volatility map. Joining river tributaries, blue in the land cover class map, show different behaviors from one another in the conversion volatility map.

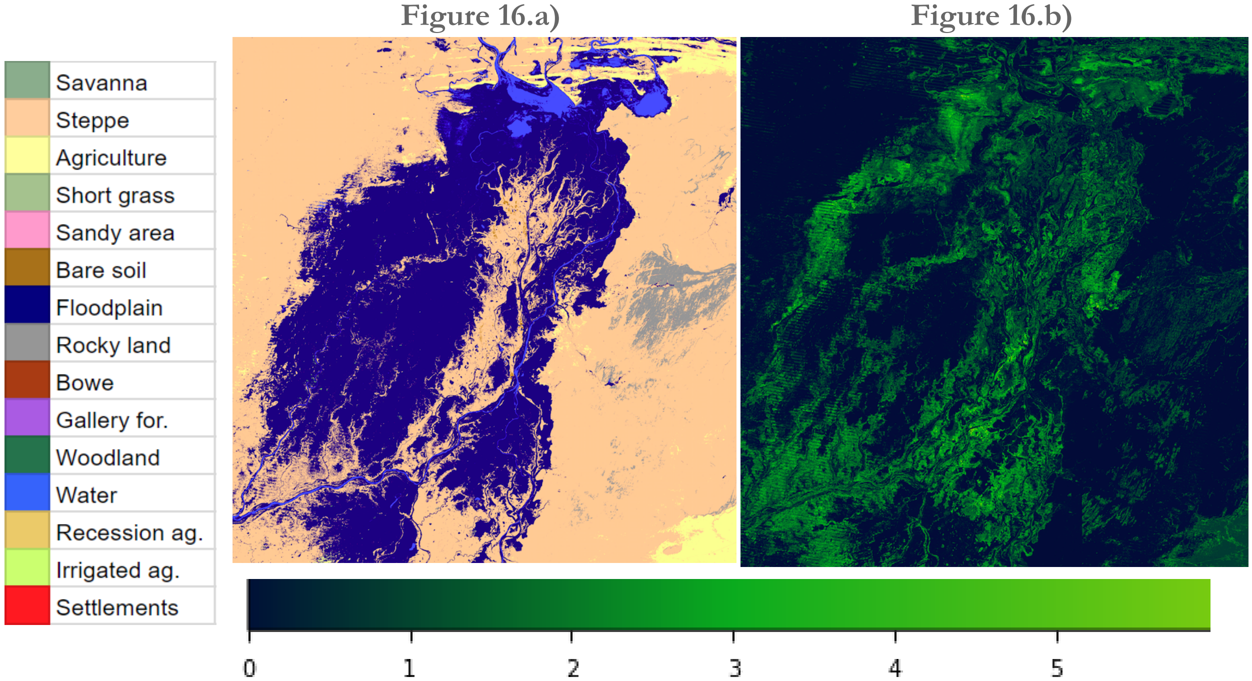
Figure 15.a) **Figure 15.b)**



As the Niger river heads into the Sahara desert, it encounters a wetland in the area surrounding the port city of Mopti. The river spreads out and slows down in this delta before continuing on northward. The flooding in this area is seasonal, September to December, fed by rain in the Guinean Highlands and to a certain extent local rainfall as well. During the flood season, the inundation area in the delta can grow to over 31,000 km^2 from a dry season area of 3,800 km^2 (Zwarts 2010). Major economic and subsistence activities in the region include seasonal rice farming and fishing alongside pastoralism supported by the delta. Variable flood seasons, either anomalously wet or dry, have an enormous impact on the one million people who depend on the delta for their livelihoods. An annual land cover map can identify the floodplain of the delta, but the conversion volatility map reveals a much more complex landscape with heterogeneous hydrologic behavior. This additional information on the hydrology of the region can be incorporated into water resources management and flood forecasting.

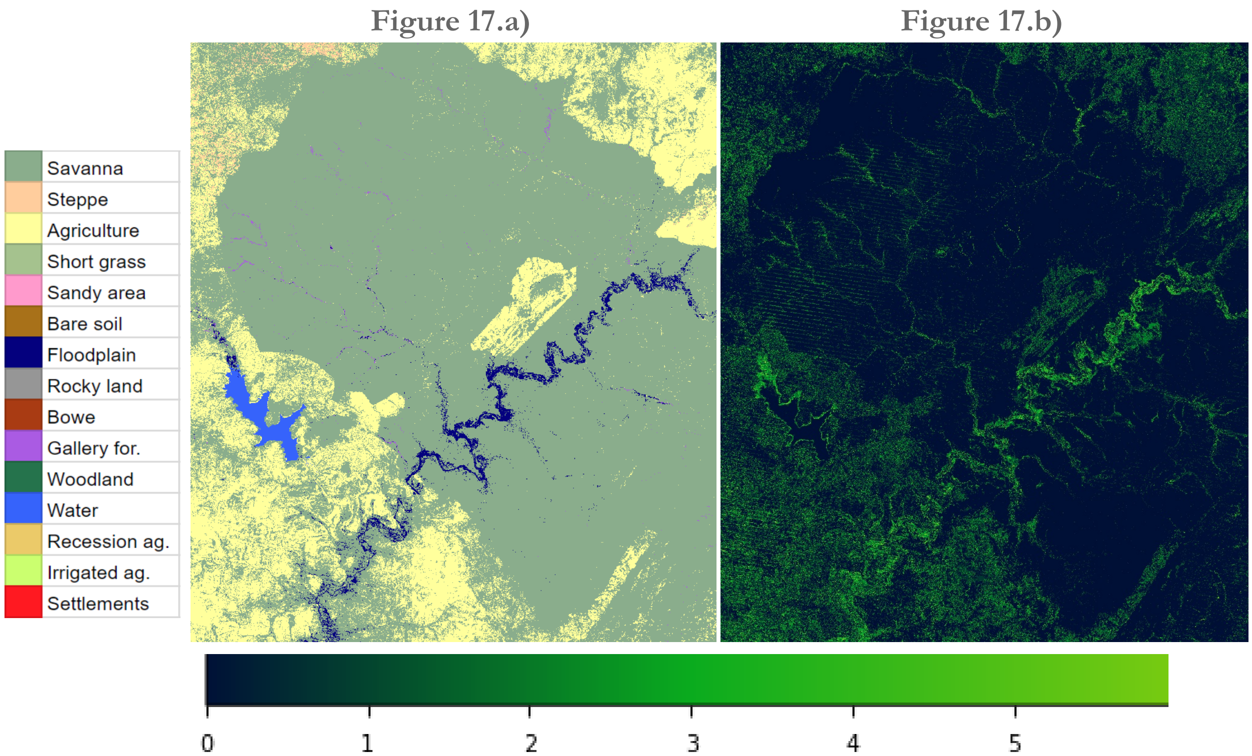
Figure 16. Inland Niger River Delta, northern Mali. (a) 2016 AtlasV2 land cover map. (b) Conversion volatility map. Note the spatial structure that stands out in the conversion volatility map that is indistinguishable in the single-year land cover map.

Figure 16.a) **Figure 16.b)**



There are a number of possibilities for using conversion volatility maps for hydrologic applications. Conversion volatility could be used to identify differences in hydrologic behavior of rivers, central river channels within a floodplain, and monitoring lake level volatility. Conversion volatility offers insight on hydrologic behavior not necessarily represented in land cover maps. Further, there are places in the landscape, such as in the Madjoari Reserve in eastern Burkina Faso, where the conversion volatility map is able to pick out water features by their characteristic changes where they do not show up clearly in the land cover map.

Figure 17. Madjoari Reserve in eastern Burkina Faso. (a) 2016 AtlasV2 land cover map. (b) Conversion volatility map. Note the river features that appear in the conversion volatility map that are not so easily distinguishable in the land cover map.



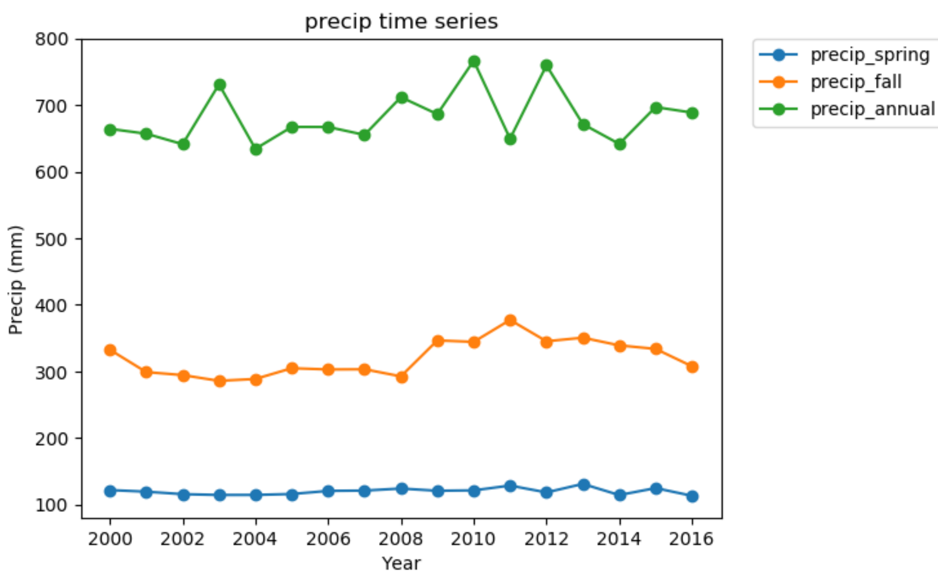
It has been well-established that the Sahel has undergone drastic changes in land cover. The identification of areas of high conversion volatility could have major implications for land management strategies, geographically focusing efforts where they will have the most impact. The spatial organization of high conversion volatility can offer insight into possible mechanisms influencing conversion, which might inform both land management strategies and predictions about the future of LULC under climate change. The impacts of climate change on the Sahel region are highly uncertain. With this new information about the conditions in which land cover is highly variable, decision-makers may be able to improve their climate change adaptation plans.

Role of precipitation

The relationship between vegetation and precipitation in the Sahel is long and well established. Within the active debate on recent land cover changes in the Sahel and their drivers, it is increasingly held that precipitation strongly influences regional-scale land cover (Tucker et al. 1991; Tucker & Nicholson 1999; Seaquist et al. 2009; Gonzalez et al. 2012; Hickler et al. 2005). Overall trends at the regional scale, however, do not necessarily translate to dynamics observed at a more local scale. Findings of spatial heterogeneity and smaller scale variation in greening trends have been related to local anthropogenic and environmental effects (Herrmann et al. 2005; Hiernaux et al. 2016; Dardel et al. 2014). These localized effects can dominate short timescale changes in land cover, particularly because land cover has a lagged response to long term trends in rainfall (Brandt et al. 2017; Zeng et al. 1999).

The last few decades of precipitation in the West African Sahel have been characterized by sizable interannual variations rather than overall trend. The figure below shows precipitation from the CHIRPS dataset at an annual timestep, as used in the feature construction for the land cover classification algorithm. Data is a regional spatial average, with one series for annual precipitation, and one each for the fall and spring seasons. The interannual variation in annual precipitation is evident, along with the lack of a strong interannual trend.

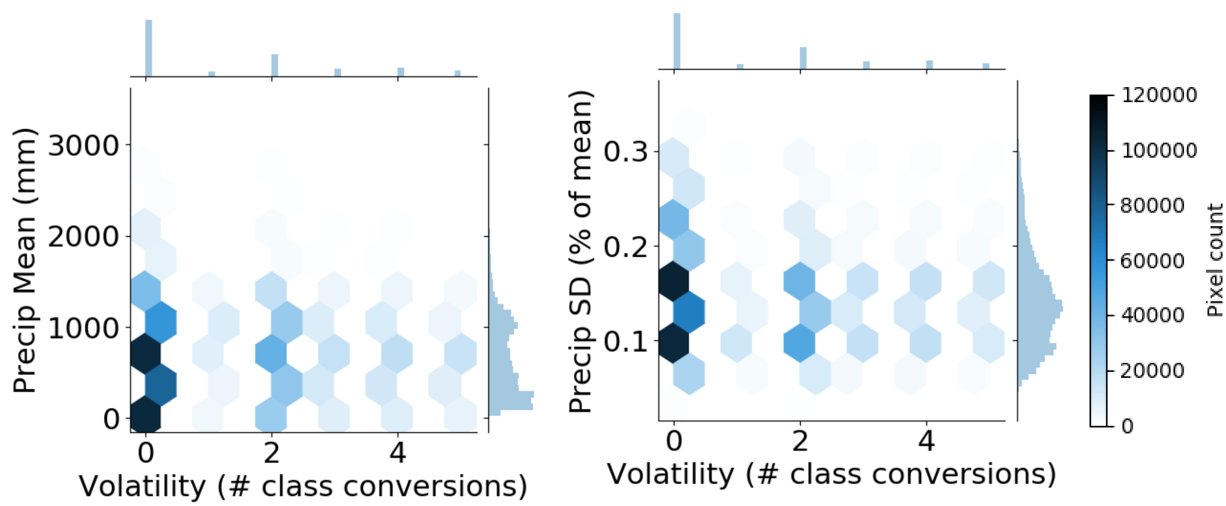
Figure 18. Annual time series of CHIRPS precipitation for 2000-2016, taken as a spatial mean of Atlas areas. All time series are three-year smoothed averages, as used for the classification algorithm features. Green is the mean total annual precipitation, orange is total fall precipitation, blue is total spring precipitation. Season definitions follow classification features: fall season is defined as mid-September to mid-November; spring season is defined as mid-March to mid-May.



To evaluate the possible role of precipitation in land cover type volatility, the figure below plots precipitation metrics against pixel volatility. For every pixel in the dataset, the precipitation metrics are calculated along with a volatility score, i.e. the number of times the pixel changed class between 2000 and 2016. Neither mean annual precipitation nor standard deviation of annual precipitation show a relationship with volatility.

Figure 19. Precipitation mean and standard deviation vs. land cover conversion volatility. In both plots, volatility is on the x-axis, in number of land cover class conversions over the 2000-2016 time period. Highest volatility bin includes pixels with 5 or more conversions. a) Mean annual precipitation vs. volatility; b) Precipitation standard deviation vs. volatility, where standard deviation of annual precipitation is shown as a percent of the mean annual precipitation. Density in pixel count displayed in color. Marginal distributions plotted above and to the right of the main plot in light blue. Precipitation data is from CHIRPS.

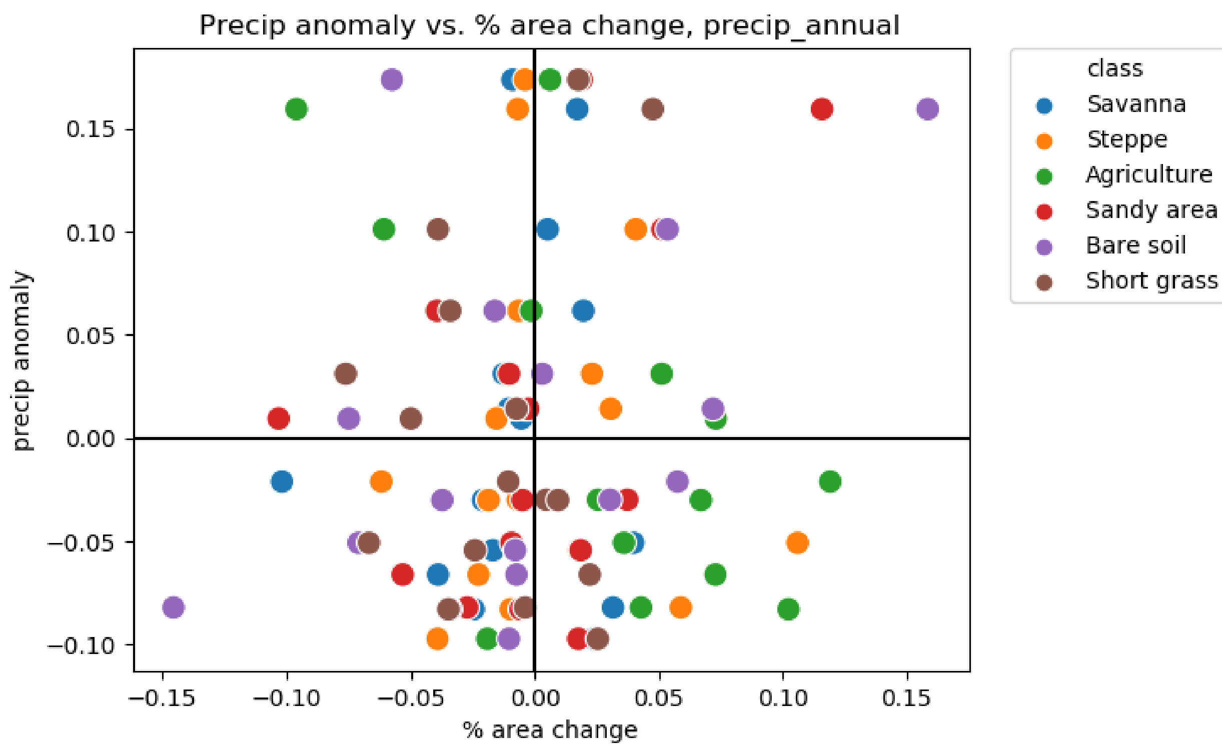
Figure 19.a) **Figure 19.b)**



The plot below investigates the relationship between precipitation variability and land cover changes on an annual basis. Annual precipitation anomaly (difference from mean divided by standard deviation) is calculated from the CHIRPS time series, smoothed with a three-year moving average, and plotted on the y-axis. Net percent change in class area is calculated as $\frac{\text{area}_y - \text{area}_{y-1}}{\text{area}_{y-1}}$ for each class and each year and plotted on the x-axis.

There is no discernable relationship between precipitation anomaly and class area change. Note that by design, the three-year moving average protocol smooths out signal from single years. Rather, this is an evaluation of variability at the landscape scale, at longer timescales. It may be that no relationship exists between precipitation and land cover type at the landscape scale, or more likely, that the precipitation time series does not include sufficient variability to create a signal in land cover type change.

Figure 20. Scatter plot of precipitation anomaly against net % change for each land cover class. Precipitation anomalies are three-year moving averages, reflecting the feature construction in the classification algorithm. There is no discernable relationship between precipitation anomaly and net % change for any land cover class.



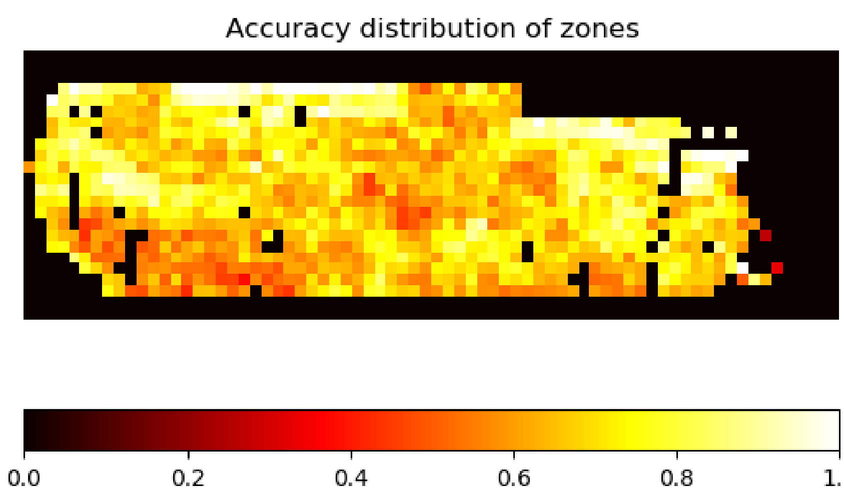
While precipitation is the most important feature for classifying land cover, by itself it does not show a relationship with land cover change over the 17 years. This supports the hypothesis that precipitation alone is not sufficient to explain changes in land cover in the West African Sahel. Because the AtlasV2 includes land use (most importantly, agriculture) alongside land cover, one would expect the dataset to represent socioeconomic dynamics alongside and in interaction with biophysical relationships. The observed behaviors at the regional scale leave room for the possibility that the relationships and mechanisms shaping land cover change and trends in the AtlasV2 dataset are heterogeneous across space, in line with gathering evidence in the region.

Classifier Performance

Accuracy maps and distributions

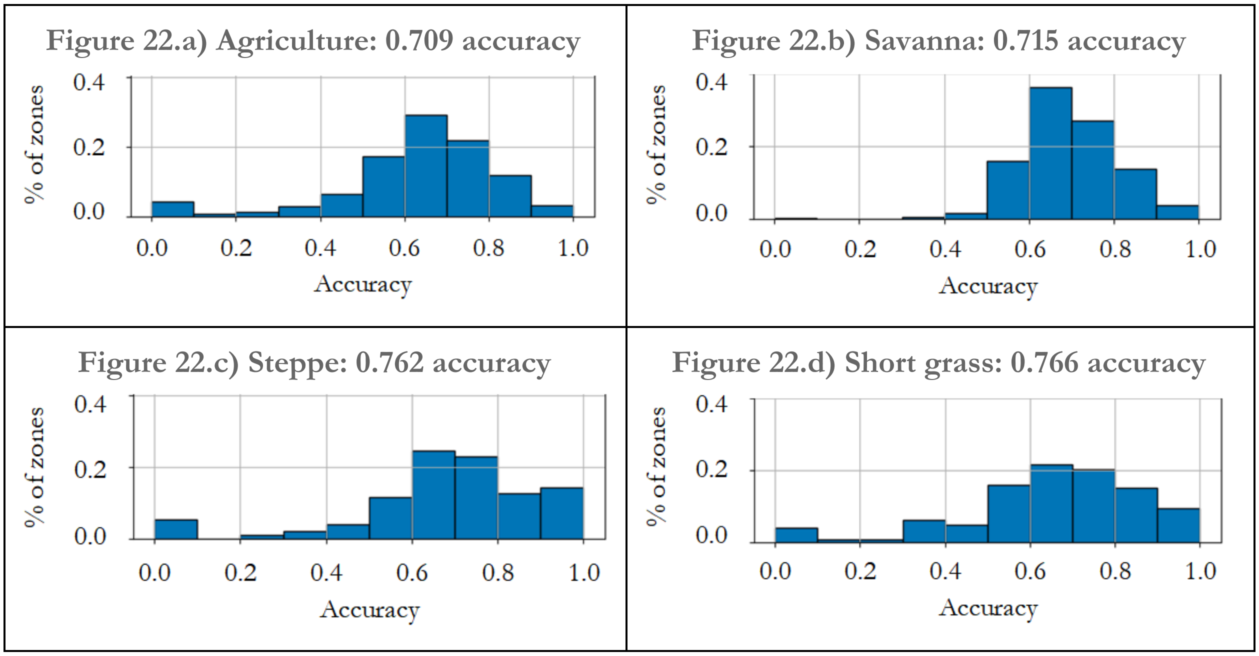
As detailed in the Data and Methods section above, the Sahel region was split into 0.5-degree zones and a separate classification algorithm trained in each zone. Because classification was carried out by distinct classifiers in different zones, it was possible to examine the spatial pattern of zonal class accuracy instead of only a single accuracy score for the entire region. Additionally, because each zone classifier produces an accuracy score by class, it is possible to look at the frequency distribution of accuracy by class in aggregate across zones. The geographic structure of overall accuracy, and the frequency distribution of class accuracy across zones can help identify the strengths of the AtlasV2 maps for applications in smaller regions. This data can also suggest areas of focus for future development of the dataset, and regions to target for accuracy improvements.

Figure 21. Map of overall accuracy of all 0.5-degree classifier zones. As detailed in the Data and Methods section, the Sahel area was divided into 0.5-degree zones and a separate classification algorithm trained for each zone. Each zone has its own accuracy scores by class. Overall accuracy of each individual zone is calculated by taking the area-weighted mean of all class accuracies. This overall accuracy of each zone is plotted in color in the below map.



Frequency distributions of class accuracy across zones are plotted in the figure below. Plots (a) through (d) are the four most prevalent land cover classes: agriculture, savanna, steppe, and short grass savanna, respectively. Savanna, for example, shows a relatively tight distribution around its aggregate accuracy of 71.5%. Short grass has a higher aggregate accuracy (76.6%), but the distribution is more widely spread. In other words, most zones do well with classifying savanna, whereas zones have more mixed performance for classifying short grass. Information on the frequency distributions of class accuracies can be included in the factors to optimize for future development of the AtlasV2.

Figure 22. Frequency distributions of accuracy for the four most common land cover classes: a) agriculture; b) savanna; c) steppe; d) short grass savanna. Class accuracies from all zones are gathered to create the frequency distributions. Frequency on the y-axis; accuracy on the x-axis. Mean class accuracy denoted in subplot titles.



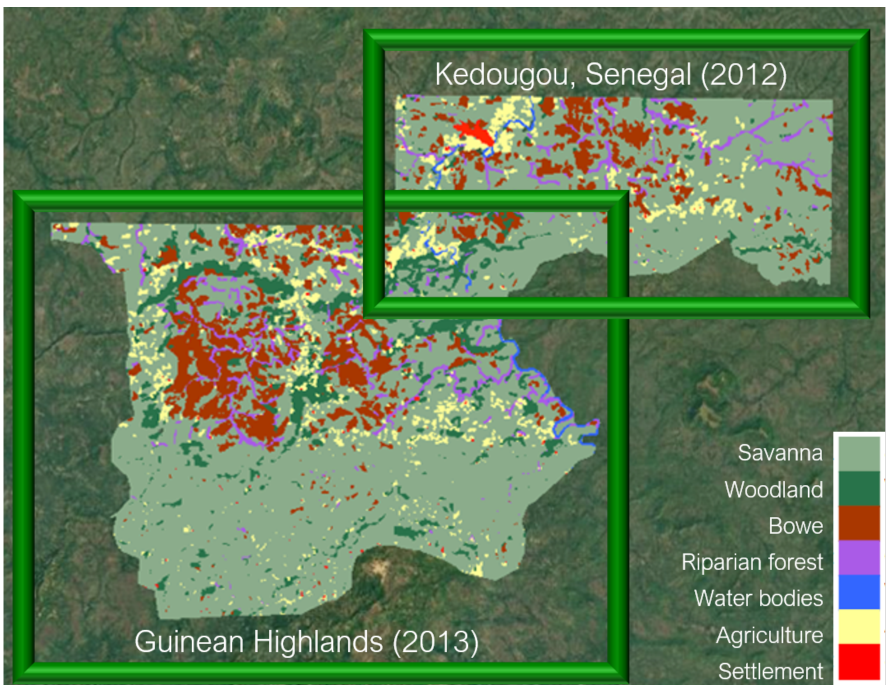
Atlas accuracies

It is important to note that the measurement of "accuracy" of the V2 product is actually a metric of match with the original Atlas. Measuring the true accuracy of the Atlas is challenging: there is no region-wide, validated, accurate data set against which to evaluate Atlas or AtlasV2. Without regional-scale data for validation, the original Atlas was evaluated with expert input, peer review, and field visits for ground truthing. Because of feasibility constraints, these methods are applied at sub-regional scales, as case study spot checks or qualitative sense checks. Accuracy of the Atlas is by no means uniform across space or time, and these methods do not yield a definitive regional-scale accuracy evaluation. Rather, they are best available approaches to evaluating the data product.

AtlasV2 faces the same scale-based evaluation challenges. In lieu of regional-scale validation, case studies provide an opportunity to validate and compare the two Atlas products. For small areas where independent high-resolution verified land cover data exists, relative accuracies of the Atlas and AtlasV2 products can be evaluated. An "ultra-high resolution"

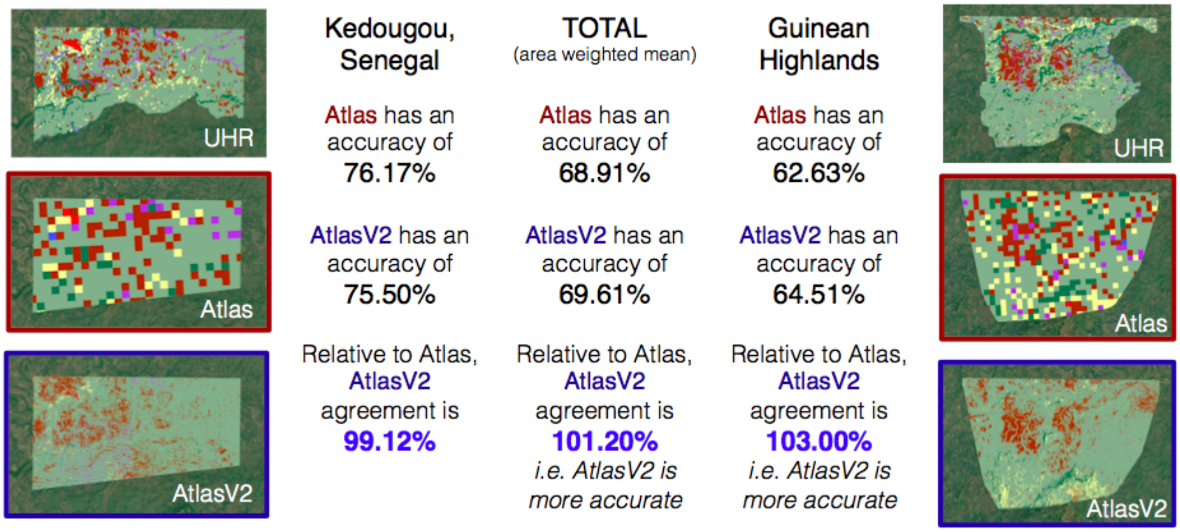
(UHR) dataset exists for the area of the Guinean Highlands and Kedougou, Senegal (Nelson 2010). The UHR map was visually classified from 15 m Advanced Spaceborne Thermal Emission and Reflection Radiometer imagery (ASTER; Abrams 2000), and has been intensively quality controlled and verified for accuracy. Using this common benchmark, Atlas and AtlasV2 can be compared and evaluated. The Kedougou and Guinean Highlands area has advantages as a case study for accuracy evaluation. The landscape is characterized by small-scale spatial heterogeneity in land cover class patterns. Further, in this particular location, the land cover classes present generally look relatively similar to one another.

Figure 23. Map of Kedougou and Guinean Highlands UHR datasets. The two datasets overlap slightly in space and are from two different years, 2012 and 2013 respectively. The small-scale spatial heterogeneity in land cover class is an advantage for use as an accuracy evaluation case study.



The UHR data for Kedougou and the Guinean Highlands are separate datasets. The areas covered by the two datasets overlap slightly and the datasets are from two different years, 2012 for Kedougou and 2013 for the Guinean Highlands. Because of this, accuracy metrics were calculated for the two areas separately, then combined using an area-weighted mean. The accuracies presented in the first two rows of the figure below are percent match with the UHR classified dataset. Note that the AtlasV2 product has higher accuracy than the original Atlas. In other words, AtlasV2 is better at matching the UHR dataset than the original Atlas.

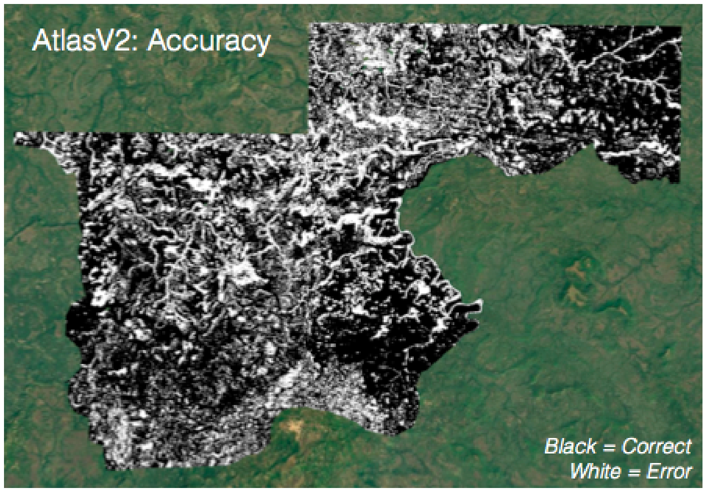
Figure 24. Evaluating accuracy at Atlas data point locations. Accuracy comparisons for Atlas and AtlasV2.



In the previous section, AtlasV2 accuracies were defined by how well AtlasV2 matched the original Atlas. Taken as an objective score, this metric assumes the original Atlas is 100% accurate. While the original Atlas is certainly far more accurate than any previously available regional land cover dataset, it would be remiss to assume it to be flawless, its accuracy perfect. Calculating the accuracies of both the Atlas and AtlasV2 datasets against the common benchmark of the UHR data provides a more representative evaluation of how well the AtlasV2 identifies land cover and how that compares to the original Atlas. The third row of the table below shows this comparison. It is a calculation of how well AtlasV2 matches UHR , relative to how well Atlas matches UHR. An agreement score of 100% would indicate that Atlas2 is equally as accurate as the original Atlas. Here AtlasV2 is more accurate than the original Atlas, a relative accuracy of 101.2%.

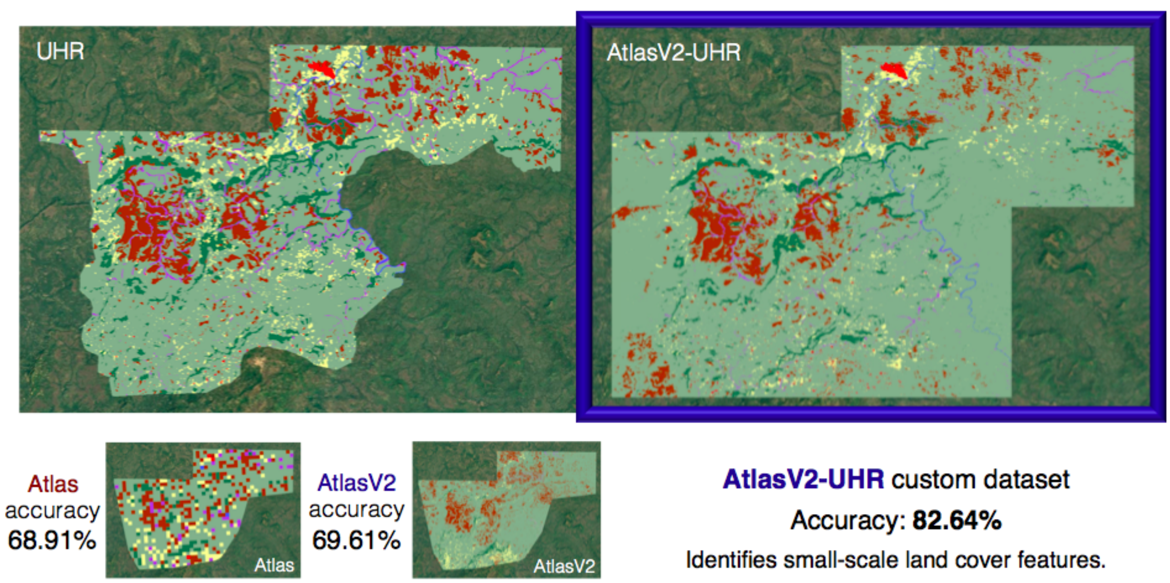
Further, the method developed to produce the LULC dataset was designed to be modular and customizable. This means that with a UHR LULC dataset available, a new LULC dataset can be created that is tailored to that region and augmented by the higher resolution. For example, a map of where AtlasV2 misclassifies land cover in the Kedougou/Guinean Highlands region shows errors for narrow sinuous landscape features such as rivers and riparian forest. The Atlas, because it was built from one 30m classification every 2 km, is not very skillful at identifying such landscape features. V2, because it was built from Atlas, inherited these limitations.

Figure 25. AtlasV2 error map (black = correct; white = error).



There are, however, modifications that can be made to ameliorate some of these inaccuracies. Because the pipeline is modular, the training data set can be swapped out. Replacing the Atlas training set with the UHR land cover data set and re-running the pipeline created a new LULC data set. The base map of the product was still Landsat, but the higher resolution and higher accuracy UHR offered more data for the algorithm to train on, and this was a training set that could identify sinuous landscape features. Indeed, the resulting custom AtlasV2 LULC dataset improved from an accuracy of 69.61% to an accuracy of 82.64%, and identified small-scale landscape features including rivers and riparian forest.

Figure 26. Custom LULC datasets with UHR data. AtlasV2-UHR custom dataset comparison.



These modifications were cheap, requiring approximately 90 minutes for the complete process: swapping out the training map, retraining the algorithm, classifying the LULC map, and publishing the new data on Earth Engine. Possible future improvements include also swapping out the base map, exchanging Landsat for ASTER, so the dataset would be built on a 15 m instead of 30 m LULC map.

This accuracy evaluation of, and comparison between, Atlas and AtlasV2 is only a case study of a small area within a large and heterogeneous region; accuracies reported for this case study are not expected to be representative for the region as a whole. As shown in the accuracy by zone map, classification accuracy for the V2 dataset is not uniform across space. It is likely that this is the case for the Atlas as well. This may be caused by any combination of: land cover classes present and spatial landscape patterning being more or less difficult to classify, differences in the quality of the available base map data, or geographic differences. For example, the southern regions are cloudier, which restricts the amount of data available. There may also be differences among the technicians who classified the Atlas data, or differences in the quality control post-processing of the Atlas.

It should be emphasized that this was a case study. Nevertheless, the success demonstrated in this area pointed toward the power of the V2 method and dataset. The case study served as proof of concept, and suggested that the true accuracy of the V2 data set may be even higher than that of the original Atlas. Further, it demonstrated the ease with which the product can be adapted, and the drastic accuracy gains available through the use of this modular pipeline and the production of a custom LULC dataset tailored to a particular region. With different training data, this pipeline could be adapted for different areas, different use cases, and regions outside of West Africa.

Temporal transferability

One of the important questions for an approach such as the AtlasV2 is the transferability of the trained algorithm to different years of data. There are a number of reasons that transferability might degrade when applied to years not in the training dataset. There is the potential for overfitting in the classification algorithm if the characteristics of the observational data or the the underlying relationships to land cover types is not year independent. Interannual variability and gradual changes over time could both contribute to this situation.

For example, one would expect that in a dry period, land cover characteristics change accordingly. Perhaps even the relationships between land cover type and indicators such as surface reflectance change. From a systems point of view, this interannual variability can be represented as movement within state space. Observing the system in one region of state space (e.g. a dry period) does not necessarily afford enough information to represent the system in a different region of state space (e.g. a wet period). By training an algorithm with information from only a limited subspace of the system's full range of variability, the algorithm potentially performs poorly in other regions of state space. In addition to interannual variability, gradual shifts over time in land cover characteristics or sensor bias can contribute to the deterioration of a classification algorithm over time. The temporal drift in the information about the system limits the lifetime of a classifier. There is a restriction on its ability to accurately classify land cover in years temporally removed from the years for which it was trained. In this case, information on how quickly the accuracy of a classifier decreases could contribute to planning when another hand-classification campaign is necessary.

To gather information on the temporal transferability of this classification method, accuracy tests were run exploring permutations of temporally segmented algorithm training and evaluation data. The classifiers trained on combined data from 2000/2013 were evaluated on 2000 data and 2013 data separately. In addition, a set of classifiers was trained on data from 2000 only and another set trained on 2013 only. Both sets were then evaluated on both years of Atlas data individually. Results of these accuracy assessments appear in the table below. The 2000/2013 classifier performed well on the single years of data. The single year classifiers likewise do well on their own year, but for both the 2000 classifier and the 2013 classifier, performance was notably worse on the other year of data. Note that in all cases, the data used to evaluate the classifier for a particular year or years was held out from the training process; in other words, the accuracy assessment was conducted with data the classifier had not seen. This procedure makes possible an honest evaluation of classification accuracies.

Table 3. Classifier accuracies

Classifier:	2000/2013			2000		2013	
Test years:	2000/2013	2000	2013	2000	2013	2000	2013
Savanna	.7148	.7281	.6986	.7228	.6376	.7117	.6967
Steppe	.7618	.7707	.7527	.7627	.6853	.6988	.7490
Agriculture	.7095	.6885	.7243	.6861	.6705	.5777	.7163
Sandy area	.8407	.8404	.8410	.8387	.7788	.7240	.8315
Bare soil	.6592	.6596	.6587	.6480	.6144	.5612	.6397
Short grass	.7659	.7775	.7527	.7738	.6442	.6955	.7556
Avg/Total	.7296	.7336	.7255	.7235	.6530	.6573	.7176

The limited skill of an algorithm trained on a single year to classify a different year leaves open the question of which aspect of that setup is most detrimental. It may be that the relationships between features and land cover type are highly year-specific, enough to compromise the ability of an algorithm to classify a year not seen in its training data. This would present a particular challenge to the task of classifying the years between the two Atlas maps, and exploring interannual trends and volatility. Alternately, it may be that a single year does not cover enough of the variability range of the system to accurately classify a year outside of the explored phase space. Having data representing a wider region of phase space would improve this deficiency, without the need for data from every year.

The evidence from this accuracy assessment is not conclusive about the time transferability of classifiers. It does, however offer insight into the factors affecting temporal transferability. In the case of high annual specificity, one would expect that classifiers trained and evaluated on data from the same year would perform better than classifiers trained on a combination of data from temporally distant years and then evaluated on only one of the years. Instead, for both 2000 and 2013, the 2000/2013 algorithm outperforms the classifier built on that year alone. This indicates that capturing interannual variability, in other words a wider elaboration of the state space, is more important for constructing a skillful classifier than temporal fidelity. With two years of Atlas data for training and evaluation, it is clear that including both years more fully covers the phase space of the system. It remains unclear how well those two years cover the entirety of the phase space. It is encouraging that the two Atlas map years are at or near the beginning and end of the AtlasV2 dataset, and that between these two time points there have been significant and large-scale changes in prevalence of the major land cover types in the Sahel.

Investigation of AtlasV2 classifications for years without associated training data will, by necessity, include sources of land cover data other than the Atlas. While MODIS is perhaps not an ideal evaluation standard (Kaptué Tchuenté et al. 2011), there are small-scale high resolution land cover datasets from various sources for the Sahel region, both visually classified and field-based. These datasets can serve as more local case study evaluations of AtlasV2 for years not covered by Atlas. One such example is detailed in the previous section. In addition, there is an increasing number of high-resolution land cover datasets produced for the continent of Africa (e.g Midekisa et al. 2017; ESA CCI 2017). Comparison with these datasets, while not an evaluation against ground truth, will provide insight into the characteristic tendencies of datasets produced with different methodologies which can inform further development of the products.

Open access methodology

In addition to the regional land cover time series itself, a fully Earth Engine-based classification routine was implemented to facilitate classification of future years of data, and to make the methodology accessible for open use and customization. With this tool, users can change the input data and preprocessing techniques, select any region in the West Africa domain on which to train a custom algorithm, or upload their own training data for anywhere in the world. For a single 0.5 degree zone, the entire pipeline—ingestion and compositing of Landsat input data, custom algorithm training, and subsequent classification of land cover for the entire zone—takes only seconds. This is a tremendous advance for the field of land cover classification, and offers both the foundation and the flexibility for land cover practitioners to create their own implementations tailored to any number of applications.

Chapter Two.
Development of Land Cover Classification Algorithms
Methodological insights

Introduction

To create the dataset presented in the first chapter, it was necessary to develop a machine learning protocol specifically for training algorithms to classify land cover types in the West African Sahel. This development process led to two insights key to the success of the project. First, the flexibility and tractability of random forests outweighs the tunability of support vector machines, even on smaller datasets. Further, geographic clustering is more important than the size of the training data. These results, while specific to this Sahel classification endeavor, add to the underdeveloped literature on optimizing land cover classification tasks, and call attention to factors that should be considered when developing algorithms.

Algorithm choice

Two machine learning algorithms were investigated for the classification routine: support vector machines (SVM) and random forests (RF), using scikit-learn (Pedregosa et al. 2011). Support vector machines are computationally intensive to train, but have an established reputation for performing well on land cover classification. Existing work finds that for land cover classification, SVM outperforms methods such as artificial neural networks and maximum likelihood estimators (Huang et al. 2002; Melgani and Bruzzone 2004; Shao and Lunetta 2012 among others). Huang et al. (2002), for example, find SVM algorithms are better classifiers when using a higher percentage of the total data. They find that increasing the number of features supplied to a given classification algorithm has a greater impact on accuracy than either increasing the number of training samples or choosing a different algorithm. In their study, the speed of SVM training is particularly sensitive to number of training samples, choice of kernel, and class separability. While SVMs are slow to train on large sample sizes, the authors maintain that SVM is a preferred algorithm for land cover classification, and that as many features as possible should be included.

Random forests have also been shown to perform well on land cover classification tasks, with results comparable to or better than SVMs in some cases (Pal 2005; Rodriguez-Galiano et al. 2012; Adam et al. 2014). The evaluation by Rodriguez-Galiano et al. (2012) of random forests found that they are competitively skilled at land cover classification, and further, have some advantages over other classification methods. A random forest provides an estimate of generalization error and feature importance. It is a method efficient for both large and high-dimensional datasets, and robust to small training samples and noise. Belgiu and Dragut (2016), however, in their overview of recent algorithm evaluation work, emphasize that random forests appear to be sensitive to training data sampling design, but reports are contradictory as to the effects of imbalanced training data.

Toward the goal of building a skilled and robust classifier for land cover in West Africa, and in light of the myriad potential sensitivities of different algorithms, both support vector machines and random forests were explored. The classifier development was carried out in parallel. At each stage in designing the classification routine, two classifiers were independently optimized: both a support vector machine and a random forest. This allowed comparison of overall classification accuracies, and of the sensitivities of each method. In this chapter, an overview of support vector machines and random forests is provided. This is followed by an exploration of the effects of input data transformations on classification results. The training section details bottlenecks encountered in the classifier development process, the effects of input training data size, and unexpected findings on the role of spatial scale in the final classification results. Final results and discussion follow.

Support Vector Machines

For classification tasks, a support vector machine draws a plane through feature space to separate the input data into classes. A plane that maximizes the margins between itself and the nearest input data observations of different classes is determined to be the best solution. Those data observations at the edges of class groupings used to determine the plane margins are called the support vectors. For data that are not perfectly separable, a cost parameter defines how much an SVM prioritizes avoiding misclassifications. For non-linear solutions, the support vector machine transforms the feature hyperspace according to some function F and then draws a plane through the remapped hyperspace. Because the input data are mapped into the transformed hyperspace through dot products, the explicit form of F does not have to be found. Instead, optimal parameters are found for a kernel function K, where K is the dot product of the mapping function F. Details of the theoretical underpinnings of the support vector machine algorithm can be found in Huang et al. 2002, Vapnik 1995 and 1998, and Burges 1998, among others.

Preventing overfitting

One of the routines required in training an SVM is the use of k-fold cross-validation. This procedure prevents overfitting of the algorithm. An overfit algorithm is too closely tuned to the training data such that the generalizability of the algorithm suffers. The overfit algorithm will perform poorly on data not included in its training set, despite misleadingly high accuracies demonstrated in training. In k-fold cross-validation, the training data is split into k sections. The training for any particular set of parameters is completed in k iterations, each time holding out a different section of the data as the test data. The accuracies of each of these k iterations are then averaged to determine the overall accuracy of the algorithm with whatever parameterizations had been applied.

Figure 27. Schematic of 3-fold cross-validation.

Optimization of the input parameters requires testing many different values for the parameters. The accuracy for each parameter set is determined by its own full k-fold cross-validation procedure. A percentage of the total training data is held out entirely from the k-fold cross-validation process; 10% was used during development of the V2. Once the optimal kernel parameters are determined, a final classifier is trained on the entire training dataset, less the held-out validation data. This held-out data is then used to evaluate the final classifier. The reservation of the validation data until the final evaluation of the classifier minimizes the bias in the final accuracy score.

Choosing and parameterizing a kernel

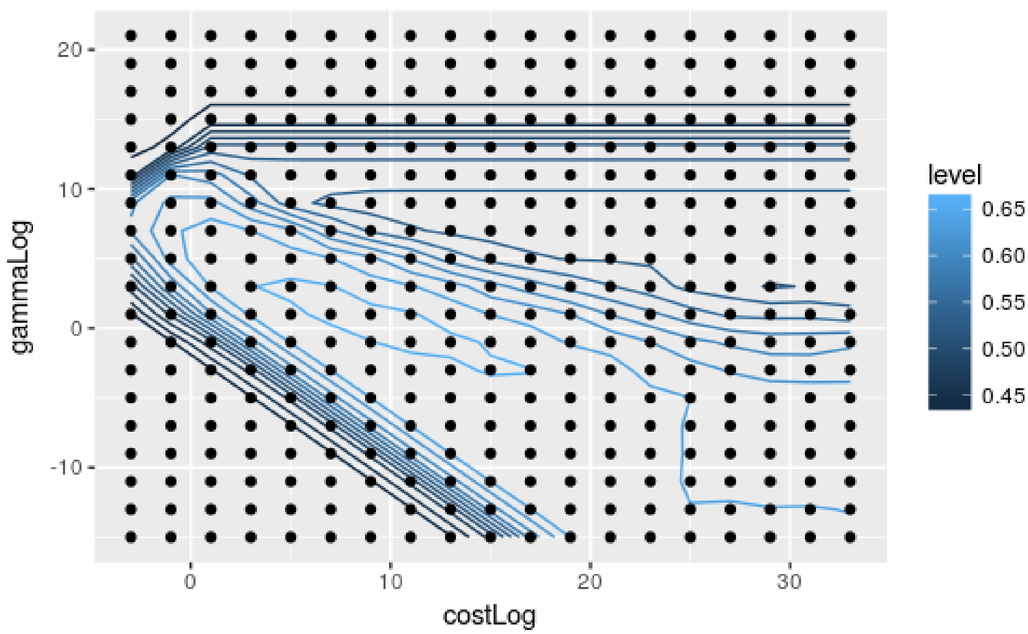
Support vector machines require the selection of a kernel to describe the mapping of data into higher dimensional space. The first kernel tested was the radial basis function (RBF):

$$K(x, y) = e^{-\gamma\|x-y\|^2}$$

The RBF was selected because it is generally a skillful kernel; its use requires optimizing only two parameters, γ and cost; and it can accommodate nonlinear mappings. The parameter γ for the RBF kernel sets the radius of influence for individual points. The cost parameter sets the penalty for an incorrect classification. Higher cost incurs a larger penalty.

Following Hsu et al. 2003, a grid search was conducted in parameter space to optimize the parameters for classification accuracy. Stepping at intervals of 2^{n+2} for both γ and C, classifiers were trained and evaluated with 5-fold cross validation. This exploration of the accuracy topology in (C, γ) space was thus a systematic and comprehensive optimization protocol.

Figure 28. Accuracy surfaces from the grid search.



Training of a single SVM algorithm is computationally expensive. When multiplied by necessary parameterization routines and k-fold cross-validation, the resources required quickly inflate. For an application with a relatively low number of data observations, training an SVM algorithm likely remains tractable; datasets with many more observations are potentially more difficult. The linear SVM kernel was explored, replacing the RBF, in an attempt to attenuate some of these computational resource requirements. Kernel choice can impact the speed of training a support vector machine significantly, and the linear kernel is recommended for large low-dimensional datasets (Hsu et al. 2003), but on this dataset the linear kernel did not yield satisfactory results. As such, the RBF kernel was retained for further development of the SVM algorithm. Ultimately, computational requirements of the SVM method proved a substantial hurdle in the algorithm development process.

Random Forests

A random forest classification approach was developed in tandem with the SVM in order to choose the most appropriate method for the AtlasV2 classification routine. Random forests are generally simpler than support vector machines, more interpretable, and far less computationally expensive. The random forest method is an ensemble technique wherein a classification decision is made by a collection of decision trees. Each decision tree within the random forest is composed of a branching structure which an observation traverses to reach a classification result. The final classification is determined by collective vote of all the decision trees in the forest.

To grow a decision tree, the training routine finds the feature and feature threshold value that best splits the training data into its constituent classes. Each node of the structure imposes this criterion which is used to determine which of the two emanating branches a data sample is subsequently passed to. This routine is repeated sequentially, finding the feature and threshold value that best splits the samples passed along by the previous step. For a decision tree classifier, the user must assigns the minimum number of samples required in a node to qualify for another split. When the decision process reaches this sufficiently terminal "leaf," the process is complete and the resulting classification is the vote that decision tree casts. A minimum leaf size of one was used for the AtlasV2 classifiers.

The training routine tests the accuracy gains with each available feature from a randomly permuted feature list order. To prevent overfitting and limit the correlation of the constituent decision trees, each tree is given random subsamples, of both the training data and the input data features, from which to build its structure. By choosing the number of features available to each decision tree, the user can tune the random forest to be more generalizable (fewer features available) or to be more fitted to the training dataset (more features available). The accepted rule of thumb for choosing the number of features available is the square root of the total number of features. Heuristic exploration completed on the Atlas training data confirmed that a classifier with a restricted number of features available to each decision tree performed better than a classifier with all features available to all decision trees.

Parameters for random forest classifiers include the number of decision trees in the random forest. More trees produce a more robust classifier up to a certain limit. Above that number, there is little to no accuracy gain with a higher number of trees. Once all of the decision trees are trained, each tree in the ensemble casts a vote for the classification of each land cover pixel. Because of the ensemble approach to random forest classification, one of the metrics available from the classified validation dataset is the fraction of trees that voted for a particular class. This provides additional information about the certainty of the classification, and by proxy, about distances between classes in feature space.

Another advantage of the random forest method is that the algorithm is robust to extra features, which accelerates the process of optimization. Extra features can be added without depressing accuracy results with the additional noise. Further, results from training a random forest classifier include a metric of importance of each feature included in the input data. These insights may inform mechanistic understandings of processes affecting land cover;

they can also further improvements in the RF algorithm development, and the development of other empirical or mechanistic models of land cover in the region.

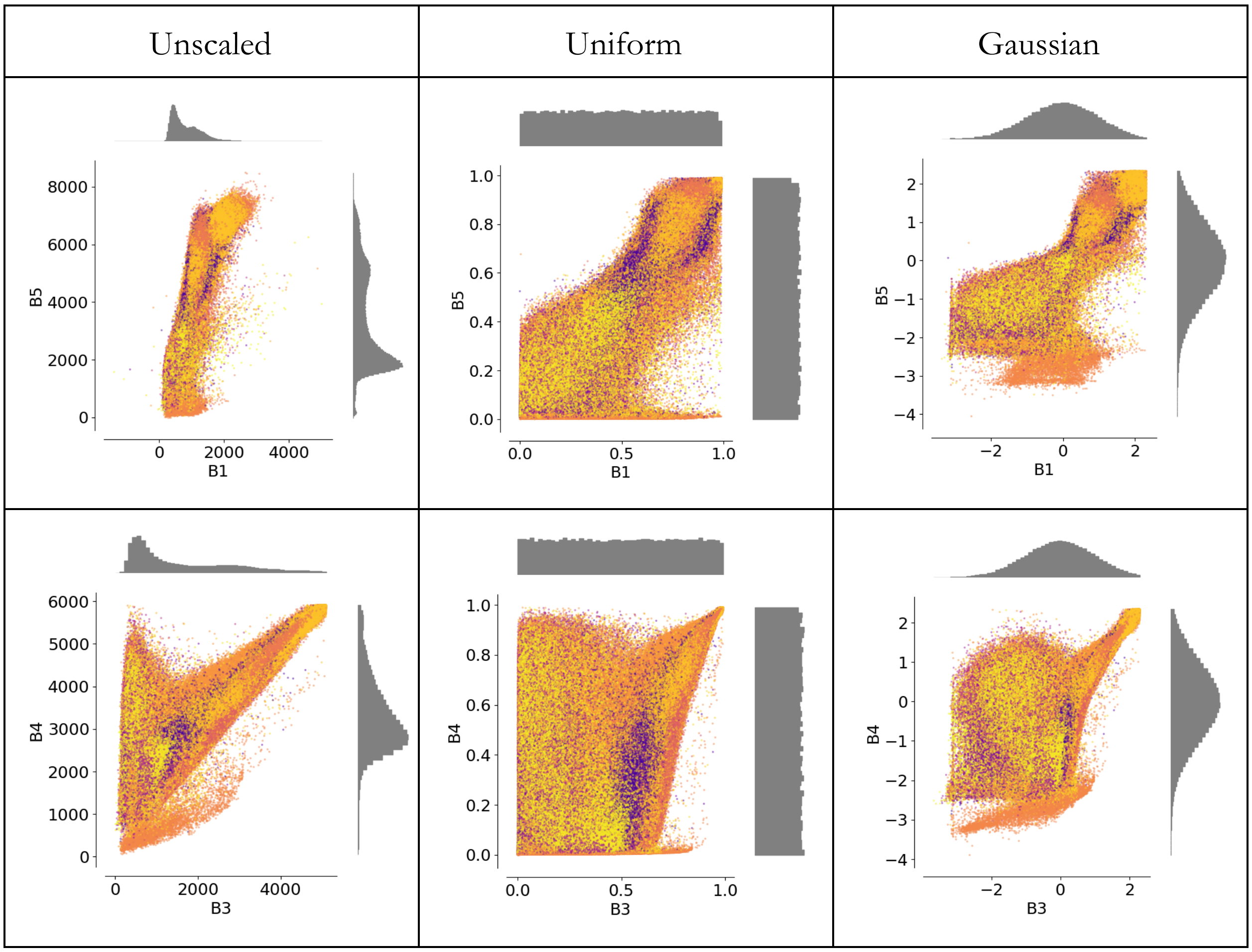
Detailed descriptions of decision trees and random forests, with a focus on their application to land cover classification can be found in the following: Friedl and Brodley 1997; DeFries and Chan 2000; Breiman 2001; Pal and Mather 2003; Pal 2005; Gislason et al. 2006; Rodriguez-Galiano et al. 2012; and Adam et al. 2014, among others.

While random forests are fast to train, simple, and interpretable, however, there are often trade-offs in accuracy, so for the V2 both SVM and RF approaches were developed, and each method evaluated for performance as applied to land cover classification in West Africa.

Data transformation

One technique for improving machine learning classification results is to transform the input data. Such transformation can improve data separability and computational tractability. Transformations can be applied either across feature space, or to input data features individually.

Figure 29. Linear, uniform and Gaussian transformations of two-dimensional projections of Landsat band feature space. Top row is band 4 vs. band 1. Bottom row is band 7 vs. band 2. Bands refer to wavelength ranges in Landsat 7 data.



For the SVM method, feature values must be scaled to unify their ranges. This prevents a feature having outsized influence on the classification simply because the values assigned to that feature are significantly larger than the other feature values. For the SVM algorithm, smaller feature values are more tractable. Both (-1,1) and (0,1) are good choices for the range to which all features are standardized. Note the importance of consistent scaling of a feature no matter the particular input data. Once scaling parameters are chosen to transform the input training data, those same parameters must be used for the classification data. With scaling parameters from the training data, the new data may fall slightly outside of the chosen feature value range. As long as the input data is all processed the same way, slight deviations from the specified value range do not pose a problem. The naïve method for transforming a feature to the unified value range is a simple linear scaling.

In the SVM method, additional data transformations can improve the skill of the classifier. The SVM transforms parameter space in order to draw hyperplanes separating classes. The transformation of input features can give the algorithm a head start. The figure shows the training data used here projected onto two dimensional space. The top row is the projection of band 1 and band 4 of Landsat data; the bottom row is the projection of band 2 and band 7. In the figure, each data observation is color-coded according to class membership. The left plot is the simple linear scaling, the middle is a uniform transformation, the right a Gaussian transformation. In the transformed data, for these particular projections with the uniform transformation, the data is distributed across the space and the groups of classes are more clearly differentiated even to the eye. A small-scale SVM classifier trained on transformed data produced overall precision scores of 0.570 for the untransformed (linearly scaled) data, 0.587 for the uniform transformed data, and 0.625 for the Gaussian transformed data; accuracy gain with the Gaussian transformation was a substantial 5.5%.

The user must consider, however, that different machine learning algorithms respond differently to data transformations. The SVM algorithm finds continuous hyperplanes in transformed feature space, while the random forest makes linear slices in feature space with decreasing increment size. These differences in methodology for separating data into classes and different levels of sensitivity can mean that data transformation is not universally a useful technique to improve classification skill. The random forest method, for example, when trained on the same input data transformations, shows no significant improvement in accuracy.

Training

Bottlenecks

In the methodology development process, factors associated with training bottlenecks included the size of the dataset, heuristic algorithm development, and parameter optimization. Minimum and maximum requirements for training dataset size were influenced by several factors: which machine learning technique was used, model parameterization and customization (e.g. what kernel used for SVM), noise present in the training data, and features of the training data itself. Even subsetting the 1.2M observations, each iteration of

SVM training incurred heavy computational cost. Ultimately, computational time was the dominant bottleneck for development of the SVM process. In contrast, the computational tractability of the random forest algorithm (even on the full dataset) allowed for far more flexibility in the model development process.

One of the key challenges for model development was the parameter optimization process. This proved prohibitively expensive for the SVM algorithm, while the RF was well-suited to a complete exploration of parameter space. The RBF kernel used for the SVM has relatively few parameters, a distance of influence metric (gamma) and a cost for misclassification (C). A methodical grid search of parameter space was conducted, training with all pairings of parameters in 2^{n+2} increments. To prevent overfitting, each parameter pair was tested with 5-fold cross-validation. This parameter optimization procedure, while thorough, required many iterations of algorithm training. That, combined with the resource-intensive nature of the SVM algorithm, meant that a complete search of parameter space was not a tractable task. As a result, only an under-optimized algorithm was possible, failing to capture potential accuracy gains from better parameterization.

The poor tractability of SVM proved an insurmountable barrier to its use in a significantly heuristic development process. Development, aiming to design a complete classification pipeline for a dataset and a region that had never before been successfully analyzed with machine learning classification techniques, included many heuristic components. Examination of classification results was followed by iterative attempts to improve the results. This included exploring feature design, data pre-processing, and data sub-setting methodologies. The high overhead required by the SVM algorithm restricted capacity for testing different solutions, while the RF was well-suited to this sort of heuristic development process.

Training data size

One of the methodological variations tested for accuracy improvements was training on subsets of the available data. For the SVM method, this approach arose from tractability limitations, which were present even when the training was executed with cluster computing. To create a reasonably tractable training routine, the full domain dataset was randomly sampled to provide a training subset for the SVM routine. The computational requirements of SVM limited this subset to no more than 20% of the total data region-wide. Classifiers trained on 10% and 20% of the full dataset performed with accuracies no better than 0.440. Because the random forest method can accommodate training datasets on the order of at least 10^6, it enabled a classifier to train on the entire West Africa domain. This single algorithm was then used to classify LULC across the region.

Spatial scale

In another approach tested for its ability to improve classifier accuracy, multiple classifiers were trained on multiple, smaller domains within West Africa. This technique reduced the number of training observations for each classifier, which had the potential to detract from their accuracy. In this process, however, classifiers on smaller domains performed better than classifiers on larger domains. 4-degree, 2-degree, and 0.5-degree zones were tested; locally-specific and spatially coherent classifiers performed better than classifiers for larger regions using both SVM and RF. The improved accuracy of these smaller-scale classifiers supports the spatial heterogeneity of land cover class appearance across West Africa, which is one of the reasons cited that machine learning or algorithmic approaches to land cover classification generally perform poorly in the Sahel. Training multiple small classifiers addressed this challenge.

Figure 30. Zone size map.

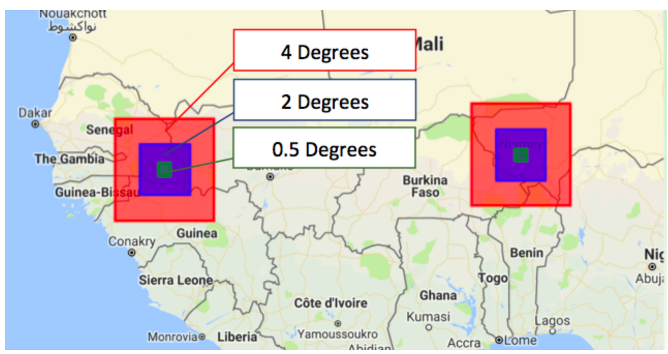
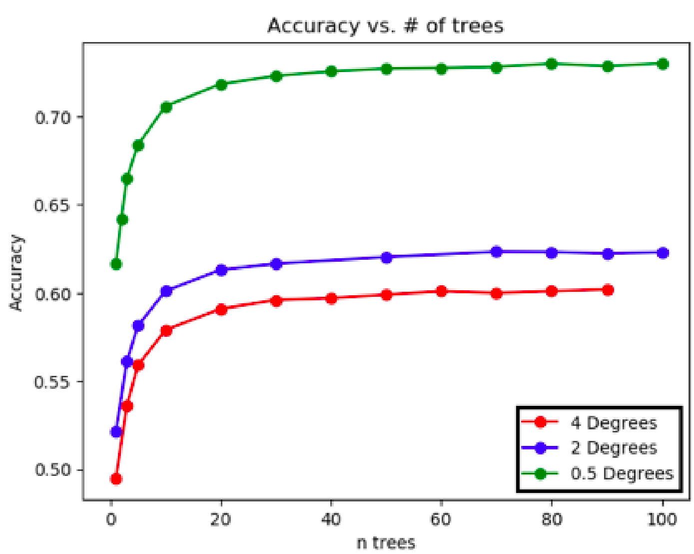


Figure 31. Accuracy vs. number of trees by grid cell size.



Results and discussion

Table 4. Best SVM model accuracy table.

	precision	recall	f1-score	support
Forest	0.409	0.180	0.250	100
Savanna	0.666	0.830	0.739	20152
Floodplain	0.600	0.371	0.459	2080
Steppe	0.735	0.810	0.771	17196
Plantation	0.478	0.062	0.109	178
Mangrove	0.757	0.750	0.754	208
Agriculture	0.701	0.707	0.704	20128
Water	0.804	0.699	0.748	545
Sandy area	0.820	0.698	0.754	3338
Rocky land	0.689	0.475	0.562	1262
Bare soil	0.609	0.452	0.519	2190
Settlements	0.639	0.202	0.307	341
Irrigated ag.	0.562	0.269	0.364	402
Gallery for.	0.303	0.007	0.014	1370
Degraded for.	0.643	0.138	0.228	65
Bowe	0.629	0.272	0.380	1384
Thicket	0.346	0.138	0.198	65
Recession ag.	0.496	0.182	0.266	385
Woodland	0.541	0.153	0.238	1290
Swamp for.	0.417	0.147	0.217	68
Short grass	0.738	0.710	0.724	9910
Herbaceous sav.	0.585	0.169	0.262	142
Open mine	0.500	0.400	0.444	5
avg / total	0.691	0.701	0.685	82804

In this project, SVMs were found to be sensitive to input data variation and parameter optimization. Additional tuning refinements could potentially increase the accuracy of the classifier; however, these refinements, whether systematic or heuristic, were prohibitively expensive in computing resources and time. SVMs tend to perform best on smaller training datasets. Even working with half-degree zones, however, the SVM training routine was computationally intractable on this dataset. Thus SVMs, while successful in some applications to land cover classification, were ill-suited for this project.

Table 5. Best RF model accuracy table.

	precision	recall	f1-score	support
Forest	0.58140	0.18657	0.28249	134
Savanna	0.71482	0.86072	0.78101	68049
Floodplain	0.64367	0.42863	0.51459	7118
Steppe	0.76179	0.82989	0.79438	67058
Plantation	0.62500	0.10802	0.18421	324
Mangrove	0.79775	0.81143	0.80453	700
Agriculture	0.70947	0.70494	0.70720	59656
Water	0.83029	0.66746	0.74002	2111
Sandy area	0.84073	0.75327	0.79460	13006
Rocky land	0.73205	0.52807	0.61355	4827
Bare soil	0.65918	0.50598	0.57251	8696
Settlements	0.75904	0.17166	0.28000	1101
Irrigated ag.	0.64238	0.32199	0.42897	1205
Gallery for.	0.53250	0.04821	0.08842	4418
Degraded for.	0.50000	0.13636	0.21429	22
Bowe	0.66180	0.31882	0.43033	4548
Thicket	0.44737	0.21795	0.29310	78
Recession ag.	0.63652	0.29829	0.40622	1227
Woodland	0.61831	0.22461	0.32952	3397
Swamp for.	0.57143	0.17508	0.26804	297
Short grass	0.76588	0.75530	0.76055	40600
Herbaceous sav.	0.61538	0.32653	0.42667	343
Open mine	0.66667	0.16667	0.26667	24
avg / total	0.72962	0.73487	0.72228	288939

Random forests are much simpler and faster than SVMs. Although random forests tend to be less accurate than SVM models under optimal circumstances, in this work they were more suited to iterative model development. With the tractability limitations on how well and how quickly an SVM model can be optimized, even a preliminary random forest model of LULC change in West Africa has comparable accuracy to the best-model SVM that was found. The ease of training opened more opportunities for heuristic improvements of the RF model.

Because the random forest method is computationally inexpensive and relatively robust to input data processing, it was much more suited to an application for which future sustainability is important. The full algorithm development pipeline can feasibly be implemented on Earth Engine, ensuring wider access to the method and availability for future use and improvements. The algorithm development procedure can be easily changed, a flexibility that has potential applications for adaptation to specific use-cases or other data sources. Further, this implementation allows for the possibility of the classification methodology to be adapted and used for other parts of the world and with other training datasets.

The development of the machine learning classification of land cover in West Africa yields two major methodological insights, one on algorithm choice and one on training data subsetting. The results of the paired SVM and RF classifier development add to the existing literature on algorithm choice for land cover classification. For the AtlasV2 application, the flexibility and tractability of the random forest outweighs the customizability of the support vector machine algorithm. This finding supports the use of random forests for land cover classification. The result of the impact of zone size on classification accuracy also has implications for machine learning land cover classification applications more broadly. Improved classifier performance with smaller spatial domains highlights the importance of variations across space in the relationships of input features to land cover class. In the AtlasV2 setting, this spatial heterogeneity effect outweighs any positive effects of providing larger datasets to the training routine. For land cover classification applications more broadly, this result establishes the importance of considering spatial domain in the design of machine learning classification algorithms.

Chapter Three.
Future Work and Next Steps for Land Cover Classification

Introduction

The dataset presented here is best described as a first working version of this product, a version zero. There remain many possibilities for improving and extending the dataset, these methods and development pipelines, and their accompanying capabilities. This future work includes classification improvements, additional analyses, comparisons with other land cover datasets, and extending user collaboration and applications.

Input data processing

Improvements of the land cover classification are possible for every component of the data classification pipeline. The first stage of the pipeline is the development of the feature library. Version zero used Landsat 7 bands, CHIRPS precipitation, and SRTM topography data, and these input data required preprocessing to be useful as components of the feature library. Scenes were selected from a chosen season, filtered for clouds and saturated pixels, and the median value per pixel of all the remaining scenes in the relevant time range was taken. This procedure, while sufficient to achieve the accuracies in the version zero product, can be modified for additional potential improvements in accuracy.

As an example, the composite imagery is not currently corrected for the scan lines present in Landsat 7 data. While the current compositing procedure smooths out much of the scan line error, some artifacts still appear in the resulting land cover data set. These scan line artifacts usually manifest as erroneous land cover classification in the spatial pattern of the scan lines. Future work includes addressing the scan lines at the data preprocessing stage. The cloud masking method is another area where modification of the methodology may improve results: a custom built cloud detection procedure may improve the resulting composite.

The version zero data set was built from three-year composites of landsat seven. Future work includes training classifiers for the other landsat campaigns. Note that because Atlas maps address 1975, 2000, and 2013, they can be used to train classifiers that span the full time period of Landsat campaigns, 1972 to present.

Table 6. This table details the base map/training data/time period combinations.

Training	Basemap	Classified Time Span
Atlas 1975	LS1	1972-1978
Atlas 1975	LS2	1975-1983
Atlas 2000	LS5	1984-2012
Atlas 2000	LS7	1999-present
Atlas 2013	LS7	1999-present
Atlas 2013	LS8	2013-present
ESA20m (2016)	LS7/8	1999-present
ESA20m (2016)	S2	2013/14-present

New high resolution satellite data and the publication of other land cover data sets for Africa, e.g. the European Space Agency (ESA) 20 m product (ESA CCI Land Cover Project 2017) and the Malaria Elimination Initiative land cover map (Midekisa et al. 2017), provide other opportunities for the use of the new data set and algorithm development pipeline. The 2016 V2 map can be compared with both the ESA 20 m LULC product and ESA 20 m training data set. Comparing the data sets will identify locations and characteristics of data set agreement. This information informs the development of both the V2 and the ESA products. The classification pipeline can build a LULC dataset using Landsat 7 and 8 as the base map and the ESA 20 m data set (full map and/or ESA training data) as training data. These data sets can then be compared with both the original V2 data sets and with the Atlas 2000 and 2013 maps. A V2 data set built with Sentinel as the base map and training on ESA 20 m will allow comparison of the V2 and ESA algorithms and methods, and extend the ESA 20 m dataset to the full range of Sentinel (2013/14 to present).

Feature Development

As discussed, random forests are robust to superfluous features and easily scalable for a data set with many features, and this flexibility supports heuristic addition of features to the library in pursuit of higher classification accuracies. Future feature exploration could include additional data, such as temperature and higher tier products derived from Landsat data (e.g. NDVI, EVI, SAVI, NDMI, NBR)[1], as well as transformations or combinations of existing features. Further, because land cover evolves continuously in time, including system memory features may be advantageous. This would entail, for example, including last year's rainfall as

[1] NDVI: Normalized Difference Vegetation Index
EVI: Enhanced Vegetation Index
SAVI: Soil Adjusted Vegetation Index
NDMI: Normalized Difference Moisture Index
NBR: Normalized Burn Ratio

a feature for the current year's classification. Another way to include temporal components in a future library would be the use data from multiple seasons. The current product includes information for two seasons (April and October), and future work could expand upon this, including data from the entire year divided into any number of seasons.

The limitation on adding information to feature collection comes not from the random forest algorithm, but from data input/output requirements to port the training classification from Google Earth Engine to Savio. Intended future improvements to Earth Engine implementation of the random forest training and classification will aim to make the entire pipeline feasible at full-scale on Earth Engine, obviating these data input/output limitations.

Algorithm Improvements

Areas of focus for algorithm improvements include regional classifier performance, tailoring for specific use cases, and zone edge smoothing. At the regional scale, one of the major challenges for land cover classification is obtaining sufficient imagery for the Gulf of Guinea coastal regions. These areas receive high annual rainfall, spread out over much of the year, during which time they appear cloudy and no Landsat data can be collected for surface reflectance. The current AtlasV2 dataset does not include these coastal regions, because the random forest method required that all included features have no missing data; due to the spotty Landsat imagery, classifications there were not accurate enough to be useful. Creating a skillful classifier for the cloudy southern regions will require a more innovative approach. The V2 pipeline has a key and powerful characteristic: classification routines come not from a single region-wide classifier, but from a collection of small scale (0.5 degree) classifiers, and the feature libraries for these 0.5° zones do not have to be identical. This means that a smart feature selection protocol could be implemented. A master feature library would be created, one which includes all of the potentially useful features, even if these do not appear in all zones. Each individual zone would check which of those features have no missing data in that zone, and then only those features would then be included in the feature library for that zone. This would allow each zone to implement its custom feature library, without constraining the features available to a region-wide common denominator.

Other algorithm improvements include tailoring for specific use cases. In the development of an algorithm, choices are made to maximize the performance of the classifier. The evaluation of what constitutes good "performance," however, is determined by the priorities of the user. This version zero product was shaped by interest in aggregate precision squares, with attention to the agriculture class in particular. Other use cases might prioritize recall, or accuracy of a different class. These priorities affect decisions made along a heuristic development pathway; different use cases may call for significantly different choices. The future work here is would not be about developing an algorithm for predetermined use cases, but about making the algorithm development pipeline transparent and accessible.

Users could then create custom algorithms and data sets optimized for specific use cases.

Edge effects are another area in which future development stands to greatly improve the V2 product. Each 0.5° zone classifier was trained on the Atlas data contained by the zone boundaries. As such, the training data for a zone only included the classes that were present in that particular zone in the 2000 and/or 2013 Atlas maps. Land cover change dynamics, however, do not neatly match the boundaries of these classifier zones. For example, a land cover class that had never appeared in a particular zone can begin to populate that zone as time goes by. If the zone's classification algorithm had not seen land cover of that class in its training process, the algorithm will not know how to classify the new land cover type, or even that this class of land cover exists at all. This difficulty is also present in cases where the classification algorithm has little (instead of no) information about that class.

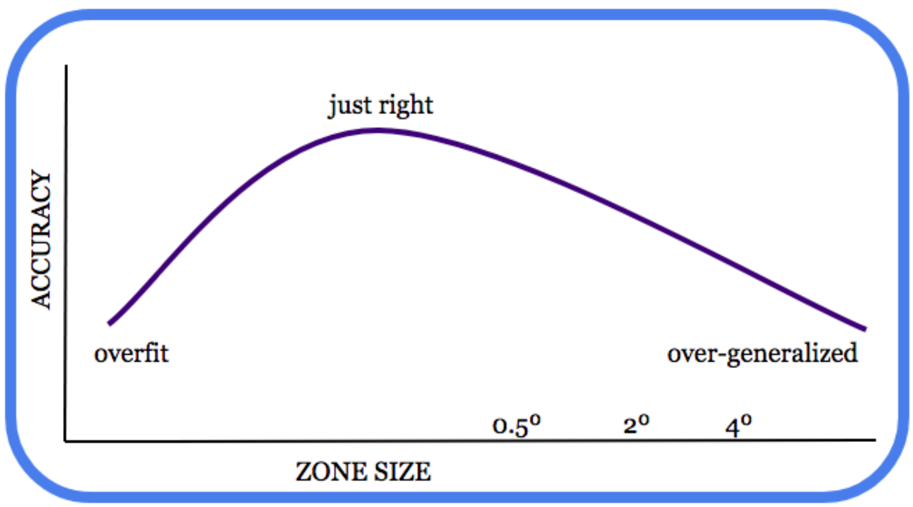
Along the western and Southern boundaries of the LULC map, the coastline cuts through the regular zone grid such that some zones are only partially covered by land, with the remainder covered by ocean. In this situation, the coastal edge zone has less information from which to draw on to learn to classify the land surface. This exacerbates difficulties with identifying land cover classes that were scarce or nonexistent in the zone's training data. The first kind of edge effect (call it "landlocked" edge effects) reveals a trade off between locally specific classifiers versus widely generalizable classifiers. Zone size accuracy testing indicated that 0.5° zones perform better than the larger zones, which suggests a need for methods to smooth edge effects without losing the local specificity of the classifiers. Larger zones might smooth edge effects, but would sacrifice accuracy in the process.

The edge smoothing method currently implemented is a local kernel technique. The classifier for each zone is trained on data from the surrounding eight zones. The information from the surrounding zones is incorporated into the classifier, which then remains responsible for classifying only the single center zone. This technique does improve the edge effects of the final region-wide classification. Note that the overall accuracy of the region-wide classification is not substantially different with and without this local kernel implementation. This is a good example of use case based design priorities. How important is reducing edge effects versus improving region-wide accuracy? Work remains to be done exploring the parameterization of the local kernel technique in pursuit of further improvements in zone edge effects. Parameterizations include the shape of the kernel function as well as its width. Currently the kernel is uniform in shape with a width of one zone. Other possibilities include a Gaussian kernel with a wider sphere of influence, or a dynamic box size.

For coastal regions, a more custom approach will be necessary. The superposition of the coastline on the regular zone grid results in zones only partially covered by land surface pixels, with water in the remaining area. This limits the land surface information available for training the classifier. Issues arise when the classifier can distinguish differences in land cover type but does not necessarily have the land cover class vocabulary to accurately assign the classes. Performance in the coastal regions, therefore, might be improved by redistributing pixels from partial coverage zones. Land cover data from partial coverage zones could be reassigned to nearby more complete zones. Alternately, partial coverage zones could be pooled together to form aggregate coastal zones with approximately the same number of pixels has the 0.5° zones.

These edge effect techniques are part of a broader future exploration of zonation methodology. Classifiers trained on zones of three different sizes were tested for region-wide accuracy; those trained on 0.5° zones, the smallest tested, performed best. Presumably, were increasingly small training zones to be tested, further accuracy gains would at some point be offset by overfitting effects. A peak of this accuracy plot has not yet been identified, and further exploration of smaller zones is warranted.

Figure 32. Schematic of accuracy vs. zone size: overfit; just right; over generalized.



Other methods for assigning zone boundaries might benefit region-wide accuracy or be well suited to particular use cases or applications. Zones may be assigned by eco-region, by country (to capture Atlas technician differences), or by areas of different agricultural practices.

Analysis

The analysis of the V2 results that was presented in the previous chapter represents only a fraction of the exploration possible with this rich source of new information. Much work remains to be done, and many new analyses will be possible because of this dataset; only a few are detailed below.

The dataset captures class transitions on an annual 3-year smoothed timescale. For the first time, therefore, it is possible to look at the character, conditions and predictors for land cover class transitions. Another step in the analysis of land cover change in this data set is exploring alternate methods for determining significance thresholds for land cover class transitions. The conversion volatility maps presented here are filtered by a tree agreement parameter, described in chapter one. Future analysis could include finer grained examination of conversion type (what class a pixel is converting from or to). Establishing significance for this analysis might include conducting a conversion analysis on spatially shuffled data, for example. Further, a Monte Carlo type approach to classifier training will provide an indication of the stability and significance of the land cover maps and accuracy values.

The AtlasV2 LULC data set was built on a feature library that included spectral landsat data, which enabled analysis of classification topology and spectral signatures by land cover class. The land cover class schema utilized in the Atlas dataset was chosen based on both the land cover types present in the region and the class distinctions which are useful to researchers, land managers, and decision-makers in the region. This mapping is related but not identical to the topological structure present in the distribution of land cover data in feature hyperspace. Mapping the land cover data into features space (or two dimensional eigenvector space) may provide insight on classification challenges and on the classes themselves. Proximity or overlap of classes, for example, can indicate classification challenges and inform addition of other distinguishing features. A focus on mapping the land cover data into Landsat band space specifically may yield insight useful for the broader research questions on remote-sensing land cover in the region.

Projecting the data into spectral space can aid in the development of a spectral library for each land cover type. While earlier or more general attempts to classify land cover in the region based on spectral signature have been unsuccessful, AtlasV2 data allow us to make advances in this vein. The map of agriculture in spectral hyperspace may show more or less coherence around a particular spectral signature that characterizes agriculture. The spectral mapping might show sub-groupings that could indicate different types of agriculture. Further, because a full time series is now available for land cover data, a shift in the spectral characteristics of agriculture may be discernible over time. The knowledge that more locally specific classifiers are more accurate than regional classifiers indicates that a land cover type spectral library should be similarly localized. Through a combination of visual map inspection, geographic spatial organization and an evaluation of the tightness of class grouping in spectral space, it may be possible to identify localized spectral signatures for different land cover classes. Depending on the separability of land cover classes based on spectral signature, spectral unmixing may be a feasible way to identify land cover at a sub-30 m scale.

User Collaboration

Future improvements and extensions of this data set and platform hinge on the ongoing collaboration with users of the data set. Possibilities include: the development of a custom user interface with built-in analysis functions; and/or the development of a customizable algorithm training and classification platform. The data set development platform is designed to be modular such that it can be adapted for other basemaps, other training data sets and for other regions in the world. Applications for the data set reach far beyond purely environmental concerns. Land cover data represents landscape characteristics and spatial organization and is also an indicator of people in space. This information has disease eradication applications. The locations of settlements and agricultural fields can help identify for example, how malaria moves across the landscape into different populations in Burkina; for where health workers should target ebola vaccination efforts in central Africa.

The identification of ephemeral water bodies can guide pastoralists in need of water sources for their animals. The location of land cover conditions favorable to Locust ovopositioning can inform pest control efforts to avoid famine. Land cover dynamics affect flood risk and agricultural stability. Information on these dynamics can inform land management decision-making.

The needs and priorities of the end users will guide the future development of this dataset and platform. It is likely that the most important features for future development are not anticipated here without detailed and ongoing inputs from the researchers, land managers and decision-makers in the region. This is the crux of the endeavor. The data set is possible because of years of discussion, review, decision-making and labor of experts in the region. The goal of the project described herein is to build on these efforts, creating a tool that can be adapted for myriad applications.

Chapter Four.
Seasonality and Spatial Patterns of Sahelian Rainfall

Introduction

The past twenty-five years have seen a major shift in Sahelian rainfall. A decades-long drought has given way to some recovery of annual precipitation, but with changes in interannual and seasonal characteristics of rainfall (Giannini et al. 2016; Janicot et al. 2011; Lafore et al. 2016). Studies on recent interannual rainfall trends in the Sahel point toward increased annual variability, continued deficit of number of rainy days, and a possible increase in rainfall intensity (Sanogo et al. 2015; Panthou, Vischel & Lebel 2014; Ly et al. 2013; Nicholson 2013). These trends are subject to high spatial variability of rainfall, and there is limited consensus on long-term rainfall trends, especially with regard to annual precipitation totals (Biasutti 2013; Joly et al. 2007; Biasutti & Giannini 2006; Cook & Vizy 2006; Douville et al. 2006). Through the "upped-ante" mechanism, climate models predict a delay in the onset of the rainy season in the West African Sahel and a subsequent shortening of the rainy season (Neelin et al. 2003; Chou & Neelin 2004; Sobel & Camargo 2010; Chou et al. 2001; Biasutti & Sobel 2009; Biasutti 2013). After providing background on precipitation in the Sahel, this chapter analyzes small-scale rain gauge data for seasonal trends present in the recent rainfall record. Then follows a large-scale spatial analysis of rainfall over the region with an analysis of seasonality and annual precipitation. The last section compares precipitation products for their spatially explicit representation of seasonality trends.

Background

The first half of the 20th century is described as a wet period in the record of annual precipitation in the West African Sahel. The late 1960s, however, marked the onset of a decades long severe drought in the region (Lamb 1982; Nicholson 1983; Katz and Glantz 1986; Hulme 2001; Dai et al. 2004; Trenberth et al. 2007; Greene et al. 2009; Nicholson 2018). For the next 35 years, climate scientists debated the cause of the drought—the largest change in climate anywhere in the world over the entirety of the 20th century (Giannini 2016).

Narratives about the effects of agriculture and pastoralism shape perspectives on the culpability of local people for negative changes in climate and land cover change. In 1975, Charney, a meteorologist, proposed that the catastrophic region-wide drought that began in 1968 was the result of soil denuding caused by overgrazing (Charney et al. 1975). He suggested that a biophysical coupling between the land surface and climate could be the mechanism driving the drought. A reduction in vegetation would lead to an increase in albedo; the land surface and the boundary layer atmosphere would be relatively cooler and convection therefore suppressed. Charney acknowledged the limitations of the then-current climate modeling. He noted that this local suppression of convection would eventually be overwhelmed by larger-scale climate dynamics returning the system to equilibrium (Charney et al. 1977). In the decades since, subsequent modeling studies have confirmed the plausibility of such a biophysical feedback, but the reduction in rainfall exhibited in the modeling studies is only ~25-50% of the total observed reduction in rainfall during the drought (Taylor et al. 2002).

In parallel, beginning with the work of Folland et al. (1986), modeling studies were used to investigate the possible role of the oceans in the Sahel drought. It was not until 2003 that the dominant role of the oceans in the drought was confirmed, though land-atmosphere feedbacks (Giannini 2003).

Since the mid 1990s, annual rainfall in the Sahel has shown signs of return to higher levels, but with increased interannual variability (e.g. Loudoun et al. 2013; Nicholson 2013; Nicholson 2005; Ali & Lebel 2009; Salack et al. 2011). Increases in annual rainfall have not been uniform across the region; the Central Sahel has seen more rainfall recovery than the far west regions (Lebel & Ali 2009). Further, seasonal rainfall is characterized by fewer more intense rainstorms than in previous periods (Ly et al. 2013; Sanogo et al. 2015; Panthou et al. 2014; Lebel et al. 2003).

Precipitation patterns in West Africa are the combination of synoptic, meso, and local scale dynamics with a strong north-south gradient from wet forest ecosystems on the southern coast to arid steppe landscapes at the edge of the Saharan desert. At the synoptic scale, annual shifts in the position of the intertropical convergence zone bring monsoon precipitation northward to the West African Sahel in the boreal summer. This band of precipitation then retreats back to the south with the advance of the fall equinox (overviews of the West African Monsoon can be found in, e.g.: Lafore et al. 2016; Nicholson 2013; Janicot et al. 2011; Cappelaere et al. 2009; Louvet et al. 2003; Sultan & Janicot 2003). This annual procession of the monsoon rains creates a single peaked climatology in the Sahel with maximum precipitation in August. Southern coastal regions experience a double-peaked precipitation climatology as the monsoon rains pass by on their north-south transit.

In the Sahel, seasonal precipitation is marked by an onset period in April to May, a plateau in rainfall in June followed by a jump to peak precipitation amounts in August, and a quick decline through September and August (e.g. Sultan & Janicot 2003; Thorncroft et al. 2011, Louvet et al. 2003). At mesoscales, West African precipitation dynamics include squall lines that propagate east to west (e.g. Cappelaere et al. 2009). Finally, West Africa is one of the regions of the world with the strongest land-atmosphere couplings (Koster et al. 2004; Zeng et al. 1999; Findel et al. 2009). Vegetation and soil moisture impact local convection such that local precipitation can vary as much as 30 mm/km, far outstripping the general north-south gradient of 1 mm/km (Lebel et al. 2009; Lebel et al. 1997). Soil moisture evaporation contributes to local atmospheric water content and supports local convective activity such that "wet get wetter" (Lebel et al. 2009; Taylor et al. 2010).

After decades of work investigating possible causes of the variability of Sahelian precipitation, there is general agreement on relevant factors. The major contributors to changes in precipitation in the Sahel is sea surface temperature (SST) dynamics. Sahelian precipitation is influenced by local conditions and global teleconnections. SST dynamics that have been shown to influence rainfall in the Sahel include: interhemispheric SST gradients (Hurrell et al. 2006; Knight et al. 2006; Kang et al. 2009); the Atlantic Multidecadal Oscillation (Kushnir 1994; Enfield & Mestas-Nuñez 1999; Mann & Emanuel 2006); difference between SSTs in the North Atlantic and the global tropics (Giannini et al. 2003; Giannini et al. 2013); the Gulf of Guinea (Lamb 1978a, b; Nicholson 1980, 1981; Fontaine et al. 1998; Vizy & Cook 2001, 2002; Losada et al. 2010); the Indian Ocean (Giannini et al. 2003; Bader & Latif 2003; Kerr 2003); and the El Niño Southern Oscillation (Joly et al. 2007). Greenhouse gasses have been shown to affect precipitation in the Sahel through both direct mechanisms (atmospheric warming) and indirect mechanisms (SST warming) (Biasutti & Sobel 2009). Anthropogenic sulfate aerosols have also been shown to have an effect, through cooling of the North Atlantic (Rotstayn & Lohmann 2002; Chang et al. 2011; Chiang et al 2013). The drought in the Sahel corresponded to an uptick in the warming trend of the Indian Ocean (Du & Xie 2008). Further, sulfate aerosol emissions were rising in the northern hemisphere, producing a cooling effect in the North Atlantic, until the mid 1980s when legislation was introduced to curb emissions connected to acid rain in Europe and North America (Chang et al. 2011; Booth et al. 2012).

The influences of SST and atmospheric warming on Sahelian precipitation are now thought to be related to moisture transport and atmospheric stabilization (Giannini et al. 2013; Neelin et al. 2003; Chou & Neelin 2004). Top of atmosphere (TOA) warming through greenhouse gas effects combined with large scale TOA warming from local deep convection stabilizes the atmospheric column (Chou & Neelin 2004; Yang et al. 2003; Sugi & Yoshimura 2004). This creates an "upped ante" for convection (Neelin et al. 2003; Chou & Neelin 2004; Sobel & Camargo 2010; Chou et al. 2001). With sufficient moisture advection, this higher threshold can be overcome and convection can occur (Giannini et al. 2013). SST gradients in the North Atlantic, Gulf of Guinea, Indian Ocean and global tropics all influence moisture advection into the West African monsoon system (Giannini et al. 2013; Biasutti et al. 2008). Variability in these factors, such as the cooling of the North Atlantic with the Atlantic Multidecadal Oscillation (AMO), contribute to the interannual variability of total precipitation in West Africa (Knight et al. 2006; Ting et al. 2009). The increased convection threshold which is overcome by increased moisture at the boundary layer creates fewer more intense storms, as observed in recent years in the Sahel (West et al. 2008; Salack et al. 2011; Lodoun et al. 2013; Lebel et al. 2003).

Climate model projections generally do not agree on the effects of continued climate change on Sahelian annual precipitation, so much so that the sign of projected precipitation change is uncertain (Biasutti & Giannini 2006; Cook & Vizy 2006; Douville et al. 2006; Joly et al. 2007; Biasutti 2013; Roehrig et al. 2013; Tian & Peters-Lidard 2010). There is agreement, however, in the projections of seasonal precipitation dynamics. Models agree on delay and shortening of rain season (Biasutti & Sobel 2009; Biasutti 2013). This is in keeping with the "upped ante" mechanism wherein it takes longer into the summer to generate the boundary layer moisture necessary for convection (Giannini et al. 2013; Biasutti & Sobel 2009; Seth et al. 2011). It has yet to be shown, however, if this delayed season appears in observational data.

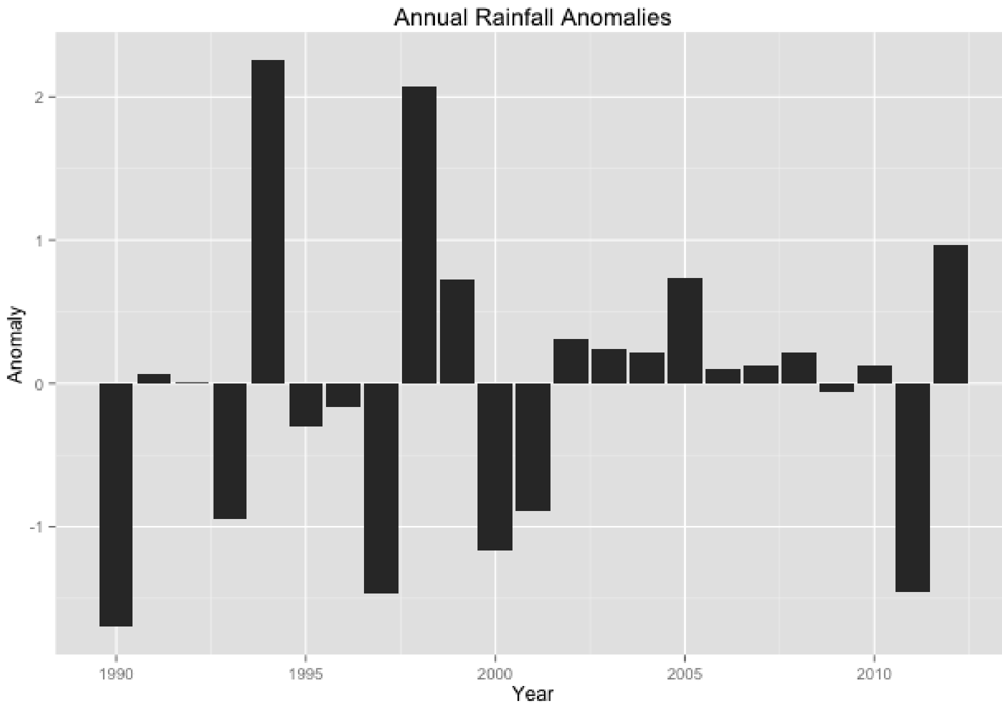
In light of the complexity of climate dynamics in the Sahel, this chapter undertakes an analysis of Sahelian precipitation through an array of methods and at a range of spatial scales.

Small-scale rain gauge data

The African Monsoon Multidisciplinary Analysis - Coupling the Tropical Atmosphere and the Hydrological Cycle (AMMA-CATCH) project provides an uncommon opportunity to use high frequency observational data to examine how rainfall patterns in the Niamey area of Niger have changed over the past two decades (Lebel et al. 2010; Cappelaere et al. 2009). The gauge-based rainfall dataset collected at the Niamey mesosite of the AMMA project covers the period 1992-2012 for a single degree box southeast of Niamey. This is a direct-observation dataset, without the errors particular to higher-order satellite products. The trade-off of course, is spatial coverage.

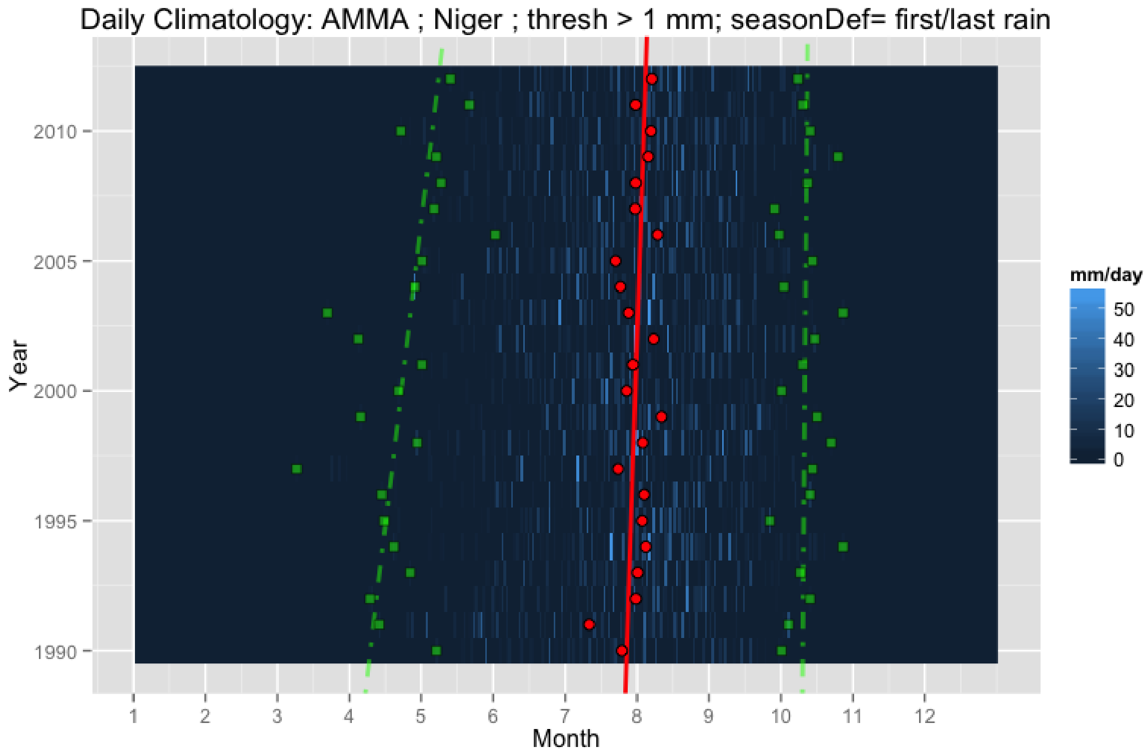
The dataset analyzed here is a relatively high resolution gridded precipitation product derived from rain gauge data using eulerian block kriging with a climatological variogram. The data runs from 1990-2012 at 3 hourly resolution and covers the area bounded by 13-14 degrees latitude and 1.5-3 degrees longitude at 0.25 degree resolution, a continuous time series for 24 grid cells.

Figure 33. AMMA-Niger annual precipitation anomalies.



AMMA annual rainfall anomalies for this time period show high temporal variability with respect to wet and dry years. To further investigate changes in the structure of the rainy season through time, daily precipitation is plotted in three dimensional space, with year on the y-axis, day of year (DoY) on the x-axis, and precipitation represented by color. This allows visual evaluation of changes in the annual distribution of rainfall over time.

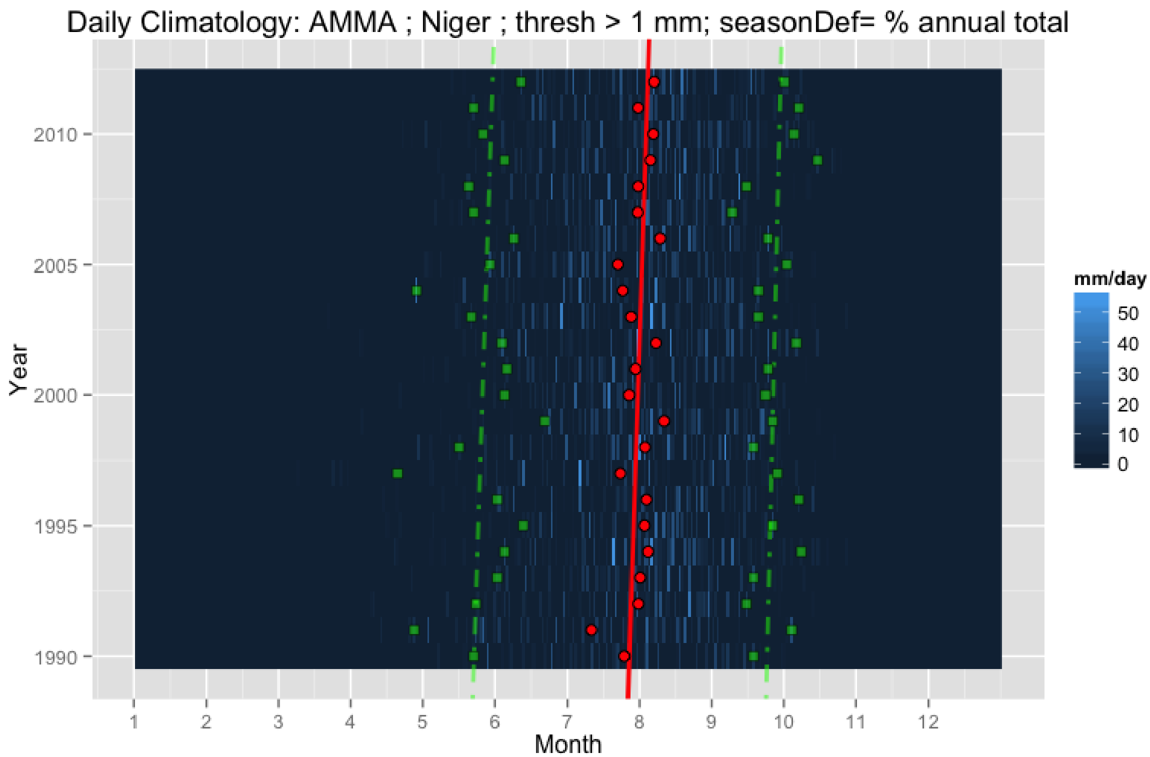
Figure 34. AMMA-Niger seasonal rainfall trends. Rainy season beginning and end, defined as first and last rainfall thresholded at 1mm, are plotted in green with a dashed green linear fit line. DoY means are plotted with red dots and an accompanying linear fit line. The slopes (in change of DoY per year) along with p-values are shown in the table below.



Trends	Onset	MidPoint	End
Definition	FirstRain	Mean	LastRain
Slope	0.04291516	0.01169527	0.00269641
pValue	0.02469629	0.09988125	0.77805754

The slopes of all of these statistics are positive, indicating a shift in rainfall distribution toward later in the year, especially in the season onset. The shift in the onset of the rainy season (minimum) toward later is the season is the most significant, with a p-value of 0.02. The conclusions about seasonal trends, however, are sensitive to the definitions used for the start and end of the rainy season.

Figure 35. AMMA-Niger seasonal rainfall trends, rainfall data as above. Rainy season beginning and end, here defined as 3% and 97% of the cumulative distribution function, respectively, are plotted in green with dashed linear best fit lines. DoY means are plotted in red with accompanying linear best fit line. Slopes (in change of DoY per year) along with p-values are shown in the table below.



Trends	Onset	MidPoint	End
Definition	3 %_cdf	Mean	97 %_cdf
Slope	0.011825221	0.011695266	0.008576534
pValue	0.46147678	0.09988125	0.37954889

When the rainy season is defined as the time period between accumulation of 3% and 97% of the annual precipitation cumulative distribution function (CDF), the AMMA data do not show a significant trend in season onset. The sensitivity of trend detection to onset definition is potentially indicative of nuanced changes in rainfall characteristics, but with such a limited spatial domain there is not enough evidence to draw conclusions. Because the AMMA data are so limited in spatial extent, and the delay of the rainy season is hypothesized to be a large-scale phenomena, a spatially explicit approach is called for to examine large-scale seasonal and interannual precipitation patterns.

Spatially explicit analyses

Empirical orthogonal functions

It has been established that there is significant spatial variation in rainfall behavior within the Sahel region, calling for a spatially explicit approach to regional precipitation patterns (Lebel & Ali 2009). For this task, West Africa gauge-based precipitation data have prohibitive limitations in their spatial resolution and temporal continuity. Satellite precipitation observations offer spatial coverage, although the length of satellite records is somewhat limited. Tropical Rainfall Measuring Mission (TRMM) 3B42 precipitation data is widely used for the Sahel region and thus is used in this analysis as well (Kummerow et al. 1998). Discussed below are two approaches for analysis of spatial precipitation data: empirical orthogonal functions and self organizing mapping.

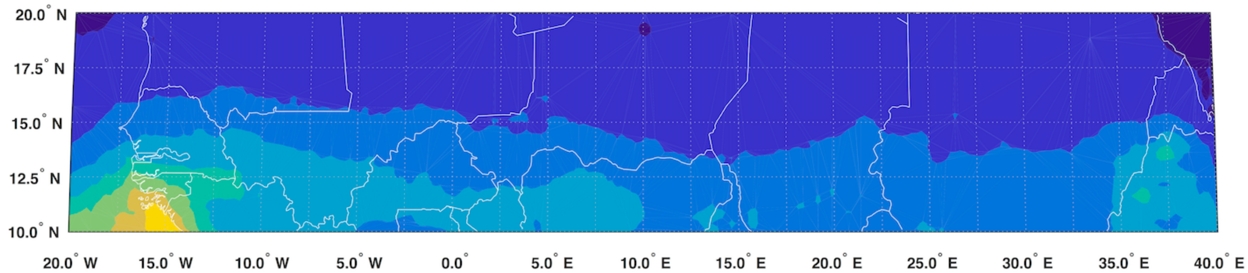
Empirical orthogonal function (EOF) analysis is a common tool for the analysis of spatial climatological patterns. An EOF analysis is a spatially weighted principal component analysis (PCA). As in PCA, EOF analysis identifies modes of variability that are orthonormal by eigenvector transformation. In other words, the modes of variability identified in an EOF analysis are by definition independent. While this design ensures the separability of the modes, in physical reality, modes of variability are not necessarily independent. As such, EOF modes represent constituent components of variability (building blocks of variability). The EOF modes themselves, however, do not necessarily represent any spatial pattern that occurs in the physical world.

Empirical orthogonal function (EOF) pattern identification is a traditional method for spatial analysis of climatological variables, but the method has a number of drawbacks. EOFs are limited to linear combinations of orthogonal features and the spatial patterns resulting from an EOF analysis are not physically meaningful. The EOF method is more suited to identifying distinct modes of variability in a system rather than a continuum. An EOF analysis produces a set of maps, or patterns. These patterns are modes of variability within the system, building blocks with which to create the overall system dynamics. An eigenvalue spectrum (also known as a scree plot) of these mode maps shows the eigenvalue of each pattern in descending order. A high eigenvalue of a mode map indicates that much of the system's variability can be explained using that building block. Generally speaking, in an EOF or PCA, the scree plot will contain a handful of higher eigenvalue modes and then fall off to a noise floor.

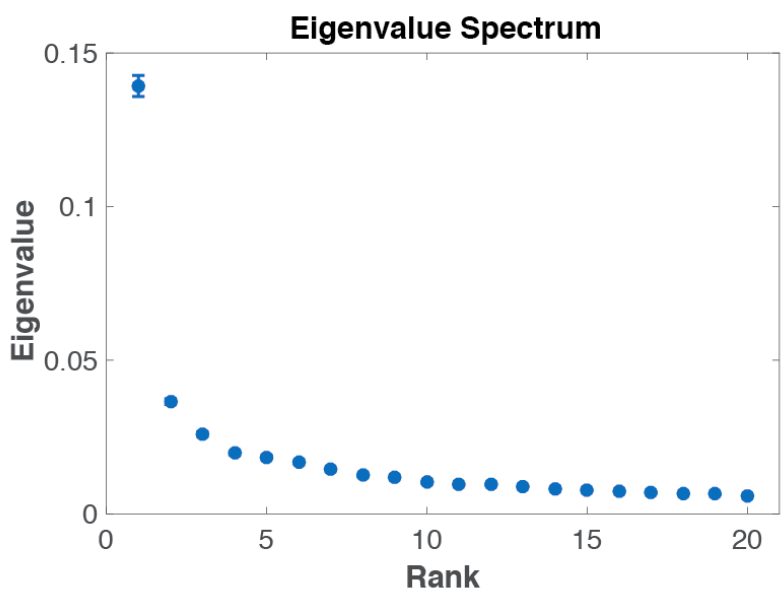
In the case below, based on an EOF analysis of TRMM precipitation data over West Africa from 1998 to 2014, the eigenvalues of the constituent modes of variability drop off steeply after the first building block mode. This suggests that a single orthogonal mode dominates the explanatory power of modes of variability in the system. It does not indicate that there is only one pattern that governs the variability of the system. Recall that EOF analysis requires constituent modes be orthonormal to one another. While this is a mathematically sound approach to the decomposition of a system, a physically meaningful representation of that system may require relaxing the independence and linearity constraints. Without this flexibility, the EOF analysis is of limited utility when looking for finer dynamics present in the system or evidence that points toward physical explanations of precipitation variability.

Figure 36. Top (a) shows the first EOF pattern; Bottom (b) is the scree plot of the eigenvalue spectrum resulting from EOF analysis.

a)



b)



Self-organizing mapping

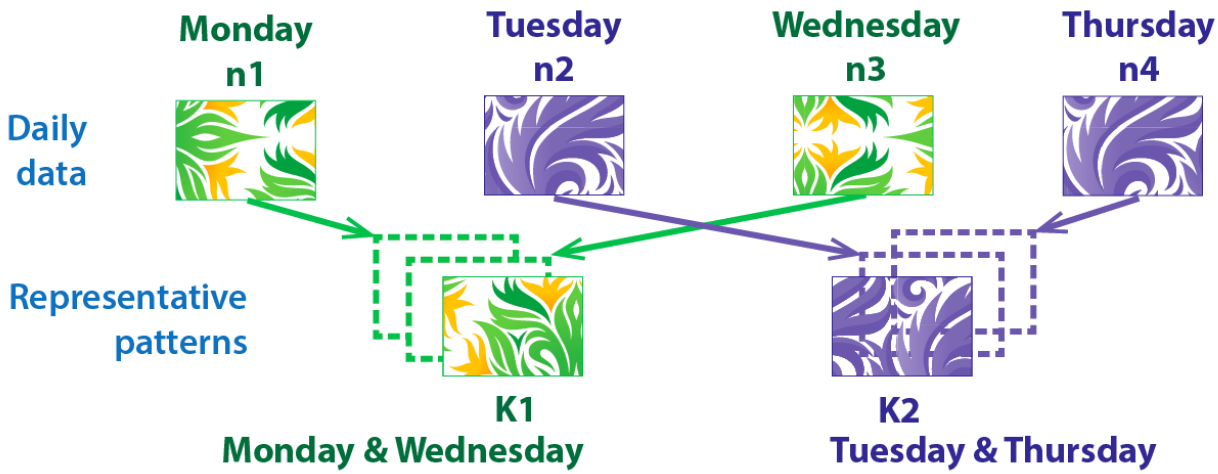
Self-organizing mapping (SOM) provides an alternate approach to pattern identification (Sheridan & Lee 2011; Johnson et al. 2008; Hewitson & Crane 2002). Developed in the 1980s, SOM is an artificial neural network method similar to K-means (Kohonen 1989, 1990, 1991, 1995, 2001). The key modification on K-means is the introduction of a neighborhood kernel, whereby neighboring nodes (patterns) are adjusted in relation to one another. As a result, the resulting representative patterns are returned in a matrix organized by similarity. Each pattern output from the SOM method is a kernel-weighted composite of its constituent members. A method such as Sammon mapping (Sammon 1969) can be used to quantify and visualize the distance between SOM patterns in parameter space. SOM patterns preserve the density topology of the underlying data. Patterns will cluster in data-dense regions of parameter space, and outliers are less likely to be subsumed in an ill-suited pattern group (Nicholls et al. 2009; Hewitson & Crane 2002). Further, the SOM method accommodates missing data, which can be interpolated using the method itself (Hewitson & Crane 2002; Richardson et al. 2003).

Application of SOM in the climate sciences has been growing in popularity since its introduction and adoption in the 1990s and early 2000s (e.g. Hewitson & Crane 1994, 2002; Crane & Hewitson 1998; Cavazos 1999, 2000). In the climate sciences, SOM has often been used to examine the relationships between precipitation and atmospheric circulation (e.g. Cavazos 1999, 2000; Hewitson & Crane 2002) along with validation of general circulation models (e.g. Hewitson & Crane 2006; Sheridan & Lee 2010). Advances in SOM methodologies in the climate sciences have included introducing a statistical distinguishability criterion (Johnson 2013), implementing the distinguishability test on data not used for the SOM training (Chang & Johnson 2015), and accounting for temporal autocorrelation (ibid.).

Evaluations of SOM applications in the climate sciences have included direct comparisons with EOF or principal component analysis (PCA). Note that EOF and PCA are distinct methods similar enough that they are often used interchangeably in the climate literature (Lorenz 1956; Kutzbach 1967; Walsh 1978; Cohen 1983; Smith et al. 1996; Jolliffe 2002). In comparison with EOF, SOM has generally been shown to more closely identify underlying patterns and frequencies in both synthetic and observational climate data (Chang & Johnson 2015; Reusch et al. 2005; Liu et al. 2006; Rousi et al. 2015). The orthogonality constraint in EOF analysis contributes to the tendency for EOF patterns to be mixtures of underlying component patterns identified by SOM. The orthogonality of EOF analysis sacrifices the correspondence to physically meaningful patterns, while SOM retains this relationship and is less sensitive to underlying data distributions. Thus while it is substantially more computationally intensive, SOM accommodates nonlinear continuum dynamics while preserving density distributions of underlying data and physically meaningful patterns.

While the characteristics governing the order of the output patterns may not be obvious to the user, the organization of the maps can be helpful for indicating potential physical or mechanistic explanations of the patterns. Quantitatively, Sammon distance mapping can be used to determine the similarity distances along the output pattern grid. Self organizing mapping is a pattern recognition technique accomplished through a form of artificial neural network analysis. It is an iterative procedure wherein a user-specified number of patterns are identified to best represent a set of observations. A self organizing mapping analysis is accomplished as follows.

Figure 37. Illustration of the self-organizing pattern recognition method.



All observations are vectorized, that is, all observations z_n are distributed in j-dimensional phase space where n=1:N total observations. Each z_n is a vector of length j, where j is the number of characteristics contained in each observation. In the case of climatological patterns in geographic space, j equals the number of variables multiplied by the number of grid points in each observation. Having established the j-dimensional phase space, m_k "nodes" are initialized in the phase space. Each m_k node will become one of the patterns representing observations in the dataset. Subscript k ranges from 1:K, where K is the total number of patterns requested by the user. The method used to initialize the m_k nodes into phase space is determined by the user. Options include a random initialization or an initialization based on EOF analysis results. At the same time that the m_k nodes are initialized in j-dimensional phase space, they are also cast into "SOM space." SOM space is the topological organization of the m_k nodes (or patterns) with respect to one another. Like K, the dimensions of SOM space are determined a priori by the user. As the m_k patterns evolve during the training process to best represent the underlying observations, they will likewise sort themselves with respect to one another in SOM space.

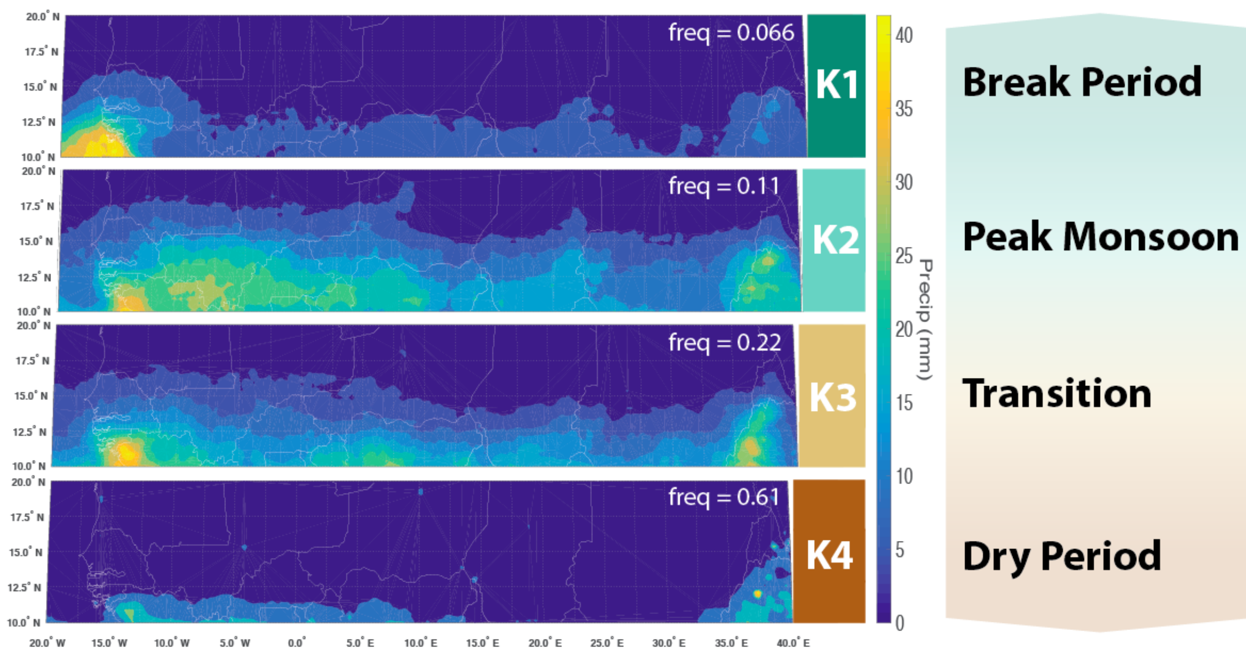
For each step in the training process, a single observation z_n is selected. The Euclidean distances between that z_n and all m_k are calculated. The node m_k with the minimum Euclidean distance from observation z_n will be activated, along with its SOM space node neighbors (regardless of the neighboring nodes' position in j-dimensional phase space). With each training step, the activated nodes are adjusted in phase space toward the observation z_n, that is, the pattern m_k is itself adjusted toward a better representation of observation z_n. A neighborhood kernel specified by the user determines how neighboring nodes are activated and adjusted toward z_n once activated. Kernel options include a bubble kernel wherein all nodes within a certain radius are adjusted equally or distance decaying kernels such as the Gaussian or Epanechnikov functions. The radius for qualifying neighbors and the amount such neighbors are adjusted (learning rate) can also be a function of training iteration. Large initial changes are followed by finer adjustments at later stages of training.

The activation and adjustment of neighboring nodes during the training process causes the nodes, i.e. the representative patterns, to organize themselves with respect to one another. At the end of the training process, the m_k patterns represent not only their constituent data observations but also the influence of neighboring groups. The SOM patterns then are more than a simple average of their discrete constituent data observations. This is a key difference between SOM and K-means clustering, and also a key component in the suitability of SOM for the representation of continuum dynamics. See the following references for more information on the self-organizing mapping method and its applications: Liu et al. 2006; Johnson et al. 2008; Johnson 2013; Chang and Johnson 2015.

Results

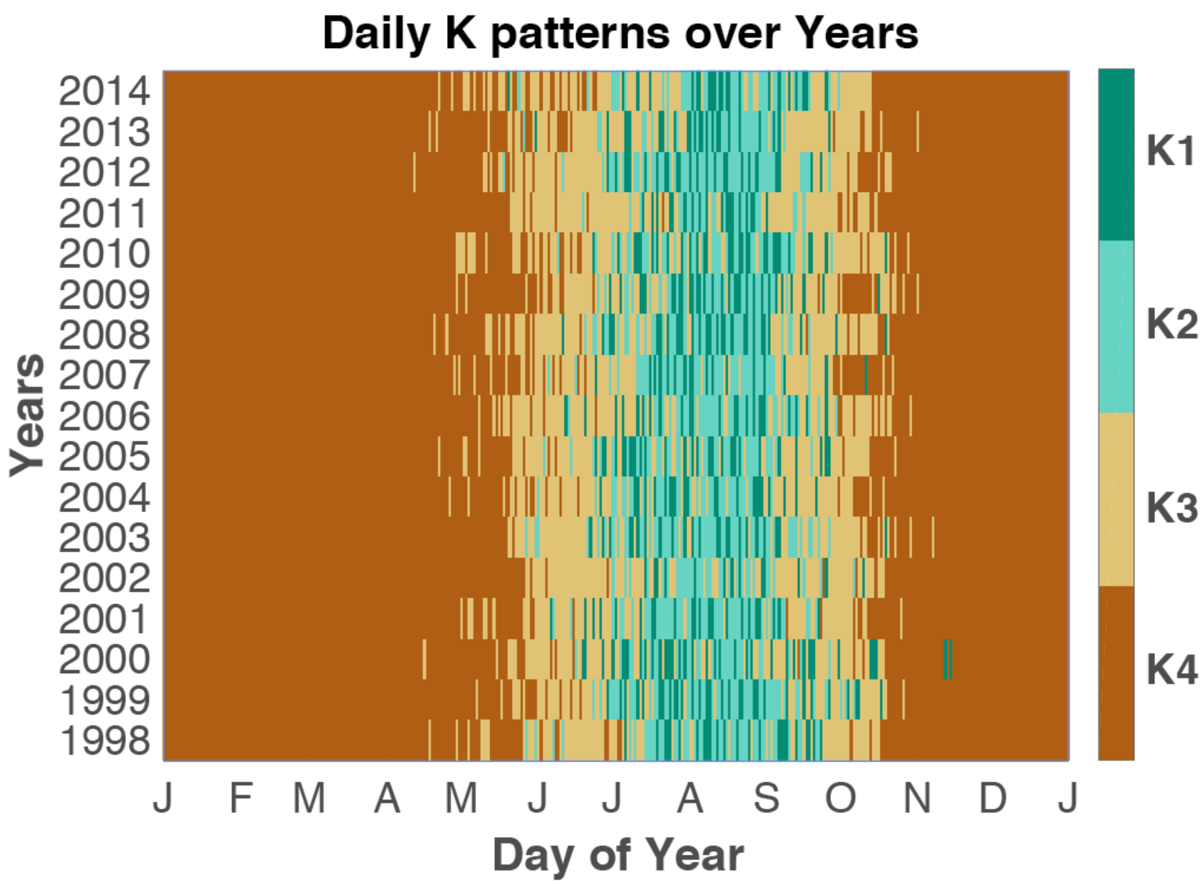
In the analysis presented below, a self-organizing mapping analysis of TRMM precipitation over the Sahel is carried out. Four patterns in a 4x1 orientation are requested. The Epanechnikov kernel is used (after Liu et al. 2006).

Figure 38. Output maps from a K=4 SOM analysis of TRMM precipitation over the Sahel. Frequency values describe the relative pattern occurrence over all daily precipitation data.



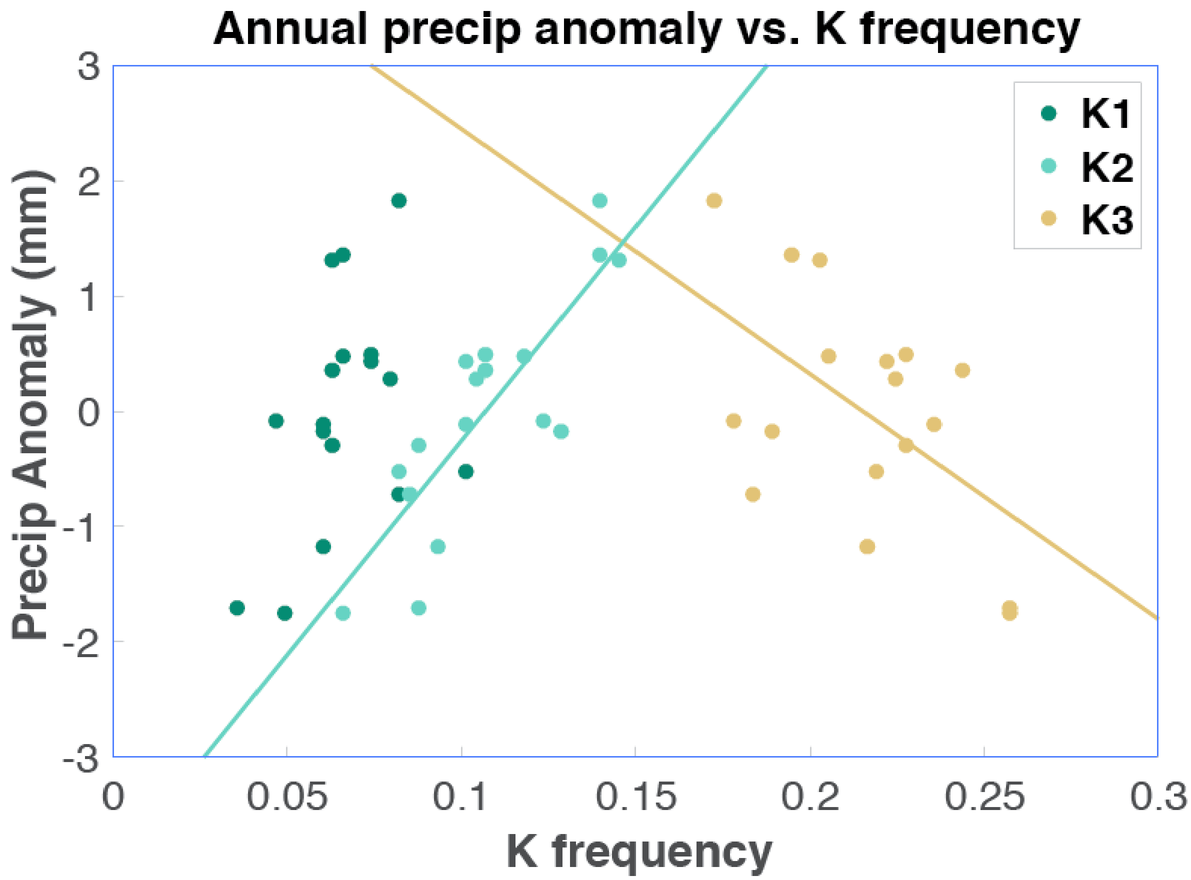
The interpretation of the patterns is based on three sources of information: common understanding of regional precipitation dynamics, the organization of the patterns with respect to one another, and the seasonal timing of pattern occurrence. Patterns K4-K2 suggest the phases of the monsoon over its north-south transit. Pattern K1 suggests a break period within the active monsoon. The suggested role of each SOM pattern is borne out in the seasonal timing of pattern occurrence.

Figure 39. Pattern occurrence for each day of the year (x-axis) over all years (advancing along the y-axis).



This is 4-dimensional figure: two time dimensions—seasonal and interannual—and two spatial directions represented by the pattern assigned to each day. Pattern K4 represents the dry season, with the highest frequency (0.61). K3 indicates the monsoon transition period, appearing at the beginning and end of the rainy season. K2, the peak monsoon, and K1, the break period, occur interspersed at the height of the rainy season.

Figure 40. Annual precipitation anomaly plotted against the annual frequencies of SOM patterns with linear regression lines of best fit. Adjusted R squared and F-statistic p-values follow in the table below.



	K1	K2	K3
adjRsq	0.0996	0.6930	0.2591
fStatP	0.1168	0.00005	0.0214

The analysis identifies a correlation of annual precipitation anomaly with pattern frequency. Both K2 (peak monsoon) and K3 (transition period) show strong correlation with annual precipitation anomaly with adjusted R squared values of 0.6930 and 0.2591 and F-statistic p-values of of 5E-5 and 0.0214, respectively. Annual precipitation anomaly is positively correlated with the number of peak monsoon days and negatively correlated with the number of monsoon transition days. K1, conversely, does not show a correlation with annual precipitation anomaly (line of best fit not shown). In other words, annual precipitation is not related to the frequency of break periods within the peak monsoon, but with the lengths of the transition and peak periods of the monsoon.

Despite the suggestion of a trend in the rainy season onset date in the AMMA data, precipitation from TRMM fails to reproduce this trend in a SOM analysis. The TRMM dataset exhibits a significant trend in neither seasonal timing of pattern occurrence nor in pattern frequency. Explanations for the lack of trend in the TRMM data include: there is indeed no trend; the trend predicted in the climate model studies has not yet begun to manifest; the TRMM record is too short to identify a trend; the TRMM precipitation dataset does not detect the rainfall involved in the changing onset trend. Further study is needed to investigate these possible explanations.

Satellite product comparison

Satellite precipitation products for the region have mixed performance in representing observational precipitation (Roca et al. 2009; Ali et al. 2005). Previous work on the evaluation of satellite precipitation products for West Africa shows that these products detect the onset of the rainy season before the onset as determined by gauge data (Gosset et al. 2013). It is therefore plausible that a trend toward a delay in the rainy season would not be detected by satellite precipitation products. It has yet to be investigated how different satellite products represent trends in seasonal rainfall over the Sahel.

Spatial maps of season trends

Because precipitation patterns over West Africa are spatially heterogeneous, a spatial map is used to investigate seasonal trends in three satellite precipitation products: TRMM, GPCP, and RFE2 (respectively: Kummerow et al. 1998; Adler et al. 2003; Novella & Thiaw 2013). The spatial resolution of the three datasets is scaled to a common resolution of 0.25 degrees; the season definition used is % annual rainfall to reduce the influence of outliers; the time domain (1998-2012) and precipitation threshold (1 mm) are likewise unified across the datasets. For each pixel of a given precipitation product, season indices are calculated for every year 1998 to 2014. A linear regression is then fit to each of the season indices for each pixel. A map of the slopes of these linear regressions can then be made. The result is a spatially explicit view of season trends where the slope of the best fit line is represented in color as change in day of year per year. Below are three sets of such maps, one for each precipitation product: TRMM, GPCP, and RFE2. The set for a single precipitation product contains four maps: annual climatology, and one trend map for each of the three season indices. None of the satellite products show a strong trend for rainy season onset in the area of the AMMA site in Niger, or indeed in the central Sahel more broadly. All three satellite products show a trend toward later onset in the northwest region as well as the northeastern area of the spatial domain.

The lack of convincing seasonal trend in space indicates that the aggregation into spatial SOM patterns is not obscuring underlying geographically specific seasonal trends. The degree of system state aggregation in the SOM methodology is a function of the number of patterns used. Using a higher number of constituent patterns would more finely disaggregate smaller-scale dynamics (both in time and in space).

Figure 41. TRMM climatology and season trends. Onset, midpoint, and endpoint of rainy season defined by 3%, 50%, and 97% of cumulative annual rainfall, respectively.

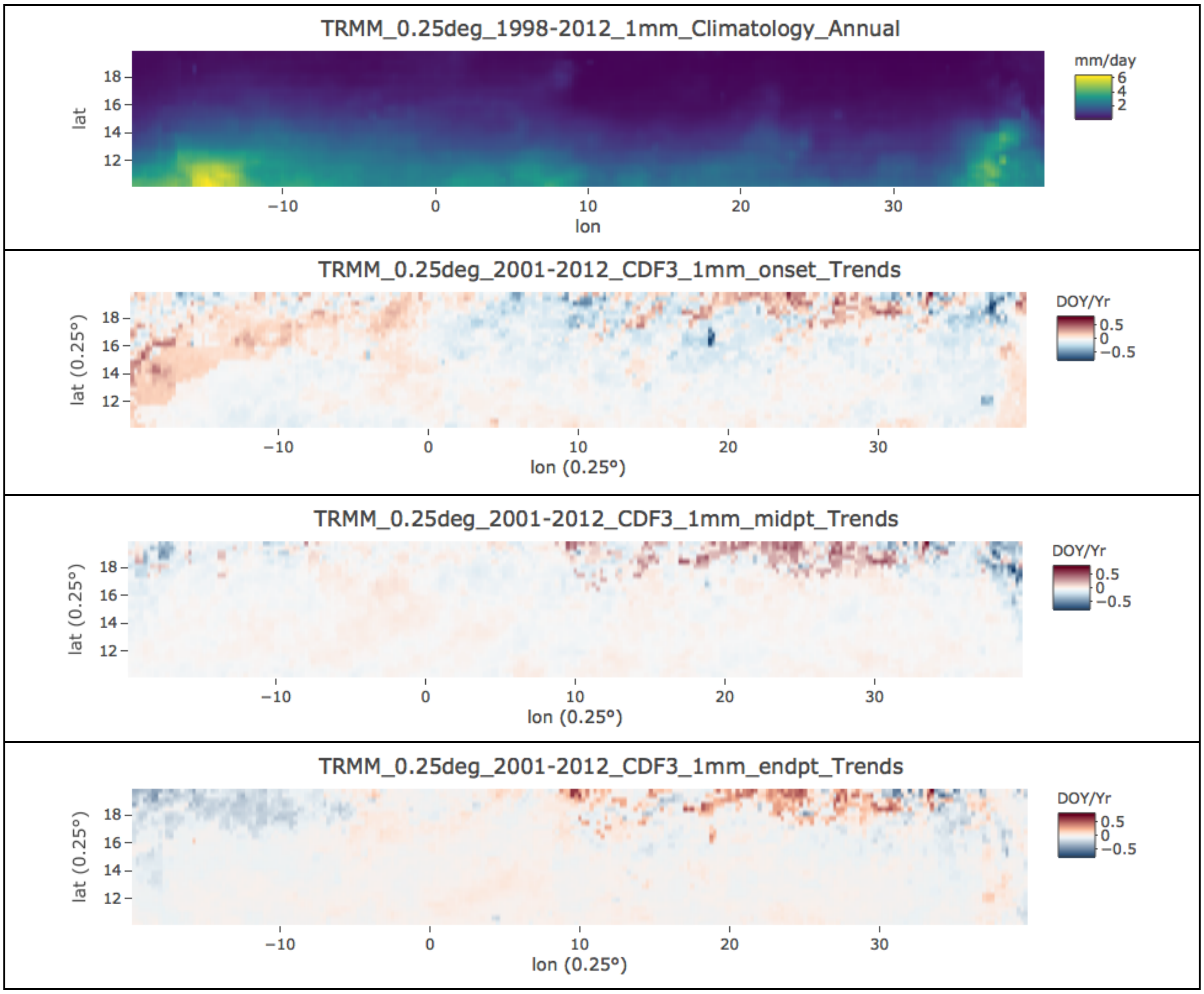


Figure 42. GPCP climatology and season trends.

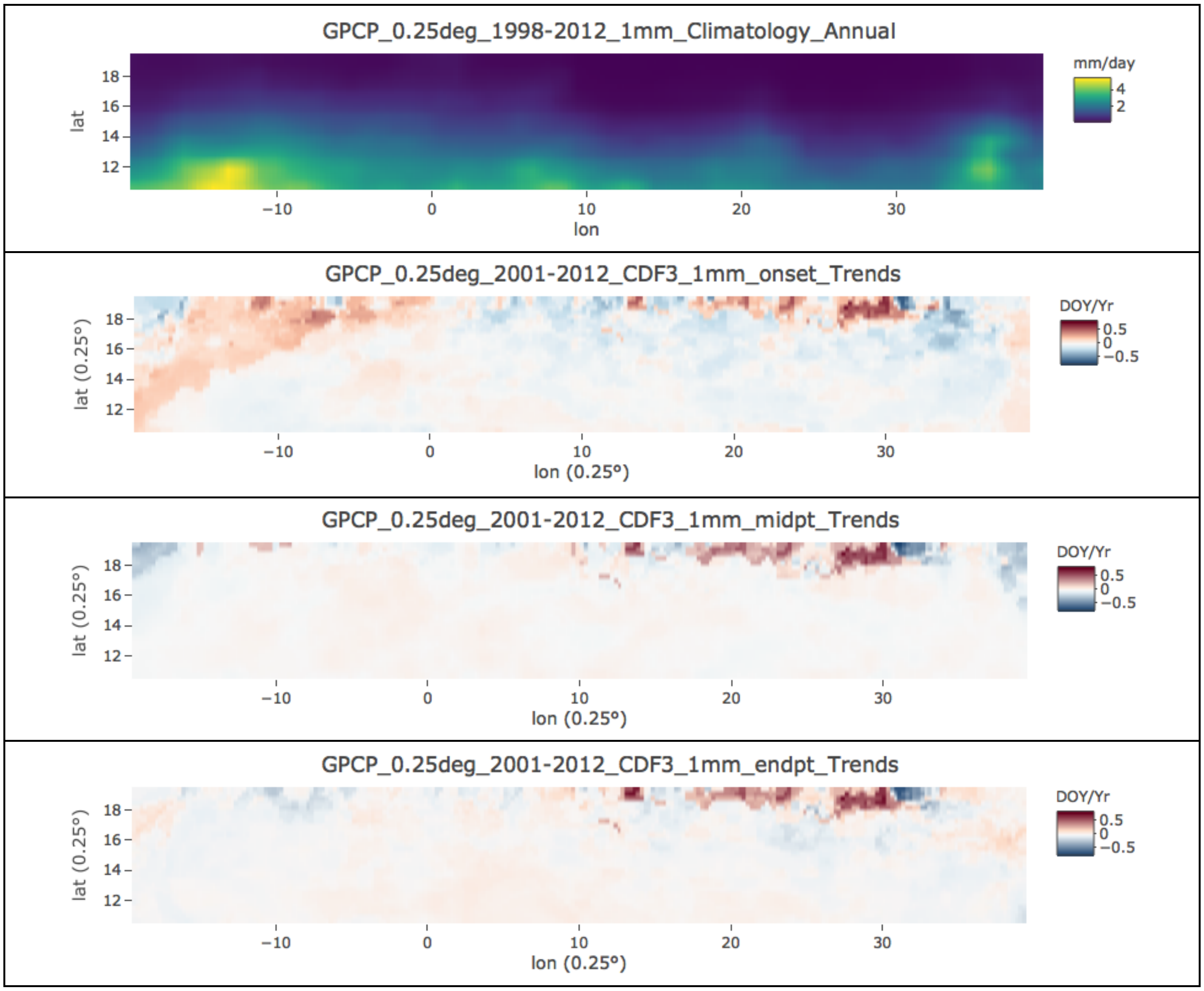
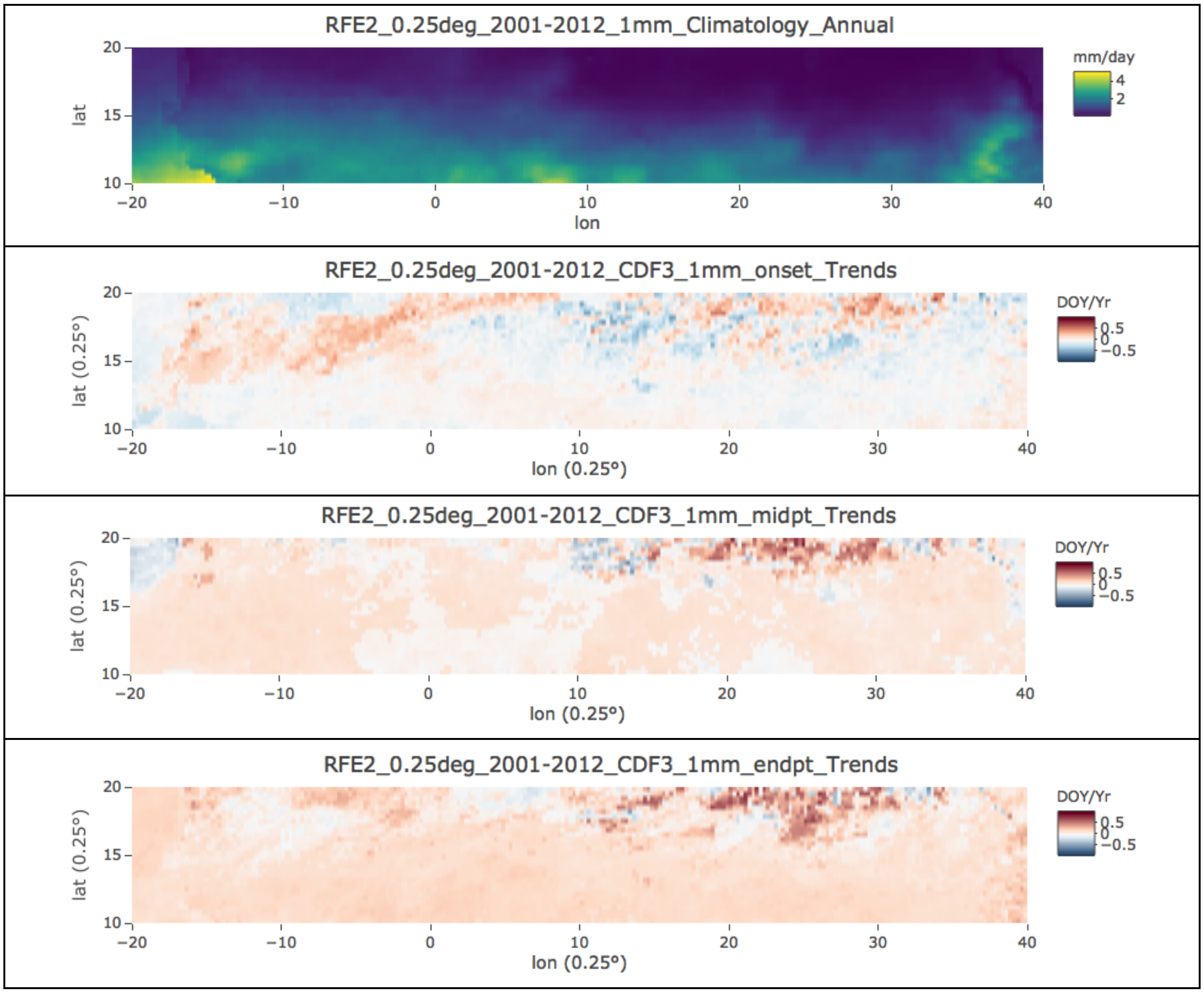


Figure 43. RFE2 climatology and season trends.



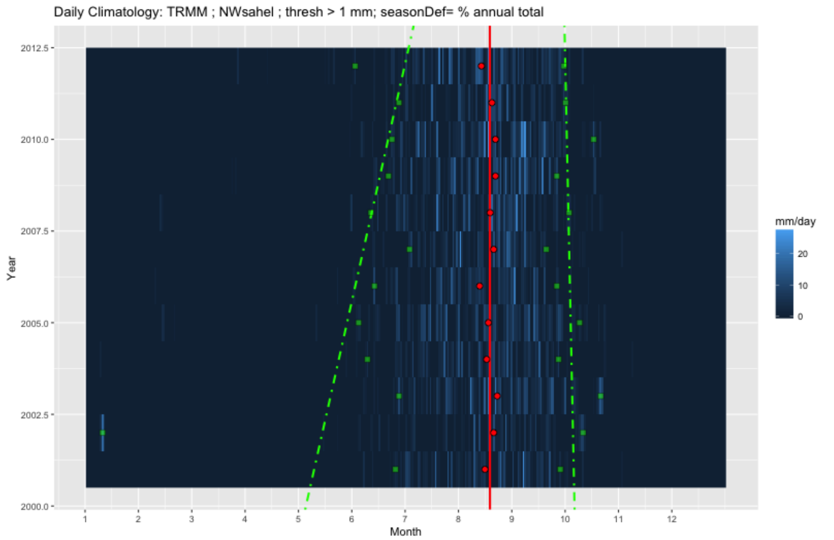
Spatially averaged satellite precipitation

Having honed in on a few geographic locations with potentially interesting seasonal trend dynamics, returning to a spatial average view can be informative. Naïve domain choices for spatial averaging can muddy results if trend behavior varies with overlapping geographic boundaries or if it varies at a smaller spatial scale than the domain for averaging. The spatial map of trend behavior makes it possible to select domains with coherent trend behavior for a closer investigation of temporal dynamics. To further investigate the observed trends in the northwestern and northeastern Sahel, spatial averages of these areas were taken for each of the three precipitation products, plotted in year vs. DoY space, and then linear regressions fit to the season indices (Figures 44-45). Note that the northwestern trend is likely an artifact of the anomalous intense precipitation event that occurred in that region during the dry season of 2002 (Meier & Knippertz 2009). This early precipitation drags the linear regression model toward a positive slope. A linear regression without the year 2002 may be more representative of any trends present in the seasonal onset of the rainy season. The cause of the northeastern precipitation delay is less clear (Lyon & DeWitt 2012). There is little total annual precipitation in this region, and thus the seasonal trend analysis is subject to the effects of noise. The fact that all three satellite products exhibit it, however, for all three seasonal metrics, hints that there may be a meaningful change occurring in this region. In both cases, further investigation is warranted.

Statistical significance of spatially explicit trends

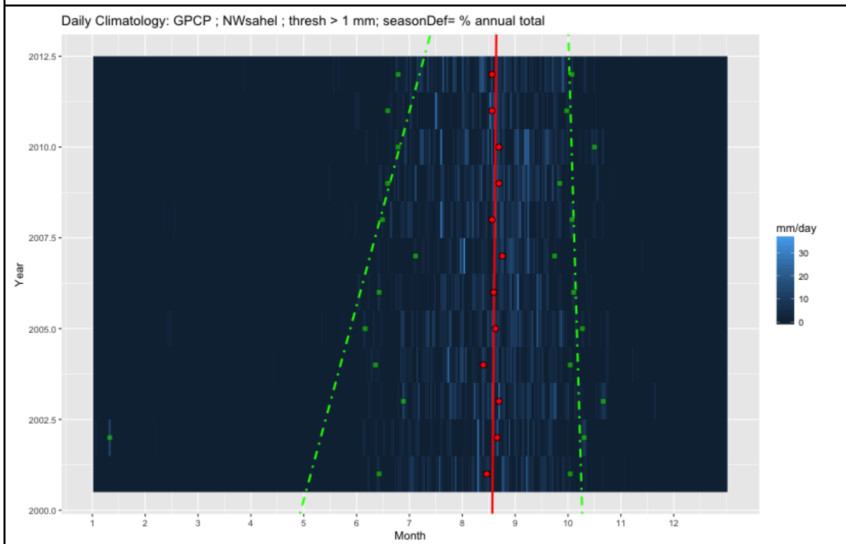
Evaluating the robustness of the detected trends in the spatially explicit season trend maps requires further investigation. Using TRMM as an example, for each season metric, root mean squared error (RMSE) and R^2 values are calculated for the linear fits of each pixel. These metrics are then plotted as spatially explicit maps for comparison with the trend maps. In addition, the trend map is replotted using a filter to remove all pixels with p-values > 0.05 (Figure 46). In the case of TRMM, the onset trend map is the only one in which substantial parts of the map persist pass the p-filtering, specifically the central Sahel with earlier onset and the northwestern Sahel with onset delay. Because precipitation in the Sahel is a system in which a certain amount of seasonal variability is to be expected, the RMSE is of limited utility. The R^2 maps are more useful and indeed, the spatial distribution of high R^2 corresponds with the p-value filtered onset map.

Figure 44. Seasonal trends for a spatial average of the northwestern Sahel.



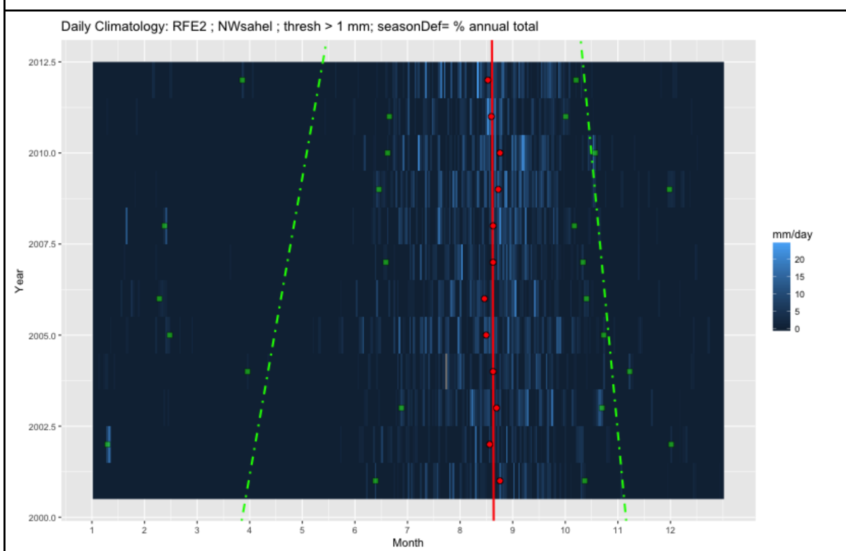
TRMM
Northwestern Sahel
Onset/End: % annual total

Note precipitation anomaly in dry season of 2002



GPCP
Northwestern Sahel
Onset/End: % annual total

Note precipitation anomaly in dry season of 2002



RFE2
Northwestern Sahel
Onset/End: % annual total

Note precipitation anomaly in dry season of 2002

Figure 45. Seasonal trends for a spatial average of the northeastern Sahel.

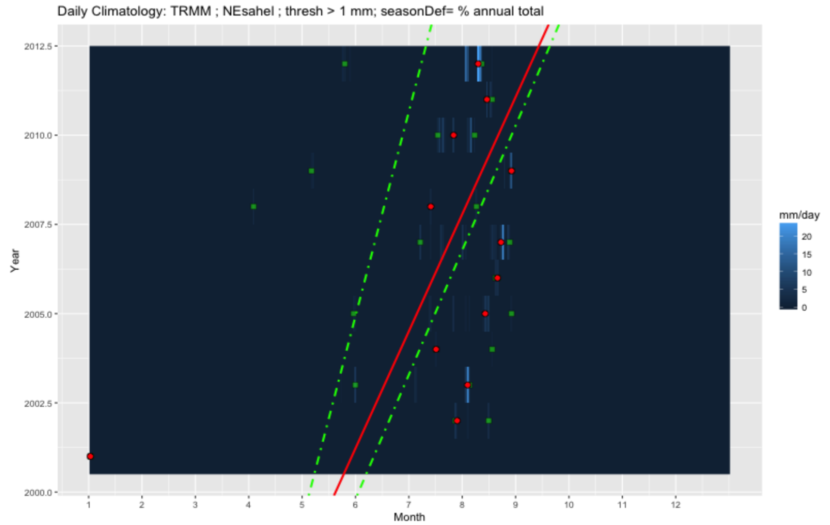
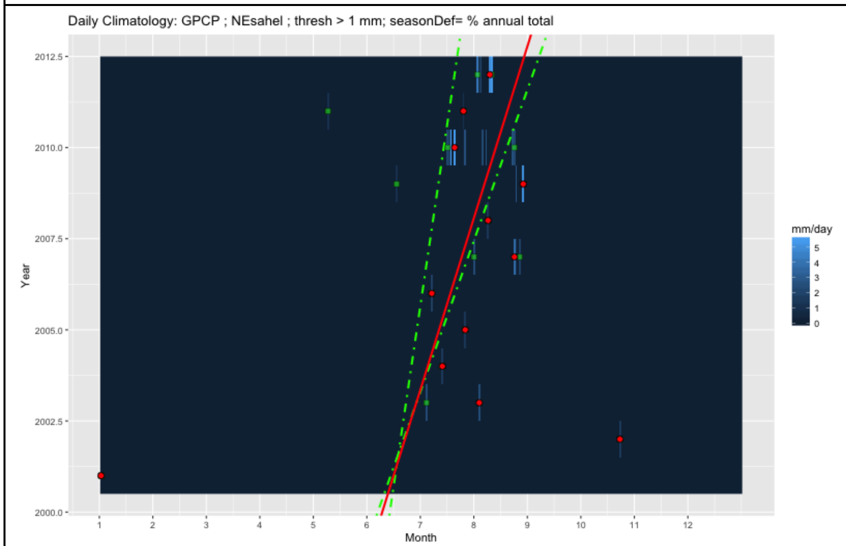
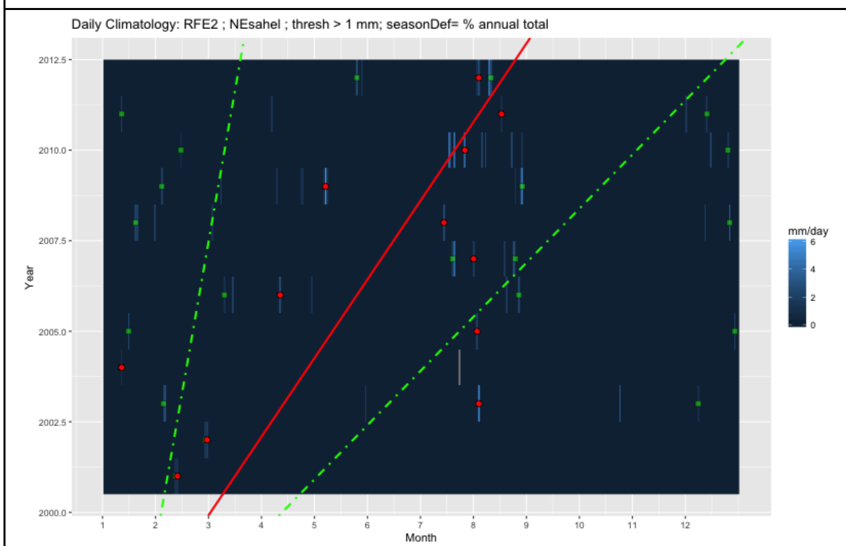
	TRMM Northeastern Sahel Onset/End: % annual total
	GPCP Northeastern Sahel Onset/End: % annual total
	RFE2 Northeastern Sahel Onset/End: % annual total

Figure 46. Maps over the Sahel of trends in TRMM rainy season timing. a) Onset, b) midpoint, and c) endpoint of rainy season timing are defined by accumulation of annual rainfall total, 3%, 50%, and 97%, respectively. Each season index has a set of four plots, from top to bottom: a map of the slopes of pixel-wise linear regressions on season index trends over the period 1998-2014; RMSE map of variance from the pixel-wise linear regression models; R^2 map of variance percent explained by the linear regression models; another map of season trend slopes now filtered for $p < 0.05$ to reject the null hypothesis of zero trend.

Figure 46.a) TRMM rainy season onset trends and regression metrics.

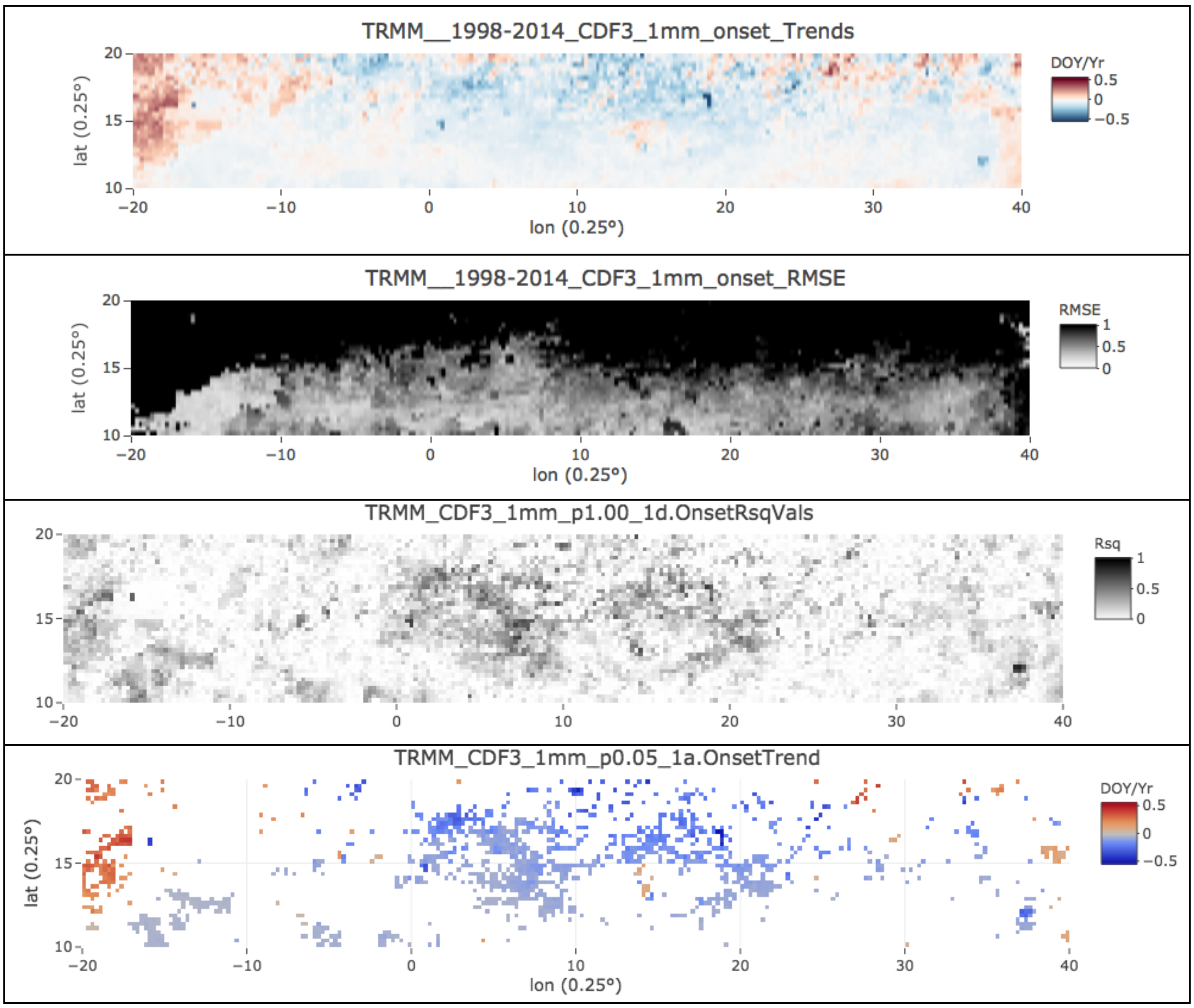


Figure 46.b) TRMM rainy season midpoint trends and regression metrics.

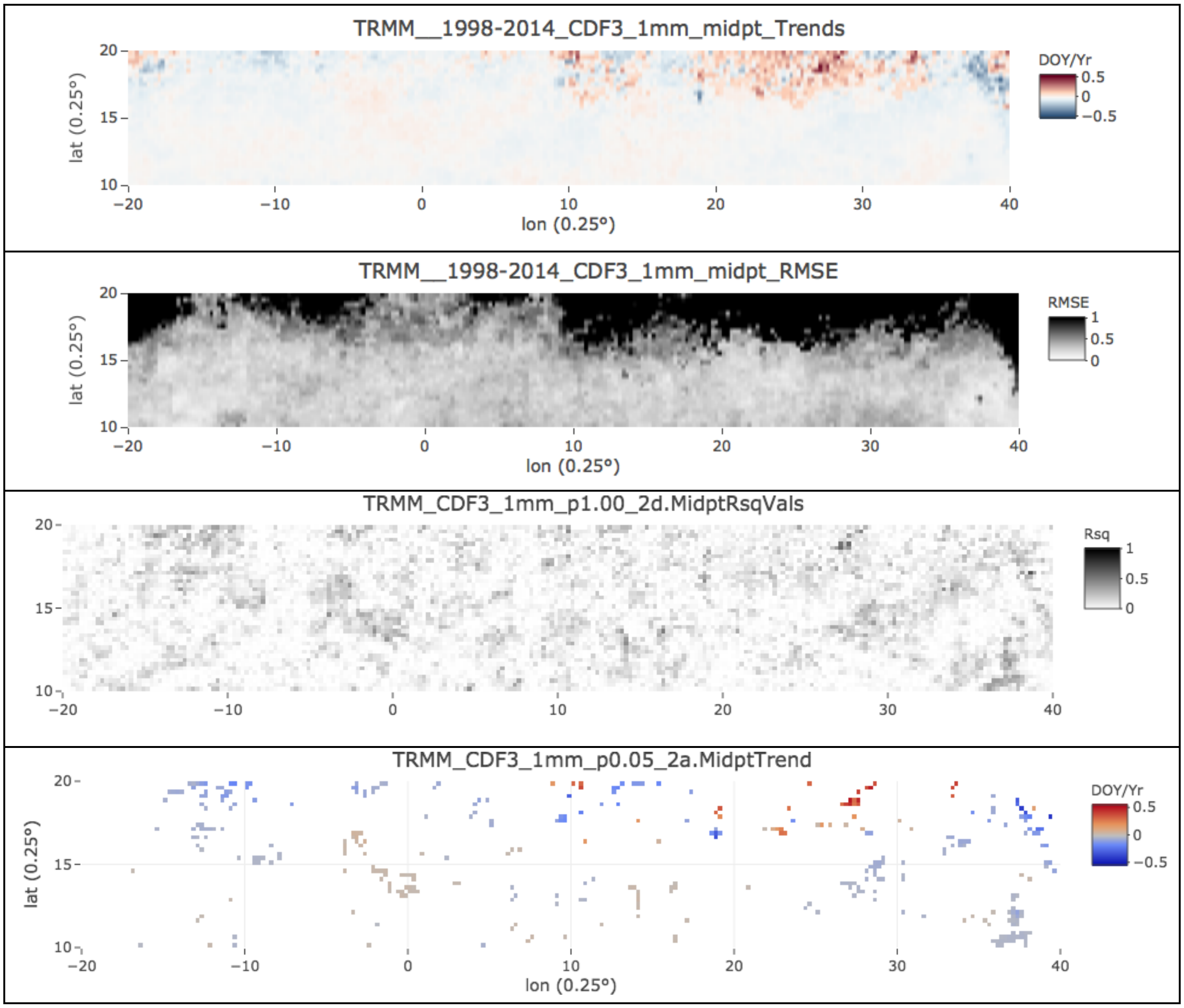
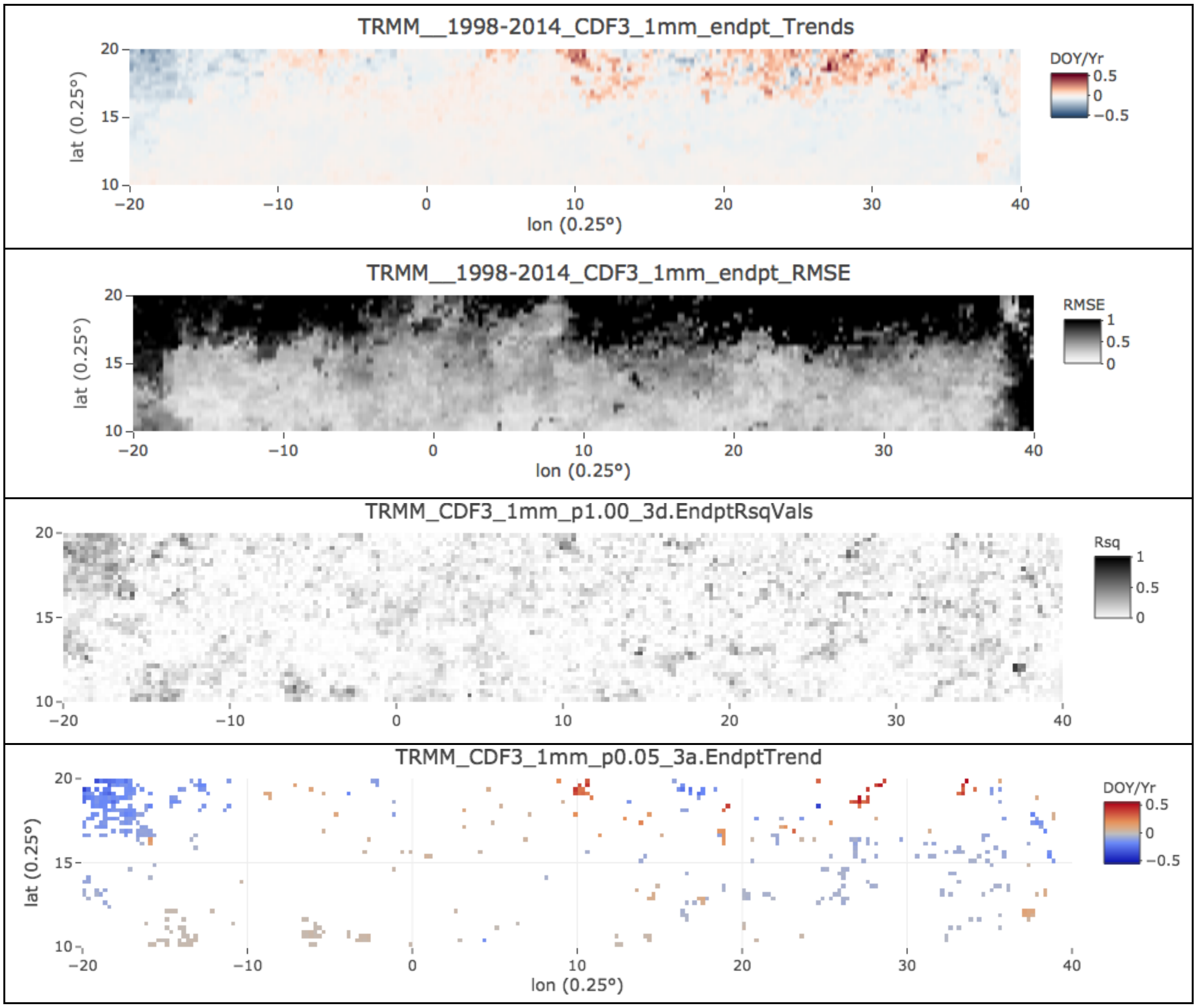


Figure 46.c) TRMM rainy season endpoint trends and regression metrics.



Future Work

Future work includes:

A. Correlation of patterns to other climate indicators such as sea surface temperature in the Gulf of Guinea and the North Atlantic.
B. A SOM analysis with a higher number of patterns to resolve detail in the dynamics of the rain season.
C. SOM analysis using different precipitation datasets such as the Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT) precipitation product, which has a longer time domain and is built on gauge data (Maidment et al. 2017). The TAMSATv3 precipitation dataset is produced specifically for Africa and has a much higher resolution (0.0375° compared to TRMM at 0.25°) and a much longer record (1983 to present). The longer record may make it more possible to identify any trends present in rain season timing.
D. Spatial trend analysis accounting for 2002 rainfall anomaly event and possible mechanisms for northeastern trends in seasonal timing of precipitation.

Conclusion

Results of trend analysis of seasonal timing show no discernable coherent trend in season timing of phase shifts. This neither supports nor refutes the prediction of later season onset with increasing global warming. It does, however, support that at near-term timescales, any potential seasonal timing trends are outweighed by interannual variability. In other words, this time period is generally thought to be characterized by increased variability, which would make it harder to detect trends. Seasonal timing does vary, but on an interannual scale instead of a coherent trend over time.

A longer peak period is associated with a higher precipitation anomaly. This is intuitive: more heavy rain days in a year are associated with more annual precipitation. A longer transition period is associated with a lower precipitation anomaly. This finding is not obvious. The transition period could lengthen either at the expense of dry pattern days (leading to more annual precipitation), or at the expense of peak season days (leading to less annual precipitation). In this case, the longer transition period being associated with lower precipitation anomaly indicates that the lengthening of the transition period is replacing peak days instead of dry days. This finding is coherent with the influence of the upped-ante mechanism. The transition season persists into what would otherwise be peak rainy season, without sufficient heat or moisture to power convection. The suggestion of the role of upped-ante mechanism in interannual variability of annual precipitation, and without significant sub-regional spatial structure, is another piece of evidence supporting the primary role of large-scale (global) climate dynamics in determining precipitation of West Africa over the role of local land cover effects.

A self-organizing mapping approach can examine the role of the myriad underlying spatio-temporal precipitation patterns in the overall changes in variability and timing of precipitation. It can also distinguish, at inter- and intra-annual time scales, regional scale precipitation patterns associated with the West African monsoon system. Examining precipitation in West Africa with the higher-dimensional, more flexible method of self-organizing mapping provides a new tool for disentangling the underlying behavior responsible for precipitation changes in this region, indicating the systems that will dominate changes in precipitation over West Africa as climate change progresses. Linking precipitation anomalies to spatial-temporal patterns of rainfall supports the pursuit of mechanistic explanations, for both precipitation dynamics in the Sahel and how Sahelian precipitation may change in the future. This proof-of-concept example shows the utility of the SOM approach to the study of spatial-temporal dynamics in the Sahel.

Changes in pattern occurrence over the course of the season is a robust way to define seasonal transitions such as the onset of the rainy season. Without pattern identification, determining seasonal transitions has been a matter of spatial averages of rainfall combined with precipitation or rainy day thresholds. Particularly as more studies address the possible effects of climate change in the seasonal timing of rainfall in the Sahel, a spatial physically meaningful pattern-based definition of season stages can contribute to mechanistic understandings of precipitation in the Sahel.

End Matter.

Conclusion.
Bibliography.

Conclusion.

The work herein describes a set of methods used to investigate Earth system dynamics in West Africa. By design, this portfolio of approaches is transferable, not only to other geographic regions but to other types of questions and to other disciplines. Beyond application of a particular method to a particular problem however, the work requires the careful consideration of a question and its basis, the evaluation of different frameworks of analysis, the search for or development of a method that is appropriate and effective, all the while critically engaging in the broader human and institutional components and effects of the research. This critical engagement is not ancillary to the research; it shapes and informs every stage of the endeavor: conceptualization, foundation, framing, practice, process, analysis, results, communication, feedback. Vignettes on the real-world contexts in which this body of work operates are presented below, followed by deeper considerations specific to the AtlasV2. Finally, AtlasV2 results provide a juncture point, an opportunity to reframe the desertification narrative, for which I lay out a proposal.

Science in the real world

Applied science

The importance of applied science, and the sometimes mismatch with priorities of academia, were highlighted in a West Africa regional LULC conference I attended in Accra, Ghana in 2018. Attendees were experts in remote sensing and geographic information systems (GIS) from across the region, from government and public sectors, local to international scale actors, with representation from the Economic Community of West African States (ECOWAS), NASA, and USAID as well. The scientists in the room worked on projects supporting international convention reporting, development planning, national natural resource management, and local decision-making about land use planning. The purpose of the conference was to open a dialog about how to coordinate and harmonize LULC mapping efforts across the region. One of the major themes that arose was the critical importance of the end user and the usefulness of the LULC product over the merits of science conducted in a vacuum.

Cheikh Mbow, head of START-International (Global System for Analysis, Research and Training) and Dan Irwin, head of NASA-SERVIR, were among those to express the primary importance of the applications of science: What good is the science to anyone but yourself if all you do with it is publish papers and present at conferences? We as scientists have a responsibility to action even if our career metrics don't account for it. Patrice Lumumba, head of l'Institut supérieur d'études spatiales et des télécommunications (ISESTEL) in

Burkina Faso passionately put forth the challenge: What is the point of perfecting the minutiae of your methods in an echo chamber of academics if "life in the village is still hard?" Applied or not, scientific research is inextricably embedded in human and institutional contexts. Climate and land surface research is no exception. The matter of data accessibility illustrates the impacts of these embeddings on multiple fronts.

Data access

Access to land cover and climate datasets for West Africa, for example, is limited but crucial for climate change and climate change adaptation research (Washington et al. 2006). This information contributes to understandings of what changes have been going on in the region, what the causes have been, and what to expect in the future. In current climate models, West Africa has globally high uncertainty for peak season precipitation (Tian & Peters-Lidard 2010). The models don't even agree on the sign of the precipitation predictions for the future (Biasutti & Giannini 2006; Cook & Vizy 2006; Douville et al. 2006; Joly et al. 2007; Biasutti 2013; Roehrig et al. 2013). In this context, ground-based data is important. And while the coverage of field data in the region is far more sparse than in regions like Europe or North America, the data do exist, sometimes with a record going back to the 1900s or earlier. But almost none of this data is publicly available (Mahe et al. 2008). The National Meteorological Services of the countries in the region collect and maintain an archive of this data, but for researchers working at institutions outside of the country, and often for researchers at institutions within the country as well, the data are largely available only for a fee, one that is prohibitively expensive for many research efforts.

I don't think it is well known even in the climate science community, but this arrangement is not purely the result of fiscal prioritization on the parts of the national governments themselves. There are bigger global contexts that come into play. In the 1990s many of the countries in West Africa took on loans from the International Monetary Fund (Boughton 2012). The Structural Adjustment Programs attached to the loans imposed severe austerity measures. With these economic changes, many countries converted their National Meteorological Services to a market-based profit model for access to meteorological data (Descroix et al. 2015). The effect of this policy is that the field record of climate data in West Africa remains behind a paywall for researchers in the Global North and in the Global South. As with Landsat imagery when it was commercialized in the 1980s and 90s, the overall effect is that less research gets done with the data (Wulder et al. 2012; Descroix et al. 2015).

Still, the question of policies for sharing data produced by researchers and institutions in the Global South is not a straightforward one. Legacies of colonial exploitation and differences in resources and capacities among those producing and using data complicate the idea of open data policies (Serwadda et al. 2018; Dove et al. 2016). Concerns include "parachute research" wherein researchers from the Global North drop in to extract data, and then head off to do analysis and publish results without input, feedback, or involvement of the people who originated the data. Differences in capacity mean that researchers in the Global North may be able to churn out research and publications on the data sooner than researchers in the Global South, monopolizing the intellectual capital. Further, some types of data raise concerns about privacy, ethics, and safety. These questions are active and ongoing; their negotiation will continue as new types of data, research, and collaborations are forged.

Remote sensing

Remote sensing data, more specifically earth observation satellite data, can be seen as a potential solution to democratizing environmental data availability and access. NASA and ESA are two of a growing list of institutions and corporations that have satellite programs which collect data over the entire globe. These data are then freely and publicly available, more or less depending on the data supplier, the data consumer, and the proposed application. Indeed, this can be a major advance for inputs into climate change adaptation efforts, disaster management, land use and development planning, and resource monitoring, especially in countries where ground-based data is limited. The satellite imagery data collection method is seemingly the model for equity: space satellites collect data the same way over the entire globe, the data are gathered and centrally processed and then published for open access. Yet even here, the effects of uneven development influence the availability of satellite data, and in a way that is largely invisible.

The Landsat 5 satellite, which was active from 1984 to 2013, included no onboard data recording capability. Ongoing land surface observations taken as the satellite traveled along its orbit were continuously overwritten with new observations. Instead of saving the observations onboard, the satellite depended on data transmission in real time to a geosynchronous Tracking Data Relay Satellite (TDRS) network, which could then pass the data along to a receiving station on the ground. In 1992, however, the TDRS relay technology aboard Landsat 5 failed, leaving the satellite without a way to communicate with its companion TDRS satellites. From that point on, any transmission of data observations by the Landsat satellite had to be directly downlinked to a ground station in real time. Without storage capacity onboard the satellite, only data that was transmitted in real time to ground stations could be collected and archived. Otherwise, no record of the satellite observations would persist (Wulder et al. 2016; Goward et al. 2006).

Over areas such as the U.S. and Europe, ground station coverage was dense enough that the Landsat data could be transmitted continuously. Over Africa, that was not the case. A lower density of scientific infrastructure meant that no ground stations existed to receive the real time transmissions from the Landsat satellite. Large swaths of Landsat observations over Africa were simply overwritten without being recorded. This created gaps in the Landsat record specifically for the places on Earth that did not have sufficient ground stations to receive the data as the satellite went by. A theoretically geographically equitable data record is now missing data for exactly the places that perhaps have more limited technological resources for generating other sources of information (Wulder et al. 2016; Goward et al. 2006). While understanding this background does not change the past, it can inform a researcher's perspective on the particular context she is working in, influence project design for future campaigns, and illuminate some of the disparities in constraints and challenges faced by researchers working in different regions of the world.

AtlasV2

Among my portfolio of graduate projects, the AtlasV2 project was conceived and carried out to be useful applied research. It was not the most scientifically cutting-edge. It was not pursuing a revolutionary answer to a scientifically pivotal question. This project was not in my portfolio for its academic or intellectual caché. It was, instead, solving a practical problem with practical applications. It has since become by far the most meaningful and impactful of the work I have done in the last six years. Concurrently, the AtlasV2, and its potential impact in the region, is in tension with land cover discourses and with regional agendas in a number of ways, including ownership, collaboration, methods, and communication.

As with any academic or implementation-based collaboration, negotiations around issues of ownership are pervasive in the Atlas and AtlasV2 projects. Differences in geographies and institutional capacities and resources add further layers of complexity. For the Atlas products to be useful, used, and maintained at the local or regional levels, the research must be owned at those levels. These questions expand far beyond the claim of credit, to include idea generation, method development, research planning, implementation, and dissemination.

While the creation of the original Atlas was lead by USGS, AGRHYMET and their regional partners have retained strong ownership of the work. The inputs, methodology, process, and outputs of the original Atlas are transparent to researchers at AGRHYMET both because the methodology is familiar and because of their direct and guiding role in the entire cycle of the project. The case of AtlasV2 is somewhat different. As a graduate student and a newcomer to collaboration with AGRHYMET, I was operating as unknown and unproven. Further, the methods I used for the AtlasV2 are unfamiliar to more traditional practitioners of land cover science. These factors, combined with the temporal and geographic constraints of my graduate studies, limited my collaboration with AGRHYMET during the development stage of the project. This is a critical disadvantage for designing a project that matches needs and priorities in the region.

Enduring partnership, meanwhile, is the road to transfer or joint ownership. The progression of the AtlasV2, its proven success, and the interest of NASA-SERVIR as an embedded established partner of AGRHYMET has bolstered my direct collaboration with AGRHYMET and other partners in the region. This in turn fosters increasing ownership of the AtlasV2 by region-based partners. It remains that the methodologies I use to create the algorithm-based classification, as well as the technical tools to interact with the data and the development pipeline, tend to be unfamiliar to traditional land cover scientists, but this becomes less of a sticking point as partnerships continue.

The impact of ownership was strikingly clear at the workshop I ran at AGRHYMET in July of 2018 to hand over the AtlasV2. Participants included land cover scientists from across the region working in local research institutions, government ministries, and international coalition organizations. What interested the workshop participants far more than access to and analysis of the final land cover data product, or the ability to replicate the classification process, was being able to use and adapt the data creation pipeline itself. It was the tool, the means, instead of the product that was most important.

The constraints shaping the collaborative relationship with AGRHYMET, as well as institutional and situational contexts, also shape the scale of analysis, intervention, and collaboration. The AtlasV2 project development and outcomes have relied on AGRHYMET exclusively for engaging with regional stakeholders and operationalizing research outcomes. This includes local land planners, all levels of government, and international agencies. In some ways, this is absolutely appropriate; I have neither the expertise, experience, nor positionality requisite for that task. Nevertheless, the next phase of development of AtlasV2 requires wider collaborative relationships that can engage with a localization of the product development process.

The development of AtlasV2 is near the ceiling of what is possible to do with an eye only on the regional scale and without expertise or information to move to the local scale. Development of the AtlasV2 product at the local level is necessary to benefit the dataset and methodology as a whole. Some of this takes the form of using local land cover maps from different sources to compare and improve the AtlasV2 classification. Perhaps more importantly, engagement with end-users or collaborators working at the local scale focuses the existing needs and applications to guide further AtlasV2 development. As ever, this requires navigating collaboration across institutional practices. As more connections are made over time and over many interactions, the engagement with end users and potential co-developers expands, while stronger collaborative relationships can build as well.

With algorithm-based classification of land cover made possible at a regional scale, there is potential for a de-localization in how land cover data is produced and applied. Focus can be redirected from local, spatially small-scale heterogeneous features and dynamics. This is a tendency widely cautioned against in, for example, Behnke & Mortimore's collection of writings about land cover change in the Sahel (2016). From what I can see of the perspectives and priorities of my collaborators and interlocutors, however, there is widespread and firm grounding in the importance and heterogeneity of the local scale.

Mismatches in science communication and methodological expertise on top of perception and ownership factors can create stumbling blocks for building constructive partnerships. For example, downscaling land cover maps from 2 km to 30 m radically changes the appearance of errors in the dataset. Because of its coarse resolution, the 2 km land cover product more readily disguises classification error. Once the map is downscaled to 30 m, however, it becomes much easier to qualitatively identify errors in the classification. These include errors in the representation of small-scale spatial heterogeneity patterns as well as errors at a larger scale such as at the boundaries between classification zones in AtlasV2.

This creates an opening for methodological and science communication negotiation. From one perspective, the apparent increase in noticable error in the downscaled product is an artifact that does not detract from its advancement over the coarser product, which certainly has errors as well even if they are less obvious. From another perspective, the qualitatively perceived accuracy is critical to the validity and usefulness of the land cover product. Sitting in the first perspective, the second might look ill-informed or methodologically naïve. Especially in this context of applied science, however, perception can trump technical accuracy as the dominant factor for the utility of the science. Working to incorporate both perspectives shapes the design goals of project and contributes to building ownership.

Machine learning also introduces sites of methodological negotiation and tricky contingencies. Thorough understanding of the limitations, validity, and bias of any particular implementation of machine learning is crucial for robust ethical use of machine learning products. It also often requires technical specialized knowledge. For AtlasV2, the potential real-world applications of the data and methodology make for an acute tension between the need and barriers to comprehension. There is no universal resolution to this tension. Broad collaboration is part of the response, distributing knowledge and expertise rather than warehousing it. Making the AtlasV2 data production pipeline open and modifiable is a necessary step, although an open process does not necessarily mean a transparent process.

Institutional contexts and resources are likewise considerations relevant for the Atlas and AtlasV2 projects. Concretely, the time, labor, and associated expense required to produce the original hand-classified Atlas is at issue. Researchers and technicians in West Africa were financially supported, at least in part by USAID, for the duration of the 22-year project. An algorithm-based rapid classification methodology obviates the need for time, labor and expense. These characteristics of AtlasV2 were part of the project design, with the idea that researchers and technicians freed from repetitive time-consuming hand-classification could instead move on to advancing research efforts. AGRHYMET, however, is in large part funded by project-based grants from international and multilateral donors. Cost reduction in one area does not automatically mean those resources can be redistributed to a different area.

Results from the AtlasV2 offer insights on changes in land cover relevant to food security planning and natural resource management, as well as perspective on land cover narratives in the region. AtlasV2 offers a confirmation of the extent, location, and pace of agricultural expansion since 2000. It also provides a large-scale view of the relative changes in other major land cover types, for example savanna is in faster decline than short grass or steppe. The absence of significant increase in the area of bare soil or sand in the Sahel since the year 2000 refutes simplistic desertification narratives. Further, the assertion that desertification is not occurring in the Sahel, based on a definition of bare soil and sandy area, is not surprising among social and physical scientists who study land cover change in the Sahel, but it is directly at odds with the language used both in the international development sphere and in environmental strategies at the national level.

Refuting the desertification narrative has consequences far beyond the technical science findings. The narrative of desertification is leveraged by both national and international institutions to garner international attention and support, including financial resources. Refuting the desertification narrative has the potential to reduce available resources in the region. This is the motivation for generating an alternate equally compelling narrative that can augment the availability and access to resources at the local level, while fostering a perspective that allows for variation at the local level of identified issues and appropriate solutions.

Reframing Desertification

Desertification as a framework for understanding and approaching land cover change in the Sahel is no longer appropriate, if it ever was. It does not accurately represent observed land cover dynamics in the Sahel. Persistent and high-profile aspects of the desertification narrative have included the ever-expanding advance of the desert, the encroachment of bare soil and sandy landscape. These behaviors do not accurately represent land cover change in the Sahel, a conclusion of the AtlasV2 dataset that adds to the compendium of supporting evidence. Even vaguely defined, scientific consensus is that desertification is not occurring in the Sahel. Further, the legacy of the desertification framework as a tool of coercive colonial control continues to foster a bias toward exogenous top-down blanket responses to land cover dynamics seen as locally caused problems (Mortimore 2016). Better alternatives to this approach are both conceivable and possible.

Narrative is crucial in political domain: compelling storytelling captures attention, changes opinions, and attracts funding. Development agendas designed to accomplish those outcomes tend toward dramatic, simple, general, urgent (Swift 1996). Huntsinger adds morality to the criteria for a successful narrative (Huntsinger 2016). Desertification meets all four of Swift and Huntsinger's proposed criteria for an impactful narrative. The UNCCD definition of desertification is simultaneously both simple and general. The morality component is embedded with the implication of local people as the cause of desertification. The impending catastrophe of drastic, perhaps irreversible change that renders the landscape uninhabitable is suitably dramatic and urgent.

Moving land cover science toward (for example) data-based, nuanced, locally grounded, scale specific approaches easily results is a weakening or displacement of the cleaner more powerful desertification narrative. This leads to a tension wherein science and political agendas are at odds. Divergence of the discourse around desertification in international development contexts from consensus in scientific communities illustrates a striking outcome of this tension. The narrative negotiation of scientific results is fundamental to the practice and communication of science. These narratives are also subject to pressure to be compelling, through political interfacings with science, science application agendas, and within the scientific community itself. This pressure can create tensions between nominal objectivity and underlying agendas. Subsequent disconnects can arise wherein, for example, scientists or journalists express personal opinions or perspectives that differ from those they publicly profess (Jiang 2016; Shanahan 2016). Narrative choice shapes not only the ontology of the issue at hand, but also the conceivable solutions. Stafford Smith (2016) advocates for Sahel land cover change narratives that promotes empowerment and solutions.

The results of the AtlasV2 classification firmly refute the dominant desertification narrative. They also provide an opportunity and a foundation to offer an alternate narrative. My formulation of a proposal for an alternate narrative follows below. The project of crafting a narrative is a fundamental part of science and science communication. Whether acknowledged or not, it is always part of the practice of science, one which cannot be accomplished with data alone. Whether considered or not, any narrative serves a particular agenda, expresses different priorities, and has different potential implications.
In developing an alternate framework it is crucial to explicitly think through these considerations. In direct acknowledgement and engagement with the socio-institutional embeddings of land cover science, I lay out an explicit treatment of the agenda and priorities involved in the development of an alternate narrative.

My proposed working agenda for the development of an alternate narrative is as follows:

- **An alternate framework should be a framework that supports efforts to channel resources toward environmental management strategies that serve the needs of the local people.**

- **An alternate framework should be a framework that is effective in the ways it shapes discourse, action, and outcomes.**

My proposed priorities for an alternate narrative:

Local perspective

Emphasis on localization and decentralization is a common thread across current writing on alternate approaches to land cover change in the Sahel. One such example is the proposal of a "resilience" framework to take the place of the desertification narrative (Mortimore 2016). "Resilience" in general is a concept with history and meaning not only in the development sphere, but in the field of complexity and systems science (Folke 2006). In the present discussion, reference to the "resilience" framework is restricted to Mortimore's interpretation (2016).

This "resilience" based approach focuses on local endogenous solutions realized through the positive impacts of local land management. Implicit within this framework is an inversion of the cause-solution attribution across scales. The desertification paradigm predisposes exogenous solutions to what are significantly, if not exclusively, locally caused environmental problems. In the resilience framework, exogenously caused negative impacts such as climate change serve as an implicit if not exclusive counterpoint to the focus on local solutions. A shift in focus to localized solutions also allows for heterogeneity across space, both in terms of existing dynamics and appropriate responses, in a way that the broad sweeping generalization of desertification does not.

Direct problem framing

If public narrative and private perspective have so diverged over the desertification narrative, the proposal of an alternate narrative is an opportunity to identify and foreground the actual issues that scientists and land managers in the region see as priorities. The results from AtlasV2 and other work refuting any universal, region-wide, locally caused southward advance of the Sahara desert would indicate that the desert is not, indeed, the threat. Face-to-face conversations about desertification with leading scientists in the region quickly turn instead to the issues they are de facto concerned with. From these perspectives in the

Sahel, finding locally appropriate solutions that achieve agriculture sufficiently productive to feed the growing population is paramount. There is a strong sense that population growth is not the driving problem, that it is the state's responsibility to be able to feed all of its people, and that it is immaterial whether land degradation is a result of human activity or climate. There is scale and urgency and solution-oriented thinking embedded in this off-stage discourse, all powerful ingredients for a potential alternate narrative. Instead of holding onto desertification as a proxy narrative, I propose directly framing the major issues and priorities in the region, while keeping in mind the importance of maintaining the level of influence wielded by the desertification narrative.

Positive forward-looking solutions

Local land management and drylands knowledges can be seen as positive opportunities and advantages instead of amelioration activities. In this light, the extensification of agriculture looks like an enormous opportunity for proactive beneficial land management instead of the progression of an environmental crisis. The absence of an increase in bare soil or sand accompanying the drastic increase over the past two decades in agricultural area region-wide supports the compatibility of increasing land use with environmental sustainability. Grounding in the local scale is important for the outcomes of the framing. Otherwise, agricultural improvement solutions can be blanket, universal projects, such as large scale irrigation projects in the Sahel backed by the World Bank (World Bank 2015).

My proposal for an alternate narrative:

There remains, then, the matter of how one crafts an effective narrative to fulfill the agenda and priorities above. Building a narrative based on current scientific understanding of existing dynamics, while true to orthodox science protocol, has not been an effective strategy for crafting a compelling alternative narrative for land cover change in the Sahel. Instead, I propose to build backward from the qualities characteristic of an impactful narrative. While the implications of those qualities are arguably problematic, the formulation of characteristic ingredients can guide the development of a narrative that prioritizes impact. Adopting Huntsinger's criteria for an effective narrative: general, simple, and moral (and leaving aside Swift's dramatic and urgent criteria), and following the agenda and priorities detailed above, I propose the following alternate narrative to replace the desertification story.

From: "Local people are causing widespread potentially uncontrollable environmental destruction."

To: "Local people have the power to create widespread robust and sustainable food systems given locally appropriate support."

A framework doesn't solve anything, but it provides a structure from which to start.

Summary

The first chapter of this dissertation presents a new LULC dataset for West Africa. This is my applied science. The second chapter details the methods used to create the dataset. This is an explicit treatment of the importance and influences of the "how" of science, regardless of whether it is evident in the final results. The third chapter expands on the future work for the continued development of the LULC classification product and methodology. The second and third chapters taken together are recognition of the importance of open science, methodological sharing and collaboration, particularly when working across differences in institutional resources and access. Chapter four is more than anything an exposition of methodologies to explore multidimensional patterns in time and space. It is a demonstration of the importance of scale and space, the insights to be gained from a continuous systems dynamics perspective, the importance of examining one's data instead of taking its truth for granted. Finally, building from an understanding of the science, with an eye on the relevant social-institutional contexts, I offer an alternative to the desertification narrative of land cover change in West Africa. These projects are all beginnings. There is much more work to be done.

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