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Characterizing the spatio-temporal fire regime in Ethiopia using the MODIS-active fire product: a replicable methodology for country-level fire reporting

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In many regions of the world, fire is an integral part of land-use practices. The accurate spatio-temporal characterization of the fire regime can, therefore, inform land-use policy at many scales. Satellite-based fire detections can be manipulated with GIS methodologies to investigate the spatio-temporal patterns of fire across a landscape. However, caveats and accuracy limitations of data and analysis methodologies must be understood in order to avoid misrepresentation of the fire regime and its impacts. This research uses moderate resolution imaging spectroradiometer (MODIS) active fire detections (MCD14ML) together with land cover data (MOD12), (MOD44B), population data (Afripop) and information on land use drawn from the literature. A case study is presented for Ethiopia reporting on a 7-year period. Results show that 91% of fires occur in the woody savanna and savanna biomes, and fire activity is inversely correlated with population density. A 0.05° latitude/longitude grid is used to report fire density and indicated as more adequate than the existing 0.5° MODIS Climate Modelling Grid. Fire occurs with highest density in north-western Ethiopia, where smaller clusters of high fire activity are pointed out. Caveats and lessons learned are discussed in order to provide a best-practice methodology for country-level fire reporting.

Keywords: Fire; MODIS; Ethiopia; Africa; land cover

Introduction

Ethiopia is the largest country in the Horn of Africa with an area of 1.22 million km². It is home to the largest mountain complex in Africa and borders with Djibouti, Eritrea, Kenya, Somalia and Sudan. The highlands above 1,500 m elevation, comprise 43% of the country (Hurni, 1988) and as a result of the altitudinal gradient in the country a number of micro-climates have developed, driving differing patterns of rainfall with very high seasonal variability.

On the highland plateau covering the central, northern and western parts of the country, rainfall amounts can be 60 times larger in the maximum peak of August than in the minimum low of February, creating significant runoff and soil erosion problems...
In Ethiopia, there are both areas with unimodal rainfall patterns and areas with bimodal rainfall patterns, with two, three or four seasonal rainfall regimes. That said, in the western half of the country, where most of the fires occur, there is a distinct dry season between November and February and a wet season between June and September. The central and eastern parts of the country have bimodal rainy seasons: the Kiremet from June to September and the Belg from February to May, and one dry season in between – the Bega – in October and January. In the south and south-east lowland regions, however, there is considerably less vegetation and a more arid environment, with a four seasonal regime in which the rain falls mainly between March and June and then September to November, with drier periods in between (USDA, 2003).

The ecosystem is sensitive to intra-annual rainfall variability, which causes erosion and flooding problems and leads to soil degradation and loss of productivity. This sensitivity is exacerbated by the inter-annual rainfall variability, which often produces droughts in this region. The susceptibility of the more arid zones of Eastern Africa to climactic fluctuations has been shown by the severe droughts which struck the Sahel in the 1970s and 1980s, and Ethiopia in particular in 1984–1985 (Legesse, Vallet-Coulobm, & Gasse, 2003), in 1998–2000 (Bekele & Mengesha, 2001; Carter, Little, Mogues, & Negatu, 2007) and again in 2004 persisting through 2009 (ReliefWeb, 2010; Reuters, 2009) devastating the agricultural and livestock production and impacting the livelihoods of millions of Ethiopians, increasing mortality, malnutrition and poverty (BBC, 2004; The Economist, 2009). Environmental pressure also comes from increasing population density. In 2008, there were 80 million inhabitants in Ethiopia, having grown by 15 million in 8 years and with a large part of this population living in poverty. As of 2011 Ethiopia ranked 174th out of 187 countries in the Human Development Index (UNDP, 2009). Furthermore, historically, ecological and environmental issues have played into the political instability of the country (Rembold, Carnicelli, Nori, & Ferrari, 2000).

Africa has been referred to as the ‘fire continent’ as its vegetation burns frequently across all of its vegetated biomes (FRA, 2001; Pyne, 2004; FAO, 2006) and more than any other continent (FAO, 2006), with the savanna and shrubland/cropland/grassland mosaic landscapes of Eastern Africa and the Horn of Africa contributing to this regime (FRA, 2001). The importance of fire in the tropical savanna landscapes is well documented, and it has been proposed that African savannas owe their existence more to the effects of fire than to those of climate (Skarpe, 1992) as fire in savanna biomes is a necessary ecological disturbance, needed for the optimal reproduction and regeneration of the vegetation (FAO, 2006).

In Ethiopia, the agricultural sector accounts for roughly half of the country’s Gross Domestic Product and three quarters of the export revenue, providing the livelihood for an estimated 85% of the population (Bekele & Mengesha, 2001; World Bank, 2008). Most of the farming is small scale, with an average holding size of 1.5 ha per family, producing food crops, commodity crops and most of the livestock (Bekele & Mengesha, 2001).

Fires in Ethiopia are prevalently associated with agricultural and pastoral land-use practices, as well as land-use conversion (Angassa & Beyene, 2003; FRA, 2001; Gashaw & Michelsen, 2002; Goldammer et al., 2002; FAO, 2006; Jacobs & Schloeder, 2002; Reid et al., 2000; Tegene, 2002; Zeleke & Hurni, 2001). Today, in the eastern to north-eastern part of the country, the predominant land cover types ranged from desert to grasslands and woodlands with grazing being the predominant land use, and 65% of the land area being burned periodically to rejuvenate dry grasses. In the lower areas
within the north and north-east, fire is also used for hunting and to manage pests (tsetse fly, ticks) and in the highlands of central Ethiopia, the west and north-west, fire is used for inducing growth in pastures, clearing land and converting it from woodlands and forest to croplands (Bekele & Mengesha, 2001; FRA, 2001; Jacobs & Schloeder, 2002). Fire is also caused simply by negligence and arson (FAO, 2006). Natural fires ignited by lightning do occur but are considered to be only a small fraction of the total fires occurring in this region.

There are many ways in which fire can impact the environment and people, either by directly affecting their health or indirectly by impacting their livelihoods and economy. Fire can impact local populations acutely, for example, by burning through inhabited areas and incurring in loss of property and loss of life (FAO, 2006). Over time instead, at both local and regional scales, the mismanaged use of fire can lead to environmental problems, changing the species composition, vegetation structure and soil properties, increasing erosion, degradation and leading eventually to the loss of land productivity (Pyne, 2004). Soil degradation increases the potential for famine in the region (Hurni, 1988). Air quality issues from the emissions of gases and particulate are also relevant, especially when they persist over time, as they can become a significant detriment to human health. Over the savannas of Africa the low incidence of rain in the dry season may increase the time that aerosols remain suspended, deteriorating further the air quality (Scholes & Andreae, 2000).

On the other hand, too little fire can lead to fuel build up and less frequent but more intense and destructive fires as well as bush encroachment of rangelands (Angassa & Beyene, 2003; Angassa & Oba, 2008; FAO, 2006; Pyne, 2004). Bush encroachment has been found to become problematic when its cover exceeds 30% of the grassland (Oba, Post, Syvertsen, & Stenseth, 2000), causing pasture degradation and leading to lower production yields. One study found that in southern Ethiopia the degradation of rangelands affected over 70% of the land area (Oba et al., 2000). In all of east Africa, bush encroachment is associated by pastoralists with a reduction of animal reproduction, and the increased mortality of livestock (Oba et al., 2000). The slash-and-burn clearing is pervasively used in African landscapes to convert woodlands and forested areas into cropland. These fires can easily spread to neighbouring vegetation and cause unwanted damage to the landscape (FAO, 2006). In 2000, for example, while suffering from a severe drought, large wildfires burnt in Ethiopia and were partially managed by an effort lead by the Global Fire Monitoring Centre that involved tens of thousands of people (Bekele & Mengassa, 2001).

On longer temporal scales, both at regional and global scales, the greenhouse gas and aerosol emissions from fires are a large contribution not only to the degradation of air quality, but also to global warming and the hydrological cycle. While savanna fires are thought to account for 85% of global burned areas, and 50% of global carbon emissions (Mouillot & Field, 2005; Mouillot, Narasimha, Balkanski, Lamarque, & Field, 2006; Schultz et al., 2008), they are not a net source of greenhouse gas emissions, as most of the pyrogenic carbon emitted during the dry season originates from photosynthesis during the previous growing season (McNaughton, Stronach, & Georgiadis, 1998; Scholes & Andreae, 2000). However, it is undoubtedly important, as Scholes and Andreae (2000) note, to reduce the uncertainties in the amount and composition of the vegetation that burns in order to make accurate inventories and predictions of the impacts that emissions have on the atmosphere (Scholes & Andreae, 2000).

Fire management is particularly important where there are interactions of environmental, economic and political vulnerability such as Ethiopia. However, while fire is
understood to be a prevalent tool used in shaping and managing land in Ethiopia, there have been no synoptic wall-to-wall satellite remote-sensing studies characterizing the spatial and temporal patterns of fire, linking it to changes in land cover, land use, climate and other factors such as population. For these reasons, increased spatial and temporal granularity in fire reporting can be of great benefit for strategic land-use planning in Ethiopia.

Methodology
This research uses the Fire and Thermal Anomalies (MOD14 and MYD14) data from NASA’s moderate resolution imaging spectroradiometer (MODIS) onboard the Terra and Aqua satellites together with land cover data (MOD12), vegetation continuous fields (MOD44B), population data (Afripop) and information on land use drawn from the literature to investigate the spatio-temporal patterns of fire in Ethiopia over a 7-year period.

The temporal and spatial variations of fire are investigated for the period 2002–2009; a subset of the available 2000-present MODIS time series. Spatially, fire is assessed on national, regional and local administrative units as well as on a 0.05° grid that allows a granular understanding of fire incidence per unit area. Fire is assessed based on its spatial interactions with land cover types, vegetation structure, population distribution and qualitative land-use information taken from the literature. The correlation of fire and land-use practices is discussed in general, but not analyzed in detail at a fine spatial resolution, as sufficient spatially explicit information on the use of fire in land use does not exist other than for a few locations. The active fire data-set has sub-daily temporal resolution and can therefore be used to create representations of fire activity at a range of temporal scales; this research focuses on monthly and yearly time scales, describing inter- and intra-annual variations in fire occurrence.

The fire detection accuracy of the MODIS MOD14 Fire and Thermal Anomalies product (Giglio, Descloitres, Justice, & Kaufman, 2003) for Ethiopia was assessed utilizing Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data building on the well-established MODIS active fire validation methods (Giglio et al., 2008; Morisette et al., 2005a, 2005b; Schroeder et al., 2008). These methods were developed to create summary statistics of omission and commission and detection probability curves based on fire size.

Active fire data
The source of active fire data is the MCD14ML archive of active fire locations as processed by the MOD14 Fire and Thermal Anomalies product (Figure 1) (Giglio et al., 2003) and made available by the Fire Information for Resource Management System (FIRMS) now housed at the NASA Goddard Space Flight Centre (GSFC) as part of the Earth Observing System Data and Information System Land Atmosphere Near Real-time Capability for EOS and formerly at the University of Maryland. FIRMS services and data are also available through the Food and Agriculture Organization (FAO) of the United Nations (UN), where it is known as the Global Fire Information Management System. FIRMS archives global MODIS fire detections and distributes them to the public in several value-added formats. The FIRMS archive obtains data from the NASA MODIS Adaptive Processing System and MODIS Rapid Response pipelines at the NASA GSFC. The MCD14ML product is a monthly ASCII file of detected fires,
available also as a raster-format MODIS Climate Modelling Grid (CMG). These data sources currently provide Collection 5 active fire data. The origin of these data is the MOD14 (Terra) and MYD14 (Aqua) Fire and Thermal Anomalies products, whose automatic detection algorithm was produced by Kaufman et al. (1998), then revised in Collection 3 (Justice et al., 2002) and subsequently in Collection 4 to remove persistent false detections and the omission of small, yet obvious, fires (Giglio et al., 2003). The current Collection 5 data-set has improved detection confidence values and has been released concurrently with the new version of the MODIS Fire User Guide (v2.5).

**Validation using ASTER**

The validation of the active fire data-set is possible using coincident imagery provided by the ASTER sensor on-board the Terra satellite. Only the MOD14 product from the Terra satellite can be validated with this method but is assumed to provide an accurate description of the accuracy of the entire MCD14ML archive that contains also MYD14 (Aqua) detections. Several papers have been published on the ASTER-based MOD14 validation: two for the Brazilian Amazonia (Morisette, Giglio, Csiszar, & Justice, 2005a; Schroeder et al., 2008), one for the Siberian boreal forests (Csiszar, Morisette, & Giglio, 2006), and one for southern Africa (Morisette et al., 2005b) which discussed tropical grasslands and savanna biomes. While Morisette et al. (2005a), Schroeder et al.
and Csiszar et al. are not necessarily representative of the Ethiopian landscapes, Morissette et al., 2005b probably is, as it focuses on similar land cover types, but not at comparable elevation. For this reason, an ad hoc accuracy assessment was performed.

The MOD14/ASTER validation data were obtained as a subset of the MOD14 global validation project (http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD14). The global validation study covered Ethiopia with 24 ASTER Level 1B images. For the current study, the sample of 24 images was expanded to include a total of 59 images in order to have better spatial coverage (Figures 2 and 3). Tabular data containing the ASTER-MODIS correlation of fire detections included: the number of ASTER pixels flagged as fire, fire clustering, VCF and MOD12 values for every MODIS pixel centroid. Using these tabular data, the accuracy statistics were then calculated and characterized by their correlation with clustering, VCF and MOD12 values.

**Temporal analysis methodology**

Temporally, the following dimensions were considered: intra- and inter-annual variability in both yearly and monthly resolutions, reported in relation to the fire-year. The available active fire data ranged from 2000 to 2012, however, only observations from August 2002 to July 2009 were used. The active fire archive contains 16 months of Terra-only observations from November 2000 to May 2002, which would have shown lower numbers of

![Figure 2](image.png)

Figure 2. Red triangles represent ASTER/MODIS validation scenes from Schroeder et al.‘s unpublished MODIS validation paper in preparation, the magenta dots are the additional scenes that were selected out of the available ones (yellow). Together the red triangles and magenta dots are all the scenes assessed in this accuracy assessment.
fires and likely different spatio-temporal trends of fire activity than the years with both Aqua and Terra observation together. Subsequent data have become available; however, it is not believed to add or alter the objective and conclusions of this study.

The active fire data were obtained in yearly subsets and clipped to the country boundaries. Yearly files were then aggregated into a single text file, which ultimately had 397,133 active fire points organized in a tabular format with attributes of latitude, longitude, satellite platform, time of overpass, date, confidence and fire radiative power (Davies, Ilavajhala, Wong, & Justice, 2009; Giglio et al., 2003).

The fire-year was established to be different from the calendar year. The Ethiopian fire-year is at its apex in December/January; therefore, fire reporting on a calendar year would have been misleading, splitting each fire season between two separate reporting periods (Boschetti & Roy, 2008). We found that in Ethiopia July and August had equally the lowest fire activity. We chose 1st August as the beginning of the fire year. The data utilized, in this study, therefore contains active fires for 7 fire-years, beginning August 2002 and ending in July 2009.

Spatial analysis methodology

A Geographical Information System (GIS) was utilized to correlate the active fire detections (points) with administrative units (polygons), MOD12 land cover data (raster), MOD44B vegetation continuous fields (VCF)(raster) and Afripop population density (raster). The resulting data-set reported active fire detections according to raster class ownership and administrative unit by: land cover type, per cent tree cover range, popu-
lation density range and administrative unit. This spatial reporting was disaggregated temporally, as described in the temporal analysis methodology.

There are inherent accuracy errors that result from deriving spatial statistics from the spatial intersection of data in different formats (raster and vector) and different spatial resolutions. These accuracy errors add to the declared accuracy limitations of the individual input data-sets. Other than the error from false fire detections, the active fire data have three sources of spatial inaccuracy. Fire detection points represent the centroid of a 1 km MODIS pixel, which, as Morisette et al. (2005a) described, actually contains fire detections from a 1 to 2 km footprint, in the along-track and along-scan directions as a result of the sensor’s point-spread function. Second, the detected fire event could be located anywhere within the area of the MODIS pixel and not just at its centroid location. Third, there could be several distinct fire events within the fire pixel, which are not detected as such because of the coarse spatial resolution of the sensor.

The spatial intersection of fire detections with land cover pixels does not co-register, as the MOD12 land cover map has 500 × 500 meter pixel resolution. If the MODIS active fire pixels were the same size and coregistered with the land cover pixels, the spatial intersection would yield a one-to-one correlation of land cover value for each active fire detection. Instead, there are several possible land cover values (pixels) within the MODIS AF pixel, while only one value is sampled by the centroid of the active fire pixel. This sampling approach of intersecting fire points to land cover pixels has been used by several authors for local fire assessments (Jaenicke, Rieley, Mott, Kimman, & Siegert, 2008; Langner & Siegert, 2009; Robbins, Eckelmann, & Quiñones, 2008) and rests on the principle for which over a large sample population of data points (over 300,000 in our case) the results accurately depict the proportions of active fire detections in each land cover class.

A different approach would use the raw raster MOD14 HDF fire masks (or CMG) in place of the FIRMS-delivered MCD14ML vector product. In this approach the land cover classification (MOD12) raster data would be down-sampled (made coarser) and assigned a single land cover value from (at least) 4 pixels of separate values in order to have the same resolution as the 1 km raster HDF fire mask (4500 m pixels within a 1 km pixel at Nadir). In alternative, the binary fire mask (fire/no fire) pixel value could be assigned to each of the 4 land cover pixels, even though the actual fire might have occurred in only one, two or three of the land cover pixels. This approach has also been used in several studies, including a global study of fire in croplands (Korontzi, McCarty, Loboda, Kumar, & Justice, 2006), in the validation of the MODIS burned area product (Roy, Boshcetti, Justice, & Ju, 2008) and in the probability analysis of detection in validation studies (Morisette et al., 2005b; Schroeder et al., 2008).

Both approaches have benefits and limitations. The methodology in this paper introduces classification error by sampling land cover with active fire points. The raster-to-raster approaches introduce error by generalization, resulting in either simple majority or averaging of the land cover values within a MODIS fire pixel. The generalization error, in a region where the land cover is highly mosaicked and with small scale crop holdings of an average 1.5 ha (or 150 m × 150 m) (Bekele & Megesha, 2001; Laris, 2005) we think introduces enough inventory error to make it comparable to the sampling error of the methodology used in this study (Campbell, 2007). In this study, the methodology used, however has a great advantage, as using the MCD14ML active fire detection data is more accessible, less onerous and more user friendly for users who don’t have the specialized software, training and time necessary to work with MODIS lower level products.
The administrative units used to report fire incidence are the Global Administrative Unit Layers data-set, from the FAO of the UN – European Commission joint Food Security Programme, and downloaded from FAO Geonetwork (EC-FAO Food Security Programme, 2010; GeoNetwork, 2007). The choice of land cover data depended on availability and spatial and temporal resolution compatibility with the active fire data. While the FAO and European Space Agency’s (ESA) GlobCover product has global coverage at a 300 m pixel resolution, the temporal resolution is a snapshot of the 2004–2006 period, from which it is composited (Defourny et al., 2006). The MOD12 Land Cover Classification (Friedl et al., 2002) instead is a yearly product available at a 500 m pixel resolution and has been previously used in MOD14 validation papers (Schroeder et al., 2008). The MOD12 classification scheme used was the International Geosphere-Biosphere Programme (IGBP) scheme, chosen because of comparability to previous MOD14 validation papers.

The MOD44 Vegetation Continuous Fields (VCF) product used is derived from MODIS L1b reflectance composites and provides the percentage of tree cover within a 500 m pixel (Hansen et al., 2003). The VCF data-set was selected as it gives us an understanding of the spatial occurrence of fire without the inherent generalization error of a classified land cover product (Hansen et al., 2003). Although the product is only available for the 2000–2005 period, it provides good temporal resolution (yearly).

The Afripop population density product (Tatem, Noor, von Hagen, Di Gregorio, & Hay, 2007) was acquired for Ethiopia by downloading the freely available continental product with 1 km resolution, and then subsetting Ethiopia. The Afripop population density was visually overlaid with the active fire points and fire density grids.

**Results: the Ethiopian fire regime**

**Accuracy assessment of MOD14 in Ethiopia**

A confusion matrix was used to assess the accuracy of MODIS fire detections. Figure 4 illustrates how the confusion matrix approach is used. The classification data (MODIS) and the reference data (ASTER) have different minimum mapping units however (1 km vs. 30 m), making a confusion matrix insufficient for assessing accuracy, as fire size being the main modulating factor in the detection probability inevitably causes the lower resolution sensor to have significant omission errors (Morrisette et al., 2005b). A confusion matrix remains useful in quantifying MODIS fire detection commission error.

The confusion matrix results show that there is low commission and some omission. MOD14 produced only two false positives (0.7% commission error); however, 1520 ASTER fires were omitted (82% omission error). This omission error is in line with what has been observed by Schroeder et al. (2008) as most of these omitted fire detections are from considerably smaller fires than the detection capabilities of the MODIS sensor. As a function of cloud cover, overpass frequency and the mosaicked landscape with small land-use fires, the MOD14 product is providing an underestimation of the total fires occurring on the ground.

Modelling a detection probability curve shows exactly how fire size modulates the MODIS detection accuracy (Figure 5) (Csizsar et al., 2006; Morrisette et al., 2005a; 2005b; Schroeder et al., 2008). The global MODIS-active fire detection validation used 2500 ASTER scenes and calculated detection probability as a function of several factors, showing a 50% probability of detection when ASTER fire size was at least 70–80 pixels, and a 90–95% detection probability when fire size was at least 150–200 ASTER pixels (unpublished data).
Figure 4. MOD14 pixels flagged as fire in agreement with ASTER are in magenta, MODIS pixels not flagged as fire when ASTER flagged them as fire are in yellow (omission error), pixels not flagged as fire by either MODIS or ASTER are in black and MODIS pixels flagged as fire in disagreement with ASTER are in blue (commission error).

Figure 5. Probability of fire detection based on number of ASTER fire detections within a MODIS pixel.
Our results were comparable but indicated a better performance of the MOD14 product in Ethiopia compared with the global results. Results showed 90% probability of detection when at least 65 ASTER pixels where flagged as fire, compared with about 150 in the global validation. In terms of area that means the MOD14 product in this region has 90% detection probability of detection when the entire area of 65 ASTER pixels, or 58,000 m² (0.58 km²) which is 5% of the MODIS footprint contains an active fire. The MOD14 product also had 90% detection probability when there were at least 5 adjacent ASTER fire pixels, which, if we assume the fire to take the entire ASTER pixel (30 m²), means that 90% detection accuracy occurred when fires were at least 150 m² (5 × 30 m²). Because these area calculations are based on the assumption that the entire ASTER pixel contains an active fire, whereas the ASTER minimum detectable fire size is theoretically 1 m², but varies greatly (Giglio et al., 2008), it is not straightforward to deduce fire size from the quantity of ASTER pixels flagged as fire. Only a very small percentage of active fires will occupy an entire ASTER 30 m pixel when flagged. Comparing MODIS and ASTER detection coincidence allows us to characterize MOD14 detection characteristics in this region. MOD14 can detect more easily fires represented by ASTER fire clusters, even if they take less area than the necessary non-clustered fire pixels for an equal probability of MODIS detection. This is because larger clusters of ASTER fire detections are likely to represent larger flaming or smouldering fires. The clustered fire pixels also suggest that the fire(s) on the ground are big enough to continue onto adjacent pixels in the cluster, probably burning the area within that pixel more completely (Giglio et al., 2008).

**Temporal characteristics of the fire regime**

The average fire season had 57,000 detections. The most active fire season was 2007–2008, with about 10,000 more fire detections than average. The lowest fire activity was in 2006–2007 with 53,000 detections. Observations at the country level showed a clear increase in fire activity between November and April, peaking in January and with a low in July/August (Figure 6). On average for all years, July/August both have about 1%
of the maximum fire activity; May and October have about 8% of the maximum fire activity, and detections within 10% of each other. November and March are also within 5% variation of each other and have about 44% less fires than the peak fire months. Fire activity in the peak season of December, January and February varies by no more than 4% between months. The spike in fire activity at the onset of the fire season, between October and November each year is in the order of a 700% increase (Figure 7). There is, therefore, very high intra-annual variability in fire incidence.

Figure 7. Active fire counts for the study period, all months.

Figure 8. Inter-annual variability of fire at the monthly scale. In December 2005, there were 16,000 Active fires detected – while a year after in December, there were 8,000 active fires detected.
Inter-annual fire variability is similarly high. In December 2005, there were about 16,000 active fires detected, and a year later, there were 50% less (~8000), likewise in February 2007, there were about 9000 fires detected, and a year later, there were 170% more fires detected (~16,000) (Figures 7 and 8).

**Spatio-temporal analysis of the fire regime**

While it is still used by many, point-cloud data visualisation (Figure 1) is deceptive in portraying the density of fires over a given area. An often better alternative is to summarize fire detections on a raster grid which displays fire density per unit area. The fire density can then be displayed also using isobars derived from the raster (Figures 9 and 10). Results show that while intra- and inter-annual fire activity varies, and the spatial distribution of fire detections also varies, the spatial distribution of fire density per unit area is relatively constant from year to year. Most fire activity is concentrated in the west and north-west of the country. Of the 8 first-level administrative units, Benishangul Gumuz, in the north-west, bordering Sudan, has the highest fire activity. Benishangul Gumuz is only bigger by area than two other states, Tigray and Gambella, and has the highest fire density of any other state. Benishangul Gumuz has 85% more fire activity than the second highest ranking state by fire density, Oromia.

![Figure 9. Fire density for all years. The density is displayed using a colour scale, blue representing 0–3 detections/25 km² and red representing 90 detections/25km². Single-year fire density plots revealed almost identical density patterns.](image-url)
Of the 68 second-level administrative units (zones), there are 30 which have more than 1000 active fire detections over the entire study period (Figure 11). The highest activity at this level occurs in Metekel, accounting for over 80,000 fire detections between 2002 and 2009. North Gonder is second with 58,000 and Asosa third with 46,000 detections.

Fire density is also inversely correlated with population density in Ethiopia (Figure 12). The highest fire activity is in areas that have less than 10 inhabitants per 25 km Sq. However, a significant amount of fire activity occurs at the interface of savanna and woody savanna ecosystems with the cropland mosaic that is more densely inhabited. In Ethiopia population density, altitude and vegetation type are all correlated, so this result was not surprising. A higher resolution investigation of the linkage between land-use, population and fire would provide useful insight into the linkages between these factors but goes beyond the objective of this first country-level fire report.

**Fire and vegetation continuous fields**

About 66.5% of Ethiopia is in the VCF class of 0–9% tree cover, 10.2% is in the 10–19% tree cover range, and 13.3% is in the 20–29% range (Figure 13). The remaining 10% is in higher percent tree cover ranges, which are rare in the Horn of Africa. Most of the south, east and northeast of the country is in 0–9% VCF values, with higher percent tree cover values in the north-west and west, as well as the southern central highlands south of the Rift Valley (Figures 14).
The distribution of active fire detections does not follow the distribution of per cent tree cover in Ethiopia, which is explained by the fact that while 66% of Ethiopia is in the 0–9% tree cover range, in those areas, there is either not enough vegetation to create fuel for fires, or not enough vegetation to support the land-use practices in which fire is utilised as a land management tool. Those areas are also sparsely populated. Only 16% of active fire detections fall within the 0–9% VCF range, 14.5% fall in the 10–19% VCF range and the majority of active fires (39%) fall in the 20–29% VCF range, which only covers 13% of the country. 11.4% of detections occur in the 30–39% range and 16.6% occur in the 40–49% range. Above 50% tree cover fire detections are very minimal with about 2.4% of total.

The incidence of fires in specific VCF per cent tree cover ranges can be followed through time as well. The most visible trend is in the 20–29% tree cover range, which is the range that burns the most. In the 2005–2006 fire year, for example, the active fires increased in this range; this is in line both with the increase overall fire activity in that year as well as a 3% increase in area for this VCF range for that year. Other fire detections per VCF range correlations follow the same trend over time, showing a good correlation between these data-sets.

**Fire and land cover**

The MOD12 Land Cover Classification results show that the western half of the country is dominated by savanna and woody savanna land cover types, gradually mixing with cropland in the northern and central regions of the country, and a cropland and forest.
mosaic in the central region and the south-west. Grasslands in the south, eastern central highlands and the Rift valley become gradually the vast open shrublands of the eastern lowlands. The most prominent land cover types are open shrubland, savanna and woody savanna. Variations in land cover over the 7 years have been analysed. Between 2005 and 2008, the area of woody savanna increased by about 30,000 km², or 2% of the country’s total area, and the area of savanna decreased by the same amount. These

Figure 12. The highest fire density in Ethiopia occurs in sparsely populated areas.

Figure 13. On the left (a) the per cent of land area in the VCF per cent tree cover ranges and on the right (b) the percent share of total fire observations in the same VCF classes.
variations can be explained either by real-world physical changes, or by the accuracy limitations of the data and a more detailed investigation is outside of the scope of the paper.

Most fire activity occurs in the savanna and woody savanna land cover classes, 55 and 36%, respectively. Cropland mosaic fires account for 3% and grassland fires 2%; 15% of fire activity occurs in barren/sparsely vegetated areas and 3% in all other classes, including cropland (Figure 15 and 16). A large portion of the fires occurring in the barren/sparsely vegetated land cover seem to be attributed to the volcanic activity in the eastern part of the country, notably with events in September 2001 and June and November 2009. The fragmented land cover and small-scale agriculture is likely to account for an underestimation of fire activity occurring in croplands. As slightly different results were obtained with the ESA GlobCover product (DeFourny et al., 2006), these small differences and under/over estimations are likely to depend on the land cover classification product used and not physical differences.

The monthly scale analysis of active fire detections reveals patterns of woody savanna and savanna fires. Figure 17 shows the fire detections plotted by month for the entire study period. Savannas burn the most at the beginning of the fire season, between October and December, and then activity slowly declines until the fire activity ceases in May. Fire activity in the woody savanna class instead gradually grows in November, peaking in February and then declining rapidly in April. Savanna is prominent in the north-western part of the country, whereas woody savanna is predominantly found south
of the savanna class. This observation is in line with the north-south gradient of the temporal cycle of burning observed in Africa (Roy et al., 2008). In Figure 18, the same temporal variation is analysed for all other land cover classes. The cropland/vegetation mosaic fire activity peaks in February, probably as a consequence of the clearing of dry-season residue from fields in preparation for new crops. Grassland fires also peak in February, showing steady activity from November to March. Forest fires are low year
round, until their number goes up for February and March, when they are perhaps more likely to be ignited by adjacent land-use fires.

**Conclusions**

This paper uses satellite remote sensing data to obtain descriptive statistics of the incidence of fire in Ethiopia for the period 2002–2009, using the MODIS-active fire points provided by FIRMS. A MODIS MOD14 fire detection algorithm local validation was produced using coincident ASTER data, which showed low commission error (0.7%) and some omission error (82%). Omission was a function of the lower spatial resolution of the MODIS sensor compared with ASTER. A detection probability curve based on
number and clustering of ASTER-detected fires was performed and the results were in line with those found in the global and regional validation literature. However, results indicated better regional performance of the MOD14 detection algorithm for Ethiopia, compared with global validation results, with 90% detection probability when 65 ASTER active fires pixels were present, as opposed to 150 for the global detection probability. The fire detections presented in this paper represent a conservative number, as the small average land holding size, and considerably mosaicked landscape in the region are likely to lead to many land-use fires being very small and going undetected.

Results show the vast majority of fires occur in the western and north-western areas of the country, mostly in the 20–29 Vegetation Continuous Fields per cent tree cover range (39% of all fires), and predominantly in the MOD12 IGBP Woody Savanna and Savanna classes (91% of all fires). These results agree with the reports of fire being used as a land management tool for pastoralism and agriculture in this region (Angassa & Beyene, 2003; Angassa & Oba, 2008; Bekele & Mengesha, 2001; FAO, 2006) and find comparatively very little fire activity in more densely forested areas, cropland mosaic, cropland and barren/sparse areas.

Fire density is as high as ~2.4 fire pixels per km² in one year and up to ~16.4 fire pixels per km² over the entire 7 fire-season study period. This result suggests that the analysis of fire density at this scale may be quite useful to create an indicator of land-use intensity per unit area, which could be used for strategic, sustainable land-use planning.

The fire year follows a normal distribution, beginning in August and ending in July with peak fire activity in December, January and February. Results show that cropland fires peak in February, while being very low the rest of the year. This could coincide with the clearing of senescent vegetation to prepare fields for sowing (Bekele & Mengesha, 2001). Savanna fires peak early in the fire season (November) and are low at the height of the fire season (January) when fire activity in the woody savanna starts increasing.

Forest fires are only a small fraction of the total fires, when correlated with MOD12 land cover classes, while they represent a higher percentage of the total (17%) when correlated with the 2005 GlobCover product. This is a result of the larger area of the country classified as forest by the GlobCover product and reiterates the importance of understanding the classification schemes and accuracy limitations of the input data-sets as well as the GIS methodologies used. While the literature reports a large forest fire in 2000, it also notes the absence of notable forest fire episodes in the previous decade (Bekele & Mengesha, 2001). Results show also that the woody savanna area grew in the study period, accounting for a proportionally larger share of annual fires; however, it is debatable whether or not observed trends of fire incidence by land cover over time are significant or are explained by the accuracy limitations in the classified products.

The fire regime has inter-annual variability shown in particular by variations in the period 2004–2009, with a low of 53,000 detections in 2007 and a high of 66,000 in 2008. Likewise, the peak month of the fire season varies, with 2006 peaking in December, 2007 peaking in March and 2008 peaking in February. A more in-depth understanding of these variations could be investigated together with vegetation indexes as well as dryness/wetness of the fuel derived from rainfall activity.

Fire activity seems to be inversely proportional to population density when compared with the Afripop product. In Ethiopia the highest population density is not found in the savanna and woody savanna classes, so this result was expected. Correlation with
population density, and its change over time would be more relevant in Ethiopia if done at a local scale, with much higher spatial resolution and just for those areas at the interface between savanna and woody savanna and the cropland and cropland mosaic land cover classes.

While focused on Ethiopia, this paper discusses the caveats and accuracy limitations of using the MODIS MOD14 product in conjunction with other data-sets to create country-level fire reports. The ecological, environmental and social impacts of fire are not easily quantified at the country level; however, future work could focus on developing fire density-based indicators of anthropogenic land-use pressure on the environment. This study summarized fire density on a coarse resolution $5 \times 5$ km cell grid. For Ethiopia, we observed this unit of area to be more adequate in correlating fire density with land use and land cover than the existing $0.5^\circ$ ($50 \times 50$ km at the equator) MODIS fire CMG (Justice et al., 2002) or the $0.25$ ($25 \times 25$ km at the equator) finer scale CMG proposed by Giglio (2013) in the MODIS-Active Fire user guide.

Globally, regional- and national-level studies that assess and monitor fire regimes spatio-temporally are needed, as these provide valuable information to stakeholders and policymakers involved in land-use planning and management (FAO, 2006). The fire regime report provided in this paper can be used by the environmental, agricultural and development communities in their land-use planning and management efforts as well as demonstrating a replicable best-practice methodology that can be used in regional- and country-level fire assessments.

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