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Humans and climate modulate fire activity across Ethiopia

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Abstract

Background Fire occurrence is influenced by interactions between human activity, climate, and fuels that are difficult to disentangle but crucial to understand, given fire's role in carbon dynamics, deforestation, and habitat maintenance, alteration, or loss. To determine the relative balance of climatic and anthropogenic influences on fire activity, we quantified interannual variability in burned area across Ethiopia from 2001 to 2018 and developed a statistical model to assess climate and human factors contributing to patterns of area burned.

Results Annual burned area declined nationally and within several regions from 2001 to 2018 and was closely related to climate, particularly antecedent temperature. Of the area that burned at least once, 62% reburned at 1–3-year intervals and the geographic region of frequent-fire areas did not shift over time. Despite increased enforcement of a fire ban over the past 20 years, no strong spatiotemporal shifts in fire occurrence patterns were detected at a national level.

Conclusions Our results suggest that human influence combined with dynamics of vegetation and fuels strongly influenced fire occurrence in Ethiopia, indicating that geographic variation in cultural fire practices was highly influential and relatively unchanging between 2001 and 2018. In contrast, interannual variability in total burned area was strongly related to climate and the influence of climate on fuel abundance. Our results highlight that climate can strongly influence short-term variability in fire activity even as longer-term patterns may depend more strongly on human influence.

Keywords Fire occurrence, Burned area, MODIS, Random forest, Fire history, Cultural fire practices, Fire policy, Tsetse flies

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Resumen

Antecedentes La ocurrencia de incendios está influenciada por interacciones entre actividades humanas, clima y combustibles, que son difíciles de desentrañar, pero que es crucial entender dado el rol del fuego la dinámica del carbono, en la deforestación y en el mantenimiento, alteración o pérdida de hábitats. Para determinar el balance relativo del clima y las influencias antropogénicas en la actividad de los incendios, cuantificamos la variabilidad interanual en el área quemada a través de Etiopía desde 2001 y hasta 2018, y desarrollamos un modelo estadístico para determinar los factores climáticos y humanos que contribuyen a los patrones del área quemada.

Resultados El área total quemada disminuyó en el territorio nacional y en varias regiones y se relacionó muy estrechamente con el clima, particularmente con las temperaturas precedentes. De las áreas quemadas al menos una vez, el 62% se volvieron a quemar a intervalos de 1 a 3 años, y la región geográfica de áreas de fuegos frecuentes no cambiaron en el tiempo. A pesar de la prohibición de quemas en los últimos veinte años, no hubo fuertes cambios en los patrones espacio-temporales de ocurrencia de fuegos detectados a nivel nacional.

Conclusiones Nuestros resultados sugieren que la influencia humana, combinada con la dinámica de la vegetación y los combustibles, influencian la ocurrencia de incendios en Etiopía, indicando que la variación geográfica en prácticas culturales de manejo del fuego tuvieron mucha influencia y no cambiaron relativamente entre 2001 y 2018. En contraste, la variabilidad interanual en el área total quemada fue relacionada muy fuertemente con el clima y su influencia en la abundancia de combustibles. Nuestros resultados resaltan que el clima puede influenciar fuertemente en el corto plazo la actividad de los incendios aun cuando los patrones a más largo plazo pueden depender más fuertemente de la influencia humana.

Background

Trends and drivers of fire occurrence and burned area (BA) are important to identify because fire effects influence human livelihoods, carbon flux and storage, biodiversity, and ecosystem health (Kelly et al. 2020; Bliege Bird et al. 2008). Since 2000 CE, BA has declined globally and this decline has been attributed to both expansion and intensification of agriculture (Andela et al. 2017; Jones et al. 2022). In Africa, BA is thought to have been in decline for at least the past 4000 years (Archibald et al. 2012). Yet there is significant geographical variation in fire occurrence and its drivers (Jones et al. 2022). Here, we use BA to refer to the total burned area aggregated over broad (regional to national) extents, fire occurrence to refer to spatiotemporal patterns of burning, and fire activity as a broad term to encompass both BA and fire occurrence. Drivers of fire activity are complex and include characteristics and flammability of fuels and vegetation; climate change and variability; and human influences on ignitions, fire suppression, fuels, and grazing patterns that affect buildup of biomass (Wahl et al. 2019; Mann et al. 2016; Zubkova et al. 2019; Hempson et al. 2018). Accurately characterizing drivers of fire activity at national scales, in relation to fire policy and resource management, is particularly crucial to support evidence-based decision-making. Given the importance of forest and woodlands for ecosystem carbon storage, fire management is key to the success of the UN's Reducing Emissions from Deforestation and forest Degradation (REDD+) program (Barlow et al. 2012; Weatherley-Singh and Gupta 2015).

Quantifying human influence on fire activity is challenging due to a complex array of both direct (ignitions or fire suppression) and indirect (livestock grazing that reduces fuel, land use change) effects that influence fuel connectivity (Archibald 2016). Human contributions to fire activity can be represented through factors like land cover and ownership, road networks, population density, and livestock density (Archibald et al. 2009; Probert et al. 2019) or by indices that summarize overall human impact (Krawchuk et al. 2009). Africa accounts for 68% of global BA (Lizundia-Loiola et al. 2020) and observed declines in Africa BA since 2000 have been attributed to a combination of agricultural expansion and increasing moisture which are thought to have reduced flammability in humid areas (Grégoire et al. 2013; Andela and Van Der Werf 2014; Zubkova et al. 2019). The relative balance of these climate and anthropogenic influences on observed fire occurrence and BA in Africa is debated (Wei et al. 2020; Zubkova et al. 2019; Andela and Van Der Werf 2014); a better understanding of climate and human drivers at regional to national scales is needed to predict future fire activity and formulate effective fire policy.

Here, we use Ethiopia as a test case to evaluate an approach to disentangle human and climatic influences on annual fire activity from 2001 to 2018 at the national scale. Drivers of annual fire occurrence and BA have not been comprehensively analyzed at a national scale in Ethiopia, although Molinario et al. (2014) described general geographic and seasonal patterns of fire and van Breugel et al. (2016) modeled the effects of climate change on projected fire regimes and vegetation type distributions. Ethiopia, like many African countries, is striving to manage fire activity (and natural resources in general) in the face of limited scientific evidence. Ethiopia's current fire policy is based primarily on evidence from other regions and policymakers and institutions lack the resources needed to predict and manage forest fires or adapt fire policy to changing social and ecological conditions (Teketay et al. 2010). Fire policy in Ethiopia has evolved over the past 20 years. In 2007, the "Proclamation for the Forest, Development, Conservation and Utilization: Proc. 542/2007" included a ban of forest fire. The contribution of fire to forest degradation is a particular concern for policymakers in Ethiopia because the country seeks to promote reforestation and forest conservation through its participation in REDD+ (Johansson et al. 2021; Lemenih and Kassa 2014). In 2013, the Ministry of Environment and Forests was established as an independent ministry, and forest governance moved from a focus on protection to sustainable economic use with conservation of biodiversity and enhancement of carbon stocks. With the formation of the Ministry of Environment and Forests, efforts to enforce forest fire suppression policy intensified, particularly in regions where forest fires have been frequent. In 2018, a new "Forest Development, Conservation and Utilization, Proclamation No. 1065/2018" was released with increased penalties for starting forest fires and bushfires. Natural resource governance in Ethiopia is decentralized, and each regional state can adapt national resource and fire management policies to fit regional conditions, but states have limited resources for local adaptation. Further, enforcement and educational campaigns differ among regions due to variation in resources and priorities. Consequently, the effects of the ongoing fire ban in Ethiopia and recent increases in its enforcement at a national scale remain unclear, as do region-level trends in fire activity (Johansson et al. 2018; Tsegaye et al. 2010; Angassa and Oba 2008).

Patterns of fire occurrence in Ethiopia are also likely to have been influenced by land use changes, namely expansion of cropland and developed areas over the past three decades (Kassawmar et al. 2018; Betru et al. 2019). Although trends vary extensively within Ethiopia, these land use changes have often included decreases in forest cover and dense vegetation and increases in large-scale commercial farming (Kassawmar et al. 2018; Degife et al. 2018; Gebrehiwot et al. 2014; Belete et al. 2021). Finally, the distribution of tsetse flies (*Glossina* spp.), which are vectors for the livestock disease trypanosomiasis that limits the productivity of livestock and sometimes the viability of keeping livestock, may affect fire activity by either encouraging frequent burning to control trypanosomiasis or by reducing density or completely excluding livestock grazing from areas with a high likelihood of trypanosomiasis.

To disentangle human and climatic influences on fire occurrence and BA in Ethiopia, we first investigated the contribution of climate variation to interannual variability in annual BA using the Moderate Resolution Imaging Spectroradiometer (MODIS)-based FireCCI51 product (Lizundia-Loiola et al. 2020). Then, we built a statistical model of the annual proportion of 16-km^2 grid cells burned to identify the importance of climate, fuels, and human factors on fire occurrence. This approach of empirically modeling fire activity over both space and time has been used at daily-to-annual time scales within grid cells of $\geq$ 1 km^2 to forecast climate change impacts on fire activity (Preisler et al. 2004; Preisler and Westerling 2007) and to quantify factors controlling fire activity over gradients of climate or weather, fuels, terrain, and human impacts (Westerling and Bryant 2008; Park et al. 2021; Masrur et al. 2022). In some analyses of large and heterogenous regions, the study area has been divided into smaller ecoregions each represented by a local model (Padilla and Vega-García 2011). However, local models may overfit and hence be less generalizable, and a single broader model may outperform local models in predicting fire activity particularly when a nonlinear modeling framework is used (Park et al. 2021). Therefore, we conducted our analysis at a national scale. We hypothesized that temporal trends in BA would be partially explained by climate and land cover change, but there would be a decline in fire occurrence consistent with increased enforcement of the fire ban policy. Although the fire ban is not limited to forest land, we expected to see greater policy impacts on fire activity in areas with greater forest cover due to the particular interest in protecting forests.

Methods

Study area

Ethiopia is ecologically diverse, with vegetation that ranges from desert and savanna at low elevation to closed forest and heathlands at high elevation (Friis et al. 2010). Elevation gradients strongly control the spatial distribution of vegetation types, and these vegetation patterns contribute to a distinct spatial distribution of fire frequency (Figs. 1 and 2). A high plateau at 1500–3000-m elevation covers much of central Ethiopia, divided by the African Rift Valley. Annual precipitation increases from east to west and with increased elevation (Fig. 2). Most of Ethiopia experiences a primary rainy season from June to September (*kiremt*) and a secondary rainy season from February to May (*belg*) also occurs in the south and in the highlands of southeastern, central, and northeastern Ethiopia (Philip et al. 2018; Seleshi and Zanke 2004). Correspondingly, much of the BA in Ethiopia occurs from

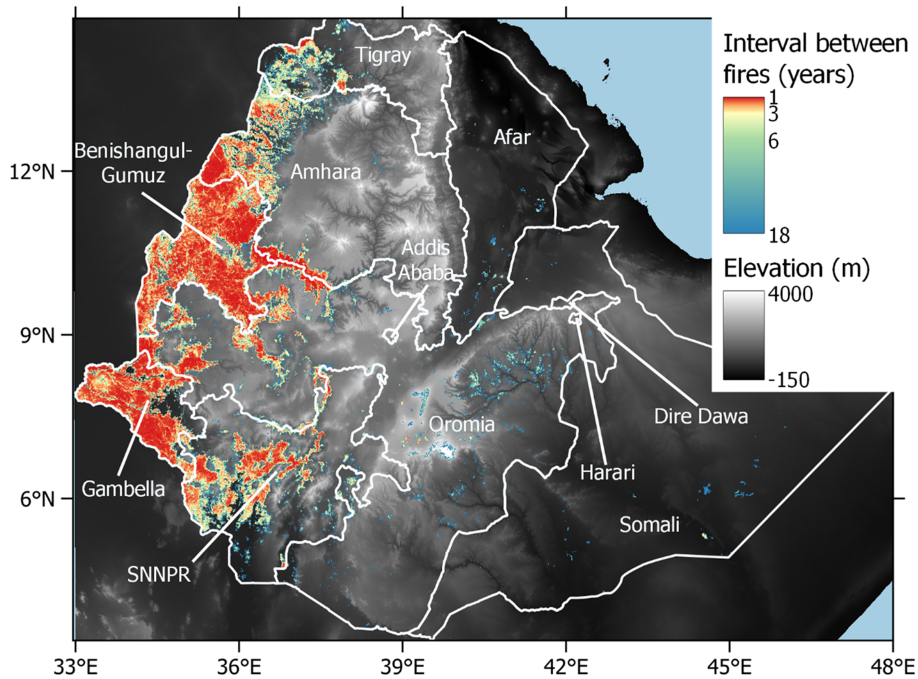

Fig. 1 Mean interval between fires from 2001 to 2018 across Ethiopia, based on the FireCCI51 dataset. Regional names and boundaries are also shown along with elevation

November to March with minimal BA in June and July (Molinario et al. 2014). The El Niño/Southern Oscillation influences precipitation patterns, but this influence is complex and varies spatially and by season (Seleshi and Zanke 2004; Dinku et al. 2018). Accordingly, correlations between El Niño/Southern Oscillation and BA anomaly vary in both strength and directionality across Ethiopia (Andela and Van Der Werf 2014). Lightning-ignited fires are uncommon in Ethiopia, even in montane areas where lightning strikes occur in forests and heathland during the dry season (Molinario et al. 2014; Johansson et al. 2012). Rather, most fires are set by people for harvesting honey, improving pasture, and controlling woody plant encroachment (Johansson et al. 2012; Angassa and Oba 2008); facilitating hunting and firewood collection (Jensen and Friis 2001); production of charcoal (Andaregie et al. 2020); and rotational burning of croplands and crop residues (The Oakland Institute 2011; Kassawmar et al. 2018). Ethiopia's regional states (Fig. 1) were used for visualizing results and for assessing BA trends at a sub-national level. Under Ethiopia's ethnic federalism, each of these regions also represents the homeland of a different ethnic group or groups (Aalen 2011), each with their own cultural practices and social-ecological systems.

Fire occurrence datasets

Two MODIS fire occurrence datasets were considered for this study. The MCD64A1 dataset (Giglio et al. 2018), with a pixel size of 500 m, has been widely used along with its predecessors for analyses of BA in Africa (Zubkova et al. 2019; Archibald et al. 2009; Hempson et al. 2018). The FireCCI51 dataset, which uses just the finer-grained bands from MODIS, can detect fires at 250 m pixel size and offers greater detection accuracy for small fires (Lizundia-Loiola et al. 2020). Based on an accuracy assessment of each dataset within Ethiopia (see Supplementary Material), we proceeded to use FireCCI51 rather than MCD64A1 for further analysis.

Seasonality

Because monthly BA was minimal from June–August, during the primary rainy season, area burned was aggregated into "fire years" beginning on 1 July (e.g., the 2001 fire year was 1 July 2001–30 June 2002). Google Earth Engine (Gorelick et al. 2017) was used to extract burn date for each MODIS pixel within each fire year from 2001 to 2018 across Ethiopia. The earliest day of burn was selected in the case of multiple fire detections in the same pixel because the earliest date is more likely to represent the actual day of burn, although we did not account for the possibility of burning happening with a given pixel twice within the same fire year. To provide background information on fire seasonality, we calculated 10-day running means of BA for each year, nationally and by region as well as vegetation type (Figs. S2 and S3, see the "Factors affecting fire occurrence" section).

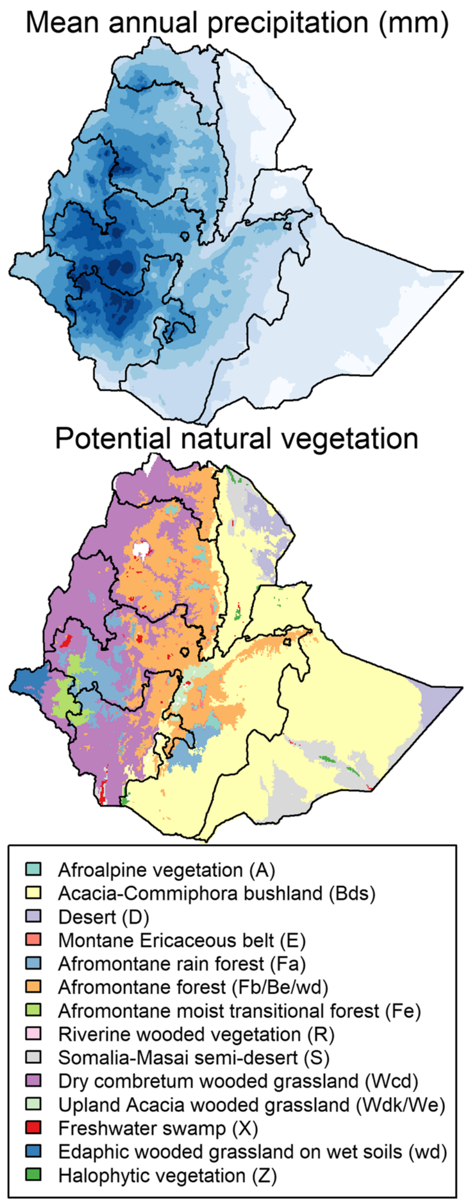

Fig. 2 Mean annual precipitation from 2001 to 2018 across Ethiopia, and potential natural vegetation types from van Breugel et al. (2015)

Climate

To investigate climate influences on annual BA and fire occurrence, we considered rainfall, temperature, and soil moisture (Table 1). Antecedent climate as well as fire-season climate was assessed because antecedent climate over the prior 1–2 years can influence BA in the fire year via biomass productivity (Andela and Van Der Werf 2014; Zubkova et al. 2019; Abatzoglou et al. 2018). Variables were aggregated over five time periods to represent a range of possible climatic influences: (1) by fire year (July 1–June 30), (2) November to April of the fire year (main fire season), (3) calendar year to capture antecedent conditions in the months leading up the main fire season, (4) two calendar years (e.g., 2000 and 2001 for the 2001–2002 fire year), and (5) prior two calendar years (e.g., 1999 and 2000 for the 2001–2002 fire year). We also calculated climate anomalies relative to 2001–2019 means for each variable and time period.

We used the Climate Hazards group Infrared Precipitation (CHIRP) dataset (Funk et al. 2015) for monthly precipitation because it provides highly accurate estimates at this time scale in Ethiopia and has lower bias than the CHIRPS dataset which integrates station data (Dinku et al. 2018). For estimates of annual and seasonal temperature and soil moisture at 0–10-cm depth, we used the Famine early warning system network Land Data Assimilation System (McNally et al. 2017), which was developed to monitor drought and has been previously used to model BA across Sub-Sahara Africa (Zubkova et al. 2019). Finally, we considered the influence of El Niño/Southern Oscillation interannual variability on BA using the National Oceanic and Atmospheric Administration's Oceanic Niño Index (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/detrend.nino34.ascii.txt).

Factors affecting fire occurrence

We used an array of geospatial datasets to quantify potential factors affecting fire occurrence (Table 1). To estimate the influence of livestock, we used the Gridded Livestock of the World v. 3 (Gilbert et al. 2018), which has a reference year of 2010. The dasymetric rasters of cattle, sheep, goat, pig, horse, and chicken densities were converted into Tropical Livestock Units (Jahnke 1982) and summed to estimate total livestock biomass per unit area. To quantify the potential influence of tsetse flies, we used a suitability map showing the probability of tsetse fly occurrence developed by Leta et al. (2015).

We evaluated three potential annual land cover datasets for our statistical model (see the "Model of fire occurrence" section), so that change in land cover could be incorporated into the analysis. The best-performing land cover dataset was a Landsat-based product created by the Regional Centre for Mapping of Resources and Development (RCMRD) (https://rcmrd.maps.arcgis.com/apps/webappviewer/index.html?id=c954194840d74c48a760485fe00ffb1e) which used a Continuous Change Detection and Classification algorithm (Zhu and Woodcock 2014) to map annual land cover in five categories: forest, grassland, cropland, wetlands, and other. The RCMRD land cover predicted fire occurrence better in our statistical model (see the "Model of fire occurrence" section) than the Midekisa et al. (2017) and the European Space Agency CCI (Li et al. 2018) land cover datasets.

Table 1 Variables considered for the model of proportion of 16-km^2 cells burned (using random forest). The final list of variables following variable selection is shown in Fig. 5. Variables which changed annually are italicized and static variables are not italicized. See Supplementary material for additional details on variables

Category	Variable	Source	Details
Response	*Proportion burned*	Lizundia-Loiola et al. (2020)	Proportion of area burned within 16-km^2 cells
Political	Region	Famine Early Warning Systems Network (FEWS NET), https://fews.net/	Regional states of Ethiopia
Time	*Year*		Fire year was included to detect temporal trends
Climate	*CHIRP precipitation*	Funk et al. (2015)	
Climate	*FLDAS soil moisture*	McNally et al. (2017)	0–10 cm depth
Climate	*FLDAS temperature*	McNally et al. (2017)	Mean monthly temperature at 2 m
Vegetation	Potential natural vegetation types	Friis et al. (2010); van Breugel et al. (2015)	Categorized into 14 vegetation types (Fig. 6 and Table S3)
Vegetation	*Normalized Differenced Vegetation Index*	MODIS vegetation indices (MOD13Q1v006)	Per-pixel maximum value from all 16-day vegetation indices layers in a given calendar year
Vegetation	*Enhanced Vegetation Index*	MODIS vegetation indices (MOD13Q1v006)	Per-pixel maximum value from all 16-day vegetation indices layers in a given calendar year
Land cover	*Land cover types*	Regional Centre for Mapping of Resources for Development, https://rcmrd.maps.arcgis.com/apps/webappviewer/index.html?id=c954194840d74c48a760485fe00ffb1e	From Landsat imagery, available annually 2000–2017
Human influence	Tropical Livestock Units per km^2	Jahnke (1982); Gilbert et al. (2018)	Calculated from Gridded Livestock of the World v. 3, relative to 2010
Human influence	Livelihood zone type	FEWS NET Livelihood Zones, https://fews.net/	Categorized into agropastoral, pastoral, cropping (Meher dominant), cropping (Belg dominant), other/unknown
Human influence	*Human population density*	Lloyd et al. (2019)	
Human influence	Protected area types	World Database on Protected Areas (https://www.protectedplanet.net/)	Categorized into: non-protected, UNESCO-MAB Biosphere Reserve, World Heritage Site, National Park, Sanctuary, Wildlife Reserve, National Forest Priority Area, Controlled Hunting Area
Human influence	Probability of tsetse fly occurrence	Leta et al. (2015)	
Terrain	Elevation	Shuttle Radar Topography Mission (SRTM) v4	90 m pixels
Terrain	Slope	SRTM	
Terrain	Terrain Ruggedness Index (TRI)	from SRTM, following Riley et al. (1999)	
Terrain	Standard deviation of elevation	from SRTM	Using a 7 × 7 pixel window (630 m)
Soils	Soil nutrient availability	Wieder et al. (2014)	Nutrient availability (SQ1)

Because the RCMRD dataset was only available annually through 2017, the 2017 land cover layer was used to represent the 2018 fire year as well. To complement the land cover data, we also used the 2018 Livelihood Zones map from the Famine Early Warning Systems Network (https://fews.net/), which identifies areas in which people share similar livelihoods.

Vegetation types were represented using a map of Potential Natural Vegetation (PNV) (van Breugel et al. 2015), which was derived from the Ethiopian atlas of vegetation (Friis et al. 2010). We also developed vegetation-based maximum annual values for the Normalized Differenced Vegetation Index (NDVI) and the Enhanced Vegetation Index from the MODIS Terra Vegetation Indices (MOD13Q1.006) product, whose 250 m pixel size matches that of the FireCCI51 BA product. To characterize the difference in soils and how they may influence vegetation productivity, we used nutrient availability (SQ1) from the Harmonized World Soil Database v1.2 (Wieder et al. 2014).

Burned area trends

As a preliminary analysis to assess changes in annual BA over the study period, the Theil-Sen slope estimator was used to assess annual BA trends nationally, by region of Ethiopia and by PNV type (Sen 1968). The Theil-Sen slope estimator is well-suited to analysis of BA trends because it is robust to outliers (Parks and Abatzoglou 2020; Collins et al. 2022), and was calculated using the "trend" R package (Pohlert 2020).

Model of annual BA

Given our particular interest in national-scale BA, we constructed a linear model of national-scale annual BA to assess the extent to which interannual variability in BA could be explained by a simple climate-only model. To identify variables to include in our model we calculated Pearson correlations (r) between each climate variable and annual BA at both the national and regional levels. For this linear model, we considered the time period from each of the four variables that was best correlated with BA but that did not have $|r| > 0.7$ with other predictors being considered, and added year to indicate trends not explained by climate. Notably, soil moisture from the prior 2 years was correlated with temperature from the prior 2 years ($r = 0.72$), so fire-year soil moisture was used instead. Stepwise selection by the Akaike Information Criterion was used to identify the most parsimonious model (using the "step" function in R), which incidentally included all five predictors.

Model of fire occurrence

To characterize the influences of the above factors on fire occurrence on a per-pixel and per-year basis, we created a random forest statistical model (RF, Breiman 2001) in which the response variable was annual proportion of area burned within 16-km^2 grid cells (hereafter PB for proportion burned), aggregated from the 250-m FireCCI51 pixels. All other variables were aggregated to this 16-km^2 grain size using either the mean or the most abundant class value (for categorical variables) (Table 1). All datasets were reprojected to an Albers Equal Area projection for analysis so that pixels were of equal size.

We used random sampling performed separately for each fire year to reduce the potential influence of both temporal and spatial autocorrelation, stratifying the samples within each year by selecting 150 cells (16-km^2) each of 0%, 1–50%, and >50% PB ($n = 450$ samples from each year) so the full range of PB was well-represented. Pixels classified as urban, impervious surface, or water in the land cover and livelihood zone datasets were not considered for sampling ($n = 165$). We then performed a two-step variable selection process. First, to address redundancy among variables, we determined all pairs of variables with a Spearman rank correlation coefficient of $|r_s| \geq 0.7$. We iteratively ran RF regression models and at each step removed the variable with lower importance (quantified by the Model Improvement Ratio [MIR], Murphy et al. 2010) in the most strongly correlated pairs until no pair of predictors had $|r_s| > 0.7$. Second, to remove variables not contributing to model accuracy, we utilized the "VSURF" R package (Genuer et al. 2015). This multi-step procedure involves repeatedly running RF models with progressively fewer variables and retaining only variables that substantially diminish model accuracy when taken out (Genuer et al. 2010).

After performing variable selection, we ran RF using default settings in the "randomForest" R package (Liaw and Wiener 2002) except that we constructed more trees ($n = 2000$). Model accuracy was assessed by withholding four fire years at random as a test dataset (2004, 2007, 2009, and 2015), such that the test dataset ($n = 1800$ samples) was temporally distinct from the training dataset ($n = 6300$ samples). To visualize relationships between individual predictors and fire occurrence, we constructed partial dependence plots (Friedman 2001) using the "pdp" R package (Greenwell 2017).

Results

Burned area trends

Annual BA in Ethiopia declined significantly from 2001 to 2019 on a national scale as well as in the central and northern regions of Oromia, Amhara, and Tigray (Table 2). The region with the highest mean annual BA, Benishangul-Gumuz, showed a marginally significant ($p < 0.1$) decrease in annual BA. Annual BA also declined in the PNV type with the majority of fire across Ethiopia, dry combretum wooded grassland, but did not change significantly in most other types (Table 3).

Table 2 Mean (± standard deviation) annual burned area (BA) from 2001 to 2019 by region of Ethiopia and trends assessed with the Theil-Sen slope estimator

Region	Mean annual BA (kha)	Theil-Sen slope
Benishangul-Gumuz	3002 ± 300	−29.3†
Gambella	1594 ± 116	−2.6
Oromia	1220 ± 242	−39.2**
Amhara	1155 ± 253	−45.8**
SNNPR	1077 ± 278	+8.1
Tigray	240 ± 125	−18.7**
Afar	8 ± 5	−0.2
Somali	7 ± 8	+0.3
Total	**8303 ± 893**	**−122.6***

† $p < 0.1$, *$p < 0.05$, and **$p < 0.01$ after a Holm-Bonferroni correction was applied

Table 3 Annual burned area (BA) trends by potential natural vegetation type assessed with the Theil-Sen slope estimator

Vegetation type	Mean annual BA (kha)	Theil-Sen slope
Dry combretum wooded grassland (Wcd)	6969 ± 795	−114.2*
Edaphic wooded grassland (wd)	580 ± 45	0.9
Afromontane moist transitional forest (Fe)	489 ± 70	−8.3
Acacia-Commiphora bushland (Bd/Bds)	74 ± 60	1.4
Afromontane forest (Fb/Be/wd)	73 ± 15	−1
Afromontane rain forest (Fa)	50 ± 15	−1.1
Freshwater swamp (X)	42 ± 11	−1.8*
Afroalpine vegetation (A)	10 ± 19	0.1
Semi-desert (S)	5 ± 3	0.1
Halophytic vegetation (Z)	5 ± 2	−0.2
Desert (D)	2 ± 2	0
Acacia tortilis woodland (We)	1 ± 1	0
Montane Ericaceous belt (E)	0 ± 1	0

† $p < 0.1$, *$p < 0.05$, and **$p < 0.01$ after a Holm-Bonferroni correction was applied

Climate and annual BA

Annual BA at a national scale corresponded strongly with mean temperature over the prior two years ($r_s = 0.76$, $p < 0.05$). The linear model of interannual variability in BA indicates variation could mostly be explained by climate:

$$\mathrm{BA} = \mathrm{T} \times 3500 - \mathrm{SM} \times 51963 - \mathrm{ONI} \times 150 + \mathrm{P} \times 4.67 - \mathrm{year} \times 46.6 + 26608$$
$$\left(\text{adjusted } \mathrm{R}^2 = 0.85, \mathrm{p} < 0.05 \text{ for all predictors except ONI } [\mathrm{p} = 0.15]\right)$$

where *BA* is national annual BA in kha ($n = 18$ fire years), *T* is mean temperature over the prior 2 years in degrees Celsius, *SM* is fire-year soil moisture in $m^3\ m^{-3}$, *ONI* is November–April Oceanic Niño Index, and *P* is total precipitation of the prior 2 years in mm. When the "year" term was removed from this model, adjusted R^2 decreased to 0.80. Regional-level climate correlations showed that in most of Ethiopia BA was negatively but not significantly related to precipitation, soil moisture, and El Niño/Southern Oscillation and positively related to temperature, except for the arid eastern regions which comprised <0.2% of national BA (see Fig. 3).

Model of proportion burned

The RF model explained 67.2% of annual PB at the level of 16-km^2 cells. An examination of mean PB over the period of analysis (Fig. 4 and Fig. S4) shows that areas with underpredicted burning occurred mainly in the western regions of Gambella and Benishangul-Gumuz, while areas of overprediction occurred in parts of the Southern Nations, Nationalities, and Peoples' Region (SNNPR) and the northern regions of Amhara and Tigray. Overprediction of burning occurred primarily in years with low antecedent temperature when observed total BA was low (Figs. S5 and S6), indicating that the model was unable to fully reproduce climatic influences on fire within these areas.

A calculation of fire frequency in 250-m resolution pixels shows that in areas that experienced at least one fire, 62% burned at intervals of ≤ 3.0 years on average and 45% burned at intervals of < 2.0 years (Fig. 1). Moreover, correlations (r_s) between rasters of PB were ≥ 0.78 for all possible combinations of fire years (Fig. S7), indicating strong spatial dependence in PB and fire frequency that did not shift appreciably over time.

After variable selection, the model of PB contained 13 variables. Population density was the most important variable followed by four other variables with importance > 0.7: NDVI, elevation, land cover type, and November–April precipitation (Fig. 5). PB tended to be greater if population density was low, elevation was low, NDVI was high, and the probability of tsetse fly occurrence was high (Fig. 6). According to the land cover dataset, grasslands tended to have higher proportion burned and croplands had lower PB (Fig. 6). In a model without tsetse fly occurrence, low livestock occurrence was also associated with higher PB, but was removed from the model during variable selection when tsetse fly occurrence was considered due to a high correlation between the two and better predictive ability of tsetse fly occurrence.

The climate variables in the model showed that low precipitation and low soil moisture anomalies during the fire season (November to April) led to greater PB, along with high antecedent precipitation and soil moisture

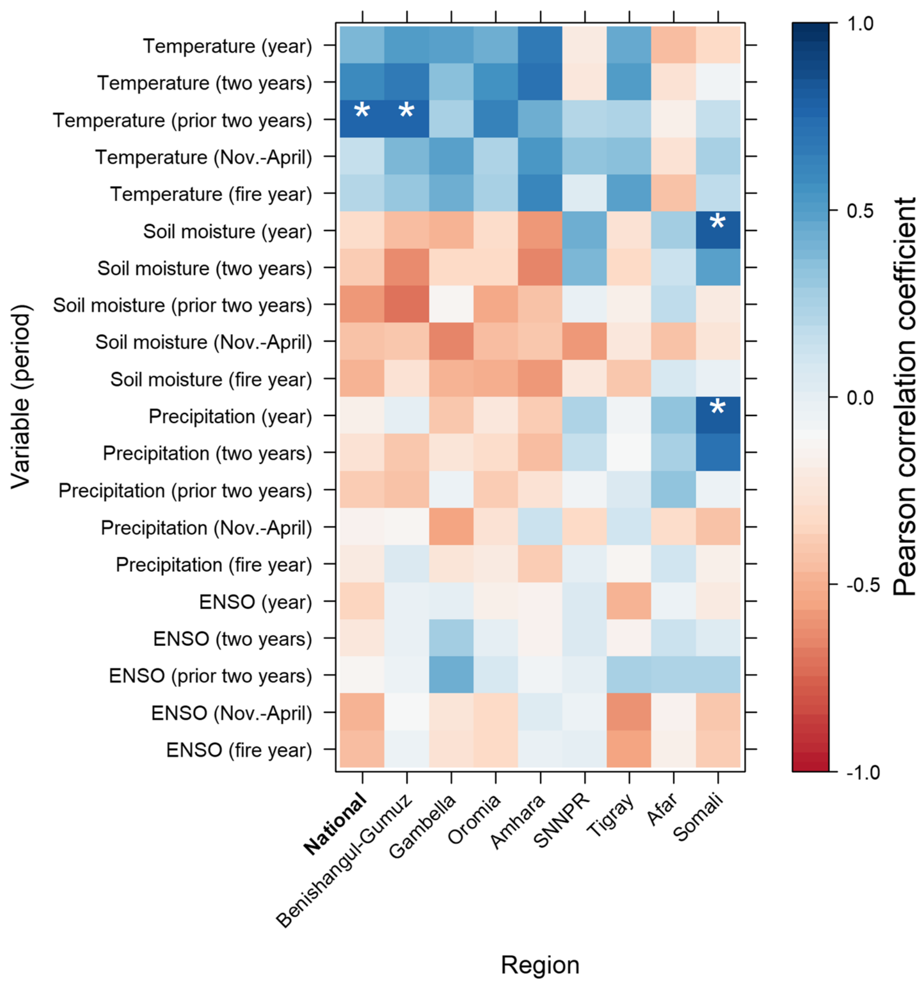

Fig. 3 Pearson correlation coefficients between annual burned area and climate aggregated over different periods, over all of Ethiopia and by region. Significant relationships ($p < 0.05$ with a Holm-Bonferroni correction applied) are indicated with *. ENSO is El-Niño/Southern Oscillation

(Fig. 6). Moreover, some vegetation types tended to burn more than otherwise expected: wet areas (R, X, wd), Afromontane moist transitional forest (Fe), and dry combretum wooded grassland (Wcd).

Discussion

Fire activity is driven by a complex combination of human, climatic, and fuel-related factors making it difficult to identify controls (Forkel et al. 2019). Moreover, the controls of fire activity that emerge are likely to vary depending on whether an analysis focuses on space or time; temporal analyses are more likely to highlight controls that vary substantially from year to year (Zubkova et al. 2019; Wei et al. 2020; Andela and Van Der Werf 2014) as seen in our analysis of climatic influence on annual BA, spatial analyses are likely to highlight the biophysical template (e.g., van Breugel et al. 2016) and analyses that are both temporal and spatial such as our PB model are likely to reflect both.

We were initially surprised by the relatively weak influence of climate on PB across Ethiopia given that climate explained the majority of interannual variability in national BA. A simple explanation is that climate varied from 2001 to 2018 whereas human influence on fire remained nearly constant over time when viewed at a national scale. The strong spatial correlation in PB across all sets of fire years in our analysis supports a narrative of consistent human influence as well as consistent patterns of fuel continuity and structure (e.g., as indicated by NDVI and annual land cover). This result is surprising given (a) the national fire ban in Ethiopia and changes in its enforcement and (b) dramatic land use changes documented in different parts of the country including expansion of cropland and deforestation in some areas (Belete et al. 2021; Duriaux-Chavarría et al. 2020; Betru et al. 2019; Degife et al. 2018).

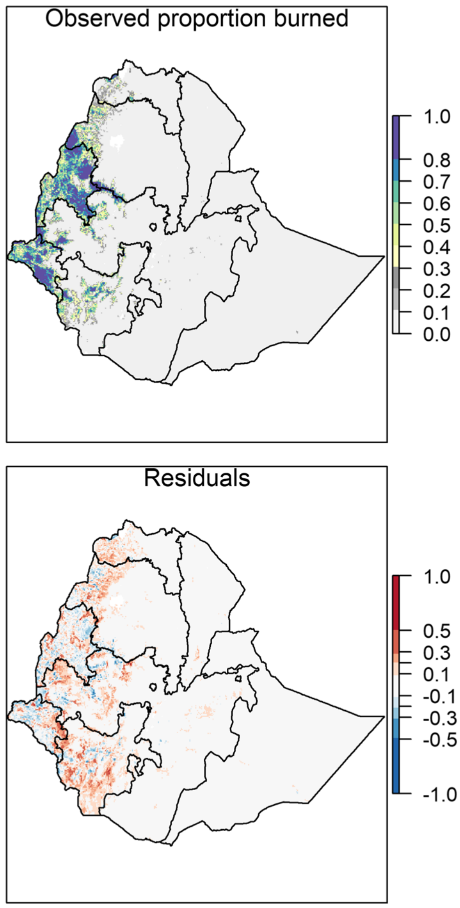

Fig. 4 Mean proportion burned averaged across the 2002–2018 fire years as observed and predicted by the random forest model, along with model residuals (reds indicate overprediction in residual plot). Regional boundaries of Ethiopia are shown

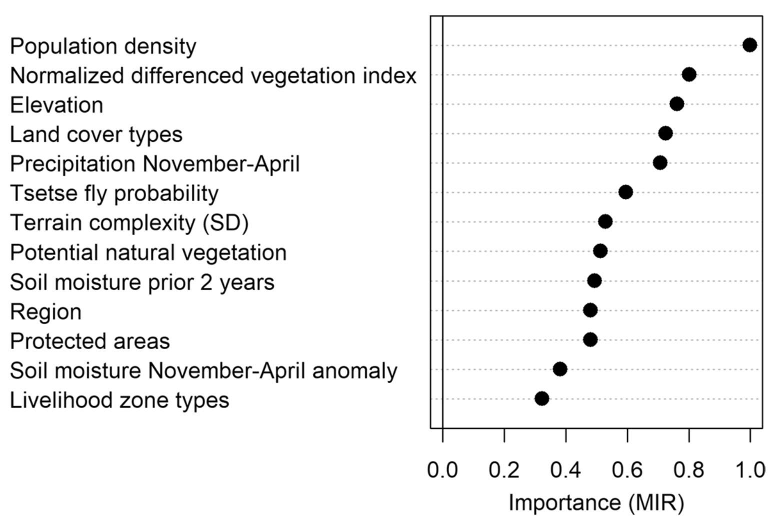

Fig. 5 Variable importance (model improvement ratio, MIR) from random forest model of fire occurrence. MIR is scaled such that the most important variable in a given model is 1 and 0 indicates no contribution to model accuracy

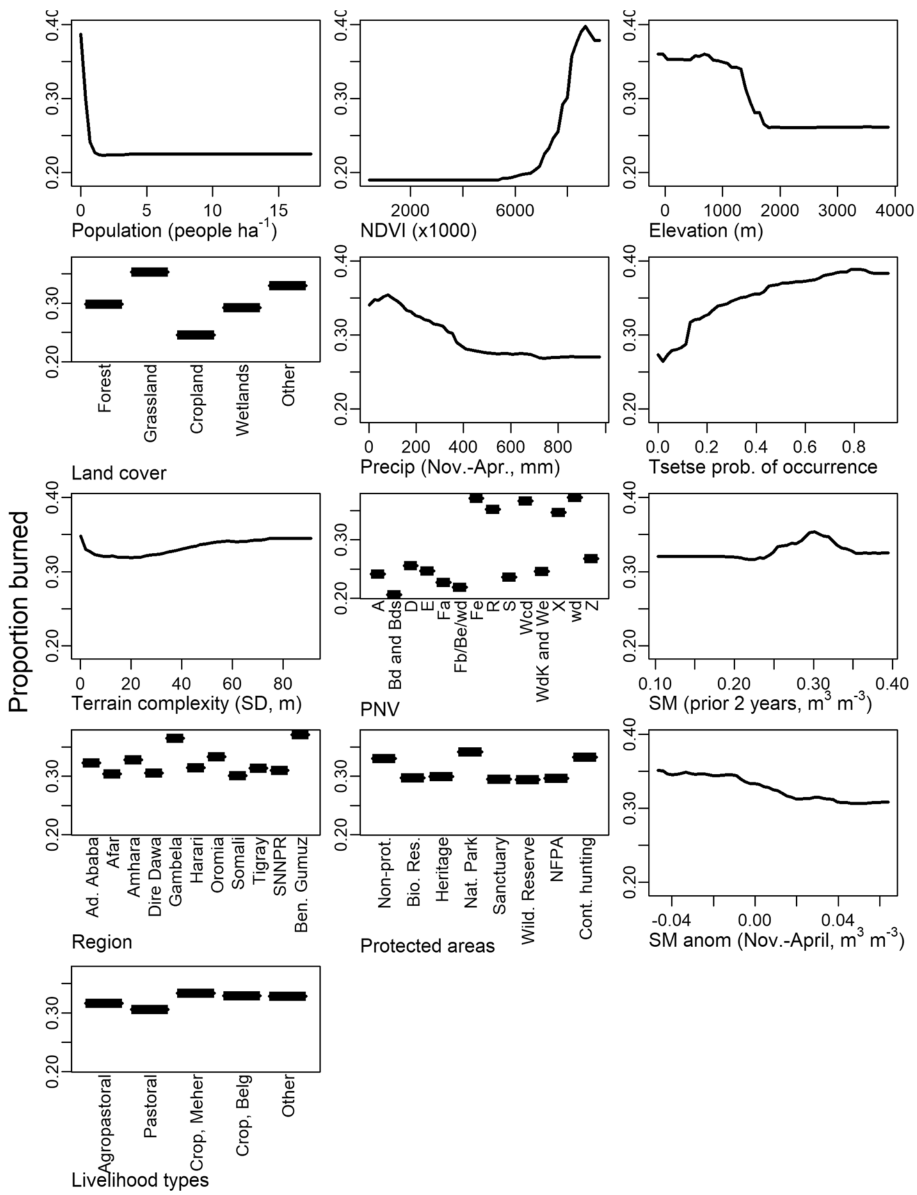

Fig. 6 Relationships between fire occurrence (proportion of 16-km^2 pixel burned) and predictor variables in the random forest model, shown using partial dependence plots. Variables are in order of importance from top left to bottom right (see Fig. 5). For details on the variables, see Table 1. Potential Natural Vegetation (PNV) classes are as follows: A = Afroalpine vegetation, Bd = Somalia-Masai Acacia-Commiphora deciduous bushland and thicket, Bds = Acacia-Commiphora stunted bushland, D = desert, E = montane Ericaceous belt, Fa = Afromontane rain forest, Fb/Be/wd = complex of Afromontane undifferentiated forest with wooded grasslands and evergreen or semi-evergreen bushland and thicket at lower margins, Fe = Afromontane moist transitional forest, R = riverine wooded vegetation, S = Somalia-Masai semi-desert grassland and shrubland, Wcd = dry combretum wooded grassland, Wdk = upland Acacia wooded grassland, We = *Acacia tortilis* wooded grassland and woodland, X = freshwater swamp, w = water bodies, wd = edaphic wooded grassland on drainage-impeded or seasonally flooded soils, Z = halophytic vegetation, Zw = lakes with Halophytic shoreline vegetation

Apparently, the changes in national fire policy and land use have not yet substantially impacted burning practices in the sparsely-populated and remote areas where burning was most frequent. Gambella, Benishangul-Gumuz, and SNNPR, where our results show fire frequency as highest, have experienced a large-scale transfer of land to agricultural investors particularly since 2008 (Shete et al. 2016; Shete and Rutten 2015; Moreda 2017). Although the results of this study do not yet show a significant impact on fire regimes from this land use change, continued expansion of commercial agriculture could dampen burned area as has been observed at a global scale (Andela and Van Der Werf 2014; Andela et al. 2017). Humans modulate fire-climate relationships through socio-ecological burning practices, land use, and land management policy, which can sometimes produce dramatic shifts in fire regimes (Archibald et al. 2012; Pausas and Keeley 2014; Taylor et al. 2016). Therefore, future demographic or policy changes may strongly affect fire occurrence in Ethiopia as they now affect spatial patterns of BA over our period of analysis.

We had expected to find indirect evidence of national fire policy and an ongoing fire ban on fire activity, yet our analysis did not find strong support for policy-driven declines in fire activity at a national level. Annual BA did decline significantly over the study period and the negative effect of year in the model of annual BA suggests that some of this negative trend was not explained by climate. However, climate did account for the majority of influence on annual BA, and BA did not decline significantly in dominantly forested vegetation types which should be most strongly affected by the national fire policy due to an interest in reducing forest fires. Although the strong role of population and land cover in the RF model suggests a strong human influence on fire regimes, this influence did not appear to change over the period of analysis. Instead, interannual variability in BA was well-explained by climate at a national scale. Differences in BA trends among regions seemed to arise from differences in climatic controls on BA, namely whether antecedent or fire-season conditions were more influential, and these controls are likely to vary at subregional scales, particularly in geographically diverse regions like Oromia and Amhara. The fact that including year did not improve the RF model further suggests that there were no strong PB trends over time at a national scale that were not attributable to the factors considered in the model, although the inclusion of region in the model does suggest some otherwise-unexplained spatial variability. Finally, maps of model residuals for each year did not show any strong temporal trends, such as those that would be created by a strong shift in fire policy or its enforcement. It is possible that the declines in BA in Tigray, Amhara, and Oromia could in part be explained by regional variation in the success of fire ban enforcement due to higher population densities, greater resources, and expertise. Because our analyses were aimed primarily at identifying national-scale trends, we cannot rule out policy impacts at local to regional scales.

We found that fires occurred less frequently in croplands and areas with moderate to high population density, consistent with prior work (Andela et al. 2017; Molinario et al. 2014; Archibald 2016). Much of the frequent-fire areas of Ethiopia are comprised of sparsely populated lowlands characterized by shifting cultivation, where fields are often left fallow for 1–2 years (The Oakland Institute 2011; Kassawmar et al. 2018) and 3 or more years in Gumuz communities (Wagino and Amanuel 2021; Moreda 2017). Moreover, annual burning has been observed in these areas to facilitate hunting and firewood collection within woodlands (Jensen and Friis 2001). Only 4% of area burned every 2 years or less was cropland in 2018 according to the land cover dataset we used (cropland made up 23% of the entire country), suggesting that frequent fire is not limited to cropland but rather is regionally extensive. Grasslands within the frequent-fire areas are often dominated by *Hyparrhenia rufa*, a tall native annual grass that grows rapidly in the dependable rainfall of western Ethiopia and contributes to frequent fire in tropical grasslands and savannas worldwide (D'Antonio and Vitousek 1992). Ethiopia has had limited success in enforcing fire control policy, and given that the areas with the highest frequency have low population density and lack of roads, infrastructure to stop fire spread is likely to remain a major hurdle (Degife et al. 2018; Archibald 2016). This combination of cultural burning practices, vegetation-fire interactions, and infrastructure likely explains the association between low population density and frequent fire that we observed. According to the population data in our analysis (Lloyd et al. 2019), total area with a population density of < 1 person ha^{-1}, where fire was most likely according to our model, decreased by 9% from 2001 to 2018. This suggests that population growth in rural areas in Ethiopia may be responsible for a modest decrease in observed annual BA and could perhaps account for the negative effect of year in our BA model.

The strong relationships between climate and annual BA suggest that climate was responsible for the majority of recent changes in BA in Ethiopia, as is true more broadly across sub-Saharan Africa (Zubkova et al. 2019; Wei et al. 2020). However, the strong role of antecedent temperature on BA that we found was unexpected because previous research on BA in Africa has focused on the importance of antecedent moisture (Andela and Van Der Werf 2014; Zubkova et al. 2019), although Wei et al. (2020) also noted a positive effect of temperature on fire activity in mesic areas. High antecedent temperatures may increase fuel productivity in relatively mesic areas, which would account for the temperature-BA relationship that was particularly strong in the relatively mesic west-central regions of Benishangul-Gumuz and Oromia. In southwestern Ethiopia, fire-season soil moisture was instead the strongest correlate with BA, perhaps because this area experiences a secondary rainy reason from February to May that may dampen fire activity (i.e., stronger or earlier *belg* rainfall corresponds with higher fire-season soil moisture).

The spatial distribution of fire frequency in Ethiopia is striking, with fires occurring every 2 years or less across western lowlands compared with less frequent fire elsewhere. This pattern is influenced by spatial variability in climate, which van Breugel et al. (2016) found to be the strongest influence on fire frequency across Ethiopia, and by vegetation cover and type as reflected in the high importance of NDVI and land cover in our model of PB and the moderate importance of vegetation type. Elevation and terrain complexity in our PB model also in part represent the spatial template of climate and vegetation as it influences fire regimes. However, this spatial variability in fire regimes may also arise from differences in cultural burning practices, which affect landscape management and vegetation dynamics (Kimmerer and Lake 2001; McKemey et al. 2020).

The Gambella and Benishangul-Gumuz regions, where fire frequency was particularly high, are home to ethnic groups that speak languages that belong to the Nilotic language group whereas the rest of the ethnic groups in Ethiopia belong to the Afroasiatic language group (Ado et al. 2021). There is evidence that neighboring Nilotic-speaking groups use fire to manage tsetse fly (Glossinidae) populations to control trypanosomiasis risk (Langlands 1967), but while non-Nilotic neighbors do use fire to manage pasture resources in other parts of Ethiopia (Johansson et al. 2012, 2018), there are no reports that they use fire to manage tsetse flies. The Spearman rank correlation between the tsetse fly occurrence and fire frequency was $r = 0.50$ and tsetse fly occurrence was the 6th most important variable in our RF model; however, causation and the directionality of the relationship are not known. The effect of tsetse flies was related to livestock density, as livestock density was included in a preliminary RF model without tsetse fly occurrence, but was excluded when tsetse fly occurrence was added. In general, high livestock densities tend to constrain fire activity by reducing fuel quantity and increasing fuel heterogeneity (Archibald and Hempson 2016). Communities in areas with high rates of trypanosomiasis may have developed frequent burning practices that reduce trypanosomiasis risk, or high rates of trypanosomiasis may keep livestock populations low thus contributing to higher fuel loads. If the former, fire suppression policy in regions with high occurrence of tsetse flies could increase trypanosomiasis risk. In the second case, expansion of veterinary extension services that reduce the effects of trypanosomiasis and other vector-borne diseases on livestock, may act to reduce fire frequency. In either case, these topics deserve further research to guide evidence-based policymaking.

Conclusions

We conclude that, while there is strong evidence that humans play an important role in fire regimes in Ethiopia, these human influences on fire occurrence in Ethiopia did not change significantly from 2001 to 2018, and therefore that interannual variability in BA was largely attributable to climate. Our analysis also suggests that people and vegetation exert dominant influence on fire occurrence and therefore that the long-term trajectory of fire activity in Ethiopia will be shaped largely by land use and demographic changes and cultural practices and their interplay with patterns of vegetation and ignitions. Consequently, successful participation in REDD+ is likely to hinge on either selecting areas with currently low fire frequency or engaging substantially with local communities to ensure that REDD+ projects are protected from severe fire within frequent-fire areas. Unless off-set by significant changes in how people currently use fire, BA in Ethiopia could rise in the near future as temperatures increase and the fire season become hotter and drier (van Breugel et al. 2016). Our analysis suggests that the ongoing ban on fires has not substantially affected fire activity in Ethiopia at a national scale, and underscores the immense challenges involved in altering fire regimes. Our findings also help to explain how climate can be such a strong influence on short-term trends in BA even in systems known to be dominated by human-caused fires (Zubkova et al. 2019; Wei et al. 2020). Our analysis suggests that fire frequency may be interconnected with complex adaptations to specific social-ecological contexts, such as tsetse fly occurrence and associated livestock and rangeland management practices. Re-greening goals will be better informed by this study and future research that considers burning timing, land use, and cultural fire use and management (Lemenih and Kassa 2014; Mertz 2009; Khatun et al. 2017; Barlow et al. 2012).

Abbreviations

BA	Burned area
CHIRP	Climate Hazards group Infrared Precipitation
MIR	Model improvement ratio
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Differenced Vegetation Index
PNV	Potential Natural Vegetation
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RCMRD	Regional Centre for Mapping of Resources and Development
RF	Random forest
SNNPR	Southern Nations, Nationalities, and Peoples' Region

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-023-00171-w.

Additional file 1: Table S1. Comparison of burned area (in kha) between the two MODIS-based datasets and the Sentinel-based FireCCISFD11 dataset. **Table S2.** Error rates in burned area classification by region of Ethiopia, based on a comparison with the FireCCISFD11 dataset. **Table S3.** Vegetation classes and codes from the Potential Natural Vegetation dataset (van Breugel et al. 2015). **Figure S1.** Comparison of annual area burned across Ethiopia as estimated by the MCD64A1 and FireCCI51 datasets. **Figure S2.** Fire seasonality nationally and by region of Ethiopia, shown as the 10-day running mean of daily percentage burned from the FireCCI51 dataset for individual fire years and the 2001–2018 fire year means. **Figure S3.** Fire seasonality nationally and by potential natural vegetation types of Ethiopia, shown as the 10-day running mean of daily percentage burned from the FireCCI51 dataset for individual fire years and the 2001–2018 fire year means. **Figure S4.** Relative error calculated from predicted and observed mean proportion burned averaged across the 2002–2018 fire years. **Figure S5.** Residual plots showing the difference between observed and predicted proportion burned for each year. **Figure S6.** Relative error plots showing the difference between observed and predicted proportion burned for each year. **Figure S7.** Spearman rank correlation (r_s) between proportion of area burned within 16 km^2 pixels for each pair of fire years. **Figure S8.** Mean total lighting flash density over the primary fire season in Ethiopia (November–April), based on a 1998–2013 climatology (Albrecht et al. 2016).

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Authors' contributions
LBH, AHT, HK, and BP conceived this study. LBH performed the data analysis. All authors contributed to writing and read and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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References

Aalen, Lovise. 2011. *The politics of ethnicity in Ethiopia: Actors, power and mobilisation under ethnic federalism*. Leiden: Brill.

Abatzoglou, John T., A. Park Williams, Luigi Boschetti, Maria Zubkova, and Crystal A. Kolden. 2018. Global patterns of interannual climate–Fire relationships. *Global Change Biology* 24 (11): 5164–5175. https://doi.org/10.1111/gcb.14405.

Ado, Derib, Almaz Wasse Gelagay, and Janne Bondi Johannessen. 2021. The languages of Ethiopia: Aspects of the sociolinguistic profile. In *Grammatical and sociolinguistic aspects of Ethiopian languages*, 1–14. John Benjamins. https://doi.org/10.1075/impact.48.

Andaregie, Adino, Aemro Worku, and Tessema Astatkie. 2020. Analysis of economic efficiency in charcoal production in Northwest Ethiopia: A Cobb-Douglas production frontier approach. *Trees, Forests and People* 2 (August): 100020. https://doi.org/10.1016/j.tfp.2020.100020.

Andela, N., D.C. Morton, L. Giglio, Y. Chen, G.R. Van Der Werf, P.S. Kasibhatla, R.S. DeFries, et al. 2017. A human-driven decline in global burned area. *Science* 356 (6345): 1356–1362. https://doi.org/10.1126/science.aal4108.

Andela, Niels, and Guido R. Van Der Werf. 2014. Recent trends in African fires driven by cropland expansion and El Niño to La Niña transition. *Nature Climate Change* 4 (9): 791–795. https://doi.org/10.1038/nclimate2313.

Angassa, Ayana, and Gufu Oba. 2008. Herder perceptions of impacts of range enclosures, crop farming, fire ban and bush encroachment on the rangelands of Borana, Southern Ethiopia. *Human Ecology* 36 (2): 201–215. https://doi.org/10.1007/s10745-007-9156-z.

Archibald, Sally. 2016. Managing the human component of fire regimes: Lessons from Africa. *Philosophical Transactions of the Royal Society B: Biological Sciences* 371 (1696): 20150346. https://doi.org/10.1098/rstb.2015.0346.

Archibald, Sally, and Gareth P. Hempson. 2016. Competing consumers: Contrasting the patterns and impacts of fire and mammalian herbivory in Africa. *Philosophical Transactions of the Royal Society B: Biological Sciences* 371 (1703): 20150309. https://doi.org/10.1098/rstb.2015.0309.

Archibald, Sally, David P. Roy, Brian W. van Wilgen, and Robert J. Scholes. 2009. What limits fire? An examination of drivers of burnt area in Southern Africa. *Global Change Biology* 15 (3): 613–630. https://doi.org/10.1111/j.1365-2486.2008.01754.x.

Archibald, Sally, A. Carla Staver, and Simon A. Levin. 2012. Evolution of human-driven fire regimes in Africa. *Proceedings of the National Academy of Sciences of the United States of America* 109 (3): 847–852. https://doi.org/10.1073/pnas.1118648109.

Barlow, Jos, Luke Parry, Toby A. Gardner, Joice Ferreira, Luiz E.O.C. Aragão, Rachel Carmenta, Erika Berenguer, Ima C.G. Vieira, Carlos Souza, and Mark A. Cochrane. 2012. The critical importance of considering fire in REDD+ programs. *Biological Conservation* 154: 1–8. https://doi.org/10.1016/j.biocon.2012.03.034.

Belete, Fikire, Melesse Maryo, and Alemtshay Teka. 2021. Land use/land cover dynamics and perception of the local communities in Bita district, south western Ethiopia. *International Journal of River Basin Management* 0 (0): 1–12. https://doi.org/10.1080/15715124.2021.1938092.

Betru, Teshome, Motuma Tolera, Kefyalew Sahle, and Habtemariam Kassa. 2019. Trends and drivers of land use/land cover change in western Ethiopia. *Applied Geography* 104 (February): 83–93. https://doi.org/10.1016/j.apgeog.2019.02.007.

Bliege Bird, R., D.W. Bird, B.F. Codding, C.H. Parker, and J.H. Jones. 2008. The 'fire stick farming' hypothesis: Australian aboriginal foraging strategies, biodiversity, and anthropogenic fire mosaics. *Proceedings of the National Academy of Sciences of the United States of America* 105 (39): 14796–14801. https://doi.org/10.1073/pnas.0804757105.

Breiman, L. 2001. Random forests. *Machine Learning* 45: 5–32 http://link.springer.com/article/10.1023/A:1010933404324.

Collins, Luke, Hamish Clarke, Michael F. Clarke, Sarah C. McColl Gausden, Rachael H. Nolan, Trent Penman, and Ross Bradstock. 2022. Warmer and drier conditions have increased the potential for large and severe fire seasons across south-eastern Australia. *Global Ecology and Biogeography* 31 (10): 1933–1948. https://doi.org/10.1111/geb.13514.

D'Antonio, Carla M., and Peter M. Vitousek. 1992. Biological invasions by exotic grasses, the grass/fire cycle, and global change. *Annual Review of Ecology and Systematics* 23 (May 2021): 63–87.

Degife, Azeb W., Florian Zabel, and Wolfram Mauser. 2018. Assessing land use and land cover changes and agricultural farmland expansions in Gambella Region, Ethiopia, using Landsat 5 and Sentinel 2a multispectral data. *Heliyon* 4 (11): e00919. https://doi.org/10.1016/j.heliyon.2018.e00919.

Dinku, Tufa, Chris Funk, Pete Peterson, Ross Maidment, Tsegaye Tadesse, Hussein Gadain, and Pietro Ceccato. 2018. Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society* 144: 292–312. https://doi.org/10.1002/qj.3244.

Duriaux-Chavarría, Jean Yves, Frédéric Baudron, Sarah E. Gergel, Kevin F. Yang, Ian M.S. Eddy, and Terry Sunderland. 2020. More people, more trees: A reversal of deforestation trends in southern Ethiopia. *Land Degradation and Development* 2019 (February): 1–12. https://doi.org/10.1002/ldr.3806.

Forkel, Matthias, Wouter Dorigo, Gitta Lasslop, Emilio Chuvieco, Stijn Hantson, Angelika Heil, Irene Teubner, Kirsten Thonicke, and Sandy P. Harrison. 2019. Recent global and regional trends in burned area and their compensating environmental controls. *Environmental Research Communications* 1 (5): 051005. https://doi.org/10.1088/2515-7620/ab25d2.

Friedman, Jerome H. 2001. Greedy function approximation: A gradient boosting machine. *The Annals of Statistics* 29 (5): 1189–1232.
Friis, Ib, Sebsebe Demissew, and Paolo van Breugel. 2010. *Atlas of the potential vegetation of Ethiopia*. Copenhagen: The Royal Danish Academy of Sciences and Letters. https://doi.org/10.1093/aob/mcq242.
Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, et al. 2015. The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. *Scientific Data* 2: 1–21. https://doi.org/10.1038/sdata.2015.66.
Gebrehiwot, Solomon Gebreyohannis, Woldeamlak Bewket, Annemieke I. Gärdenäs, and Kevin Bishop. 2014. Forest cover change over four decades in the Blue Nile Basin, Ethiopia: Comparison of three watersheds. *Regional Environmental Change* 14 (1): 253–266. https://doi.org/10.1007/s10113-013-0483-x.
Genuer, Robin, Jean Michel Poggi, and Christine Tuleau-Malot. 2010. Variable selection using random forests. *Pattern Recognition Letters* 31 (14): 2225–2236. https://doi.org/10.1016/j.patrec.2010.03.014.
Genuer, Robin, Jean-Michel Poggi, and Christine Tuleau-Malot. 2015. VSURF: An R package for variable selection using random forests. *The R Journal* 7 (2): 19–33.
Giglio, Louis, Luigi Boschetti, David P. Roy, Michael L. Humber, and Christopher O. Justice. 2018. The collection 6 MODIS burned area mapping algorithm and product. *Remote Sensing of Environment* 217 (July): 72–85. https://doi.org/10.1016/j.rse.2018.08.005.
Gilbert, Marius, Gaëlle Nicolas, Giusepina Cinardi, Thomas P. Van Boeckel, Sophie O. Vanwambeke, G. R.William Wint, and Timothy P. Robinson. 2018. Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010. *Scientific Data* 5: 1–11. https://doi.org/10.1038/sdata.2018.227.
Gorelick, Noel, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* 202: 18–27. https://doi.org/10.1016/j.rse.2017.06.031.
Greenwell, Brandon M. 2017. Pdp: An R package for constructing partial dependence plots. *The R Journal* 9 (1): 421–436.
Grégoire, J.M., H.D. Eva, A.S. Belward, I. Palumbo, D. Simonetti, and A. Brink. 2013. Effect of land-cover change on Africa's burnt area. *International Journal of Wildland Fire* 22 (2): 107–120. https://doi.org/10.1071/WF11142.
Hempson, Gareth P., Catherine L. Parr, Sally Archibald, T. Michael Anderson, Colin J. Courtney Mustaphi, Andrew P. Dobson, Jason E. Donaldson, Thomas A. Morrison, James Probert, and Colin M. Beale. 2018. Continent-level drivers of African pyrodiversity. *Ecography* 41 (6): 889–899. https://doi.org/10.1111/ecog.03109.
Jahnke, Hans E. 1982. *Livestock production systems and livestock development in tropical Africa*. Vol. 40 https://pdf.usaid.gov/pdf_docs/pnaan484.pdf.
Jensen, Michael, and Ib Friis. 2001. Fire regimes, floristics, diversity, life forms and biomass in wooded grassland and dry forest at Gambella, western Ethiopia. *Biologiske Skrifter/Det Kongelige Danske Videnskabernes Selskab* 54: 349–387.
Johansson, Maria U., Masresha Fetene, Anders Malmer, and Anders Granström. 2012. Tending for cattle: Traditional fire management in Ethiopian montane heathlands. *Ecology and Society* 17 (3). https://doi.org/10.5751/ES-04881-170319.
Johansson, Maria U., Carl A. Frisk, Sileshi Nemomissa, and Kristoffer Hylander. 2018. Disturbance from traditional fire management in subalpine heathlands increases Afro-alpine plant resilience to climate change. *Global Change Biology* 24 (7): 2952–2964. https://doi.org/10.1111/gcb.14121.
Johansson, Maria Ulrika, Firew Bekele Abebe, Sileshi Nemomissa, Tamrat Bekele, and Kristoffer Hylander. 2021. Ecosystem restoration in fire-managed Savanna woodlands: Effects on biodiversity, local livelihoods and fire intensity. *Ambio* 50 (1): 190–202. https://doi.org/10.1007/s13280-020-01343-7.
Jones, Matthew W., John T. Abatzoglou, Sander Veraverbeke, Niels Andela, Gitta Lasslop, Matthias Forkel, Adam J.P. Smith, et al. 2022. Global and regional trends and drivers of fire under climate change. *Reviews of Geophysics* 60 (3): 1–76. https://doi.org/10.1029/2020rg000726.
Kassawmar, Tibebu, Gete Zeleke, Amare Bantider, Gizaw Desta Gessesse, and Lemlem Abraha. 2018. A synoptic land change assessment of Ethiopia's rainfed agricultural area for evidence-based agricultural ecosystem management. *Heliyon* 4 (11): e00914. https://doi.org/10.1016/j.heliyon.2018.e00914.
Kelly, Luke T., Katherine M. Giljohann, Andrea Duane, Núria Aquilué, Sally Archibald, Enric Batllori, Andrew F. Bennett, et al. 2020. Fire and biodiversity in the anthropocene. *Science* 370 (6519): eabb0355. https://doi.org/10.1126/science.abb0355.
Khatun, Kaysara, Esteve Corbera, and Steve Ball. 2017. Fire is REDD+: Offsetting carbon through early burning activities in south-eastern Tanzania. *Oryx* 51 (1): 43–52. https://doi.org/10.1017/S0030605316000090.
Kimmerer, R.W., and F.K. Lake. 2001. Maintaining the mosaic: The role of indigenous burning in land management. *Journal of Forestry* 99 (11): 36–41. https://doi.org/10.1093/jof/99.11.36.
Krawchuk, Meg A., Max A. Moritz, Marc André Parisien, Jeff Van Dorn, and Katharine Hayhoe. 2009. Global pyrogeography: The current and future distribution of wildfire. *PLoS One* 4 (4). https://doi.org/10.1371/journal.pone.0005102.
Langlands, B.W. 1967. Burning in eastern Africa. *East African Geographical Review* 5 (April): 21–37.
Lemenih, Mulugeta, and Habtemariam Kassa. 2014. Re-greening Ethiopia: history, challenges and lessons. *Forests* 5 (8): 1896–1909. https://doi.org/10.3390/f5081896.
Leta, S., Y. Habtamu, G. Alemayehu, M. Chanie, B. Ayele, Sh. Tesfaye, and F. Mesele. 2015. Spatial analysis of the distribution of tsetse flies in Ethiopia using high resolution environmental datasets and Maxent modeling technique. In *National syposium on trends and challenges in adoption of science, technology and innovation in local development endeavours*. Wollega University, Nekemte, Ethiopia.
Li, Wei, Natasha MacBean, Philippe Ciais, Pierre Defourny, Céline Lamarche, Sophie Bontemps, Richard A. Houghton, and Shushi Peng. 2018. Gross and net land cover changes in the main plant functional types derived from the annual ESA CCI land cover maps (1992-2015). *Earth System Science Data* 10: 219–324. https://doi.org/10.5194/essd-2017-74.
Liaw, Andy, and Matthew Wiener. 2002. Classification and regression by randomForest. *R News* 2/3 (December): 18–22.
Lizundia-Loiola, Joshua, Gonzalo Otón, Rubén Ramo, and Emilio Chuvieco. 2020. A spatio-temporal active-fire clustering approach for global burned area mapping at 250 m from MODIS data. *Remote Sensing of Environment* 236 (May 2019): 111493. https://doi.org/10.1016/j.rse.2019.111493.
Lloyd, Christopher T., Heather Chamberlain, David Kerr, Greg Yetman, Linda Pistolesi, Forrest R. Stevens, Andrea E. Gaughan, et al. 2019. Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. *Big Earth Data* 3 (2): 108–139. https://doi.org/10.1080/20964471.2019.1625151.
Mann, Michael L., Enric Batllori, Max A. Moritz, Eric K. Waller, Peter Berck, Alan L. Flint, Lorraine E. Flint, and Emmalee Dolfi. 2016. Incorporating anthropogenic influences into fire probability models: Effects of human activity and climate change on fire activity in California. *PLoS One* 11 (4): 1–21. https://doi.org/10.1371/journal.pone.0153589.
Masrur, Arif, Alan Taylor, Lucas Harris, Jennifer Barnes, and Andrey Petrov. 2022. Topography, climate and fire history regulate wildfire activity in the Alaskan Tundra. *Journal of Geophysical Research: Biogeosciences*.https://doi.org/10.1029/2021jg006608.
McKemey, Michelle, Emilie Ens, Yugul Mangi Rangers, Oliver Costello, and Nick Reid. 2020. Indigenous knowledge and seasonal calendar inform adaptive Savanna burning in northern Australia. *Sustainability (Switzerland)* 12 (3): 1–18. https://doi.org/10.3390/su12030995.
McNally, Amy, Kristi Arsenault, Sujay Kumar, Shraddhanand Shukla, Pete Peterson, Shugong Wang, Chris Funk, Christa D. Peters-Lidard, and James P. Verdin. 2017. A land data assimilation system for sub-Saharan Africa food and water security applications. *Scientific Data* 4: 1–19. https://doi.org/10.1038/sdata.2017.12.
Mertz, Ole. 2009. Trends in shifting cultivation and the REDD mechanism. *Current Opinion in Environmental Sustainability* 1 (2): 156–160. https://doi.org/10.1016/j.cosust.2009.10.002.
Midekisa, Alemayehu, Felix Holl, David J. Savory, Ricardo Andrade-Pacheco, Peter W. Gething, Adam Bennett, and Hugh J.W. Sturrock. 2017. Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud computing. *PLoS One* 12 (9): 1–15. https://doi.org/10.1371/journal.pone.0184926.
Molinario, Giuseppe, Diane K. Davies, Wilfrid Schroeder, and Christopher O. Justice. 2014. Characterizing the spatio-temporal fire regime in Ethiopia using the MODIS-active fire product: A replicable methodology for

country-level fire reporting. *African Geographical Review* 33 (2): 99–123. https://doi.org/10.1080/19376812.2013.854708.
Moreda, Tsegaye. 2017. Large-scale land acquisitions, state authority and indigenous local communities: Insights from Ethiopia. *Third World Quarterly* 38 (3): 698–716. https://doi.org/10.1080/01436597.2016.1191941.
Murphy, Melanie A., Jeffrey S. Evans, and Andrew Storfer. 2010. Quantifying Bufo boreas connectivity in Yellowstone National Park with landscape genetics. *Ecology* 91 (1): 252–261. https://doi.org/10.1890/08-0879.1.
Padilla, M., and C. Vega-García. 2011. On the comparative importance of fire danger rating indices and their integration with spatial and temporal variables for predicting daily human-caused fire occurrences in Spain. *International Journal of Wildland Fire* 20 (1): 46–58. https://doi.org/10.1071/WF09139.
Park, Isaac W., Michael L. Mann, Lorraine E. Flint, Alan L. Flint, and Max Moritz. 2021. Relationships of climate, human activity, and fire history to spatiotemporal variation in annual fire probability across California. *PLoS One* 16 (11 November): 1–20. https://doi.org/10.1371/journal.pone.0254723.
Parks, Sean A., and J.T. Abatzoglou. 2020. Warmer and drier fire seasons contribute to increases in area burned at high severity in western US forests from 1985 to 2017. *Geophysical Research Letters* 47 (22): 1–10. https://doi.org/10.1029/2020GL089858.
Pausas, Juli G., and Jon E. Keeley. 2014. Abrupt climate-independent fire regime changes. *Ecosystems* 17 (6): 1109–1120. https://doi.org/10.1007/s10021-014-9773-5.
Philip, Sjoukje, Sarah F. Kew, Geert Jan van Oldenborgh, Friederike Otto, Sarah O'Keefe, Karsten Haustein, Andrew King, et al. 2018. Attribution analysis of the Ethiopian drought of 2015. *Journal of Climate* 31 (6): 2465–2486. https://doi.org/10.1175/JCLI-D-17-0274.1.
Pohlert, Thorsten. 2020. "Trend: Non-parametric trend tests and change-point detection. R package version 1.1.4." https://cran.r-project.org/package=trend.
Preisler, Haiganoush K., David R. Brillinger, Robert E. Burgan, and J.W. Benoit. 2004. Probability based models for estimation of wildfire risk. *International Journal of Wildland Fire* 13 (2): 133–142. https://doi.org/10.1071/WF02061.
Preisler, Haiganoush K., and Anthony L. Westerling. 2007. Statistical model for forecasting monthly large wildfire events in western United States. *Journal of Applied Meteorology and Climatology* 46 (7): 1020–1030. https://doi.org/10.1175/JAM2513.1.
Probert, James R., Catherine L. Parr, Ricardo M. Holdo, T. Michael Anderson, Sally Archibald, Colin J. Courtney, Andrew P. Dobson, Jason E. Donaldson, Grant C. Hopcraft, and Gareth P. Hempson. 2019. Anthropogenic modifications to fire regimes in the wider Serengeti - Mara ecosystem. *Global Change Biology* 25: 3406–3423. https://doi.org/10.1111/gcb.14711.
Riley, S.J., S.D. DeGloria, and R. Elliot. 1999. A terrain ruggedness index that quantifies topographic heterogeneity. *Intermountain Journal of Sciences* 5 (1–4): 23–27.
Seleshi, Yilma, and Ulrich Zanke. 2004. Recent changes in rainfall and rainy days in Ethiopia. *International Journal of Climatology* 24 (8): 973–983. https://doi.org/10.1002/joc.1052.
Sen, Pranab Kumar. 1968. Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association* 63 (324): 1379–1389. https://doi.org/10.1080/01621459.1968.10480934.
Shete, Maru, and Marcel Rutten. 2015. Impacts of large-scale farming on local communities' food security and income levels - Empirical evidence from Oromia region, Ethiopia. *Land Use Policy* 47: 282–292. https://doi.org/10.1016/j.landusepol.2015.01.034.
Shete, Maru, Marcel Rutten, George C. Schoneveld, and Eylachew Zewude. 2016. Land-use changes by large-scale plantations and their effects on soil organic carbon, micronutrients and bulk density: Empirical evidence from Ethiopia. *Agriculture and Human Values* 33 (3): 689–704. https://doi.org/10.1007/s10460-015-9664-1.
Taylor, Alan H., V. Trouet, Carl N. Skinner, and S.L. Stephens. 2016. Socioecological transitions trigger fire regime shifts and modulate fire-climate interactions in the Sierra Nevada, USA 1600-2015 CE. *Proceedings of the National Academy of Sciences USA* 113 (48): 13684–13689. https://doi.org/10.1073/pnas.1609775113.
Teketay, Demel, Mulugeta Lemenih, Tesfaye Bekele, Yonas Yemshaw, Sisay Feleke, Wubalem Tadesse, Yitebetu Moges, Tesfaye Hunde, and Demeke Nigussie. 2010. Forest resources and challenges of sustainable forest management and conservation in Ethiopia. In *Degraded forests in eastern Africa: Management and restoration*, ed. Frans Bongers and Timm Tennigkeit, 19–63. Abingdon: Earthscan. https://doi.org/10.4324/9781849776400.
The Oakland Institute. 2011. *Understanding land investment deals in Africa - Country report: Ethiopia*. The Oakland Institute, Oakland, California, USA.
Tsegaye, Diress, Stein R. Moe, Paul Vedeld, and Ermias Aynekulu. 2010. Land-use/cover dynamics in Northern Afar rangelands, Ethiopia. *Agriculture, Ecosystems and Environment* 139 (1–2): 174–180. https://doi.org/10.1016/j.agee.2010.07.017.
van Breugel, Paolo, Ib Friis, Sebsebe Demissew, Jens Peter Barnekow Lillesø, and Roeland Kindt. 2016. Current and future fire regimes and their influence on natural vegetation in Ethiopia. *Ecosystems* 19 (2): 369–386. https://doi.org/10.1007/s10021-015-9938-x.
van Breugel, Paolo, R. Kindt, Jens Peter Barnekow Lillesø, M. Bingham, S. Demissew, C. Dudley, Ib Friis, et al. 2015. *Potential natural vegetation map of Eastern Africa (Burundi, Ethiopia, Kenya, Malawi, Rwanda, Tanzania, Uganda and Zambia)*. 2.0. Forest and Landscape (Denmark) and World Agroforestry Centre (ICRAF) http://vegetationmap4africa.org.
Wagino, Abbebe Marra, and Teshale W. Amanuel. 2021. Community adaptation to climate change: Case of Gumuz people, Metekel zone, northwest Ethiopia. In *African handbook of climate change adaptation*, ed. Walter Leal Filho, Nicholas Oguge, Desalegn Ayal, Lydia Adeleke, and Izael da Silva, 2339–2362. Springer. https://doi.org/10.1007/978-3-030-45106-6_244.
Wahl, Eugene R., Eduardo Zorita, Valerie Trouet, and Alan H. Taylor. 2019. Jet stream dynamics, hydroclimate, and fire in California from 1600 CE to present. *Proceedings of the National Academy of Sciences*: 1–6. https://doi.org/10.1073/pnas.1815292116.
Weatherley-Singh, Janice, and Aarti Gupta. 2015. Drivers of deforestation and REDD+ benefit-sharing: A meta-analysis of the (missing) link. *Environmental Science and Policy* 54: 97–105. https://doi.org/10.1016/j.envsci.2015.06.017.
Wei, Fangli, Shuai Wang, Bojie Fu, Martin Brandt, Naiqing Pan, Cong Wang, and Rasmus Fensholt. 2020. Nonlinear dynamics of fires in Africa over recent decades controlled by precipitation. *Global Change Biology* 26 (8): 4495–4505. https://doi.org/10.1111/gcb.15190.
Westerling, A.L., and B.P. Bryant. 2008. Climate change and wildfire in California. *Climatic Change* 87 (1 SUPPL). https://doi.org/10.1007/s10584-007-9363-z.
Wieder, W.R., J. Boehnert, G.B. Bonan, and M. Langseth. 2014. *Regridded harmonized world soil database v1.2*. Oak Ridge. https://doi.org/10.3334/ORNLDAAC/1247.
Zhu, Zhe, and Curtis E. Woodcock. 2014. Continuous change detection and classification of land cover using all available Landsat data. *Remote Sensing of Environment* 144: 152–171. https://doi.org/10.1016/j.rse.2014.01.011.
Zubkova, Maria, Luigi Boschetti, John T. Abatzoglou, and Louis Giglio. 2019. Changes in fire activity in Africa from 2002 to 2016 and their potential drivers. *Geophysical Research Letters* 46 (13): 7643–7653. https://doi.org/10.1029/2019GL083469.

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