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Patterns and drivers of disturbance in tropical forest reserves of southern Ghana

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Supplementary material for this article is available online

Abstract

Ghana has retained a substantial area of tropical forests in an extensive network of protected reserves. These forests are impacted by land uses such as logging, mining, and agriculture as well as wildfires. We studied forest disturbance and recovery from 2013 to 2020 using annual maps of forest cover derived from Landsat imagery. Fire-associated disturbance was distinguished using VIIRS active fire data. We used boosted regression trees to model disturbances in closed and open forests as a function of climate variability, human accessibility, and landscape structure. A total of 3562 km^2 of forest reserves were disturbed, of which 17% (615 km^2) were fire disturbances and 83% (2946 km^2) were non-fire disturbances. Of the total disturbed area, 68% was degradation (change from closed to open forest), 28% was open forest loss, and only 4% was closed forest loss. Over the same period, 2702 km^2 of forest reserves recovered, with 1948 km^2 of these recovering to closed-canopy forests. Fire disturbances were strongly associated with precipitation anomalies and occurred mostly in drier years, whereas non-fire disturbances had weaker relationships with precipitation. Disturbances in closed forests occurred in landscapes where closed forest cover was already low. In contrast, disturbances in open forests were most common in locations with intermediate levels of population pressure from nearby cities and proximity to non-forest land cover. The results support the idea that forest disturbance in Ghana is a multi-stage process involving degradation of closed forests followed by loss of the resulting open forests. Although non-fire disturbance rates are consistent from year to year, sharp increases in fire disturbance occur in drought years. Locations with the highest disturbance risk are associated with measurable indicators of climate, human pressure, and fragmentation, which can be used to identify these areas for conservation and forest restoration activities.

1. Introduction

Tropical forests sequester 1.7 Gt of carbon per year (Harris *et al* 2021), are home to about half of Earth's biodiversity, and provide essential ecosystem goods and services for more than 1.2 billion people (Malhi *et al* 2014, Lewis *et al* 2015). However, these forests are experiencing significant ecological disturbances, including loss of forests to other land uses and degradation that changes forest structure, species composition, and biomass within intact forests (Shapiro *et al* 2016, Matricardi *et al* 2020). Forest disturbances are driven by human activities, such as agriculture, logging, and mining, due to pressure from fast-increasing human populations (Gibbs *et al* 2010, Malhi *et al* 2014). These dynamics are also influenced by climate change, including stronger and more frequent droughts (Malhi *et al* 2014, Edwards *et al* 2019) that cause vegetation dieback and increase the risk of wildfires (Brando *et al* 2019). In recent years, wildfires have become a common occurrence in tropical forests, despite the high moisture in most of these ecosystems (Brando *et al* 2019, Edwards *et al* 2019). Most of these fires have been observed during

El Nino-related droughts (Aragão *et al* 2007, 2008) with the largest ones occurring in disturbed forests (Cochrane *et al* 1999, Cochrane and Laurance 2002, de Faria *et al* 2017, Dwomoh *et al* 2019). Yet, there is still a need to identify the geographic factors that make locations vulnerable to future forest loss and degradation, and to expand our limited knowledge of how tropical fire regimes may respond to increasing human populations and changing environments. We addressed these knowledge gaps by conducting a study of historical disturbances in the Upper Guinean Forest (UGF) region of West Africa and using the results to highlight susceptible areas where conservation and restoration efforts can be targeted.

The UGF region is a globally significant biodiversity hotspot (Myers *et al* 2000) but is also among the most climatically marginal (Malhi and Wright 2004) and human-modified (Norris *et al* 2010) tropical ecosystems in the world. Persistent and severe droughts have occurred in recent decades and are expected to become more common with intensifying climate change (Sylla *et al* 2016). The population of West Africa increased almost six-fold between 1950 and 2020 (72–420 million) and is projected to reach 801 million by 2050 (UN DESA Population Division 2022). In Ghana, almost all the remaining forest is found in protected reserves located in the southern third of the country. In this region, annual precipitation ranges from more than 2000 mm in the southwest to less than 750 mm at the northern edge of the forest zone (Amissah *et al* 2014), influencing the distribution of forest types along a gradient from wet evergreen (WE) to dry semi-deciduous (Hall and Swaine 1976). These reserves are heavily impacted by agricultural encroachment, logging, mining, and wildfires (Acheampong *et al* 2016, Boadi *et al* 2016, Kouassi *et al* 2021). Historically, forest fires were rare, with occasional low-intensity burns in the dry semi-deciduous (fire subtype) zone (Hall and Swaine 1981). However, forest fires were widespread during the severe drought of the 1980s and more recently in 2016, especially in the dry and moist forest types (Swaine 1992, Dwomoh *et al* 2019). Strong positive feedbacks between fires, land use, and forest structure have caused permanent shifts from forest to non-forest vegetation (Dwomoh and Wimberly 2017). These dynamics offer an excellent opportunity to study the effects of climate and human population pressure on fire and non-fire disturbances within tropical forests.

Forest disturbance is the outcome of complex interactions between human decisions and actions and ecological and biophysical processes (Flores and Staal 2022). We aimed to identify measurable predictors that could be used to delineate locations where forest disturbance is most likely. We considered three groups of variables that were hypothesized to influence forest disturbance. First, we characterized climate variability by using data on precipitation. Fires are most common in drier tropical forest types (Hall and Swaine 1981). Severe drought is associated with increased tree mortality throughout the tropics (Phillips *et al* 2010), but also affects fire behavior by altering the availability of understory fuels (Cochrane *et al* 1999). Second, we assessed human accessibility as a measure of the effect of land use pressure, including agricultural encroachment, logging, and mining as well as fire ignitions. Reserves located close to large human populations are more likely to be disturbed and this risk is expected to decline with decreasing population sizes and increasing distance from settlements (Güneralp *et al* 2013, Herrmann *et al* 2020). Finally, we incorporated landscape structure to assess how the legacies of past change influence forest disturbance. Strong positive feedbacks exist between forest structure and disturbance risk (Flores and Staal 2022). Forest degradation and loss thin and fragment the forest canopy and affect vegetation, fuels, and microclimate, rendering forests more susceptible to fire (Laurance and Williamson 2001). Historical disturbance also increases the risk of non-fire disturbance, as disturbed forests are preferred over intact forests for land use activities such as crop cultivation and grazing (Carvalho *et al* 2019, Herrmann *et al* 2020, Wang *et al* 2020).

The overarching goal of this study was to characterize spatial patterns and drivers of fire and non-fire disturbances within tropical forests of Ghana. Specific objectives were to; (1) map spatiotemporal patterns of fire and non-fire disturbances in protected reserves of southern Ghana from 2013 to 2020, and (2) identify the main drivers related to climate variability, human accessibility, and landscape structure influencing fire and non-fire disturbances in open and closed forests. We combined annual maps of forest cover derived from Landsat imagery with active fire detections from the Visible Infrared Imaging Radiometer Suite (VIIRS) to distinguish fire from non-fire disturbance and used machine learning techniques to quantify the effects of climate variability, human accessibility, and landscape structure variables. Understanding these relationships is essential for targeting conservation and forest restoration activities in Ghana and similar tropical forest regions.

2. Materials and methods

2.1. Data sources and preprocessing

2.1.1. Forest change data

Annual forest canopy cover estimates from 2013 to 2020 for all protected forest reserves in southern Ghana were generated using Landsat imagery combined with training and validation data from very high-resolution satellite imagery (Wimberly *et al* 2022). The random forests algorithm was used to predict annual canopy cover and the LandTrendr algorithm (Kennedy *et al* 2018) was applied to

Table 1. Definitions of the five change categories used to classify disturbance types and recovery in Ghana.

Change type	Description	Disturbance type
Closed forest loss	Closed forest to low tree cover	CFD
Degradation	Closed forest to open forest	CFD
Open forest loss	Open forest to low tree cover	OFD
Closed forest recovery	Open forest to closed forest	N/A
Open forest recovery	Low tree cover to open forest	N/A

Table 2. List of variables used in boosted regression tree models.

Description	Name
1. Forest dynamics	
Closed forest fire disturbance[a]	CFD fire
Closed forest non-fire disturbance[a]	CFD non-fire
Open forest fire disturbance[a]	OFD fire
Open forest non-fire disturbance[a]	OFD non-fire
2. Climate variability	
Mean annual precipitation[b]	Precipitation (mm)
Annual standardized precipitation anomalies[b]	PrecipAnom
3. Human accessibility	
Population gravity index[c]	PopulationIndex
Distance from non-forest areas[d]	DistNonForest (km)
Distance from roads[e]	DistRoads (km)
4. Landscape structure	
Fragmentation type[d]	FragmentationType
Percent closed forest[d]	%ClosedForest (%)
Slope[f]	Slope (degrees)

[a] Landsat-derived forest change data (Wimberly *et al* 2022) and VIIRS active fires (Schroeder *et al* 2014).
[b] CHIRPS pentad data (Funk *et al* 2015).
[c] WorldPop (Leasure *et al* 2020) and Africapolis urban boundaries (OECD/SWAC 2020).
[d] Landsat-derived canopy cover data (Wimberly *et al* 2022).
[e] Global Roads Open Access Data Set (CIESIN—Columbia University & ITOS—University of Georgia, 2013).
[f] SRTM DEM (Farr *et al* 2007).

identify periods of relative stability, disturbance, and recovery. The continuous canopy cover predictions were reclassified into low tree cover (<15% canopy cover), open forest (15%–60%), and closed forest (>60% canopy cover). Maps of the canopy cover classes for 2013–2020 are provided in Figure A1 in supplemental materials. Five change categories were defined: closed forest loss, degradation, open forest loss, closed forest recovery, and open forest recovery (table 1). Degradation and closed forest loss were reclassified as closed forest disturbance (CFD) and open forest loss was reclassified as open forest disturbance (OFD). The canopy cover predictions and mapped disturbances were previously validated, and details and accuracy assessment results are provided in supplemental materials.

2.1.2. VIIRS active fires

We used daily VIIRS active fire detections derived from the instrument's I-Band with 375 m nominal spatial resolution (Schroeder *et al* 2014). The I-Band pixel area is approximately ten-fold smaller than the Moderate Resolution Imaging Spectroradiometer (MODIS) pixel area at nadir, thus VIIRS is better suited for detecting small and low-intensity fires (Zhang *et al* 2017). We removed fire detections flagged as low confidence and used an interpolation algorithm to convert active fire observations into burned area estimates by grouping pixels separated by a maximum distance of 2000 m and a maximum time interval of 2 d and converting clusters of pixels to burned patches with a convex hull algorithm (see supplemental materials).

2.1.3. Disturbed and unchanged locations

To assess drivers of forest disturbance, disturbed locations were contrasted with unchanged locations that did not experience forest loss, degradation, or recovery. For each year, the binary grids of CFD, OFD, and unchanged pixels were aggregated by a factor of three to identify 90 m cells in which all nine of the smaller pixels belonged to the given class. This approach focused our analysis on a 0.81 ha minimum mapping unit and increased our confidence that the locations were dominated by either disturbed or unchanged forest. The fire data were overlaid on the disturbance grids to assign each disturbed cell to one of four categories: (1) fire disturbances in closed forests (CFD fire), (2) fire disturbances in open forests (OFD fire), (3) non-fire disturbances in closed forests (CFD non-fire), and (4) non-fire disturbances in open forests (OFD non-fire).

2.1.4. Predictor variables

Climate variability was measured using pentad precipitation records obtained from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) at 5 km spatial resolution (Funk *et al* 2015). Mean annual precipitation was calculated using precipitation totals for the 1991–2020 hydrological years. A hydrological year was defined as the period between May 1st (beginning of rainy season) and April 30th of the following year (Dwomoh *et al* 2019). Pixelwise annual standardized anomalies for each hydrological year (yr) from 2014 to 2020 were calculated following the procedure by Saatchi *et al* (2013) as departures from the 1991 to 2020 mean, excluding the measurement from that year (yr), and normalizing by the standard deviation.

Human accessibility was characterized using the population gravity index, proximity to roads, and proximity to non-forest areas. The population gravity index accounts for the size of nearby cities as well as their proximity to the forest reserves (Polyakov *et al* 2008). It is highest when large human populations are located nearby and decreases when populations are smaller or located further away. We calculated the population gravity index for each grid cell using gridded population estimates from WorldPop (Leasure *et al* 2020) and urban boundaries from the Africapolis project (OECD/SWAC 2020) (see supplemental materials). We extracted road information from road features acquired from Global Roads Open Access Data Set (CIESIN—Columbia University and ITOS—University of Georgia 2013) and computed Euclidean distances from the nearest road. We also calculated Euclidian distance from each reserve pixel to the nearest non-forest (low tree cover) pixel for each year in 2013–2019.

Landscape structure was measured using forest fragmentation type, percent closed forest, and topographic slope. Fragmentation type was calculated using methods described by Vogt *et al* (2007a) and implemented by Parent *et al* (2007). First, forest cover from 2013 to 2019 was reclassified into two groups: forest (a combination of closed and open forest classes) and non-forest (low tree cover). We used the Landscape Fragmentation Tool to classify forest pixels into six groups with varying degrees of fragmentation: large core (most intact), medium core, small core, inner edge, edge, and patch (most fragmented) (Vogt *et al* 2007a, 2007b, Shapiro *et al* 2016). We used an edge distance of 300 m which is considered appropriate for measuring edge effects into unfragmented tropical forests (Shapiro *et al* 2016, 2021). Percent closed forest was generated from the 30 m canopy rasters using a 210 m radius circular moving window. Slope angle was derived from the 30 m Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) (Farr *et al* 2007). All variables used in the models were rescaled to match the 90 m resolution of the aggregated forest disturbance raster grids. All predictor variables are listed in table 2 and maps of the predictor variables are provided in figure A2 in the supplemental materials.

2.2. Data analysis

Annual data on forest disturbances in all forest reserves in southern Ghana were summarized for 2013–2020 to describe changes and their geographic patterns. We used boosted regression tree (BRT) models to analyze the influences of climate variability, landscape structure, and human accessibility factors on forest disturbance. BRT is a machine learning method that uses ensembles of regression trees to generate nonparametric models that capture nonlinear relationships and interactions among predictor variables and are robust to outliers and missing data (Elith *et al* 2008). We used the dismo package in R (Hijmans *et al* 2021) for BRT modeling.

A separate BRT model was fitted for each disturbance type (CFD fire, OFD fire, CFD non-fire, and OFD non-fire). For each model, a random sample of 1000 disturbed and 10 000 unchanged locations (see supplemental materials) was randomly split into a training (70%) and a validation (30%) set. The fitted models were used to make spatial predictions of the probability of each disturbance type using landscape conditions in 2020 and two climate scenarios: (1) average precipitation with standardized precipitation anomalies set to 0, and (2) extreme drought with standardized precipitation anomalies set to −2. Disturbance risk grids for closed and open forests were combined to obtain continuous surfaces of fire and non-fire disturbance risk within the reserves. The relative importance of each predictor variable was estimated based on the number of times a variable was selected to create a split, weighted by the squared improvement to the model resulting from these splits, and averaged over all trees (Friedman and Meulman 2003, Elith *et al* 2008). We identified predictors with relative influence above that expected by chance (Müller *et al* 2013), obtained by dividing 100 by the number of predictors (8 in this study). We also created partial dependence plots for the five most important variables for each model to assess the effect of each variable after accounting for the average effects of all other variables used in the model (Elith *et al* 2008). We used the validation datasets to compute the area under the receiver operating characteristic curve (AUC) for the four models.

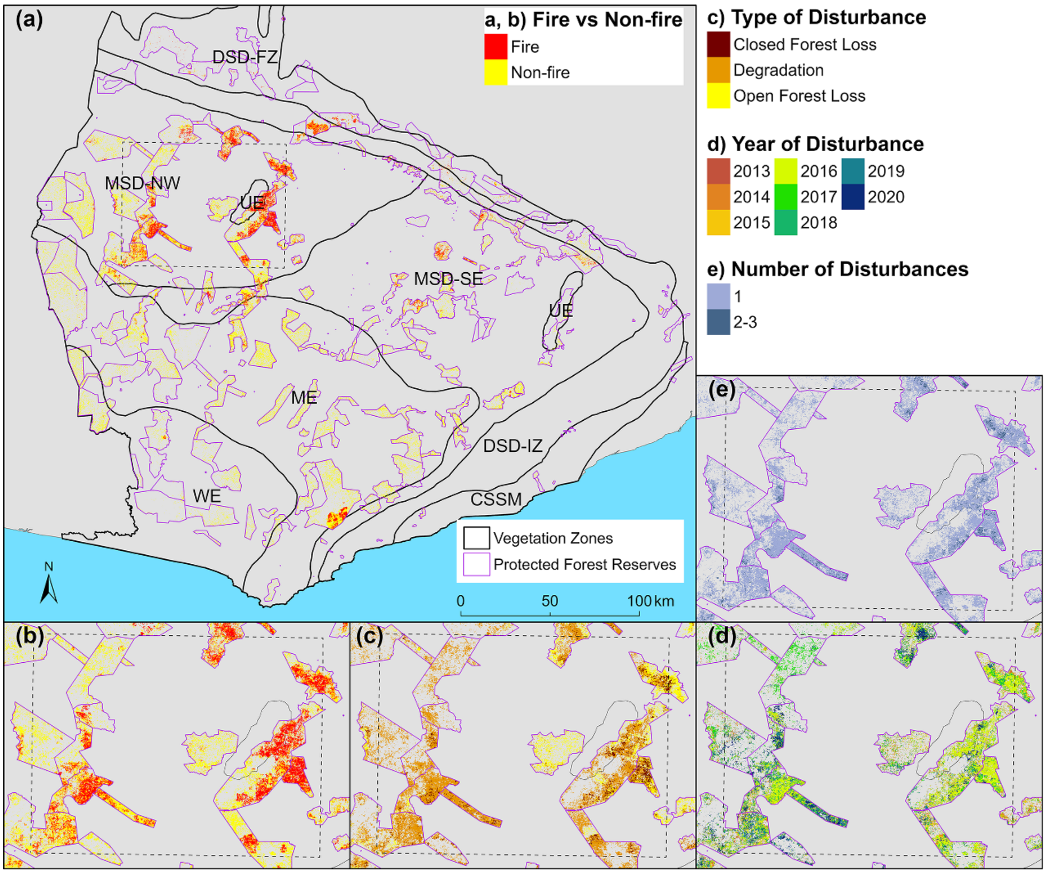

Figure 1. Forest disturbances in tropical forest reserves in southern Ghana from 2013 to 2020. (a) Spatial patterns in the distribution of fire-related vs non-fire disturbances within protected reserves in the eight vegetation zones of southern Ghana. The vegetation zones are coastal savanna southern marginal (CSSM), dry semi-deciduous fire zone (DSD-FZ), DSD inner zone (IZ), ME, MSD-NW, MSD-SE, upland evergreen (UE), and WE. (b) Fire and non-fire disturbances zoomed in to the MSD-NW vegetation zone. (c) Types of disturbances in the MSD-NW vegetation zone. (d) Year of latest disturbance in the MSD-NW vegetation zone. (e) Total number of disturbances in the MSD-NW vegetation zone. Figures (b)–(e) highlight patterns in disturbance characteristics in the most disturbed forest zone in southern Ghana. Maps showing results for the whole study area are available in figure B1 in supplemental materials.

3. Results

3.1. Patterns of forest change

A total of 3562 km^2 of forest reserves in southern Ghana were disturbed from 2013 to 2020. We estimated 17% (615 km^2) of this area to be fire disturbances and 83% (2946 km^2) to be non-fire disturbances. Most of these disturbances were in the moist semi-deciduous northwest (MSD-NW), moist evergreen (ME), and MSD southeast (SE) vegetation zones, amounting to 1419 km^2, 1110 km^2, and 584 km^2, respectively over the 8 year period (figures 1, 2(c), (d), and B1). There was significant fire activity in 2016, during which fire disturbances were detected in 449 km^2 of the reserves, accounting for 45% of all disturbances that year and 73% of all fire disturbances over the 2013–2020 period (figure 2(a)). In the MSD-NW vegetation zone, fires accounted for 72% (327 km^2) of the disturbed area in 2016 and 28% (396 km^2) over the entire 8 year period (figures 1 and 2(c)). During other years, fire disturbances were less than 22 km^2 per year.

Forest disturbance was mostly degradation and open forest loss with less closed forest loss. From 2013 to 2020, 50% (305 km^2) of all fire disturbances resulted in forest degradation while another 34% (210 km^2) led to open forest loss. Over the same period, 71% (2102 km^2) of all non-fire disturbances led to forest degradation and another 26% (772 km^2) resulted in open forest loss. Over the eight-year period, 184 km^2 within the protected reserves were disturbed more than once (figure B1, supplemental materials). These were mostly locations that were first degraded and later experienced open forest loss. During that period, 2702 km^2 of forest reserves recovered, with 1948 km^2 of these recovering to closed forests (figure B2, supplemental materials). Of all recovered closed-canopy forests, 85% (1647 km^2) were found in the ME and MSD (NW and SE) vegetation zones. Between 2013 and 2020, closed forests declined from 9075 km^2 to 8374 km^2, open forests increased from 3517 km^2 to 3856 km^2 and areas with low tree cover increased from 4177 km^2 to 4538 km^2 (figure B3, supplemental materials).

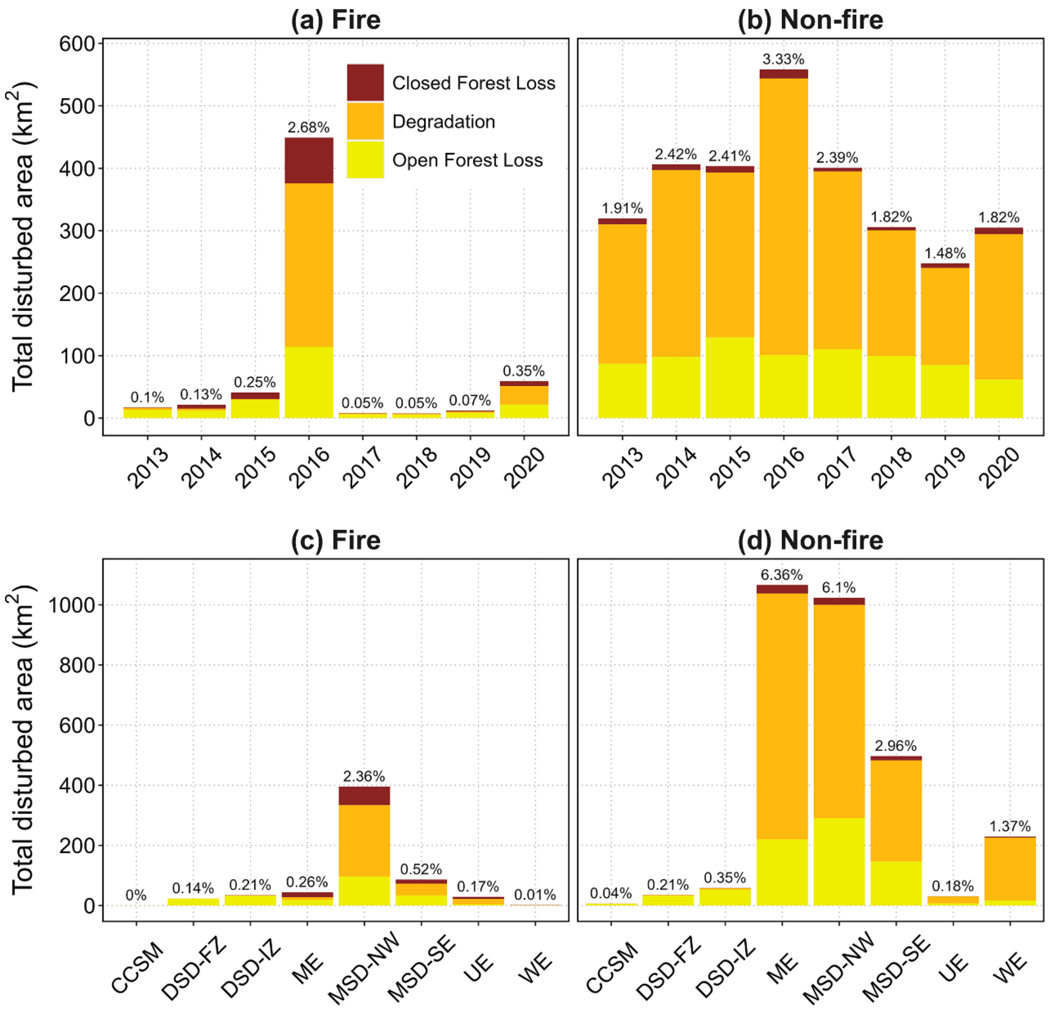

Figure 2. Distribution of fire vs non-fire disturbances from 2013 to 2020. Areas of fire disturbances (a) and non-fire disturbances (b) by year. Areas of fire disturbances (c) and non-fire disturbances (d) by vegetation zone. The vegetation zones are CSSM, DSD-FZ, DSD-IZ, ME, MSD-NW, MSD-SE, UE, and WE. Labels above each bar represent the percentage of the total reserve area (16 770 km^2).

These changes were not linear and there were periods when net changes differed from the overall trend. For example, the areas of forest recovery were larger than those of degradation and loss in 2013 and 2018–2020, resulting in net increases of 472 km^2 in closed forest and 168 km^2 in open forest during these years. However, the total area of recovered forests was less than that of degraded and lost forests in 2014–2017, resulting in net losses of 1104 km^2 of closed forest and 396 km^2 of open forest.

3.2. Drivers of forest disturbance

BRT models of fire disturbances within closed forests had higher accuracy (AUC = 0.97) compared to those in open forests (AUC = 0.91). Models of non-fire disturbances also had higher accuracy within closed forests (AUC = 0.90) compared to open forests (AUC = 0.84). In both closed and open forests, fire-related disturbances were more accurately predicted than non-fire disturbances. Different types of disturbance were influenced by different predictor variables. Precipitation anomalies, distance from non-forest areas, and population gravity index were among the top five most influential predictors in all four models, with varying levels of influence (figure 3). Fire disturbances in both open and closed forests were strongly influenced by both long-term precipitation averages and annual precipitation anomalies. In addition, percent closed forest and population gravity index were important predictors of fire disturbances within closed forests and open forests, respectively. For non-fire disturbances in closed forests, percent closed forest was the single most important predictor with a relative importance of 70%. Non-fire disturbances in open forests were influenced by a wider range of variables including precipitation anomalies, distance from non-forest areas, and fragmentation type.

Disturbance risk was highest in drier years (negative precipitation anomalies) and in locations with mean annual precipitation averaging 1300–1400 mm (figure 4). The risk also increased sharply with population gravity index, peaking at around 2000, above which it quickly diminished and remained low.

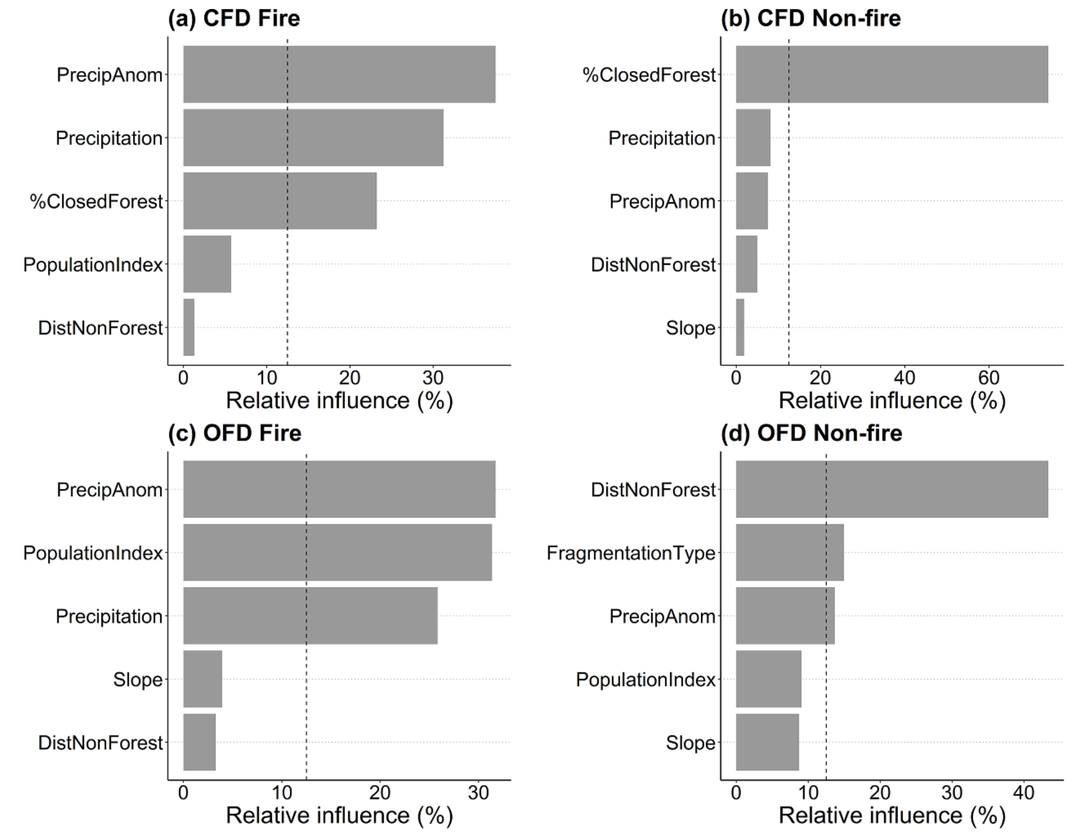

Figure 3. Relative importance of the five most influential variables used in predicting disturbance risk in protected reserves of southern Ghana. (a) and (b) Most important variables predicting fire and non-fire disturbance risk respectively in closed forests. (c) and (d) Most important variables predicting fire and non-fire disturbance risk respectively in open forests. The dotted line represents relative influence expected by chance (Müller *et al* 2013).

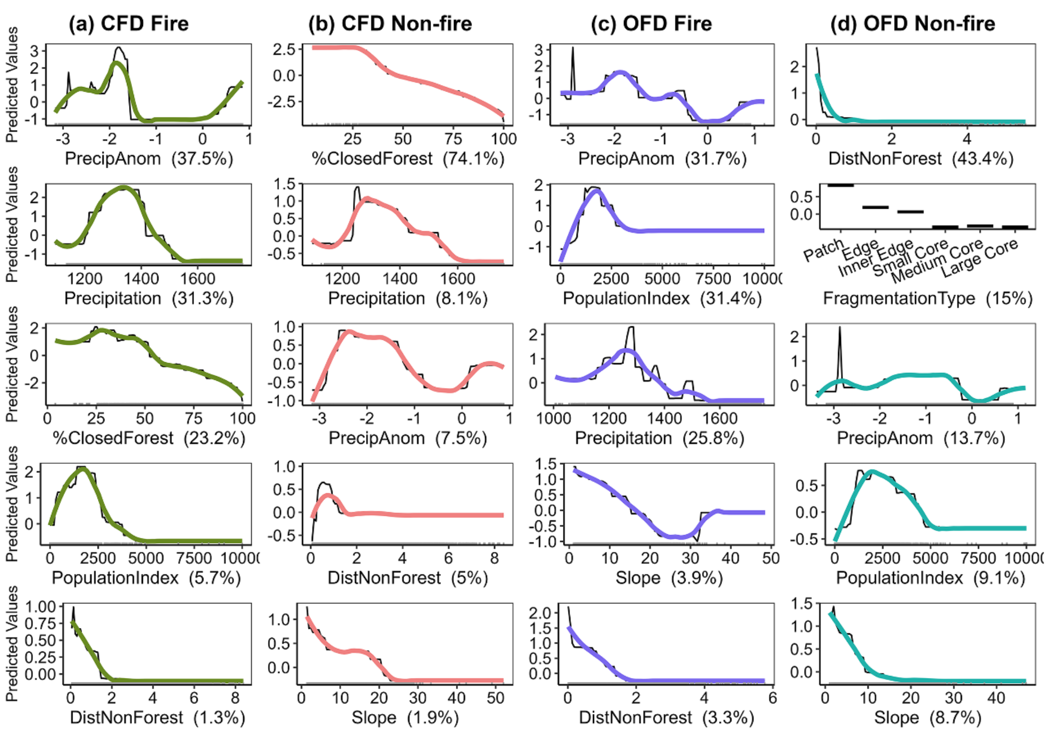

Figure 4. Partial dependence of forest disturbance risk on the top five predictors from models of four disturbance types: (a) fire disturbance within closed forests, (b) non-fire disturbance within closed forests, (c) fire disturbance in open forests, and (d) non-fire disturbance in open forests. Thin black lines represent the fitted function for predictors and relative forest disturbance risk. Thick lines represent a smoothed approximation and lines with the same color indicate variables from the same model.

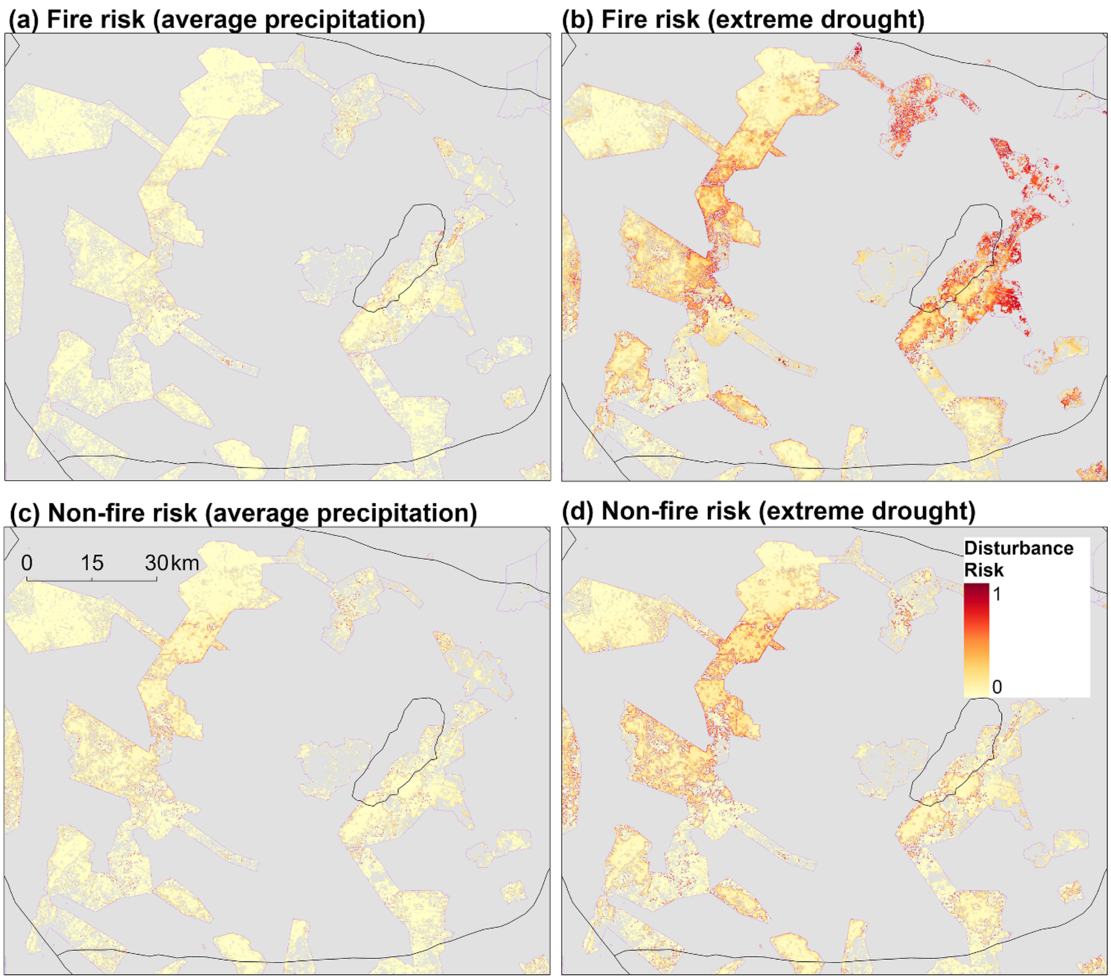

Figure 5. Fire and non-fire disturbance risk surfaces within the MSD-NW region. (a) and (b) Spatial patterns of fire disturbance risk in the average precipitation and extreme drought scenarios, respectively. (c) and (d) Spatial patterns of non-fire disturbance risk in the average precipitation and extreme drought scenarios, respectively.

Disturbance risk increased with decreasing closed canopy forest in the surrounding landscape and was highest at values less than 25%. Forests within 1 km of non-forest areas were most likely to be disturbed, with the highest risk observed for those directly adjacent to non-forest areas. Fragmented forests had a higher risk of being disturbed than more intact forests.

Disturbances were predicted to be more widespread in the extreme drought than the average precipitation scenario, reflecting the negative precipitation anomalies during drought events (figure 5). There was also considerable spatial variation in both scenarios that reflected the effects of human accessibility and landscape structure. High disturbance risk occurred in areas where degradation and forest loss had already occurred, and at more accessible locations along the reserve boundaries.

4. Discussion

Disturbances of closed canopy forests primarily resulted in degradation rather than forest loss, whereas forest loss occurred primarily in open forests. Most disturbances of closed and open forests from 2013 to 2020 were not directly caused by fire, and instead reflected the direct effects of overstory tree removal from logging, mining, or agriculture. However, fire was a significant disturbance at certain times and locations. During the El Niño–Southern Oscillation associated drought of 2016, fires accounted for 45% (449 km^2) of the total disturbed area of open and closed forests across all forest reserves. In the MSD-NW vegetation zone, fires accounted for 72% (327 km^2) of the disturbed area in 2016 and 28% (396 km^2) over the entire eight-year period. Although direct tree mortality resulting from moisture stress is well documented during droughts in the tropics (Phillips *et al* 2009, 2010), most of the additional forest disturbance in Ghana during the 2016 drought was associated with fires.

Climate was the strongest driver of fire disturbance with the highest risk observed in years with negative rainfall anomalies and locations with low mean annual rainfall. In tropical forests, fuel moisture is typically too high to support combustion and sustained drought is necessary for forests to burn. Higher fire detections have been associated with reduced precipitation in tropical forests of Southeast Asia (Sloan *et al* 2017, Sze and Lee 2019) and Amazonia (Aragão *et al* 2008). The MSD-NW zone of Ghana, where most of the fires occurred, was drier than the moist and WE zones further south. Although the 2016 rainfall anomalies were not as extreme in this zone as in other parts of Ghana (Dwomoh *et al* 2019), the reduction in fuel moisture was sufficient to allow widespread burning. If droughts become more common because of climate change, increased fire occurrence has the potential to increase forest degradation and loss. Negative precipitation anomalies had a weaker association with non-fire disturbances, which likely captured direct effects of drought on tree mortality as well as possible misclassification of burned areas not captured by the VIIRS active fire data.

Human accessibility affects forest disturbance through multiple pathways. In Ghana, forests close to non-forest land cover were at a higher risk of being disturbed than forests located further away. The removal of forests is typically associated with land uses such as agriculture and mining, and nearby locations are therefore susceptible to further human disturbance and spread of fire used for land clearing. Disturbance risk was also highest at intermediate levels of the population gravity index. Proximity to dense human populations is associated with higher demands for natural resources and agricultural products, and research in Southeast Asia and Africa has attributed increased forest disturbance to larger or closer settlements (van Khuc *et al* 2018, Sze and Lee 2019, Gou *et al* 2022). However, locations in our study with the highest population gravity index were very close to large cities, and they may experience less disturbance if there is less use of fire and more surveillance for illegal activities. These results emphasize that forest disturbance risk is likely to intensify in Ghana due to increasing human populations, rapid urbanization, and associated land use and land cover changes.

Past disturbances influence forest and landscape structure, which in turn affects the likelihood of future disturbances (Vieira *et al* 2004). Degradation reduces canopy cover, tree density, and biomass, while forest loss alters vegetation structure and microclimate at forest edges. These changes increase the probability of fire by allowing more solar radiation into the forest understory, which can increase surface fuel loads and decrease fuel moisture (Cochrane *et al* 1999, Laurance and Williamson 2001). Open forests, forest edges, and flat terrain can be preferred for land uses such as farming and logging (Busch and Ferretti-Gallon 2017, Edwards *et al* 2019) because less effort is required for land clearing. The forest structure variables that we used may also be proxies for unmeasured factors that influence the rate of disturbance in particular locations. For instance, degradation in the MSD-NW forests is related to the abundance of valuable commercial timber species in this zone (Adam *et al* 2006), and the lower proportions of closed-canopy forest in this area may reflect differences in species composition that have made these forests desirable for logging in the past and in the future. Other studies in the Amazon and Southeast Asia have also concluded that previously disturbed forests are likely to be disturbed again (Cochrane *et al* 1999, Adrianto *et al* 2020, Wang *et al* 2020, Qin *et al* 2021) and continued disturbance can lead forests to shift permanently to non-forest states (de Dantas *et al* 2016).

A major strength of this study was the use of high-quality, annual disturbance maps calibrated and validated within the study area (Wimberly *et al* 2022), which were combined with burned area estimates from 375 m VIIRS active fire data to identify fire disturbances. Although the scale mismatch likely resulted in some misclassification of fire and non-fire disturbances, we were able to identify distinctive sets of drivers for each disturbance type. We focused on predictors that were measurable using geospatial data and did not include variables on forest governance systems, policies, and logging histories because these data were not accessible. We did not also consider disturbances that do not have an instantaneous effect on canopy density such as the long-term cultivation of crops in forest understories. Nevertheless, our models classified forest disturbance accurately (AUCs 0.84–0.97). Although we cannot elucidate the proximal causes of forest disturbance, the models do have the capability to highlight the locations and climatic conditions under which disturbances are most likely.

Our results provide new insights into the disturbance regimes within the forest reserves of Ghana. The extent of non-fire disturbance is relatively constant from year to year. Fire typically affects less area than non-fire disturbance but can increase sharply in response to drought. Areas where previous disturbances opened the forest canopy and caused fragmentation were more susceptible to disturbance than intact forests, supporting the hypothesis that positive feedbacks are driving forest degradation and loss (Dwomoh and Wimberly 2017). Understanding these dynamics is important for conservation and forest restoration activities in Ghana and similar tropical forest regions. Models based on climate variability, human accessibility, and landscape structure can identify where and when disturbance risk is highest and help target these actions accordingly.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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