Title: Elevated fires during COVID-19 lockdown and the vulnerability of protected areas

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Abstract

There is little robust, quantitative information on the impacts of the COVID-19 pandemic on the extinction crisis. Focusing on Madagascar, one of the world's most threatened biodiversity hotspots, we explore if the cessation of on-site protected area management activities due to the pandemic were associated with increased burning inside protected areas. We identify monthly excess fire anomalies by comparing observed fires to those predicted based on historical and contemporary fire and weather data for all of Madagascar's protected areas, for every month 2012-2020. Through to 2019 excess fire anomalies in protected areas were few, short in duration, and in some years coincident with social disruption linked to national elections. By contrast in 2020, COVID-19 meant on-site management of Madagascar's protected areas was suspended from March to July. This period was associated with 76-248 % more fires than predicted, after which burning returned to normal. At a time when international biodiversity conservation faces unprecedented challenges, our results highlight the importance of on-site management for maintaining protected area integrity.

Main

The year 2020 was supposed to be a "super year" for biodiversity conservation during which the parties to the Convention on Biological Diversity (CBD) would agree ambitious targets for the next decade[1]. However, the COVID-19 pandemic has both postponed the decade's most significant meeting in international biodiversity, and caused unprecedented disruption to conservation activities[2–4]. Lockdowns dramatically interrupted on-site protected area management activities in many countries[3] and introduced uncertainty and economic difficulties to local communities[5], including from reduced tourism revenue[6]. While early studies have shown that the pandemic increased fires in Colombia[7] and decreased fires in the southeastern United States[8], there has been no robust assessment of the impact of the pandemic on protected area integrity.

One of the most important threats to biodiversity in much of the world is land-use change and habitat conversion to agriculture[9,10]. Effectively preventing this is an important objective of many protected areas[11]. Where habitat loss is associated with shifting agriculture, such as in much of Africa[9,12], the prevalence of fires is commonly used as an indicator of land conversion[13,14] and the performance of conservation interventions[15,16]. Fires occur as a result of complex interactions between climatic and anthropogenic drivers[13] making it essential to control for climatic drivers when exploring the impact of changes in direct anthropogenic drivers. Forecasting fire activity using seasonal climate variables is still in its infancy[17,18], but precipitation is widely recognized as an important predictor[19].

Madagascar is world-renowned for its extraordinary biodiversity, but also for the exceptional pressures faced by that biodiversity[20,21]. Over the last decade Madagascar has seen a rapid expansion of its reserve network[22]. However, there are concerns that the network is inadequately managed and that protected area expansion efforts have paid insufficient attention to building local support and governance structures[23,24].

Drawing on the excess mortality approach which has become widely understood as a metric for quantifying the impacts of pandemics[25], we explore whether the cessation of on-site protected area management activities which followed the start of the COVID-19 pandemic, and the subsequent extended period of closed borders and economic hardship, coincided with greater than expected fires in Madagascar's protected areas. Using remote sensed data on fire and precipitation, we first predict the number of fires for each month for each year between 2012 and 2020 based on precipitation that month, precipitation in the previous month, accumulated precipitation over the last 12 months, and interactions with biome, using a zero-inflated negative binomial model. We then look at the deviations between our predicted fires and those observed in order to estimate numbers of fires not predicted by weather conditions or forest type. Our analyses uncover an unprecedented increase in fires in Madagascar's protected areas between March and July 2020 (the period when on-site activities were prevented) but also reveal that fires quickly dropped to those predicted by our model as management activities resumed. Taking advantage of the unique quasi-experimental setting provided by the first year of the COVID-19 pandemic, we are thus able to show strong evidence for the importance of well-managed protected areas for retaining the integrity of globally important areas for biodiversity conservation.

Seasonality of fires in Madagascar

Madagascar's climate is highly seasonal (Fig. 1) which affects the agricultural cycle. Farmers burn vegetation in preparation for planting crops before the rains, to provide fresh forage for cattle, and to control tree and shrub encroachment into pastures[26]. Such anthropogenic factors interact with the changing combustibility of vegetation, producing a distinct seasonal pattern of fires in Madagascar's protected areas with a peak in all biomes in October (Fig. 1A), at the end of the dry season (Fig. 1B). Fires begin earlier in desert and xeric scrubland protected areas (April onwards) and dry broadleaf forest protected areas (May onwards), compared to the moist broadleaf forest protected areas (August onwards) (Fig 1A). Mean precipitation is quite variable across years (for example the beginning of 2020 was drier than previous years (Fig. 1B, Fig. S1), meaning a climate-adjusted model of predicted fires is needed to identify fire anomalies.

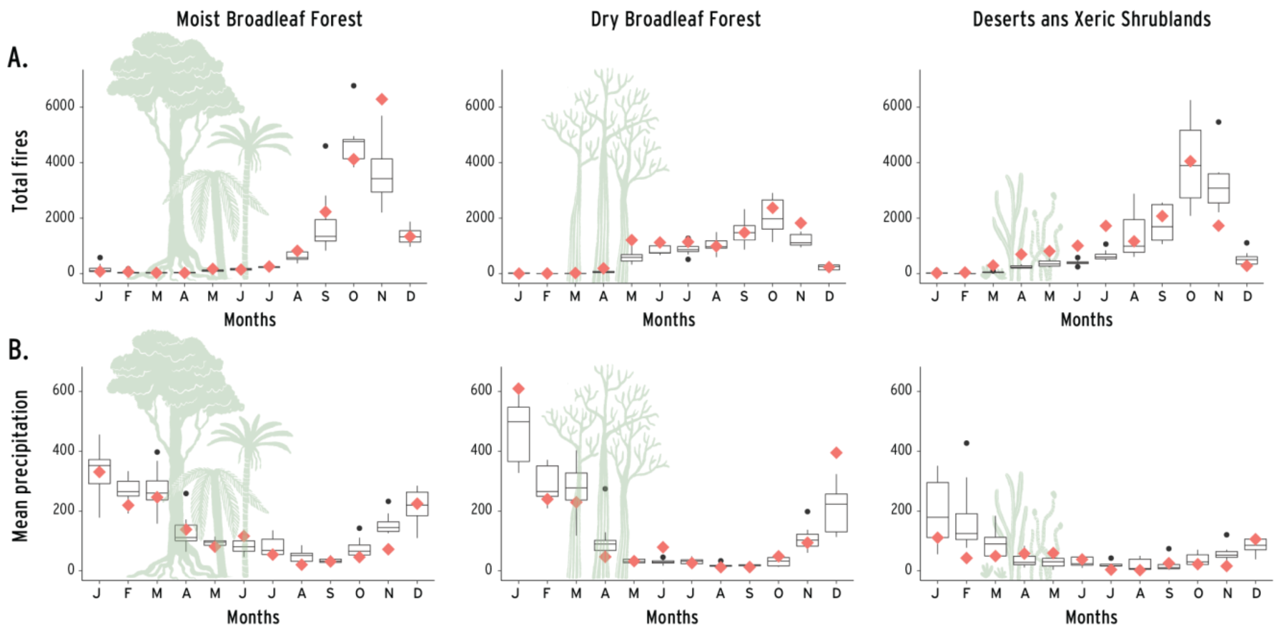

Figure 1. Yearly seasonal patterns in fire occurrence (A) and precipitation (mm) (B) in protected areas across the different biomes. The boxplots (center line, median; box limits, upper and lower quartiles; whiskers, 1.5× interquartile range; points, outliers) show the variation for the years 2012-2019 and diamonds show the values for 2020.

Our climate-based model accounting for lags in precipitation and interactions with biomes (for details see Methods and SI) shows in general that an increase in precipitation in the same month is linked to a decrease in fires, and confirms that the timing of burning differs between biomes (SI Supplementary tables). Accumulated rainfall over the 12 past months is a significant, positive predictor of fires during the autumn months (Aug, Sept, Nov, Dec); (SI Supplementary tables). Overall, the model fit is reasonable, with observed fires falling within the 95 % confidence intervals around predicted fires for 63 out of 95 months (Fig. S2) and with model accuracy metrics (Mean Absolute Error (MAE); Root Mean Squared Error (RMSE); Normalized Root Mean Squared Error (nRMSE) indicating that the model performed poorly only in August 2015 (apparently because of unusually high rainfall during the past 12 months in three protected areas; SI; Fig S3).

Excess fires prior to pandemic

Two noticeable differences between observed fires and those predicted by our model occurred in October-November 2013 and September 2018; both periods are associated with presidential elections (Fig. 2). The 2013 election (the first after the 2009 coup d'état) was particularly fiercely contested[27] and our data show that this political unrest was associated with two consecutive months of excess burning. The finding that political events maybe correlated with increased deforestation has been observed in a recent study looking at election cycles and deforestation in Brazil[28] and across 55 tropical forest nations[29].

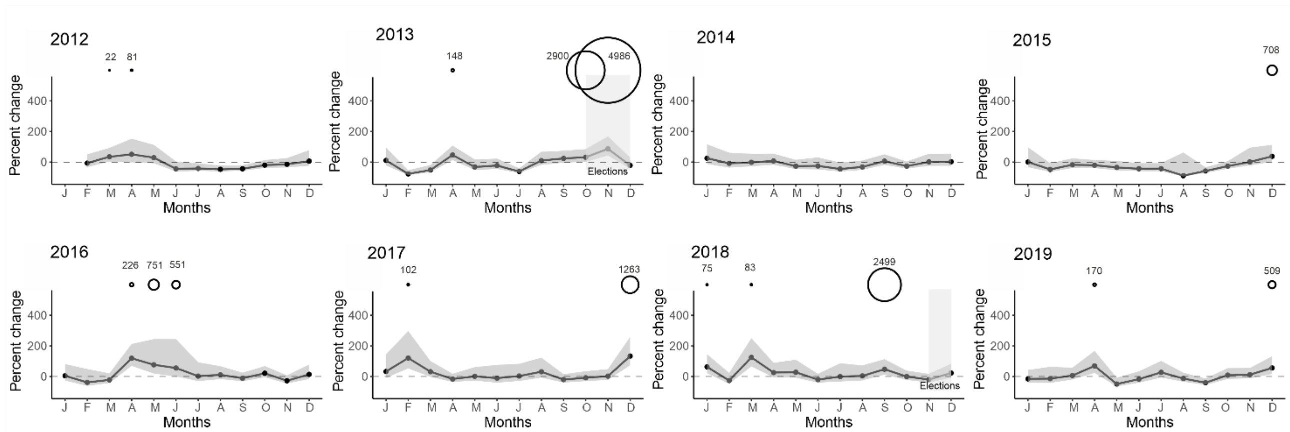

Figure 2: The occurrence of months with excess fires in protected areas presented as the percent change between the total number of observed and predicted fires across all protected areas modelled for each month for the time period 2012-2020. Shaded area around the lines corresponds to the 95 % confidence intervals. The size of the circles is relative to the number of excess fires in those months with significantly more fires than predicted based on climate and biome and the numbers above the circles refer to the number of excess fires for the month in question.

Burning during the pandemic

Madagascar responded rapidly to the threat of COVID-19 by closing its borders and instituting a series of lockdowns (Fig. 3). Travel around the country, including by ministry officials and protected area managers, and field activities were substantially curtailed from March 20, 2020 and only started to recover from July onwards (Fig. 3). This meant that most on-site management activities (including enforcement patrols, community engagement and livelihood support projects) were effectively stopped for a period of approximately four months. International tourism into Madagascar, which contributed nearly 7% of gross national product in 2019[30] and is an important source of revenue for Madagascar's protected area network[31], only reopened in autumn 2021.

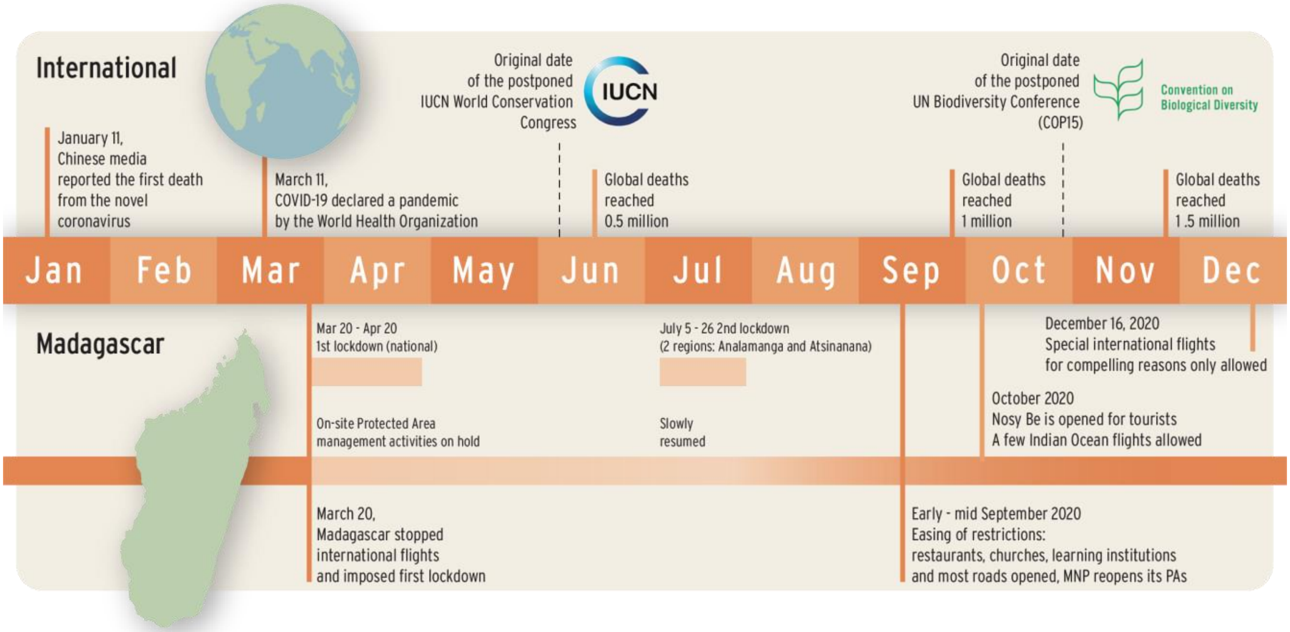

Figure 3. Timeline of key events associated with COVID-19 internationally and in Madagascar during 2020. For sources, see SI.

Comparing observed fire frequency for 2020 in Madagascar's protected areas with those predicted by our climate-adjusted model shows that the shutdown of conservation management activities from March to July was associated with an unprecedented 5-month upsurge in fires inside Madagascar's protected areas (Fig. 4). In August 2020 there were slightly fewer fires than predicted, but burning quickly returned to levels predicted by our model after this. Despite a fear that the September onset of the burning period in the eastern humid forests would lead to elevated fires in the autumn of 2020[32], this was not seen and burning inside protected areas remained at the levels predicted by climatic variables for the rest of 2020 (Fig. 4). The period of excess burning persisted for far longer (5 consecutive months, cf median of 1 month for 12 previous anomalies in 2012-2019), and was characterized by far greater increases in relative fire frequency, with 76-248% more fires than predicted by our model (March: 209 %, April: 223 %, May 78 %, June 248 %, July 76 %; cf 32 – 134 % across all previous excess months, 2012-2019).

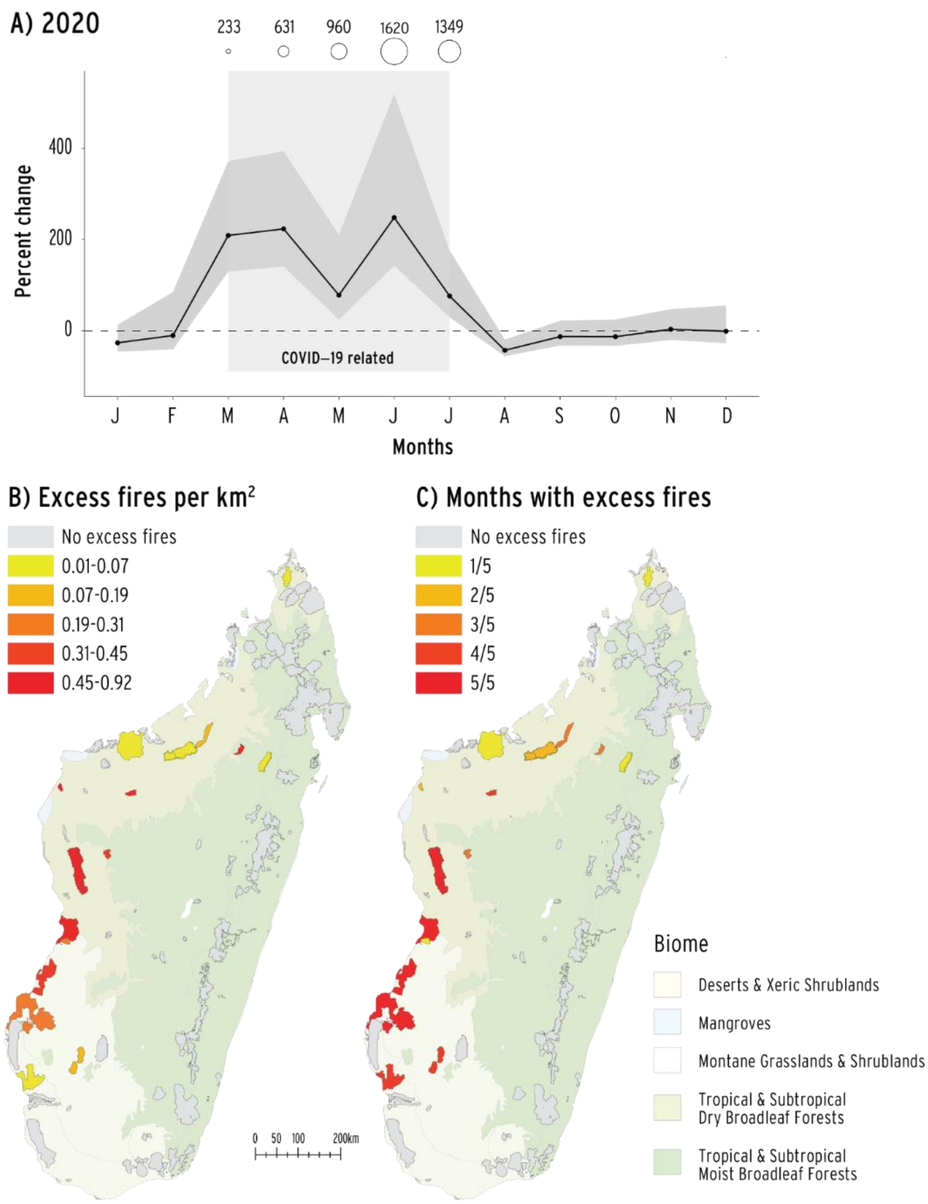

Figure 4. Extent and location of excess protected area fires in 2020 in Madagascar. A) The occurrence of months with excess fires in protected areas presented as the percent change between

the total number of observed and predicted fires across all protected areas modelled for each month of 2020. Shaded area around the lines corresponds to 95 % confidence intervals. The size of the circles for those months with significantly more fires than predicted based on climate and biome is relative to the number of excess fires in those months and the numbers above the circles refer to the number of excess fires for the month in question. B) The spatial distribution of excess fires among Madagascar's protected areas shown as the sum of excess fires March to July 2020 divided by size of protected area, and (C) the number of months (out of 5) for which a protected area experienced excess fires.

Spatial patterns of burning

Most of the excess fires registered in 2020 were concentrated in 16 protected areas in the west of Madagascar (Fig. 4). This pattern was not associated with any known management or governance factors, such as IUCN management category or management authority (Fig. S4). There were no differences in performance between protected areas managed by the parastatal Madagascar National Parks and the more recently established protected areas managed under different types of collaborative agreements with local communities and non-governmental organizations (Fig. S4).

However, during the period when management activities were on hold (March to July 2020) it is generally too wet for protected areas in the moist forest biome to burn (Fig. 1)[33–35], which may explains why the excess fires were concentrated in the west where forests are more vulnerable at this time of year. Analysing the spatial distribution of fire anomalies in previous years (Figs. S5-11) confirms that excess burning occurring earlier in the year is clustered in the west (Figs. S5A; S8A,B,C; S10A; S11A,B), whereas anomalies later in the year are spread across the country (Figs S5B; S6C; S9A; S10B,C), supporting the conclusion that the time of the year the pandemic hit, rather than any specific type of protected area governance, explains the spatial patterns in excess burning.

Discussion

Focusing on one of the world's most megadiverse countries, we show for the first time that the COVID-19 pandemic was linked to a reduction in protected area integrity. The overlap between excess fires and the suspension of on-site management activities suggests a causal mechanism whereby fire prevention inside protected areas depends on such active engagement. However, increased pressures, driven by people clearing more land in anticipation of lost non-agricultural incomes, may also have played a role. Soon after on-site management resumed, burning inside Madagascar's protected areas quickly reverted to levels predicted by our model. This is despite the economy of Madagascar not yet opening up and continued economic hardship[36], including a drought-induced famine in the south[37]. Our findings therefore provide strong empirical evidence supporting previous correlational studies showing that active protected area management can buffer against population declines[38–40] and providing evidence that this also applies for land-use change pressures for which the evidence base has been inconclusive[41–43].

Like any analyses relying on remotely-sensed data and building counterfactual scenarios, there are important caveats to our work. It is important to remember that the VIIRS thermal anomalies only serve as a proxy for fire incidence and ground validation was not possible due to the pandemic. However, previous studies have shown that the VIIRS product provides more coherent fire mapping compared to MODIS 1 km fire data and that the nominal confidence fire detections showed average commission error of 1.2%[44]. VIIRS is documented as having good capacity to detect real fires[44] and temporal patterns converge with on-the-ground observations[8]. VIIRS is also commonly used for practical fire management[45,46]. Despite the high performance of the VIIRS data we nevertheless caution that our fire incidence data may underestimate the true number of fires as agricultural fires in sub-Saharan Africa are often small[47]. We chose to study fire because remote sensing data allows us to quantify changes in this threat at fine spatial and temporal scales; however, this tells us nothing about the dynamics of other potentially important threats such as hunting, grazing, or extraction of wild harvested products[3]. Our analyses also do not account for COVID-19 induced burning outside protected areas, and, thus, we cannot say how well the protected areas mitigated potentially increased pressures compared to unprotected land. Finally, modelling what would have happened in the absence of the COVID-19 pandemic is challenging as such a counterfactual is inherently unknowable. Our predictive model only takes account of climatic drivers, for which we have relatively good annual data, however the fire frequency in any given year will have been influenced by a complex mix of social and economic drivers.

The longer-term effects of COVID-19 on international conservation remain to be seen. The four times delayed meeting to agree the global post-2020 biodiversity framework[1] is due to be held in the third quarter of 2022. However, this will be happening in the context of continued economic uncertainty in many parts of the world[48], probably affecting international support for conservation. The prolonged effects of the pandemic on tourism and on economies more broadly will harm local livelihoods and place additional pressures on protected areas. It is important to keep monitoring the situation to evaluate long-term impacts of COVID-19 and to assess how the prolonged lack of tourism revenues may be affecting protected area performance. Our work has practical implications in that it can inform policy makers and park agencies about the importance of finding creative ways of keeping on-site protected area management going in times of turmoil. Our results clearly demonstrate the dramatic impact that management interruptions can have, and indicate that it may be important for politicians to consider protected area management an essential service which needs to continue through times of lockdowns and travel restrictions. In Madagascar, some protected area authorities started to increase collaboration with local communities to keep on-site activities running[49] - an approach that might enhance conservation outcomes in the long-term[50] and beyond the pandemic.

Methods

Overview

We built models (based on fire and climatic data from 2012-2020) to predict the monthly fires in Madagascar's protected areas. We compared the observed number of fires in a given protected area in a given month to identify fire anomalies (where observed and predicted fires did not align) and used this to explore the temporal and spatial distribution of excess fires. Spatial analyses were done using ArcGIS 10.8[51] and Python 3.8.5[52] and all statistical analyses were performed using the software R 4.0.2[53]. Package ggplot2[54] was used for visualizations.

Data sets used

Protected area boundaries were identified using spatial information from the World Database of Protected Areas[55]. The June 2020 release was compared to the list of protected areas by the Malagasy protected areas platform Forum Lafa and identified in Goodman et al.[56] and those occurring in both were kept and clear overlaps removed, resulting in 114 protected areas being included in the analyses (Table S2).

Data on biomes was sourced from the RESOLVE ecoregions project[57] and we used the higher level classification identifying the following main biomes for Madagascar: Tropical & Subtropical Moist Broadleaf Forests (comprised of the humid and subhumid forests), Tropical & Subtropical Dry Broadleaf Forests (comprised of the dry deciduous forest), and Deserts and Xeric Shrublands (comprised of the spiny thickets and the succulent woodlands; Fig. 4). Protected areas were assigned to one biome based on highest spatial overlap (Table S2).

We used the Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m active fire product from the joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 satellites[58] as this product provides near real-time open-access data on thermal anomalies and active fires at a finer spatial resolution than other satellite-based fire products[44]. The 375 m data complements Moderate Resolution Imaging Spectroradiometer (MODIS) fire detection and the previous VIIRS product at resolution 750 m[44]. Previous studies have shown that these coarser resolution products tend to miss especially smaller fires[47,59]. At the moment, the VIIRS 375 m data is the finest resolution publicly available data; we note its use for near real-time fire management alerts[45,60]. We sourced the full data for Madagascar from the first observation (20 January 2012) until the 31 December 2020. Note that the data is almost immediately released as a near real-time version, and later undergoes post-processing, meaning that in our dataset downloaded the 29.01.2021 the data consisted of the final full product from 20.1.2012-31.5.2020 and the near real-time release for 1.6.2020-31.12.2021. The confidence values are set to low, nominal and high by the data provider[60]. According to the data provider, low confidence daytime fire pixels are typically associated with areas of sun glint and lower relative temperature anomaly (<15K) in the mid-infrared channel I4. Nominal confidence pixels are those free of potential sun glint contamination during the day and marked by strong (>15K) temperature anomaly in either day or nighttime data. High confidence fire pixels are associated with day or nighttime saturated pixels. We only included the nominal and high confidence pixels and omitted the low confidence observations (13.88 % of all pixels), possibly omitting some smaller fires, in order to make sure our predictions are conservative. This might have increased the zero observations in our dataset, something we consequently dealt with using a zero-inflated negative binomial approach, specifically incorporating the uncertainty behind zero observations (see details below). The resulting data was overlayed with the protected area polygons and after that summed to number of observed fires per month per protected area for all the years (2012-2020). We excluded January 2012 due to its incomplete nature (only 11 days of data).

Monthly precipitation data was sourced from the Global Precipitation Measurement (GPM) mission[61] (for years 2016-2020) and its predecessor The Tropical Rainfall Measuring Mission (TRMM)[62] (for years 2011-2015) at spatial resolution 10 km. Mean precipitation per protected area per month for 2011-2020 was calculated as the average of the precipitation data cells that intersected the protected area (zonal mean).

Explanatory variables in the fire prediction model

In the tropics and subtropics, the total amount of fires reflects a complex interaction between climate and human activities[63] with precipitation being an exceptionally important driver of inter-annual and seasonal variability in burned area[19]. Thus controlling for precipitation variability is critical for assessing trends in fire activity. Higher precipitation prior to the onset of the main fire season may increase fire activity in arid regions because greater moisture availability enhances biomass production and this vegetation can then burn, whereas higher levels of precipitation during the fire season may suppress fires due to the increased moisture[13]. In general, precipitation is negatively correlated to burned area in the short term in humid savannas and tropical forests, but positively correlated in the long term in more xeric savannas and grasslands[19].

To control for the effect of precipitation on fire occurrence and thus establish a robust counterfactual of expected fires against which to compare observed fires, we built monthly models predicting the number of fires inside protected areas based on a set of precipitation variables. We expected precipitation to interact with biome and so included biome as an interaction term. To account for the possible difference in long- versus short-term effects of precipitation we explored including a number of time lags but were also concerned to avoid over-fitting. Thus we calculated accumulated precipitation over the last 12 months based on summing the precipitation during the past 12 months. Our final model included accumulated precipitation together with the precipitation in the month in question, plus precipitation during the past month, plus their interactions with biome (factor). Explanatory variables were standardised using the R function ‘scale’ on all precipitation variables in the data set by dividing the (centered) columns of each factor by their standard deviations. Standardised variables were evaluated for collinearity by visual inspection of the data and by calculating Pearson’s correlation coefficients.

Predicting fires and identifying fire anomalies

To establish the null model for expected occurrence of fires given the levels of precipitation and in the absence of COVID-19 and other changes in human activities, we built monthly models explaining the sum of fires inside protected areas from 2012 to 2020 based on fires in other years and precipitation variables. The fire occurrence data is count data and since we had many protected areas with not a single fire in a given month, our data was also zero inflated. To account for this, we explored the use of zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) regression models using the R package pscl[64]. Using a likelihood ratio test, we found that ZINB outperformed ZIP (SI) for our data due to overdispersion in the non-zero count data[65], and therefore proceeded with ZINB. Previous studies have also found that ZINB-models are well suited for modelling fire incidence[66,67].

The number of fires was thus modeled using a zero-inflated negative binomial modelling approach[65]. The probability density function for the random variable y_i denoting the fire count is

$$P(y_i = j) = \begin{cases} \pi_i + (1-\pi_i)\left(\dfrac{k}{\mu_i + k}\right)^k & \text{if} \quad j = 0 \\ (1-\pi_i)\,\dfrac{\Gamma(k+y_i)}{\Gamma(y_i+1)\Gamma(k)}\left(\dfrac{\mu_i}{\mu_i+k}\right)^{y_i}\left(\dfrac{k}{\mu_i+k}\right)^k & \text{if} \quad j \geq 0 \end{cases} \qquad (1)$$

where π_i denotes the probability of having a zero count, μ_i is the mean, k is the dispersion parameter and $\Gamma(\cdot)$ is the gamma function[65,68]. The mean μ_i was modeled using the log link function and predictor variables. The zero counts were modeled assuming equal probability for each zero count. The fire count predictor variables were monthly precipitation, precipitation from previous month and accumulated precipitation during last 12 months, which all had an interaction with the biome type. The log-transformed size of protected areas was used as an offset variable.

We fitted the model for each month for each year (2012-2019), using data from the corresponding month during all other years in the data series. Further model selection was not done as we were not interested in finding out which specific explanatory variables best explained fires, but rather in excluding the potential effect of any of them. Model validation was done using residual diagnostics following the procedures described in Zuur et al[69]. Based on the fitted model, we predicted the expected fires based on the model parameters and precipitation values for the month and year in question. For example, fires in April 2016 were predicted using the model fitted based on April 2012, 2013, 2014, 2015, 2017, 2018, and 2019. Excess fires were defined as the difference between observed and predicted fires. For 2020, we repeated the same procedure and fitted the model for each month using the 2012-2019 data and then predicting 2020 fires based on the 2020 covariate values. We assessed model forecasting accuracy using two commonly used measures, the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE)[70]. However, as these are both absolute measures, we also report the Normalized Root Mean Squared Error (nRMSE), which divides the RMSE by the range (max-min) and thus allows for comparisons across the months and years[70].

Effect size measures and confidence intervals

We summed predicted and observed fires across the 114 protected areas for each month of each year and created 95% confidence intervals around the predictions by bootstrapping[71]. We resampled the predicted values for each month of each year 10 000 times using package boot in R[72]. We used the normal 95 % confidence intervals to determine for which months there were statistically significantly more fires than predicted by our model. For these months, we identified individual protected areas with excess fires as those with more fires than the 95 % confidence interval around the mean for all protected areas in that month.

For the 2020 anomaly, for each protected area we calculated excess fires per km^2 by summing excess fires for March, April, May, June, and July 2020 and dividing by the size of the protected area (km^2). We tested if the excess fires per km^2 differed by IUCN management category or management authority using the nonparametric Kruskal–Wallis one-way analysis of variance test due to the non-normality of the data.

Data Availability

The data supporting the findings of this study are available on Zenodo: https://doi.org/10.5281/zenodo.6366888

Code Availability

Code used for this work is available from the corresponding author upon reasonable request.

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Author contributions

J.E., A.B., J.P.G.J., T.T., and J.G. designed the research; J.E. and A.P.J. prepared the data for analyses; J.E. performed the analysis with input from A.B., M.R., A.P., and J.P.G.J.; J.E, A.B., J.P.G.J., O.S.R., D.R., and J.G. contributed to the interpretation of results; J.E. drafted the manuscript; and all authors participated in manuscript editing.

Declaration of interests

The authors declare no competing interests.

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