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

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30

31

32 **Abstract**

33 There is little robust, quantitative information on the impacts of the COVID-19 pandemic on the
34 extinction crisis. Focusing on Madagascar, one of the world’s most threatened biodiversity hotspots,
35 we explore if the cessation of on-site protected area management activities due to the pandemic
36 were associated with increased burning inside protected areas. We identify monthly excess fire
37 anomalies by comparing observed fires to those predicted based on historical and contemporary fire
38 and weather data for all of Madagascar’s protected areas, for every month 2012-2020. Through to
39 2019 excess fire anomalies in protected areas were few, short in duration, and in some years
40 coincident with social disruption linked to national elections. By contrast in 2020, COVID-19
41 meant on-site management of Madagascar’s protected areas was suspended from March to July.
42 This period was associated with 76-248 % more fires than predicted, after which burning returned
43 to normal. At a time when international biodiversity conservation faces unprecedented challenges,
44 our results highlight the importance of on-site management for maintaining protected area integrity.

45 **Main**

46 The year 2020 was supposed to be a “super year” for biodiversity conservation during which the
47 parties to the Convention on Biological Diversity (CBD) would agree ambitious targets for the next
48 decade¹. However, the COVID-19 pandemic has both postponed the decade’s most significant
49 meeting in international biodiversity, and caused unprecedented disruption to conservation
50 activities²⁻⁴. Lockdowns dramatically interrupted on-site protected area management activities in
51 many countries³ and introduced uncertainty and economic difficulties to local communities⁵,
52 including from reduced tourism revenue⁶. While early studies have shown that the pandemic
53 increased fires in Colombia⁷ and decreased fires in the southeastern United States⁸, there has been
54 no robust assessment of the impact of the pandemic on protected area integrity.

55 One of the most important threats to biodiversity in much of the world is land-use
56 change and habitat conversion to agriculture^{9,10}. Effectively preventing this is an important
57 objective of many protected areas¹¹. Where habitat loss is associated with shifting agriculture, such
58 as in much of Africa^{9,12}, the prevalence of fires is commonly used as an indicator of land
59 conversion^{13,14} and the performance of conservation interventions^{15,16}. Fires occur as a result of
60 complex interactions between climatic and anthropogenic drivers¹³ making it essential to control for
61 climatic drivers when exploring the impact of changes in direct anthropogenic drivers. Forecasting
62 fire activity using seasonal climate variables is still in its infancy^{17,18}, but precipitation is widely
63 recognized as an important predictor¹⁹.

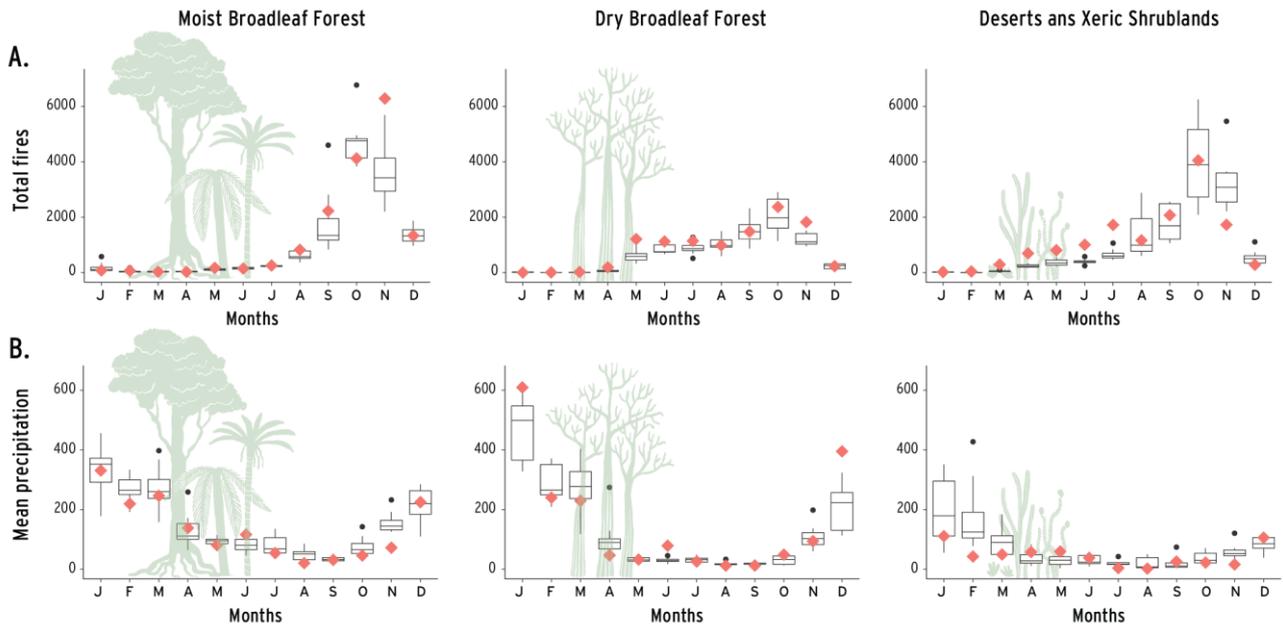
64 Madagascar is world-renowned for its extraordinary biodiversity, but also for the
65 exceptional pressures faced by that biodiversity^{20,21}. Over the last decade Madagascar has seen a
66 rapid expansion of its reserve network²². However, there are concerns that the network is
67 inadequately managed and that protected area expansion efforts have paid insufficient attention to
68 building local support and governance structures^{23,24}.

69 Drawing on the excess mortality approach which has become widely understood as a
70 metric for quantifying the impacts of pandemics²⁵, we explore whether the cessation of on-site
71 protected area management activities which followed the start of the COVID-19 pandemic, and the
72 subsequent extended period of closed borders and economic hardship, coincided with greater than
73 expected fires in Madagascar's protected areas. Using remote sensed data on fire and precipitation,
74 we first predict the number of fires for each month for each year between 2012 and 2020 based on
75 precipitation that month, precipitation in the previous month, accumulated precipitation over the last
76 12 months, and interactions with biome, using a zero-inflated negative binomial model. We then
77 look at the deviations between our predicted fires and those observed in order to estimate numbers
78 of fires not predicted by weather conditions or forest type. Our analyses uncover an unprecedented

79 increase in fires in Madagascar's protected areas between March and July 2020 (the period when
80 on-site activities were prevented) but also reveal that fires quickly dropped to those predicted by our
81 model as management activities resumed. Taking advantage of the unique quasi-experimental
82 setting provided by the first year of the COVID-19 pandemic, we are thus able to show strong
83 evidence for the importance of well-managed protected areas for retaining the integrity of globally
84 important areas for biodiversity conservation.

85 **Seasonality of fires in Madagascar**

86 Madagascar's climate is highly seasonal (Fig. 1) which affects the agricultural cycle. Farmers burn
87 vegetation in preparation for planting crops before the rains, to provide fresh forage for cattle, and
88 to control tree and shrub encroachment into pastures²⁶. Such anthropogenic factors interact with the
89 changing combustibility of vegetation, producing a distinct seasonal pattern of fires in
90 Madagascar's protected areas with a peak in all biomes in October (Fig. 1A), at the end of the dry
91 season (Fig. 1B). Fires begin earlier in desert and xeric scrubland protected areas (April onwards)
92 and dry broadleaf forest protected areas (May onwards), compared to the moist broadleaf forest
93 protected areas (August onwards) (Fig 1A). Mean precipitation is quite variable across years (for
94 example the beginning of 2020 was drier than previous years (Fig. 1B, Fig. S1), meaning a climate-
95 adjusted model of predicted fires is needed to identify fire anomalies.



96

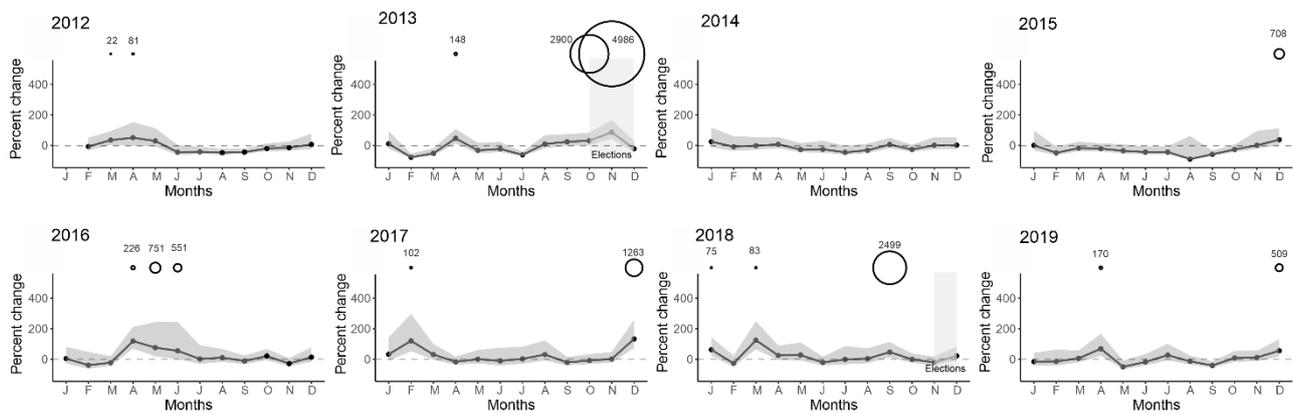
97 **Figure 1.** Yearly seasonal patterns in fire occurrence (A) and precipitation (mm) (B) in protected
 98 areas across the different biomes. The boxplots (center line, median; box limits, upper and lower
 99 quartiles; whiskers, 1.5× interquartile range; points, outliers) show the variation for the years 2012-
 100 2019 and diamonds show the values for 2020.

101

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

112 **Excess fires prior to pandemic**

113 Two noticeable differences between observed fires and those predicted by our model occurred in
114 October-November 2013 and September 2018; both periods are associated with presidential
115 elections (Fig. 2). The 2013 election (the first after the 2009 coup d'état) was particularly fiercely
116 contested²⁷ and our data show that this political unrest was associated with two consecutive months
117 of excess burning. The finding that political events maybe correlated with increased deforestation
118 has been observed in a recent study looking at election cycles and deforestation in Brazil²⁸ and
119 across 55 tropical forest nations²⁹.

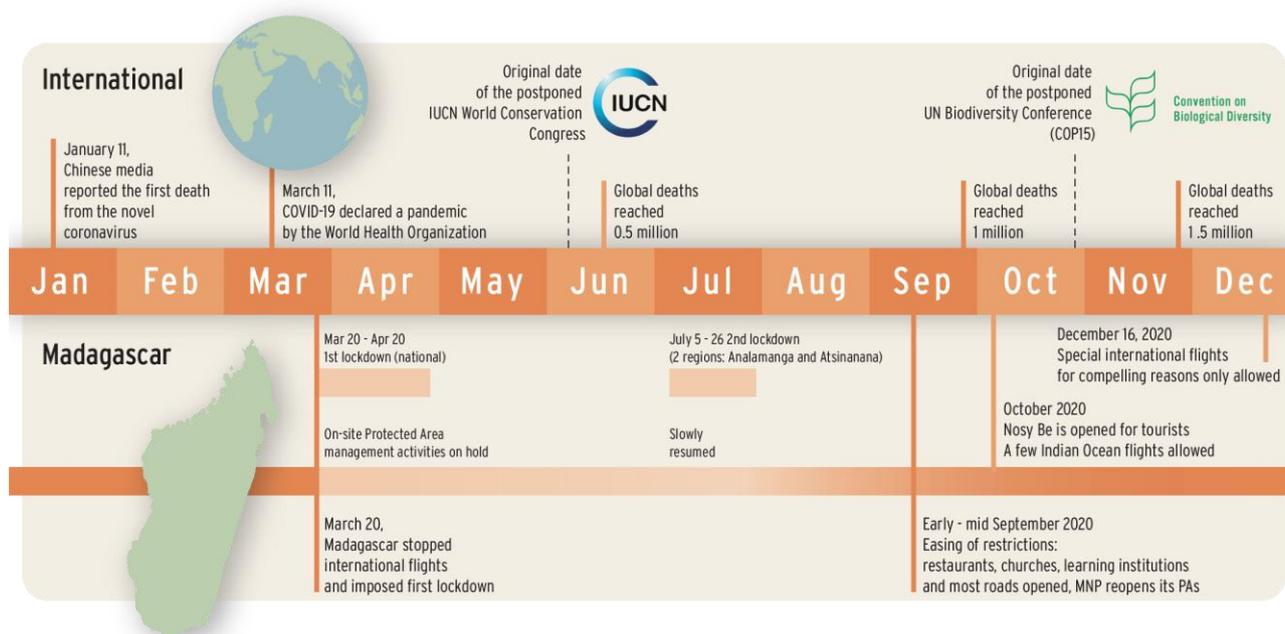


120
121 **Figure 2:** The occurrence of months with excess fires in protected areas presented as the percent
122 change between the total number of observed and predicted fires across all protected areas modelled
123 for each month for the time period 2012-2020. Shaded area around the lines corresponds to the 95
124 % confidence intervals. The size of the circles is relative to the number of excess fires in those
125 months with significantly more fires than predicted based on climate and biome and the numbers
126 above the circles refer to the number of excess fires for the month in question.

127 **Burning during the pandemic**

128 Madagascar responded rapidly to the threat of COVID-19 by closing its borders and instituting a
129 series of lockdowns (Fig. 3). Travel around the country, including by ministry officials and

130 protected area managers, and field activities were substantially curtailed from March 20, 2020 and
 131 only started to recover from July onwards (Fig. 3). This meant that most on-site management
 132 activities (including enforcement patrols, community engagement and livelihood support projects)
 133 were effectively stopped for a period of approximately four months. International tourism into
 134 Madagascar, which contributed nearly 7% of gross national product in 2019³⁰ and is an important
 135 source of revenue for Madagascar's protected area network³¹, only reopened in autumn 2021.

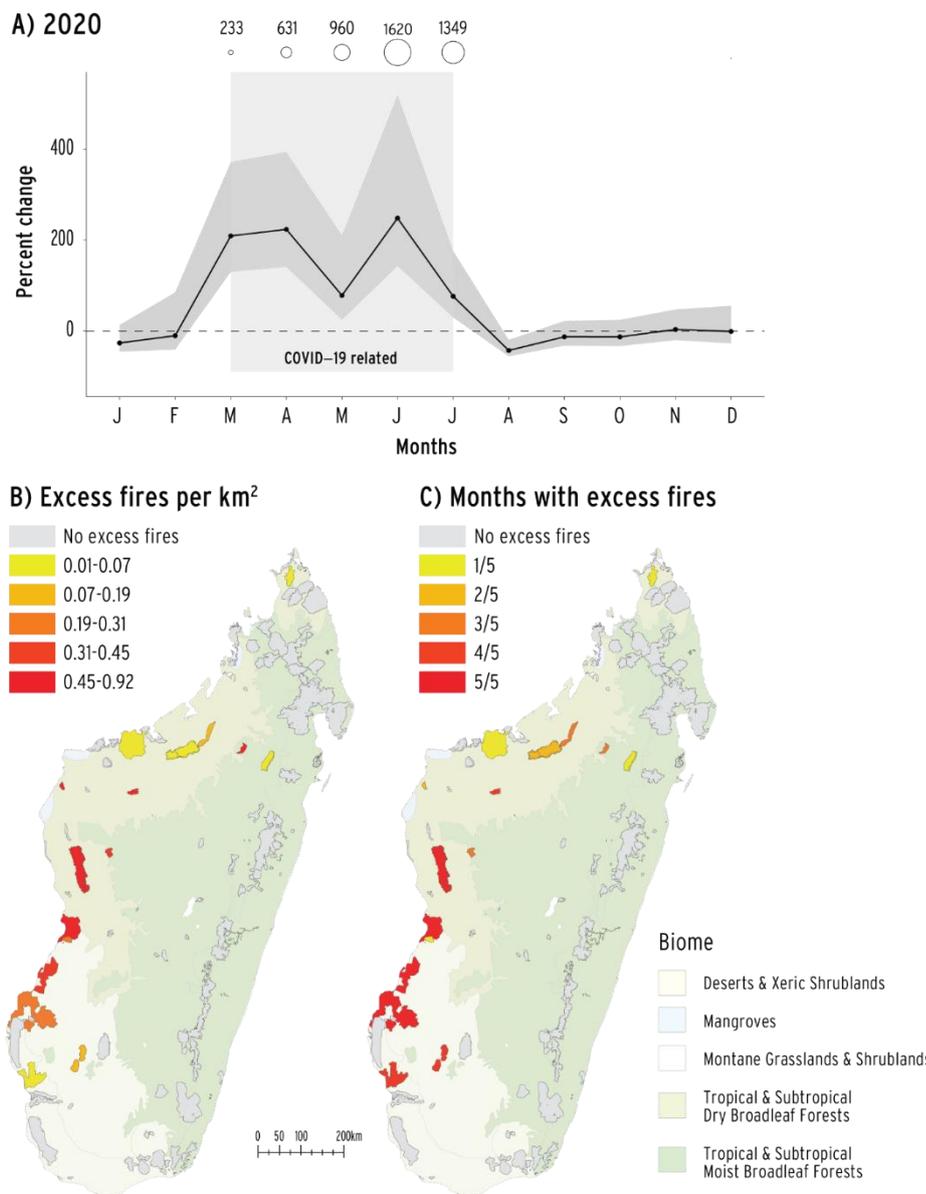


136 **Figure 3.** Timeline of key events associated with COVID-19 internationally and in Madagascar
 137 during 2020. For sources, see SI.
 138

139 Comparing observed fire frequency for 2020 in Madagascar's protected areas with those predicted
 140 by our climate-adjusted model shows that the shutdown of conservation management activities from
 141 March to July was associated with an unprecedented 5-month upsurge in fires inside Madagascar's
 142 protected areas (Fig. 4). In August 2020 there were slightly fewer fires than predicted, but burning
 143 quickly returned to levels predicted by our model after this. Despite a fear that the September onset
 144 of the burning period in the eastern humid forests would lead to elevated fires in the autumn of
 145 2020³², this was not seen and burning inside protected areas remained at the levels predicted by

146 climatic variables for the rest of 2020 (Fig. 4). The period of excess burning persisted for far longer
 147 (5 consecutive months, cf median of 1 month for 12 previous anomalies in 2012-2019), and was
 148 characterized by far greater increases in relative fire frequency, with 76-248% more fires than
 149 predicted by our model (March: 209 %, April: 223 %, May 78 %, June 248 %, July 76 %; cf 32 –
 150 134 % across all previous excess months, 2012-2019).

151



152

153 **Figure 4.** Extent and location of excess protected area fires in 2020 in Madagascar. A) The

154 occurrence of months with excess fires in protected areas presented as the percent change between

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

163 **Spatial patterns of burning**

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

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

179 **Discussion**

180 Focusing on one of the world's most megadiverse countries, we show for the first time that the
181 COVID-19 pandemic was linked to a reduction in protected area integrity. The overlap between
182 excess fires and the suspension of on-site management activities suggests a causal mechanism
183 whereby fire prevention inside protected areas depends on such active engagement. However,
184 increased pressures, driven by people clearing more land in anticipation of lost non-agricultural
185 incomes, may also have played a role. Soon after on-site management resumed, burning inside
186 Madagascar's protected areas quickly reverted to levels predicted by our model. This is despite the
187 economy of Madagascar not yet opening up and continued economic hardship³⁶, including a
188 drought-induced famine in the south³⁷. Our findings therefore provide strong empirical evidence
189 supporting previous correlational studies showing that active protected area management can buffer
190 against population declines³⁸⁻⁴⁰ and providing evidence that this also applies for land-use change
191 pressures for which the evidence base has been inconclusive⁴¹⁻⁴³.

192 Like any analyses relying on remotely-sensed data and building counterfactual
193 scenarios, there are important caveats to our work. It is important to remember that the VIIRS
194 thermal anomalies only serve as a proxy for fire incidence and ground validation was not possible
195 due to the pandemic. However, previous studies have shown that the VIIRS product provides more
196 coherent fire mapping compared to MODIS 1 km fire data and that the nominal confidence fire
197 detections showed average commission error of 1.2%⁴⁴. VIIRS is documented as having good
198 capacity to detect real fires⁴⁴ and temporal patterns converge with on-the-ground observations⁸.
199 VIIRS is also commonly used for practical fire management^{45,46}. Despite the high performance of
200 the VIIRS data we nevertheless caution that our fire incidence data may underestimate the true
201 number of fires as agricultural fires in sub-Saharan Africa are often small⁴⁷. We chose to study fire
202 because remote sensing data allows us to quantify changes in this threat at fine spatial and temporal

203 scales; however, this tells us nothing about the dynamics of other potentially important threats such
204 as hunting, grazing, or extraction of wild harvested products³. Our analyses also do not account for
205 COVID-19 induced burning outside protected areas, and, thus, we cannot say how well the
206 protected areas mitigated potentially increased pressures compared to unprotected land. Finally,
207 modelling what would have happened in the absence of the COVID-19 pandemic is challenging as
208 such a counterfactual is inherently unknowable. Our predictive model only takes account of climatic
209 drivers, for which we have relatively good annual data, however the fire frequency in any given
210 year will have been influenced by a complex mix of social and economic drivers.

211 The longer-term effects of COVID-19 on international conservation remain to be seen. The four
212 times delayed meeting to agree the global post-2020 biodiversity framework¹ is due to be held in
213 the third quarter of 2022. However, this will be happening in the context of continued economic
214 uncertainty in many parts of the world⁴⁸, probably affecting international support for conservation.
215 The prolonged effects of the pandemic on tourism and on economies more broadly will harm local
216 livelihoods and place additional pressures on protected areas. It is important to keep monitoring the
217 situation to evaluate long-term impacts of COVID-19 and to assess how the prolonged lack of
218 tourism revenues may be affecting protected area performance. Our work has practical implications
219 in that it can inform policy makers and park agencies about the importance of finding creative ways
220 of keeping on-site protected area management going in times of turmoil. Our results clearly
221 demonstrate the dramatic impact that management interruptions can have, and indicate that it may
222 be important for politicians to consider protected area management an essential service which needs
223 to continue through times of lockdowns and travel restrictions. In Madagascar, some protected area
224 authorities started to increase collaboration with local communities to keep on-site activities
225 running⁴⁹ - an approach that might enhance conservation outcomes in the long-term⁵⁰ and beyond
226 the pandemic.

227 **Methods**

228 **Overview**

229 We built models (based on fire and climatic data from 2012-2020) to predict the monthly fires in
230 Madagascar's protected areas. We compared the observed number of fires in a given protected area
231 in a given month to identify fire anomalies (where observed and predicted fires did not align) and
232 used this to explore the temporal and spatial distribution of excess fires. Spatial analyses were done
233 using ArcGIS 10.8⁵¹ and Python 3.8.5⁵² and all statistical analyses were performed using the
234 software R 4.0.2⁵³. Package ggplot2⁵⁴ was used for visualizations.

235 **Data sets used**

236 Protected area boundaries were identified using spatial information from the World Database of
237 Protected Areas⁵⁵. The June 2020 release was compared to the list of protected areas by the
238 Malagasy protected areas platform Forum Lafa and identified in Goodman et al.⁵⁶ and those
239 occurring in both were kept and clear overlaps removed, resulting in 114 protected areas being
240 included in the analyses (Table S2).

241 Data on biomes was sourced from the RESOLVE ecoregions project⁵⁷ and we used
242 the higher level classification identifying the following main biomes for Madagascar: Tropical &
243 Subtropical Moist Broadleaf Forests (comprised of the humid and subhumid forests), Tropical &
244 Subtropical Dry Broadleaf Forests (comprised of the dry deciduous forest), and Deserts and Xeric
245 Shrublands (comprised of the spiny thickets and the succulent woodlands; Fig. 4). Protected areas
246 were assigned to one biome based on highest spatial overlap (Table S2).

247 We used the Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m active fire product from the
248 joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20

249 satellites⁵⁸ as this product provides near real-time open-access data on thermal anomalies and active
250 fires at a finer spatial resolution than other satellite-based fire products⁴⁴. The 375 m data
251 complements Moderate Resolution Imaging Spectroradiometer (MODIS) fire detection and the
252 previous VIIRS product at resolution 750 m⁴⁴. Previous studies have shown that these coarser
253 resolution products tend to miss especially smaller fires^{47,59}. At the moment, the VIIRS 375 m data
254 is the finest resolution publicly available data; we note its use for near real-time fire management
255 alerts^{45,60}. We sourced the full data for Madagascar from the first observation (20 January 2012)
256 until the 31 December 2020. Note that the data is almost immediately released as a near real-time
257 version, and later undergoes post-processing, meaning that in our dataset downloaded the
258 29.01.2021 the data consisted of the final full product from 20.1.2012-31.5.2020 and the near real-
259 time release for 1.6.2020-31.12.2021. The confidence values are set to low, nominal and high by the
260 data provider⁶⁰. According to the data provider, low confidence daytime fire pixels are typically
261 associated with areas of sun glint and lower relative temperature anomaly (<15K) in the mid-
262 infrared channel I4. Nominal confidence pixels are those free of potential sun glint contamination
263 during the day and marked by strong (>15K) temperature anomaly in either day or nighttime data.
264 High confidence fire pixels are associated with day or nighttime saturated pixels. We only included
265 the nominal and high confidence pixels and omitted the low confidence observations (13.88 % of all
266 pixels), possibly omitting some smaller fires, in order to make sure our predictions are conservative.
267 This might have increased the zero observations in our dataset, something we consequently dealt
268 with using a zero-inflated negative binomial approach, specifically incorporating the uncertainty
269 behind zero observations (see details below). The resulting data was overlaid with the protected
270 area polygons and after that summed to number of observed fires per month per protected area for
271 all the years (2012-2020). We excluded January 2012 due to its incomplete nature (only 11 days of
272 data).

273 Monthly precipitation data was sourced from the Global Precipitation Measurement
274 (GPM) mission⁶¹ (for years 2016-2020) and its predecessor The Tropical Rainfall Measuring
275 Mission (TRMM)⁶² (for years 2011-2015) at spatial resolution 10 km. Mean precipitation per
276 protected area per month for 2011-2020 was calculated as the average of the precipitation data cells
277 that intersected the protected area (zonal mean).

278 **Explanatory variables in the fire prediction model**

279 In the tropics and subtropics, the total amount of fires reflects a complex interaction between
280 climate and human activities⁶³ with precipitation being an exceptionally important driver of inter-
281 annual and seasonal variability in burned area¹⁹. Thus controlling for precipitation variability is
282 critical for assessing trends in fire activity. Higher precipitation prior to the onset of the main fire
283 season may increase fire activity in arid regions because greater moisture availability enhances
284 biomass production and this vegetation can then burn, whereas higher levels of precipitation during
285 the fire season may suppress fires due to the increased moisture¹³. In general, precipitation is
286 negatively correlated to burned area in the short term in humid savannas and tropical forests, but
287 positively correlated in the long term in more xeric savannas and grasslands¹⁹.

288 To control for the effect of precipitation on fire occurrence and thus establish a robust
289 counterfactual of expected fires against which to compare observed fires, we built monthly models
290 predicting the number of fires inside protected areas based on a set of precipitation variables. We
291 expected precipitation to interact with biome and so included biome as an interaction term. To
292 account for the possible difference in long- versus short-term effects of precipitation we explored
293 including a number of time lags but were also concerned to avoid over-fitting. Thus we calculated
294 accumulated precipitation over the last 12 months based on summing the precipitation during the
295 past 12 months. Our final model included accumulated precipitation together with the precipitation
296 in the month in question, plus precipitation during the past month, plus their interactions with biome

297 (factor). Explanatory variables were standardised using the R function ‘scale’ on all precipitation
 298 variables in the data set by dividing the (centered) columns of each factor by their standard
 299 deviations. Standardised variables were evaluated for collinearity by visual inspection of the data
 300 and by calculating Pearson’s correlation coefficients.

301 **Predicting fires and identifying fire anomalies**

302 To establish the null model for expected occurrence of fires given the levels of precipitation and in
 303 the absence of COVID-19 and other changes in human activities, we built monthly models
 304 explaining the sum of fires inside protected areas from 2012 to 2020 based on fires in other years
 305 and precipitation variables. The fire occurrence data is count data and since we had many protected
 306 areas with not a single fire in a given month, our data was also zero inflated. To account for this, we
 307 explored the use of zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB)
 308 regression models using the R package `pscl`⁶⁴. Using a likelihood ratio test, we found that ZINB
 309 outperformed ZIP (SI) for our data due to overdispersion in the non-zero count data⁶⁵, and therefore
 310 proceeded with ZINB. Previous studies have also found that ZINB-models are well suited for
 311 modelling fire incidence^{66,67}.

312 The number of fires was thus modeled using a zero-inflated negative binomial
 313 modelling approach⁶⁵. The probability density function for the response variable y_i ($i = 1, \dots, n$)
 314 denoting the fire count is

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

315
 316
 317 where π_i denotes the probability of having a zero count, μ_i is the mean, k is the dispersion
 318 parameter and Γ is the gamma function^{65,68}. The mean μ_i was modeled using the log link function

319 and predictor variables. The zero counts were modeled assuming equal probability for each zero
320 count. The fire count predictor variables were monthly precipitation, precipitation from previous
321 month and accumulated precipitation during last 12 months, which all had an interaction with the
322 biome type. The log-transformed size of protected areas was used as an offset variable.

323 We fitted the model for each month for each year (2012-2019), using data from the
324 corresponding month during all other years in the data series. Further model selection was not done
325 as we were not interested in finding out which specific explanatory variables best explained fires,
326 but rather in excluding the potential effect of any of them. Model validation was done using residual
327 diagnostics following the procedures described in Zuur et al⁶⁹. Based on the fitted model, we
328 predicted the expected fires based on the model parameters and precipitation values for the month
329 and year in question. For example, fires in April 2016 were predicted using the model fitted based
330 on April 2012, 2013, 2014, 2015, 2017, 2018, and 2019. Excess fires were defined as the difference
331 between observed and predicted fires. For 2020, we repeated the same procedure and fitted the
332 model for each month using the 2012-2019 data and then predicting 2020 fires based on the 2020
333 covariate values. We assessed model forecasting accuracy using two commonly used measures, the
334 Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE)⁷⁰. However, as these are
335 both absolute measures, we also report the Normalized Root Mean Squared Error (nRMSE), which
336 divides the RMSE by the range (max-min) and thus allows for comparisons across the months and
337 years⁷⁰.

338 **Effect size measures and confidence intervals**

339 We summed predicted and observed fires across the 114 protected areas for each month of each
340 year and created 95% confidence intervals around the predictions by bootstrapping⁷¹. We resampled
341 the predicted values for each month of each year 10 000 times using package boot in R⁷². We used
342 the normal 95 % confidence intervals to determine for which months there were statistically

343 significantly more fires than predicted by our model. For these months, we identified individual
344 protected areas with excess fires as those with more fires than the 95 % confidence interval around
345 the mean for all protected areas in that month.

346 For the 2020 anomaly, for each protected area we calculated excess fires per km² by
347 summing excess fires for March, April, May, June, and July 2020 and dividing by the size of the
348 protected area (km²). We tested if the excess fires per km² differed by IUCN management category
349 or management authority using the nonparametric Kruskal–Wallis one-way analysis of variance test
350 due to the non-normality of the data.

351 **Data Availability**

352 The data supporting the findings of this study are available on Zenodo:

353 <https://doi.org/10.5281/zenodo.6366888>

354 **Code Availability**

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

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366 **Author contributions**

367 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
368 analyses; J.E. performed the analysis with input from A.B., M.R., A.P., and J.P.G.J.; J.E, A.B.,
369 J.P.G.J., O.S.R., D.R., and J.G. contributed to the interpretation of results; J.E. drafted the
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371 **Declaration of interests**

372 The authors declare no competing interests.

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