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ORIGINAL ARTICLE

An alert system for Seasonal Fire probability forecast for South American Protected Areas

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Abstract

Timely spatially explicit warning of areas with high fire occurrence probability is an important component of strategic plans to prevent and monitor fires within South American (SA) Protected Areas (PAs). In this study, we present a five-level alert system, which combines both climatological and anthropogenic factors, the two main drivers of fires in SA. The alert levels are: High Alert, Alert, Attention, Observation and Low Probability. The trend in the number of active fires over the past three years and the accumulated number of active fires over the same period were used as indicators of intensification of human use of fire in that region, possibly associated with ongoing land use/land cover change (LULCC). An ensemble of temperature and precipitation gridded output from the GloSea5 Seasonal

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Forecast System was used to indicate an enhanced probability of hot and dry weather conditions that combined with LULCC favour fire occurrences. Alerts from this system were first issued in August 2020, for the period ranging from August to October (ASO) 2020. Overall, 50% of all fires observed during the ASO 2017–2019 period and 40% of the ASO 2020 fires occurred in only 29 PAs were all categorized in the top two alert levels. In categories mapped as High Alert level, 34% of the PAs experienced an increase in fires compared with the 2017–2019 reference period, and 81% of the High Alert false alarm registered fire occurrence above the median. Initial feedback from stakeholders indicates that these alerts were used to inform resource management in some PAs. We expect that these forecasts can provide continuous information aiming at changing societal perceptions of fire use and consequently subsidize strategic planning and mitigatory actions, focusing on timely responses to a disaster risk management strategy. Further research must focus on the model improvement and knowledge translation to stakeholders.

KEYWORDS

conservation, disaster risk reduction, mitigation, wildfires

1 INTRODUCTION

Wildfires lead to severe negative impacts on people, ecosystems and climate. The impacts on people include threat to lives, loss of goods such as homes, agricultural production, forest products, infrastructure (communication, energy and road networks), disruption of the transport system, and increased incidence of diseases associated with increased air pollution, among other economic losses (Butt et al., 2020; Campanharo et al., 2019). It has been estimated that fires associated with deforestation in the Amazon cause approximately 3000 premature deaths annually (Reddington et al., 2015). The impacts on ecosystems are related to the loss of biodiversity, reduction of carbon stocks, wildlife mortality, soil and forest degradation, as well as effects on other services such as maintenance of local temperature and the recycling of water to the atmosphere (Martins et al., 2012; Silva et al., 2020; Xaud et al., 2013). Climate impacts are directly associated with fire-mediated carbon emissions to the atmosphere, which could lead to more extreme weather conditions, such as increased frequency of droughts and prolonged dry seasons (Jiang et al., 2021).

The year 2020 was marked by massive wildfires worldwide. In the first six months of 2020, Australian bushfires, which started at the end of 2019, burnt more than ~97,000 km^2, threatening many species under risk of extinction (Ward et al., 2020). In Sichuan province in southwest China, 19 people died fighting the bushfires, and up to June, large wildfires were reported in the Indian state of Kerala, in south Jersey, the Florida Panhandle and Arizona in the United States, in Poland's biggest national park, Biebrza, in Turkey's Aegean province of Manisa, in Northern Cyprus and in Scotland, with the total socio-economic and environmental impacts yet to be accounted for. During the period from July to October 2020, the fire outbreaks in the Brazilian Amazon and Pantanal wetlands, and along the US West Coast have attracted international attention not only due to their scale but also due to the political context of how they were managed.

At the continental level, in South America, the highest number of fire occurrences since 2011 were observed in 2020 between February and June and again between August and October (ASO). During March, April and May of 2020, the number of temperature anomalies detected by satellites, also known as 'hot pixel' or 'active fires' data, processed by the Center for Weather Forecasting and Climate Studies/National Institute for Space Research (CPTEC/INPE) were 21%, 49% and 10% higher, respectively, than previously registered peaks in the same period since 1998. In ASO of 2020 fires were 3.5%, 9.3% and 17% higher, respectively, than the previous peak in 2011 (INPE, 2021). Moreover, during the 2020 COVID-19 pandemic, smoke from fires aggravated the health of thousands in South America, increasing not only the pressure upon health systems but also the population exposure to the coronavirus when seeking care in the urban centres (de Oliveira et al., 2020; Morello, 2021).

The Sendai Framework for Disaster Risk Reduction adopted in 2015 at the Third United Nations World Conference has recognized the need for increasing the number of countries with national and local disaster risk reduction strategies by 2020, and the availability and access to multi-hazard early warning systems and disaster risk information and assessments by 2030, as two of the main targets. The high fire occurrence in 2020 demonstrates that effective strategies and investment for prevention, monitoring, combating and planning actions to manage and combat fire are urgently needed. Currently, in South America at the regional scale, there are a limited number of early warning systems for monitoring and forecasting fire occurrence. For example, the *Programa Queimadas* from INPE/CPTEC covers the entire South American continent with real-time fire occurrence and a three-day fire probability forecast, to support response actions (http://sigma.cptec.inpe.br/queimadas/index_old.php). This works by integrating meteorological forecasts and a vegetation map with other variables such as the number of previous days without rainfall. The University of California-Irvine (UC-I) fire severity season for the Amazon has information at the state/departmental level, based on the sea surface temperatures (SSTs) in the tropical Pacific Ocean and North Atlantic Ocean, updated annually using data available at the end of May (www.ess.uci.edu/~amazonfirerisk/ForecastWeb/SAMFSS2019.html#fire). The firecast, developed by Conservation International, provides both daily flammability risk forecasts for the entire Amazon and the UC-I fire season severity forecasts for Peru at the country scale, and at the state level for the Amazonia states of Bolivia and Brazil (https://firecast.conservation.org/DataMaps/FireSeasonSeverity). The Global Forest Watch Fires Programme allows country-level, ecoregion or basin-level real-time monitoring of fire occurrence, depicting a fire alert level by comparing the number of fire alerts over selected time intervals with the available historic data (https://www.globalforestwatch.org/topics/fires). The Global Wildfire Information System (GWIS) provides forecast maps of fire danger levels for one to nine days ahead (https://gwis.jrc.ec.europa.eu/apps/gwis_current_situation/index.html). All these systems greatly contribute towards monitoring and providing information for response teams to act during fire events. However, given the need to improve preparedness and to reduce the likelihood of fire occurrences, forecasts covering longer timescales, with improved spatial prioritization and with longer lead times are needed. Therefore, a seasonal forecast of fire probability can provide information for priority areas at a temporal scale which allows planning and fire mitigation actions ahead of the fire event.

Protected areas (PAs) across South America are regions of particular relevance for fire management activities. PAs are geographical spaces where long-term conservation of nature, ecosystems services and cultural values are recognized, following the definition by the International Union for Conservation of Nature (IUCN, 2021). As recognized areas by law at different governmental levels, those areas have an institutional structure, legal framework and, in most cases, a management plan that allows the use of fire forecast information to guide actions on the ground. Although PAs have been effective in containing the advance of deforestation (Nelson & Chomitz, 2011; NEPSTAD et al., 2006) and fire in some locations (Armenteras et al., 2013), these areas are vulnerable to degradation in other ways, which can threaten its conservation efforts (Armenteras et al., 2019; Nogueira et al., 2018; Schulze et al., 2018; Walker et al., 2020).

In this paper, we present the development of an integrated method aiming to build an alert system based on a novel seasonal fire probability forecast for South American PAs. By combining measures accounting for anthropogenic drivers of fire occurrence with probabilistic seasonal forecasts of rainfall and temperature, we have categorized the PAs fire threat into five alert levels, to support the management of prioritized PAs. This study emerged from the Climate Science for Service Partnership (CSSP) Brazil project, where one of the main goals is to inform decision-making and contribute to disaster risk reduction. In this context, two technical reports to inform decision-makers were prepared during 2020. The first report was issued in August 2020 and forecast the ASO period (Anderson et al., 2020a), and the second was issued in December 2020, for the December 2020 to February 2021 period (Anderson et al., 2020b). The methods used to produce the fire alerts were revised between these two reports. We present here the most up-to-date version of the method, and used as a study period ASO 2020. It is expected that new technical reports and an online tool will be developed during 2021, contributing to disseminating disaster risk management information. This effort aims at increasing the societal awareness related to the fire risk and the conservation of critical environmental benefits delivered to the human population and all life forms by PAs.

2 | MATERIALS AND METHODS

2.1 | South American Protected Areas and fire diagnostic

The analyses were performed based on data from the World Database on Protected Areas (WDPA), compiled by the International Union for the Conservation of Nature (IUCN; UNEP-WCMC, 2021).[11] The WDPA collates official information on PAs around the world, which is

Country	Number of protected areas	Protected area (km²)	% country area
Brazil	2,184	2,902,781	34
Colombia	1,168	283,878	25
Argentina	354	430,671	15
Peru	237	293,970	23
Chile	148	274,297	37
Bolivia	146	289,418	27
Venezuela	110	503,233	55
Paraguay	97	78,686	20
Ecuador	56	63,910	25
French Guiana	26	46,313	55
Uruguay	20	21,245	12
Suriname	16	34,961	24
Guyana	6	17,859	8
Total	**4,568**	**5,241,225**	

FIGURE 1 Number, size and fraction of PAs in each South American country

continually updated, including the spatial distribution and management attributes, such as categories, status, creation year and others. We only consider regions designated PAs within South America. We excluded marine and international PAs, as well as duplicate areas with different category designations. The final data comprised 4568 PAs, with almost half of the area under protection – 2.5 million km^2 – located in Brazil (34% of the country's area), followed by 503,233 km^2 in Venezuela (55% of the country's area), and the same share of protection area in French Guiana (Figure 1).

2.2 | Fire probability categories

Wildfires can result from a combination of human activities, such as the use and management of the land, with climatic conditions related to temperature and precipitation patterns. Our forecasting of fire probability in each South American Protected Area combines observed trends of recent anthropogenic activity with seasonal forecasts of the coming meteorological conditions, with three months in advance.

We considered five variables that represent the anthropogenic and climatological conditions that increase the probability of fire occurrence. The anthropogenic components of the forecast are the (i) trend in the number of active fires over the past three years and (ii) accumulated number of active fires over the same period. The number of active fires and their trend can be measured using the 'hot pixels' in satellite-based data sets, described below. A positive trend in the number of hot pixels can be interpreted as a recent increase in the use of fire in that region, which can be associated with ongoing land use/land cover change. Fire is the main tool used for eliminating biomass either after a forest clear cut or for land management activities. These are considered intentional fires, while native vegetation uncontrolled fires can be considered unintentional since these start either accidentally or for arson. The accumulated number of hot pixels was used to identify the areas with high fire occurrence in the period analysed. The climatological conditions that we selected for the forecast are: (i) the length and duration of the dry season for the period studied, and probabilistic forecasts of (ii) below-average rainfall and (iii) above-average temperature. These latter two variables were prioritized due to an adequate skill on the probabilistic forecasts. The focus period of the study, ASO, was chosen as it represents the time of year with the highest fire occurrence in South America's Southern Hemisphere. A summary of the data used is presented in Table 1, and more details are provided in next sections.

2.2.1 | Anthropogenic factors

We used the Visible Infrared Imaging Radiometer Suite (VIIRS) Standard (Science Quality) active fire product from the VIIRS sensor aboard the Suomi National Polar-orbiting Partnership (Suomi NPP) satellite as observational data to calculate the trend and accumulated hot pixels for each PA (Figure 2a). The VIIRS product has a high spatial resolution of 375 m and provides a better response over fires of relatively small areas (Schroeder et al., 2014). The time series for this study covers the months from ASO, from 2017 to 2020. This period has been selected to capture the recent local fire use, rather than natural fires (those occurring due to lightning) or the long-term pattern, which may be more variable or influenced by other climatic extremes, such as extreme droughts or wet years. For instance, most of the fires associated with deforestation occur in the same year or the subsequent year (Alencar et al., 2020; Aragão et al., 2008; Silveira et al., 2020), while agricultural fires occur yearly or bi-annually (Chen et al., 2013; Eloy et al., 2018; Fidelis et al., 2018; Jakimow et al., 2018). Similarly, fire return intervals in savanna areas of South America, associated with biomass recovery after fires, are between one and four years (Bilbao et al., 2010; Pereira et al., 2014), and natural fires occur in a longer time interval (Durigan & Ratter, 2016; Pivello, 2011). Therefore, by accounting for a period of three years, we ensure that we are looking in the time-window most relevant to track the presence of ignition source and are able to generate a trend line with a statistical assessment.

A positive fire trend, therefore, means that the use of fire in ASO increased from 2017 to 2019, and thus ignition sources are likely to be present in the year 2020. On the other hand, a negative fire trend from 2017 to 2019 indicates that less fire has been used year by year, and thus it is less likely to have fire occurrences in that location in 2020. The fire trend was calculated using the hot pixel accumulation in each ASO in 2017–2019, for every PA (Figure 2b). The

TABLE 1 Classification summary of the individual factors that go towards defining the fire alert level. Each of the five variables is classified into two or three categories. The combination of different categories determines the alert level (Supporting Information Figure S2). The variables associated with increased fire probability are highlighted in red. Each factor is described in the main text

Anthropogenic variables		Climatic variables		
Accumulated hot pixels	**Hot pixel occurrence trend**	**Drought condition**	**Temperature above median probability**	**Precipitation below median probability**
> 75%	Positive (+)	0 = Out of the dry season.	> 60%	> 60%
< 75%	Negative (-)	1 = During dry season, outside the critical period.	< 60%	< 60 %
0		2 = During critical period: last two months of the dry season or first month of the rainy season.		

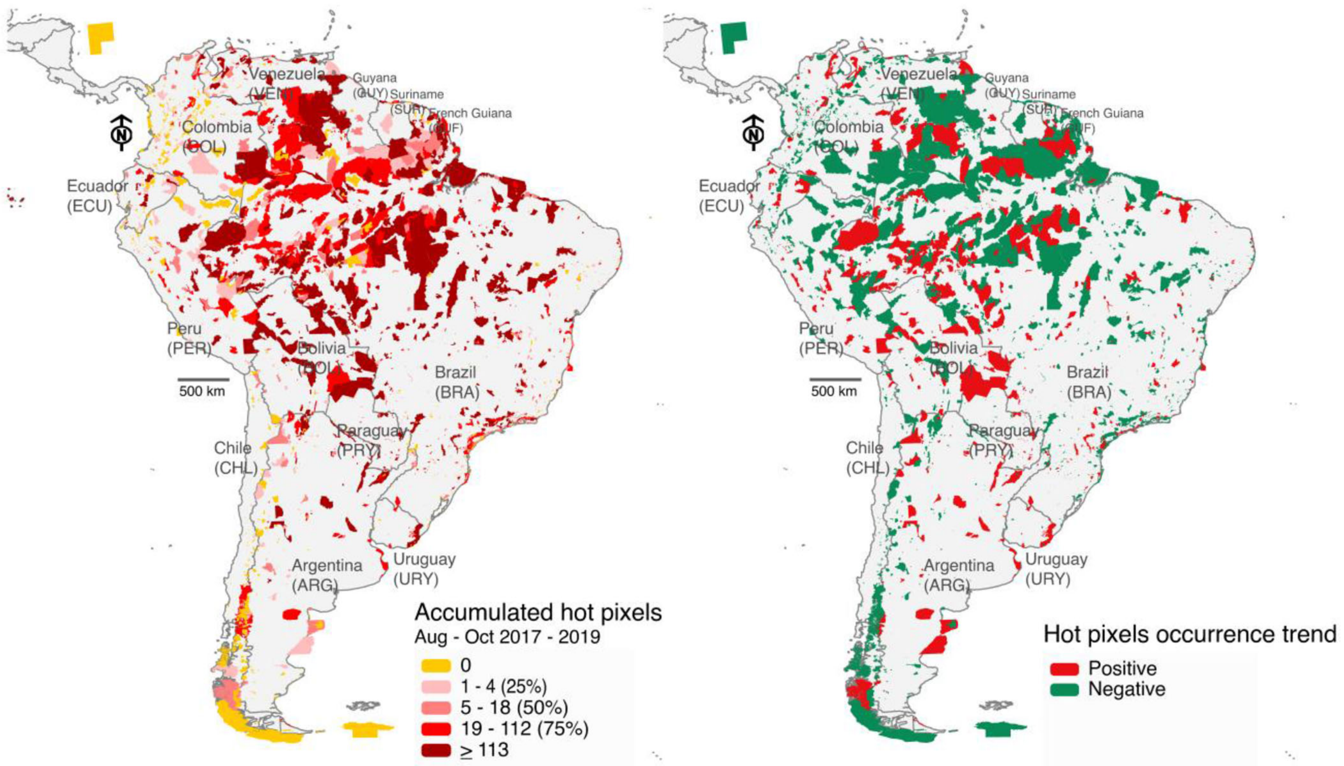

FIGURE 2 (a) Accumulated hot pixels occurring in the ASO period from 2017 to 2019. The colour categories correspond to the quartiles of the distribution over all PAs. (b) ASO fire occurrence trend over 2017–2019 in each protected area. Coloured areas refer to the PAs

slope of the trend regression, b, is defined as (Equation (1))

$$b = \frac{\sum (x - \overline{x})(y - \overline{y})}{\sum (x - \overline{x})^2}, \quad (1)$$

where x corresponds to the specific year (independent variable), $\overline{x}$ is the average of all years, y is the number of hot pixels (dependent variable) for the specific year x, and $\overline{y}$ is the average of hot pixels between all years.

In addition to the fire trend, we considered the distribution of the total accumulated hot pixels in ASO over all PAs in 2017–2019. Each PA can be categorized using the quartiles of the distribution over all PAs; thus, the areas in which 50% or 75% of all South American PA fires occurred during the analysed period can be highlighted and used to stratify the fire probability.

2.2.2 | Climatological conditions

Three datasets were used as an input for the climatological conditions. The first, rainfall observations from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS; Funk et al., 2015) were used to assess the dry

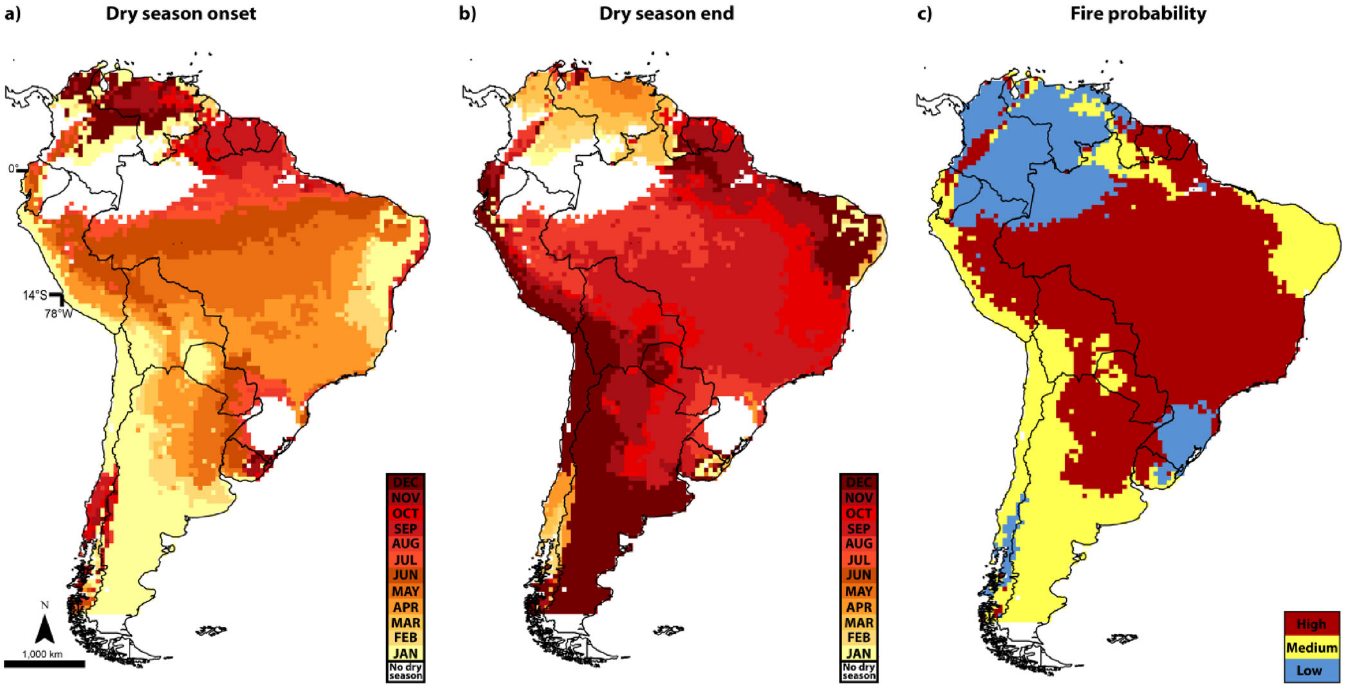

FIGURE 3 (a) Long-term (1981–2019) dry season onset and (b) end for South America. The dry season onset is defined as when rainfall is lower than 100 mm. (c) The fire probability region according to the dry season category for the ASO period (see text for details)

season length and duration. For the probabilities of rainfall and temperature, seasonal forecasts from the GloSea5 system were used (MacLachlan et al., 2015). More details are presented below.

To investigate the spatio-temporal variability of the dry season, we used the 39-year monthly time series (1981–2019) from CHIRPS. These data are available with a spatial resolution of 0.05°, and were resampled to 0.5° using bilinear interpolation, in order to match the GloSea5 product used in this study. The mean monthly precipitation of each grid cell was calculated, assuming a 100-mm threshold to define the dry season (Da Rocha et al., 2004; von Randow et al., 2004) (Figure 3). Note that the Northwestern Amazon and the extreme south of Brazil have no dry season according to this definition. The regions with the longest dry season duration are concentrated in the south of the continent and in the northeast of Brazil. In both cases, all months of the year have rainfall below 100 mm on average. In general, the peak in fire occurrences is three months after the driest month in South America (Chen et al., 2013).

However, since the fringes of the Amazon present the highest fire density, we stratified the rainfall-related fire probability categories according to the ASO drought condition (Carvalho et al., submitted):

1. Low probability: grid cells where August, September and/or October are not included in the dry season or in the first month of the rainy season.
2. Medium probability: grid cells where August, September and/or October are included in the dry season, but do not correspond to the last two months of the dry season.
3. High probability: grid cells where August, September and/or October correspond to the last two months of the dry season and/or the first month of the rainy season.

The probabilistic seasonal forecasts of ASO mean rainfall and temperature are based on data from the GloSea5 seasonal forecasting system, produced by the Met Office Hadley Centre. GloSea5 is based on the Global Coupled 2 configuration of the HadGEM3 climate model (Williams et al., 2015), and is run operationally, producing two forecast realizations per day. A 42-member forecast ensemble is produced by collating the forecasts initialized over the preceding three weeks. To produce the forecasts for the ASO period, we used the forecasts available up to 10 July 2020. To assess model skill and correct forecast biases, a hindcast is also produced operationally, covering the period 1993–2016. Seven hindcast ensemble members are produced on four dates each month, and the nearest hindcast dates to each daily forecast are collated to make a model ensemble climatology (see MacLachlan et al., 2015, for details). The forecast ensemble is used to assess the probability of above-median temperatures and below-median rainfall, with respect to the hindcast climatology (Supporting Information Figure S1). We use a threshold of 60% of model ensemble members to mark increased fire risk (i.e. increased probability of above-median temperatures and below-median rainfall) in both cases. This threshold of 60% of members was chosen as an indication of enhanced probability compared with normal, but not an extreme level of confidence, which would not be robust. Although we have not calibrated the forecast probabilities from the model, we will refer to our indicative choice of 60% of members as '60% probability' for brevity. The use of relative humidity was also considered (as in, for example, Bett et al., 2020), but there was insufficient skill for the ASO season.

2.2.3 | Data integration

The fire trend and the accumulated hot pixels in each fire season (ASO 2017–2019) were calculated for all the PAs in South America. The climatological conditions, defined here as the probability of temperature being above the climatological median, and rainfall being below the median, for ASO 2020, were obtained by area-weighted averaging of the grid cells in each PA. The onset and dry season length was also included as one criterion to identify the likelihood of fire occurrence. A drought condition value for each PA was assigned based on the most frequent pixel value in each area. All the variable combinations that determine the alert levels are supplied in Supporting Information Figure S2.

We used five Alert categories: High Alert, Alert, Attention, Observation and Low Probability. These categories correspond to the probability of an increased occurrence of fire events, based on the number of variables associated with increased fire probability (Supporting Information Figure S2).

The description of each category is as follows:

High Alert: All five variables indicate increased probability;

Alert: Four variables, including at least one of the temperature and rainfall conditions, indicate increased probability;

Attention: Three variables indicate increased probability; or, all variables *except* accumulated hot pixels indicate increased probability;

Observation: Two variables indicate increased probability of fire occurrences;

Low Probability: One or no variables indicate increased probability of fire occurrences.

2.2.4 | Meteorological forecast verification and skill assessment

To assess the performance of the meteorological forecasts for temperature and precipitation in ASO 2020, we compare the model with ERA5 re-analysis data (Hersbach et al., 2020) as a proxy for observations, over the same period as the hindcast (1993–2016). As described above, we are using a fixed probability threshold for both temperature and rainfall to indicate enhanced probability of fires. We can therefore evaluate the forecast performance in broad terms by looking at where these forecasts of enhanced probability resulted in the 'hot', 'dry' or 'hot and dry' conditions indicated. We can assign the standard contingency table categories of a hit, miss, false alarm and correct rejection (e.g. Wilkis, 2019) according to whether the enhanced probability matches the observed situation. To use temperature as an example, where the model shows a probability of at least 60% of being above the median in ASO 2020, and the observations show that temperature was indeed above the climatological median, then we label the forecast as a hit. If the model shows a probability of at least 60% of being above the median but the observed temperature was below the median, then the forecast would have been a false alarm. As described above, there are three types of event that we consider to lead to increased fire probability: above-median temperatures, below-median precipitation and both occurring simultaneously. The forecast performance for each of these three types of event is assessed separately.

This verification method also informs about how well the forecast performed in 2020. To understand how skilful the forecast system is, generally, we also compare the model hindcast against observations year to year, using the same baseline period of 1993–2016. For each of the 24 years of the hindcast, we find when >60% of the 21-member ensemble were forecasting above-median temperature, or below-median precipitation, where the median is calculated from the other 23 years of the hindcast. We use the same categories of 'hit', 'miss', 'false alarm' and 'correct rejection', and calculate the hit rate (HR) and false alarm rate (FAR) according to the standard definitions:

$\mathrm{HR} = N_{\mathrm{hits}} / (N_{\mathrm{hits}} + N_{\mathrm{misses}})$,

$\mathrm{FAR} = N_{\mathrm{falsealarm}} / (N_{\mathrm{falsealarm}} + N_{\mathrm{correctreject}})$,

where N refers to the number of years in that category, calculated separately for each grid cell.

In addition to calculating the HR and FAR for hot conditions, dry conditions and the combination of hot and dry conditions, we also calculated the rates for when the model forecasts hot conditions, and the observed conditions are hot and dry. Similarly, we calculated the rates for when the model forecasts dry conditions and the observed conditions are hot and dry. This gives more information on the skill of each variable. The results are shown in Section 3.2.

2.2.5 | Fire trend assessment

Four analyses were carried out to assess the fire forecast probability. First, a general evaluation of the spatial

TABLE 2 Summary of the main combinations to assess the fire trend. The # symbol is used to summarize the other combinations (mixtures of zero and non-zero values)

Fire trend	Difference of hot pixel	Assessment
0	0	Null
< 0	< 0	Correct rejection
< 0	> 0	Miss
> 0	< 0	False alarm
> 0	> 0	Hit
#	#	Other

TABLE 3 Summary of the main combinations to identify changes in fire trend between fire trend of ASO 2017–2019 and ASO 2017–2020. The # symbol is used to summarize the other combinations

Fire trend (2017–2019)	Fire trend (2017–2020)	Assessment
#	#	It has remained null or has become null
< 0	< 0	It has remained negative
< 0	> 0	It has become positive
> 0	< 0	It has become negative
> 0	> 0	It has remained positive

dynamics of fires in South America was executed, assessing the extent to which a positive or negative fire trend over 2017–2019 was followed by an increase in the number of fires in 2020 compared with the 2017–2019 mean. This analysis was carried out on a grid with 100 km spatial resolution, by assessing the 2017–2019 fire trend alongside the difference in accumulated fires between ASO 2020 and the mean ASO accumulation over 2017–2019, for each grid cell. In this assessment, five main combinations were considered: if the fire trend and difference in hot pixels are not statistically different from zero ($p < 0.05$), it is classified as 'Null'. The 'Correct rejection' class refers to a negative fire trend and a negative difference in hot pixels (i.e. the 2020 fire accumulation was less than the 2017–2019 mean). The 'miss' class refers to a negative fire trend and a positive difference in hot pixels. 'False alarms' were identified in areas with positive fire trend and negative difference in hot pixels. Finally, the 'hits' class was identified when positive fire trends and greater than zero differences were detected (Table 4). This evaluation provides a spatial representation of the trend pattern of fires for each grid cell.

The second analysis aimed to investigate whether the fire trend for each PA was confirmed. Therefore, we compared the fire trend with the difference of fire pixels, which was calculated by the accumulated fires in the period from ASO 2020 minus the average of accumulated fires in ASO 2017–2019 per PA (Table 2). For better understanding, the results were stratified by each fire probability category. This evaluation provides a spatial representation of the trend pattern of fires during the last years in South America for each PA. To test whether there was a significant difference in the number of hot pixels observed in 2020 for the different alert categories of PAs, we used the Kruskal–Wallis non-parametric statistical test. To eliminate the size effect, we normalized the number of hot pixels observed in 2020 by the area of each PA. The Kruskal–Wallis test is equivalent to analysis of variance (ANOVA), which compares three or more groups to test the hypothesis that they have the same distribution (Bonnini et al., 2014; Gibbons & Chakraborti, 2011; Hettmansperger & McKean, 2010). To identify how the fire trend probability categories differ from each other, the paired Dunn post hoc test was performed. In the Kruskal–Wallis test, we use the 'agricolae' R package (de Mendiburu, 2021; R Core Team, 2021). For all of the tests, a significance level of 95% ($p < 0.05$) was adopted.

The third assessment aimed to identify whether or not there was a change in the sign of fire trend (positive to negative or negative to positive) for each PA. For this analysis, a fire trend for the period ASO 2017–2020 was compared with the original data (fire trend ASO, 2017–2019). Five main possible combinations were quantified: PA where at least one of fire trends were null, PA where both periods present negative or positive fire trends, and the two possible combinations with one period with positive and one period with negative fire trend (Table 3).

Finally, an integrated analysis between the anthropogenic factors and climatological conditions were carried out to assess the High Alert fire probability, which allows the identification of the most critical category, where all five variables except for the fire trend were related to increased probability.

3 | RESULTS

3.1 | Verification of the seasonal forecast

Comparing the forecast to the observed temperature for the ASO 2020 period (Supporting Information Figure S3), the model correctly predicts higher than average temperature (occurring when the probability of forecast is >60%) across the majority of the continent, particularly the north, east and far south. Two areas in the centre and south of the continent are shown as a 'miss', where hot conditions in the observations were forecast to be less likely than 60%. The areas of 'correct rejection' and 'false alarm' are smaller, mainly concentrated in the southeast and east of the continent, respectively.

For precipitation, most of the continent experienced drier than average conditions over ASO. Some of these areas were correctly forecast (i.e. with probability >60%), across central and eastern regions, and the far south, but dry areas across the north and south were predicted with lower probabilities ('miss'). There were several areas classed as 'correct rejections', where conditions were forecast as likely to be wetter than average, which is also an important consideration for forecasting reduced likelihood of fire.

The forecast performed worse when showing a high likelihood of hot and dry conditions together. Again, the forecast 'misses' the hot and dry conditions that occur across the north and south, which we can see is mainly limited by the performance of the precipitation forecast. Several areas around the coastlines are categorized as 'correct rejection', i.e. correctly giving a low probability of hot and dry conditions. From Supporting Information Figure S3, many of the PAs that are in the Alert and High Alert categories fall within the areas correctly forecast as likely to be hot and dry, where the model predictions had the greatest success.

We can understand the performance of the 2020 forecasts by comparing them against the skill of the forecast system more generally, based on the model hindcasts. This is shown in terms of the hit rate and false alarm rate of different conditions in SI Figure S4. The hit rate for temperature is highest across the north and east of the continent, as well as some regions in the far west across Peru and southeast in Argentina (Supporting Information Figure S4a). For precipitation, the main area of skill (in terms of the hit rate) is along the northeast coast, with some areas in central and southern regions also showing skill (Supporting Information Figure S4b). For both the precipitation and temperature forecast, the false alarm rate is low across most of the continent (Supporting Information Figure S4f and g).

When considering simultaneous hot and dry conditions, the region with the highest hit rate, and therefore where there is the highest confidence in the forecast year to year, is along the northeast coast. However, just using the temperature forecast (labelled 'M = hot'; Supporting Information Figure S4d) gives a much higher level of predictability for hot and dry conditions across the north, northeast and south. This implies that the lower skill of the precipitation forecasts is largely serving to add noise in these regions, degrading the quality of the forecasts. Temperature is a better predictor of dry conditions than the model precipitation itself in this case.

3.2 | Spatial explicit assessment of the fire trends

The South America grid evaluation indicated that 'hit' was the class with the highest percentage (33.7%), indicating there was an increase in fires in 2020 compared to the 2017–2019 mean, as well as a positive trend over the 2017–2019 period. The second most frequent combination was 'miss' (28%), when the 2017–2019 trend indicated a decrease in the fire occurrences, while an increase was observed in 2020. In this case, if the other variables were indicating increased fire probability, it was classified as Alert level. These areas are especially important because they point to an increase in fires where it was not expected, which can be linked to several reasons, such as increased deforestation, increase in spatial coverage of agriculture and livestock, land conflict, loss of control of intentional fires, hotter and drier conditions, among others. The 'Correct rejection' class, i.e. areas that showed a negative 2017–2019 trend and a lower number of fires in ASO 2020, occurred in 16.7% of the grid cells. Finally, 'false alarm' cases, where there was a positive 2017–2019 trend but a reduction in fires in ASO 2020 than in the 2017–2019 average, covered 16.4% of the grid cells. Table 4 presents the summary of the main combinations to assess the fire trend and 2020 occurrence in each grid cell. Overall, approximately 61.7% ('miss' and 'hit' classes) of the grid cells showed an increase in the number of fires in 2020 compared with the average from 2017 to 2019.

TABLE 4 Summary of fire trend vs 2020 occurrence category in each grid cell in South America. (Compare with Table 5 for the category definitions.)

Assessment	Frequency	%
Null	48	3
Correct rejection	256	17
Miss	430	28
False alarm	252	16
Hit	517	34
Other	33	2

In terms of countries, only Chile, Colombia and Venezuela had their territory with lower numbers of fires in 2020 than the average in ASO 2017 to 2019, while the other countries presented in more than 50% of the grid cells the classes 'miss' and 'hit' (Table 5; Supporting Information Figure S5). Brazil and Argentina present the highest frequency of the 'miss' (negative recent trend and observed increase in the number of fires) and 'hit' categories (positive recent trend and observed increase in the number of fires). It is interesting to note that in Uruguay, a higher fire occurrence in ASO 2020 coincided with an upward trend in the preceding years (the 'hit' category) over practically the whole country (Supporting Information Figure S5). The results in Bolivia and Peru are also largely in the 'miss' and 'hit' classes, i.e. an increase in the number of fires.

There were, in total, 969 grid cells with more fires in ASO 2020 than in the ASO 2017–2019 average (63%), 510 grid cells (33.2%) with fewer fires, and approximately 3.7% of pixels with no difference. Spatially, large regions with

TABLE 5 Assessment of fire trend for the period ASO 2017 to 2019 in relation to the fire occurrences in 2020, in each country

Country	Null	%	Correct rejection	%	Miss	%	False alarm	%	Hit	%	Other	%
Argentina	15	5	35	13	50	18	53	19	119	43	8	3
Bolivia	0	0	10	11	27	29	19	20	36	38	2	2
Brazil	5	1	138	19	271	38	85	12	203	29	8	1
Chile	18	24	6	8	12	16	12	16	22	29	5	7
Colombia	2	2	17	19	17	19	34	38	15	17	4	4
Ecuador	0	0	1	5	5	25	6	30	7	35	1	5
French Guiana	1	17	0	0	1	17	2	33	2	33	0	0
Guyana	1	6	4	24	4	24	0	0	7	41	1	6
Paraguay	0	0	4	13	14	44	5	16	9	28	0	0
Peru	0	0	10	9	14	13	14	13	64	60	4	4
Suriname	0	0	2	14	3	21	3	21	6	43	0	0
Uruguay	0	0	0	0	1	6	0	0	17	94	0	0
Venezuela	6	8	29	39	11	15	19	25	10	13	0	0

a high number of fires in 2020 are observed in part of Argentina and on the border with Paraguay, in southern Mato Grosso state in Brazil and the north and south of Bolivia, and Pará state, over the central-eastern Brazilian Amazon (Supporting Information Figure S5). The information in each country is available as Supplementary Information in Supporting Information Table S1.

3.3 | Assessment of fire trends and alerts in protected areas

Overall, in terms of extent in km^2, 59.4% of the fire probabilities were correct, covering an area of 3,111,846 km^2 and 34.2% were incorrect, covering 1,796,385 km^2. Among the 13 countries analysed, in nine of them the correct forecast was provided above 50% and in 6 it was above 70%. The best performances were achieved in Suriname, Uruguay and Guyana, with 94%, 90% and 79% correctness of the areas, in km^2, while the worst performance occurred in Bolivia, French Guiana and Paraguay, with 39%, 26% and 16%, respectively (Supporting Information Table S2).

In relation to the number of PA, among all of them, 6% were classified as ‘hit’, which means that the fire trend in the ASO 2017–2019 period was positive, and the observed fire pixel count in ASO 2020 was higher than the ASO 2017–2019 average. In another 6%, classified as ‘miss’, the PAs were predicted a negative trend in fire occurrence, but the fire pixel count in ASO 2020 was higher than in the ASO 2017–2019 average, depicting a change in the local fire use. These PA were located mainly in the Brazilian central-western Amazon (Figure 4). For 9% of all PAs, we obtained ‘false alarm’ results, which means that we estimated a positive fire occurrence trend, but the hot pixel count during ASO 2020 was lower than the ASO 2017–2019 average. However, 9% of the PA with ‘false alarms’ had accumulated fire pixels in the upper quartile, compared with other PA in the ASO 2020 period ($\geq$ 113 fire pixels). If we consider the median (>18 fire pixels), this number increases to 33%. This shows that even with a decrease in ASO 2020 fire pixels compared with the 2017–2019 average, the occurrence of fire in many of these areas was still high compared with other areas, which does not mischaracterize the alert of fire probability (Table 5).

Among the five Alert categories, the High Alert presented 34% of ‘hit’ and 64% ‘false alarm’, indicating that in 37 PAs the high fire probability occurrence may be considered overestimated. Nonetheless, among these 37 PAs, 38% registered a high occurrence of fire ($\geq$ 113 fire pixels), and 81% of them registered fire occurrence above the median (> 18 fire pixels), depicting the local presence of the ignition source, and thus wildfire probability, in its territory. In two cases, the PA showed precipitation and temperature observed during ASO 2020 higher and below the average, respectively, and in six others, only one climatic variable that increased fire was observed. In 18 of them, although fire occurrences were high during ASO 2020, they were below the ASO 2017–2019 average.

Under the Alert category, 30% (65 PAs) presented ‘hit’ and 29% of the PA were ‘correct reject’, with both the trend and ASO 2020 fire occurrence confirming the probability forecast. In addition, 18% of the Alert level PAs were classified as ‘miss’, indicating that these areas may be under an increasing threat of fires. The Observation alert level presented 188 PAs (32%) classified as ‘correct rejection’ result, and under the Low Probability alert status, 87% and 5% were classified as ‘null’ (fire trend and difference in hot

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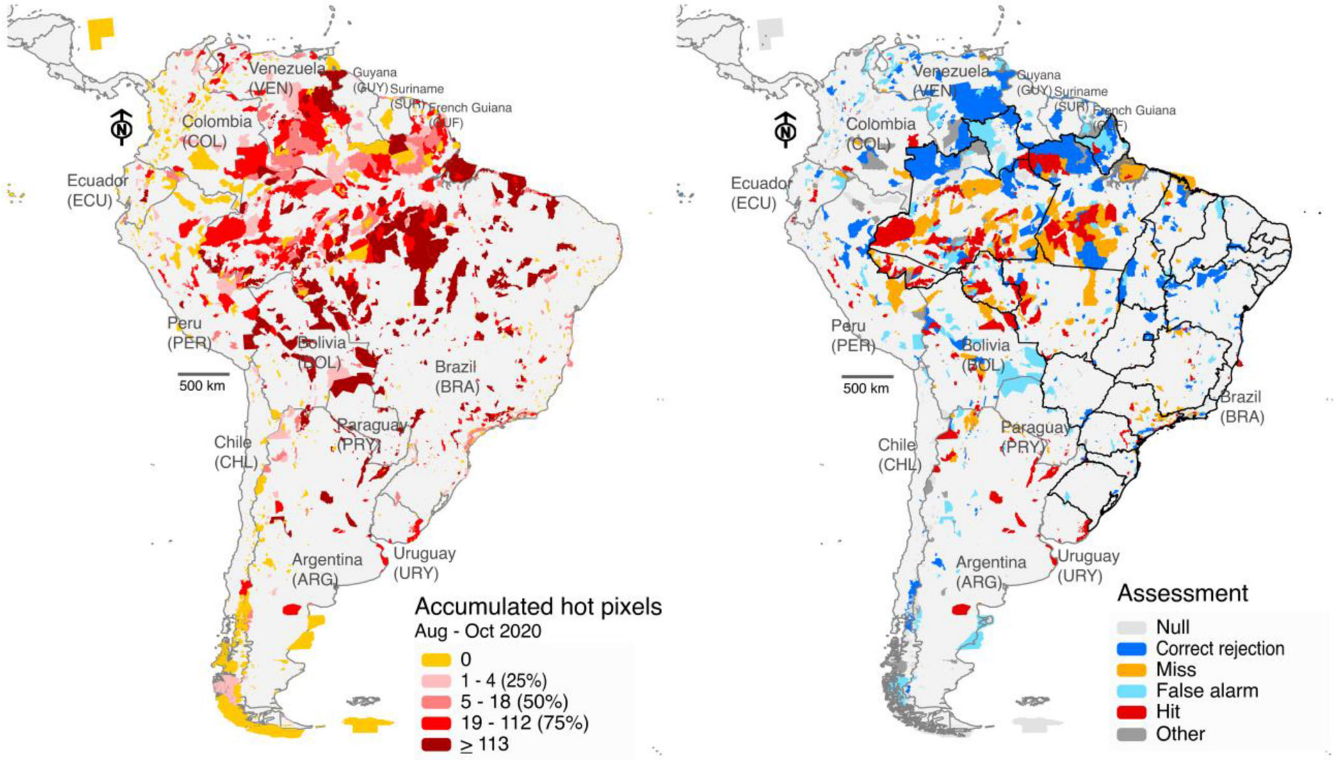

FIGURE 4 (a) Accumulated hot pixels during the period ASO 2020 in each PAs. The percentages indicate the quartiles used to classify the map. In dark red are all PAs that presented an accumulated hot pixel greater than the third quartile (≥ 113) during ASO 2020. (b) Fire occurrence trend assessment (i.e. 'hit' is where the fire trend in the ASO 2017–2019 period was positive and the observed ASO 2020 fire pixel count was higher than in the ASO 2017–2019 average)

pixels equals zero) and 'correct reject', respectively (Table 6). The category with the highest percentage of true results was Alert with 59% correctness being equally distributed between positive and negative.

Considering the area instead of the PA number, Attention was the alert status that presented the highest percentage of false results (56%). Observation presented the highest percentage of true results with 62%, of which 53% are 'correct rejection' (Table 6).

Comparing the ASO 2017–2020 fire trend with the ASO 2017–2019 trend demonstrated that, in 26% of the PAs, the trend kept the same sign (positive or negative, not including PA with a null trend). This corresponds to 60% of the area protected. Interestingly, in 16% of the PA territory, the fire trend changed from negative to positive (Table 7). In 11% of PA territory, a positive fire trend became negative. The spatial distribution of the PA where the trend has changed from negative to positive largely agrees with the ones that presented 'miss' results (Supporting Information Figure S6). In the High Alert category, the trend of 28% of PAs has changed from positive to negative. However, this represents only 13% of the area under protection. In terms of area, 83% of the PAs under High Alert have continued to have a positive fire occurrence trend.

Finally, the Kruskal–Wallis test showed a significant difference (KW = 2185.181 and $p < 0.05$) between the occurrence of hot pixels in 2020 for the different alert categories (Supporting Information Table S3). While a lower density of hot pixels was observed for the Low Probability category (0.038 ± 0.378 hot pixels km^{-2}), the highest density was observed for the Alert category (0.402 ± 0.841 hot pixels km^{-2}). In addition, the paired Dunn post hoc test showed that the pixel density observed for the Alert category did not differ from the High Alert category (0.303 ± 0.423 hot pixels km^{2}).

3.4 | Protected areas alert levels

We identified 58 PAs under High Alert, with 62% of them (36 PAs) located in Brazil, followed by 33% (19 PAs) in Bolivia, covering an area of more than 195,000 km^2. Within the Alert level, there were 216 PA, of which 75% (161 PAs) were located in Brazil, and 17 PAs in each of Bolivia and Paraguay. Argentina showed a similar number with 7% (15 PAs). The lowest numbers in the Alert level occurred in Ecuador (1), French Guiana (1), Peru (2) and Venezuela (2), totalling over one million km^2 (Figure 5). A total of

TABLE 6 Number and area of PAs per fire alert status in each validation output

	Null	Correct rejection	Miss	False alarm	Hit	Other	Total
Hight Alert							
Frequency (*N*)				37	20	1	58
				64%	34%	2%	100%
Area (km^2)				80,395	114,594	60	195,049
				41%	59%	0%	100%
Alert							
Frequency (*N*)		62	39	50	65		216
		29%	18%	23%	30%		100%
Area (km^2)		269,234	258,321	206,080	351,888		1,085,523
		25%	24%	19%	32%		100%
Attention							
Frequency (*N*)	1	108	88	211	125	34	567
	0%	19%	16%	37%	22%	6%	100%
Area (km^2)	173	278,753	322,281	367,802	229,134	41,665	1,239,808
	0%	22%	26%	30%	18%	3%	100%
Observation							
Frequency (*N*)	1	188	111	119	64	97	580
	0%	32%	19%	21%	11%	17%	100%
Area (km^2)	39	698,001	239,890	166,645	118,986	104,592	1,328,153
	0%	53%	18%	13%	9%	8%	100%
Low Probability							
Frequency (*N*)	2735	156	54	10	13	179	3147
	87%	5%	2%	0%	0%	6%	100%
Area (km^2)	615,398	424,748	142,992	11,979	10,889	186,685	1,392,691
	44%	30%	10%	1%	1%	13%	100%
Total							
Frequency (*N*)	2737	514	292	427	287	311	4568
	60%	11%	6%	9%	6%	7%	100%
Area (km^2)	615,610	1,670,735	963,484	832,901	825,492	333,002	5,241,225
	12%	32%	18%	16%	16%	6%	100%

576 PAs were classified under the Attention level, with the majority in Brazil (430 PAs - 74%), Peru (30 PAs, – 6%), Bolivia (28 PAs – 5%) and Colombia (22 PAs – 4%). The Observation (580 PAs) and Low Probability (3147 PAs) levels were mostly located in Brazil (336 PA – 58%) and Brazil and Colombia (1221 PAs; 1100 PAs – 38% and 34%, respectively) (Figures 5 and 6).

In total, 3% of the territory in PAs was under High Alert, followed by an almost equal share, in terms of area, of the other alert levels, varying from 20% in the Alert level to 26% in the Low Probability level (Figure 6). These results suggest that if resources were limited, the Alert categories can be used to guide strategic decisions, allowing prioritization in areas at higher risk.

Most of the PAs under High Alert and Alert levels were located in the central area of South America, covering the southern parts of the Amazon, Cerrado and Chaco-Pantanal, while the PAs under the other three alert levels were more present in the northern and southern regions of South America (Figure 7).

4 | DISCUSSION AND SUMMARY

Globally, from 2001 to 2018, 4.1% of the protected forest area globally experienced increased forest loss, with South and Central America responsible for the largest proportion, 32% (Wade et al., 2020). In their study, a peak was identified in 2016, related to forest fires, highlighting the vulnerability of these areas to fire, threatening their conservation. Moreover, it has been identified that 42% of South America PAs can be exposed to the highest risk from future climate

TABLE 7 Number and area of PAs per fire alert status in each possible fire occurrence trend change direction

	It has remained null or has become null	It has remained negative	It has remained positive	It has become negative	It has become positive	Total
Hight Alert						
Frequency (*N*)	1		41	16		58
	2%		71%	28%		100%
Area (km^2)	77		161,533	33,439		195,049
	0%		83%	17%		100%
Alert						
Frequency (*N*)	1	73	94	21	27	216
	0%	34%	44%	10%	13%	100%
Area (km^2)	1,652	338,707	463,645	94,323	187,196	1,085,523
	0%	31%	43%	9%	17%	100%
Attention						
Frequency (*N*)	12	142	265	84	64	567
	2%	25%	47%	15%	11%	100%
Area (km^2)	41,613	371,017	353,691	237,966	235,521	1,239,808
	3%	30%	29%	19%	19%	100%
Observation						
Frequency (*N*)	16	235	138	94	97	580
	3%	41%	24%	16%	17%	100%
Area (km^2)	36,243	772,654	215,908	101,830	201,517	1,328,153
	3%	58%	16%	8%	15%	100%
Low Probability						
Frequency (*N*)	2,742	178	20	55	152	3,147
	87%	6%	1%	2%	5%	100%
Area (km^2)	624,870	455,591	14,426	88,756	209,049	1,392,691
	45%	33%	1%	6%	15%	100%
Total						
Frequency (*N*)	2,772	628	558	270	340	4,568
	61%	14%	12%	6%	7%	100%
Area (km^2)	704,456	1,937,969	1,209,203	556,314	833,283	5,241,225
	13%	37%	23%	11%	16%	100%

patterns by 2050 (Tabor et al., 2018). In the work of Fonseca et al. (2019), projections of fire probability showed an increase of 10.6% and 73.2%, by 2100 for the Amazon, under their *Sustainability* scenario (involving maintenance of the PA network, among other factors), and their *Fragmentation* scenario (involving a decrease in the extension and level of protection of the PAs, among other factors), respectively. Here, we identified that 63% of the grid cells in South America presented more fires during ASO 2020 than the 2017–2019 ASO average, and in 16% of the PAs, the fire trend over ASO 2017–2020 became positive in comparison with ASO 2017–2019.

The diagnostic, methods, tools and forecast monitoring platforms under development can and should be used to the benefit of the society and the environment as a key element for improving societal preparedness in PAs. While weather forecasts (5–10 days) have already achieved a high degree of confidence and are known by the majority of the population, the temporal scale of sub-seasonal to seasonal forecasting (one to six months) is an emerging topic (Vitart & Robertson, 2018). There are a number of initiatives looking at fire forecasting on seasonal time scales. In the United States, there is the National Significant Wildland Fire Potential Outlook (NIFC, 2021), where the fire potential is spatially represented as above, below and normal categories; in Canada, there is the Wildland Fire Information System (CWFIS), which accounts for the effects of fuel moisture and wind on fire behaviour, rate of fire spread, fuel available for combustion, and the frontal fire intensity probabilistic forecast for the next four months. For

	Protected areas (N)					Area alert status (km²)					Total (N)	Total (km²)
	High Alert	Alert	Attention	Observation	Low Probability	High Alert	Alert	Attention	Observation	Low Probability		
Brazil	36	161	430	336	1,221	119,171	806,332	808,727	696,288	472,264	2,184	2,902,781
Colombia			22	46	1,100			27,422	27,720	228,736	1,168	283,878
Argentina		15	18	52	269		52,872	109,402	96,042	172,354	354	430,671
Peru	2	2	30	28	175	7,527	16,774	111,879	76,220	81,571	237	293,970
Chile			2	9	137			634	60,121	213,543	148	274,297
Bolivia	19	17	28	23	59	67,367	126,112	74,792	7,603	13,544	146	289,418
Venezuela		2	11	36	61		11,505	56,687	299,474	135,568	110	503,233
Paraguay	1	17	10	24	45	983	55,823	10,050	9,853	1,976	97	78,686
Ecuador		1	8	7	40		2,510	19,306	17,077	25,018	56	63,910
French Guiana		1	4	6	15		13,595	6,318	23,588	2,812	26	46,313
Uruguay			2	5	13			12,563	6,585	2,098	20	21,245
Suriname			2	7	7			2,029	3,867	29,065	16	34,961
Guyana				1	5				3,715	14,144	6	17,859
Total	58	216	567	580	3,147	195,049	1,085,523	1,239,808	1,328,153	1,392,691	**4,568**	**5,241,225**

FIGURE 5 Summary of alert levels in PAs in South America, for each country, for ASO 2020

Status	Number of protected areas	Area alert status (km²)
High Alert	58	195,049
Alert	216	1,085,523
Attention	567	1,239,808
Observation	580	1,328,153
Low Probability	3,147	1,392,691
Total	**4,568**	**5,241,225**

FIGURE 6 Summary of the South American PAs in each fire probability category in ASO 2020

the Amazon region, there is the fire season severity forecasts (Chen et al., 2011), at the state-level political boundaries spatial resolution, indicating below and above average predictions of fire activity. At the global scale, Chen et al. (2020) propose a seasonal fire outlook, which combines endogenous and exogenous predictors with a one month forecast lead time, explaining 52% of the variability in the global fire emissions anomaly. In our research, by combining fire dynamics and trends, dry season length and seasonal forecasts of temperature and rainfall, stratified alert levels were generated, which allows for prioritization and guiding strategic planning. Despite the availability of such information, it must be recognized that most agencies and organizations are better prepared to deal with response actions (Musinsky et al., 2018), and fire suppression, for example, is the largest item in the Brazilian federal fire policy budget (Fonseca-Morello et al., 2017). The budget for fire suppression in Brazil is even higher than the budget to perform strategic planning and carrying mitigation actions. Investments can be further limited particularly during periods of economic, political, environmental and health crises faced by many South American countries in recent years (ASCEMA, 2020; Barlow et al., 2020; Caetano, 2021; de Oliveira et al., 2020; Hope, 2021; Levis et al., 2020; Schmidt & Eloy, 2020; Suarez et al., 2018; Vilani & Leal Filho, 2020).

Fire is the third most commonly reported threat globally to PAs (Schulze et al., 2018). A large-scale survey analysis with institutions and organizations involved in the management and monitoring of PAs has identified a great number of challenges for using fire monitoring data in their work (Musinsky et al., 2018), which can also be considered a barrier for sub-seasonal and seasonal fire probability information. The two main difficulties reported in their study included limited internet access and difficulties in communicating the information to other stakeholders.

Although an online system is not yet operational, the results for the protected area fire probabilities generated in ASO 2020 and December–February 2020/2021 developed by this team of scientists were sent as a report to many agencies in South America, in addition to being shared on social media as factsheet summaries, in Portuguese, Spanish and English. This effort was aimed at increasing the visibility of the information generated, and the accessibility to a larger non-specialist group (Hargittai et al., 2018). This may be a particularly appropriate strategy, given that, driven by the COVID-19 pandemic, the use of WhatsApp and other social media platforms has increased, not only for social networking but also as a working communication tool. Nevertheless, the use of the information in the reports to increase awareness and catalyse wildfire mitigation actions must be appropriately assessed.

It also has to be acknowledged that, despite the information availability, institutions responsible for the management of PAs also face lack of sufficient resources to support field staff such as forest patrols and trainers. This has been

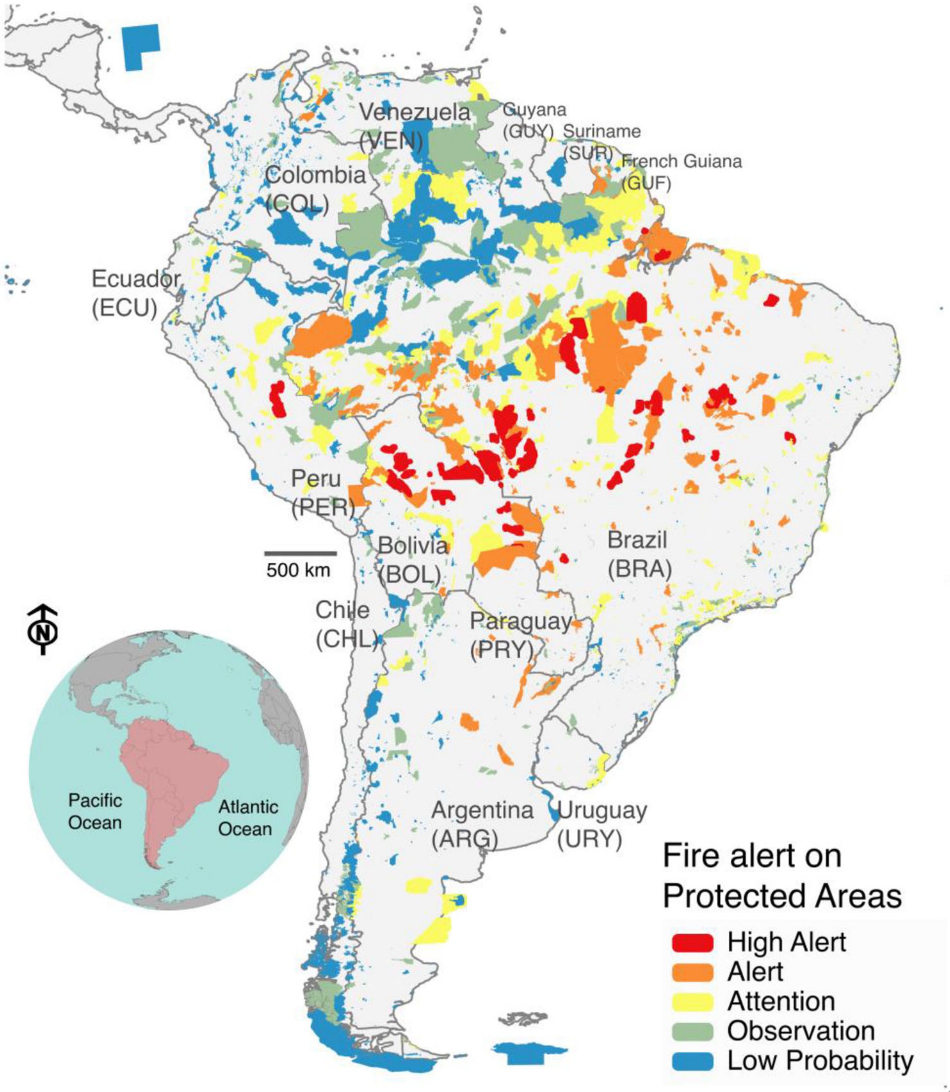

FIGURE 7 Spatial distribution of the protected areas categorized according to the fire alert status

reported since the study of Mares (1986) and is still a limiting factor (Musinsky et al., 2018). In addition, for many PAs, the accessibility of and communication with the population that live inside or around the boundaries of these areas are difficult, restricted and limited, which poses further challenges to communicate, plan and develop mitigation actions to prevent wildfires.

The four main categories of PAs assessed in our study are parks, indigenous lands, management areas and reserves, which represent 70% of the areas in the dataset, and we can consider these separately. Looking at the parks, we have observed that 230 out of 650 presented at least one fire pixel between 2017 and 2019. Indigenous lands presented fires in 85% of cases (418 areas from 503 in total). Management areas exhibited fires in 35%, and reserves presented fires in 10% of cases. This pattern is expected, because fire is used as a tool, and may be a way to ensure food security by many traditional populations, such as those living in sustainable use reserves or indigenous areas (Mistry et al., 2016; Nóbrega et al., 2020). However, it is remarkable that 50% of all fires observed during the ASO 2017–2019 period, and 40% of the ASO 2020 fires, occurred in only 29 PAs, all under the High Alert and Alert categories: four located in Bolivia, one in Paraguay and the remaining in Brazil, representing just 0.63% of all PAs. This concentration in the occurrence of fire indicates not only the vulnerability of these areas to this phenomenon, but also the institutional fragility of these areas in view of the weakening of public environmental policies (Andrade et al., 2021; Vale et al., 2021). Nevertheless, this concentration makes monitoring and combating illegal actions within PAs restricted to a few critical areas due to financial and human resources limitations.

Finally, it is important to acknowledge current uncertainties and potential future improvements. First, the spatial heterogeneity of the clouds distribution during any analysed period may impact the fire pixels detection, and thus result in a larger number of 'false negatives' in cloudy areas when compared with fires in less cloudy areas. For example, Martins et al. (2018) have quantified that north-western Amazonia presents persistent cloud coverage above 80% throughout the year, while the southern Amazon presents up to 20% cloud coverage. Although using a three-month time scale and a cell-by-cell spatial analysis for the fire pixel data reduce this problem, one possible update to the current model would be to use the fire pixel data from all satellites currently available, and thus increase the likelihood of fire activity detection. Second, fire pixels located close to a PA boundary may be occurring either inside or outside of the PA, leading to false negatives or false positives in the current model. For example, fires on edges of PAs classified as inside the PAs would lead to false positives. Nonetheless, in many cases, the fires that affect a PA come from the surrounding areas (Nepstad et al., 2006), increasing the threat and occurrence of wildfires inside the PA. In Brazil, by Law, PA buffer zones should also be targeted by public policies to reduce fire incidence in these areas (Laws and Decrees in Brazil: Law n° 9.985,2000; Decree n° 4.340, 2002; Decree n° 5.746, 2006; Decree n° 5.758, 2006). Therefore, one possible improvement in the model would be to include a buffer zone for the PA, since fires in these areas can be considered a hazard to the conservation.

According to Chen et al. (2013), in South America, the three months immediately before the fire peak month are often the driest months. Thus, an important next step is to include the dry season onset and length assessment in relation to the threshold used, in this case rainfall below 100 mm, which can be overestimated in drier biomes and in subtropical regions of the continent. Moreover, the relationship of both metrics to the seasonality of fire in South America must be further investigated and incorporated into our method if possible. For example, the inclusion of relative humidity as a predictor from the climate model forecasts was also considered (following Bett et al., 2020), but there was insufficient skill for the ASO season.

Other potential improvements focusing on more regional patterns could also be implemented in the model. One example is the well-established relationship between deforestation and fires in the Amazon. Silveira et al. (2020) have demonstrated that about 25% of fires in the Brazilian Amazon occur in up to 500 m of new deforestation, and up to 80% of the fires occur up to 5 km of these areas. Therefore, by coupling a regional spatial analysis in the probabilistic model could potentially improve the anticipated alert.

In this study, we presented a method and its assessment for a seasonal fire probability forecast for South American PAs. We combined empirical fire knowledge with climate forecast to produce a five-level alert system. Although future development in our method is planned, the current results encourage the use of the alert system for guiding strategic planning by the PA stakeholders. One of the greatest challenges will be the information dissemination and assessment of both its use and how the probability forecast information may have impacted the local fire dynamics.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All data used are open source and data sharing will be provided.

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