Climate change and drought amplify the potential for uncontrollable fires in Nepal

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Abstract

In 2021, Nepal underwent its most severe fire season, resulting in a fire rate 10 times greater than the historical average in many areas of the country with record-high air pollution levels. Leading the fire outbreaks in March of 2021, the country experienced an extreme precipitation deficit and drought in the post-monsoon season. Current community forest management practices and resultant forest growth may have exacerbated the conflagration, but an analysis using observational, reanalysis, and climate model ensemble data indicates that climate variability and climate change induced severe drought conditions that resulted in the anomalous fire season. While warning of the likely re-occurrence of extremely active fire seasons in Nepal through the end of the 21st century, this research also proposes a statistical model for sub-seasonal prediction that could help mitigate the projected effects of the drought-fire paradigm.

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Climate change and drought amplify the potential for uncontrollable fires in Nepal

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Key Points:

- Nepal underwent a record breaking fire season in 2021 with active fire counts ten times greater than the historical average.
- This fire season was exacerbated by climate change and future projections suggest increased drought conditions and more active fire seasons.
- In response to this risk, a simple empirical prediction model is made to forecast active fire counts one to two months in advance.

Abstract

In 2021, Nepal underwent its most severe fire season, resulting in a fire rate 10 times greater than the historical average in many areas of the country with record-high air pollution levels. Leading the fire outbreaks in March of 2021, the country experienced an extreme precipitation deficit and drought in the post-monsoon season. Current community forest management practices and resultant forest growth may have exacerbated the conflagration, but an analysis using observational, reanalysis, and climate model ensemble data indicates that climate variability and climate change induced severe drought conditions that resulted in the anomalous fire season. While warning of the likely re-occurrence of extremely active fire seasons in Nepal through the end of the 21st century, this research also proposes a statistical model for sub-seasonal prediction that could help mitigate the projected effects of the drought-fire paradigm.

1 Introduction

In the winter of 2020 through the spring of 2021, Nepal experienced a historic fire season. While seasonal fires after the summer monsoon are commonly used to manage farmlands and pastures (Matin et al., 2017), extremely dry conditions resulted in uncontrollable blazes throughout April. Impacts were felt throughout the nation. Almost 20 lives were claimed by fire, school closures were widespread due to hazardous air quality conditions, and black carbon fallout was observed across the Himalayas which has been linked to more rapid melt of glaciers and mountain snow (Qian et al., 2011). This extreme fire season was concomittent with the lowest average precipitation for October through March since 1980 (Figure S1). Similar cases of drought have been identified as one of the primary forcings for several severe fire seasons in Nepal, most notably in 2008 and 2016 (Matin et al., 2017). Although there is a general understanding that high-fire years in Nepal follow severe winter droughts, the historical relationship between meteorological drought and fire potential is largely unknown.

Research also suggests that this drought is part of trend towards drier winter conditions partly fueled by anthropogenic climate change (S.-Y. Wang et al., 2013). Decreased precipitation from satellite and rain gauge observations and decreased soil water have been noted in tandem with increased temperature – a recipe for enhanced drought stress (Hamal et al., 2020; Shrestha et al., 2012; Wang et al., 2013). Warming in the Himalayan region has outpaced the global average (A. B. Shrestha et al., 1999) and the potential for climate change to have greater ecosystem impacts on high elevation regions further implicates that Nepal is highly vulnerable to drought (Alamgir et al., 2014; Bhatta & Aggarwal, 2016; Macchi et al., 2015; Pandey & Bardsley, 2015). Additionally, fires in Nepal are managed by communities rather than a centralized agency. Community forest management is very successful for forest sustainability, however, an increase in forest fires and changing land use practices may jeopardize the effectiveness of community management (Sapkota et al., 2015). The potential for climate change to disproportionately impact Nepal makes it imperative to understand the impact of climate change on drought and fire in the region.

Sub-seasonal drought and fire prediction has emerged as an important tool for environmental planning and fire management (Chen et al., 2020; Marshall et al., 2021; Turco et al., 2018) and Nepal's community fire management may similarly benefit from prediction tools that are generally accessible. Humans are a major source of fire frequecy and fire ignitions in

Nepal, with approximately 58% of the fires in Nepal started intentionally by people (Kunwar & Khaling, 2006). This suggests that changes to community management in response to sub-seasonal drought forecasts might mitigate fire potential.

As drought has been anecdotally associated with recent fire extremes, we will analyze the historical relationship between drought and fire frequency for Nepal. Given the vulnerability of Nepal to climate change and the recent extreme fire season, we will then provide climate change projections of the relationship between drought and fire frequency using the Coupled Model Intercomparison Project Version 6 (CMIP6). As a potential tool for adaptation to the expected impacts of climate change on regional fire, we produce a simple empirical prediction model to provide fire outlooks one-to-two months in advance.

2 Data and Methods

2.1 Observational Data

Observed data in this study is obtained from meterological stations in Nepal (Department of Hydrology and Meteorology, Government of Nepal) that recorded temperature precipitation data for at least 80% of the days in the record from 1980–2021. This criteria resulted in the use of 117 stations, of which the daily data was converted into monthly averages. We use this data to compute the Standardized Precipitation and Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), using precipitation and potential evapotranspirtation (PET) from the Thornthwaite method (Thornthwaite, 1948). SPEI was used at monthly (SPEI-1), seasonal (SPEI-3) and annual (SPEI-12) timescales.

For active fire points, we used the Moderate Resolution Imaging Spectroradiometer (MODIS) (aqua and terra combined) active fire detection products (Giglio & Justice 2015). The combined MODIS data are available from 2002 that are used in this study. MODIS detects active fire points not individual fire events, and one large fire can consist of many active fire points. Therefore, it is analogous to burned area and the correlation coefficient between burned area and active fire points from November through March is 0.96 from 2001 through 2021. The rest of this study will use these active fire points as an analog of burned area and fire potential. Further description of observational data can be found in the supporting information, Text S1.

2.1 Model Data

We also use the CMIP6 ensemble with the historical, natural and SSP585 high-emissions scenario. To attribute changes in the historical fire record for Nepal, we compare the SPEI-1 and SPEI-12 in the historical (incuding anthropogenic greenhouse gas emissions) and natural runs from 1981–2014. SPEI-1 and SPEI-12 are computed from these scenarios using the Thronthwaite method. For the future projection of active fire counts in Nepal under the SSP585 scenario, we use the historical relationship of SPEI-3 and fire count to project the relationship of anthropogenically driven drought on active fire counts to the end of century. All CMIP6 data considered in this study represent the multi-model ensemble mean. Monthly mean temperature and precipitation were bias corrected relevant to the observed data. More information about biased-correction scheme can be found on Hawkins et al. (2013) and Mishra et. al., (2020).

2.3 Empirical fire outlook

We use a nonlinear regression model to evaluate the empirical predictability of active fire count from SPEI-3:

$$active\ burn\ counts(t) = a * \ e^{-\beta * SPEI3(t)} + \varepsilon\ ,$$

where α and β are regression coefficients, e is Euler's number (approximately 2.718), t is the year, and ε is an error term. The SPEI-3 index from January and February are used as predictor variables for March fire count. The β parameter is optimized at an α of 250 using non-linear least squares to fit the model to the training data. The model is cross-validated, using a leave-one-out and a leave-three-out cross validation. In the leave-one-out validation, the model is trained with all the observed data except for the value which is to be predicted. The leave-three-out cross validation entails training the model without one-sixth of the observed data to provide a more robust validation (L. Wang et al., 2017). The correlation and the R^2 value between the observed fire count and the predicted fire count used to measure the skill of the prediction.

4 Results

4.1 Observed relationships between drought and fire

Starting in November 2020, the SPEI more than doubled across Nepal compared to an average of the 18 previous seasons (Figure 1a, top). Drought conditions were persistent from November through March (Figure 1a), and the associated number of fires was well above normal (Figure 1a, bottom). The cumulative active fire points by March and April surpassed each dry season in the historical record (Figure S2). During Nepal's fire seasons between 2003 and 2020, the months of November through April averaged 2,327 active fire points; this six-month aggregate was exceeded in just one month–March of 2021. The surges were greatest in Nepal's western lowlands, the region immediately southeast of the Annapurna Conservation Area, and the countryside surrounding the Kathmandu Valley; all of which saw a 10-fold increase in the active fire points in 2020-21 compared to the long-term mean (Figure 1b,c).

This record-setting fire season did not occur in a static fire fuels environment. An analysis of leaf area index (LAI), obtained from a global reanalysis of vegetation phenology during 1981–2012 indicates that the January-April average of LAI increased by about 10% from that period (Figure 1c). Satellite-derived LAI change from 2003 to 2020 suggests a continual increase (result not shown). The LAI analysis aligns with recent research showing forest cover expansion across Nepal (Fox et al., 2019; Van Den Hoek et al., 2021).

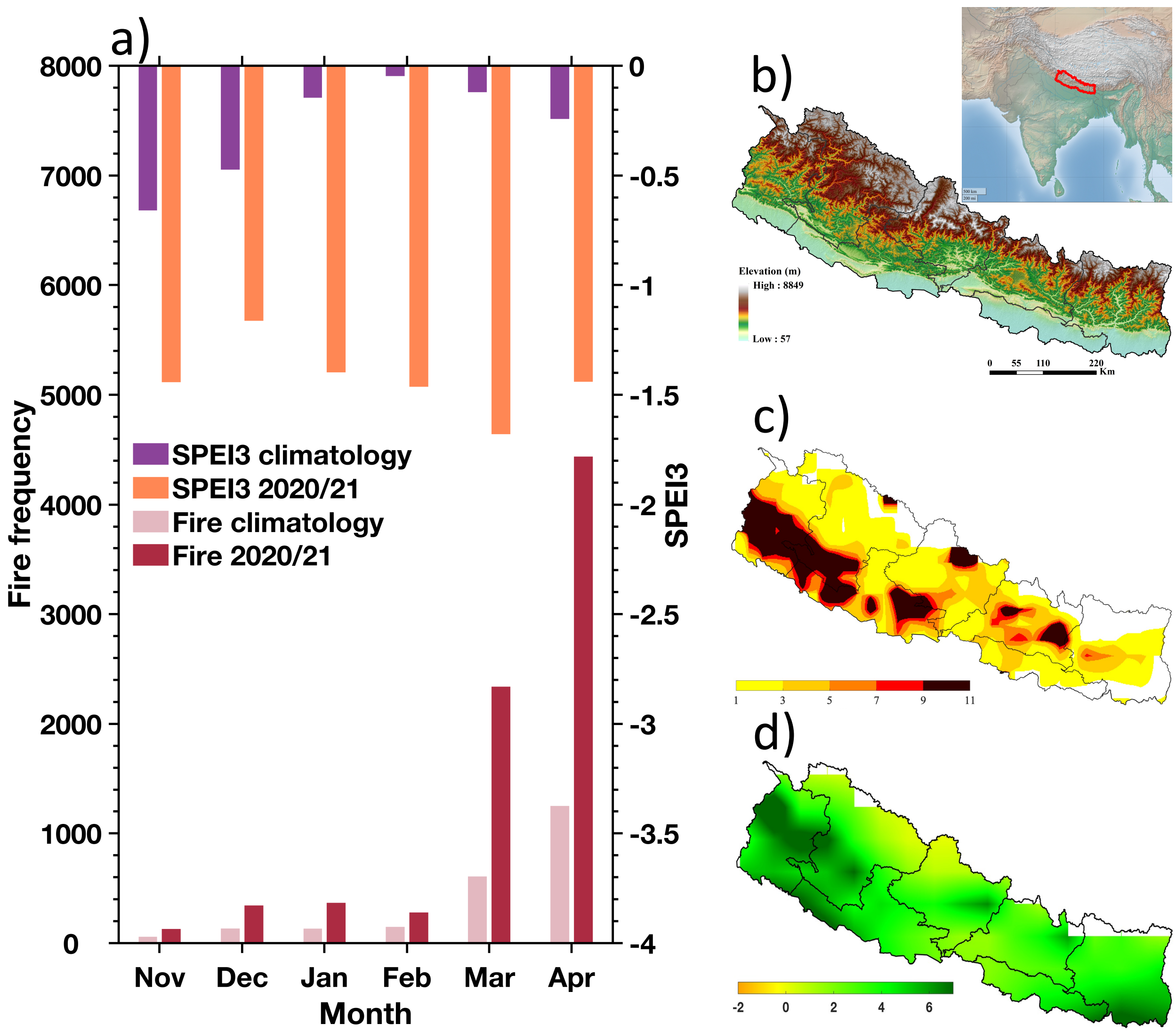

Figure 1: MODIS (Aqua and Terra satellite) measured fire detection points and observed precipitation and SPEI for November through April (long-term average and 2020–2021) in Nepal. a) Total monthly fires during 2020–2021, long-term average from 2003-2020, and the SPEI 3-month drought index. b) Topography of Nepal. c) ratio of the number of fires in 2020–2021 to the long-term average (2003–2020) for November through March. d) change in LAI (%) from 1981-1990 compared to 2001–2010. Inserted Map in upper right shows South Asia and Nepal with average JFMA LAI outlining the forests.

Our examination of the relationship between monthly precipitation deficits and drought (Figure 2a) shows a robust correlation between SPEI and the number of active fire points, ranging from a strong signal ($p<0.1$) when November and December precipitation are considered together, to a very strong signal ($p<0.01$) when January and February are included as well. Including the months of March and April nominally strengthens the relationship (Figure 2a). The relationship between the active fire points and SPEI-3 (Figure 2b) is best quantified by a nonlinear model based on the correlation coefficient (Figrue 2a). The fire prediction model for each month from January to May with the lead time 0- and 1-month shows good correlation with observational fire (Table S1) however the bias is large, mainly during the high fire months (March and April). The aim of the prediction model is to predict the qualitative fire prediction, not the quantitative. The record number of active fire points in 2021 were associated with the most severe SPEI-3 values observed in the last 18 years. Drought quantified by the SPEI-3 explains a crucial 75% of the variability in active fire points.

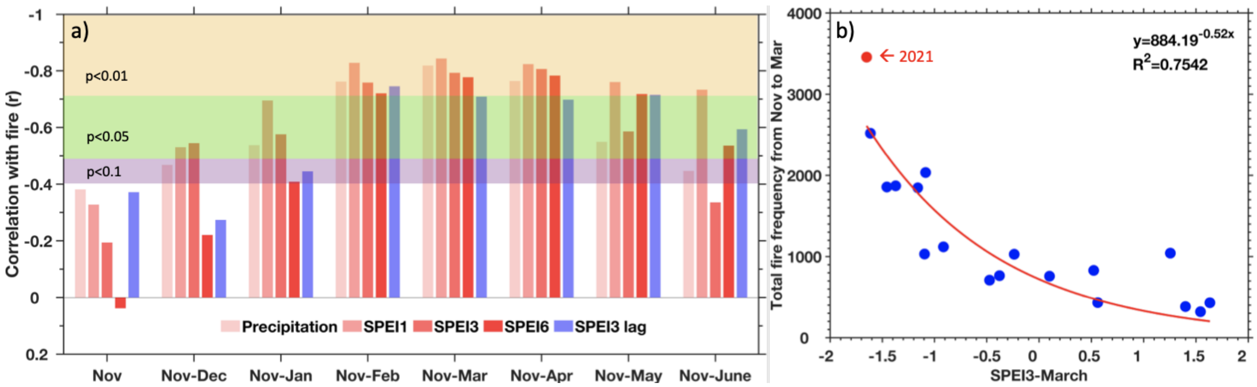

Figure 2: The relationship between 2002–2020 monthly precipitation deficits and subsequent fire season behavior in Nepal. a) shows the correlation coefficient between the total number of fires, starting in November, and average precipitation from the preceding month, average SPEI-1 from Oct to a given month, a given month's SPEI-3 and SPEI-6, and preceding month lag for SPEI-3 from left to right, respectively. The 99% ($p<0.01$), 95% ($p<0.05$), and 90% ($p<0.1$) significant levels are shaded with purple, green and yellow, respectively. b) shows the scatter plot relationship between November-March total fire frequency and the SPEI-3 in March and the non-linear regression fit (red line). 2021 is highlighted via an arrow.

4.2 Attribution of drought and future projections fire

Observed dry-season drought frequency and intensity in Nepal has increased over the past four decades and the strong relationship between drought and fire for the region indicates that this increase in drought is partially responsible for enhanced fire potential. It is noteworthy that SPEI-1 and SPEI-12, which both exhibit fluctuating but predominantly positive values between 1981 and 2005, has been mostly negative since then (Figure S3), underscoring the drought trend. However, low-frequency climate variability can also result in drought conditions over Nepal (Wang & Gillies, 2013), so we evaluate the role of anthropogenic climate change to determine if these trends are associated with changes to the climate mean state.

This analysis was conducted using the CMIP6 ensemble of single-forcing experiments, based on the multi-model and multi-realization average 1981–2014 trends of seasonal SPEI-1 and annual SPEI-12. The historical simulations of SPEI-1 and SPEI-12, which included all anthropogenic forcings, are both substantially negative. Histograms comparing trends from the 68 "historical" simulations to the 50 "natural", as shown in Figure 3, were found to be distinguishable at a high level of statistical significance via a Student's t-test ($p<.01$). Comparison of the observations to the model over the same 1981–2014 periods reveals that the trend over the entire 1981–2020 observations could not be attained in any of the simulations without human changes to the composition of the atmosphere. We therefore conclude that anthropogenic climate change has contributed to the noticeable drying trend in Nepal during the winter-dry season; this is comparable to previous work based on earlier-generation simulations of CMIP5 (Wang et al., 2013).

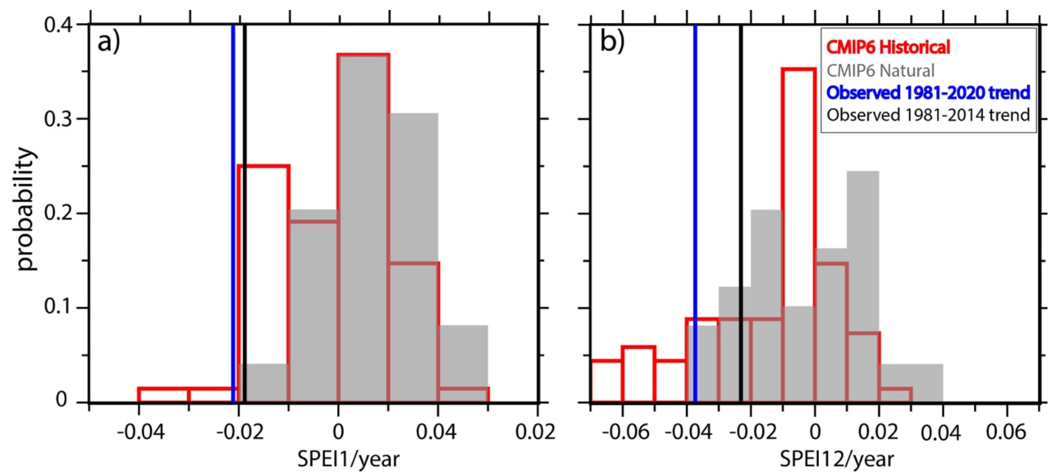

Figure 3: Histograms of CMIP6 simulated 1981–2014 trends in October-March SPEI-1 (a) and annual SPEI-12 (b). Red bars are the historical all-forcing runs and gray bars are the natural runs. The observed trends over this simulation period are shown as a black vertical line and the observed trends are shown as the blue vertical line.

Given the significant correlations between SPEI-3 and seasonal fires (Figure 2) and the role of anthropogenic warming on drought (Figure 3), we provide a projection of active fire counts in Nepal based on the calculation of SPEI-3 from the CMIP6 high-emission ensemble simulations. To calculate SPEI-3, model monthly precipitation and temperature were bias-corrected within the historical period. The CMIP6 SPEI-3 was then used to estimate the November-March active fire counts using the regression model from Figure 2b. The CMIP6 ensemble mean of March SPEI-3 and its spread, under the SSP585 warming scenario, indicates a distinct decreasing trend has begun and is projected to continue through the end of 21st century (Figure 4a), giving rise to more periods of worsening drought. Based on statistical modeling, the derived active fire counts are projected to increase in association with drought driven by climate change (Figure 4b). Notably, the spread in active fire count anomalies across individual CMIP6 model projections becomes amplified in the latter part of the 21st century (Figure 4b). Regardless of the spread, active fire counts are projected to increase above the average historic levels.

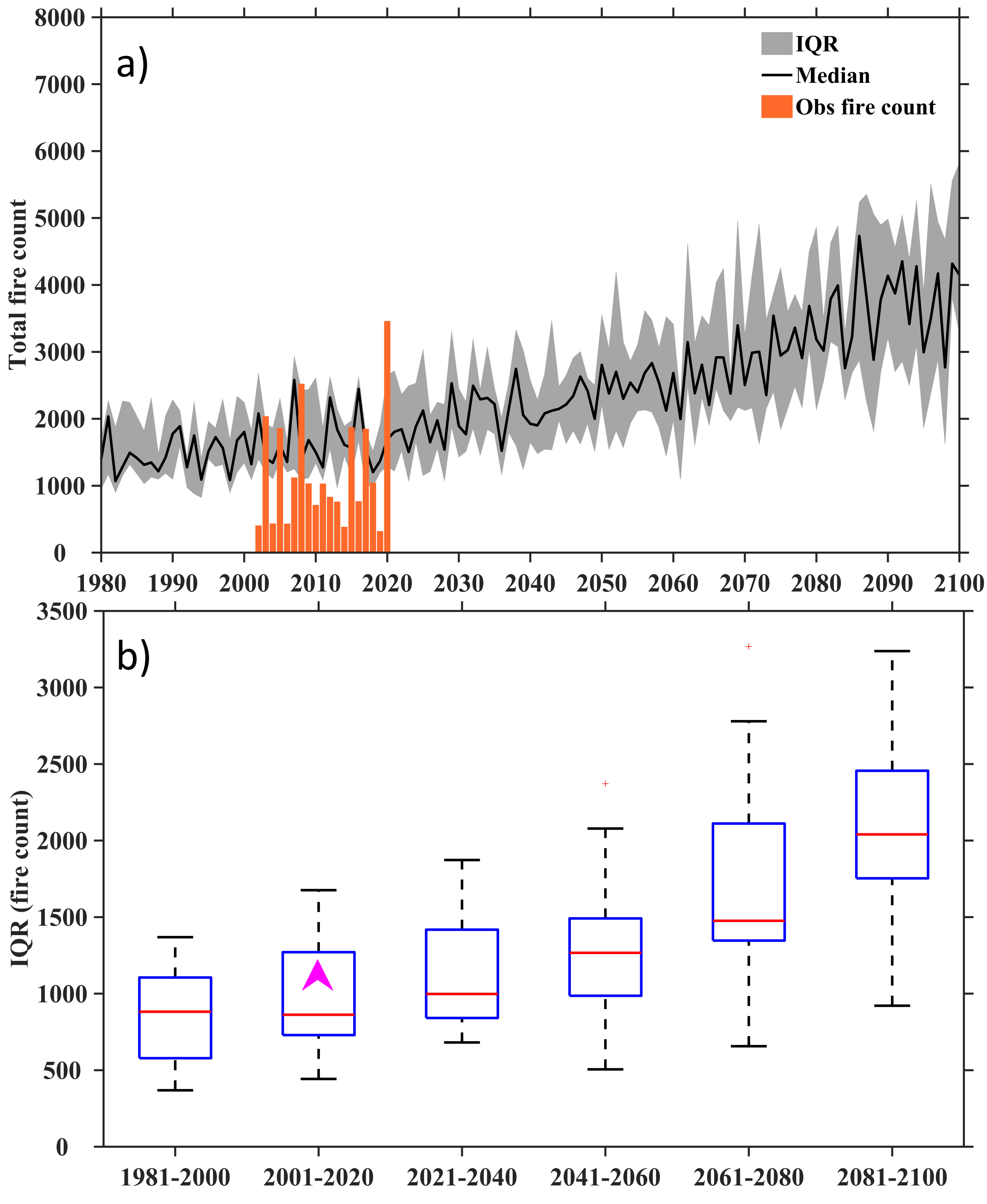

Figure 4: a) CMIP6 future projection of active fire counts from November to March over Nepal with observed active fire counts (orange bars). b) Inter Quartile Range (IQR) box plots of historical and projected active fire counts with the purple arrow indicating the observed median for active fire counts.

4.3 Sub-seasonal empirical prediction

The strong historical and projected relationships between drought and fire suggest that nationwide fire outlooks are possible at short lead times with antecedent drought conditions. Using nonlinear regression, Figure 5 depicts the two-month (Figure 5a,b) and one-month predictions (Figure 5c,d) of March active fire counts in Nepal using SPEI-3 from January and February respectively. The regression model trained with all data points, the hindcast, accounts for a significant amount of variance in the total time series of March active fire points at both the two-month and one-month lead times. The regression model has modest skill for the cross-validation as well, with the leave-one-out and leave-three-out methods producing similar results to the hindcast. These regression models predicted the active fires in March of 2021 but fell short of the record-setting magnitude. This shortcoming may be caused by anthropogenic forcings (the regression model does not account for changes to the frequency of human ignitions or the impacts of climate change) or the inability of SPEI-3 alone to account for fuel moisture and abundance. Regardless, these simple regression models show good skill (high r^2 values, low error and bias) towards fire outlooks for March in Nepal with information about the fire tendency (Table S2). Fire count in April is highly predictable at a 1-month lead using these same methods but the 2-month prediction lacks skill (Figure S4). Summary statistics of model error, bias and parameter estimates are provided in Table S2.

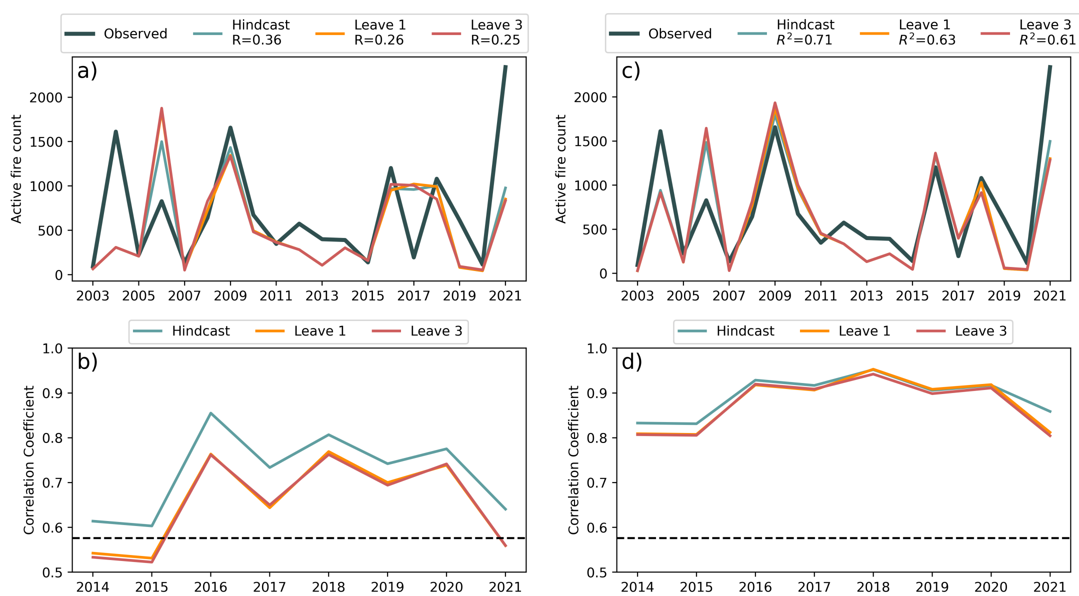

Figure 5: a) Observed active fire count in March along with the hindcast from the regression of January (two-month lead) SPEI-3. Leave-one and leave-three-out cross-validated models are shown in orange and red respectively. b) Twelve-year rolling correlation of observed March active fire counts and regressed active fire counts from January SPEI-3. c) Same as 5a, but for February SPEI-3. d) Same as 5b, but for February SPEI-3. The black dotted line indicates the 95% confidence level for 10 degrees of freedom.

5 Discussion and conclusions

Anthropogenic impacts on fire in Nepal are not restricted to climate change however, as community forest management has also changed. Under localized control policies, which began in 1976, about 3 million hectares of forests in Nepal are now under the control of community-based forest management groups, and these groups have been widely credited with driving significant increases in forest growth via restoration efforts over the past 45 years, an uncommon phenomenon in developing nations over recent decades (Ghimire & Lamichhane, 2020). Despite clear benefits in sequestering carbon (Devkota, 2020; Ghimire, 2019) and sustaining biodiversity, the fact that Nepal's forests feasibly cover more area now than in past years (Figure 1d) may well impact fire potential, particularly in association with the increasing trend of post-monsoonal drought. Of note, the largest forest restoration developments are observed in the western lowland and western mid-mountain regions of Nepal, where the recent, more numerous, and fierce conflagrations occurred in 2009, 2016 and the most recent fire season (Figure 1c). Two other areas of high 2020–21 fire activity, i.e., in the southeast of Annapurna and the Kathmandu Valley, were also areas of significant LAI gain (Figure 1c). In summary, increased forest area and/or forest density is an ideal circumstance with respect to the addition of fire fuel. These reforestation gains, concurrent with decades of increasingly prolonged and severe droughts (Figure S3), are arguably prospective grounds for a marked increase in fires (Figure 4).

The CMIP6 results for Nepal echo prior research that projects declining winter precipitation, alongside moderately increased monsoon precipitation, under the SSP585 high-emissions scenario (Almazroui et al., 2020). Arguably, this transition may already be underway, as significant declines have been identified in Mediterranean-originating winter precipitation sources (Dakhlaoui et al., 2019; Marchane et al., 2017). In addition, persistent warming in the Indian Ocean has acted to enhance the winter drought trend in Nepal through modifications in the local branch of the Hadley circulation, associated with strengthened subsidence over northern India and the Himalayas (Wang et al., 2013a). While the 2020–21 fire season was exacerbated by climate change, climate variability likely played an important role in the seasonal drought conditions. The winter of 2020–21 saw a strong La Niña event which often induces drought conditions in Nepal (Hamal et al., 2020). As some El Niño and La Niña teleconnections have strengthened in the warming climate (Wang et al., 2015; Stevenson, 2012), the increased spread in projected fire frequency near the end of century (Figure 4b) may be partially attributed to natural variability amplified by global warming. These observed impacts of climate change and model-based projections suggest drought conditions will likely continue and are expected to amplify, enabling a higher potential for fire risk through to the end of the 21st century.

Mitigating risk will require an improved understanding of the factors that contribute to fire in Nepal, but the nation currently lacks a significant and active drought and fire forecasting efforts. Previous studies have succeeded in generating fire-risk maps for Nepal (Parajuli et al., 2020; Sharma et al., 2014), however the society at large lacks predictive models that can be employed to better prepare for fire on a monthly, seasonal, or long-term basis. To these ends, the study undertaken here offers: i) a practical statistical tool, derived from easily obtainable climate variables, towards sub-seasonal fire outlooks for the nation as whole, ii) knowledge through CMIP6-based projections that indicate the likelihood of more drought and fire events through the remainder of this century, and iii) an account of the suspected anthropogenical, climatological and sociological drivers of the anomalous 2020–21 fire season. Thus, this study provides a platform for Nepal to formulate future strategies to ameliorate the environmental hazards the country will face in a changing climate.

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Data Availability Statement.

MODIS active fire count data was used in this study can be freely accessed from https://firms2.modaps.eosdis.nasa.gov/download/, CMIP6 bias corrected data is generated by Mishre et. al. (2020) and can be freely accessed from https://zenodo.org/record/3873998#.YavSVi8RoTt. CMIP6 GHG and Natural run data are freely available at https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6. Groud-based raingauge data can be purchased from Department of Hydrology and Meteorology, Government of Nepal (DHM) (www.dhm.gov.np/).

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