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Amplified drought trends in Nepal increase the potential for Himalayan wildfires

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Abstract
In spring 2021, Nepal underwent a record wildfire season in which active fires were detected at a rate 10 times greater than the 2002–2020 average. Prior to these major wildfire events, the country experienced a prolonged precipitation deficit and extreme drought during the post-monsoon period (starting in October 2020). An analysis using observational, reanalysis, and climate model ensemble data indicates that both climate variability and climate change-induced severe drought conditions were at play. Further analysis of climate model outputs suggests the likely reoccurrence of drought conditions, thus favoring active wildfire seasons in Nepal throughout the twenty-first century. While the inter-model uncertainty is large and direct modeling of wildfire spread and suppression has not been completed, the demonstrated relationship between a drought index (the standardized precipitation and evapotranspiration index) and subsequent fire activity may offer actionable opportunities for forest managers to employ the monitoring and projection of climate anomalies at sub-seasonal to decadal time-scales to inform their management strategies for Nepal's wildlands.

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1 Introduction

Wildfires have major impacts on forest health. While many forests are adapted to, if not dependent on, low-to-moderate severity fire, high-severity wildfires can negatively impact the ecological function of the natural landscape, devastating native species and human communities (Sullivan et al. 2022). Wildfires also are major sources of toxic gases and aerosols that contribute to significant increases in air pollution both locally and far downstream (Jaffe et al. 2020; Stockwell et al. 2016). The extent and severity of fires are dependent on numerous factors including fuels, weather, and topography, as well as fire management strategies. Wildfires in South Asia are mostly human-ignited—sometimes accidentally and sometimes intentionally to prepare land for shifting cultivation, as part of commercial timber harvesting operations, for controlled burning, to encourage grass regrowth, for the collection of minor forest products, and due to firewood burning (Reddy et al. 2020). The role of climate drivers in fire regimes is ecosystem-dependent, and a range of regional climate-fire relationships have been well-documented in the USA (Littell et al. 2018) and Australia (Canadell et al. 2021). However, similar analyses are less common in South Asia in general and especially in Nepal.

In 1976, Nepal adopted a community forest management program focused on the nation's middle-elevation hills (those between 200 and 3000 m) and the southern plains (known as terai, at elevations less than 200 m) (Springate-Baginski et al. 2003). These reforms were followed in 2010 with the establishment of a new forest fire management strategy which includes policy, legal, and institutional reform, community awareness campaigns, participatory research, and strengthening collaboration with national and international stakeholders working in forest fire management (MFSC 2014; Pandey et al. 2022). Under these policies, about 3 million hectares of forests in Nepal came under the control of community-based forest management groups. These groups have been widely credited with driving significant increases in forest growth via restoration efforts, an unusual achievement among developing nations (Ghimire and Lamichhane 2020). However, reforestation may increase the chances of forest fires (Sapkota et al. 2015) as more fuel is available with the potential for both inadvertent and adverse effects on local communities.

Seasonal fires after the summer monsoon ends are common in Nepal as farmers burn residual of agricultural biomass to manage farmlands and pastures (Matin et al. 2017). Most of these fires occur during the hot and dry season, which lasts from March to May (Matin et al. 2017). In the winter of 2020 through the spring of 2021, however, Nepal experienced a historic wildfire season (https://phys.org/news/2021-04-nepal-worst-wildfires-decade.html). Multiple lives were claimed by the widespread fires, which also forced school closures due to hazardous air quality conditions (https://earthobservatory.nasa.gov/images/148185/a-fierce-fire-season-in-nepal). Meanwhile, black and brown carbon deposition was observed across the Himalayas (Choudhary et al. 2022; Gertler et al. 2016; Li et al. 2016). This extreme fire season followed anomalously low precipitation between October and March (only 23% of normal, the lowest Nepal-wide precipitation recorded since 1980). Similar cases of drought have been identified as one of the primary drivers for other notable wildfire seasons in Nepal, such as 2008 and 2016 (Matin et al. 2017).

Past research reveal that remote sensing data are central to the study of wildfire activity around the globe (Goss et al. 2020; Radočaj et al. 2022; Seydi et al. 2022; Wang and Zhang 2020). These data are not only useful to assess the characteristics of wildfire (Reddy et al. 2020; Seydi et al. 2022), but also to understand post-fire impacts (Radočaj et al. 2022) and to evaluate the impact of climate change on wildfire (Goss et al. 2020). The recent drought is part of a longer trend of consecutive and worsening winter drought conditions since 2000 (Wang et al. 2013). Decreased precipitation from satellite and rain gauge observations, and the associated decreases in soil moisture, have been noted in tandem with increased temperature—a recipe for enhanced drought intensity (Hamal et al. 2020a; Shrestha et al. 2012; Wang et al. 2013). Warming in the Himalayan region has outpaced the global average (Shrestha et al. 1999), increasing Nepal's susceptibility to drought impacts (Alamgir et al. 2014; Bhatta and Aggarwal 2016; Macchi et al. 2015; Pandey and Bardsley 2015). While wildfire activity is strongly influenced by other factors, including fuel loading, fuel characteristics, human fire suppression, and human ignition (Abatzoglou et al. 2019; Hantson et al. 2015; Littell et al. 2018), climate change is expected to drive increases in fire activity in most regions amidst fire and fuel feedbacks (Abatzoglou et al. 2021). Although there is a general understanding that active wildfire years in Nepal follow severe winter droughts, the physical relationship between meteorological drought and fire potential in Nepal has not been quantitatively assessed either historically or into the future.

Mitigating risk associated with fire in Nepal will require forecast tools, but the nation currently lacks operational drought and fire forecasting services. Previous studies have generated long-term fire risk maps for Nepal (Parajuli et al. 2020; Sharma et al. 2014). While drought has been anecdotally associated with recent wildfire extremes worldwide (Son et al. 2021a), climate-based fire prediction has emerged as an important tool for environmental planning and fire management (Chen et al. 2020; Marshall et al. 2022; Turco et al. 2018), and Nepal's community fire management may similarly benefit from readily-available prediction tools. Here, we present the first analysis of the historical and projected relationships between drought and wildfire activity in Nepal. Our main objective is to leverage historical drought and fire relationships to evaluate historical fire activity and to project fire activity under a high-emissions greenhouse gas scenario. Given the exceptional vulnerability of Nepal to climate change (World Bank Group 2022) and the extreme wildfire season of 2021, we aim to highlight the impacts and compounding factors of extreme fire seasons in Nepal. Finally, as a potential adaptation tool for fire variability from year-to-year, we assess the potential for sub-seasonal predictability of fire activity from drought indices.

2 Materials and methods

2.1 Study area

The study area covers all of Nepal (Fig. 1a), located in South Asia between India and China with a total geographical area of 147,516 km^2. About 42% of this area is covered by forests with ten major classes of forest that are distributed along altitudinal gradients (Aryal 2022). The climate of this area is dominated by the south Asian summer monsoon (SASM) system during June–September and transient westerly disturbances in December–February (Hamal et al. 2020a; Sharma et al. 2020b).

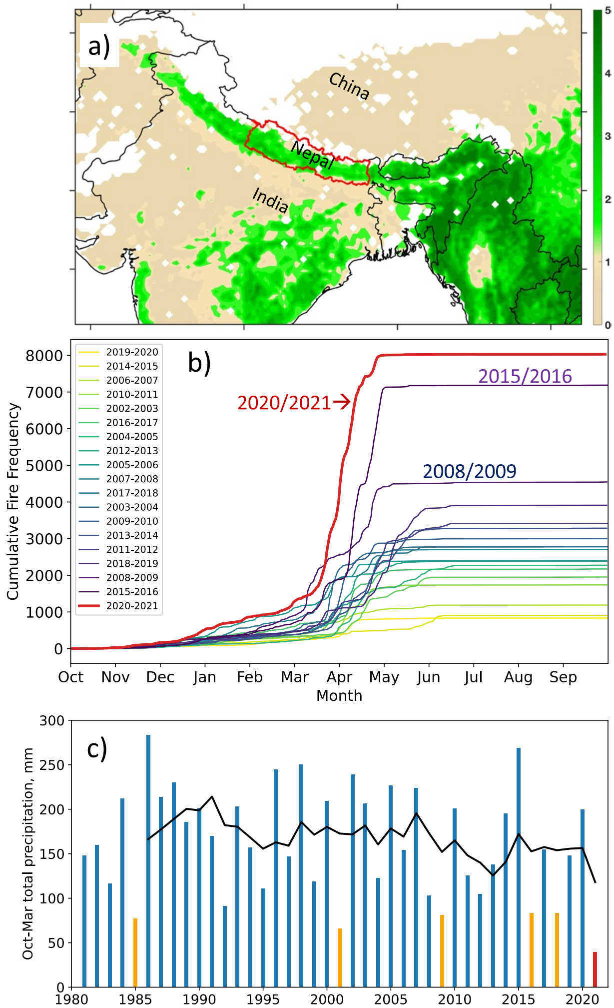

Fig. 1 **a** Average LAI from January to April over the period of 1981–2010 in the southern Himalayas, **b** cumulative fire detections from Aqua and Terra MODIS from 2002/2003 to 2020/2021, and **c** total precipitation from October to March based on rain gauge data in Nepal. The black line in lower panel **b** indicates the 6-year moving average; the orange bar indicates drought defined as precipitation less than 15 mm; and the red bar indicates the 2020/2021 drought

2.2 Observational data

More than 300 climatological stations in Nepal are maintained by the Department of Hydrology and Meteorology (DHM). Some of these stations were established after 2000 and do not feature continuous climate data (Sharma et al. 2020a). After screening all available climatological stations, 117 stations were identified in which both temperature and precipitation data we recorded on at least 80% of the days in the record from 1980 to 2021. From these data, annual, seasonal, and monthly averages of temperature and totals for precipitation have been computed. The stations are unevenly distributed, with greater density in the lower-lying southern areas of the country and increased scarcity over the mountainous northern regions (Chen et al. 2021). Such a paucity of coverage that is not uncommon in many mountainous regions of the world (Sun et al. 2018). Due to its ruggedness and sparse population, remote sensing is the only long-term observational data set available to study wildfire characteristics in Nepal and the Himalayan region (Bhujel et al. 2022; Matin et al. 2017; Qadir et al. 2021).

Various drought indices are used to quantify drought and its relationship with fire occurrence or intensity (Littell et al. 2016) including the Palmer drought severity index (PDSI) (Littell et al. 2009; Miller et al. 2012) and the standardized precipitation index (SPI) (Riley et al. 2013), as well as relationships with key meteorological variables such as precipitation and temperature (Littell et al. 2009, 2016; Morgan et al. 2008). Vapor pressure deficit (VPD), a composite variable that includes air temperature and relative humidity, has emerged as one of the most reliable indicators of fire conditions (Chiodi et al. 2021; Seager et al. 2015; Williams et al. 2014). However, in Nepal, only temperature and precipitation variables are available in long-term measurement networks. Thus, to analyze the relationship between drought and fire potential, we used the standardized precipitation and evapotranspiration index (SPEI), because it could be calculated from the available meteorological variables in Nepal's in situ measurement network. SPEI also has a simpler methodology that provides robust results (Liu et al. 2018; Vicente-Serrano et al. 2010), and it overcomes some of the known limitations of the SPI and PDSI. Here, SPEI is calculated using a time series of precipitation and potential evapotranspiration (PET) as introduced by Vicente-Serrano et al. (2010). PET is calculated using the Thornthwaite method (Thornthwaite 1948), which uses only temperature and has been widely used in previous studies in Asia (Talchabhadel et al. 2019; Van der Schrier et al. 2011). Other methods for calculating PET are considered superior to the Thornthwaite method (e.g., Penman–Monteith); those methods require more variables (e.g., relative humidity) and thus are not adopted here. The Thornthwaite method has been used effectively for several drought and fire studies in Nepal (Hamal et al. 2020b, 2021; Sharma et al. 2021). Here, we considered three different timescales, monthly (SPEI-1), seasonal (SPEI-3, SPEI-6), and annual (SPEI-12), to compute the drought indices. A summary of all observational data used in this study and explained here is given in Table S1 and includes the data periods of record, temporal and spatial resolutions, and data sources.

2.2.1 Fire data

To depict active fire points in Nepal, we used the Moderate Resolution Imaging Spectroradiometer (MODIS) (Aqua and Terra combined) active fire detection products (data accessed from: https://firms.modaps.eosdis.nasa.gov/active_fire/) (Giglio and Justice 2020). These data sets include latitude and longitude at the center of the pixel where the fire is detected, the retrieved fire radiative power (FRP), and the fire detection confidence level that is provided as a percentage. We only used data with a confidence level of 30% or greater, assuring fewer false detections. The combined MODIS data are available from 2002, and burned area product are used in this study simply for a qualitative assessment of wildfire and not for the wildfire-drought analysis. This is because MODIS detects active fire points and not individual fire events; thus, one large fire can consist of many active fire points. As the Pearson correlation coefficient between burned area and active fire points from November through March is 0.96 during 2002—2021, we use daily active fire points as an analog for burned area.

2.2.2 Fire weather index

To analyze the relationship between climate and fire weather conditions in Nepal, we use the fire weather index (FWI) from the Canadian National Wildfire Coordinating Group (Van Wagner et al., 1987), calculated from ERA5 reanalysis data (Vitolo et al. 2020). The FWI estimates the atmosphere's impact on fire weather through wind, temperature, humidity, and precipitation. It also accounts for the impact of the atmosphere on fuel moisture at three subsurface levels. Generally, an increase in the depth and compactness of fuel moisture results in a slower response to atmospheric forcing (Vitolo et al. 2020). The FWI is then produced from an integration of fire spread potential due to fuel moisture and surface winds, along with the potential heat release in heavier fuels, resulting in a unitless index of extreme fire behavior potential (Van Wagner 1987). These data are available from the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/).

2.2.3 Aerosol observations

We used the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) Level 2 vertical feature mask product derived from lidar backscatter measurements (Han et al. 2022; Yao et al. 2018). The CALIPSO product provides vertical profile information about aerosol subtypes and the location of each aerosol layer at a resolution of 30 m vertical and 333 m horizontal, up to an altitude of 8.2 km (Omar et al. 2009; Winker et al. 2007). This information is crucial to the identification of the distribution, transport, and dominant types of aerosols and is also used to observe particulate matter concentration, forest fire, and black carbon globally (Shikwambana 2019; Yao et al. 2018). In this study, we use the latest version (4.21) of the standard vertical feature mask, which classifies tropospheric aerosols into seven subtypes (e.g., dust, polluted dust, clean continental, polluted continental/smoke, elevated smoke, clean marine, and dusty marine) based on combined lidar measurements and surface type (Kim et al. 2018; Omar et al. 2009).

2.2.4 Leaf area index

Vegetation plays a key role in land-atmospheric interactions through evapotranspiration and controls the amount and type of fuel for wildfire. To evaluate how changes to vegetation during the past three decades may have contributed to the 2020–21 fire season, we employed the MODIS leaf area index (LAI), which is defined for broadleaf canopies as the one-sided green leaf area per unit ground area and in coniferous canopies as half the total needle surface area per unit ground area (Myneni et al. 2015). We considered LAI data from a global reanalysis of vegetation phenology (Stöckli et al. 2011) to analyze the vegetation coverage climatology in Nepal.

2.2.5 Sea surface temperature

The relationship between sea surface temperature (SST) variability and fire weather in Nepal was assessed using correlation analysis of monthly optimum interpolation SSTs and local fire weather from the FWI. Monthly SST data at 1° horizontal resolution was obtained from the National Oceanic and Atmospheric Administration with a consistent data record available from 1979 through near-present (Reynolds et al. 2002).

2.3 Climate model projections

We use the Coupled Model Intercomparison Project Version 6 (CMIP6) ensemble with the historical, natural, and SSP585 high-emissions future scenario. We utilize two different CMIP6 products. The first one is the high-resolution, bias-corrected downscaling data generated by Mishra et al. (2020) for South Asia consisting of 13 models (hereafter high-resolution CMIP6). They used the output from 13 CMIP6-GCMs of daily precipitation, maximum temperature, and minimum temperature for the historical and four scenarios (SSP126, SSP245, SSP370, SSP585), which are available at different resolutions. For the downscale and bias correction, empirical quantile mapping (EQM) was applied to statistically downscale the daily maximum and minimum temperatures and precipitation for South Asia and Indian sub-continental river basins. A non-parametric transformation approach has shown better skill in comparison to parametric methods in reducing biases from GCM as well as regional climate model (RCM) outputs. Observations for the three variables at the resolution of 0.25–degree are obtained from the India Meteorological Department (IMD) for the Indian Region and Sheffield et al. (2006) for grid-points within and outside India, respectively, used for bias-correction. The high-resolution CMIP6 data are considered for the historical simulation of 1951–2014 and high-emission scenario (SSP585) future projection of 2015–2100, considering 13 models (Table S2). The high-resolution CMIP6 monthly mean temperature and precipitation were further bias-corrected for Nepal with respect to the observed data by following the methods of Hawkins et al. (2013) that used “delta” (change factor) and “nudging” (bias correction) approaches. We then calculate the SPEI and estimate the future fire projection under the SSP585 scenario, based on the statistical relationship of SPEI-3 and active fire points.

The second version of CMIP6 data has a coarser (original) spatial resolution, and it includes two more single-forcing runs: all-forcing (historical) and natural (without anthropogenic greenhouse gas emissions) runs. This coarser-resolution CMIP6 data set contains twelve models with 68 and 50 ensembles for the all and natural forcing runs, respectively (Table S3). Using this coarser-resolution CMIP6 allows for future examination on the climate change signal and provides a comparison with the historical fire record. Here, we compare the SPEI-1 and SPEI-12 in the all-forcing and natural runs from 1981 to 2014 that are computed from each ensemble member using low-resolution CMIP6 data. We are limited here by the availability of bias-corrected downscaled products as they are usually confined to the historical all-forcings and future scenario experiments. However, in a previous analysis of PDSI in North America, bias correction substantially increased projected future drought (Wehner et al. 2011). We do not expect that SPEI trends would behave differently; hence, the native resolution CMIP6 results could be considered a conservative estimate of the anthropogenic influence on SPEI. Readers may consider this coarser-resolution CMIP6 data as a supplemental analysis for climate attribution purposes.

2.4 Non-linear fire prediction

The empirical relationship between SPEI-3 and active fire points in Nepal, together with the ability to calculate SPEI-3 from near real-time temperature and precipitation data from Nepal’s weather stations, makes antecedent SPEI-3 a potential predictor for fire activity with 1- to 2-month lead time. Empirical prediction is computationally inexpensive in depicting large-scale burned areas (Eden et al. 2020; Turco et al. 2018). After comparing various regressive models and accessing their skill (see example in Fig. S1), we found a non-linear regression model (also known as exponential regression) that shows the best skill in using SPEI-3 as a predictor to predict the March and April active fires (Fig. 4b), as follows:

$$March\ active\ fire\ points(t) = 200 * e^{-\beta * SPEI3(t)} + 150 + \varepsilon,$$

$$April\ active\ fire\ points(t) = 150 * e^{-\beta * SPEI3(t)} + 700 + \varepsilon,$$

where β is a regression coefficient, e is Euler's number, t is the year, and ε is the error term. Here, we use January and February SPEI-3 to predict March active fire points, while February and March SPEI-3 are predictors for April active fire points. The β parameter is optimized so that the sum of the squared residuals is minimized for a given intercept and alpha value. The optimization of β is done using the Python package SciPy and its optimizing curve fitting function (https://docs.scipy.org/). As a single parameter can be optimized for user specified α and intercept values, we iteratively fit the non-linear regression model for alpha values and intercepts ranging from zero to 1000 at intervals of 50 to find the combination of alpha and the intercept that yield the lowest residual standard error. The model is cross-validated using leave-one-out and leave-three-out cross-validation practices (Wang et al. 2017). The leave-three-out technique involves iteratively removing 3 consecutive years from the observed data and training the model with the remainder. For a measure of fit of these non-linear regressions, we employ a pseudo-R^2 value from Schabenberger and Pierce (2001), which is calculated by subtracting one by the dividend of the sum of squares of the residuals by the total sum of squares (sum of the squared distance between observations and the mean). While this pseudo-R^2 ("hereafter" pR^2) provides a sense of model fit, it cannot be interpreted as the percent of variance explained by the regression model (Schabenberger and Pierce 2001). Additionally, we include the standard error of the residuals, along with mean bias, which is obtained by calculating the percent difference between the average predicted fire points and observations.

3 Results

3.1 Putting the 2020–2021 drought and fire into perspective

Fire events in Nepal from 2002 through 2021 can be observed through the cumulative fire frequency in Fig. 1b suggesting that the 2021 fire events were anomalous, with more than 8000 detections counted through April. By January, the accumulated count exceeded the 20-year average, and by mid-March, it exceeded all other years. As was the case in other years, including two other notably anomalous fire seasons, 2008–2009 and 2015–2016, fire activity declined soon after the summer monsoon season began. October through March total precipitation from 1980 to 2021 indicates that, as was especially evident during 2020–2021, drought was present during the 2008–2009 and 2015–2016 seasons (Fig. 1c). This demonstrates the likelihood that low precipitation in October–March can enhance the number of fire events during the pre-monsoon season. Figure 2a shows the widespread nature of fire detections, ranging from the lowlands to the mid-hills during 2 days

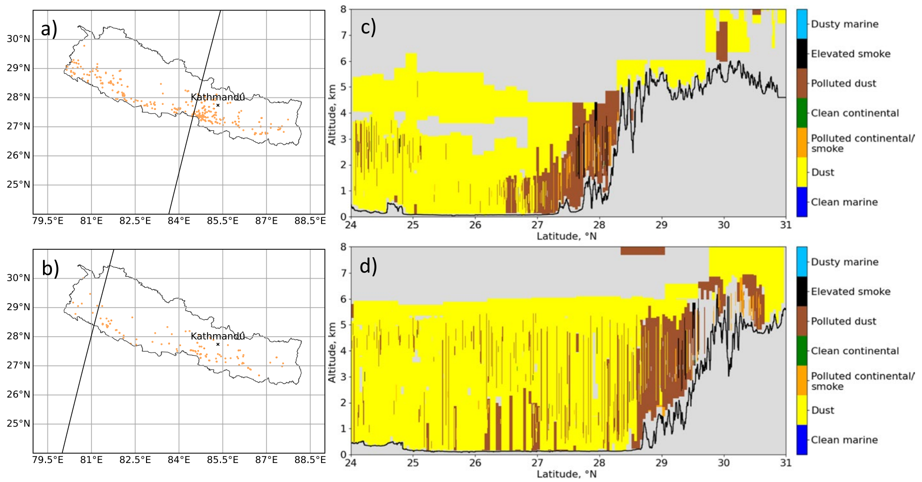

Fig. 2 MODIS fire detections (dots in left panel, **a** and **b**) and vertical distribution of aerosol subtypes, which are depicted with different colors from CALIPSO measurements (right panel, **c** and **d**). Upper and lower panels are based on 25 March and 28 March 2021 measurements, respectively. The orbital path of the CALIPSO satellite is shown by the red line in **a** and **b**

in late March, a period when numerous uncontrolled fires were burning across Nepal. At this same time, CALIPSO data indicates dust and smoke reached up to 8 km in elevation, depositing pollutants throughout the Himalaya region (Fig. 2c–d).

Preceding these events, a negative SPEI that was more than twofold the long-term average was observed beginning in November 2020 (Fig. 3a, top). Excessively dry conditions persisted through April (Fig. 1b). In each of these months, the number of fires was well above the long-term average (Fig. 3a, bottom). Between 2002 and 2020, the sum of active fire points from November through April averaged 2,327; this 6-month total was exceeded in March of 2021 alone. It then doubled again in April. Fire activity was highest in Nepal's western lowlands, the region immediately southeast of the Annapurna Conservation Area, and the countryside surrounding the Kathmandu Valley. Both regions saw a tenfold increase in the active fire points in 2020–2021 compared to the long-term mean (Fig. 3b).

This record-setting fire season corresponds to an environment with increasing fuels. An analysis of leaf area index (LAI), obtained from a global reanalysis of vegetation phenology, indicates that the January–April average of LAI increased by about 10% during 1981–2010 (Fig. 3c). Satellite-derived LAI change from 2003 to 2020 indicates a continual increase following that trend (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), suggesting greater fuel availability now than 30 years ago.

Next, we examined the non-linear relationships between March fire detection points and seasonal precipitation deficits and drought as outlined in Sect. 2.4. Figure 4a shows a robust regression skill between SPEI and fire, ranging from a strong relationship ($pR^2 > 0.3$), when November and December precipitation are considered, together to a very strong skill ($pR^2 > 0.7$) when January and February are included. Including the months of March and April nominally strengthens the relationship (Fig. 4a, center). However, the relationship between the active fire points and March SPEI-3 appears best quantified by a non-linear, or exponential, model (Fig. 4b) based on the November–March total active

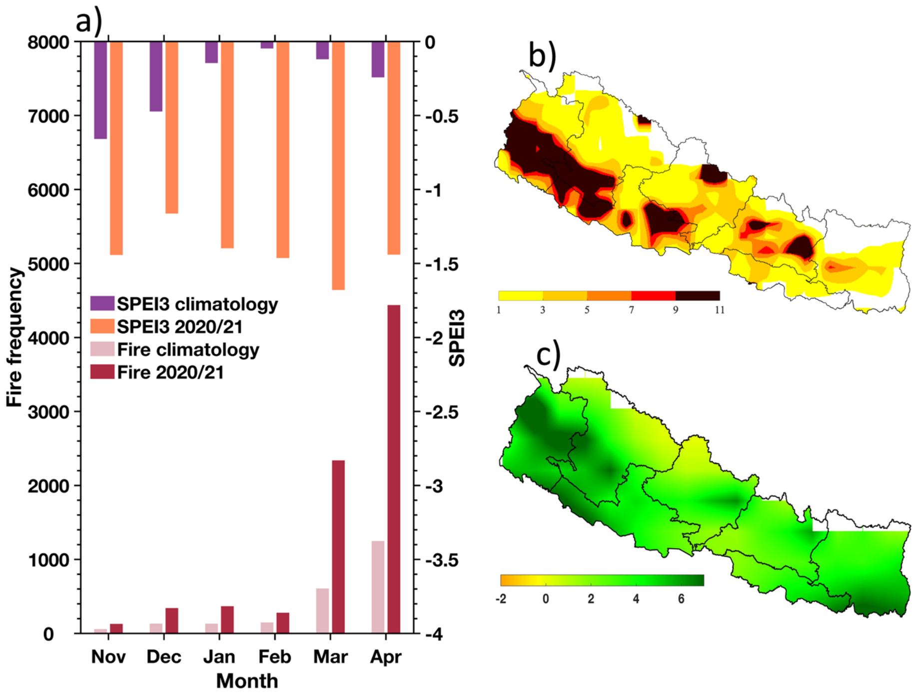

Fig. 3 MODIS (Aqua and Terra satellite) measured fire detection points, leaf area index (LAI) and observed SPEI3. **a** Total monthly fires during 2020–2021, long-term average fires from 2002 to 2020, the SPEI 3-month drought index for November through April during 2020–2021, and SPEI3 long-term average in Nepal. **b** Ratio of the active fire points in 2020–2021 to the long-term average (2003–2020) for November through March. **c** Change in LAI (%) from 1981 to 1990 compared to 2001–2010

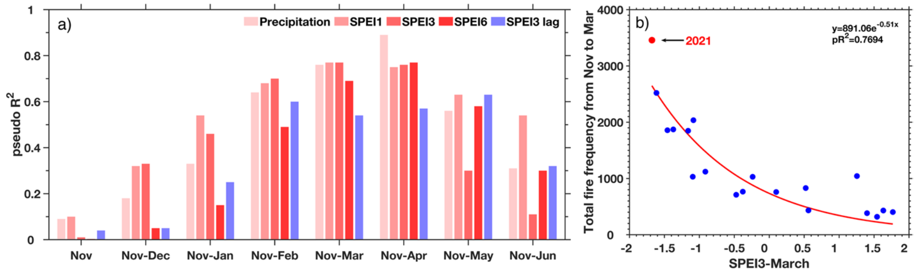

Fig. 4 The relationship between 2002–2020 monthly precipitation deficits and subsequent active fire points in Nepal. **a** shows the skill of regression (pseudo-R^2) between the total active fire points, starting in November, and average precipitation from the preceding month, average SPEI-1 from October to a given month, a given month's SPEI-3, and preceding month lag for SPEI-3 from left to right, respectively. For example, November fire is regressed with SPEI-1 and precipitation averaged for October and November, November–December fire is regressed with SPEI-1 averaged for October, November, and December. Fire for Nov is regressed with SPEI-3 of November, fire for Nov-Dec is correlated with SPEI-3 of December, and so on. Similarly, November fire is correlated with SPEI-lag (SPEI of October), November–December fire is regressed with SPEI-lag (November SPEI-3), and so on. **b** shows the scatter plot relationship between November-March total active fire points and the SPEI-3 in March and the non-linear regression fit (red line); 2021 is highlighted via an arrow

fire points. The record number of active fire points in 2021 was associated with the most severe SPEI-3 values observed in the past 18 years and closely follows the best-fit line from non-linear regression (Fig. 4b). The fire prediction model for each month from January to May, with a lead time of 0 and 1 month, performs well as indicated by small bias and high pR^2 (Table 1). However, the bias is greater during the high-fire months (March and April). Regardless, drought quantified by SPEI-3 strongly fits fire detection points over Nepal, a relationship that is comparable with different forests/climates like California (Son et al. 2021b) and is consistent with studies connecting global wildfire and VPD (Abatzoglou et al. 2021, 2018).

3.2 Attribution of the drought trend

The identified association between drought and wildfire in Nepal indicates that the observed increase in drought is partially responsible for the enhanced wildfire potential. We note that SPEI-1 and SPEI-12, which both exhibited fluctuating but predominantly positive values between 1981 and 2005, have been mostly negative ever since (Fig. S2), underscoring the long-term drought trend. However, low-frequency climate variability can also result in prolonged drought conditions over Nepal (Wang and Gillies 2013). To address this, we evaluated the role of anthropogenic climate change to determine if these trends are associated with changes to the climate mean state, using the low-resolution CMIP6 ensemble (Table S3) of all-forcing experiments. This analysis is based on the multi-model and multi-realization average of the 1980–2014 trends of SPEI-1 and SPEI-12. The SPEI-1 and SPEI-12 trends were calculated from individual model ensembles (Table S3) before being averaged for the ensemble means. The historical simulations of SPEI-1 and SPEI-12, which included all anthropogenic forcings, are substantially negative. Histograms comparing trends from the 68 "historical" simulations to the 50 "natural" ones, as shown in Fig. 5, reveal a shift toward negative values when anthropogenic forcings are included in the simulations. While there is considerable overlap between these distributions, a Student's t test ($p<0.01$) indicates they are statistically distinguishable. Within either of these distributions, the observed 1980–2014 annual trends are low-probability events, and the longer observed 1981–2020 annual trends are even lower. But as the likelihood of the observations is higher in the simulations, including anthropogenic forcing, than it is without, we conclude that anthropogenic climate change has contributed to the drying trend in Nepal during the winter-dry season. While these low-resolution CMIP6 results are not bias-corrected, Wehner et al. (2011) found that bias correction increased simulated drought trends, not decreased. Hence, our conclusion of an attributable human influence on SPEI trends is likely conservative. This result is

Table 1 Statistics and parameters of the non-linear regression models (exponential model) used to predict from January to May active fire points at 0- and 1-month leads Bias for the cross-validation techniques is obtained by determining the percent difference between the average predicted active fire points and monthly observations from 2002 and 2020

Month (SPEI3/fire)	Model	pR^2	Bias (%)
Jan/Jan	$y=94.993e^{-0.419x}$	0.45	−18.5
Jan/Feb	$y=114.51e^{-0.46x}$	0.76	44.13
Feb/Feb	$y=120.89e^{-0.46x}$	0.74	−4.25
Feb/Mar	$y=417.92e^{-0.721x}$	0.68	289.19
Mar/Mar	$y=444.59e^{-0.712x}$	0.55	−19.35
Mar/Apr	$y=992.18e^{-0.602x}$	0.77	−167.74
Apr/April	$y=885.32e^{-0.714x}$	0.44	−21.21
April/May	$y=188.52e^{-0.801x}$	0.14	73.84
May/May	$y=188.07e^{-0.482x}$	0.33	39.18

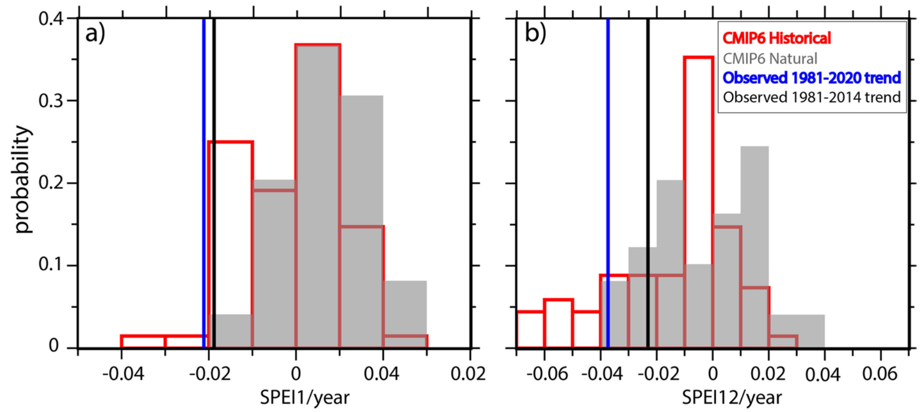

Fig. 5 Histograms of CMIP6 simulated 1981–2014 trends in October–March SPEI-1 (**a**) and annual SPEI-12 (**b**). Red bars are the all-forcing runs, and gray bars are the natural runs. The observed trends over this simulation period are shown as a black vertical line, and the observed trends are shown as a blue vertical line

also comparable to previous work based on earlier-generation simulations of CMIP5 (Wang et al. 2013).

Given the observed relationship between SPEI-3 and seasonal wildfire detections (Fig. 4) and the role of anthropogenic warming on drought (Fig. 5), we next provide a simple projection of fire activity in Nepal. This projection is based on the calculation of SPEI-3 from the high-resolution CMIP6 ensemble of the historical and high-emission scenario (SSP585) simulations. To calculate SPEI-3, model monthly precipitation and temperature were used for each member from high-resolution CMIP6 data. The CMIP6 SPEI-3 was then used to estimate the November–March active fire points using the regression model from Fig. 4b. The interquartile range (IQR) and median is calculated based on the active fire points of all ensembles. The CMIP6 ensemble mean of March SPEI-3 from historical period (1980–2014) and under the SSP585 warming scenario (2015–2100) and its multi-model spread (Fig. 6) indicates a distinct decreasing trend that began in the early twenty-first century and is projected to continue through the end of the twenty-first century. This indicates longer periods of increasingly severe drought. Based on statistical modeling, the derived active fire points in association with drought are also projected to increase, a trend that prior research has indicated to be driven by climate warming, which will lower fuel moisture in Nepal (Hamal et al. 2022). Notably, the spread of fire anomalies across individual CMIP6 model projections becomes amplified. However, readers should not directly compare CMIP6 data to the 2021 fire season because the historical CMIP6 simulations end in 2014; thus, it is unclear whether CMIP6 would have reflected the severity of that event.

The statistical nature of this future assessment and the single predictor of SPEI-3 for wildfire detections warrant further caution, as well. Many factors, including fire suppression strategies, available fuels, land-cover change, and vegetation type, distribution, and density can also impact wildfire metrics (as measured through active fire detections and burned area) and how fire behaves and ultimately spreads (Abatzoglou et al. 2021, 2018; Littell et al. 2018). These factors are not included in the presented model. Additionally, as

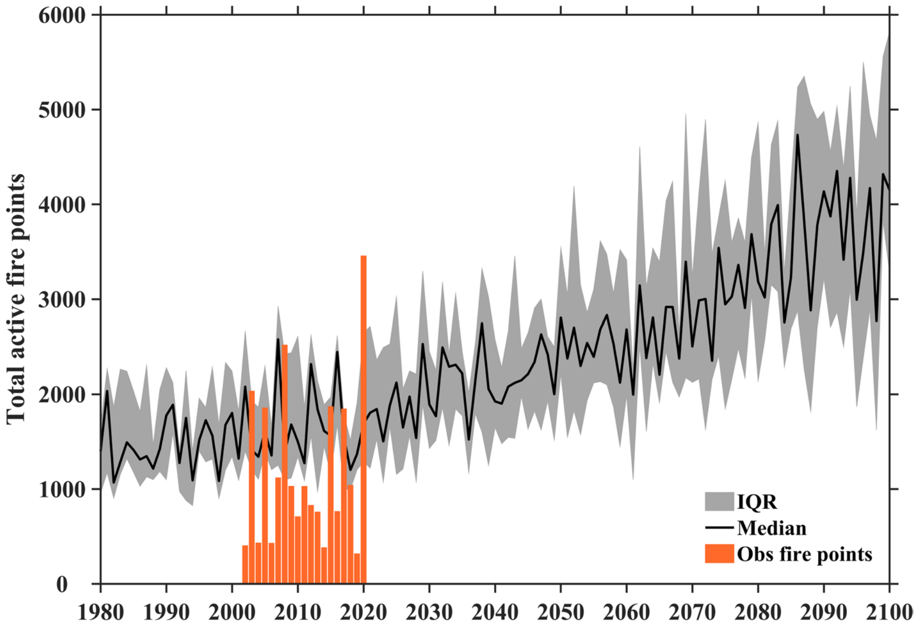

Fig. 6 CMIP6 historical and future projection of active fire points from November to March over Nepal with observed fire (orange bars)

the spread of active fire points grows with time, its cause may increasingly come from the diverged future conditions between ensemble members or the extremes of exponential relationships (Abatzoglou et al. 2018; Littell et al. 2018). Regardless, the signal of anthropogenic warming on drought and the fire points it derives is robust and is likely to increase beyond historical levels.

3.3 Sub-seasonal predictability

Using non-linear regression, Fig. 7 depicts the one-month predictions of fire points in March (Fig. 7a) and April (Fig. 7b) using SPEI-3 from February and March, respectively. Active fire points in March and April are highly predictable at the 1-month lead, but the 2-month prediction lacks skill for both months (Fig. S1). The regression model has good skill for the cross-validation as well, with the leave-one-out and leave-three-out methods producing similar results to the hindcast; the summary statistics of residual standard error and mean bias are provided in Table S4. These regression models predicted the increased fires in March 2021 but fell short of its record-setting magnitude (Fig. 7a). This shortcoming is mostly likely caused by non-climatic factors, such as fuel characteristics, frequency of human ignitions, suppression, fire behavior in complex terrain, and vegetation distributions and response to climate change, as well as the inability of SPEI-3 alone to account for fuel moisture and abundance at finer scales. Regardless, the fact that these simple regression models show good skill for most fire years (high pseudo-R^2 values, low error, and bias) suggests this simple method of assessment offers potentially useful fire outlooks for March and April in Nepal, peeking into the following month's wildfire tendency.

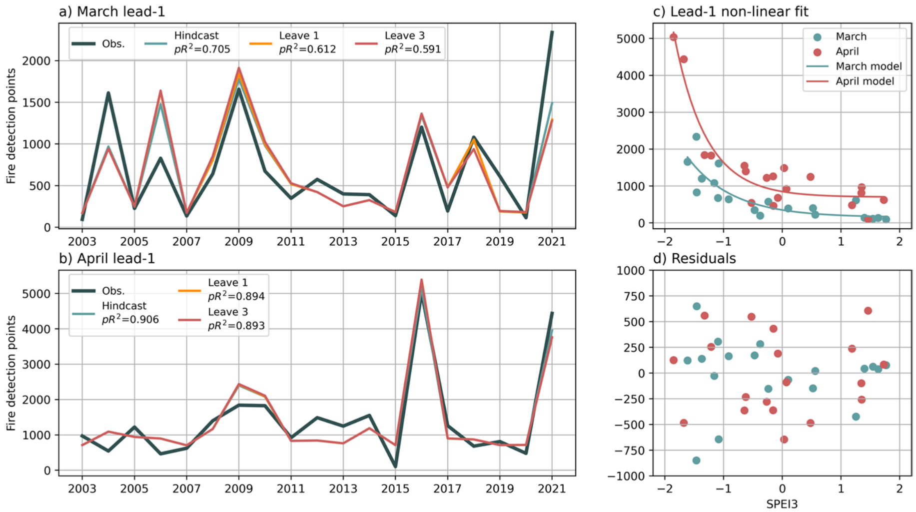

Fig. 7 One-month lead, cross-validated hindcasts of March (**a**) and April (**b**) fire detection points from non-linear regression with SPEI3 as the independent variable. Leave-one-out and leave-three-out cross-validated models are shown in orange and red, respectively. Pseudo-R^2 values are included in the figure legend for (**a**) and (**b**). The scatter plot of March and April fire detection points is included in (**c**) along with the fitted relationships from non-linear regression (solid lines). Panel (**d**) shows the well distributed residuals from non-linear regression

3.4 Interannual variation

While the 2020–2021 fire season appears to have been exacerbated by climate change, climate variability likely played an important role in the seasonal drought conditions. Historically, Nepal's winter climate variability correlates with the El Niño and La Niña events (Hamal et al. 2020a). Further analysis shows that the global sea surface temperature anomalies (SSTA) from November 2020 to March 2021 outlines a canonical La Niña pattern in the equatorial Pacific Ocean (Fig. 8a), while the SSTA correlation maps with March FWI in Nepal (Fig. 8b) and "reversed" March SPEI-6 (Fig. 8c) demarcate clear La Niña features that bear a marked resemblance with the 2020–2021 SSTA structure. El Niño and La Niña teleconnections have strengthened in an anthropogenically driven warming climate (Stevenson et al. 2012; Wang et al. 2015). Thus, the increasing spread with time in the projected fire activity (Fig. 6) may be partially attributed to natural variability and amplified by global warming. In addition, persistent warming in the Indian Ocean has acted to enhance the winter drought trend in Nepal through modifications of the local Hadley circulation, which strengthens subsidence over northern India and the Himalaya region (Wang et al. 2013). In 2020–2021, warm SSTA were observed in the Northern Indian Ocean (Fig. 8a), strengthening the subsidence in Nepal (figure not shown).

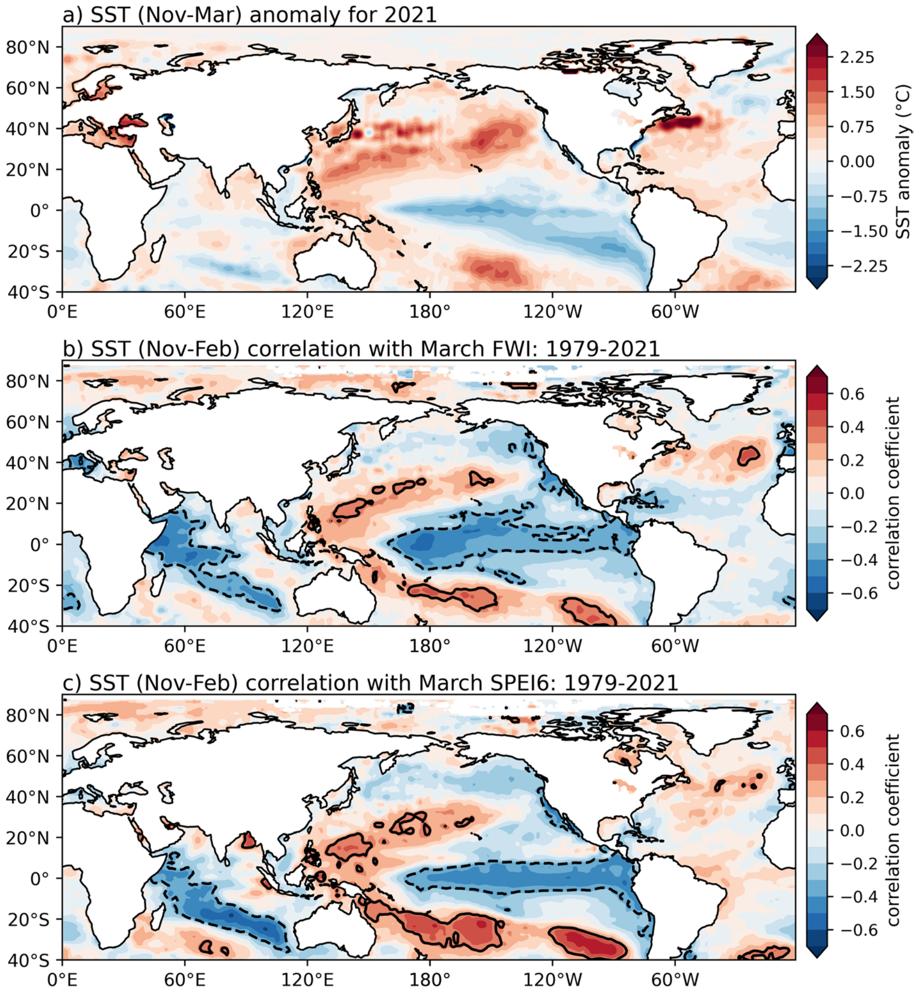

Fig. 8 Sea-surface temperature (SST) anomalies over the Northern Hemisphere. **a** shows the average SST anomalies from November through March 2021. **b** and **c** show SST (November–February) Pearson correlations with the March fire weather index (FWI) and March SPEI6, respectively. The correlation analysis in **b** and **c** was applied on data from 1979 to 2021, and area under black dashed line represents the significant values with $p < 0.05$ (2-tailed). SPEI6 is multiplied by -1 for sign consistency

4 Discussion

Decades of increasingly prolonged and severe droughts since 2000 (Fig. S2) appear to be leading to an unintended consequence of increased wildfires, a situation that may be being exacerbated by well-intentioned community-led efforts to re-forest Nepal. Given that fires in Nepal are managed by communities rather than a centralized agency, with no national-level policy or plan for forest fire management, an increase in forest fires poses a significant challenge to the effectiveness of community management (Sapkota et al. 2015). While the Nepal Army is often mobilized if a fire threatens settlements, there is no dedicated team to suppress wildland fires in Nepal, and local community members are often trained as firefighting volunteer groups at the district or village level (Matin et al. 2017; Parajuli et al. 2022). Assuming that there is no significant change in these policies at a national level, community-based fire management capacity will be critical to control and, when needed, to suppress wildfires in Nepal to ensure successful and sustainable forest management (Parajuli et al. 2022), and these ad hoc groups may benefit from easily derived prediction metrics and a reference of early warming.

Qadir et al. (2021) developed a fire forecast model for Nepal that used multiple sources of satellite data. They found that temperature and precipitation are key factors for forest fire occurrence. However, our statistical model is much simpler than the Qadir et al. (2021) model and can potentially predict the anomalous fire activity 1–2 months earlier. Matin et al. (2017) also indicated three main factors for the forest fire in Nepal that include temperature, fuel availability, and ignition potential. These studies highlight drought factors as key environmental components of wildfire in Nepal. The main limitations of our study are that we did not consider fuel types, fire behavior, fire suppression, or ignitions, and these are among the many factors that could impact future predictability using our statistical model, which is dependent upon the stationarity of the previously observed relationship between between SPEI and fire activity. In future work, we plan to improve the fire prediction model by considering these other factors to further inform fire management strategies.

Previous studies on wildfire in Nepal have mainly focused on fire climatology, forest mapping, and factors affecting forest fire management (Parajuli et al. 2020; Sapkota et al. 2015), and, as far as we know, no previous work has utilized a climate projection model approach to provide insight about the future of forest fires in Nepal. The projections in this study should nonetheless be interpreted with caution, owing to substantial uncertainty at local scales in climate model projections, particularly in complex terrain such as the Himalayan region. Nonetheless, the CMIP6 results for Nepal echo prior research that projects declining winter precipitation under the SSP585 high-emissions scenario, alongside moderately increased monsoon precipitation (Sharma et al. 2021). 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).

5 Conclusion

Nepal's 2020–2021 fire season commenced 4 months earlier than normal, resulted in a fire detection rate 10 times greater than the long-term average, and elevated air pollution to hazardous levels. We investigated the connections between Nepal's climate and wildfires and found a strong drought-fire association in observational data that is also projected by future climate simulations. We developed a fire prediction non-linear regression model at sub-seasonal timescale and used this model to assess future trends of fire risk as inferred from projected changes in drought severity within Nepal. The historical climate model simulations also indicate that climate change likely bore significant responsibility for the prolonged drought conditions that led to the exceptional 2020–2021 fire activity. While forewarning a likely reoccurrence of intensified fire seasons in Nepal through the end of the twenty-first century (if anthropogenic climate change continues along a high emissions scenario), this research also proposes a simple, accessible statistical model for sub-seasonal fire activity prediction that warrants future research and may offer actionable opportunities for preparation, mitigation, cooperation, and capacity-building in a nation in which forest management is handled at the community level. We suggest that simple predictive models can be employed to aid national fire watch efforts on a monthly basis, since 58% of the fires in Nepal were started intentionally by people (Kunwar and Khaling 2006). Taking these factors into account, changes to community management in response to sub-seasonal drought forecasts might mitigate the fire hazard during anomalously dry conditions.

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Data availability MODIS active fire point 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 Mishra et. al. (2020) and can be freely accessed from https://doi.org/10.5281/zenodo.3987736. CMIP6 GHG and Natural run data are freely available at https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6. Ground-based raingauge data can be purchased from the Department of Hydrology and Meteorology, Government of Nepal (DHM, www.dhm.gov.np/) by email to the data section (metdatadhm@gmail.com). Rain gauge data are available in daily and monthly timescales.

Declarations

Conflict of interest The authors declare no competing interests.

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