Monitoring fire regimes and assessing their driving factors in Central Asia postprint

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Abstract

Relatively little is known about fire regimes in grassland and cropland in Central Asia. In this study, eleven variables of fire regimes were measured from 2001 to 2019 by utilizing the burned area and active fire product, which was obtained and processed from the GEE (Google Earth Engine) platform, to describe the incidence, inter-annual variability, peak month and size of fire in four land cover types (forest, grassland, cropland and bare land). Then all variables were clustered to define clusters of fire regimes with unique fire attributes using the K-means algorithm. Results showed that Kazakhstan (KAZ) was the most affected by fire in Central Asia. Fire regimes in cropland in KAZ had the frequent, large and intense characters, which covered large burned areas and had a long duration. Fires in grassland mainly occurred in central KAZ and had the small scale and high-intensity characters with different quarterly frequencies. Fires in forest were mainly distributed in northern KAZ and eastern KAZ. Although fires in grassland underwent a shift from more to less frequent from 2001 to 2019 in Central Asia, vigilance is needed because most fires in grassland occur suddenly and cause harm to humans and livestock.

Full Text

Preamble

Monitoring Fire Regimes and Assessing Their Driving Factors in Central Asia

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Abstract

Relatively little is known about fire regimes in grassland and cropland ecosystems in Central Asia. In this study, we measured eleven variables characterizing fire regimes from 2001 to 2019 using burned area and active fire products obtained and processed from the Google Earth Engine (GEE) platform. These variables describe the incidence, inter-annual variability, peak timing, and size of fires across four land cover types (forest, grassland, cropland, and bare land). We then applied the K-means algorithm to cluster these variables and define distinct fire regime clusters with unique fire attributes. Our results demonstrate that Kazakhstan (KAZ) is the most fire-affected country in Central Asia. Fire regimes in cropland in KAZ exhibit frequent, large, and intense characteristics, covering extensive burned areas with long durations. Grassland fires primarily occur in central KAZ and are characterized by small scale but high intensity, with varying quarterly frequencies. Forest fires are mainly distributed in northern and eastern KAZ. Although grassland fires in Central Asia have shifted from more to less frequent between 2001 and 2019, continued vigilance is needed because most grassland fires occur suddenly and cause significant harm to humans and livestock.

Keywords: fire regime; burned area; active fire; K-means algorithm; Central Asia

1 Introduction

Fire regimes can be generalized as a particular combination of fire characteristics, including frequency, intensity, variability, seasonality, size, extent, duration, and spatial pattern [?, ?]. With global climate change, the increasing frequency of extremely dry weather, unreasonable human use of fire, and growing instability of factors influencing fire regimes, fire regimes are becoming topics of worldwide concern due to the series of social, environmental, and economic problems they cause [?, ?, ?]. Fire also poses serious threats in Central Asia, particularly in Kazakhstan (KAZ). To better understand and manage fire regimes, there is growing interest in monitoring fire distribution and assessing potential drivers [?, ?]. However, to date, large-scale schemes for characterizing fire regimes are limited, and few studies have considered the impact of fire on grassland in Central Asia.

Data for mapping fire regimes can be obtained from historical records (interviews, diaries, and literature searches), paleoecological evidence (charcoal in lakes, soil sediments, and tree scars), and remote sensing data of fire patterns [?, ?]. Considering the integrity, availability, spatial convergence, and relative cost of these data records, satellite data are often employed for reconstructing maps of fire regimes [?, ?]. In recent years, as algorithms for mapping burned area, including MCD45A1, MCD64A1, and FireCCI5.1, have become more powerful and widely calibrated [?, ?], these products have been used to map fire regimes in real time and across spatial extents [?, ?, ?, ?], enabling extensive research on biomass burning at spatial resolutions of 500 m and approximately 250 m [?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?]. Active fire data represent the approximate central location of a fire, but cannot accurately portray the shape and size of large fires [?, ?]. Therefore, burned area products play a key role in mapping medium and large fire regimes. To address these limitations, researchers have combined active fire and burned area data to map fire regimes in numerous studies [?, ?, ?]. The Landsat satellite provides high spatial resolution, enabling fire regime monitoring using spectral indices such as the normalized burn ratio (NBR), burned area index (BAI), mid-infrared burn index, and global environment monitoring index (GEMI), allowing analysis of single fire effects through post-burn carbonization and vegetation disappearance or assessment of ecological recovery across regions [?, ?, ?, ?, ?, ?, ?, ?]. However, Landsat images are typically used to analyze differences between pre- and post-fire images in specific research regions. Due to contamination from cloud cover in Landsat images and limited time scales that cannot distinguish between new and old fire scars, MODIS (Moderate Resolution Imaging Spectroradiometer) is a more popular method for characterizing the temporal and spatial distribution of fire regimes across broad geographical regions [?, ?].

As fire has been rarely studied in Central Asia, the results of this study will help fill this research gap. In this study, we analyzed all available time series images (FireCCI5.1, Fire Information for Resource Management System (active fire data) for Central Asia in Google Earth Engine (GEE)) to: (1) develop an easy and robust method to map fire regimes; (2) apply this method to reconstruct and characterize maps of fire regimes in Central Asia; (3) analyze the monthly number of active fires in different land cover types (grassland and cropland) from 2001 to 2019 in Central Asia; and (4) discuss the impact of fire on grassland productivity, the effects of drought on grassland fires, and seasonal differences in cropland fires in Central Asia.

2.1 Study Area

Central Asia (35°07 -55°26 N, 46°29 -89°19 E) is located in the Eurasian mainland and has a semi-arid to arid climate [?, ?]. The study area includes five countries (KAZ, Kyrgyzstan (KGZ), Tajikistan (TJK), Turkmenistan (TKM), and Uzbekistan (UZB)), which are collectively referred to as Central Asia in this study. As shown by the MODIS land cover product in 2018 (Fig. 1 [Figure 1: see original paper]), approximately 75% of the land in Central Asia is covered by grassland, though coverage density is uneven based on the mean leaf area index (LAI). Forest is mainly located in eastern KAZ, northern KAZ, and Aqmola in KAZ. According to analysis of annual forest area from 2001 to 2018 based on the MODIS MCD12Q1 V6 product, the forest area in KAZ has undergone a process of large-scale deforestation followed by gradual recovery. Agriculture in Central Asia can be roughly divided into two types: rainfed cropland, mainly distributed in northern KAZ (including North KAZ, Aqmola, and Qostanay) and primarily growing wheat and barley, making this region one of the world' s most important wheat exporters; and irrigated cropland, mainly located in central and southern Central Asia [?, ?].

As indicated by long-term climate records, Central Asia is generally arid, especially in southern UZB and northern TKM where average annual precipitation is less than 100 mm, though relatively humid regions exist, such as northern KAZ (approximately 400 mm) and the eastern mountainous regions (600–800 mm) [?, ?]. In recent decades, Central Asia has experienced severe and growing water deficits with increasing temperatures and variable precipitation patterns, causing frequent drought events [?, ?, ?]. Simultaneously, unmanaged fires in cropland place great pressure on firefighting efforts in Central Asia.

Fig. 1 Main types of land use in Central Asia in 2018 (a) and fire burn scars based on Landsat 8 images in central KAZ (b–g, marked as A–F in Figure 1a). A, northeastern Aktobe; B, northeastern Aktobe; C, southern Qostanay; D, southern Qaraghandy; E, southern Qaraghandy; F, East Kazakhstan. KAZ, Kazakhstan; UZB, Uzbekistan; TKM, Turkmenistan; KGZ, Kyrgyzstan; TJK, Tajikistan. Abbreviations are the same as in the following figures.

2.2 Data Sources

Three MODIS products were used in this study: (1) MODIS active fire data from the Fire Information for Resource Management System; (2) the FireCCI5.1 burned area product; and (3) the MODIS land cover type product collection 6 (MCD12Q1 V6).

The Fire Information for Resource Management System (FIRMS) dataset contains active fire products processed by the Land Atmosphere Near Real-time Capability for EOS (LANCE) that integrate MOD14/MYD14 fire and thermal anomaly products in raster format, with the active fire location representing the centroid of a 1-km pixel [?, ?].

The FireCCI5.1 products, developed as part of the European Space Agency (ESA) Climate Change Initiative (CCI) program, are new monthly global burned area products at approximately 250 m resolution [?, ?]. To analyze fire regime characteristics including duration, size, area, variability, and seasonality, we processed burned area (FireCCI5.1) and active fire (FIRMS) products from 2001 to 2019.

The MCD12Q1 collection 6 land cover product (MCD12Q1 V6), generated using supervised classifications of MODIS Terra and Aqua reflectance data, provides annually updated global land cover data from 2001 to 2019 at 500 m spatial resolution [?, ?]. The MCD12Q1 V6 improves upon previous versions and contains five global land classification systems. We selected the International Geosphere-Biosphere Program (IGBP) classification scheme, merging its seventeen land cover classes into four vegetation types: forest, grassland, cropland, and bare land. Non-vegetation land cover types including permanent wetland, urban areas, built-up areas, permanent snow, ice, and water bodies were excluded from the study. These variables were obtained from GEE and resampled to 250 m resolution.

2.3 Methods

Eleven variables were measured to characterize fire regimes and their attributes, reflecting the timing, spatial distribution, size, and peak month of fires in Central Asia (Table 1). These attributes consider the annual average characteristics of fires, inter-annual variability, size distribution, fire duration, peak month, and vegetation effects. Variables 1, 3, and 5 were calculated using burned area data, while variables 2, 4, 6, 7, 8, 9, 10, and 11 were calculated using active fire data.

The Gini index (GI) characterizes fire size distribution by measuring the extent to which burned area is concentrated in a small number of large fires versus distributed across many smaller fires [?, ?]. A higher GI value indicates greater concentration of burned area in large fire regions. Fire duration is monitored using the confidence band of the FIRMS dataset from 10% to 90% to track the period from fire occurrence to extinction [?, ?]. The peak month of fires is calculated based on the month with the highest total number of active fires at each location from 2001 to 2019 [?, ?]. The percentage of each vegetation type affected by fire is based on the ratio of active fire counts in each vegetation type to total active fire counts in the grid cell [?, ?].

The eleven calculated indicator maps were integrated into a multiband image in GEE. The K-means algorithm for unsupervised classification in GEE was applied using 5000 sample points. By computing Euclidean distances between sample points, the algorithm groups points with smaller similarities and discrepancies into classes, forming multiple clusters where samples within the same cluster have high similarity and large differences exist among clusters. This classification method offers advantages of simple principle, easy implementation, fast convergence, and obvious inter-class differences [?, ?], making it very effective for processing high-dimensional images while conserving the original cluster structure [?, ?]. Therefore, the K-means algorithm was applied in this study.

For a given number of k clusters, the K-means algorithm classifies the data. However, selecting the appropriate number of clusters is critical for classification quality. A high k value does not necessarily signify better information quality [?, ?], while too few clusters can produce ambiguous results that fail to convey true meaning. Based on 5000 sample points from the image, we determined the optimal number of clusters through analysis to obtain the most robust K-means results. The clusGap function in the R language cluster package uses Gap statistics to determine k [?, ?] and employs bootstrap sampling of the data to compare internal differences (500 samples were selected in this study). This method is considered more effective for determining k than other approaches [?, ?]. Evaluation results were based primarily on silhouette analysis and cluster number statistics according to Gap statistics.

3.1 Characteristics of Fire Regime Variables

Figures 2 and 3 show annual fire incidence in Central Asia and its respective inter-annual coefficient of variance from burned area and active fire products. In Figure 2 [Figure 2: see original paper], ABAY (average annual burned area) reveals that the largest burned areas occurred in KAZ and the Nukus Irrigation District in UZB, with additional burned areas in the Ahal and Mary regions of TKM. KAZ experienced the most severe fires in Central Asia, particularly in eight north-central states (West KAZ, Aqtobe, Qostanay, North KAZ, Aqmola, Pavlodar, Qaraghandy, and East KAZ) and the Syr Darya and Chuhe River basins. Similarly, Figure 3 [Figure 3: see original paper] shows AFOF (average annual active fire frequency), confirming frequent fires in these areas. In TJK and KGZ, fire area and frequency were low, possibly because the FireCCI5.1 burn detection algorithm has a high threshold in mountainous areas and cannot detect active fires or burned areas there.

As expected, regions with high fire occurrence (ABAY and AFOF) generally show lower inter-annual coefficients of variance, while regions with low fire occurrence exhibit weak stability in inter-annual variability, particularly for the inter-annual coefficient of variance in active fires (CVFP). The inter-annual coefficients from different datasets in central KAZ show strong variability, while the coefficient of variation around northern KAZ is small, with the same phenomenon observed in the Chuhe River Basin in KAZ, the Nukus Irrigation District in UZB, and the Ahal and Mary regions of TKM.

In Figure 4 [Figure 4: see original paper], FPDT (peak month of fires) occurred in spring in northern KAZ (Qostanay, North KAZ, and Aqmola), the Syr Darya and Chuhe River basins in KAZ, and the Nukus Irrigation District in UZB. In summer, FPDT was mainly distributed in central KAZ, including West KAZ, Aqtobe, Qostanay, Qaraghandy, and East KAZ. Additionally, Tashkent city and the Fergana Valley in KGZ showed high-density fire regions. In TKM, FPDT was unevenly distributed and occurred mainly in winter and summer. Overall, high-density fire locations varied by month.

The FPSD (seasonal duration of fires) result is presented in Figure 5 [Figure 5: see original paper]. Regions with the longest durations in KAZ include North KAZ, Qostanay, Aqmola, East KAZ, the Chuhe River Basin, the Syr River Basin, and the border region between KAZ and KGZ. The longest durations also occurred in the Nukus Irrigation District and near Tashkent city in UZB, and in the Ahal and Mary states of TKM. Active fires in central KAZ had shorter durations. The GI (Gini index) shows high values in the KAZ region, particularly in northern Qostanay, North KAZ, Aqmola, the Chuhe River Basin, the Syr River Basin, and the border region of KAZ and KGZ, as well as in the Nukus Irrigation District of UZB. In central KAZ, low GI values indicate many small fires with more evenly distributed burned area or few fires in the region. Additionally, high GI values in parts of KGZ and TJK indicate concentrated fires with a few large fires in those regions.

Vegetation types affected by fire were derived from the annual MODIS land classification IGBP product. Forests in Central Asia are relatively sparse and less affected by fire, with major fires occurring in East KAZ and North KAZ states (Fig. 6 [Figure 6: see original paper]). The vegetation type most affected by fire in Central Asia was grassland, particularly in KAZ and in the Nukus Irrigation District and Ahal and Mary regions of TKM. Farmland burning occurred simultaneously with fires in the region, with generally high frequencies of farmland burning. The occurrence of farmland burning is extremely frequent in Central Asia, and fires in cropland differ in straw burning timing due to crop ripening variation (Fig. 6).

3.2 Clustering of Fire Regimes

Figure 7 [Figure 7: see original paper] shows that fires in Central Asia exhibit an unbalanced spatial distribution with many indicator outliers. Three variables (ABAY, AFOF, and GI) reached extreme values in few locations, indicating that burned area, frequency, and fire size in these regions were much larger or smaller than in other parts of Central Asia.

The K-means algorithm classification requires selecting an appropriate number of clusters. Gap statistics calculated by the clusGap function determine the optimal classification number. A higher silhouette value is considered a prerequisite for successful clustering [**?**, **?**], with 0.60 representing a good result \cite{Lletí et al., 2004}. Surprisingly, the silhouette value obtained in this experiment is 0.88, meeting experimental analysis requirements. After silhouette analysis, k=5 emerged as the best classification.

Based on the median tendency of eleven variables, we divided the characteristics of the five fire clusters into three to four quantitative levels, summarized in Table 2 . A map of fire regimes in Central Asia is presented in Figure 8 [Figure 8: see original paper], showing that 43% of land in Central Asia is threatened by fire. Table 2 lists five fire regime types from the clustering process:

Fire regime 1: Primarily distributed in bare land, these areas are less threatened by fire with low fire frequency, possibly due to low-density fuel beds, accounting for 57.0% of the overall fire-affected area.

Fire regime 2: This regime represents fires in cropland, including medium burned areas, frequent active fires, high inter-annual variability in burned areas, large intense fires, and low fire duration, occupying 5.8% of the overall fire-affected area in southwestern Central Asia. Peak fire months occur mainly in winter and summer, likely related to crop ripening and farming habits.

Fire regime 3: Characterized by large burned area, medium frequency and inter-annual variability of active fire, and more frequent long-duration fires in grassland in July, this regime occurs mainly in central KAZ, covering 17.9% of the overall fire-affected area.

Fire regime 4: This regime features irregular burned area, low-frequency small fires, and more grassland fires in July, with high inter-annual variability, accounting for 15.8% of the overall fire-affected area.

Fire regime 5: Mainly distributed in northern KAZ, the Syr River Basin, and Nukus Irrigation District, this agricultural area regime is characterized by large burned areas and high frequency of large, intense, long-duration fires, accounting for approximately 4.0% of the overall fire-affected area. Peak fire months occur mainly in spring.

3.3 Time Series of Active Fires in Grassland and Cropland

As grassland fires occur suddenly and are destructive, time series analysis provides valuable information for fire prevention and control. Using monthly active fire counts from 2001 to 2019 in Central Asia, we analyzed seasonal fire changes in grassland and cropland. Figure 9 [Figure 9: see original paper] shows that fire regime conditions across countries exhibit different seasonal patterns over time. Before 2010, grassland fires in KAZ were concentrated from April to October, after which active grassland fires suddenly decreased. Before 2008, KGZ had many active fires in April, August, September, and October, after which active fires gradually became more decentralized. The year 2007 was an important turning point for active fire distribution. Before 2007, active fires in TJK occurred mostly in March, while grassland fires in UZB were concentrated from March to October and active fires in TKM were mainly distributed in February-March and June-October. After 2007, active fires became concentrated in March, August, and September for TJK; March-April for UZB; and February-March for TKM. Overall, active fires in grassland have significantly decreased in recent years across Central Asia.

Figure 10 [Figure 10: see original paper] shows that all Central Asian countries practice seasonal straw burning to improve soil quality. In KAZ, straw burning occurs between April and May. In KGZ, straw burning occurs in March-April and August-October. In TKM, the straw burning period is similar to KGZ, concentrated in February-March and June-July. In UZB, this practice occurs in July. Unlike other countries, straw burning months in TJK are relatively scattered. However, straw burning not only pollutes the air but also causes large-scale grassland fires.

4.1 Impact of Fire on Grassland Productivity

Fire can quickly reduce or remove surface biomass, increase soil temperature, decrease soil water content, and affect vegetation water use efficiency [**?**, **?**]. Some scholars state that fire promotes grassland ecosystem renewal and can even create fire dependence [**?**, **?**]. In central KAZ, grasslands are frequently burned. To explore fire impacts on grassland productivity, we selected the annual MODIS net primary productivity (NPP) product (MOD17A3HGF V6) to study how vegetation NPP varies after grassland burning.

All six regions—including northeastern Aktobe (A and B), southern Qostanay (C), southern Qaraghandy (D and E), and East KAZ (F)—burned from August to September 2016 (Fig. 11 [Figure 11: see original paper]). Regions A, B, and C belong to Fire Regime 3 and are characterized by large burned areas, high-intensity, and long-duration fires. Regions D, E, and F belong to Fire Regime 4 and are characterized by irregular burned areas and small, low-intensity fires. Regions A, B, and C burned in 2016, and results show that grassland NPP began to decline in 2017, reflecting poor vegetation recovery ability. However, for Fire Regime 4, grassland NPP decreased in 2016 after burning then gradually increased, indicating that moderate-scale fires are conducive to grassland regeneration and restoration. While grassland productivity is also influenced by precipitation, temperature, grazing, and human activities [**?**, **?**], Fire Regime 4 leads to better long-term vegetation recovery than Fire Regime 3 after fire.

4.2 Seasonal Differences of Fires in Cropland

In Central Asia, active agricultural fires are closely related to straw burning. Due to large straw volumes and high transportation costs, burning is the least expensive method for straw removal after harvest [?, ?]. Burning time is closely related to local planting and harvesting schedules.

Normalized difference vegetation index (NDVI) in agricultural areas reflects crop phenological cycles from growth to ripening [?, ?]. A single crest in the time series indicates one ripening event per year, two crests indicate two ripening events, and three peaks indicate three ripening events annually [?, ?]. To explore reasons for seasonal differences in cropland fires, we obtained long-term NDVI products (MOD13Q1 V6) from GEE and plotted NDVI change trends for major agricultural regions.

Figure 12 [Figure 12: see original paper] shows single peaks in KAZ and KGZ, indicating these countries' main agricultural regions ripen once annually, explaining why straw burning occurs in spring and autumn. In UZB, the Nukus Irrigation District shows one peak, while southern Tashkent and the Fergana Valley show two peaks, indicating summer replanting when straw burning occurs. In UZB, agricultural areas with twice-yearly planting are larger than the once-yearly Nukus Irrigation District, and more fires occur in summer. Agricultural areas in TKM and TJK plant crops twice annually, and cropland fires occur twice in summer as well.

4.3 Effects of Drought on Grassland Fires

Drought is an important factor causing frequent natural fires. In drought-prone regions like Central Asia [?, ?, ?, ?], long-term high temperatures and scarce precipitation cause rapid vegetation drying, making these areas more fire-prone. To explore whether drought severity increases fire likelihood, we examined relationships between fire regime and drought conditions in KAZ grassland at annual and monthly scales. We used the Palmer Drought Severity Index (PDSI) [?, ?] because it successfully quantifies drought severity across different climates [?, ?].

Figure 13a [Figure 13: see original paper] shows PDSI changes from 2001 to 2018, with ratios of near-normal, wet, and drought years being 0.39, 0.22, and 0.39, respectively, suggesting drought dominated Central Asia during this period. To determine if higher drought degree means higher fire risk, we analyzed correlations between PDSI and annual fire accumulation frequency and cumulative area (Fig. 13b), finding that annual cumulative burned area and fire frequency in grassland do not correlate well with drought. Therefore, at annual scale, drought condition is not the main factor affecting cumulative burned area and fire frequency in Central Asian grassland.

The relationship between grassland burned area and PDSI shows that near-normal and humid conditions occurred in most months, while dry months became increasingly concentrated over time. Figure 14a [Figure 14: see original paper] shows drought concentrated from April to October, especially in June and September, consistent with high-frequency active fires in grassland (Fig.

14b). In winter, regardless of drought or wet conditions, grassland burned area was very small. In summer, persistent droughts often result in large-scale grassland fires. Statistics show that when PDSI indicates moderate or more severe drought in summer, the probability of grassland burned area exceeding 5000 km^2 is 73.3%, possibly related to maximum vegetation biomass at that time. Moreover, large monthly burned areas in grassland (1$\$\times10^{\{4\}-3\times10}\{4\}\$$ km^2) are negatively correlated with PDSI (r = -0.41, P = 0.017), while monthly burned areas exceeding 35,000 km^2 are strongly positively correlated with PDSI (r = 0.82, P = 0.020). This indicates that certain scales of grassland burning are closely related to drought at monthly scale.

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5 Conclusions

The overall distribution of fires in Central Asia is uneven, with KAZ being the country most threatened by fire. Grassland in KAZ is the vegetation type most affected by fire. Fires in grassland across the five countries have gradually decreased in recent years, demonstrating that government fire control efforts have achieved remarkable results. Cropland fires are mainly caused by straw burning, with inconsistent timing across countries. However, due to the sudden occurrence of grassland fires and their substantial impacts on humans and livestock, continued vigilance is needed. Our study has some shortcomings, particularly the omission of ignition sources as an important fire regime component due to lack of ground fire survey data, making it difficult to distinguish between natural and human-caused fire sources using only remote sensing data. As a topic for future research, fire risk analysis will be conducted under the interactive influence of human activities and natural factors, using multiple indicators and algorithms to test correlations between fire variables and ecological and human factors.

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