Title: How does landscape change after fire? Assessing the global patterns and influential factors

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Key points

1. Burred areas that experienced post-fire land cover changes represented 0.36-0.74% of the total global burned areas from 2005 to 2015.
2. The most common land cover change types were forest-to-agriculture, forest-to-shrubland and agriculture-to-forest.
3. The burned area size appears to be the strongest predictor of post-fire land cover change, followed closely by vegetation cover diversity.

Plain language summary

Fire, as a strong disturbance type, can exert significant impacts on both nature and human society. These impacts could trigger both critical transitions in ecosystems and dramatic changes in landscapes, which can be detected as alternations in land cover types. Understanding the pattern and influential factors of this process on a global scale great value in terms of advancing our knowledge of fire ecology and assisting the creation of more sustainable fire management policies. In this study, we found that about 0.36-0.74% of the global burned areas experienced post-fire land cover changes from 2005 to 2015. The most common post-fire landscape change type was from forest to agriculture. Forest and agriculture as well as forest and shrubland commonly change to each other after fire. Burned area size and vegetation cover diversity were the two strongest predictors of changes. Future fire management plans should fully consider these patterns and influential factors and be adjusted accordingly.

Abstract

Fire, as a strong disturbance type, can exert significant impacts on biosphere, hydrosphere, geosphere, cryosphere, atmosphere and human society. It can inherently trigger both critical transitions in ecosystems and dramatic changes in landscapes, which can be detected as alternations in land cover types. However, the general changing patterns and possible influential factors of post-fire landscape change remain largely unclear on a global scale. Obtaining such knowledge is of great value in advancing the understanding of fire ecology and promoting sustainable fire management. Here, we combined the satellite observations of long-term land cover and burned areas to assess the global post-fire landscape change patterns from 2005 to 2015. The results showed that the identified areas with post-fire

landscape change accounted for approximately 0.36–0.74% of the annual global burned areas during the study period and were most common in countries such as Brazil, Argentina, and the D.R. Congo. The most common landscape change types were "forest-to-agriculture" (31.93%), "forest-to-shrubland" (26.23%) and "agriculture-to-forest" (18.74%) in 2005, 2010 and 2015, respectively. In addition, the conversion between agriculture and forest as well as the shrubland and forest after fire were found to be bidirectional. After assessing 14 fire-related climatic, topographic, ecological and socioeconomic factors that could potentially influence the post-fire landscape change occurrence probability, burned area size and vegetation cover diversity were identified as the two strongest predictors, followed by aspect, fire intensity and slope. Our results provide a global overview of post-fire landscape change patterns and offer guidance for making sustainable fire management policies.

Keywords: post-fire; landscape conversion; land cover change; global; pattern; influential factor

Introduction

Fire is a strong disturbance type that can lead to significant changes in the biosphere, hydrosphere, geosphere, cryosphere and atmosphere (Bowman et al., 2020). Both fire and its cascading consequences of fires, including post-fire floods, erosion, debris flows and pyrocumulonimbus might cause tremendous impacts on both wildlife and human well-being (Gomez Isaza et al., 2022; Napier et al., 2022). These impacts on natural and social systems can trigger critical transitions in ecosystems and dramatic changes in landscapes after fires, which can be detected as alternations in land cover types (Wiggins et al., 2018; Song et al., 2018). These potentially drastic landscape changes after fire could lead to severe consequences, such as loss of biodiversity and the release of greenhouse gases into the atmosphere. For example, during the 2019-2020 fire season alone, the mega-fire in Australia destroyed approximately 5.8 million ha of temperate broadleaf forests (Boer et al., 2020). Enright et al. (2015) also reported lower regeneration rates for woody plant species that are obligate seeders after more frequent fires due to seeding growth and maturation failure, which could lead to local extinction of the species. Significant amounts of greenhouse gases can also be released not only through direct burning but also subsequent changes in local climate and possible land cover change (Galford et al., 2010; Walker et al., 2019; Z. Zhao et al., 2021). During the 2019-2020 wildfire events in Southeast Australia, the calculated emission of CO_2 due to the fire reached 517 to 867 tera-grams, which was twice more than the original estimations (van der Velde et al., 2021). Moreover, Gibson et al. (2018) reported increased emissions of methane after fire-caused permafrost thaw in boreal peatlands.

Since the causes of fire events can be both natural and anthropogenic, it is impossible to eradicate fire, but it is crucial to understand its related impacts and manage them accordingly (Zhang et al., 2021). For instance, studies have shown that natural causes like lightning are the major drivers of boreal forest fires, which could be responsible for about 90% of the areas burned in Canada (Veraverbeke et al., 2017; Hanes et al., 2019). On the other hand, prescribed fires are also frequently used to maintain fire-adapted ecosystems, such as the longleaf pine-grassland in the southeastern United States (Darracq et al., 2016). Slash-and-burn cultivation, which involves artificial fire burning, is still a common agricultural practice in many regions across the globe today (van Vliet et al., 2013). Zhao et al. (2021) found that small-scale slash-and-burn practices occurred in approximately 52% of the forest edges in Africa. As climate change and socioeconomic development are making fire to become more frequent, longer in duration and stronger in intensity in many parts of the world (Turco et al., 2018; Fonseca et al., 2019; Ren et al., 2022), the need for a thorough understanding of fire-related impacts becomes increasingly urgent across the globe.

To address the challenge, there have been attempts to quantify post-fire changes in landscape and ecosystems, particularly on local and regional scales. For instance, Stevens-Rumann et al. (2018) showed that post-fire regeneration success of trees decreased significantly in the U.S. Rocky Mountains. Styger et al. (2018) studied the impacts of human-environmental drivers of the extreme Chilean fires in 2017 and reported how extensive land cover modification ensued. Stewart et al. (2021) also found that seed production could exhibit high temporal variability by over two orders of magnitude after assessing the effects of 19 wildfires in California. Nonetheless, most previous studies assessing fire impacts on landscapes were mainly constrained in space and/or single fire event. There is still a great lack of understanding of the general patterns and possible influential factors of post-fire landscape change on a global scale. Obtaining such knowledge is critical for understanding how fire impacts both natural and social systems and creating more sustainable fire management plans.

To narrow these key knowledge gaps of where and how post-fire landscape and ecosystem transformation occur around the world, we first used remote-sensed burned area and land cover data to obtain a global distribution of post-fire landscape change patterns in 2005, 2010 and 2015. Then, by analyzing the probability of post-fire land cover change occurrence and 14 potential fire-related climatic, environmental and socioeconomic influential factors, we tried to answer the following three questions: 1) where do post-fire land cover changes occur; 2) what are the important influential factors for post-fire land cover change occurrence; 3) did the post-fire land cover change patterns change over time?

Methods

Post-fire Landscape Changes Identification

For the global burned area identification, we used the widely-used monthly Moderate Resolution Imaging Spectroradiometer (MODIS) global burned area product (MCD64A1 v006) with 500 m spatial resolution for 2005, 2010 and 2015 (available at https://lpdaac.usgs.gov/products/mcd64a1v006/) as the source (Andela et al., 2017; Wooster et al., 2021). The global burned areas are available on a daily temporal scale and mainly calculated by the changes in a burn-sensitive vegetation index, VI = $(\rho_{5,i} - \rho_{7,i})/(\rho_{5,i} + \rho_{7,i})$ (Giglio et al., 2018). For each study year, the 12 months of burned area data were compiled to an annual global dataset by aggregation. Once we acquired the global map of burned area distribution for the study years, we converted the original raster map to polygons in ArcMap (v.10.7) and calculated the area size of each polygon. These polygons serve as sample pools for the analysis of post-fire land cover changes. To reduce the uncertainty from detection errors of burned areas, we only kept burned areas with a size of over 1 km^2 for further analysis.

For the land cover (proxy for landscape) types, we obtained long-term global land cover data from the ESA Climate Change Initiative (CCI) Ecosystem Cover Project (available at http://maps.elie.ucl.ac.be/CCI/viewer/download.php) with 300 m resolution over the study period. The CCI land cover classification includes a total of 22 "global" classes and 15 "regional" classes. The major global classes are "rainfed cropland", "irrigated cropland", "mosaic cropland (>50%)/natural vegetation", "mosaic natural vegetation (>50%)/cropland", "evergreen broadleaved forest", "deciduous broadleaved forest", "evergreen needleleaved forest", "deciduous needleleaved forest", "mixed forest", "mosaic tree and shrub (>50%)/herbaceous cover", "mosaic herbaceous cover (>50%)/tree and shrub", "shrubland", "grassland", "lichens and mosses", "sparse vegetation (<15%)", "fresh or brackish water flooded forests", "saline water flooded forest", "flooded shrub or herbaceous cover", "urban", "bare", "water bodies" and "permanent snow and ice." More detailed descriptions of the land cover dataset can be found in Arino et al. (2007).

In our study, the occurrence of post-fire land cover change was defined as when the CCI land cover global classes were different before and after the burn year (i.e., 2005, 2010 and 2015). To minimize the possible effects of land cover misidentification, we only analyzed the changes when the land cover types were consistent in the three consecutive years before and after the burn year. For example, for the study year of 2015, we examined the land cover types in 2012 to 2014 (Before) and 2016 to 2018 (After) and ensured the land cover types were the same within the Before and After years for further analysis. To depict a more general pattern of global post-fire land cover changes, we further grouped the 22 classes into nine more general categories according to the CCI land cover product user guide, which are "Agriculture", "Forest", "Shrubland", "Grassland", "Sparse Vegetation", "Wetland", "Urban", "Bare" and "Water Bodies". More detailed descriptions regarding the grouping scheme can be found in the supplementary Table S1.

Although fire is a strong disturbance type, we acknowledged that post-fire land cover changes might result from causes other than fires, such as forest clearing. Therefore, our identified post-fire land cover changes would be an overestimation if they were viewed as land cover changes completely induced by fire. However, we believe our approach could still reveal a generally reliable global pattern of fire-related impacts on landscapes. Studies like Xu et al. (2021) examined the effects of multiple disturbances, such as forest clearing and fire on global terrestrial live biomass from 2001 to 2019, and found the area size with overlapping disturbance types was actually small over the course of the 19-year period.

Potential Influential Factors

To study the potentially influential factors of post-fire land cover change occurrence, we paired the burned area with post-fire land cover change with the closest burned area (< 10 km radius) that did not experience post-fire land cover change as control sites. The assumption is that the two closest burned areas would have similar long-term climatic conditions and fire regimes, which refer to the characteristic syndrome of fire behavior, frequency, spatial extent and pattern (Bowman et al., 2020). Consequently, after specific fire events, whether the burned area would experience land cover change or not should be mostly attributed to the differences in various local and short-term factors, such as the characteristics of specific fire events, local climate variations, topographic conditions, ecosystem differences and socioeconomic disparities. Therefore, we used the distance between two burned areas to control possible long-term and large-scale drivers of the post-fire land cover change occurrence probability (Peng et al., 2014) and applied exploratory data analysis methods to identify the potentially most influential local and short-term predictors (Yang et al., 2021). To ensure the robustness and validity of the distance threshold (i.e., 10 km), we also tested the radius of 5 and 20 km and found no statistically significant differences in further results (Figure S1).

A total of 14 variables that both theoretically and empirically influence post-fire land cover change occurrence were examined as potential influential factors. These variables are the burned area size, number of burned days, fire intensity, temperature, precipitation, vapor pressure deficit (VPD), soil moisture, elevation, slope, aspects, economic development level (proxy by nighttime light value), population density, vegetation productivity and vegetation cover diversity. All data of influential factors were resampled to a 300 m resolution to match the resolution of land cover.

Fire-related Factors: burned size, number of burned days and fire intensity

The first and foremost potential influential factors of post-fire land cover change are the factors related to fire characteristics. Among them, the size of burned area is one of the most important characteristics of fire as it defines the visible extent of fire impacts. For this factor, we calculated the size of the converted burned area polygons in ArcMap v.10.7 to study its effects.

In this study, the number of burned days refers to the number of days of burning found within each delineated burned area. As long as there is any pixel within the burned area extent detected as burning, we counted the date of detection as a day of burning and accumulated all such days in a year as the annual burned duration of the particular burned area.

Finally, fire intensity has been shown to be the determinant of many fire effects and thus is included as another potential factor (Ramo et al., 2021). Fire radiative power, which is calculated through temperature difference, is a widely used indicator for fire intensity and thus was also used in our study (Justice et al., 2002). The 2005, 2010 and 2015 data for the fire radiative power were obtained from the MODIS MYD14 fire products processed at a 0.05º resolution before resampling (available at https://feer.gsfc.nasa.gov/data/frp/).

Climatic Factors: temperature, precipitation, vapor pressure deficit and soil moisture

Climate factors, such as temperature and dryness, are shown to be strong influencing factors of fire intensity, ecosystem stability and socioeconomic development policies, which makes the climate a possible underlying determinant of post-fire land cover change occurrence (Deb et al., 2020; Wang et al., 2021; Jain et al., 2022). To be specific, in burned areas, temperature and water availability-related climate factors were found to play significant roles in determining ecosystem functions (Berdugo et al., 2020; C. Li et al., 2021). Therefore, we first included the mean temperature and precipitation of all burned areas as two potential influential factors. The annual mean temperature and precipitation for 2005, 2010 and 2015 were obtained from the high-resolution monthly TerraClimate dataset with about a 4 km resolution before resampling (http://www.climatologylab.org/terraclimate.html). The dataset was produced from climatically-aided interpolation, combining high-spatial-resolution climatological norms from the WorldClim dataset and other data with varying coarser resolution times (i.e., monthly). More details of the dataset can be found in Abatzoglou et al. (2018).

Since VPD and soil moisture can reflect relative atmospheric and soil dryness and are shown to be two strong drivers of fire behavior and ecosystem conditions, we also included them as potential influential factors of post-fire landscape changes (Cochrane & Ryan, 2009; Liu et al., 2020; Ellis et al., 2021). It is calculated as the difference between saturated and actual water vapor pressure, which are determined by near-surface temperature and relative humidity, respectively (Liu et al., 2020). The VPD and soil moisture data for 2005, 2010 and 2015 were also obtained from the high-resolution monthly TerraClimate dataset with a 4 km resolution before resampling.

Topographic Factors: elevation, slope and aspects

Studies have long shown that topography is also a major influential factor of fire behavior, ecosystem conditions and land use (Y. Zhao et al., 2014; P. Wei et al., 2019; Xiao et al., 2022). Therefore, we included the three most relevant topographic factors, namely elevation, slope and aspects, to represent the potential effects of topography on post-fire land cover. The elevation was obtained from the digital elevation model (DEM) and averaged for the studied burned areas in the given study years. The global 7.5 arc-second GMTED2010 data were used as the source of DEM (available at https://www.usgs.gov/coastal-changes-and-impacts/gmted2010). The slope and aspects were derived from DEM and averaged in the potential route zone as two other potential influential factors of post-fire land cover changes.

Socioeconomic Factors: nighttime light and population density

Since different socioeconomic backgrounds could also influence land cover changes, we included economic development level and population density as two potential socioeconomic drivers of post-fire land cover changes as well (Song et al., 2018; Tyukavina et al., 2018). Firstly, we used nighttime light, which is widely utilized as an indicator of economic development status (Chen & Nordhaus, 2011; Levin & Duke, 2012). We obtained the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) global nighttime light data with 1 km resolution for the three study years (i.e., 2005, 2010 and 2015) at https://doi.org/10.6084/m9.figshare.9828827.v2. A stepwise calibration method was applied to the original DMSP-OLS nightlight data from various satellites to generate a temporally consistent dataset (X. Li & Zhou, 2017). Noises from aurora, fires, boasts, and other ephemeral lights were all excluded (X. Li & Zhou, 2017). Although the more recent Visible Infrared Imaging Radiometer Suite nightlight data has better spatial resolution than the DMSP-OLS dataset, it has only been available since 2012, and there is still no highly reliable method to integrate these two datasets (X. Li et al., 2020).

Not only the intensity of socioeconomic development could significantly drive land cover changes but also the size of socioeconomic development (Burrell et al., 2020; C. Li et al., 2021). Therefore, we used the population density in the burned areas as an indicator of the size of socioeconomic demand and pressure. The data were calculated from the LandScan™ global population data with a 1 km resolution from the Oak Ridge National Laboratory (available at https://landscan.ornl.gov/landscan-datasets). The dataset mainly relies on sub-national census counts but is also validated by land cover, roads, slope, city and village locations and remote sensing images.

Ecological Factors: vegetation productivity and vegetation cover diversity

It has been shown that ecosystem productivity can indicate the stability of ecosystems (Donohue et al., 2016; Kéfi et al., 2019). In order to assess whether more productive ecosystems would influence the probability of post-fire land cover change occurrence, we included the Net Primary Productivity (NPP) of 14 vegetation cover types (i.e., “evergreen broadleaved forest”, “deciduous broadleaved forest”, “evergreen needleleaved forest”, “deciduous needleleaved forest”, “mixed forest”, “mosaic tree and shrub (>50%)/herbaceous cover”, “mosaic herbaceous cover (>50%)/tree and shrub”, “shrubland”, “grassland”, “lichens and mosses”, “sparse vegetation (<15%)”, “fresh or brackish water flooded forests”, “saline water flooded forest”, “flooded shrub or herbaceous cover”) in the burned areas as one of the influential factors. The yearly MODIS NPP dataset (MOD13A3HGF v006) with a 1 km spatial resolution and global coverage from 2003 to 2018 was used as the source of NPP. We downloaded the data from the NASA Land Processes Distributed Active Archive Center at https://lpdaac.usgs.gov/products/mod17a3hgfv006/.

In addition, since many studies have found that low vegetation diversity (e.g., monocultures) could also contribute to the scale and intensity of fire (Levine et al., 2016; Gómez-González et al., 2018; Bowman et al., 2019), we tried to study whether it would induce land cover change after fires. Since the widely-applied Shannon-Weiner diversity index is also applicable in assessing land cover diversity (Kallimanis & Koutsias, 2013), we adopted this index to estimate the diversity of vegetation cover (14 types in total) in the burned areas (Eq.1):

$$H_j = -\sum_{i=1}^{14} |(\frac{n_{ij}}{N_j}) \times \ln (\frac{n_{ij}}{N_j})| \quad \text{(Eq. 1)}$$

where H_j is the vegetation cover diversity in the burned area j; n_{ij} represents the percentage of coverage of vegetation cover type i in the burned area j; and N_j stands for the size of the burned area j.

Statistical Analysis

To identify the most relevant and independent influential factors for post-fire land cover change occurrence, we first used the collinearity test on all potential influential factors (SPSS v.25) and then applied the random forest classifier to assess the importance of each factor on the probability of post-fire land cover change occurrence. The random forest classifier grows unpruned classification trees and uses the majority of classification results from every individual tree to generate the final result (Svetnik et al., 2003). It is an effective and reliable method for dealing with noisy data that contain various types and sources; hence, widely used in ecological, medical and geographic studies (Liang et al., 2020; M. Wei et al., 2021; Santi et al., 2022). In this study, we grew 1000 trees (random state set as 0) to ensure the stabilization prediction error of the model. The Gini index was used as the impurity function to calculate the contribution rate of each predictor to the reduction in weighed impurity for the relative importance ranking (Menze et al., 2009).

Last but not least, we used partial dependence plots to understand how exactly each factor affects the post-fire land cover change occurrence probability. The partial dependence plots display the average marginal effects of the influential factor of interest on the predicted outcome (post-fire land cover change occurrence in this case) by marginalizing the model output over the distribution of all factors except the one of interest (Graf et al., 2015; Greenwell, 2017). By doing so, a function that only depends on the factor of interest can be obtained while considering the interactions with other factors (Graf et al., 2015; Greenwell, 2017). The random forest analysis and partial dependence plots were both performed using the scikit-learn python package.

Results

Global Post-fire Land Cover Change Pattern

In 2005, 2010 and 2015, a total of 1,785, 1,258 and 1,009 polygons of burned areas with post-fire land cover changes were identified, respectively (Figure 1). They cover an area of approximately 29,483, 17,313 and 12,338 km^2 in the three study years, which represents about 0.74%, 0.46% and 0.36% of the total global burned areas in 2005, 2010 and 2015, respectively. The number of identified paired-unchanged burned areas without land cover changes within the 10 km radius was 1,425 in 2005, 973 in 2010 and 830 in 2015 (Figure 1). Some of the control burned areas were paired with more than one burned area with post-fire land cover changes. These paired-unchanged areas were located 2.05 (1.91-2.11) km away from their paired areas with land cover change on average. At the country level, Brazil (14.97%), Argentina (8.82%), Paraguay (7.37%), Russia (5.78%) and D.R. Congo (4.84%) were the top five countries that accounted for most post-fire land cover change occurrences across the three study years (Figure 1).

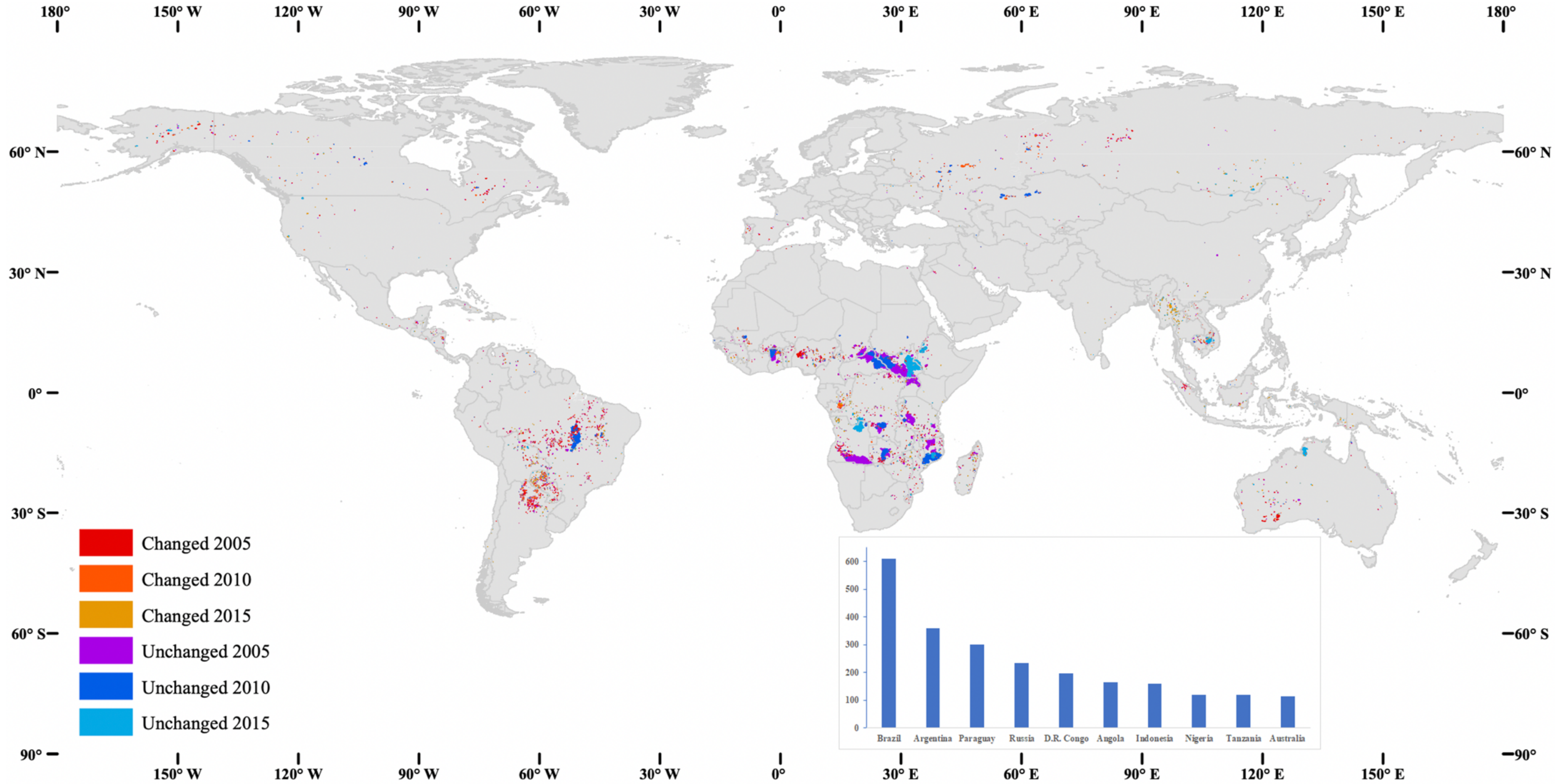

Figure 1. Global distribution of the burned areas with post-fire land cover changes and paired burned areas without land cover changes in 2005, 2010 and 2015. Insert shows the top ten countries with the highest number of burned areas with land cover changes across the three study years.

In terms of the common post-fire land cover change patterns, a total of 44 land cover change types were identified across the three study years out of the 81 possible combinations of the nine general land types (Figure 3). Among the 44 identified change types, the "Forest-to-Agricultural" (31.93%), "Forest-to-Shrubland" (26.23%) and "Agricultural-to-Forest" (18.74%) change types were the most common in percentage in 2005, 2010 and 2015, respectively (Figure 2). These three land cover change types were most common in Brazil, Argentina and D.R. Congo, respectively (Figure 3). In addition to the three types, the types of "Shrubland-to-Forest" (6.28%-14.37%), "Shrubland-to-Agricultural" (3.67%-13.59%) and "Forest-to-Forest" (5.83%-11.20%) were also very common (all with an average parentage over 8%) (Figure 2). Although the Chi-squared test result found the differences in post-fire land cover change type composition were significant across the study years, the aforementioned six change types were consistently the most common ones (except for the "Shrubland-to-Agricultural" type in 2015) among all study years, which implied a generally similar post-fire land cover change pattern on the global scale (Figure 2 and Table S2). In 2015, the "Grassland-to-Forest" change type became the sixth most common post-fire land cover change type (7.04%) and made the "Shrubland-to-Forest" change type the seventh among the 32 types (Figure 2).

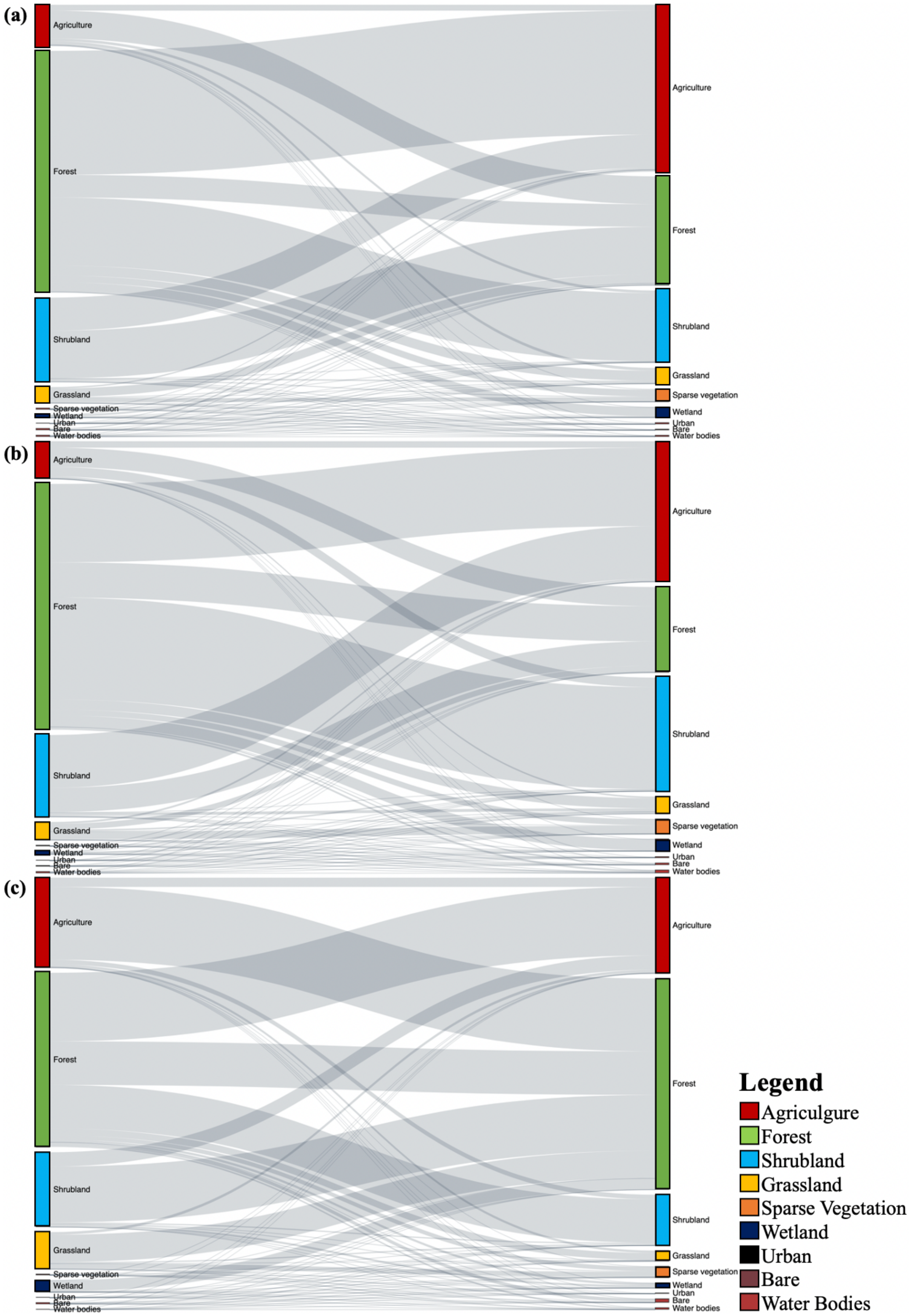

Figure 2. Sankey diagrams of global post-fire land cover change types in 2005 (a), 2010 (b) and 2015 (c).

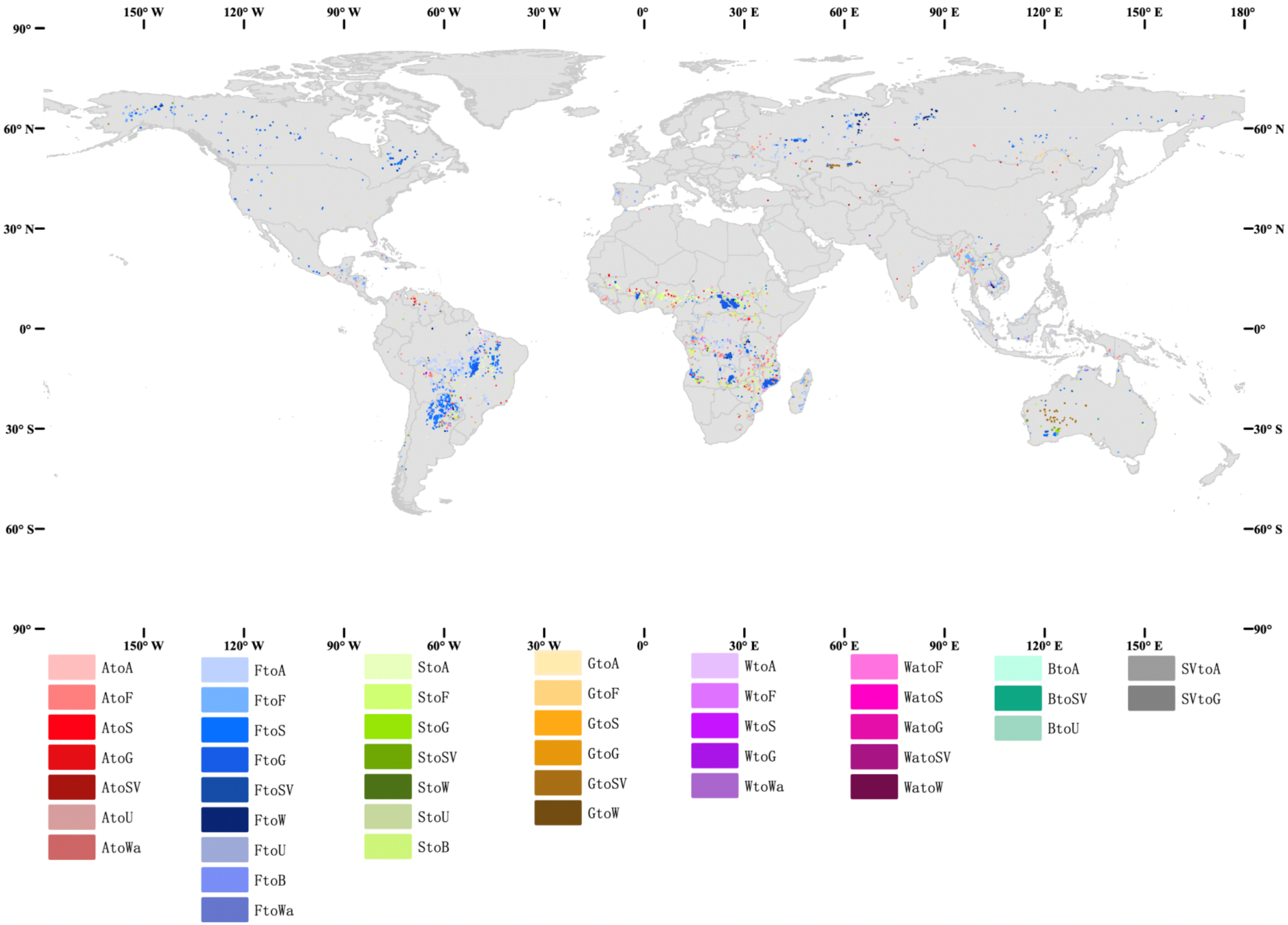

Figure 3. Global distribution of post-fire land cover change types. The abbreviation for each land cover is: A-agriculture; F-forest; S-shrubland; G-grassland; W-wetland; Wa-water bodies; B-bare; and SV-sparse vegetation.

Post-fire Land Cover Change Occurrence Influential Factors

After assessing the relative importance and effects of influential factors on the post-fire land cover change occurrence probability for the three study years separately, we found that the importance ranks of factors were highly similar (p-value = 0.608 from the Kruskal-Wallis test, $H = 0.994$) across different years (Figure S2). Therefore, we pooled the data from all three years together to generate a larger dataset (N = 7,280) for identifying more general influential factors. Among the 14 potential influential factors for post-fire land cover change occurrence, it was found that the area size of the burned areas was the strongest influential factor, followed by vegetation cover diversity (Figure 4). Their Gini indices of importance were similar (0.111 and 0.105) and higher than the other factors (the average Gini index of the other 12 factors was 0.065). The factors of aspect, fire intensity, slope, NPP, soil moisture, VPD, elevation, temperature and precipitation all had similar importance (0.071 to 0.078), which implied no large differences in their contributions to post-fire land cover change occurrences. The three influential factors with the least importance were the number of burned days, population density and nighttime light, which had an average Gini index of only 0.041 (Figure 4).

The two leading influential factors both exhibited evident non-linear effects on the probability of post-fire land cover change occurrences (Figure 4a and 4b). For the burned area size, it was found that the probability of post-fire land cover change occurrence diminished quickly after the burned size exceeded approximately 20 km^2 (Figure 4a). The probability of post-fire land cover change occurrence also increased quickly as the vegetation cover became more diverse but would hit an asymptote of about 0.60 after the Shannon-Weiner diversity index reached approximately 0.80 (Figure 4b). In comparison, the effects of other factors on the post-fire land cover change occurrence probability were more subtle and generally linear (Figure 4c to 4o).

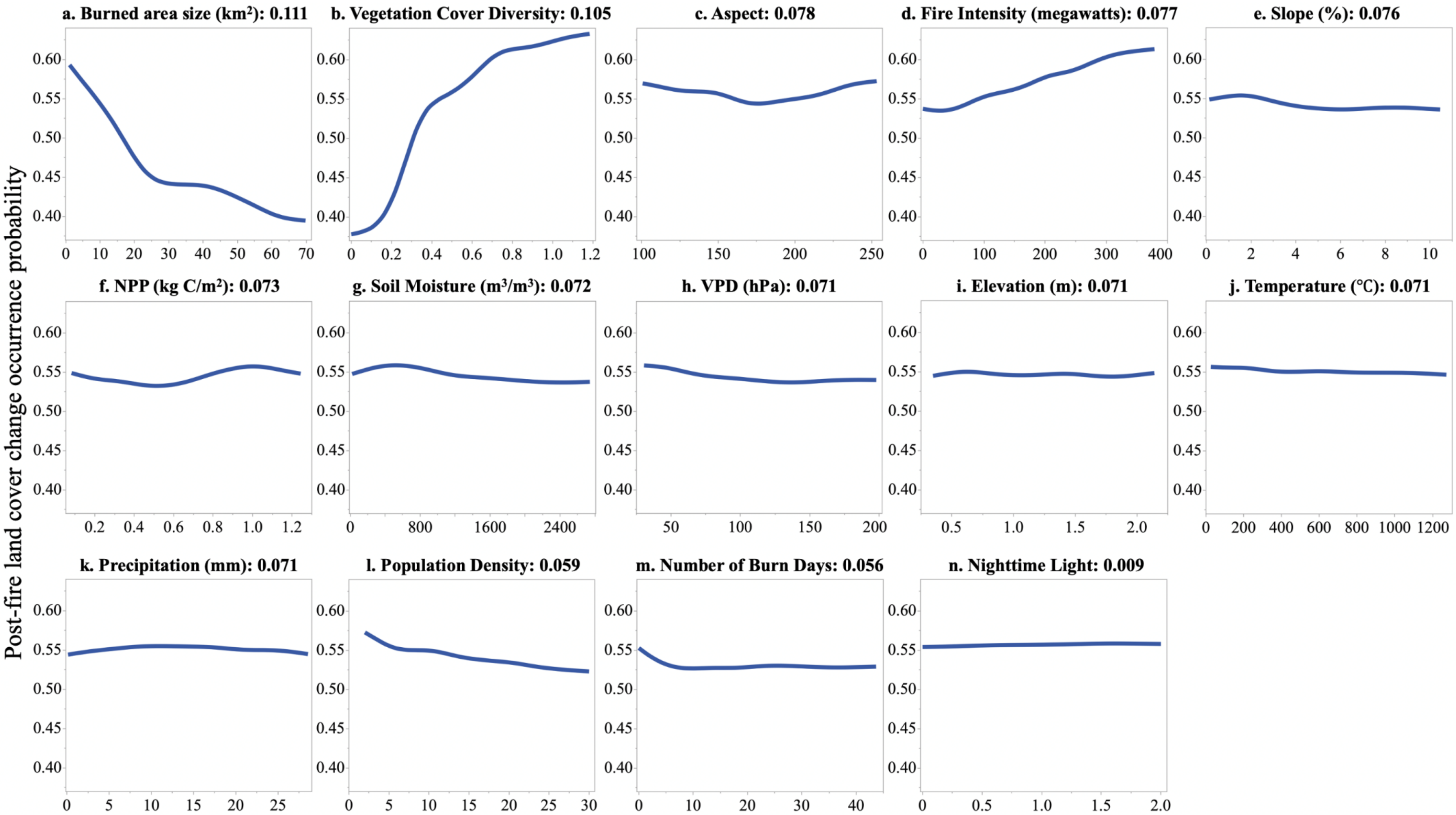

Figure 4. Partial dependence plots of the effects of 14 potential influential factors on the post-fire land cover change occurrence probability. The numbers are Gini indices, which indicates the importance of the factor.

To understand whether the importance of influential factors varies in different post-fire land cover change types, we further performed random forest classification analyses on the three most common land cover change types (i.e., Forest-to-Agricultural, Forest-to-Shrubland and Agricultural-to-Forest). The results showed the importance ranks of influential factors among the three types were similar in general (p-value = 0.847 from Kruskal-Wallis test, H = 0.331), and the two most important influential factors were still the burned area size and vegetation cover diversity (Figure 5). However, for the "Forest-to-Agricultural" and "Forest-to-Shrubland" change types, the vegetation cover diversity surpassed size as the most influential factor. As for the "Agricultural-to-Forest" change type, the importance rank of population density increased from the 12th in the overall result to the 5th in this specific land cover change type (Figure 5). Furthermore, we examined whether the rankings of influential factor importance differed in Brazil, Russia, and the Democratic Republic of the Congo, three countries with the highest number of post-fire land cover change occurrences but very different socioeconomic backgrounds. The results showed no statistically significant differences among the three countries (Figure S3).

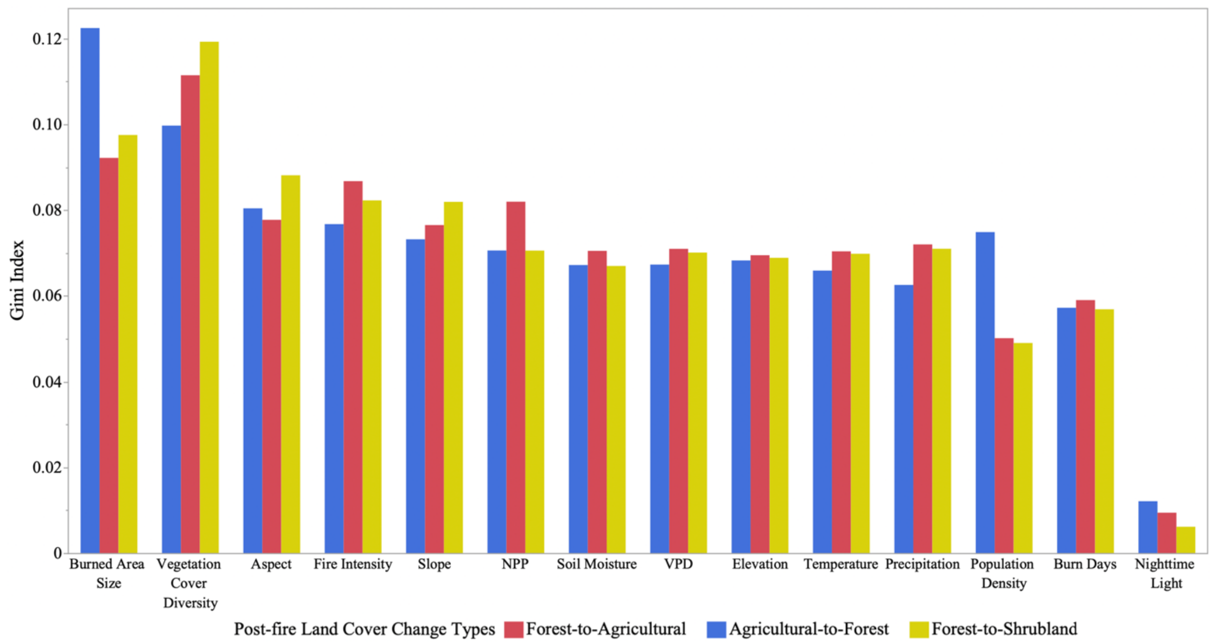

Figure 5. Gini indices of the 14 influential factors of the occurrence probability of the three most common post-fire land cover change types (Forest-to-Agricultural, Forest-to-Shrubland and Agricultural-to-Forest) during the study years.

Discussion

Although our results showed a decrease in the total size of burned areas with post-fire land cover changes, which is consistent with the decreasing trends in the global burned area

(Andela et al., 2017), the general patterns of post-fire land cover change remained mostly consistent. One of the most prominent and consistent patterns was the bidirectional conversion between agriculture and forest as well as shrubland and forest after fires (Figure 2). The post-fire conversion from forest to agricultural land could be largely attributed to the slash-and-burn practices around the world (Pelletier et al., 2012; Z. Zhao et al., 2021). One of the main purposes of this traditional agricultural practice is to create cultivable land from non-crop vegetation. Meanwhile, in areas where people commonly practice shifting agriculture, it is also common to find trees regenerated naturally or through planting in abandoned fields after burning (Lebrija-Trejos & Bongers, 2008; de Oliveira, 2008). These could be detected as the change in land cover from agriculture to forests as shown in our results. Previous studies have shown that species, such as endangered trees and birds, could be conserved during this type of conversion process (Mandal & Shankar Raman, 2016; Reang et al., 2022).

The shift from forest to shrubland after fire could be seen as a form of degradation. Studies have shown that fire could be a cause of forest loss across all boreal, temperate and tropical forest ecosystems (Veblen et al., 2003; Cochrane, 2009; Song et al., 2018). For instance, Xu et al. (2021) estimated the global carbon emissions from forest fire were about 0.38 PgC per year over the 21st century, which translated to a significant amount of live biomass loss across various biome types. On the other hand, the reasons for the conversion from shrubland to forest might be related to multiple factors. Firstly, it could be attributed to the better regeneration of fire-adapted tree species in areas previously with mixtures of both tree and shrub species. For example, the serotinous cones of *Pinus, Picea mariana* and some populations of *Larix gmelinii* require the high temperatures generated by fire to open; thus, they can only regenerate massively after fire events. In many frequently burned regions around the world, tree species have also developed traits, such as thick, corky barks, better-protected buds and root suckers, to enable fast resprouting after surface fires (Charles-Dominique et al., 2017; Osborne et al., 2018). These traits would give trees a selective advantage over shrub species like *Quercus laevis* and *Ouercus geminate* (Williamson & Black, 1981; He et al., 2012). Another possible cause for the post-fire change from shrubland to forests in the observed land cover types could be the removal of shrubs in areas that should supposedly be forests. For instance, in Australian *Eucalyptus* woodland, the shrubs would overtake the trees as the dominant vegetation type without regular fire disturbances; the "should-be" woodland could be identified as shrubland in land cover products until those shrubs were removed by fire (Fernandes & Botelho, 2003).

In terms of the influential factors of post-fire land cover change, we found the smaller area size and high vegetation cover diversity well explained higher probabilities of such change occurrence (Figure 4). Possible reasons for the susceptibility of smaller burned areas to land cover change might be related to the origin of fire and/or variations in ecosystem resilience. Compared to natural fires, anthropogenic fires are usually smaller in size, as several studies have shown (de Groot et al., 2013; van Vliet et al., 2013). These man-made fires could be set with the purpose of land cover change, such as the previously mentioned "slash-and-burn" practices (Pelletier et al., 2012; van Vliet et al., 2013). Moreover, in larger burned areas, the complete change in land cover types could be avoided through mechanisms such as higher resistance to disturbance provided by the larger habitat size (Greig et al., 2021) and a higher probability of spatial self-organization in ecosystems (Rietkerk et al., 2021). These more diverse spatial patterns could enable the systems to remain stable under a wide range of conditions (Rietkerk et al., 2021). In addition, we expected to find that burned areas with more diverse vegetation covers were more vulnerable to experience land cover change after fires. It is because fire, as a strong disturbance type, could make the preoccupied niche available to the more fire-adapted species (Cavallero & Raffaele, 2010; HilleRisLambers et al., 2012). There is mounting evidence showing that changes in species composition could occur after burning due to differences in competitive abilities among species (Müller et al., 2007; Dudinszky & Ghermandi, 2013; Loydi et al., 2020).

Finally, it should be noted that a variety of factors could limit the validity of our findings. First of all, since our analyses are essentially based on the observed land cover types and burned areas, false identification of these data could affect the accuracy of the results. However, as Boschetti et al. (2019) validated the global MODIS burned area product and reported an overall accuracy of 99.7% in burned area identification, we believe that the used datasets should be generally reliable. Furthermore, due to the overall spatial scale of the study, some other local factors, such as spatial patterns of vegetation, species richness, management and policy effects, etc., were not included in the analysis. They could also lead to the potential omission of important predictors of fire behavior and landscape changes, and should be tested for their effects in areas with available data (Isbell et al., 2015; Radchuk et al., 2019; Rietkerk et al., 2021). Moreover, we acknowledge that fire could happen during the years before our study period in the burned areas with post-fire land cover changes. In other words, the post-fire land cover change might not only relate to the fire events within our study years but could also be affected by the lagging effects of previous fire events. The existence and extent of such possible lagging effects should be further studied to quantify.

Conclusion

In this study, we showed the general patterns of post-fire landscape changes on a global scale and identified possible influential factors for their occurrence probability. Agriculture-forest and shrubland-forest commonly convert to each other after fires. The burned area size and vegetation cover diversity were found to be the two strongest predictors. The global patterns and the influential factors of post-fire land change occurrences remained generally similar from 2005 to 2015. In current Earth-system models, fire and its interactions still remain poorly represented, and their performance struggles with rapidly changing future climates (Sanderson & Fisher, 2020). Our results suggest the exact effects of fire on the landscape are variable on a global scale, but the most important underlying drivers of the effects are generally similar. Therefore, the next challenge should be to further quantify the spatial heterogeneity of these fire impacts and manage the impact drivers according to local policy goals in order to not only reduce uncertainties in climate-fire-vegetation model projections but also promote sustainability in long-term socioeconomic development.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author statement

SW contributed to the conception and design of the study and wrote the first draft of the manuscript. DL acquired and analyzed data of the study. DL, LL, JS, KL, WenZ, WeiZ and LZ contributed to the design of the study. LZ also supervised the study. All authors contributed to manuscript revision, read, and approved the submitted version.

Data Availability Statement

All data used in this study were procured from different publicly-available sources. The monthly Moderate Resolution Imaging Spectroradiometer (MODIS) global burned area product (MCD64A1 v006) with 500 m spatial resolution for 2005, 2010 and 2015 can be found at https://lpdaac.usgs.gov/products/mcd64a1v006/. The long-term global land cover data from the ESA Climate Change Initiative (CCI) Ecosystem Cover Project are available at http://maps.elie.ucl.ac.be/CCI/viewer/download.php/. The 2005, 2010 and 2015 data for the fire radiative power were available at https://feer.gsfc.nasa.gov/data/frp. The annual mean temperature, precipitation, VPD and soil moisture for 2005, 2010 and 2015 are available from the high-resolution monthly TerraClimate dataset at http://www.climatologylab.org/terraclimate.html. The global 7.5 arc-second GMTED2010 data for DEM data were available at https://www.usgs.gov/coastal-changes-and-impacts/gmted2010. The Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) global nighttime light data were obtained at https://doi.org/10.6084/m9.figshare.9828827.v2. The LandScan™ global population data are available at https://landscan.ornl.gov/landscan-datasets. Finally, the yearly MODIS NPP dataset (MOD13A3HGF v006) with a 1 km spatial resolution and global coverage from 2003 to 2018 are from the NASA Land Processes Distributed Active Archive Center at https://lpdaac.usgs.gov/products/mod17a3hgfv006/.