Monitoring Landsat Based Burned Area as an Indicator of Sustainable Development Goals

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Abstract The “United Nations 2030 Agenda for Sustainable Development” adopted in 2015 covers 17 Sustainable Development Goals (SDGs). Fire is a common form of disaster and has a wide range of impacts on climate, biogeochemical cycle and human health, highly related to the SDGs. Satellite remote sensing technology provides an effective way for the dynamic monitoring of global burned area (BA). However, the existing global BA products are mainly at low and medium spatial resolution, which is difficult for detecting small fires, and also has large errors in calculating area of burned land. Based on Landsat 8 surface reflectance data and Google Earth Engine platform, a novel multi-year (from the starting year of SDGs [2015] to the nearest year [2019]) 30 m resolution global BA products were generated. Based on these products, spatial distribution, influencing factors and change characteristics of BA were analyzed. The results show that from 2015 to 2019 the total area of BA in the world was 365.27, 368.56, 374.56, 345.55, and 363.09 × 10^6 ha. From 2015 to 2019, the total area of global BA was relatively stable, however there were significant differences among various continents and regions. During the study period, BA in the Amazon and Australia changed dramatically. The huge Amazon fire in 2019 caused a reduction of 4.67 × 10^6 ha of vegetated area in the Amazon basin, an increase in BA of 119.25% compared with 2018. In 2019, BA on the eastern and southeastern coasts of Australia increased abnormally. The possible reasons for these changes were comprehensively discussed and analyzed.

Plain Language Summary Fire is a common form of disaster, and has a wide range of impacts on climate, surface vegetation and human health. The “United Nations 2030 Agenda for Sustainable Development” has been implemented for 5 years, and fire is highly related to the Sustainable Development Goals, for which global information on fire effects is a key variable. In order to carry out high-precision and fine monitoring of the spatial distribution and changes of fire within the past 5 years, in this study 30 m global burned area (BA) products were generated and analyzed from 2015 to 2019. During the study period, we found that the total area of global BA was relatively stable, however there were significant differences among various continents and regions. For example, the huge Amazon fire in 2019 caused a reduction of 4.67 × 10^6 ha of vegetated area in the Amazon basin, an increase in BA of 119.25% compared with 2018. In 2019, BA on the eastern and southeastern coasts of Australia increased abnormally. The possible reasons for these changes were comprehensively discussed and analyzed.

1. Introduction

The “United Nations 2030 Agenda for Sustainable Development” adopted in 2015 covers 17 sustainable development goals (SDGs) and 169 specific goals (United Nations, 2015), and fire is highly related to the SDGs, explicitly related to seven of the SDGs: Goal 1 (no poverty), Goal 2 (zero hunger), Goal 3 (good health and well-being), Goal 6 (clean water and sanitation), Goal 13 (climate action), Goal 14 (life below water), and Goal 15 (life on land) (Martin, 2019). Fire is a common form of disaster, which significantly changes the vegetation structure and plays an indispensable role in shaping ecosystem characteristics (Bond et al., 2005), and has a wide range of impacts on climate, biogeochemical cycle and human health (Andela et al., 2017; Butt et al., 2020; Nawaz & Henze, 2020). Fires affect global climate by changing vegetation and soil carbon, surface albedo, and aerosol and greenhouse gas concentrations in the atmosphere (Andela et al., 2017). Climate change will also increase the risk of fire. The latest IPCC Assessment Report believes that if the temperature is 1.5°C higher than the current conditions, there is a high possibility of increasing the fire risk (IPCC, 2018). Under the background of global climate change, fire is closely related to climate change. Extreme high temperature and drought caused by climate change are the important driving factors leading...
to catastrophic fire, and fire will have a great impact on the earth and human health. Therefore, fire monitoring and management is particularly important for achieving the SDGs and the well-being of all people.

Satellite remote sensing technology provides an effective way for the dynamic monitoring of global burned area (BA). However, the existing satellite-based global BA products mainly have low and medium spatial resolution, such as GBS (8 km) (Carmona-Moreno et al., 2005), Global Burned Area 2000 (GBA2000, 1 km) (Tansley et al., 2004), GLOBSCAR (1 km) (Simon et al., 2004), GlobCarbon (1 km) (Plummer et al., 2006), L3JRC (1 km) (Tansley et al., 2008), MCD45 (500 m) (P. Roy et al., 2005), Global Fire Emissions Database 4s (GFED4s) (0.25°) (van der Werf et al., 2017), MCD64 (500 m) (Giglio et al., 2016), and Fire_cci (250 m) (Chuvieco et al., 2018), of which the highest spatial resolution is only 250 m. It is difficult to detect small burned patches with such spatial resolution burned area products, and there are also large errors in determining fires location and calculating area of burned land. Compared with existing global BA products, Landsat sensors can provide higher accuracy and spatial details in most areas on the earth (Stroppiana et al., 2012). Great attention has been paid to the development of BA products based on Landsat data in the past 10 years (Bastarrika et al., 2011; Hawbaker et al., 2020; Stroppiana et al., 2012), but all the Landsat based BA products were regional products. In order to solve these problems, a novel 30 m spatial resolution global annual burned area mapping (GABAM) technique was proposed based on Landsat 8 time series land surface reflectance data and machine learning algorithm, and the commission and omission errors of GABAM 2015 were 13.17% and 30.13%, respectively, and the overall accuracy reached 93.92%. Cross-comparison between the recent Fire_cci and GABAM BA products found a similar spatial distribution and a strong correlation ($R^2 = 0.74$) between these two products. While the result of GABAM 2015 showed finer boundaries of BA, which can be useful for the statistics of the area of biomes actually burned, compared with that of the Fire_cci product (Long et al., 2019; Zhang et al., 2020).

The “United Nations 2030 Agenda for Sustainable Development” has been implemented for 5 years, and fire is highly related to the SDGs, for which global information on fire effects is a key variable (Chuvieco et al., 2019). In order to carry out high-precision and fine monitoring of the spatial distribution and changes of fire within the past 5 years, in this study, GABAM algorithm was employed to generate 30 m global burned area products from 2015 (the starting year of SDGs) to 2019 (the nearest year). Based on these products, spatial distribution and dynamic changes of fires were monitored and analyzed from different perspectives, including global, continental, and fire-prone regions.

## 2. Methodology

### 2.1. Burned Area Mapping

Quality Assessment (QA) band of Landsat 8 land surface reflectance data were used to mask pixels of low quality, that is, cloud, cloud shadow, and snow. All the available time-series Landsat-8 images (including the previous and the current years) and several sensitive spectral parameters were employed to calculate burned probability of each pixel using random forest by Google Earth Engine (GEE), which were globally trained with stratified (considering both fire frequency and type of land cover) random sampling method. Multiple carefully designed logical filters (Normalized Difference Vegetation Index (NDVI) filter, Normalized Burned Ratio (NBR) filter, temporal filter, and probability filter) were used for determined BA seeds selection, with the help of the MODIS Vegetation Continuous Fields (VCF) 250-m Version 6 (MOD44B) product (DiMiceli et al., 2015). Then a region growing algorithm was utilized to shape the global BA distribution. It is worth noting that the GABAM product only included the spatial range of fires that occurred in the current year, and burned scars that occurred in previous years, but had not yet recovered were excluded from the annual BA map of the current year. The workflow for BA mapping is shown in Figure 1.

#### 2.1.1. Model Training

In this study, the BA mapping algorithm was implemented on the GEE platform. One hundred and twenty Landsat-8 surface reflectance scenes from 2015 were selected based on the stratified (considering both fire frequency and type of land cover) random sampling. The maximum number of training samples was limited by the memory of GEE platform. Therefore, an average of 90–100 sample points were collected by experienced experts from each Landsat-8 image, making the total number of sample points to 12,881 (6,735 burned samples and 6,146 unburned samples). Note that each sample point covered a few (five on average)
Landsat pixels; these pixels were obviously burned or not affected by fire. Specifically, the Shortwave Infrared (SWIR2), Near Infrared (NIR) and green bands were synthesized into a combination of Red, Green, Blue (RGB) in order to visualize BA better. We selected clear burn pixels, and avoid pixels near the borders of burned scars and located in the burning flame or covered by smoke. Unburned pixels are randomly extracted from areas not affected by fire, including vegetation, impervious area, bare land, terrain shadows, lakes, etc.

Land surface reflectance in the six bands (blue, green, red, NIR, SWIR1, and SWIR2) and eight sensitive spectral indices (NBR (Key & Benson, 1999), NBR2 (Lutes et al., 2006), BA Index (Martin, 1998), Mid-Infrared Burn Index (Trigg & Flasse, 2001), NDVI (Rouse et al., 1974), Global Environmental Monitoring Index (Pinty & Verstraete, 1992), Soil-Adjusted Vegetation Index (Huete, 1988), and Normalized Difference Moisture Index (Wilson & Sader, 2002)) of the collected samples were extracted in order to train the random forest classifier. We limited the number of decision trees in the forest to 100 for a trade-off between accuracy and efficiency. In addition, we selected the “probability” mode for GEE’s random forest algorithm, where the output was the per-pixel burned probability.

2.1.2. Per-Pixel Processing

Generation of burned area in each year involved all the available Landsat data for the current year and previous year. At each pixel, the reflectance stack of six bands was divided into two stacks (the stack of the current year and the stack of the previous year) by date.

For reflectance stack of the current year, eight spectral indices were calculated, and the trained random forest in Section 2.1.1 obtained a stack of burned probability using the eight spectral indices and the reflectance of six bands. The maximum value of burned probability represented the probability that the pixel had ever appeared like a burned scar in the whole year. Four quantities of each pixel were recorded: The date when the maximum probability was observed ($t_1$), and the burned probability ($p_{\text{max}}$), NDVI value (NDVI$_1$), and NBR value (NBR$_1$) of that date. Our product only contains the newly increased burned area in the study year, so it is necessary to make summary statistics for the current year and the previous year: NDVI$_2$, the maximum NDVI value in the 2 years (current year and previous year); $t_2$, the date of NDVI$_2$; and NBR$_2$, the minimum NBR value in the previous year.
In addition, four filters were designed (as shown in Table 1) to exclude most of unreasonable burned-like pixels to determine BA seeds. The thresholds were chosen empirically: $T_{NDVI}$ (the threshold for NDVI) = 0.2, $T_{dNDVI}$ (the threshold for NDVI2-NDVI1) = 0.2, $T_{INBR}$ (the threshold for NBR2-NBR1) = 0.1 and $T_{DAY}$ (the threshold for $t_2-t_1$) = 100 (days). Sensitivities of the thresholds were tested according to the global training samples in Section 2.1.1, and more details can be found in the work of Long et al. (2019). MODIS VCF product was used to determine whether the pixel was dominated by tree or herbaceous. For tree-covered burned-like pixels, all four filters were required. For herbaceous vegetation, only the NDVI filter and the probability filter were required, since grasslands usually recover quickly and they burn year after year.

### Table 1

**Information of Four Seeds Filters**

| Seeds filters | Constraints | Specific function |
|---------------|-------------|------------------|
| NDVI filter   | $NDVI_2 > T_{NDVI}$ and $NDVI_2 - NDVI_1 > T_{dNDVI}$ | This restriction is used to exclude pixels that actually lack vegetation but were mistakenly classified as burned area and ensure evidence of reduced vegetation when the burned occurred. |
| NBR filter    | $NBR_2 - NBR_1 > T_{INBR}$ | This constraint helps to exclude false detections of NBR and NDVI that have periodic changes, such as mountain shadows, snowmelt, flooding, and etc. |
| Temporal filter | $t_1 > t_2$ or $t_2-t_1 > T_{DAY}$ | This restriction is used to exclude falsely reported pixels and those that occurred in previous years but have not recovered. |
| Probability filter | $p_{max} >= 0.95$ | This constraint is used to filter out pixels with high burned probability. |

In addition, four filters were designed (as shown in Table 1) to exclude most of unreasonable burned-like pixels to determine BA seeds. The thresholds were chosen empirically: $T_{NDVI}$ (the threshold for NDVI) = 0.2, $T_{dNDVI}$ (the threshold for NDVI2-NDVI1) = 0.2, $T_{INBR}$ (the threshold for NBR2-NBR1) = 0.1 and $T_{DAY}$ (the threshold for $t_2-t_1$) = 100 (days). Sensitivities of the thresholds were tested according to the global training samples in Section 2.1.1, and more details can be found in the work of Long et al. (2019). MODIS VCF product was used to determine whether the pixel was dominated by tree or herbaceous. For tree-covered burned-like pixels, all four filters were required. For herbaceous vegetation, only the NDVI filter and the probability filter were required, since grasslands usually recover quickly and they burn year after year.

#### 2.1.3. Burned Area Shaping

Based on the high-confidence seed pixels obtained by the filters, a kernel composed of 8-connected neighbors was used to synthesize the adjacent starting seed pixels into components, and the seed components with an area of less than 1 ha were removed. Then, the iterative process of region growth was performed around each seed pixel. For each iteration, if the burned probabilities of the 8-connected neighbors of the seed pixels were greater than or equal 0.5, they were gathered as burned pixels (new seeds), and when there were no more pixels that can be gathered as burned pixels, the iteration stopped.

Based on the GABAM algorithm, 30 m global BA products from 2015 to 2019 were produced. These products were projected in a geographic (latitude/longitude) projection at 0.00025° (~30 m) resolution, with the WGS84 horizontal datum and the EGM96 vertical datum. The global products were divided into 5° × 5° tiles, spanning the range 180°W–180°E and 80°N–60°S. GABAM products include uncontrolled wildfires and deliberate fires used for land clearing, charcoal production and the burning of agricultural residues (Martin, 2019) with the form of forest, grassland and farmland burned area. All the obtained 30 m global BA products from 2015 to 2019 can be freely downloaded from the website of https://vapd.gitlab.io/post/gabam.

#### 2.1.4. Accuracy Validation

Based on the spatial intersection of seven land cover types and five BA density levels, 35 strata with different land cover and fire frequencies were obtained; for details, please refer to Section 2.2 in the article of Long et al. published in 2019. For the newly produced BA products (from 2016 to 2019), in order to ensure the comprehensiveness and representativeness of the accuracy verification, the stratified random sampling method was used to randomly generate 200 verification points for each strata. In this way, a total of 7,000 verification sample points (approximately containing 2,400 burned sample points and 4,600 unburned sample points) were collected every year. An example of spatial distribution of validation points in 2019 was shown in Figure 2. Landsat satellite images, Fire_cci products and MCD64 products were used to visually judge whether the verification point was BA or not.

The error matrix for BA products validation was constructed with the validation points and classification results. Four commonly used accuracy measurement indicators (Dice, 1945; Long et al., 2019), that is, overall accuracy (OA), commission error (CE), omission error (OE), and Dice coefficient (DC), were calculated based on the confusion matrix.
2.2. Statistics of the Area of Burned Land

The area of burned land in each continent of the world and the key study areas during 2015–2019 is calculated. The algorithm formula for calculating the area of the spherical polygon of the earth based on latitude and longitude is as follows (Chamberlain & Duquette, 2007), more details can be found in the work of Chamberlain and Duquette.

\[
A = \frac{R^2}{2} \sum_{i=0}^{N-1} (\lambda_{i+1} - \lambda_i) \cdot \sin \phi
\]  

(1)

Here, the polygon is described by a series of vertices from 0 to \( N - 1 \) in a counter clockwise direction (vertex \( N \) if given is the same as vertex 0), \( \lambda_i \) is the longitude of the \( i \) point, and \( \phi_i \) is the latitude of the \( i \) point; latitude and longitude are expressed in radians. The radius of the Earth is denoted by \( R \), and the area of the polygon is denoted by \( A \).

In this study, the radian of the image pixel resolution we used is \( r_{\text{rad}} = 4.3633 \times 10^{-6} \) (about 30 m). Thus the area formula of each square pixel can be simplified to (Long et al., 2019):

\[
A_{\lambda,\phi} = R^2 \cdot r_{\text{rad}} \cdot \left[ \sin \left( \phi + r_{\text{rad}} \right) - \sin \phi \right]
\]  

(2)

where, \( A_{\lambda,\phi} \) is the area of image pixels expressed in radians; \( \lambda \) and \( \phi \) are the longitude and latitude, respectively. \( R \) equals 6,371,007.2 m (Moritz, 1980), and the spatial resolution of the image is expressed in radians.

### Table 2

| Year | OA (%) | CE (%) | OE (%) | DC    |
|------|--------|--------|--------|-------|
| 2016 | 86.97  | 5.56   | 33.09  | 0.78  |
| 2017 | 88.26  | 5.80   | 30.29  | 0.80  |
| 2018 | 86.00  | 5.73   | 34.86  | 0.77  |
| 2019 | 88.69  | 4.13   | 29.81  | 0.81  |

CE, commission error; DC, dice coefficient; GABAM, global annual burned area mapping; OA, overall accuracy; OE, omission error.

3. Results and Analysis

3.1. Accuracy Validation and Comparison With the MCD64 Product

The validation results are shown in Table 2. As can be seen from Table 2, the overall accuracy of GABAM products from 2016 to 2019 were 86.97\%, 88.26\%, 86.00\%, and 88.69\%, respectively.

In addition, we also conducted a comparison between MCD64 and the GABAM products. The monthly MCD64 products generated with the MODIS satellite images (spatial resolution is about 500 m) were...
composited into annual BA products. BA of Australia in 2019 were selected as a case study to compare GABAM product with MCD64 product (Figure 3). It can be seen from Figure 3 that the two products showed a quite similar spatial distribution of BA in Australia in 2019 (Figures 3a and 3b). However, when compared with details (demonstrated as Figures 3c–3h), the MCD64 product was not capable of detecting small or highly fragmented burned patches due to the limitation of its spatial resolution, and some mixed pixels were classified as burned pixels. Compared with MCD64 product, the result of GABAM product showed finer boundaries, which can be useful for the statistics of the area of biomes actually burned.

3.2. Spatial Distribution Analysis of Burned Area

The spatial distribution of global BA in the 5 years were displayed in Figure 4. In order to better display the spatial distribution of global BA, burned density, that is, percentage of burned pixels in each 0.25° × 0.25°
grid was used instead of directly drawing the burned pixels on a global map. As demonstrated in Figure 4 that global fires are mainly distributed in central Africa, northern Australia and central South America. Most of these areas are located in the tropics, with hot climates, abundant combustible materials, and long dry seasons, and fires frequently occur. The areas with fewer fires include cold areas (such as the Qinghai-Tibet Plateau) and areas with scarce combustible materials (such as the Sahara Desert).

Figure 4. Spatial distribution of global burned area density (percentage of burned pixels in each 0.25° × 0.25°) in 2015–2019, figures (a)–(e) corresponding to years 2015–2019, respectively.
According to statistics, from 2015 to 2019, the total area of global BA was $365.27 \times 10^6$, $368.56 \times 10^6$, $374.56 \times 10^6$, $345.55 \times 10^6$, and $363.09 \times 10^6$ ha, with an average value of $363.41 \times 10^6$ ha (Table 3). Among the 5 years, the total area of global BA was relatively stable, with a slight decline in 2018. As can be seen from Table 3, Africa had the largest BA. From 2015 to 2019, burned land in Africa was $267.56 \times 10^6$, $291.91 \times 10^6$, $273.61 \times 10^6$, $246.13 \times 10^6$, and $271.70 \times 10^6$ ha, respectively, which accounted for 73.25%, 79.20%, 73.05%, 71.23%, and 74.83% of the world's total, with an average percentage of 74.31%. Followed by Oceania, from 2015 to 2019, the BA in Oceania was $32.54 \times 10^6$, $23.56 \times 10^6$, $42.56 \times 10^6$, $48.58 \times 10^6$, and $29.98 \times 10^6$ ha, respectively, accounting for 8.91%, 6.39%, 11.36%, 14.06%, and 8.26% of the world, with a 5-year average proportion of 9.80%. Next are Asia, South America, Europe and North America, with a 5-year average proportion of 6.26%, 5.52%, 2.36%, and 1.76%, respectively.

| Year | Africa | Asia  | Europe | North America | South America | Oceania | Total  |
|------|--------|-------|--------|---------------|---------------|---------|--------|
| 2015 | 267.56 | 24.92 | 12.44  | 8.08          | 19.72         | 32.54   | 365.27 |
| 2016 | 291.91 | 22.60 | 3.25   | 5.99          | 21.26         | 23.56   | 368.56 |
| 2017 | 273.61 | 20.79 | 9.03   | 7.63          | 20.94         | 42.56   | 374.56 |
| 2018 | 246.13 | 19.87 | 11.11  | 5.45          | 14.41         | 48.58   | 345.55 |
| 2019 | 271.70 | 25.55 | 6.87   | 4.82          | 24.18         | 29.98   | 363.09 |
3.3. Regional Burned Area Changes From SDGs Starting Year

From 2015 to 2019, the total area of global BA was relatively stable (Figure 5). As demonstrated in Figure 5, the largest area of global BA was in 2017 (about 374.56 × 10^6 ha), and smallest in 2018 (about 345.55 × 10^6 ha). The difference between them was 29.01 × 10^6 ha, a decrease of 7.75%. Difference of global BA between 2015 and 2019 was only 2.18 × 10^6 ha, a decrease of 0.6%. However, Figure 5 exhibited significant differences in the changes of BA on different continents. As stated in the above section, global BA was mainly distributed in Africa, Oceania, and South America. In the following section, we will focus on analysis of BA changes in these three regions from 2015 (the starting year of SDGs) to 2019.

3.3.1. Africa

The BA of Africa comprised more than 70% of all the area burned worldwide, therefore the inter-annual variability of BA in Africa largely determined the inter-annual changes of BA in the globe. In 2015 and 2019, the BA of Africa was 267.56 × 10^6 and 271.70 × 10^6 ha, respectively. The spatial distribution of African BA in 2015 and 2019 showed similar patterns, mainly in Sub-Saharan Africa, covering the latitudes from 20°N to 20°S (Figure 6), where the land cover is dominated by tropical and subtropical savanna; the climate is very hot; fuels are abundant, and the dry season lasts for a long time (the dry season in the northern hemisphere is from October to March of the following year, and the dry season in the southern hemisphere is from May to October). All these climatic and geographical factors make these areas prone to fires, and fires in this sparsely populated open savanna region are driven by the hot Harmattan trade winds virtually unchecked during the dry season (Giglio et al., 2013). However, most fires in this region are caused by human activities for the management of crops, grazing and hunting (Grégoire et al., 2013; Lewis et al., 2015).

3.3.2. Oceania

The tropical savannas of northern Australia are among the most fire-prone regions in the world, and they accounted for most of the areas affected by fire during 2015–2019 in Australia. In addition to natural fires, in northern and central Australia, fires are used by Aboriginal people as a tool for land management in these largely remote and sparsely populated regions. Compared with Figure 7a, the spatial distribution...
pattern of BA in Australia in 2019 changed obviously, and there were significant increases in BA along the eastern and southeastern coasts of Australia (the blue rectangle in Figure 7b). These areas are the main forest distribution areas as well as population and urban distribution areas in Australia. Historically, they were not fire-prone areas. Based on the Climate Hazards Group InfraRed Precipitation with Station data (Funk et al., 2015) and air temperature data of the fifth generation of European Centre for Medium-Range Weather Forecasts atmospheric reanalysis of the global climate (Copernicus Climate Change Service, 2017) from GEE, the long-time series of average annual precipitation and temperature data in the eastern and southeastern coast of Australia (the blue rectangle in Figure 7b) were calculated; as shown in Figure 8: It was in a state of extreme high temperature and drought in 2019.

### 3.3.3. South America

Compared with 2015, the area of burned land in South America increased significantly in 2019, with an increase of 22.62%. The spatial distribution characteristics of the burned sites in South America in 2015 and 2019 was similar, and they were relatively evenly distributed throughout the continent. As can be seen from Figure 9, the increase of BA in South America in 2019 mainly occurred in the Santa Cruz Province of Bolivia (the blue circle in Figure 9) and the highly flammable Brazilian Cerrado (savanna) biome (the green circle in Figure 9) (Nogueira et al., 2017) and the drier Brazilian Amazon biome (Espinoza, Sörensson, et al., 2019; Fonseca et al., 2017).

![Average annual precipitation and temperature in eastern and southeastern Australia from 1981 to 2019.](image)

**Figure 8.** Average annual precipitation and temperature in eastern and southeastern Australia from 1981 to 2019.
3.4. Interannual Dynamic Change of Burned Area in Amazon Basin

Amazon has the largest tropical rainforest and terrestrial ecosystem in the world (Jenkins et al., 2013). The area, spatial distribution, and annual dynamics of Amazon forests will affect regional and even global environmental systems, and play an extremely important role in regulating climate and maintaining global carbon balance. Influenced by climate change, deforestation and fires, Amazon forests are increasingly threatened (Xu et al., 2020).

Based on the boundary of the Amazon basin, BA in the Amazon basin from 2015 to 2019 is obtained (Figure 10). The area of the burned land in the Amazon basin from 2015 to 2019 is $4.33 \times 10^6$, $4.69 \times 10^6$, $5.07 \times 10^6$, $2.13 \times 10^6$, and $4.67 \times 10^6$ ha, respectively, with evident inter-annual variations during this time period.

During 2015–2016, the most severe drought event since 1901 occurred, affecting more than 80% of the Amazon basin, spanning from September 2015 to May 2016 (Fonseca et al., 2017; Ribeiro et al., 2018), and El Niño and tropical Pacific and tropical North Atlantic warming were the main driving factors for this extremely severe drought (Panisset et al., 2018; Qin et al., 2019). Long-term drought is an important reason for the increase in fire frequency, and large-scale forest fires occurred in 2015 and 2016 (Figure 11). As shown in Figures 11a and 11b, the distribution pattern of the BA in Amazon basin in 2015 and 2016 is similar, extending from the northern part of the Amazon basin to the central and southeast.

In 2017, the Amazon basin had the largest burned land in the past 5 years. Compared with 2018, there were a lot of fires in the southeastern region in 2017 (Figures 11c and 11d). Fire mainly occurred during the dry season from July to October in South America. Although droughts did occur in the southern Amazon in 2017 (Espinoza, Ronchail, et al., 2019; Espinoza, Sörenson, et al., 2019), most fires in this area in 2017 were caused by human activities, such as farmers in the Amazon set fires to clear land for agricultural expansion and grazing (Lizundia-Loiola et al., 2020; World Economic Forum, 2018). While 2018 is a low fire year, and the Amazon region in 2018 had the smallest burned land in the past 5 years, which is consistent with the statistics of the number of fires in BDQueimadas of INPE (INPE, 2020).

Figure 9. Comparison of burned area distribution in South America in 2015 (a) and 2019 (b).

Figure 10. Burned area statistics of Amazon Basin.
Fire has a great impact on vegetation biomass and productivity (Pellegrini et al., 2018). In order to analyze the impact of fire on vegetation productivity, MODIS Net Primary Production (NPP) products (MOD17A3H Version 6) (Running et al., 2015) of 2018 and 2019 were used to detect the impacts of fires in 2019 on vegetation productivity. First, the NPP difference map between 2019 and 2018 was calculated based on the GEE platform and reprojected and resampled to match the GABAM product. Then the

Figure 11. Comparison of the distribution of burned area (BA) in the Amazon Basin in (a) 2015, (b) 2016, (c) 2017, (d) 2018, (e) 2019 and NPP difference between 2019 and 2018 in the BA of the Amazon Basin of 2019 (f).
NPP difference map was spatially intersected with the BA map of the Amazon area of 2019 and the NPP difference between 2019 and 2018 in the BA of the Amazon Basin of 2019 was obtained (Figure 11f). As shown in Figure 11f, fire had serious impacts on vegetation NPP. Statistics show that in 2019, the NPP in the BA of the Amazon basin had a large-scale decline, with 76.56% of NPP difference less than zero, 15.04% between 0 to 0.05 kg C m$^{-2}$, and 8.4% more than 0.05 kg C m$^{-2}$. The NPP unchanged or slight increased areas may be caused by the difference in spatial resolution of the MOD17A3H (500 m) and GABAM (30 m) products or the rapid recovery of vegetation in tropical or subtropical areas (Zhang et al., 2020).

4. Discussion

In this study, 30 m resolution global BA products from 2015 to 2019 are generated using time series Landsat land surface reflectance data and machine learning technique. Based on these products, the spatial distribution, influencing factors and change characteristics of the BA from 2015 to 2019 were monitored and analyzed from different perspectives, including global, continental and fire-prone regions, such as Africa, Oceania, South America, and the Amazon basin. The high spatial resolution and accurate boundaries of the GABAM products can provide high-precision global BA distribution information support for global fire monitoring and climate change related studies. However, as with any remote sensing data set, when using GABAM products, there should be some caveats: The BA of continuously cloudy areas will be underestimated, especially in tropical areas, where vegetation grows fast. The next step is to quantify the degree of this potential deviation, which may be accomplished by using multi-platform observations including ground observations and airborne observations (Giglio et al., 2013) or using multi-source data fusion. A study in South Africa shows that using both Landsat-8 and Sentinel-2 satellite sensors can achieve higher burned area extraction accuracy (Roy et al., 2019).

GABAM products can effectively depict the temporal and spatial patterns of vegetation areas affected by fires. In the section of “Interannual Dynamic Change of Burned Area in Amazon Basin,” it was found that NPP in BA was severely affected. To better assess the impact of fire, biomass and other data before and after the fire are needed to estimate the carbon loss caused by biomass burning (Potter et al., 2001). In addition, this article only uses the 5-year global BA products from 2015 to 2019, and fails to study the relationship between global climate change and fires in a longer time scale. In the future, we will generate and release long time series (1980s to present) high spatial resolution global BA products to study the relationship between global climate change and fires in a longer time scale.

The abnormally huge forest fires in eastern and southeastern Australia in 2019 had severely affected Australia’s scarce forest resources, wildlife, and people’s lives. The observation records of the Australian Bureau of Meteorology (Australian Bureau of Meteorology, 2019) indicate that most areas in Australia in 2019 were warmer than previous years, especially in eastern and southeastern Australia, with Sydney, Canberra, Brisbane, and Hobart all observing their highest annual mean maximum temperature on record. Much of Australia were affected by drought in 2019, which was especially severe in New South Wales and southern Queensland. A very strong positive Indian Ocean Dipole (IOD) was one of the main influences on Australia’s climate during 2019, and contributed to very low rainfall and severe drought in southern Queensland, New South Wales, and Victoria. The extremely high air temperature and drought (Figure 8) caused by climate anomalies are important causes of the rare forest fires in eastern and southeastern Australia in 2019 (Ridder et al., 2020). In the future, we should strengthen the monitoring of extremely high air temperature and drought caused by climate change, and take effective forest protection and fire prevention measures in areas and time periods of extremely high air temperature and drought to mitigate the positive feedback pressure between climate change and fires.

The huge Amazon fire in 2019 (Figure 11e) led to a sharp decline of the vegetated area. Compared with 2018, the area of burned land in Amazon in 2019 increased by 119.25%. The Amazon fire in 2019 may be related to the high temperature and drought caused by climate change, but the main reason is the unreasonable land management activities of the local people (Barlow et al., 2020; Kelley et al., 2020; Lizundia-Loiola et al., 2020), which is similar to 2017. There have been increasing incidents of arson and deforestation in the Amazon region in order to promote the development of agriculture and animal husbandry. Researches conducted by others shown that the Amazon fire is closely related to the deforestation process (de Oliveira, Chen, Mataveli,
et al., 2020; Van der Werf et al., 2009). Logging activities in the Amazon region led to an increase in the amount of debris on the forest floor, thus increasing the amount of fuels, coupled with the occurrence of arid climate, leading to an increase in the frequency of fires in the region (Joly et al., 2014). Or cut down the forest and leave it dry, then burn it to prepare for agriculture or pasture (de Oliveira, Chen, Mataveli, et al., 2020; de Oliveira, Chen, Stark, et al., 2020), thus the fire has become a cleaning tool to transform farmland or pasture.

Extreme climate events (El Niño, La Niña, etc.) have a significant impact on the global precipitation distribution, and thus affect the spatial distribution of global fires (Chen et al., 2016). Human activities are also important factors affecting global fire distribution and changes. By analyzing the dynamic change of BA and its response to extreme climate events, we can clarify the mechanism of climate factors and human activities on fire occurrence and spread in the context of global climate change, so as to provide decision-making basis for fire warning and disaster prevention and strengthening resilience and adaptive capacity to climate-related fire hazards in all countries. In addition, BA is associated with multiple SDG indicators, and transdisciplinary communication and collaboration are needed to carry out studies on BA and other SDGs indicators in the future.

5. Conclusions

In this study, a novel multi-year (from the starting year of SDGs 2015–2019) 30 m resolution global BA products were generated and acted as an SDG indicator. Based on the 2015–2019 5-year GABAM products, spatial distribution, influencing factors and change characteristics of BA were analyzed from different perspectives, including global, continental and some fire-prone regions. The results show that from 2015 to 2019 the total area of BA in the world was 365.27 × 10^6, 368.56 × 10^6, 374.56 × 10^6, 345.55 × 10^6, and 363.09 × 10^6 ha, respectively, with an average value of 363.41 × 10^6 ha. On a global scale, the BA are mainly distributed in central Africa, northern Australia and central South America. From 2015 to 2019, the total area of global BA was relatively stable, however there were significant differences among various continents and regions. The Amazon region in South America and Australia were selected to conduct impact analysis. The Amazon fire in 2019 caused a reduction of 4.67 × 10^6 ha of vegetated area in the Amazon basin, an increase of 119.25% compared with 2018. In 2019, burned area on the eastern and southeastern coasts of Australia increased abnormally. Inter-annual changes of BA were influenced by a variety of factors, including climate anomalies, for example extremely high air temperature and drought caused by climate change, and human activities, for example deforestation and arson for land clearing.

Therefore, in order to achieve sustainable development goals, we should take action to clarify the mechanism of climate factors and human activities on fire occurrence and spread in the context of global climate change so as to provide decision-making basis for catastrophic fire warning and disaster prevention and mitigation.

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 study.

Data Availability Statement

The authors comply with AGU’s data policy. Accesses to all the data sets are as follows: The burned area data set can be downloaded from https://vapd.gitlab.io/post/gabam.

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