International Journal of Remote Sensing

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tres20

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To cite this article: Maria Zubkova, Michael L. Humber & Louis Giglio (2023) Is global burned area declining due to cropland expansion? How much do we know based on remotely sensed data?, International Journal of Remote Sensing, 44:4, 1132-1150, DOI: 10.1080/01431161.2023.2174389

To link to this article: https://doi.org/10.1080/01431161.2023.2174389

Published online: 07 Mar 2023.

INTERNATIONAL JOURNAL OF REMOTE SENSING
2023, VOL. 44, NO. 4, 1132–1150
https://doi.org/10.1080/01431161.2023.2174389

Is global burned area declining due to cropland expansion? How much do we know based on remotely sensed data?

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ABSTRACT

The global extent of the amount of burned area seems to have changed substantially in the last two decades. Discussions regarding the main force behind the current trends have dominated research in recent years, with several studies attributing the global decline in wildfires to socio-economic and land-use changes. This review discusses the uncertainties and limitations of remotely sensed data used to determine global trends in burned areas and changes in their potential drivers. In particular, we quantify changes in the amount of burned area and cropland area and illustrate the lack of consistency in the direction and magnitude of the trend in cropland land cover type specifically within sub-Saharan Africa, the region where data show a strong trend in the amount of burned area. We state the limitations of remote-sensed fire and land cover products. We end by demonstrating that based on the currently available data and research methods applied in the literature, it is not possible to unequivocally determine that cropland expansion is the primary driver of the decline in fire activity.

ARTICLE HISTORY

Received 27 October 2022
Accepted 24 January 2023

KEYWORDS

wildfire; burned area trends; African savannas; cropland expansion

1. Introduction

Fire is a global phenomenon whose relationship with vegetation developed soon after the appearance of terrestrial plants (Bowman et al. 2009; Glasspool, Edwards, and Axe 2004). Within the last million years, humans have become an important part of fire-climate -vegetation interactions (Archibald, Staver, and Levin 2012; Bowman et al. 2009; Pausas and Keeley 2009; Santín and Doerr 2016). Fire was first used as a tool for cooking and heat and later for 'fire-stick farming' (Bird et al. 2008), where it started to influence vegetation and biodiversity. Despite such a long history of human coexistence with fires and the growing body of wildfire research, our understanding of how vegetation, landscape, climate, and humans shape fire activity across biomes is still limited (Bowman et al. 2020).

Many argue that our knowledge of global fire activity is constrained by the quality of the available data (Bowman 2018). While fire occurrence databases, land survey records, and palaeoecological evidence of past fires offer multiple decades of observations in some regions, only satellite-derived data provides global coherent multi-temporal spatial information (Benali et al. 2017; Earl and Simmonds 2017). An

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important caveat is that remotely sensed data have several limitations that propagate mapping errors, which are not always properly characterized when the results are interpreted, or conclusions are drawn. In particular, many authors assert that the short time span of remotely sensed data is insufficient to study fire trends, especially within regions with long fire reoccurrence periods and high year-to-year variability (Bowman et al. 2020; Krawchuk and Moritz 2014). Additionally, global fire products are currently only available at coarse resolution, introducing bias favouring the detection of larger fires (Boschetti et al. 2019; Laris 2005). At the same time, unknown errors exist within the boundaries of individual fires due to the so-called low-resolution bias (Boschetti, Flasse, and Brivio 2004; Humber, Boschetti, and Giglio 2019). Moreover, some fire activity remains undetected due to cloud cover, spectral confusion with adjacent unburned areas, and short post-fire signal persistence (Melchiorre and Boschetti 2018; Roteta et al. 2019; Roy et al. 2019).

The limitations of remotely sensed data are especially important to consider when the data are used to estimate spatial or temporal changes. Several recent studies based on coarse resolution remotely sensed data have revealed a decline in global fire activity (Andela et al. 2017; Earl and Simmonds 2018; Forkel et al. 2019) and attributed those changes to various environmental and socio-economic factors. The work of Andela et al. (2017) has critically influenced academic dialogue on global trends in wildfires. Subsequently, based on their conclusions, the expansion of agricultural areas became widely hypothesized as the primary force behind the current changes in global fire activity. Yet most of the previously mentioned studies do not acknowledge that the regions where these changing patterns have been observed are known to be data-poor. In particular, burned area mapping within fragmented landscapes, especially cropland, is a known and open challenge (Hall et al. 2016; Devineau, Fournier, and Nignan 2010; Laris 2005), and no reliable information on the extent of agricultural land is available in tropical savannas, nor on its temporal changes (Estes et al. 2018; Li et al. 2021; Nabil et al. 2020; Xu et al. 2018). Issues limiting the usefulness of current cropland area products include nontrivial differences in thematic product types (e.g. agricultural land vs. cropland, planted-/harvested-area vs. cropland area, inclusion of fallow land), reliability and capacity of agencies reporting agricultural statistics, low mapping accuracy (particularly in areas with low yields or intercropping practices), persistent cloud cover, and a lack of globally consistent year-to-year cropland change detection information (Vancutsem et al. 2013; Waldner et al. 2015; Whitcraft et al. 2019).

The objectives of this review are to demonstrate key limitations of the currently available burned area (BA) and land cover (LC) datasets that can be used for trend detections, highlight recent fire trend studies and hypothesize likely effects of the choice of datasets on their conclusions. Specifically, we argue that to legitimately conclude that the reported global decline in BA is driven by cropland expansion, three conditions must be met. First, negative trends should be global in scope, not localized to a specific continent or region. Second, the trends in both fire activity and cropland expansion must be supported by data that definitively demonstrate such trends over time. And finally, the decline in BA must be documented within or proximal to the areas of cropland expansion.

2. Data and method

Since previously published trends were based on different time intervals, here we reported changes in BA over the past 20 years (2001–2020) separately for each of the 14 GFED regions (Giglio et al. 2006) based on the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6 (C6) MCD64A1 BA product (Giglio et al. 2018). The slope of the trends in BA was estimated using the non-parametric Theil-Sen regression (Birkes & Dodge 1993). The Mann-Kendall trend test (Kendall 1975; Mann 1945) was used to estimate the significance of the trends.

To demonstrate the importance of the choice of LC data, we presented the spatial distribution and time-series of cropland LC type based on all currently available LC products that offer successive maps for change detection. The MODIS Land Cover Type product (MCD12Q1) C6 at 500 m resolution provides data from 2001 to 2020 (Sulla-Menashe et al. 2019). Although the C5.1 MCD12Q1 (2001–2013, Friedl et al. 2010) product was deprecated in January 2019 and removed from data archives by NASA, it is included in this work because several studies that analysed the relationship between fire and cropland extent were based on the now-deprecated version of the product (e.g. Andela and van der Werf 2014; Andela et al. 2017). In this paper, we used the International Geosphere Biosphere Programme (IGBP) legend for both versions of MCD12Q1. ESA CCI LC v2.0.7 (1992–2015) is based on a combination of AVHRR, SPOT-Vegetation, MERIS, and PROBA-Vegetation acquisitions (ESA 2017) and was utilized in numerous fire studies (e.g., Abatzoglou et al., 2018; Forkel et al., 2019; Zubkova et al., 2019, 2021). The Copernicus Climate Change Service (C3S) offers global LC maps consistent with ESA CCI for the 2016–2019 period based on the PROBA-Vegetation and Sentinel-3 OLCI time series (ECMWF 2021). Both products have the same spatial resolution (300 m) and together offer 28 years of LC data suitable for change detection. For simplicity, we refer to the combination of ESA CCI v2.0.7 and C3S as CCI_LC. Additionally, we included the only multi-year moderate resolution global LC product, GLOBELAND30, at 30 m resolution based on data from Landsat TM/ETM+ and the Chinese BJ-1 and HJ-1 sensors (Chen et al. 2015). While it does not provide yearly LC maps, thus precluding detection of the exact time of LC shift (Broich et al. 2011) and analyses of interannual LC – fire relationships, GLOBELAND30 data is available every 10 years (2000, 2010, 2020), which can be used for the estimation of the overall temporal changes in land use. Here, we analysed the time-series of cropland (MCD12Q1 class 12; CCI_LC classes 10, 20; GLOBELAND30 class 10) and mosaic of cropland and natural vegetation (MCD12Q1 class 14; CCI_LC classes 30, 40).

To explore the relationship between BA and land use, we adopted the approach proposed by Andela et al. (2017). According to which, BA and cropland datasets were rescaled to a 0.25° spatial resolution, and the sub-grid cell spatial correlation (Pearson's correlation coefficient [$\boldsymbol{r}$]) was calculated at 1.5° spatial resolution from all 0.25° pixels within each larger 1.5° grid cell ($N = 36$). However, instead of using regional spatial correlations between the mean annual BA and one arbitrary year of cropland extent, we calculated the correlation between the Theil-Sen BA trend and the difference in the cropland extent between the last (2013 for MCD12Q1 Col.5.1 and 2020 for other LC products) and the first year of data (2001). BA trends were calculated using 2001–2013 data for MCD12Q1 Col.5.1 and 2001–2020 data for the rest of LC products. Only the 'pure' cropland LC type was used in this analysis.

3. Global trends in area burned

Despite several studies reporting a recent global decline in BA (e.g. Andela et al. 2017; Forkel et al. 2019), a closer analysis of fire statistics demonstrates that regional trends show differences in the direction and the amplitude (Bowman et al. 2020; Giglio, Randerson, and van der Werf 2013). For example, Giglio, Randerson, and van der Werf (2013) detected an upward trend in six out of 14 GFED regions using MODIS BA from August 2000 to mid-2012. Similarly, Bowman et al. (2020) demonstrated that many highly populated counties/regions experienced an increase in fire activity in the last several decades, such as Canada, Western U.S.A, Portugal, and New South Wales (Australia). Additionally, Southern Hemisphere Africa (SHAF) and Australia and New Zealand (AUST), two GFED regions that contribute to almost half of the global BA, are good examples where the duration of time interval heavily influences the magnitude and the direction of calculated trends. Specifically, Giglio, Randerson, and van der Werf (2013) reported a positive trend in SHAF (2000–2012), while Zubkova et al. (2019), using a longer time series (2002–2016), found the trend to be opposite but not significant. In AUST, Giglio, Randerson, and van der Werf (2013) calculated a drastic decrease of 10.7% year^{-1} (2000–2012), while Andela et al. (2017) found a modest increase of 1.53% year^{-1} by analysing a slightly different time interval (2003–2015).

Here, utilizing 20 years of MODIS BA data, we can observe that five out of 14 regions experienced a positive trend in BA, none of which were statistically significant (Figure 1). Overall, depending on the significance level, negative trends were significant in the four regions at $\boldsymbol{p}<0.05$ and one at $\boldsymbol{p}<0.01$ (Northern Hemisphere Africa – NHAF). Considering an even broader scale and a more stringent confidence level ($\boldsymbol{p}<0.01$), only two continents, Africa and Europe, experienced a significant negative trend in BA over the past 20 years (Table 1).

It is important to note that while ordinary least-squares regression (OLS) is the most common approach for estimating BA trends (e.g. Andela and van der Werf 2014; Andela et al. 2017; Collins et al. 2022; Keeley and Syphard 2021; Zubkova et al. 2019) and therefore presented in Figure 1, OLS might not be sufficiently robust, especially within regions having high year-to-year variability. A poor fit of a linear trend can be particularly evident in SHAF, especially once residuals are plotted (not shown), possibly since fire activity there is mainly driven by year-to-year variability in precipitation which is strongly influenced by the El Niño/Southern Oscillation (Andela and van der Werf 2014; Archibald et al. 2009, 2010; Nicholson and Kim 1997). Forkel et al. (2019) addressed this issue by fitting a quantile regression and did not find statistically significant BA trends in any region except NHAF, concluding that trends in BA are highly influenced by abnormal BA at the beginning and end of the time series.

The confusion between global and African trends in BA comes from the fact that the pervasiveness of fire in sub-Saharan Africa (SSA) is such that changes in BA in the region drive global trends (Andela et al. 2017; Giglio et al. 2018). Fires in higher latitudes contribute little to the global area burned (Giglio et al. 2018). A larger portion of the global BA comes from the tropics, particularly tropical savannas (Daniau et al. 2013; Saha et al. 2019; van der Werf et al. 2008), which are predominant in SSA. The overwhelming amount of BA in Africa (67% of the global BA) contributes to a common misconception in

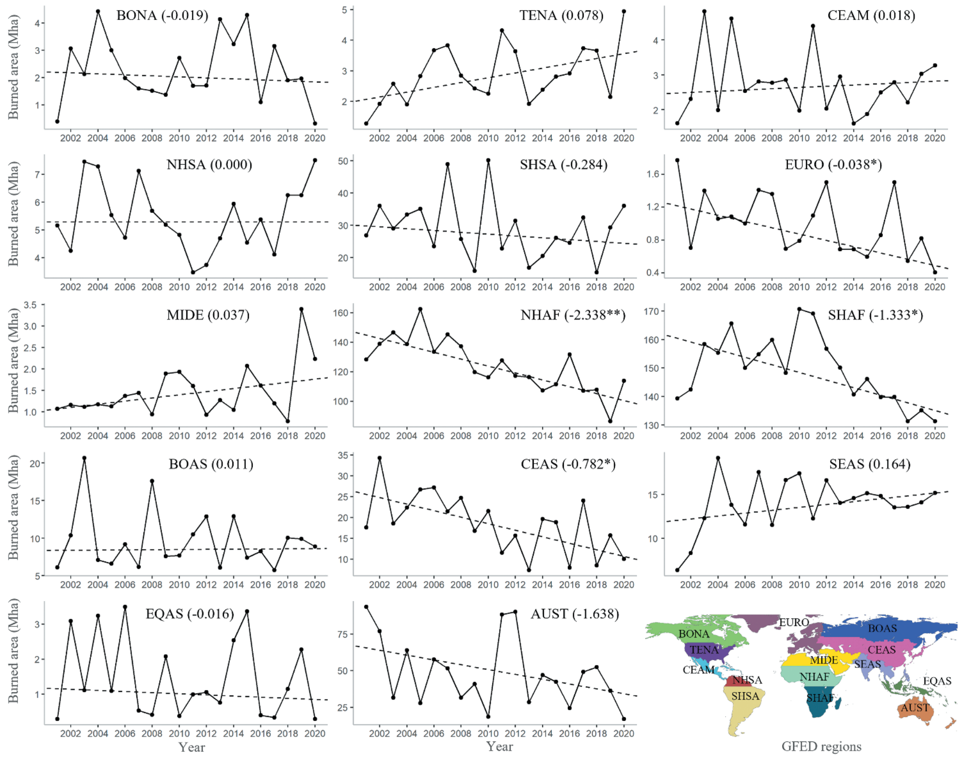

Figure 1. Time series (2001–2020) of burned area derived from MODIS MCD64A1 C6 summarized over a calendar year with the respective trends represented by the dashed lines calculated for each GFED region. The slope of the BA trends is shown in parentheses (Mha year-1), while its significance is denoted with asterisks (*p < 0.05, ** $p < 0.01$). GFED regions abbreviations: BONA – Boreal North America, TENA – Temperate North America, CEAM – Central America, NHSA – Northern Hemisphere South America, SHSA – Southern Hemisphere South America, EURO – Europe, MIDE – Middle East, NHAF – Northern Hemisphere Africa, SHAF – Southern Hemisphere Africa, BOAS – Boreal Asia, CEAS – Central Asia, SEAS – Southeast Asia, EQAS – Equatorial Asia, AUST – Australia and New Zealand.

Table 1. Burned area statistics at the continental level: average annual burned area (BA, 2001–2020), annual trend estimated using the Theil-Sen regression, and annual linear trend from Andela et al. (2017) study that covered the 2003–2015 time frame. Significant trends from this study are denoted with asterisks (*p<0.05, **p<0.01, and ***p<0.001). ^ Opposite of Europe and Asia, Andela et al. (2017) calculated trends within Eurasia and Southeast Asia; therefore, caution is required when the results between the two studies are compared.

Continents	Average BA (Kha)	Trend (Kha year^{-1})	Trend (% year^{-1})	% of Global Change	Trend (% year^{-1}) from Andela et al. (2017)
Africa	274251.4	−3620.3***	−1.32***	56.23	−1.60
Asia	39005.5	−534.2*	−1.37*	8.30	−0.62^
Australia	48507.5	−1643.4	−3.39	25.54	1.53
Europe	6796.5	−343.9**	−5.06**	5.35	−2.23^
N. America	7936.2	3.8	0.05	−0.06	0.61
S. America	34405.3	−296.7	−0.86	4.61	−1.40
Oceania	12.3	0.8	6.50	−0.01	-

the literature about the *global* decline in burned area when in fact, most of the trend is driven by the significant decline in *African* burned area.

4. Limitations and biases of remotely sensed fire products

Several limitations of the remote-sensed fire data and, in particular, coarse resolution products need to be considered since they are currently the only data sets available for assessing temporal changes in fire activity on a global scale. As previously noted, the short time span of remotely sensed data restricts our understanding of temporal changes in fire activity; however, in SSA, where savanna fires reoccur every five years or less (Archibald et al. 2010; Knowles et al. 2016), this limitation is likely not as crucial as in many other regions.

On the other hand, several other data limitations may profoundly impact the estimated trend in fire activity in SSA. We argue that we cannot be certain regarding the detected magnitude of the decline in BA if the following assumptions cannot be confirmed: the fire products either detect the majority of BA in SSA, or the commission-to-omission error ratio does not change significantly over time.

The validation of the MCD64A1 product using moderate resolution imagery (Boschetti et al. 2019; Roteta et al. 2019; Roy et al. 2019) has shown that the first assumption is false. Those studies confirmed that the coarse resolution MCD64A1 product used to estimate current trends in BA severely underestimates BA in Africa. Moderate-resolution maps detected 80% more BA than MCD64A1, and omission errors depend strongly on the size of BA scars and land cover type (Roteta et al. 2019). The highest underestimation was found for the smallest fire scars (<25 ha) and within the cropland LC type, which is not surprising since the poor performance of global coarse resolution BA products within agricultural land has been documented by previous studies (Boschetti et al. 2019; Hall et al. 2016; Hall, Argueta, and Giglio 2021; Lasko et al. 2017). Consequently, Ramo et al. (2021) raised concerns about the validity of the current reported decline in BA in Africa.

Additionally, while moderate-resolution maps of BA in Africa offer a big improvement in understanding the drivers and consequences of fire, these maps currently provide data for a single year and are not immune to commission and omission errors. For instance, the majority of BA maps are produced based on post-fire reflectance changes of vegetation (Roy et al. 2019), which, when occurring in cropland, are often indistinguishable from pre-planting, harvesting, or post-harvest, making accurate mapping of BA within agricultural land particularly challenging (Hall et al. 2016; Korontzi et al. 2006).

As an alternative to BA, some authors utilized active fire (AF) products, e.g. MODIS MOD14/MYD14 (Giglio, Schroeder, and Justice 2016), to reduce the mapping bias towards large fires (Earl and Simmonds 2017, 2018). AF products detect fires significantly smaller than a pixel, though this capability is a function of the fire's intensity (Giglio et al. 2003). However, to be detected, those fires must be actively burning, unobscured by clouds and smoke during the satellite overpass, and have sufficient intensity to enable detection (Giglio, Schroeder, and Justice 2016; Roy et al. 2008). Therefore, since in tropical regions, cloud cover is persistent and small, low-intensity fires are prevalent, it is prudent to analyse data from both BA and AF products to reduce the uncertainties in detected trends.

The under-detection of small fires alone does not necessarily invalidate the overall trend, provided that the commission-to-omission error ratio is approximately constant over time, i.e. if classification bias remains stable, then the overall trend will be unaffected. Current research on the topic of error rate trends for burned area products is inconclusive and requires more research (Forkel et al. 2019; Earl and Simmonds 2018). Imperfect algorithm design is a potential source of increased bias through time, though most burned area products show agreement in the relative annual burning variability (Humber, Boschetti, and Giglio 2019). Multi-annual error assessment protocols have been proposed by the fire remote sensing community, but the required number of sample observations remains a barrier for estimation of year-to-year error rates with reasonable confidence (Boschetti, Stehman, and Roy 2016; Padilla et al. 2017).

Since most omission errors are attributed to satellite data's low spatial resolution (according to Roteta et al. (2019), the use of moderate resolution data (20 m) for BA mapping led to a reduction of commission error by more than 50% compared to the 500 m MCD64A1), an implicit assumption of BA trend studies is that the distribution of fire sizes remains constant. This assumption might not stand based on several studies in Africa demonstrating a strong negative relationship between fire size and human activity (Archibald, Staver, and Levin 2012; Archibald 2016). Humans manipulate fire size directly through fire suppression and changes in fire seasonality and indirectly by reducing the amount of available fuel and increasing landscape fragmentation by increasing livestock density, number of agricultural fields, and building infrastructure (Archibald, Staver, and Levin 2012; Le Page et al. 2010; Mouillot and Field 2005). Igniting fires to manage fuel loads before fire weather reaches its maximum to prevent large, hot, and hard-to-control distractive late-season fires has become the goal of traditional fire management in Africa (Archibald 2016; Elliott, Franklin, and Bowman 2009; Laris and Wardell 2006; Mbow, Nielsen, and Rasmussen 2000; Nieman, van Wilgen, and Leslie 2021). Since the human population is increasing in Africa (OECD/FAO 2020), it is plausible that the size of fires has been decreasing, and this trend will continue in the future (Ramo et al. 2021).

To summarize, the coarse-resolution sensors' bias towards large fires might limit our ability to accurately estimate the temporal and spatial variations in BA in Africa, a continent characterized by high landscape heterogeneity and where most vegetation fires are human-driven (Archibald 2016; Knowles et al. 2016). Additionally, severe under-detection of fires within agricultural land can introduce errors into identified functional relationships between fire and cropland. Similarly, proximity to infrastructure or highly populated areas where the landscape is more heterogeneous tends to decrease fire size, thus decreasing our ability to detect those fires and potentially explaining why humans appear to negatively influence BA based on coarse resolution data but not based on higher resolution data and field observations (Devineau, Fournier, and Nignan 2010; Nakalembe et al. 2022; Nieman, van Wilgen, and Leslie 2021; van Wilgen et al. 2004). Moreover, a steady increase in human population and urban and agricultural land can enhance the under-detection of fires, plausibly explaining some of the observed decline in fire activity.

5. Constraints on accurate cropland mapping

Accurate estimates of the total land-use area for crop production are crucial for planning food security policies and environmentally sustainable development globally and especially in Africa, where the demand for food and the proportion of the population that is malnourished are markedly increasing (Cole et al. 2018; OECD/FAO 2020; Xu et al. 2018). However, producing accurate LC maps is expensive and logistically challenging due to the large-scale field data collection required on an annual or even seasonal basis (Carletto, Jolliffe, and Banerjee 2015).

For several decades, official crop production statistics were the primary source of time-series cropland data at a country level. For instance, the FAOSTAT database (2022) has been a valuable source for assessing food security and global trade (Brink and Eva 2009; FAO 2014). However, this data source has its limitations. First, the accuracy of FAOSTAT varies greatly between countries and often between years since it is based on country-dependent reports (Liu et al. 2018), which are more readily available in developed countries than in developing nations (Hannerz and Lotsch 2008; Liu et al. 2018). Additionally, statistics can be reported using the calendar year, cropping year, or market year. For this reason, incompleteness and temporal inconsistencies were named to be the main problems with FAOSTAT data (Brink and Eva 2009; Xu et al. 2018). Second, this data source cannot be utilized for any spatial analysis at a scale smaller than the national level. And third, crop intensification in the form of double-cropping, e.g. harvesting wheat in the spring and soybeans in the fall (Alkhalil, Kadaoure, and Kouadio 2020; Wei, Lu, and Wu 2018), can lead to double-counted areas in aggregated statistics.

As an alternative to agency inventory statistics, LC maps based on remote-sensed imagery provide consistent, free-of-charge data at a pixel level (Fritz, See, and Rembold 2010; See et al. 2015; Xu et al. 2018). Unfortunately, like mapping burned scars within human-managed land, mapping agricultural fields remain challenging in Africa due to the prevalence of small field sizes, high landscape heterogeneity, and high variability within the cropland class (due to differences in crop types, crop rotations, planting density and common intercropping practices), and cloud cover (Nabil et al. 2020; Yu, Wang, and Gong 2013). Even though more LC products are being developed using various spatial resolution satellite data (10–500 m), their accuracy remains low (Samasse et al. 2018), and the discrepancies among different products are especially high in the most rapidly developing regions (Estes et al. 2018; Nabil et al. 2020; Wei et al. 2020).

The overall accuracy of the cropland area estimates decreases as landscape fragmentation increases (Chen et al. 2015; Gong et al. 2013; Nabil et al. 2020; Wei et al. 2020) due to mixed pixel classification error (Estes et al. 2018). This is particularly an issue in Africa, where the landscape is highly heterogeneous (Leroux et al. 2014; Li et al. 2021). Most agricultural field sizes fall between 0.15 and 1.5 ha (Pérez-Hoyos et al. 2017). Additionally, the confusion between the spectral properties of cropland and savannas LC classes and the presence of the residual trees within agricultural fields impedes accurate mapping of cropland in Africa (Debats et al. 2016; Estes et al. 2016; Fritz and See 2008; Sweeney et al. 2015; Verburg, Neumann, and Nol 2011). Another challenge is distinguishing permanent cropland fields from fallow (Li et al. 2021). Tong et al. (2020) estimated that the cropland LC class typically contains of 57–63% of fallow fields in the Sahel.

It is also worth noting that while the spatial resolution of the LC maps has been increasing, higher resolution does not guarantee better classification accuracy when it comes to cropland mapping in Africa. For example, an assessment of the ESA-CCI (European Space Agency Climate Change Initiative) 20-m LC map of Africa, based on Sentinel-2A observations (https://www.esa-landcover-cci.org/?q=node/187), did not show an improvement in cropland mapping accuracy compared to coarser resolution products (Alkhalil, Kadaoure, and Kouadio 2020).

6. Discrepancies between global land cover products

The discrepancies in the spatial distribution of cropland based on remote-sensed data were assessed in numerous studies. For example, Wei et al. (2020) reported a low agreement between 5 commonly used LC products in 63% of Africa. High disagreement was detected in the Sahelian belt (Fritz, See, and Rembold 2010; Hannerz and Lotsch 2006; Nabil et al. 2020) and West Africa (Nabil et al. 2020; Samasse et al. 2018), regions of particular interest in terms of the decline in fire activity. Samasse et al. (2018) went further and concluded that coarse resolution products could not be used for accurate estimation of cropland within a fragmented landscape commonly found in West Africa. Surprisingly, neither the discrepancies between LC products nor the effects of error propagation from inaccurate cropland detection have been widely acknowledged in fire-human analyses.

By simply plotting the cropland extend from four LC datasets, the dissimilarities in the spatial distribution (Figure 2a), as well as the overall extent (Figure 3) become clear.

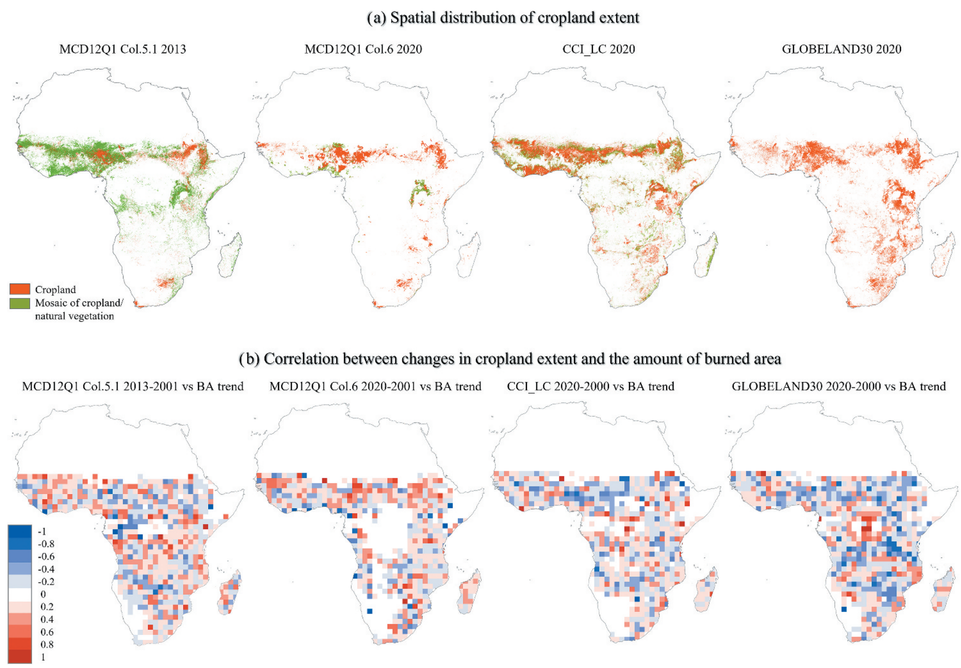

Figure 2. Spatial distribution of cropland and mosaic of cropland and natural vegetation (if applicable) land cover types in Sub-Saharan Africa using the most recent year of four global land cover products (a). Pearson's correlation between the annual trends of BA and changes in cropland extent (the difference between the last and the first year of data) for the 36 0.25° pixels within each 1.5° grid cell (b).

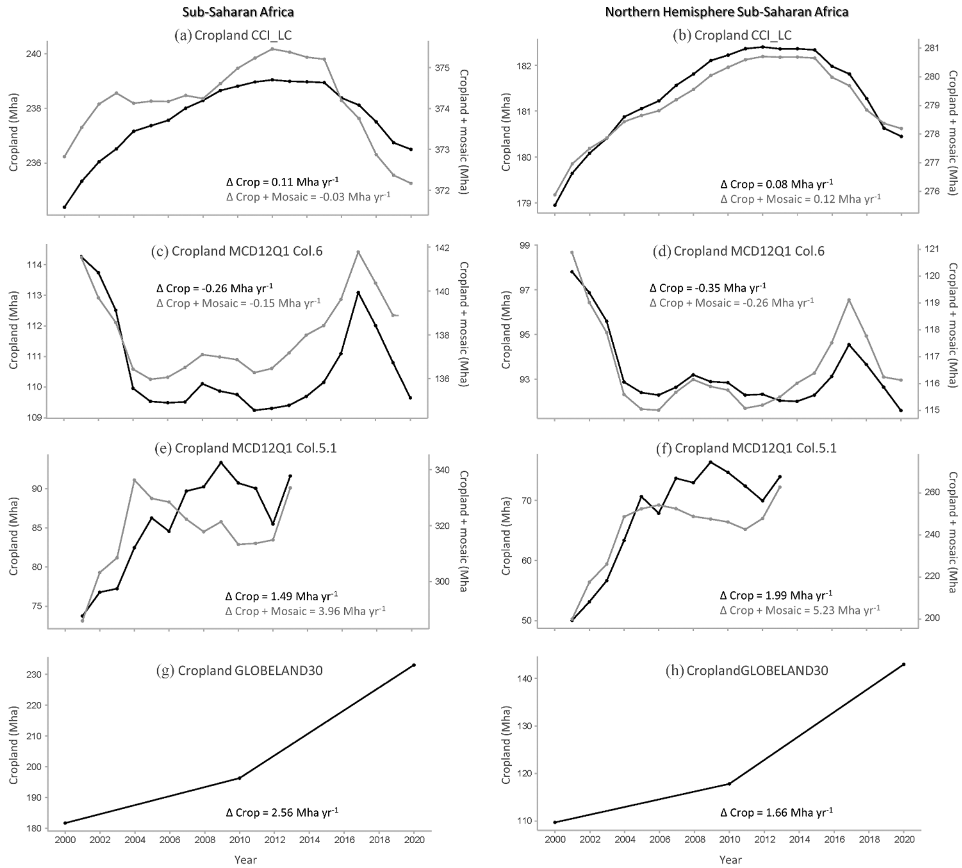

Figure 3. Time series of cropland extent in sub-saharan Africa (left) and the northern hemisphere part of sub-saharan Africa (right). Cropland extent (black colour) and cropland and mosaic of cropland and natural vegetation (grey colour) derived from four global land cover products. Since the time series are nonlinear, the difference in the cropland extent between the last and the first year of data was reported instead of a linear trend.

Mapped cropland area varies, from 85Mha per year for MCD12Q1 C5.1 to 238Mha per year for CCI_LC. Likewise, Liu et al. (2018) concluded that CCI_LC overestimates cropland in most countries, similar to the finding of Laso Bayas et al. (2017), Nabil et al. (2020), and Samasse et al. (2018). Additionally, Wei, Lu, and Wu (2018) estimated that cropland from CCI_LC had the largest dispersion with FAOSTAT, while the opposite was found regarding the 2010 GLOBELAND30 LC map. Samasse et al. (2018) identified GLOBELAND30 from 2010 to be the most accurate LC product in West Africa with an accuracy of 79.5%, followed by CCI_LC, while the accuracy of MCD12Q1 C5.1 only reached 44.9%. The authors reported that MCD12Q1 C5.1 highly overestimates cropland in West Africa; on the other hand, Estes et al. (2018), using the same product, found a severe underestimation of South African cropland. Meanwhile, Leroux et al. (2014) estimated higher user accuracy of cropland in the Western part of NHAF than in the Eastern part, with substantially high omission and commission errors (56% and 42% on average, respectively).

Differences in the definition of cropland were named as one of the main sources of discrepancies between LC products (Hu et al. 2020; Tsendbazar et al. 2016). Even between two versions of the same MCD12Q1 product, the extent of cropland and mosaic of cropland and natural vegetation varies drastically (Figure 2a).

Upon reviewing the striking inconsistencies of the spatial distribution of cropland in SSA, it should not come as a surprise that global LC datasets disagree in not only the magnitude but also in the direction of changes in cropland extent over time (Figure 3). While MCD12Q1 C6 showed the overall cropland decline, according to GLOBELAND30, substantial cropland expansion was observed in SSA. Additionally, an average gain of 2.6Mha/year (GLOBELAND30) was in good agreement with cropland and arable land reported by FAO (2.8Mha/year and 2.3Mha/year accordingly, FAOSTAT 2022). However, the 'OECD-FAO Agricultural Outlook 2020-2029' (OECD/FAO 2020) reported a 13.88Mha increase in the total land use for crop production in SSA in the last 10 years (2009–2019), accounting for multiple harvests per year, which is almost three times lower compared to GLOBELAND30 that showed a 36.64Mha increase of cropland between 2010 and 2020. Depending on the choice of the LC product, the magnitude of the estimated changes in cropland extent can be explained from none to only a part of the decreasing trend in BA in SSA, which according to MCD64A1, declined by 53.4Mha between 2009 and 2019.

7. Uncertainties in fire-cropland analyses

The previously mentioned level of uncertainties of the current remote-sensed fire and LC products might explain the lack of clarity behind the drastic decline in fire activity in Africa. For example, the continental-scale study conducted by Andela and van der Werf (2014), while identifying cropland expansion as the main driver of the decreasing fire activity in NHAF, was only able to attribute 20% of this decline to changes in cropland extent based on the deprecated version of MCD12Q1 (C5.1), the product that depicted the greatest yearly increase in cropland area. Accounting for the lower accuracy of MCD12Q1 C5.1 compared to the replacement C6 version (Sulla-Menashe et al. 2019) and the opposing trends in the cropland area, it is fair to question the sensitivity of the results to the choice of LC data. The same study found that a larger portion of the decline in BA in NHAF (25%) could be explained by changes in precipitation, corroborated by later studies that found greening, an increase in the number of wet days per month, and an increase in soil moisture to be the main drivers of the decreasing fire activity in Africa (e.g. Earl and Simmonds 2018; Forkel et al. 2019; Zubkova et al. 2019).

In contrast to these studies, the global analysis by Andela et al. (2017) found precipitation to be a less important driver of the changes in fire activity compared to human drivers, specifically cropland expansion. The conclusion, however, relied solely on the spatial correlation between the average BA and a single-year cropland map derived from MCD12Q1 C5.1. Therefore, the spatial analysis approach does not directly assess temporal changes. The authors did not demonstrate that BA was, in fact, decreasing within areas experiencing substantial cropland expansion. Rather, the regression of cropland vs. BA was extrapolated and applied to an assumed expansion of cropland area. Moreover, the authors did not address how their choice of datasets may affect the reported negative spatial correlations between cropland and BA.

To complement this discussion, we reproduced the spatial correlation analysis of Andela et al. (2017), but here we calculated correlation between the trends in BA and changes in cropland extent. The second row of maps in Figure 2 demonstrates high variability of the relationship between cropland expansion and changes in BA. Unsurprisingly, the strongest positive relationship was observed within tropical forests where the expansion of mechanized agriculture substantially increases fire activity (Morton et al. 2008; van der Werf et al. 2008). In addition, several studies that analysed recent changes in LC in Africa concluded that cropland was mainly expanded at the expense of forest and shrubland rather than highly flammable grassland (Fenta et al. 2020; Ordway, Asner, and Lambin 2017).

On the other hand, even within more fire-prone ecosystems (tropical savannas), cells with a positive correlation between changes in BA and cropland were observed using data from all four LC products. For instance, in NHAF tropical savannas (above 4° N), 10.9% of the cells had a strong positive correlation (***r***>0.4) versus 5% that showed negative correlation using MCD12Q1 C6, and 7.2% and 5.7% for C5, respectively. For CCI_LC, 5.7% of the cells experienced a strong positive relationship versus 9.4% with negative (***r*** < − 0.4). The relationship was predominantly negative utilizing data from GLOBELAND30, where 3.5% of cells had a strong positive correlation versus 11.2% with ***r*** below − 0.4. Overall, correlation coefficients were near zero in NHAF tropical savannas (0.03, 0.03, −0.04, and −0.06 for MCD12Q1 C5.1, MCD12Q1 C6, CCI_LC, and GLOBELAND30 respectively).

The presence of cells with the positive relationship between BA and cropland can be explained by the importance of fire in agricultural practices across the world and particularly in African where fire is a common tool in rural communities (Wood et al. 2022). According to Amoako, Gambiza, and Singh (2022) and Knowles et al. (2016), fire in African savannas is used not only as a part of slash-and-burn practices to clear and fertilize land for cropping but also to burn postharvest stubble, control pests and weed as well as promote grazing. Similarly, in other regions with a high proportion of agricultural land, such as Eastern Europe and South and Southeast Asia, a positive relationship between fire activity and cropland was detected as a result of residue burning (Hall et al. 2016; Hall, Argueta, and Giglio 2021; Pettus 2009; Vadrevu et al. 2019). In fact, in Southeast Asia, the highest fire activity was detected within cropland, while in South Asia, many forest fires were attributed to agricultural fires spreading from nearby farms (Vadrevu et al. 2019).

8. Conclusion

Current research on the decrease in global BA points to agricultural expansion as a primary driver. While the decrease in BA totals is undeniable, characterizations of the causes are arguably more controversial. First, global trends are primarily driven by fires in Africa due to the overwhelming amount of burning occurring on an annual basis (approximately two-thirds of global BA). Patterns in other regions are increasingly less significant in the statistical sense as well as in their contribution to the global totals, leading to a misrepresentation of global fire trends as monolithic when in fact, they are regionally and locally nuanced.

The analysis methods to determine the cropland-fire relationships are highly sensitive to the data used to identify the trend. Issues associated with the non-robust methods are compounded by a high uncertainty in the data itself. While BA products generally converge on the interannual variability of total BA, the available LC maps that provide cropland area do not, and there is little consensus with inventory statistics to identify a single best cropland map. A cursory sensitivity analysis of different land cover products (Figure 2b) illustrates that the (temporally sensitive) correlation between BA and cropland area is not spatially uniform, both within and between products.

In conclusion, this review demonstrates that additional thorough investigation into fire-cropland dynamics is needed before it can be unequivocally determined that cropland expansion is the primary driver of declines in fire activity in Africa. Increased precision in how this relationship is reported is required to accurately characterize the phenomenon, and robust methods that focus on a convergence of evidence are needed to ensure that the observed trends are genuine and not a result of biases in data or statistical methods. Such studies are critically dependent upon future fire management and environmental policies, sustainable development, conservation planning, and carbon emission mitigation (Jacobson et al. 2015; Roy et al. 2019; Russell-Smith et al. 2021; Zhao et al. 2021).

Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data that support the findings of this study are openly available from following repositories: MCD64A1: https://lpdaac.usgs.gov/products/mcd64a1v006/ MCD12Q1: https://lpdaac.usgs.gov/products/mcd12q1v006/ CCI_LC: https://www.esa-landcover-cci.org/?q=node/164 GLOBELAND30: http://www.globallandcover.com/home_en.html.

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