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Spatial and temporal variability and trends in 2001-2016 global fire activity

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Key points

There is a significant decline in 2001-2016 global fire activity, especially in the northern hemisphere and in Africa.

Fire activity is increasing in China and India due to rapid agricultural intensification.

Areas with a strong weekly cycle give a good indication of where fire management is being applied most extensively.

Abstract

Fire regimes across the globe have great spatial and temporal variability, and these are influence by many factors including anthropogenic management, climate and vegetation types. Here we utilise the satellite based 'active fire' product, from MODIS sensors, to statistically analyse variability and trends in fire activity from the global to regional scales. We split up the regions by economic development, region/geographical land-use, clusters of fire-abundant areas or by religious/cultural influence. Weekly cycle tests are conducted to highlight and quantify part of the anthropogenic influence on fire regime across the world. We find that there is a strong statistically significant decline in 2001-2016 active fires globally linked to an increase in net primary productivity observed in northern Africa, along with global agricultural expansion and intensification, which generally reduces fire activity. There are high levels of variability however. The large-scale regions exhibit either little change or decreasing in fire activity except for strong increasing trends in India and China, where rapid population increase is occurring, leading to agricultural intensification and increased crop residue burning. Variability in Canada has been linked to a warming global climate leading to a longer growing season and higher fuel loads. Areas with a strong weekly cycle give a good indication of where fire management is being applied most extensively, e.g. the USA, where few areas retain a natural fire regime.

Index terms and keywords

3322 Land/atmosphere interactions
3309 Climatology
3305 Climate change and variability

3360 Remote sensing

Fire activity, satellite data, trends, global scale

1. Introduction

Wildfires and large-scale fires have an important influence on ecosystems over much of the planet and impact significantly on a wide range of human activities. The reduction of trees by fire has resulted in the evolution of some of the most biodiverse ecosystems in the world, and facilitated the rise of grass-dominated ecosystems [Bond *et al.,* 2005]. Fires however, pose a major threat to human health through the release of aerosols and are the main sources of air pollution in large parts of Canada, Siberia, Africa, South America and Australia [Lelieveld *et al.*, 2015]. Fire affects the global climate and all biomes to some extent, and Mouillot and Field [2005] estimate that 86% of global fires during the 20th century occurred in tropical savannas. Fires are caused both naturally (mostly by lightning) and anthropogenically (through “prescribed” burning of forests and savannahs for land clearing/management for agricultural and domestic uses). Throughout the world, fire regimes are controlled by climate and vegetation, with precipitation suppressing immediate fire levels, however, encouraging future fires through fuel build up [Marlon *et al.,* 2008; Earl *et al.,* 2017]. Precipitation patterns are strongly influenced by large-scale atmospheric structures and processes, such as the Intertropical Convergence Zone, the subtropical ridges, the El Niño–Southern Oscillation [ENSO; Nicholls, 1991] and the Indian Ocean Dipole [IOD; Cai *et al.*, 2009]. Humans have always influenced the fire regime and today are the main source of ignition in many different ecosystems including tropical forests and savannas. Fire activity in many regions over the globe has been shown to follow a weekly cycle [Earl *et al.,* 2015], highlighting the anthropogenic influence on their behaviour. In a changing climate and with population increasing, it is important to monitor fire activity throughout the world to diagnose how it varies temporally and spatially and determine what drives these variations.

The availability of satellite data have revolutionised fire monitoring, allowing for a more consistent and comprehensive evaluation of temporal and spatial patterns of fire occurrence and area burned, especially since the launches of the MODIS sensors on the Terra (launched December 1999) and Aqua (May 2002) satellites. A recent study by Andela *et al.* [2017] found that there was a global statistically significant decline in burned area (BA), fire size and fire numbers between 1998 and 2015, using multiple satellite data sets. They focused mainly on the Global Fire Emissions Database (GFED4) BA data set, which utilises data from MODIS and its predecessors. This decreasing trend is consistent with the results of burned forest area analysis of van Lierop *et al.* [2015] and previous analysis by Giglio *et al.* [2013] who found that between 1996 and 2012 detected global BA decreased (although the statistical significance of this was not tested) slightly over this period. Hantson *et al.* [2015] also found a negative relationship between population density and observed mean fire size over the globe. Andela *et al.* [2017] conclude that agricultural expansion and intensification is the main cause for the decrease. However, such a relationship is not apparent in all locations across the globe, as Rabin *et al.* [2015] shows, with cropland enhancing or suppressing fire at different times of year within individual regions compared to the natural vegetation.

Fire variability and trends vary greatly in different regions and ecosystems all over the world, and these are heavily influenced by population, agriculture and livestock density [Rabin *et al.*, 2015; Andela *et al.*, 2017]. The relationship between these factors and burned area is generally negative, though it varies greatly with agricultural practises, economic development and degree of tree cover of the region. A higher proportion of cropland usually means better management and reduced fires levels, however in parts of Asia, for example, widespread agricultural waste burning produces a positive correlation with burned area [Andela *et al.*, 2017]. Conversion from natural to anthropogenically managed land alters the fire characteristics depending on the natural vegetation with tropical forests seeing a sharp increase in fire levels, whereas semi-arid savannas experience a decrease. These varying characteristics resulted in general declining fire level tendency throughout the 1997-2012 period in Northern Hemisphere (NH) Africa but not in the Southern Hemisphere (SH) part of that continent [Giglio *et al.*, 2013]. These contrasting African regional trends (which were not subjected to statistical significance testing) are likely to be associated with the increase in net primary productivity (NPP) observed in NH Africa from 2000 to 2009 and the drought-related decline observed in SH Africa during the same time period [Zhao and Running, 2010], resulting in less variable fire counts. We stress that many of these studies do not take the important step of conducting statistical tests on diagnosed trends, so it is open to question whether identified trends are above the noise level. In our study we are at pains to conduct such tests, as did Earl and Simmonds [2017] and Andela *et al.* [2017], and point to the importance of ascertaining statistical significance before discussing and interpreting the results. In Australia, fire level trend studies have much discrepancy (see Earl and Simmonds [2017]).

In our study we make use of an approach that gives insight into the anthropogenic influence on fire behaviour. This is done by determining whether the data exhibit a statistically significant weekly cycle. Nothing in nature occurs on a 7-day cycle over an extended period, so any signal seen in meteorological [Simmonds and Keay, 1997; Earl *et al.*, 2016] or fire [Earl *et al.*, 2015] data must be due to anthropogenic influences. Some anthropogenic fire activity also occurs outside of a weekly cycle (e.g. emergency fuel reductions), so any signal detected suggests a highly managed fire regime. The signal will also be damped by any weekly cycle seen in smoke, pollution or clouds [Rosenfeld, 2000].

In this paper we use a 16-year series of daily satellite-based global active fire (AF) data to comprehensively examine recent variability and trends across the globe and compare the AF data with more commonly used BA products. We examine global and hemispherical AF trends, and also the time series for 18 regions which are categorised in terms of economic development, land-use, fire-abundance and cultural influence. We also apply the weekly cycle method to all of these domains. Our investigation will extend to seasonal analyses and the explanation of how the results of these provide further understanding of the key mechanisms associated with the trends and other behaviours.

2 Data and Methods

2.1 Fire Data

There are many different metrics for measuring fire levels and their consequences. One must choose an appropriate product before detailed analyses can be conducted. Measures which have been used include BA products, AF products, carbon monoxide emissions, economic losses, and number of human casualties caused by fires. Studies utilising different fire level measures can arrive at different conclusions when investigating fire variability and trends [e.g., Hantson *et al.,* 2013, San-Miguel-Ayanz *et al.,* 2013, North *et al.,* 2015, Doerr and Santín, 2016]. BA and AF products are most commonly used for measuring fire levels of a region, and they have both advantages and disadvantages [see Earl and Simmonds, 2017]. BA products are, by their nature, less sensitive to changes in smoke and cloud cover as they draw upon multiple satellite overpasses, collecting data after the fire event, whereas the AF daily product is based on passes from individual days [Randerson *et al.,* 2012]. AF products are able to detect fires that are considerably smaller than the spatial resolution of an individual pixel due to nonlinearity dependence of radiative power on temperature [Giglio, 2015]. Here, we utilise the AF product for a number of reasons as discussed in Earl and Simmonds [2017]. The key reason we use the AF data in this analysis is that it is available at daily resolution, which means that we are able to establish whether weekly cycles are apparent in the data.

An AF product, giving the location of burning fires, has been developed by the MODIS Fire Team consisting of daily (0000 UTC to 0000 UTC) global data (June 2000-present). This is made up of two daily passes (from the Terra satellite passing over the equator at around 10:30am and 10:30pm local time) at each location, and is available at the NASA Earth Observations website (http://neo.sci.gsfc.nasa.gov/view.php?datasetId=MOD14A1_M_FIRE). We utilise all available complete calendar years 2001-2016. The MODIS AF product builds on heritage algorithms for operational fire monitoring used with the Geostationary Operational Environmental Satellites (GOES) and Advanced Very High Resolution Radiometer (AVHRR) sensors, providing information on the specific location of fires, allowing for estimations of emitted energy and the flaming and smouldering ratio [see Justice *et al.,* 2006]. These data have been gridded at 0.1-degree resolution from the 1 km official MODIS AF product (MOD14A1), which is a level 3 tile-based product from the recently-developed MODIS Collection 6. Each pixel assigned to 'fire' has a count of the number of fires within the pixel, ranging from 0 to 30. The detections use infrared anomalies relative to the neighbouring pixels during each of the satellite overpasses. The algorithm uses brightness temperatures derived from the MODIS middle infrared (4 μm) and thermal infrared (11 μm) channels, testing whether the signals in the identified fire pixels are different from those of surrounding, non-fire pixels [see Giglio, 2015].

As part of the Collection 6 land-product reprocessing (commenced in May 2015), advancements have been made to the fire detection algorithm and swath-level product, which has reduced some of the limitations of Collection 5, including fires obscured by smoke [Giglio *et al.*, 2016] and false alarms from solar reflection [see He and Li, 2011]. Collection 6 MOD14A1 data can still be disrupted by cloud cover, blocking the satellites line of sight, however, Earl and Simmonds [2017] demonstrate that there was no significant impact when correlated with high-quality CALIPSO cloud fraction data. There are other AF products available, e. g. from GOES WF-ABBA [Koltunov *et al.*, 2012], AVHRR based products [see Li *et al.*, 2001; He and Li, 2012], Suomi National Polar-Orbiting Partnership [Hillger *et al.*, 2013] and active fire products from the European Space Agency/ European Space Research Institute [Arino and Mellinotte, 1998]. However, MOD14A1 is ideal for our study because it has global coverage, a relatively long time series, high levels of data completeness and the fact that it is still operational (which allows for real-time updates of our analysis approach).

2.2 Fire Counts and missing data

The number of fires were calculated by summing each daily AF counts data for each 0.1 degree pixel within each study area, over 2001-2016, annually and for each season. These data are in units of fire counts per 1000 km^2, gridded at 0.1° resolution by the MODIS Land Science Team. We have normalised these data, following the method of Earl *et al.* [2017], meaning that they represent the fire counts in each 0.1° x 0.1° grid box (adjusting for the fact that the area covered by such boxes changes with latitude) for numerical convenience. Regions of interest are split up by country where appropriate (e.g. USA and Mexico are very different economically), by region/geographical land-use (e.g. the Amazon), by clusters of fire-abundant areas (e.g. eastern Europe/western Russia) or by religious/cultural influence NH/SH Africa.

Of the 5844 days during 2001-2016, there were only 71 (1.2%) days with no data available. These missing days are scattered throughout the year and drop outs occur from one to 19 consecutive days. There were always missing data points due to the gaps between the polar orbiting satellite swaths. The number of missing data points were totalled for each day and the mean number and standard deviation of these determined for each study area. If the proportion of 'no data' points was too high within each study region, therefore giving a non-representative measure of the region's fire levels, these days were considered 'missing' in addition to the days with no data. The threshold for this was more than one standard deviation above the mean of the number of missing data points. The missing days were replaced by the mean of number of fires for that year for that study region. This could lead to seasonal bias if the only available data for a region occurred at a time of high (or low) fire levels.

2.3 Weekly cycle statistical test

Using the 'random thinning' method of Earl *et al.* [2015; 2016], we test the null hypothesis that the amplitude of the AF mean weekly cycle does not differ significantly from zero. This Monte Carlo test is based on the range between the days of the week with the minimum and maximum AF fire counts. It is conducted by randomly removing 5% of the data while retaining the chronological order of the remaining components of the daily time series. This procedure closely preserves the autocorrelation of the data, and hence effectively accounts for the reduction in the degrees of freedom. From this the total fire counts are calculated for each week day and the maximum-to-minimum range taken from each simulated weekly cycle, creating a Monte Carlo based probability density function from 10,000 realizations (of the range in AF counts) which is then compared to the original. If the original weekly cycle range of a region is larger than, for example, 9900 of the simulated ranges for that region, the p-value of the AF weekly cycle would be 0.01 (1%).

3 Results and discussion

Figure 1 shows the global distribution of fires which have occurred over the period 2001-2016 (representing an extension of the period along with the updated Collection 6 data, from Collection 5 presented by Earl *et al.* [2015]) and split into four seasons. The broad global fire distribution seen in the 0.1° AF data is similar to coarser global AF and BA maps [see Giglio *et al.,* 2006; 2013; Chuvieco *et al.,* 2008; Krawchuk *et al.,* 2009; Oom and Pereira, 2013; Andela *et al.,* 2017]. In less economically developed and/or sparsely populated areas such as Africa, South-east Asia and Siberia, fires tend to follow the more natural fire seasons, occurring during the summer/dry seasons, especially in the SH summer (DJF). Fire levels are more consistent throughout the year in wealthier countries such as the USA and Australia, especially in highly populated areas due to fuel management practises occurring during the cooler/wetter non-fire season.

3.1 Global trends

Figure 2 shows the global and hemispherical fire time series from 2001-2016. There is a very strong decline in global fires (statistically significant at the 0.1% confidence level; hereafter $p < 0.001$), present in each season except December-February ($p < 0.1$). The NH is also experiencing a very strong decline ($p < 0.001$) largely resulting from trends in the June-November semester. The SH also displays a strongly significant trend ($p < 0.01$), though not as strong as for the globe or NH. There is much inter-annual variability across the globe, with 2013 experiencing just 75% of 2001 total. This level of variability is also apparent in both hemispheres.

A high degree of similarity exists between our long series of global AF annual variability (Figure 2) and global studies that utilise the BA product. Our results are also comparable with the 2003-2015 number of fires annual variability and trend of Andela *et al.* [2017] who utilised the monthly MODIS 500m product (MCD64A1). They found a significant ($p < 0.05$) decline for their shorter time period. When comparing our results to those of Giglio *et al.* [2013], the overlapping years are consistent with stable fire activity between the 2002-2007 period and a decline in 2008-2009 with 2009 the lowest over the 2001-9 period. This was suggested to be partly due to lower deforestation leading to lower fire levels in South America and tropical Asia (explored in more detail below), while Andela *et al.* [2017] attribute the decline to agricultural expansion and intensification across the globe. There is a difference, however, for 2001 where we find a peak which is not apparent in the Giglio *et al.* [2013] study due to them using the BA product rather than AF as discussed in section 2.1. We and Giglio *et al.* [2013] find 2012 to be a highly active year, going against the overall decline, which is shown to continue in our study until 2016. van Lierop *et al.* [2015] also found a decrease, in their case between 2003 and 2012 for burned land and forest area. Again the annual variability is similar, except they found a relatively low fire level for 2012. It is unclear why their 2012 value is low compared to our AF study and the BA value reported by Giglio *et al.* [2013].

3.2 Hemispheres

The hemispherical trends (Figure 2) are strongly linked to fire-abundant Africa (accounting for 43% of the global 2001-2016 total). The northern part of the continent is experiencing a decreasing trend whereas the SH part exhibits a slightly increasing trend according to Giglio *et al.* [2013], which is the reason for the less extreme decrease over the entire SH. The strongest decreases in the NH occur when the NH part of Africa experiences its fire season (September-February). The decrease has been reported to be linked to NPP increase [Giglio *et al.*, 2013].

3.3 Regional areas across the globe

The global time series conveys much interesting information, however, as we have stressed, the nature of climate and fire variability changes significantly over different parts of the globe. For this reason it is valuable to split up the global AF data by country and by clusters of fire-abundant areas [see Earl *et al.*, 2015], making up 18 regions in all (these being indicated in Figure 1). Figure 3 shows that most of these large-scale regions of the world exhibit little change or decreasing in fire activity except India (box 14) and China (box 17 – taken here as the central and southern parts of the eastern half of China where the vast majority of fires occur, see Figure 1), with a weak non-significant signal in Canada. These trends are not uniform throughout the year but are dominated by changes in activity in specific seasons. The decreasing trends in the fire-abundant Africa and the Amazon are a major factor in the global decline. The importance of these regions in governing the global fire regime is also highlighted in the global weekly cycle pattern in figure 4, very similar to the African (box 6) and Amazon (box 5) signals (discussed below).

The Amazon area accounts for a significant 14% of worldwide AFs, whereas the Giglio *et al.* [2013] BA product study indicated that the SH part of South America accounted for around 7%. This difference is due to the repeated monitoring of the same event in AF compared with BA. Roy *et al.*, [2008] argued that the AF product is more suitable for thick forest areas, though our analysis still underestimates the number of fires identified by van Lierop *et al.* [2015]. Note that part of the Amazon is in the NH, so this is not a direct comparison, with our study providing a new, perspective on this key fire active area.

3.3.1 Global trends dominated by large fire areas – Africa and the Amazon

The African continent (Figure 3- box 6) has experienced an almost-linear decline ($p < 0.05$) in annual fire activity, however the only season to experience a significant decrease is DJF. Box 7 indicates that the NH part of Africa is experiencing the a similar decreasing trend, whereas the SH part is not (box8). This is in agreement with the results from the shorter records of van der Werf *et al.* [2010] and Giglio *et al.* [2013].

It is valuable to obtain measures of the influence of anthropogenic activities in these trends. As mentioned earlier a powerful approach to this is to explore the purely anthropogenic signal of a weekly (7-day) cycle. A strongly statistically significant weekly cycle is apparent in Africa annually (Figure 4 – box 6), and in all seasons (Figure 5). However, the weekly cycle is not as apparent in the African NH than the SH (Figure 4 – boxes 7 and 8 respectively). This indicates that anthropogenic factors are not the main influence in the African fire regime and may not have an impact on the overall decreasing trend. However, Earl *et al.* [2015] note that this may be due to NH part of Africa containing both Muslim and Christian populations, so the weekly cycle may not be the best indicator of anthropogenic activity over this area. As mentioned, the NH African decline is linked to the NPP increase observed in NH Africa from 2000 to 2009 [Zhao and Running, 2010], therefore the African decline in fires is associated with both anthropogenic fire management and changes in NPP. Grégoire *et al.* [2012] observe that this conversion of natural land to cropland is also occurring in Africa and that the expansion of agriculture across Africa is reducing the percentage area of land burnt.

We saw in Fig. 3 that the Amazon region (box 5) exhibits a weak decreasing trend, significant only in JJA. Part of the reason for this lack of overall significance is the large interannual variability, and this level of variability is in accord with that demonstrated by van der Werf *et al.* [2010] and van Leirop *et al.* [2015], despite differences in methods as discussed. van der Werf *et al.* [2010] suggested that the decrease is due to the decline in deforestation over recent years. Yang *et al.* [2014] point out that decreasing forest conversion to pasture and increasing forest conversion to cropland and mechanized agriculture, seen in the Amazon in the early 2000s [Morton *et al.*, 2006], is likely to be contributing to declining trends in fire activity as pastureland is prone to larger and more frequent fires than cropland. This is in line with Andela *et al.* [2017] who point out this transition causes an increase in fires. Furthermore, less burning is required for conversion to cropland and repeat burning is also reduced. The Amazon exhibits a highly significant weekly cycle signal (Figure 4), which highlights the impact of the anthropogenic effect. However, as seen in Africa, in the season where the decline is strongest (JJA), this cycle is less apparent (Figure 5). This could indicate a natural response, though it could be to do with fire management practises being more reactive than proactive during this fire abundant part of the year [see Earl *et al.*, 2015]. Zhao and Running [2010] found NPP increases over this area, which acts as another contributor to the decline. The 2005 and 2010 Amazon droughts, as reported by Faria *et al.* [2017], increased AFs during these years, having the 2nd and 3rd fire highest annual fire levels over the 16-year period, indicating that natural forcing is still important despite improved fire management practices.

3.3.2 Canada, China and India

Canada (box 2 Fig. 3) does not display a statistically significant trend, however Canada's longer term fire regime has been linked to global climate change [Kasischke and Turetsky, 2006]. The 2001-2015 increase, seen in Figure 3, was brought about by increases during the summer season. The absolute values only account for 1% of global fire activity, so this pattern did not greatly influence the global trend. This increase is seen in other studies [e.g. van Lierop *et al.*, 2015] and Oris *et al.* [2013] suggested that increased burning generally in the boreal zone is a result of a warming global climate, which in turn has positive feedbacks on boreal fire activity. Studies of fire management records [Gillett *et al.*, 2004; Kasischke and Turetsky, 2006] indicate that average annual fire levels at a decadal scale increased every decade from 1960 through 2000 for Canada, consistent with the warming trend in this region during the fire season (May-August). Our study (based on the AF product rather than BA product) indicates that this continued over the 2001-2015 period, though 2016 had the third lowest annual total over the 16 years, especially from June-August (lowest since 2001; not shown), due to high rainfall during this period. Kasischke and Turetsky [2006] report that human ignition in Canada and Alaska decreased from the 1960s to 1990s. This supports the view that climate is the driving factor in changes in the fire regime, with warmer conditions a allowing for a longer growing season and therefore enhancing vegetation growth and fuel load and in turn, heightened fire levels. Our weekly cycle analysis indicates, however, that fire management continues to be influential for Canadian fire counts (Figure 4 and 5), with statistically significant weekly cycle in all seasons except summer (June-August).

India (box 14) and China (box 17) are the other regions experiencing significant increases in active fires (p < 0.01 and 0.001 respectively). These areas have experienced rapid population increases during this period, though China's population growth rate has eased especially over the last 5 years. Agricultural intensification is occurring with population growth and economic development and with the dominant fire activity being crop residue burning in these areas [Andela *et al.*, 2017], this has a substantial influence on the fire levels. China exhibits the strongest increase in fire levels of any of our 18 regions, with the seasons MAM and JJA responsible for this annual increase (both with p < 0.001). JJA is outside the natural fire season for China (March-June; September-November), which supports the hypothesis that this increase is caused by anthropogenic factors, though relevant weekly cycle analysis is non-conclusive. Figure 3 shows that the active fire trend has levelled out since 2007 which is could be the result of 'The Agricultural Residues Burning Reduction Act' coming into effect during the 2000s [see He *et al.* 2007], which bans the open air burning of crop residue. Andela *et al.* [2017] analysed these interesting areas as part of larger domains, so they did not find significant increases.

3.3.3 Mexico and USA

Mexico (box 4) is experiencing no trend in AFs. This is consistent with the earlier work of Andela *et al.* [2017] who found that the broader Central American region experienced a slight decrease ($p < 0.1$) in number of fires for 2003-2015. There is also no trend in Alaska (box 1), though the absolute fire numbers are low. The mainland USA (box 3) displays no 2001-2016 trend in AFs, which is generally consistent with recent AF analysis [see Doerr and Santín, 2016]. This is also the case for the satellite-based BA studies [Giglio *et al.*, 2013; Andela *et al.*, 2017], though BA has been found to be increasing in some surface based USA studies [see Doerr and Santín, 2016]. This is surprising, as the economic costs of wildfire in the USA have risen substantially in recent decades and from 1992-2012, with anthropogenically ignited wildfires accounting for 84% of all wildfires [Balch *et al.*, 2017]. There is no trend in temperate North America [Giglio *et al.*, 2013; Andela *et al.*, 2017] which is at variance with the reported increase in BA in the boreal north and USA [Doerr and Santín, 2016]. This discrepancy is likely to be due to the variety of methods being applied, highlighting different characteristics of the fire regime. Fewer but larger and more intense fires have been reported over recent years [Rocca *et al.*, 2014], due to suppression of previous fires producing higher fuel loads [North *et al.*, 2015]. The USA has the strongest weekly cycle of fires in the world [Figure 4; Earl *et al.*, 2015], highlighting the level of management that occurs here despite the increasing number of anthropogenically ignited wildfires. Indeed, work conducted by Parisien *et al.* [2016] suggested that there are few purely natural fire regimes in North America today. This aggressive fire suppression has resulted in human-induced disequilibrium between plant communities and climate as the climate changes [Parks *et al.*, 2016]. This disequilibrium will amplify under a warmer climate and will likely result in increased fire severity in future decades in the USA.

3.3.4 Europe

Spain/Portugal (Figure 3 - box 9) is the only European Mediterranean region displaying a statistically significant ($p < 0.001$) annual decline in AFs, mainly during the summer and autumn. Greece (box 11) is also experiencing a summer decrease, but no significant annual trend. Figure 5 shows that Greece has a significant weekly cycle during this time, indicating anthropogenic burning. Italy (box 10) has no trend in fire activity over the last 15 years. A decline in BA over the

Iberian Peninsula was also found by Giglio *et al.* [2013] (2001-2012) and in AFs by San-Miguel-Ayanz *et al.* [2013] (2001-2010), who provide a comprehensive summary of the Mediterranean fire climate, though BA was not decreasing over that period. The period from 1980 to 2001 exhibited a strong increase in fire in the Mediterranean region (though not BA) and due to mild summers allowing for good fire management, there was a decline in the early 2000s [San-Miguel-Ayanz *et al.* 2013]. Since then there has been a few very large fires, continuing the low AF count but also seeing spikes in annual BA [San-Miguel-Ayanz *et al.*, 2013]. Andela *et al.* [2017] (2003-2015) use the whole of Europe as a domain and indicate that BA is declining but AF is stable, highlighting again the discrepancy between the two products for this region, again indicating improved fuel load management with fewer large uncontrolled fires.

3.3.5 Eastern Europe/Western Russia and Kazakhstan

The Eastern Europe/Western Russia (box 12) and Kazakhstan (box 13) regions are experiencing a rapid decline in AFs, the latter at a highly statistically significant rate ($p < 0.01$ and 0.001 respectively). The decrease is greatest in summer for Eastern Europe/Western Russia and autumn for the Kazakhstan region which are fire active times of year (Figure 2). In Eastern Europe there has been continued and widespread abandonment of agricultural land since the dissolution of the Soviet Union [Alcantara *et al.*, 2013], so those regions are no longer being burned in autumn and winter for clearance before spring planting.

3.3.6 Tropical Asia

The mainland southeast Asian area of Thailand, Myanmar, Laos, Cambodia, and Vietnam (box 15) generally exhibited a strongly increasing trend during JJA, which the annual trend does not. This highly significant increase in fire activity is during the wet season, when fire activity is at a minimum (Figure 2), which is the reason that this increase does not greatly affect the annual trend. It is likely that this is due to increased land management, with prescribed burning increasing during the wet season and conversion from natural to anthropogenically managed land altering the fire characteristics tropical forests seeing a sharp increase in fire levels [Rudel *et al.*, 2009]. Support for the suggestion of anthropogenic impact come from the fact that the region displays a significant weekly cycle in March-May (Fig. 5), a season which exhibits a, albeit modest ($p < 0.10$), significant increase in fire activity.

The global decline in fire emissions was thought to be partly due to lower deforestation fire emissions in tropical Asia [van der Werf *et al.*, 2010] including Indonesia. However, our analysis with a longer record show that the decrease ended in 2010 and fire levels peaked in 2015 for the Indonesia/Papua New Guinea region (box 16) (and the overall trends are not significant for either the annual or totals or any of the four seasons). This however did not affect the global trend. Andela *et al.* [2017] also display no trend in 1998-2015 BA or 2003-2015 AF. Giglio *et al.* [2013] is in agreement with an absence of a trend over 2001-2012 BA, though the interannual variability is not similar to that seen in Figure 3, due to the AF product picking up thick forested area fires more effectively than BA. Again, the proportion of the global AF total seen here (1.5%) is far higher than the BA reported by Giglio *et al.* [2013] (0.6%) as seen in the Amazon indicating that the AF product is more suitable for tropical rainforests [Roy *et al.*, 2008]. However, Andela *et al.* [2017] show little difference for the trends between the BA and AF products over Indonesia.

3.3.7 Australian regional fire trend

Studies into recent trends of Australian fire activity seem indicate an overall decline, however there is much annual variability and even a reported 2007-2013 increase by Dutta *et al.* [2016]. Earl *et al.* [2017] found that the 2001-2015 AF trend was not statistically significant for the annual trend, though summer (DJF) exhibited a significant decrease. The ‘climate shift’ of 2011, 2012 as reported by Dutta *et al.* [2016], was short lived and 2013-2015 had returned to 2003-2010 levels. The present study shows that there is still no Australian annual trend and that 2016 was the 2nd lowest on record behind 2010 (Figure 3 – box 18), confirming the lack of any such shift.

5 Conclusions

In this paper, we utilise the satellite based ‘active fire’ Collection 6 product, from MODIS sensors aboard the Terra platform, to statistically analyse variability and trends in fire activity from the global to regional scales. We split up the regions by economic development, region/geographical land-use, clusters of fire-abundant areas or by religious/cultural influence, unlike many studies that use climate zones. We also analyse seasonal trends and weekly cycles to further our understanding of the trend-causing mechanisms. There is a very strong decline in 2001-2016 global fires ($p < 0.001$), apparent in both hemispheres (NH $p < 0.001$, SH $p < 0.01$) with high levels of spatial variability. The extreme NH trend is largely due to the NH part of Africa, which has been linked to the 2000-2009 increasing NPP trend [Giglio *et al.*, 2013], but decreased in the SH part of Africa [Zhao and Running, 2010]. Andela *et al.* [2017] suggested that agricultural expansion and intensification is the main cause for the decrease. The large-scale regions of the world exhibit little change or decreasing in fire activity except for India and China where strong increasing trends are present ($p < 0.01$ and 0.001 respectively).. These regions are experiencing rapid population increase and economic development, leading to agricultural intensification and increased crop residue burning [Andela *et al.*, 2017].

Of the regions which exhibit trends over the past 16 years, all had varied seasonal trends, which gives us further insight into why the trends are occurring, e.g. in China the strongest increasing trends occur outside of the natural fire season, which supports the hypothesis that this increase is caused by anthropogenic factors. Areas with a strong weekly cycle give a good indication of where fire management is being applied most extensively, for example the USA. There is generally great similarity between the AF and more commonly used BA products, indicating that this product is suitable for global and regional trend analysis. There are some differences, the main one being AF data giving a better estimation of fire activity in tropical rainforest areas than BA.

Our analysis has presented new and updated perspectives on the global distribution and trends of fire activity. It has also emphasised the dangers of drawing conclusions on trends based on short data records and without appropriate statistical significance tests. We have also presented a quantification of how anthropogenic activities may be influencing fire trends.

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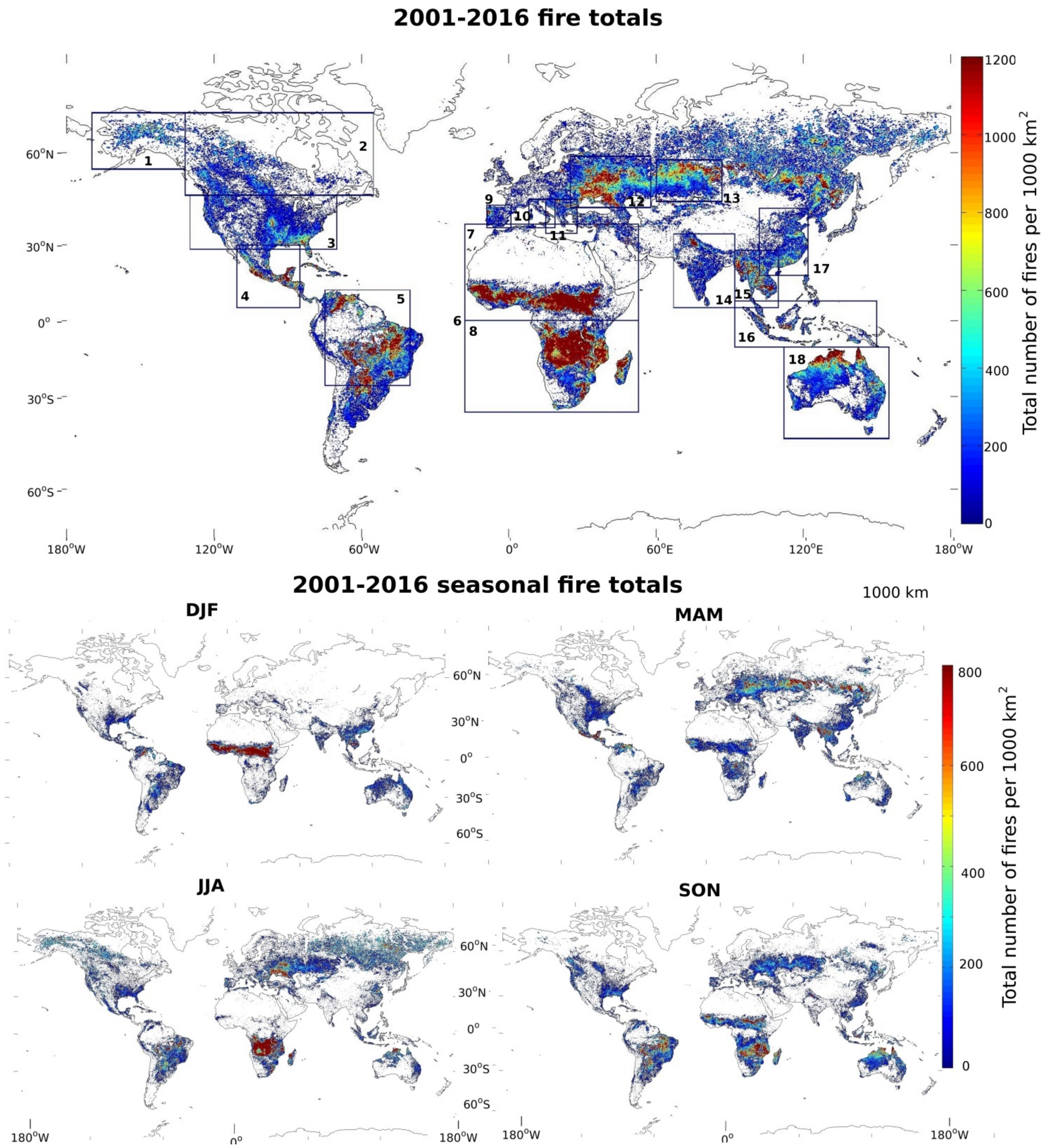


Figure 1 – Total number of annual and seasonal active fires for the period 2001-2016. The units are fires per 1000 km^2 . The 18 regions of interest (see section 3.3) are highlighted. The geographical domains of these regions are: 1 Alaska – 2 Canada – 3 USA – 4 Mexico – 5 Amazon – 6 Africa – 7 Northern Africa – 8 Southern Africa – 9 Spain – 10 Italy – 11 SE Europe – 12 Eastern Europe/Western Russia – 13 Kazakhstan – 14 India – 15 Mainland Southeast Asia – 16 Indonesia– 17 Eastern China – 18 Australia

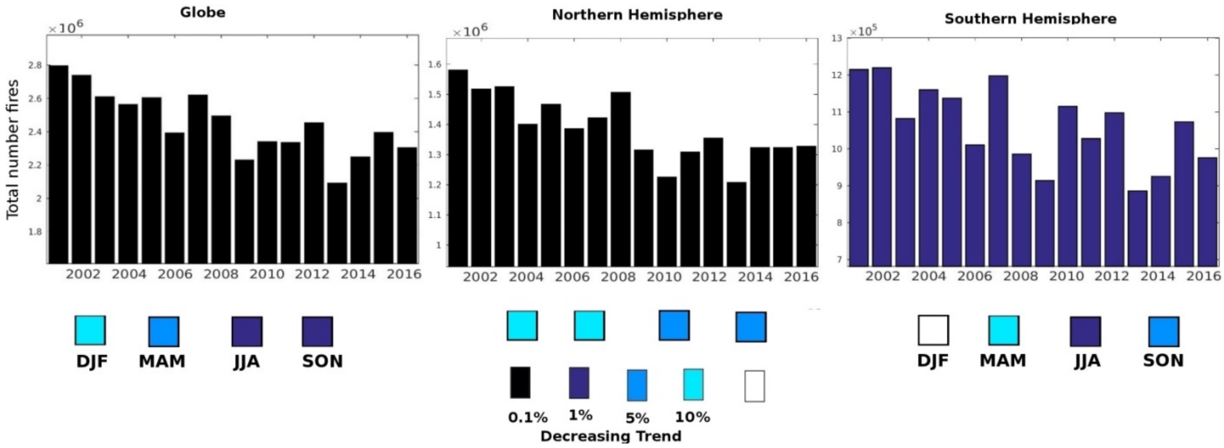


Figure 2 – Global and Hemispherical 2001-2016 fire counts. Levels of significance displayed for the annual trends (colour of bars – decreasing trend: black p < 0.001, dark blue p < 0.01, middle blue p < 0.05, light blue p < 0.1) and for each season (represented by the 4 boxes beneath each histogram. Note – the vertical scales are different in all histograms.

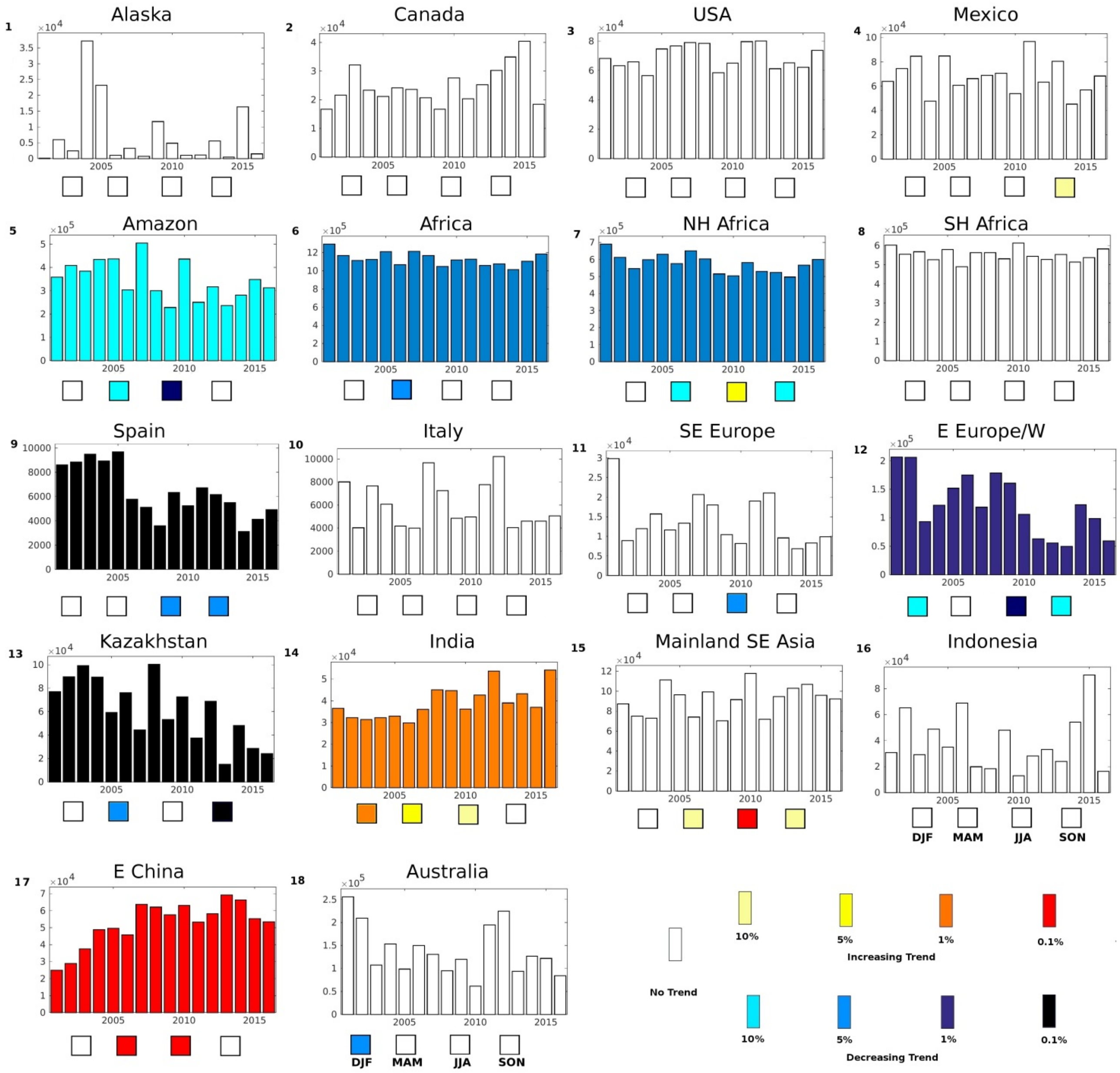


Figure 3 – Fire time series for the 18 regions of interest of the globe for 2001-2016. Trends in annual AF count totals with significance levels (colour of bars – decreasing trend: black $p < 0.001$, dark blue $p < 0.01$, middle blue $p < 0.05$, light blue $p < 0.1$; no trend: white; increasing trend: red $p < 0.001$, orange $p < 0.01$, yellow $p < 0.05$, light yellow $p < 0.1$). The statistical significance of seasonal trend levels are also indicated (squares – from left to right) December-February, March-May, June-August and September-November. Note- scales on the time series are different for the various regions.

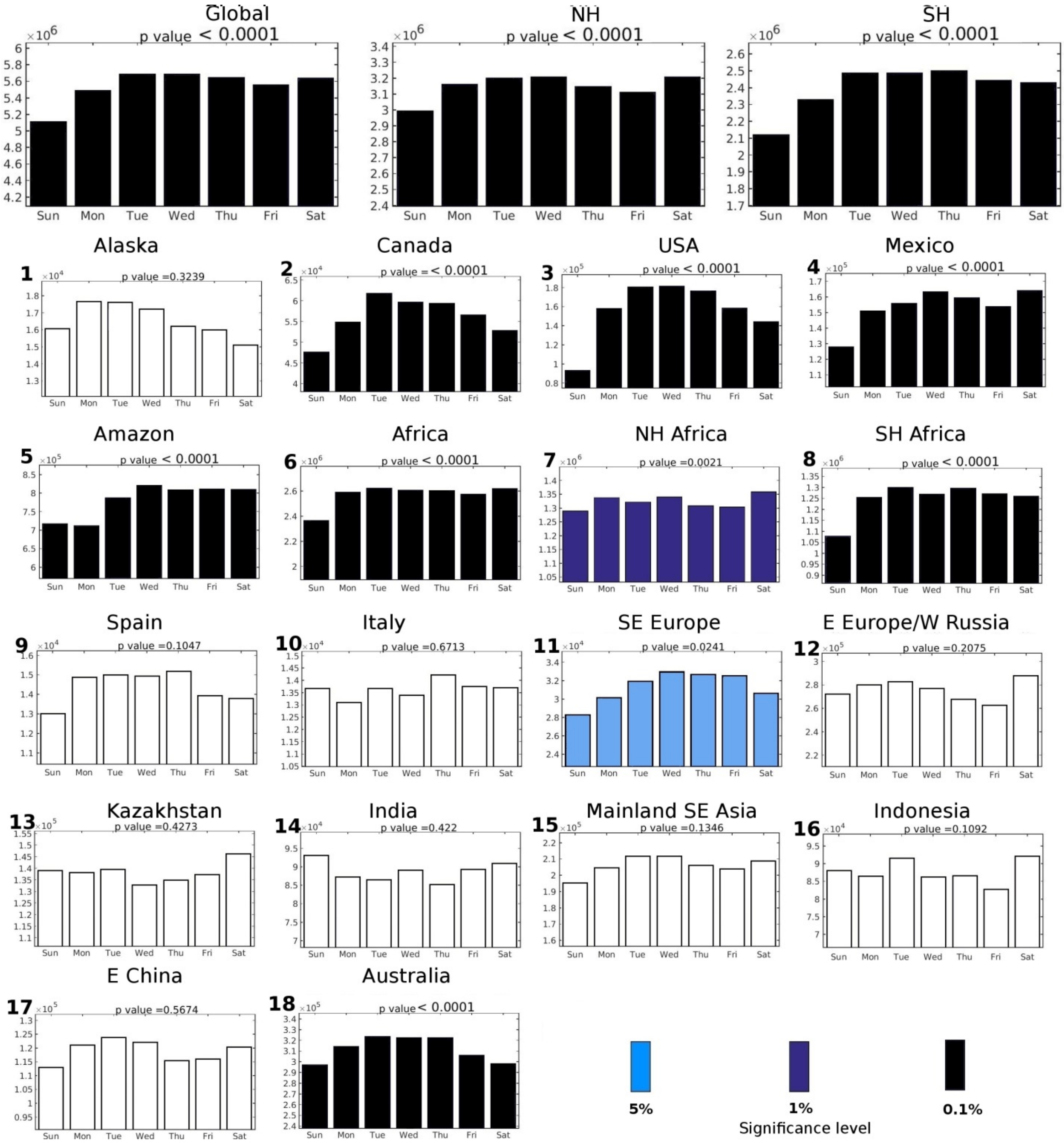


Figure 4 – Weekly cycles of global and hemispherical AFs and for the AFs for our 18 regions for 2001-2016. *p*-values are from the Monte Carlo analysis described in section 2.3 and colour of bars also represent significance (significant weekly cycle: black p < 0.001, dark blue p < 0.01, middle blue p < 0.05; no weekly cycle: white).

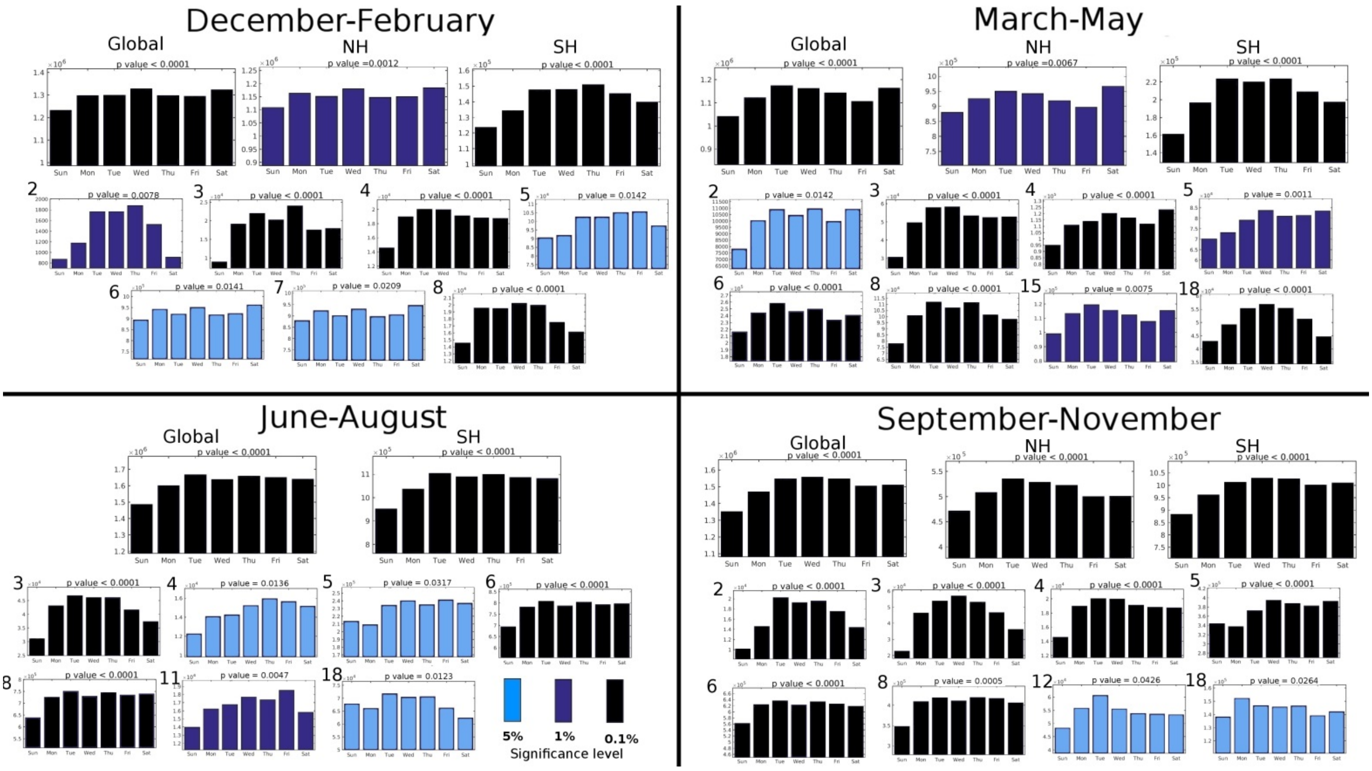
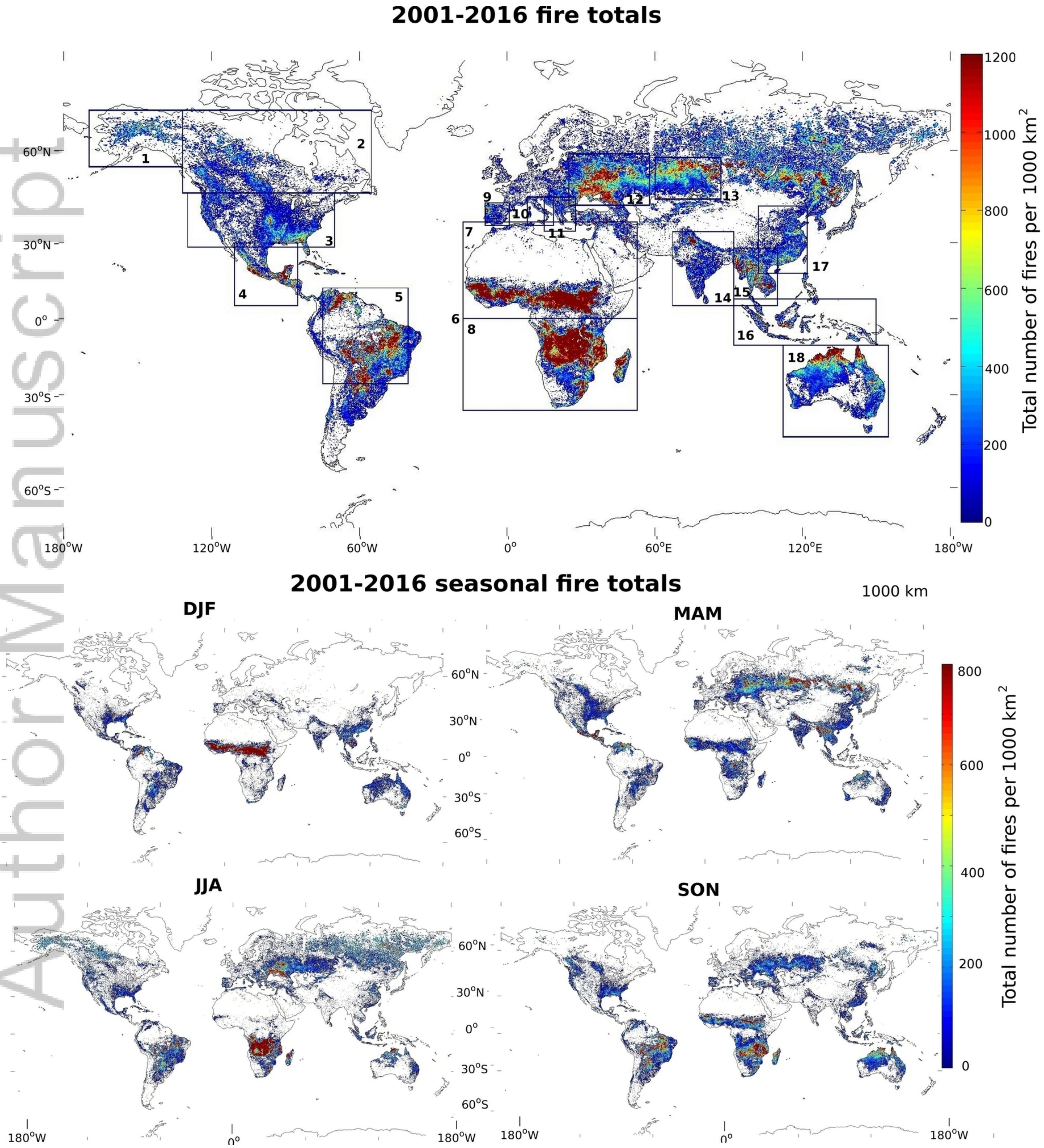


Figure 5 – As for Figure 4, but for the seasonal behaviour and only displaying statistically significant ($p < 0.05$) AF weekly cycles , this time for each season (significant weekly cycle: black $p < 0.001$, dark blue $p < 0.01$, middle blue $p < 0.05$). Regions: 2 Canada – 3 USA – 4 Mexico – 5 Amazon – 6 Africa – 7 Northern Africa – 8 Southern Africa 11 SE Europe – 12 Eastern Europe/Western Russia –15 Mainland Southeast Asia – 18 Australia



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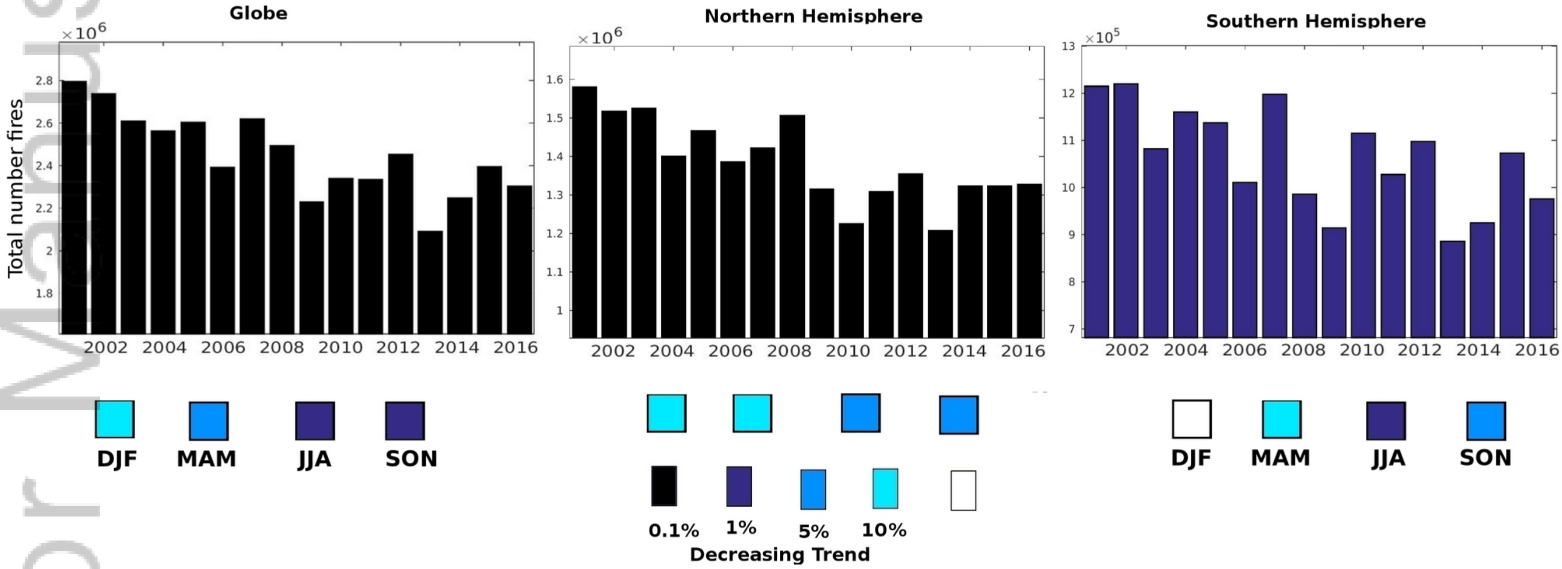

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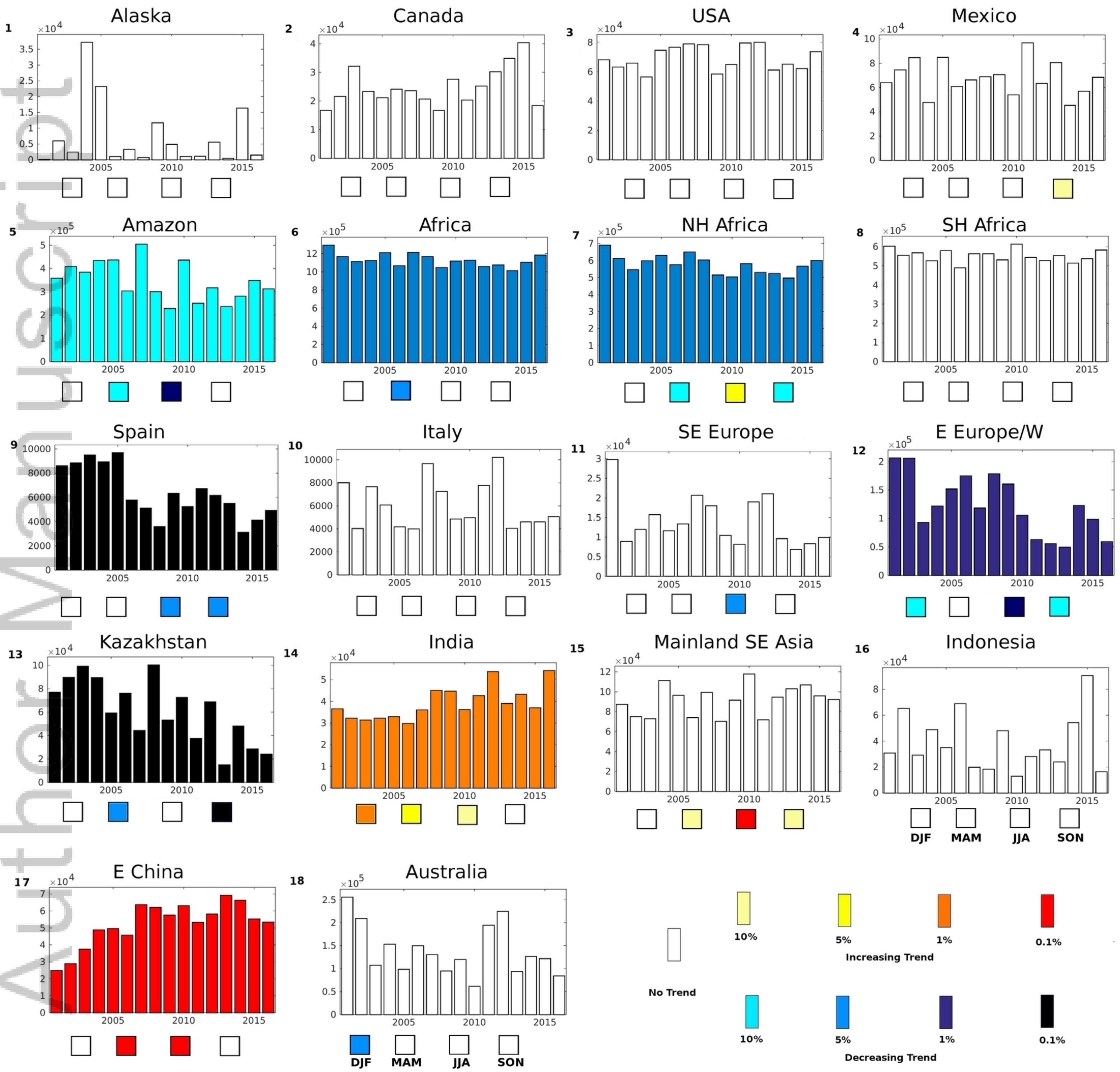

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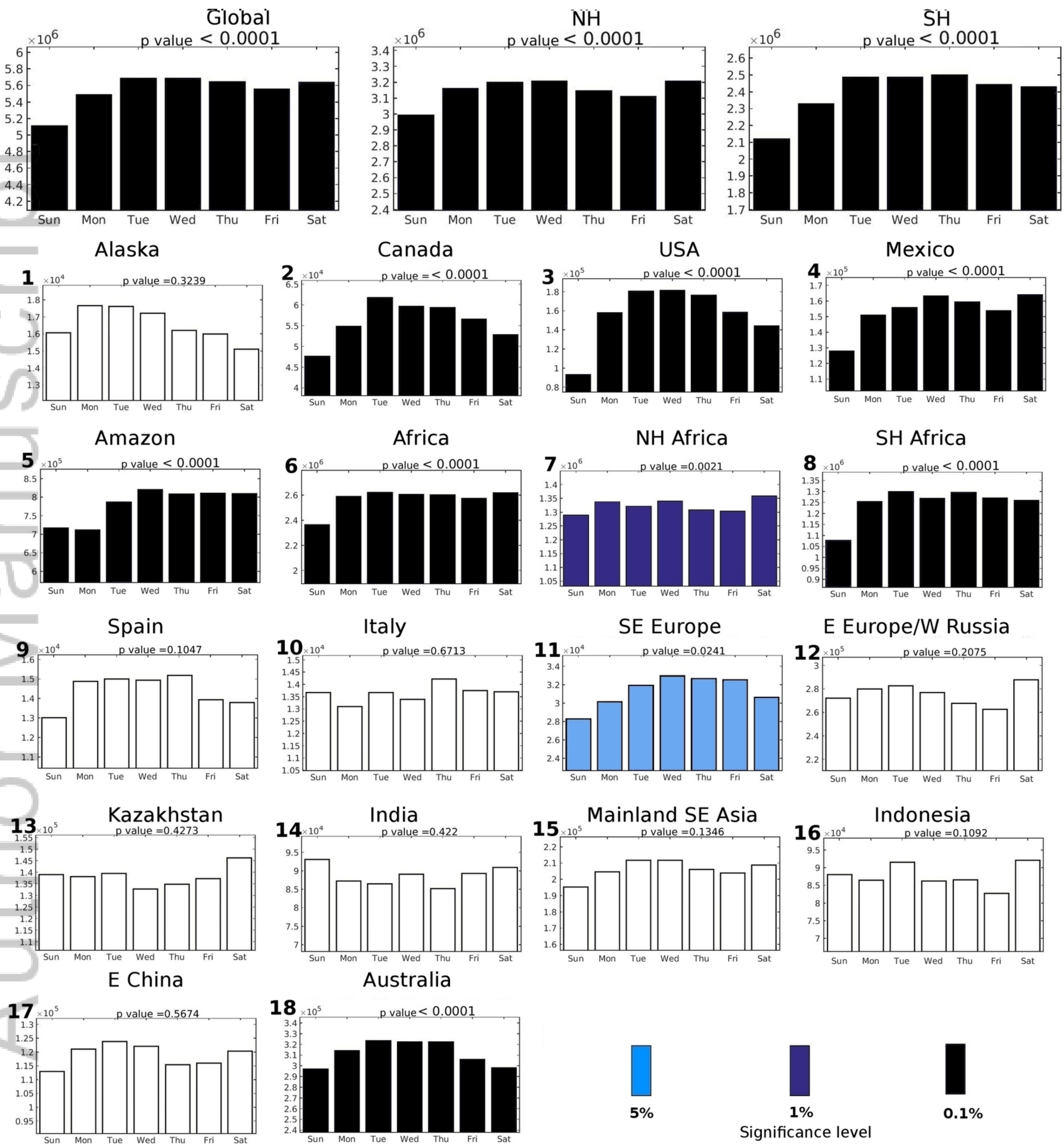

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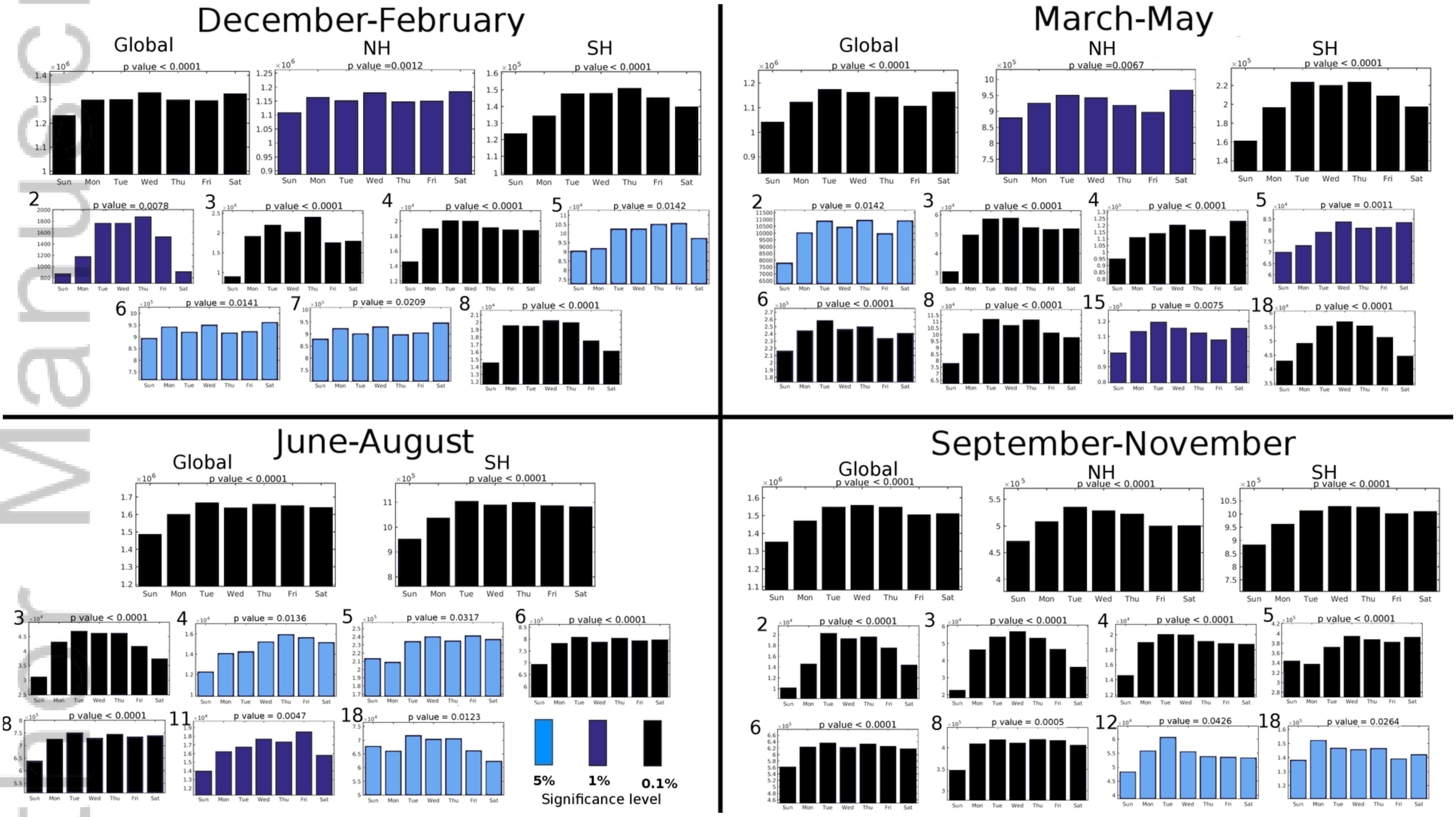

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