Combining Satellite-Based Fire Observations and Ground-Based Lightning Detections to Identify Lightning Fires Across the Conterminous USA

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***Abstract*—Lightning fires are a common natural disturbance in North America, and account for the largest proportion of the area burned by wildfires each year. Yet, the spatiotemporal patterns of lightning fires in the conterminous US are not well understood due to limitations of existing fire databases. Our goal here was to develop and test an algorithm that combined MODIS fire detections with lightning detections from the National Lightning Detection Network to identify lightning fires across the conterminous US from 2000 to 2008. The algorithm searches for spatiotemporal conjunctions of MODIS fire clusters and NLDN detected lightning strikes, given a spatiotemporal lag between lightning strike and fire ignition. The algorithm revealed distinctive spatial patterns of lightning fires in the conterminous US While a sensitivity analysis revealed that the algorithm is highly sensitive to the two thresholds that are used to determine conjunction, the density of fires it detected was moderately correlated with ground based fire records. When only fires larger than 0.4 km^2 were considered, correlations were higher and the root-mean-square error between datasets was less than five fires per 625 km^2 for the entire study period. Our algorithm is thus suitable for detecting broad scale spatial patterns of lightning fire occurrence, and especially lightning fire hotspots, but has limited detection capability of smaller fires because these cannot be consistently detected by MODIS. These results may enhance our understanding of large scale patterns of lightning fire activity, and can be used to identify the broad scale factors controlling fire occurrence.**

***Index Terms*—Fire, lightning, MODIS, NLDN.**

I. Introduction

LIGHTNING is the most common natural ignition source of wildfires, and lightning fires are a major form of natural disturbance in many ecosystems in North America [1]–[3]. On average, lightning fires burn more area than human ignited fires (average burned areas of 333.76 ha and 77.64 ha, respectively, based on the US Federal Fire Occurrence Database for years 2000–2008; Bar-Massada, unpublished) because they often occur in remote areas, where they are detected later and are less accessible to suppression forces [1]. A lightning fire ignition is the outcome of a complex sequence of events, and depends on the lightning flash and thunderstorm characteristics, coupled with fuel conditions [4]–[8]. The spatial and temporal patterns of lightning fires are affected by various driving factors including large-scale climatic patterns [9]–[11], local weather conditions [8], [12], [13], land cover [3], [14], [15], and topography [3], [16], [17]. However, our understanding of the causes of spatiotemporal variability in lightning fires is still limited, partly due to a lack of good spatial data on lightning fire occurrences.

Ground-based lightning detection systems are relatively new. All lightning flashes radiate electromagnetic energy at a broad range of frequencies, which travels through the lower atmosphere for hundreds to thousands of kilometers, depending on flash type and electromagnetic frequency [18]. Different frequencies of electromagnetic energy can be detected by ground-based receivers located in meteorological stations. When electromagnetic energy is detected by two or more receivers, the location of a lightning strike can be triangulated with moderate to very high accuracy, depending on the detector type and the spatial configuration of the detection network relative to the lightning strike location. Triangulation provides the spatial component for lightning records, which makes research on lightning ignition patterns feasible.

In the US, the National Lightning Detection Network (NLDN) has been providing real-time, continental-scale lightning information since 1989 [18], [19]. The NLDN consists of 106 sensors using the Improved Accuracy through Combined Technology (IMPACT) algorithm, which requires as few as two combined sensors to optimize the detection of lightning location, denoted by latitude, longitude, and discharge time. IMPACT sensors, in contrast to earlier sensors, combine two detection technologies (Time-of-Arrival, or TOA; and Magnetic Direction Finder, or MDF) to improve detection accuracy. Thereby the two sensors provide redundant information about the location of a strike, and this enables the optimization of its location detection [18]. The estimated flash detection efficiency (i.e., the proportion of correct detections) of the NLDN following the IMPACT upgrade is 84% (if strokes less than 5 kA are excluded), or 72% (for all strokes) [20], and the median location accuracy is 484 m [21]. Both detection efficiency and location accuracy increase with stroke peak current, and vary among lightning storms, possibly due to variations in lightning characteristics [20]. However, lightning data has been of limited use for fire research because it does not depict whether a lightning strike ignited a fire or not.

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Satellite observations of active fires show promise for broad-scale assessments of fire occurrence. Broad-scale active-fire detections have been based on four primary sensors: the National Oceanic and Atmospheric Administration's (NOAA) Advanced Very High Resolution Radiometer (AVHRR) [22], the European Space Agency's (ESA) Along Track Scanning Radiometer (ATSR) [23], NOAA's Geostationary Operational Environmental Satellite (GOES) [24], and the National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) active fire sensor [25]. The MODIS sensor, onboard NASA's Earth Observing Satellites (EOS) TERRA and AQUA satellites, provides fire detections for each orbit, resulting in multiple daily observations over most of the globe with 1-km spatial resolution [25].

Of these four sensors, MODIS is the most widely used and was specifically designed for ecosystem monitoring including fire detection [25]. Therefore, we focused our analysis on MODIS, but our methods could potentially be adapted to other sensors. MODIS active fire data have been used to quantify several aspects of fire occurrence, such as the human role in Russian wildfires [26], the tropical diurnal fire cycle [27], the global distribution of agricultural fires [28], global fire activity [29], [30], and global fire distribution and seasonality [31]. Ten years of data from MODIS and its predecessor active-fire sensor NOAA AVHRR were used to study spatio-temporal fire occurrence in Borneo, revealing the effect of extreme weather (El Nino years) on fire activity [32]. The effects of population density and land cover on fire occurrence were assessed in Mediterranean-climate ecosystems [33], and globally [30]. However, the common limitation to all types of satellite fire detection data is the lack of information about the source of the ignition. This is unfortunate, because the spatiotemporal patterns of fire occurrence can provide invaluable information for development of management strategies and fire risk assessments [34], [35], by identifying which areas are more likely to burn in human dominated landscapes and natural ecosystems alike.

The question is if NLDN and MODIS data together can provide the information needed for broad-scale fire assessments that neither dataset can provide by itself. Our goal was to develop and evaluate an algorithm that combines MODIS fire detections and NLDN lightning detections to identify which MODIS detected fires may be caused by lightning. We applied our algorithm in the entire conterminous US, based on data from late 2000 to 2008, to quantify the spatiotemporal patterns of lightning fires in that region.

II. Methods

A. Lightning Data

We used the federally-owned NLDN data, obtained from the National Interagency Fire Center (Boise, ID) and the Desert Research Institute (Reno, NV), to determine the location and timing of lightning strikes detected within the conterminous US between late 2000 and 2008. The raw data were converted from tabular form to daily GIS point datasets (based on the geographic location of each lightning strike). We screened out any lightning strike located outside the boundary of our study area, the conterminous US Each point dataset represented all cloud-to-ground (CG) lightning strikes that were detected by the NLDN during a single day.

B. MODIS Fires—Data Acquisition and Pre-Processing

The MODIS active fire detection algorithm identifies the characteristic signature of active fires in the 3.9-μm and 10.5-μm channels, and tests whether the signals in these channels are different from those of surrounding, non-fire pixels [36]. MODIS detects fire activity within pixels rather than detecting individual fires (thus there may be more than one active fire per pixel), and the theoretical detection rate of a 100-m2 fire is 50% [36]. MODIS detection accuracy depends on fire size (larger fires are better detected), temperature (hotter fires are better detected), and the temperature difference between the fire and its surrounding area (i.e., a higher contrast between the temperature of the fire and the surface temperature in its vicinity results in better detection). In practice, although MODIS often fails to detect small fires, it consistently detects larger fires [37], which are ecologically more relevant [38]. Another factor limiting active fire detection by MODIS and all other satellite sensors is cloud cover. Since satellite sensors cannot detect active fires that are obscured by clouds, the detected fire activity is an underestimate of actual fire activity, but we did not know in advance to what extent. This is especially true for lightning fires, which ignite under thunderstorm clouds but can only be detected after the storm passes. Because individual thunderstorms pass within a matter of minutes to hours while many wildland fires persist for days to weeks, ignition masking by clouds typically delays but does not prevent fire detections.

We downloaded the 1-km daily TERRA and AQUA based MODIS thermal anomalies and fire daily imagery (MOD14A1 and MYD14A1, respectively) from the US Geological Survey (USGS) FTP site (TERRA data: ftp://e4ftl01.cr.usgs.gov/MOLT/MOD14A1.005/, AQUA data: ftp://e4ftl01.cr.usgs.gov/MOLA/MYD14A1.005/, last accessed February 21st 2011), starting from November 2000 for TERRA, and July 2002 for AQUA. We used the MODIS reprojection tool (MRT, available from the USGS Land Processes Distributed Active Archive Center: https://lpdaac.usgs.gov/lpdaac/tools/modis_reprojection_tool, last accessed February 21st 2011) to mosaic individual footprints into a single image for the entire study area. Then, we reprojected the mosaics from MODIS's native sinusoidal projection to NAD 1983 Albers projection which is suitable for analyses of the entire conterminous US. Finally, we combined the TERRA and AQUA daily mosaics by assigning daily fire occurrence for each pixel if either TERRA or AQUA reported a fire in that pixel in a given day. We used only high confidence detections (MODIS reports three confidence levels for fire detections, low, nominal, and high) to obtain the most conservative indication of fire activity. In addition, we are aware that combining both satellite datasets prevented us from analyzing intra-daily differences in fire patterns. Yet, we still opted for doing this since having multiple satellite overpasses per day reduces the negative effects of cloud obscuration on fire detection. In addition, we assumed that most of the fires that our algorithm detected were multi-day events, thus major differences between datasets were not expected.

C. MODIS Fires—Generation of Fire Clusters and the Conjunction Algorithm

MODIS fire data denote fire activity within pixels, regardless of fire size, number of fires, or fire location within the pixel; therefore it is not possible to use MODIS fire data directly to identify ignition locations or individual fire perimeters. However, it is possible to generate proxies of individual fires using a clustering algorithm [37]. The algorithm identifies groups of fire pixels that are adjacent in space (have a shared boundary in a given day) and time (occur in the same location on subsequent days) to delineate fire clusters. The underlying assumption is that fire clusters represent individual fire events, although some may represent several small fires that occur very close to each other. On the earliest day on which a given fire cluster appeared, its location is considered to represent a "fire seed", or a potential ignition location. Since the size (number of pixels) of a fire seed may have an effect on the conjunction algorithm (see below), we also quantified the size distribution of fire seeds.

Starting with the MODIS fire seeds, we identified lightning fire clusters by employing a spatiotemporal conjunction algorithm to jointly evaluate MODIS and NLDN data. We assumed that if a MODIS fire seed overlapped or occurred within a certain distance threshold d from the location of a nearby lightning strike (to account for geo-location errors in both datasets), and occurred within a certain temporal threshold t after the corresponding lightning strike (to account for smoldering, cloud obscuration, and fire size growth until it can be detected by MODIS), then lightning was the likely cause of that MODIS fire seed. Given that the distance threshold d and the temporal threshold t were unknown in advance, we employed the conjunction algorithm with three distance thresholds (1 km, 2 km, and 3 km) and 15 temporal thresholds (zero, or same day, up to 14 days). The shortest distance threshold accounts for the location accuracies of the lightning data (median 500 m) and the geolocation accuracy of the MODIS instrument onboard TERRA (mean geolocation errors of 18 m ($\pm$38 m) across-track and 4 m ($\pm$40 m) along-track [39]). The potential influence of the MODIS point-spread function, which results in a larger spatial footprint with increasing scan angles and potential distortion in fire locations, was also reduced as our distance thresholds increased. We restricted the longest distance threshold to 3 km to limit the possibility of chance conjunctions, or commission errors (i.e., human ignited fires that had a lightning strike in their vicinity that did not contribute to the ignition).

We used a long range of temporal thresholds to account for the two possible causes of fire misdetection by MODIS: fire size and cloud obscuration. Fires had to grow to a size that could have been detected by MODIS. The longer the lag, the higher the chance of a fire being large enough and consequently being detected during satellite overpass. Since lightning fires ignite under cloud cover, they cannot be immediately detected by MODIS. As time passes, the storm front moves while the fire grows, decreasing the chance of cloud obscuration during subsequent satellite overpasses. Because each is a function of time, the range of temporal thresholds is necessarily wide.

Finally, for visualization purposes, we converted the MODIS lightning fire seeds from groups of pixels to point locations by determining their centroids, and tallied the number of lightning fire seeds within square units of 25 km by 25 km which were overlaid as a grid across the conterminous US We generated raster maps for each threshold combination to compare the spatial patterns of MODIS lightning fire seeds across the entire study area.

D. Comparison With Federal Fire Data

To assess how our lightning fire detection algorithm compares to ground-based data, we compared the number of MODIS detected lightning fires to the number of lightning fires on federal lands as reported in the Federal Fire Occurrence Database. The Federal Fire Occurrence Database (http://fam.nwcg.gov/fam-web/weatherfirecd/fire_files.htm, last accessed February 21st, 2011) reports the characteristics of every fire suppressed on or near federal lands. However, federal lands cover only about 30% of the conterminous US, thus for a large proportion of the nation there are no consistent wildland fire records. In addition, limited quality control, reporting errors (in location, timing, and cause of fires), missing or duplicate records, and difference among agencies hamper the usability of this vast dataset for a national scale study of spatio-temporal patterns of fires [40]. Still, the relatively high accuracy in the places that the Federal Fire Occurrence data are collected makes it a suitable dataset for comparison (not validation) with our satellite-based detection algorithm. To reduce inaccuracies in the database, we modified the approach used by [13]. We checked whether the ignition location of each reported lightning fire was within 2 km, and up to two days after, each lightning strike recorded in the NLDN. Fires that did not satisfy these spatiotemporal lag criteria were considered to have a high probability of being erroneously identified as lightning fires, and were omitted from the subsequent analysis. The 2 km distance rule accounts for potential location errors of both the fire and the lightning data [13], [21]. We then compared the fire ignition data from the refined federal dataset to our MODIS lightning fire seeds.

Since we anticipated that MODIS would fail to detect small fires [37], we conducted the comparison twice, first with all sizes of federally reported fires, then with federally reported fires larger than 0.4 km^2 (100 acres) since they would have a better chance of being detected by MODIS. We performed the comparison only inside federal lands since the federal fire database does not provide consistent information about fires outside federal lands. We employed the same 25 km by 25 km grid system we used for summarizing the MODIS lightning fire clusters as the basis of our sampling (i.e., the number of fires per square sample unit was compared between the MODIS and federal datasets over the entire study period). To ensure maximal overlap between datasets, we conducted the comparison only in sample units that contained 100% federal lands. This resulted in 91 final sample units (out of 7529 sample units that contained at least some portion of federal lands). To compare between the MODIS detections and the federal dataset, we calculated Spearman's correlation coefficient (since the data were not normally distributed) between the MODIS and federal fire counts at the 91 final sample units from the grid system described above, and also calculated the root mean square error (RMSE) between datasets at the same sample units. Finally, we used Spearman's correlation coefficient to compare the fractions of lightning fires out of all fires between datasets (i.e., what proportion of all fires seeds detected by MODIS are attributed to lightning, versus the proportion of federally reported lightning-ignited fires out of all federally reported fires).

E. Spatial Patterns of Cloud Obscurationm

The MODIS sensor cannot detect active fires when cloud cover is present. The MODIS fire products include a cloud mask that identifies pixels that were cloud obscured to a level that could have prevented active fire detection. However, MODIS-fire data products are available as eight-day stacks, where each daily observation may have resulted from several satellite overpasses, depending on latitude. In these cases, overpasses with fire or clear land detections are given a higher priority than cloud detections in the final assignment of pixel values (e.g., if in a single day there was one fire overpass and one cloud overpass, the pixel value will be 'fire'). Therefore, it is not possible to directly detect which MODIS fire seeds (or federal fire detections for that matter) are cloud-obscured (especially since there may also be a slight location error in both datasets). We used the MODIS cloud mask information to identify pixels where it was impossible to know if there was fire activity, since there was consistent cloud obscuration at the time of satellite overpass. We tallied the number of cloud detections per pixel during the prominent burning season in the US, from April to September.

III. Results

A. Patterns of Lightning Strikes and MODIS Lightning Fire Seeds

Between 2000 and 2008, there was a distinctive spatial pattern of CG lightning strikes across the conterminous US, with the most frequent lightning in the south-eastern and the central US (Fig. 1). Other, more isolated areas of lightning activity occurred in the mountainous south-west in Arizona and New Mexico, and the eastern slopes of the Rocky Mountains in Colorado. These results are similar to the patterns reported by [41] for past periods.

The average size of the MODIS fire seeds was 4 km^2, with a standard deviation of 6.81 km^2. Twenty-eight percent of the fire seeds consisted of a single pixel, while 23%, 14%, 8%, 5%, and 4% consisted of two, three, four, five, and six pixels, respectively. Thus, 82% of the MODIS fire seeds had six or fewer pixels, corresponding to a ground area of up to 5.15 km^2. On the other hand, 8% of the MODIS fire seeds were larger than 10 km^2, and there were 11 fire seeds larger than 100 km^2.

The number of MODIS lightning fire seeds detected by the spatiotemporal conjunction algorithm was strongly affected by the temporal threshold, and was moderately affected by the distance threshold (Fig. 2). Longer temporal thresholds and larger distance thresholds increased the number of MODIS fire seeds being identified as associated with lightning. When the temporal threshold was zero (i.e., fire occurred at the same day as lightning strike), the numbers of lightning fire seeds in the entire study period (2000–2008) were 4446, 6090, and 7445 for the 1 km, 2 km, and 3 km distance thresholds, respectively. These numbers increased almost linearly to 37455, 49225, and 57487 at the sixth day, after which they started to gently taper off. At the longest temporal threshold, 14 days, the numbers of lightning fire seeds were 69940, 87342, and 98480 for the 1 km, 2 km, and 3 km distance thresholds, respectively. These values represent a 1473%, 1334%, and 1222% increase from their corresponding values at the temporal threshold of zero, at the three distance thresholds, respectively. Therefore, the spatiotemporal conjunction algorithm was highly sensitive to the choice of temporal threshold and to a lesser extent to the choice of spatial threshold.

The proportions of lightning fire seeds out of all fire seeds (i.e., including those that did not conjunct with lightning strikes

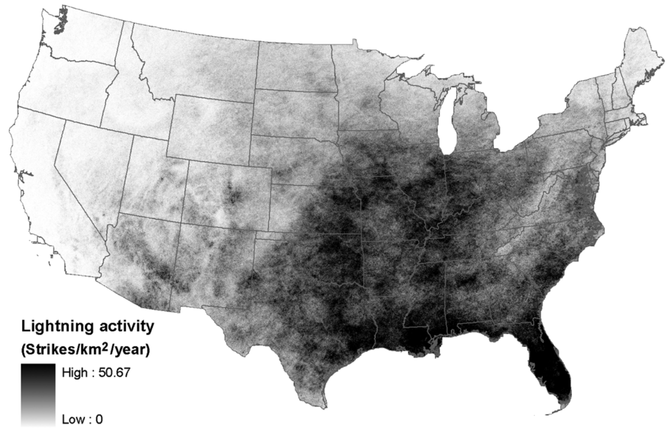

Fig. 1. Mean annual lightning activity in the conterminous US from 2000 to 2008. Each pixel is shaded based on the annual average number of NLDN detected lightning strikes during the study period.

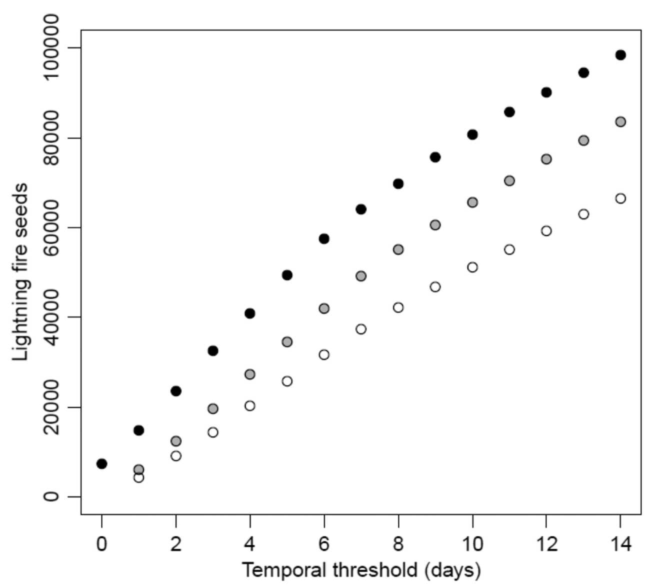

Fig. 2. Effects of temporal (x-axis) and distance thresholds (circle colors: 1 km—white, 2 km—gray, and 3 km—black) on the number of MODIS lightning fire clusters between 2000 and 2008 across the conterminous US.

at a given thresholds) also varied by distance and temporal thresholds. At a temporal threshold of zero, lightning fire seeds were 2.1%, 17.5%, and 32.5% of all MODIS fire seeds, for distance thresholds of 1 km, 2 km, and 3 km, respectively. These percentages increased to 2.9%, 23.2%, and 41.2% on the sixth day at the corresponding distance thresholds, and up to 3.5%, 27.2%, and 46.6% at the longest temporal threshold of 14 days.

Regardless of choice of threshold, the lightning fire patterns detected by MODIS did not follow the patterns of lightning strikes very closely, and differed especially in the northwestern U.S (Figs. 1 and 3), although there was a better agreement in the southwestern US and in Florida. Lightning fire activity peaked in the Southeast, especially in Florida, Alabama, Louisiana, and eastern and central Texas. Another hotspot of lightning fire activity occurred in Kansas and Oklahoma. In the western US, isolated hotspots of lightning fire activity were detected in the Pacific Northwest, especially in the border region between central Idaho and Montana, and in central Oregon, in southern Montana and northern Wyoming; and in other Western states including northern Nevada, along the border of Nevada, Utah, and Arizona, and in central Arizona and western New Mexico. Most of these areas were subjected to considerably lower lightning activity compared to the southeastern US, but still had pronounced lightning fire activity.

B. Comparison With Federally Reported Lightning Fires

At the majority of temporal and distance threshold levels, the federal fire database reported more lightning fires than our algorithm when all fire sizes were considered (Fig. 4). The number of federally reported lightning fires had a low to moderate correlation (Spearman's r from 0.24 to 0.61) with the number of MODIS lightning fire seeds (Fig. 5(a)). Larger distance thresholds almost always increased the correlation, while longer temporal thresholds increased the correlation until the seventh day, after which the effect of temporal threshold on the correlation between datasets was minor.

When only federal fires larger than 0.4 km^2 were compared with the MODIS lightning fire seeds, our algorithm tended to report more fires than the federal fire database, except for the shorter temporal and distance thresholds (Fig. 4). The correlation between datasets increased regardless of threshold levels (Fig. 5(b)). The highest correlation, 0.71, was obtained at the 2-km/7 days thresholds combination. Here, too, longer temporal thresholds increased the correlation among datasets until the seventh day, after which the correlation slightly decreased and then stabilized at day 10. The 3 km distance threshold yielded the highest correlations on the first three days, after which the 2 km distance threshold consistently yielded the highest correlations at any subsequent temporal threshold. Finally, in all threshold combinations, the number of MODIS lightning fire seeds was larger than the number of federally reported lightning fires that were larger than 0.4 km^2.

The root mean square error (RMSE) between the number of MODIS fire seeds and the number of federal fires was moderate (15.26–18.07, depending on threshold combination) when all federally reported fire sizes were included (Fig. 5(c)), and low (1.71–5.53) when only fires larger than 0.4 km^2 were compared (Fig. 5(d)). When all federally reported fires were compared with MODIS fire seeds, the RMSE decreased with an increasing temporal threshold (i.e., the similarity between datasets increased) and slightly decreased with an increasing distance threshold. In contrast, when only fires larger than 0.4 km^2 were accounted for, the opposite trend occurred, as the RMSE increased with both distance and temporal threshold. This was caused by commission errors, since the federal fire database had many zeros (68%) in the sample plots, therefore any increase in the number of MODIS fire seeds (which would be expected with increasing thresholds) would have increased the difference from zero, and subsequently increased the RMSE. In contrast, when all fire sizes were accounted for, the federal database usually had more fires per sample plot (compared to the MODIS data),

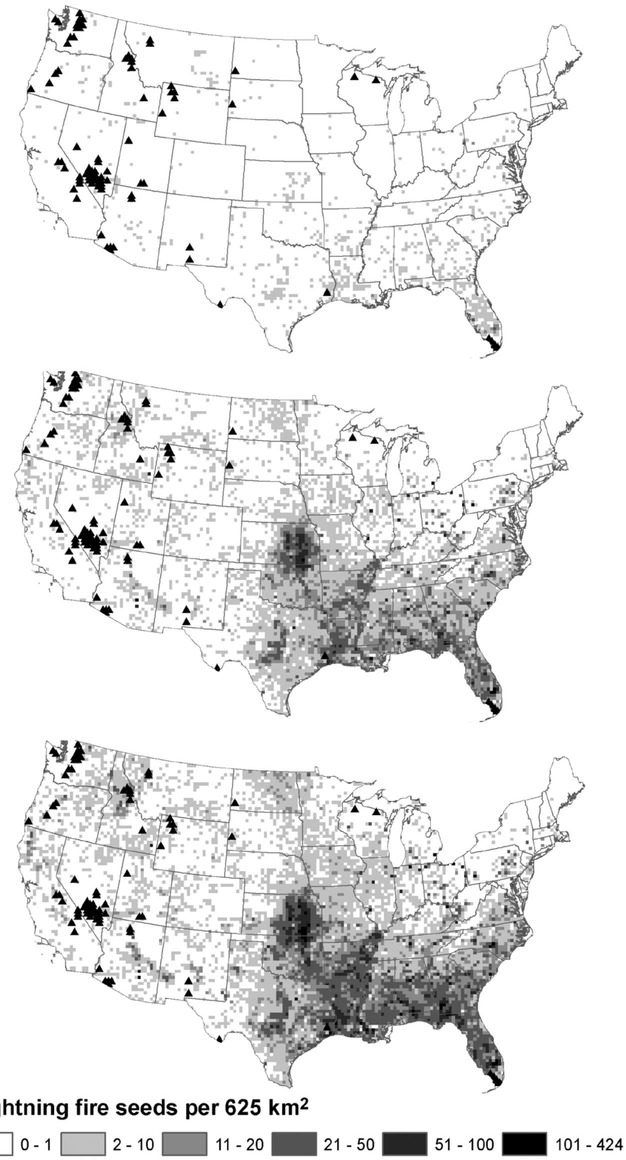

Fig. 3. Spatial patterns of MODIS lightning fire seeds across the entire conterminous U.S, between 2000 and 2008, at three threshold combinations: zero days/1 km (top), seven days/2 km (middle), and 14 days/3 km (bottom). The numbers of MODIS lightning fire seeds are tallied for 25 km by 25 km pixels for visualization. The sample units used for comparing the MODIS and federal datasets appear as black triangles. State boundaries appear in gray.

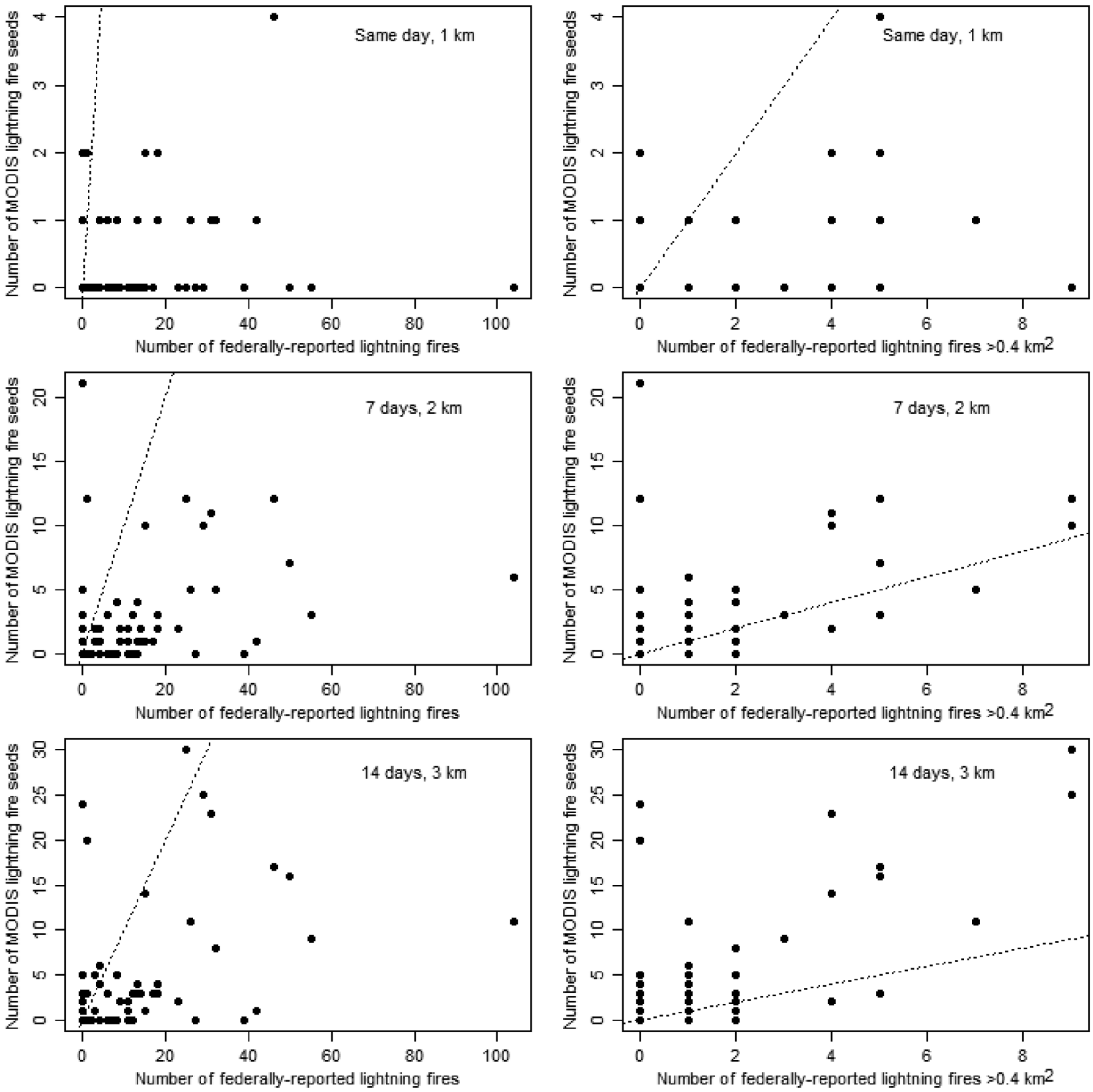

Fig. 4. Relationships between the number of MODIS lightning fire seeds and federally reported lightning fires in the 91 sample plots (black circles) across the federal lands of the conterminous US. Each sample plot is a square of 25 km by 25 km, consisting of 100% federal lands (to ensure complete coverage of the federal database). Plots in the left column are based on all fire sizes from the federal database, while the right column is based on federally reported fires that were larger than 0.4 km^2. The temporal and distance thresholds denoting the data appear at the top of each plot. The dotted line denotes a 1:1 fit (i.e., data point under the line depict cases where there was more federally reported fires than MODIS fire seeds, and vice versa).

so any increase in the number of MODIS fire seeds decreased the differences in fire counts, and subsequently decreased the RMSE.

The correlations between the proportions of MODIS lightning fire seeds (out of all MODIS fire seeds) and the proportion of lightning-ignited federally reported fires (out of all reported fires) were generally low (0.11–0.36), and depended mainly on the choice of temporal threshold. Higher correlations were typically associated with intermediate temporal thresholds (8–9 days) and the 2 km distance threshold, though the overall relationships were not as consistent as those obtained from the comparison of fire counts.

C. *Patterns of Cloud Obscuration*

Cloud obscuration between April and September varied greatly across the conterminous US ranging from less than 10% of days in the southwestern US (especially in southern California), up to more than 30% in the Rockies and Cascade Mountains in the West, and the Appalachian Mountains in the East (Fig. 6). The Canadian Rockies had the largest proportion of cloudy days by far, with 30.4% of the days between April and September classified as consistently cloudy. The southeastern US, which had the largest number of lightning fires, had a moderate level of cloud obscuration, with about 15% cloudy days.

IV. Discussion

MODIS active fire products provide a unique and valuable data source for broad-scale studies of fire occurrence due to the sensor's high temporal resolution and moderate spatial resolution [25], [30], [31]. However, the MODIS fire data do not provide information about the causes of fire ignitions, which is a

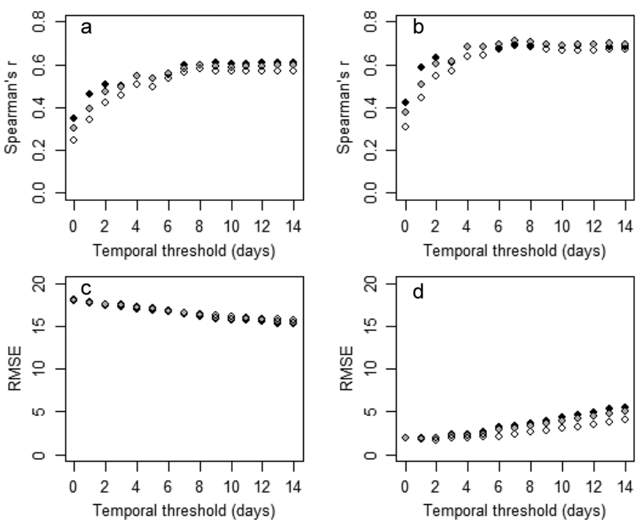

Fig. 5. Correlations and root-mean-square errors (RMSE) between the numbers of federally reported lightning fires and MODIS lightning fire seeds at different temporal (x-axis) and distance thresholds (1 km—white, 2 km—gray, and 3 km—black). (a) correlation with all federally reported fire sizes; (b) correlation with fires larger than 0.4 km^2; (c) RMSE with all federally reported fire sizes; (d) RMSE with fires larger than 0.4 km^2.

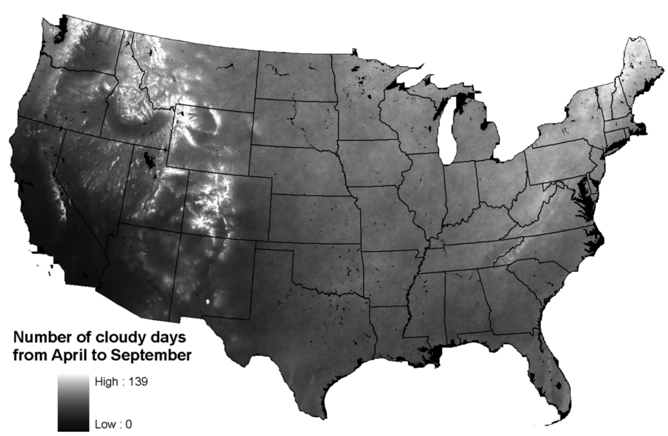

Fig. 6. Average number of MODIS daily cloud detections from April to September.

major component in understanding past and present fire patterns and risk. Here, we addressed this limitation by developing a spatiotemporal conjunction approach, in which the cause of fires, in this case lightning, was identified by the conjunction of fire activity from MODIS and lightning activity from the NLDN. Even though MODIS is limited in its ability to detect small fires [37], and does not provide direct information about individual fire events but rather fire occurrence within pixels, there was a large number of MODIS fire seeds that co-occurred with NLDN detected lightning strikes, and the results of our algorithm were moderately correlated (in some threshold combinations) with ground-based reports of lightning fire occurrence, especially when smaller fires ($< 0.4\ \mathrm{km}^2$) were excluded. This enhances the understanding of broad scale spatiotemporal patterns of lightning fire occurrence, and may facilitate research about the factors that determine lightning fire activity.

Despite the algorithm's sensitivity to the choice of temporal and distance thresholds, the locations of the major lightning fire hotspots were consistent across different threshold values, and only the number of fires varied. Similarly, though the correlation between MODIS lightning fire seeds and federally reported lightning fires increased with both temporal and distance thresholds, maximum correlations were reached after a seven day temporal threshold and did not change much at longer thresholds. This is because in the sample plots, almost no fires occurred within the distance threshold buffer more than eight days before the onset of the MODIS fire seed (even though the number of assigned lightning fire events increased overall across the entire study area). Moreover, differences between MODIS and federally reported lightning fire counts were low for fires larger than 0.4 km^2, but moderate when all fire sizes were accounted for. In contrast, correlations between the proportions of lightning fires (out of all fire types) in the MODIS and federal fire occurrence database were low. This was expected given the limitations of both datasets in identifying the ignition source correctly. These outcomes suggests that the spatiotemporal conjunction algorithm can detect large scale spatial patterns of lightning fire occurrence (especially when fires are large), but is less suited for quantifying the number of fires or the fraction of lightning fires out of all fires because of MODIS's inability to detect small fires [37], and the effect of cloud obscuration that hinders fire detection by satellite-borne sensors.

Between 2000 and 2008, the US had a pronounced spatial pattern of lightning fire activity, with several fire hotspots, mostly in the Southeast, but also in the Southwest, the Central Plains, and the northwestern US In contrast to the general perception of lightning fires occurring mostly in the western U.S, our results highlight pronounced lightning fire activity in the southeastern US, where there is almost no federal land, and therefore less consistent collection of fire occurrence data. However, the central US hotspot of lightning fire activity was a surprise to us, since the central US is not commonly considered to be a hub of lightning fire activity. This hotspot may be an overestimate though, caused by the abundance of agricultural fires [42], as prescribed burning of pasture lands by ranchers at the onset of the growing season has been a common in this region for the past century [43].

The reliability of the spatiotemporal conjunction approach depended on several factors, first and foremost the detection characteristics of both MODIS and the NLDN. The ability to detect active fires by MODIS is affected by fire characteristics (especially the amount of thermal radiation, since the detection algorithm exploits the radiometric contrast between active fires and their surroundings), the timing of satellite overpass versus fire activity [27], and cloud cover (which can obscure fire activity). MODIS has difficulties detecting small fires [37], especially at large scan angles where only a limited amount of energy reaches the sensor [36], [44]. Therefore, we assumed that most of the fires detected by our algorithm were large, as large fires are also more likely to persist longer, which reduces the risk of cloud obscuration. Since the conjunction algorithm was based on the spatial and temporal overlap of fires and lightning strikes, there is a higher probability of overestimating lightning fires at the expense of human caused fires in areas that have an extremely high number of both fires and lightning strikes. Out of the large numbers of lightning fires identified by our algorithm in the southeastern regions, some may have actually been human caused fires that were erroneously labeled as lightning fires. This is a possibility because of the widespread human development in the Wildland Urban Interface in the Southeast, which is correlated with increased human fire ignitions [35], [45]. In these areas, chance occurrence of lightning strikes at the time of human-ignited fires may increase the commission error (identifying non lightning fires as lightning fires), and thus our results probably represent the upper bound for lightning fires.

In several mountain regions, especially in the Rockies and the Appalachians, cloud obscuration occurred on more than 30% of the days between April and September. Given that these areas are known hotspots of lightning fire activity, this cloud obscuration may have caused an underestimation of lightning fire detections by our algorithm. Mountain regions typically exhibit longer periods of consistent cloud cover, which causes satellite-based fire detections to underestimate the number of fires regardless of ignition source, but the underestimation of lightning fires will be more pronounced since lightning is more likely on cloudy days. Cloud obscuration is an inherent limitation of satellite based fire detections, so the use of these detection tools requires identification of those areas most prone to cloud cover; in our case the mountainous regions of both the eastern and western US.

Beyond the detection capability per se, the grouping of MODIS fire pixels into fire clusters, based on the approach of [37], may have impacted the results. The fire seed identification and fire pixel clustering approach assumed that neighboring pixels that burn at the same time are part of the same fire. Due to MODIS's data structure and resolution (fire activity per pixel rather than individual fires), the number of fires may be underestimated, especially when many small fires burn near each other. According to a separate analysis of the Federal Fire Occurrence Database (Bar-Massada *et al.*, unpublished), 6.4% of the lightning fires burned within 1 km of each other on the same day, so it is possible that some of the fire clusters identified here actually consist of several individual fires lumped together. However, duplicate fire records from different agencies, which are difficult to identify and remove automatically, are another potential source of error in the Federal Fire Occurrence Database and counteract this bias, tending to inflate the number of fires. Errors caused by fire seed clustering can affect both the detection efficiency (as seed locations may misrepresent actual fire ignition areas), and the number of fires detected (by merging separate small fires in close geographic proximity via the clustering algorithm).

The most important assumption affecting the performance of our algorithm was that conjunction, i.e., fire and lightning occurrence in the same space and at the same time, indicates the ignition source as lightning. This assumption may have biased the results in several ways. First, ignition locations (strikes) and fire locations may be spatially (and temporally) inaccurate, thus affecting the conjunction locations, and cluster seeds may be quite large for rapidly spreading fires, thus increasing the probability of conjunction with a chance lightning strike. Second, it is possible that a lightning strike occurred within the perimeter of a human ignited fire. For example, the strong winds that accompany thunderstorms can down power lines which in turn provide an ignition source, resulting in a fire classified as human-caused. Lightning strikes may well coincide with the ignition locations of such fires.

Despite its limitations, the dataset generated in this study is the only national scale analysis of lightning fire activity conducted in a consistent manner, and reveals where and when lightning fires occur. As such it sets the stage for research into the driving factors of lightning fire occurrence and dynamics and for the identification of high risk areas [35], [45], [46]. Both lightning fire patterns and identification of high fire risk areas have widespread application and utility for fire management.

To conclude, we developed, tested, and applied a novel approach to identify lightning fire patterns across broad spatial scales and at fine temporal scales. We found that the method performed moderately well in identifying broad scale spatiotemporal patterns of lightning fire activity in the conterminous United States despite the inherent limitations that emerge from the nature of MODIS active fire data. Given the global coverage of MODIS data, coupled with the availability of lightning detection networks in other regions of the world [18], it may be possible to conduct this analysis in other countries as well. In areas with insufficient data about lightning fire activity, and in remote areas where fires burn without human intervention (or even detection), this approach could provide a basis for building a fire record in lieu of ground-based fire reports. Results from such investigations could facilitate additional studies to enhance our understanding of the climatic driving forces behind broad scale lightning fire activity.

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