WHAT IS A FIRE? IDENTIFYING INDIVIDUAL FIRE EVENTS USING THE MODIS BURNED AREA PRODUCT

by

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What is a Fire? Identifying Individual Fire Events Using the MODIS Burned Area Product

Thesis directed by Associate Professor Jennifer Karareka Balch

Fire events, which delimit the extents of fires as well as fire start and end dates, provide important information for understanding fire regimes, including ignition points, spread rates, seasonality, and final size. Rates and patterns of spread associated with individual events are critical for modeling fire behavior across varied ecoregions and informing fire management. Fire events are not available from satellite-derived burned areas directly, and therefore a consistent process for aggregating burned pixels into fire events is needed. This study presents a flexible flood-fill algorithm that aggregates burned pixels into fire events based on varying spatial and temporal proximity. We tested our approach using data from the Moderate Resolution Imaging Spectroradiometer (MODIS) Burned Area product (MCD64A Collection 5.1) for the western U.S. in the year 2007. We used a range of spatial (number of pixels) and temporal (number of days) distances to cluster Burned Area pixels into events. We then compared Burned Area perimeters to perimeters based on the Landsat-derived Monitoring Trends in Burn Severity (MTBS) product for the same events. Based on this comparison, we determined that for the western U.S., a distance of five pixels and nine days constituted the best spatial and temporal thresholds to define individual fire events with the MODIS Burned Area product. We present a fire event dataset for the continental U.S. based on MODIS burned area for 2001-2016. Our fire event maps include important metrics of the fire regime, such as ignition point, fire size, fire spread rate, and the start and end dates of each individual fire event. The comparison between the

MODIS Burned Area derived fire events and the MTBS, as the ground truth data, showed that omission, commission errors, and final accuracy are 12%, 38% and 88% respectively. We expect that the five-pixel, nine-day criteria may vary by ecoregion or land use type, and have designed the code so that these aggregation criteria can be adjusted for different regions. Our aggregation method increases the utility of the MODIS Burned Area product for fire modeling and management by enabling the analysis of fire behavior for individual fire events.

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CHAPTER I.

1. INTRODUCTION

The practice of remotely sensing fires (NOAA Satellite and Information Service 2012; Flannigani and Vonder Haar 1986; Robinsoni 1991) and the increasing capabilities of newer generation satellite images (e.g., Moderate Resolution Imaging Spectroradiometer; MODIS) have called into question what fundamentally defines a fire event. Remotely-sensed fires, based on thermal thresholds (Giglio et al. 2009; Giglio et al. 2003; J. Kaufman et al. 1998; Giglio, Kendall, & Justice, 1999) or change detection through time series' (Roy et al. 2008), have provided valuable information on fire characteristics such as fire size and shape (Cattau et al. 2016), total burned area (Pozo-Vazquez, Olrno, and Arboledas 1997), duration (Smith and J Wooster 2005), and spread rate (Andela et al. 2017). However, critical to determining these characteristics is defining what an actual fire event is from pixel-level designations, including the perimeter, total area, and the start and end date of burning.

Burned area has been extracted from different satellite sensors (Mouillot et al. 2014; Holden 2008) including MODIS (MCD45A1 and MCD64A1 products) (Roy et al. 2008), SPOT-VEGETATION (BA GEOLAND-2) product (Tansey et al. 2008; Zhang et al. 2003), Advanced Very High Resolution Radiometer (AVHRR) (Moreno Ruiz et al. 2013), Landsat (Eidenshink et al. 2007), and others. The comparison of six different global fire products suggests that the MODIS-based MCD64 (Giglio et al. 2009) and MCD45 (Roy et al. 2008) with 27% and 25% commission error and 10% and 8% omission error respectively are the most accurate global burned area products (Padilla et al. 2015). However, there are key challenges to extracting fire

events from satellite-sensor based detections. First, the defined pixel size of satellite sensors (e.g., 500-m for MODIS) may not be appropriate given the fundamental size distribution of fire events measured on the ground.

The average fire size in over 1.5 million U.S. government wildfire records is 23.5 ha, which is approximately the size of one MODIS pixel (Short 2014). However, fire sizes range from a maximum of 225,800 ha and a minimum of 0.004 ha (Short 2014). Second, unburned areas within a fire perimeter are common (Kawchuk et al. 2016), making it important to determine how homogeneous a burn needs to be, or whether some degree of heterogeneity will be allowed within a single fire perimeter of the same event. Unburned areas within fire perimeters could also be caused by errors in the burned area products, which sometimes miss detections due to clouds or missing data (Roy et al. 2008).

The challenge of designating fire events from remote sensing data is akin to determining how paleocharcoal records should be considered in the context of modern-day observed fires or how weather events are delineated (McIntosh and Yuan 2005) because the methodology used or the sensor type selected can fundamentally alter the definition of an event. Critical to understanding the physical drivers and ecological effects of fire is the delineation of individual fire event boundaries, as opposed to knowing only total burned area. The total burned area could be a function of a single large fire or many small fires (Hantson, Pueyo, and Chuvieco 2015) which are driven by different climate and fuel conditions and have different ecological impacts. Larger fires are the result of more extreme conditions (high fuel availability, low humidity, high temperatures and high wind speed) and often have greater impacts than smaller fires, even if total area burned is the same (Hantson, Pueyo, and Chuvieco 2015; Graham, McCaffrey, and Jain 2004).

Fires of different sizes can have very different ecological effects (Cochrane and Ryan 2009; Keane et al. 2008; Russell-Smith, Ryan, and Durieu 1997; Hudak, Fairbanks, and Brockett 2004). For example, large fires tend to burn hotter and have greater severity in boreal ecosystems (Ryan and Ryan 2015). Also, the landscape structure of large fires is different from small fires (Romme et al. 1998). Large fires tend to have larger patches (low patch density) that are more regular in shape (high landscape shape index) with less edge than smaller fires (Keane et al. 2008). Finally, the spatial patterns produced by different types of fire regimes have unique ecological consequences. The most pertinent example is the patch-mosaic which is a heterogeneous pattern of burned and unburned patches within a fire perimeter (Russell-Smith, Ryan, and Durieu 1997; Hudak, Fairbanks, and Brockett 2004; Laris 2011). Aggregating individual burned area pixels into fire events allows researchers to better consider the drivers and effects of fire.

Analysis of fire events and fire size distributions (Chuvieco et al. 2016) based on pixel aggregation methods is an emerging field of study (Archibald and Roy 2009; Balch et al. 2013; Fusco et al. 2016; Andela et al. 2017). However, previous studies have not included an in-depth exploration of the role of different spatial and temporal contiguity criteria in producing the most accurate fire event maps. Archibald and Roy (Archibald and Roy 2009), one of the first to extract individual fire events using the MODIS Burned Area product, developed a modified flood-fill algorithm to compare individual burned pixels with its eight neighbors to determine whether the neighbors also burned within an eight-day period. Their research indicated that many of the fires identified by the algorithm were very small in comparison to field data available for fire events in South Africa (Archibald and Roy 2009). Balch and colleagues (Balch et al. 2013) applied the same approach but with different spatial and temporal contiguity criteria (one-pixel, two-days).

They used the extracted fire events map to explore how invasive grasses changed the fire regime in the western US. Fusco and colleagues (Fusco et al. 2016) studied the human influence on fire ignition across the western US by mapping fire events by aggregating pixels that were within two days and two pixels, or within three days if pixels were adjacent. Notably, in some cases where large fire complexes burned for several weeks, these criteria were not appropriate (Fusco et al. 2016). Andela and colleagues (Andela et al. 2017) extended the work of Archibald and colleagues (Archibald and Roy 2009) to develop an algorithm to distinguish fires and to characterize their attributes.

Despite recent efforts of researchers to extract fire event information based on spatial and temporal contiguity criteria, there has been no comprehensive analysis examining the systematic impact of choosing different spatial and temporal contiguity criteria for producing a reliable fire events map. Therefore, in this research, we develop a flexible flood-fill algorithm to identify fire events using the MODIS Burned Area product from 2001-2016 (MCD64A1) (Giglio et al. 2016). Although there are different global burned area products available (e.g., GLOBSCAR) (Simon et al. 2004), we used the MODIS Burned Area product to extract fire events which is available at 500-m spatial resolution (Roy et al. 2005a). The temporal coverage of the MODIS Burned Area dataset is from April 1st 2000 (Roy et al. 2008) to present day, and the estimates of the reporting accuracy of burned area detection dates are generally accurate to within an 8-day interval (Boschetti et al. 2010).

The resulting fire event dataset at the large scale provides the perimeter and location of each individual fire event as well as the size, and the start and end dates. To produce the fire event maps, we explore different spatial and temporal contiguity criteria and evaluate the final maps based on the Monitoring Trends in Burn Severity (MTBS) product for the year 2007 (Eidenshink et al. 2007). We then designate the best criteria to extract the fire events for the western U.S. using the MODIS Burned Area product at the continental scale. Ultimately, extracting individual fires and spatio-temporally characterizing them will help fire researchers to bridge the gap between landscape-scale and global fire regime characterization (Yue et al. 2014) because it provides information about the fires at a new scale. The study area is the western U.S. and the results of this research have a potential to be applied at the continental scale.

We used MTBS product as the main source of evaluation, although this product has some limitations. Unfortunately, due to resource constraints and technical limitations, the MTBS project could not, and cannot map every fire that has occurred (Eidenshink et al. 2007, Kolden et al. 2015). MTBS does not provide information on small fires in the western (< 1,000 acres) and eastern US (< 500 acres) (Schwind, 2008; Masek and Healey 2017; Eidenshink et al. 2007). This product has other limitations. For example, MTBS data are mostly based on assessments of pre-burn and post-burn image-pairs. When image-pairs are not available, MTBS perimeters are only based on a single post fire image (Lukić et al. 2017). This can result in a lower accuracy of identified fire perimeters. Also, the process of producing MTBS is subjective (Eidenshink et al. 2007) and is dependent on analyst understanding, skill, and the interpretation of where is the boundary of the fire burned area. MTBS product is a satellite-based product but not a satellite imagery then we do not define a spatial and temporal resolution for this product directly. In general, all MTBS raster datasets are generated from Landsat (TM/ETM+/OLI) image data

which is acquired at a spatial resolution of 30 meters (Eidenshink et al. 2007, Kolden et al. 2015).

Despite the limitations of MTBS, this product is the best available product that we can use to evaluate our final fire event maps. For example, this product has been available from 1984 for the entire U.S. and it is free to download. The accuracy of MTBS products has increased significantly in recent years due to the advancements in technology, software, and satellite data (Eidenshink et al. 2007).

The MTBS product preserves the minimum information about each individual event that is just a boundary of fires, but the question is how we can extract and keep the maximum information about each individual fire event extracted from satellite imageries. To answer this question we need to know what is an event in general, what do we mean by the maximum information, and how GIScience can help to keep the maximum information about an individual event.

Event is defined as an occurrence of something in space and time. Each event contains a process that is a sequence of dynamically related states, and states shows how something evolves in space and time (Yuan 2001). In GIScience, two basic models are used to define and keep the maximum information about a complex geographic phenomenon or an event. First is the exact object model and the second model is the continuous field model (Yuan 2001). In the exact object model, the boundary of individual events are important. In these cases, the event acts as a container for attributes that apply uniformly over the event (Macintosh and Yuan 2000). This model that has been used in the MTBS product cannot provide a complete representation of a distributed phenomenon such as wildfire that has both spatial and temporal aspects. In the continuous field model an event fills with attributes that vary continuously over space. This

model helps us to keep fire information on a cell-by-cell basis. In fact, this model allows us to define "space-time" events that are different from events in the MTBS product. The MTBS product provides an attribute table that shows the general information of fire events such as the area and the start fire date. Although this information is useful for phenomena such as wildfire, their properties vary across an extended area (Macintosh and Yuan 2000). A more complex data model that combines the object and field models is required to preserve all the information about an event.

After extracting fire events from satellite-based data it is ideal to keep the maximum information about the individual fires. The maximum information contains the border and also the spatiotemporal behavior of the fire within each fire event. We use a continuous field model to present the space-time fire events as a map. These maps not only support queries on the attribute table but also provide answers to spatial and temporal queries including spatial and temporal range, spatial and temporal relationship, spatiotemporal range and spatiotemporal behavior (Macintosh and Yuan 2000). For example, using the final fire event maps we can answer where the average spread rate decreases by 3 square km on May 10th (spatial-temporal range), or how the spread rate of a specific fire event changed over the life of the event (spatio-temporal behavior). This model enhances our ability to understand the spatiotemporal patterns within a distributed fire event.

In the last 20 years, different advanced models have been developed to study the events as an individual phenomenon. Event-based SpatioTemporal Data Model (ESTDM) is one of these models. This model is designed to explicitly represent change over space relative to time. ESTDM stores change relative to time, procedures for answering queries relating to temporal relationships, as well as analytical tasks for comparing different sequences of change. In this

model, events represents a change in state (i.e., change in properties, attribute, or value). The change can be caused by some catastrophic event such as a forest fire, or change can be gradual, such as the amount of rainfall (Peuquet et al. 1995). After a primary model presented by Peuquest and colleagues in 1995, Claramunt and Theriault (1995) modeled events as a set of processes that transform entities and describe events with object versions. Allen and his collaborators (1995) proposed a "causal model" which also considered events as changes of state in objects. In 1998 Cheng and his colleague (Chen and Molennar, 1998) represented the changes of natural phenomena as a set of dynamic processes such as move, erode, or split (Chen and Jiang, 2000). All these studies show that the models which are able to track the spatial and temporal information about an event are important factors in defining and using fire events in the spatiotemporal models.

2. STUDY AREA AND METHODS

This study focuses on the 2007 fire season in 11 western U.S. states: Washington, Oregon, California, Idaho, Nevada, Arizona, Utah, Montana, Wyoming, Colorado, and New Mexico (figure 1). This year was one of the largest wildfire years during the past decade, with over 37,749 km^2 burned across the U.S. (National Interagency Fire Center Statistics ,2015). The western U.S. consists of a variety of fire-prone ecosystems (Noss et al. 2016; Sugihara et al. 2006; AgeeJK 1993; Veblen et al. 1994) with individual fire events ranging in size from < 1 ha to hundreds of km^2 (Short 2014; Eidenshink et al. 2007). The diversity of fire, both in frequency and size, across the western U.S. creates an ideal study system for testing different spatial and temporal contiguity criteria for identifying individual fire events. Figure 1 shows the temporal history of fire occurring in the western U.S. in 2007. In this figure the earliest fire burn date is day 19 based on the Julian calendar and the latest date is day 365.

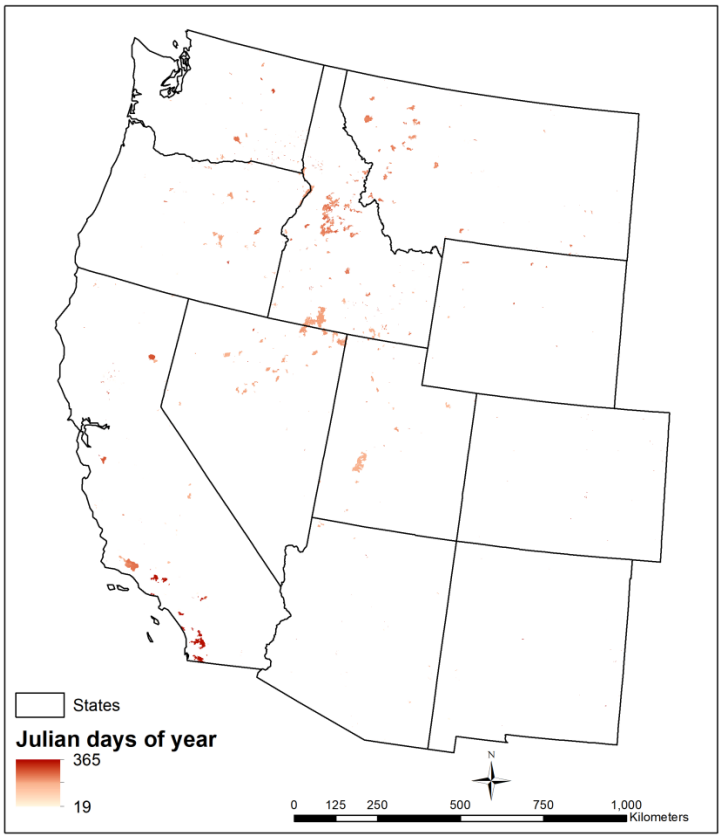

Figure 1: Study Area

The study area includes 11 western U.S. states and red patches are pixels identified as burned during the year 2007 by the MODIS Burned Area product (MCD64A1). Darker colors burned later, based on Julian day of the year. The map projection is Albers equal-area.

We used the MODIS Burned Area product from 2007 to determine the appropriate spatial and temporal thresholds to designate individual fire events (MCD64A1 Collection 5.1) (Giglio et al. 2016). Then the developed flood-fill algorithm was applied to the available range of the MODIS product, from 2001-2016 for the U.S. (data is publically available at NASA Earth Science Data, 2017).

The MODIS Burned Area product has been reprocessed periodically with improved calibration methods and algorithm refinements, e.g., Collection 6.0 was available at time of

publication submission (NASA Earth Science Data, 2017). Each pixel of this product is given a designation of unburned or burned, based on the estimated Julian date of burn. In the MODIS Burned Area MCD45 product, burned areas are characterized by residual charcoal and ash, and changes in vegetation structure (Pereira et al. 1997; Roy et al. 1999; Masek and Healey 2017). In the MODIS Burned Area MCD64 product, surface reflectance and active fires are also used to help determine burned area (Giglio et al. 2016; Giglio et al. 2009; Roy et al. 1999). The spectral reflectance, temporal pattern, structural change, and thermal characteristics are the main factors that are used to produce the MODIS Burned Area products (Roy et al. 2005b). These products provide valuable information on the spatial and temporal distribution of fires (Nyasha 2013; Roy et al. 2008) that allow for the exploration of fire regime characteristics, such as fire extent, seasonality, size, and return intervals (Archibald et al. 2010; Hantson, Pueyo, and Chuvieco 2015).

In this study we determined the best spatial and temporal contiguity criteria for combining nearby burned pixels into single fire events for the western United States. Spatial contiguity criteria refer to the number of neighboring pixels surrounding a given pixel that also burned. For example, a given pixel has eight direct neighbors at one-pixel distance, 24 within two-pixel distance, 48 within three-pixel distance and so on (figure 2). The neighboring pixels can be either direct or indirect neighbors. Direct neighbors are burned pixels which share a common boundary. Indirect neighbors are burned pixels that meet the spatial and temporal contiguity criteria but do not have a common boundary with the main burned pixel. We considered the neighbors up to a six-pixel distance in this analysis. Temporal contiguity criteria refer to the number of days between a given burned pixel and neighboring burned pixels, for example, two consecutive days have a difference of one day. We considered a temporal

difference ranging from one to 12 days. However, the results showed that the number of individual fire events designated did not increase beyond six neighboring pixels (see results).

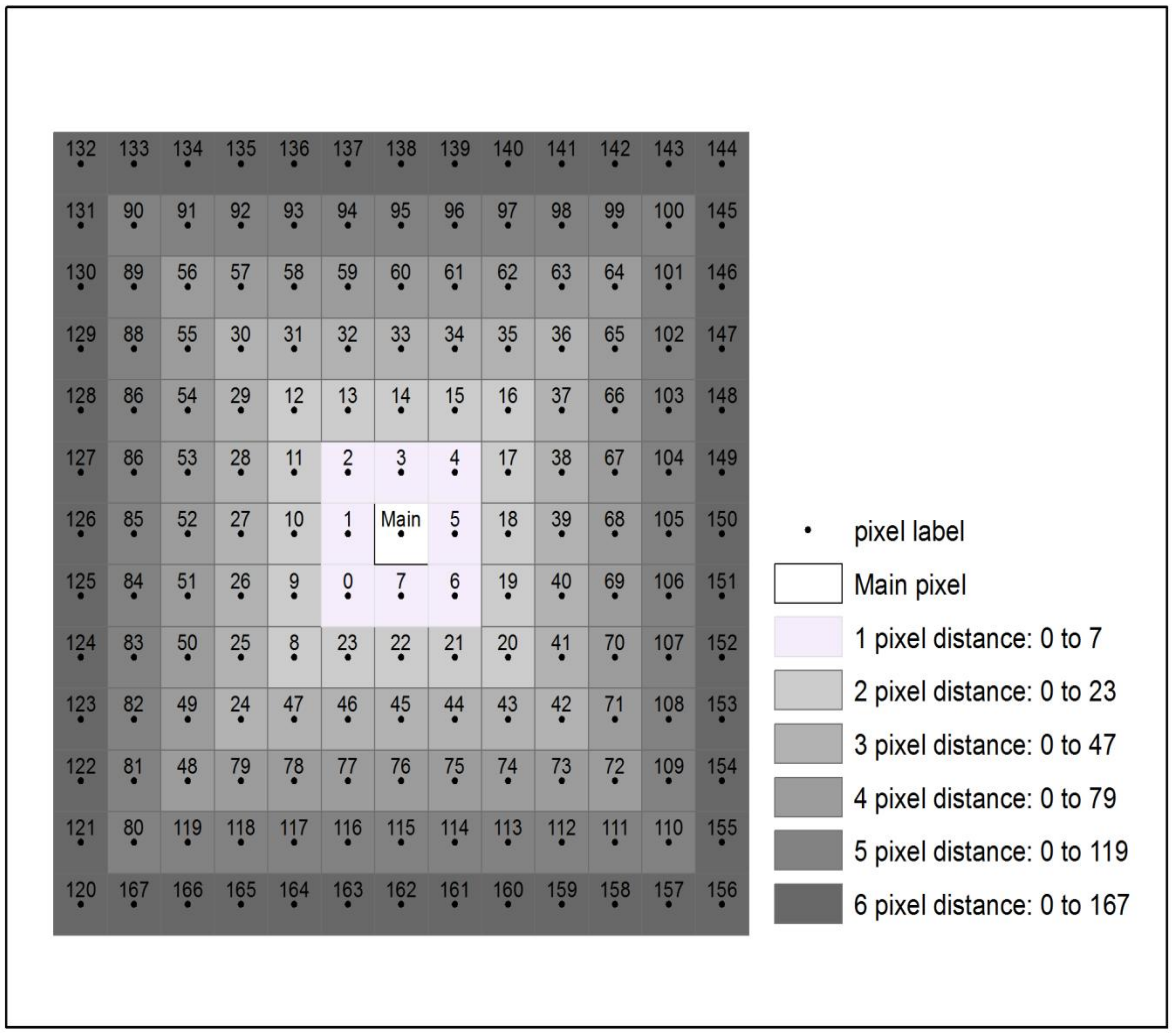

Figure 2: Neighboring pixels

Each pixel in MODIS Burned Area product is compared with 1 to 6 neighboring pixels. Increasing the order from 1 to 6 pixels, increases the neighboring pixels from 8 to 168 neighboring pixels.

Although the MODIS Burned Area product is available in monthly increments, we created an annual mosaic of the data to avoid artificially splitting fires that span two or more months. These annual mosaics were a more reasonable place to split because fire occurrence is

very low in the continental U.S. during the winter months, but the timing of the split should be re-evaluated for fire studies in the southern hemisphere.

We developed a flood-fill algorithm to determine whether to lump the neighboring burned pixels into the same fire event and to produce a fire event map. This algorithm compares each pixel of the MODIS Burned Area product, that is a two-dimensional array, with neighboring pixels in both space and time. In general, flood-fill algorithms determine the area connected to a center node in a multi-dimensional array and generates the bounded areas around the nodes as different objects. Diagram 1 shows the primary steps of the code.

To lump neighboring pixels into a single fire event, we need to have a clear definition of what the neighboring pixels mean. We used spatial and temporal contiguity criteria to define a neighbor pixel. Spatial contiguity criteria is the extent to which two pixels are situated close to each other in space. Temporal contiguity criteria is the extent to which two pixels are close together in time. Different orders of spatial contiguity criteria and temporal contiguity criteria can be used to define a fire event. In this research, we developed a python code that allows us to study how different orders of contiguity criteria can result in producing different fire events.

The python code first identified a burned pixel in the input array (i.e., the 2007 MODIS Burned Area layer) which is then compared to its neighbors. If any of those neighbors in any directions meet the spatial and temporal contiguity criteria, those pixels are combined into the same fire event. Next, all the neighboring pixels which have been designated as the same fire event are compared to their neighboring pixels until no further pixels are found that meet the spatial and temporal contiguity criteria. When there are no remaining pixels which meet the spatial and temporal contiguity criteria for the first identified fire, the next unclassified pixel in

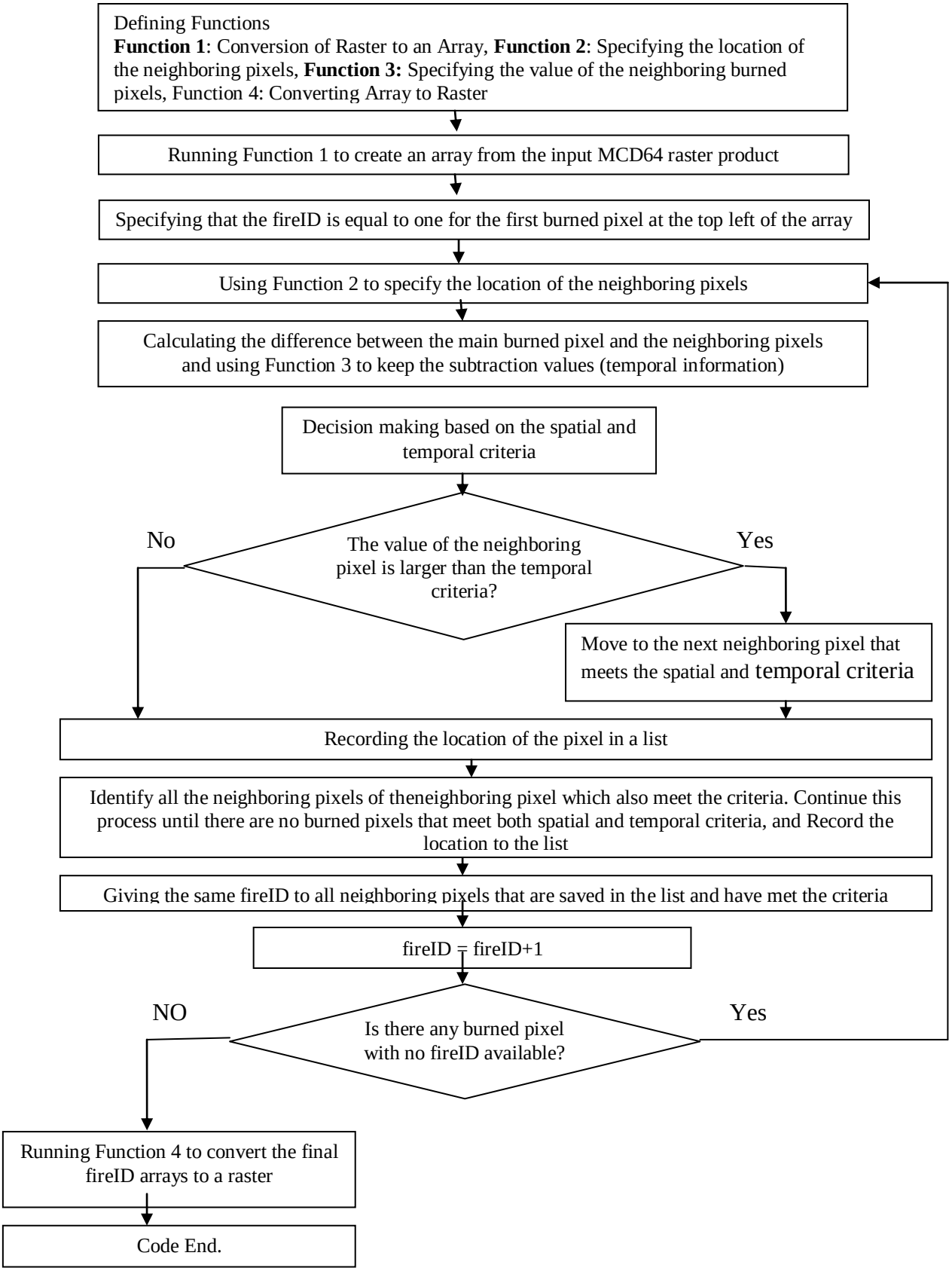
Defining Functions
Function 1: Conversion of Raster to an Array, **Function 2**: Specifying the location of the neighboring pixels, **Function 3:** Specifying the value of the neighboring burned pixels, Function 4: Converting Array to Raster
Running Function 1 to create an array from the input MCD64 raster product
Specifying that the fireID is equal to one for the first burned pixel at the top left of the array
Using Function 2 to specify the location of the neighboring pixels
Calculating the difference between the main burned pixel and the neighboring pixels and using Function 3 to keep the subtraction values (temporal information)
Decision making based on the spatial and temporal criteria
No
The value of the neighboring pixel is larger than the temporal criteria?
Yes
Move to the next neighboring pixel that meets the spatial and temporal criteria
Recording the location of the pixel in a list
Identify all the neighboring pixels of theneighboring pixel which also meet the criteria. Continue this process until there are no burned pixels that meet both spatial and temporal criteria, and Record the location to the list
Giving the same fireID to all neighboring pixels that are saved in the list and have met the criteria
fireID = fireID+1
NO
Is there any burned pixel with no fireID available?
Yes
Running Function 4 to convert the final fireID arrays to a raster
Code End.

Diagram 1: The primary steps of the python code
This code is used to extract individual fire events from MODIS Burned Area product.

the input array is designated as the second fire and the process repeats until all the burned pixels in the array are assigned to a unique fire event. The code stops running when all the burned pixels in the MODIS Burned product get a fire ID. If there is no neighbor around the burned pixel but there are still some burned pixels in the image, they are identified as new fire events.

The python code always considers the first burned pixel at the top left of the image as the first burned pixel so there is no concern about how the start point will be chosen and how it may affect the fire events. To make sure that the start point does not affect the identification of fire events and there is no path dependency on the starting point, we ran the code from three randomly selected points and compared both the number and size of fire events in each fire event map. The results showed that running the code from different start points produces the same fire event maps which have the same number of fire events and the exact fire size. The results also confirmed that our flood-fill algorithm connects the pixels to the node no matter where the node is located. In our study, the first node is the first burned point to which other burned pixels within the spatial and temporal connects.

We successively determined the number of fire events based on one-pixel distance and one day apart, two-pixel distance and two days apart, etc. until we reached six-pixel distance and 12 days apart. We did not increase the spatial and temporal contiguity criteria beyond 6-pixel and 12 days because this did not lead to an increased number of identified fire events (see results).

The flood-fill algorithm is implemented as a Python script (Python Software Foundation. Python Language Reference,Version 2.7,2017). Refer to the provided readme files for information about how to modify the spatial and temporal contiguity criteria or annual split. Geospatial processing was done using both ArcPy and the Geospatial Data Abstraction Library (GDAL) (Geospatial Data Abstraction Library, 2017). GDAL is an open source library for reading and writing raster and vector geospatial data formats. We wrote the code with ArcPy at first but this package has some limitations because it is not an open source package. For example, it was not possible to run the ArcPy code on supercomputers. To solve this problem we provided the code in GDAL.

To evaluate the accuracy of fire event maps we used MTBS data product for year 2007 (Eidenshink et al. 2007). At first, we classified the MTBS fire polygons as small (< 1,204 ha), medium (>1,204 ha and <14,290 ha), and large (>14,290 ha) fires. A standard classification method (Abboud, Samet and Adelfio 2009) was used to classify the MTBS data based on natural breaks. This method identifies the best group of similar values and then maximizes the difference between classes. The features are divided into classes whose boundaries are set where there are relatively large differences in the data values. After calculating the number of fire events identified through our methodology, the total number of fire events in each small, medium, and large fire category was compared with the number of MTBS fire polygons in that same size category. In the process of evaluation, those MTBS fire perimeters which were not spatially and temporally matched with MODIS burned area pixels were excluded from direct comparative analysis of overlapping fire events because these MTBS fire perimeters do not have any role in the evaluation (see results).

For the final step, we calculated the omission and commission errors of the total number of fire events in our derived maps. To calculate the omission error, we divided the false negative

errors by the total of the false positive and negative errors, and to calculate the commission error, we divided the false positive errors by the total of the false positive and negative errors (see results). We used the omission errors to calculate the final accuracy of fire event maps.

3. RESULTS

We compared fire perimeters based on our flood-fill algorithm to MTBS fire perimeters defined as small, medium or large. In the western U.S., this included 369, 31, and 5 MTBS perimeters, respectively. Out of the 369 small fires, 85 MTBS polygons were not used for evaluation because there were no MODIS burned area pixels identified within those perimeters and these 85 MTBS polygons do not have any role in the evaluation process. This highlights that the MODIS burned area product does have identified omission errors (Tsela et al. 2014). Increasing both the spatial and temporal contiguity criteria strongly improved overlap between the MODIS and MTBS fire perimeters (figure 3).

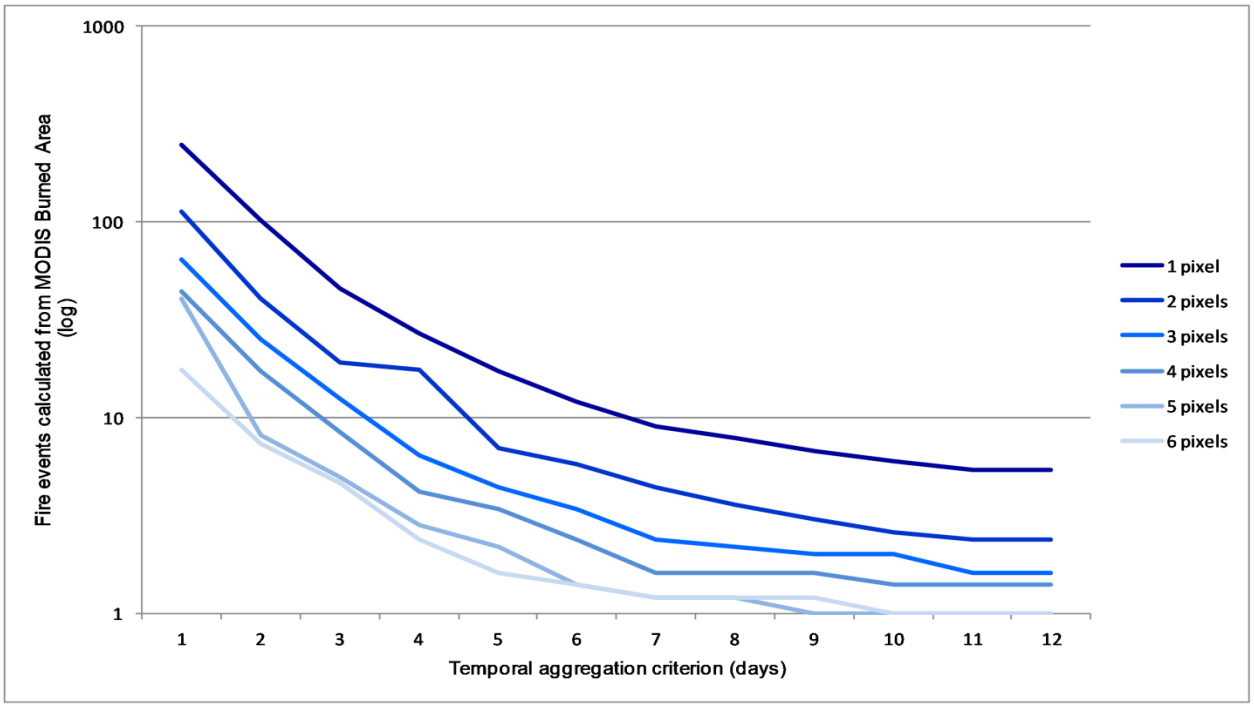

Figure 3: Fire event counts for MODIS vs. MTBS

The ratio of fire events calculated based on MODIS to number of fire events identified by MTBS in 2007. As the spatial and temporal aggregation criteria get broader (more days to the right and

more pixels in darker colors), there is a higher agreement between fire event counts for MODIS vs. MTBS.

Using only 1-2 pixels of search distance always split fire events more finely than MTBS, particularly for medium and large fires. With a simple one-pixel and one-day distance, the number of MODIS fire events was 247, 42, and 5 times greater for large, medium, and small events, respectively, when compared with MTBS fire perimeters (Appendix 1, figure 3). The example illustrated in Fig 4 demonstrates the importance of assessing aggregation criteria when implementing a flood-fill algorithm for fire perimeters. Narrow spatial and temporal contiguity criteria can lead to an excess of fire 'splitting', which can overestimate the total number of fire events. In figure 4, we see how different spatial and temporal contiguity criteria can create a different number of fire events. For example, figure 4 part B shows that choosing 1 pixel as a spatial contiguity criteria and 3 days as a temporal contiguity criteria creates 8 fire events while in the same area spatial contiguity criteria of 3 pixels and temporal contiguity criteria of 3 days create one fire event. This figure illustrates how small criteria can tear apart one fire event.

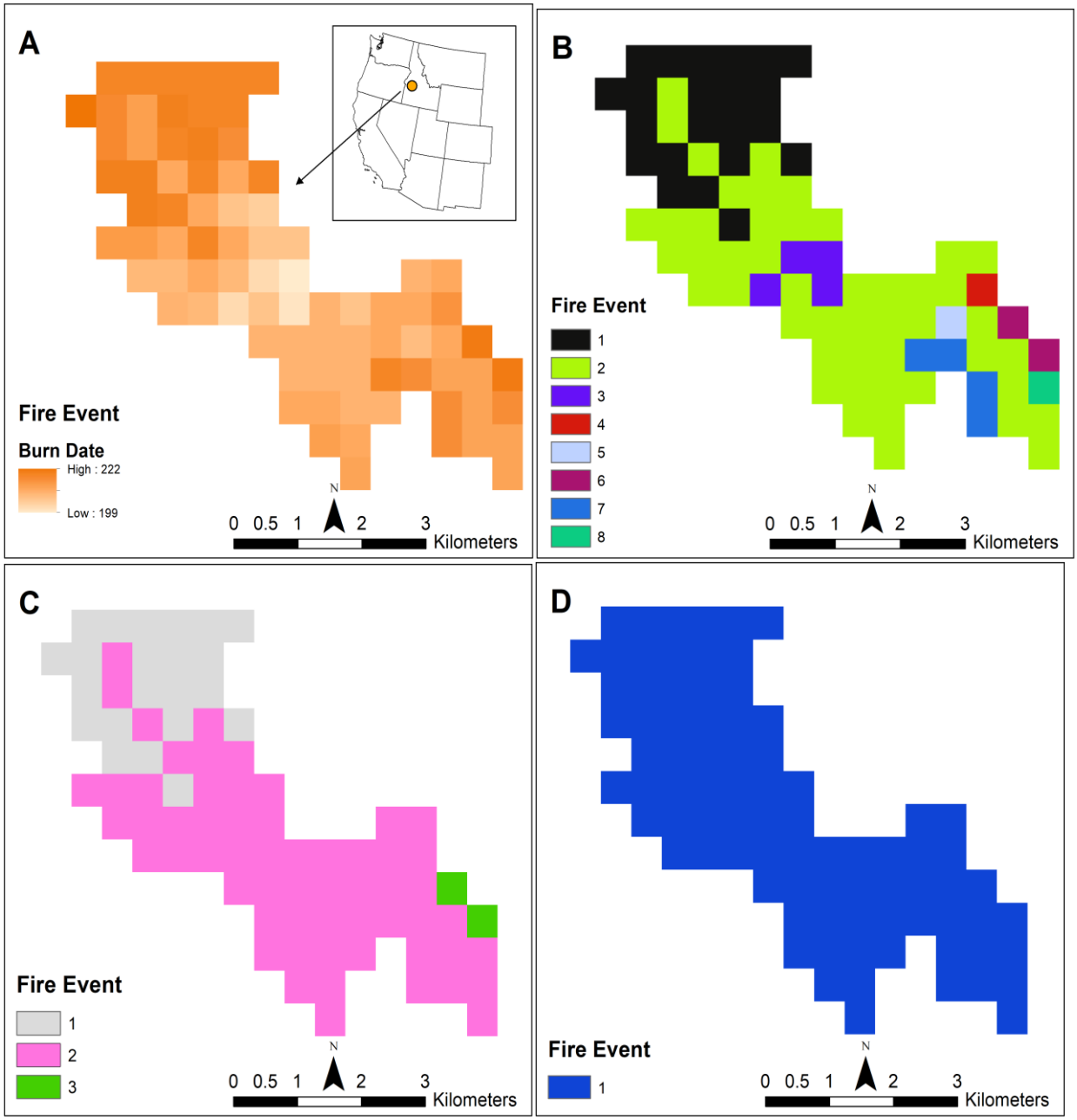

Figure 4: Illustration of fire event perimeters from MODIS Burned Area data

A) original data where numbers indicate Julian day of burning, B) Aggregation using a spatial distance of 1 pixel and temporal distance of 3 days, C) Aggregation using a spatial distance of 2 pixels and temporal distance of 3 days, D) Aggregation using a spatial distance of 3 pixels and temporal distance of 3 days.

Identifying MODIS fire events to within 10% of the same number as MTBS fire events (ratios of 0.9-1.1 in figure 3; table 1) was achieved for all fire sizes using a spatial search window of 5 pixels and a temporal search of 9 days. However, the need for broader aggregation criteria was greatest for large fires. Given the scientific focus on studying large fires (Barbero et al. 2014; Stavros et al. 2014), these broad criteria are appropriate. However, medium-sized fires were correctly identified using a five-pixel and eight-day difference, while small-sized fires were correctly identified using a five-pixel and three-day difference. Figure 5 illustrates how these search criteria were used to identify four fire events designated by MTBS. Using the broader aggregation criteria could cause some lumping of small fires (appendix 1); the values less than 1 in the following tables indicates the over aggregating because the number of fire events in the fire event maps are less than number of fire events in the MTBS product. However, even for small fires, the 5-pixel and 9-day criteria still identified 90% of unique MTBS perimeters.

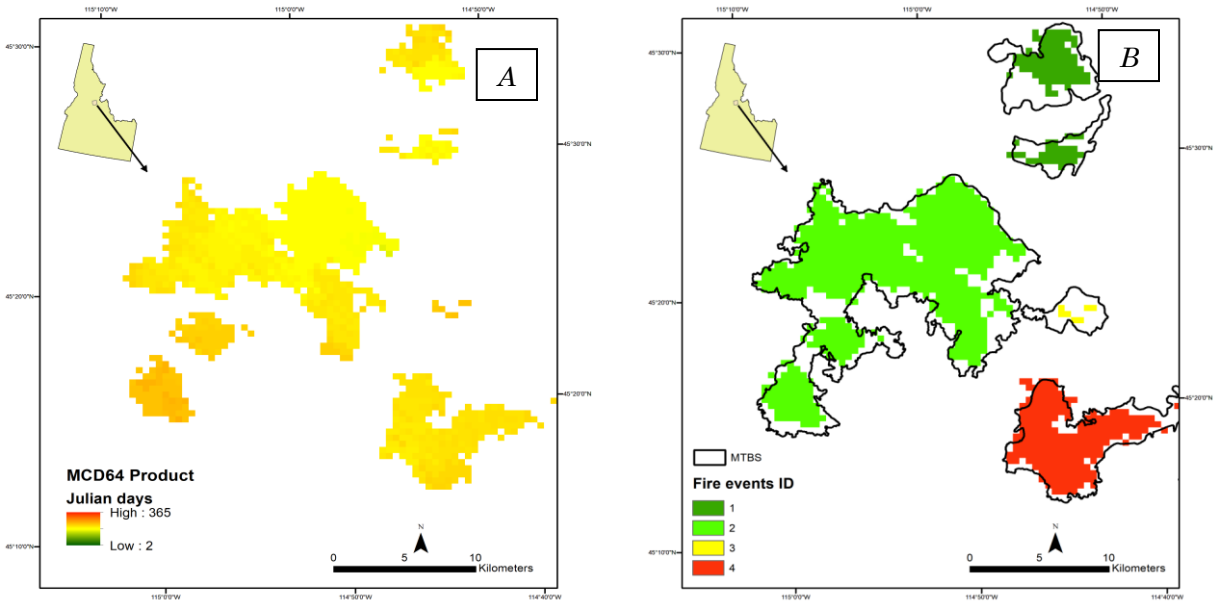

Figure 5: Illustration of fire event aggregation for four fire events in Idaho
A) Raw data with warmer colors illustrating later burned dates associated with each pixel.
B) Aggregated fire event map based on five pixels and nine days.

For the year 2007, there were a total of 94,417 MODIS Burned Area pixels across 11 western states. Using the five pixel, nine-day difference, we identified a total of 629 unique events in the western U.S. in 2007. These fires ranged in size from a single pixel (0.21 km^2) to a fire complex of over 2500 km^2 in Washington state (table 1). The average fire size in 2007 was 3200 ha. Idaho and California experienced the largest burned area in 2007, with 7,151 km^2 (31,551 MODIS pixels) and 4,084 km^2 (18,019 MODIS pixels) burned, respectively. For the entire MODIS record of burned area products (2001-2016), 2002 was the year with the fewest number of fires (996 fire events) and 2006 was the year with the highest number of fires (3,493 fire events) across the U.S.

Table 1: The number of MODIS Burned Area pixels, total burned area, and resulting fire sizes in each state for 2007.

State	Number of Burned pixels	Total Area Burned (km2)	Min. Fire Size (km2)	Max. Fire Size (km2)	Mean Area(km2)
Colorado	228	51.7	0.64	8.58	2.07
New Mexico	244	55.3	0.64	13.52	3.57
Arizona	971	220.1	0.21	48.94	5.86
Wyoming	1,046	237.1	0.64	66.32	15.17
Washington	3,621	820.7	0.21	2515.7	13.57
Oregon	7,038	1595.2	0.21	463.44	30.03
Utah	8,302	1881.6	0.42	1069.64	56.22
Montana	10,995	2492.0	0.21	372.64	34.26
Nevada	12,402	2810.9	0.21	2066.3	99.16
California	18,019	4084.0	0.21	954.8	32.49
Idaho	31,551	7151.0	0.21	2209.69	52.36

When aggregated to fire events, individual fire sizes ranged from 0.21 km^2 (a single pixel) to over 2,500 km^2.

We compared the number of fire events derived from the MODIS Burned Area to the number of MTBS polygons to calculate the omission and commission errors (table 2). This table shows that there were 603 fire events in our final fire event map that are not available in the MTBS product. From these 603 fires, 550 fires are less than 404 ha. As we know that MTBS product does not provide information about fires smaller than 404 ha, we did not use these fires in calculating the omission error. The table also shows that 239 fire events were identified in both MTBS and MODIS Burned Area product. Also, there are 85 MTBS fire polygons that were not identified in the MODIS Burned Area product. All MTBS fire polygons are larger than 404 ha.

Table 2: Number of individual fires in MODIS Burned Area product compare to MTBS product

		MTBS	
		Available in the MTBS product	Not available in the MTBS product
MODIS Burned Area derived fire events	Available in the MODIS Burned Area	239	603 (550 <= 404 ha) (53> 404 ha)
	Not available in the MODIS Burned Area	85	------
	Total	324	603

We used table 2 to calculate the omission errors, commission errors, and the total accuracy of the fire product. The following equations show how we calculated these errors and

the final accuracy. The results show the omission errors of 12%, 87% of commission error, and the final accuracy of 87%.

Omission error = False negative/Total= 85/(85+603) = 0.12 = 12%

Commission error = False positive/Total = 603/(85+603) = 0.87 = 87%

Total accuracy = 100% - Omission error = 88%

4. DISCUSSION

The major contribution of this work is to use the MODIS Burned Area data to reconstruct individual fire events and associated information on fire size and spread. A key advantage of using the MODIS Burned Area product is that we can reconstruct fire spread, which enables us to derive the spread rate, start and end dates, and ignition point for individual fires in the next step of this research. Expanding on existing burned area products to reasonably derive individual fire events will enable better understanding of fire regimes, particularly how fires spread. The Landsat-based MTBS product, for example, does not provide spread information as is. Further, we can provide information on smaller fire events (21 to 200 ha). These are not captured in the MTBS product (Eidenshink et al. 2007), although events as small as 4 ha have recently been provided in a new Landsat-derived product (Hawbaker et al. 2017).

We determined that for the western U.S. the best criteria to lump burned area pixels to create these events was a five-pixel (approximately 2.5 km) distance and nine days. We applied different spatial contiguity criteria (1-6 pixels) and temporal contiguity criteria (1-12 days) and evaluated each resulting fire event map against the MTBS product. The results showed that greater thresholds decreased the accuracy of fire maps. Other efforts to delineate individual fire perimeters have constrained the lumping criteria to one pixel and eight days (Archibald and Roy 2009) and two pixels and two days (Balch et al. 2013). Here, we demonstrate that these initial efforts would artificially increase the number of identified events in the western U.S., given our comparison with MTBS data. Other efforts have used the MODIS Active Fire product (Cattau et al. 2016) to cluster and determine fire size and ignition points in Indonesian tropical forests, given the difficulty of detecting understory burns in tropical forests. We also considered how

these spatial and temporal contiguity criteria function for different sized events. Our results showed that the same spatial and temporal contiguity criteria can be used to extract small, medium, and large fire events from MCD64A1 product.

The identification of individual fire events is important for a diverse group of users such as fire ecologists, climate change scientists, land managers, and policy makers. Individual fire maps can be useful for a wide range of research, including developing a broader understanding of how fire extent and frequency impact environmental processes (Giglio, Kendall, & Justice. 1999; Ichoku et al. 2003), understanding the distribution of fire sizes globally (Hantson, Pueyo, and Chuvieco 2015), characterizing the fire regime (Pereira et al. 2011), and also improving fire prevention policies and fire management (Moreira et al. 2010).

The vast application of individual fire information in both research and fire management makes it necessary to improve the quality and quantity of information for individual fires (Benali et al. 2016). A key limitation of this and any satellite-derived product is that we are still getting an incomplete picture of a fire event with any single product (Kolden et al. 2012; Short 2015). This can be due to cloud or canopy cover obstruction, gaps due to overpass time, rapid disappearance of char or vegetation response, or limited information on how a fire started and its burn heterogeneity. Persistent cloud cover and intact tree canopy that mask burned areas are major obstacles in satellite burned area detection (Giglio et al. 2010), particularly for tropical forests. Selecting generous spatial and temporal contiguity criteria may overcome some of the challenges in lumping what appear to be disconnected burned pixels into single fire events. Further, when fires burn they create a patchwork of different fire intensities and severities (Turner and Romme 1994), leaving unburned patches (Kolden et al. 2012; Kawchuk et al. 2016). These fire refugia are important ecologically, but we do not address how to capture these

components within a fire event. In addition, fire complexes, which are multiple fire events that start in close proximity often due to a series of lightning strikes, can eventually merge. These are classified as single events in our product, but there may be reasons to keep these defined as separate events. A key future challenge is determining what additional aspects are important to preserve when defining an individual fire event. The fire event maps for the U.S. (2001-2016) are freely available for the fire community at (Dadashi, Balch, and Bradley, 2017A) and (Dadashi, Balch, and Bradley, 2017B).

We used the MTBS product to validate our final fire event maps. The MTBS product is available from 1984 for the entire U.S., so we did not have limitations to access a validation source. If other researchers outside the U.S. use the same code to produce fire event maps and they do not have access to a comprehensive satellite-based product such as MTBS, the field data can be used for validation. However, field-based fire burned area data usually are not highly accurate and may affect the validity of the validation.

We produced fire event maps that are not simply the fire extent maps. These maps contain valuable information, such as the extent of an individual fire event, the ignition points, and also the endpoints. Ignition points and endpoints indicate the first and last day of burning in a fire event, respectively. Each individual fire event may have one or more ignition points. The location of these points are clear within a fire event. We used start point and end point to calculate the fire range for each fire event, then we calculated the mean fire spread rate by dividing the area of an individual fire event by fire range. The unit of the calculated fire spread rate is reported as square kilometers per day. The fire start and end dates partially determine the weather and fuel conditions under which a wildfire occurs and also the fire behavior, size, and

severity of effects (Benali et al, 2016). Compare to MTBS product, fire event maps provide more complete information about the individual fire events, such as the mean fire spread.

MTBS product is a vector-based product that shows the boundary of each individual fire event. This product has no information about the location of ignition points or endpoints within a fire event, so it is not possible to use MTBS product in the fire spread analysis. Also, the MTBS product just shows the maximum extent of a burned area and does not show the fire patches within a fire event. In reality, a burned landscape is always heterogeneous with a combination of burned and unburned patches, especially in medium to large fires. The information about these patches is important in many studies. For example, the spatial distribution of burned and unburned areas can influence the reestablishment of plant species on burned sites (Turner and Romme, 1994), which is important in plant conservation and protected area management. While the MTBS does not provide the information about the burned and unburned patches, our fire event map, that is based on MODIS burned product, can provide the more accurate estimation of burned and unburned patches that in general leads to more accurate data on the area burned.

Fire can start from one point and spread in different directions or it can start from different points. In most of medium to large fires, the number of ignition points is more than one. Fortunately our fire event map can specify the location of ignition points that is very important in fire spread modeling. Figure 6 (A) shows an example of fire spreading in a single fire event. This fire is located in Montana and is called Corporal. Based on the MTBS product, the area of the Corporal fire is approximately 5,500 ha. In this fire event we can see that fire starts from the left and spreads to the right and the north (figure 6-A). Figure 6-B shows the daily fire spread rate in the same fire. As demonstrated, the fire spread rate at the start dates (light blues in figure 6-A) are as low as 172 ha per day, while the highest daily fire spread rate (dark brown in figure 6-B) is

mostly related to the end of the fire's life. This pattern of fire spread rate is not the same for all the fire events. For example, it is possible that the fire spread rate is the highest at the start dates and decreases and increases at the middle and end dates of a life of fire event. Study of the fire spread rates in different ecoregions and landcovers provides valuable information about the fire spread pattern. This will help fire mangers to develop more accurate plans for preventing from uncontrolled fire spreading.

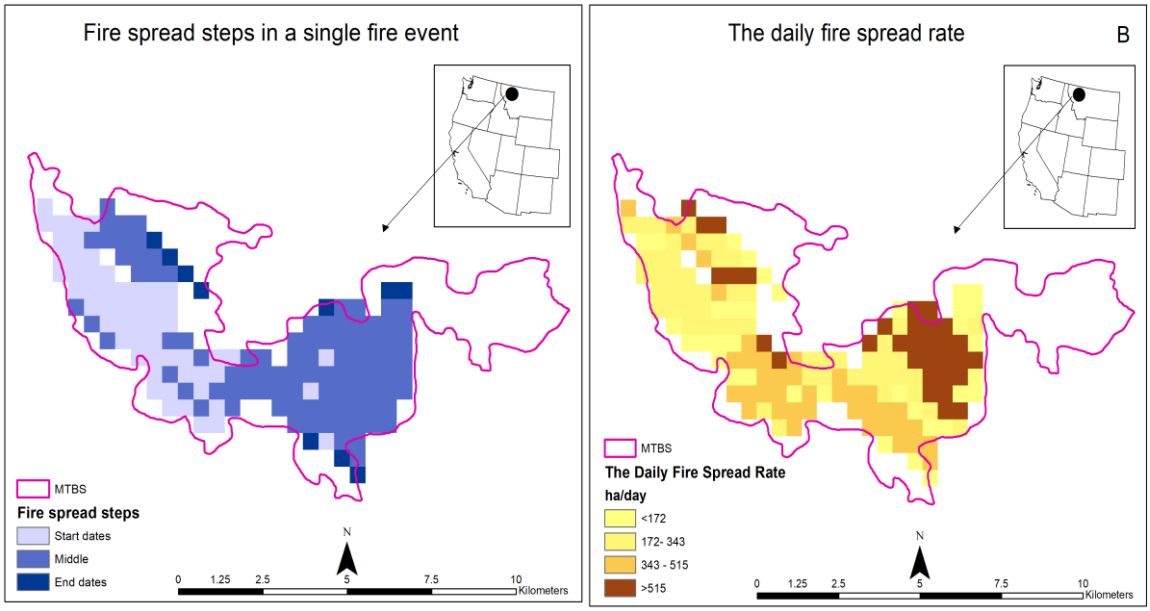

Figure 6: A sample of fire spread steps (A) and a daily fire spread rate (B) in a single fire event

5. CONCLUSION

The output of this research is information on the spatio-temporal pattern of fire events of any size in the coterminous U.S. Although most fires in the U.S. are in the range of a few hundred hectares (Short 2014), there are mega-fires that burn more than 20,000 hectares (Bowman et al. 2009). Small and large fires can be mapped using the algorithm developed in this paper, which was tested for the western U.S. Fire event maps and code for the algorithm will be available for those who are interested in modifying the code for their specific study area. We anticipate that the best spatial and temporal contiguity criteria would vary based on different patterns of fire sizes and spread patterns by ecoregion and/or landuse. For example, agricultural fires (Korontzi et al. 2006), which are intended to be smaller and controlled, may require more constrained spatial contiguity criteria. In conclusion, this new fire event product from satellite-based detections of burned areas will help advance the understanding of fire regimes with new information on fire size and fire spread patterns.

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APPENDIX

The ratio of number of fire events in the fire event map to number of fires in MTBS product based on different spatial and temporal contiguity criteria. Table a, b, c show the ratio for small, medium, and large fires respectively. Red indicates when ration is one, or the same number of events are designated by our algorithm and MTBS.

a)Small fires	Spatial contiguity criteria						
Temporal contiguity criteria		1	2	3	4	5	6
	1	5.1	3.5	2.8	2.5	0.9	2
	2	2.9	2	1.6	1.5	1.3	1.3
	3	1.9	1.5	1.3	1.2	1.1	1.1
	4	1.6	1.3	1.2	1.1	1	1
	5	1.4	1.2	1.1	1	1	1
	6	1.3	1.1	1	1	1	1
	7	1.2	1.1	1	1	1	0.9
	8	1.2	1.1	1	1	0.9	0.9
	9	1.2	1.1	1	1	0.9	0.9
	10	1.2	1.1	1	1	0.9	0.9
	11	1.2	1.1	1	1	0.9	0.9
	12	1.2	1.1	1	1	0.9	0.9

b)Medium fires	Spatial contiguity criteria						
Temporal contiguity criteria		1	2	3	4	5	6
	1	42.3	19.3	11.7	8.9	5.7	5
	2	17.4	7.5	5.1	3.9	3.1	2.7
	3	8.4	4.3	3	2.4	2.2	1.9
	4	5.5	3	2.2	2.1	1.6	1.4
	5	4	2.5	1.8	1.6	1.5	1.3
	6	3	2.2	1.6	1.5	1.3	1.1
	7	2.6	1.9	1.5	1.4	1.3	1.1
	8	2.5	1.8	1.4	1.3	1.1	1.1
	9	2.5	1.6	1.3	1.1	1.1	1.1
	10	2.5	1.6	1.3	1.1	1.1	1.1
	11	2.4	1.6	1.3	1.1	1.1	1.1
	12	2.3	1.6	1.3	1.1	1.1	1.1

c)Large fires	Spatial contiguity criteria						
Temporal contiguity criteria		1	2	3	4	5	6
	1	247.2	113.8	64.8	44	40.6	17.6
	2	102	40.8	25	17.4	8.2	7.4
	3	45.6	19.2	12.4	8.4	5	4.6
	4	27	17.6	6.4	4.2	2.8	2.4
	5	17.4	7	4.4	3.4	2.2	1.6
	6	12	5.8	3.4	2.4	1.4	1.4
	7	9	4.4	2.4	1.6	1.2	1.2
	8	7.8	3.6	2.2	1.6	1.2	1.2
	9	6.8	3	2	1.6	1	1.2
	10	6	2.6	2	1.4	1	1
	11	5.4	2.4	1.6	1.4	1	1
	12	5.4	2.4	1.6	1.4	1	1