Developing a Semi-automated Random Forest Classification Scheme to Analyze Burned Area Using Landsat Imagery in Southern India

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Abstract

Fire regimes, or the pattern, frequency, and intensity of fires over a landscape, has begun to shift over much of the dry tropical regions of the world. The complexity of the pressure fire exerts on the landscape is intensified by the intimate relationship humans have cultivated with this process, especially in regions where traditional burning has taken place. However, the departure from the pre-historic and more recent historical use of fire as a management tool, generally due to conservation regulations, presents unique research challenges to understand how major shifts in human relationships to fire, management regulations of fire prone ecosystems, and vegetation composition, may be driving changing fire behavior and regime. The Biligiriranganatha Hills Temple Reserve (BRT) and Sathyamangalam Forest Reserve (SFR) are adjacent protected areas southern India have similar ecologies, rainfall seasonality, yet have different histories of regulation, species invasions, and human resource use, within the last two decades that may result in key differences in fire regimes. This study therefore sought to construct a fire history across this region to quantify potential differences in burning patterns, compare these patterns to those available with MODIS burned area product (MCD64A1.006), and to explore the potential of this detection method to evaluate and characterize frequency and the proportion of area burned across landcover types (forest, savanna, and other). I used Landsat 7 remotely sensed data and the Random Forest algorithm in Google Earth Engine to develop a semi-automatic method to detect burned area across a time series. The RF classifier was trained using a subset images in which burned pixels were manually classified and then used identify burned area across all available images from 2003-2019 (N= 115 images). Separate classifiers were developed over ~ 5-year time steps due to computational limitations but demonstrated high overall accuracy at 99% for unclassified pixels within the training images and 98% for images not included in the training data. Classified images were composited to develop annual fire maps that were accurate to the Landsat resolution (30M). the Landsat product performed far better at detecting small fires not flagged by MODIS and, in cases of large fires, created fire perimeters similar to MODI. The majority of burned pixels in both reserves experienced burns approximately every 3-4 years. The proportion of burned area by land cover type was highest for savanna in both reserves and the proportion of burned area in forest was higher in BRT than in SFR, potentially indicating landscape-level shifts in ecosystem flammability. Overall, this study developed an efficient semi-automatic classification system for Landsat 7 data that created 30m

resolution annual fire summaries which can be used to better inform on the ground research by Indian conservation organizations.

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Introduction

Fire regimes, or the pattern, frequency, and intensity of fires over a landscape, have begun to shift over much of the dry tropical regions of the world (Bond and Keeley 2005; Wagner 1978). Humans have caused extensive shifts in these patterns through forest degradation, farming, and facilitating advantageous burning patterns through the use of specified burning practices(Bowman et al. 2011; Laris 2002; Sathya and Jayakumar 2017). Fire has existed in the Seasonally Dry Topical Forest (SDTF) landscape for millennia and exhibited pressures on the environment from vegetation distribution and growth to the overall structure of the landscape (Bowman et al. 2011; Roos et al. 2014). SDTFs exist between 20 degrees latitude and are characterized by a distinct dry season extending between 2-10 months(Mondal and Sukumar 2014). They are often associated with tropical savannas and have highly mosaiced vegetation types such as both deciduous and evergreen forests, woodlands, and thornscrub that make generalizations of this system difficult (Scariot and Vieira 2006). This distinct dry season however, influences fire regime as fuels have the opportunity to build up and dry out over the course of a season. This and the variability in vegetation create a complex and fire prone system. The complexity of the pressure fire exerts on the landscape is intensified by the intimate relationship humans have cultivated with this process. The use of fire has always carried cultural significance and as the use of fire continues to evolve so does the human relationship with it. The departure from the pre-historic and more recent historical use of fire as a management tool presents unique research challenges to understand how major shifts in human relationships to fire, management regulations of fire prone ecosystems, and vegetation composition, may be driving changing fire behavior and regime in SDTF across ecosystems (Laris 2002; Trauernicht et al. 2015).

Traditional Burning as Management

Consistent human intervention may have been a key factor in limiting large-scale high severity canopy fires in SDTF. Across the seasonally dry tropics, indigenous cultures from Australia, Africa, Brazil, and India have a history of managing land through low intensity surface fires, or seasonal burning for a variety of purposes. These include increasing certain types of nontimber forest products (NTFPs), enhancing production of pasture and animal fodder, and decreasing the risk of large scale late season fires that could be damaging to the surrounding forests and settlements (Berry, Wevill, and Curran 2011; A. J. Hiremath and Sundaram 2005; Laris 2002; Mistry et al. 2005; Trauernicht et al. 2013). In the context of SDTF, traditional burning modulates when and how the landscape burns relative to pronounced dry seasons. Typically, by starting fires earlier in the dry season, fires are contained to small dry extents of the landscape. These early dry season burns, when temperatures are cooler and vegetation retains some moisture, are used to burn specified “patches” in the region creating a mosaic of burned and unburned plots(Bowman et al. 2011). These patches due to decreased fuel continuity and higher fuel moisture will burn at a lower intensity than later in the season and thereby reduce the likelihood of fire spreading into nearby forest, agriculture lands, and homes. This early season patch burning by indigenous peoples in fire prone systems, demonstrates how the timing of burning can alter the fire size and intensity as these low intensity fires promote heterogeneity and decrease plant and animal mortality (Trauernicht et al. 2015). While late season fires may burn the same proportion of land as these early season burns the post fire effects can be severe. A fire later in the season may burn longer and hotter due to fuels being cured, lower humidity, and without early season patch burning, a more continuous fuel bed. Late season fires can still occur in SDTF managed by traditional burning, however with abundant fuels unchecked by these management practices, these fires can devastate plant and animal life while extending into surrounding area, an encroachment which may cause ecological change as forests can be converted to savanna or economical damage as surrounding agriculture fields are ignited (Hoffmann et al. 2012).

In contrast to these traditional methods and perceptions, the creation of conservation zones in fire prone landscapes often frame fire as a solely negative impact on the forest and emphasize the use of fire suppression to manage this perceived threat (Johansson et al. 2019; Kodandapani, Cochrane, and Sukumar 2008; Laris 2002). Ironically, the removal of indigenous burning – whether via policy (e.g. India, N. America) or socioeconomic change and cultural erosion (N. America, Australia), it is increasingly apparent that these historical changes are actually increasing the occurrence of high intensity, ecologically destructive fires ((Johansson et al. 2019; Madegowda and Rao 2017; Trauernicht et al. 2013). The idea of burning early in the season to prevent late season destructive fires is prevalent in Africa in the savannas of Mali, where traditional indigenous farmers perform early season burns in order to protect crops and resource rich land from more destructive and higher intensity late season fires(Laris 2002). In

Ethiopia, in the Bale mountains, where patch fire management was common before the creation of the conservation unit, fire has been branded as a destructive and illegal practice. Yet empirically, banning this practice has correlated with the increased size of fires within the park boundaries and with more late season, high intensity conflagrations, again demonstrating obvious changes in fire regime once human activities within the park ceased (Johansson et al. 2019). In Kakadu National Park, Australia, after the discontinuation of patchy burning practiced by the aboriginal culture and the designation of the land as a protected area, the prevalence of high intensity wildfires increased while species diversity within the savanna mosaic decreased, resulting in an overall negative shift in the system (Trauernicht et al. 2013). Each of these studies points to human intervention via fire management, generally seasonal burning by the indigenous peoples for a multitude of reasons, as a key component of the ecological baseline for fire regimes of these regions in terms of maintaining low intensity surface fires.

Detecting and mapping the incidence of fire in these regions is therefore critical to analyze how these shifts may be affecting ecological cycles, species distribution, populated areas, and how they may be changing currently and into the future(Johansson et al. 2019; Laris 2002). Accurate measurements and detections of burned area are necessary for a variety of applications ranging from quantifying trends in burned areas to understanding spatiotemporal patterns of fire in the landscape (Allison et al. 2016; Gitas et al. 2012; Hawbaker et al. 2017; Mallinis and Koutsias 2012; Padilla et al. 2015). However, to understand how fire and burned area may be affecting the landscape, consistent data collected over a number of years is necessary. The use of remote sensing and satellites imagery within the past 20 years have dramatically improved our ability to detect and map fires, the standardization and use of this data is critical to build long term data sets for future analysis and discovery in the field of fire ecology such as creating fire histories, measuring burned area, and understanding spatial and temporal spread of fire (Hawbaker et al. 2020; Szpakowski and Jensen 2019; Trauernicht 2019).

Seasonal Fires in Southern India

Fire is a seasonal occurrence in India, however recent evidence indicates that the size, frequency and seasonality of fire occurrences in this region of the world are changing (Kodandapani 2013; Roveta 2008). In Southern India, a network of protected areas creates the larger Nilgiri Biosphere, an interconnected network of adjoining parks near the confluence of the

Eastern and Western Ghats. This study focuses on the Biligiriranganatha Hills Temple Reserve (BRT) and Sathyamangalam Forest Reserve (SFR). These reserves, due to the mosaic pattern of the landscapes, contain a variety of interface landcover types such as seasonally dry tropical forests(SDTF) which experience burns commonly and both deciduous and evergreen forests, generally located at the interior of these zones which are generally, least likely to be affected by fire in the landscape(Agee 1996; Cochrane, Alencar, Schulze, Jr, et al. 1999; Mallegowda et al. 2015). These reserves both experience a discrete seasonality in rainfall that fluctuates due to the ebb and flow of the monsoon seasons present in this region which can roughly be divided into a wet season extending from late May to early October and a dry season extending from mid-December to the beginning of May(Hamilton, Penny, and Hall 2020; Sinha and Bawa 2002). These seasonal fluctuations are one of the main drivers of fire occurrence in the region but, differences in vegetation and management histories may also potentially be driving a difference in fire regimes that has been documented between these reserves over the last two decades (Kodandapani, Cochrane, and Sukumar 2008).

There have been significant points of management intervention in these regions with relevance to fire occurrence. This whole region has experienced seasonal burning performed by indigenous groups. However BRT specifically has banned the use of fire as a management tool by the indigenous peoples since the early 1970s, shortly after which the first indication of late season canopy fires was recorded(A. J. Hiremath and Sundaram 2005). In 2011, BRT was included as part of the Tiger Project, increasing regulations and limiting overall access to the forest(Kutty et al. 2019). In contrast, in SFR , fire has continued to be a part of the reserve as indigenous peoples are allowed to seasonally burn and prescribed burns were a distinct portion of the SFR management plan until 2010 (Ramasubramanium 2010). In 2013 SFR was established as part of the Tiger Project and policies during the course of this study may have changed. However, prior to either of these regions' conservation designations, there were patterns of early dry season indigenous burning similar to those in Australia and Africa (Laris 2002; Trauernicht et al. 2013). The latter regions similar in ecosystem dynamics, are experiencing a shift in fire regime due to disruptions caused by increased regulation of fire and it may be possible that BRT and SFR are experiencing similar disruptions in burning regime and concurrent patterns in fire behavior to those that have been recorded in these regions(Johansson et al. 2019; Laris 2002; Trauernicht et al. 2013).

Disruptions in burning patterns in BRT and SFR are additionally affected by increasing abundance of non-native plant species. *Lantana camara*, a highly invasive non-native plant, has begun to dominate forests in this region and may be driving new fire behaviors and shifting ecosystem dynamics (A. Hiremath and Sundaram 2014). This plant has overtaken large portions of areas within BRT and SFR, suppressing native understory species and overstory regeneration, decreasing species diversity and dramatically increasing the vertical continuity- of *L. camara*- between forest floor and canopy (Sundaram, Krishnan, and Hiremath 2019). The *Lantana*-fire cycle, described at length by(A. J. Hiremath and Sundaram 2005), creates a positive feedback where in *L. camara* invasion increases the likelihood of high intensity canopy fires that destroy native vegetation and increase the subsequent invasion by *L. camara*. This cycle results in compositional and functional simplification of the forest ecosystem but beyond ecological impacts, this also impacts local communities who depend on native forest species collections for a large part of their livelihoods(Ganesan and Setty 2004).

BRT and SFR are found in one of the most densely populated ecologically important biodiverse zones in the world (Kodandapani, Cochrane, and Sukumar 2004). In human affected landscapes such as BRT and SFR the spatial scale and distribution of landscape elements is largely driven by human interaction with the environment (Archibald et al. 2010). The subsequent shift from millennia of human activity in reserves to little human interaction may have some effect on the spatial distribution and behavior of fire in the region (Sundaram, Hiremath, and Krishnaswamy 2015). As such, historical changes in these regions' fire regimes are difficult to establish. However, the work of the Ashoka Trust for Research and Ecology in the Environment(ATREE) and their community based approach for studying ecological change over the last 30 years as well as additional works (e.g. Kodandapani, Cochrane, and Sukumar 2004), have given context to some of these changes and continue to add to the body of research in this region. Local researchers are particularly interested in comparisons between BRT and SFR specifically because ongoing indigenous burning in SFR may be key to limiting *Lantana* invasion. Although explicitly linking fire occurrence to on the ground land use and vegetation was beyond the scope of this project, the overall goal of this study was to provide a high quality, baseline fire history for the reserves to allow local researchers to begin addressing these questions. Therefore, it is necessary to identify and build a fire history in these regions to establish and quantify burning patterns and fire behavior. With the capabilities of new remote sensing tools capturing recent fire events and landscape cover there is an opportunity to set a precedent for future studies and improve current understanding of these dynamics (Andela et al. 2019; Hawbaker et al. 2020; Sathya and Jayakumar 2017).

This study used the forest reserves of BRT and SFR as a context to explore automating burned area detection using Google Earth Engine and Landsat 7 in order to begin to understand fluctuations in patterns of fire regime between reserves. There are three major objectives of this thesis: 1) to develop a semi-automated classification process using Landsat imagery that identifies burned area at 30m resolution using a random forest algorithm with Google Earth Engine 2) to develop annual fire maps that are as temporally accurate as possible with Landsat imagery and 3) explore the use of these maps to evaluate and characterize aspects of fire regime in these regions.

Remote Sensing

Remote sensing or the use of satellite imagery, unmanned aerial vehicles(UAV), and aerial imagery to obtain information about the surface of the earth has been widely applied to understanding fire events (Allison et al. 2016; Mallinis and Koutsias 2012; Szpakowski and Jensen 2019). Due to the varying size and inaccessibility of fires and the corresponding burned area, satellite sensors and imagery have become an invaluable tool in the analysis of these events(Lentile, Holden, Smith, Falkowski, Hudak, et al. 2006). The use of this imagery has practical applications in the case of wildfires such as mapping burned area extents, tracking progression, and assessing burn severity (Allison et al. 2016; Collins et al. 2020; Hawbaker et al. 2020; Lentile, Holden, Smith, Falkowski, Hudak, et al. 2006; Parks et al. 2018; Szpakowski and Jensen 2019).

Monitoring burned area as well as active fires is possible with remote sensing due to the apparent thermal and spectral changes induced by fires which are consistently captured by sensors (Hawbaker et al. 2017). One of most widely used platforms utilized to detect these spectral changes has been the Moderate Imaging Spectroradiometer or MODIS (2000-present), moderate-resolution (50-1000m) sensors aboard the Terra and Aqua polar-orbiting satellites. A suite of products including thermal anomalies (MOD14A1.006), burned area (MCD64A1.006), and landcover types (MCD12Q1.006) as well as many others (Boschetti et al. 2019; Giglio et al. 2009; Padilla et al. 2015; Sulla-Menashe et al. 2019) have been developed and used to identify a number of landscape level changes. Each MODIS provides daily overpasses, lending the products high temporal resolution. However, pixel-based analysis to distinguish burned area is only available up to 500m resolution and begins to lose accuracy in regions where regimes are characterized by smaller fires which can be smaller than individual pixels (Lentile, Holden, Smith, Falkowski, Hudak, et al. 2006; Padilla et al. 2015).

Despite the developments in publicly available remotely sensed products, accurately measuring burned patterns on the landscape requires imagery with adequate temporal and spatial resolution. (Mallinis and Koutsias 2012). Landsat 7/8, provides 30m spatial resolution imagery approximately every 14-16 days since 1999. Landsat 7/8 has provided a new way to understand ecosystem and fire regime by increasing the accuracy through which fire extents can be measured and landscape level impacts are assessed. This is advantageous for savanna regions such as India which may experience patchy burning which may not be captured by moderate resolution products such as MODIS and where shifts from smaller to larger fires may be a key indicator of fire regime change (Laris 2002; Trauernicht et al. 2013). However, unlike MODIS, there are currently no publicly available products that automate burned area detection from Landsat imagery. This gap limits efforts to reconstruct fire histories at the regional scale to the time-consuming process of scanning through thousands of images and mapping fires ‘by hand’ visually.

The ephemeral nature of burned area is a consistent issue in identifying and mapping burned area in highly productive regions where vegetation recovers quickly and masks the spectral changes induced by fire (Yebra et al. 2008). While the resolution of the Landsat sensor has increased the spatial accuracy and precision of burned areas can be observed, it is important to consider this data in tandem with other sensors as the ~16 day revisit cycle may miss ecologically important fires that are short lived in terms of detectability from remotely sensed imagery (Andela et al. 2019). Thus, the approach employed in this study was to seek a method to map fires across all available imagery to adequately capture fire events over the year(Deng and Wu 2013; Noi Phan, Kuch, and Lehnert 2020; Tatsumi et al. 2015). Therefore, rather than deriving training and testing data from which to classify each image individually, this study attempts to use training data from burned areas sampled from multiple images to develop and test a classifier that detects burned areas across all available images.

Automated image classification has enhanced the ability to identify and interpret landscape patterns to create thematic maps that are spatially consistent with the earth's surface at a range of spatial and temporal scales (Belgiu and Drăgu 2016; Foody 2002; Li et al. 2014; Lu and Weng 2007). Image classification has been undertaken to identify specific landcover types and transitions including burned area (Giglio et al. 2009) urban areas(Deng and Wu 2013; Goldblatt et al. 2016), and forest cover changes (Hansen et al. 2013) and has many socio-economic and environmental applications, including urban and regional planning, natural resources conservation and management and many other applications. Broadly, image classification is the process of assigning groups of pixels in a multispectral image**,** such as those produced by satellite sensors, into specific, predefined categories corresponding to the observation(s) of interest or information classes, such as burned areas. Classifiers, or models to automate image classification, are widely used by the remote sensing community to map landscape feature extents and observe changes and can be broadly divided into parametric and non- parametric classifiers (Thanh Noi and Kappas 2017). Since the amount of burned area across a landscape is generally imbalanced, as burned area only represents a small portion of the overall landcover, this study only considered non-parametric classification schemes (Belgiu and Drăgu 2016; Heydari and Mountrakis 2018; Lu and Weng 2007) . Non-parametric machine learning algorithms such as Random Forest(RF), Support Vector Machine (SVM), Classification and Regression Trees (CART) have been widely used in the classification of landcover using remote sensed images (Foody & Mathur, 2004; Nery et al., 2016, Shetty 2019). These classifiers are able to learn the characteristics of target classes (e.g. burned and unburned) from visually classified training samples and to identify these learned characteristics in the unclassified data (Belgiu and Drăgu 2016). Given the accessibility and performance of Random Forest classification in similar studies using Google Earth Engine, this methodology was selected to create annual maps of burned area in the study region(Oliphant et al. 2019; Phalke et al. 2020; Shetty 2019).

Annual Composite Maps

Beyond the classification of burned area, however, assessing fire size, seasonality, frequency and pattern of change still requires compositing data across multiple images to identify discrete incidents and summarize fire occurrence on annual or seasonal time steps

(Lentile, Holden, Smith, Falkowski, and Hudak 2006). This then allows for analyses of fire size and temporal patterns of fire frequency which are the building blocks for fire risk assessments, understanding fuel loads dynamics (Padalia and Mondal 2014) and understanding impacts of fire on sensitive ecosystems or human settlements. In the case of BRT and SFR, understanding fire frequency can lead to better predicting feedbacks between fire and plant species diversity, regeneration, and competition, especially with *L. camara*, and how these interactions may shift under climate change (Ramakant, Vaidyanathan, and Krishnaswamy 2014). Temporal specificity also provides the ability to associate fire with different landcover types and to examine the influence of fire on land cover change through interactions between pre fire conditions, and post fire regeneration of species. In BRT and SFR, this is particularly important as indigenous peoples rely on the forest for Non-Timber Forest Products(NTFPs) and temporal specificity allows for understanding aspects of fire regimes typically associated with traditional burning and its decline – namely early versus late dry season burns (Madegowada 2009; Madegowda and Rao 2017; Padilla et al. 2015). Therefore, this study ultimately sought to produce a fire history that is interpretable and useable by local scientists, managers, and communities, which with the additional understanding of climatic, social, and economic variables will allow for managers to effectively make decisions from this remote sensed data.

Methods

Study site

The Biligiriranganatha Hills Temple Reserve (BRT) is an approximately 540 KM² reserve, between 77°00'–77°16'E and 11°47'–12°09'N, that is highly heterogeneous in elevation, temperature, and rainfall, supporting a wide diversity of plant and animal life(Mallegowda et al. 2015). Temperatures in this region can range from 9°C to 16°C in the cooler months and 20°C to 38°C in the warmer months, with rainfall varying across season and elevation from 600mm to 3000mm annually (Roveta 2008; Sundaram, Hiremath, and Krishnaswamy 2015). Immediately adjoining to the south as seen in Figure 1, is the Sathyamangalam Forest Reserve (SFR), located at 11° 29’ N to 11° 49’ N, and76° 50’ E to 77° 28’ E) and covers approximately 1500 KM² (Kodandapani 2013). Temperature, elevation, and rainfall vary similarly to BRT, however, specifically rainfall only reaches between 600mm-1100mm in SFR, only exceeding this upper metric at higher elevations due to the beginnings of a rain shadow effect (Kodandapani 2013;

Ramasubramanium 2010). Again, there is a distinct monsoonal seasonality driving much of these climatic factors. This seasonality can roughly be divided as the wet season extending from late May to early October and a dry season extending from mid-December to the beginning of May.

Landcover types within reserves as seen in Figure 2 include evergreen forests, deciduous forests, tropical dry forest, and savanna ecosystems with BRT more heavily forested and SFR expressing far more savanna across the landscape (Kodandapani 2013; Roveta 2008). These ecosystems are all highly interspersed between each other creating mosaics and corridors between ecotypes, of these landcover types, savanna ecosystems are considered the most likely to experience burns(Bond and Keeley 2005; Cochrane and Schulze 1998; Skarpe 1992).

Figure 1: Map of the two study regions, located in red on the inset map

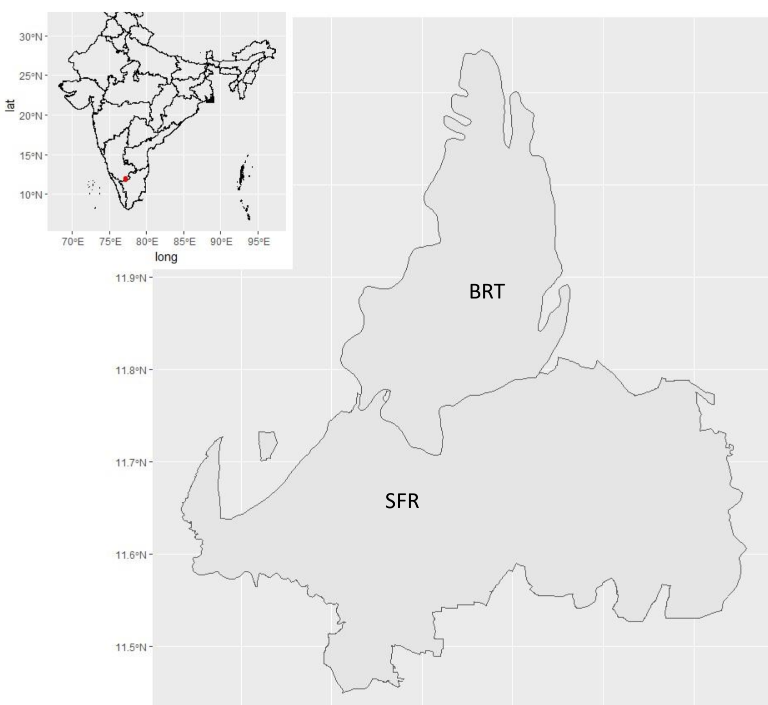
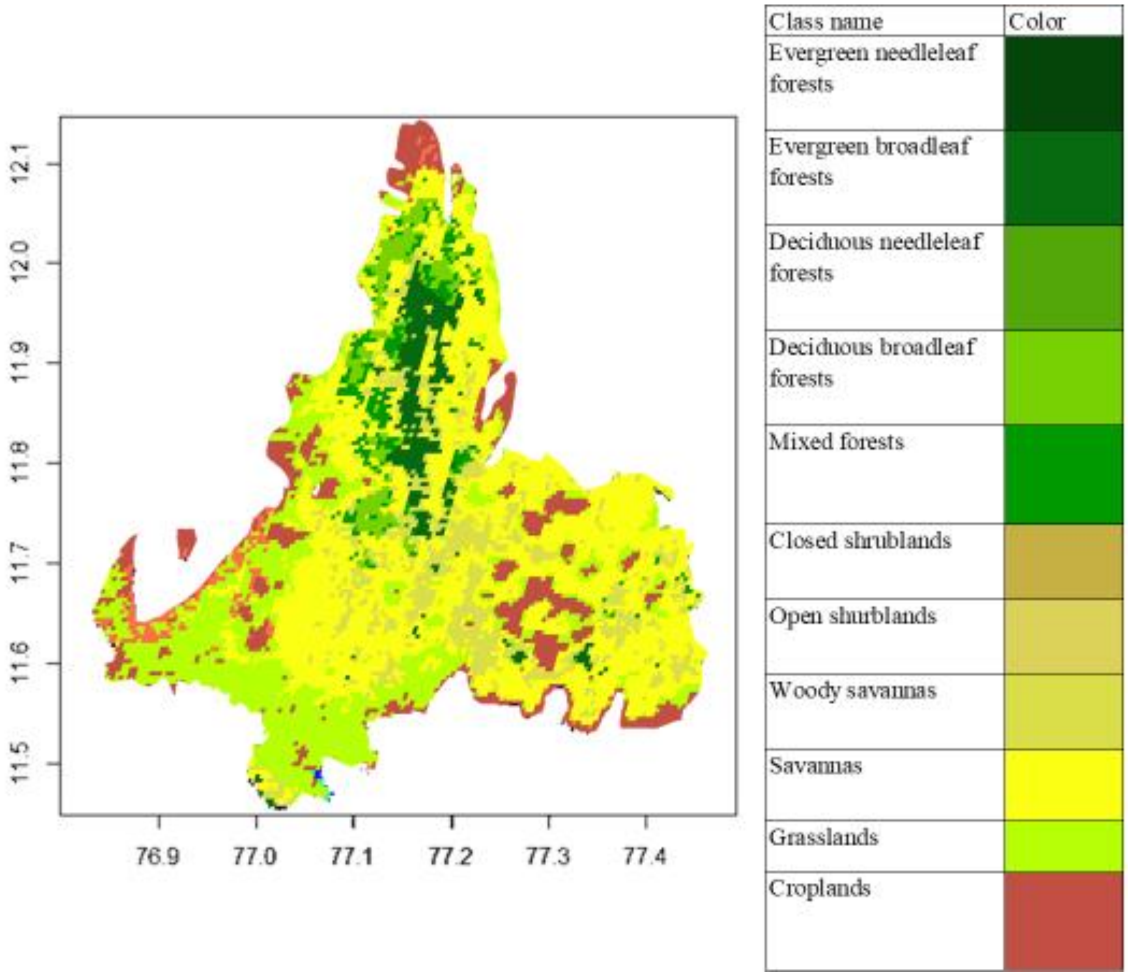


Figure 2: IGBP MODIS Landcover of BRT and SFR



Random Forest Classification

This study focused on the identification of burned area to generate annual fire maps in BRT and SFR between 2003-2019 using remote sensing techniques. Google Earth Engine (GEE; https://earthengine.google.com/) is a cloud-based platform for geospatial analysis that leverages cloud-computational services for planetary-scale analysis and consists of petabytes of geospatial and tabular data, including a full archive of Landsat scenes accessed through a JavaScript application programming interface(API) that was used for a majority of the analysis in this study(Goldblatt et al. 2016; Tsai et al. 2018). GEE has been applied to various remote sensing applications, ranging from agriculture, forestry, ecology and economics and was easily accessible for use in this study(Goldblatt et al. 2016; Noi Phan, Kuch, and Lehnert 2020).

In building an RF classifier there are a set of tuning parameters that can be defined by the user such as the number of trees, the maximum number of tree splits as mentioned above, and the number of simulation iterations (Heydari and Mountrakis 2018). The number of trees for this study was held consistent at 500 , a standard practice within the literature and considered optimal in terms of limiting overfitting in the model due to the "Strong Law of Large Numbers", while other parameters were left to the default setting in GEE to maintain consistency and can be found on the GEE developers page here (https://developers.google.com/earth-engine/apidocs/ee-classifier-smilerandomforest) (Rodriguez-Galiano, Ghimire, et al. 2012). In RF classification, data from the root node is divided into 2/3 of the samples(in-bag samples) being used to train trees, while the remaining 1/3(out of bag) are used to internally validate how well the RF model preforms allowing calculation of overall accuracy, producers and consumers accuracies, and Cohen's kappa coefficient values (Belgiu and Drăgu 2016). The validation values generated from these metrics allow for the understanding of the predictive power of the algorithm and its capacity to classify images that exist outside of the training data set, such as those that will be used in the generation of the annual fire maps.

Image Selection

Data sets used in this study were exclusively from the Landsat 7 Enhanced Thematic Mapper for the years 2003-2019. GEE provides pre-processed satellite imagery, or the Landsat 7 collection 1 Tier 1 DN values, representing scaled, calibrated at-sensor radiance and therefore atmospheric correction on the client side of the computation was not performed for this study. The areas of interest, BRT and SFR, fall under a single Landsat tile (WRS Path 144 Row:052) and images were clipped and bound to the specific regions (BRT &SFR) using boundaries derived from protected plant database in 2014 and from the Ashoka Trust for Research in Ecology and the Environment (ATREE), respectively. These images were then filtered using built in GEE algorithms to only include images where cloud cover was under a 25% threshold creating a total of 115 images used throughout the timeline of this study. This threshold was chosen using visual confirmation that above these thresholds burned area was difficult discern or otherwise absent due to cloud cover.

Training data selection

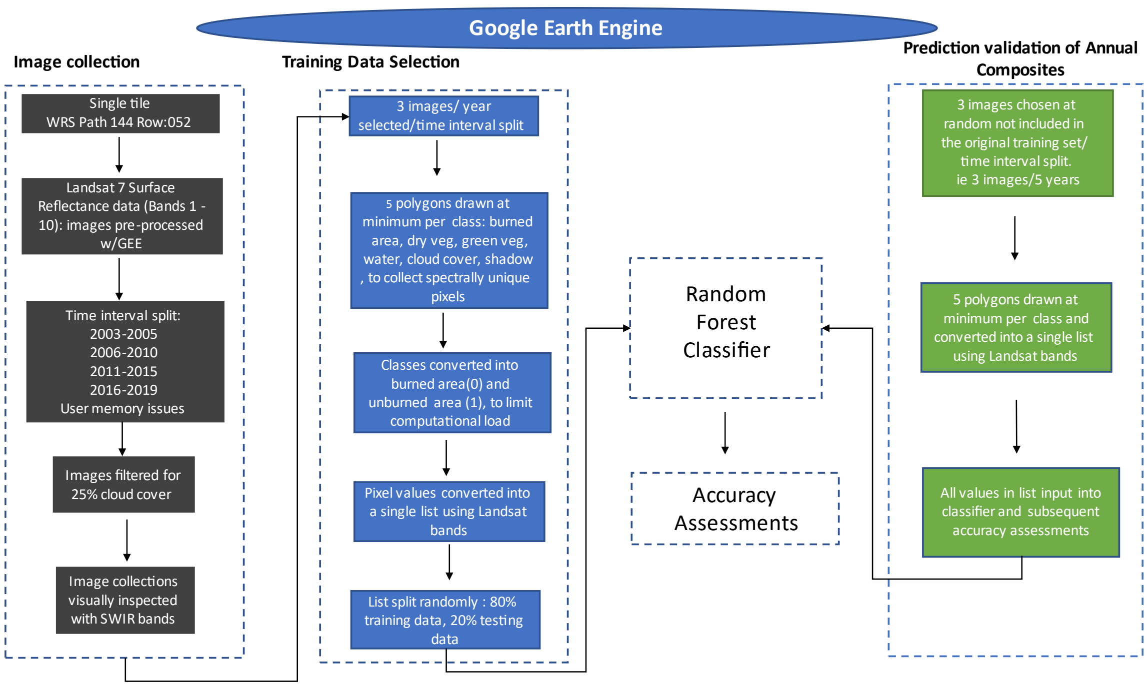
Images from the 115 image stack were then filtered on a yearly basis and visually inspected using a color composite of the SWIR bands(B7, B4, B2) for active fire and burned area anomalies as the band combination not only highlights burnt areas but also highlights ongoing fires (Sulova and Arsanjani 2021). The first image to be analyzed per year in the study was selected to contain the largest amount of useable burned area to include in the training data. Two more images per year were chosen randomly before and after the scenes containing burned area in order to provide an increased spectral diversity of pixels and to better capture potential seasonal and phenological variation such as between dry season and wet season that is present in the region (Rodriguez-Galiano, Chica-Olmo, et al. 2012). This selection process was repeated for every year in the study period producing a total of 51 images used in the selection of training data.

Visual inspection: Polygons for pixel wise classification

Processing capacity of GEE data collection and classification was limited by user memory issues. Therefore instead of developing one large classifier, the data had to be broken down to four, 3- to 5-year intervals (2003-2005, 2006-2010, 2011-2015, and 2016-2019) for each reserve (BRT, SFR) which led to the creation of 8 different classifiers total (2 reserves * 4 time intervals). Therefore, the methodology below was repeated for each set of training data and can be seen in the Figure 3 flow chart.

All training and validation samples were collected based on manual, visual interpretation of the 51 training images (i.e. 3 images/year x 17 years; or c. 9-15 images per time interval). Five to ten polygons containing burned area pixels were drawn for all images containing burned areas to generate a large enough sample size to minimize the sensitivity of this model to the imbalanced nature of the samples within the classifier(Thanh Noi and Kappas 2017). Based on previous studies, pixels in five additional classes were also defined by drawing five additional polygons per class in each image: green vegetation, dry vegetation, clouds, shadows, and water (Pelletier et al. 2016; Rodriguez-Galiano, Chica-Olmo, et al. 2012; Shelestov et al. 2017). These additional categories were chosen to consistently capture the wide variety of spectral signatures found in the images but were then merged into a single unburned category to simplify the model and the computational load in GEE. Since the polygons were hand drawn and depended on the size of a given cover type, the size of each polygon, and thus the number of classified training pixels was variable for each landcover classification per time (e.g., Noi Phan, Kuch, and Lehnert 2020). This list of classified pixels per time interval was then randomly split into training data (80%) to be input into the classifier and testing data (20%) that was left out to later be used in within image accuracy measures.

Figure 3: Flow chart of analysis within Google Earth Engine



Accuracy Measurements

Confusion matrices, overall accuracy, producer's, and consumer's accuracies, as well as Kappa coefficients were calculated for this study. The initial accuracy measurements derived from the training and testing data sets (80/20; see above) are only indicative of the accuracy of the classifier with respect to the sampled, visually classified images. However, the purpose of the study was to run the classifier and predict burned areas across all images (i.e., images from which no training data were derived). Therefore, it was necessary to develop a second set of accuracy measurements for those images that were not included in the original training data set. Thus, two separate accuracy assessments were performed. The first used the 20% testing data derived from visual classification to assess classification accuracy on images used for model training (within image accuracy). The second used testing data derived from images that were not used in the training data (across image accuracy).

Confusion matrices are a common metric used in the validation of landcover studies(Jeni, Cohn, and De La Torre 2013). In each confusion matrix, testing data are represented along columns and rows. The confusion matrix is a summary of prediction results on a classification where the number of correct and incorrect pixels identified by the algorithm are then summarized and broken down by each class. The overall accuracy is derived from this matrix as the percentage of correctly classified pixels within the confusion matrix (Sulova and Arsanjani 2021). Commission errors, or the user's accuracy, indicated the probability that a pixel classified on the map actually represents that category on the ground or the overall reliability of the map to the user and is calculated by dividing the number of correctly identified unburned pixels by their total (Koutsias et al. 2013). Omission errors, corresponding to producer's accuracy, represents how well reference pixels of the ground cover type (e.g. burned area) are classified and was calculated using the confusion matrix, by dividing the number of correctly identified burned pixels by the total. Omission errors can indicate that certain landcover categories were left out of the development of the classifier indicating that some analysis may be skewed towards categories that were more likely to be included in the study (Koutsias et al. 2013).

Cohen's kappa coefficient is a classification measure that makes some compensation for chance agreement that was used to estimate the accuracy of the classifier broadly compared to a classification preformed through random chance (Koutsias et al. 2013). The Kappa coefficient is a measure of overall statistical agreement of an error matrix, which takes non-diagonal elements into account(Foody 2002). However there has recently been some debate as to the accuracy of this measure and has been less commonly reported in studies (Heydari and Mountrakis 2018; Thanh Noi and Kappas 2017). However, for the purposes of this study we felt it lent additional support to validity of the classification results and was therefore included.

Annual Composites

After an accuracy metric was achieved all available images for the year were classified then composited together using the first date burn area was detected. This then became the single image representing the entire year. The first date that burned area was detected was used in order to clarify potential overlapping burn areas and followed previous precedents set by MODIS data, in which the first date that change is detected is also used (Boschetti et al. 2019) . This indicates that if a pixel was flagged more than once, only the first day that a burn was detected would be used in the subsequent analysis. The first day that change was detected also allows for the understanding of spatial spread of a fire, for example if a burned pixel was picked up on Jan 1 and the pixels adjacent were then flagged on Jan 14, it can be safely assumed that the fire spread between these two dates and pixels were then colored based on this date. If burned pixels were touching in the final composite, regardless of date, they became a single burned area that could then be delineated in time by color. In this way every image from the yearly stack was classified and stacked to create the annual yearly summaries. These yearly composites will serve as a representative fire history for each year in the study.

Exploratory Fire Regime Analysis

The annual composites generated by this project were then utilized to examine the total area burned, fire frequency, and spatial heterogeneity of burns in each reserve. Fire Return intervals were calculated using the annual composites from all 17 years for both landscapes, these were then stacked and processed using spatial tools in R. The fire frequency metric was calculated by recording the total fires experienced per pixel, then dividing that by the number of years in the study to create a fire return interval or how often the same pixel was flagged as burned area in this study. To understand the extent to which Landsat derived product improved available fire data, comparisons were also made with available MODIS-derived fire products for the region. Specifically, the count of individual fires was calculated to better understand detection rate between the two methods. The count of fires was determined by summing the total number of individual features that were flagged by each product per year and were then placed into a table to better observe these differences.

Total area was calculated by summarizing the number of 30-meter pixels flagged as burned area within each reserve and converted into hectares and displayed per year as total hectares burned. The total landcover types present in each reserve were derived from the MODIS IGBP landcover product (MCD12Q1.006, 500M). The 17 landcover categories present were condensed into Forest (IGBP values: 1-6), Savanna (IGBP values: 7-10), Other(IGBP values: 11-17) and can be seen in Appendix A, for the ease of analysis in this study. These categories were summed per year to calculate the total landcover type present in each reserve. The annual composites of burned area were then overlain on this landcover map and summed to gain the total area burned of each landcover type per year. This value was then divided by the total area of that category per year per reserve to indicate the proportion of landcover type burned per year.

Results

Within Image Accuracy

The same accuracy metrics were computed for each set of classifiers, meaning for each time step of ~5 years, for each reserve, accuracies were assessed resulting in 8 different tables, that were then summarized in Table 1.

In general, Overall Accuracies (OA) using the 20% within-image testing data, were consistently high for each classifier ranging between 94%-99%. Producer's and consumer's accuracies were found to be variable across classifiers. Consumer's accuracies remained relatively high between 94%-99% indicating that the product derived from this classification method can be considered accurate in terms of identifying burned area. However, producer's accuracies were more variable ranging from 74% at the lowest to 99% percent correct identification, indicating that errors of omission were the highest using this methodology. The Kappa statistic was additionally calculated, with metrics indicating that the classifiers preformed between 0.83-0.90 better than that of random chance.(Friday et al. 2015)

Table 1: Accuracy assessments of within image validation

Within Image Data Validation					
Classifier	OA	Kappa	Category	Consumer's	Producer's
2003-2005 BRT	99.49%	0.901914193	burned	98.55%	83.58%
			unburned	99.51%	99.96%
2003-2005 SFR	99.23%	0.835375367	burned	96.88%	74.57%
			unburned	99.28%	99.93%
2006-2010 BRT	99.54%	0.896110324	burned	96.37%	84.15%
			unburned	99.61%	99.92%
2006-2010 SFR	99.38%	0.878977565	burned	96.41%	81.30%
			unburned	99.45%	99.91%
2011-2015 BRT	99.01%	0.879786411	burned	96.86%	81.45%
			unburned	99.10%	99.87%
2011-2015 SFR	98.95%	0.878343734	burned	98.35%	80.24%
			unburned	98.98%	99.93%
2016-2019 BRT	99.21%	0.942243	burned	97.98%	91.54%
			unburned	99.31%	99.84%
2016-2019 BRT	98.55%	0.922821525	burned	97.09%	82.39%
			unburned	98.64%	99.81%
Average	99.17%	0.891946515	burned	97.31%	82.40%
			unburned	99.24%	99.90%

Across Image Accuracy

Table 2 shows results for across image accuracy in which OA was found to be high, between 94%- 99%. However, the variability of the producer's and consumer's accuracies became more pronounced in the predictive testing dataset. Consumer's accuracies continued to range between 94%-100% again indicating that using this method of classification to predict burned area in images is relatively reliable to the consumer. Producer's accuracies were far more variable reported between 16%-85% for burned area. Kappa values are derived from these metrics and were therefore variable as well ranging between 0.27 – 0.93.

Table 2: Accuracy assessments of images not included in the training data.

Across Image Validation					
Classifier	OA	Kappa	Category	Consumer's	Producer's
2003-2005 BRT	99.19%	0.279715869	burned	100.00%	16.39%
			unburned	99.19%	100.00%
2003-2005 SFR	94.27%	0.652916258	burned	100.00%	47.92%
			unburned	94.33%	100.00%
2006-2010 BRT	99.70%	0.830253719	burned	100.00%	71.20%
			unburned	99.69%	100.00%
2006-2010 SFR	99.79%	0.758263411	burned	100.00%	61.19%
			unburned	99.79%	100.00%
2011-2015 BRT	99.57%	0.584058098	burned	100.00%	41.43%
			unburned	99.57%	100.00%
2011-2015 SFR	99.68%	0.817857164	burned	100.00%	69.41%
			unburned	99.68%	100.00%
2016-2019 BRT	99.76%	0.933455405	burned	100.00%	87.74%
			unburned	99.75%	100.00%
2016-2019 BRT	99.74%	0.922821525	burned	100.00%	85.89%
			unburned	99.74%	100.00%
Average	98.96%	0.722417681	burned	100.00%	60.15%
			unburned	98.97%	100.00%

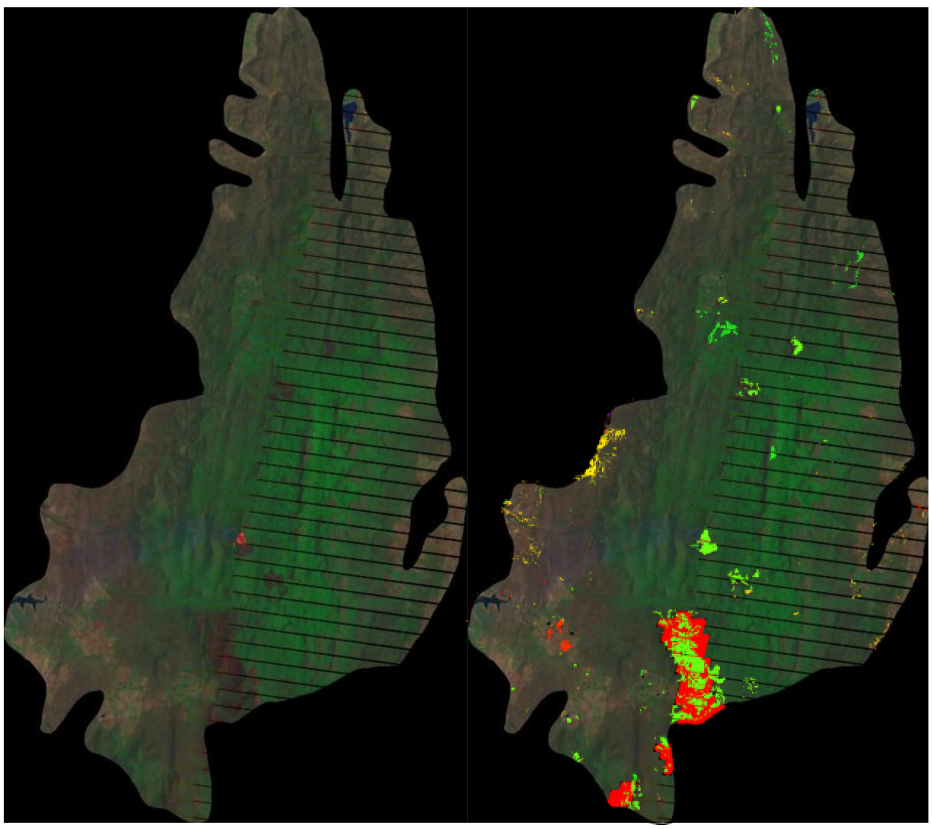
Annual Composite statistics

Identification Comparison

This study was developed to test the capacity of an RF algorithm to detect burned area at Landsat resolution. Annual metrics were then used to compare this product with the only other available fire history data from MODIS. The classified Landsat product performed extremely well in that it identified many small-scale fires that were not flagged by the MODIS burned area product, but that were easily visually discerned using SWIR bands. In terms of large fire detections, the algorithms performed similarly as can be seen in Figure 4, demonstrating the difference between the detection ability of the study algorithm vs. the MODIS algorithm over the year 2017 in BRT.

Figure 4. Panel 1:SWIR image of BRT from March 30 2017, where small fires are visually present. Panel 2: Panel 1 image overlain with MODIS product in Red and Landsat study product in green and yellow.

Panel1 *Panel 2*



For the count of fires, the expectation was that the Landsat algorithm would pick up more fires due to the extreme difference in resolution, and the numbers were consistently larger in the Landsat model for every year in the study as can be seen in Table 3.

Between reserves specifically the count of fires was recorded with the Landsat data to further inform the study and can be visualized graphically in Figure 4. In total over the timeline BRT experienced 12617 fires and SFR experienced 20265. On average BRT experienced 742 fires per year while SFR experienced 1192 at the 30 M scale.

Table 3: Total count of fires captured by both products per reserve.

Total Number of Burned Areas Captured				
Year	Landsat		MODIS	
	BRT	SFR	BRT	SFR
2003	237	410	0	0
2004	1073	1021	3	1
2005	1030	1041	5	9
2006	538	501	0	4
2007	2056	1257	1	1
2008	269	296	0	0
2009	501	537	3	5
2010	362	534	4	1
2011	167	531	0	2
2012	1151	1120	1	6
2013	401	905	2	1
2014	1027	2988	0	1
2015	465	240	1	0
2016	876	2385	0	2
2017	1067	4634	3	2
2018	289	649	0	0
2019	1108	1216	0	2

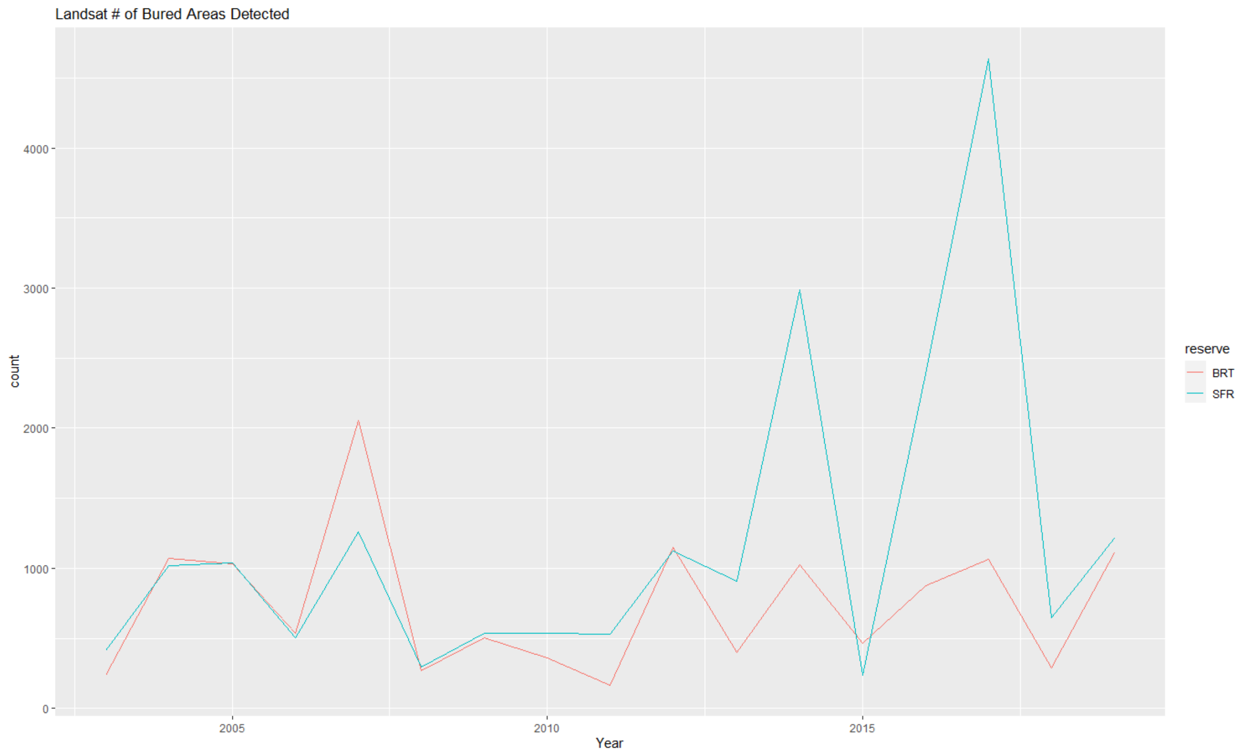
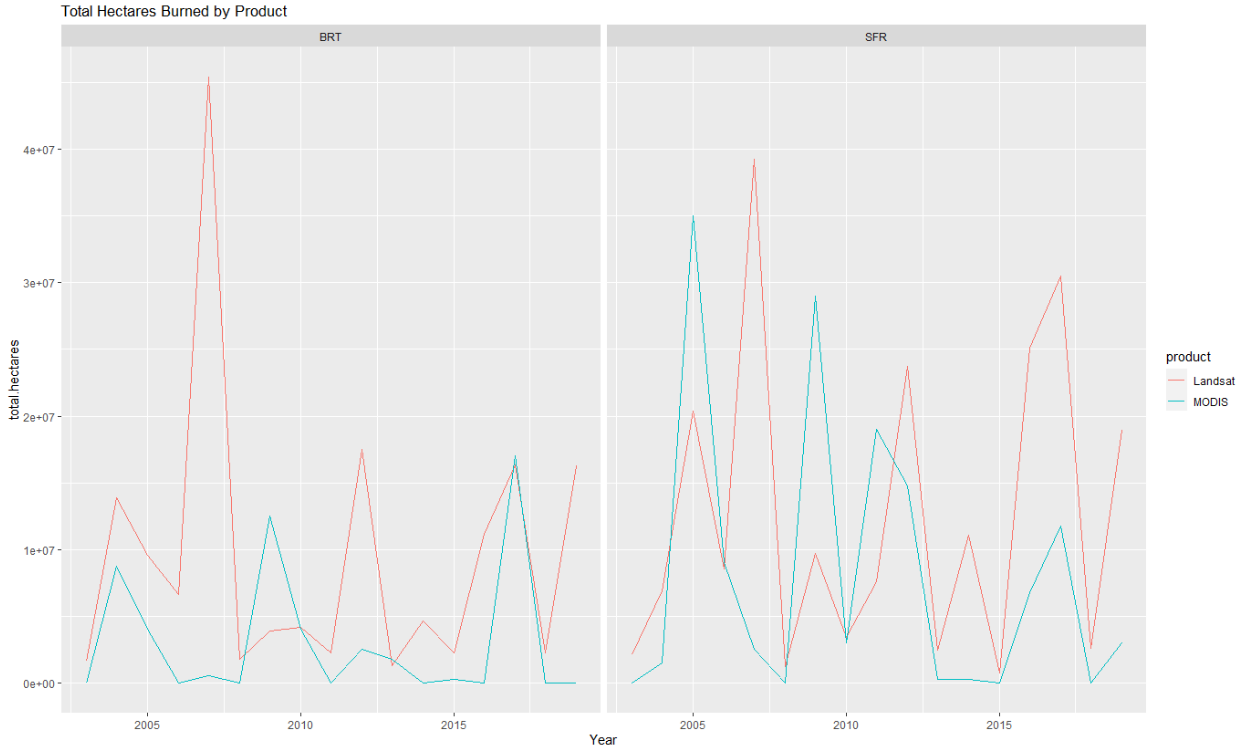


Figure 5: total count of fire events captured by Landsat product.

Total Area burned

Total area burned was calculated in hectares for each year by reserve. On average the Landsat algorithm developed in this study detected more hectares burned than the MODIS product currently available. However, there were some discrepancies where MODIS detected more hectares burned such as in 2005 in SFR and 2009 in both reserves. However, on average the products followed the same general trend, where years with high fire activity were similarly reflected in each of the products.

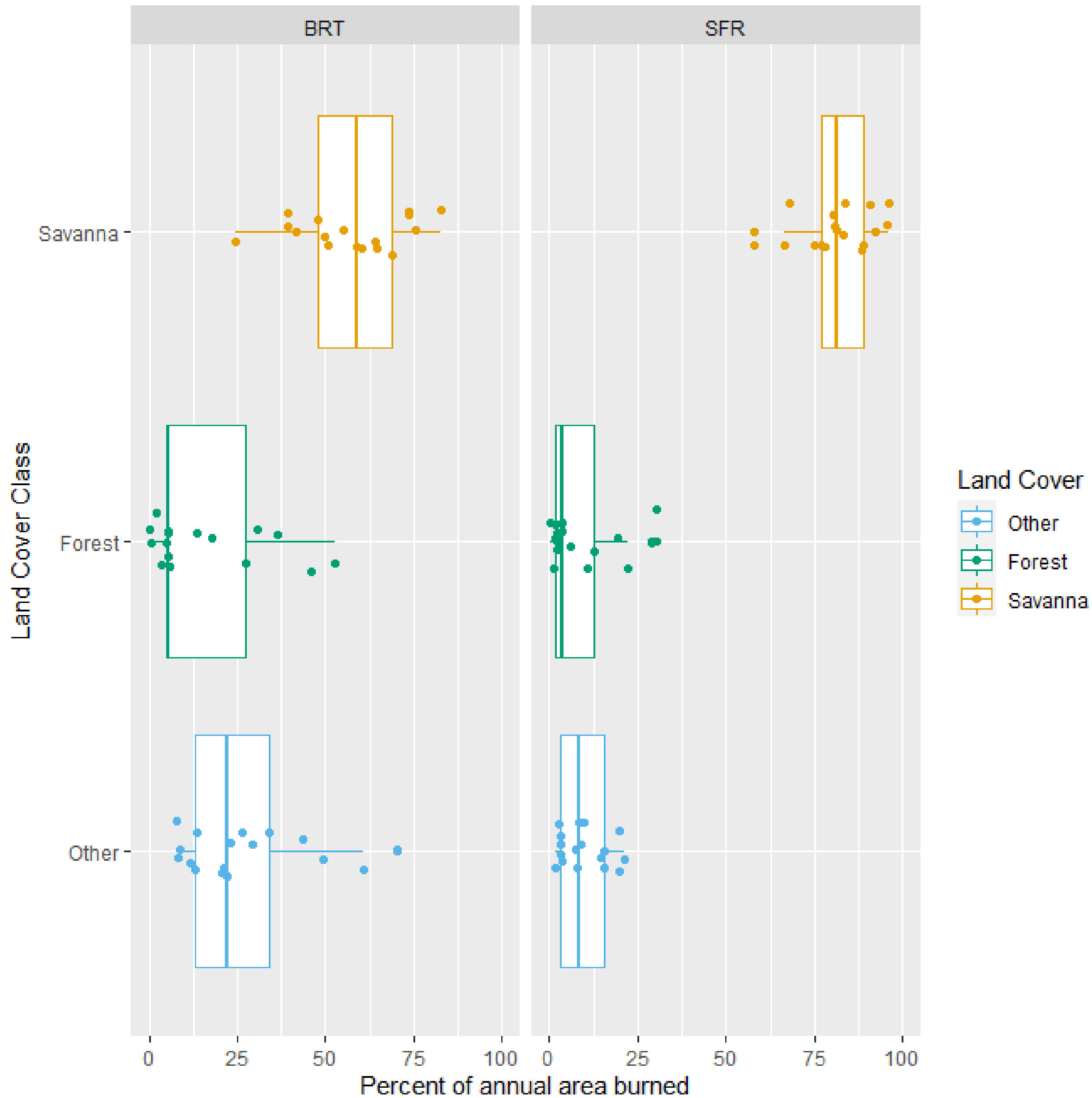
Figure 6: total hectares burned captured by both products per reserve.



The Distribution of Burned Area Across Land Cover

Overall, burned area across savanna in both reserves was very high (figure 7). BRT exhibited a wide spread in this metric year ranging from around 25% to 80% in high detection years. SFR experienced overall more proportion of savanna burning from year to year ranging from approximately 60-98% of this land cover type experiencing burns over the course of this study. Forest metrics were similarly spread in BRT, with values ranging from 0 to just past 50% and SFR experiencing proportions burned between 0 and 30%. Finally, the Other category, characterized by mainly croplands, had an range of 12% to around 60% in BRT while SFR maintained a cluster of points between 0-25%. Medians of these values were further assessed and found that overall SFR had a higher average proportion of savanna burn, While BRT had a marginally higher proportion of Forest burn as well as the Other category.

Figure 7: jitter plot of the proportion of area burned by landcover types: Savanna, Forest, and Other as captured by the Landsat study product, with Medians represented using boxplots.



Fire Return Intervals

Fire return intervals were represented by histograms for both reserves in Figure 8. The most any given pixel burned over the 17-year fire history was three times, therefore fire frequencies (#fires/yr) ranged from 0 (unburned) to 5.6. BRT and SFR were compared by examining the distribution of burned pixels across fire frequencies for each reserve. Both reserves demonstrated similar distributions despite varying number of pixels in each reserve. The spatial representations of these return intervals can be seen in Figure 9.

Figure 8: Fire return frequency by reserve

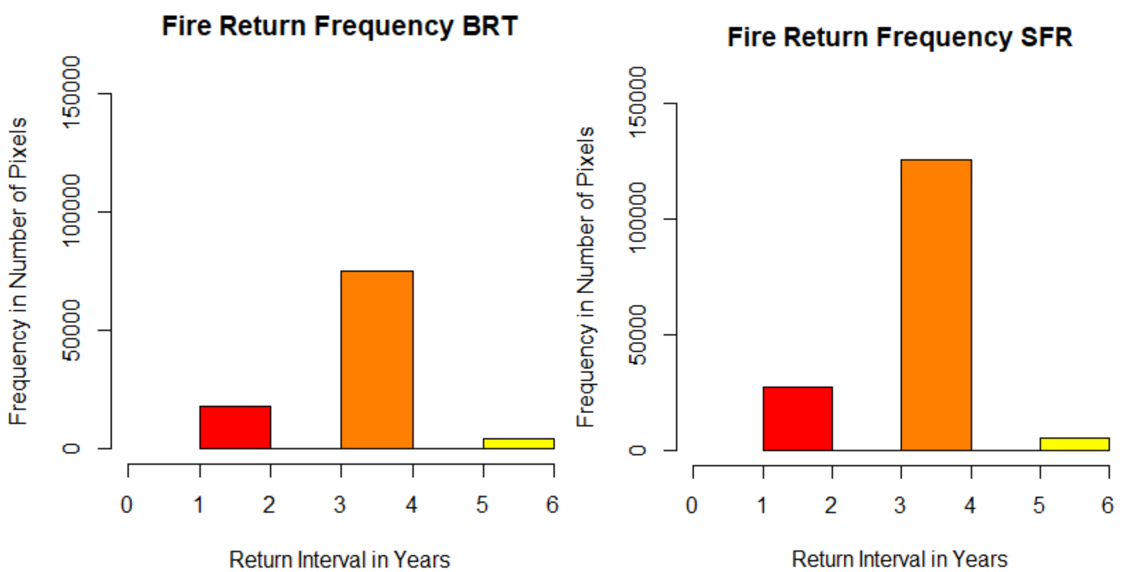
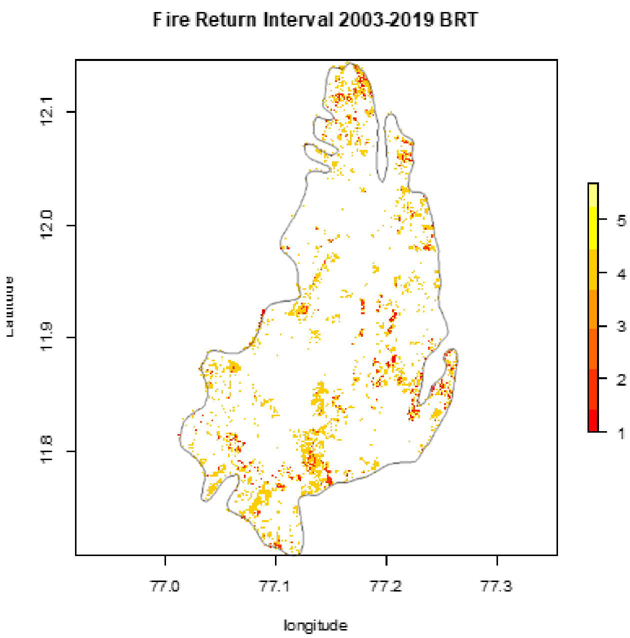
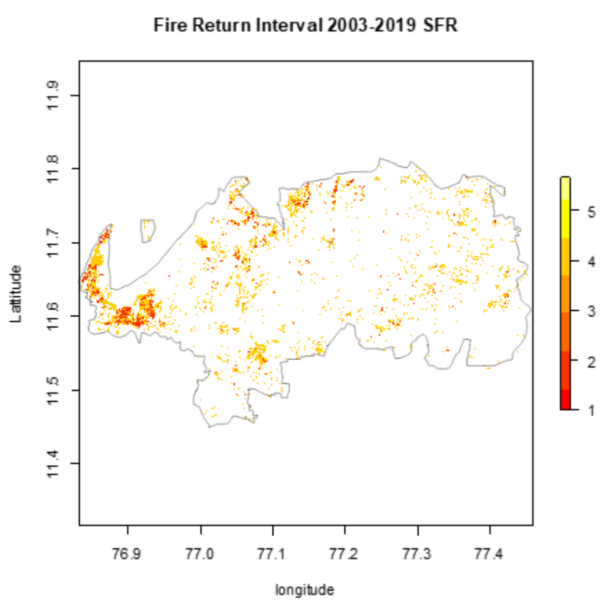


Figure 9: Map of fire return intervals displayed by reserve as a composite image of the annual year summaries, indicating that all pixels flagged as burned between 2003- 2019 are in the image and represented as varying colors. Pixels are colored in response to the fire return exhibited by each pixel and are as follows, red= 1-2 years, yellow, orange= 3-4 years, yellow = 5-6 years.





Discussion

Accuracy

This project aimed to develop a semi-automated RF classification method using GEE to better identify burned area at 30m resolution and be able to use this information to predict burned area in images not included in the training data. Overall, the use of the RF algorithm proved to be valuable and ideal for this study due to a highly unbalanced dataset, a large number of input features, and a variable number of images per training set. The creation of a Random Forest classifier to automate certain portions of the burned area mapping work flow will decrease time spent inspecting individual images or hand drawing perimeters around burned regions. Improvements in this method using GEE could transform the way in which burn histories and current burned area mapping is conducted at higher resolutions.

The method additionally showed promise as the accuracy assessments remained relatively consistent over the 5-year batches over the within image data, with fluctuations between measures being minimal. Within image accuracy metrics for user's accuracies were consistently near 99%, which indicates that the performance of this method as a classification technique is feasible for within image classification. These results indicate that if training data is assimilated from every image in the collection, then used to train the classifier there should be a high level of accuracy and maps can be trusted to accurately portray ground level features within reason. The method also showed promise in its capacity to predict images which were not within the training data set, or across image accuracy. The fluctuations between accuracy metrics were much higher and the producer's accuracy indicated that increased training data could improve this method substantially. Overall, the process could be simplified by combining the 8 different classifiers into one large classification system with increased computing power which was not possible at the time of this analysis. Additionally, inclusion of images not included due to the 25% cloud threshold, could be used to cover the subtle differences that occur when using spectral profiles in pixel wise analysis over long time periods. Overall, however, the training data used in this study to create maps of burned area provide a functional tool to help land managers identify regions of burned area from 2003-2019.

Limitations with classification

Across image validation

The most inconsistent data was found in the prediction of images not included in the training data set. The impetus of this study was to be able to predict images correctly based on a small subset of images to increase mapping efficiency. In this regard the study demonstrated mixed results. While OA was extremely high (90-99%), Kappa values and producers and consumers accuracies were extremely inconsistent (40-99%). Much of this could be again remedied by the increase of training data to capture more spectral variation over the year and the culmination of classifiers into one large RF classifier.

However, of the 8 classifiers the 2003-2005 BRT images show the most deviation from the average of the accuracy metrics. This interval contained the fewest number of images with burned area large enough to effectively add to the training data and could have contributed to the abnormally high errors of omission recorded for this dataset, reflected in the low value of the producer's accuracy (0.16). As RF classification algorithms are sensitive to the input data and there was only a limited amount of burned area pixels to draw on for this data set an increase in the data used for training may solve this issue(Rodriguez-Galiano, Ghimire, et al. 2012). Therefore, while the ability of this study to classify burned area was variable, the overall method shows potential on a larger scale with increased data, input features, and a refinement of methodology(Pelletier et al. 2016; Tatsumi et al. 2015).

Misidentification

While the OA of the original testing dataset is high, this metric alone may be misleading. Initially, while the amount of training data is large, it is only coming from a selected number of images which do not cover the entire year or full phenological variability present in the region and therefore does not cover the entirety of spectral variability that can be present in any image (Shelestov et al. 2017). While the final results of the classification were between burned and unburned area, clouds and shadows were used in the development of the classifier to capture differences between these categories and similar looking burned areas. In this case the presence of shadows or high-altitude clouds over dry areas were commonly misidentified as burned area in a number of images creating noisy images or false positives, that will need to be additionally validated. This issue and the following were generally exacerbated in the SFR dataset where noise was a considerable issue due to the significant variation in topographical features such as dry peaks and valleys which were not present in the BRT images as well as the increased size of the reserve which with the limited amount of training data allowed by GEE indicates that omission errors should on average be higher.

There are several issues with selecting polygons randomly in an image to function as training and testing data. The first of which is the concern of spatial auto-correlation, due to treating training and testing data coming from the same polygons as independent observations, despite some samples being directly adjacent to each other. However, this was the most effective way to generate a sample of burned area pixels that was large enough to use in the classifier across multiple images, as well as to collect visually homogeneous regions for training. In the future, if large data sets of polygons may be processed by GEE, it would be possible to utilize the entirety of the selected data and separate them at the polygon level as is suggested by Pelletier et al, in order to limit the effect of spatial auto-correlation or add textual features similar to (Rodriguez-Galiano, Chica-Olmo, et al. 2012). Polygons were chosen rapidly to cover the largest number of pixels of the specified category with little regard to capturing hard to discern edges and to increase the efficiency of creating training data.

Additionally, this study only used the basic bands available in the Landsat 7 imagery as inputs for the classification of the categories. The accuracy of classification is improved by adding additional input features such as elevation, NDVI, texture metrics, and additional spectral metrics (Hawbaker et al. 2017; Li et al. 2014; Rodriguez-Galiano, Ghimire, et al. 2012; Zhang, Zhang, and Du 2016). The inclusion of textural data specifically would have a positive effect in this study as it has been demonstrated to be effective at distinguishing shadows from the surrounding regions which were a common point of confusion for the classifier in this study(Rodriguez-Galiano, Ghimire, et al. 2012).

Identification comparison

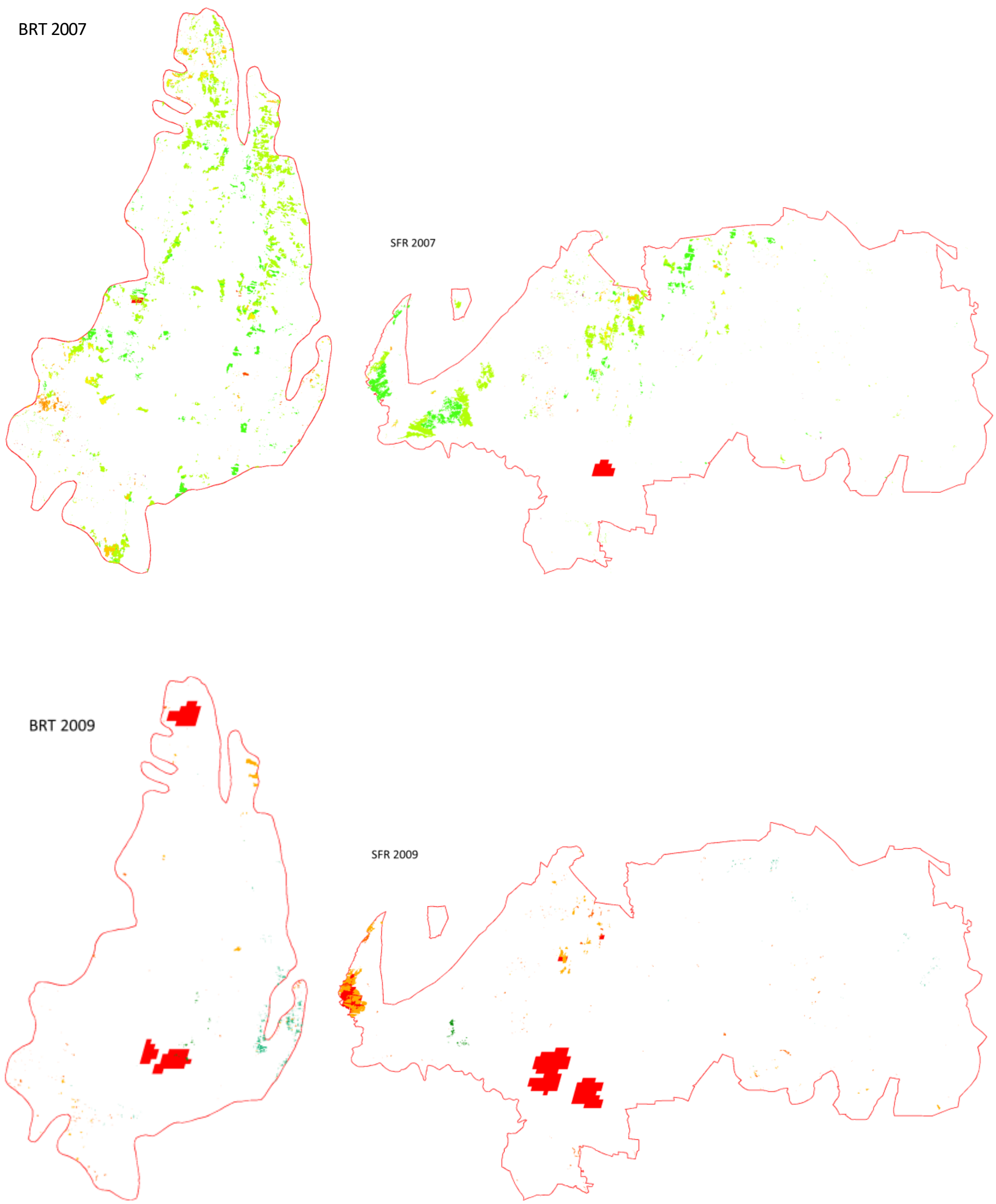
The Landsat data set was adequate to map burned areas as large regions of burned area were similar to the MODIS data set as demonstrated in Figure 3. This indicates that the developed product works similarly to the MODIS product in the case of burned areas exceeding 500M pixel resolution available with MODIS. Critically, the algorithm was able to pick up smaller burned areas that were able to be perceived by the eye but were not flagged by the MODIS product. This result indicates that the Landsat product may be able to produce more robust maps of burned area on a bi-weekly to yearly basis and improve the understanding of fire regime. This is critical in regions where small fires make up the majority of fire events such as in tropical dry forests and savanna ecosystems(Cochrane, Alencar, Schulze, Souza Jr, et al. 1999; Hoffmann et al. 2012). For instance, in BRT and SFR the ability to track the size of fires may be able to signal a switch from historically small fires present in indigenous burning regimes to more large-scale fires indicating a disruption in the perceived baseline of fire occurrence in the region. These maps when used in tandem with other spatial analysis tools such as landcover or climate products, may be able to better predict the spread and extent of future fires and elucidate how historical fire management may influence pre and post fire management strategies.

Total area burned for 2007 and 2009 between the two products can be visualized in Figure 9. When looking at the year 2007 the Landsat product indicates a high total area burned for both reserves, the largest out of the entire study in fact. However, the MODIS dataset indicates the opposite, that almost no area was burned in either reserve. Upon visual inspection of individual images in the 2007 image stack, it is clear that there were indeed a high number of burned areas in the SWIR images. This leads to the conclusion that while MODIS is a valuable tool to understand large fires, it is missing a significant portion of smaller fires that may be influencing landscape level effects in the region. The omission of these smaller burned areas may simply be due to the resolution of the product as the tool is derived in a similar way to the test product – identifies first day of spectral change - and using a product with higher resolution, such as what has been developed in this study, will improve the understanding of fire dynamics in both reserves.

In this study, there is additionally the opposite effect occurring in 2009, where the MODIS data indicates a higher amount of burned area, while the Landsat data indicates much lower values. Upon visual inspection here, the MODIS data flags 3 and 5 large events in BRT and SFR, respectively. However, upon visualizing the data these large events are not captured in a significant way by the Landsat data. This could be indicative of a few issues with the classification scheme, the first being that the spectral signatures for these pixels were not represented by the training data set, therefore the classifier missed these large events.

Alternatively, these and other events may have been left out of the data set altogether due to omission by their cloud cover falling outside of the 25% threshold used in this study. However, when fires are large enough to be flagged by the MODIS data they are similarly captured as is demonstrated by 2017 fires in BRT, where the total area burned is very similar, indicating that overestimation by the MODIS data in this case is unlikely. The year 2017 was exceptional in this study though due to clear images with easily identifiable burned regions allowing for good training data, while in other years finding enough data to train the algorithm was extremely difficult. This leads to the possibility that the training samples accurately covered the spectra in the images in 2017 and demonstrates the high potential for model improvement with additional training data and the combination of data into a single model would additionally improve the model.

Figure 10: Comparison of Landsat and MODIS burned area detection in BRT and SFR in 2007 and 2009 of years with high discrepancies in the data. 2007 illustrates identification of small burned areas missed by MODIS and 2009 reprsents large burned areas flagged by MODIS but missed by the Landsat study product.



Annual composite Statistics between reserves

Total Area Burned and Count

The summaries presented of the annual composites were performed as an example of how this tool could be utilized in the future. Any information presented is derived from the classified data set any errors there in could be perpetuated in this data. While these summaries of total area burned, proportion of burned area by landcover type, and fire frequency are useful, they are limited in their ability to provide information without additional on-the-ground context but can still be used as a tool for analysis now and in the future.

On average the total burned area per year was greater in SFR than in BRT. This is likely attributable to several factors including: 1) SFR having about twice as much area as BRT; 2) the continuance of agricultural and prescribed burns in this area; and 3) a larger proportion of highly flammable savanna type ecosystem in this reserve (Kodandapani 2013; Ramasubramanium 2010). This pattern is also reflected in the counts of fires being larger in SFR. Only in 2007 did more hectares burn in BRT than SFR, this indicates that much higher proportion of BRT burned than SFR in that year and a majority of these fires were small in scale and were missed by the MODIS product. Despite differing resolutions, both products MODIS 500m & Landsat-derived 30M fire maps demonstrated similar trends in annual variability in area burned for both reserves (figure 6). This likely related to the effect of climate in the region as studies demonstrate that interannual variability in rainfall strongly influencing fire occurrence in tropical savannas and other ecosystems (Jolly et al. 2015; Kane et al. 2017; Trauernicht 2019). Despite the similarities in the variability in annual area burned between MODIS and Landsat, the Landsat product tended to identified a greater burned area per year - these results therefore also highlight the potential of a higher resolution tool to better understand the contribution of small fires to overall patterns.

Proportion of Area Burned Across Land Cover

On average, savanna burned more often than any other landcover type. In SFR, this is most likely due to the abundance of savanna in this reserve and the high flammability of this environment (Bond and Keeley 2005; Kodandapani 2013). In BRT the spread of the proportion of annual area burned occurring in savanna relative to other landcover types was more variable.

Croplands, which comprise most of the "Other" category, accounted for large proportions of burned area in some years for BRT. Often cropland is adjacent to savanna regions and the high proportion of this category burning potentially indicates frequent agricultural fire activity that may contribute to the spread of fire out of these regions into adjacent land covers thus increasing the proportion of savanna burned(A. J. Hiremath and Sundaram 2005; A. Hiremath and Sundaram 2014; Mallegowda et al. 2015; Ramakant, Vaidyanathan, and Krishnaswamy 2014). SFR has a higher amount of Other/cropland present within the reserve as can be seen from figure 2, yet accounts for a lower proportion burned than in BRT. This could be due to the more intensive use of these regions in BRT due to the placement of nomadic peoples into permanent "podus" (Ganesan and Setty 2004; Madegowada 2009; Ramakant, Vaidyanathan, and Krishnaswamy 2014). While cropland burning patterns may implicate difference in the social drivers of fires between BRT and SFR, this is difficult to discern from satellite data and more research on this front is vital in understanding much of the fire regime in these reserves.

Forest ecosystems in this environment are less likely to experience burns than savanna due to higher rainfall and the closed-canopy structure of plant communities (Stueve et al. 2009). This was reflected in the results, as the proportion of burned forest was typically lower than other land covers in each reserve(Ratnam et al. 2019). However, in BRT there were higher proportions of burned area occurring in forests than in SFR. This may reflect the concerns surrounding the effects of increasing *Lantana camara. Lantana camara,* a highly invasive and flammable non-native plant that the increase of which is likely driving shifts in fire behavior in these forest regions as it is also a principal concern in landcover change(A. J. Hiremath, Prasad, and Sundaram 2018; A. J. Hiremath and Sundaram 2005). The savanna -forest interface has been proven important in preserving the diversity of species in the mature forest (Scariot and Vieira 2006). *L. camara* has begun to threaten this interface in SDTF in these regions as it actively shifts forest and savanna into single species, monotypic dominated shrublands which have cascading environmental effects from species distribution to fire behavior.

The proportion of burned area in BRT may also be indicative of implications of the cessation of tradional low intensity fires. As traditional burning is limited, regions that historically experienced these burns have had the opportunity for fuels build up over the last 40 years (Roveta 2008). Shortly after the initial ban of burning in BRT in 1973, the first indication of increased late season canopy fires was recorded with the implication that species such as *L. camara* had begun to spread, increasing fuel loads indicating a connection between indigenous burning as a management system for *L. camara* build up((Sundaram, Hiremath, and Krishnaswamy 2015)). As seen from Figure 9, the encroachment of burned area into the forest interior may be likely due to this unchecked spread of this plant, however more on the ground research is necessary before this connection can be made for certain. While this analysis of fire patterns is preliminary, it provides foundational data for more sophisticated analyses of how climate, landcover data, population movement, and management regulations also influence fire for future studies (Mallegowda et al. 2015; Scariot and Vieira 2006; Skarpe 1992).

Fire Return Intervals

Fire Return intervals remained relatively consistent to other studies performed in this region in an earlier period of time. (Kodandapani et al, (2004) found return intervals were ~3.3 years in SFR, which agrees with these results in which a majority of pixels had a fire frequency of between 3-4 years. The distribution of these intervals was similar across reserves indicating that although they have had differing management histories it is likely that climatic variables, landcover types, and changing forest dynamics may be more likely to explain some of the differences these regions have been experiencing.

SFR has a more abundant savanna as was classified by this study using the IGBP classifications (Appendix A), in comparison to the forest dominated BRT(figure 2). In this regard, the study expected more pixels in SFR to fall within shorter fire return intervals between 1-3 years as studies stated previously (Kodandapani 2013; Kodandapani, Cochrane, and Sukumar 2004). More surprising is that BRT demonstrated similar return intervals to SFR across the time period. The majority of BRT is dominated by an interior region dominated by woodlands to evergreen forest with higher rainfall than the surrounding area. This would lead one to the expect that, on average, the distribution of burned area would be skewed towards longer fire intervals (Ramakant, Vaidyanathan, and Krishnaswamy 2014). In this case the similarity to SFR may be indicative of landscape level changes, such as invasion of L. camara, that may be shifting this environment towards a more flammable ecosystem(Love, Babu, and Babu 2009; Niphadkar et al. 2016). This however is difficult to discern from this data set and requires to data collected on the ground or a more regionally specific landcover product to make these distinctions.

Spatially these results are unsurprising as many of the regions that experience short fire return intervals are near human settlements or agriculture land, where burning is a common agriculture technique that, although banned in the majority of BRT, clearly still occurs (Roveta 2008; Yebra et al. 2008). In BRT the interior of the reserve is a mainly forest region and figure 9 indicates that although a majority of the fires happen near the edges of the reserve, there has been some encroachment of these short return fires towards the interior of the park. Again, this could be due to a landscape level shift in vegetation cover that needs to be explored further. This study provides a foundation from which to examine additional climatic variables, country specific landcover types, population, settlement, and maps of roads within the parks which could give the analysis of these burned areas a more definitive context to land managers and interested parties in the future.

Conclusion

Overall, this method showed promise in its capacity to identify burned area in BRT and SFR between 2003-2019 using Landsat imagery and the computational power of GEE. The RF performed well in the classification of burned area especially within imagery that was included in the training data, with high accuracy metrics across the board. As far as the predictive power of the algorithm, in respect to predicting images not included in training data set, the study had mixed results. While some time intervals were highly successful based on overall accuracy, others deviated substantially and indicate that a refinement of method, preferably combining time intervals, is necessary. The exploratory analysis demonstrated the utility of compositing images into annual maps and will be highly applicable to help researchers and resource managers understand spatial and temporal trends and drivers of fire in the region. The maps would likely improve from increased training data, the amalgamation of all data into a single classifier and, of course, a physical ground truthing of conditions at the study sites. The exploratory analysis also demonstrates the promise of this method to summarize fundamental aspects of fire regimes such as total burned area, proportion of landcover types burned, and fire return interval with far greater nuance and accuracy than available MODIS fire history. This product must continue to be evaluated and compared with similar studies, additional variables, and other types of remote sensing data in the future. However, it provided the first steps to understanding fire regimes in the region and will be beneficial for future studies on the spatial and temporal spread of fire in BRT and SFR in the years to come and has the potential to be applied on a global scale in the future.

Appendix A. IGBP land cover classification system				
Class	Class name	Color	Converted Class	Description
1	Evergreen needleleaf forests		Forest	Lands dominated by needleleaf woody vegetation with a percent cover >60% and height exceeding 2 m. Almost all trees remain green all year. Canopy is never without green foliage.
2	Evergreen broadleaf forests		Forest	Lands dominated by broadleaf woody vegetation with a percent cover >60% and height exceeding 2 m. Almost all trees and shrubs remain green year round. Canopy is never without green foliage.
3	Deciduous needleleaf forests		Forest	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 m.Consists of seasonal needleleaftree communities with an annual cycle of leaf-on and leaf-off periods
4	Deciduous broadleaf forests		Forest	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 m. Consists of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods
5	Mixed forests		Forest	Lands dominated by trees with a percent cover >60% and height exceeding 2 m. Consists of tree communities with interspersed mixtures or mosaics of the other four forest types.None of the forest types exceeds 60% of landscape.
6	Closed shrublands		Forest	Lands with woody vegetation less than 2 m tall and with shrub canopy cover >60%. The shrub foliage can be either evergreen or deciduous.
7	Open shurblands		Savanna	Lands with woody vegetation less than 2 m tall and with shrub canopy cover between 10% and

				60%. The shrub foliage can be either evergreen or deciduous.
8	Woody savannas		Savanna	Lands with herbaceous and other understory systems, and with forest canopy cover between 30% and 60%. The forest cover height exceeds 2 m.
9	Savannas		Savanna	Lands with herbaceous and other understory systems, and with forest canopy cover between 10% and 30%. The forest cover height exceeds 2 m.
10	Grasslands		Savanna	Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.
11	Permanent wetlands		Other	Lands with a permanent mixture of water and herbaceous or woody vegetation. The vegetation can be present either in salt, brackish, or fresh water.
12	Croplands		Other	Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type.
13	Urban and built-up lands		Other	Land covered by buildings and other man-made structures.
14	cropland/natural vegetation		Other	ands with a mosaic of croplands, forests, shrubland, and grasslands in which no one component comprises more than 60% of the landscape.
15	snow and ice		Other	Lands under snow/ice cover throughout the year
16	Barren		Other	Lands with exposed soil,sand, rocks, or snow and never have more than 10% vegetated cover during any time of the year.
17	Water bodies		Other	Oceans, seas, lakes, reservoirs, and rivers. Can be either fresh or salt-water bodies.

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