Planted Forest Fire Burn Area and Impact Assessment Using Sentinel-2: Case Study of the University of Ilorin Teak Plantation

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Abstract. This paper presents a comprehensive assessment of the locations, extent and the impact of forest fire in University of Ilorin Teak Plantation using pre- and post-fire Sentinel-2 level 1C products. First, the pre-fire image was classified into three classes: vegetation area, bare soil and water body, using supervised classification (Maximum Likelihood method) to distinguish between vegetation and non-vegetation areas. Then, from the post-fire image, the burn areas were detected and extracted using Normalized Burnt Ratio. With the burn area polygon, impact of the fire on the planted forest was determined by isolating the vegetation class within the classified map so estimating the number of teak trees affected through extrapolation of the burn area and the tree spacing grid of 3m. The classification result shows that vegetation land cover type accounted for about 419.7 ha (66 %) of the total area while bare soil and water body take 204.3 ha (32 %) and 12.9 ha (2 %), respectively. Also, the resulting classified map produced overall classification accuracy of 95 %. Impact assessment result reveals that a total number of 49156 tree stands were affected by the fire within burnt area of 54.8 ha (8.6%). Analysis of the estimation success rate using one of the burn areas as validation site yielded approximation in excess of 3% with 17621 counted and 18222 estimated. Planted forest management and planning has many phases; so, it is necessary to understand the current and future condition of what is being manage. The fire burn map derived from this study will assist the University teak plantation management team update its current management strategy to protect it from continuous exposure to fire. From fire management perspective, the list of planning activities that require future assessments include pruning preferences, replanting, commercial thinning, spacing of planted trees, and perimeter buffering.

1. Introduction
Forests are important natural resources that perform vital economic and ecological functions, including provision of goods and livelihoods, safeguards biodiversity, protect soils from degradation and erosion, regulate water flow, and regulate climate by trapping carbon that could have been add to greenhouse gases [1]; [2]. It is reported that, in 2000, 30 percent of the world’s land area (~3.9 billion ha) are forests [3], of which the natural forests were estimated to constitute about 95 percent of the global forests and
the remaining 5 percent were plantation forest [1]. By 2015, the global natural forests have reduced to 93 percent, representing approximately 3.7 billion ha [4]. The scale and speed at which the world natural forests are been lost to resource exploitation and other anthropogenic activities, such as agriculture, industrialization and urbanization [5];[6], spiraled global calls for legally established protected areas of native forests [7]. For example, FAO [1] reported that 51 percent of global forests are available for wood supply, only 12 percent are legally protected while the remaining 37 percent are unavailable either due to physical inaccessibility or the trees within such forests are economically unviable.

Natural forests were reported to have contributed to about 78 percent of global industrial timber supply in 1995, while the remaining 22 percent came from plantations forest [3]. To reduce the pressure on natural forests as a result of increasing demands for forest products, there has been rapid expansion of large areas of the natural forest legally protected by laws and policies enforceable by multilateral agreement and treaties on forest and global timber trade [7]; [8]. This has made the natural forests less available for timber supply; and thus, generated a rising shift from reliance on natural forests as primary sources of timber supply to plantations forest. Unlike natural forests, plantation forests are intensively managed planted forest characteristically comprising of one or two species, of the same age, and generally planted at regular tree spacing [7].

Planted forests are established exclusively to produce high volume of timber in a short period of time, so as to reduce pressure on natural forest, minimise deforestation and ensure better land use [3], [4], [9]. Since the mid-19th century, plantation forests have increasingly play significant role in replacing timber products from natural forests [10]. For instance, the planted forest which represented 5 percent of global forest in 2000 delivered approximately 35% of the world's timber needs [2]. It has also been projected that by year 2025, logging on natural forest would have reduced drastically by 50%, specifically, from about 1.3 billion cubic meters in year 2000 to about 600 million cubic meters [3]. This emphasised the increasing role planted forests is playing as a major source of timber, wood and fibre production. Although, plantation forests are mostly composed of single tree species with a very different ecosystem characteristics and structure, they also provide some ecological and social services similar to the natural forest. These services include soil erosion control, ecosystem restoration, climate regulation, carbon sequestration, environmental beautification and research [3], [4], [8], [10], [11].

Teak (Tectona grandis) is among the world most well-known planted forest species of high-quality timber with vast export market. Teak is native to the tropical regions of southeast Asia, specifically Myanmar, Indonesia, Thailand and Bangladesh; however, its cultivation is economically viable across the tropical climates of Central America and Africa [9], [12]–[14]. Teak tree is one of the tropical plants that have wide and various uses because it is strong, durable, light, attractive in colour, fine grained, and resistant to termite [9], [15]. These qualities made it the industry choice for good quality outdoor furniture, house roofing, carving, boat deck/ship building, carpentry products, et cetera [7], [9], [15]. Although teak can be grown to timber sizes as wood for furniture, but in Nigeria, it is predominantly used for electricity poles.

Establishment of teak plantations is one of the assets that yields assured returns on investment for the investors. Nonetheless, critical problems confronting managing teak plantations, apart from spacing, weeding, insect and disease infestation, are pruning and fire protection [16], [17]. Fire has been identified as an integral part of forest ecosystems that contributes to major disturbances in forest ecological balance, alteration in the successional rates, and affects above and below ground biomass [18]–[20]. Every year, out of control wildfires have continue to cause extreme long-term damage to the environment, properties, wildlife, and particularly forest and agricultural holdings, and the economy. Never-ending forest fire disaster has made it increasingly necessary to map the burned area to aid in effective management and policy implementation on forest fire prevention, assessment, and monitoring.

Since the late 1970s, satellite-based remote sensing data have been extensively used to both detect active forest fires and map burned areas by exploiting thermal contrast between burning fire and the background and by assessing the effects of fire on vegetation reflectance [21], [22]. Remote sensing tools, such as MODIS [22]–[24], Landsat [21], [25], and recently, the European Space Agency (ESA) launched Sentinel-2 satellites [26]–[28], allow accurately estimating the extent of fire-affected areas and
the burn severity at different scales (local, regional and global) taking advantage of their high-quality temporal and spectral resolutions.

The need to identify and quantify fire effects over forest areas using remote sensing technique has evolved over time through the processes of image differencing to the derivation of radiometric value called the Normalized Burn Ratio [19], [21], [27], [29]. Image differencing requires highlights burn area by subtracting the SWIR band of pre-fire event from the post-fire scene because of its sensitivity to temperature difference. On the other hand, NBR (normalized burn ratio) is a ratio of the difference and sum of NIR and SWIR bands. Furthermore, other fire severity indices, including differenced normalised burn ratio (dNBR) and relativised dNBR (RdNBR) [25], [30], [31], have been developed as advancement to the NBR to discriminate the relative degree of burn. Today, the availability of multi-sensor data and advance computational intelligence (machine learning) algorithms have improved the accuracy of detection and prediction of forest fire for effective disaster mitigation planning [30]. These methods have been widely used to evaluate forest fire susceptibility to improve the detection of and response time to potential fire outbreak.

While much investigations have been done to assess the extent, intensity and severity of wildfire in natural forest, adequate attention has been given to plantation forest fire. Apart from the need to improve the detection of fire outbreak and emergency response times, there is also the need to improve post-event delineation, assessment and monitoring of the plantation affected areas. Such post-event analysis can then feedback into strategies and policies for fire prevention, prediction mitigation and response. The case study under investigation is a large expanse of teak estate known for its yearly fire outbreak; however, the extent and severity of these events have never been investigated. In this study, remote sensing and GIS techniques were employed to map the spatial extent and distribution of fire burn area in the University of Ilorin teak plantation, and to estimate the number tree stands affected by the fire incidents between December 2019 to March 2020 which mark the peak of dry season.

2. Study Area

The University of Ilorin Teak Plantation is in the north-eastern part of the university Main Campus (Figure 1). Geographically, the plantation lies between Longitude 4° 38’ 27” E and 4° 40’ 01” E and Latitude 8° 27’ 59” N and 8° 29’ 54” N, covering approximately 637 hectares (10.09 sq km). In terms of topography, the plantation sits within elevation range of 278m to 340m asl (as derived from SRTM digital elevation model). The terrain characteristically has east and west facing slope that drains to the central part to create a major river channel that flow northward. The study area falls within the tropical savannah climatic zone of Nigeria [32] that has a marked rainy and dry season - April to November and December to March, respectively. The region experiences annual temperature ranges above 18°C to 36.9°C and total rainfall that varies from 1000mm and 2000mm of rain each year [32], [33].
In 2008, the University of Ilorin embarked on massive afforestation programme in her effort to key into the national and global efforts of planting trees, especially within the highly deforested savanna zone of Nigeria. The extensive plantation development programme commenced in July 2008 with the establishment of 57 hectares of Teak (*Tectona grandis* L.F). In 2009, an additional 100 hectares of Teak were planted. Subsequently, in 2010, 2011 and 2012, the University established additional 150, 157 and 122 hectares of Teak respectively. The 30 hectares of unproductive orchard of citrus, which falls within the land areas allocated for Teak, was also converted to planting of Teak seedlings. This brought the total area of land under Teak estate to ~ 616 ha. The Teak Plantation was established with the purpose of producing poles and timber, which at maturity, will contribute immensely to the Internally Generated Revenue (IGR) of the University. Other objectives of establishing the Teak plantation include environmental protection of the savanna ecosystem; provision of aesthetic value to the vast landscape of the University; and provision of model field laboratory for teaching, research, and innovations for both staff and students of the University. In addition to Teak, other crop species established as part of University Afforestation Programme include Jatropha (44.1 ha), Date Palm (28 ha), Moringa (2.3 ha) and Cashew (15 ha). The entire plantation area of the University was considered as the most ambitious and single largest plantation own by an academic institution in sub-Saharan Africa. Hence, for intensive management of the Teak plantation alone, the plantation was divided into seven Lots and managed by contractors. However, in 2018, the University Administration centralized the management system under the Department of Works in the University.

**Figure 1.** Overview of the study area – (a) location of University of Ilorin in Kwara State, (b) map of the University Permanent Site show the position of the Teak Plantation and (c) terrain elevation view of the plantation area.
3. Methodology

3.1 Dataset

Three different datasets – Sentinel-2 Level C-1 imagery, SRTM 30 m Digital Elevation Model (DEM) and boundary vector data (Table 1) were used in this study. First is the vector file representing the boundary. This was digitized from the scanned paper map of the plantation estate obtained from the department of forestry, University of Ilorin. Second is the Sentinel-2 L1C-1 pre- and post-fire products downloaded from the Sentinel Scientific Data Hub (https://scihub.copernicus.eu/dhus/#/home). The Sentinel-2 is one of the fleets of dedicated European Union owned Satellites designed to provide the wealth of data and imagery that are central to Europe’s Copernicus environmental programme [27], [28]. The first (pre-fire) imagery which was collected on the 12th of December 2019 represents the teak plantation before the fire incident and the second (post-fire imagery) was acquired on the 10th of February, 2020. Also used in this study (for terrain visualization) is a 1-arc second DEM downloaded from OpenTopography (www.opentopography.org). The DEM is a product of the Shuttle Radar Topography Mission jointly carried out by NASA and National Geospatial-Intelligence Agency (NGA). The mission has provided topographical data for 80 percent of the earth’s land surface. The 30 m DEM delivered in Geographic Coordinate System was projected to UTM to bring the data to the same coordinate system as the other datasets.

Table 1. Dataset and their sources

| No. | Data                                         | Source                                      |
|-----|----------------------------------------------|---------------------------------------------|
| 1.  | Sentinel 2 (MSIL1C) imagery: 12/12/2019 (Before fire) 10/02/2020 (After fire) | ESA Copernicus Open access hub [www.scihub.Copernicus.eu/dhus/#/home] |
| 2.  | DEM (30 m resolution SRTM)                  | OpenTopography [http://opentopography.org]  |
| 3.  | Map of the Teak Plantation (paper map)      | Faculty of Forestry, University of Ilorin   |

3.2 Image processing and analysis

First, the satellite data was pre-processed. The satellite imagery (Sentinel-2B MSIL1C) is delivered geometrically corrected and geocoded to the Universal Transverse Mercator (UTM) coordinate system, Zone 31 North, World Geodetic System 1984 (WGS84) datum [19]. The two imagery - before and after fire event - were imported into Sentinel SNAP Toolbox, an open source remote sensing software (available via https://step.esa.int/main/download/). In SNAP Toolbox, the imagery was converted to surface reflectance and then resampled to the Band 2 and, subsequently, Bands 2, 3, 4, 8, 11 and 12 (the Blue, Green, Red, NIR and the SWIR 1 and 2) spectrally subset for exported as GeoTiff for further processing in ArcGIS 10.6 software. In ArcGIS environment, the imported bands were layer stacked as single image file for each of the acquisition date and clipped with the boundary of the study area. The information provided by the Sentinel-2 data were utilized to quantify the various parameters needed to identify, map and evaluate the impact of fire.

Once the pre-processing stage was completed, the data was subjected to image interpretation and analysis through band combinations, image classification and burnt area determination. With multispectral imaging sensors, such as those aboard the Sentinel satellites, information from different wavelengths of light is collected and stored in different bands [26], [27]. band combinations of appropriate wavelengths were selected from the subset bands of the pre- and post-fire imagery to create RGB color images. This allows better understanding of the features in imagery and provided guide to extracting specific information from them.

For the image acquired before the fire, agriculture band combination SWIR-1 (B11), near- infrared (B8) and blue (B2) was utilized. This combination is useful for monitoring the health of crops. It
leverages on the interaction of the short-wave and near infrared bands to highlight dense vegetation that appear dark green in the image. Similarly, by leveraging on the Sentinel band combination SWIR-2 (B12), near-infrared (B8) and blue (B2) bands, provides spectral discrimination that highlights fire burnt area within the plantation for visual assessment.

3.3 Image classification and burnt area determination
To evaluate the extent and magnitude of the fire, it was necessary to determine the state of the plantation area before the fire events that will allow quantitative assessment of the spatial distribution of the vegetation (teak) area and the gaps in the plantation. This was done through the process of land use/land cover classification [34]. Prior to the classification process, appropriate training samples were selected; thereafter, the imagery acquired before the fire incident was classified into three land use/land cover classes – vegetation, bare soil and water body using supervised classification Maximum Likelihood Classifier (MLC). MLC is a pixel-based classifier that is widely used and accepted as a classification algorithm that produces accurate classification result [35]. Reliability of the classification process was evaluated using the error matrix determinants – overall accuracy, user and producer accuracy and kappa coefficient [19].

With the SWIR-2 (B12) and near-infrared (B8) bands of Sentinel-2 of the imagery collected in February 2020 (post-fire), fire burnt areas in the plantation was mapped using Normalised Burn Ratio (NBR) index (Equation 1) [28] implemented Raster Calculator of ArcGIS software. Thereafter, the fire burn areas were extracted using pixel thresholding and the resulting image converted from raster to vector to obtain the area coverage. To estimate how much of the teak plants were affected, the burnt area polygon was overlay on the classified image to extract corresponding class information, from which the plantation burn areas were computed.

\[
NBR = \frac{(NIR - SWIR)}{(NIR + SWIR)}
\]  

where NIR is band 8 and SWIR is band 12 of Sentinel-2 data.

3.4 Image affected tree stands and validation
The University of Ilorin Teak Plantation estate employs a 3m by 3m plant spacing scheme. So, the number of trees stands affected in each burn area was estimated by extrapolating the 3 m grid (9 square meters) in the respective burn area [17], [36]. The success rate of the estimated number of affected trees was evaluated using the largest (20.3 ha), most recent (and accessible) fire burn location (see Fig. 2b in section 4). This was done through manual counting of the teak crowns from a high-resolution image of that portion downloaded from SAS Planet (https://sasplanet.software.informer.com/14.12/). In ArcGIS environment, each teak crown was digitized by generating point feature for ease of counting and used as reference data for comparison and estimation accuracy assessment.

4. Result and Analysis
Selecting the appropriate band combinations to create RGB images using Sentinel-2 imagery produced colour pictures that facilitate visual assessment and the identification of the features of interest (Fig. 2). By combining the SWIR-1 (B11), near-infrared (B8) and blue (B2), the different land cover types in the image are more clearly defined in the image before fire incident. For example, the pattern of vegetation presence is revealed area with much concentration of teak plant and where they are sparsely present (Fig. 2a).

Also, combination of the SWIR-2 with NIR and the blue band produced spectral discrimination that allow detecting fire burnt scars in the image (Fig. 2b). The large reddish portion in the southern part of the image which draws attention to this study is the most recent fire event. Specifically, the thermal (SWIR-2) with the NIR combined emphasizes temperature difference [27], [37] resulting to the reddish appearance in the more recent fire event. the other scorches of dark patches in the image highlights earlier fires.
Figure 2. RGB color combination of (a) image collected on December 12, 2019 before fire incidents with bands B11, B8, and (b) image acquired on February 20, 2020 after the fire occurred using Bands B12, B8 and B2.

Figure 3 shows the LULC map of the teak plantation area and the map of the spatial distribution of the burnt areas within the plantation. Outcome of the classification process offers the necessary parameters needed to comprehend the teak plantation in terms of overall landscape, the land cover types and how they occur (Fig. 3a). In the period considered (before fire), vegetation cover constituted the most extensive land cover types in the study area. Accordingly, it accounted for about 419.7 hectares (ha) which amount to 66% of the total area (Table 2). This is followed by bare soil and water body 204.3 ha (32%) and 12.9 ha (2%) of the total area, respectively.
Figure 3. Land use/land cover map of University of Ilorin Teak Plantation (a), and spatial distribution of burnt area within the plantation.

Table 2. Quantitative analysis of LULC classes, burnt area and teak estimation

| LULC classification | Burnt area |
|---------------------|------------|
| ID  | Class     | Area (ha) | No of teaks |
| ID  | Burn Area (ha) | Planted Area |
| 1   | Water      | 12.9      | 2%          |
| 2   | Vegetation | 419.7     | 66%         |
| 3   | Bare soil  | 204.3     | 32%         |
| Total| 636.9     | 693333    |

| Estimated number of affected teak plants |
|-----------------------------------------|
| Area (ha) | No. of trees |
| Total area | 44.2 | 49156 |

To determine the acceptability of the classified map, a total of 96 independent points was selected from high-resolution Google Earth image across the respective land cover classes considered and evaluated for accuracy. Out of the 96 points, 91 pixels were correctly classified, resulting into overall accuracy of 96% (Table 3). In terms of the producer’s accuracy, all the classes between 94% and 96% correct.
Table 3. Result of the LULC classification accuracy assessment of December 2019 image

| Classified      | Vegetation | Bare soil | Water | Total Ref Points | User’s Accuracy |
|-----------------|------------|-----------|-------|------------------|-----------------|
| Vegetation      | 36         | 1         | 1     | 38               | 95%             |
| Bare soil       | 1          | 30        | 0     | 31               | 97%             |
| Water           | 1          | 1         | 25    | 27               | 93%             |
| Total Classified Points | 38         | 32        | 26    | 96               |                 |
| Producer's Accuracy | 95%       | 94%       | 96%   |                  |                 |

Overall Accuracy: 95%

Analysis of the classification and burnt area (Fig. 3) allows quantitative evaluation of the forest fire impact on the Teak plantation. Map of the burnt area shows that the fire incident occurred at various locations within the teak plantation area at varying spatial extent (Fig. 3b). The area affected sums up to 54.8 ha (Table 2), constituting 8.6% of the entire plantation area. It is observed that the fire occurred majorly along the boundary and at locations close to settlement areas (see Fig. 2 and Fig. 3b). This is an indication that the origin of the fire may be connected with accessibility to the plantation, suggesting they were possibly caused by human activities. The total number of teak plants within the vegetation class is estimated to be 466333 tree stands (Table 2). Using the same deductive technique, the number of teak stands destroyed within the total burn area of 44.2 ha was estimated to be 49156 trees. Since most of the identified burn areas are not easily accessible, one of the detected burn areas covering about 20.3 ha was used as validation site (see Table 2). Analysis of the success rate from the actual number of teak stands counted (17621) and its corresponding estimate (18222) yielded an excess of 3% approximation (Table 4). On-site assessment shows that trees along the river channel are mostly not of the plantation forest species.

Table 4. Estimation success level

| Reference burn Area (ha) | Estimated | Actual | Difference | Error (%) |
|--------------------------|-----------|--------|------------|-----------|
| 16.4                     | 18222     | 17621  | 601        | +3        |

Fire and the severity of burn is critical in determining the effect of fire on forest ecosystem [37] and the regeneration process, composition and structure of forest [24]. The teak plantation is characterised by open forest (Fig. 2) of large quantity of ground layer biomass enriched with dry fallen leaves, moderately dense canopy and undergrowth shrub. One of the key challenges confronting effective management of the vast plantation estate is manpower. Though labour and capital intensive, teak requires timely pruning to improve forest health and prevent fire [9], [17]. Because pruning creates space between tree crowns, it slows down the spread of fire and minimizes damages done to the trunk. Generally, teak plant is often claimed to be highly resistant to fire [21]. Without careful assessment of the burn over some passage of time, which may require monitoring the forest over the length of the next growing season [20], [21], it is difficult to distinguish between teak recovery potential and delayed mortality. Burn severity map is a useful tool for evaluating post-fire forest recovery. But in the current case study, absence of prior knowledge of and accessibility to most of the burn locations to collect in situ data on burn severity is a hinderance to mapping burn severity for recovery monitoring and evaluation. From the pattern of the distribution of burn areas, our proposition is that the fire incidents were initiated through human activities and fueled by the trio of canopy structure, water-stressed undergrowth shrub and accumulated layers of ground biomass comprising majorly of dry leaves. It is equally hypothesized that frequent fire incursion is largely responsible for delayed growth, forest regeneration and forest gap. These propositions are subject to further enquiry using multi-temporal
vegetation analysis, burn detection, and integrating factors such as temperature, precipitation, topography, vegetation abundance and vigour, road network, land use and other social metrics [5], [38], [39].

5. Conclusions
In this study, we detected and mapped the extent and distribution of fire burn areas within the University of Ilorin Teak Plantation and assessed their impact on the teak plants using Sentinel-2 satellite imagery. Methodologically, we combined supervised classification method Maximum Likelihood classifier and Normalized Burnt Ratio to accurately delineate fire extents and provide quantitative assessment of the impact of the fire on the teak plant. The study has shown that about 419.7 ha (66%) of the teak estate is actually occupied by Teak while 204.3 ha (32%) constitutes gap (forest gap). It is further revealed that the plantation contains approximately 466333 teak plants out of which 49156 tree stands within the 54.8 ha of burnt area were affected by the fire events.

The spectral and spatial resolution of the imagery used is a limitation to discriminating between teak plant and other trees species such as cashew tree and the identification of individual tree crown for objective inventoring all of which can be achieved using Aircraft or UAV-based LiDAR and hyperspectral imaging. However, this study is a significant contribution towards improving the management strategies to boost the projected economic and ecological services. Sentinel2 data collected over time can be used to monitor the plantation, especially in relation forest recovery using this study as a baseline. Future studies are significant to better understand the driving forces behind the annual fire incidence and its contribution to plantation loss for effective risk assessment. This would further accelerate action plan on how the 204.3 ha (32%) forest gap can be replanted. In addition, socio-economic studies are necessary to provide comprehensive appraisal of the teak estate in terms of its economic and social values.

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